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

PI: Zong-Liang Yang

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)

liang@mail.utexas.edu

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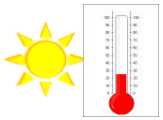
http://www.geo.utexas.edu/climate

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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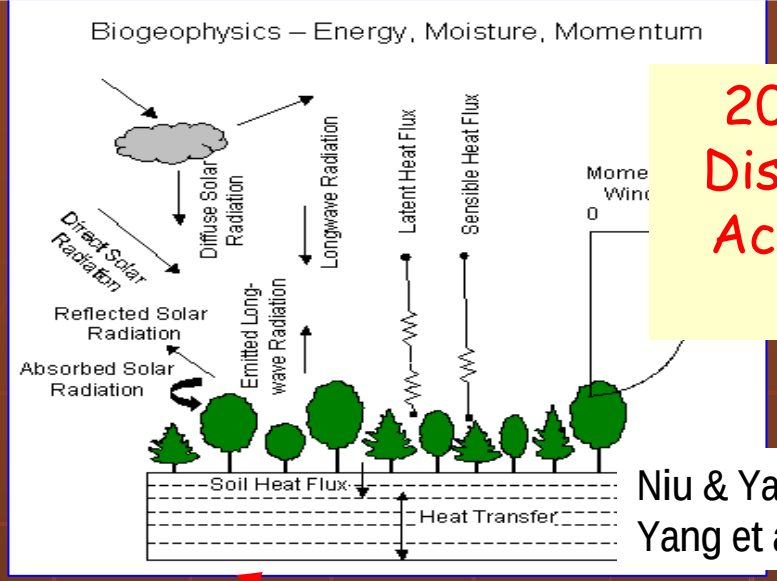
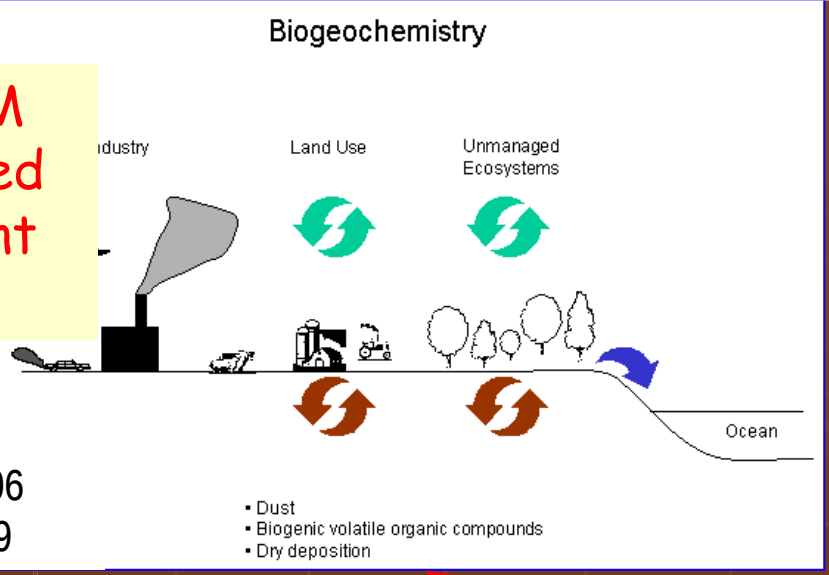
2008 CCSM Distinguished Achievement Award



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



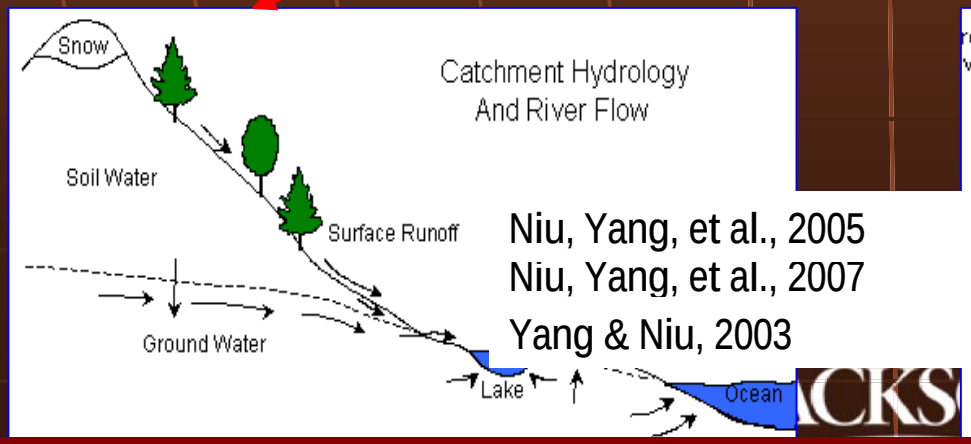
Biogeophysics

Biogeochemistry

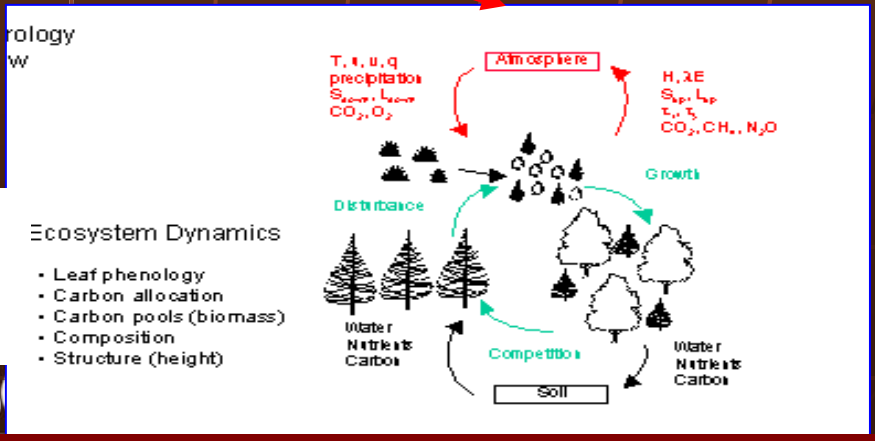
NCAR CLM 3.5

Hydrology

Ecosystem Dynamics



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

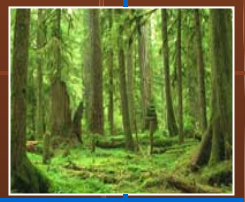


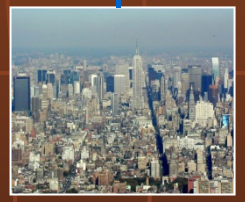
Collaborators: NCAR (Gordon Bonan, Keith Oleson, Dave Lawrence)

CLM Subgrid Structure

Gridcell

Landunits



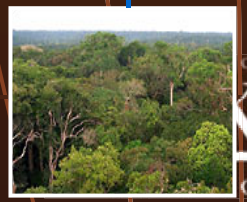


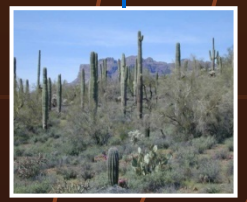
Glacier | Wetland | **Vegetated** | Lake | Urban

