The 29th Session of the GEWEX Scientific Steering Group (SSG-29)
Sanya, China, February 6-9, 2017

New Approaches to Improving NWP Generated Precipitation Predictions

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February 8, 2017

Grand Challenge on Water Resources

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From Trenberth and Asrar, 2014, Surv. Geophys.

The overarching questions:

- ✓ **How can we better understand and predict precipitation variability and changes?**
- ✓ **How do changes in land surface and hydrology influence past and future changes in water availability and security?**

One of the specific questions on precipitation modeling:

- ✓ **How do models become better and how much confidence do we have in climate predictions and projections of precipitation?**

Progresses in Numerical Weather Modeling and Predictions

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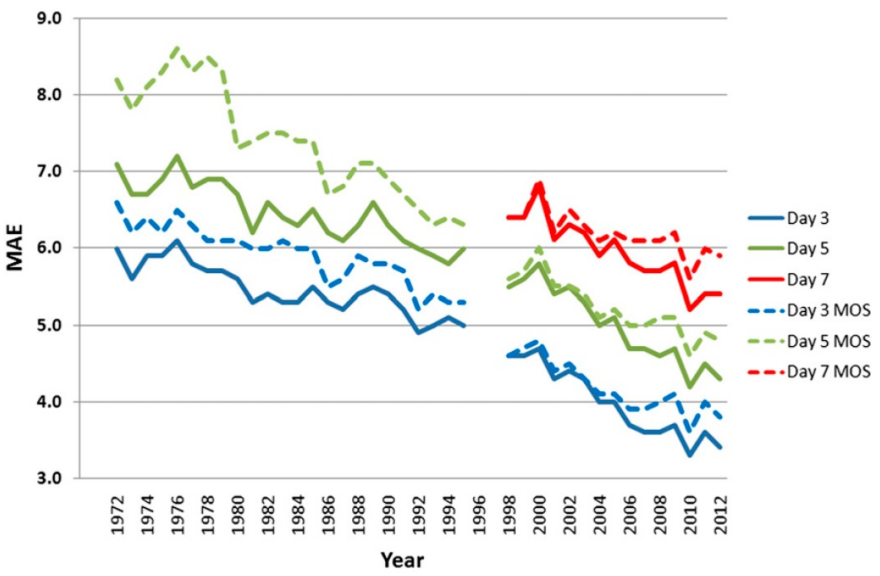
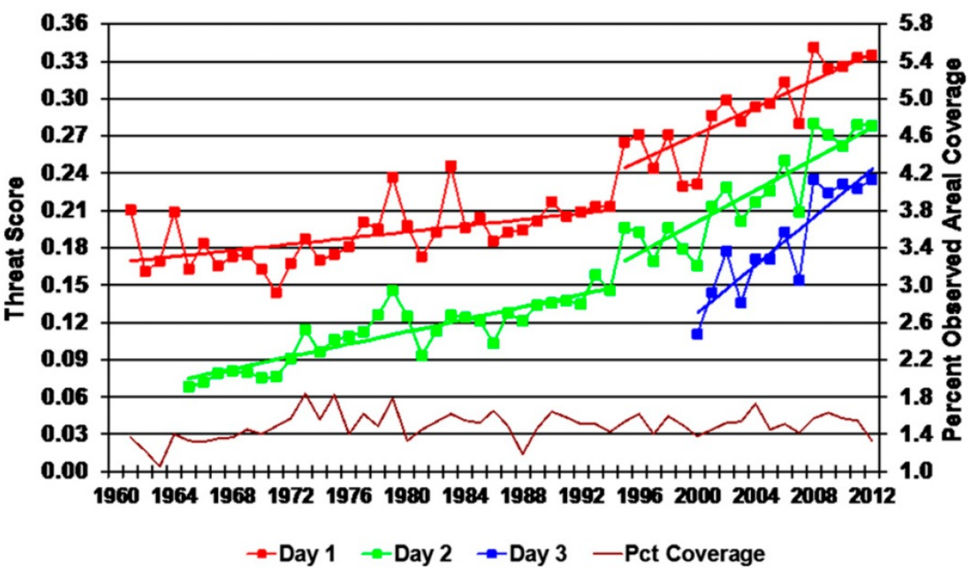
NCEP Precipitation and Temperature Forecasting Skills

Daily Max Temperature Forecast MAE



QPF Skill Scores



Novak et al., WAF, 2013

How to Improve Numerical Weather Modeling and Predictions?

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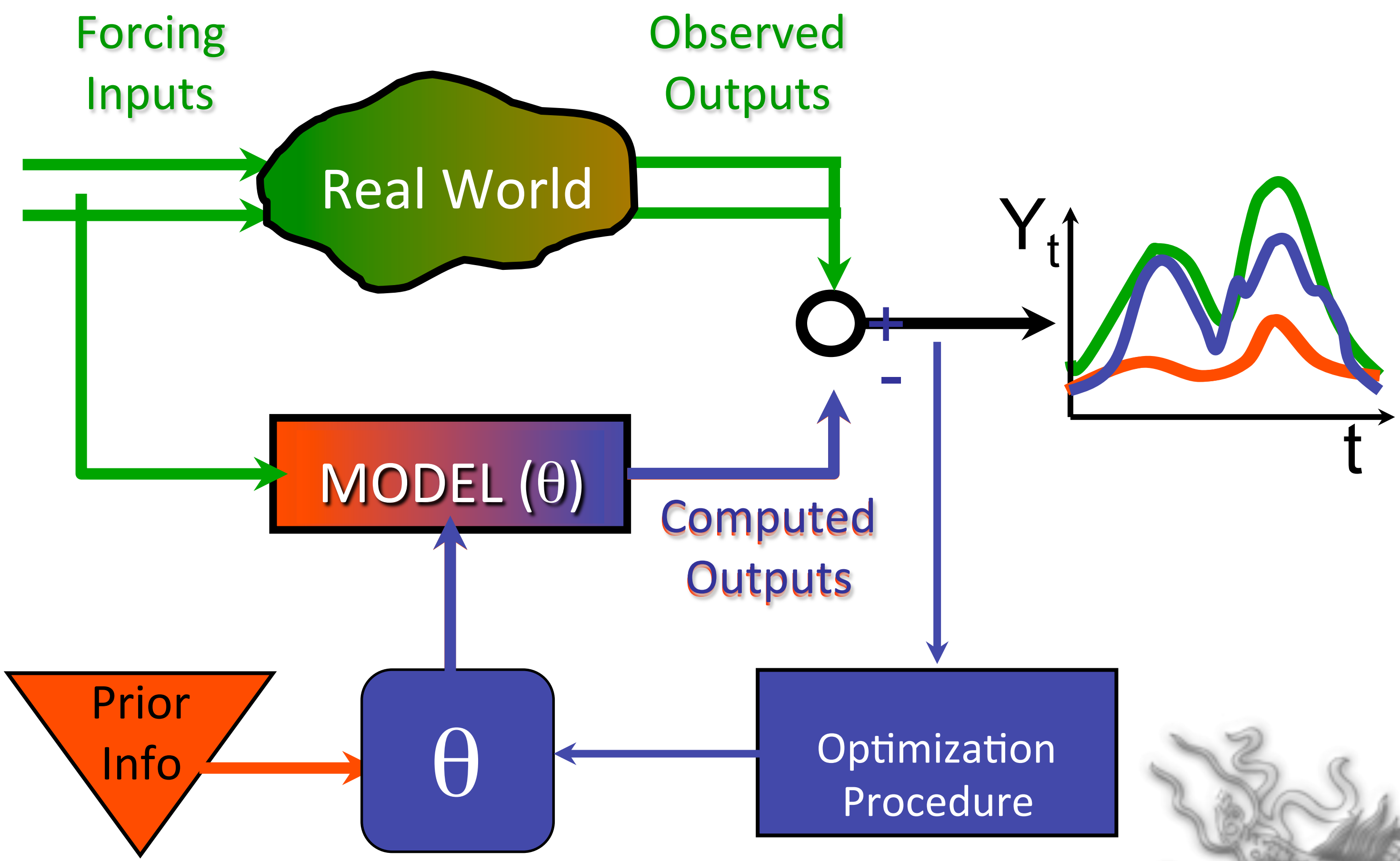
- Enhance Model Physical Representations
  - Better models
  - Higher space/time resolution
  - Better numerical schemes
  - Multi-model ensemble predictions
- Enhance Representations of External Forcings and Initial/ Boundary Conditions
  - Better Observational Systems
  - Better Data Assimilation Methods
- Enhance the Estimation of Model Parameters
  - Quantifying parametric uncertainties
  - Optimize model parameters to match simulations with observations

Two New Approaches to Improving Precipitation Predictions

- Automatic model calibration to improve precipitation predictions

- A statistical based approach to generate perturbed physics ensemble precipitation predictions

Illustrating Model Calibration



Challenges in Automatic Calibration of Large Complex Models

- High-dimensionality of the uncertain parameters (10’s -100’s)
- High-dimensionality of the model outputs (can be millions)
- Difficult to prescribe parameter uncertainties (the priors)
- Models may be expensive to evaluate (many CPU-hours)
- Complex models show highly nonlinear (may be discontinuous) input-output relationships
- Data scarcity for the full system (difficult to calibrate)
- Models are often created by data far from operating conditions
    - extrapolation may be needed
- “Unknown unknowns” can greatly complicate the UQ process.

A Model Calibration Strategy For Large Complex Models

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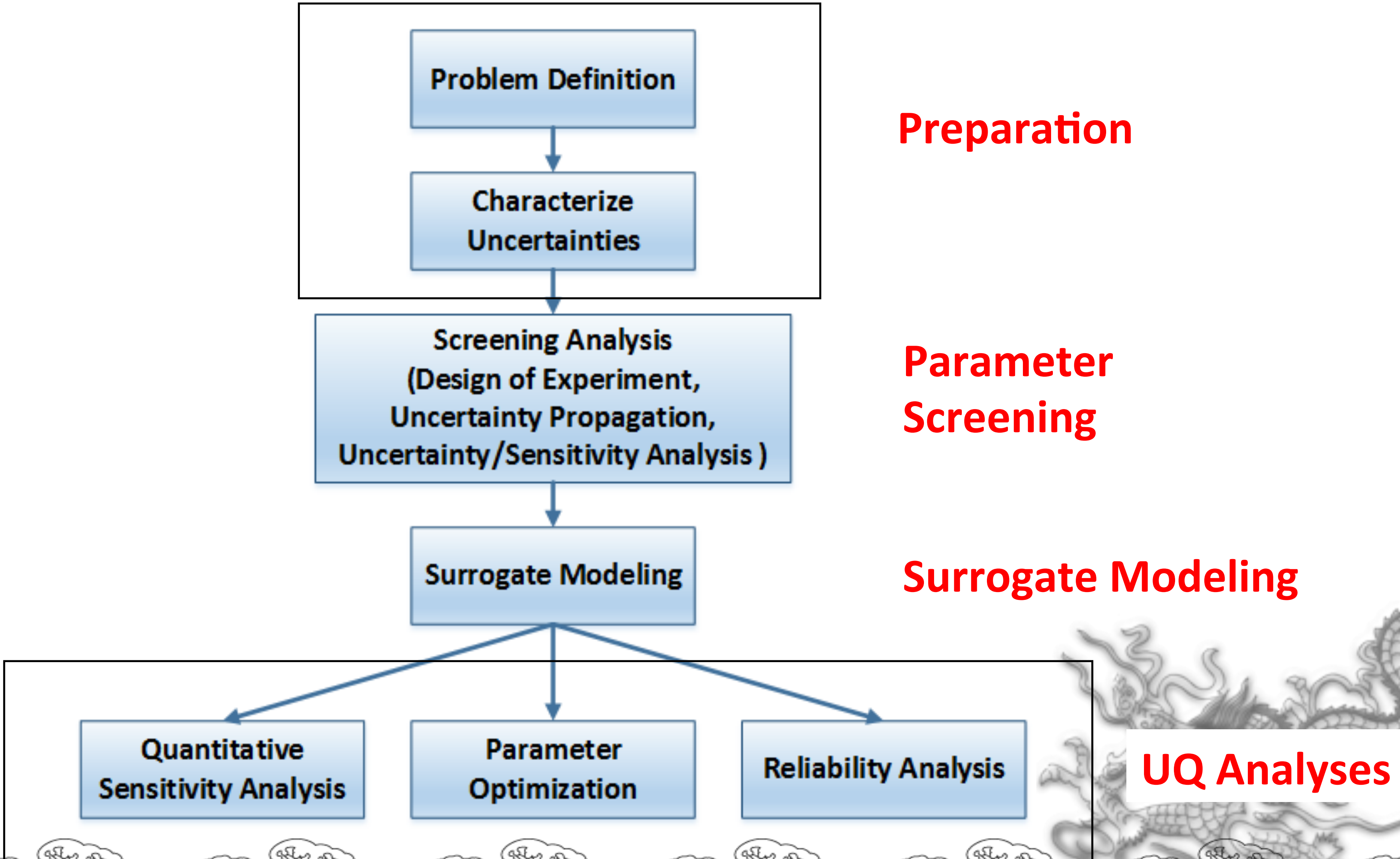
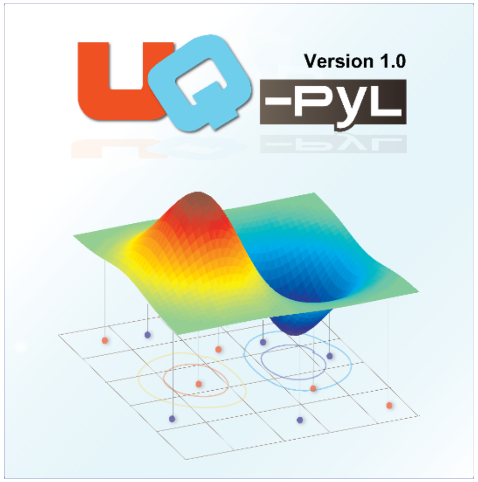


