Updates on land and atmospheric composition research using Earth Observations and Earth system modeling

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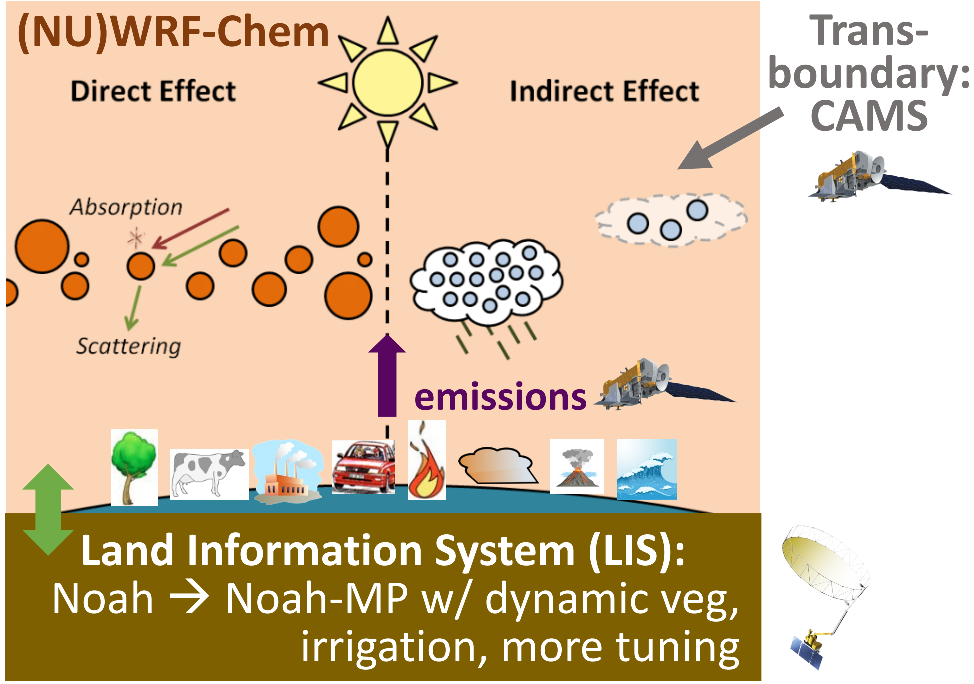
Overall approach, previous contributions to I(E)SWG, and new progress

Regional-scale land modeling and DA coupled with weather and atmospheric chemistry modeling, using NASA LIS and NUWRF:

- ISWG1 (precipitation forecasts over Australia) → ISWG2 (pollution and water vapor transport within E Asia) → ISWG3 (anthropogenic emission and ecosystem productivity in E Asia) published in Huang et al. (2018, 2020)

- **More recent and ongoing work: land surface controls on ozone (O_3) related processes in the SE US**

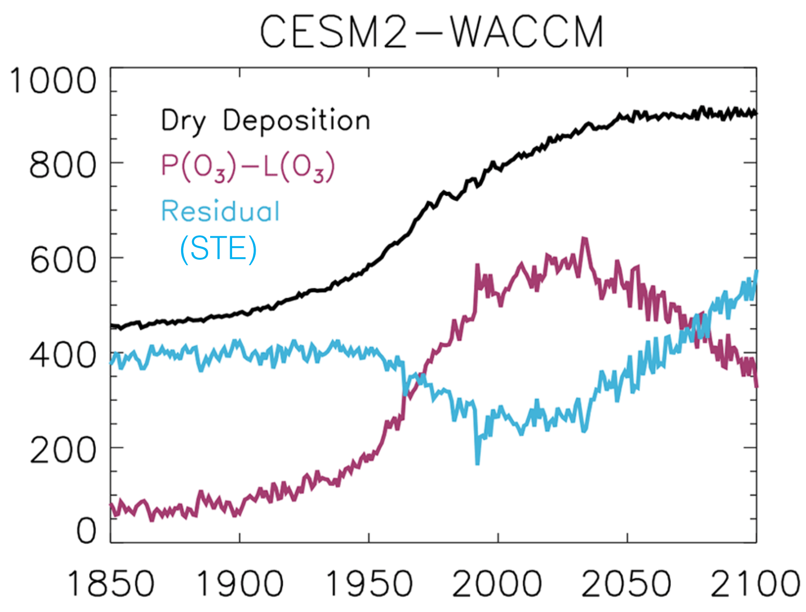
- Also studying extreme weather events (Ellicott City flood, atmospheric rivers), risk/impact assessments, connecting with environmental justice



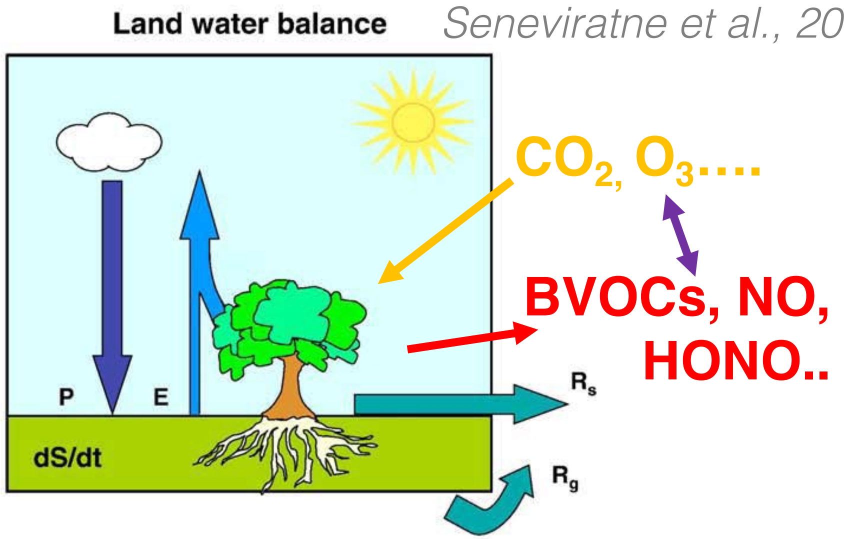
Investigating land controls on O_3 at process level

- Ground-level O_3 is a US EPA-regulated air pollutant harming human and ecosystem health
- Land conditions (including soil moisture, SM) directly and indirectly affect O_3 related processes, by:
  - ➢ Constraining plant uptake of chemicals (e.g., O_3 related and CO_2), growth, and emissions
  - ➢ Influencing weather via evapotranspiration. Many O_3 related processes are weather sensitive, such as dry deposition and biogenic emissions of O_3 precursors.
- We evaluate the impact of land DA on modeling these processes, with implications for interpreting past and predicting future O_3 pollution levels, their temporal changes and impacts

