Utilization of Geostationary Satellite Observations for Air Quality Modeling During 2013 Discover-AQ Texas Campaign

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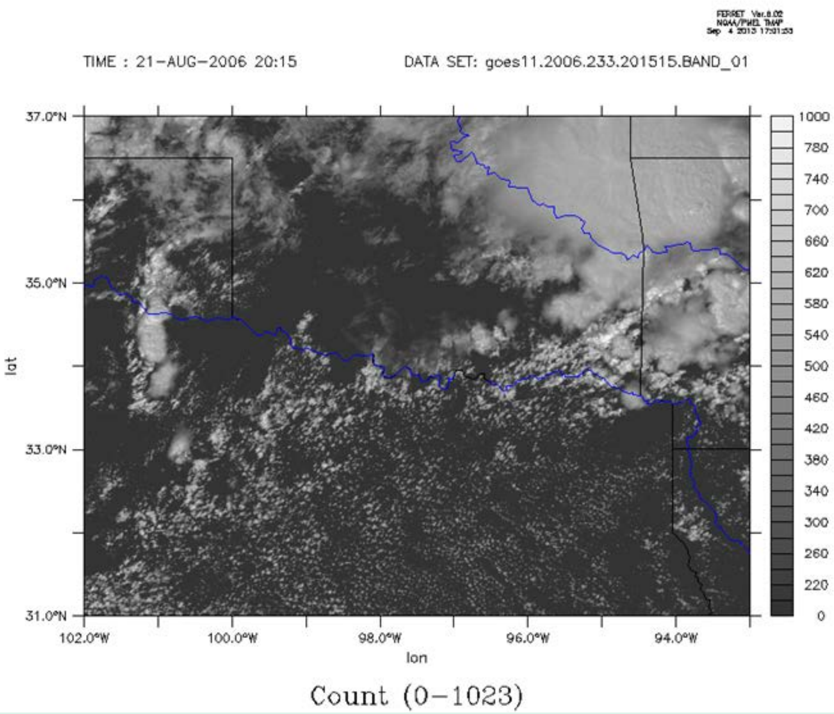
Background & Motivation

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

- **Surface insolation & temperature, BL development**
- **Regulating the photochemical reaction rates, biogenic VOC emissions**
- **Vertical mixing/transport**
- **Evolution and partitioning of particulate matter**
- **Aqueous phase chemistry, wet removal, LNOx**

Weather Forecasting/Climate

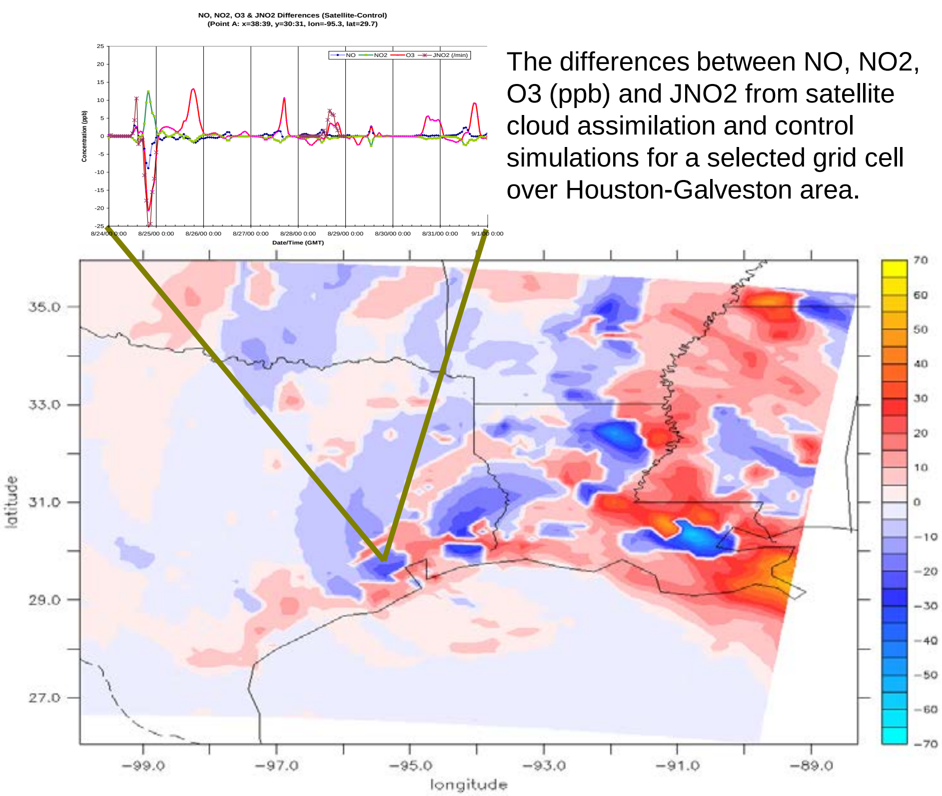
- Precipitation, impact on climate
- Evaluation: Statistical performance over large area and longer times
- Correct location and timing of model clouds being less important as long as statistical evaluation is satisfactory

Air Quality Community

- Both precipitating and non-precipitating clouds are important
- Evaluation: Statistical as well as episodic (PAIRED IN SPACE AND TIME)
- Correct location and timing of model clouds being important

Background & Motivation …

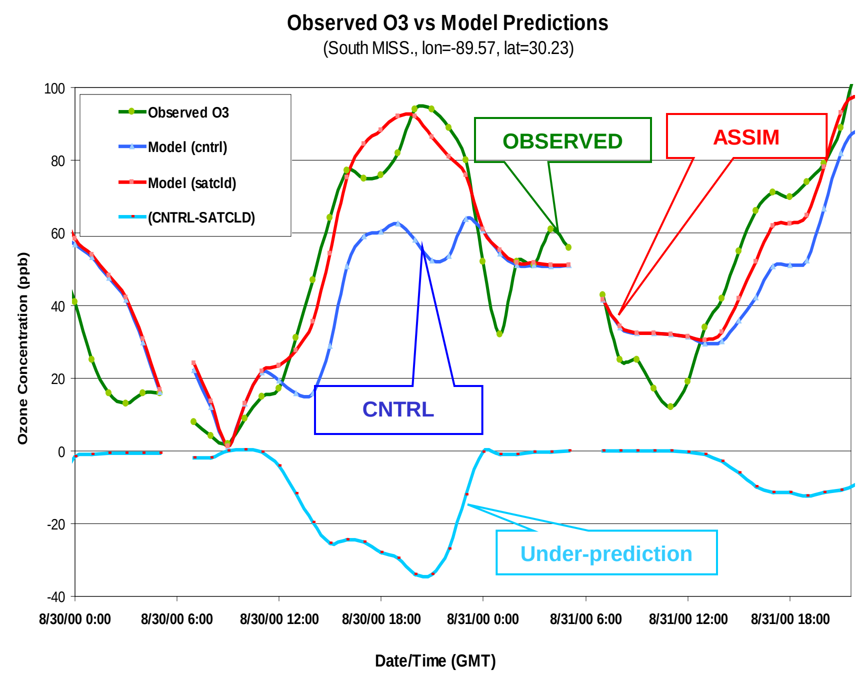
- A technique for adjusting photolysis rates in CMAQ based on goes observed clouds was included in the previous releases of CMAQ (not supported after CMAQv4.7.1).
- While the technique improved the performance of model for SIP activity, there was a fundamental disconnect between the model produced clouds and the attributes that were impacted by the assimilation.
- **There was a need to correct for biogenic emissions accordingly or correct clouds in the meteorological model. UAH attempts in accomplishing these objectives are presented here:**
  - **PAR retrieval from GOES observation.**
  - **Cloud assimilation in WRF**



The differences between NO, NO2, O3 (ppb) and JNO2 from satellite cloud assimilation and control simulations for a selected grid cell over Houston-Galveston area.

