

觀測資料對中央氣象局WRF模 式預報誤差影響之評估

江晉孝 馮欽賜

中央氣象局氣象資訊中心

張昕

美國國家大氣科學研究中心

Outline

- Introduction of FSO (Concept of FSO)
- Implementation in WRF
- Applications
- Summary
- Limitations and improvements

Introduction of FSO

- Forecast Sensitivity to Observations (FSO) is a diagnostic tool.
- Using an adjoint technique, we can trace it back to the observations used in the analysis.
- It is possible to evaluate the accuracy of NWP forecasts.
- We can determine quantitatively which observations improved or degraded the forecast.
- NWP centers (NRL,NASA,ECMWF,NCAR....) use FSO routinely to monitor their Data Assimilation and Global Observing System.

Concept of FSO

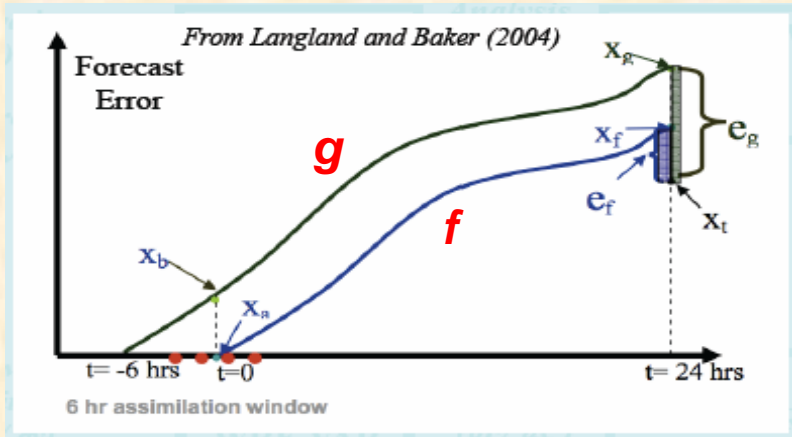
$$\delta e_f^g = \left\langle \underbrace{(y - Hx_b)}_{\substack{\text{Obs space} \\ \text{(Linear)}}}, \frac{\partial J_f^g}{\partial y} \right\rangle = \left\langle \underbrace{\delta x_a}_{\substack{\text{Grid point} \\ \text{space} \\ \text{(Linear)}}}, \frac{\partial J_f}{\partial x_a} + \frac{\partial J_g}{\partial x_b} \right\rangle \approx \left\langle \underbrace{(x_f - x_g)}_{\substack{\text{Direct from} \\ \text{model} \\ \text{(Nonlinear)}}}, \frac{\partial J_f}{\partial x_f} + \frac{\partial J_g}{\partial x_g} \right\rangle$$

Two nonlinear forecasts X_f and X_g

X_f start from analysis (X_a)

X_g start from background (X_b)

All verify analysis (X_t)



Define quadratic measures of two forecast errors

$$e_f = \langle (x_f - x_t), C(x_f - x_t) \rangle \quad (\text{A0})$$

$$e_g = \langle (x_g - x_t), C(x_g - x_t) \rangle \quad (\text{A1})$$

The **difference** between the errors of forecasts

X_f and X_g is

$$\Delta e_f^g = e_f - e_g \quad (\text{A2}) \quad \delta x_a = x_a - x_b = K(y - Hx_b)$$

$$J_f = \frac{1}{2} e_f = \frac{1}{2} \langle (x_f - x_t), C(x_f - x_t) \rangle \quad (\text{A3})$$

$$J_g = \frac{1}{2} e_g = \frac{1}{2} \langle (x_g - x_t), C(x_g - x_t) \rangle \quad (\text{A4})$$

$$\frac{\partial J_f}{\partial x_f} = C(x_f - x_t) \quad (\text{A5})$$

$$\frac{\partial J_g}{\partial x_g} = C(x_g - x_t) \quad (\text{A6})$$

$$\Delta e_f^g = \left\langle (x_f - x_g), \frac{\partial J_f}{\partial x_f} + \frac{\partial J_g}{\partial x_g} \right\rangle \quad (\text{A7})$$

"Direct from model"

exact

If we assume this **initial difference** evolves in a **tangent linear** sense into a **good approximation** of the forecast difference $e_f - e_g$

We can estimate $x_f - x_g$ using $\delta x_a = x_a - x_b$ and sensitivity gradients which the **adjoint model** had **mapped back** to initial time along the two forecast trajectories **(f,g)**

$$\delta e_f^g = \left\langle \delta x_a, \frac{\partial J_f}{\partial x_a} + \frac{\partial J_g}{\partial x_b} \right\rangle \quad (\text{A8})$$

"Grid point space"

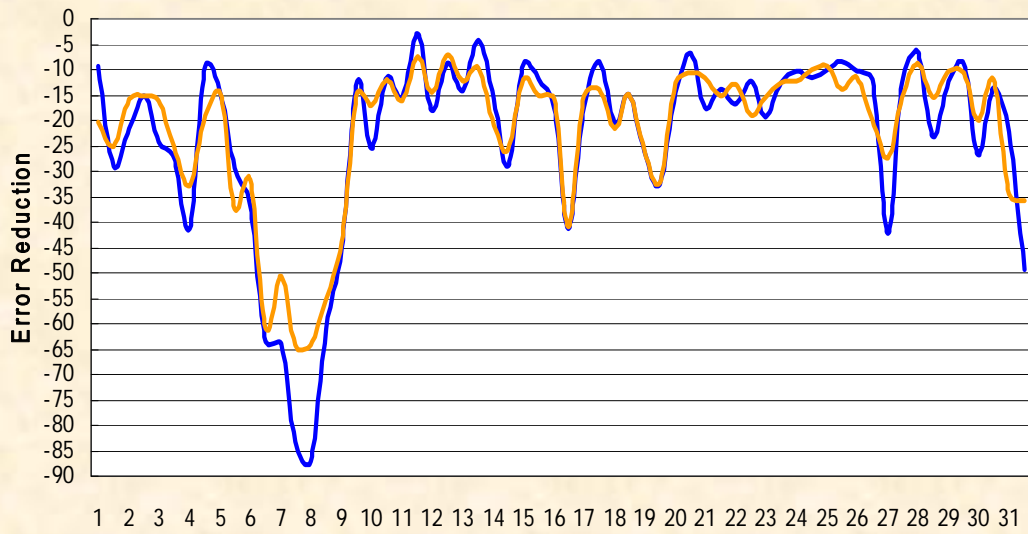
not exact

$$\delta e_f^g = \left\langle (y - Hx_b), \frac{\partial J_f^g}{\partial y} \right\rangle \quad (\text{A9})$$

"Observation space"

not exact

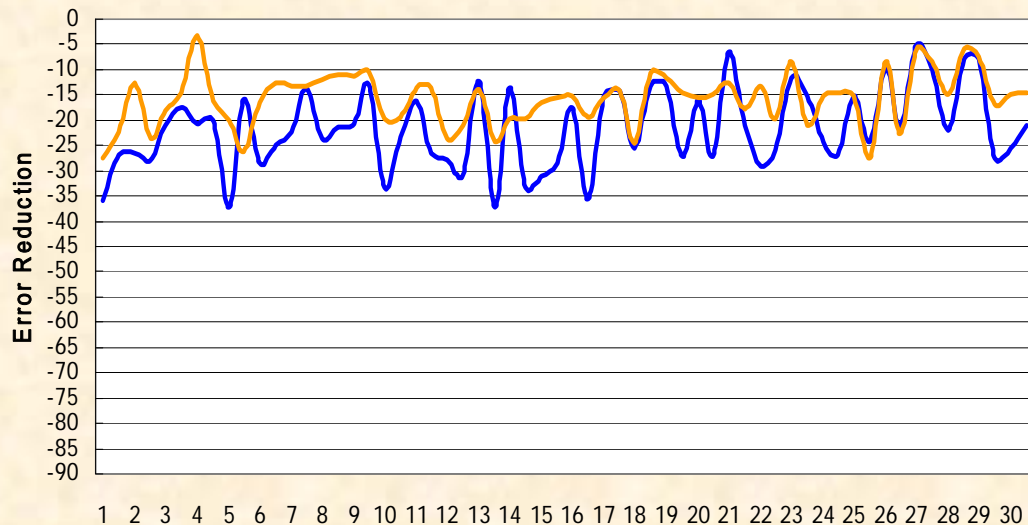
Nonlinear & Linear compare



Winter



Nonlinear & Linear compare



Summer



Non-Linear and Linear Comparison

Obs space
(Linear)

Grid point space
(Linear)