Griffiths et al., 2021: CMIP6 results

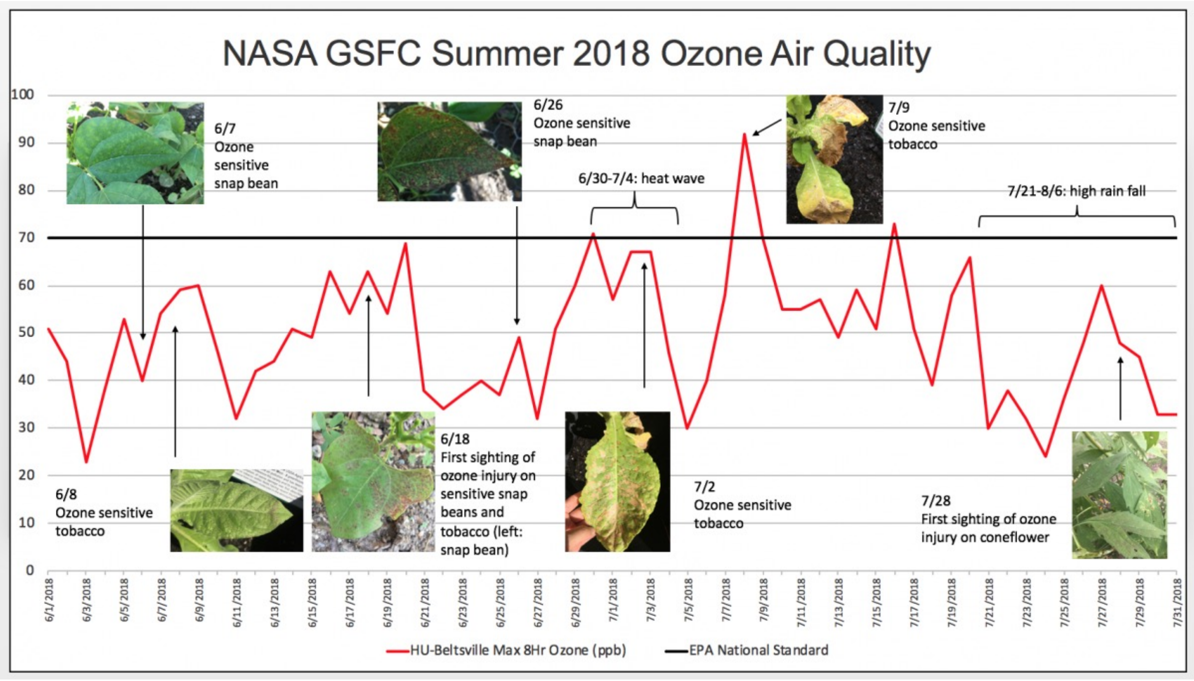


Seneviratne et al., 2010



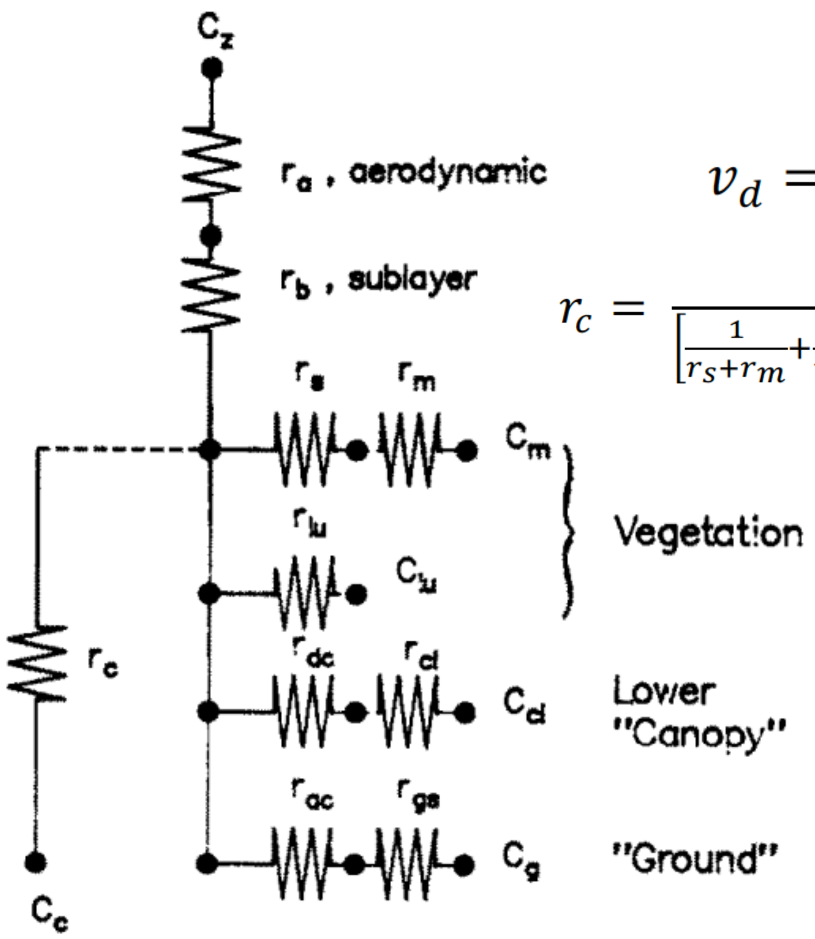
Ozone dry deposition process

- Dry deposition is a major O_3 sink, important for: 1) estimating O_3 concentrations & exceedances; and 2) assessing O_3 (along with other stresses such as water and heat) impacts on ecosystems, which is also relevant to other GHG budgets, weather and climate.



Source: NASA GSFC ozone garden

- Dry deposition velocity v_d is mostly modeled based on resistance-analogy approach. Model representations of its various pathways vary.



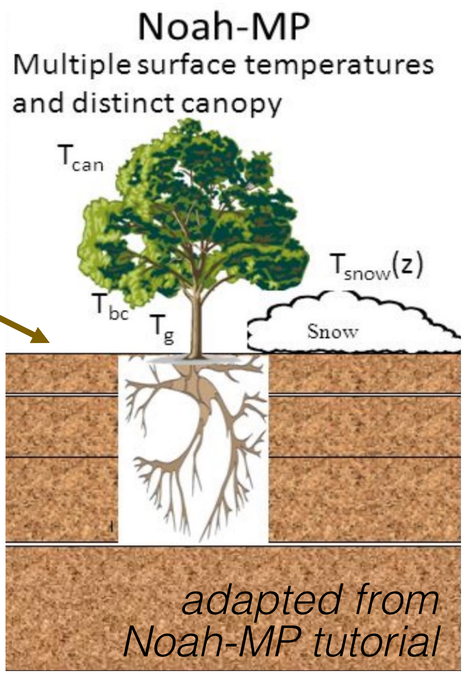
$$v_d = \frac{1}{[r_a + r_b + r_c]}$$

$$r_c = \frac{1}{\left[\frac{1}{r_s + r_m} + \frac{1}{r_{lu}} + \frac{1}{r_{dc} + r_{cl}} + \frac{1}{r_{ac} + r_{gs}}\right]}$$

Wesely, 1989

Modeling and SM DA approaches

SMAP 9 km enhanced SM data, EnKF



- Dynamic vegetation and Ball-Berry r_s scheme
- Tuned physics, irrigation included
- **Wesely and dynamic dry deposition schemes**

For dry deposition modeling:

- We focus on comparing "big-leaf" approaches which are typically used in regional/global models

Wesely (WRF-Chem default, multiplicative)

Stomatal: $r_s = r_i\{1 + [200(G + 0.1)^{-1}]^2\}\{400[T_s(40 - T_s)]^{-1}\}$

Cuticular: $r_{lux} = r_{lu}(10^{-5} H^* + f_0)^{-1}$

Dynamic (added, coupled w/ photosynthesis)

Stomatal: $\frac{1}{r_{s,i}} = m \frac{A_i}{c_{air}} \frac{e_{air}}{e_{sat}(T_v)} P_{air} + g_{min}$

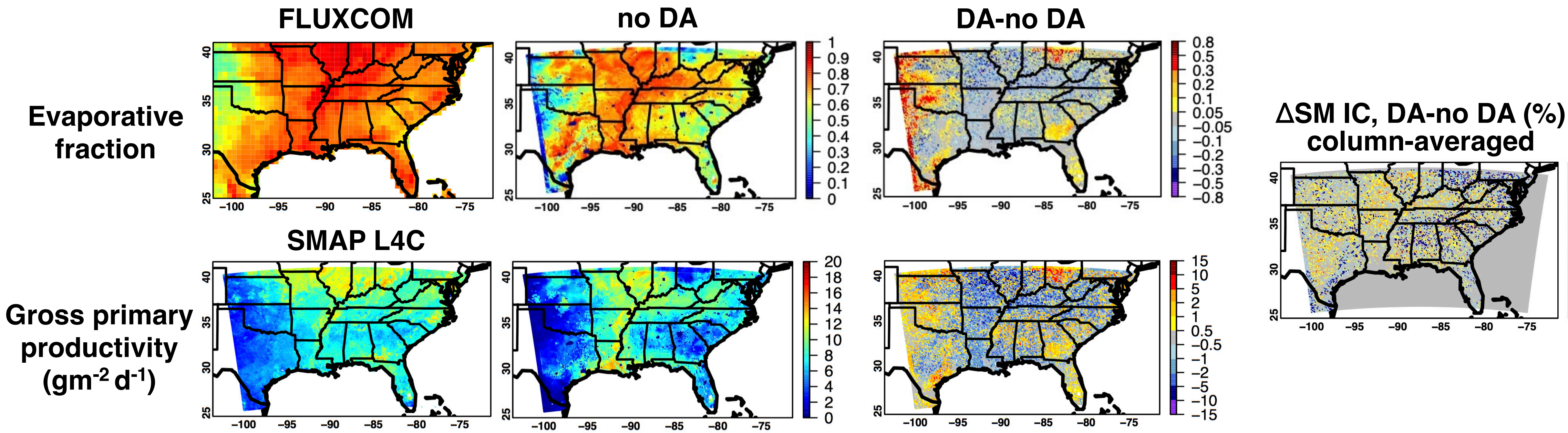
Cuticular: $R_{lu} = \frac{r_{lu}}{LAI \times (10^{-5} H + f_o)}$

i for sunlit & shaded leaves accounting for water stress, LAI..

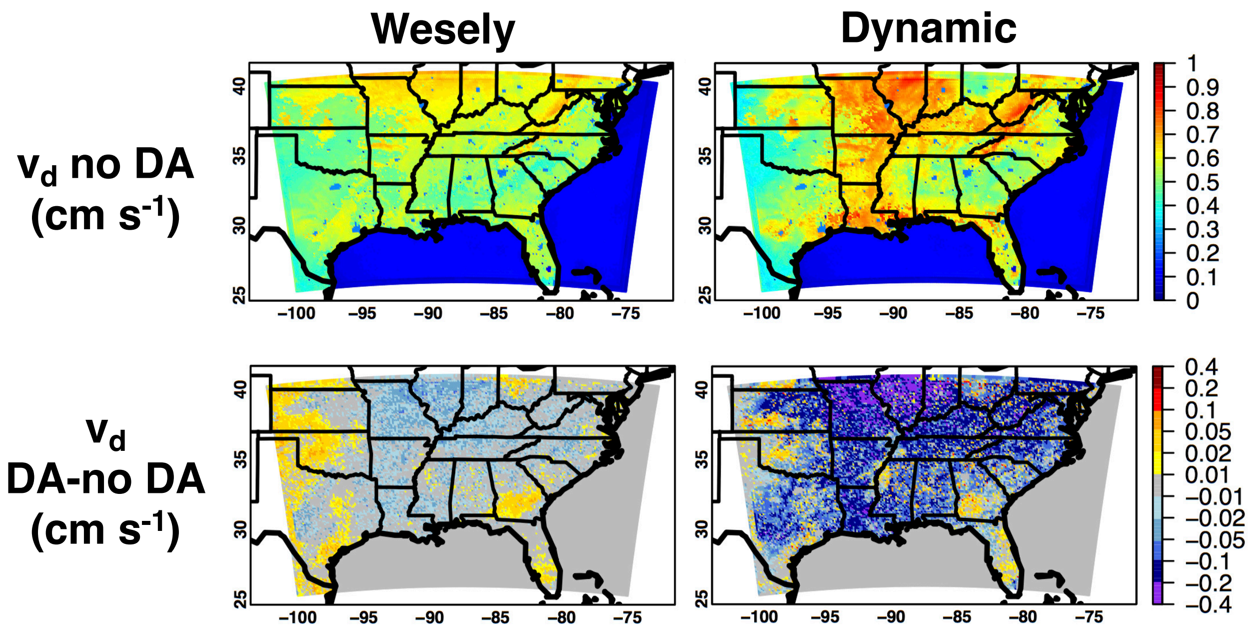
- At selected surface sites, v_d results compared with an EPA operational product which is developed using multi-canopy-layer approach (mostly used in point-scale modeling).