Max abs. diff in O3 concentration

Adapted from: Pour-Biazar et al., 2007



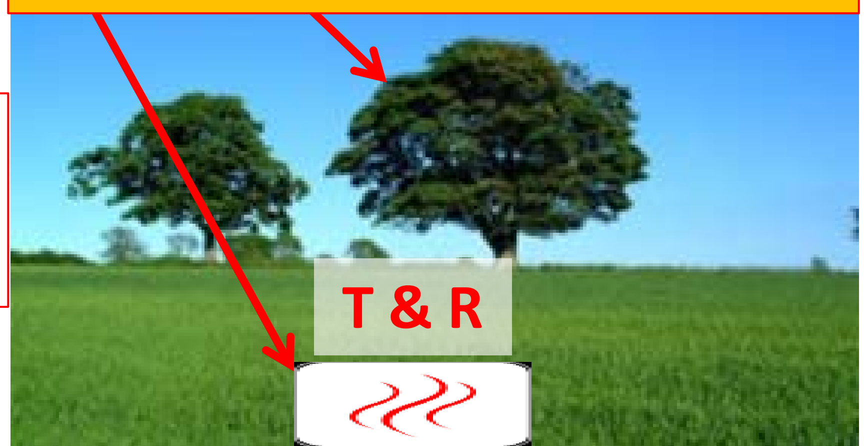
PAR and Biogenic Volatile Organic Compound (BVOC) Emissions

- BVOC estimates depend on the amount of radiation reaching the canopy (i.e. Photosynthetically Active Radiation - PAR) and temperature.
- Large uncertainty is caused by the model insolation estimates that can be corrected by using satellite-based PAR in biogenic emission models (Guenther et al. 2012)

hv

$$\text{NOx} + \text{VOC} + hv \rightarrow O_3$$

Biogenic Volatile Organic Compounds (BVOC) Emissions



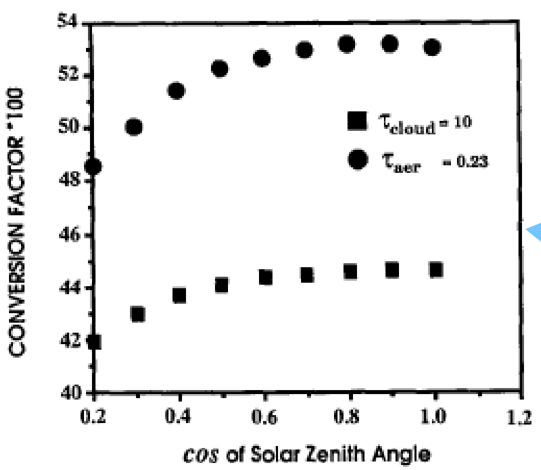
BVOC is a function of radiation and temperature

Satellite-Derived Photosynthetically Active Radiation (PAR)

$$PAR = \int_{.4}^{.7} I(\lambda)d\lambda \quad (W\ m^{-2}) = \frac{1}{hc}\int_{.4}^{.7} I(\lambda)d\lambda \quad (quantam^{-2} s^{-1})$$

$$= Insolation \times CF$$

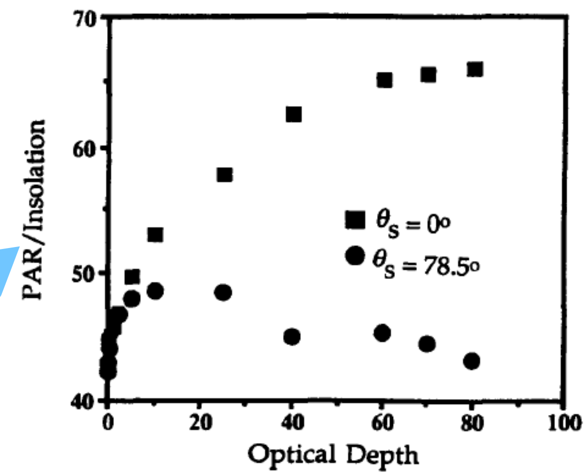
- In most applications (e.g., agriculture related) a constant conversion factor ***CF*** is used.
- But ***CF*** has to account for differences in direct and diffuse light. Highest sensitivity to clouds/aerosols and zenith angle, but not in the same direction. *(Adapted from: Frouin and Pinker, 1994; Pinker and Laszelo, 1991)*



