# Impacts of Climate Change and Land Cover Change on Biogenic Volatile Organic Compounds (BVOCs) Emissions in Texas

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**Co-PIs: D. Allen and B. Parmenter**

**Project Period: 11/1/2003 – 10/31/2006**
**(no cost extension to 10/31/2007)**

**RFA: Consequences of Global Change for Air Quality: Spatial Patterns in Air Pollution Emissions (2003)**

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**EPA STAR GRANT RD83145201**

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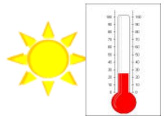
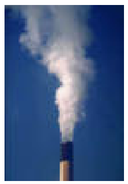
# Climate Change and BVOC Emissions



BVOCs + $NO_x$ → $O_3$

## BVOC emissions vary by species

Live Oak

American Elm

1. **Climate change** affects BVOC emissions:
- **directly:** by altering incident solar radiation, precipitation, temperature, etc.
- **indirectly:** by altering leaf area index, species composition and density

2. **Anthropogenic land-cover change** alters species composition → affects BVOC emissions

**Some challenges:**

Climate models have a high uncertainty in simulating key weather variables

Land-surface models represent vegetation as mosaics of plant functional types, not species

# Science or Research Questions

- Can climate models do a reasonably accurate job of simulating biogenic emissions?
- How are the BVOC simulations sensitive to the uncertainty in vegetation datasets?
- How much do biogenic emissions vary from year to year? What are the relative contributions of direct climate variation and indirect climate variation to interannual variability of biogenic emissions?
- How accurate is regional climate dynamic downscaling?
- What are the potential impacts of changing land use and land cover patterns, driven by urbanization and climate change, on air quality predictions?
- How do future climate change and urbanization, individually and together, affect regional air quality predictions?

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# 1. How well can LSMs simulate biogenic emissions?

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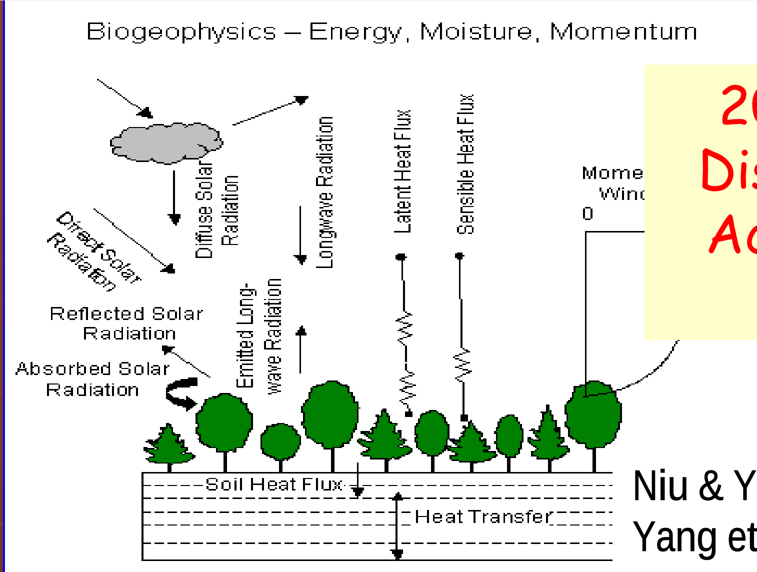
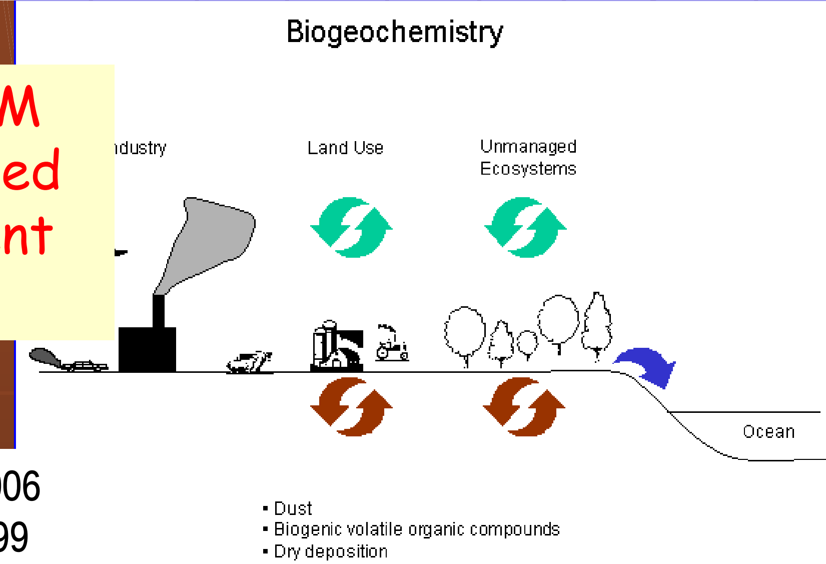



