Noah-MP developments and applications related to atmospheric chemistry

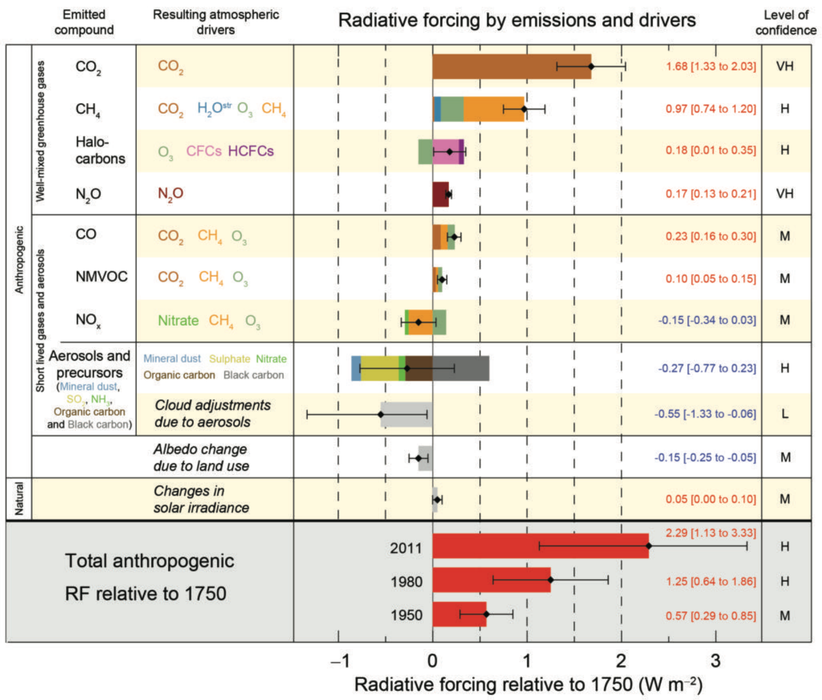
Min Huang (min.huang@nasa.gov), NASA GSFC/SSAI

With contributions from: J. Crawford, G. Carmichael, J. Santanello, S. Kumar, R. Stauffer, A. Thompson, A. Weinheimer, J. Park, K. Bowman, C. Sweeney, I. De Smedt, A. Guenther, and many more

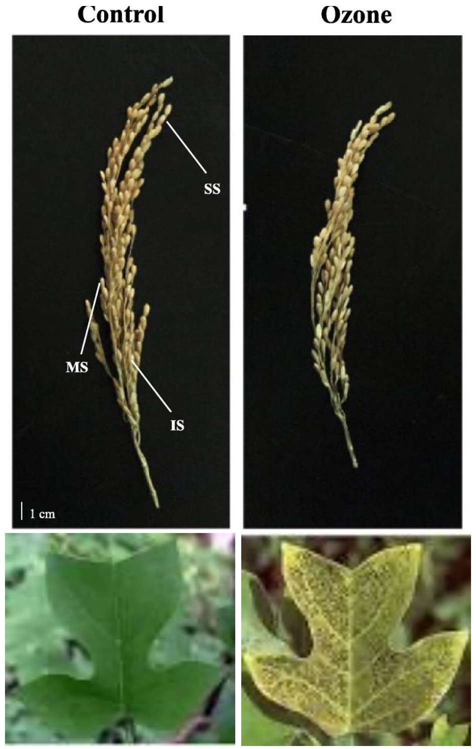
NCAR Noah-MP workshop | May 24, 2023

Atmospheric chemistry is interconnected with climate and ecosystems, affecting food security

➢ Air pollutants interact with radiation and other climatic conditions, perturbing biosphere-atmosphere interactions and vegetation growth.



➢ Air pollutants (e.g., ozone, O_3) injure vegetation, reduce crop yields and nutritional value of certain foods.



➢ Air pollutants acidify and fertilize ecosystems (e.g., via nitrogen and sulfur deposition) from where pollutants and their precursors are emitted.

