CLOUD ASSIMILATION IN WRF MODEL AND IMPACT ON SUB-DOMAINS

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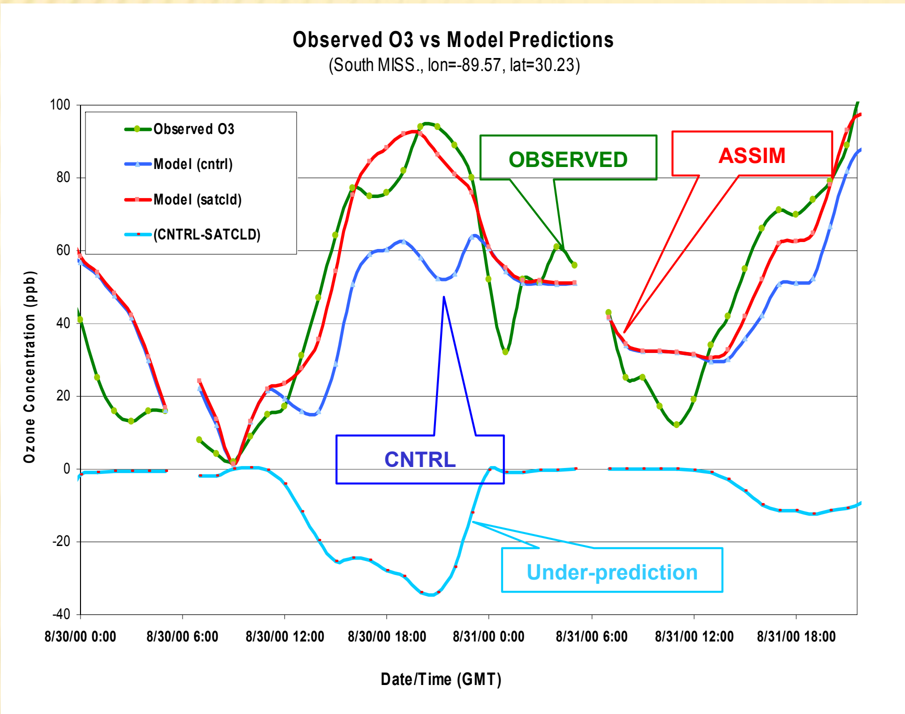
Motivation:

Model errors in location and timing of clouds are a major source of uncertainty in Air Quality Decision Models



IMPACT OF ERRORS IN CLOUD SIMULATION on AQ

- Regulating the photochemical reaction rates
- Aqueous phase chemistry
- Vertical mixing/transport
- Evolution and partitioning of particulate matter
- Wet removal
- LNOx

The current effort: improve model location and timing of clouds in the Weather Research and Forecast (WRF) model by assimilating GOES observed clouds.

Background

- The atmospheric modeling community and policy makers have long recognized the importance of accurate predicting clouds (in particular in SIP modeling).
- Satellites provide a viable means of effectively characterizing clouds at synoptic scales at high spatial resolution. GOES-7 data were used to adjust the model relative humidity field in stratiform cloudy areas (Lipton and Modica,1999).
- Previous attempts at using satellite data to insert cloud water have met with limited success. Previous studies have also indicated that adjustment of the model dynamics and thermodynamics is necessary to fully support the insertion of cloud liquid water in models (Yucel, 2003).
- Previously replaced model cloud transmissivity with satellite observed transmissivity in air quality models (McNider et al 1995, Pour-Biazar et al 2007).
    - Improved model predictions
    - Produced a physical inconsistency in the model system.

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Current Activity

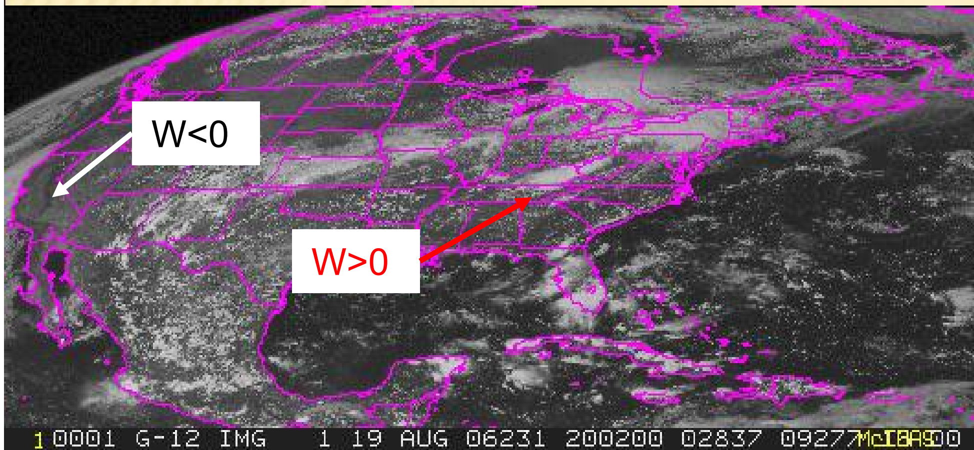
Create an environment in the model that is conducive to clouds formation/removal through adjusting wind and moisture fields.

The goal is to improve the ability of the WRF modeling system to simulate clouds through use of observations provided by the Geostationary Operational Environmental Satellite (GOES).

- **Is Adjusting horizontal divergence enough to form and/or remove clouds in the model simulation?**
- **How are nested domains influenced by lateral boundary conditions?**
- **What are the spatial/temporal scale limitations?**

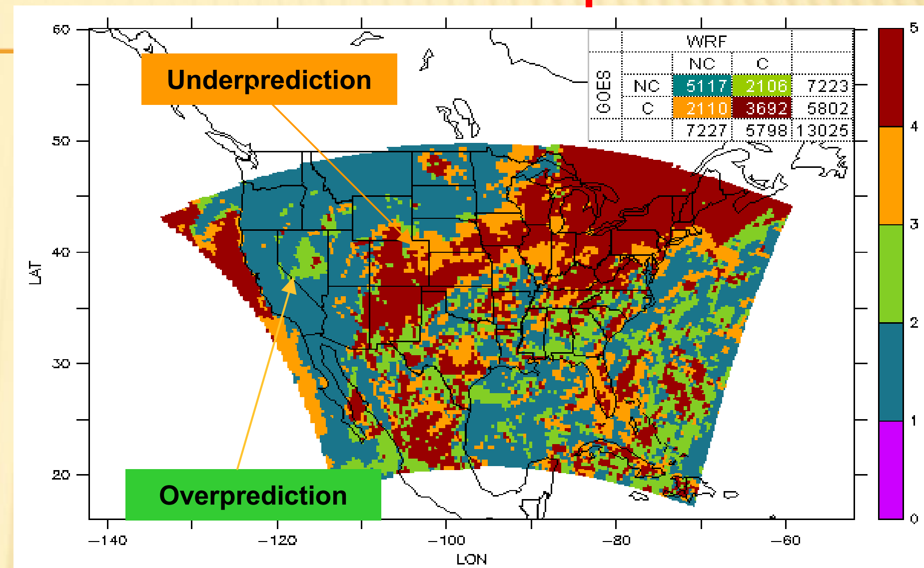
FUNDAMENTAL APPROACH

Satellite



0.65um VIS surface, cloud features

Model/Satellite comparison



- Use satellite cloud top temperatures and cloud albedoes to estimate a **TARGET VERTICAL VELOCITY (Wmax)**.
- Adjust divergence to comply with Wmax in a way similar to O'Brien (1970).
- Nudge model winds toward new horizontal wind field to sustain the vertical motion.
- Remove erroneous model clouds by imposing subsidence (and suppressing convective initiation).

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Implementation in WRF

- Focusing on daytime clouds, analytically estimate the vertical velocity needed to create/clear clouds.

CONCEPT

- Under-prediction: Lift a parcel to saturation.
- Over-prediction: Move the parcel down to reduce RH and evaporate droplets.

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ONE DIMENSIONAL VARIATION SCHEME (1D-VAR)

- Designed for adjusting the horizontal divergence fields as changing vertical wind velocity
- The horizontal wind components in the model are minimally adjusted (O'Brien 1970) to support the target vertical velocity.
- Originally the technique was implemented in a two-step process.
  - Derive multiple linear regression equations with clouds as a dependent variable.
  - Satellite observations are used to identify location of clouds and to investigate areas of the model predicted cloud errors.

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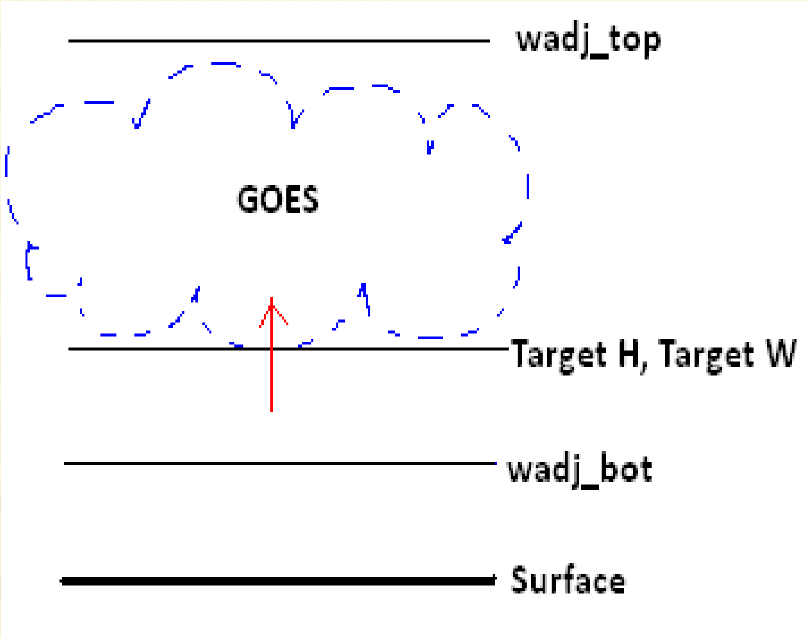
REQUIRED INPUTS FOR 1D-VAR

- ***Target W***: target vertical velocity (m/s)
- ***Target H***: where max vertical velocity is located (above mean sea level)
- ***Wadj_bot***: bottom layer for adjustment
- ***Wadj_top***: top layer for adjustment
- *target W*<0 where model clouds are to be removed, *target W*>0 in areas in which clouds are to be created.
- In the current work *Target W* is calculated analytically

THEN, HOW ARE THE VARIABLES DEFINED IN EACH CASE?