# 2008 CCSM Distinguished Achievement Award

Niu & Yang, 2003, 2006
Yang et al., 1997, 1999



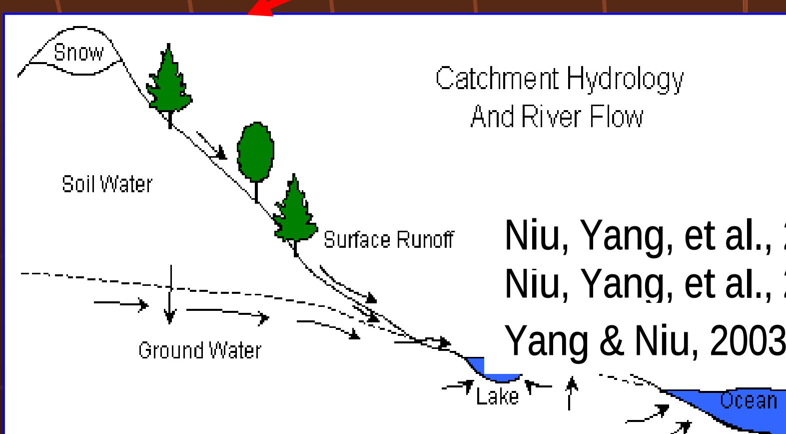

Biogeophysics

Biogeochemistry

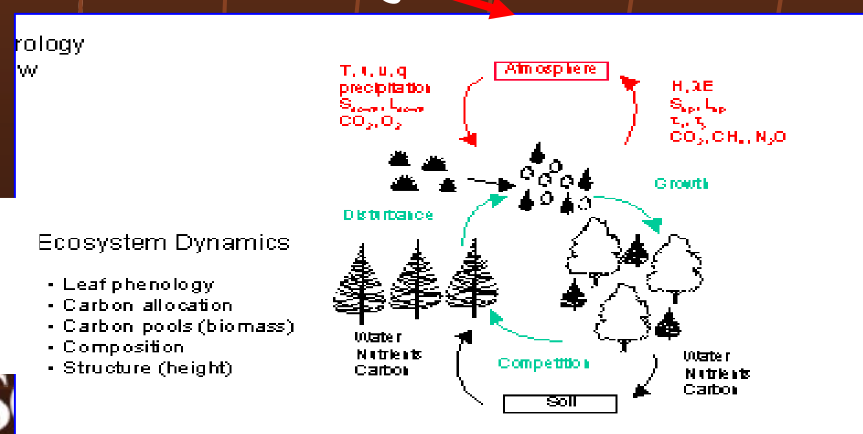
**NCAR CLM 3.5**

Hydrology

Ecosystem Dynamics

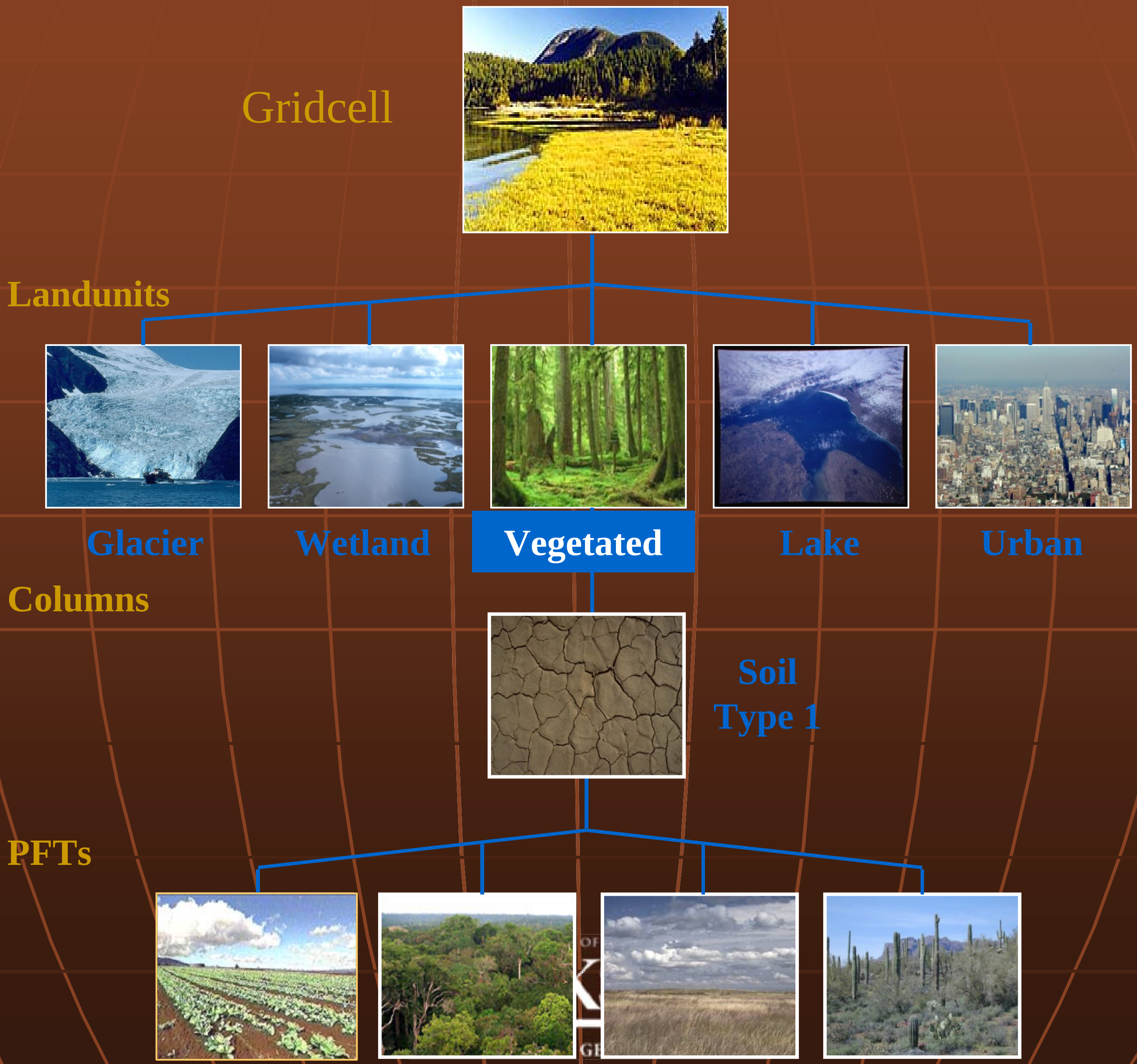



Niu, Yang, et al., 2005
Niu, Yang, et al., 2007
Yang & Niu, 2003




**Collaborators: NCAR (Gordon Bonan, Keith Oleson, Dave Lawrence)**

# CLM Subgrid Structure




Keith Oleson

# BVOC Algorithm

PFT-specific emission capacity

$$F_{BVOC} = \gamma_T \gamma_R \, \varepsilon \, D$$

canopy temp. scale factor

PAR scale factor

leaf biomass density

Developed by Guenther et al., 1995
Added to CLM3 by Levis et al., 2003

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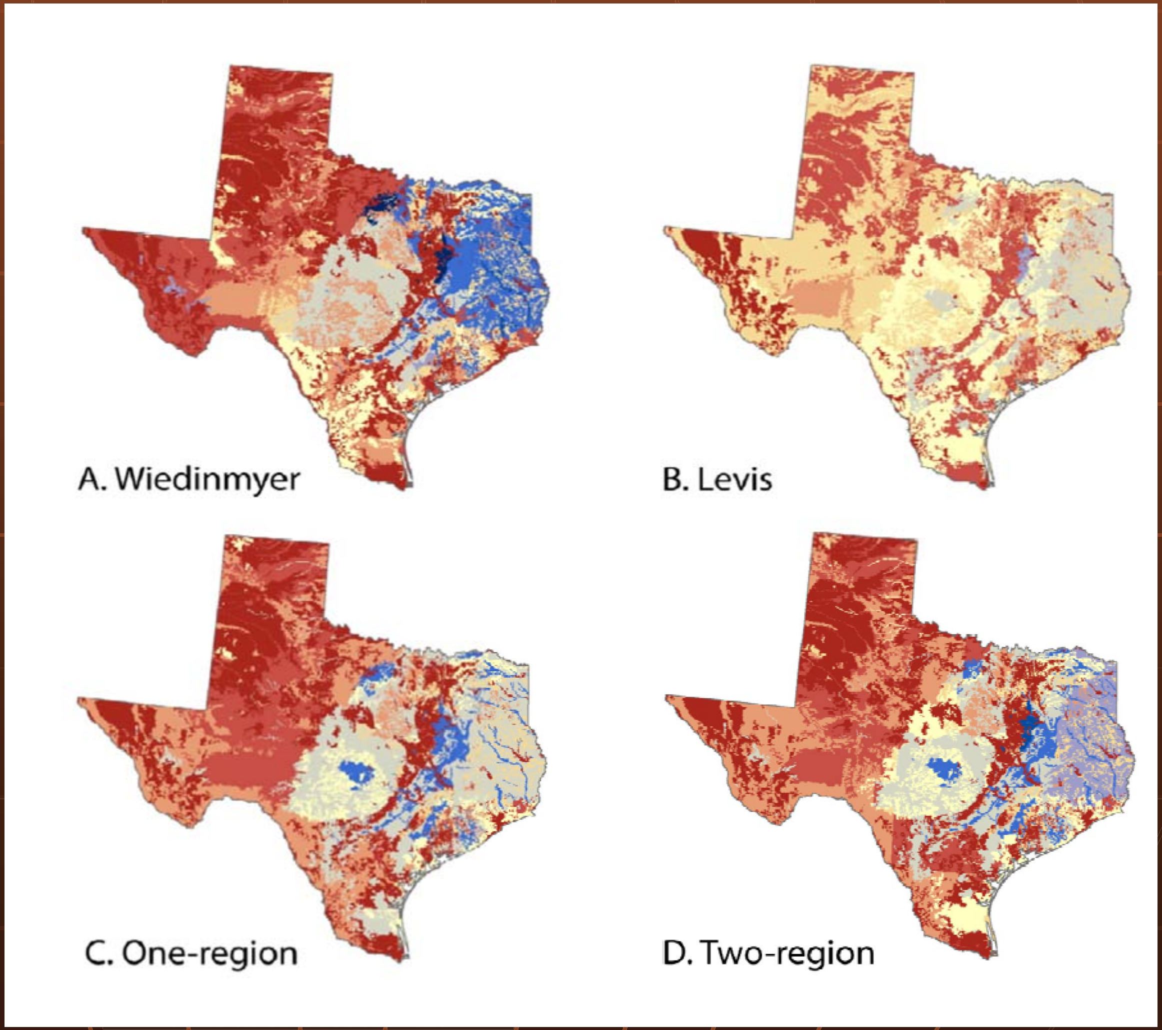
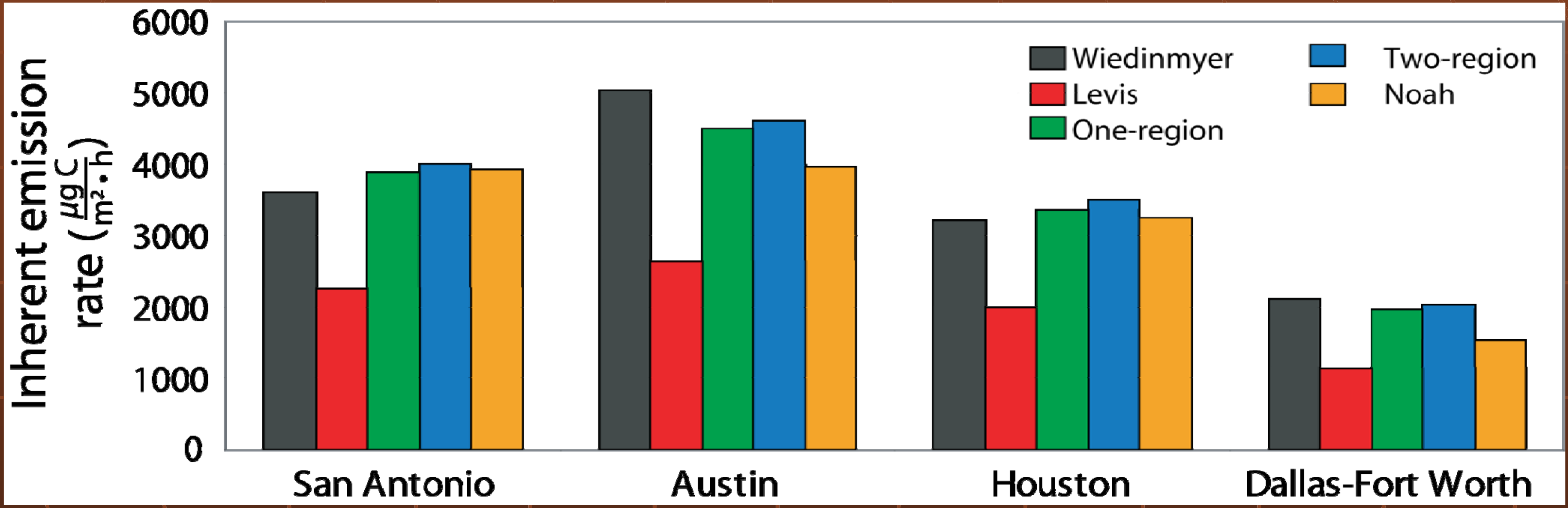
# Region-specific BVOC Emission Factors from 600+ Species

- Preserve maximum emitting capacity of landscape
- Correlate well with "true" emissions

$$F = \boxed{\varepsilon D}\,\gamma$$



# Derive region-specific, species-based BVOC emission capacities for PFTs




## LSMs can be used as a surrogate for purpose-specific biogenic emission modules (e.g. GLOBEIS)

Gulden, L.E. and Z.-L. Yang (2006), Development of species-based, regional emission capacities for simulation of biogenic volatile organic compound emissions in land-surface models: An example from Texas, USA, *Atmospheric Environment*, 40(8),1464-1479.

# 2. How much uncertainty in LSM-simulated BVOC emissions can be attributed to uncertainty in land-cover dataset?

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# Starting point: Two land-cover datasets

**Satellite-derived dataset**
(Lawrence and Chase, 2005)

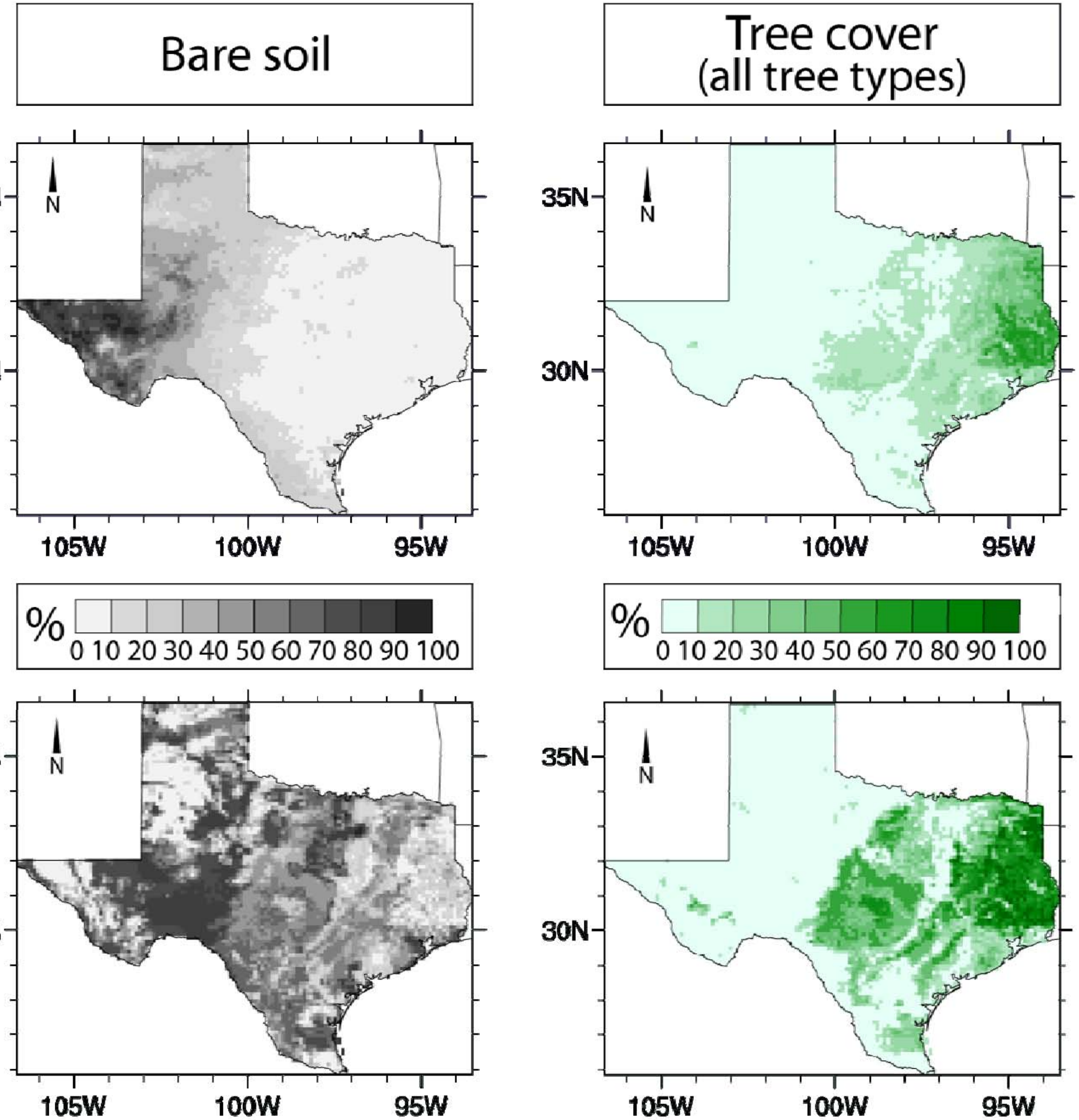
5-km resolution (original)
MODIS-, AVHRR-derived

*Contains:*
% bare soil, PFT distribution, monthly phenology, soil color

**Ground-survey–derived dataset**
(Wiedinmyer et al., 2001)

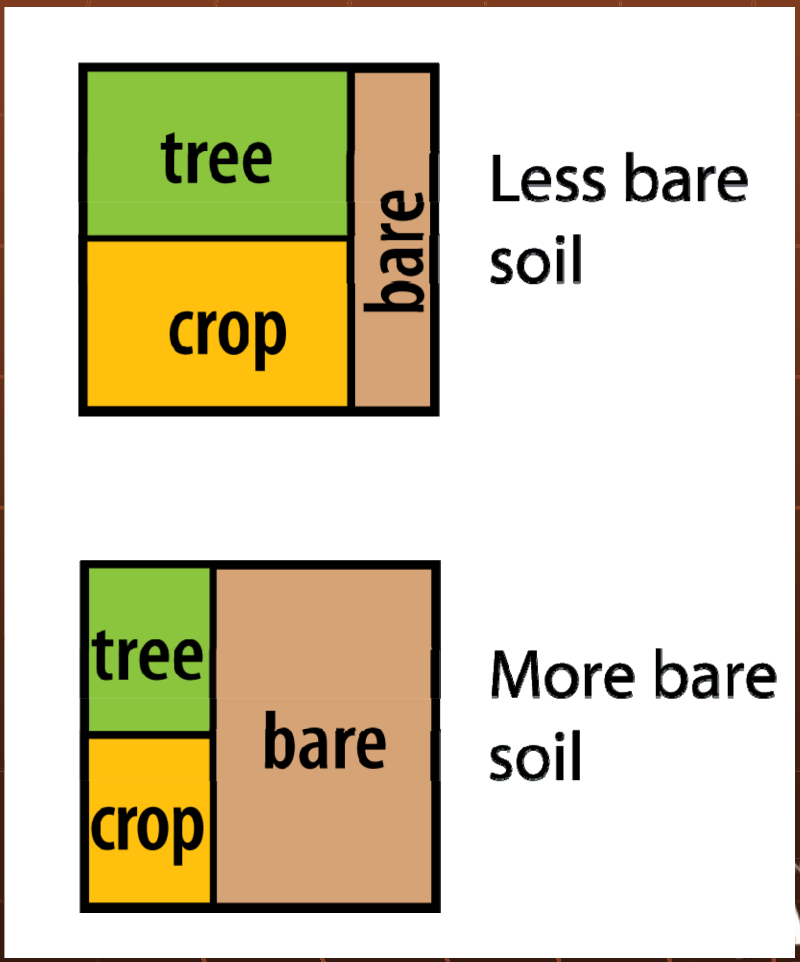
1-km resolution (original)
Species-based (~300 species; 600+ land-cover types); converted to PFTs

