Incorporating Space-borne Observations to Improve Biogenic Emission Estimates in Texas

(Project 14-017)

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Presented at:

AQRP Workshop
The University of Texas at Austin, Texas
17-18 June, 2015

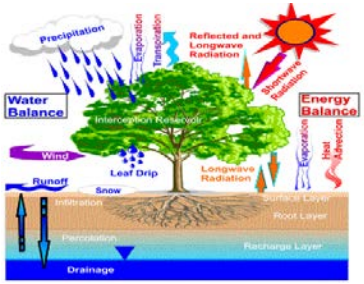
Air Quality Modeling Systems Recreate the Complex Interactions of the Environment But the Uncertainties Are Still High

- Biogenic volatile organic compounds, BVOCs, play a critical role in atmospheric chemistry, particularly in ozone and particulate matter (PM) formation.
- BVOCs comprise approximately 75%-80% of national VOC emission inventory and are the dominant summertime source of reactive hydrocarbon In the southeastern United States (Carlton et al., 2011; Wiedinmyer et al., 2001).
- Reducing uncertainties in biogenic hydrocarbon emissions is a high priority issue for Texas SIP modeling (AQRP State of the Science report).

Physical Atmosphere

Atmospheric dynamics and microphysics

Boundary layer development



Fluxes of heat and moisture

LSM describing land-atmosphere interactions

Aerosol Cloud interaction

Winds, temperature, moisture, surface properties and fluxes

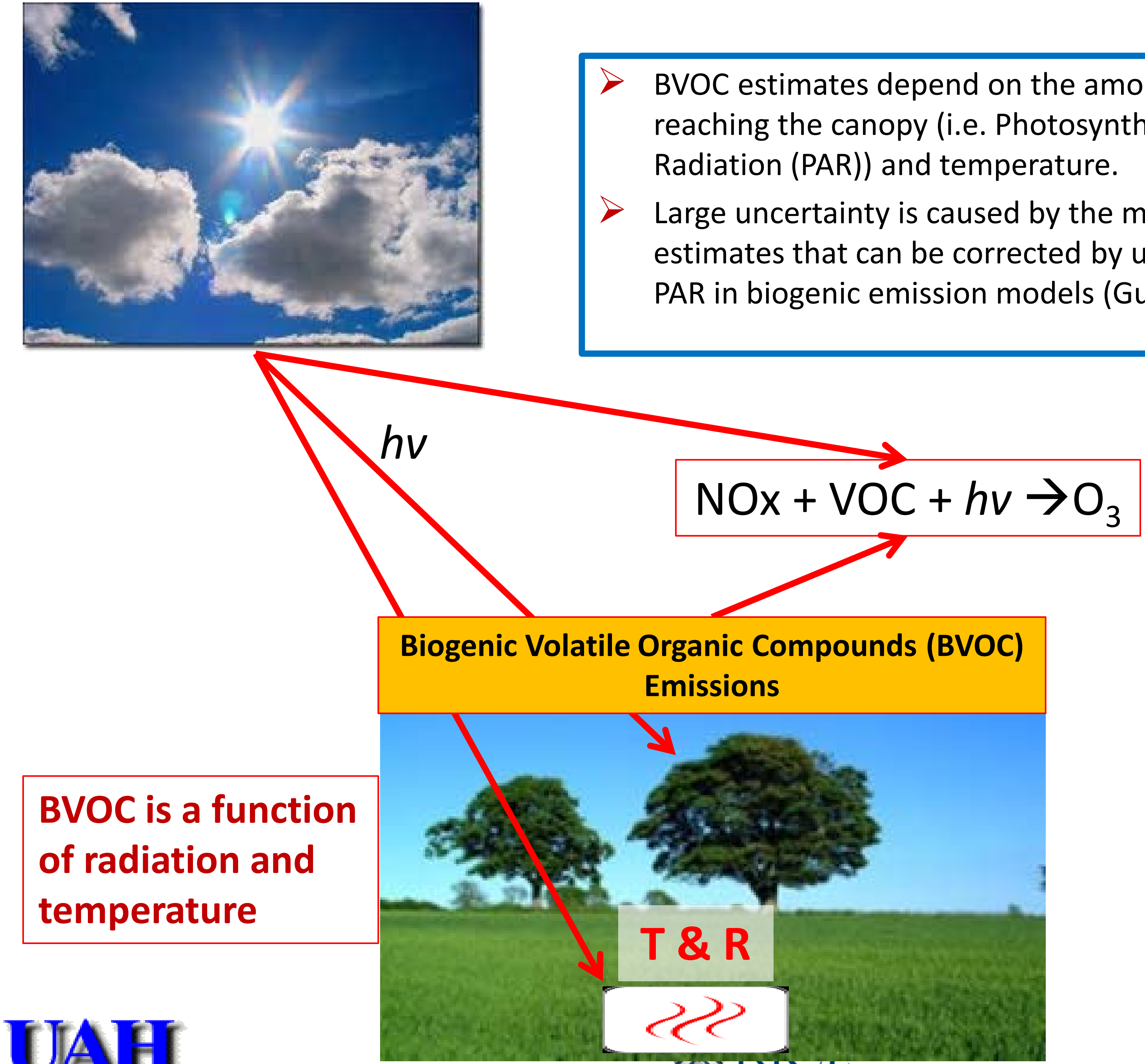
Chemical Atmosphere

Transport and transformation of pollutants

Photochemistry and oxidant formation

Natural and antropogenic emissions
Surface removal

- 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

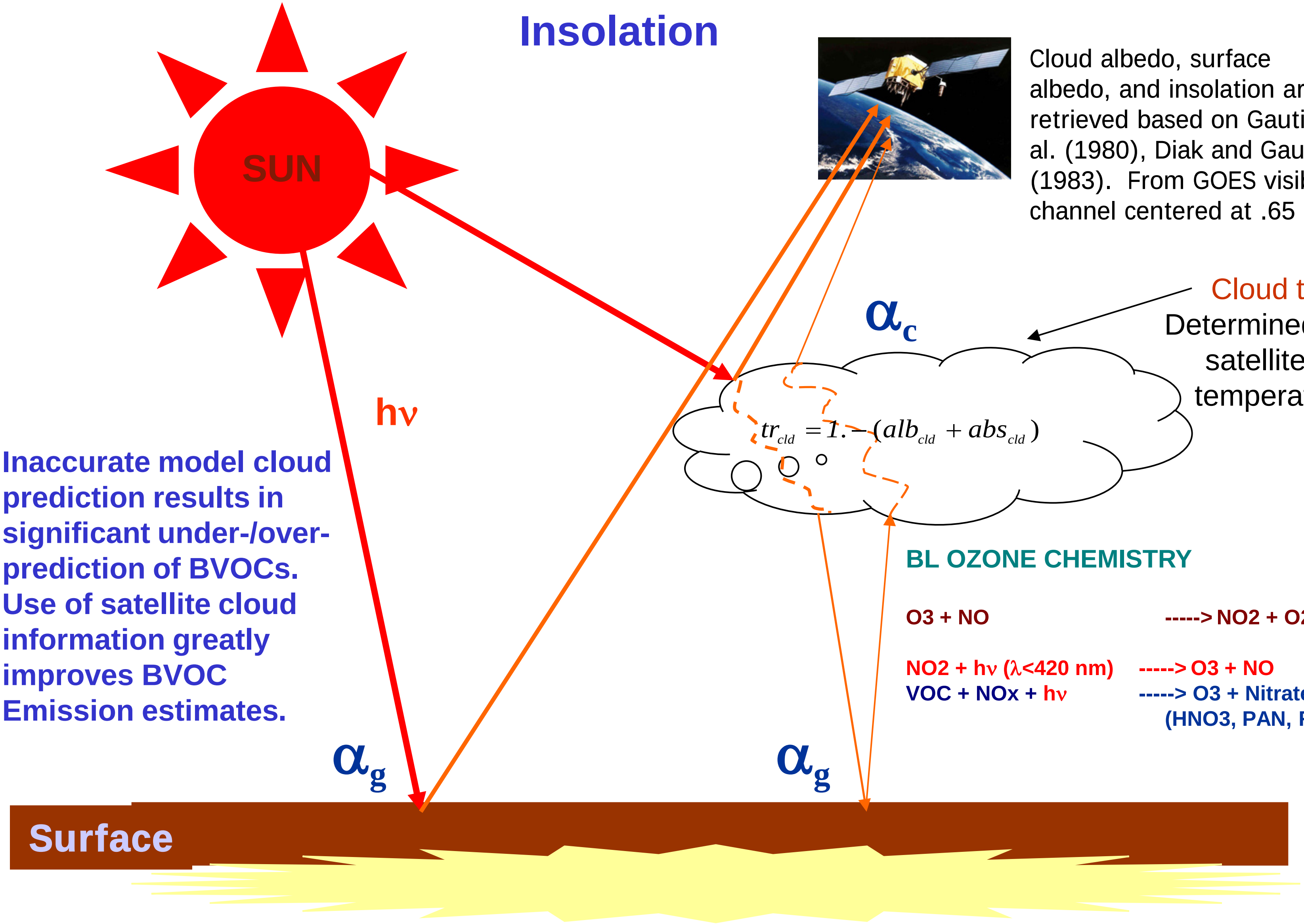
NOx + VOC + *hv* → O_3

Biogenic Volatile Organic Compounds (BVOC) Emissions

BVOC is a function of radiation and temperature

T & R

Satellite-Derived Insolation



$$tr_{cld} = 1. - (alb_{cld} + abs_{cld})$$

Cloud albedo, surface albedo, and insolation are retrieved based on Gautier et al. (1980), Diak and Gautier (1983). From GOES visible channel centered at .65 µm.

Cloud top
Determined from satellite IR temperature

Inaccurate model cloud prediction results in significant under-/over-prediction of BVOCs. Use of satellite cloud information greatly improves BVOC Emission estimates.