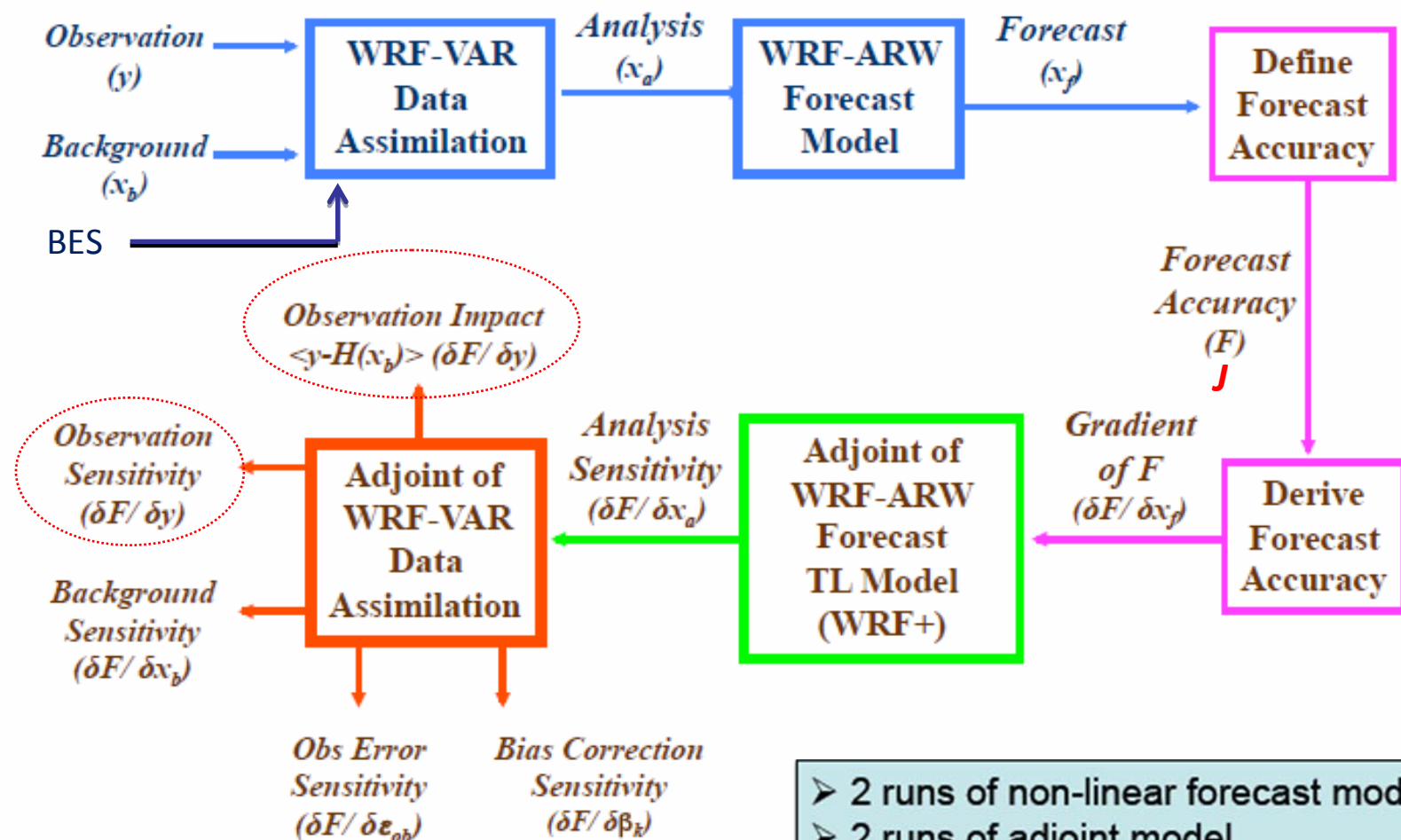
$$\delta e_f^g = \left\langle (y - Hx_b), \frac{\partial J_f^g}{\partial y} \right\rangle = \left\langle \delta x_a, \frac{\partial J_f}{\partial x_a} + \frac{\partial J_g}{\partial x_b} \right\rangle$$

$$\approx \left\langle (x_f - x_g), \frac{\partial J_f}{\partial x_f} + \frac{\partial J_g}{\partial x_g} \right\rangle$$

Direct from model
(Nonlinear)

夏季: 非線性與線性差異較大

Implementation in WRF



- 2 runs of non-linear forecast model
- 2 runs of adjoint model
- 1 run of adjoint of analysis
- The computer cost is estimated to 10-15 times the cost of the forecast model.

➤ **Reference state:** Namelist `ADJ_REF` is defined as

- 1: X^t = Own (WRFVar) analysis
- 2: X^t = NCEP (global GSI) analysis ★
- 3: X^t = Observations

➤ **Forecast Aspect:** depends on reference state

- 1 and 2: Total Dry Energy ★

$$\langle \mathbf{x}, \mathbf{x} \rangle = \frac{1}{2} \iint_{\Sigma} [u'^2 + v'^2 + \left(\frac{g}{N\bar{\theta}}\right)^2 \theta'^2 + \left(\frac{1}{\bar{\rho}c_s}\right)^2 p'^2] d\Sigma$$

According to the characteristics of the WRF model, we define the dry energy norm using

the WRF variables, especially the potential temperature and pressure:

$$J = \langle \mathbf{x}, \mathbf{x} \rangle = \frac{1}{2} \sum_{i,j,k} [u'^2 + v'^2 + \left(\frac{g}{N\bar{\theta}}\right)^2 \theta'^2 + \left(\frac{1}{\bar{\rho}c_s}\right)^2 p'^2] \quad (13)$$

where u' , v' , θ' and p' are the zonal, meridional winds, potential temperature and pressure perturbations, respectively, \bar{N} , $\bar{\theta}$, $\bar{\rho}$ and c_s are Brunt-Vaisala frequency, potential temperature, density, and speed of sound, respectively, at the reference level, \mathbf{x} is the vector representing the atmospheric state and $\sum_{i,j,k}$ represents the selected model grids for verification.

Please note that the current calculation of the J (13) in WRFDA FSO application is not a volume integration of the total dry energy norm within the verified domain and it is just a simple summation of the dry energy norm over all selected grid points. It will impact the

➤ **Script variable `ADJ_MEASURE` defined as:**

- 1: first order
- 2: second order
- 3: third order
- 4: variant of third order ★

Augmented third-order approximation

➤ Use WRF+ code to compute WRF-ARW adjoint with Namelist `ADJ_SENS=true`:

- Activate pressure in the adjoint
- Switch off intermediate forcing

➤ WRF+ is run for both trajectories from x_a and x_b

➤ Finally, both sensitivities are added together

Applications

Experiments design:

- **Model version (CWB OP24)**
 - WPS V3.3.1
 - WRFDA V3.3.1
 - WRF V3.3.1
 - WRFPLUS V3.3.1 (2011 version)
- **Period**
 - Summer** : 2008060100~2008063012
 - Winter** : 2008120100~2008123112
- **Focus** : 24hr forecast error
 - Only run 00Z & 12Z
- **Reference** : NCEP analysis

CWB WRFDA

Ingested obs data :

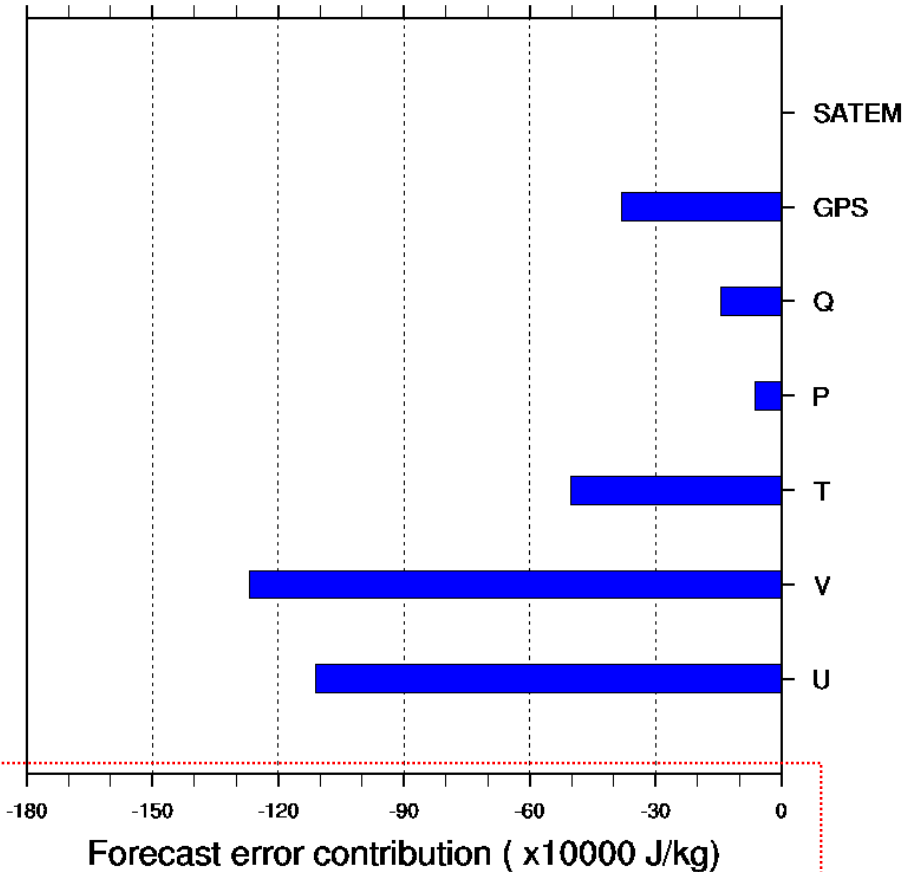
Sound
Sonde_sfc
Synop
Geoamv
Pilot
Metar
Ship
Qscat
Buoy
Airep
Satem
Gpsro
EC_bogus