UQ-PyL – Uncertainty Quantification Pthyon Laboratory

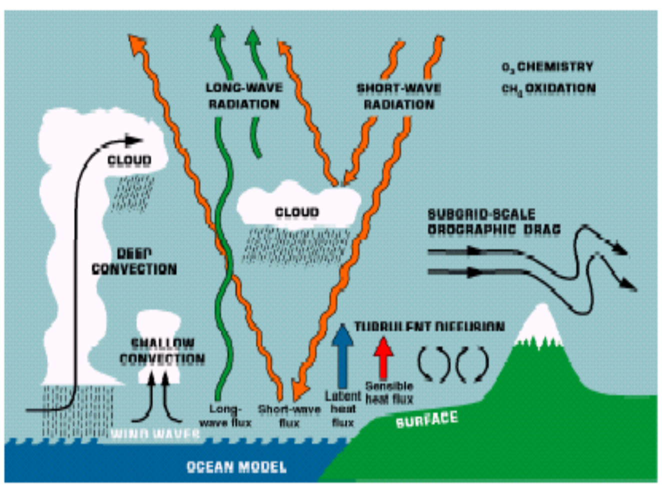
- A new, general-purpose, cross-platform UQ framework with a GUI
- Made of several components that perform various functions, including
  - *Design of Experiments*
  - *Statistical Analysis*
  - *Sensitivity Analysis*
  - *Surrogate Modeling*
  - *Parameter Optimization;*

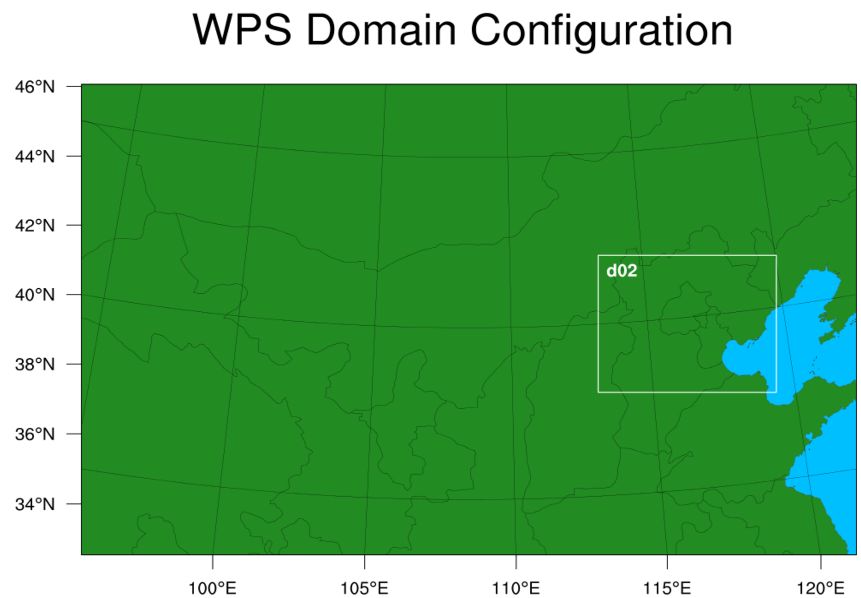


- Suitable for parametric uncertainty analysis of any computer simulation models
- Download: http://www.uq-pyl.com

Optimization of the WRF Model Parameters

- Weather and Research Forecast (WRF) is a widely used regional weather and climate modeling system. The model includes seven major physical processes:
  - Microphysics
  - Cumulus Cloud
  - Surface Layer
  - Land-Surface
  - Planetary Boundary Layer
  - Longwave Radiation
  - Shortwave Radiation





- 2-level nested grids
  - Level 1: 27km, 60×48 grids
  - Level 2: 9km, 87x55 grids

WRF Model Parameters To Be Examined

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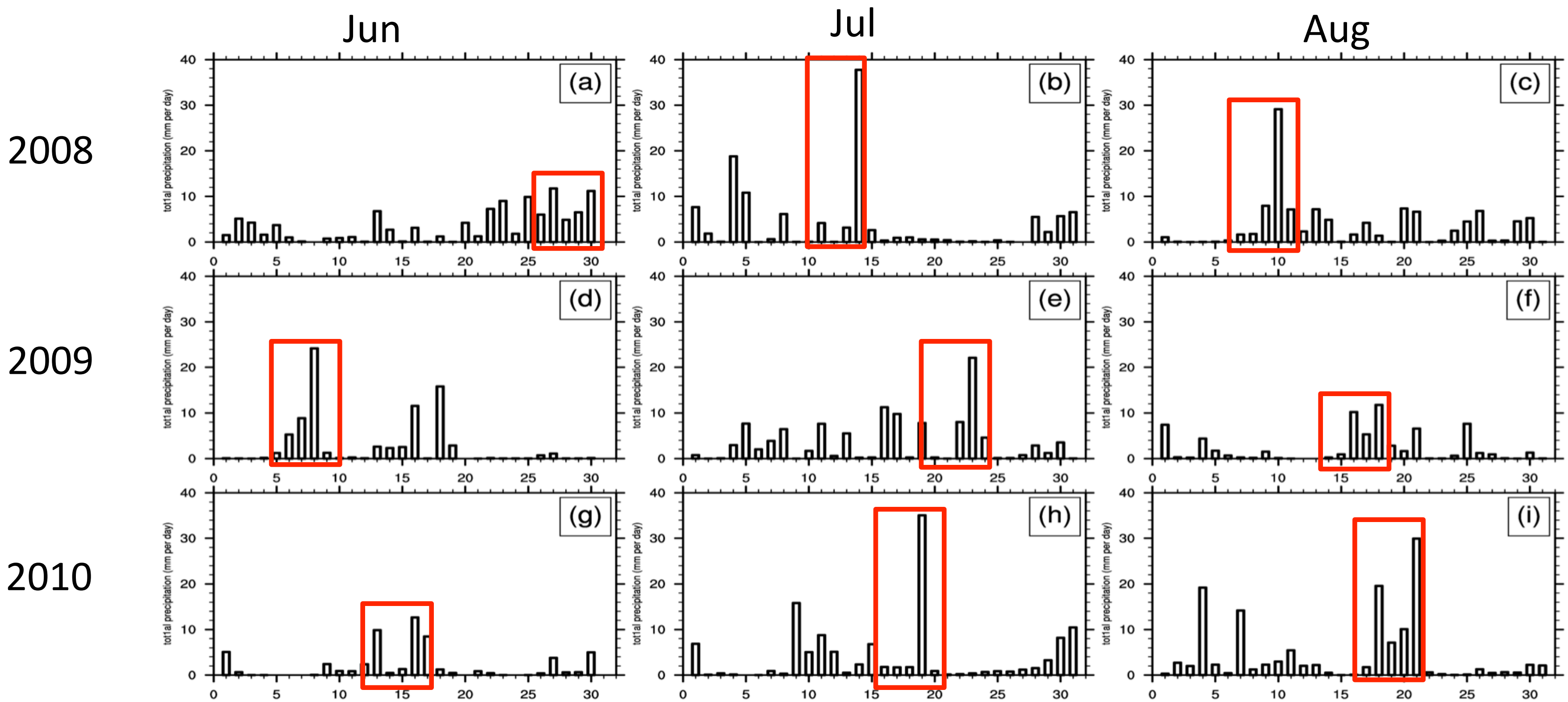
number	scheme	name	Default	range	description
1	Surface layer (module_sf_sfclay.F)	xka	0.000024	[0.000012 0.00005]	The parameter for heat/moisture exchange coefficient
2		CZO	0.0185	[0.01 0.037]	The coefficient for coverting wind speed to roughness length over water
3	Cumulus (module_cu_kfeta.F)	pd	0	[-1 1]	The coefficient related to downdraft mass flux rate
4		pe	0	[-1 1]	The coefficient related to entrainment mass flux rate
5		ph	150	[50 350]	Starting height of downdraft above USL
6		TIMEC	2700	[1800 3600]	Compute convective time scale for convection
7		TKEMAX	5	[3 12]	the maximum turbulent kinetic energy (TKE) value between the level of free convection (LFC)and lifting condensation level (LCL)
8	Microphysics (module_mp_wsm6.F)	ice_stokes_fac	14900	[8000 30000]	Scaling factor applied to ice fall velocity
9		n0r	8000000	[5000000 12000000]	Intercept parameter rain
10		dimax	0.0005	[0.0003 0.0008]	The limited maximum value for the cloud-ice diameter
11		peaut	0.55	[0.35 0.85]	Collection efficiency from cloud to rain auto conversion
12	short wave radiation (module_ra_sw.F)	cssca	0.00001	[0.000005 0.00002]	Scattering tuning parameter in clear sky
13		Beta_p	0.4	[0.2 0.8]	Aerosol scattering tuning parameter
14	Longwave (module_ra_rrtm.F)	Secang	1.66	[1.55 1.75]	Diffusivity angle
15	Land surface (module_sf_noahlsm.F)	hksati	0	[-1 1]	hydraulic conductivity at saturation
16		porsl	0	[-1 1]	fraction of soil that is voids
17		phi0	0	[-1 1]	minimum soil suction
18		bsw	0	[-1 1]	Clapp and hornbereger "b" parameter
19	Planetary Boundary Layer (module_bl_ysu.F)	Brcr_sbrob	0.3	[0.15 0.6]	Critical Richardson number for boundary layer of water
20		Brcr_sb	0.25	[0.125 0.5]	Critical Richardson number for boundary layer of land
21		pfac	2	[1 3]	Profile shape exponent for calculating the momentum diffusivity coefficient
22		bfac	6.8	[3.4 13.6]	Coefficient for prandtl number at the top of the surface laer
23		sm	15.9	[12 20]	Countergradient proportional coefficient of non-local flux of momentum moh 2002

Forecasted Events

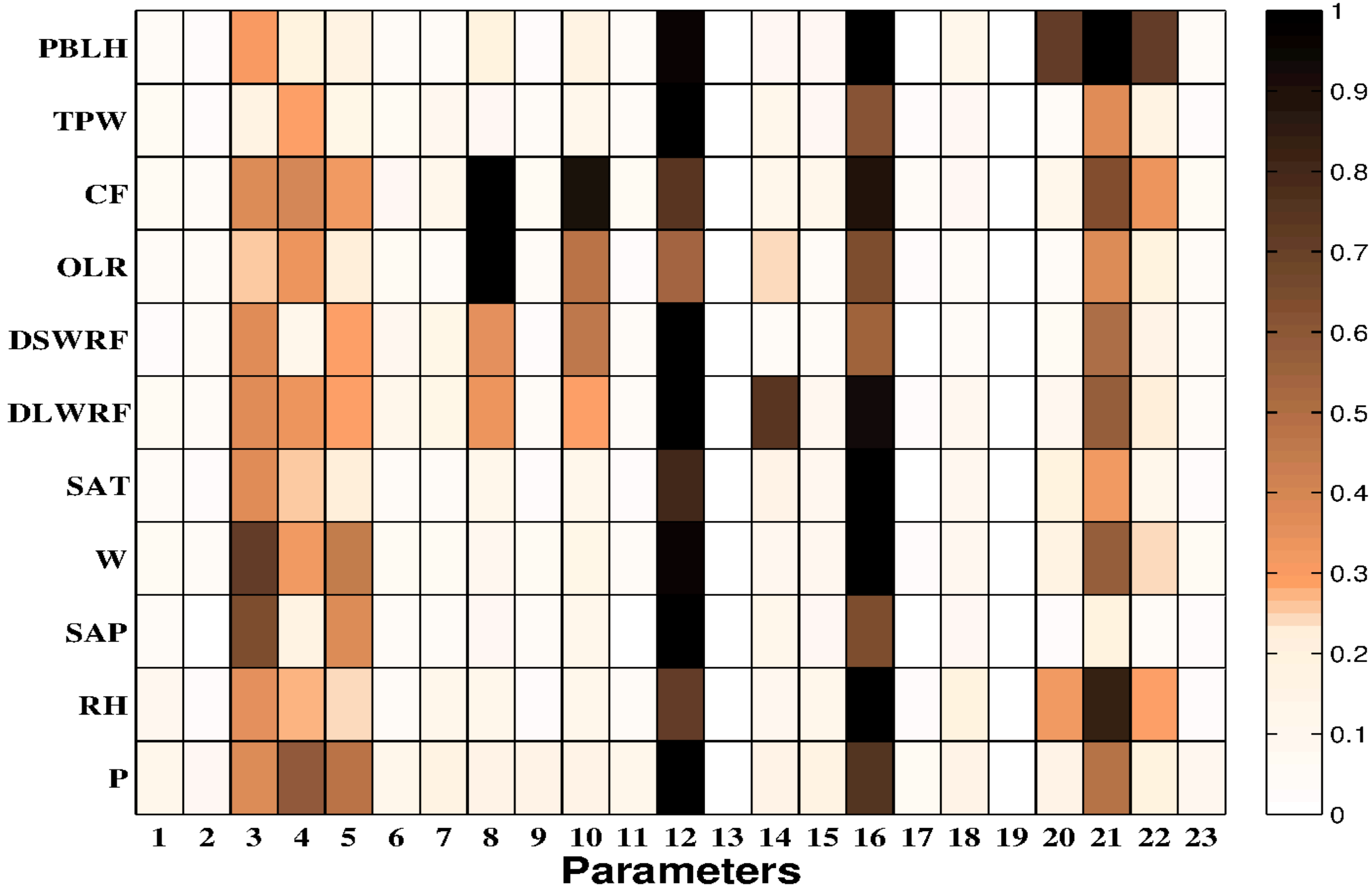


降雨事件	模拟日期	模拟日期	模拟日期
(a)---(c)	20080626-20080630	20080710-20080714	20080807-20080811
(d)---(f)	20090605-20090609	20090720-20090724	20090814-20090818
(g)---(i)	20100613-20100617	20100716-20100720	20100817-20100821