BL OZONE CHEMISTRY

$O_3 + NO$ -----> $NO_2 + O_2$

$NO_2 + h\nu$ ($\lambda < 420$ nm) -----> $O_3 + NO$
VOC + NO_x + $h\nu$ -----> O_3 + Nitrates
(HNO_3, PAN, $RONO_2$)

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Satellite-Derived Photosynthetically Active Radiation (PAR)

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

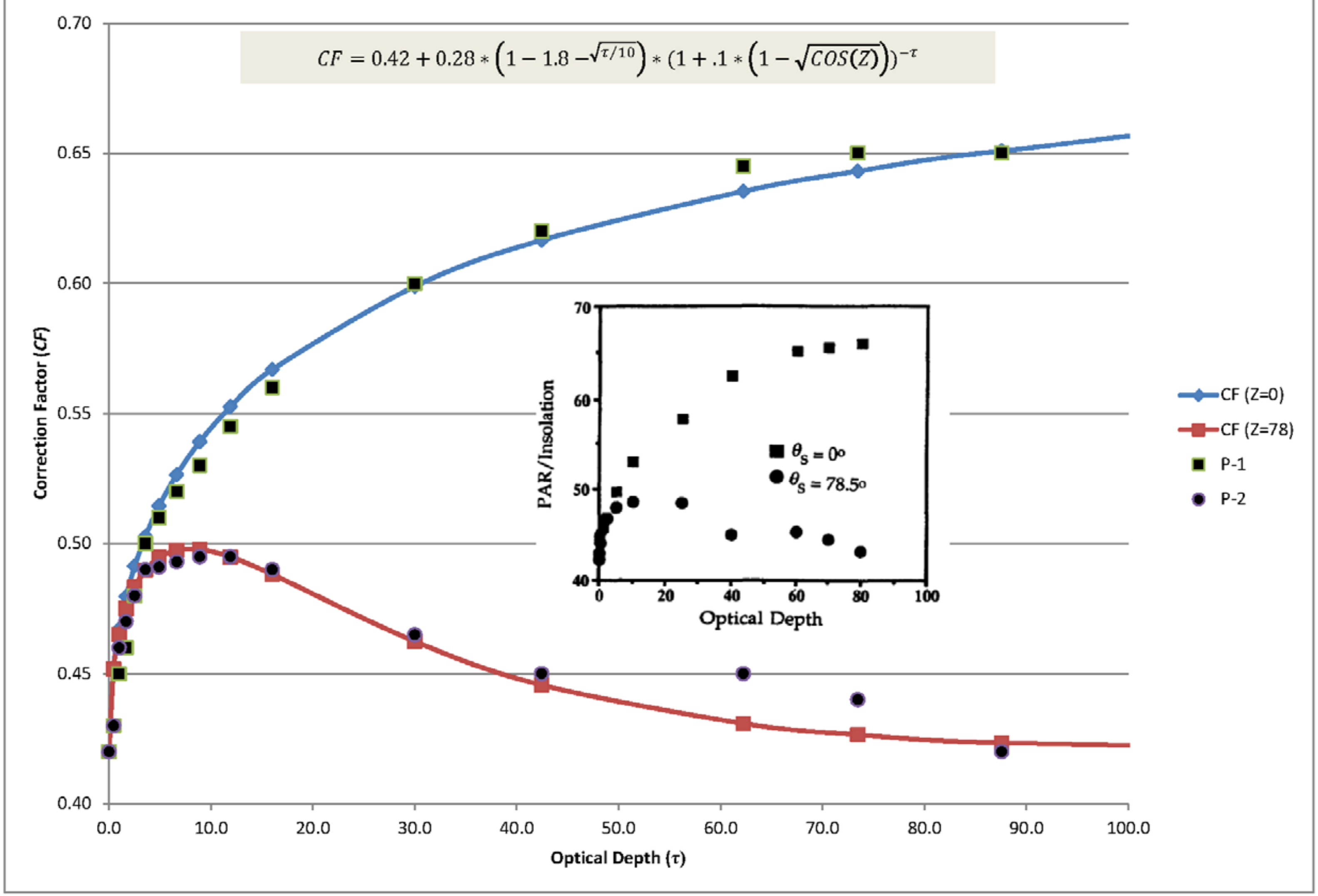
$$= Insolation \quad \times \quad CF$$

$$CF = \frac{PAR}{Insolation} = .42 + .28 * ODfactor * Zfactor$$

Based on Stephens (1978), Joseph (1976), Pinker and Laszlo (1992), Frouin and Pinker (1995)

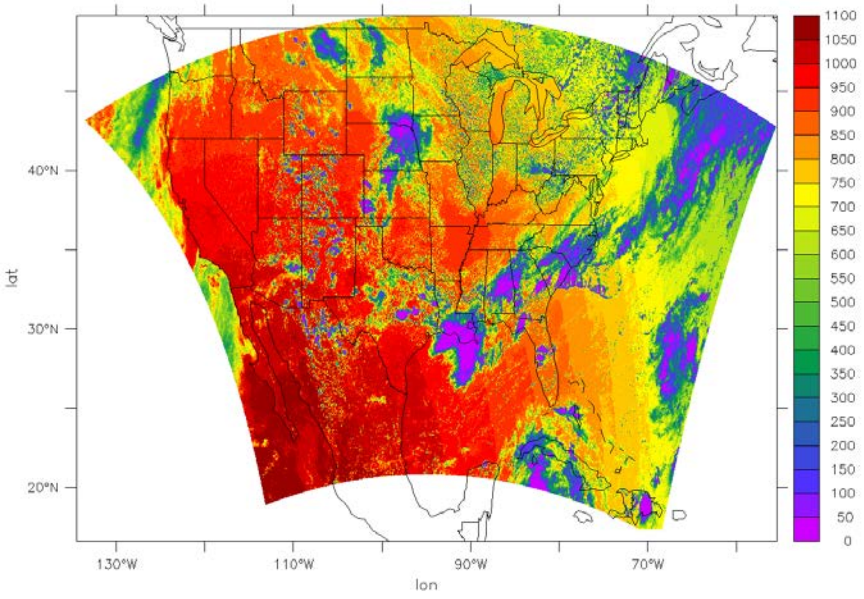
$$\tau = \frac{8\alpha_c}{(1-\alpha_c)^2}, \quad where \qquad \alpha_c = cloud\ albedo$$

Functional Form of Correction Factor

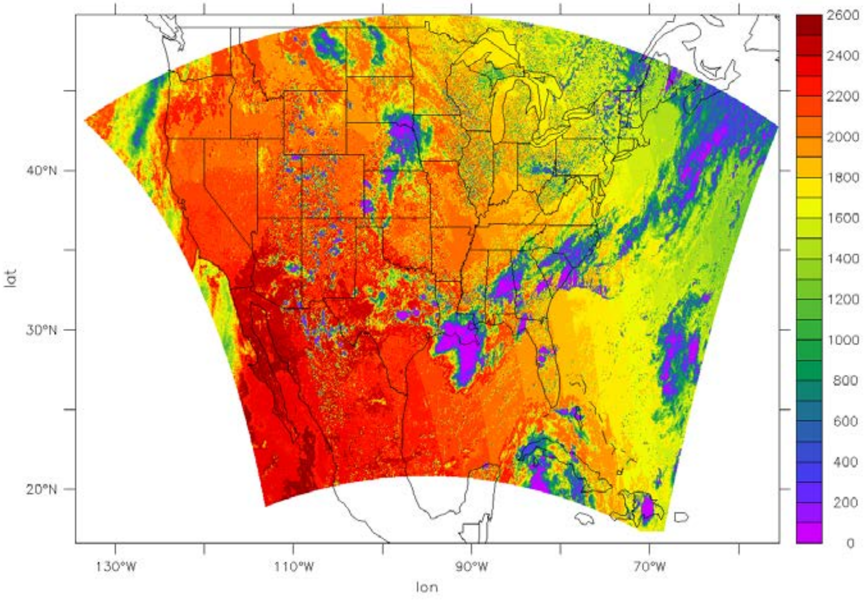


$$CF = 0.42 + 0.28 * \left(1 - 1.8^{-\sqrt{\tau/10}}\right) * \left(1 + .1 * \left(1 - \sqrt{COS(Z)}\right)\right)^{-\tau}$$

Satellite-derived insolation and PAR for September 14, 2013, at 19:45 GMT.



Insolation (W/m~2)



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

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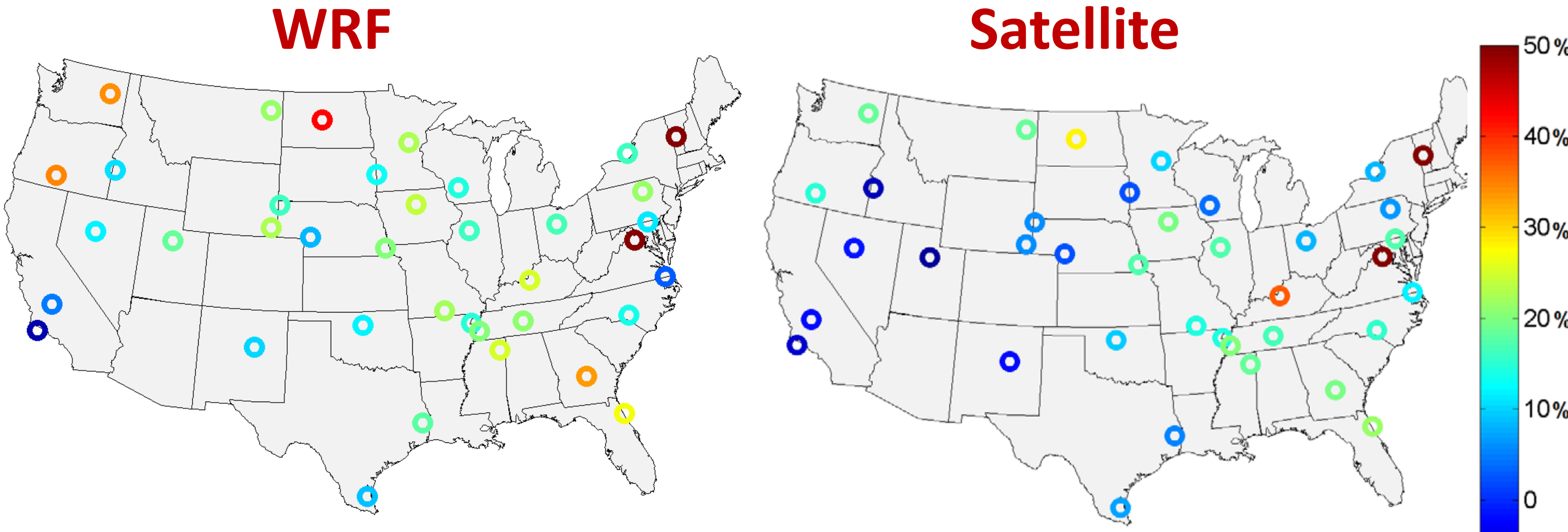
Insolation/PAR Evaluation