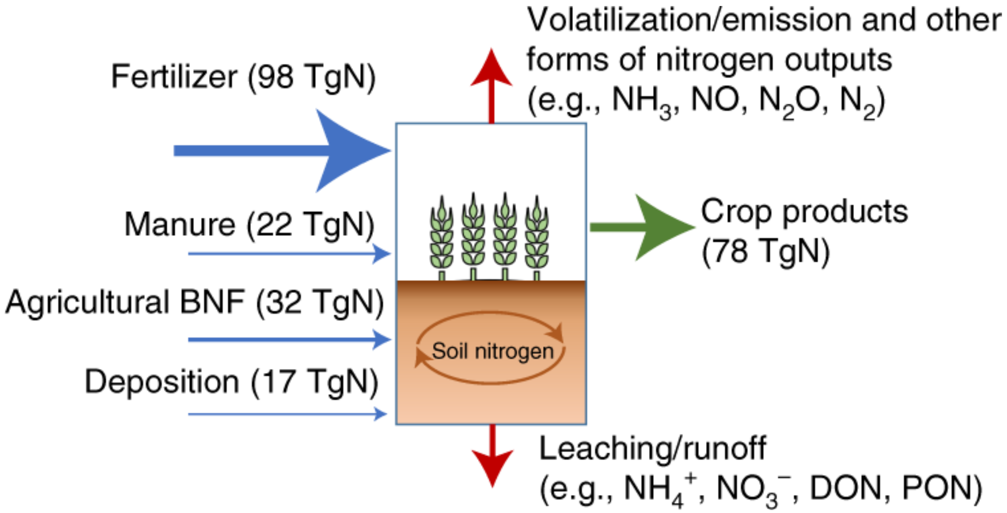
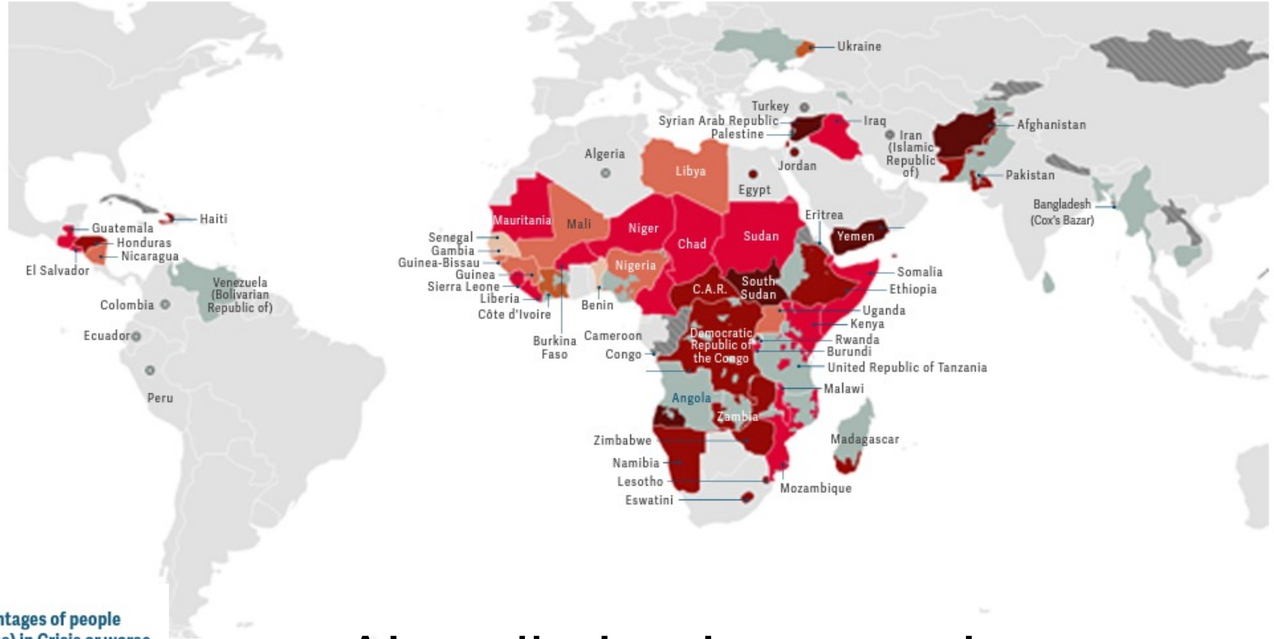
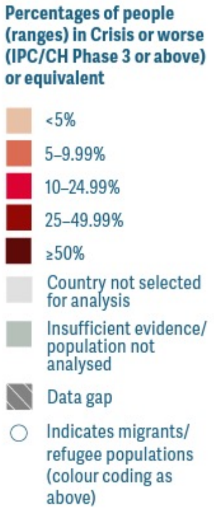


Figure sources: IPCC, NPS, Shao et al. (2020), X. Zhang et al. (2021)