The Experimental Setup: Model Setup

- 2-Level nested grids:
  - Level 1: 27 km, with 60x48 grids
  - Level 2: 9 km, with 87x55 grids
- Nine 5-day forecasts during Jun-Aug from 2008-2010
- NCEP reanalysis data used to initiate the forecasts
- 23 WRF model parameters examined for study their sensitivity with respect to precipitation forecast
- Sensitivity method used: Morris-One-At-a-Time (MOAT)
- Optimization method used:
  - Adaptive Surrogate Modeling-based Optimization (ASMO)
- Computational cost
  - 4.5 CPUs for one 5-day forecast
  - Nine 5-day forecasts require 180 CPUs

Summary of Parameter Sensitivities to Different Model Outputs



[Jiping Quan et.al. 2016, RQJMet]

Automatic Optimization of WRF Model: The Experiment Setup

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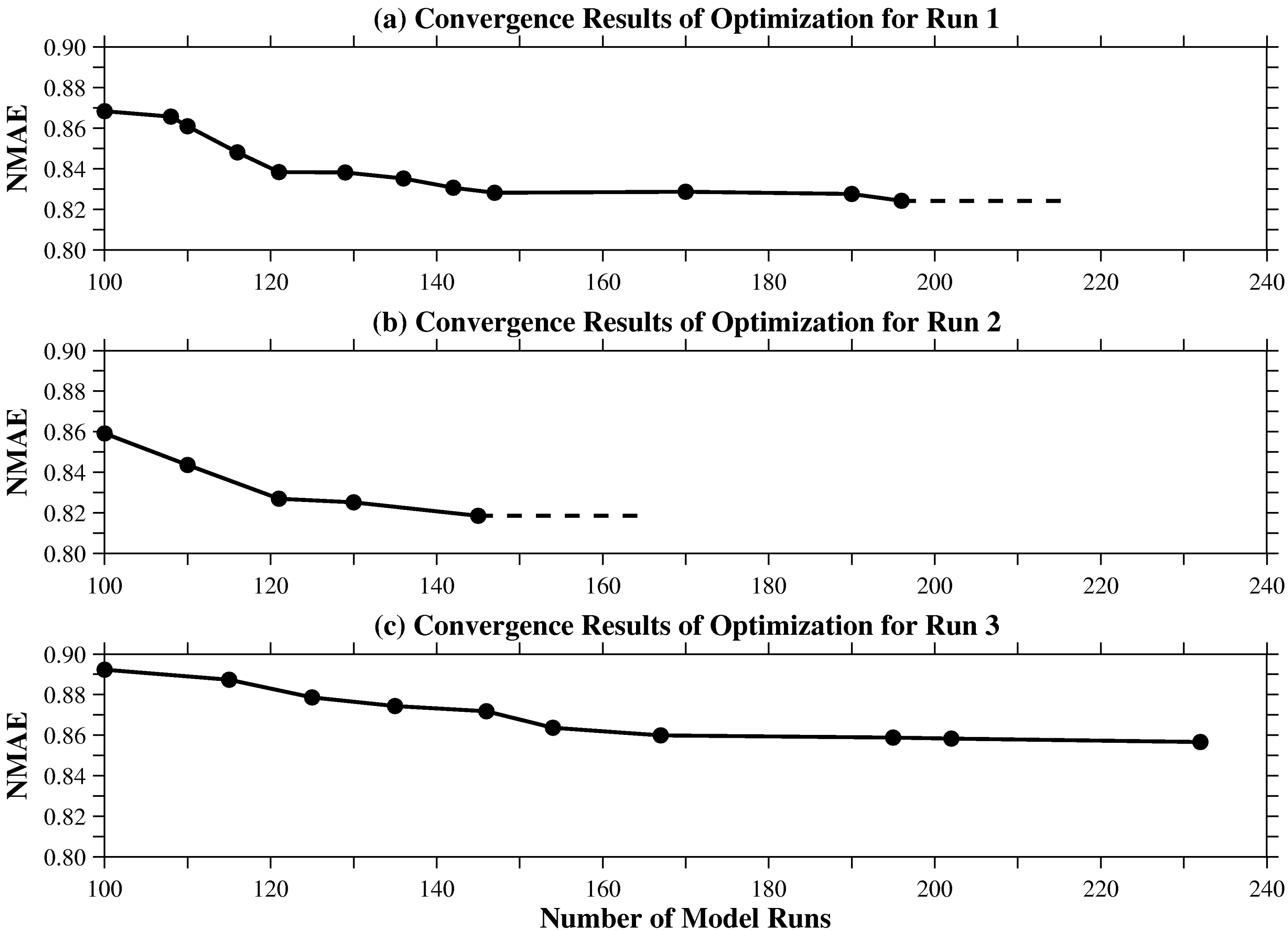
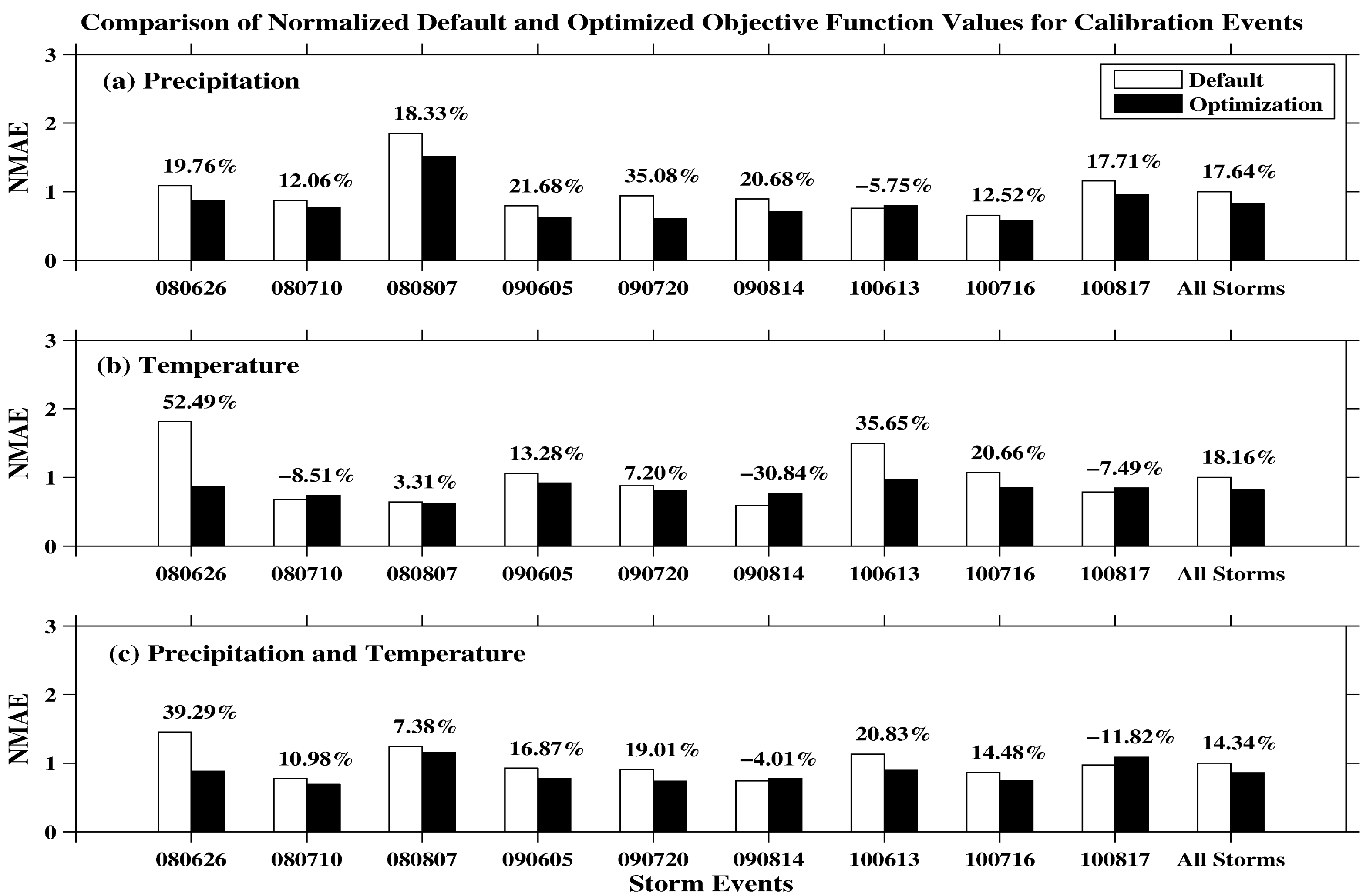
- Adaptive Surrogate Modeling based Optimization (ASMO) method is used to optimize the eight most sensitive parameters found by global sensitivity analysis:
  - Parameter optimized:
    - P3、P4、P5、P8、P10、P12、P16、P21
  - Performance measures Used:
    - Mean Absolute Error (MAE):
    - Thread Score (TS)
    - Bias Score
    - SAL (Structure, Amplitude, Location)
  - Three Optimization Runs:
    - Optimize P only
    - Optimize SAT only
    - Optimize both P and SAT