Results

2008

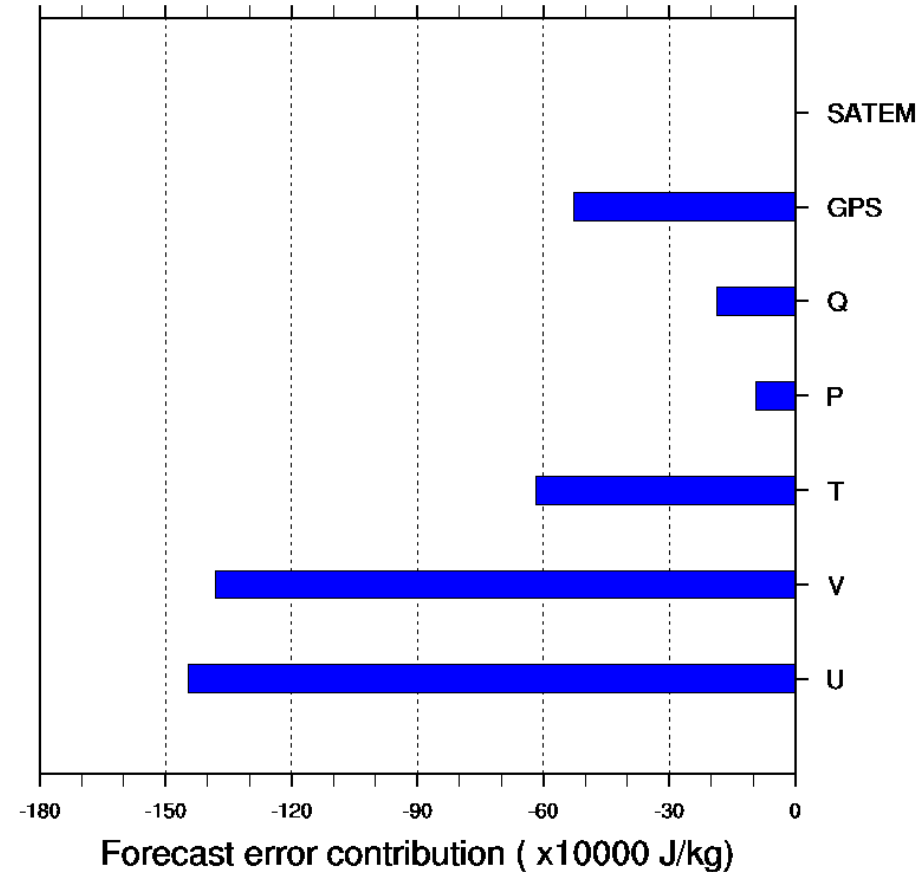
Summer & Winter

Average between 2008060100 - 2008063012 for ALLZ



Summer

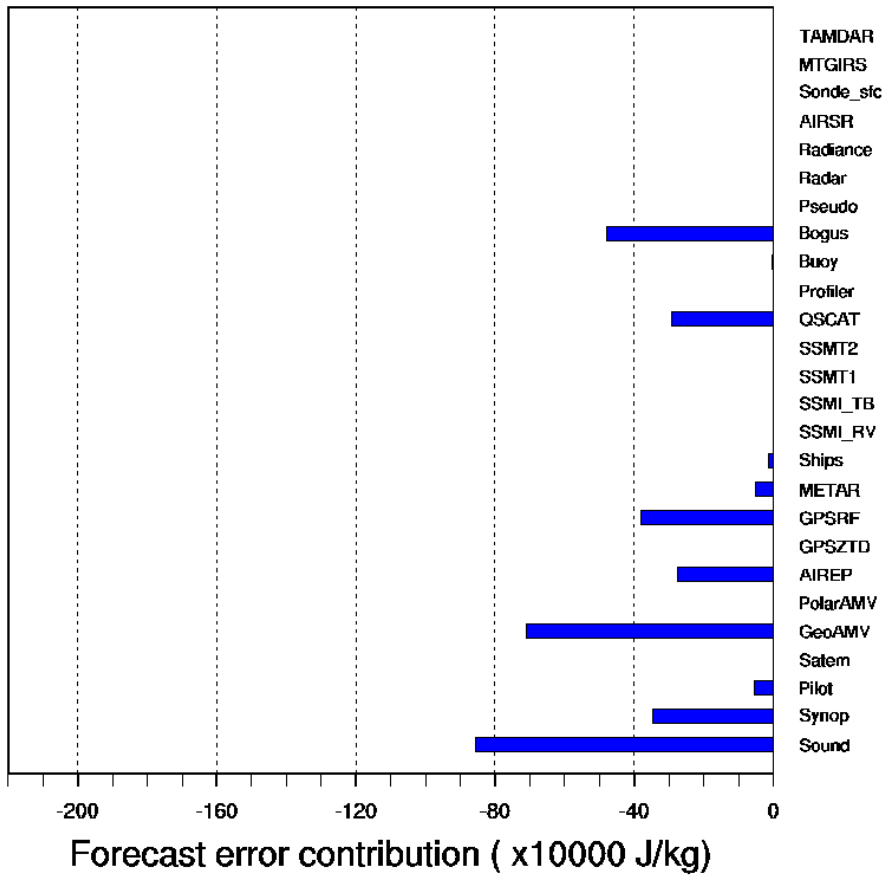
Average between 2008120100 - 2008123112 for ALLZ



Winter

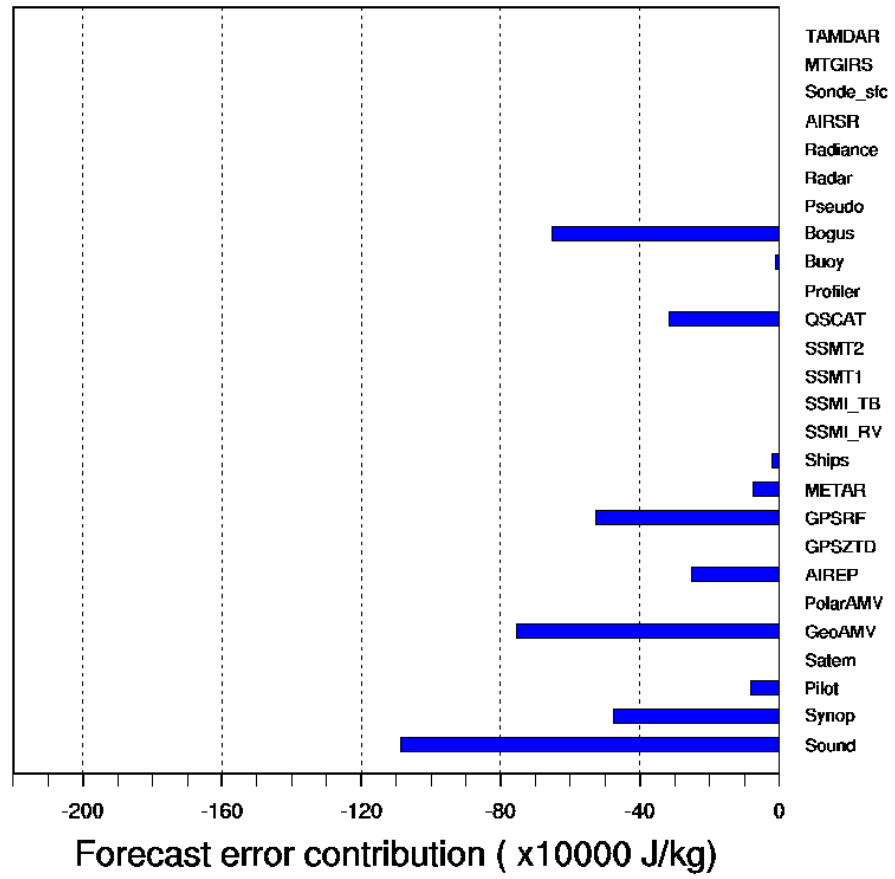
1. 觀測資料在冬季降低24hr預報誤差之效益大於夏季
2. 風場是貢獻最大的氣象變數