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



WRF

Satellite

WRF

NMB = 22%

NME = 34%

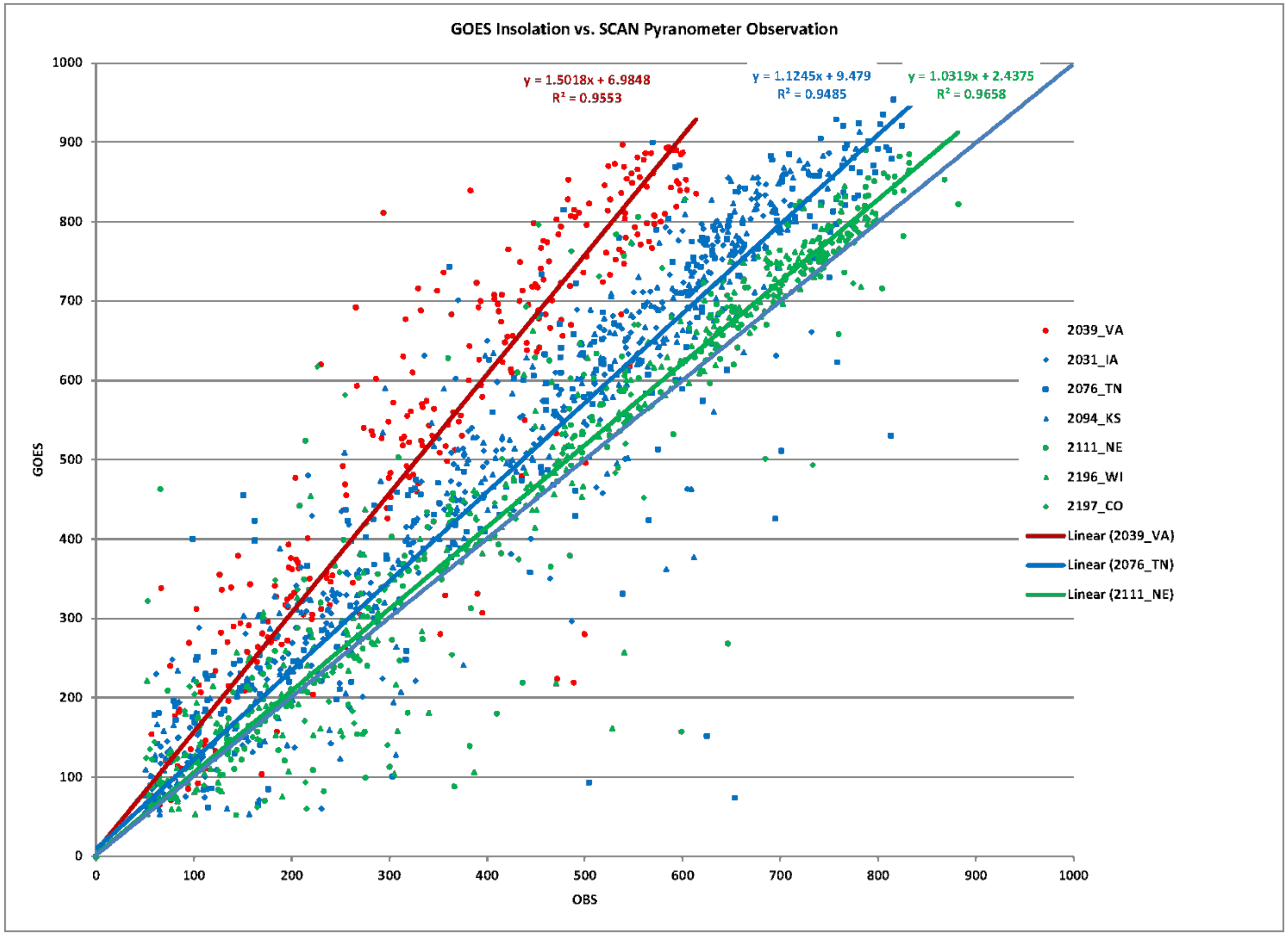
Satellite

NMB = 14%

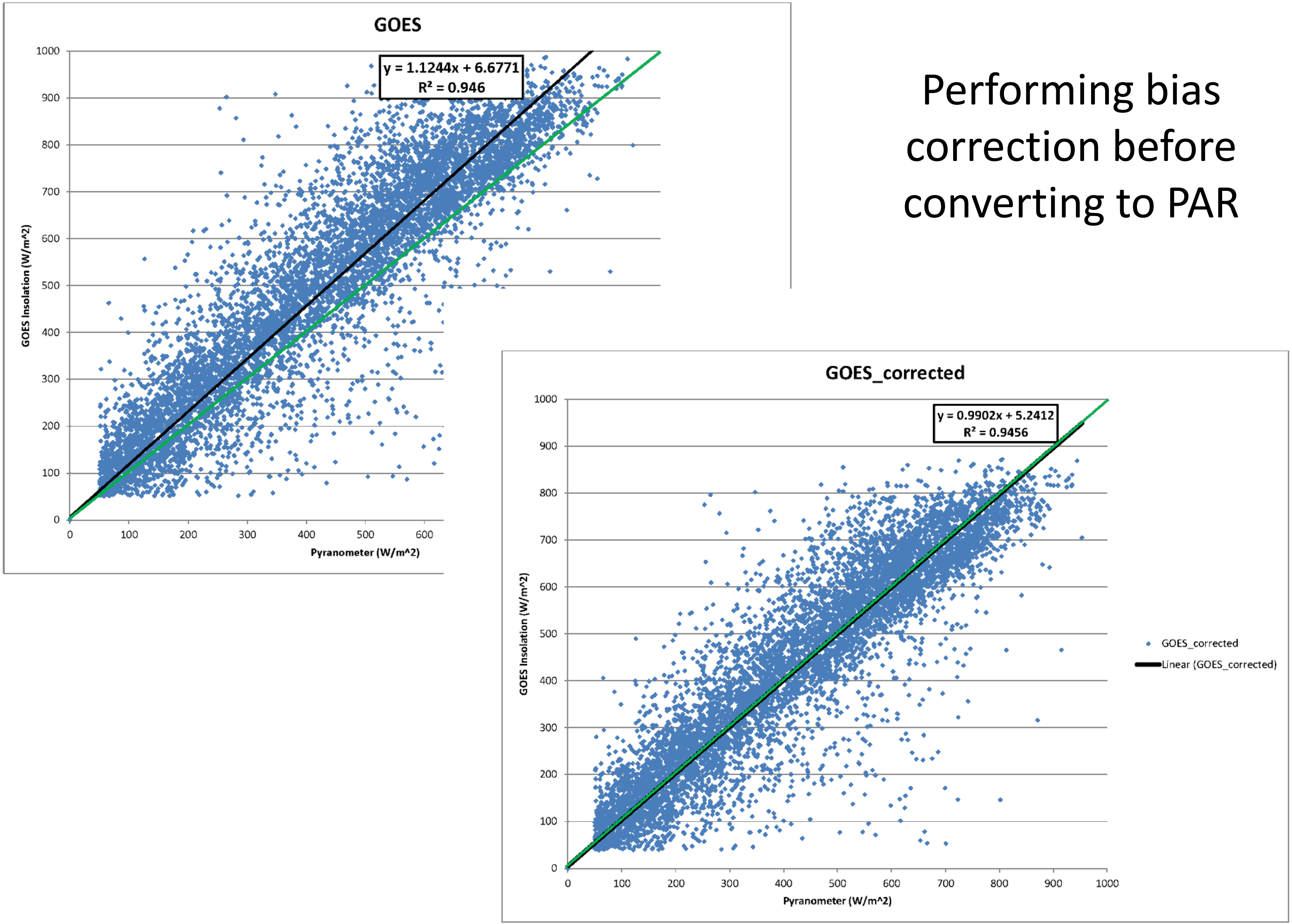
NME = 27%

GOES Insolation Bias Increases From West to East

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



Performing bias correction before converting to PAR



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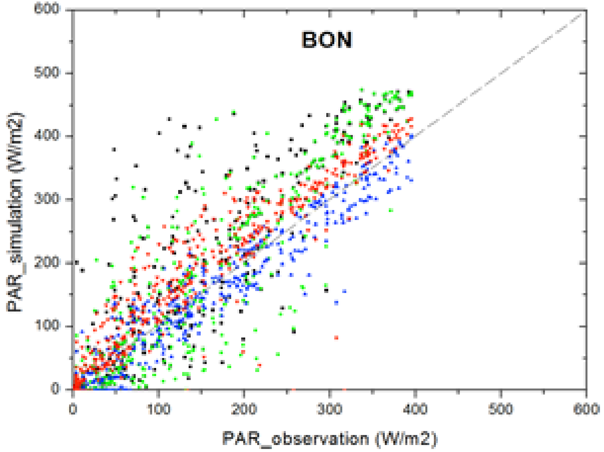