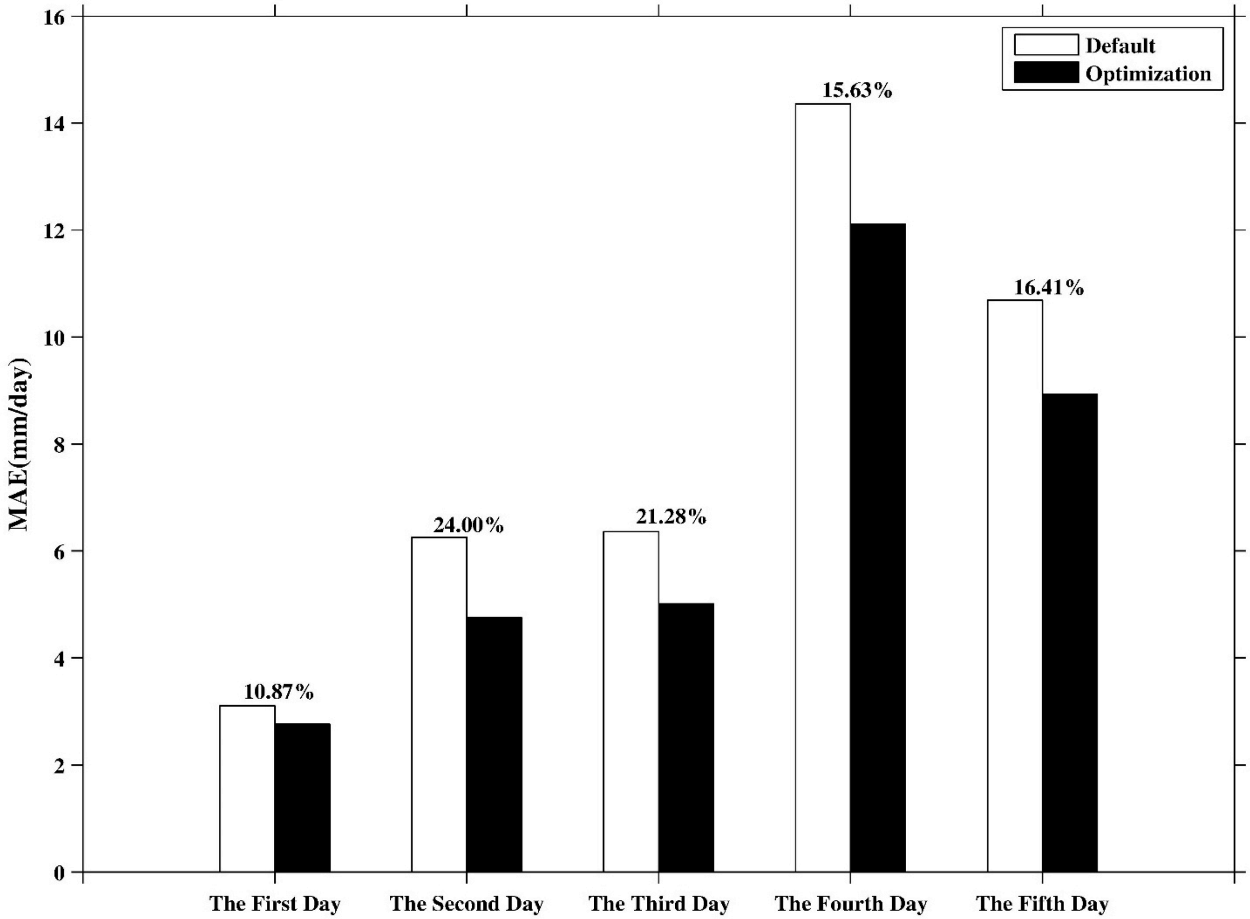
The Optimization Results



Improvement in Performance Measure - MAE



Improvement in Performance Measure Based on Lead-times

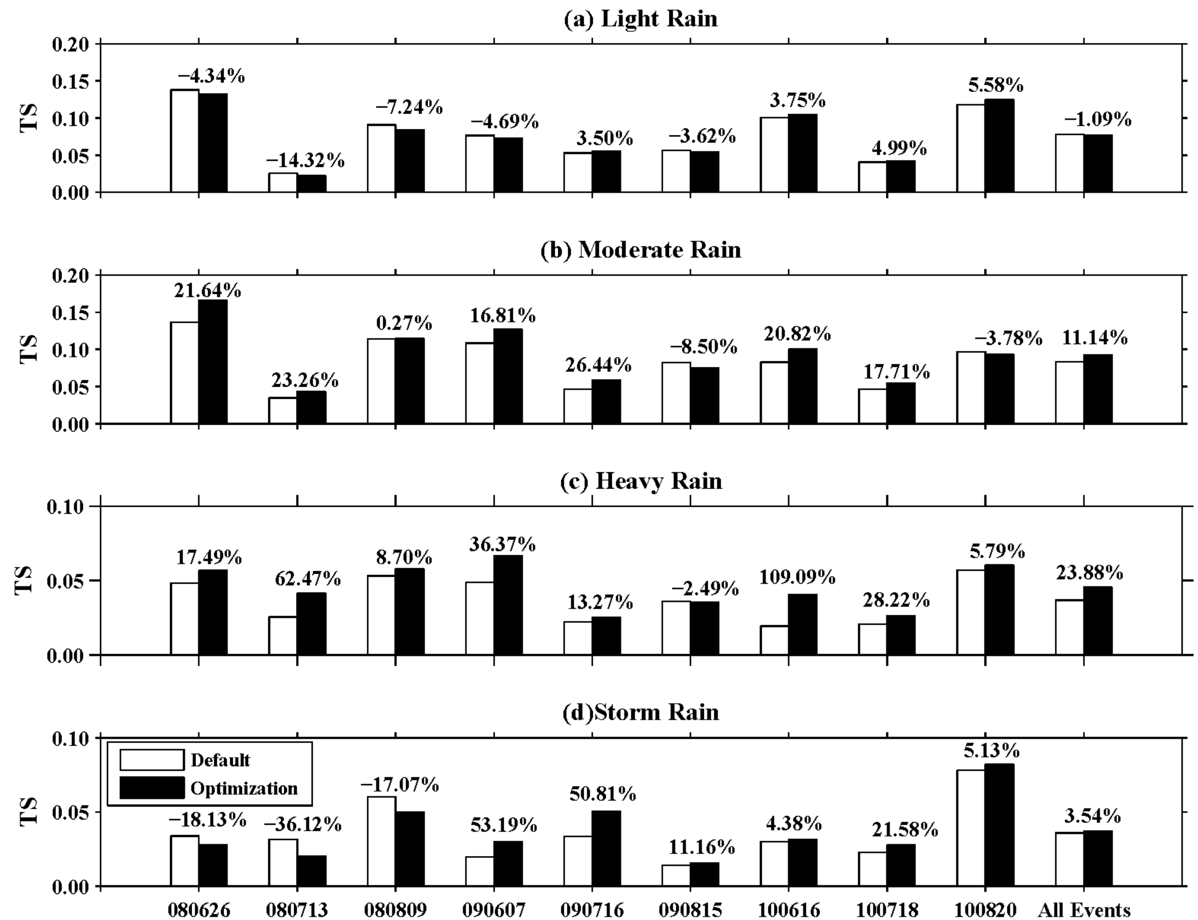


Improvement in Performance Measure - TS

$$TS = \frac{NA}{NA + NB + NC}$$

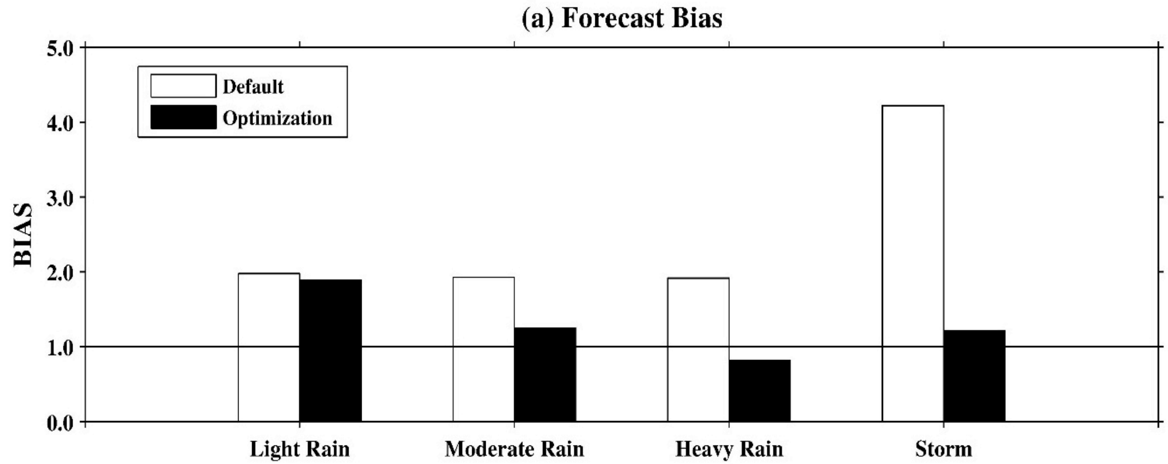
Obs\Fcst	Yes	No
Yes	NA	NC
No	NB	ND

Category	Threshold：mm
Light Rain	(0.1，10]
Moderate Rain	(10,　25]
Heavy Rain	(25，50]
Storm	(50，100]
Severe Storm	(100，250]



Improvement in Performance Measure – Other Scores (Bias & SAL)

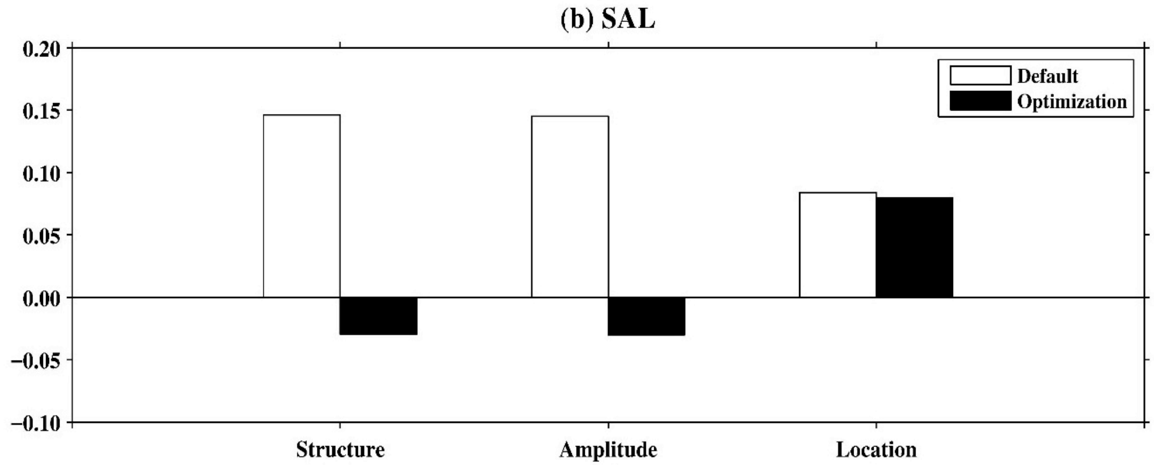
$$\text{Bias} = \frac{\text{na} + \text{nb}}{\text{na} + \text{nc}}$$



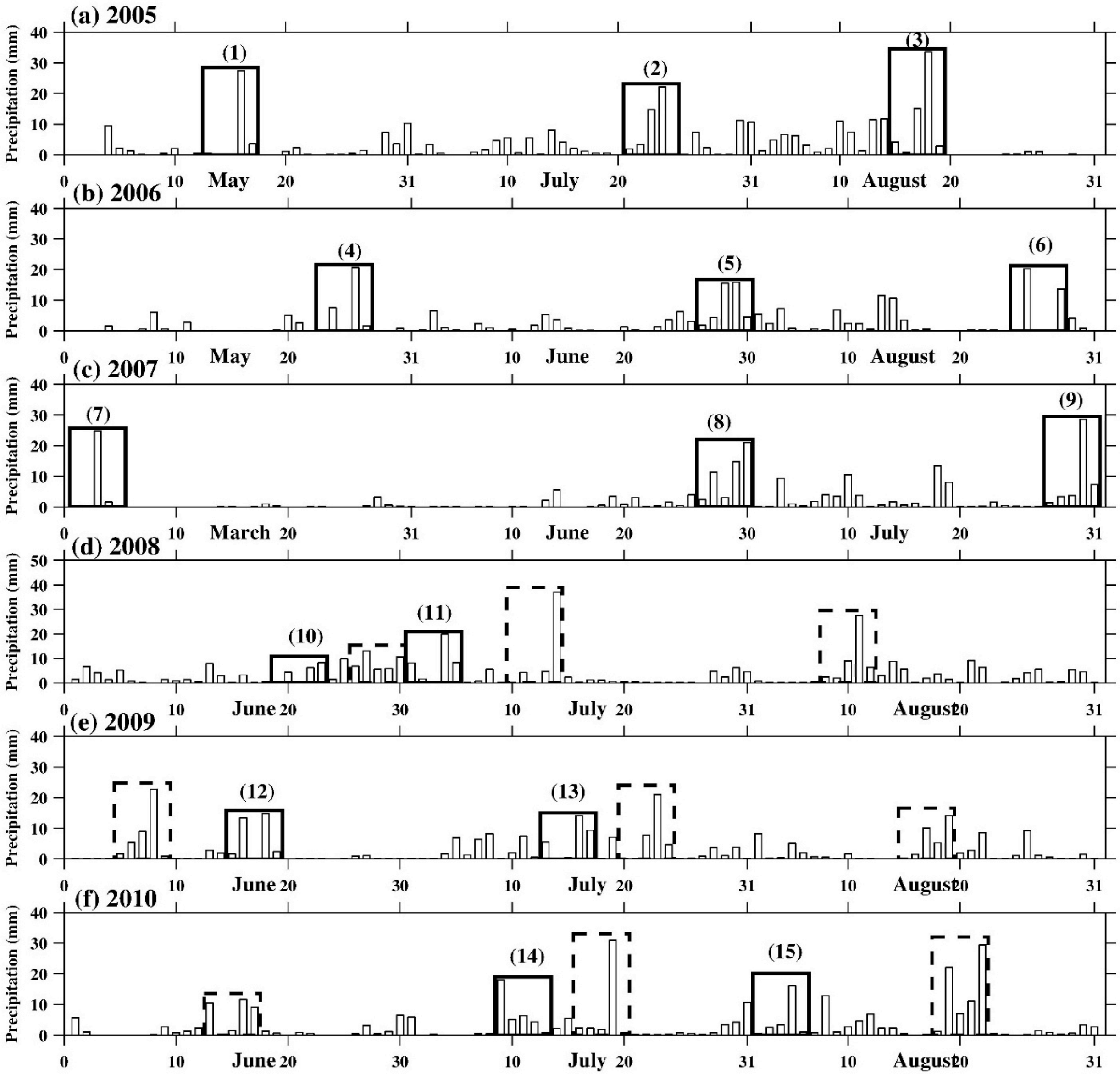
$$S = \frac{V(R_{\text{forecast}}) - V(R_{\text{obs}})}{0.5[V(R_{\text{forecast}}) + V(R_{\text{obs}})]}$$

$$A = \frac{D(R_{\text{forecast}}) - D(R_{\text{obs}})}{0.5[D(R_{\text{forecast}}) + D(R_{\text{obs}})]}$$