Average between 2008060100 - 2008063012 for ALLZ



Summer

Average between 2008120100 - 2008123112 for ALLZ



Winter

從冬夏兩季結果得知，最有影響力的觀測資料前五名依序是Sound、GeoAMV、EC Bogus、Gpsrf、Synop

時間序列-Time Series

依貢獻量級分成三類

$$\left(10^6, 10^5, 10^4 \right)$$

Order : 10^6

Sound

EC Bogus

GeoAMV

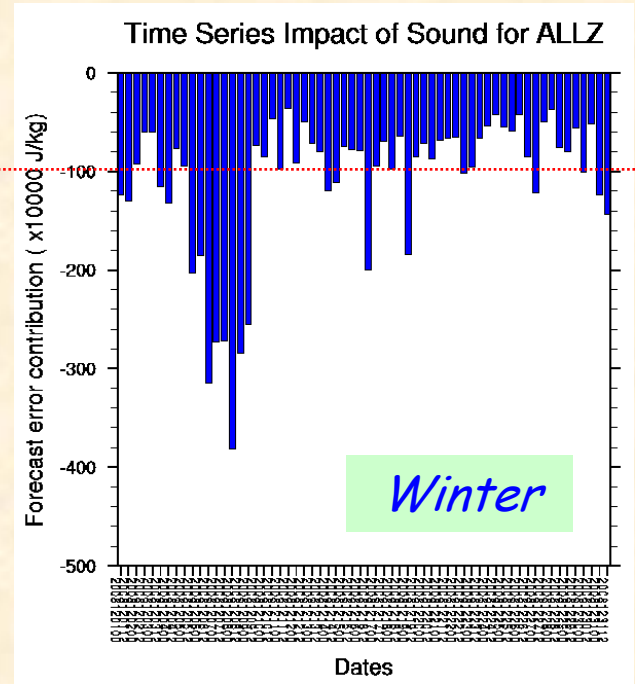
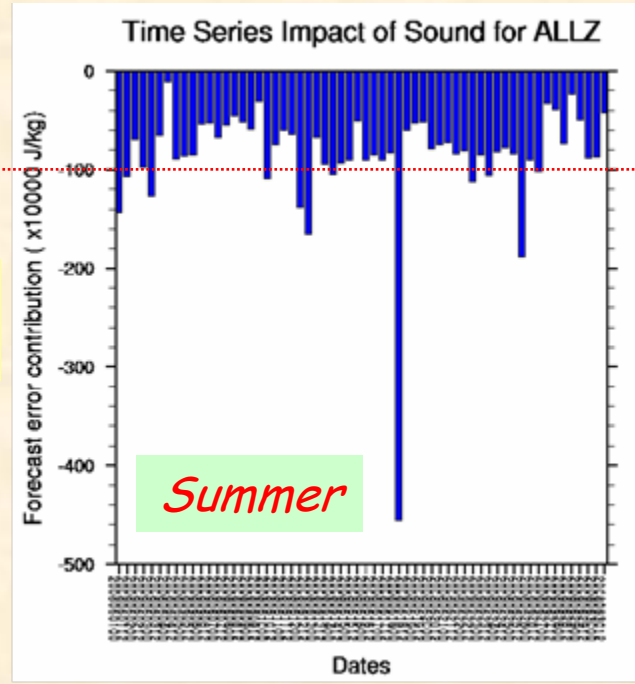
Synop

Gpsrf

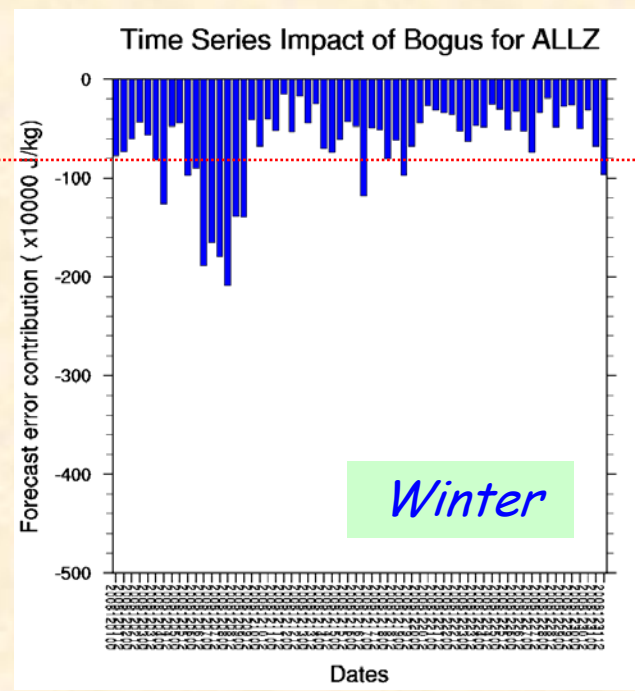
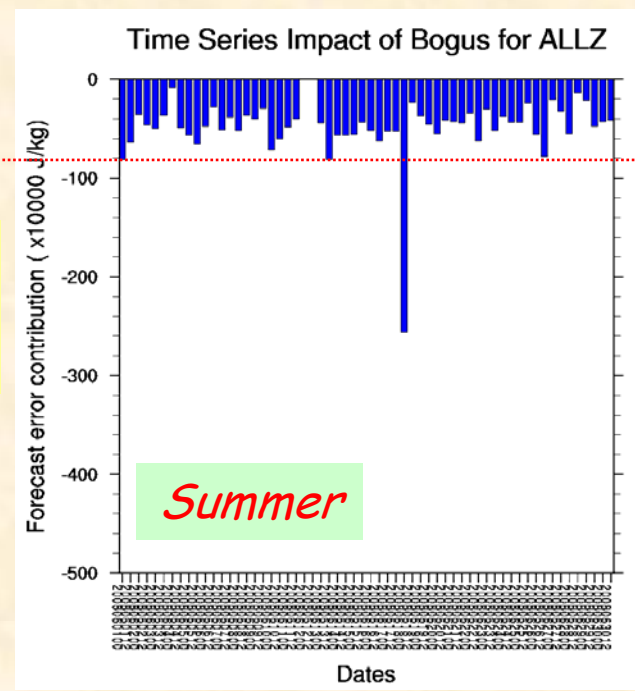
Qscat

Airep

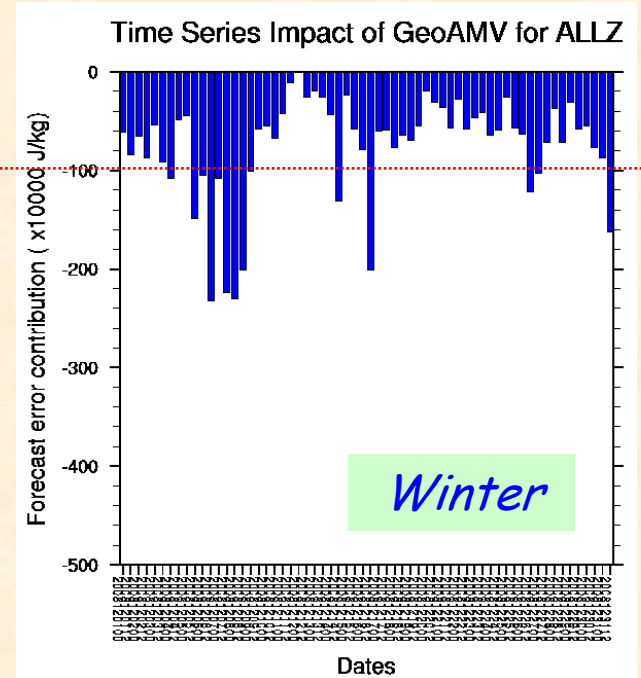
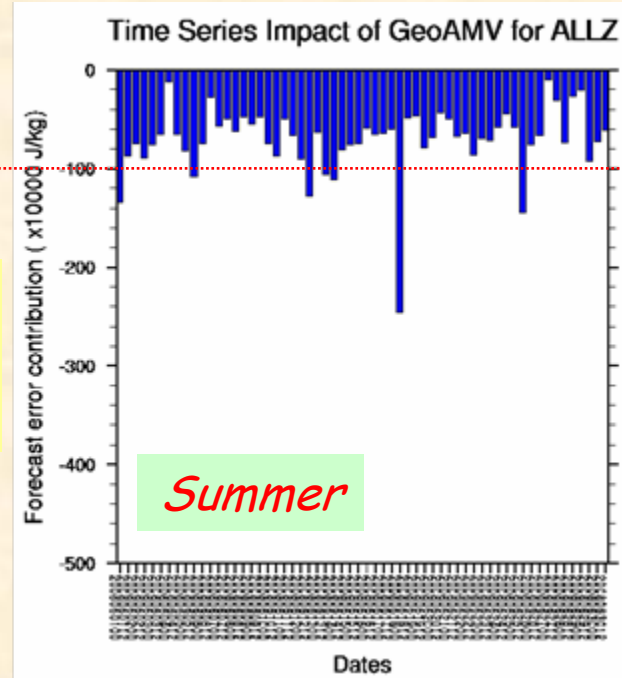
Sound資料對24hr預報誤差之改進：冬季大於夏季



