An Improved Ensemble Transform Targeting Technique for Future Lidar Observations

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Outline

- Why targeting observations for Lidar?
- Review of targeting observation schemes
- A new ET based targeting observation scheme
- A quick OSSE case: a heavy precipitation event in southwest China
- Discussion of the quick OSSE
- Numerical experiments
- Future plan

Adaptive Lidar observation system: example

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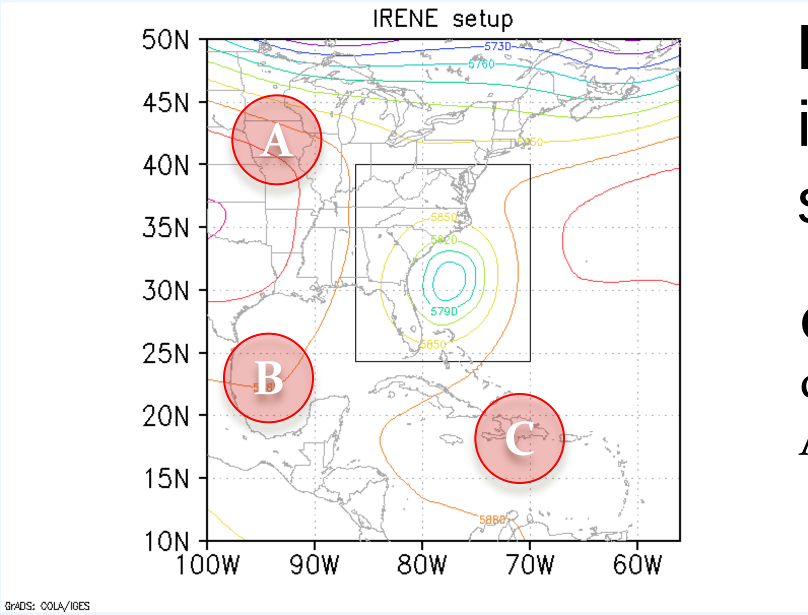
ADAPTIVE OBSERVATION



Purpose: At a given time, we try to improve forecasts by deploying some adaptive observations

Question: Where is the best regions to deploy the obs?
A, B or C, for example.

Techniques:

ADSSV *(adjoint-derived sensitivity steering vector)*
ET *(Ensemble Transform)*
ETKF *(Ensemble Transform Kalman Filter)*
SV *(Singular Vector)*

Strategy:

Sensitive Areas ← *Estimate* — Verification Areas

Sensitive Areas — *Improve Fcst* → Verification Areas

t_i *Targeting time*

t_v *Verification time*

ET: Ensemble Transform method

Analysis error covariance:

$$X_e \xrightarrow{\text{Transform Matrix C}} X_eC$$

Ensemble perturbations

Transferred perturbations by adaptive observations

Assumptions:
Large number of statistically independent ensembles. Forecast model is linear.

The transformed ensemble error covariance **A**$_{\mathbf{e}}$ can approximated by the transferred error covariance derived from the adaptive observations

Forecast error covariance:

$$\begin{aligned} P_e(v) &= M_{a\to v} A_e(a) M_{a\to v}{}^T \\ &= \frac{M_{a\to v} X_e(a) C C^T X_e(a)^T M_{a\to v}{}^T}{K} \\ &= \frac{X_e(v) C C^T X_e(v)^T}{K} \end{aligned}$$

Transformation

- ET method calculates a transformation matrix for any possible observation deployment, $Y_e = X_e C$ without rerun of forecasts. These new ensemble forecast should approximate the error covariance matrix at analysis time,

$$A = Y_e Y_e^T / K = X_e C C^T X_e^T / K$$

- For searching observation sensitive regions, it usually calculates a transformation matrix for every gridpoint.