$$L_1 = \frac{|X(R_{\text{forecast}}) - X(R_{\text{obs}})|}{d}$$



The Validation Events



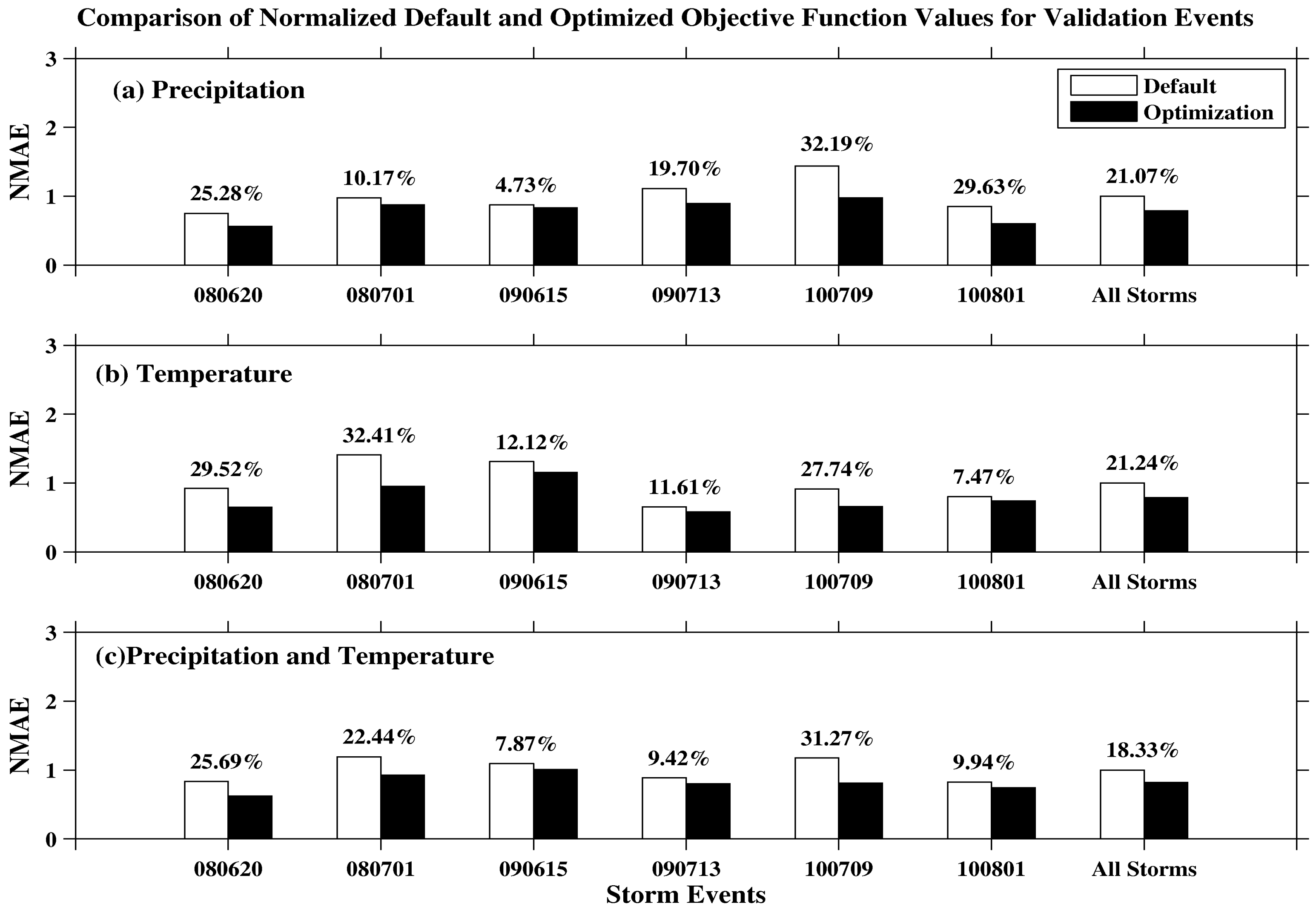
Calibration events:

- Dashed lines

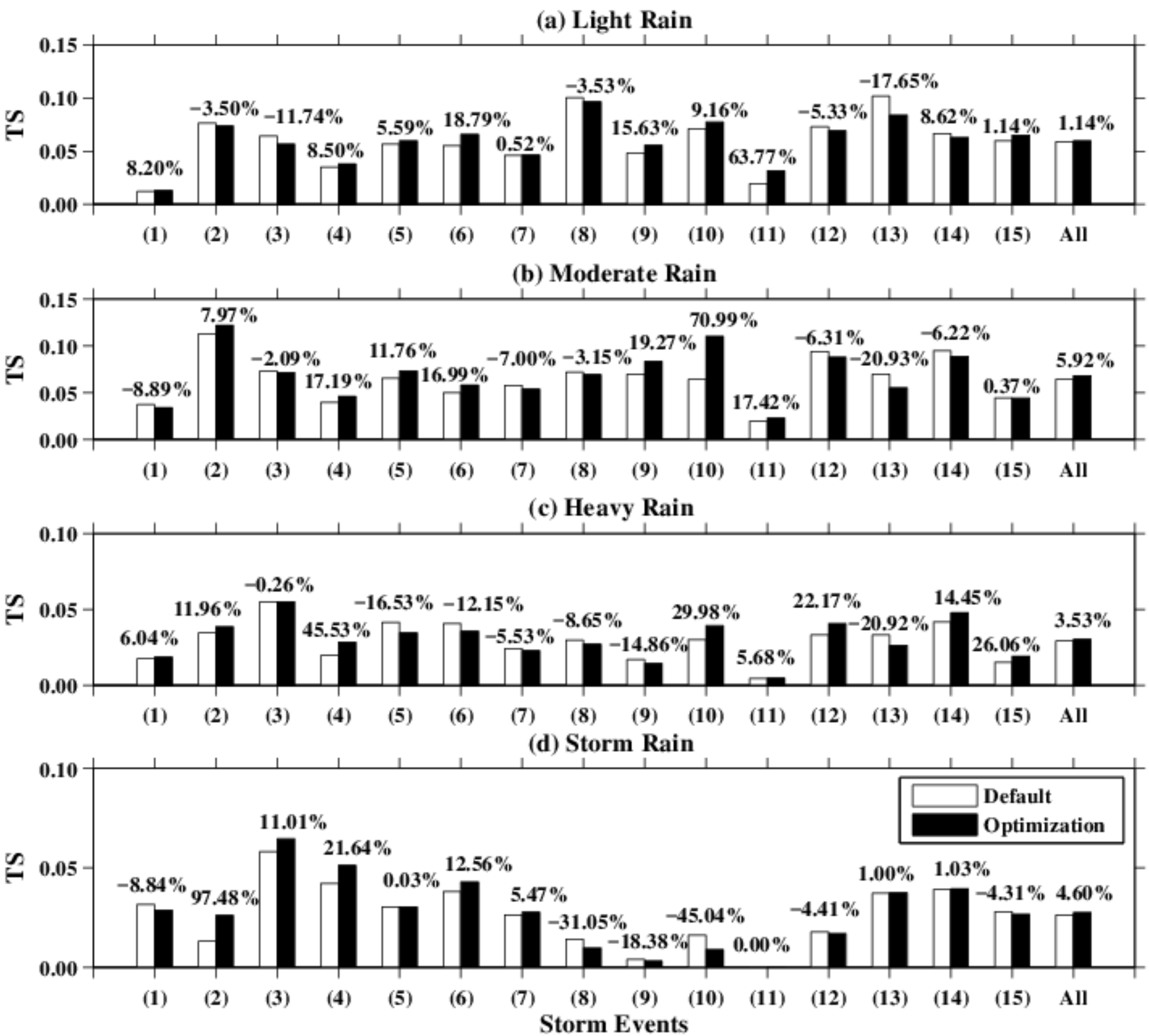
Validation events:

- Solid lines

Improvement in Validation Events



Improvement in Validation Events



Summary and Discussion of WRF Parametric Uncertainty and Optimization Research

- Considerable parametric uncertainties exist in WRF model
- The most sensitive parameters identified for precipitation and surface air temperature are:
  - P3, P4, P5, P8, P12, P16, P18, and P21
- Optimization experiments with the eight most sensitive parameters for 9 calibrated events has improved the model performance by **14-18%**
- Other performance measures for calibrated events confirmed the improvement
- Validation using 15 independent storm data shows an improved model performance by **18-21%**

The Perturbed Physics Ensemble Precipitation Predictions

➢ WRF is millions of models in one platform (WRF3.7.1):

Microphysics	Long-wave	Short-wave	Land surface	PBL+Surface layer	Cumulus
23	8	8	7	16	13

- ✓ Total potential number of combinations: $23 \times 8 \times 8 \times 7 \times 16 \times 13 =$ **2143232**

What combinations?

➢ The Objectives:

- ✓ To identify 20-30 good combinations of WRF parameterization schemes based on common skill metrics, including biases, thread scores, ranked probability scores, ROCs, etc.
  - *Accuracy*
  - *Resolution*
  - *Reliability*

The Guiding Principles

- Selection of schemes starts with the physical process that exhibits the largest variance. Then proceed with the process with the next largest variance, and so on.

- If a scheme has appeared in the best combinations based on any performance metrics, keep this scheme in the pool of potential schemes;

- If a scheme has appeared in the worst combinations consistently, eliminate this scheme from the pool of potential schemes;

- If a scheme always shows up in the middle performing category, then keep the ones which exhibit the largest variance in performance metrics.

The Selection Process

- Step 1: Remove the schemes not suitable based on prior knowledge and experience;
- Step 2: Sample a pre-specified number of combinations (~100-200) using a uniform design of experiment approach;
- Step 3: Compute the variances of all physical processes. Start with the process with the highest variance and then
  - Perform the Tukey hypothesis test to evaluate the selected combinations.
  - Retain the schemes involved in the best performing combinations
  - Get rid of the schemes that are consistently in the worst performing combinations.
  - For the schemes in the moderate performing combinations, analyze the variance of the performance metrics for each scheme. Retain the schemes whose variance is relatively large
- Step 4:For the remaining schemes, start a new round of screening by sampling a new set of combinations using a uniform design, and the repeat Step 2 and Step 3;
- Step 5: Stop when no more schemes can be removed based on the guiding principles or when 20-30 combinations are remaining;
- Step 6: Construct the ensemble from the remaining schemes, and conduct ensemble forecasting experiments and validation.

The Tukey Honest Significance Difference (TUKEY-HSD) Test

- Tukey HSD is a single-step multiple comparison procedure and statistical test. It can be used on raw data or in conjunction with an ANOVA (Post-hoc analysis) to find means that are significantly different from each other.

- It compares all possible pairs of means, and is based on a *studentized range distribution* (q).

- Tukey's test compares the means of every treatment to the means of every other treatment; that is, it applies simultaneously to the set of all pairwise comparisons

$$\mu_i - \mu_j$$

- It identifies any difference between two means that is greater than the expected standard error. The confidence coefficient for the set, when all sample sizes are equal, is exactly $1 - \alpha$. For unequal sample sizes, the confidence coefficient is greater than $1 - \alpha$. In other words, the Tukey test is conservative when there are unequal sample sizes.

Latin Hypercube Sampling

- A multidimensional stratified sampling method;
- Define the number of samples that participated in the calculation;
- Devide each input into N columns with equal probability

$$x_{i0} < x_{i1} < x_{i2} < x_{i3} < \cdots < x_{in} < \cdots < x_{in}$$

besides $P(x_{in} < x < x_{in+1}) = 1/N$

- For each column, only one sample is taken, and the location of the bin in each column is random.

o			X	
	X		o	
	o	X		
X				o
		o		X

The Screening Criteria – ETS and Bias

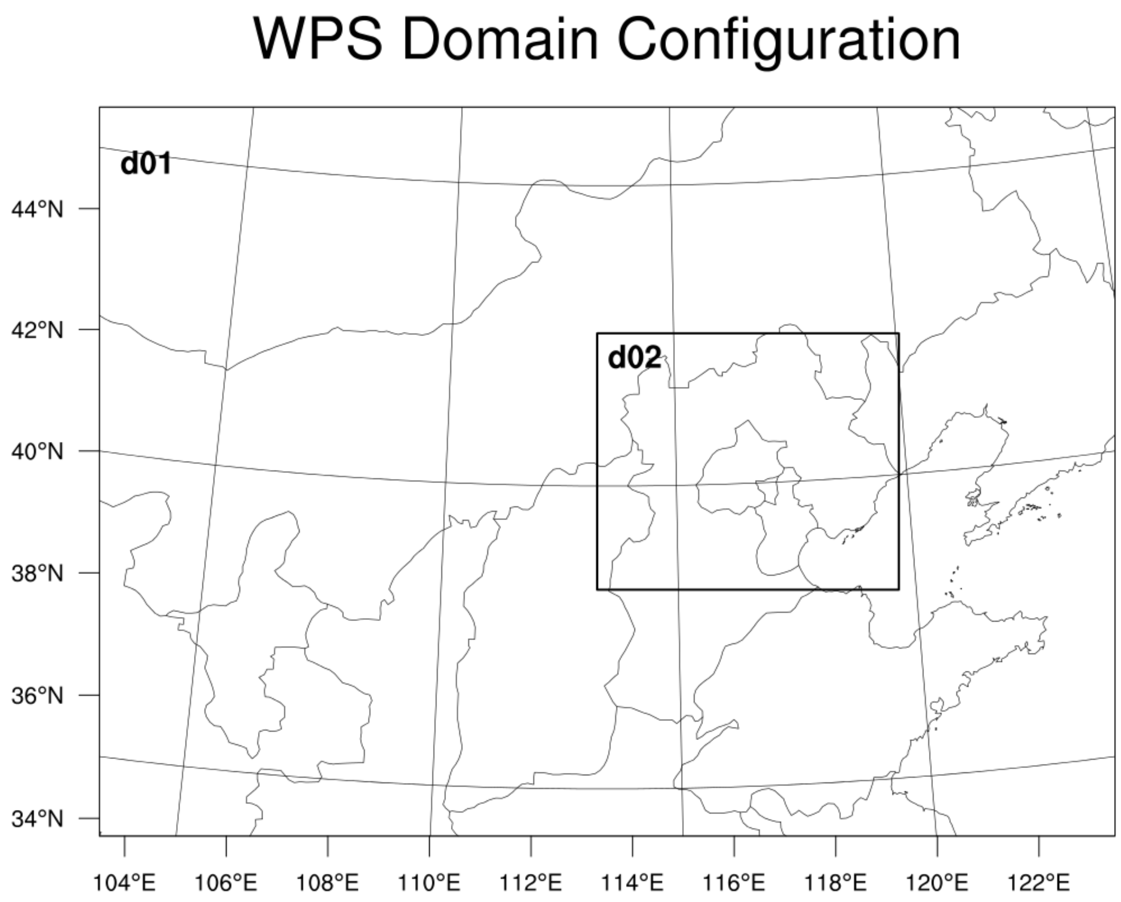
Event forecast	Event observed		
	Yes	No	Marginal total
Yes	a	b	a + b
No	c	d	c + d
Marginal total	a + c	b + d	a + b + c + d =n

$$ETS = a - r / a + b + c - r \, , \, where \; r = (a+b)(a+c)/n$$

$$BIAS = (a+b)/(a+c)$$

Rainfall intensity	Cumulative precipitation/mm(24h)
Drizzle	(0,10]
Moderat e rain	(10,25]
Heavy rain	(25,50]
Rainstor m	>50