*Contains:*
% bare soil, PFT distribution

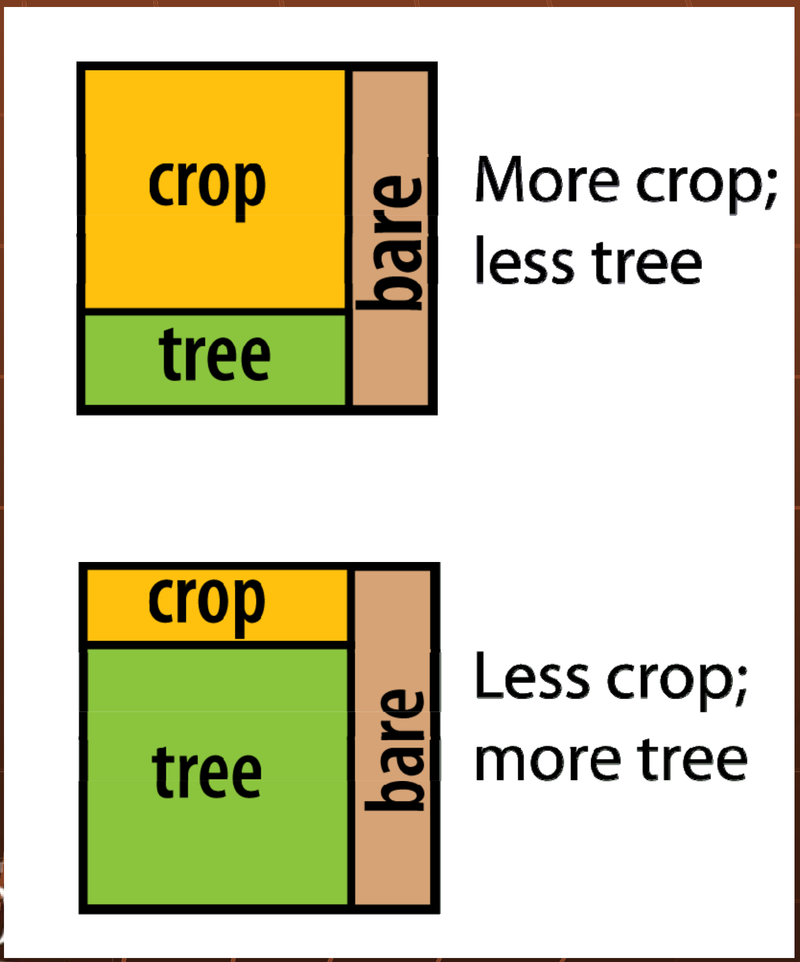


# Experiment design

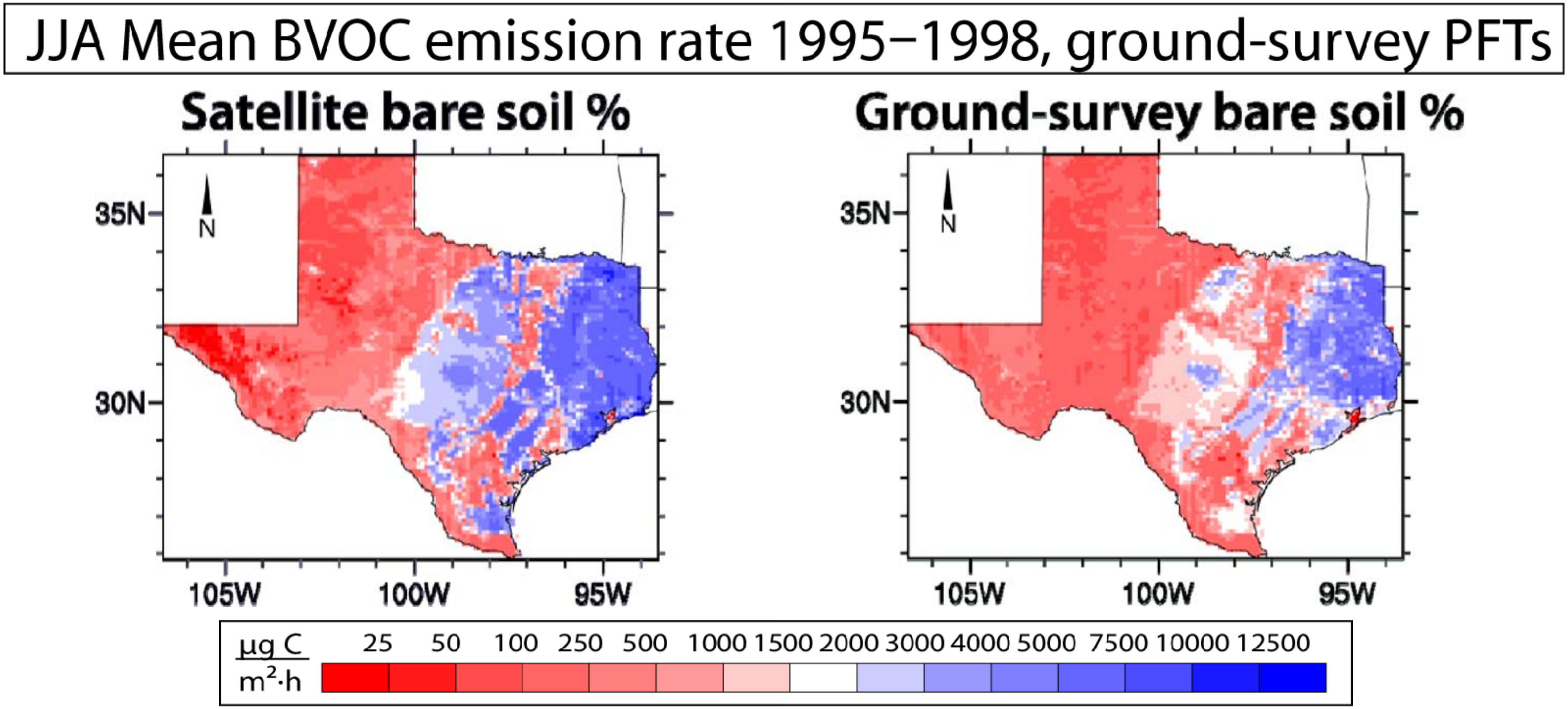
1. Keep PFT distribution constant; vary bare soil %

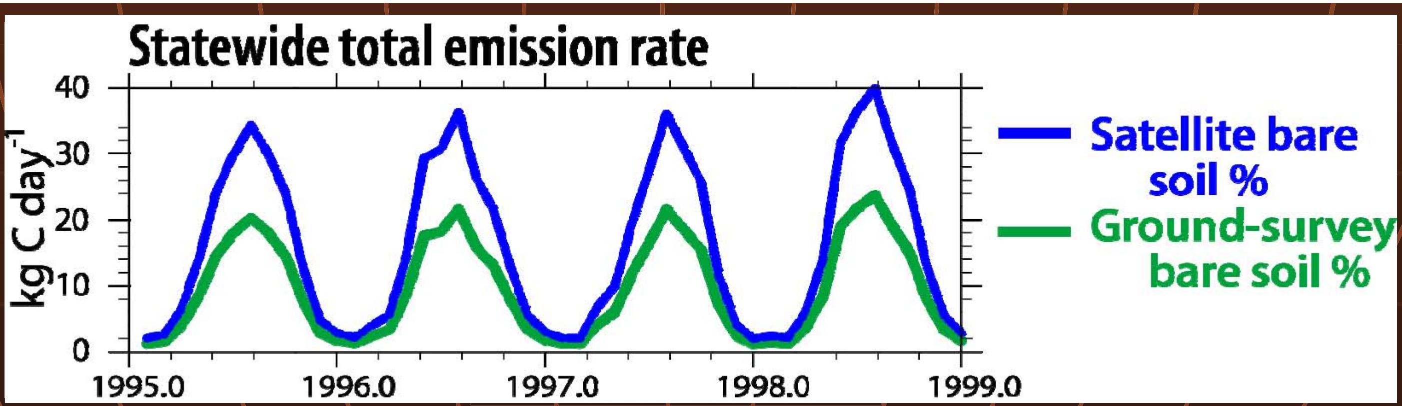



2. Keep bare soil % constant; vary PFT distribution

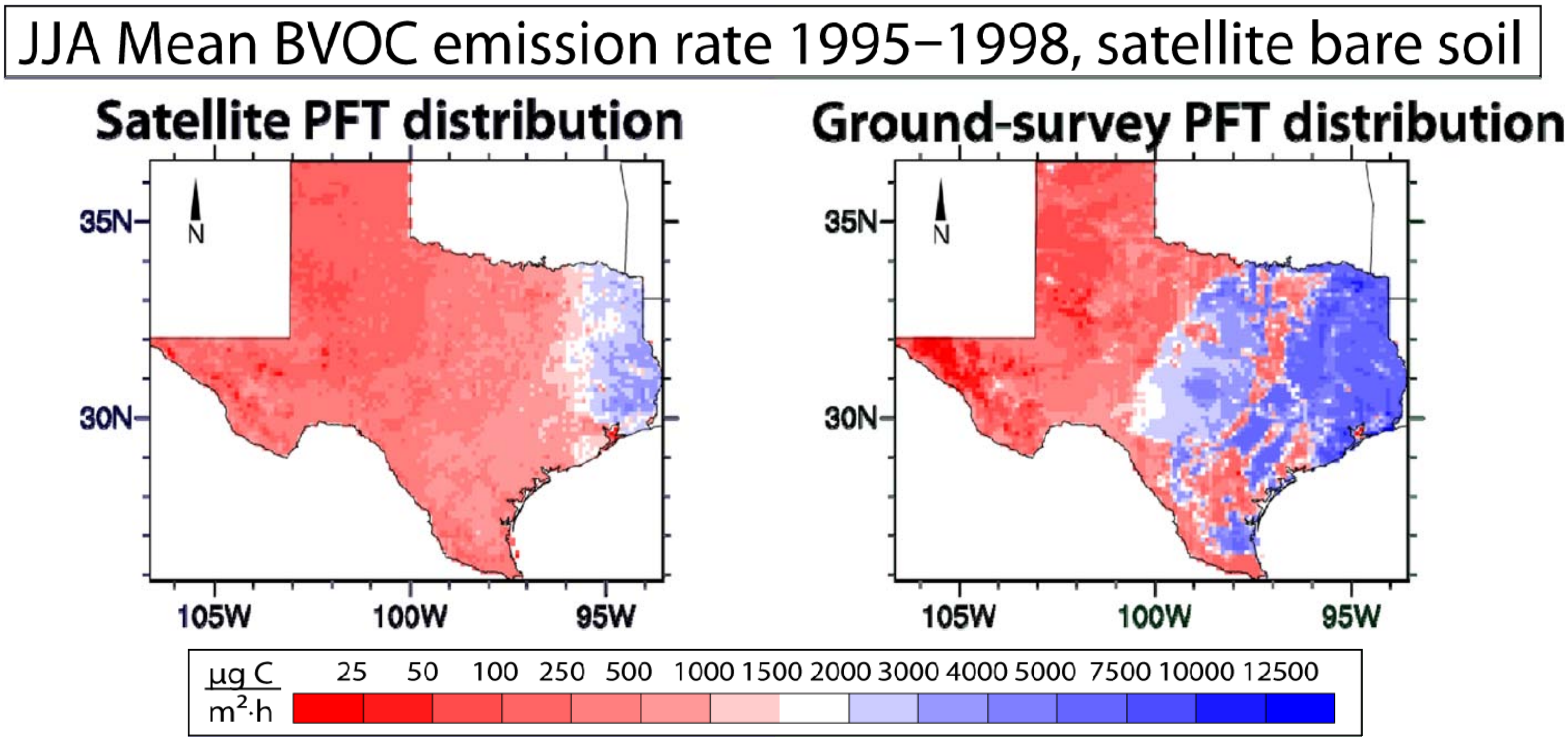


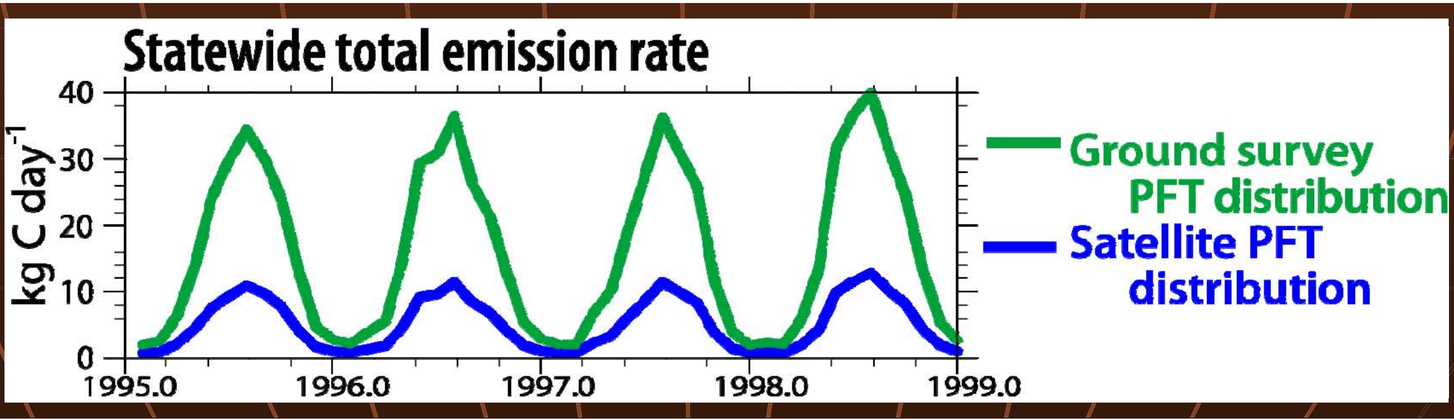
# Vary bare soil fraction



# Vary vegetation distribution



# Conclusions

1. The **large disparity** b/w satellite-derived and ground-survey-based datasets significantly influences estimated BVOC emissions **(~1 order of magnitude difference in BVOC flux estimates**)

2. **BVOC flux is most sensitive to PFT distribution** (Ground-survey PFT ~ 3 times that of satellite PFT distribution); also sensitive to bare fraction (satellite bare fraction ~ 1.7 times ground-survey bare fraction).