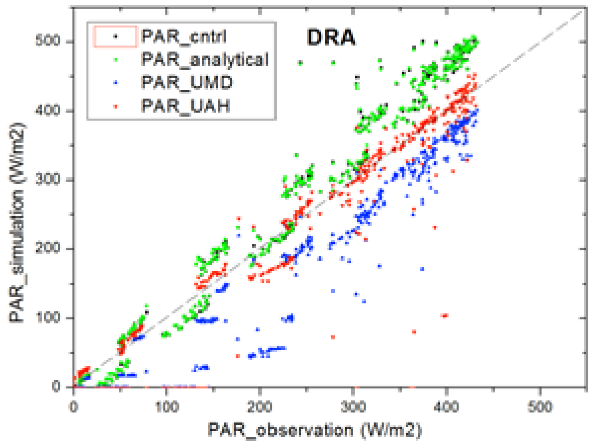

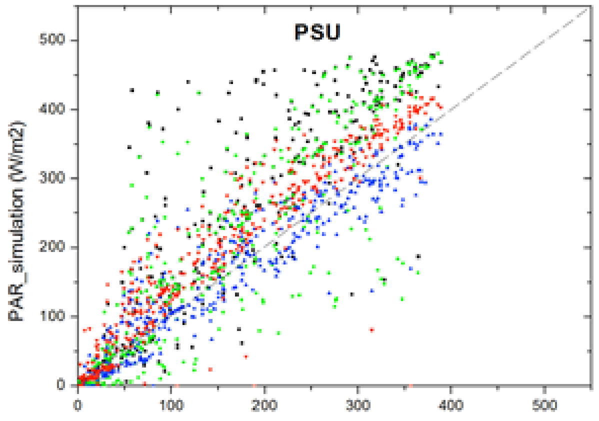

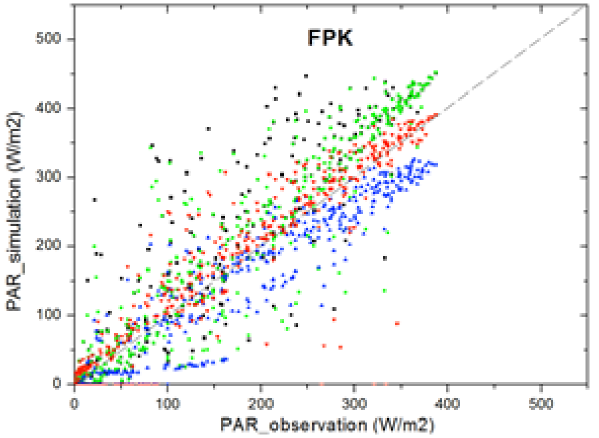

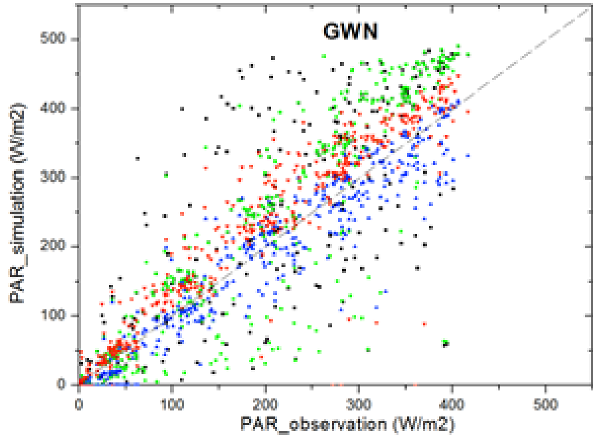

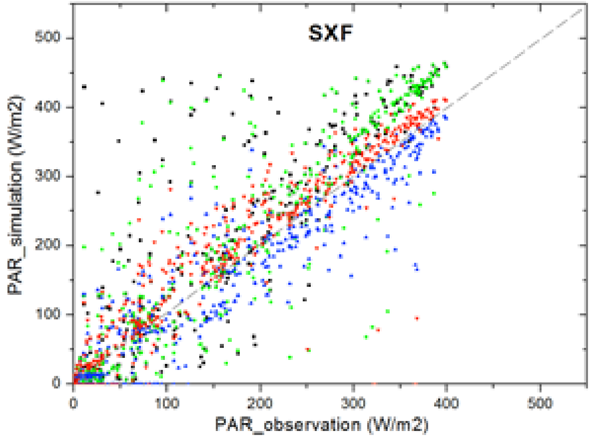

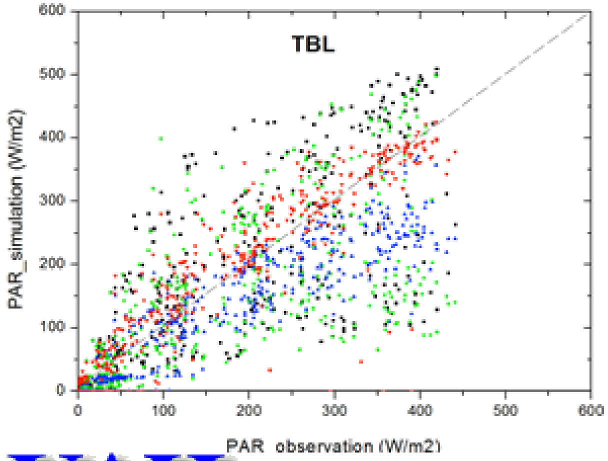

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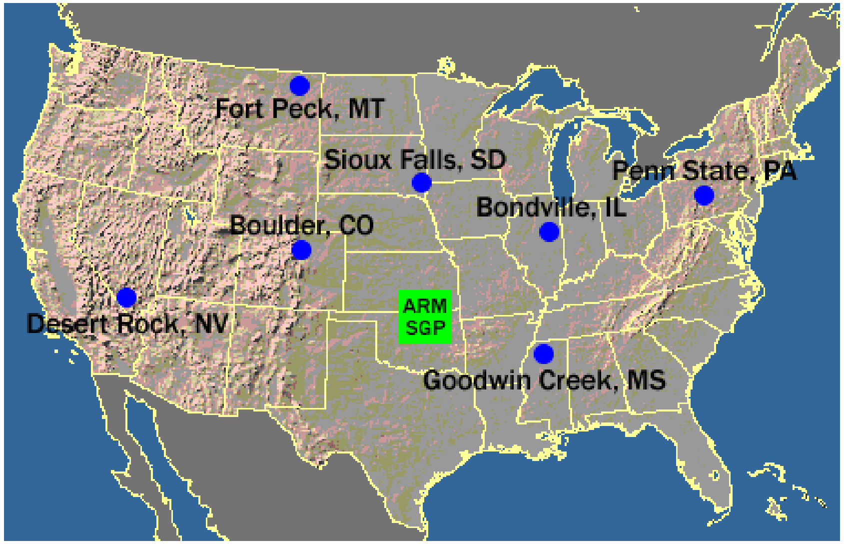
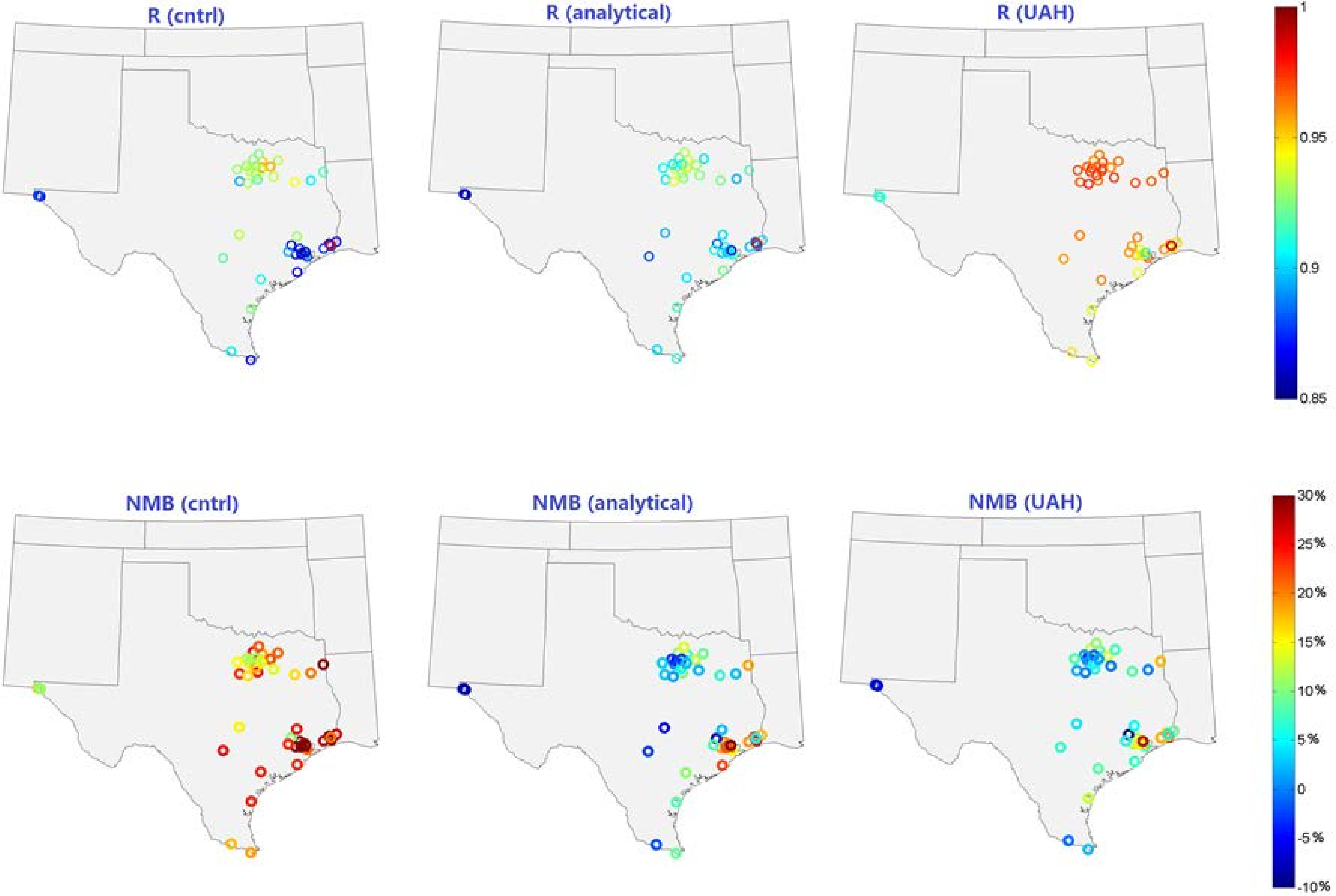
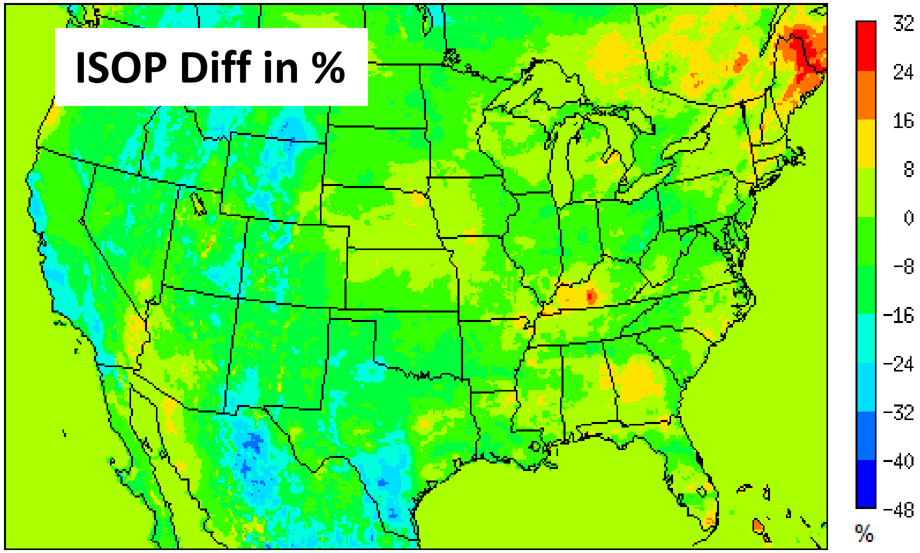


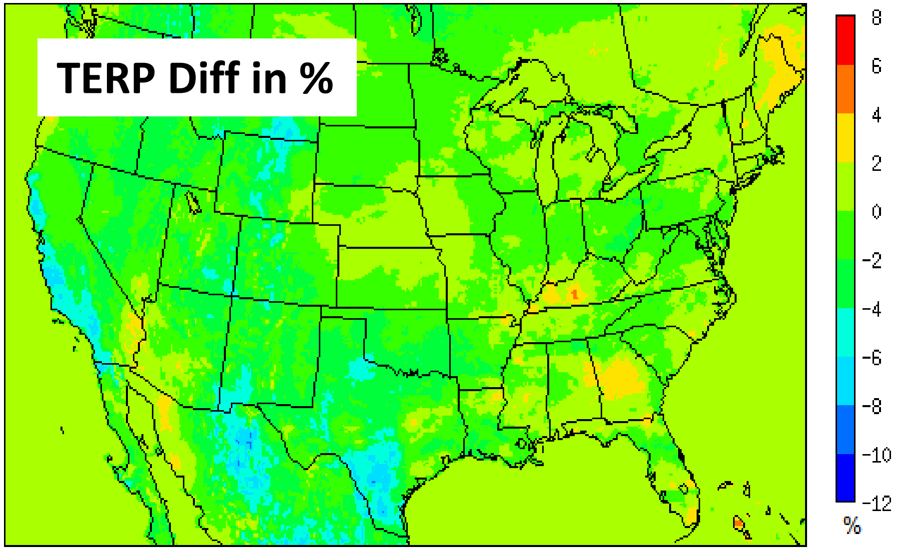
PAR evaluation against SURFRAD stations for August 2006