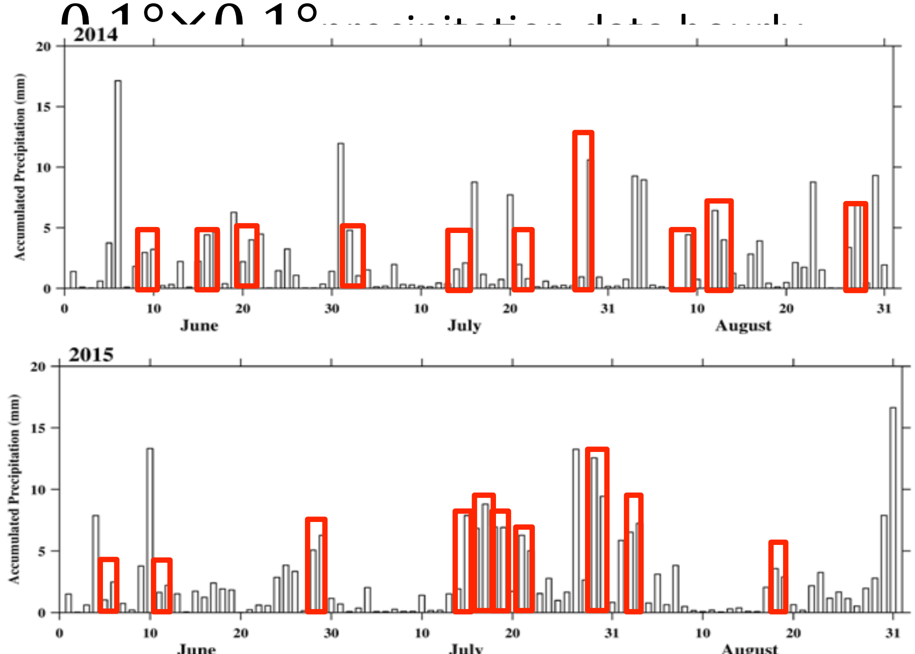
The Model Setup



- WRF 3.7.1
- Domain: The Greater Beijing Area
  - $113.35°E$—$119.55°E$
  - $38.35°N$—$42.25°N$
- D01 domain: 9 km resolution
- D02 domain: 3 km resolution
- Vertical levels:38 levels

The Driving Data and Observations

- Initialization data and lateral boundary data: GFS data
  - Global Forecast system
  - Pgbh: $0.25°\times0.25°$ grids
- Observations for model performance evaluation: Chinese Precipitation Analyses, CPA
  - Source: China Meteorological Bureau
  - Using the CMORPH data: satellite retrival of precipitation by NCEP as background, intergrate with observation data by 30 thousand stations;
  - $0.1°\times0.1°$ precipitation data hourly



2014年	2015年
6.9-6.10	6.5-6.6
6.15-6.16	6.11-6.12
6.20-6.21	6.28-6.29
7.3-7.4	7.14-7.15
7.14-7.15	7.16-7.17
7.21-7.22	7.18-7.19
7.28-7.29	7.21-7.22
8.9-8.10	7.29-7.30
8.12-813	8.2-8.3
8.27-8.28	8.18-8.19

The Pre-Screening of the Schemes

- The following schemes removed after pre-screening:
  - MP: Kessler scheme: used in ideal condition
  - MP: NSSL 2-moment scheme :used in condition that resolution is less than 2km
  - The long wave and short wave schemes are treated in tandems
  - Only three cumulus parameterization schemes are considered

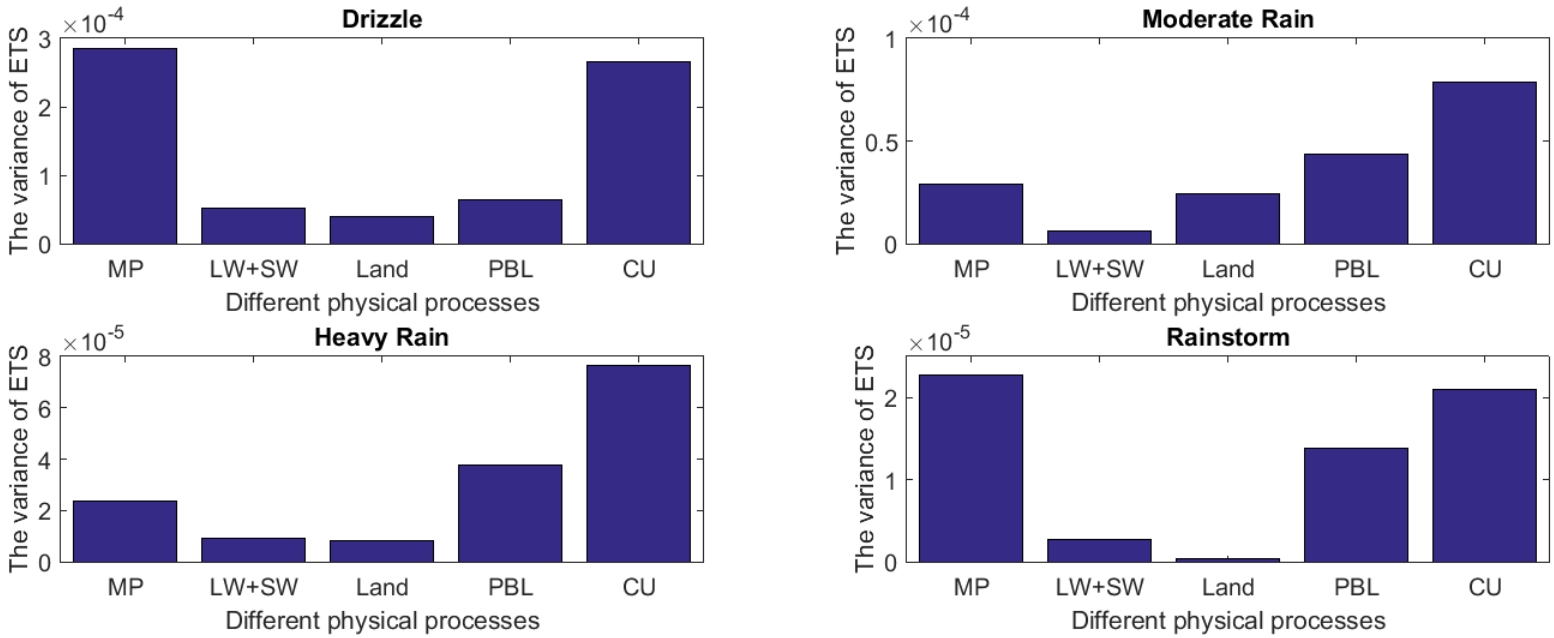
- The remaining schemes after preliminary screening :

Microphysics	**Long-wave**	**Short-wave**	**Land surface**	**PBL+Surface layer**	**Cumulus**
16(23)	6(8)	6(8)	5(7)	16	3(13)

The First Round Design of Experiment

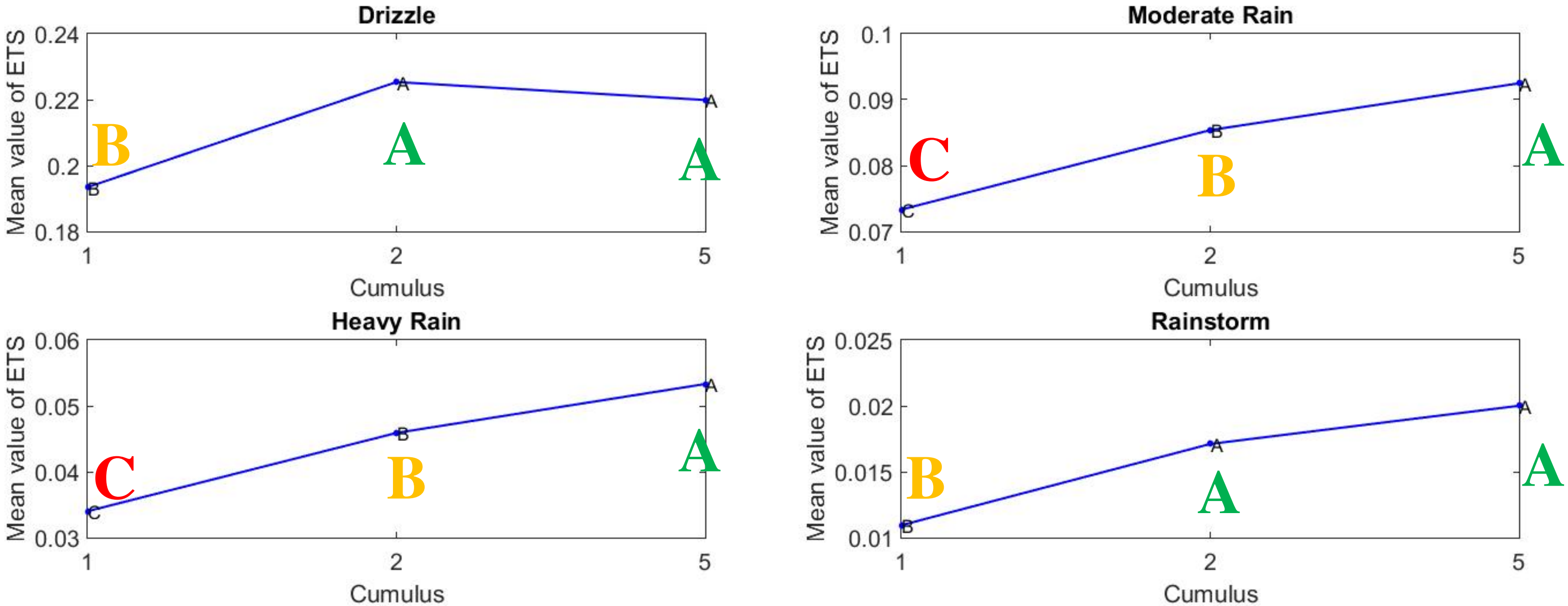
Microphysics (X1)		Long-wave (X2)		Short-wave (X3)		Land surface (X4)		PBL+Surface layer (X5)		Cumulus (X6)	
Levels	Replicates	Levels	Replicates	Levels	Replicates	Levels	Replicates	Levels	Replicates	Levels	Replicates
1	7	*1*	20	*1*	20	*1*	24	*1*	7	*1*	40
2	7	*2*	20	*2*	20	*2*	24	*2*	7	*2*	40
3	7	*3*	20	*3*	20	*3*	24	*3*	7	*3*	40
4	7	*4*	20	*4*	20	*4*	24	*4*	7		
5	7	*5*	20	*5*	20	*5*	24	*5*	7		
6	7	*6*	20	*6*	20			*6*	7		
7	7							*7*	7		
8	7							*8*	7		
9	7							*9*	7		
10	7							*10*	7		
11	7							*11*	7		
12	7							*12*	7		
13	7							*13*	7		
14	7							*14*	7		
15	7							*15*	7		
16	8							*16*	8		
16	120	6	120	6	120	5	120	16	120	3	120

ETS Variances for Different Physical Processes



The precipitation process is most sensitive to **microphysics** and **cumulus** in terms of ETS variances

The Tukey Test of ETS for Cumulus



<u>ETS Screening results:</u>

Good: **5**

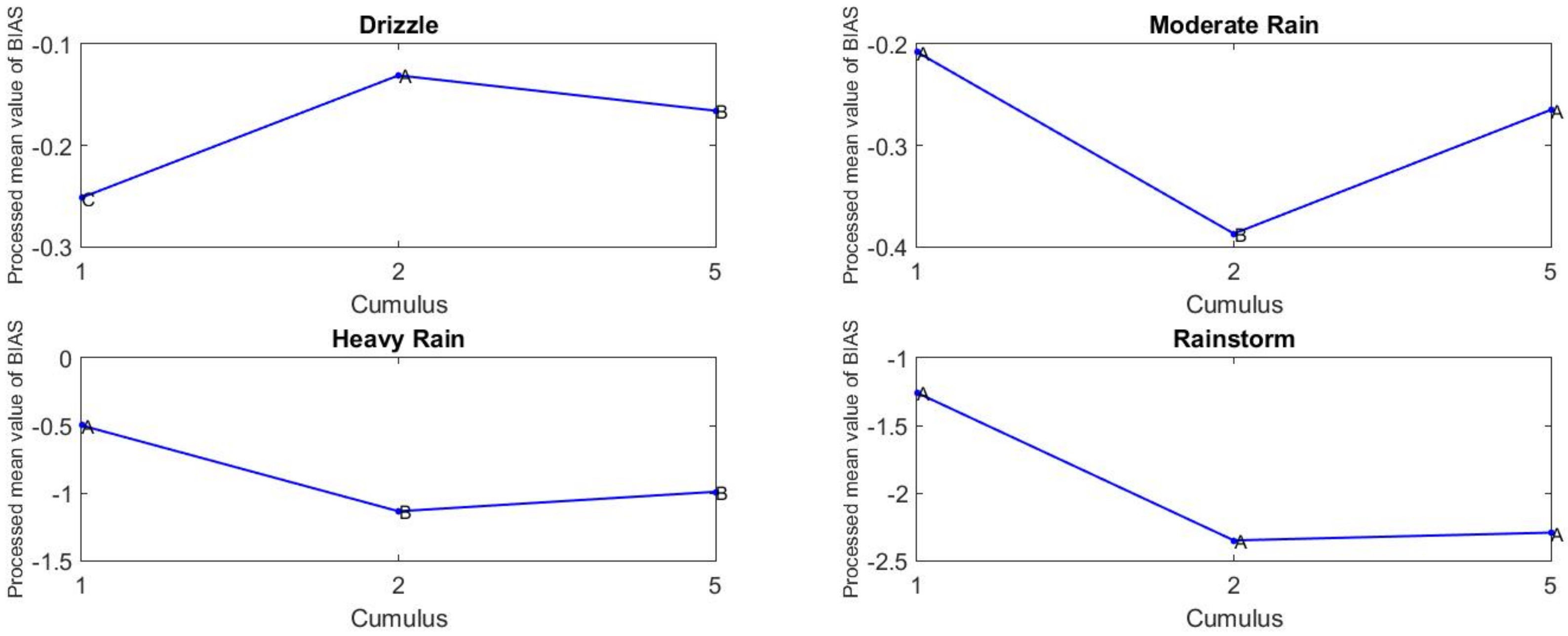
In-between: **2**

Bad: **1**

Different letters indicate **significant difference** between the schemes

The higher the mean ETS value, the better the scheme is.