$$CF = \frac{PAR}{Insolation}$$

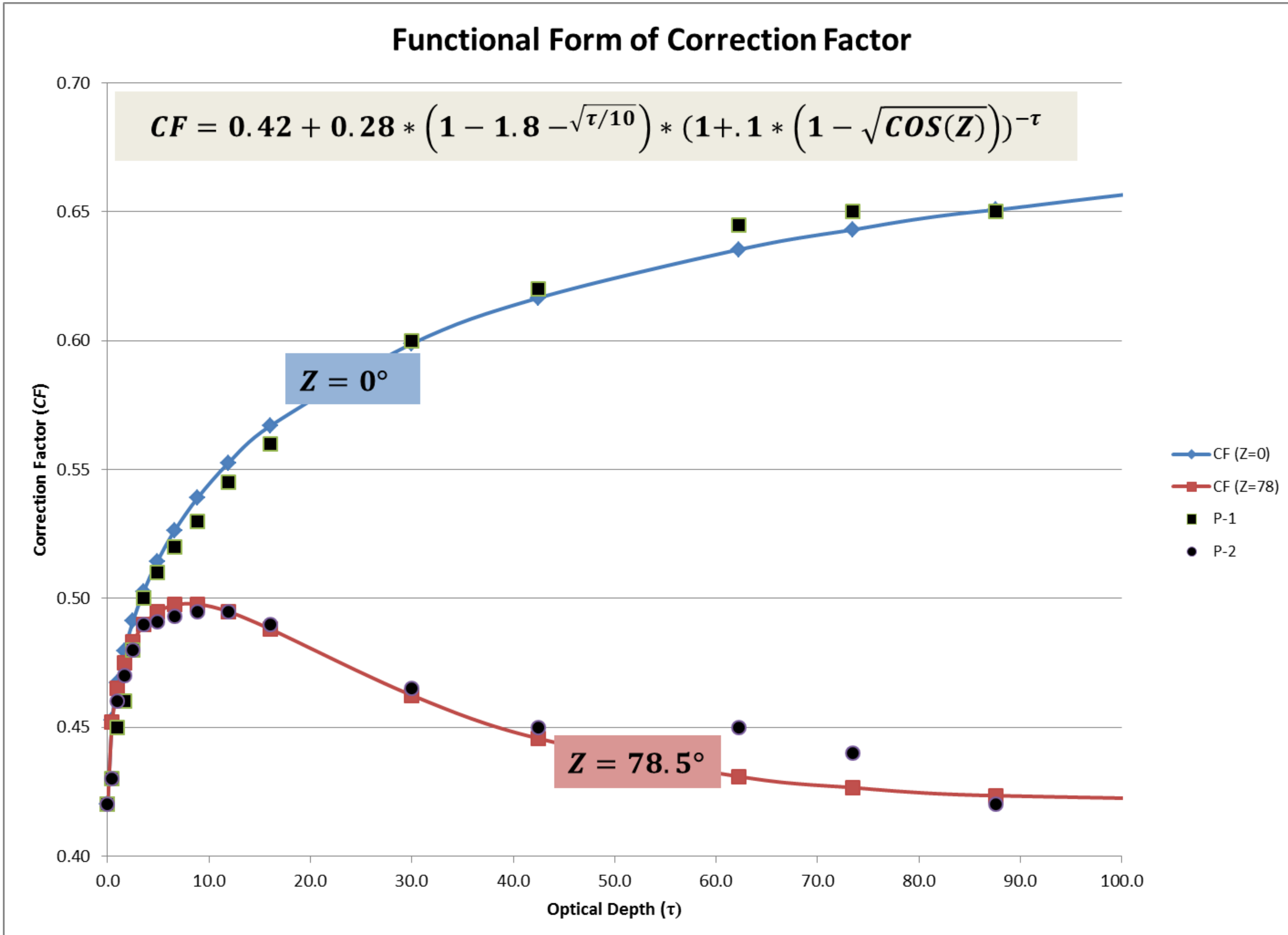
Zenith Angle dependency

Optical Depth dependency



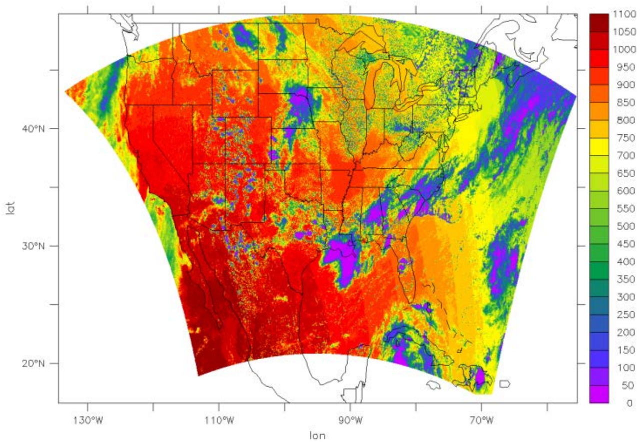
Insolation, cloud albedo, and optical depth can be estimated from satellite observation

$$\tau = \frac{8\alpha_c}{(1-\alpha_c)^2}, \quad where \quad \alpha_c = cloud\ albedo$$


Functional Form of Correction Factor
CF = 0.42 + 0.28 * (1 − 1.8 −√τ/10) * (1+.1 * (1 − √COS(Z)))−τ
Z = 0°
Z = 78.5°
Correction Factor (CF)
Optical Depth (τ)
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.0
10.0
20.0
30.0
40.0
50.0
60.0
70.0
80.0
90.0
100.0
CF (Z=0)
CF (Z=78)
P-1
P-2

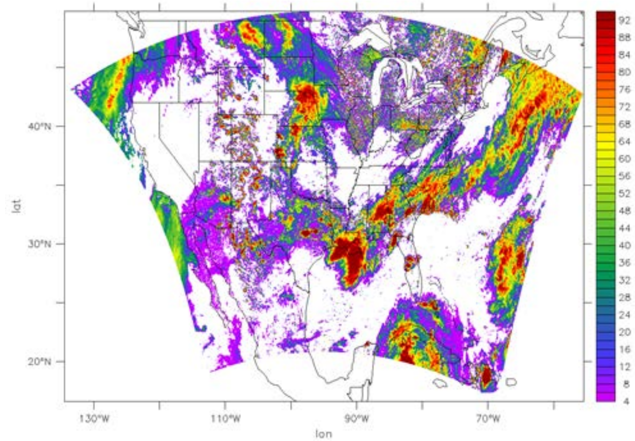
Snapshot: Insolation, Cloud Albedo, CF, and PAR

Insolation



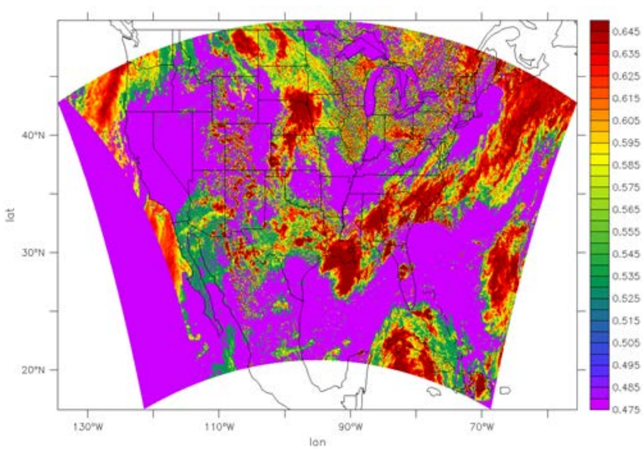
Insolation (W/m~2)

Cloud Albedo



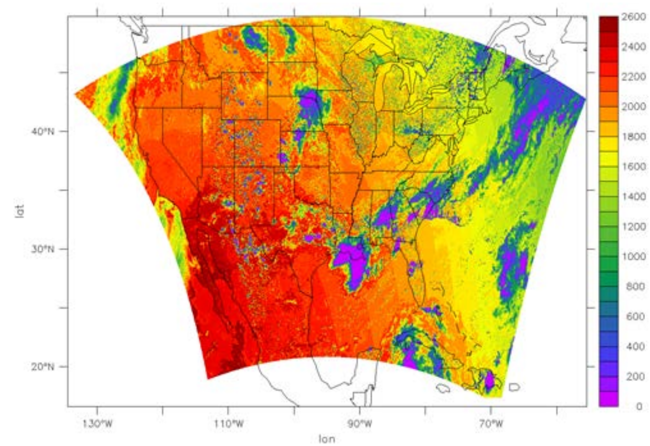
Cloud Albedo (%)

Conversion Factor



Correction Factor (fraction)

PAR



PAR (umol/(m~2.s))