Columns

Soil Type 1

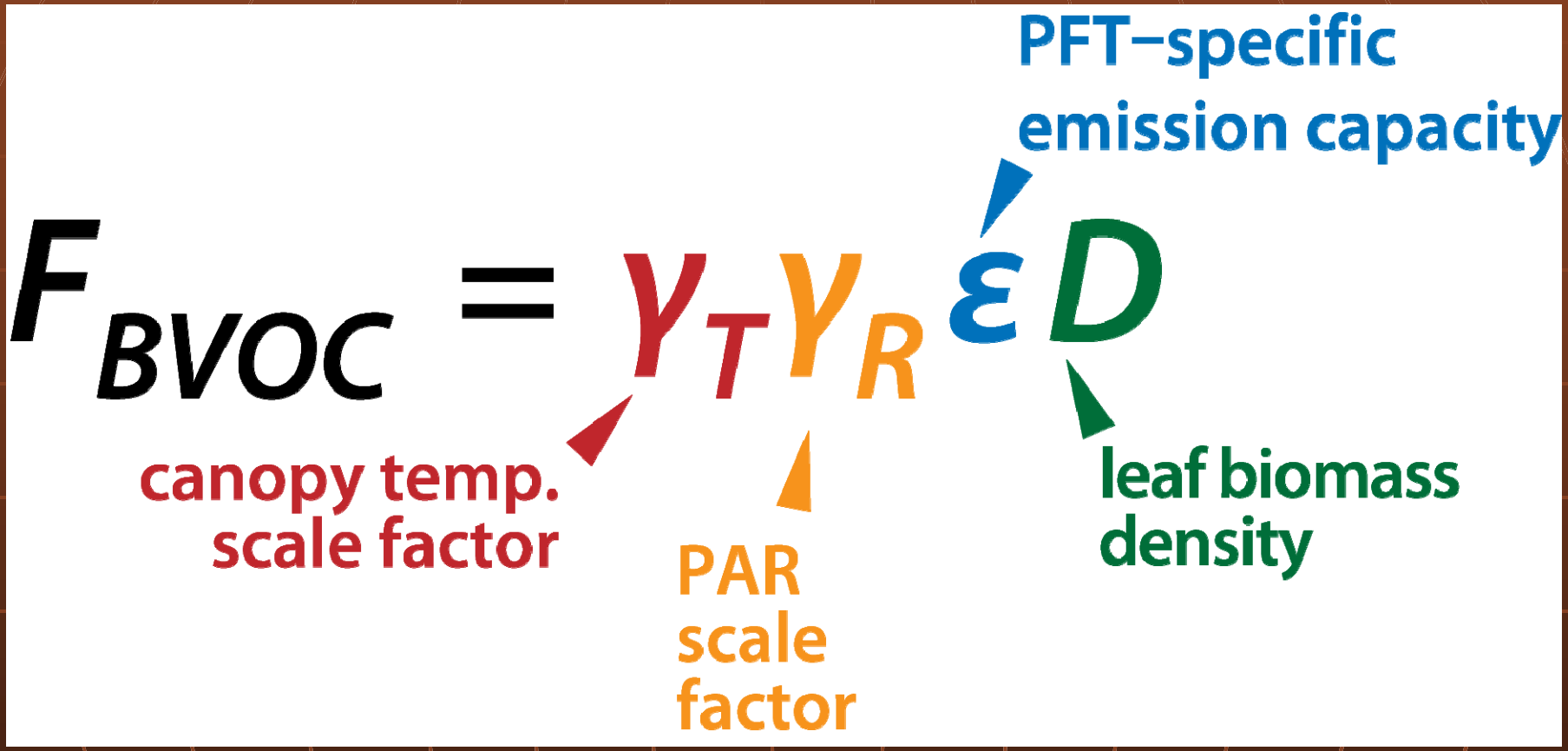
PFTs





Keith Oleson

BVOC Algorithm



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

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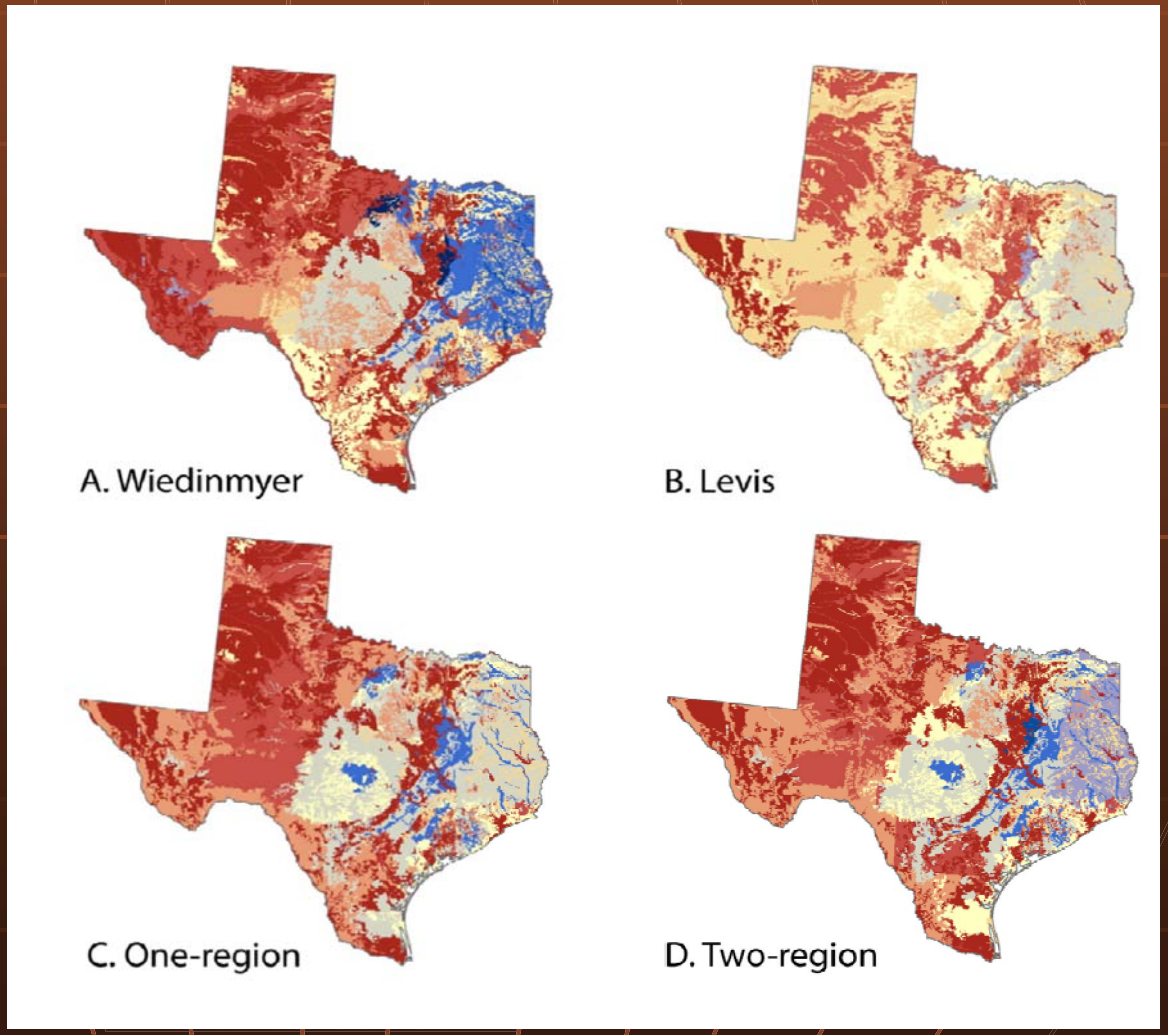
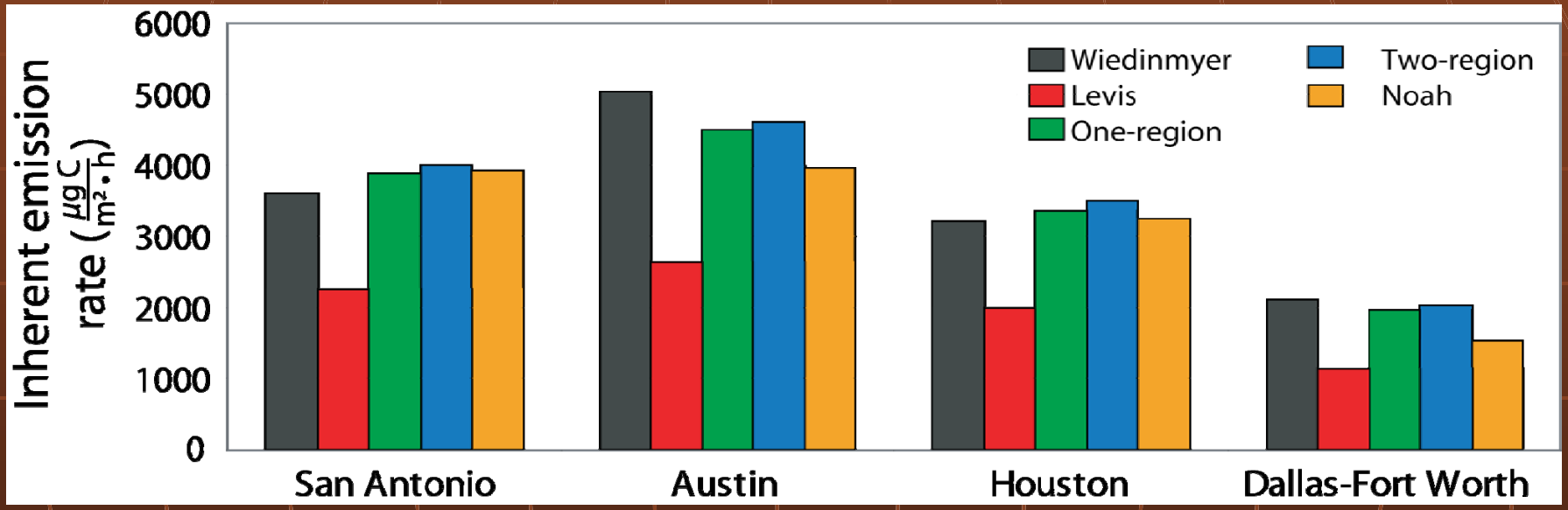
Region-specific BVOC Emission Factors from 600+ Species

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

$$F = \varepsilon D \gamma$$



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)

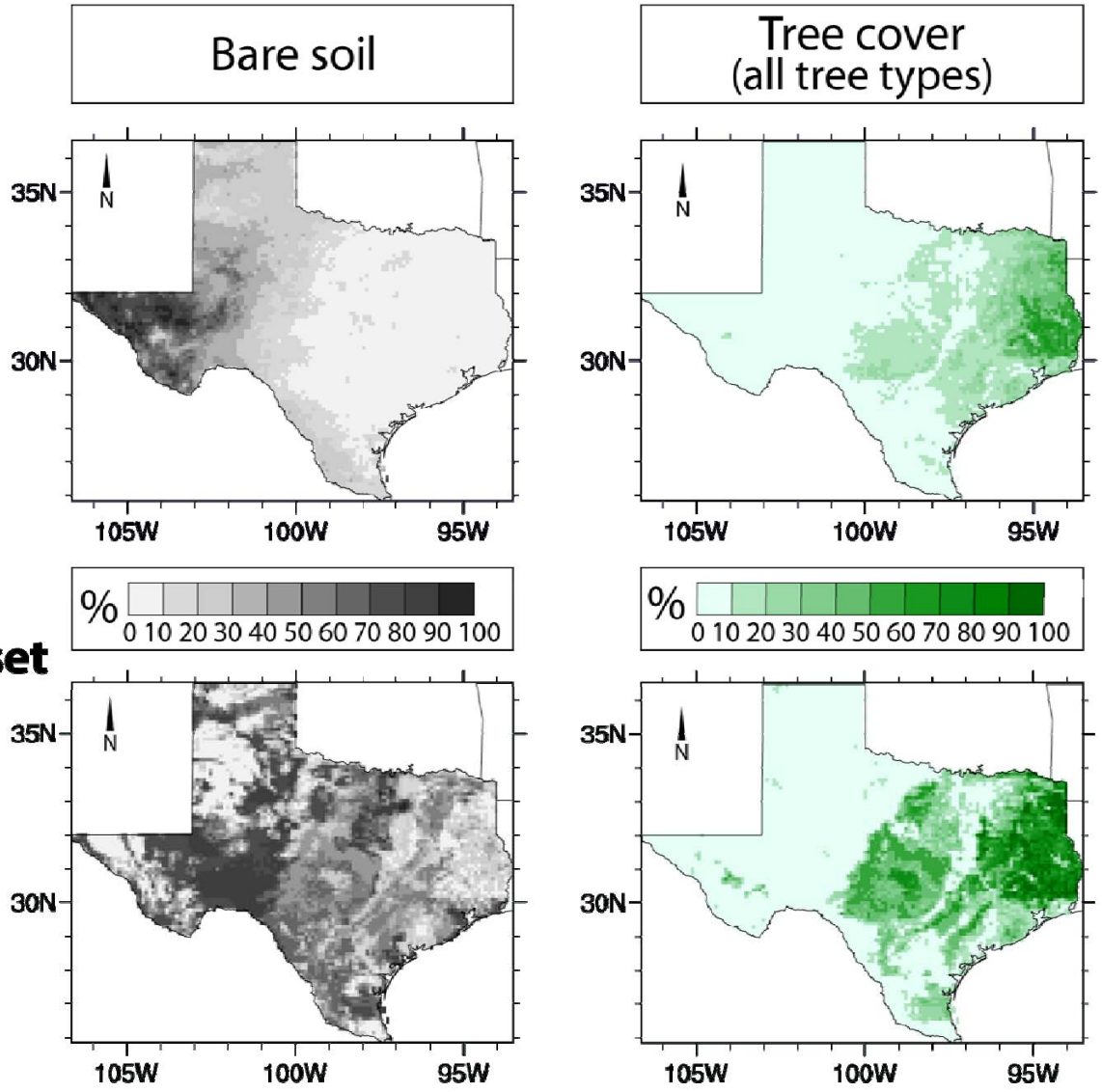
5-km resolution (original)
MODIS-, AVHRR-derived

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

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

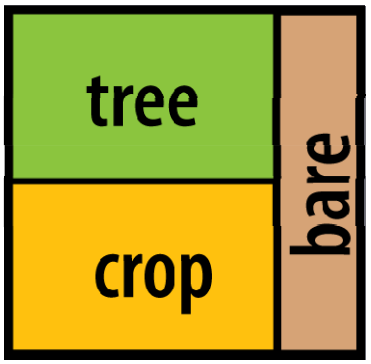
1-km resolution (original)
Species-based (~300 species; 600+ land-cover types); converted to PFTs