The Tukey Test of BIAS for Cumulus



$$\mathrm{BIAS} = -|\mathrm{BIAS}orig - 1|$$

<u>**BIAS Screening results:**</u>

No significant differences between the schemes

The Final Screening Results Based on Cumulus

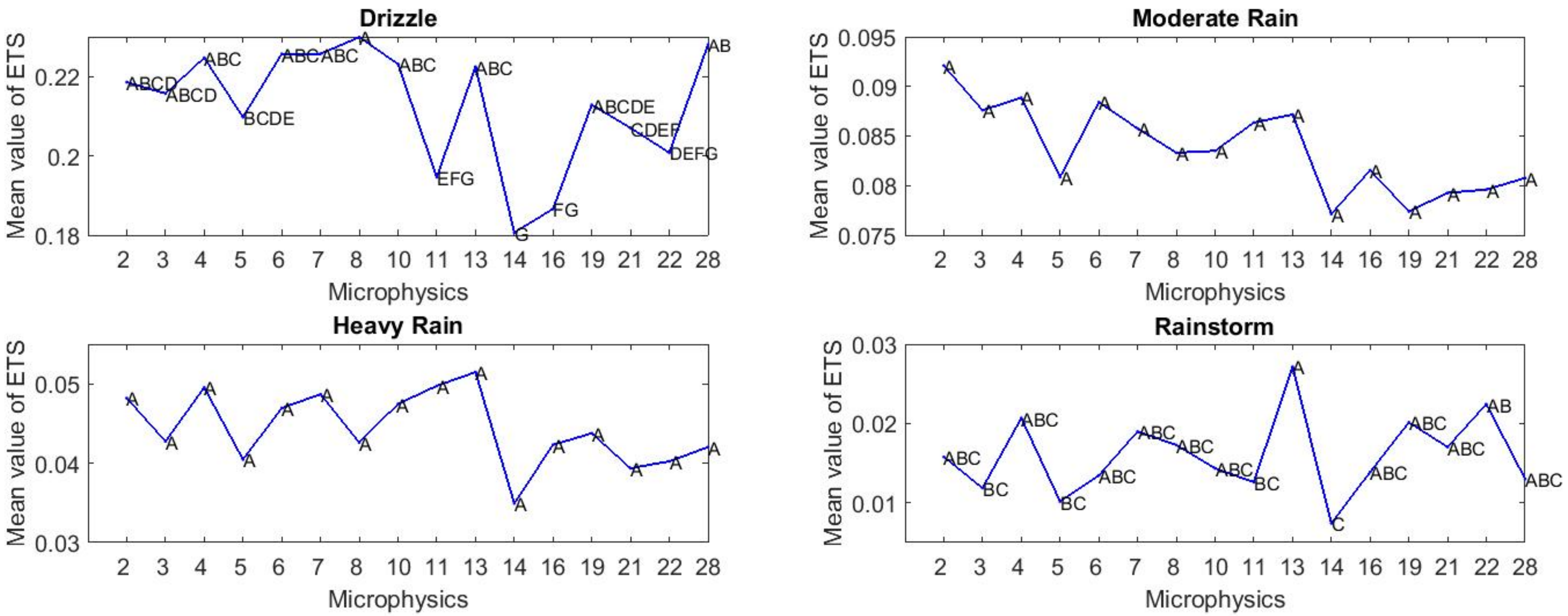
The Retained Cumulus Schemes:

The Scheme number	The Scheme Name
2	BMJ
5	Grell-3

The Removed Cumulus Scheme:

The Scheme Number	The Scheme Name
1	KF

The Tukey Test of ETS for Microphysics



<u>ETS Screening results:</u> Good: **6,7,8,10,13;**

In-between: **2,3,4,5,19,28;**

Bad: **11,14,16,21,22**.

The Results of the First Round Selection

Microphysics(9)	Long(short)-wave(6)	Land surface(4)	PBL+Surface layer(9)	Cumulus(2)
WSM3	RRTM	Noah	Monin+Boulac TKE	BMJ
WSM5	CAM	RUC	QNSE+QNSE	Grell-3
WSM6	RRTMG	CLM4	MM5+GBM	
Goddard	New Goddard	FLG	MM5+Boulac TKE	
Thompson	FLG		Pleim-Xiu+ACM2	
Morrison	RRTMG fast		MM5+UW TKE	
SYU			Monin+MYJ	
NSSL 2-mom W/o hail			MM5+ACM2	
Thompson aersol-aware			MM5+MYNN 2.5	

The Results of the Second Round Selection

Microphysics(7)	Long(short)-wave(5)	Land surface(4)	PBL+Surface layer(7)	Cumulus(1)
WSM3	RRTM	Noah	Monin+Boulac TKE	BMJ
WSM5	CAM	RUC	QNSE+QNSE	
Goddard	RRTMG	CLM4	MM5+GBM	
Thompson	New Goddard	FLG	MM5+Boulac TKE	
Morrison	FLG		Pleim-Xiu+ACM2	
SYU			Monin+MYJ	
Thompson aersol-aware			MM5+MYNN 2.5	

The Final Results of the Ensemble Selection

Serial number	mp	lw	mw	land	pbl	surface	cumulus
1	13	3	3	2	1	8	2
2	7	7	7	5	1	8	2
3	28	4	4	3	4	4	2
4	8	5	5	3	2	2	2
5	8	4	4	3	1	8	2
6	8	5	5	3	4	4	2
7	28	3	3	3	2	2	2
8	8	5	5	3	4	4	2
9	10	7	7	3	2	8	2
10	3	4	4	5	1	5	2
11	3	4	4	3	4	4	2
12	4	3	3	2	4	4	2
13	7	4	4	2	1	5	2
14	28	4	4	5	1	5	2
15	7	1	1	2	2	8	2
16	3	5	5	2	1	12	2
17	13	1	1	2	2	8	2
18	4	7	7	3	7	7	2
19	4	1	1	3	1	12	2
20	8	7	7	7	7	7	2
21	28	4	4	7	2	8	2
22	3	5	5	5	1	5	2
23	7	1	1	2	2	2	2

We choose these schemes from the results of round three and four.(Actually,the performance between the round three and four are pretty good, so we choose from both of them).And then sort them by the TS score.

The Verification of Ensemble Precipitation Predictions

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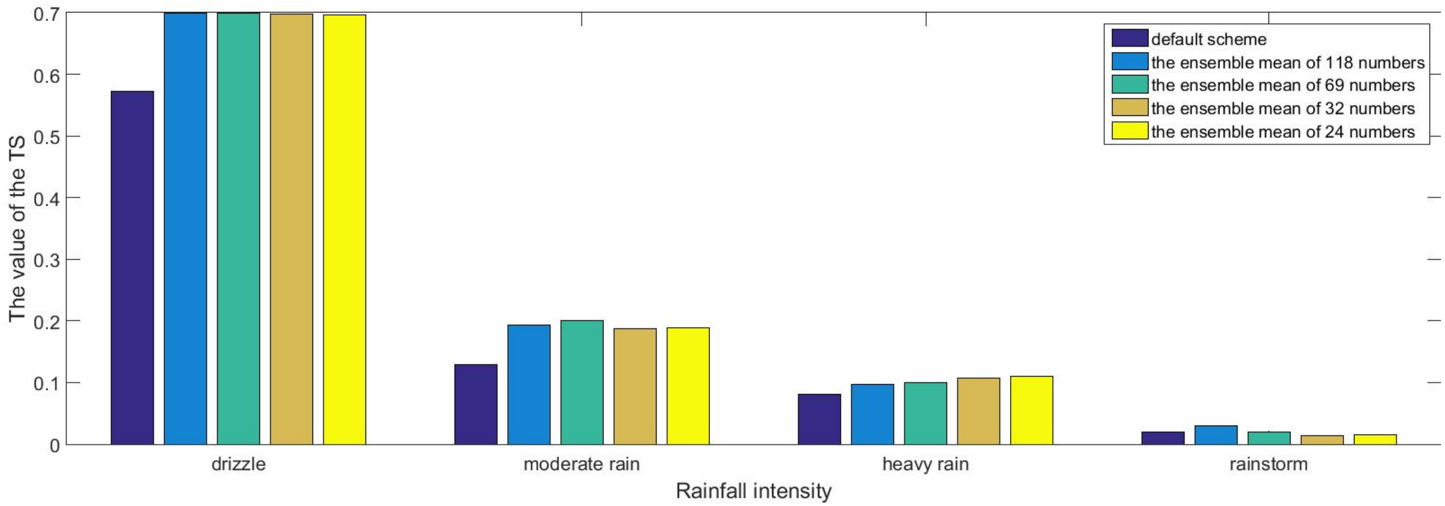
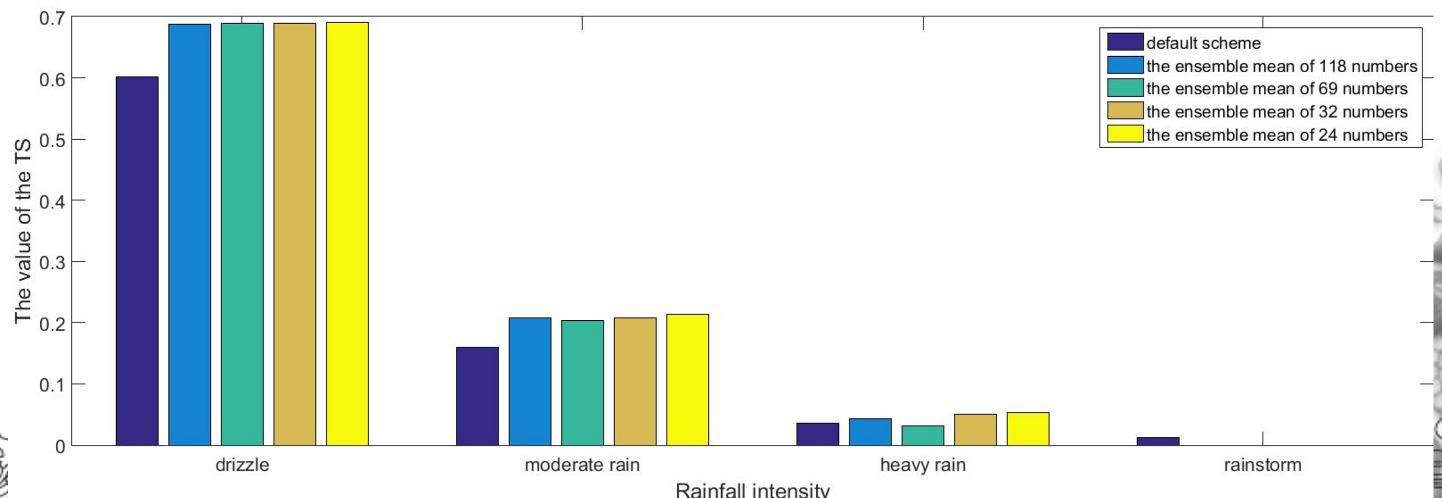
- The Performance Skill Metrics:
  - ✓ Threat Score (TS)
  - ✓ Ranked probability score (RPS)
  - ✓ Relative operating characteristic (ROC)
  - ✓ Brier Score (BS)