- Under-Prediction



- Issue: Model has no cloud at the grid cell.
- Strategy: estimate the potential height (in the model) where an air parcel is saturated when lifted.
- Wadj_top : cloud top height from the GOES top temperature
- Target H : the saturation level
- Wadj_bot : the origin layer for the parcel.
- Target W : (Target H – Wadj_bot)/30mins

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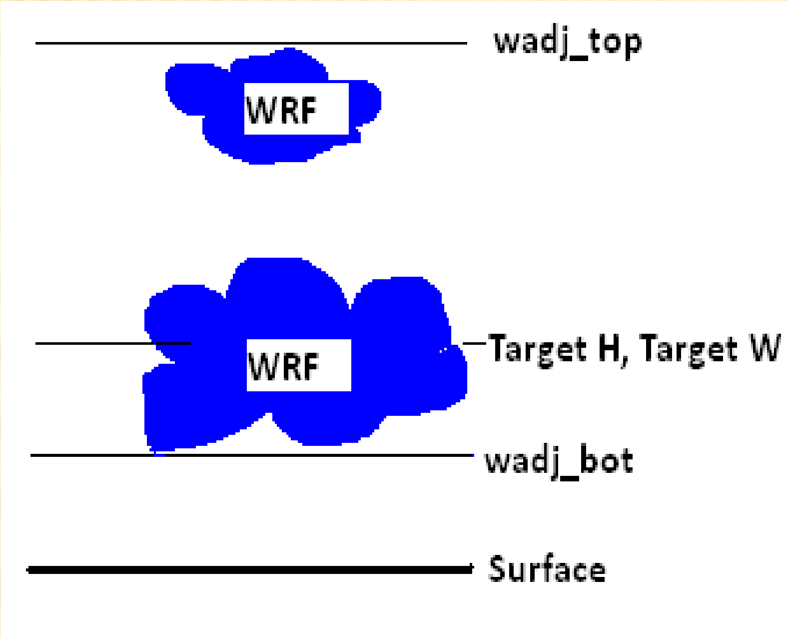
THEN, HOW ARE THE VARIABLES DEFINED IN EACH CASE?

- Over-Prediction



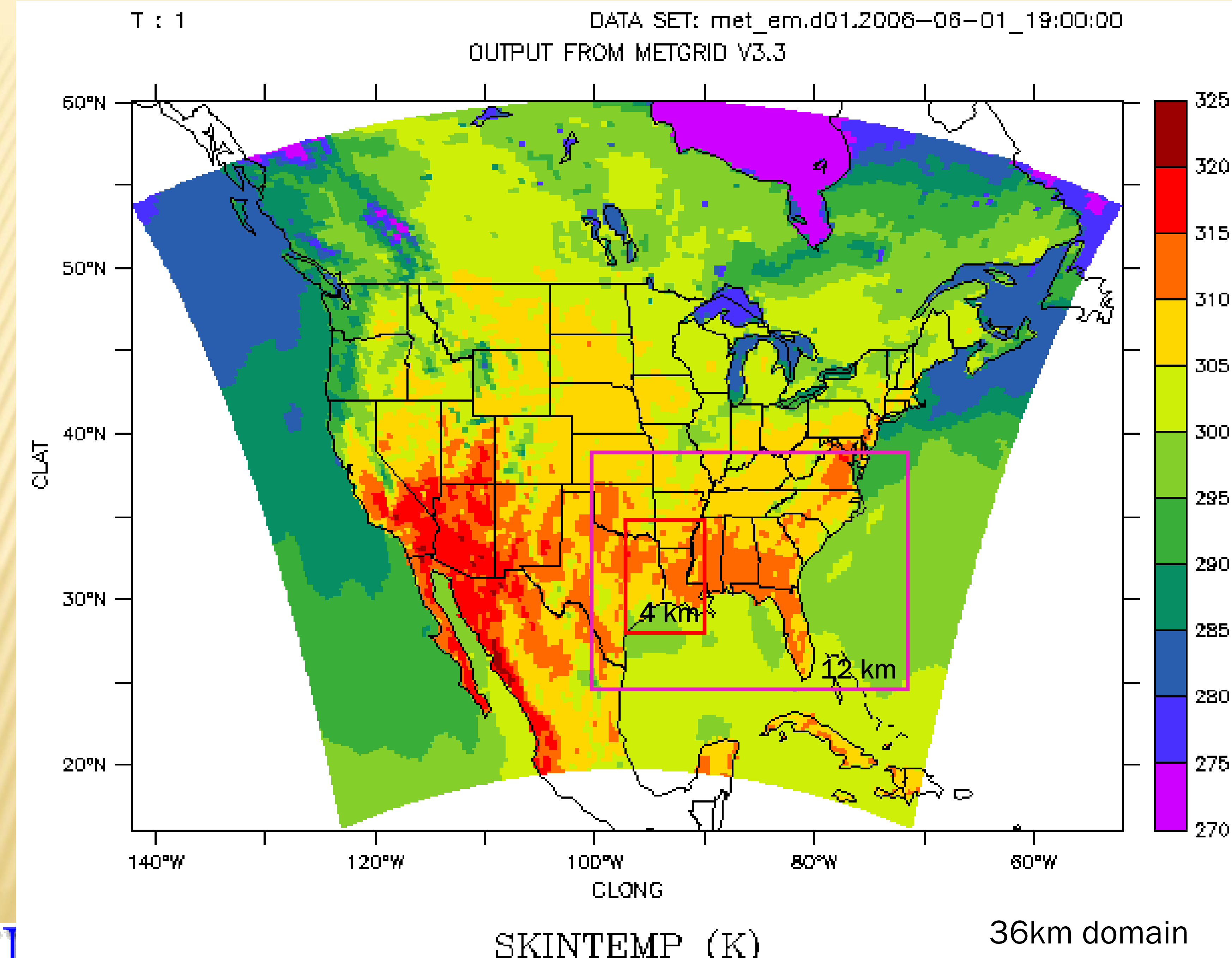
- Issue: the model is cloudy at the grid cell.
- Strategy: introduce subsidence to evaporate and remove clouds
- Wadj_top = cloud top from model (cloud water mixing ratio.)
- Target H = Model layer with maximum cloud water mixing ratio.
- Wadj_bot = lowest model layer with cloud water mixing ratio
- Target W = (Target H – Wadj_bot)/1800s

RESULTS

- 36km simulation over CONUS
- 12km simulation over SE
- 04km simulation over TEXAS

WRF CONFIGURATION

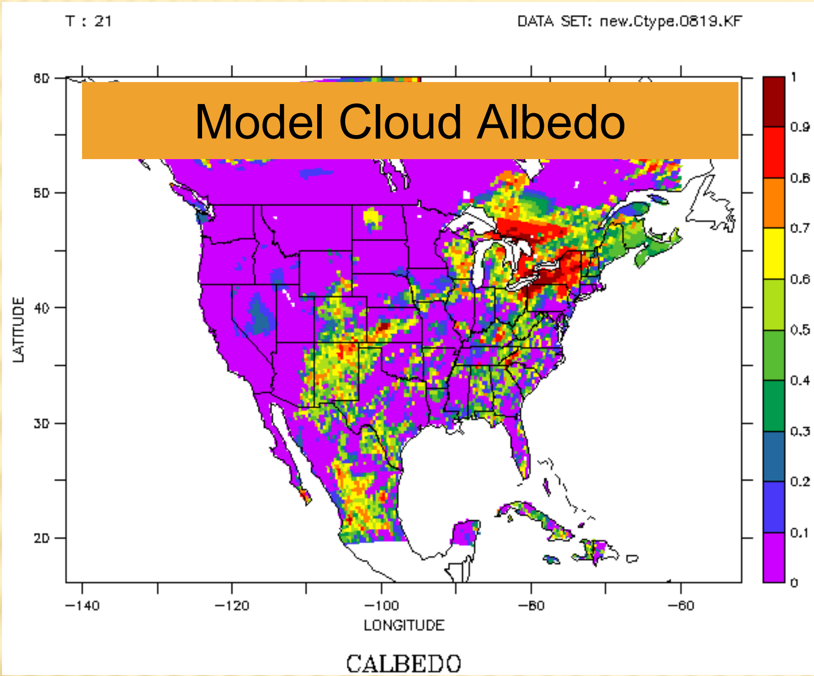
	Domain 01	Domain 02	Domain 03
Running period	August, 2006		
Horizontal resolution	36 km	12 km	4 km
Time step	90s	30s	10s
Number of vertical levels	42		
Top pressure of the model	50 mb		
Shortwave radiation	Duhia		
Longwave radiation	RRTM		
Surface layer	Monin-Obukhov similarity		
Land surface layer	Noah (4-soil layer)		
PBL	YSU		
Microphysics	LIN		
Cumulus physics	Kain-Fritsch	Kain-Fritsch	NO
Grid physics	Horizontal wind		
Meteotological input data	EDAS		
Analysis Nudging	yes		
U, V Nudging Coefficient	3x10-4	1x10-4	3x10-5
T Nudging Coefficient	3x10-4	1x10-4	3x10-5
Q Nudging Coefficient	10-5		
Nudging within PBL	Yes for U and V, NO for q and T		