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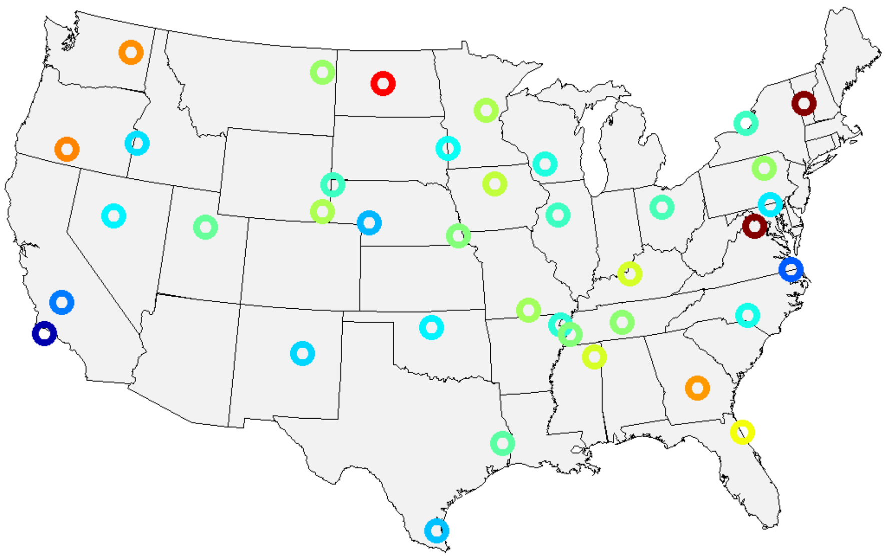
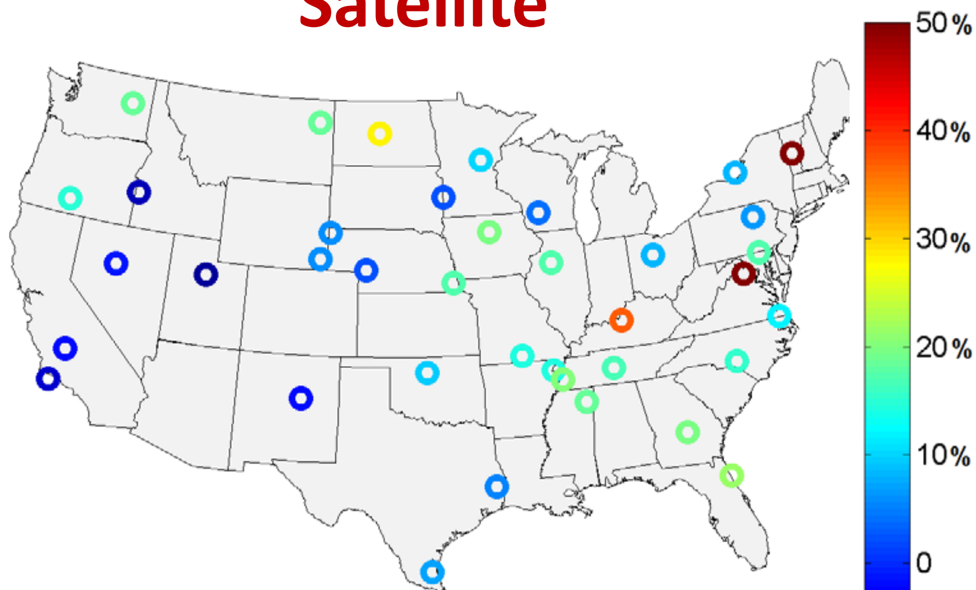
Insolation/PAR Evaluation

Spatial Distribution of NMB (normalized mean bias) Against Soil Climate Analysis Network (SCAN)