Ensemble vs Deterministic Predictions

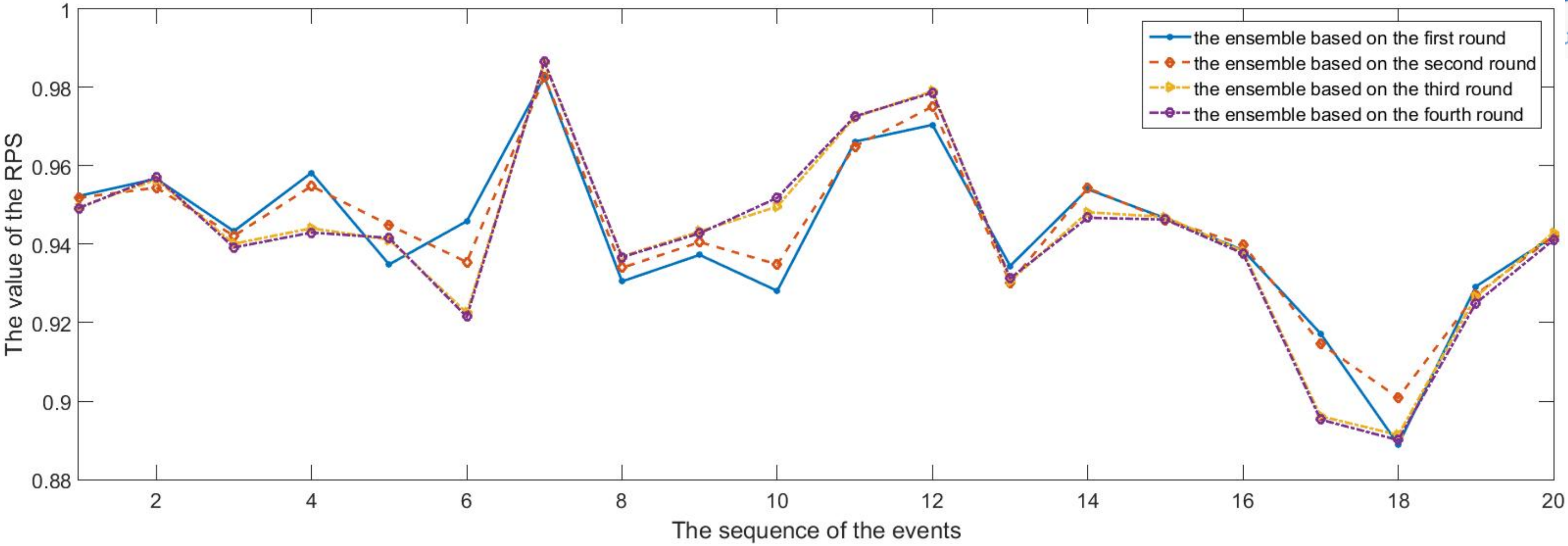
The TS value of the first 24h



The TS value of the second 24h

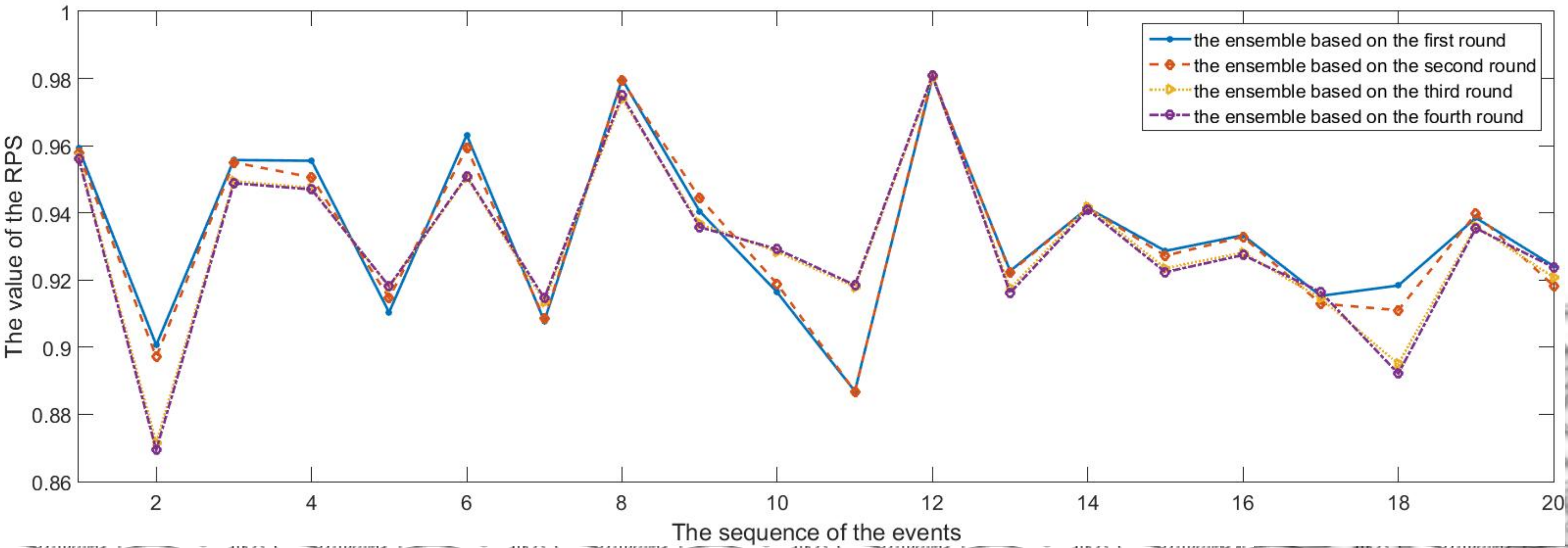


The RPS value of the first 24h



$$RPS = 1 - RPSorig$$

The RPS value of the second 24h



The ROC Curves of The Ensemble Precipitation Predictions

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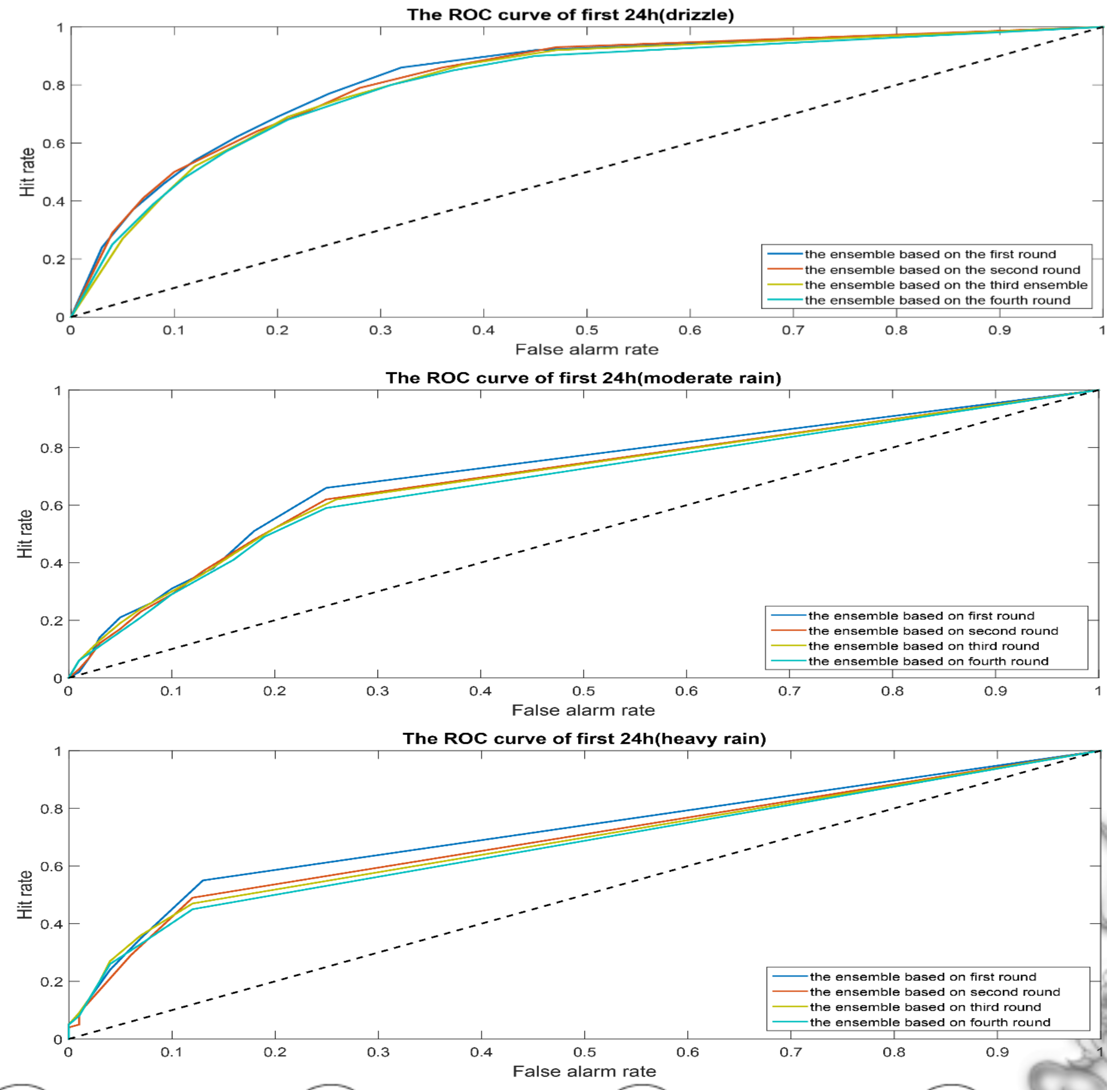

The BS Score for the Ensemble Predictions

The BS score of the ensemble forecasts (the first 24h)

Ensemble size	118	69	32	24
Drizzle	0.25	0.26	0.27	0.27
Moderate rain	0.13	0.16	0.19	0.20
Heavy rain	0.06	0.08	0.10	0.11
Rainstorm	0.03	0.05	0.07	0.07

The BS score of the ensemble forecast (the Second 24h)

Ensemble size	118	69	32	24
Drizzle	0.26	0.28	0.28	0.29
Moderate rain	0.14	0.17	0.18	0.19
Heavy rain	0.06	0.07	0.09	0.09
Rainstorm	0.02	0.03	0.04	0.05

The Perturbed Physics Ensemble Summary

- We experimented with a perturbed physics ensemble selection procedure, which is based on statistical principles and some heuristics.
- Statistical approaches such as ANOVA, Tukey HSD Test, and Latin hypercube sampling are employed.
- The Threat Scores and the Bias Score are used as selection criteria.
- The selection aims to keep the good performing schemes, removing the bad ones. For the in-between ones, we keep the ones with large variances in terms of performance metrics.
- After four rounds of screenings, we obtained an ensemble composed of 24 numbers.
- The verification of the ensemble forecasts showed that the average ensemble forecast are much better than the default deterministic forecast.
- The reliability of ensemble forecasting doesn't decrease much from the initial 118-member ensemble to the final 24-member ensemble.

Overall Summary

- Automatic model calibration is a new way to improve numerical weather forecasting

- A statistical based approach for perturbed physics ensemble precipitation predictions has shown improved accuracy over deterministic predictions and reasonable reliability

Related Publications

- Duan, Q., Z. Di, J. Quan, C. Wang, W. Gong, Y. Gan, A. Ye, C. Miao, S. Miao, X. Liang, and S. Fan, (2017): Automatic model calibration - a new way to improve numerical weather forecasting. *Bull. Amer. Meteor. Soc.,* **0**, doi: 10.1175/BAMS-D-15-00104.1.
- Gong, W., Q. Duan, J. Li, Y. Dai, (2016), Multi-Objective Adaptive Surrogate Modeling-Based Optimization for Parameter Estimation of Large, Complex Geophysical Models, Water Resour. Res., DOI: 10.1002/2015WR018230
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- Wang, C., Q. Duan, C. Tong, W. Gong, (2016): A GUI platform for uncertainty quantification of complex dynamical models, Env. Model. & Soft., doi:10.1016/j.envsoft.2015.11.004

Related Publications – cont.

- Gong, W., Q.Y. Duan, J.D. Li, C. Wang, Z.H. Di, A.Z. Ye, C.Y. Miao and Y.J. Dai, (2015), An Intercomparison of Sampling Methods for Uncertainty Quantification of Environmental Dynamic Models, J. Environ. Informatics, doi:10.3808/jei.201500310
- Di, Z., Q. Duan, W. Gong, C. Wang, Y. Gan, J. Quan, J. Li, C. Miao, A. Ye, C. Tong, 2014. Assessing WRF Model Parameter Sensitivity: A Case Study with 5-day Summer Precipitation Forecasting in the Greater Beijing Area, Geophysical Research Letters, doi. 10.1002/2014GL061623
- Wang, C., Q. Duan, W. Gong, A. Ye, Z. Di, C., 2014. An evaluation of adaptive surrogate modeling based optimization with two benchmark problems, Environmental Modelling & Software, 60, P167-179, http://dx.doi.org/10.1016/j.envsoft.2014.05.026.
- 2013 37: 727-744, doi:10.1177/0309133313494961
- Gan, Y., Q. Duan, W. Gong, C. Tong, Y. Sun, W. Chu, A. Ye, C. Miao, Z. Di, (2013), A comprehensive evaluation of various sensitivity analysis methods: A case study with a hydrological model, Environmental Modelling & Software, http://dx.doi.org/10.1016/j.envsoft.2013.09.031
- Li, J., Q. Y. Duan, W. Gong, A. Ye, Y. Dai, C. Miao, Z. Di, C. Tong, and Y. Sun, (2013), Assessing parameter importance of the Common Land Model based on qualitative and quantitative sensitivity analysis, Hydrol. Earth Syst. Sci., 17, 3279–3293, doi:10.5194/hess-17-3279-2013

Thanks!