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

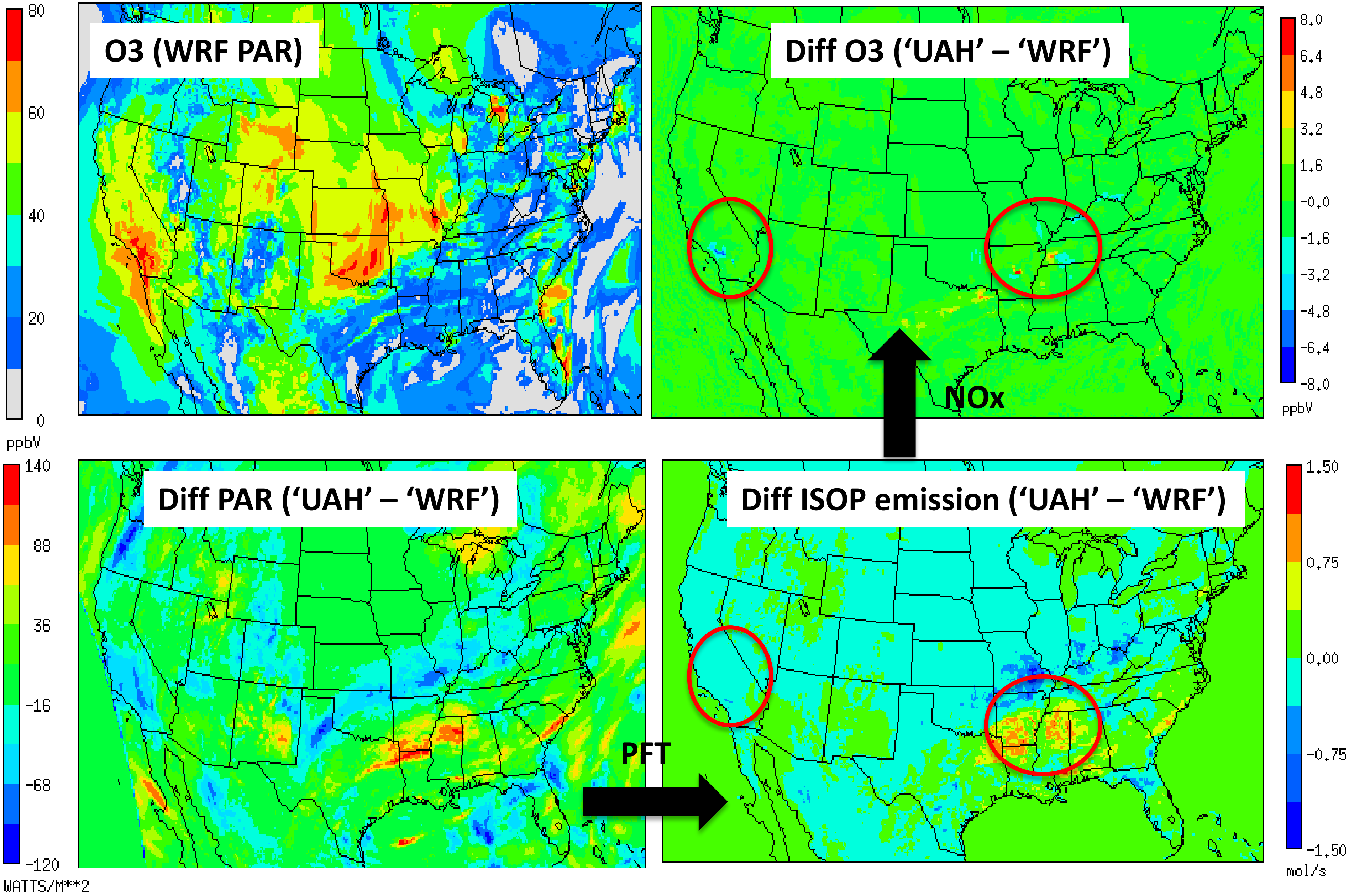
Estimated Emission Difference for September 2013 (MEGAN) (Satellite - WRF)





Isoprene emission is more sensitive to PAR inputs with the highest increase region at Northeast (> 30%) and decrease at the Northwest (> 20%). The relative change for monoterpene emission is modest (-10% to 5%).

Response for Daily Max 8-hr Average O3 concentrations (September 2013)



CONCLUDING REMARKS

- **Currently we are in the process of producing and archiving PAR for 2006-present with the new (updated) retrieval code. The new retrieval system uses a dynamic moisture field, thus correcting PAR over-estimation in the eastern United States.**

- **Compared with surface observations, satellite-based PAR tend to correct WRF overestimation; probably due to the incapability of current mesoscale meteorological model to resolve subgrid cloud.**

- **Satellite-based PAR was implemented into MEGAN model to replace the default WRF estimates and its impact on BVOC emission estimates and CMAQ simulation during the DISCOVER-AQ Houston Campaign period in September 2013.**

- **For September 2013, both isoprene and monoterpene emission rate estimates basically increased over east coast but decreased over the west coast and Texas.**

- **The impact of PAR inputs on ozone prediction depends on the local NOx/VOC ratio. Over the VOC limited region, the satellite PAR tend to shift the ground O3 prediction by 5-8%.**

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Acknowledgment

The findings presented here were accomplished under partial support from NASA Science Mission Directorate Applied Sciences Program and the Texas Air Quality Research Program (T-AQRP).

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

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Improved Soil NO Emissions Scheme

- **Berkeley Dalhousie Soil NO Parameterization (BDSNP)**
  Introduced by Hudman et al. 2012; In GEOS-Chem
  Replaces Yienger and Levy 1995 scheme

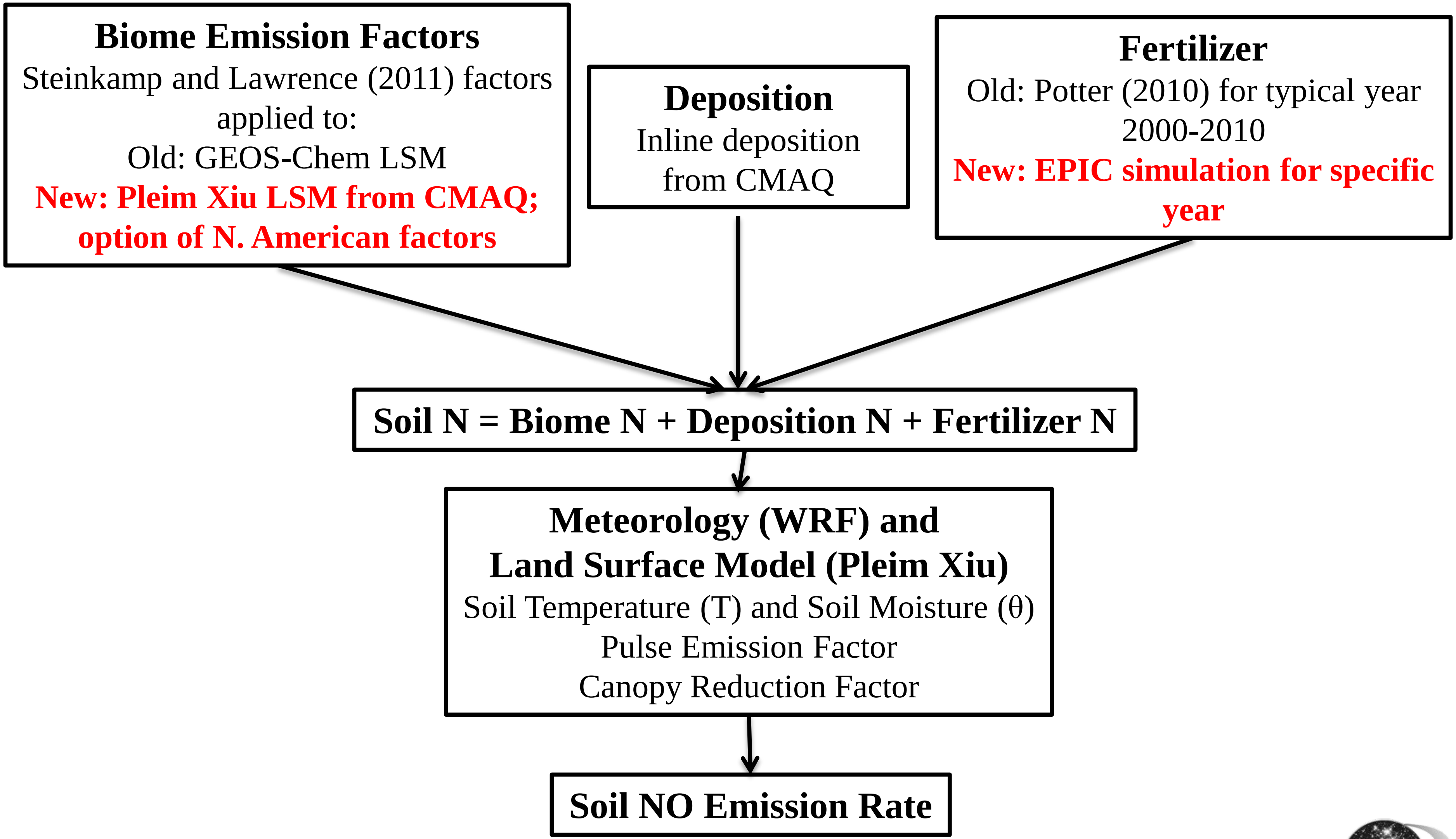
- **BDSNP has more sophisticated emission response to meteorology**
  Nonlinear response to soil moisture & T from land surface model
  Pulse of emissions when rain follows dry period

- **Implemented in CMAQ inline biogenics by Rice U**
  Soil moisture & T from Pleim-Xiu LSM
  Fertilizer and inline wet/dry N deposition add to soil reservoir

- **Offline version of BDSNP for direct creation of soil NO emission inventory using WRF or other meteorology data**
  Require assumptions about N-deposition
  Suitable for test sensitive for different land use, fertilizer application, soil biome emission factors

BDSNP Soil NO scheme implemented in CMAQ v5.0.2

Soil NO Flux = A'(Biome, Soil Nitrogen) x f(T) x g(θ) x Pulse(Dry Period) x Canopy Reduction