WRF



Satellite



WRF

NMB = 22%

NME = 34%

Satellite

NMB = 14%

NME = 27%

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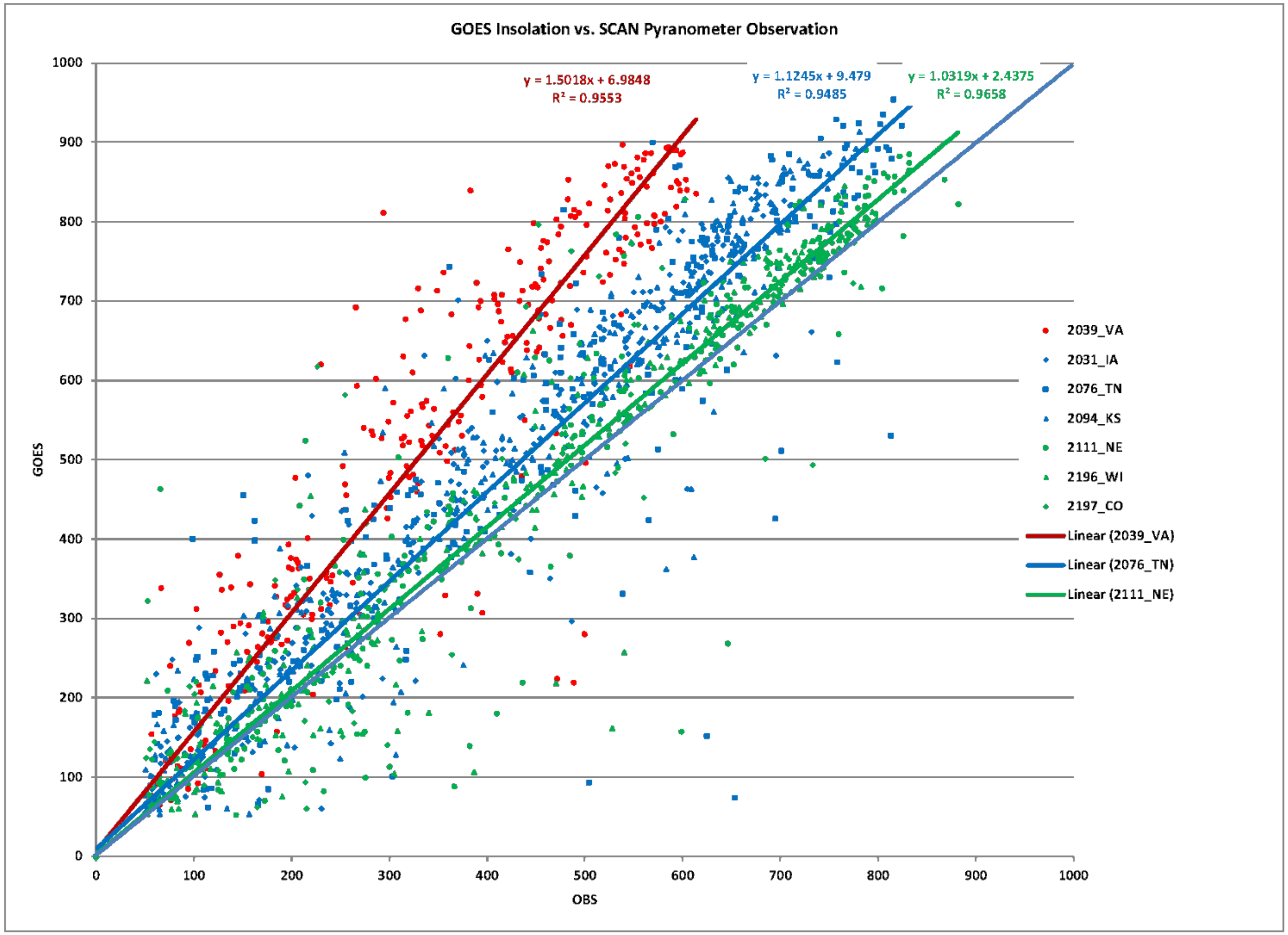
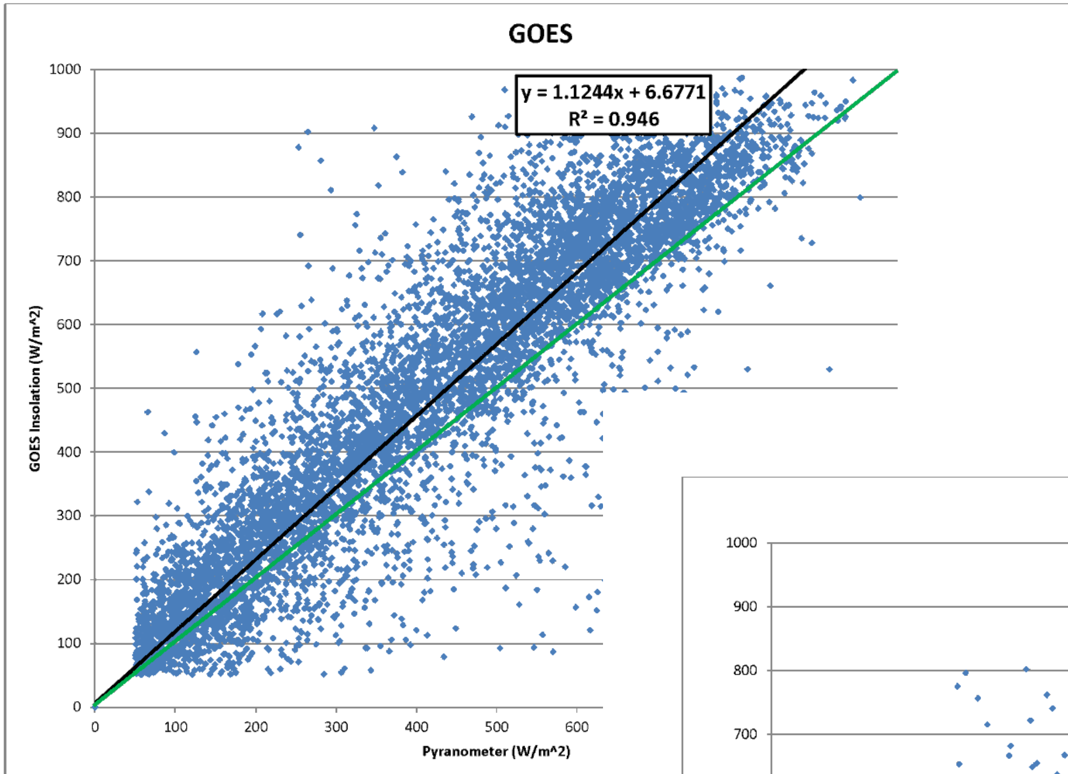
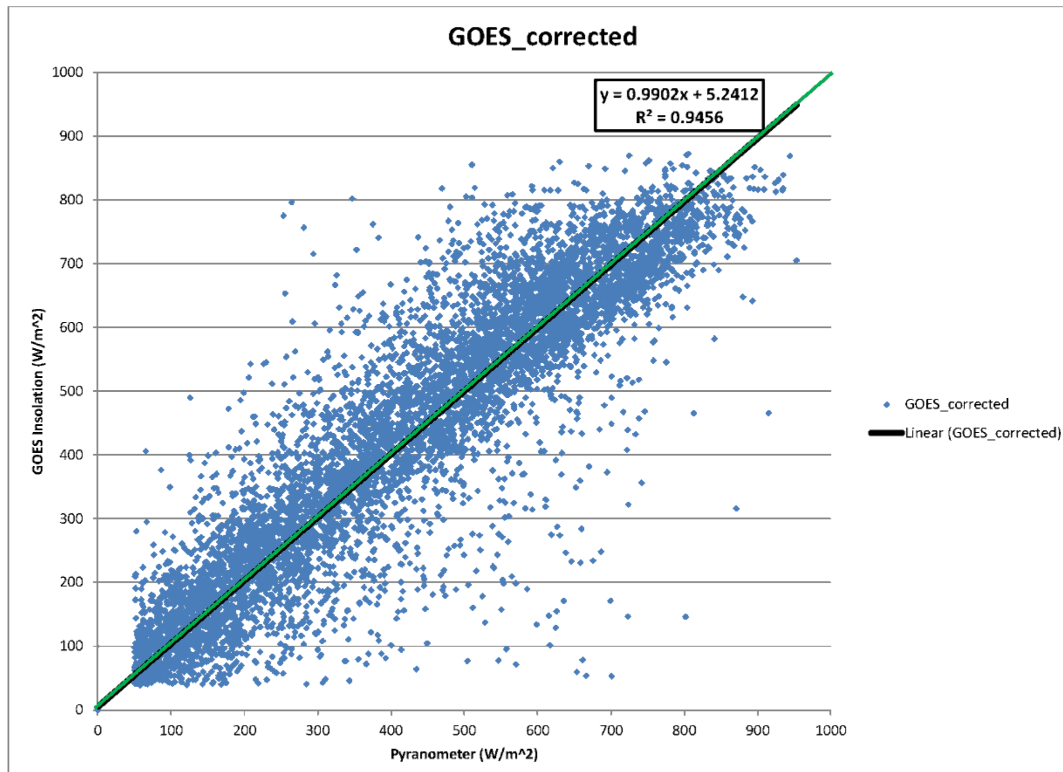
GOES Insolation Bias Increases From West to East

- The clear sky bias was partly due to the lack of a dynamic precipitable water in retrieval algorithm.
- The retrievals was re-processed to correct this issue.



Retrieval algorithm was improved by including a dynamic precipitable water field and performing a bias correction.