EC Bogus資料對24hr預報誤差之改進：冬季大於夏季

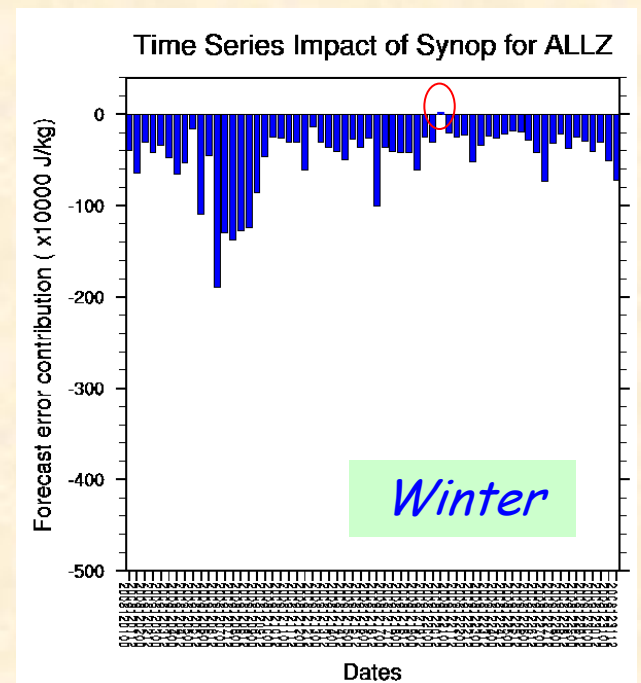
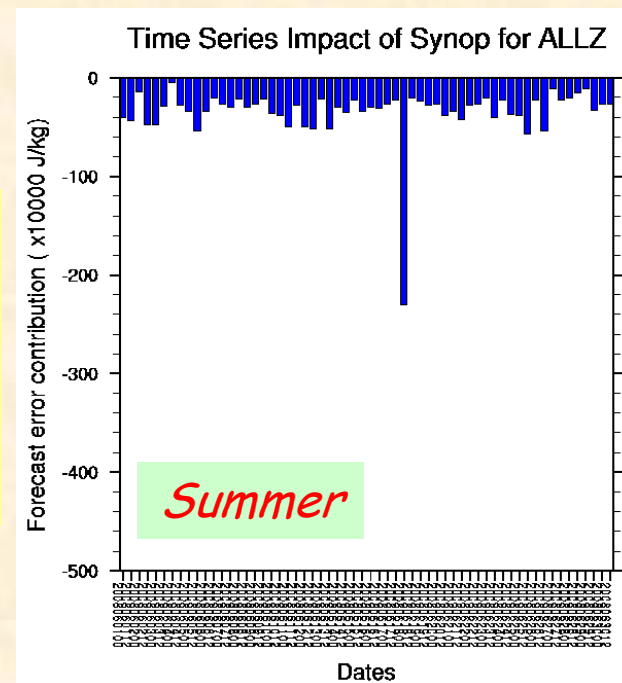


GeoAMV資料對24hr預報
誤差之改進：冬季略
大於夏季



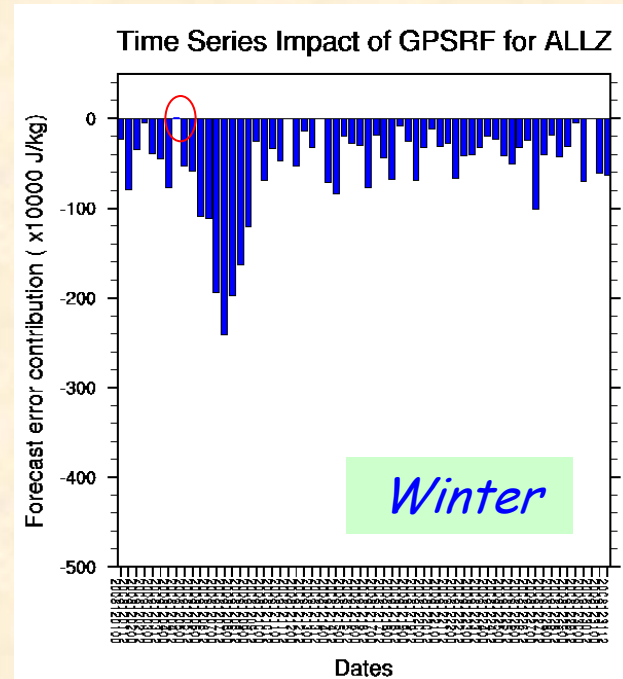
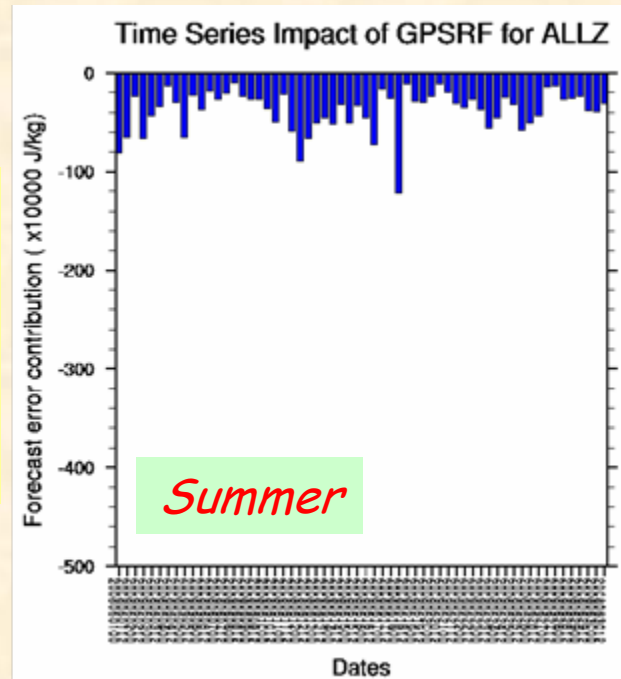
Synop資料對24hr預報
誤差之改進：冬季大
於夏季

但冬季有1個時間點呈
現負效應



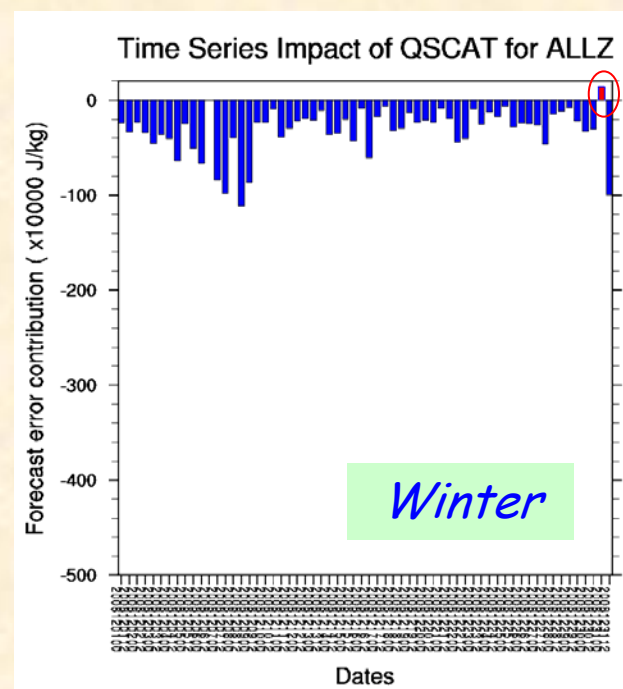
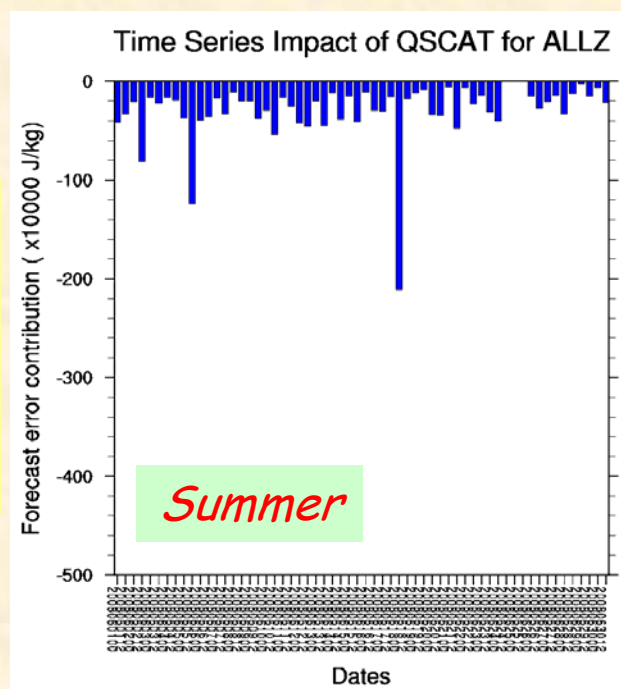
Gpsrf 資料對24hr預報
誤差之改進：冬季大
於夏季