Contains:
% bare soil, PFT distribution

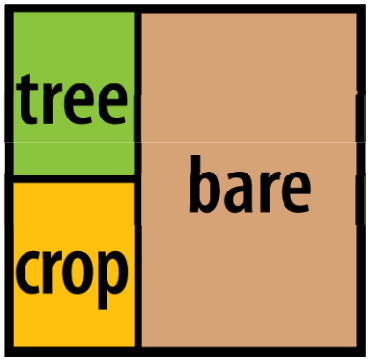


Experiment design

1. Keep PFT distribution constant; vary bare soil %

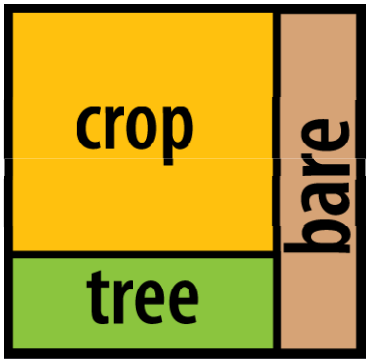


Less bare soil

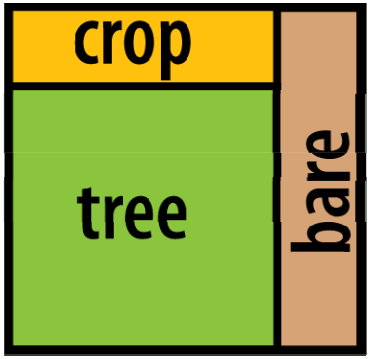


More bare soil

2. Keep bare soil % constant; vary PFT distribution



More crop; less tree



Less crop; more tree

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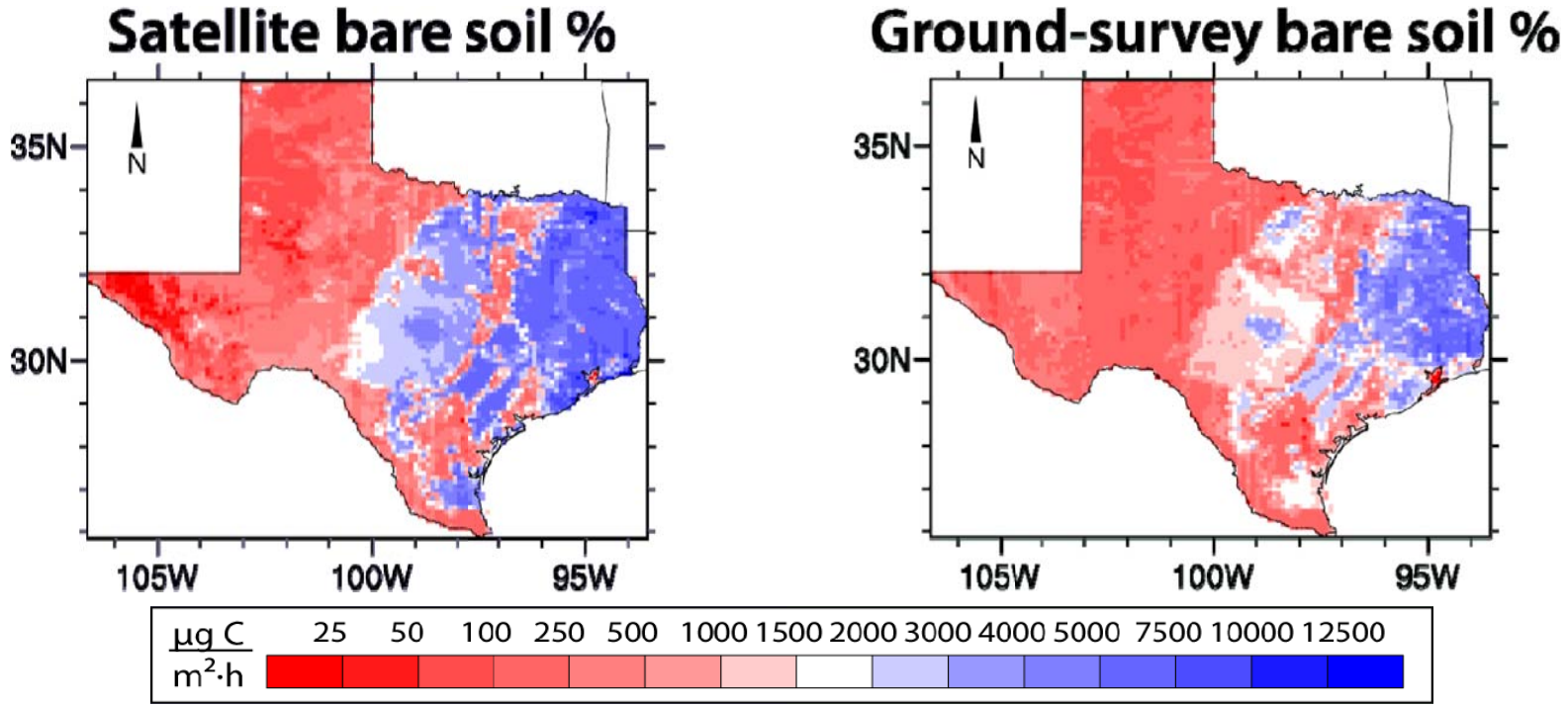
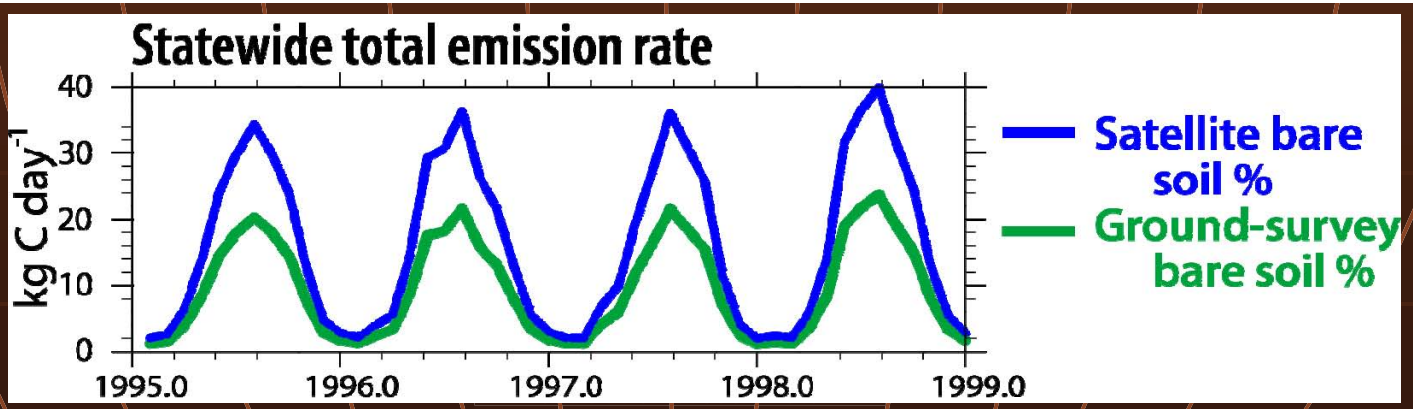
Vary bare soil fraction

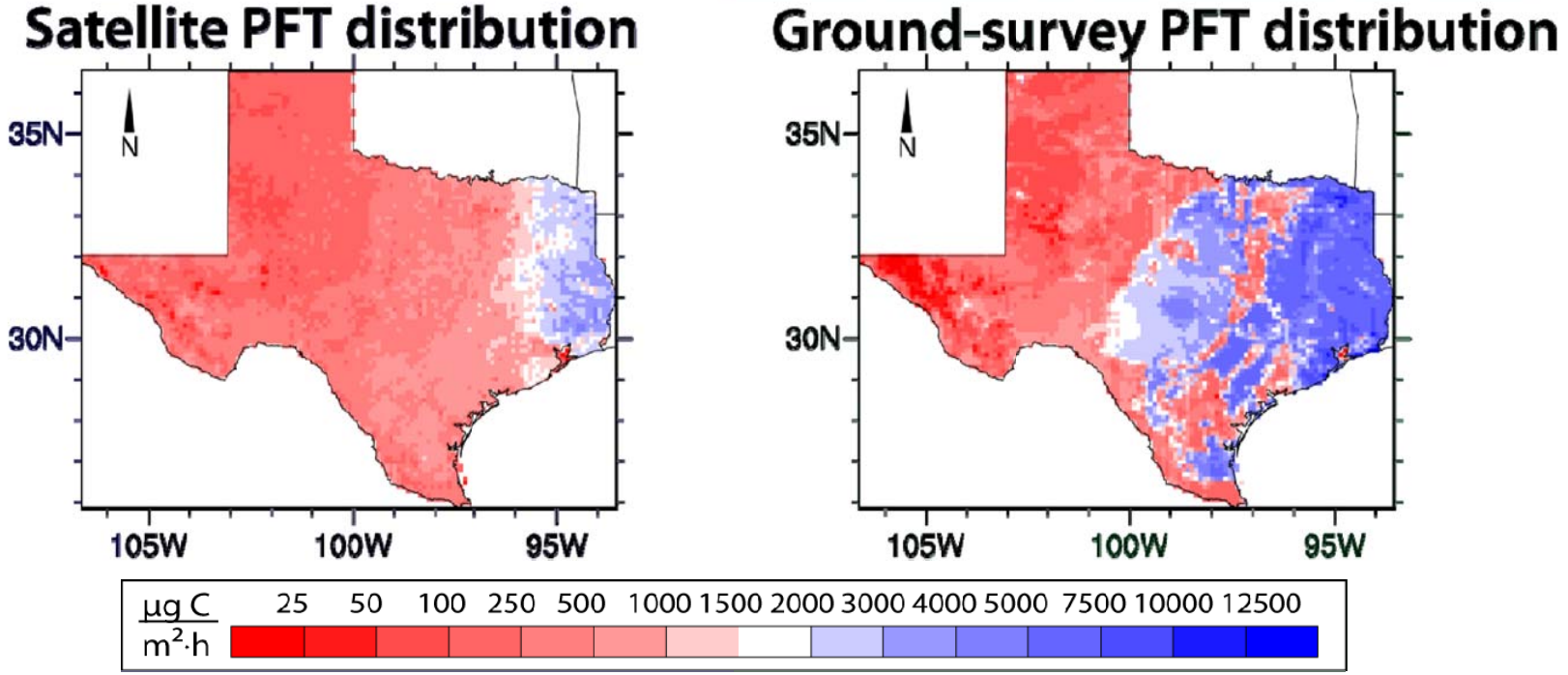
JJA Mean BVOC emission rate 1995–1998, ground-survey PFTs

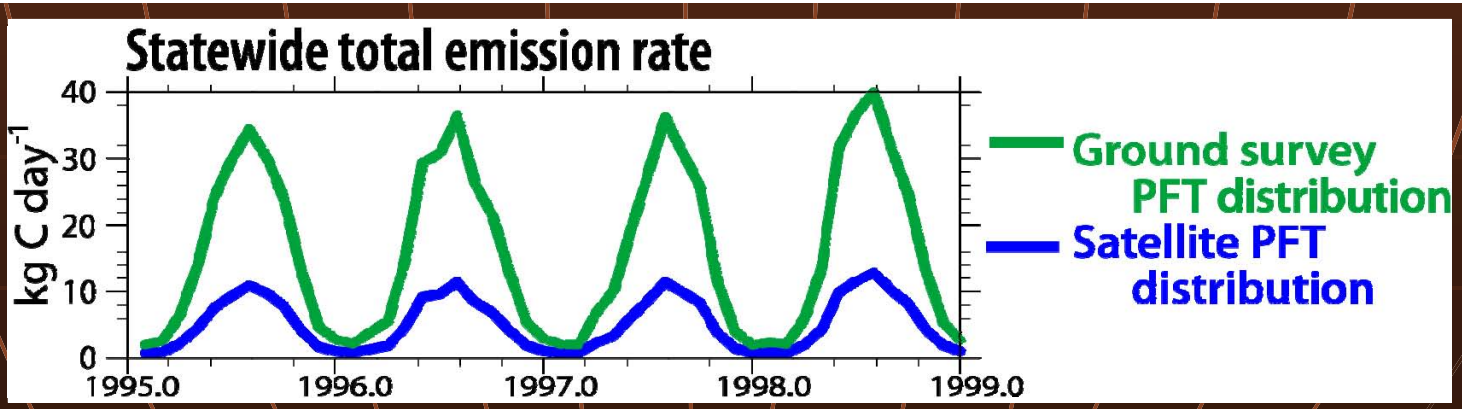




Vary vegetation distribution

JJA Mean BVOC emission rate 1995–1998, satellite bare soil





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**.