A New ET Sensitivity (ETS)

Define a reduction vector $\boldsymbol{\beta_l}$ $(l = 1, \dots L)$ of analysis error variance due to the targeting observations at all locations and all variables. Then the "new" analysis error covariance A_g (β) can be denoted as:

$$\begin{bmatrix} a_{11}\beta_1 & \dots & a_{1L} \\ \dots & \dots & \dots \\ a_{L1} & \dots & a_{LL}\beta_L \end{bmatrix}$$

Define V as the projection vector over the verification areas. We chose the dry energy norm in this study:

$$\frac{1}{2}(u'^2 + v'^2) + \frac{C_p}{T_r}T'^2 \qquad (9)$$

Then the cost function can be writed as:

$$J = V^T P(v) V \qquad (10)$$

$$J(\beta^{best}) = \min_{0<\beta_l \ (l=1,L)<1} V^T P(v) V$$

TRANSFORM MATRICES

$$C_i^{\,T} X_e(a)^T A_{gi}^{\,-1} X_e(a) C_i = KI \xrightarrow{\textbf{ET}} CC^T|_{ET} = (X^T A^{-1} X)^{-1}$$

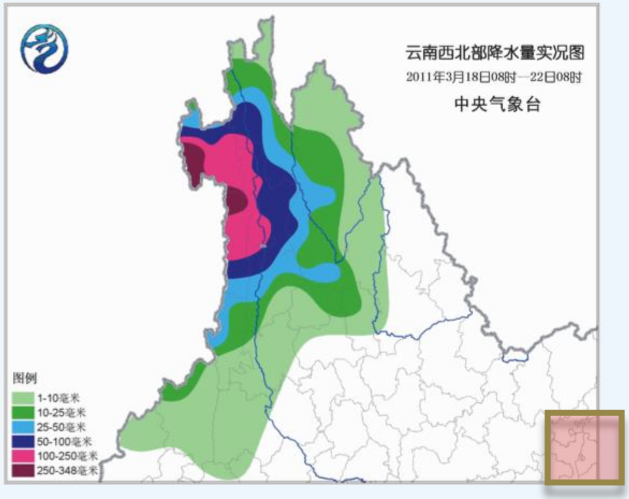
$$A_g = \frac{X_e(a) C C^T X_e(a)^T}{K} \xrightarrow{\textbf{New ET}} CC^T|_{ETVar} = (X^T X)^{-1} X^T A X (X^T X)^{-1}$$

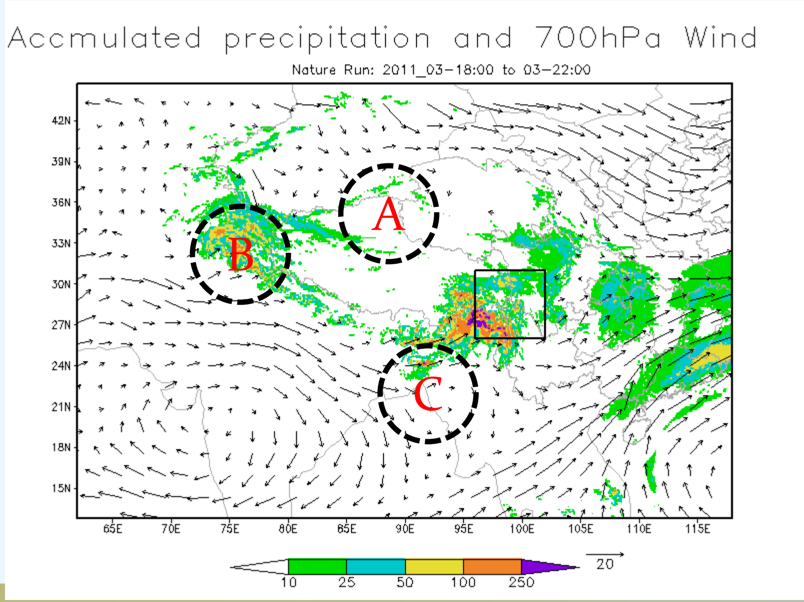
Advantages:

- ETS is more efficient without calculating transfer matrices for each possible adaptive observation
- The new ET matrix formulation directly relates ET sensitivity to analysis variance. That is, areas with large analysis variance are more likely be selected as sensitivity areas.