但冬季有1個時間點呈
現負效應

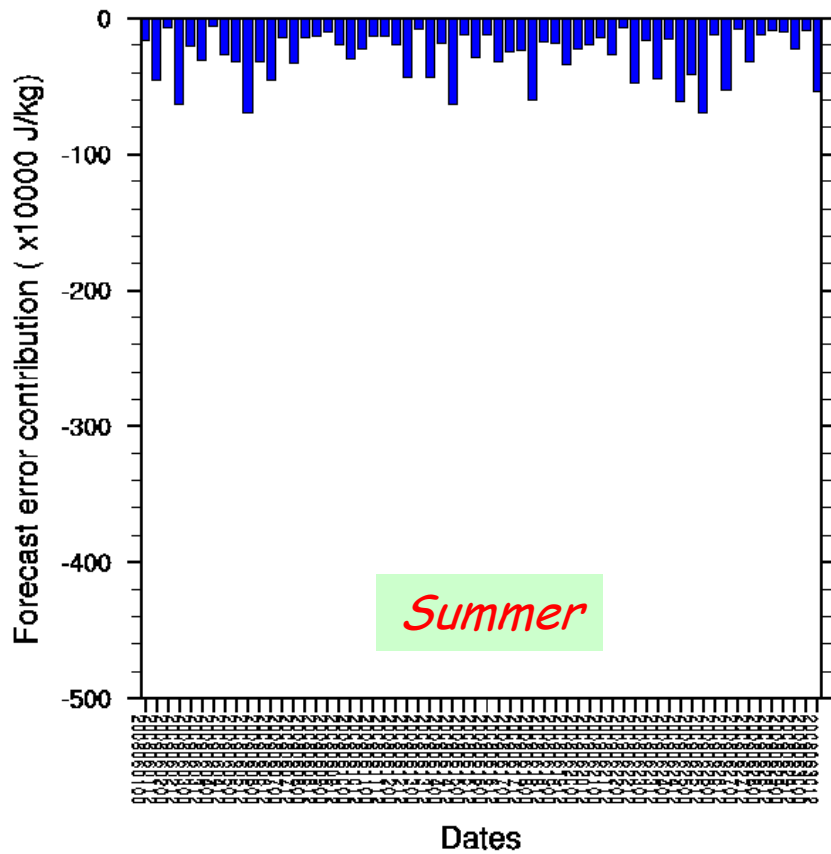


Qscat 資料對24hr預報
誤差之改進：冬季略
大於夏季

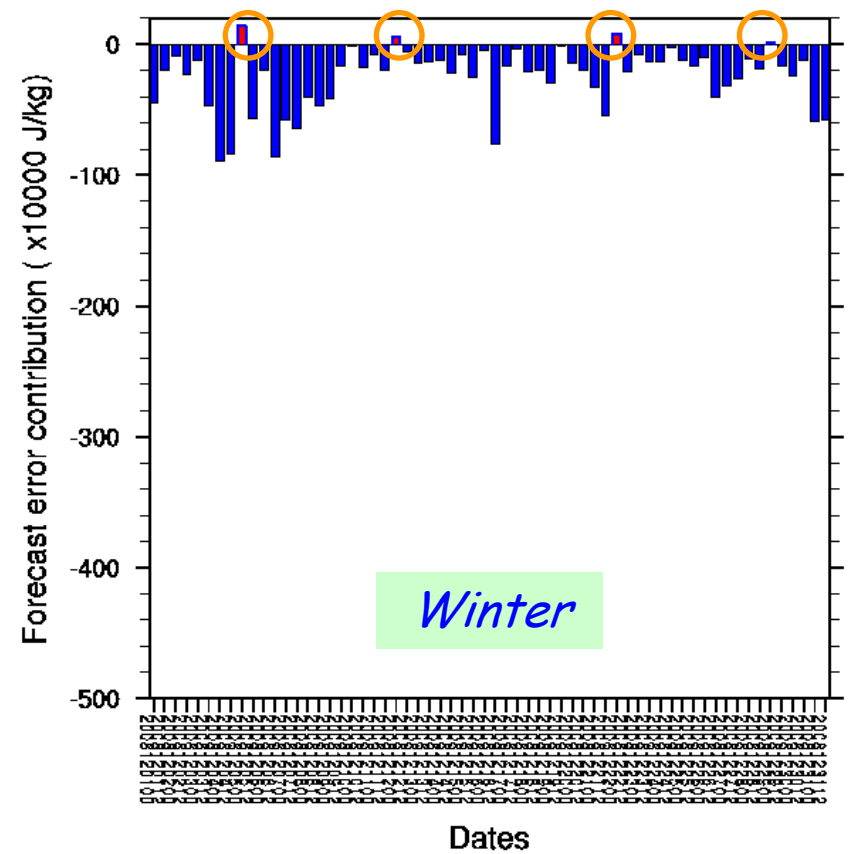
但冬季有1個時間點呈
現負效應



Time Series Impact of AIREP for ALLZ



Time Series Impact of AIREP for ALLZ



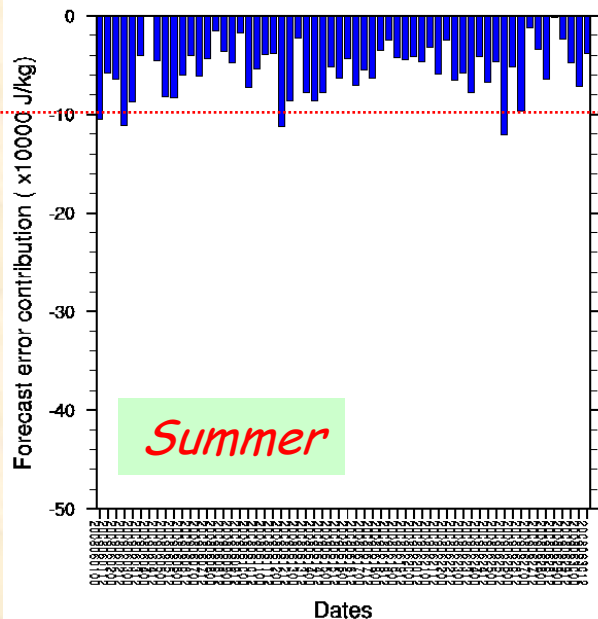
Airep資料對24hr預報誤差之改進：冬季略小於夏季
但冬季有4個時間點呈現負效應