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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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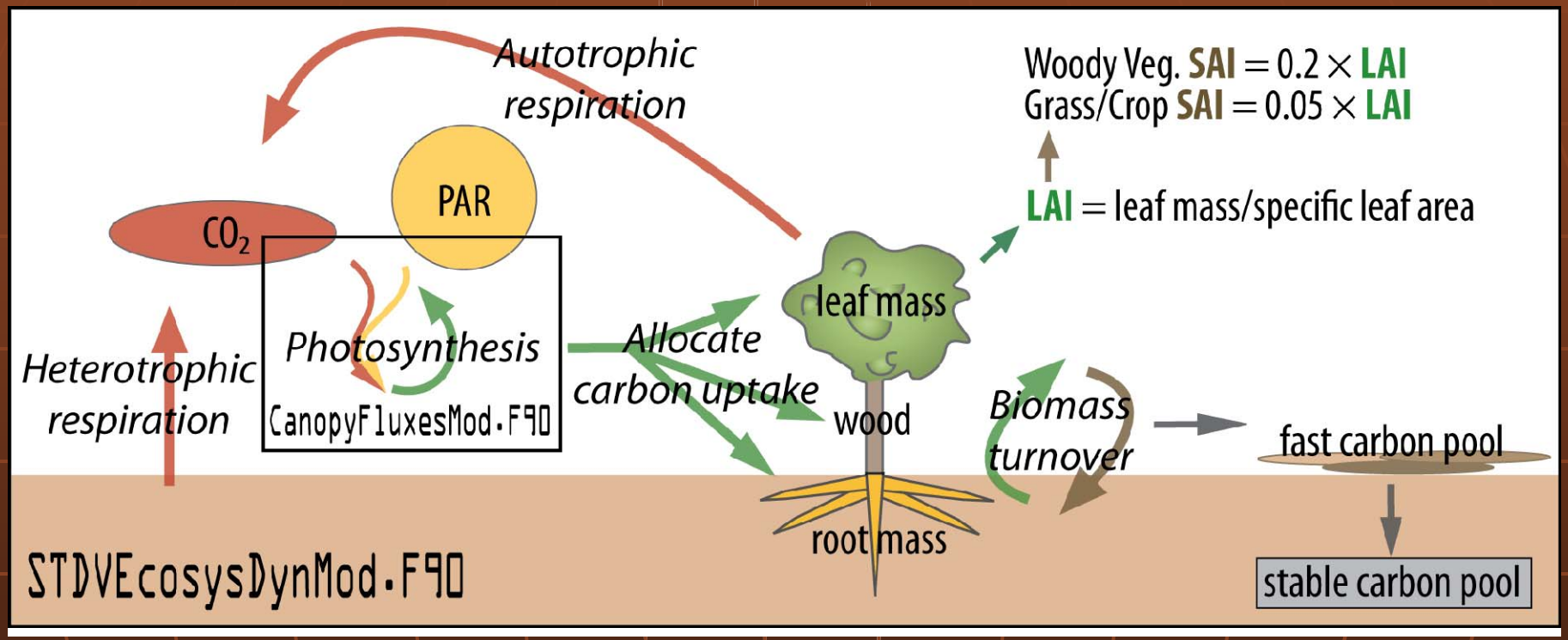
Add dynamic phenology to CLM3



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

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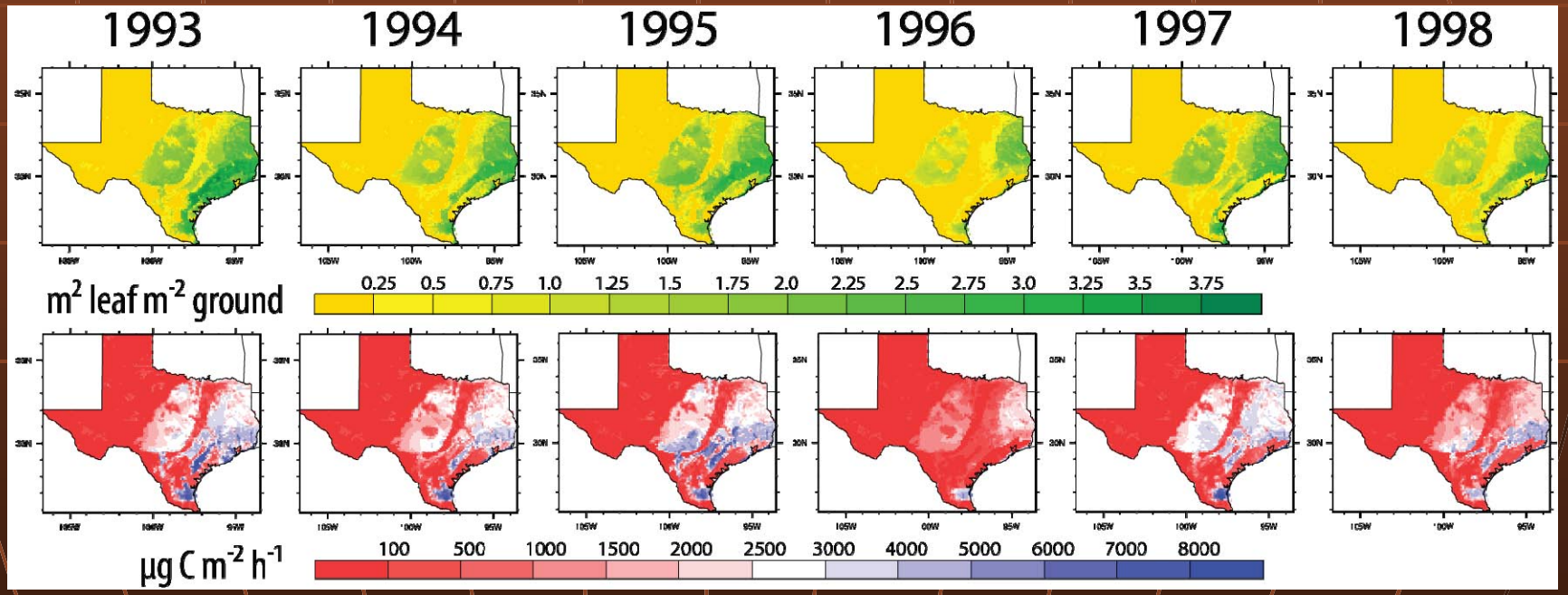
Results using CLM3 with dynamic vegetation

June-July-August Mean



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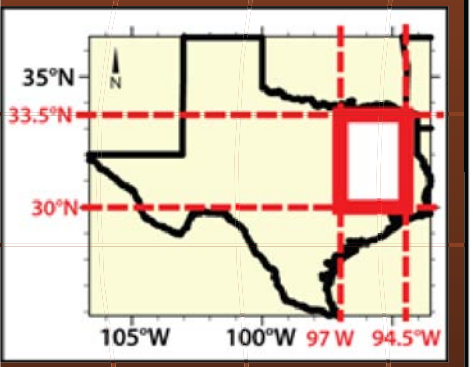
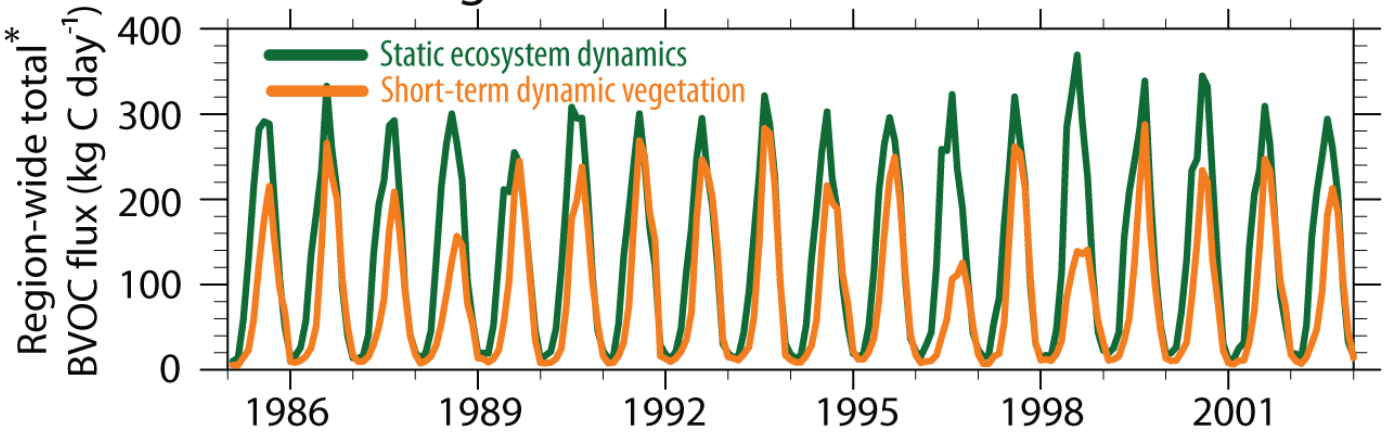
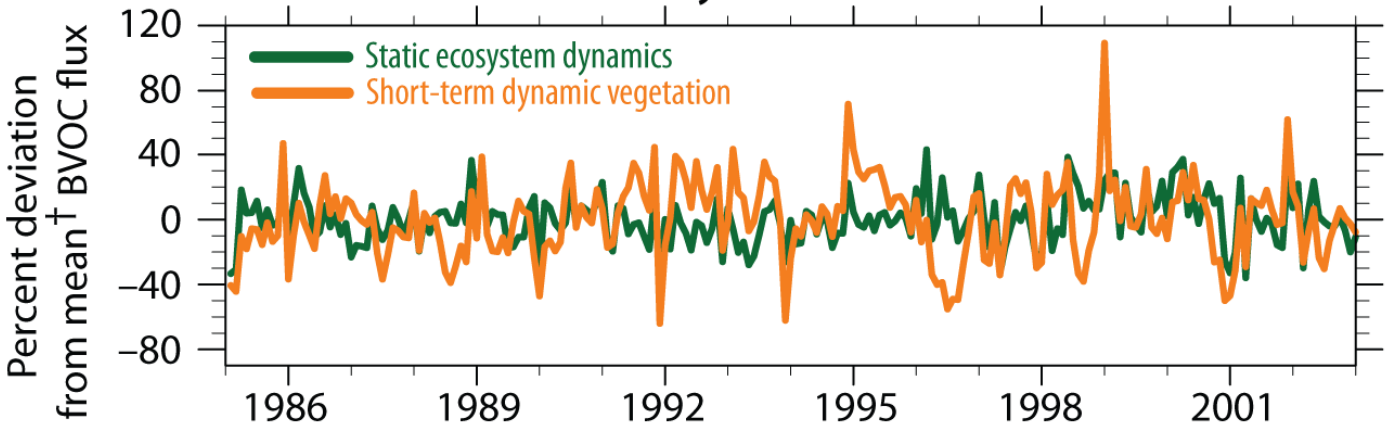