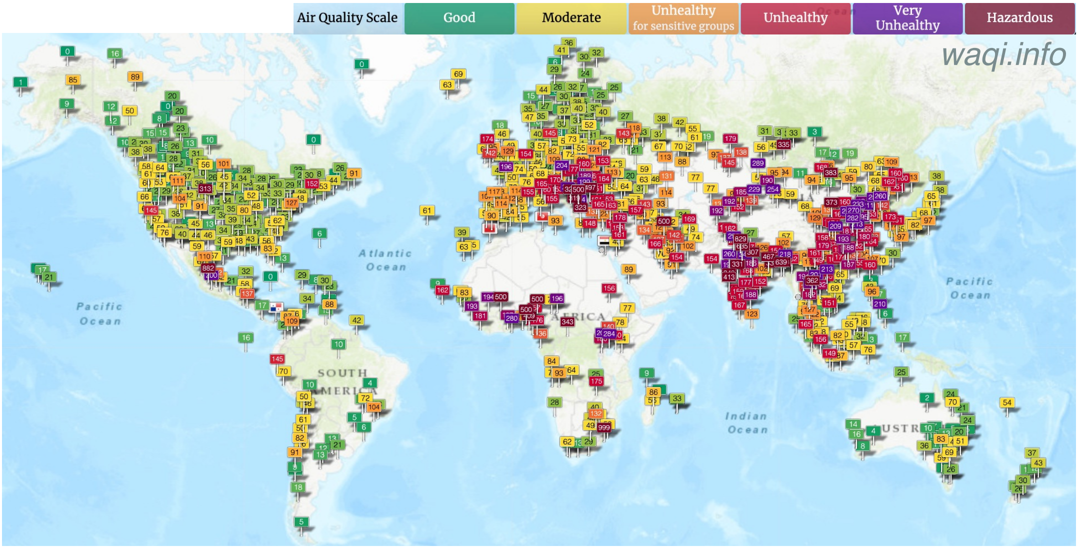
Heterogeneity in air pollution and food security levels; and disparities in ground-monitoring capabilities

Population facing food crisis *(FSIN, 2022)*

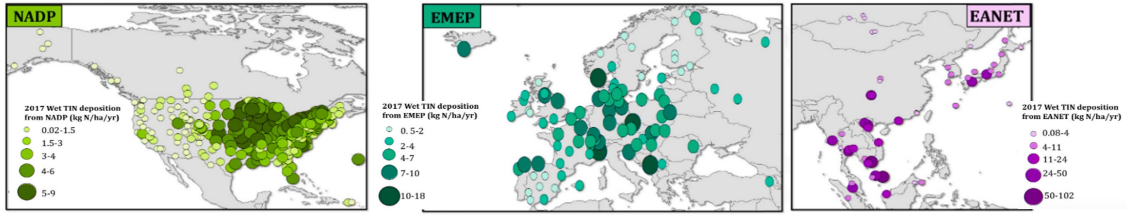




Air pollution is a growing concern in many countries where water and food security levels are low and in-situ observations are sparse. Remote sensing and Earth system modeling products are highly valuable.