3. **Indirect effects on BVOC emissions** (via modification of state variables) **are small** (bare fraction: 0-16% of inherent BVOC flux) or negligible (PFT distribution)

4. **Air quality policy decisions** based on LSM-simulated BVOC flux rates **are limited by the uncertainty of the input land-cover datasets**.

Gulden, L.E., Z.-L. Yang, and G.-Y. Niu (2008), Sensitivity of biogenic emissions simulated by a land-surface model to land-surface representation *Atmos. Environment, doi:10.1016.*

# 3. How much do BVOC emissions vary from year to year?

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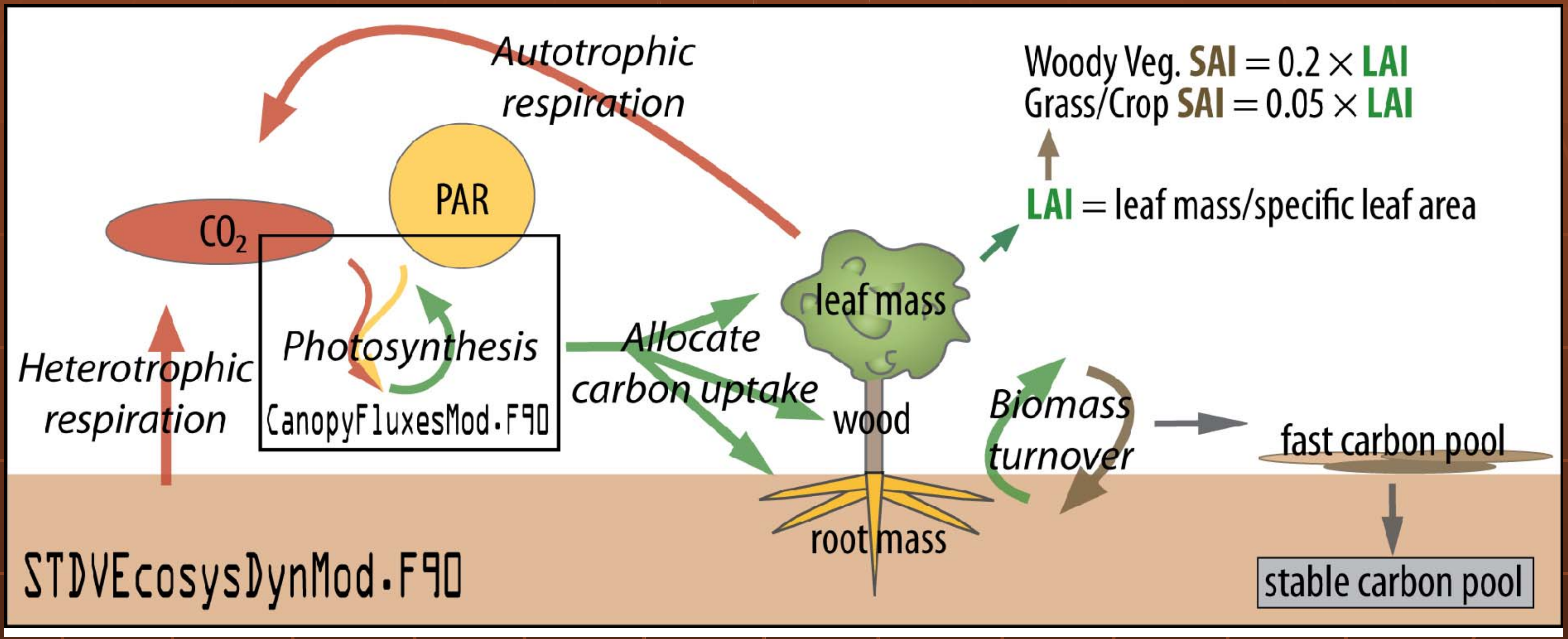
# Add dynamic phenology to CLM3




Module is a slightly modified version of BATS's dynamic phenology module (Dickinson et al., 1998)

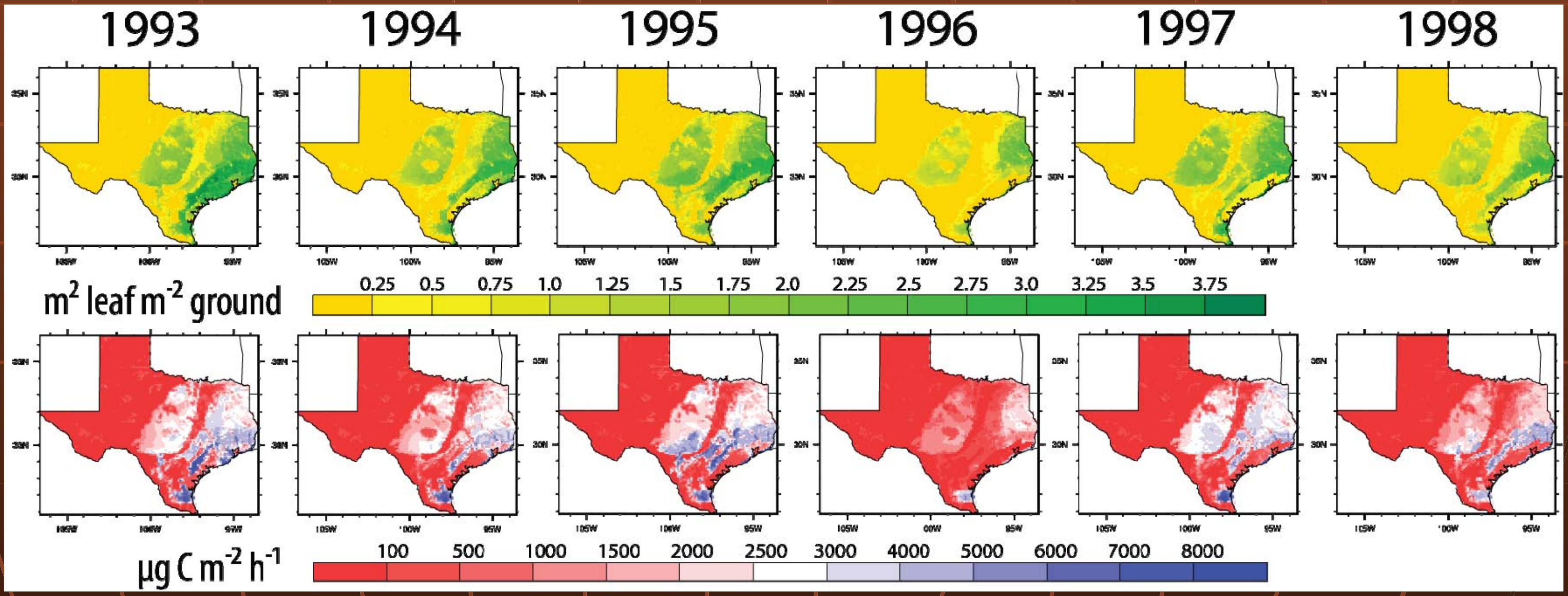
Allows leaf area index to respond to short-term environmental changes

# Results using CLM3 with dynamic vegetation

June-July-August Mean

LAI

BVOC

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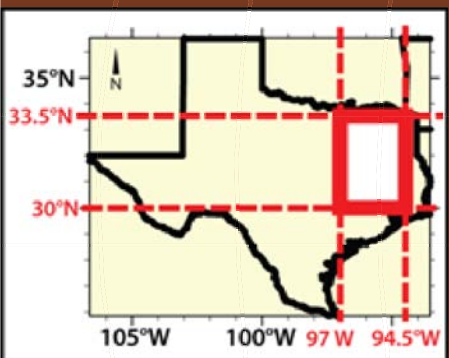
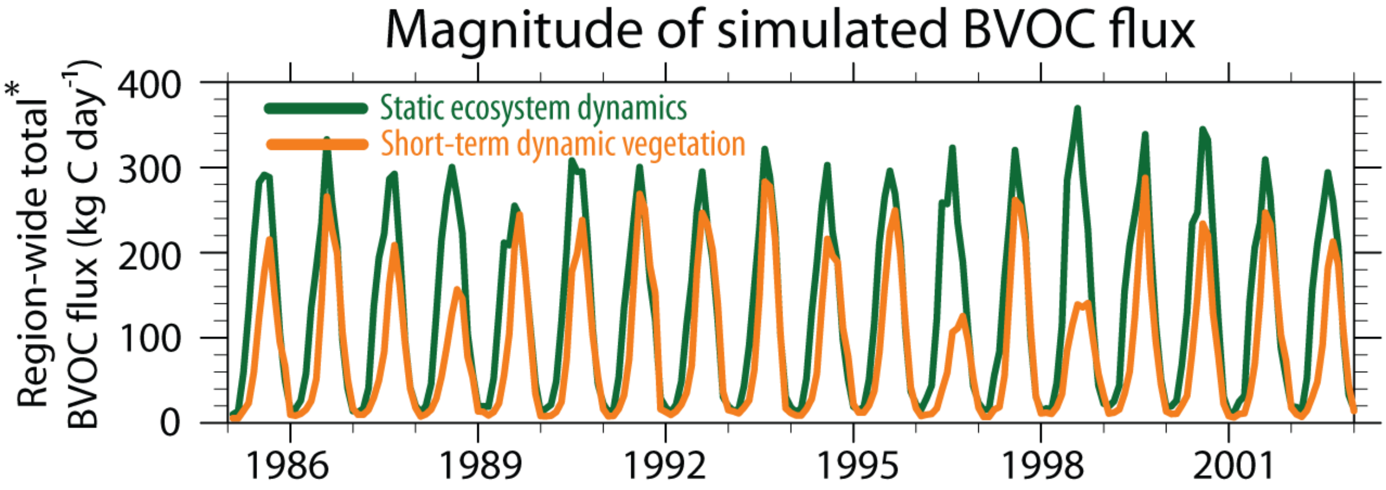
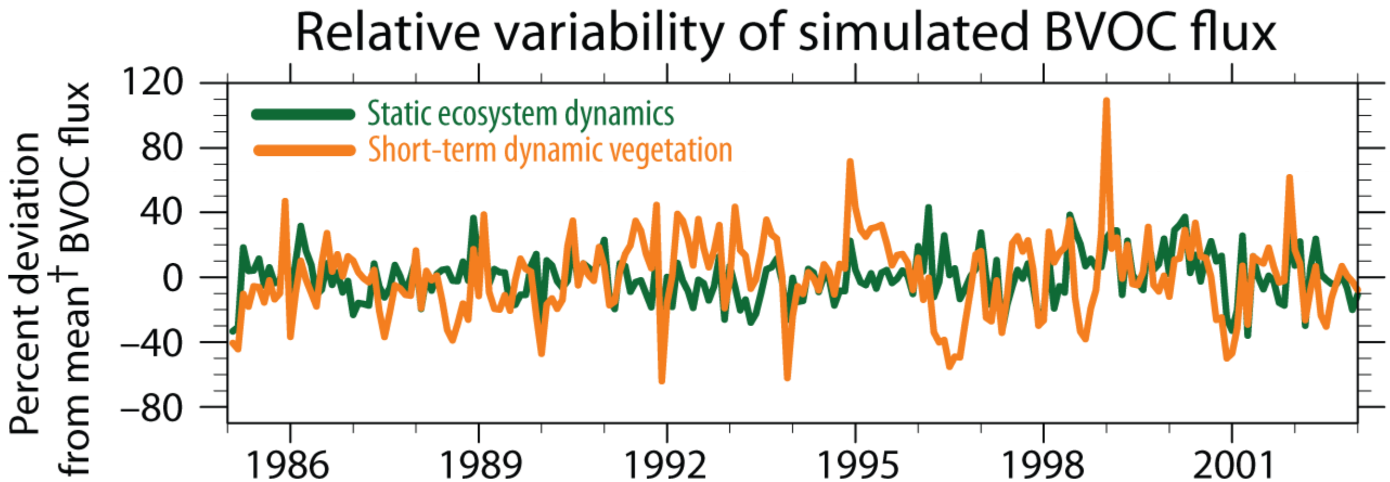