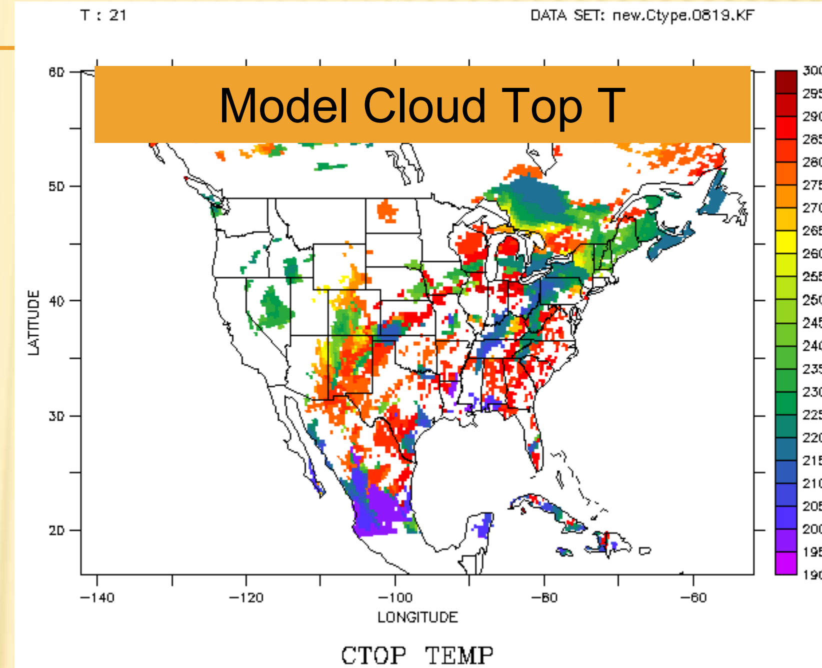


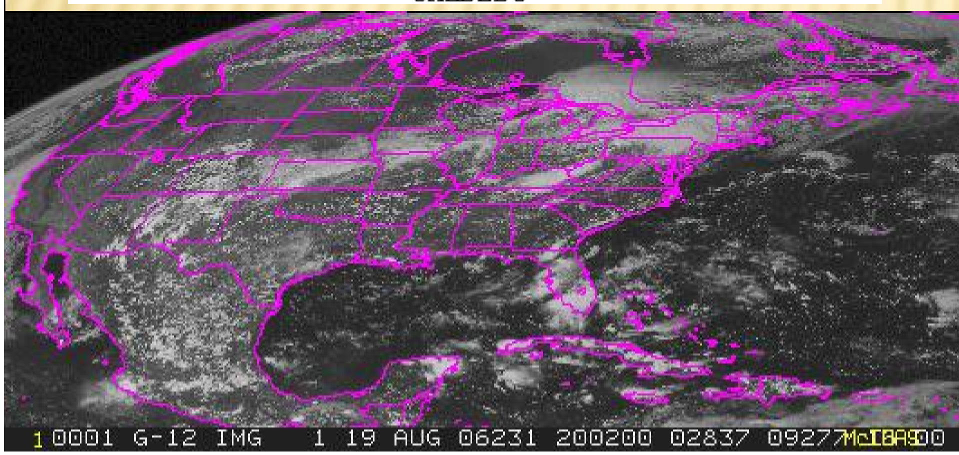
T : 1
DATA SET: met_em.d01.2006-06-01_19:00:00
OUTPUT FROM METGRID V3.3
60°N
50°N
40°N
30°N
20°N
CLAT
140°W
120°W
100°W
80°W
60°W
CLONG
325
320
315
310
305
300
295
290
285
280
275
270
4 km
12 km
SKINTEMP (K)

36km domain

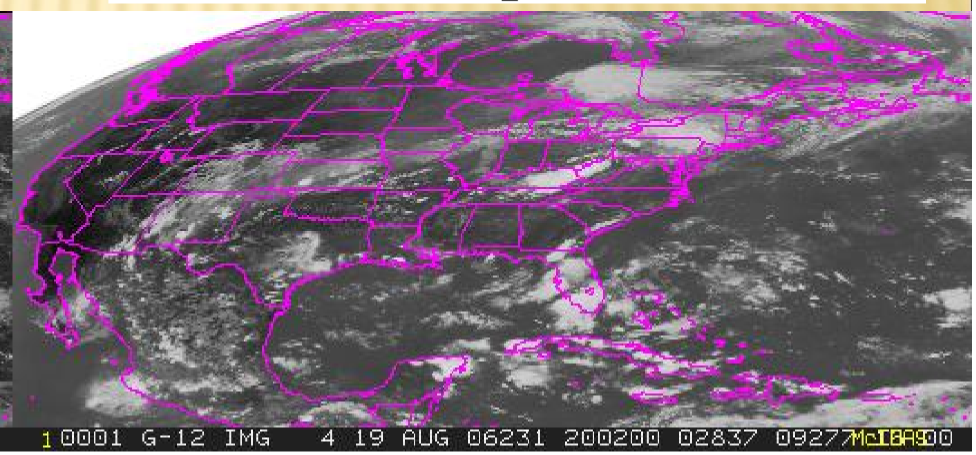
Compare Model With Satellite Observation





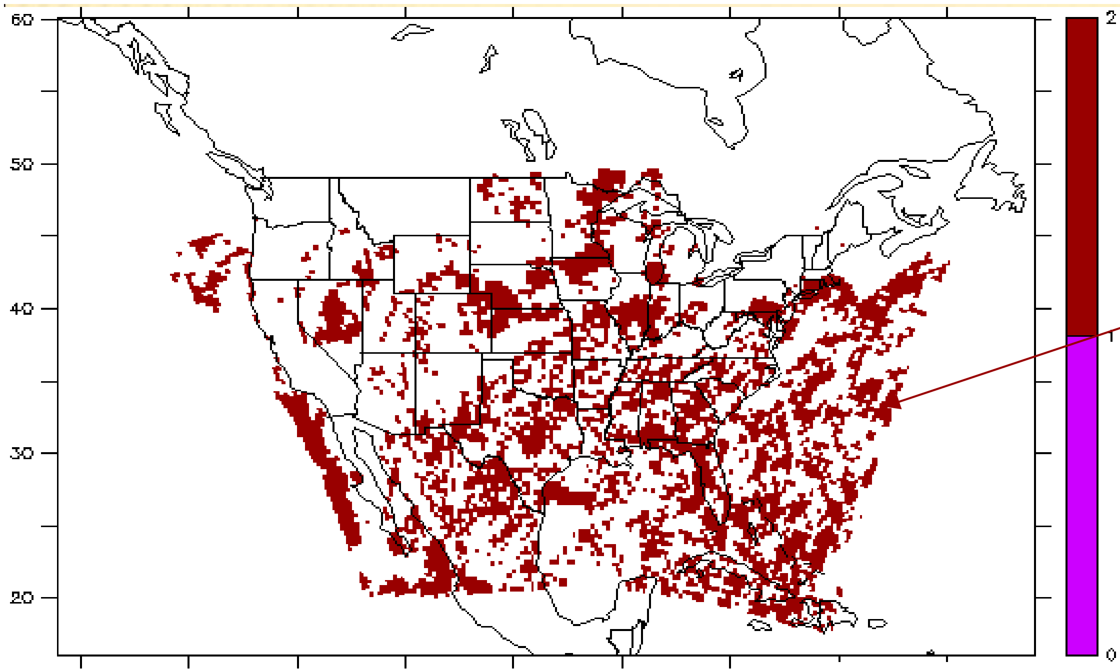


0.65um VIS surface, cloud features



10.7um IR sfc/cloud top temperature

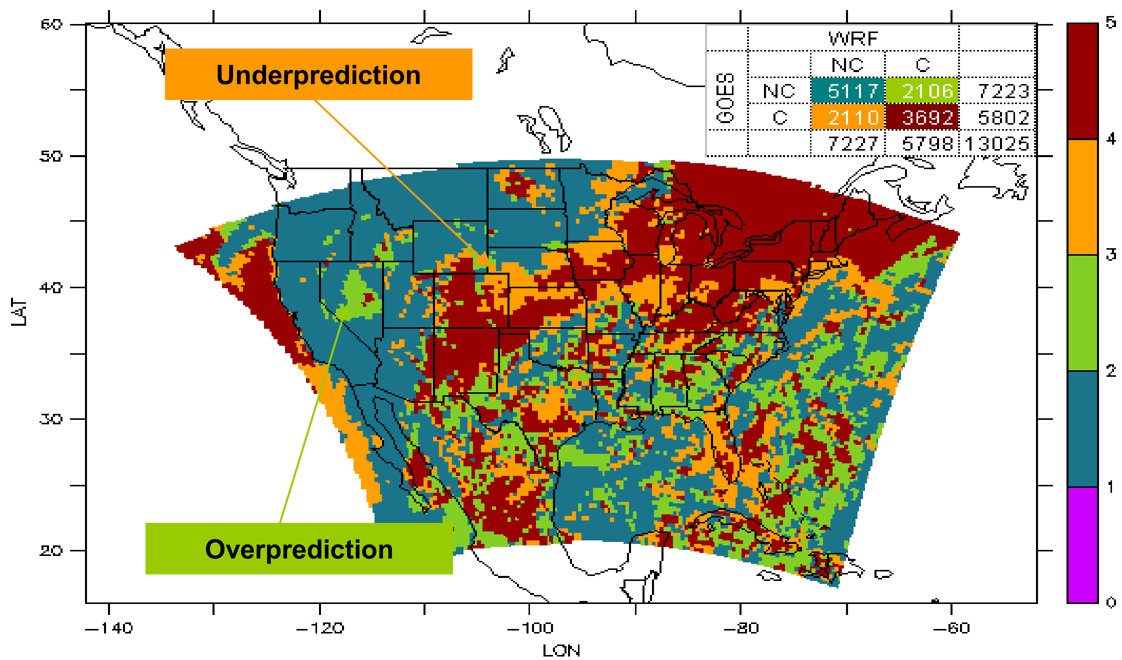
Identify Areas of Under-/Over-prediction



Areas of disagreement between model and satellite observation

A contingency table can be constructed to explain agreement/disagreement with observation

AI = (A+D)/G		**MODEL**	
		Clear	Cloud
	Clear	**A**	**B**
	Cloud	**C**	**D**
		G=(A+B+C+D)	