Quick OSSE for YunNan (SW China)

- Case
  - 18th Mar. 2011 ~ 22th Mar
  - Heavy rainfall case of southeast Tibetan Plateau





Possible adaptive OBS might improve the forecast skill over the Rainfall areas (verification areas): 26~31N, 96~102E

A Quick OSSE SETUP

- MODEL

  ARW-WRF 3.4.1

  - *WSM6 NR*
  - *WSM3 for simulation*
- Synthetic Data

  Generate from the NR

  - Data Assimilation

  GSI V3.1
- Verification:

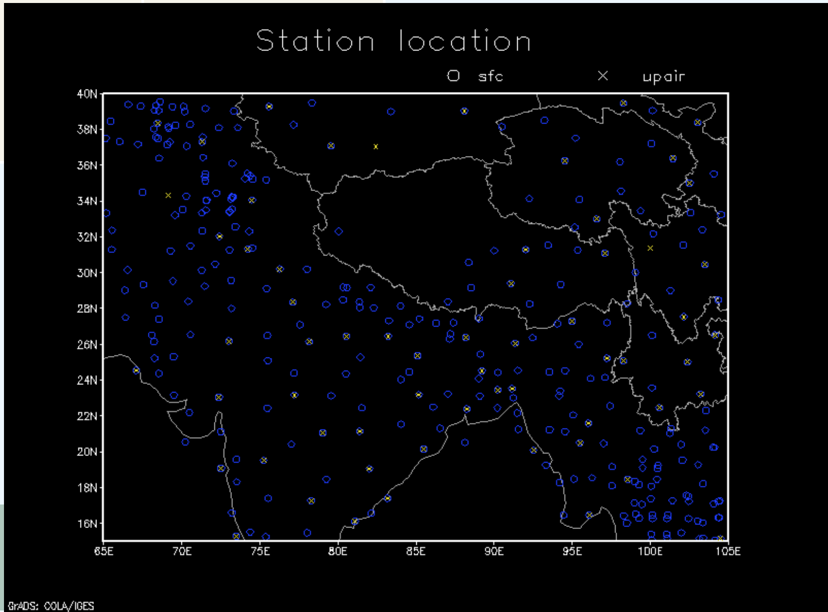
  MET V4.0

- Nature Run SETUP
  - *initial time:2011031800UTC*
  - *Fcst length: 84hr*
  - *Initial and boundary data:*
    - *GFS analysis 6hr interval*

OSSE SETUP

	Data	Initial Boundary	Fcst length	Resolution	Micro Physics
Nature Run (NR)	None	GFS ANAL	2011031812 ～ 2011032200	6km	WSM6
Control Run （CR）	Routine Obse (Synthetic sfc and raob)	GFS FCST	2011031812 ～ 2011032100	9km	WSM3
Simulation Run 1 （SR1）	Routine Obs＋ 50 Sensitive raobs				
Simulation Run 2 （SR2）	Routine Obs＋ 50 Random raobs				

Routine Observation networks



Quick OSSE Setup Discussion

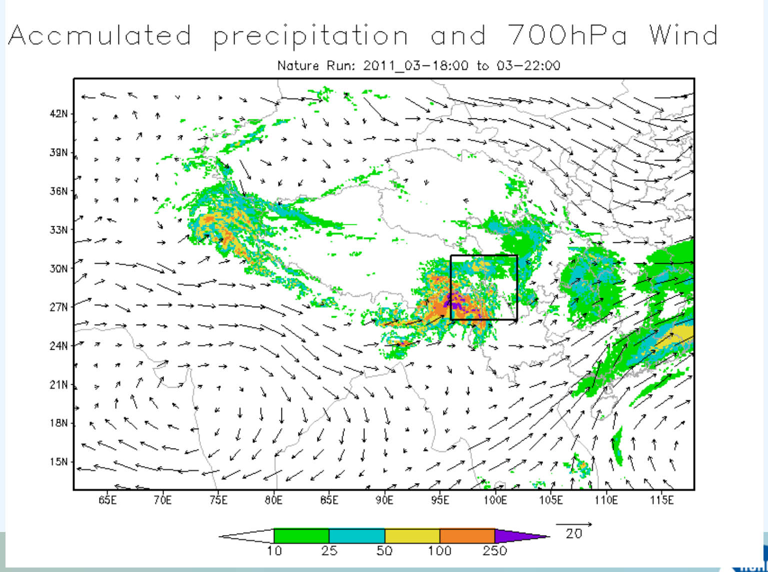
- In order to apply ET methods, ensemble forecasts are needed; For a quick OSSE, we started with a set of real time ensemble forecasts, for testing the framework and identifying issues;

- Because the ensemble forecasts reflect the NR in large scale sense, the numerical results are not used to provide adaptive observation guidance but simply serve as initial test of concept.