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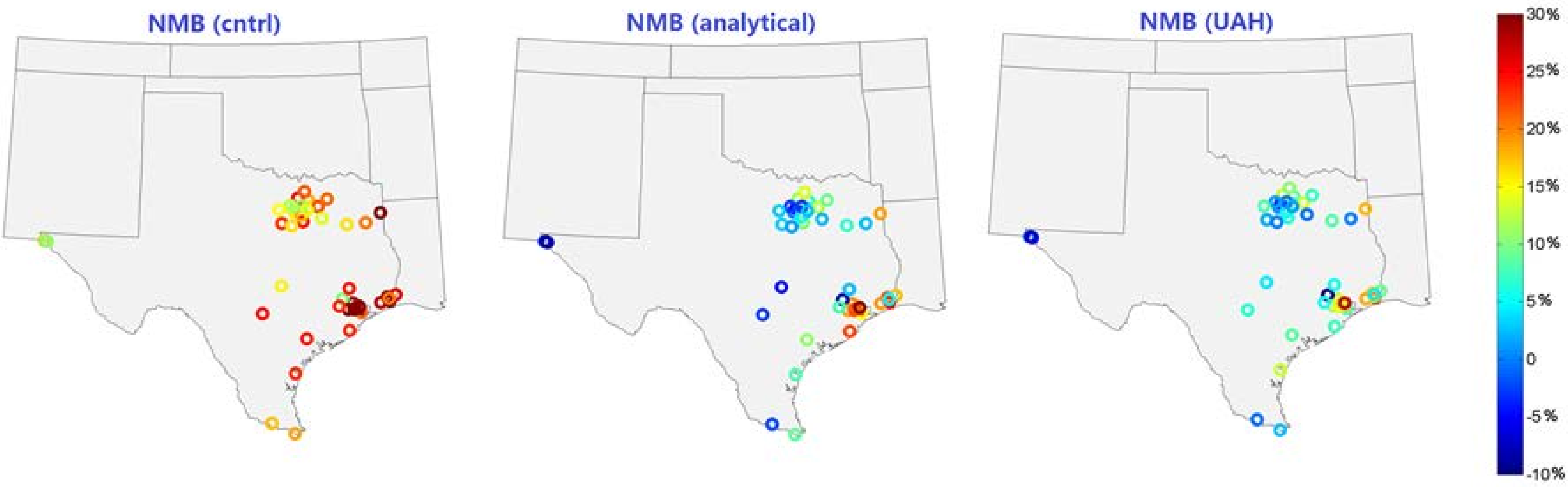
Satellite cloud assimilation reduced mean bias by 63% and NMB by 60% over 47 TCEQ sites.



Comparing August, 2006, insolation from control WRF simulation (cntrl), UAH WRF simulation (analytical), and satellite-based (UAH) against 47 radiation monitoring stations in Texas.

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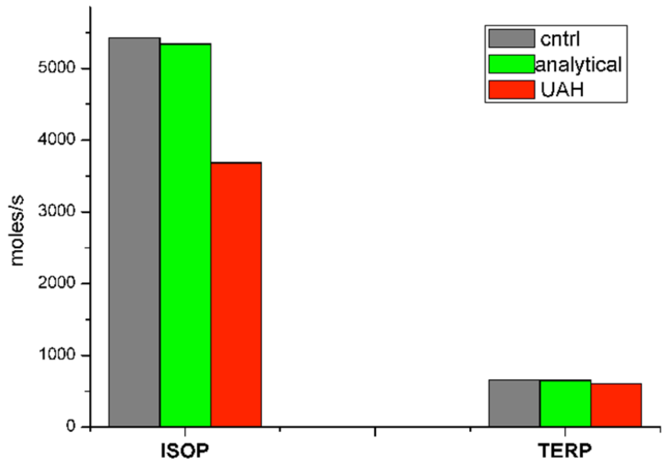
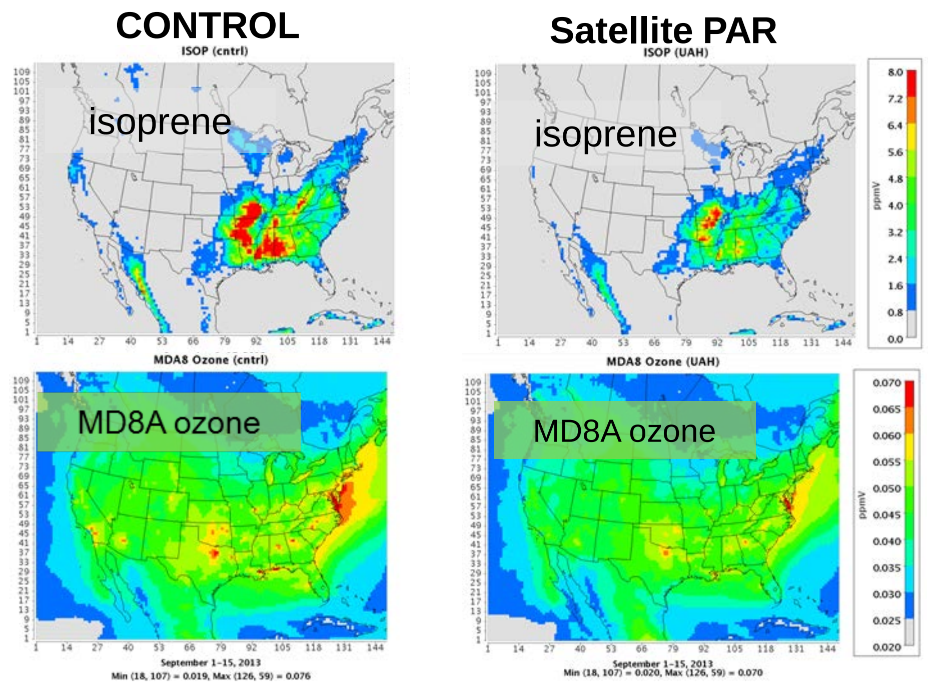
Satellite-derived PAR substantially reduced isoprene emission estimates (about 30%) during DISCOVER-AQ period and improved ozone predictions



Domain-wide sum of estimated isoprene (ISOP) and monoterpene (TERP) emission strength over Texas area using different PAR inputs in MEGAN during September 2013.

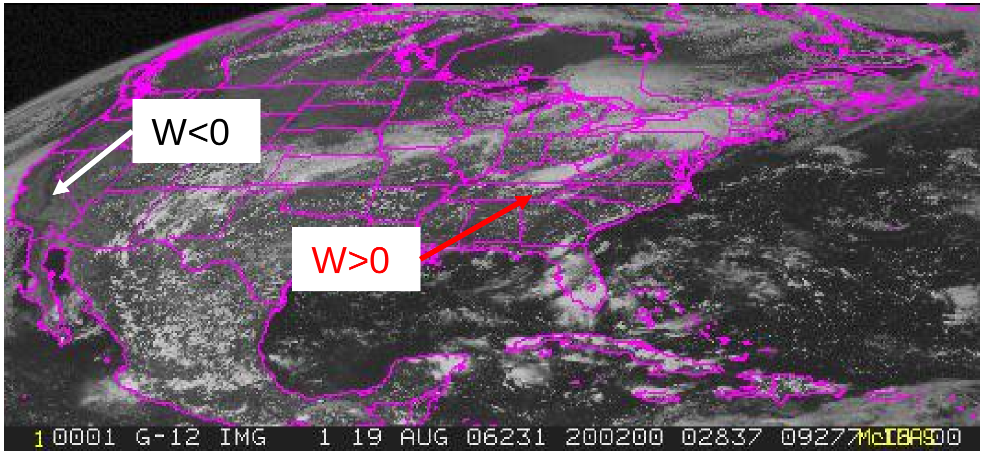


Comparison of the spatial pattern of estimated average isoprene and ozone concentrations for different PAR inputs during September 2013.