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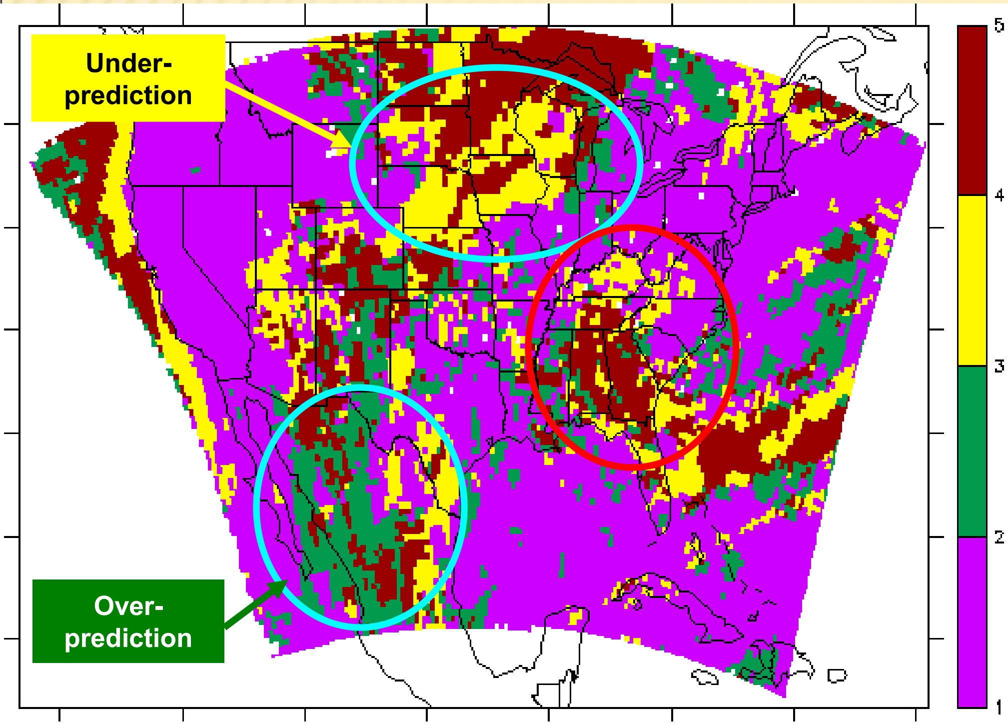
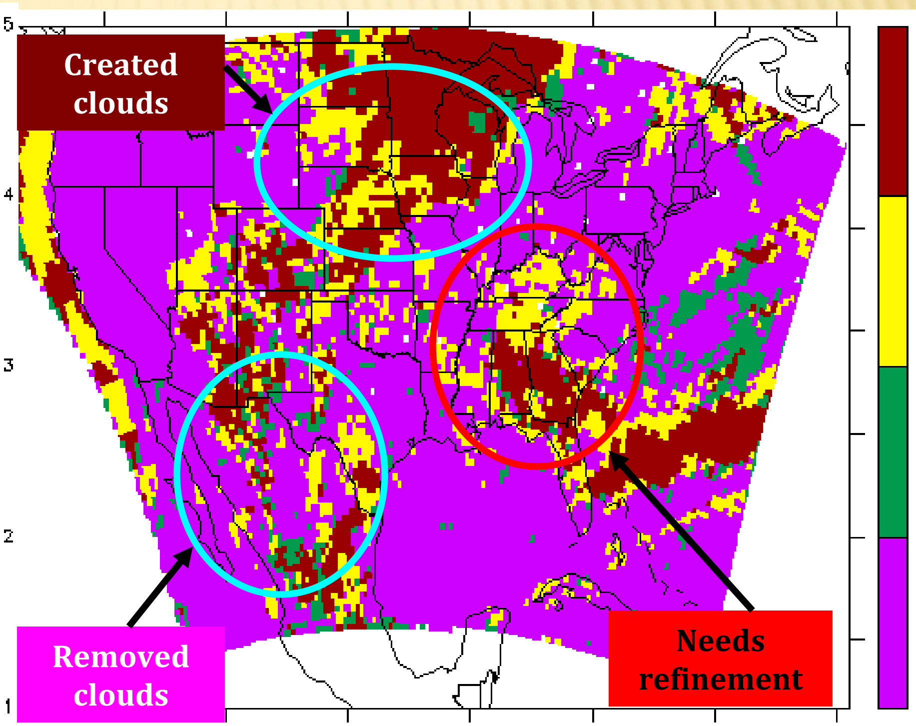
Agreement Index =
(# of cloudy/clear grids in agreement) / (Total # of grids)