Quick OSSE Setup

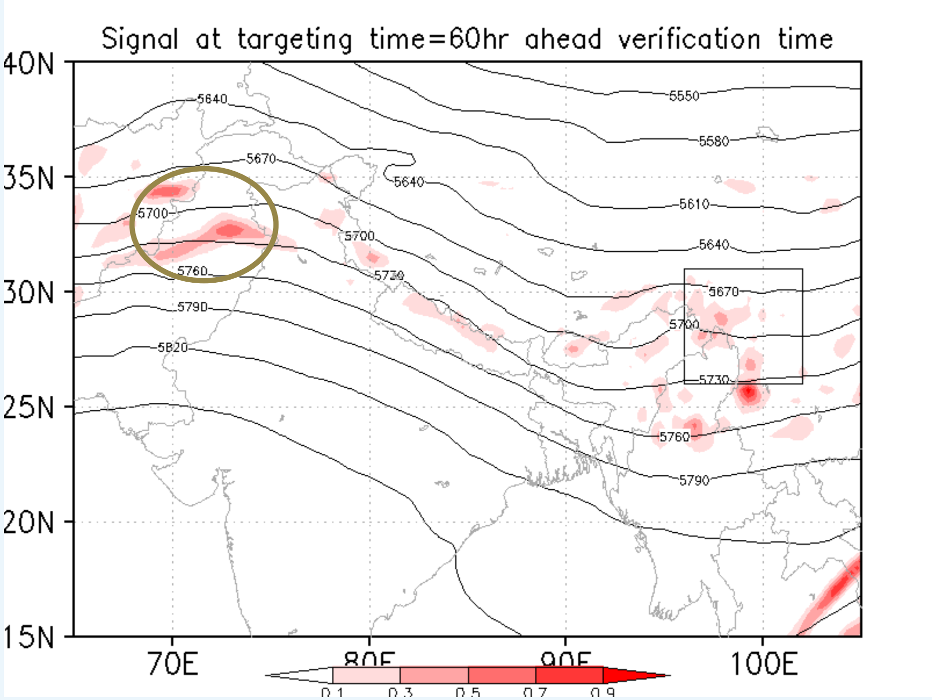
- Data
  - TIGGE ECMWF global ensemble fcst
  - *Humidity at 850/500/200hPa*
  - **0.25° ×0.25°**
  - *96 hour forecast / 12 hour interval*
  - *initial time: 18th Mar. 0000 UTC*

Verification Areas	Verification Time	Estimation Ereas
26~31N 96~102E	27th Aug. 2011 00Z	20°~45° N 65°~110° E