Observed total inorganic N wet deposition *(Q. Zhang et al., 2021)*

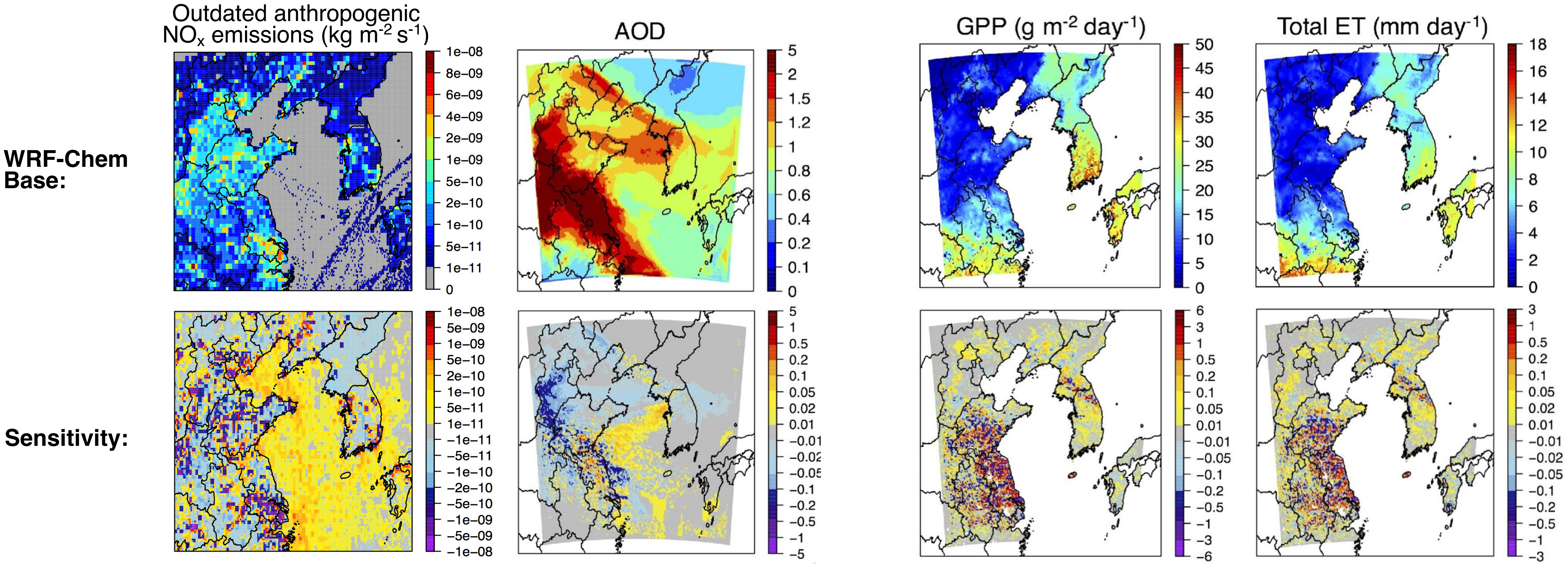


LIS/Noah-MP is run with dynamic vegetation on, coupled with WRF-Chem, evaluated/constrained with data from multiple satellites, to address a range of interdisciplinary science questions.

Aerosol precursor emission impacts on atmosphere-biosphere interactions

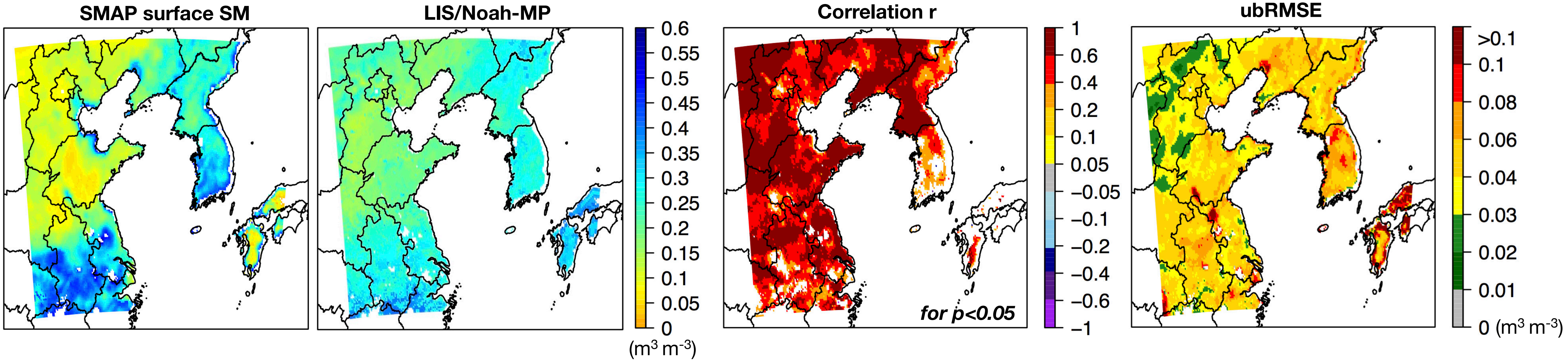
Impact of Aerosols From Urban and Shipping Emission Sources on Terrestrial Carbon Uptake and Evapotranspiration: A Case Study in East Asia *JGR, 2020*

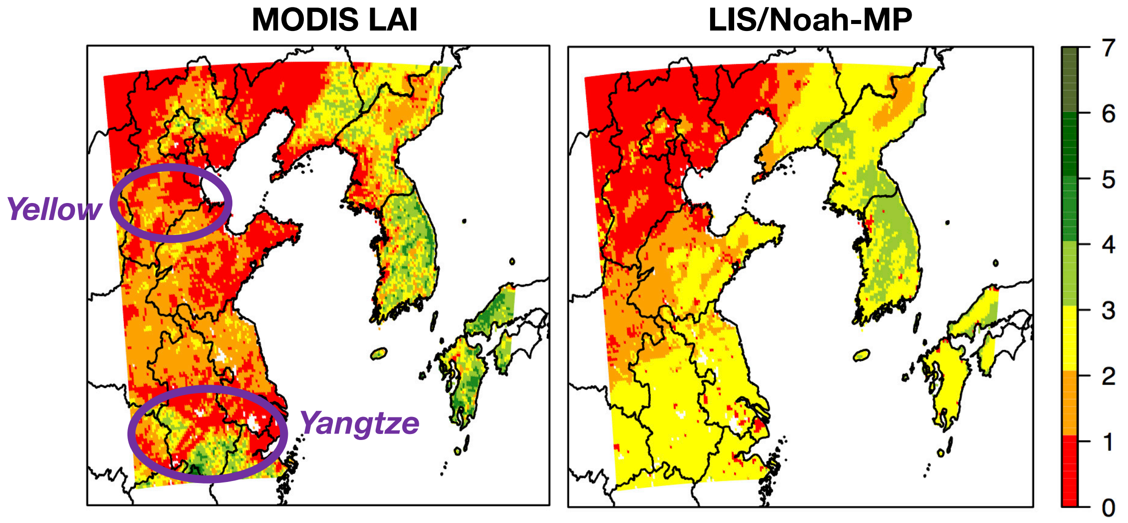
Min Huang[1], James H. Crawford[2], Gregory R. Carmichael[3], Joseph A. Santanello[4], Sujay V. Kumar[4], Ryan M. Stauffer[4,5], Anne M. Thompson[4], Andrew J. Weinheimer[6], and Jun Dong Park[7]