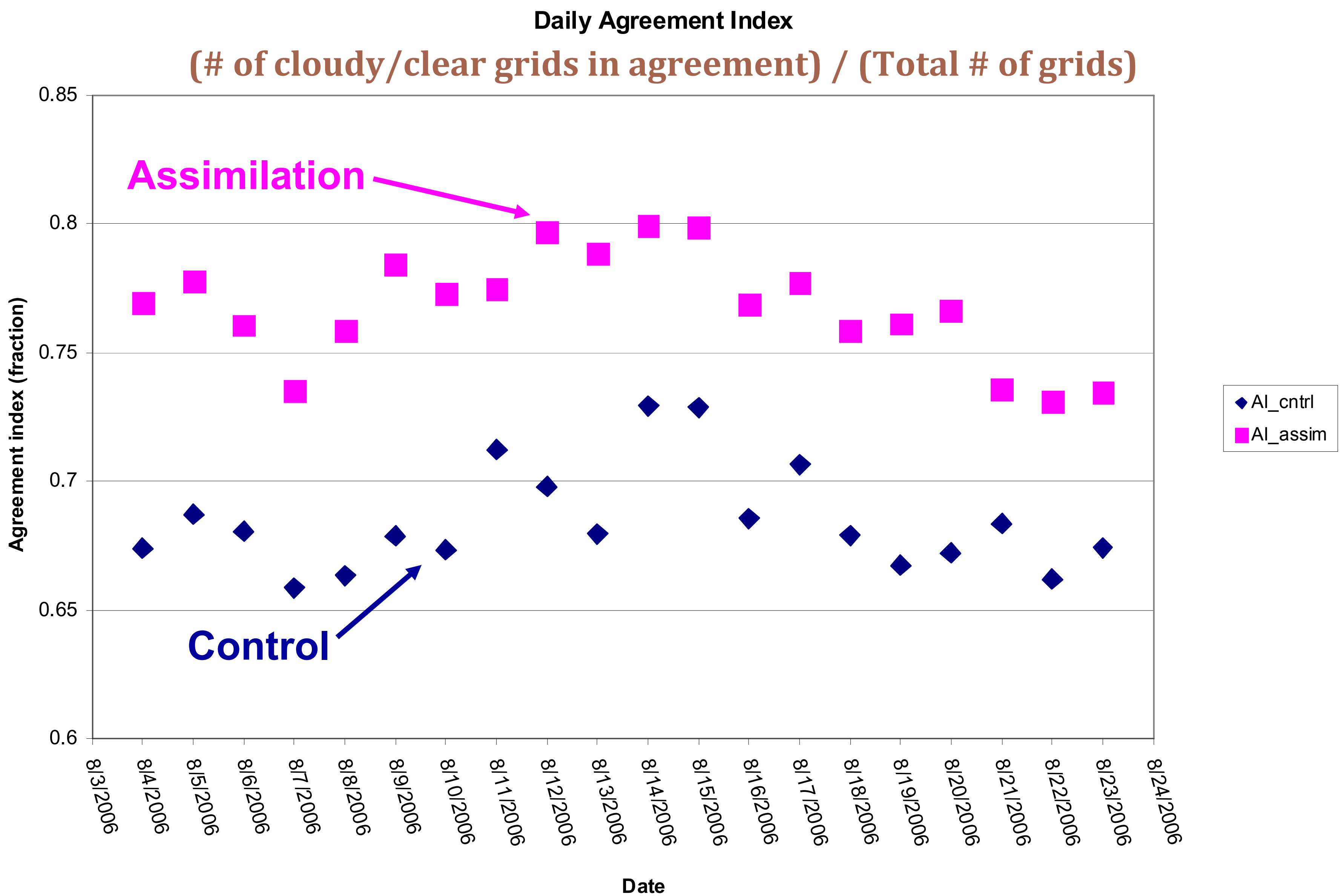


AI for WRF_cntrl

		WRF		AI=.71
		NC	C	
GOES	NC	7174	1824	8998
	C	1943	2049	3992
		9117	3873	12990

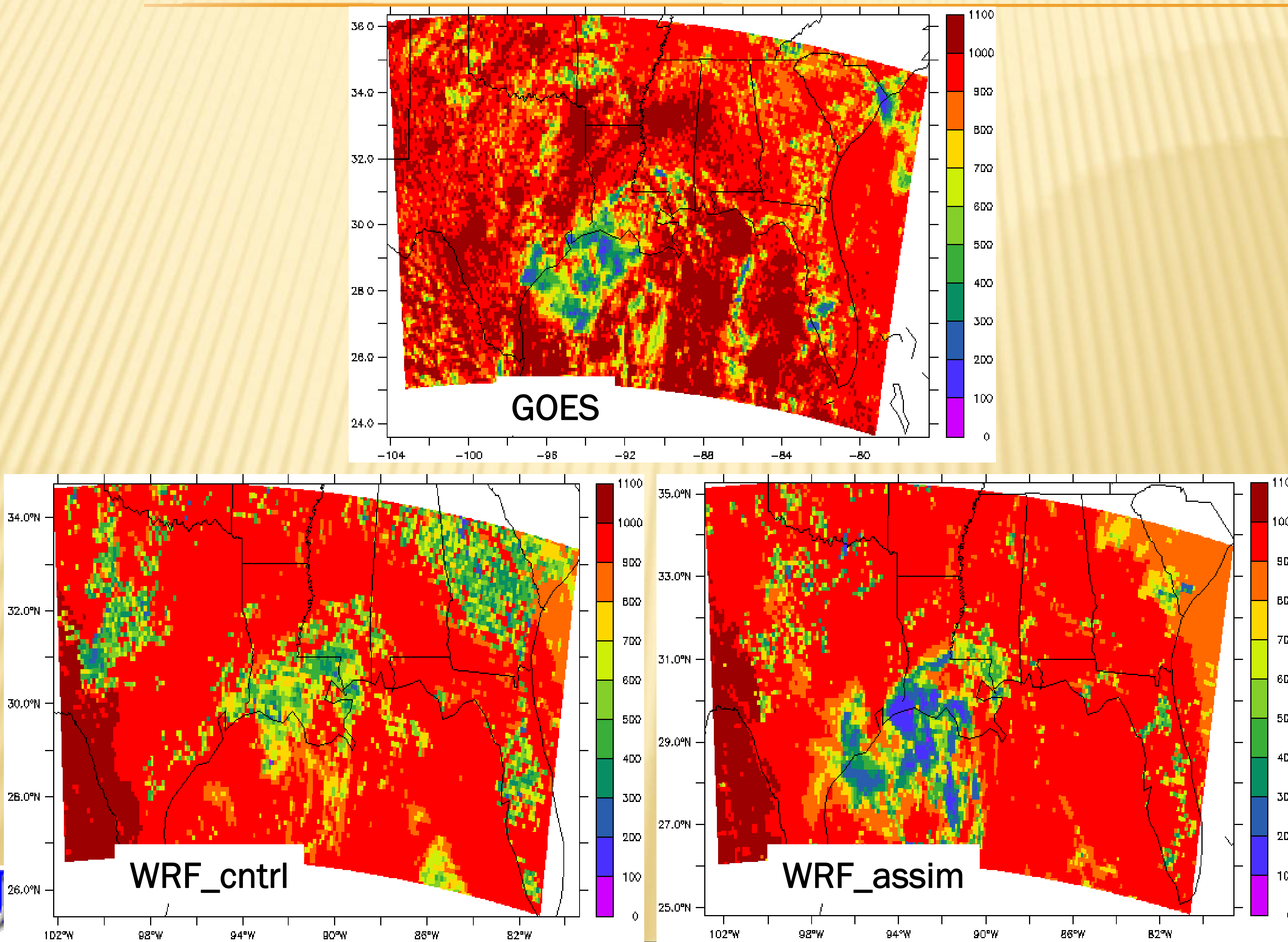
AI for WRF_assim

		WRF		AI=.80
		NC	C	
GOES	NC	8266	732	8998
	C	1892	2100	3992
		10158	2832	12990

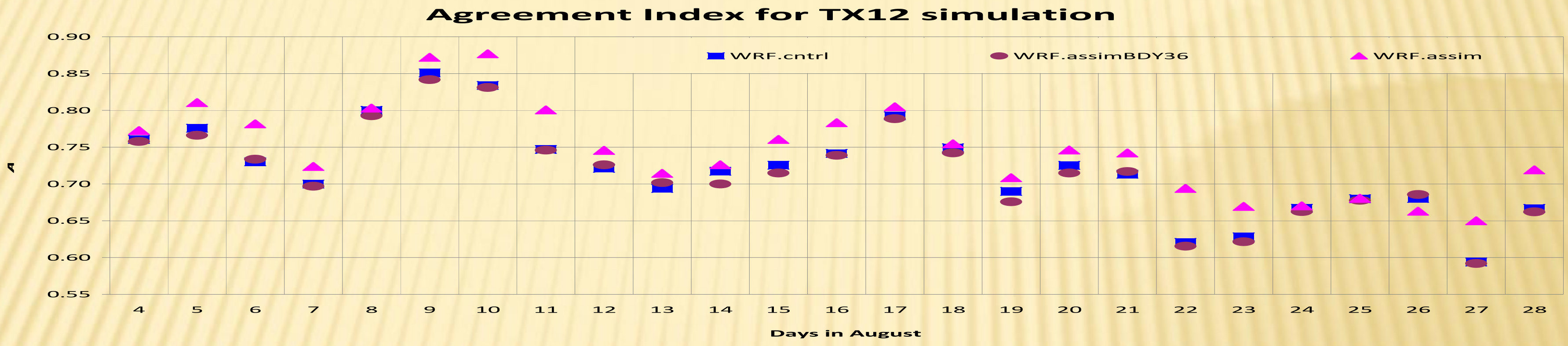


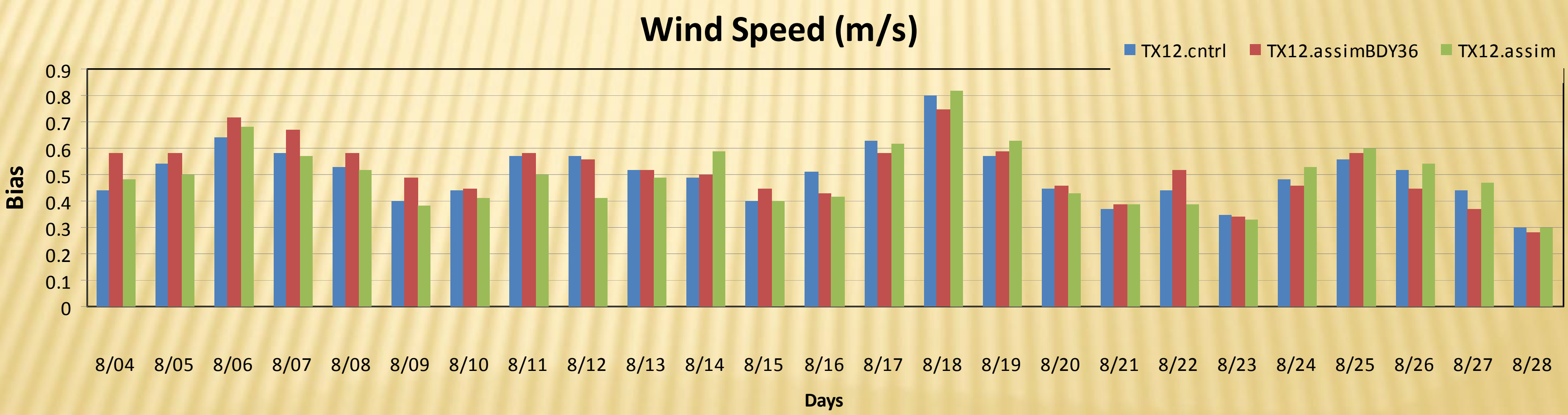
Agreement index increased by 7-10%

12-km Insolation



12-km Statistics





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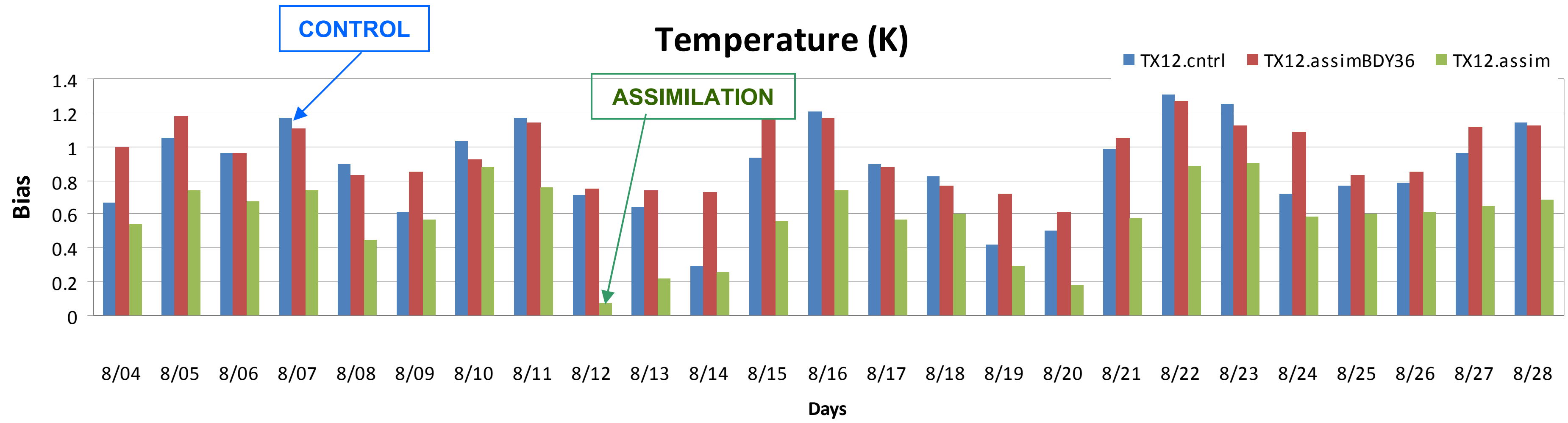
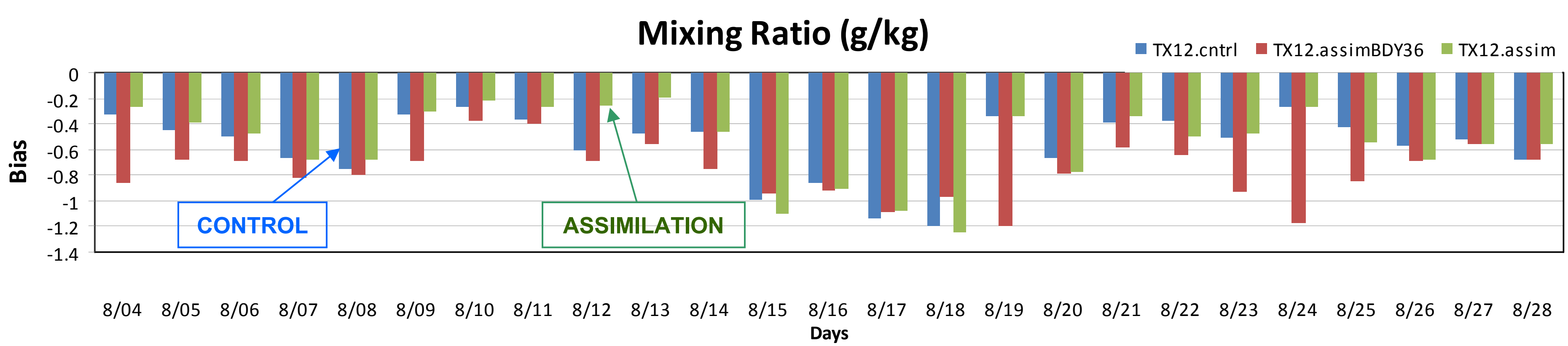
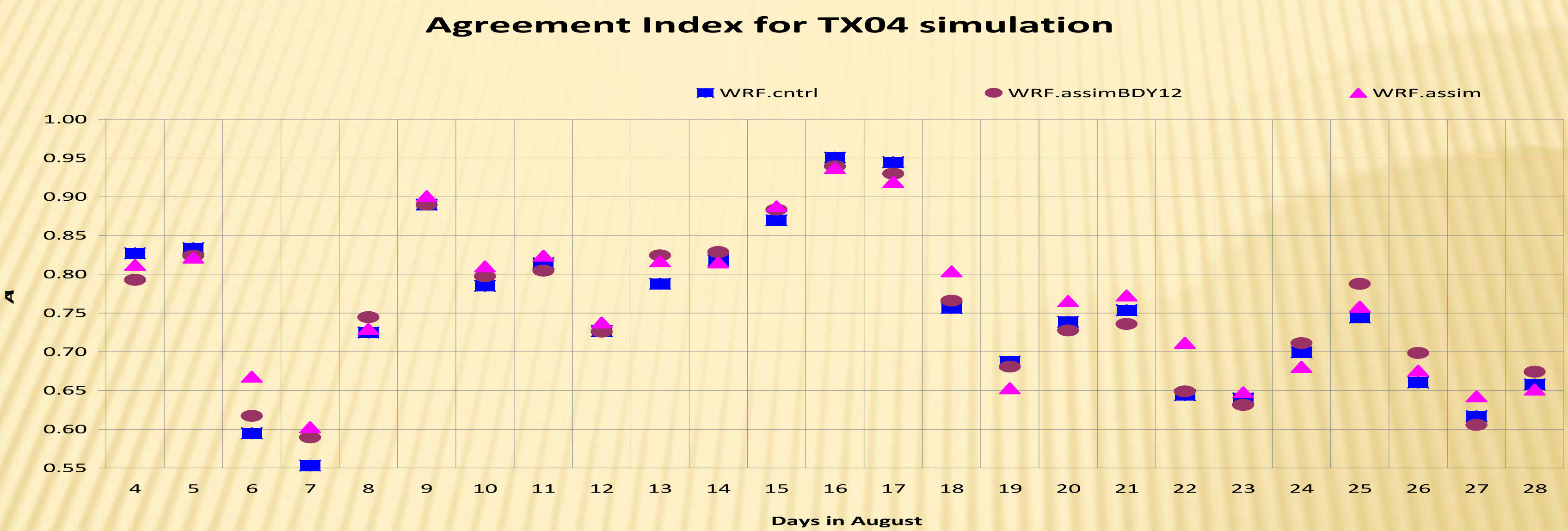
12-km Statistics