Biome Emission Factors
Steinkamp and Lawrence (2011) factors applied to:
Old: GEOS-Chem LSM
New: Pleim Xiu LSM from CMAQ; option of N. American factors

Deposition
Inline deposition from CMAQ

Fertilizer
Old: Potter (2010) for typical year 2000-2010
New: EPIC simulation for specific year

Soil N = Biome N + Deposition N + Fertilizer N

Meteorology (WRF) and Land Surface Model (Pleim Xiu)
Soil Temperature (T) and Soil Moisture (θ)
Pulse Emission Factor
Canopy Reduction Factor

Soil NO Emission Rate

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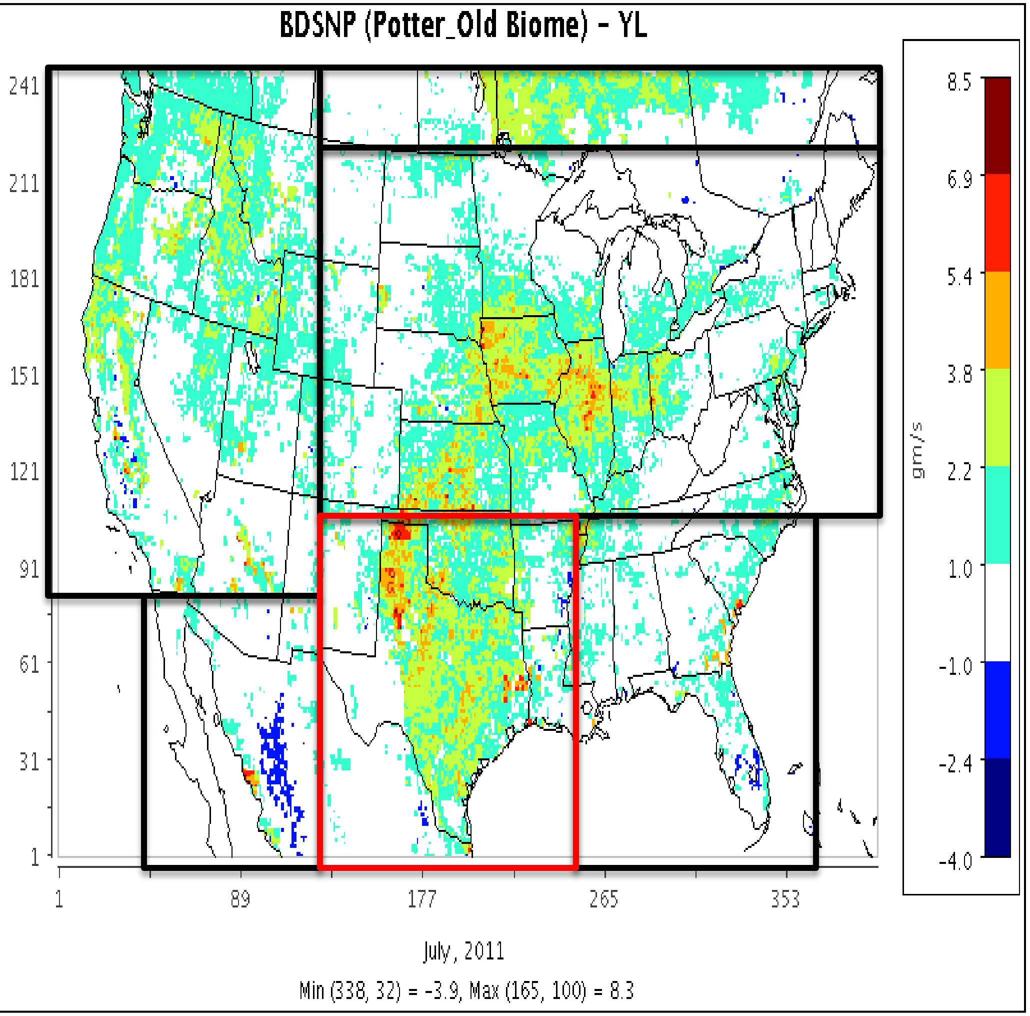
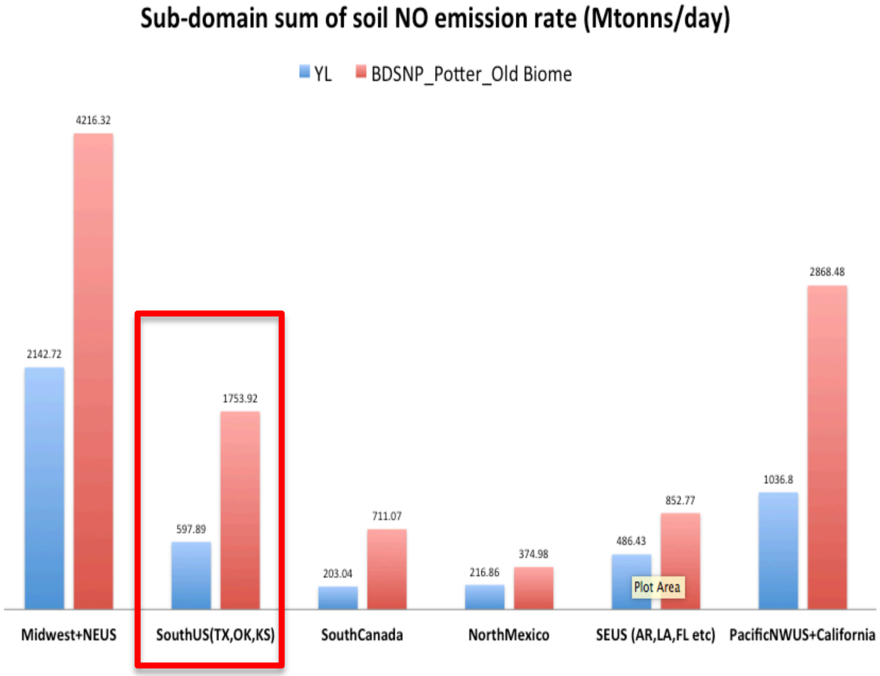
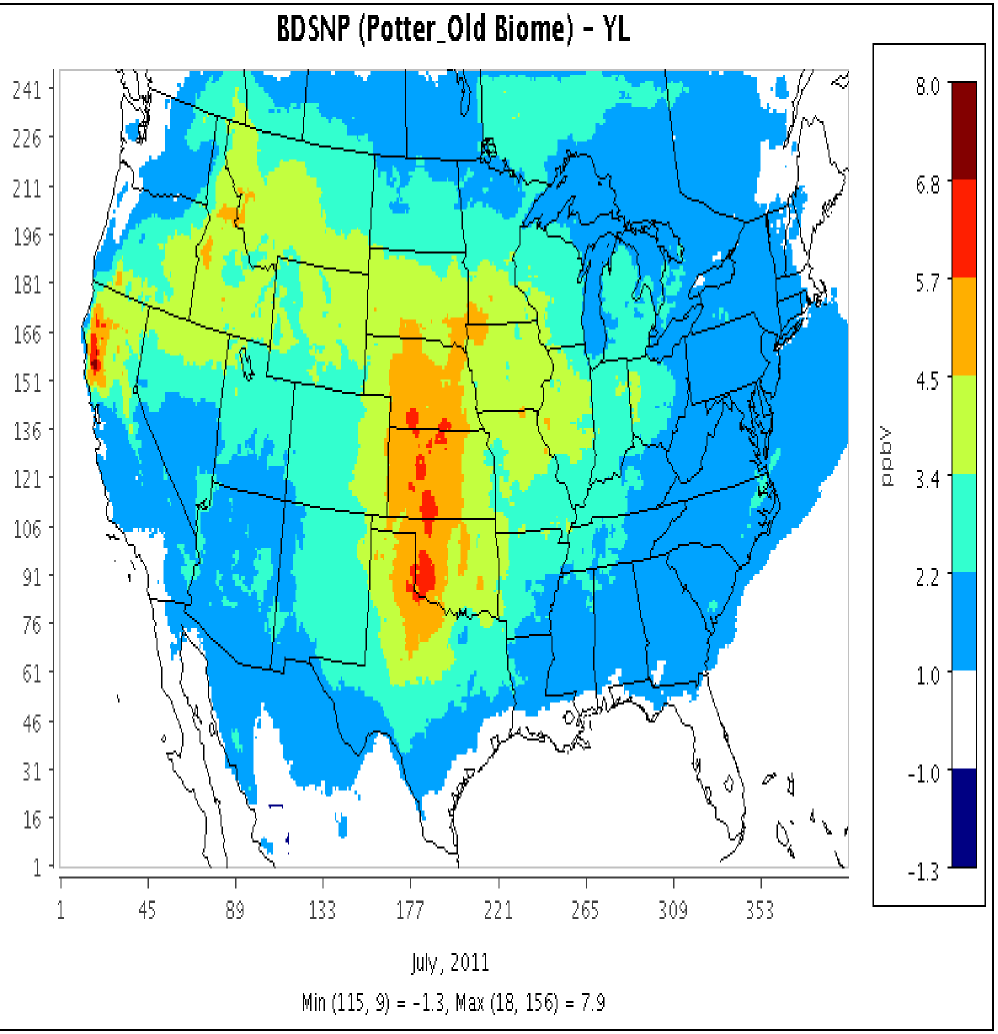
Soil NO emissions in CMAQ CONUS for July 2011: YL95 vs. original BDSNP implementation

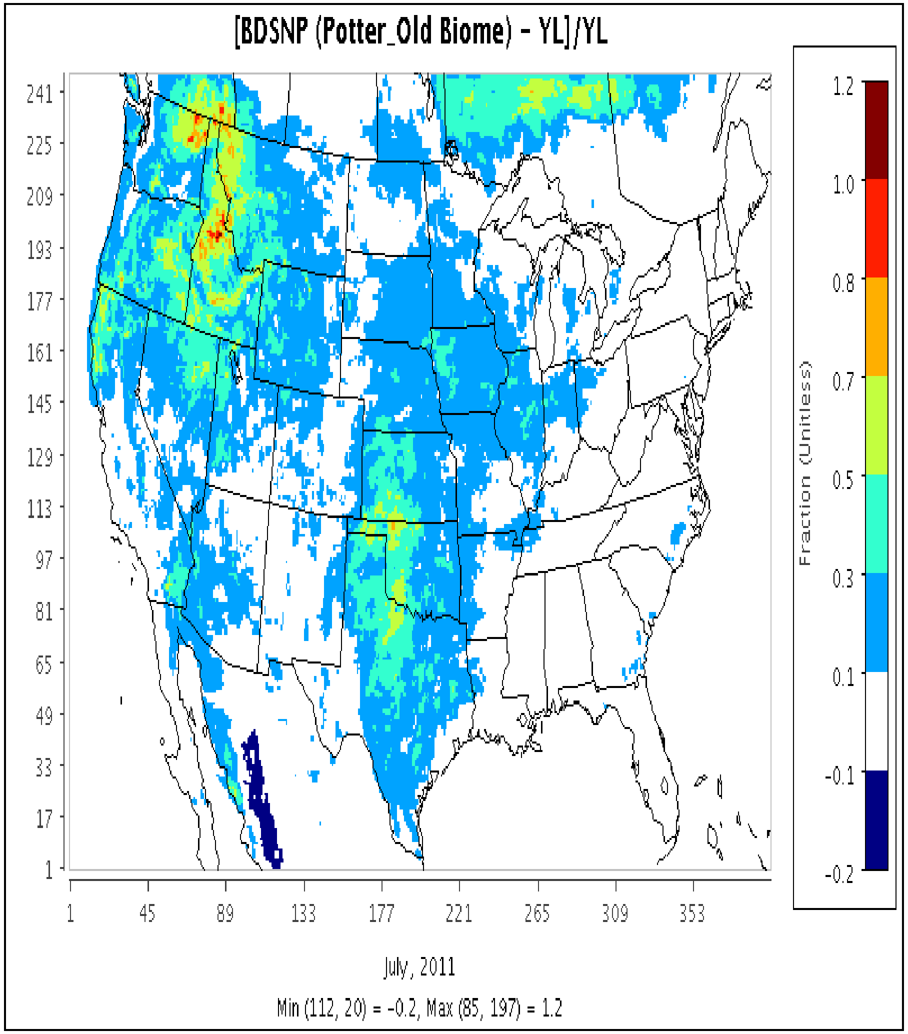




Impact of soil NO on 8h max O_3 (July 2011 avg.)