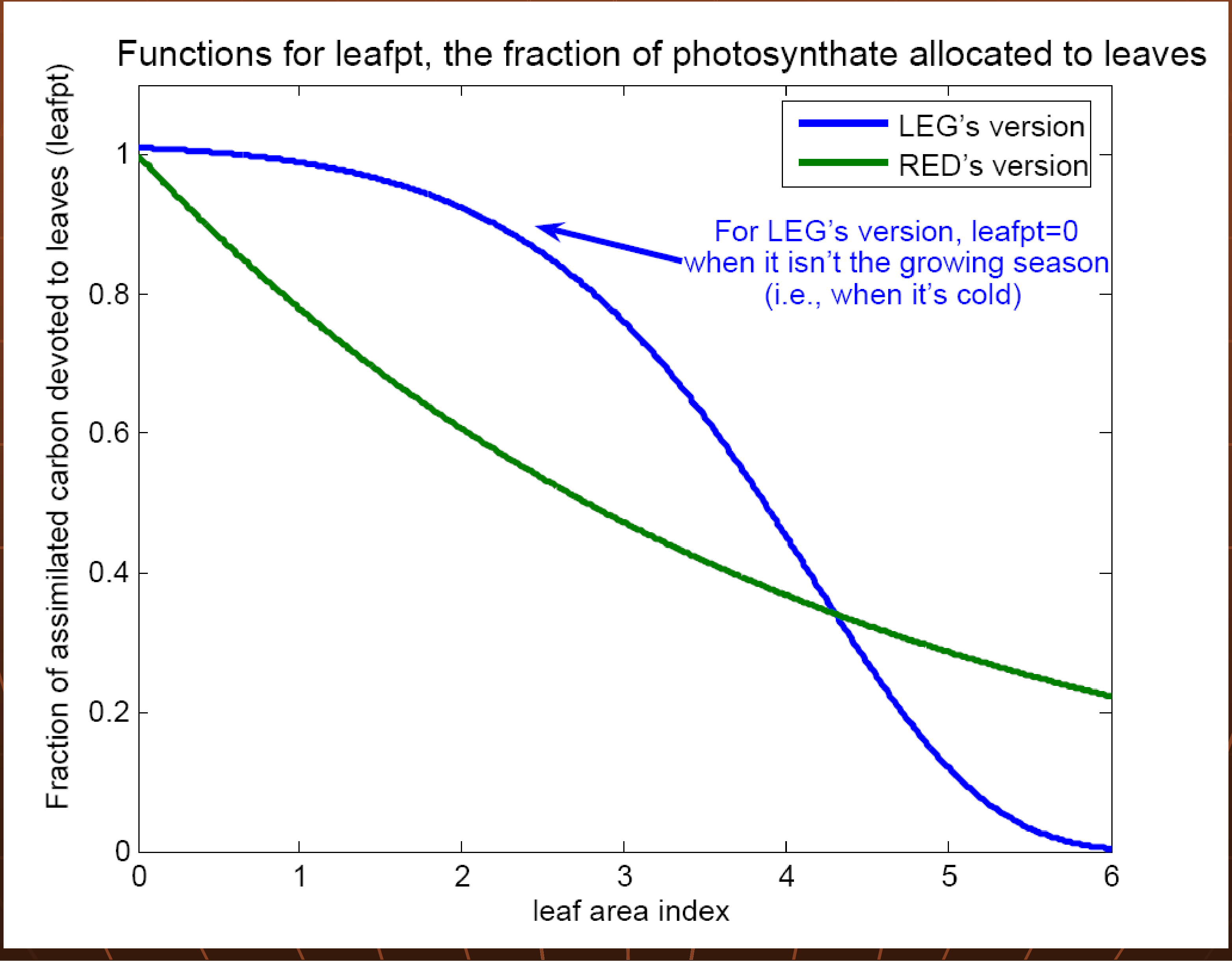

* Area-weighted average of grid-cell monthly mean BVOC flux for region shown in Fig. 5

† For month *m*, the mean BVOC flux rate is $\overline{F_m} = \frac{1}{n_{years}} \sum_{y=1}^{n_{years}} \left( \frac{\sum_{i=1}^{n_{cells}} F_{i,m,y} Area_i}{\sum_{i=1}^{n_{cells}} Area_i} \right)$

Average absolute departure from mean (prescribed LAI) = 11.7%

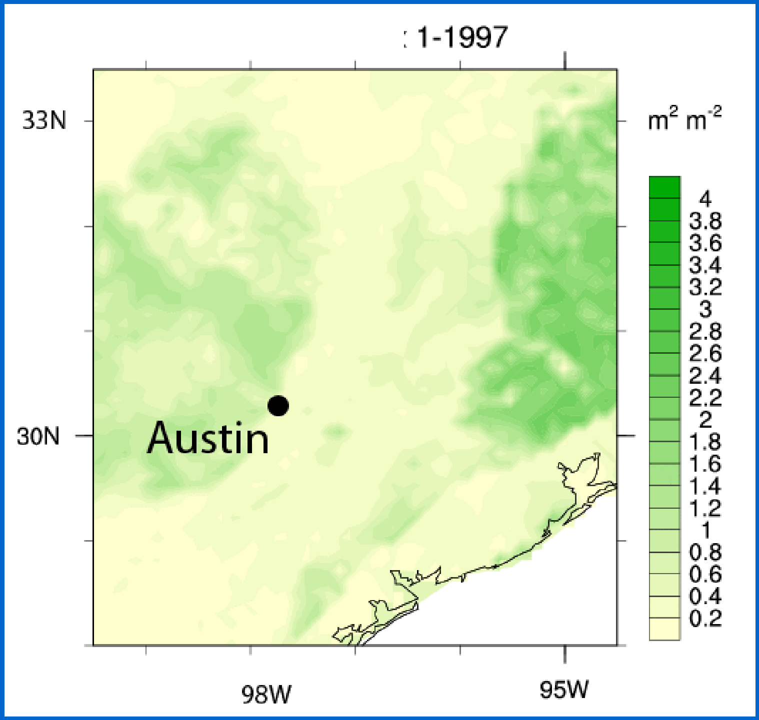
Average absolute departure from mean (short-term dynamic vegetation) = 22.4%

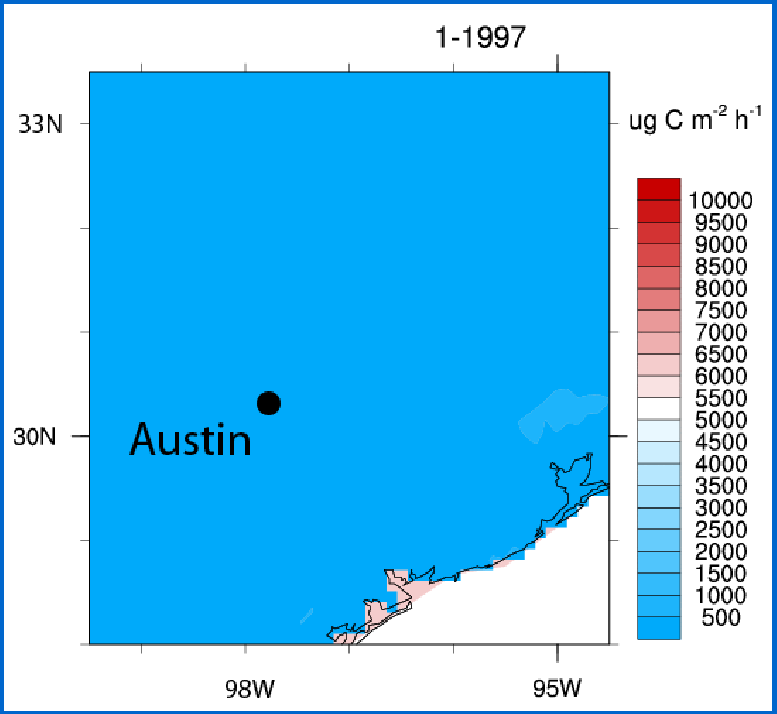
# Factors affecting the simulation of LAI



# Precipitation Variability Drives Year-to-year Changes in Leaf Biomass and Biogenic Emissions

**Leaf area index in Texas** | **Biogenic emissions in Texas**




Gulden, L. E., Z.-L. Yang and G.-N. Niu, 2007, *J. Geophys. Res.,* **112** (D14), D14103, 10.1029/2006JD008231. Gulden, L.E. and Z.-L. Yang, 2006, *Atmospheric Environment*, **40(8)**, 1464-1479.

# Conclusions

1. LSMs do a decent job of simulating BVOCs when they use region-specific, species-derived emission capacities.

2. Uncertainty in LSM-simulated BVOC emissions that is attributable to land-cover dataset is considerable (~1 order of magnitude).

3. Year-to-year climate variation dominates any observable trend in mean climate as major source of year-to-year changes in biogenic emissions.

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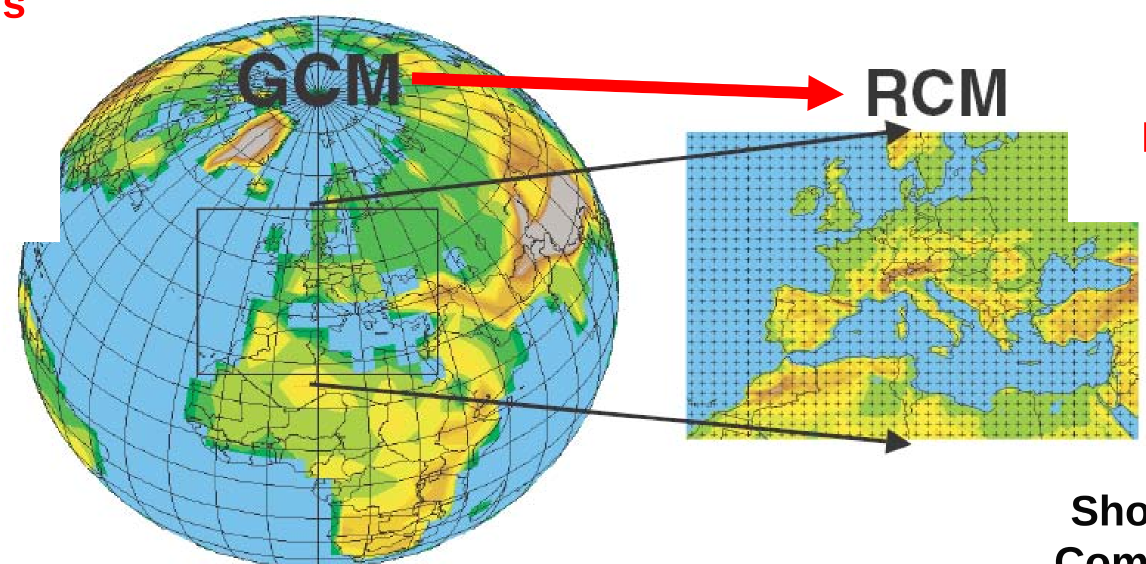
# 4. How accurate is regional climate dynamic downscaling?

General circulations
Jet streams
Major storm tracks
Monsoons
ENSO

Response
Forcing

Solar radiation
Greenhouse gases
Long-lived aerosols
Land/ocean contrasts
Large mountains




Local circulations
Low level jets
Squall lines
Land/sea breezes
Lake breezes

Response
Forcing

Short-lived aerosols
Complex topography
Coastal lines
Inland water
Vegetation distribution
Land use

~200-km grid spacing

~20-km grid spacing

Giorgi 2006

# Dynamical Downscaling Methodologies

- Continuous integration (Climate prediction mode)
  - One single initialization of large scale fields and frequent updates of lateral boundary conditions from GCMs
- Re-initialization integrations (Weather forecast mode)
  - Subdividing the long-term continuous integration into short ones. Each re-initialization is a continuous integration plus spinup considerations
- Nudging (Diagnostic study mode)
  - Use nudging or relaxation of large-scale atmospheric circulations within the interior of the computational domain of the RCM

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We are among the first to quantify which methodology is the best!

We use global reanalysis to drive the WRF model (i.e. using perfect boundary conditions).