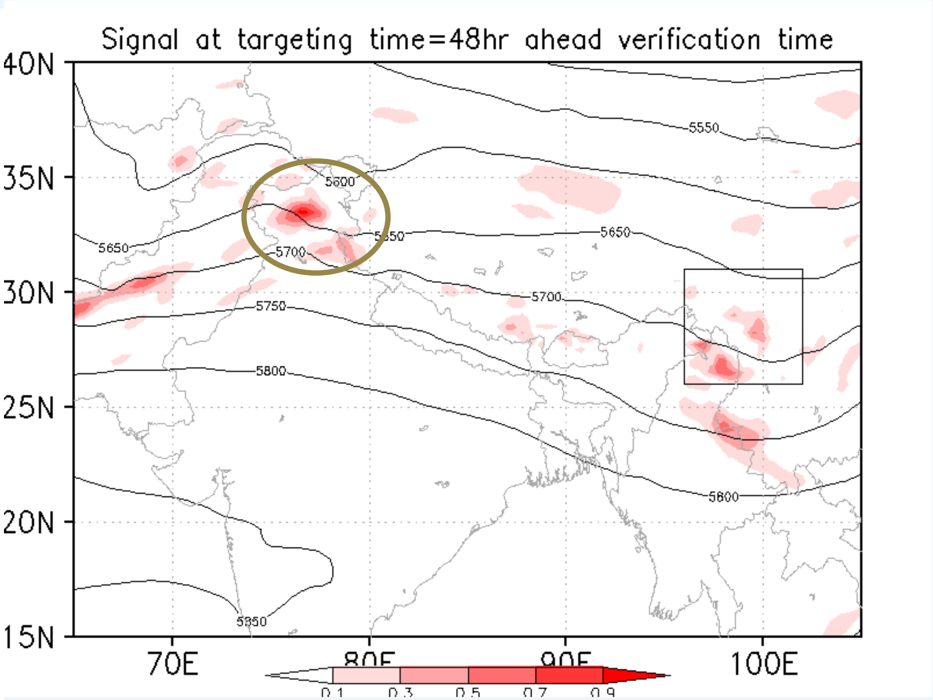


ETS Sensitivity Areas

60 hours before

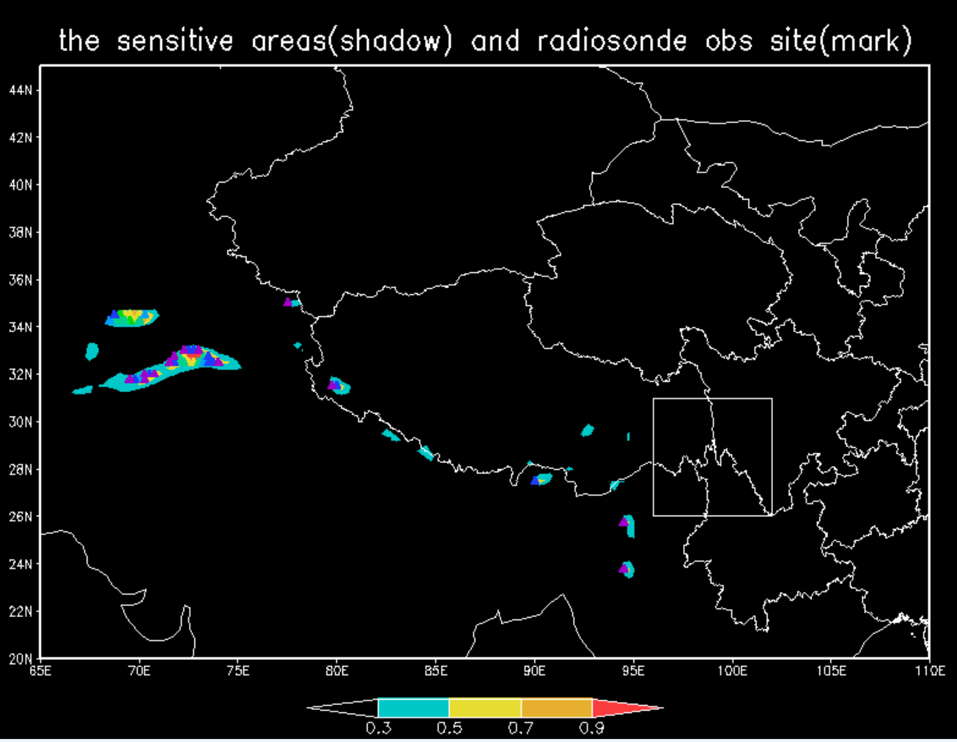


48 hours before