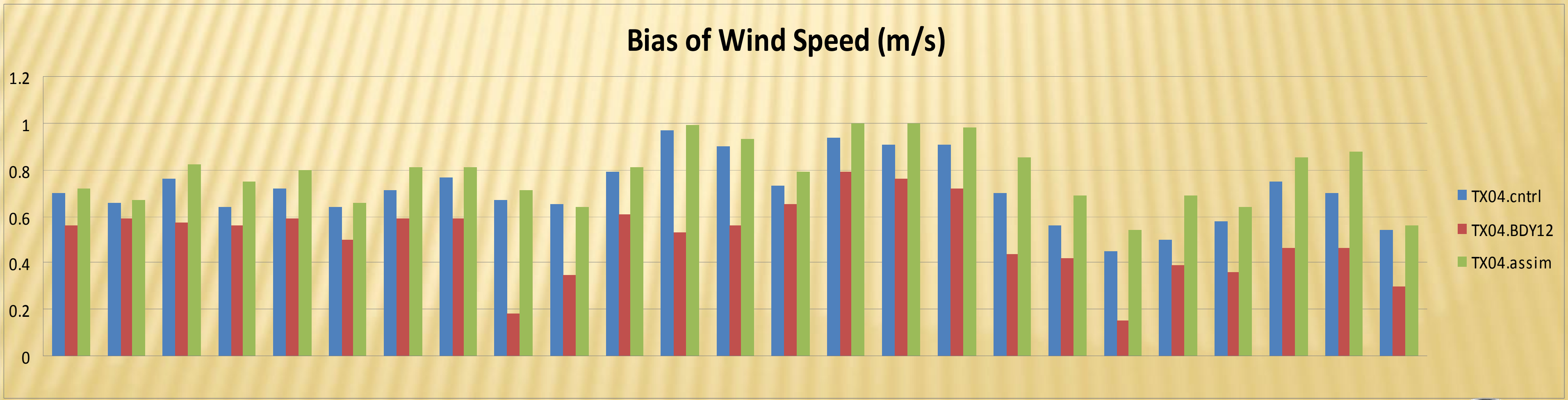
(Temperature bias is reduced)





4-km Statistics





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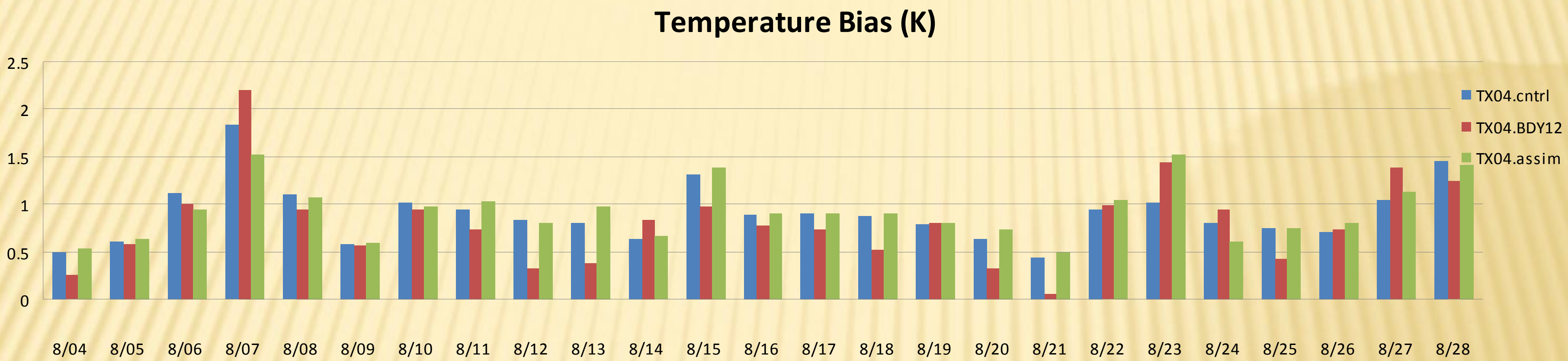
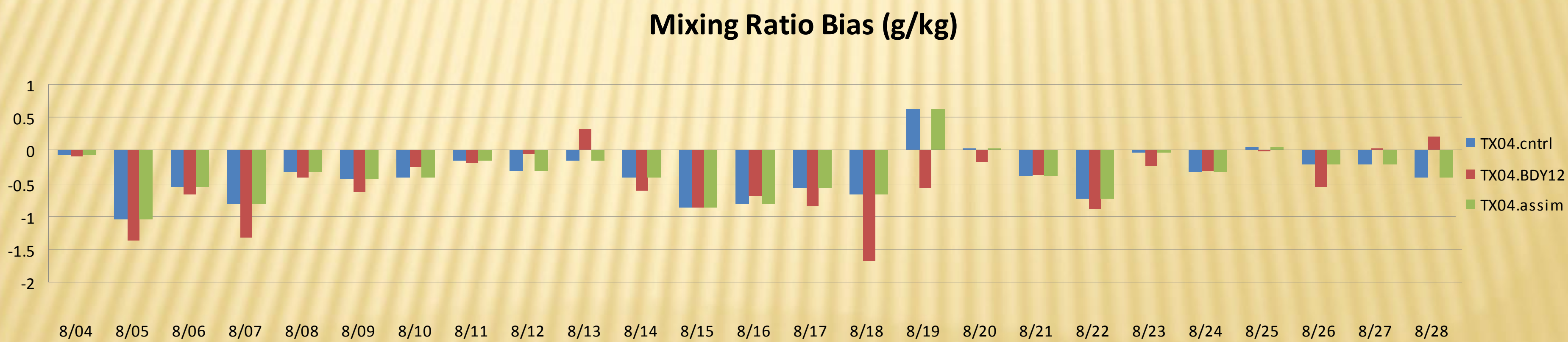
4-km Statistics





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CONCLUSION

- An alternate simple approach for analytically estimating vertical velocity was devised, implemented in WRF, and tested for a month long simulation over August 2006.
- Overall, the improvements in cloud simulation were more pronounced and more significant in the 36-km simulations.
- Satellite data assimilation did not significantly reduce wind speed bias in any of the simulations, but reduced temperature and mixing ratio bias for 36- and 12-km simulations.
- For 4-km simulation, assimilating satellite data didn't improve model performance with respect to key state variables.
- Using assimilation in 12-km simulation that provided the lateral boundary condition for the 4-km simulation reduced the bias in wind speed, temperature and mixing ratio in 4-km simulation.

ACKNOWLEDGEMENT

The findings presented here were accomplished under partial support from NASA Science Mission Directorate Applied Sciences Program and the Texas Commission on Environmental Quality (TCEQ).

Note the results in this study do not necessarily reflect policy or science positions by the funding agencies.