Magnitude of simulated BVOC flux



Relative variability of simulated BVOC flux



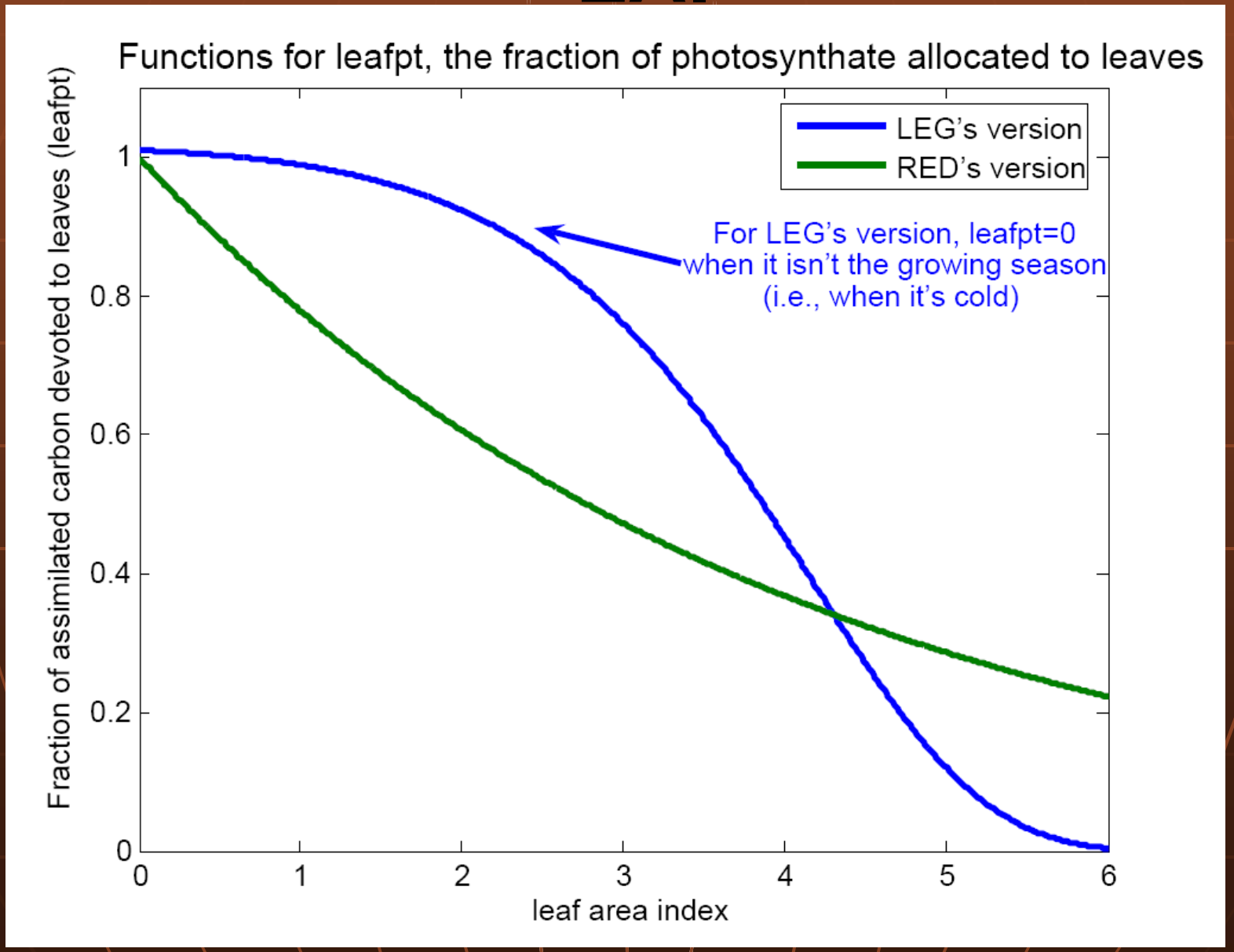
* Area-weighted average of grid-cell monthly mean BVOC flux for region shown in Fig. 5

† 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%

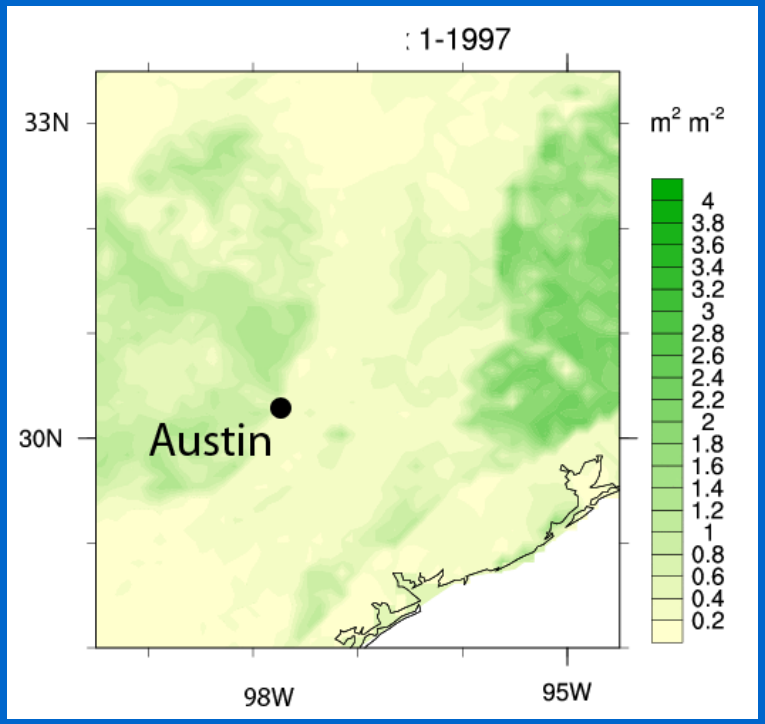
Average absolute departure from mean (short-term dynamic vegetation) = 22.4%

Factors affecting the simulation of LAI

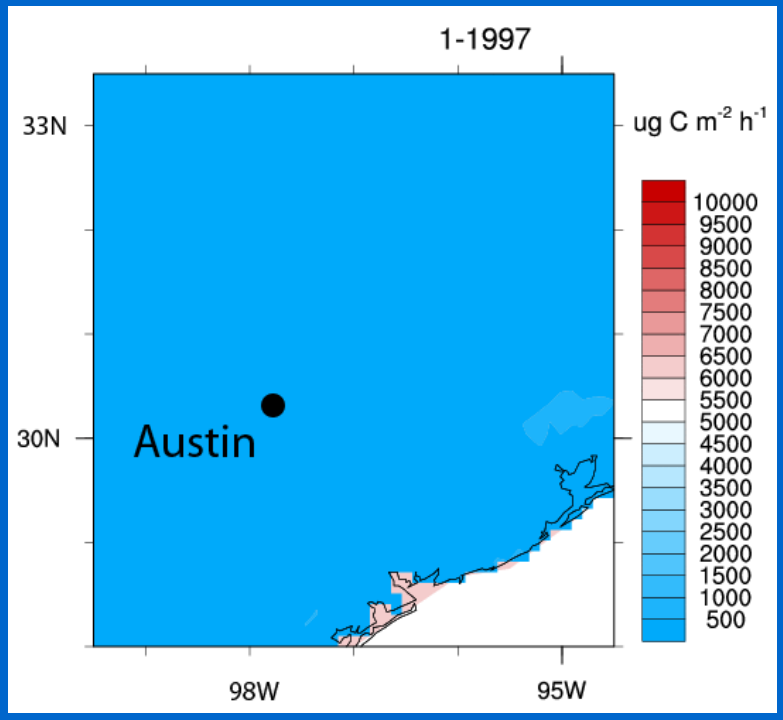


Precipitation Variability Drives Year-to-year Changes in Leaf Biomass and Biogenic Emissions

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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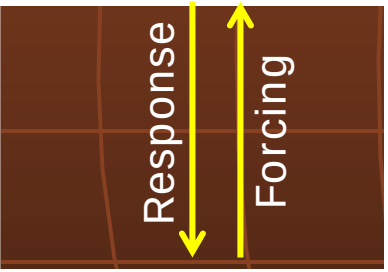
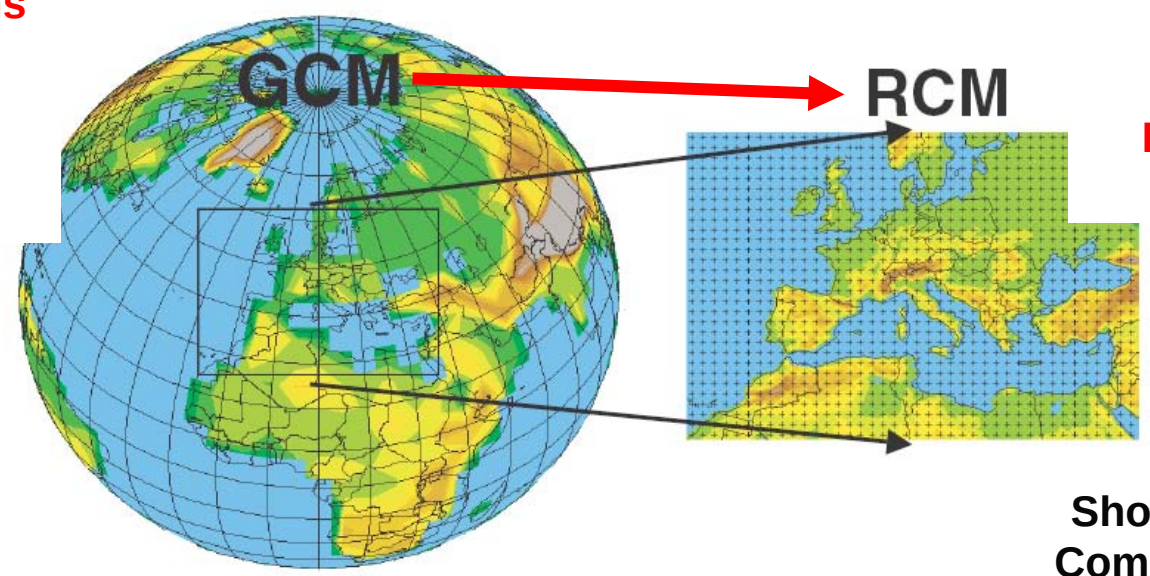
4. How accurate is regional climate dynamic downscaling?

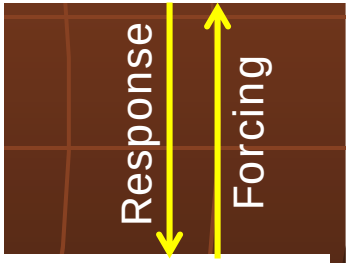
General circulations
Jet streams
Major storm tracks
Monsoons
ENSO



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



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



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

~200-km grid spacing

~20-km grid spacing

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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

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).