Cloud Assimilation in WRF

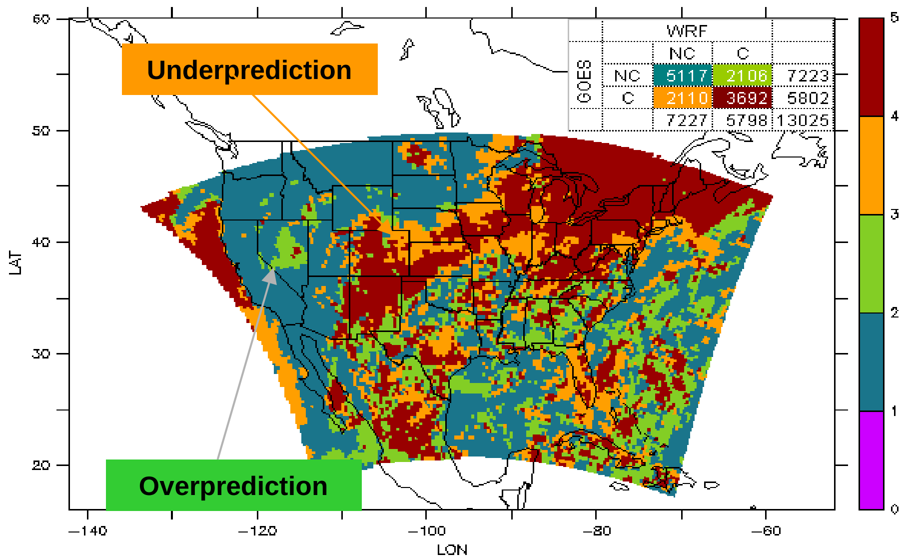
Create an environment in the model that is conducive to clouds formation/removal through adjusting wind and moisture fields and to improve the ability of the WRF modeling system to simulate clouds through the use of observations provided by the Geostationary Operational Environmental Satellite (GOES).

Satellite



0.65um VIS surface, cloud features

Model/Satellite comparison



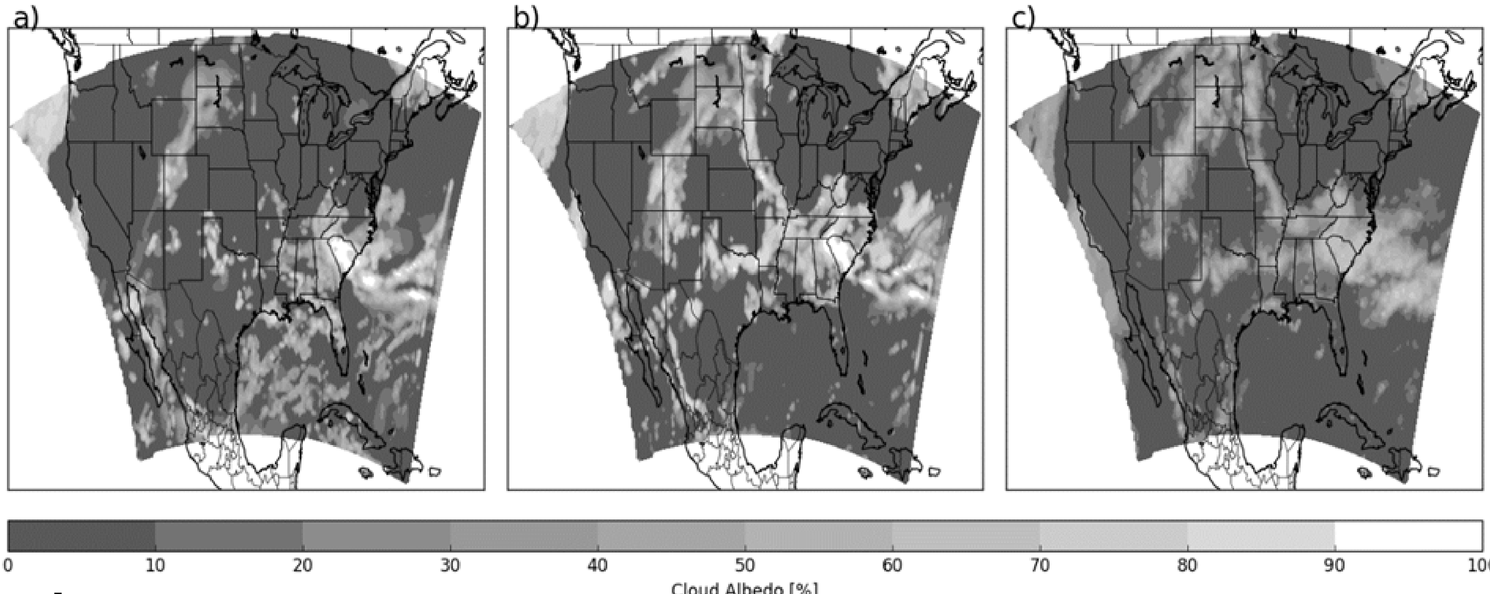
- Use satellite cloud top temperature and cloud albedo to estimate a **TARGET VERTICAL VELOCITY (Wmax)**.
- Adjust divergence to comply with Wmax in a way similar to O'Brien (1970).
- Nudge model winds toward new horizontal wind field to sustain the vertical motion.
- Remove erroneous model clouds by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

The technique was tested/validated over TexAQS2006 and Applied in 2013 Simulations

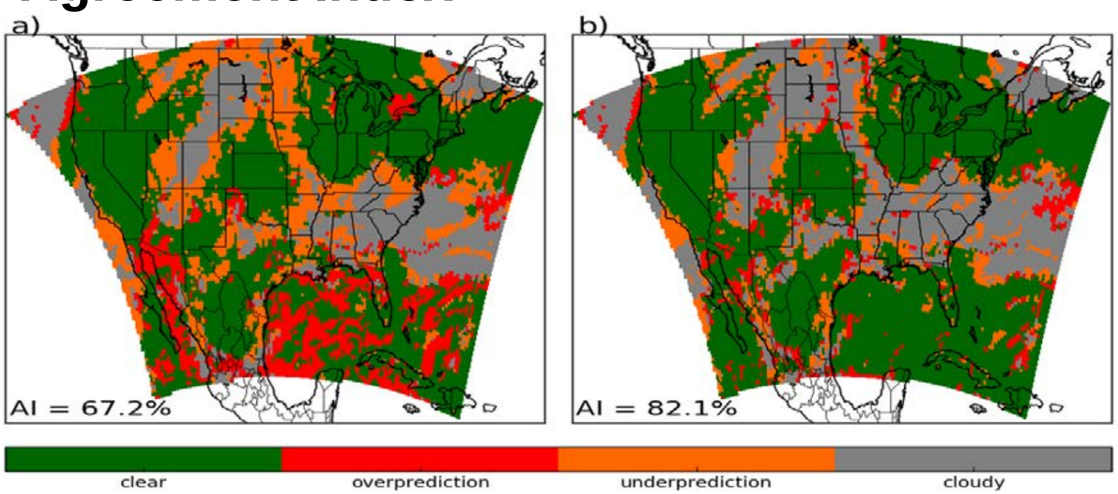
(See White et al., Poster 44, Tuesday, Oct. 25)