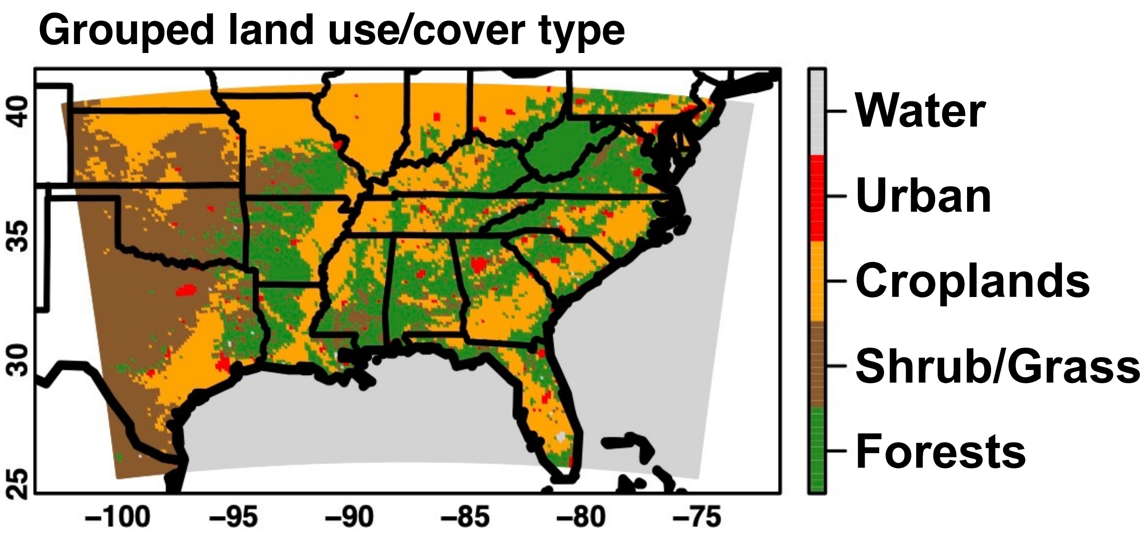
Evaluating energy & carbon fluxes

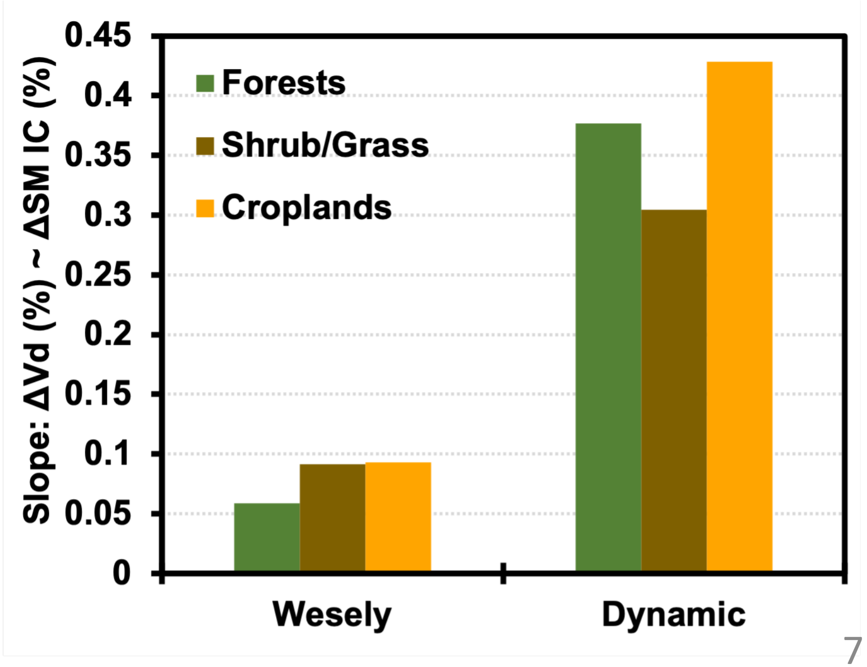
- DA affected SM throughout the soil columns. In places, fluxes in the SM DA case are closer to independent datasets.
- Additional evaluation datasets such as OCO-2 SIF and aircraft OCS are applied
- Weather fields (e.g., temperature, humidity), which were evaluated with aircraft and surface observations, were also found to be improved by DA in general



v_d and its responses to SM DA



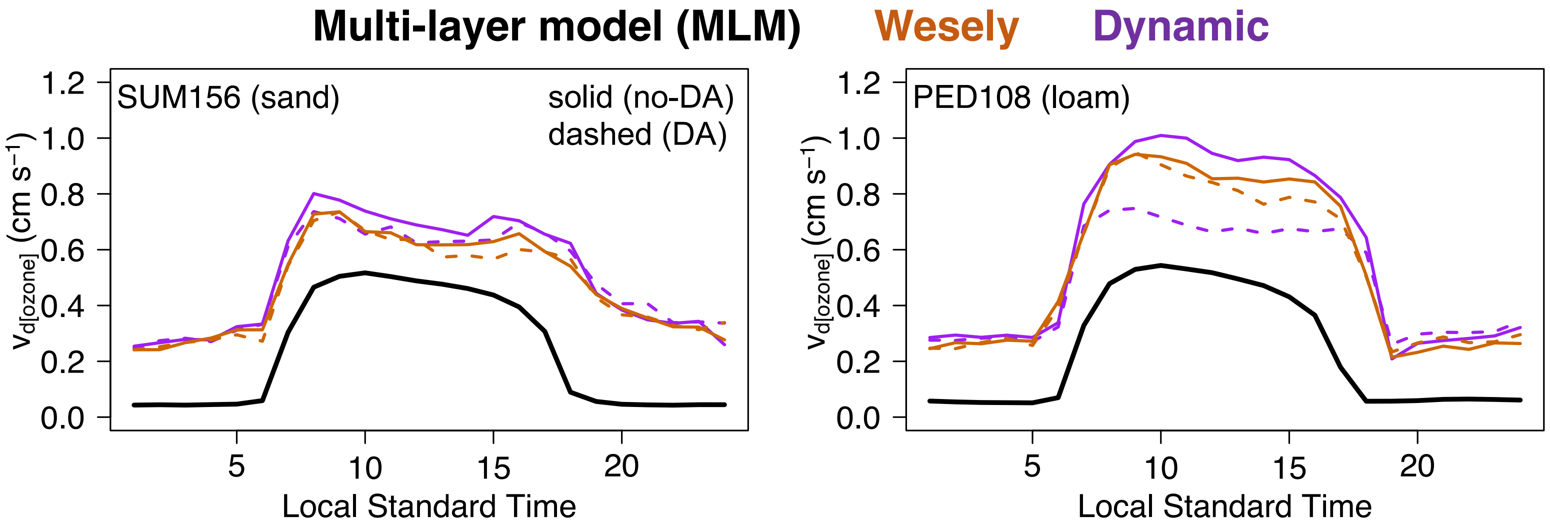


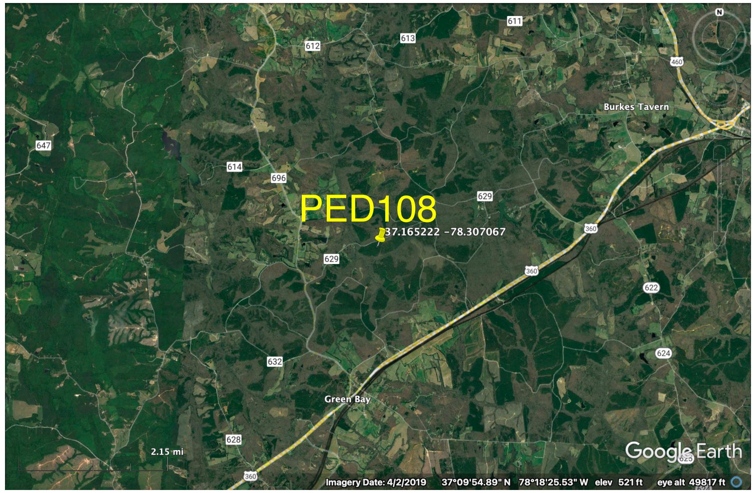


- Switching from Wesely to dynamic scheme overall enhanced v_d and its responses to the SM DA, due to the changes to r_s and r_{lu} pathways
- Dynamic scheme based v_d is several times more sensitive to column averaged SM IC changes due to DA
- Dynamic scheme based v_d and Δv_d correlate with carbon and water fluxes shown earlier