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Reinitialized Integrations vs Continuous Integration

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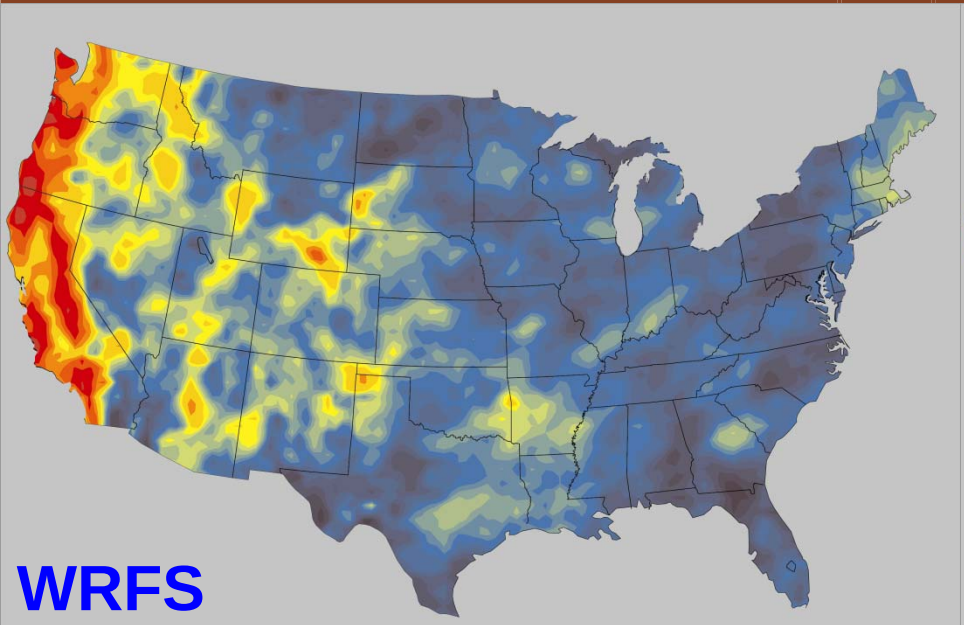
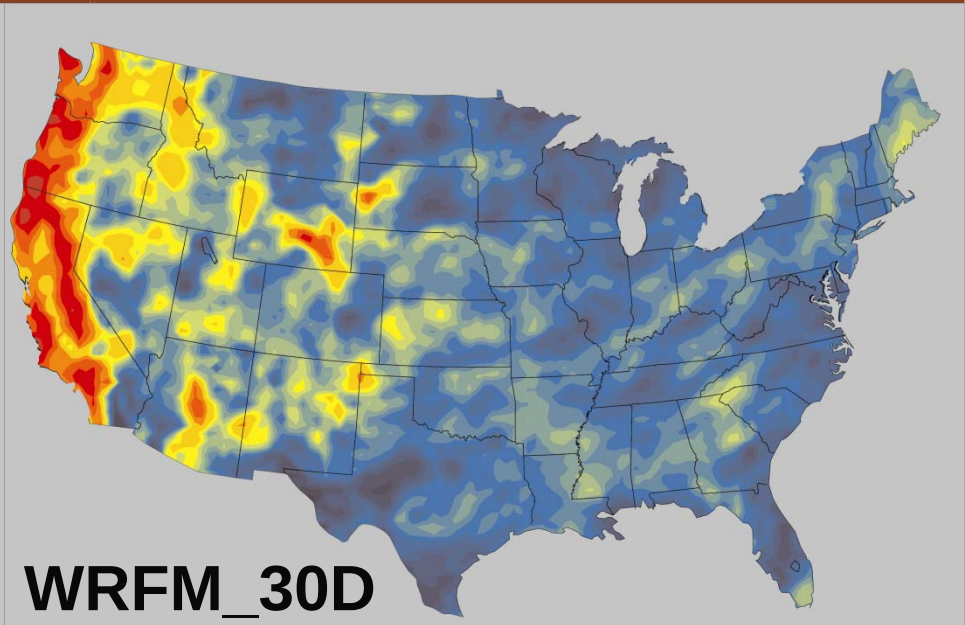
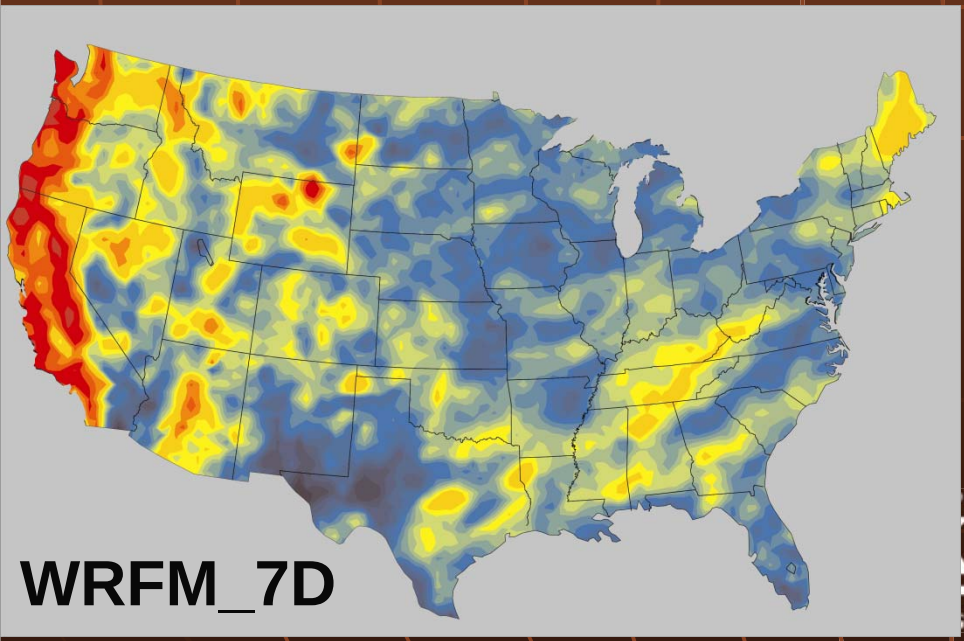
Correlation between time series of 24-h-accumulated precipitation



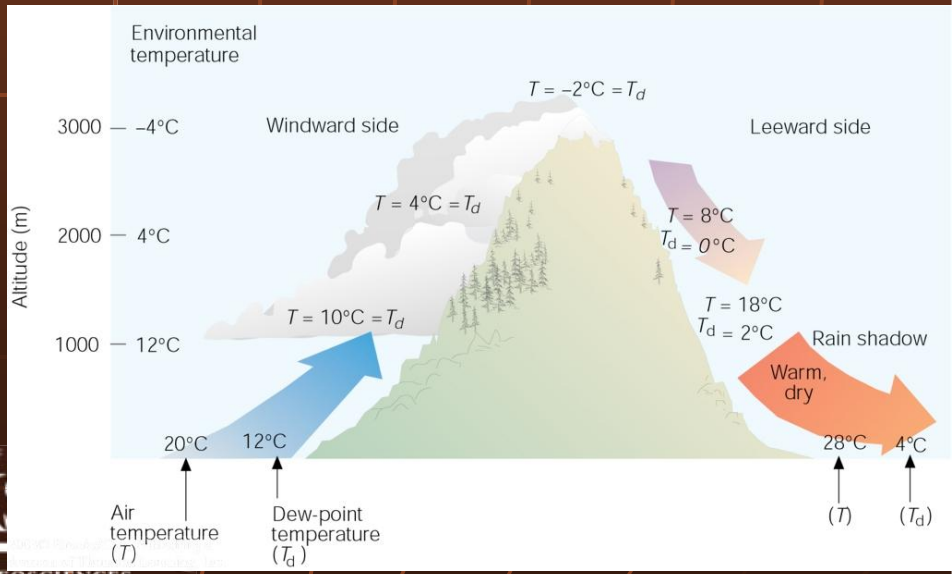
WRFS



WRFM_30D



WRFM_7D



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).

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Experiments with Analysis Nudging

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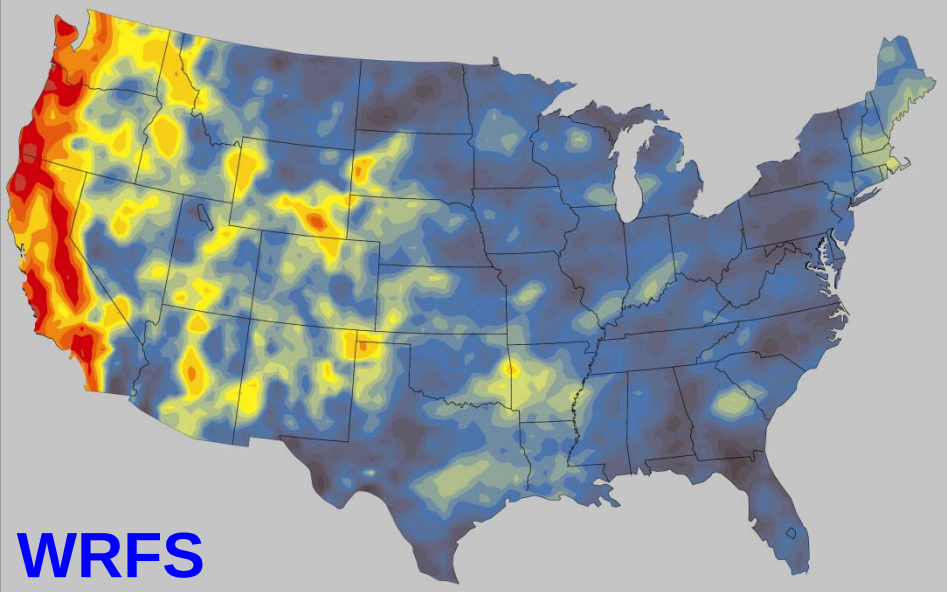
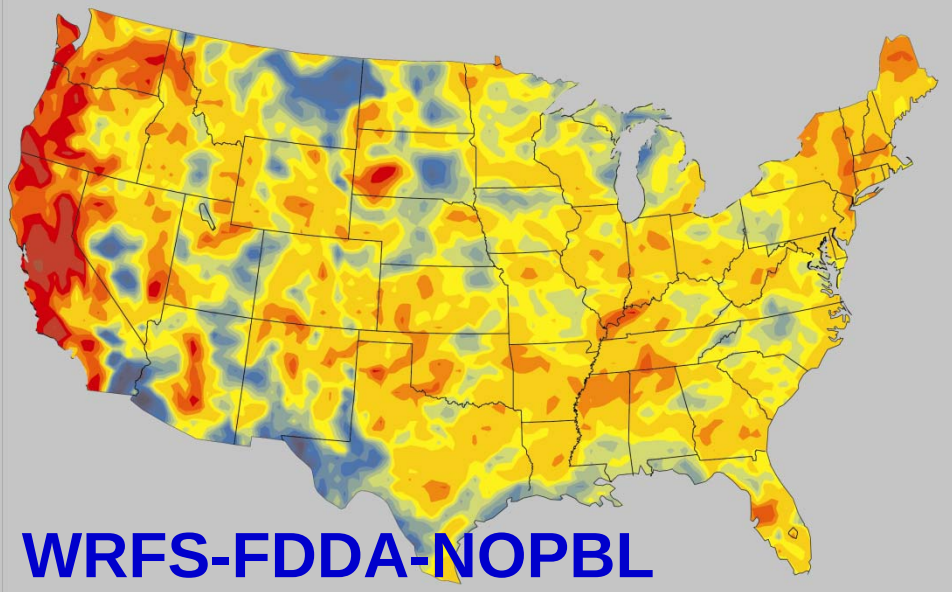
Correlation between time series of 24-h-accumulated precipitation