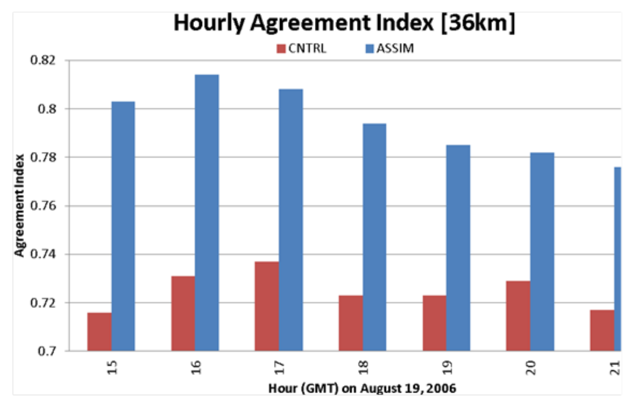
Control **Assimilation** **Satellite**

Cloud Albedo

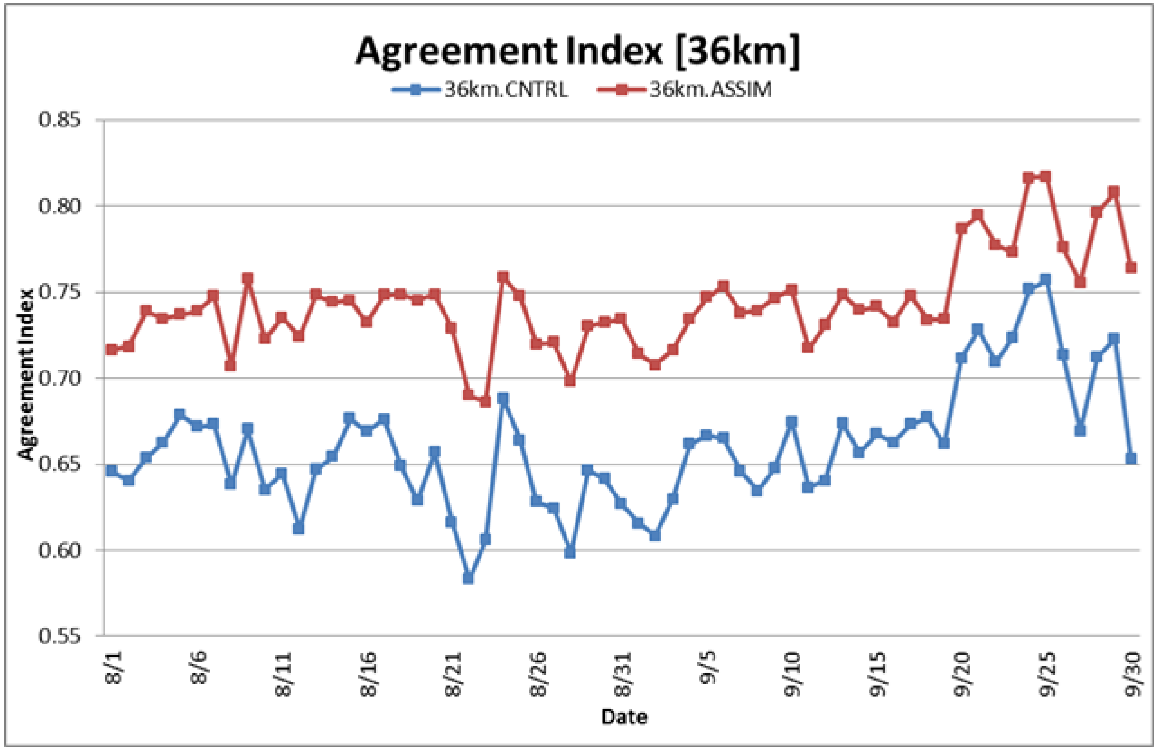


Agreement Index



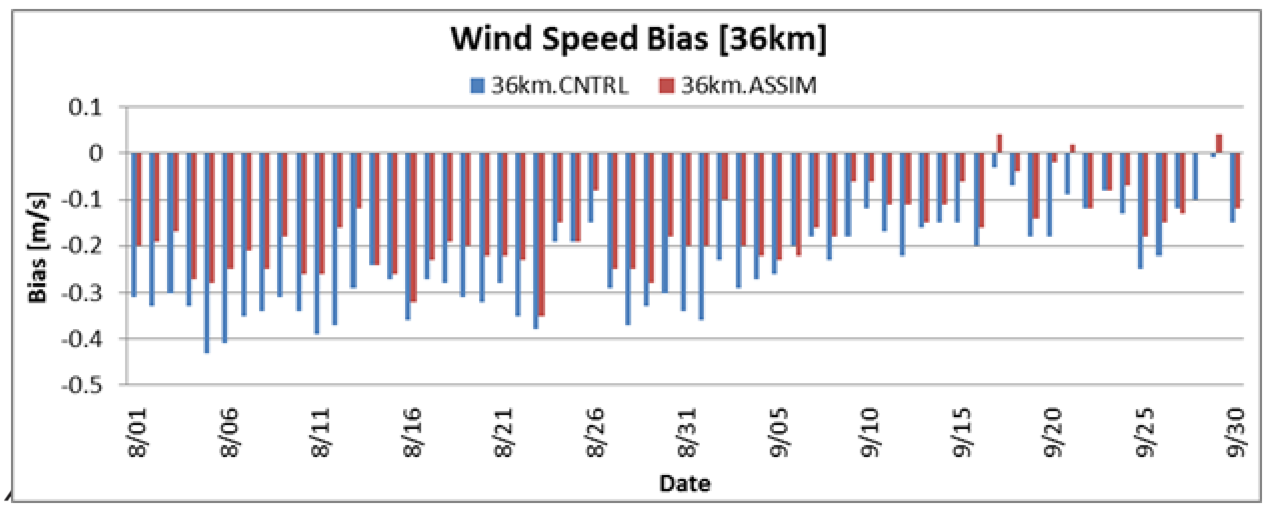


Similar Improvements Were Achieved in 2013 Simulation



AI = (A+D) / (A+B+C+D)		WRF Cloudy	WRF Clear	TOTAL
GOES	Cloudy	A	B	A+B
GOES	Clear	C	D	C+D
TOTAL		A+C	B+D	A+B+C+D

Daily agreement index for CNTRL and ASSIM 36 km WRF simulations over August-September 2013 using a 10% cloud albedo threshold.



We also see improvements in wind speed, moisture, and temperature.

Recap and Concluding Remarks

- **A new satellite-based PAR was produced and evaluated for this study.**
- **The impact of using satellite PAR on BVOC emission estimates by MEGAN and consequently on CMAQ simulation during the Texas DISCOVER-AQ Campaign (September 2013) was examined.**
- **Over east Texas, MEGAN greatly over-estimated isoprene emissions and thereby a 30% reduction in isoprene emission caused by the use of satellite PAR did not significantly affect ozone predictions.**
- **The impact of PAR input on ozone prediction depends on the local NOx/VOC ratio and is more pronounced over VOC limited regions. In this study, over the VOC limited regions, the satellite PAR changed surface O3 prediction by 5-8%.**
- **This study is being repeated using BEIS model.**

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Acknowledgment

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

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