Intercomparing modeled v_d at selected sites

Forest sites in Florida (L) and Virginia (R)



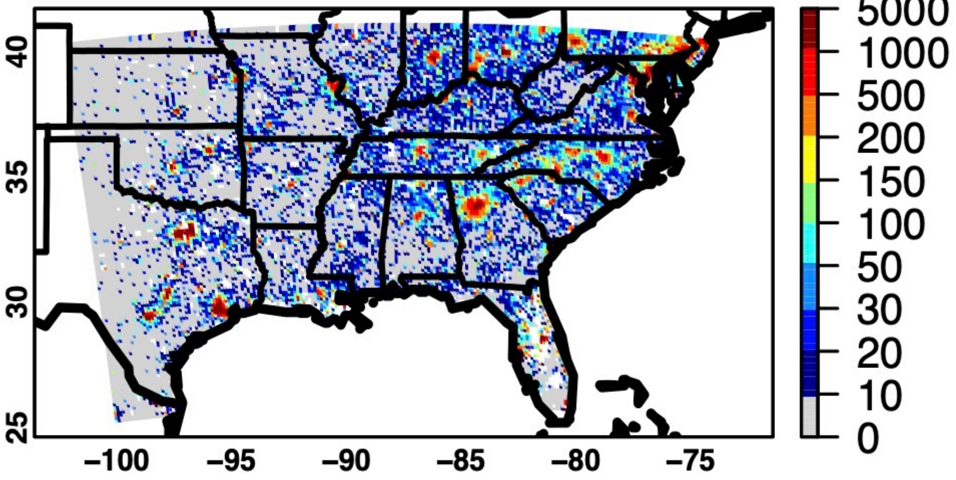


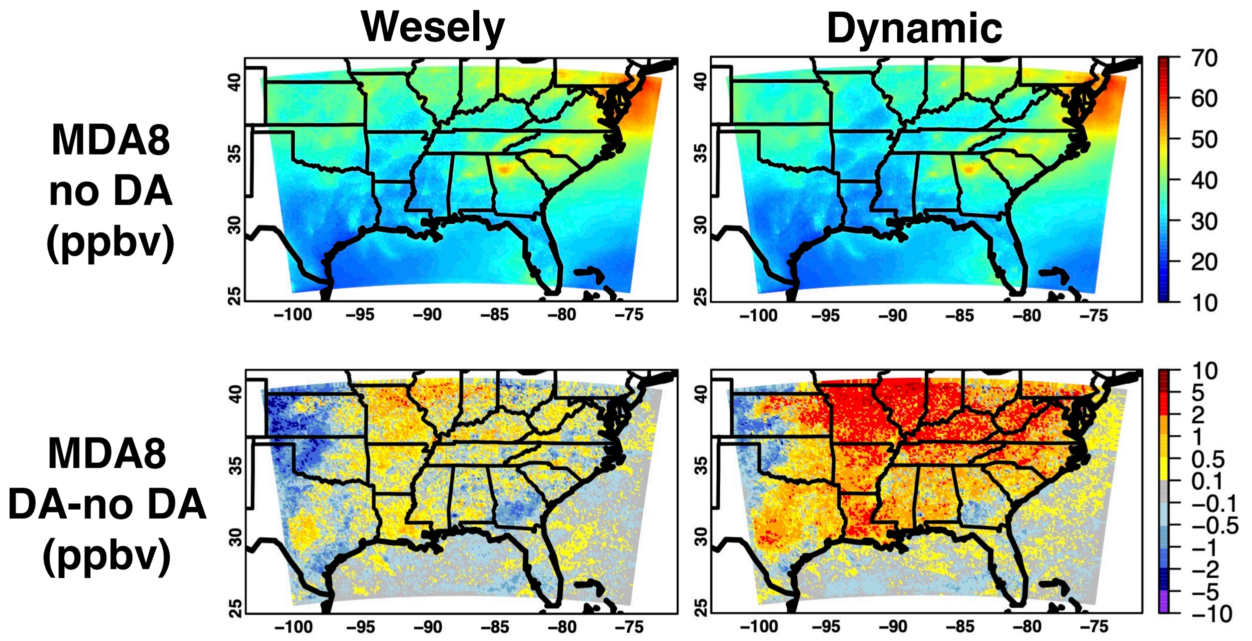
~10 km, close to satellite/model resolutions

- MLM based flux estimates are lower than WRF with Wesely and dynamic schemes, consistent with literature
- Flux responses to SM DA depend on water stress function, soil type and the modeled SM range
- Representation errors are not negligible in such point-scale analysis given the surface heterogeneity within model grids/satellite pixels

Implications for O_3 health impact assessments

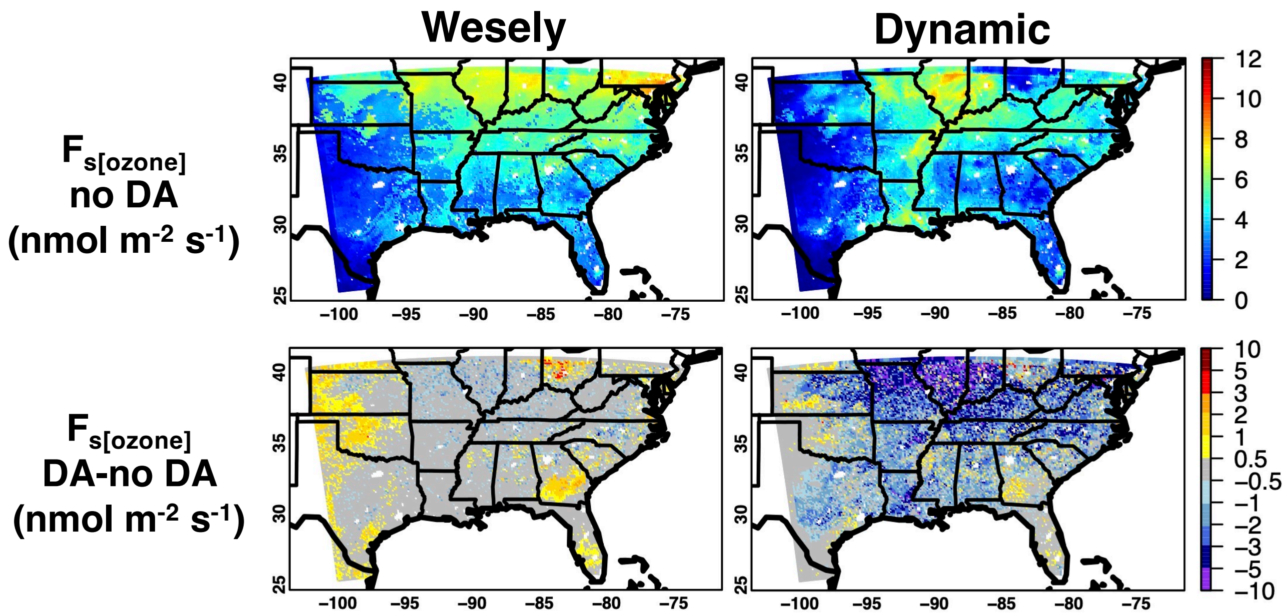
Population density in 2015 (km^{-2})