Order : 10^5

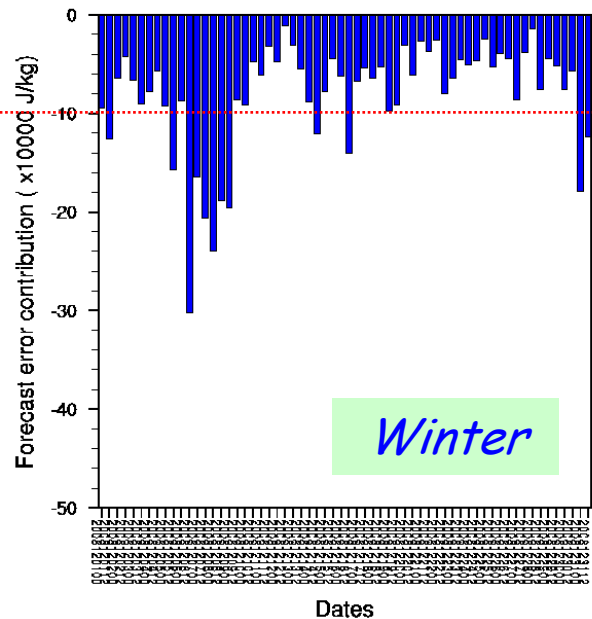
Pilot

Metar

Time Series Impact of Pilot for ALLZ

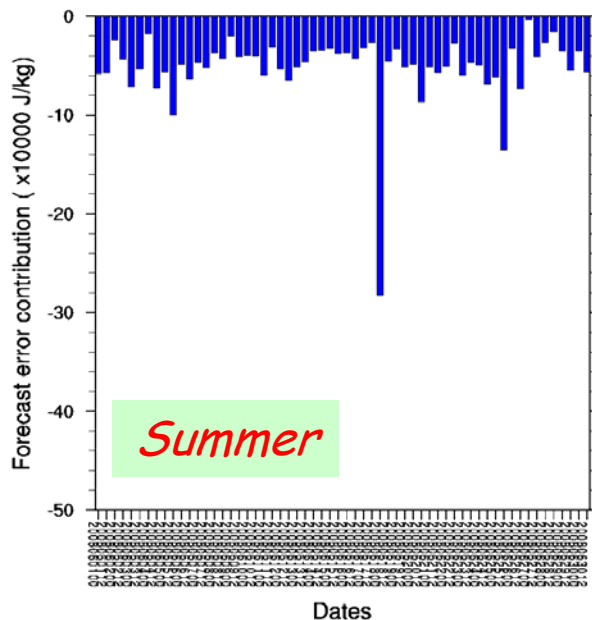


Time Series Impact of Pilot for ALLZ

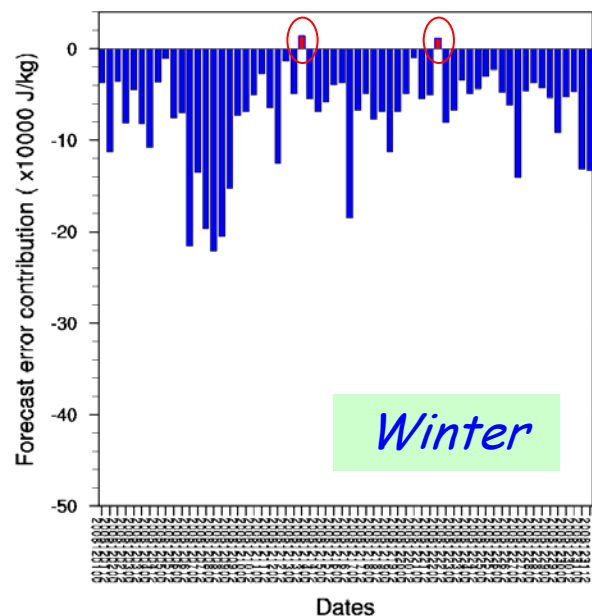


Pilot資料對24hr預報誤差之改進：冬季大於夏季

Time Series Impact of METAR for ALLZ



Time Series Impact of METAR for ALLZ



Metar資料對24hr預報誤差之改進：冬季明顯大於夏季

但冬季有2個時間點呈現負效應

Order : 10^4

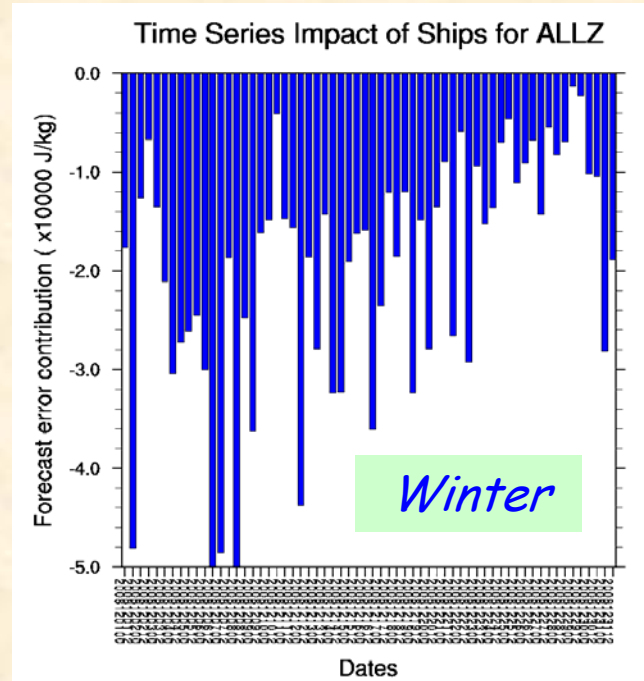
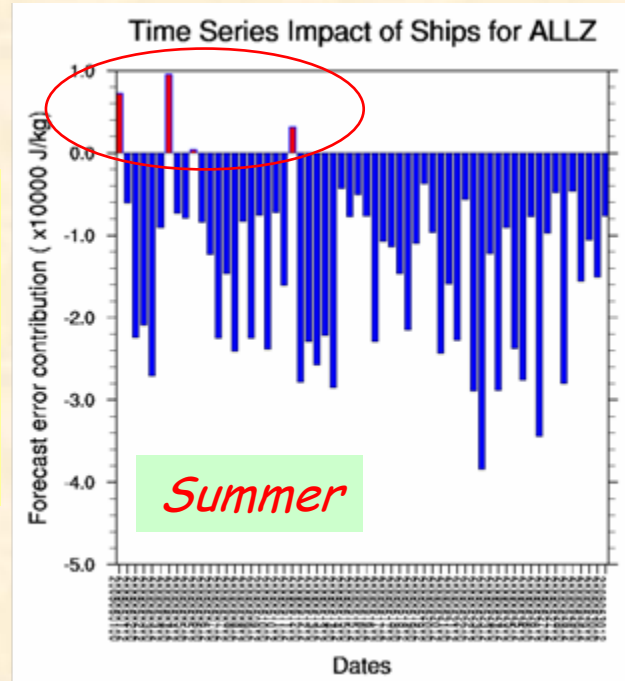
Ships

Buoy

Satem

Ships資料對24hr預報
誤差之改進：冬季**明
顯**大於夏季

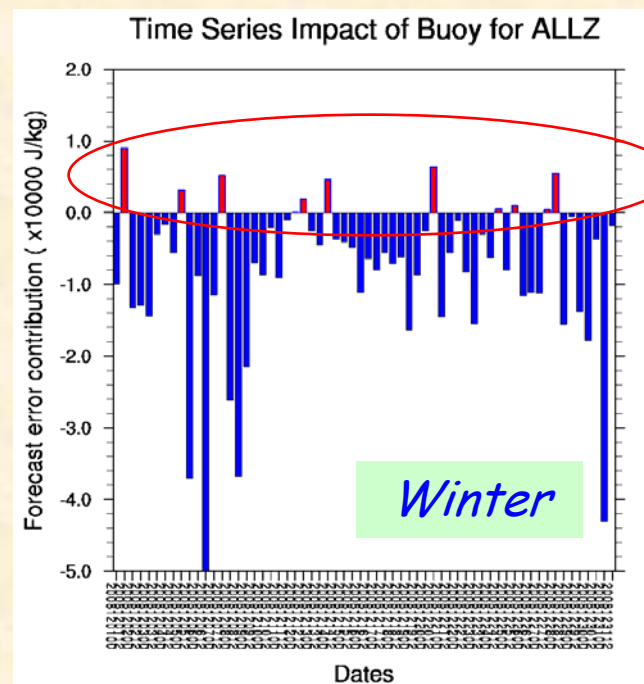
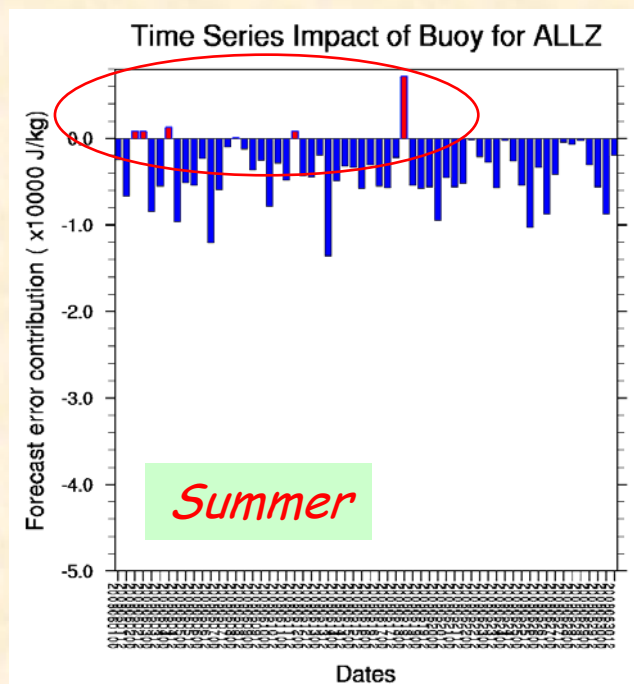
夏季有4個時間點呈現
負效應