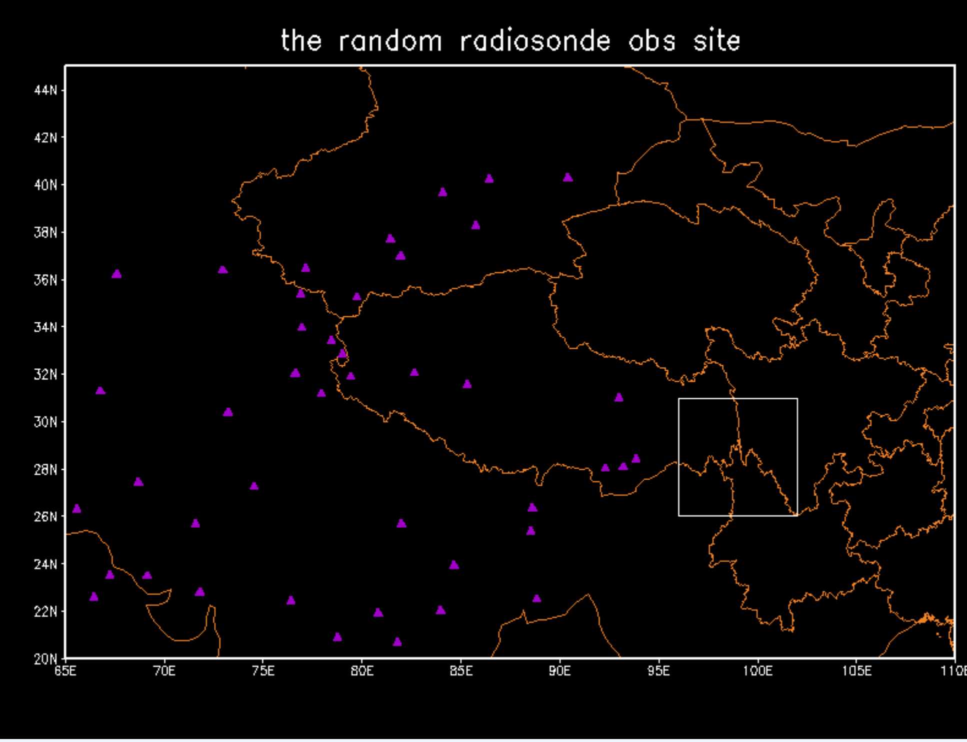


Synthetic Obs locations

ETA signal (SR1)



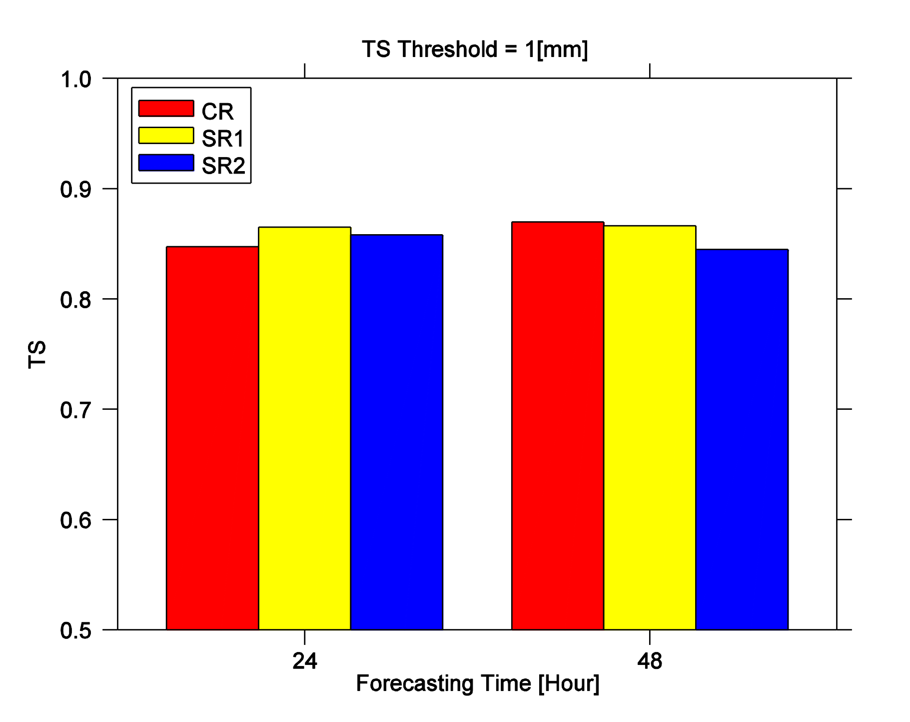
RANDOM (SR2)