# Reinitialized Integrations
# vs
# Continuous Integration

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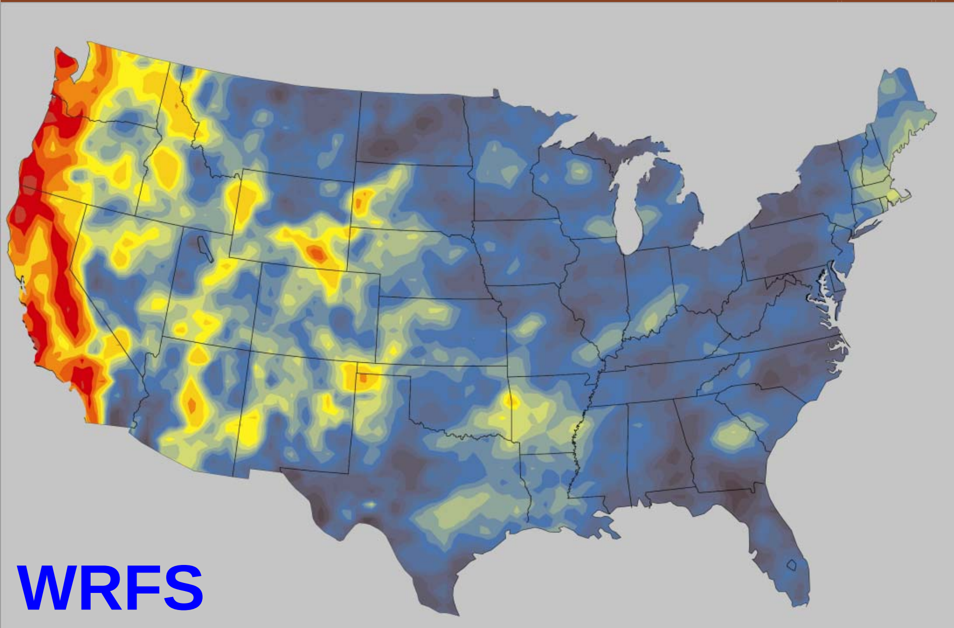
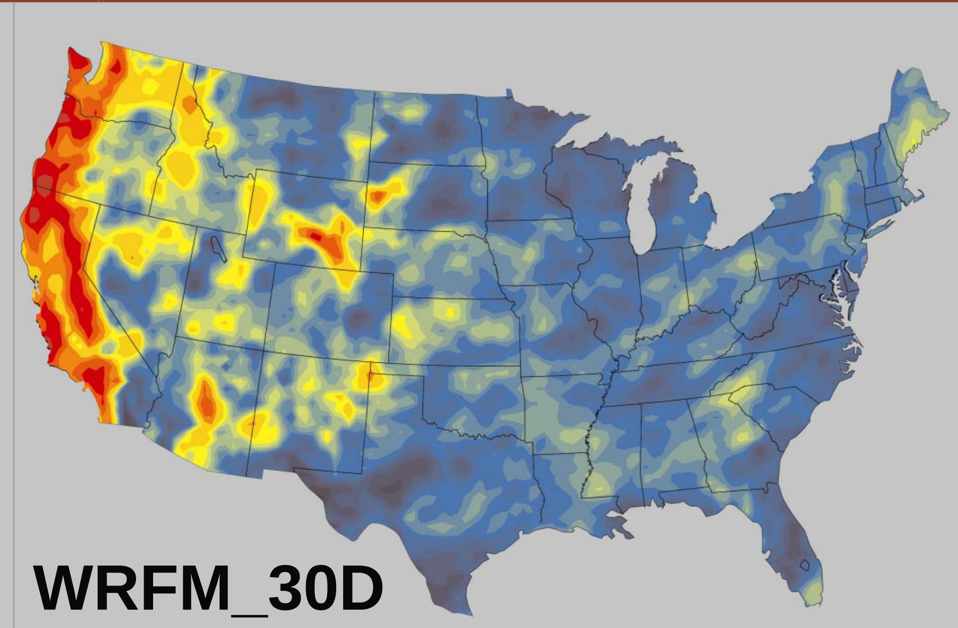
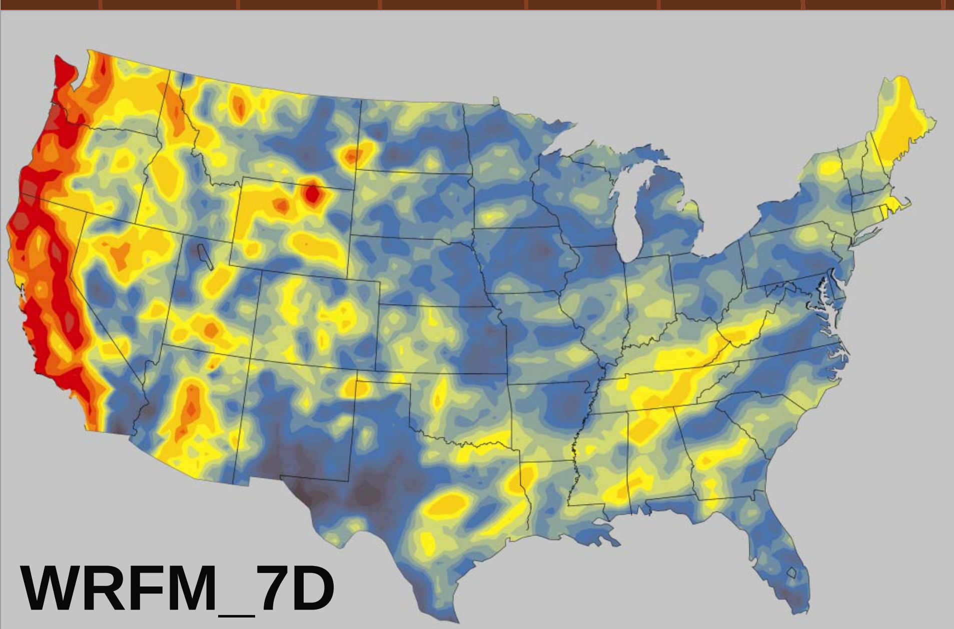
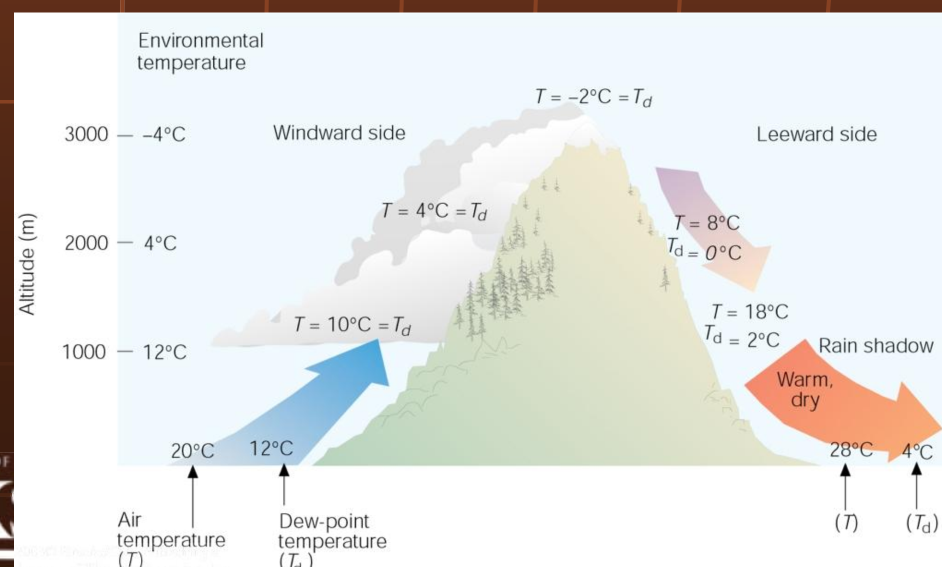
# Correlation between time series of 24-h-accumulated precipitation



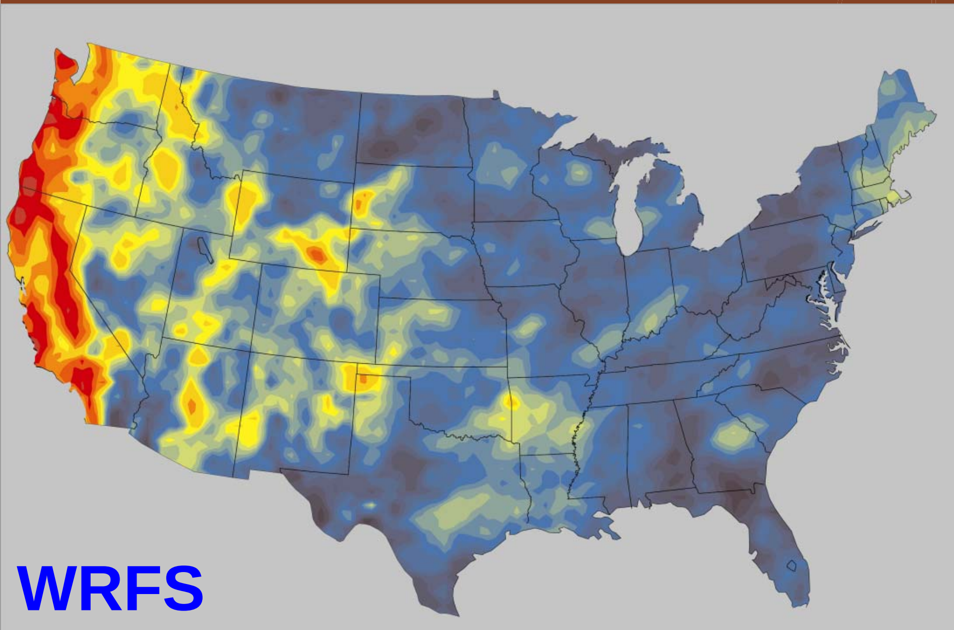



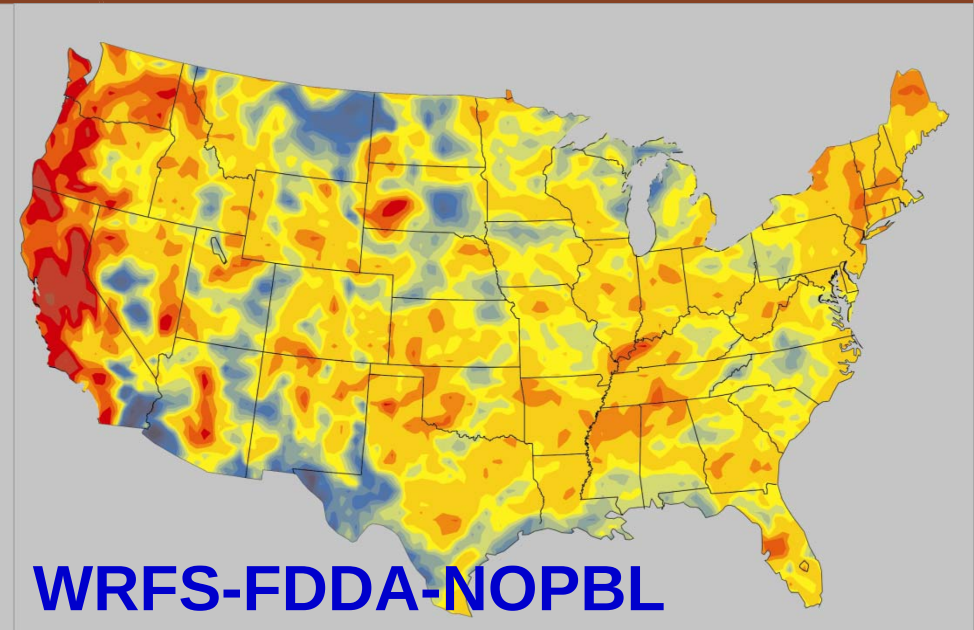
# Summary

- The re-initialization runs give a better downscaling skill than a continuous run
- A run with a more frequent (e.g. weekly) re-initialization outperforms that with the less frequent re-initialization (e.g. monthly).