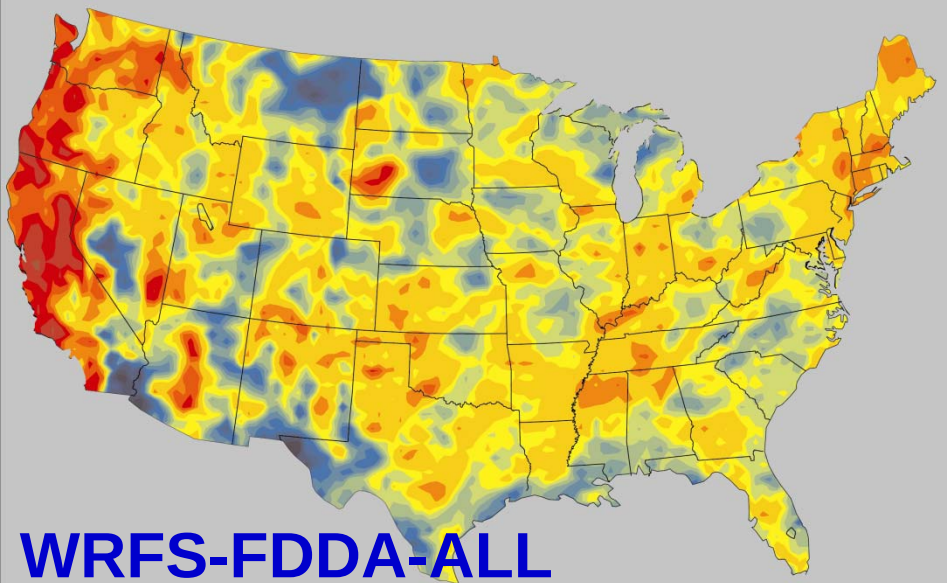


WRFS

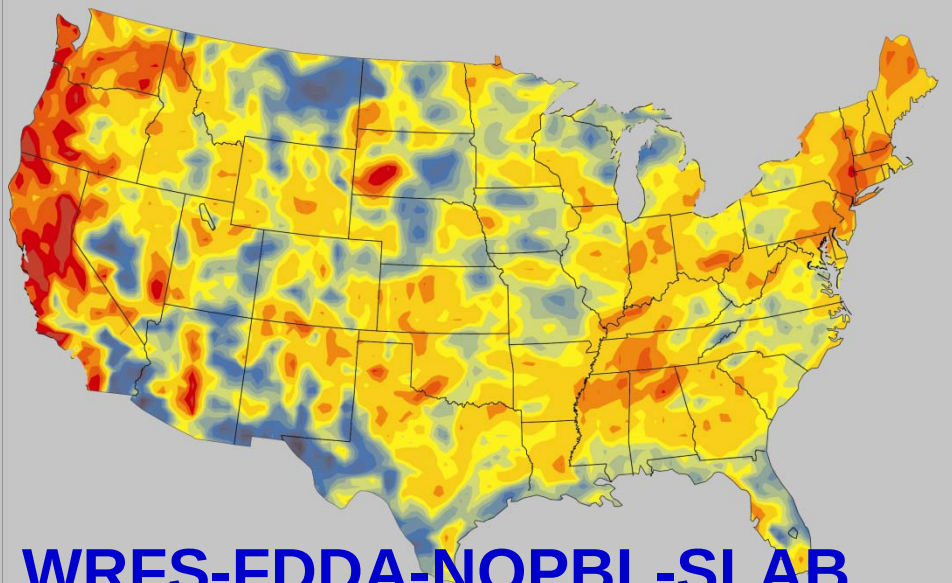


WRFS-FDDA-NOPBL

Realistic precip is a must for water resources applications.



WRFS-FDDA-ALL



WRFS-FDDA-NOPBL-SLAB

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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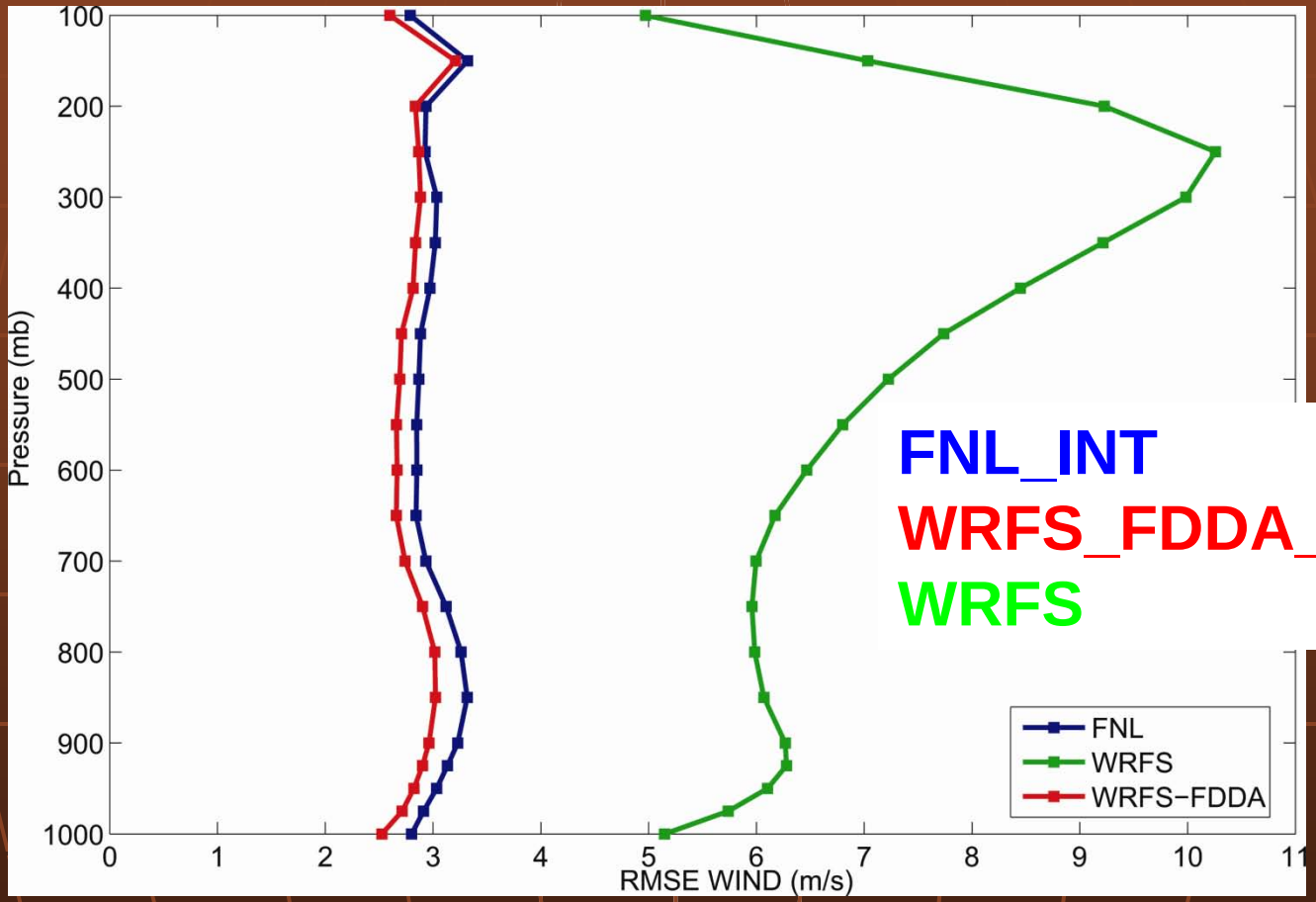
Vertical Profile of Winds



FNL_INT

WRFS_FDDA_NOPBL

WRFS

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

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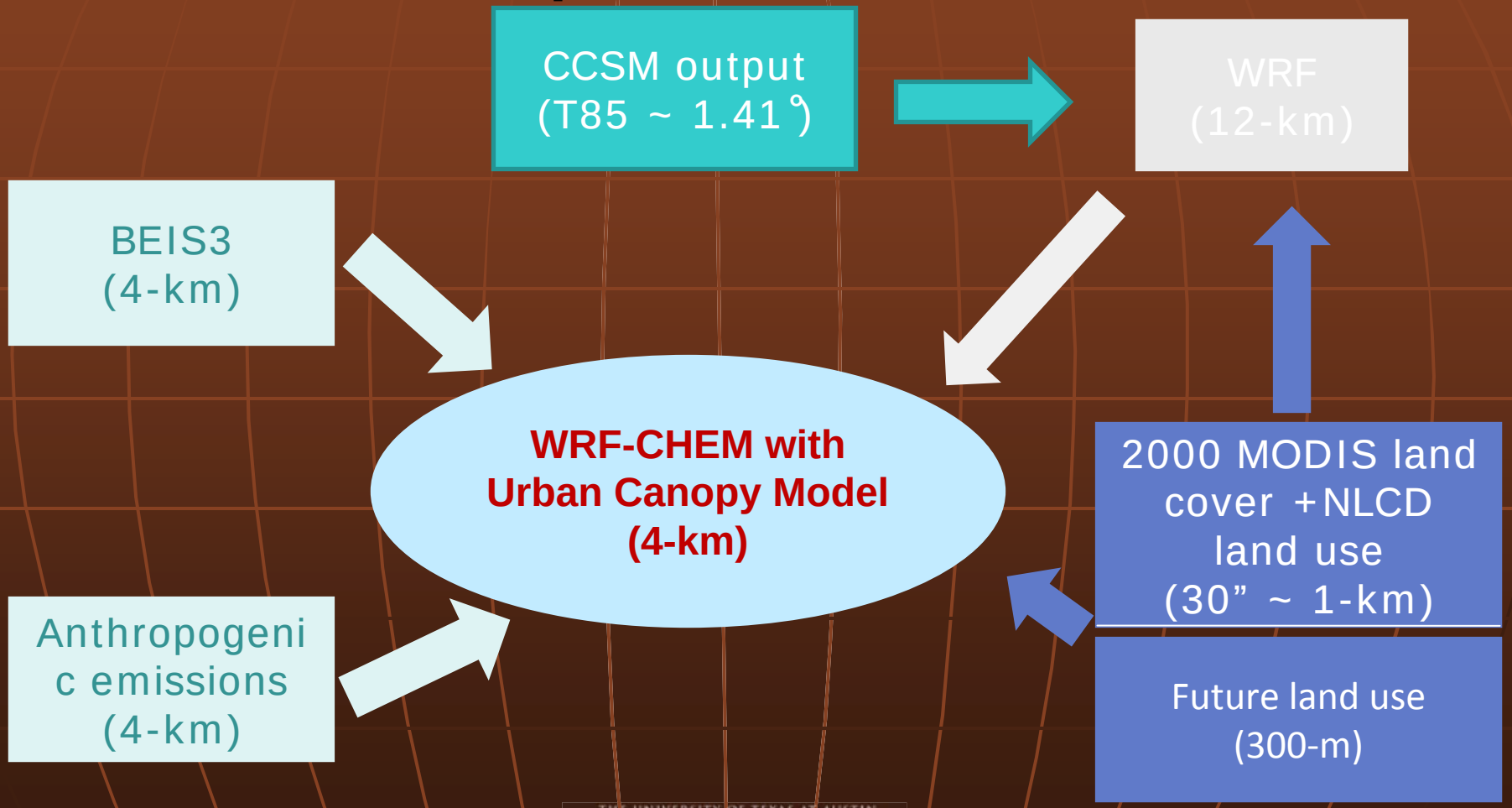
Summary