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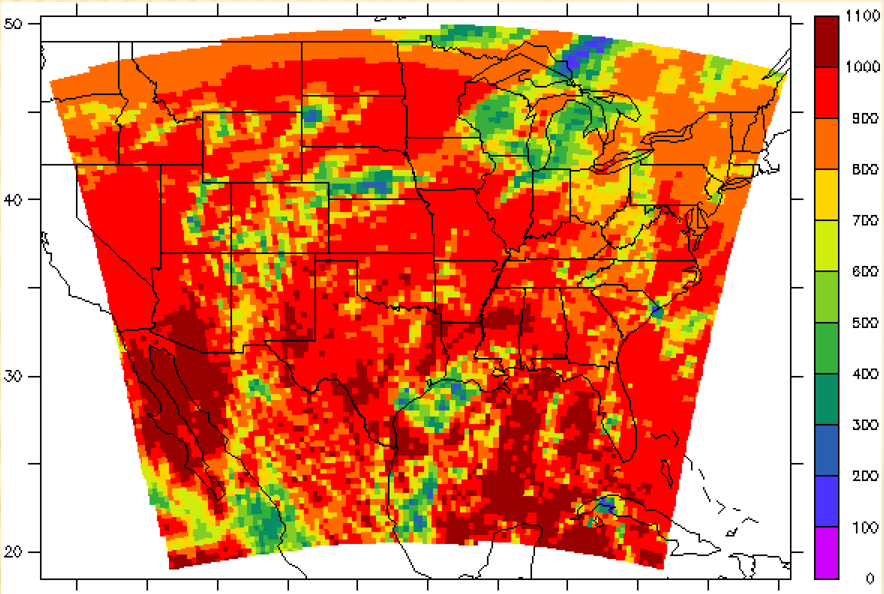
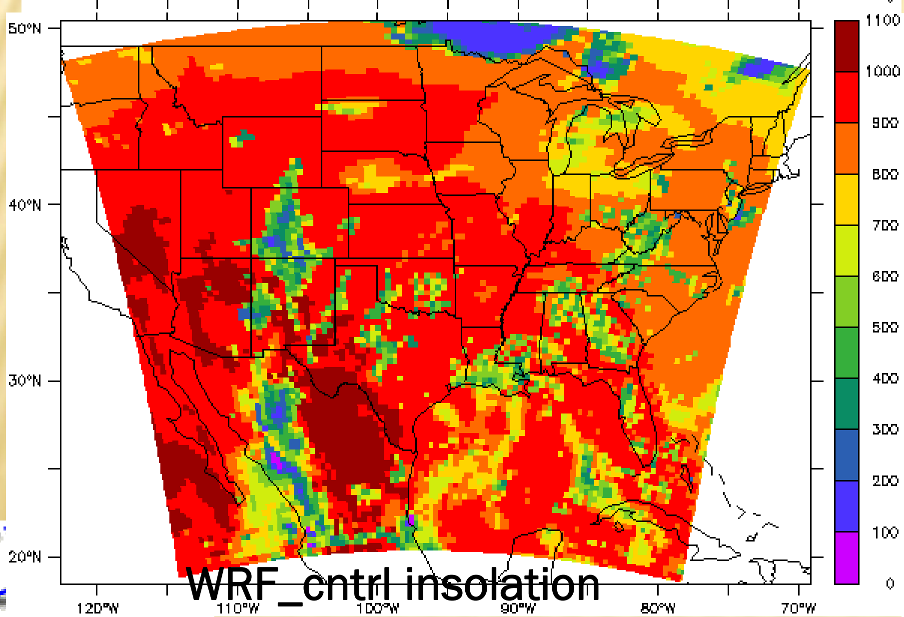
ADDITIONAL SLIDES