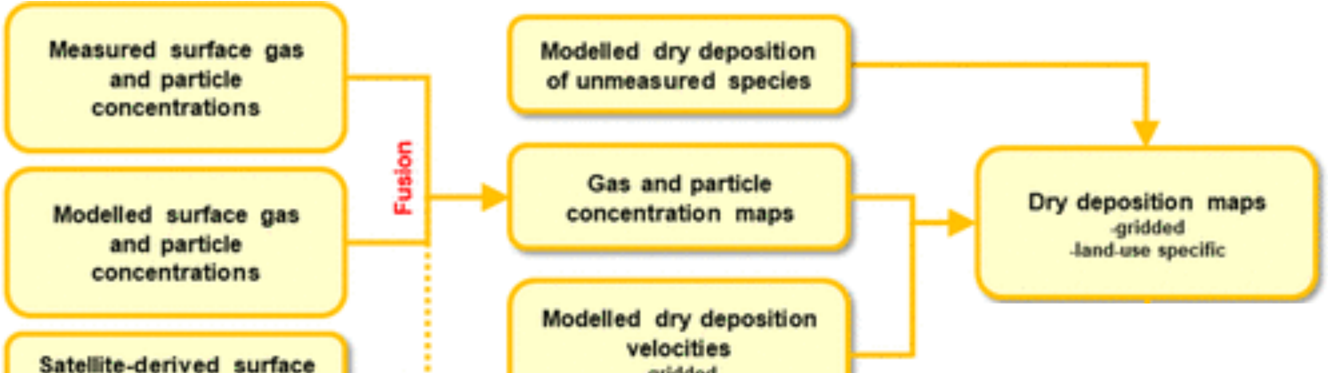


- Median MDA8 (EPA air quality standard metric) in nonurban regions ~5 ppbv lower than in urban grids where population density is >25 times larger
- When dynamic scheme is applied, ΔMDA8 in both nonurban and urban grids are stronger, and such stronger changes are more evident in nonurban grids. This demonstrates that the understanding of O_3 dry deposition mechanism can have a strong impact on the interpretation of O_3 responses to droughts.

Implications for O_3 vegetation impact assessments



WMO Measurement-Model Fusion for Global Total Atmospheric Deposition



Fu et al., 2022

For wheat (highly O_3 sensitive):

Relative Yield = –0.0064 POD_3 + 0.9756

POD_3 is derived from stomatal O_3 uptake F_s

- Model-derived mean wheat relative yield loss due to O_3 ranges from 4 to 10%. The estimates would be different if a different metric and dose-response function is chosen.

- F_s is calculated from concentrations and fluxes. A combination of chemical and land DA as well as multi-model approach would help benefit O_3 impact assessment.

New and planned efforts

- Results shown earlier are in Huang et al. (2021, 2022)
- Now dynamically modeling O_3 impacts on vegetation by applying $F_{p,o3}$ and $F_{c,o3}$ (functions of cumulative O_3 uptake, CUO) to photosynthesis and conductance rates, respectively:

$$F_{pO3} = a_p \times \text{CUO} + b_p \qquad F_{cO3} = a_c \times \text{CUO} + b_c$$

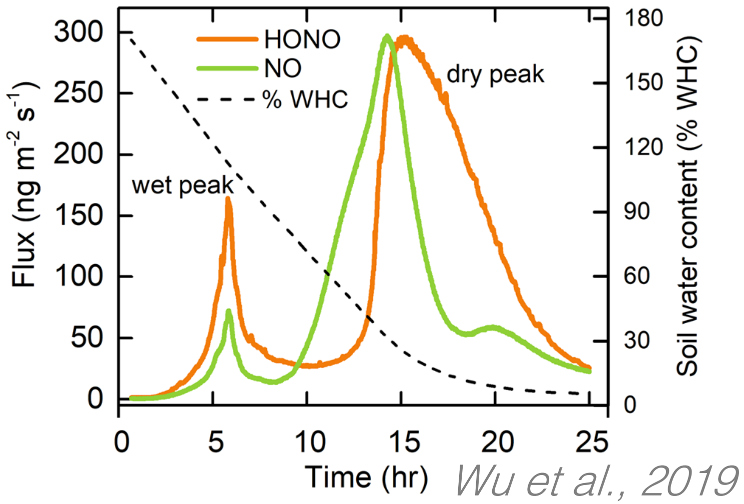
which affects GPP, v_d, latent/sensible heat, runoff, rainfall, temperature…

- Modifying model representations of multi-stress impacts on biogenic emissions of nitrogen species and VOCs, and intercomparing emissions from MEGAN and other schemes – within IGAC/TOAR II activity, publication expected in their upcoming Copernicus special issue in 2023

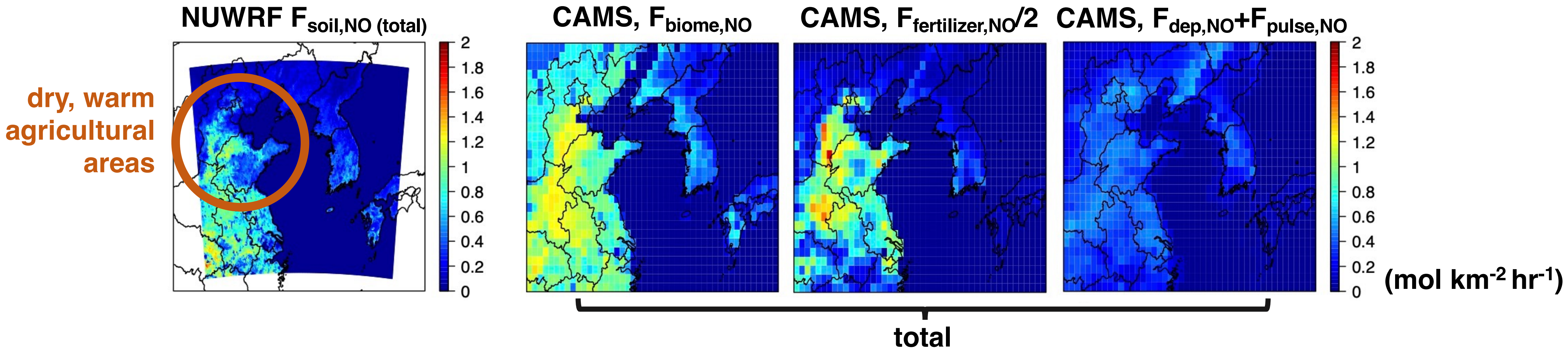
Model representations of SM impacts on soil emissions

Soil emissions are important in some regions but poorly represented in models:

- Soil NO and HONO emissions are correlated and show SM dependency: dry peak at ~15% SWC, and wet peak at >70% SWC (affected by microbial activities)
- Soil NO emissions for various surface types are largely sensitive to temperature; only the “dry peak” is reflected in some other schemes (Berkeley-Dalhousie, CAMS). Soil HONO emissions are often missing.