- 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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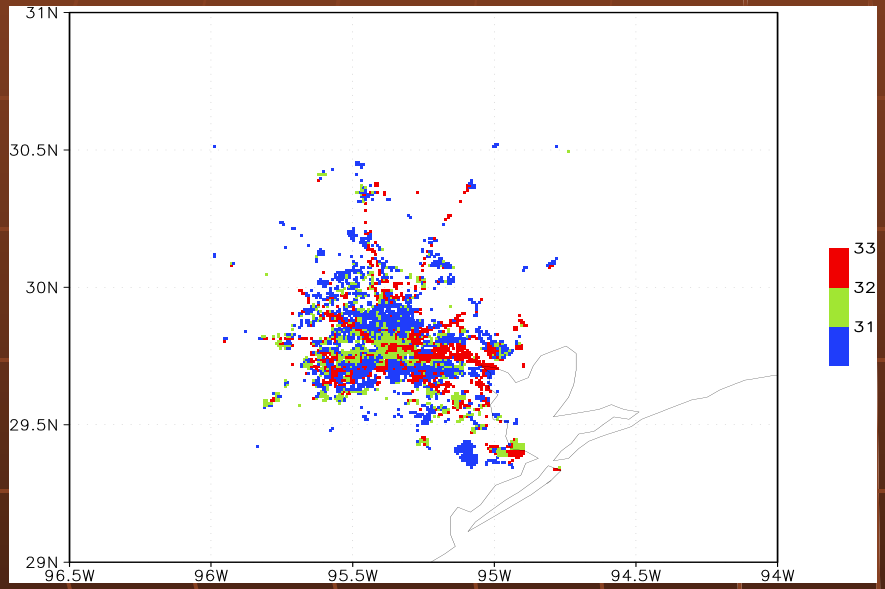
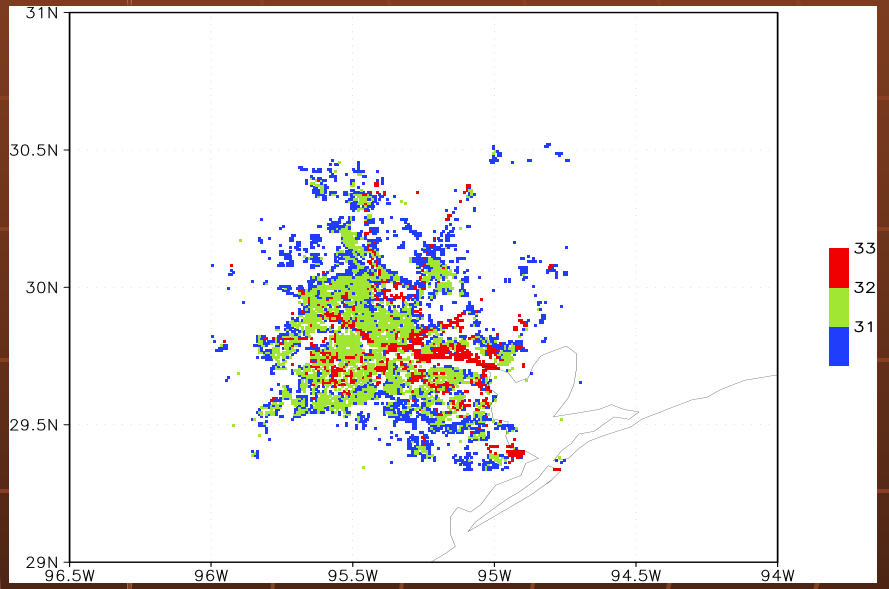
Urban Land Use data

Current land use: 2000



Future land use: 2030



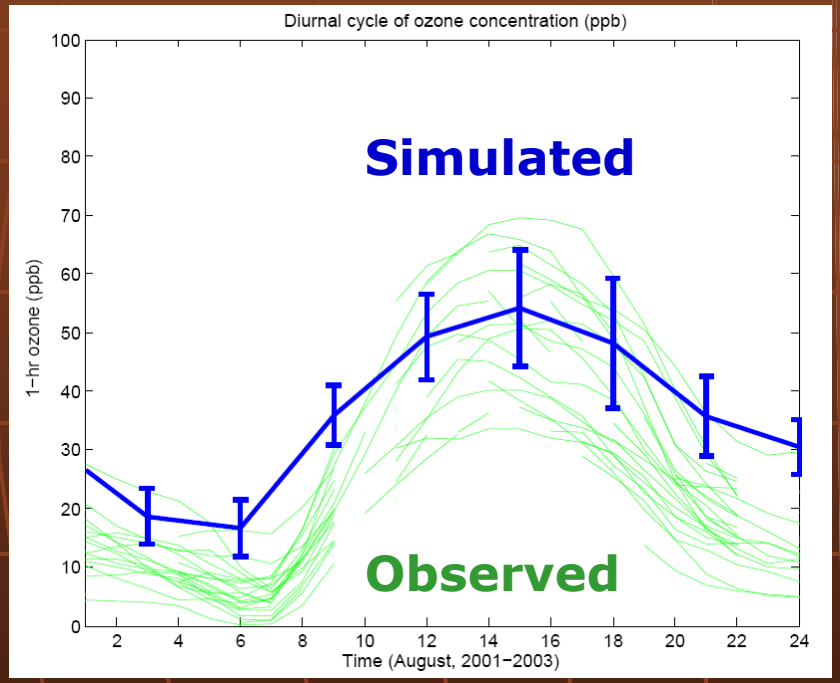
31: Low intensity Residential

32: High intensity Residential

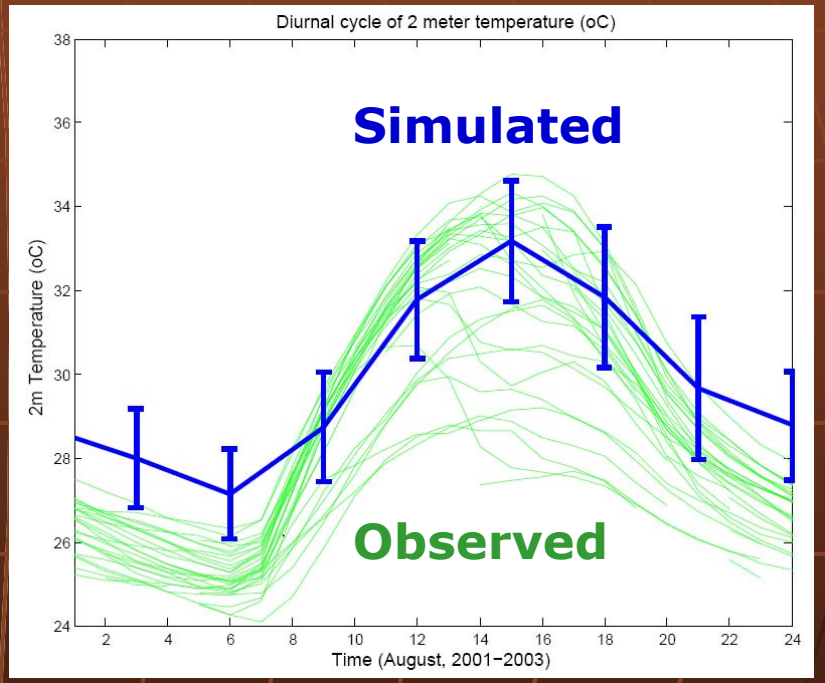
33:Industry or commercial

August Mean Diurnal Cycle (2001–2003)

Ozone

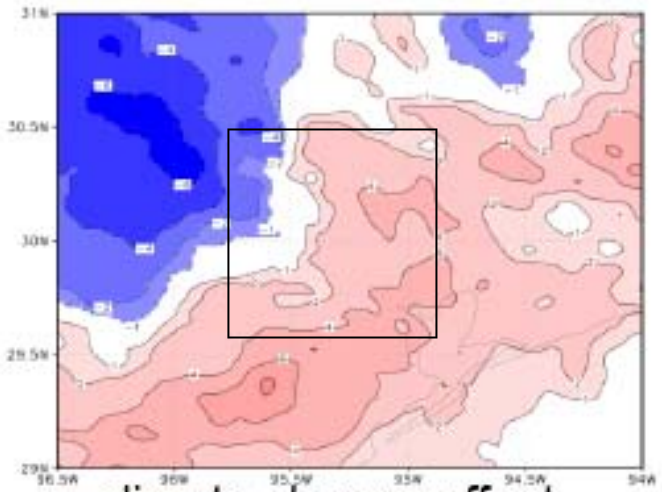


2-m Air Temperature

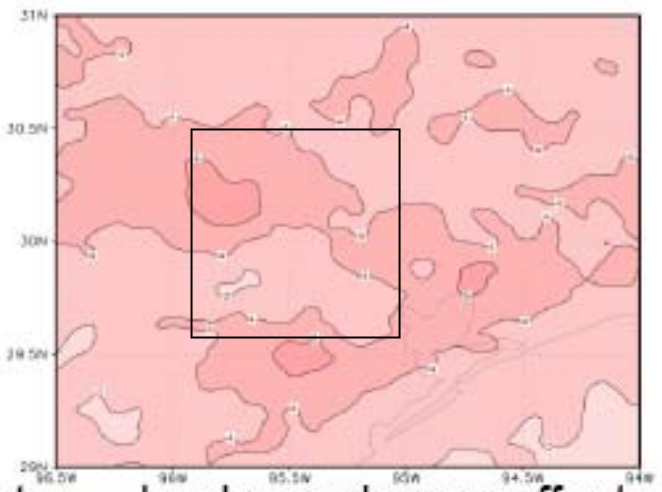


Jiang, X.-Y., C. Wiedinmyer, F. Chen, Z.-L. Yang, and J.C.F. Lo, 2008, *Journal of Geophysical Research-Atmospheres (*in press*).*

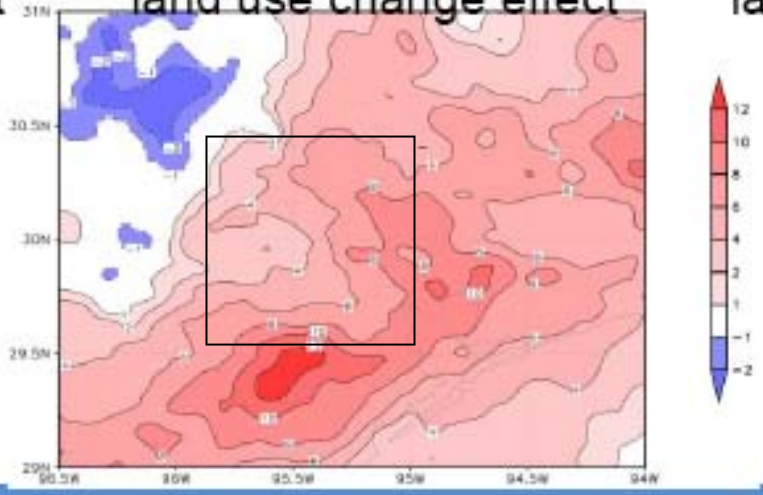
Changes in average daily maximum 8-hr ozone due to climate and land use changes (ppb)



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/)

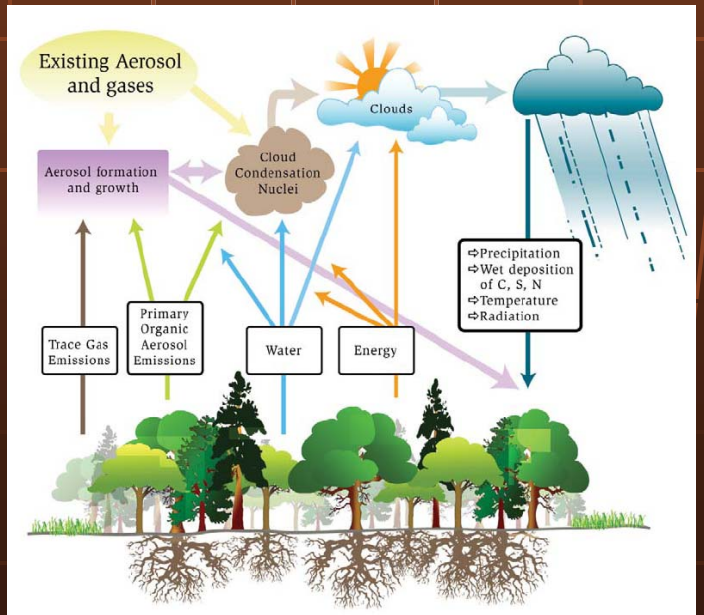


FIG. 1. Schematic of the coupling of terrestrial ecosystems and the hydrologic cycle via energy and water exchange and aerosol processing.

Barth et al., 2005. BAMS

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