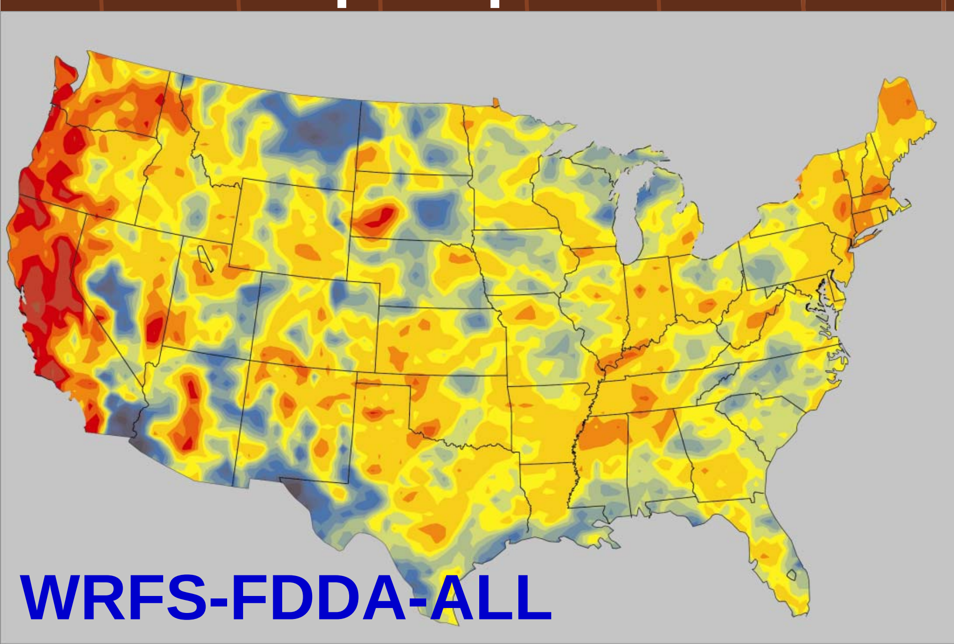
# Experiments with Analysis Nudging

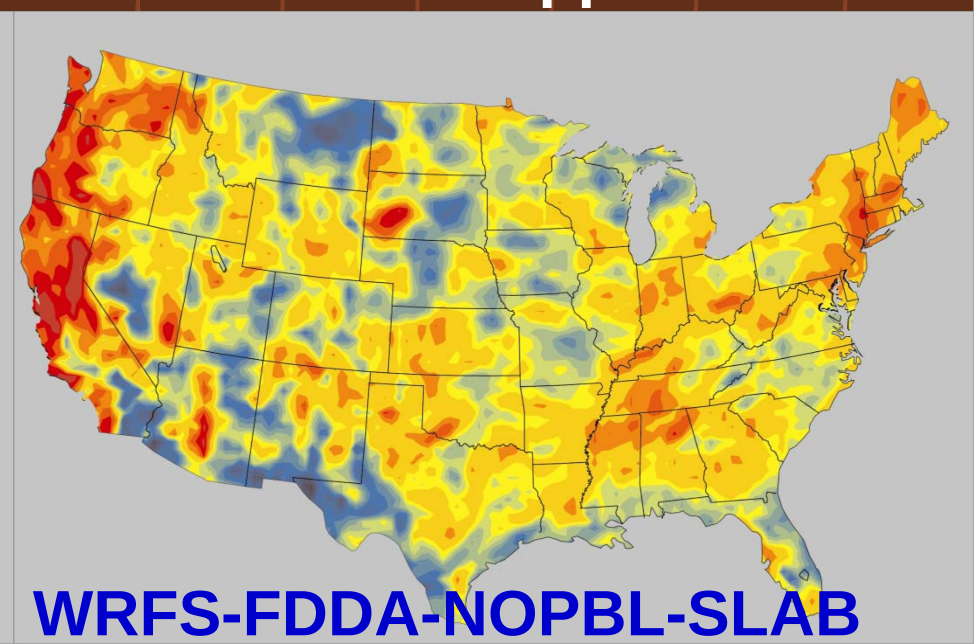
# Correlation between time series of 24-h-accumulated precipitation




**Realistic precip is a must for water resources applications.**



# Summary

- WRFS_FDDA_NOPBL performs slightly better than the other nudging experiments.
- In the nudging simulations, there are still some areas where the performance is not good in simulating precipitation.
- This result indicates that the model physics may still play an important role in regional climate downscaling especially for simulating precipitation.

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# Skill Enhancement of the WRF Downscaling

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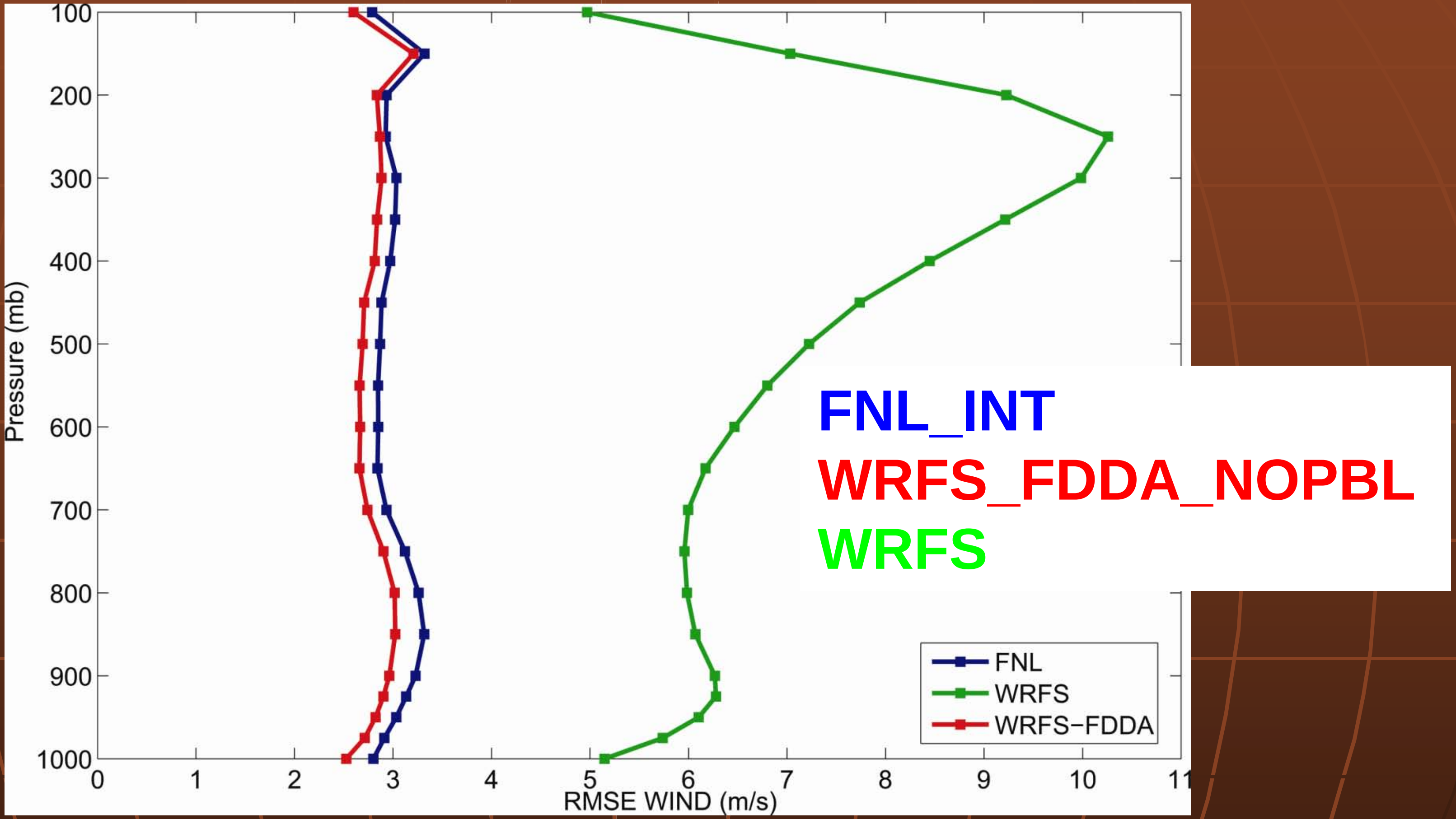
# Vertical Profile of Winds




**Realistic winds are critical for air quality applications (e.g. pollutants transport, and the size of fire area).**

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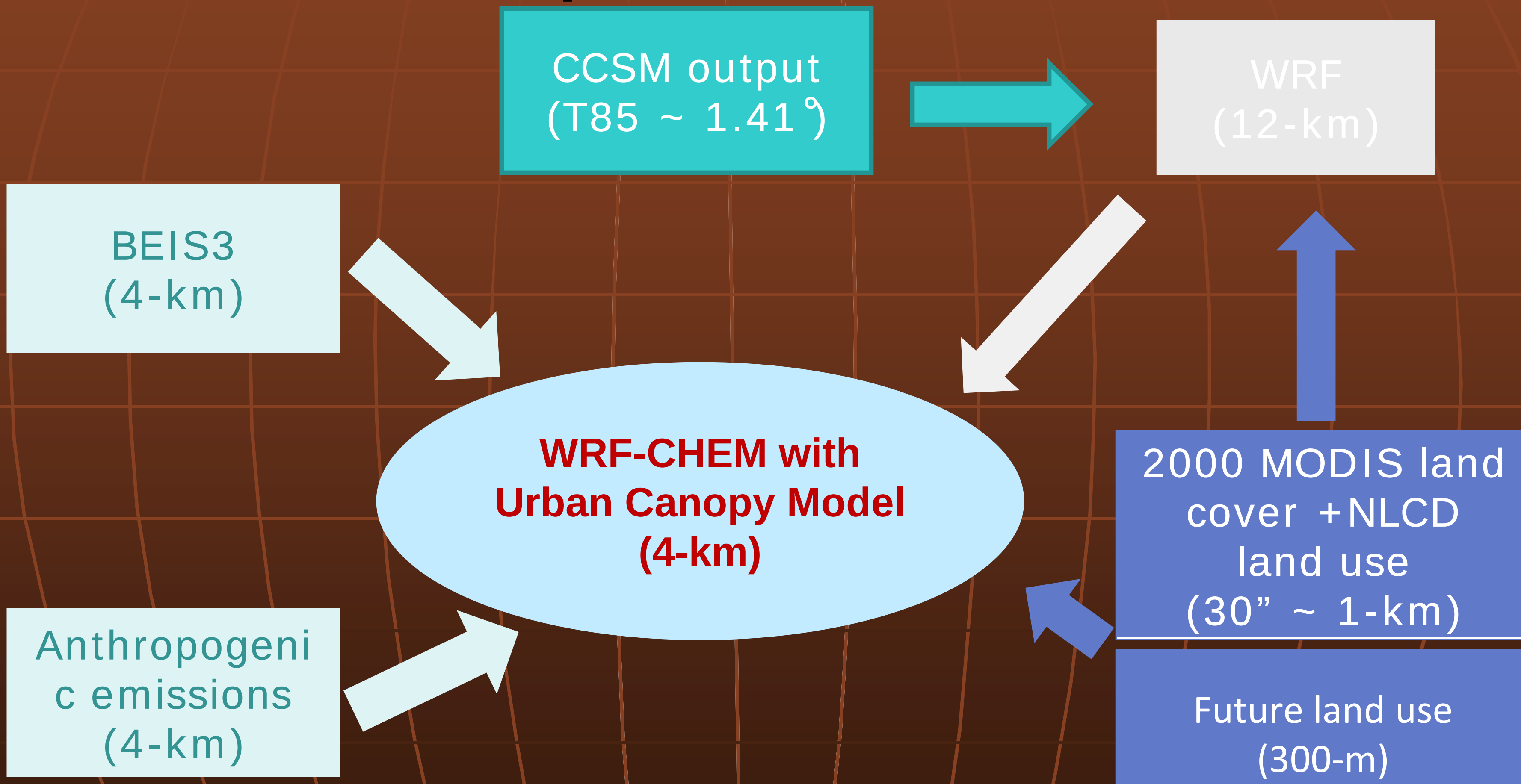
# Summary

- The traditional continuous integration approach, in all cases, shows the worst performance among the downscaling experiments.
- Compared to direct interpolation from FNL, the continuous run does a reasonable job in downscaling surface parameters because of the more detailed topography. However, for the atmospheric variables above the surface, its performance is even worse than the direct bi-linear interpolation.
- Re-initialization runs outperform continuous simulation, while a run with a more frequent (weekly) re-initialization outperforms that with the less frequent re-initialization (monthly).
- The downscaling simulations using the full 3-D analysis nudging, which constrains the error growth in large-scale circulation during the long simulation, show the highest skill.