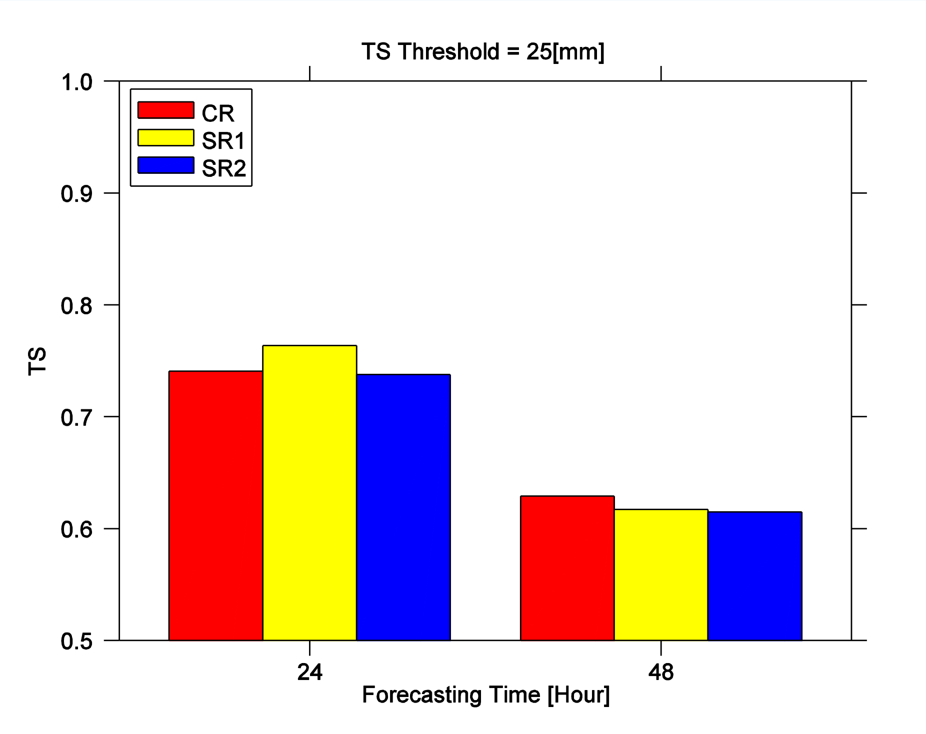


Shadow: Sensitive areas at 2011031812(UTC)
Dots: Adaptive raobs locations

Dots: Random raobs locations

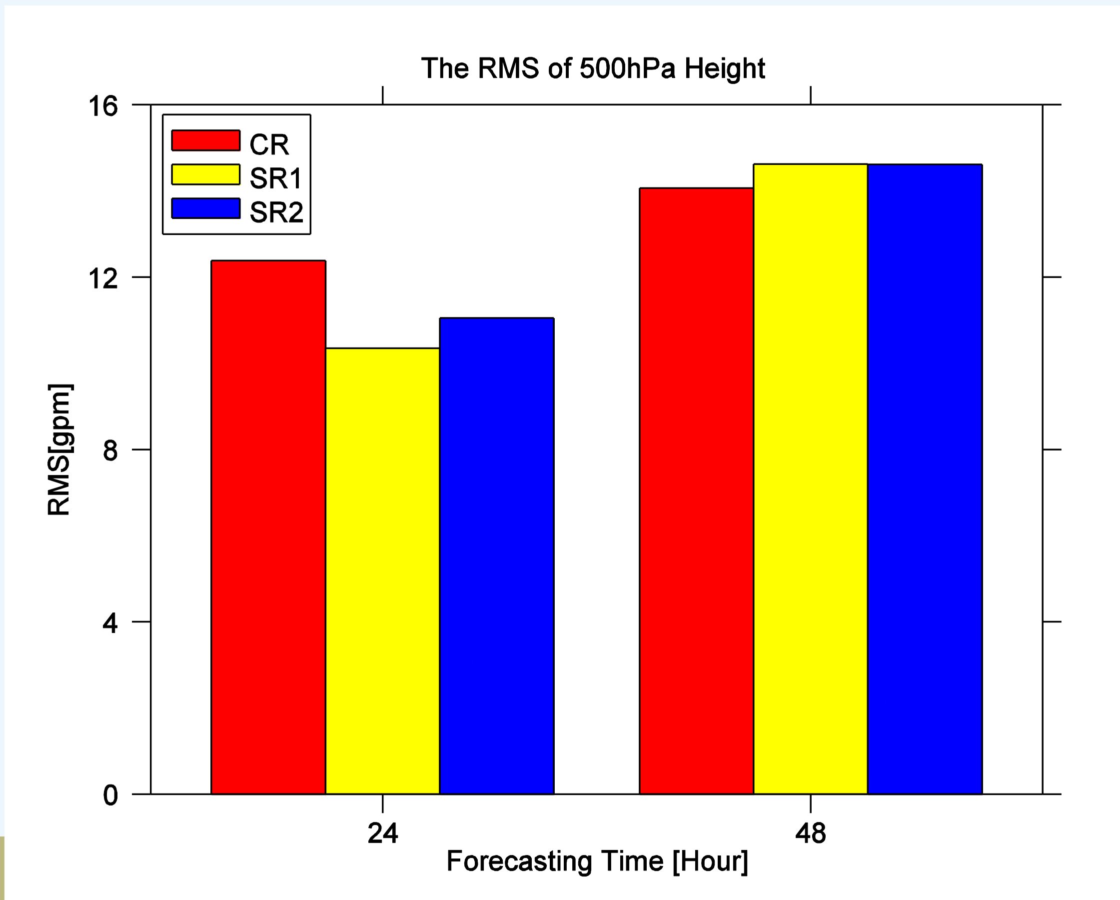
24hr Acc. Precipitation TS over the verification areas





RMSE of different variables

Height



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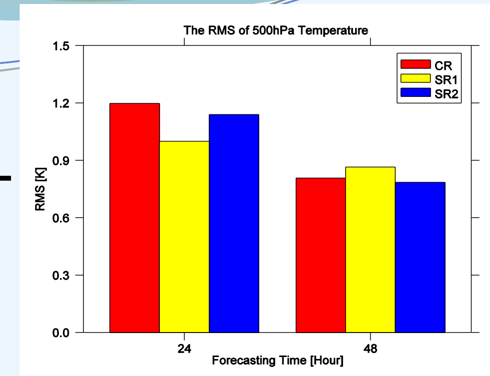
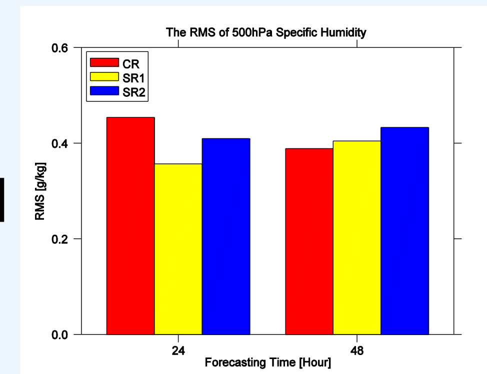
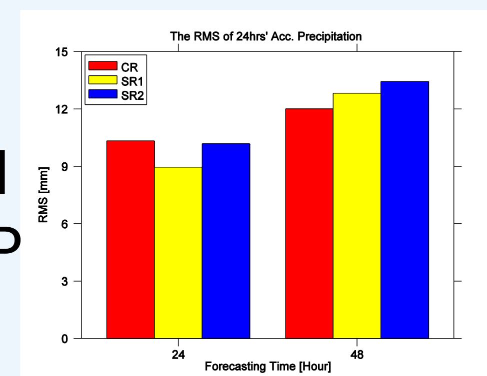


SH



24H PCP



Future Work

- Generate ensemble forecast according the NR;
- Add more dynamic related meteorological states to the ET metrics (only SH at 3 levels is used in current study);
- Test different data assimilation schemes as GSI is a large scale data assimilation scheme;
- Compare different adaptive observation schemes, such as SV or ADSSV;
- Perform more case studies before using this for practical applications.