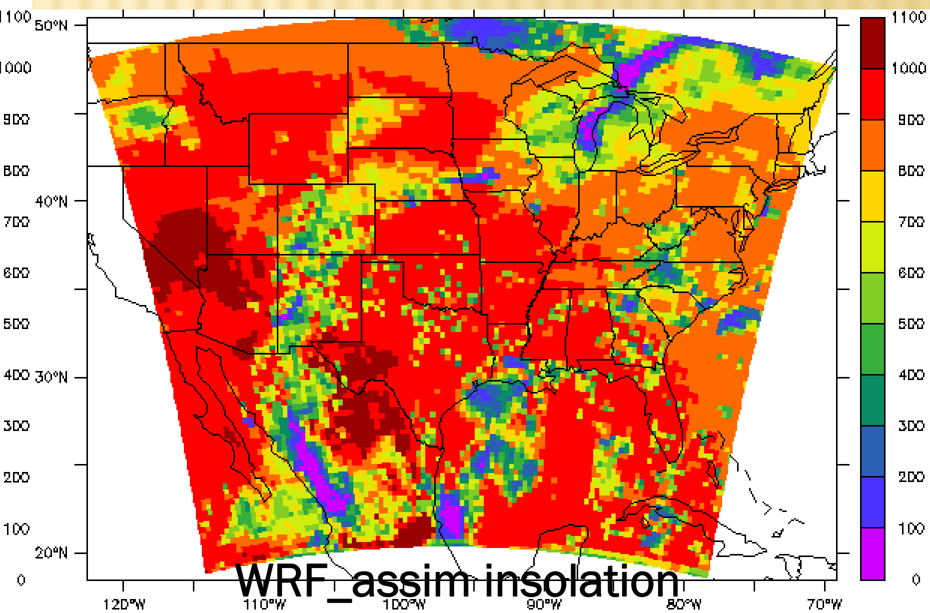
INSOLATION AT 36KM



GOES Insolation



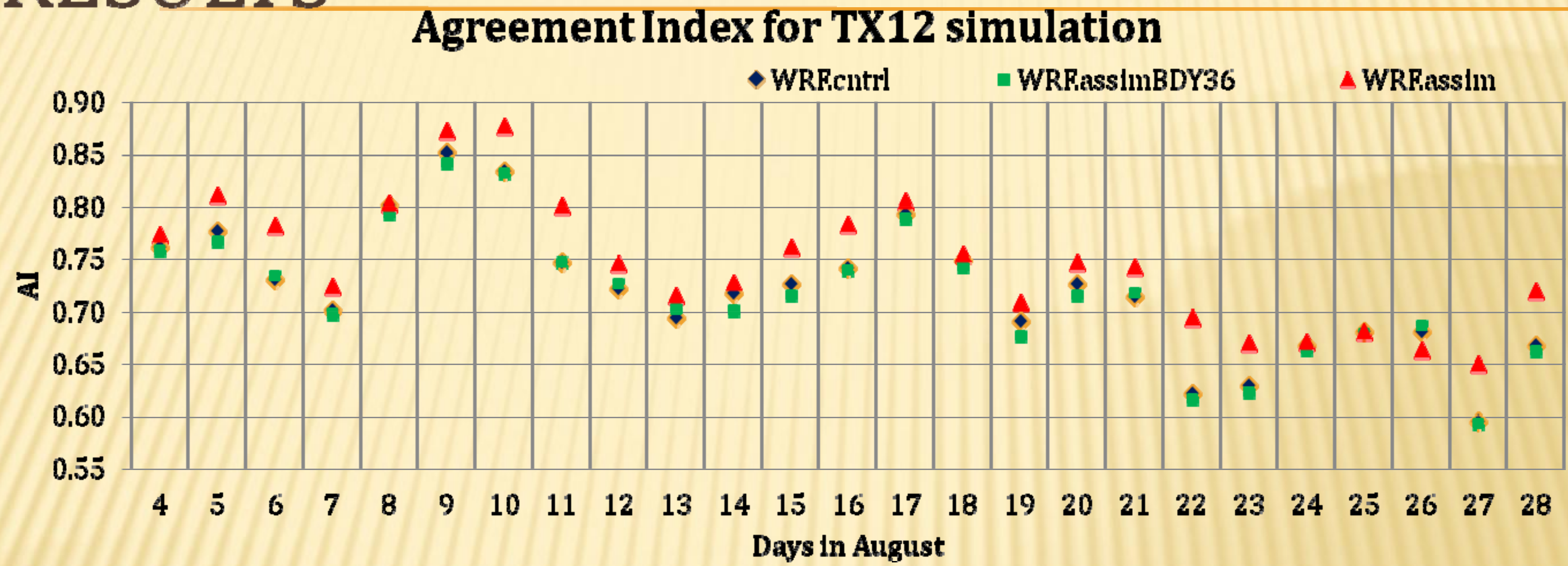
WRF_cntrl insolation

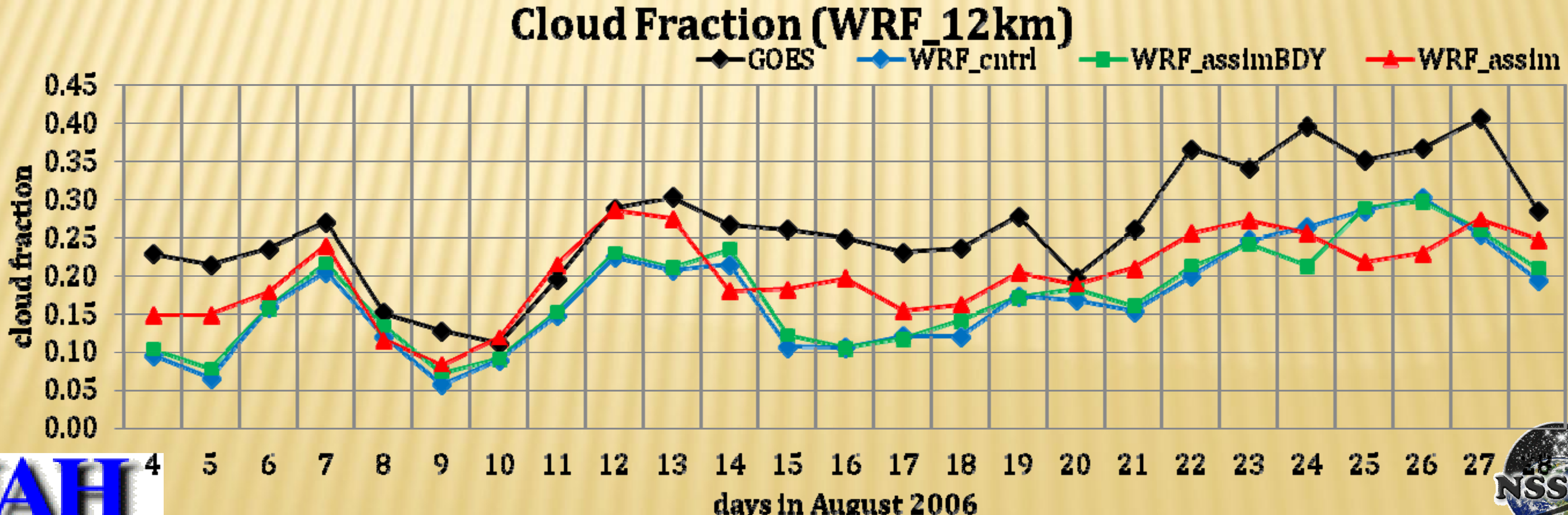


WRF_assim insolation

RESULTS

Daily averaged value during 15-20GMT





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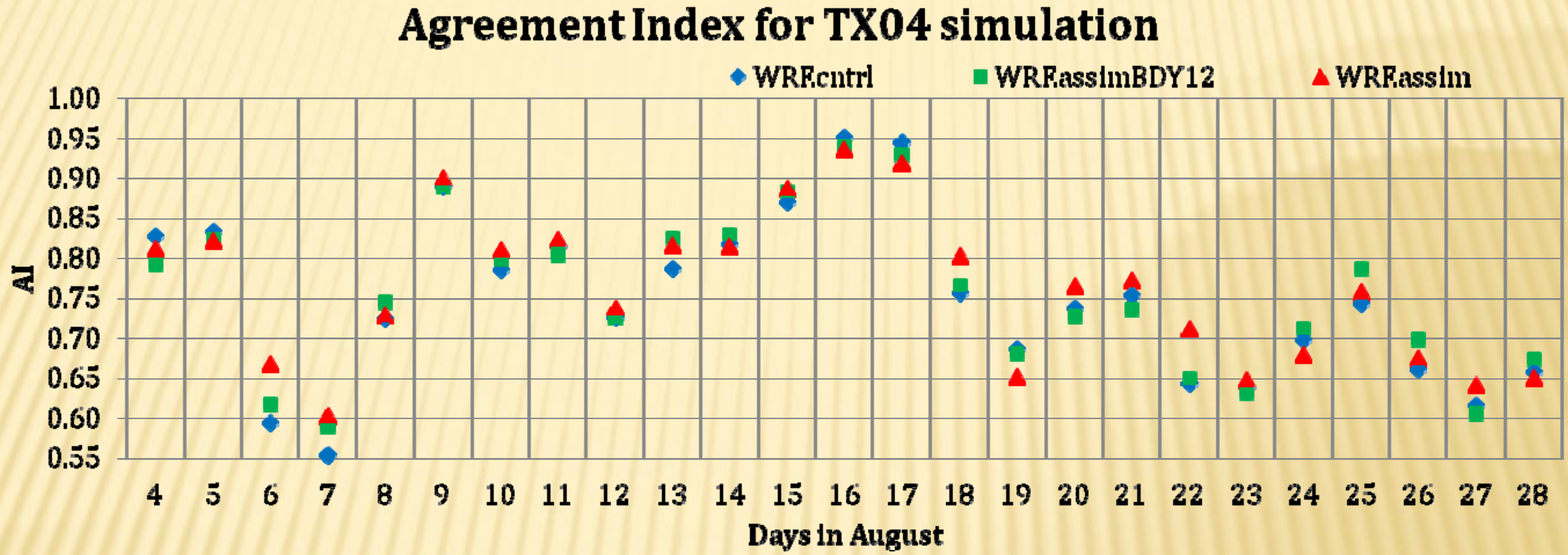
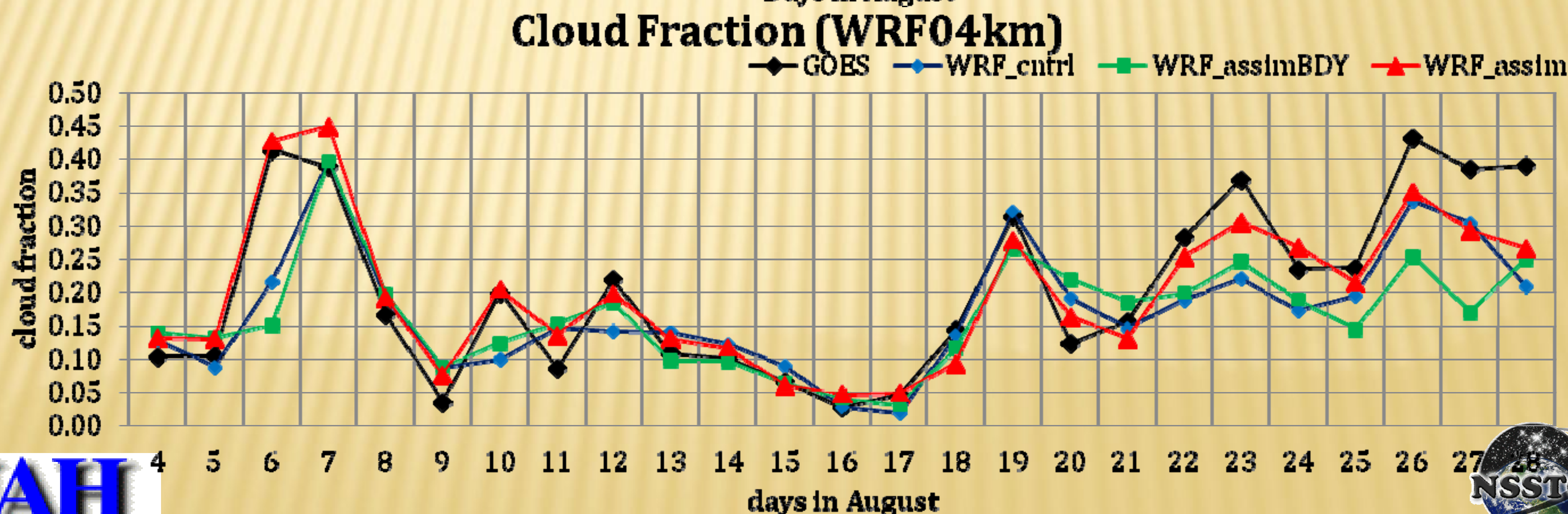
RESULTS

Daily averaged value during 15-22GMT





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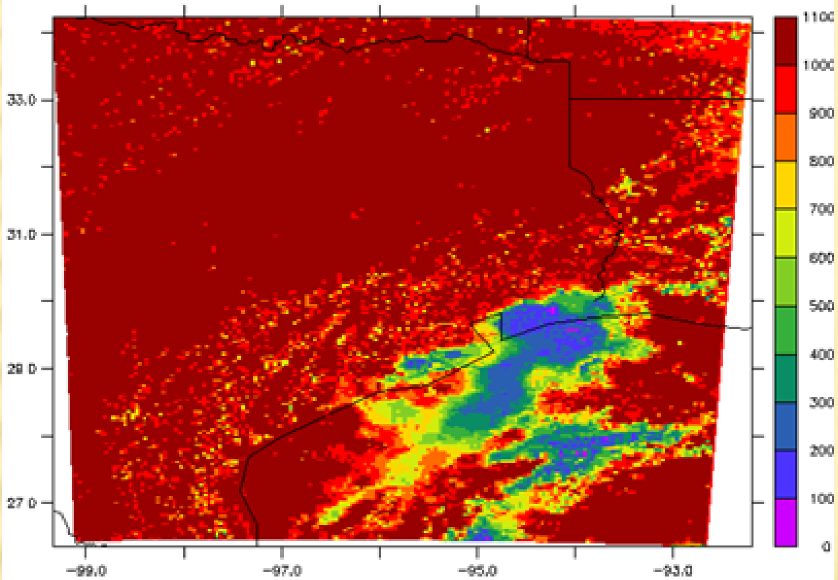
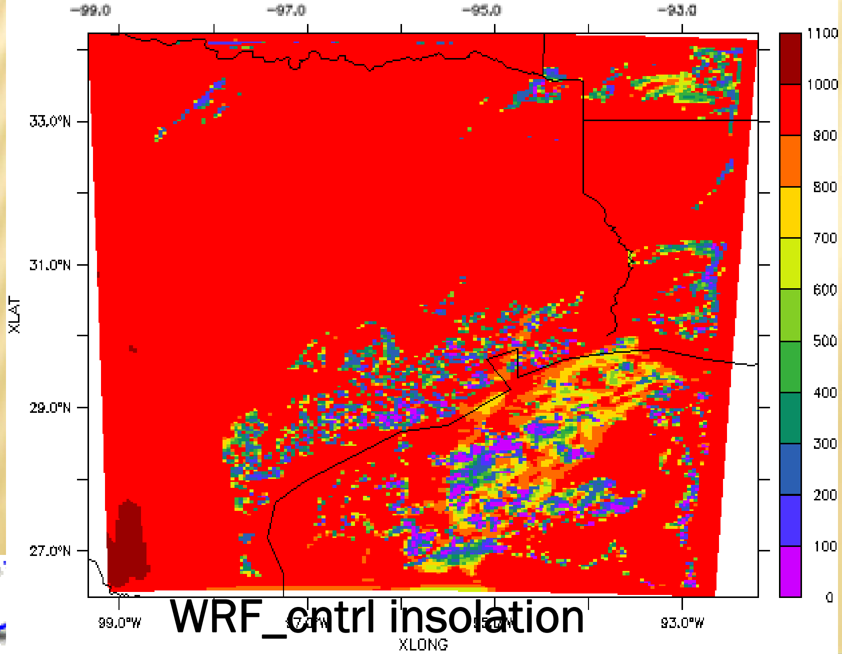
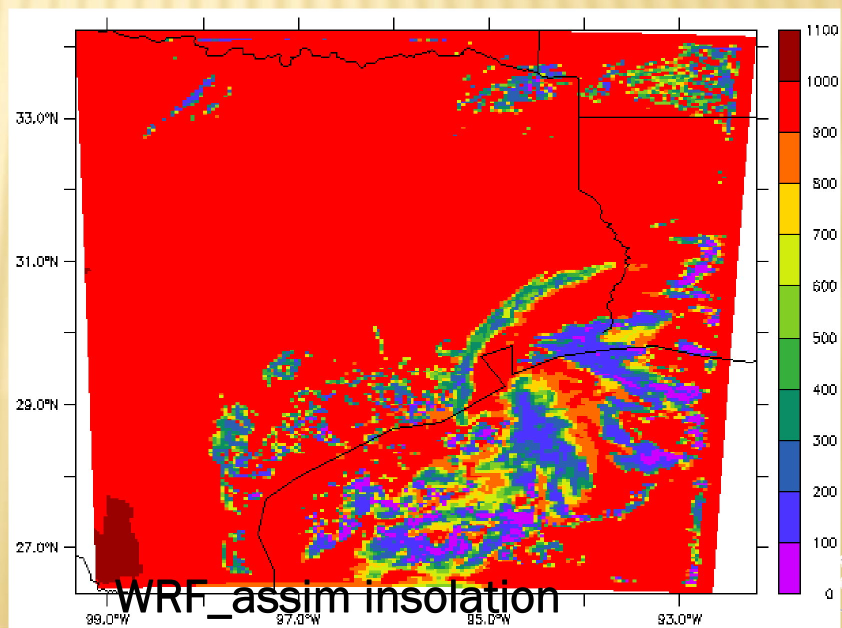
INSOLATION AT 04KM



GOES Insolation



WRF_cntrl insolation



WRF_assim insolation