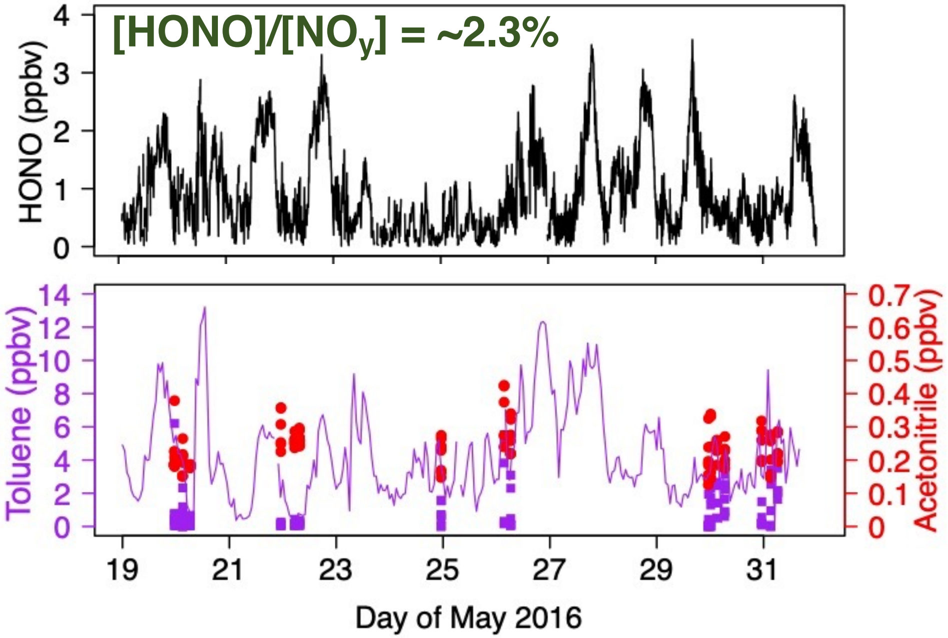


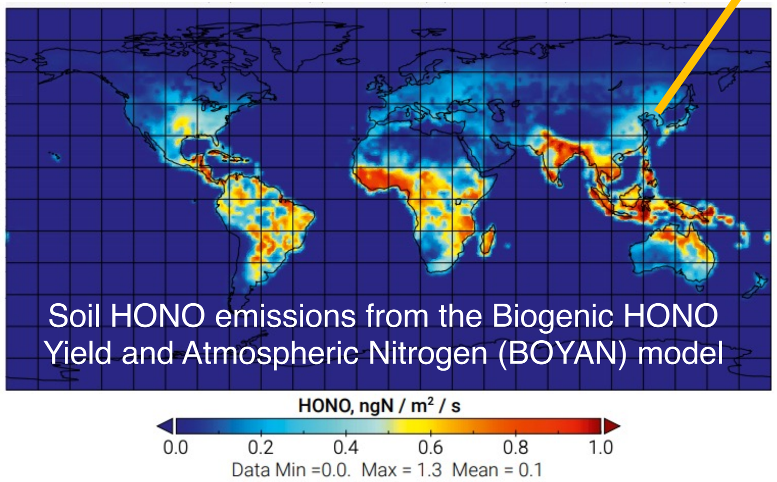
Wu et al., 2019



HONO in Seoul, S Korea

NASA KORUS-AQ campaign data: Olympic Park ground site (lines); DC-8 >800 hPa (dots)

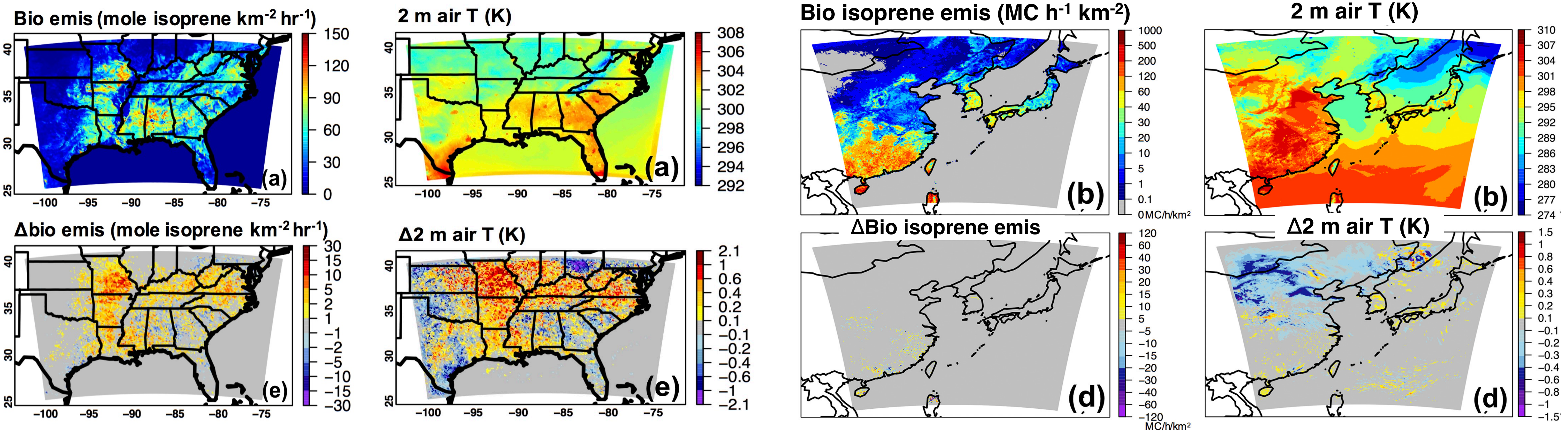




Source: MPI-C Scientific Report 2018-2020

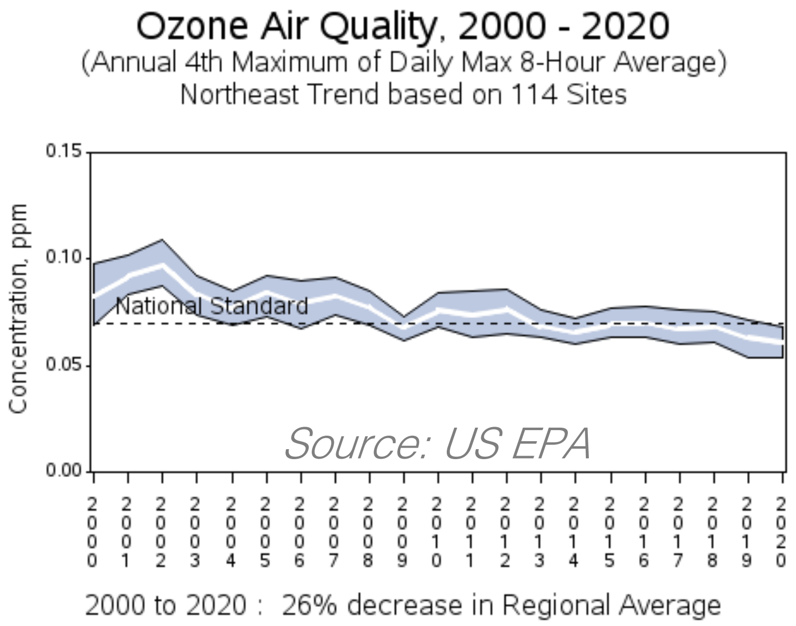
- (NU)WRF default is far from satisfactory. Collocated trace gas measurements and independent emission models indicate various sources impacting HONO in Seoul (soil, traffic, fires) that are underrepresented by the model
- Field campaigns need to regularly measure HONO at various altitudes to help better understand chemical processes and diagnose/improve models