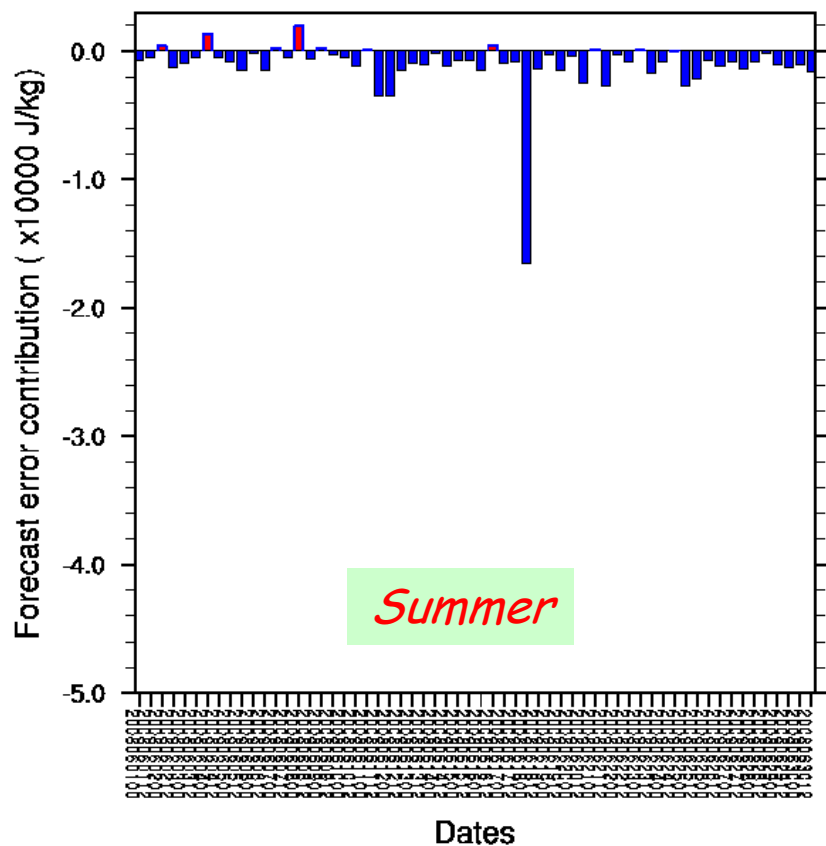
Buoy資料對24hr預報誤
差之改進：冬季**明顯**
大於夏季

夏季有6個時間點呈現
負效應

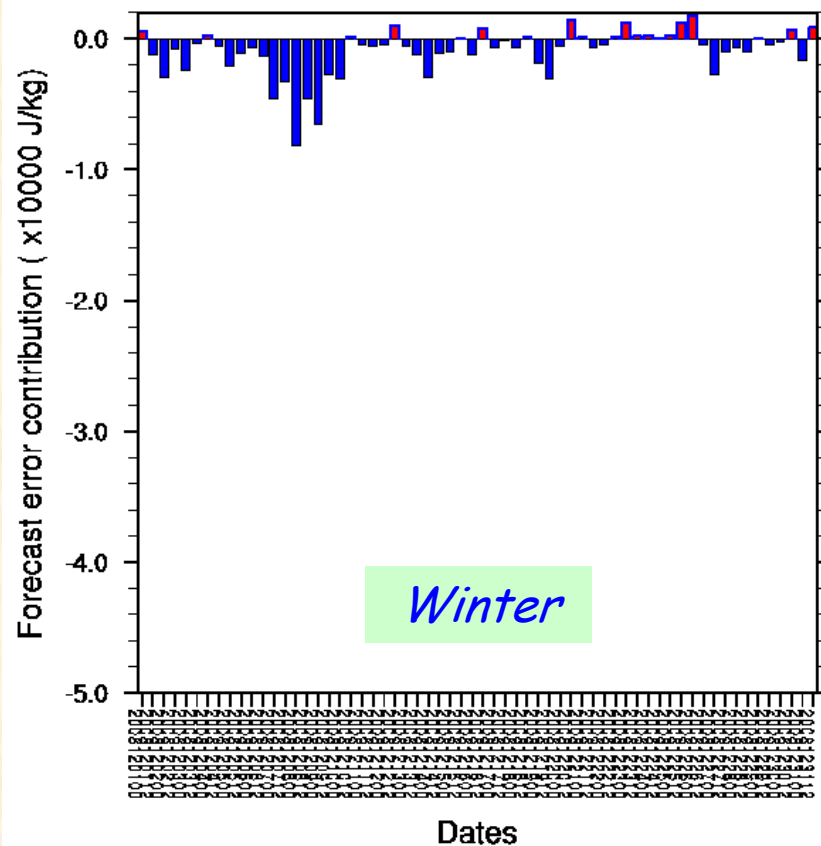
冬季有11個時間點呈現
負效應



Time Series Impact of Satem for ALLZ



Time Series Impact of Satem for ALLZ

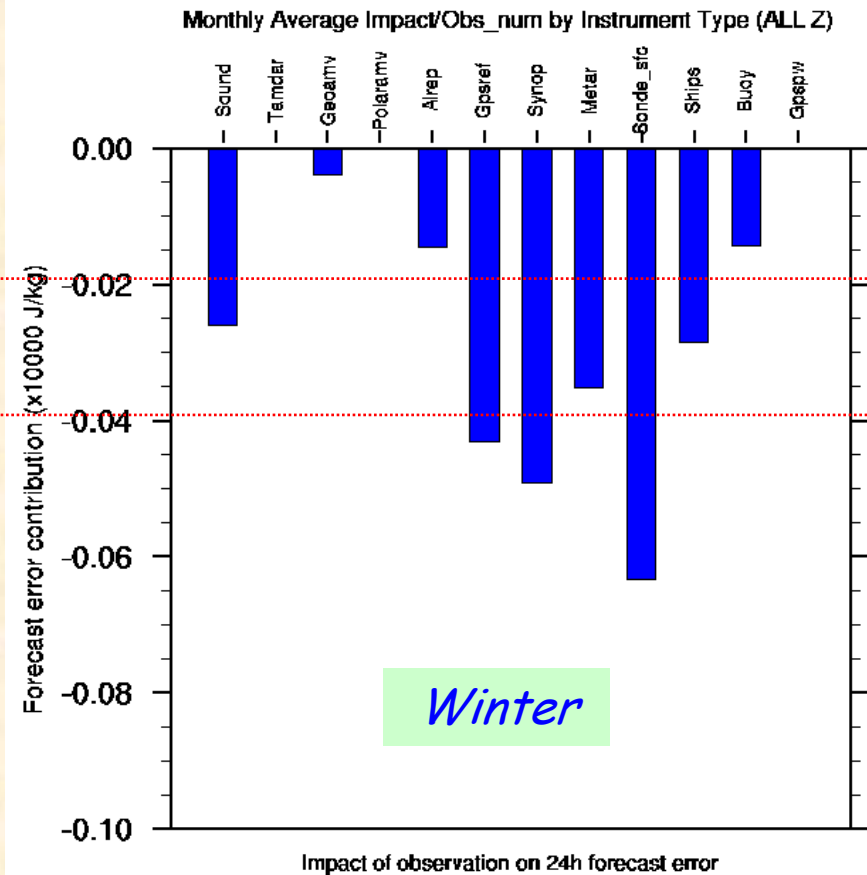
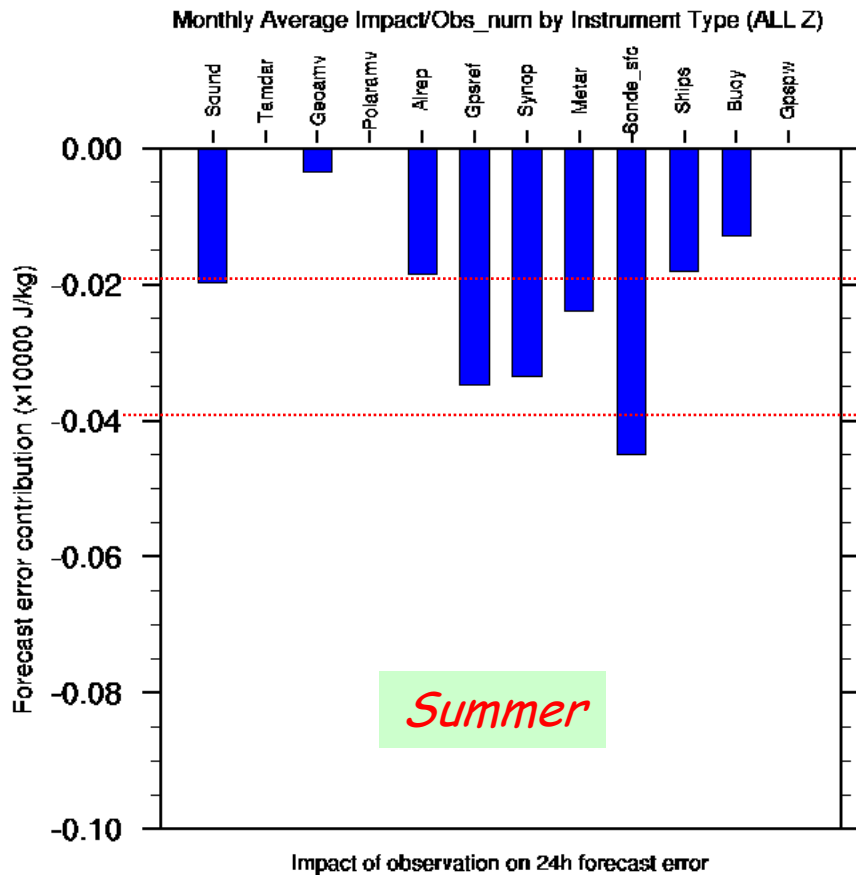


Satem資料對24hr預報誤差之改進：冬、夏季差異不大

夏季有9個時間點呈現負效應

冬季有20個時間點呈現負效應

月平均效益 / 觀測資料量



分析 “月平均效益/觀測資料量” 結果：

1. Sonde_sfc效益最高(資料點較少但貢獻程度高)
2. 其次依序為Gpsrf、Synop
3. GeoAMV之貢獻在除以資料量後發現其貢獻皆是量多所導致
4. 冬季所有觀測資料之貢獻皆高於夏季(除Airep外)

Summary

- 由冬夏兩季的實驗結果分析得到以下幾點結論：
 1. 觀測資料改進24hr預報誤差之程度，冬季大於夏季(Airep 除外)。
 2. 分析時間序列圖結果，雖然觀測資料在冬季改進程度較大，但卻有較多時間點呈現負貢獻(尤其在Buoy與Satem資料最明顯)。
 3. 風場(U&V)是貢獻最大的氣象要素，其原因應是所有觀測資料幾乎都有“風”這氣象變數。
 4. 最有影響力的觀測資料前五名依序是Sound、GeoAMV、EC Bogus、Gpsrf、Synop。
 5. Satem是對於24hr預報誤差改進效益量級與值最小的觀測資料，也是最多負貢獻的觀測資料。
- 若將月平均效益除以觀測資料量：
 1. Sonde_sfc、Gpsrf、Synop為最有效益之前三名觀測資料。
 2. 仍可看出所有資料在冬季貢獻大於夏季。
 3. 資料量最多的GeoAMV在除以資料量後，其效益就大幅降低。

Limitations & improvements

- Different definition or calculation of J will give different impact results (dry energy norm, moist energy norm, verify against precipitation).
- If J or the model is **nonlinear**, there will likely be a perturbation size for which the linearization becomes inadequate in the sense that both using a tangent linear model and using an adjoint suggest the **wrong response** to the perturbation in the nonlinear model.
- In current WRFPLUS, there are three **simplified physics** packages: large scale condensation, simplified CUDU cumulus scheme and vertical diffusion. These three packages pass the basic tangent linear and adjoint check, but their performances are still not very clear.
- The **boundary condition** treatment in the current FSO system.
- Improving the physics packages in WRFPLUS.
- Case Study.

Thanks