Fractional impact on NO_2 columns (July 2011)



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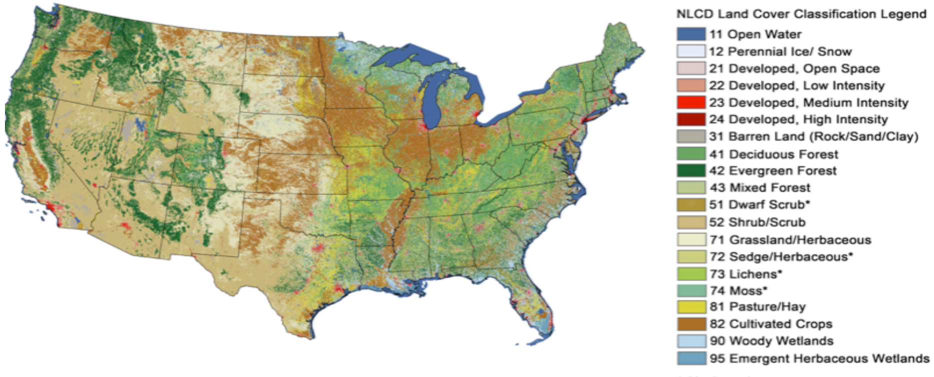
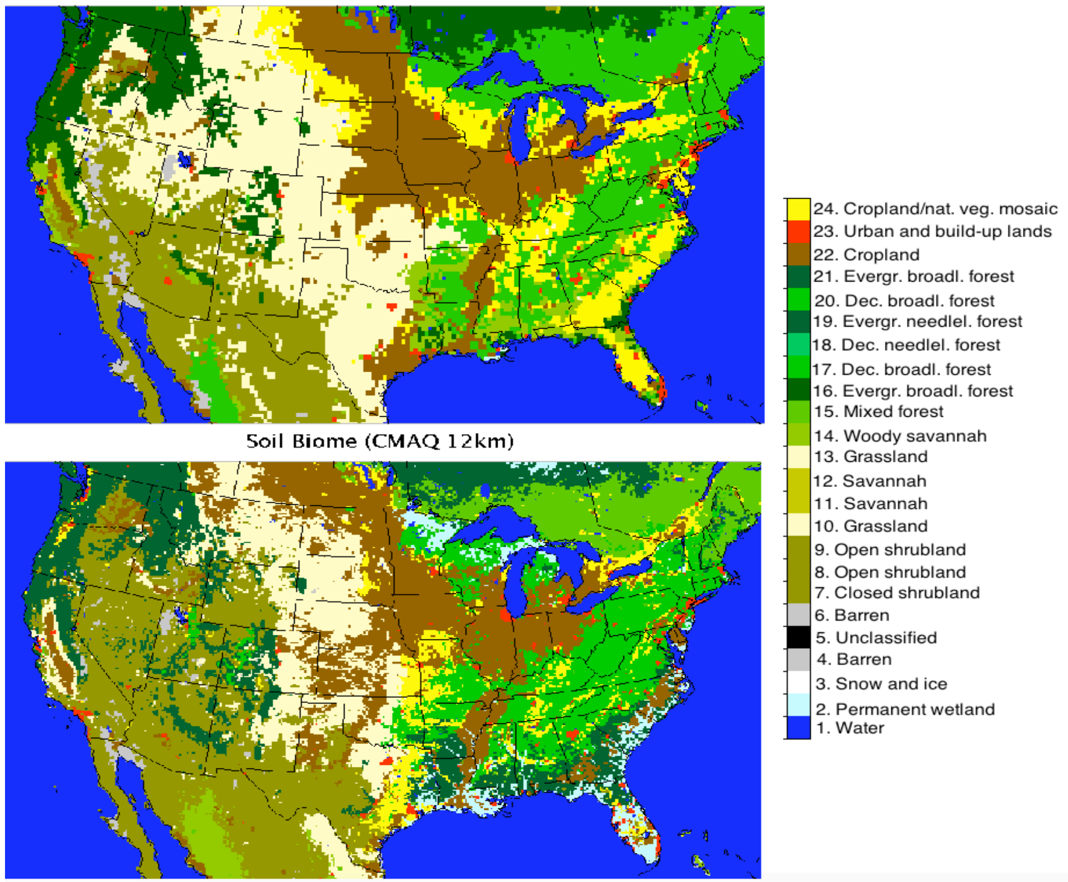
Land Cover Comparison



2011 National Land Cover Database


Soil Biome (GEOS-Chem 0.25 degree)

Soil Biome (CMAQ 12km)

GEOS-Chem Biome Types (0.25° x 0.25°)

CMAQ MODIS NLCD40 biome types (12 km)

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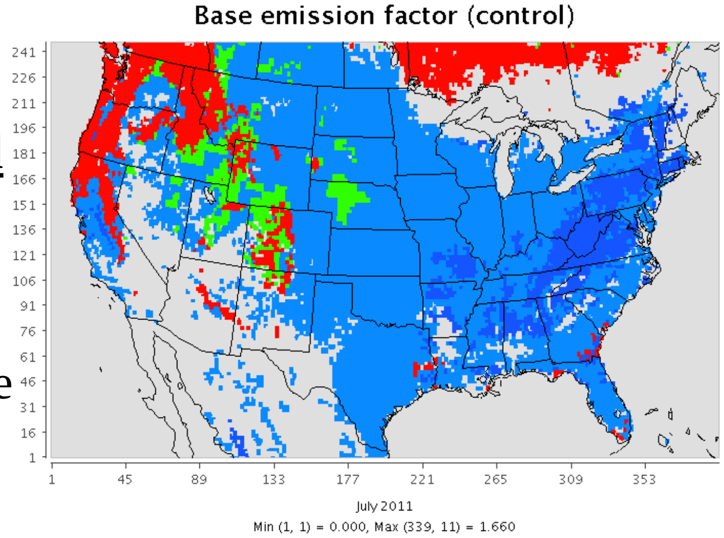
Base biome emission factors under different land cover and data

Original (GEOS-Chem Biomes)

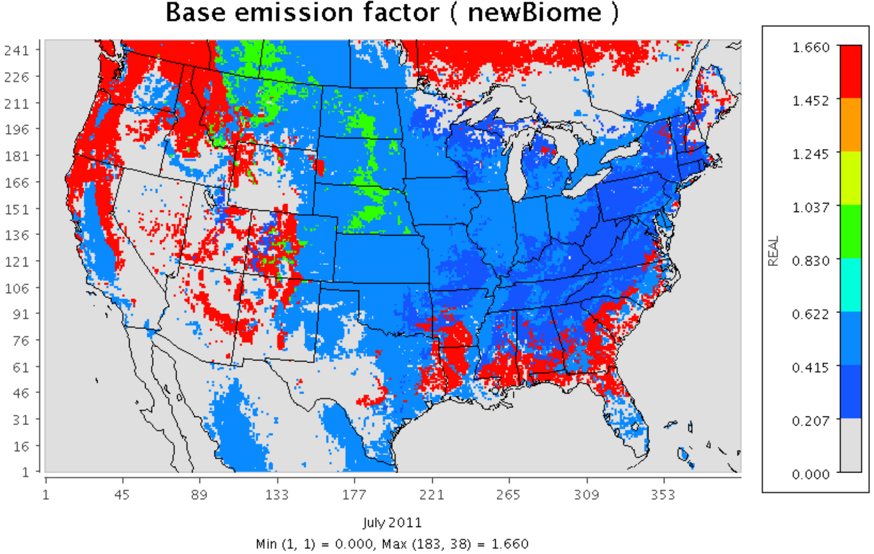
New (CMAQ NLCD Biomes)

Using **global** emission factors from Steinkamp and Lawrence


Base emission factor (control)

July 2011

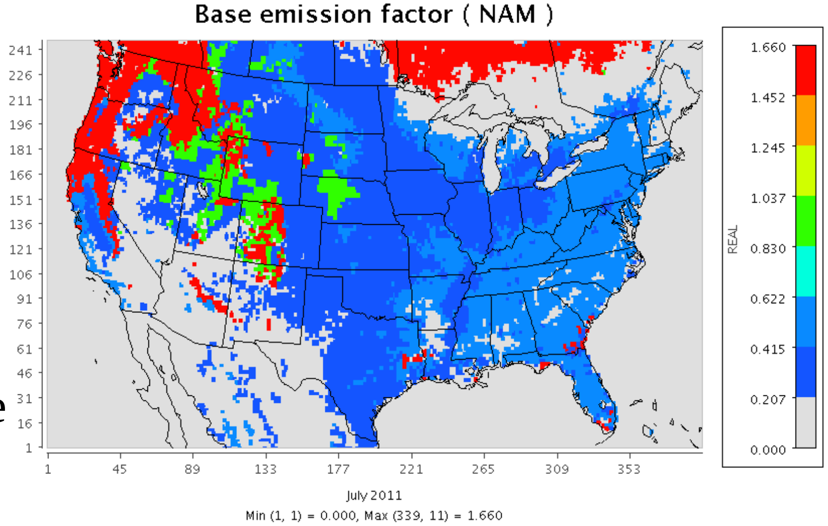
Min (1, 1) = 0.000, Max (339, 11) = 1.660


Base emission factor (newBiome)