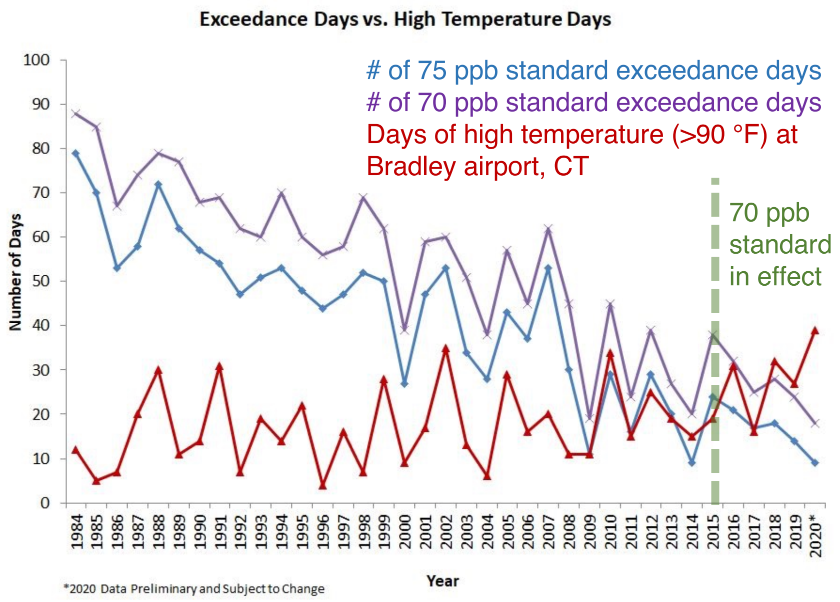
SM impacts on BVOC emissions (via weather)



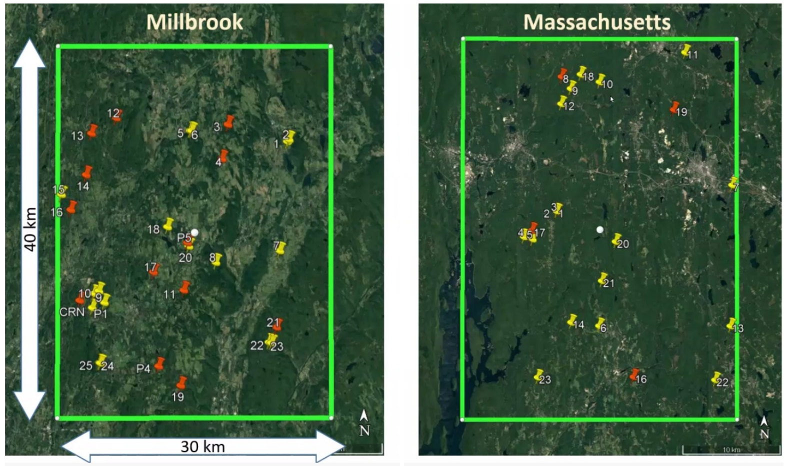
- Huang et al. (2018, 2021) show that, BVOC emissions from NUWRF/MEGAN are closely related to vegetation and surface air T. SMAP DA adjusted MEGAN BVOC emissions in NUWRF via its impacts on the weather fields.
- In Asia, most dramatic changes in air T due to SMAP DA occurred in transitional climate zones with sparse vegetation where BVOC emissions were weak.
- SM direct impacts on BVOC emissions were not accounted for. This is being addressed by modifying MEGAN SM activity factor, referring to Jiang et al. (2018).

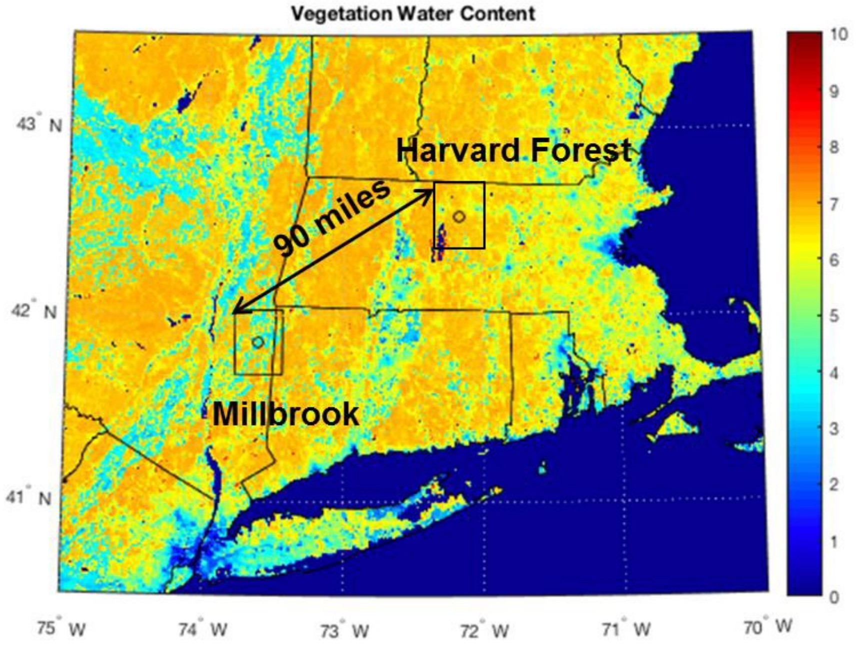
Field work benefiting the utilizations of SM data





SMAPVEX19-22 campaign focused areas





- Dramatic anthropogenic emission reductions and a warming trend in NE US, where O_3 exceedances persist
- SMAPVEX19-22 campaign: to assess satellite SM retrieval quality in temperate forest regions and SM subgrid variability within satellite pixels
- Our new model developments will be applied to study these (and other) areas, using data/findings from this campaign and other sources

Summary

- Land surface controls on dry deposition and biogenic emissions are represented by models in different ways → important sources of model uncertainty
- Land DA impacts on model estimated dry deposition, biogenic emissions, O_3 and its impact assessments strongly depend on how the related processes are parameterized in the models
- Advancements in observing systems and enhanced capability of interpreting Earth Observations would help improve the understanding and model representations of these O_3 related processes, as well as DA effectiveness
- We have been engaged in multiple IGAC activities while conducting these studies, and have stimulated conversations/collaborations with satellite/field campaign teams, other community model developers/users, and air quality stakeholders

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