Lo, J.C.F., Z.-L. Yang and R. Pielke Sr., 2008, *J. Geophys. Res., 113, D09112, doi:10.1029/2007JD009216.*

# 6. How do future climate change and urbanization, individually and together, affect regional air quality predictions?

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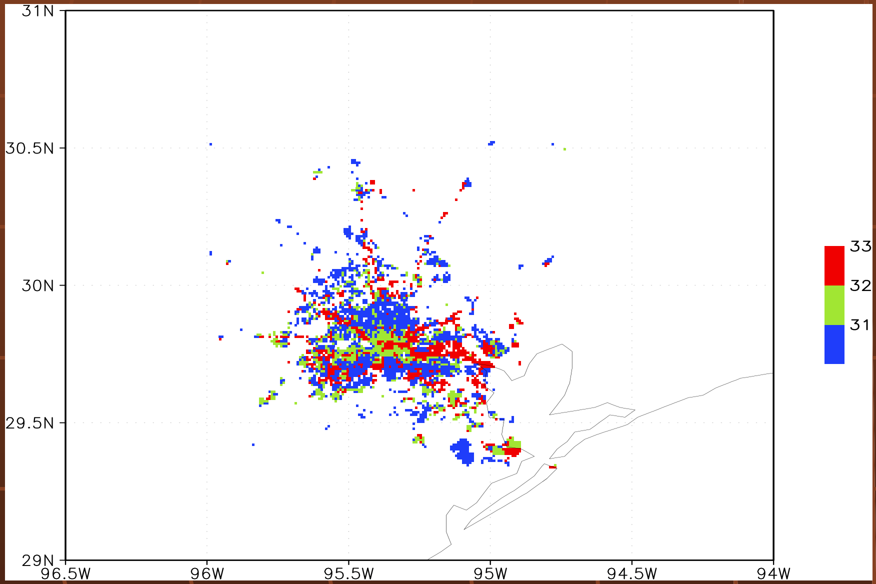
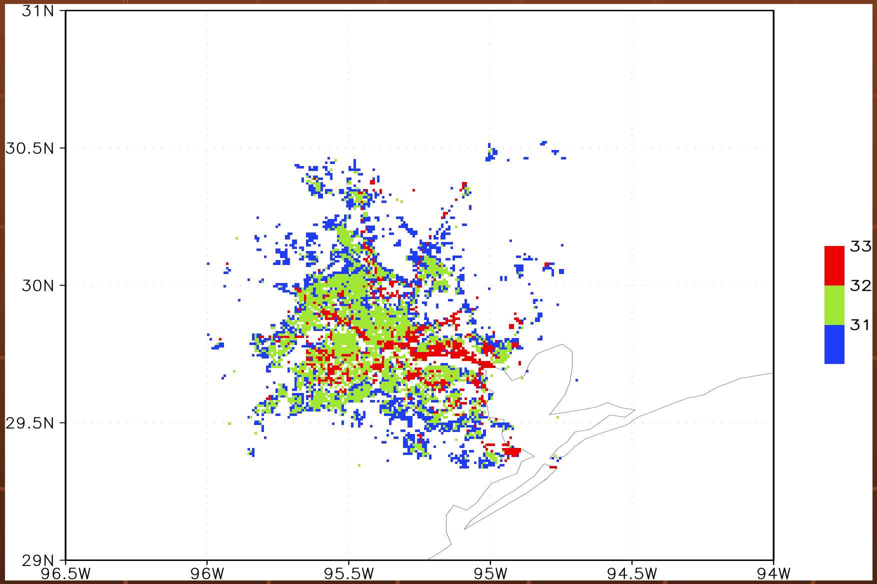
# Urban Land Use data

**Current land use: 2000**



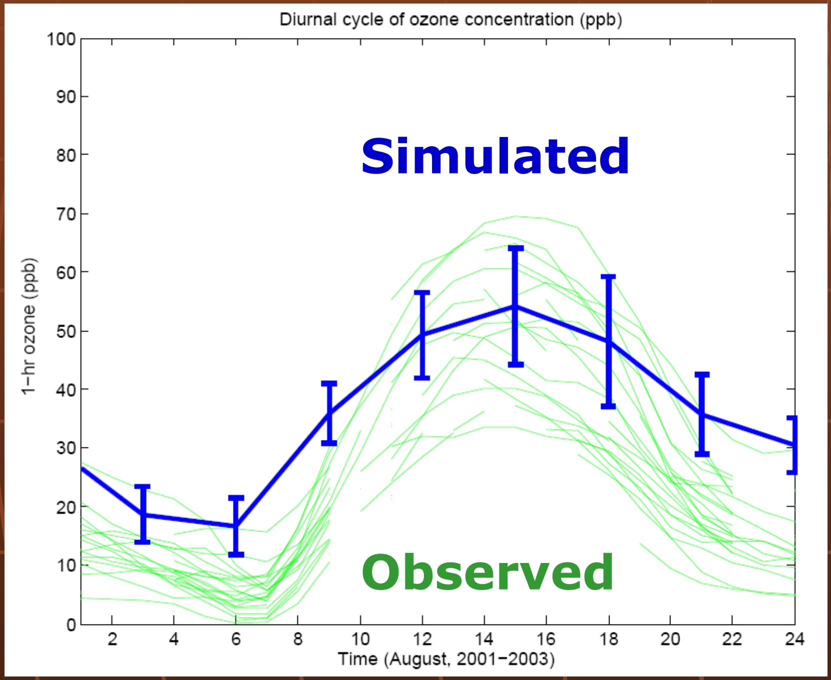

**Future land use: 2030**



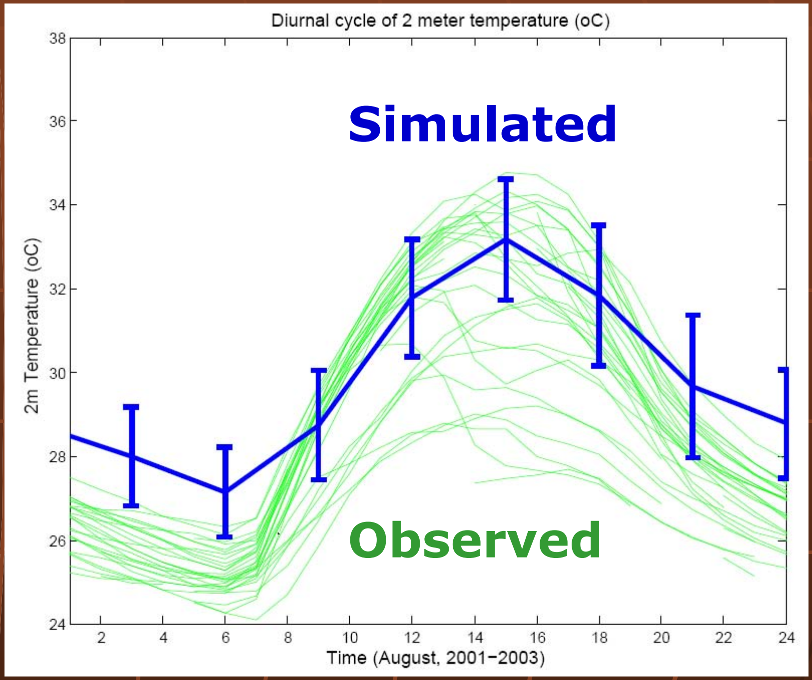

**31: Low intensity Residential**
**32: High intensity Residential**
**33:Industry or commercial**

# August Mean Diurnal Cycle (2001–2003)

Ozone

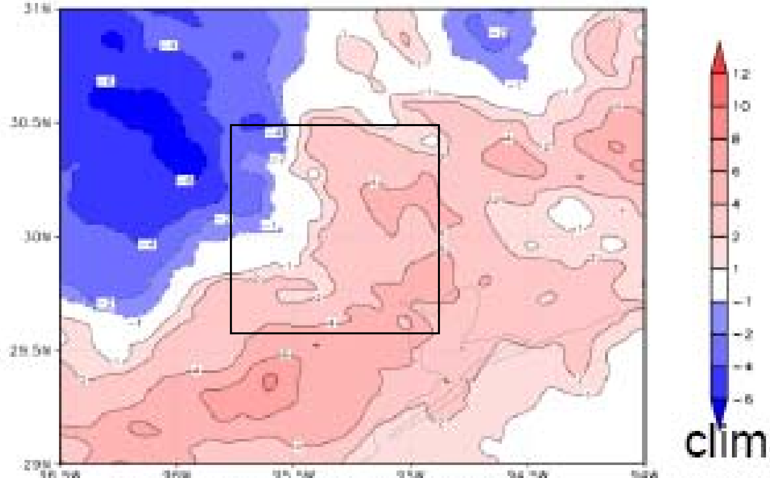



2-m Air Temperature

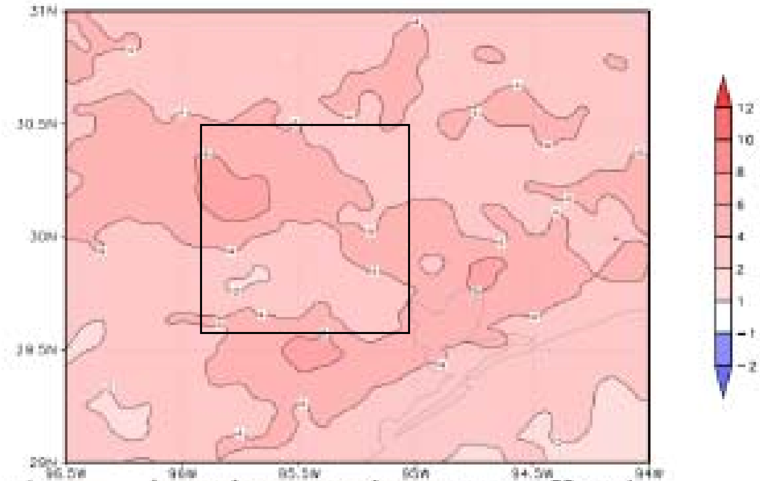



Jiang, X.-Y., C. Wiedinmyer, F. Chen, Z.-L. Yang, and J.C.F. Lo, 2008, *Journal of Geophysical Research-Atmospheres* (in press).

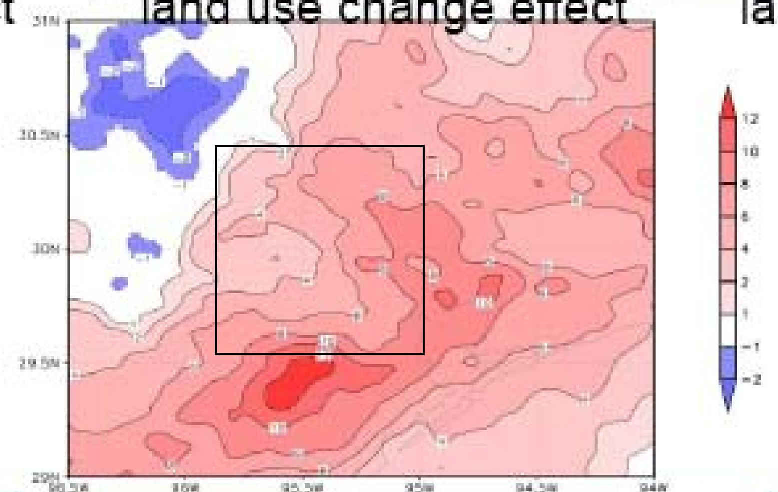
# Changes in average daily maximum 8-hr ozone due to climate and land use changes (ppb)



climate change effect



land use change effect



climate change and land use change effect

- **Summary:** These results suggest that future urban air quality studies must consider the effects of climate change and urbanization.

- Future Work: We are collaborating with NCAR scientists to further understand the interaction of the atmosphere, biosphere and hydrosphere

(www.tiimes.ucar.edu/**beachon**/index.htm/)

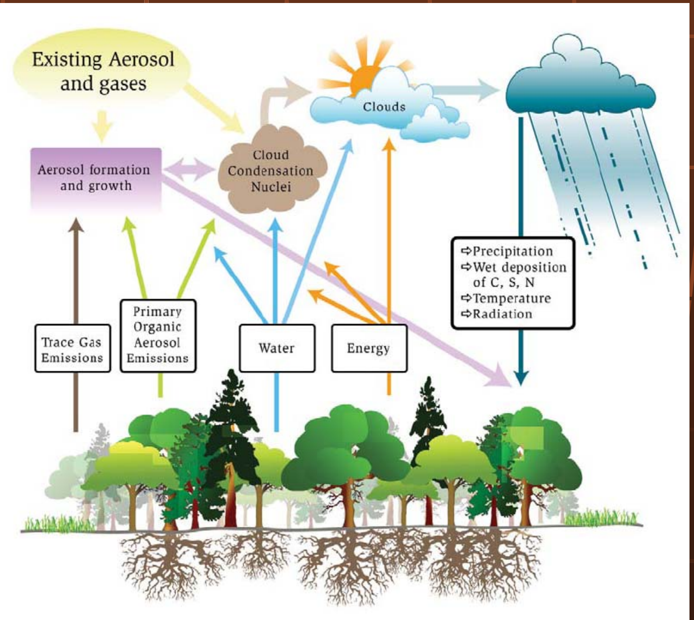



FIG. 1. Schematic of the coupling of terrestrial ecosystems and the hydrologic cycle via energy and water exchange and aerosol processing.

Barth et al., 2005. BAMS

# Acknowledgements


| | |
|---|---|
| **EPA STAR Grant:** | **RD83145201** |
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| **Co-PIs:** | **Dave Allen**<br>**Barbara Parmenter** |
| **Graduate students:** | **Lindsey Gulden**<br>**Jin-oh Kim, Jihee Lee**<br>**Xiaoyan Jiang** |
| **Postdocs:** | **Jeff Lo, Yiwen Xu** |

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http://www.geo.utexas.edu/climate