July 2011

Min (1, 1) = 0.000, Max (183, 38) = 1.660

Using **North American** emission factors from Steinkamp and Lawrence


Base emission factor (NAM)

July 2011

Min (1, 1) = 0.000, Max (339, 11) = 1.660

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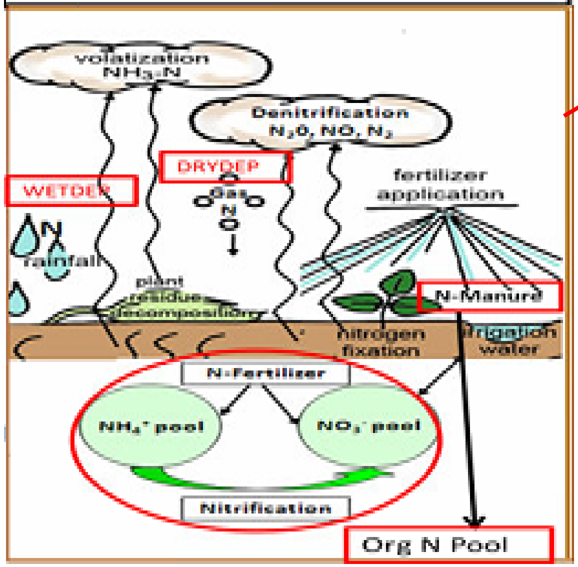
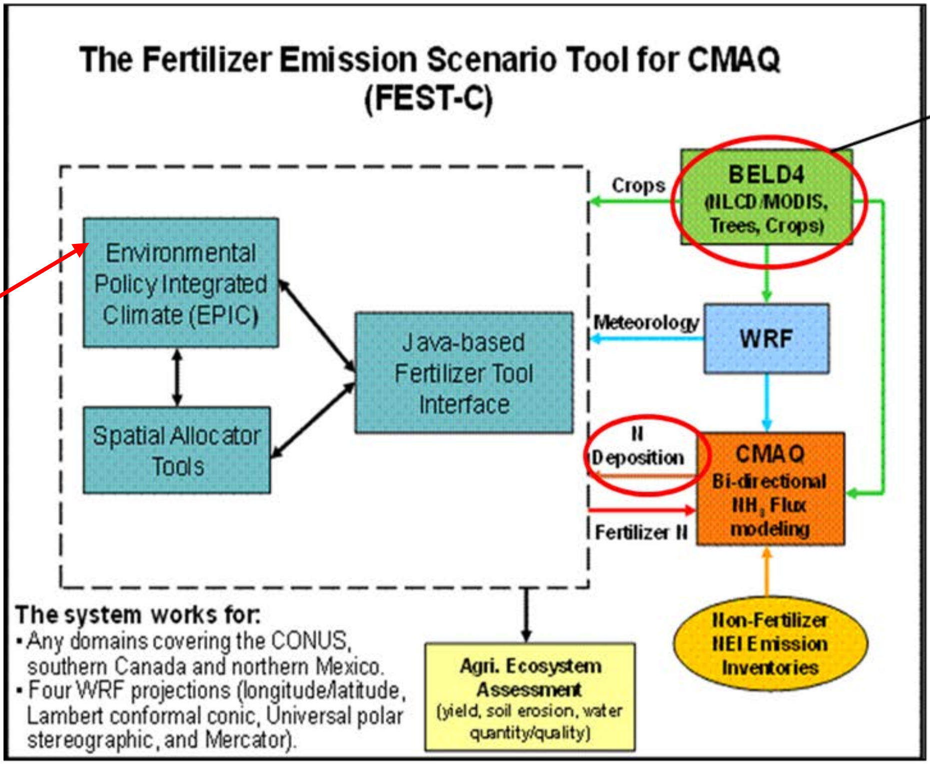
Incorporating EPIC and FEST-C into CMAQ-BDSNP: Enables Dynamic Fertilizer & Control Scenarios

Schematic of Environmental Policy Integrated Climate (EPIC) model (Cooter et al 2012)



The Fertilizer Emission Scenario Tool for CMAQ (FEST-C)



The system works for:

- Any domains covering the CONUS, southern Canada and northern Mexico.
- Four WRF projections (longitude/latitude, Lambert conformal conic, Universal polar stereographic, and Mercator).

*Adapted from FEST-C User Manual

Biogenic Emissions Land Cover Data

Crop type weights over grids

Daily Soil-N

(as separate NO_3, NH_3 and ON pools) for each crop (from FEST-C)

Daily Soil N {weighted sum of all crops} (as BDSNP Input)

Fertilizer N (NO3+ NH4 + Org N) pool input into BDSNP

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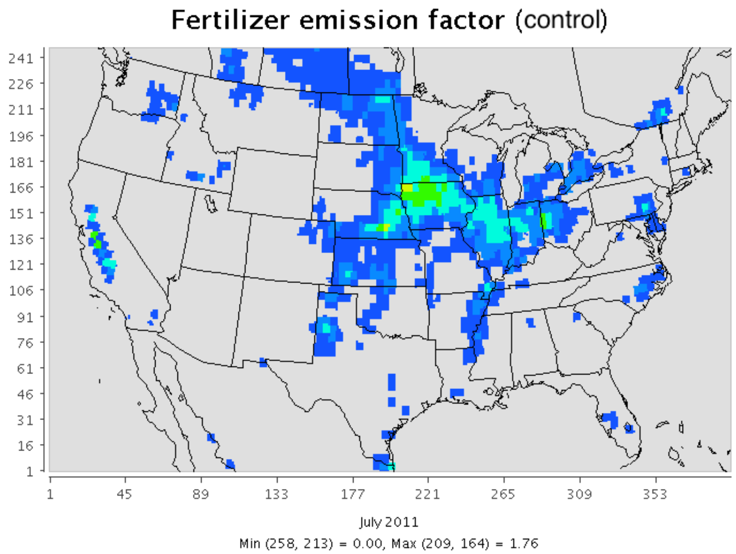
Impact of EPIC vs. Potter Fertilizer Data

Potter

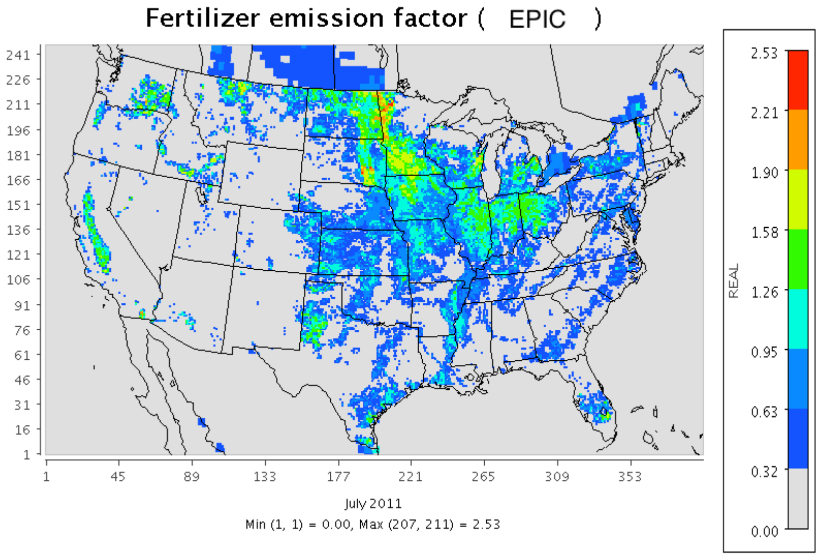
EPIC

Fertilizer Emission Factor


Fertilizer emission factor (control)

July 2011

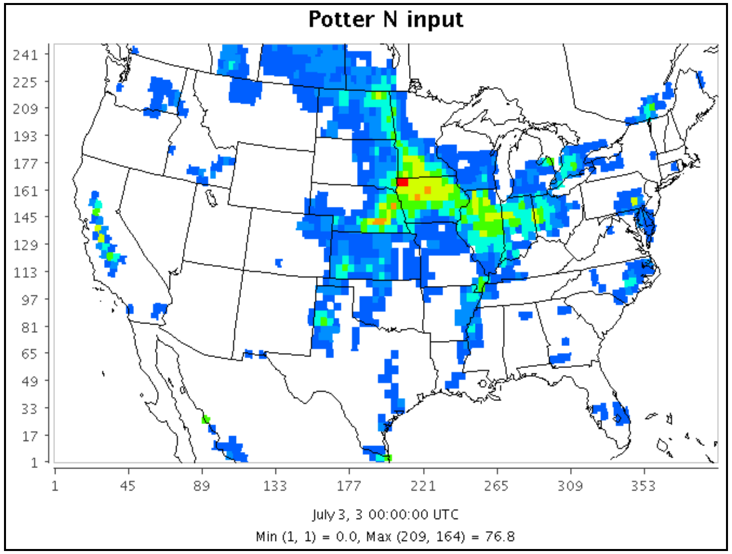
Min (258, 213) = 0.00, Max (209, 164) = 1.76


Fertilizer emission factor (EPIC)

July 2011

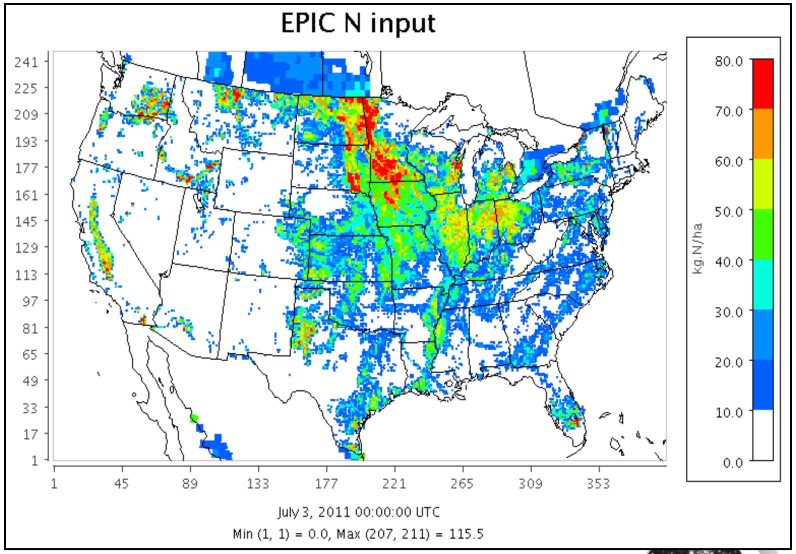
Min (1, 1) = 0.00, Max (207, 211) = 2.53

Overall Soil NO Emissions


Potter N input

July 3, 3 00:00:00 UTC

Min (1, 1) = 0.0, Max (209, 164) = 76.8


EPIC N input

July 3, 2011 00:00:00 UTC

Min (1, 1) = 0.0, Max (207, 211) = 115.5