- Referring to aircraft, ship, AERONET and GOCI observations, updating emissions of aerosol precursors such as NO_x with OMI NO_2 data improved WRF-Chem performance on a cloudy day in May 2016 during the KORUS-AQ campaign.
- Emission-induced aerosol changes interact with radiation and surface temperature, affecting GPP and ET which together indicate plants' resilience to environmental changes (i.e., water use efficiency).

Noah-MP soil moisture (SM) and leaf area index (LAI) evaluated with satellite data, May 2015-2018





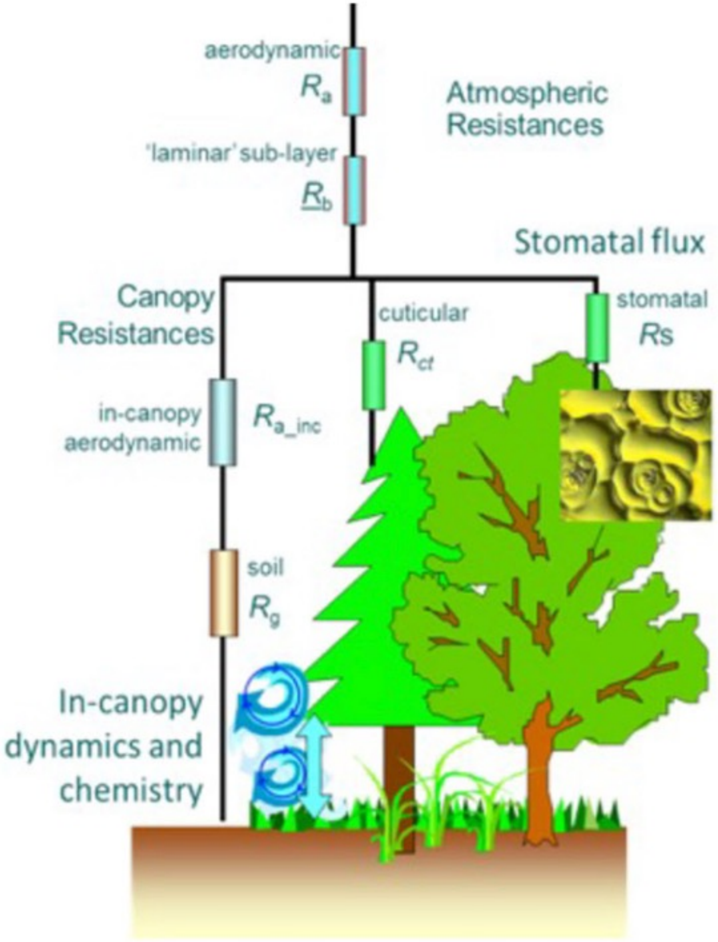
- Compared with SMAP, the model's SM dynamic range is smaller; higher r values and lower ubRMSE in N. China Plain than in S. Korea dense vegetation areas.
- Model overall under-/over-predicted LAI around China's Yellow/Yangtze river basins, similar to results in previous Noah-MP studies.

Assessing soil moisture impacts on O_3 dry deposition

Satellite soil moisture data assimilation impacts on modeling weather variables and ozone in the southeastern US - Part 2: Sensitivity to dry deposition parameterizations *ACP, 2022*

Min Huang[1,a], James H. Crawford[2], Gregory R. Carmichael[3], Kevin W. Bowman[4], Sujay V. Kumar[5], and Colm Sweeney[6]

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



Archibald et al., 2020

- Updated dry deposition scheme (Wesely → Dynamic)

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 (coupled with photosynthesis)

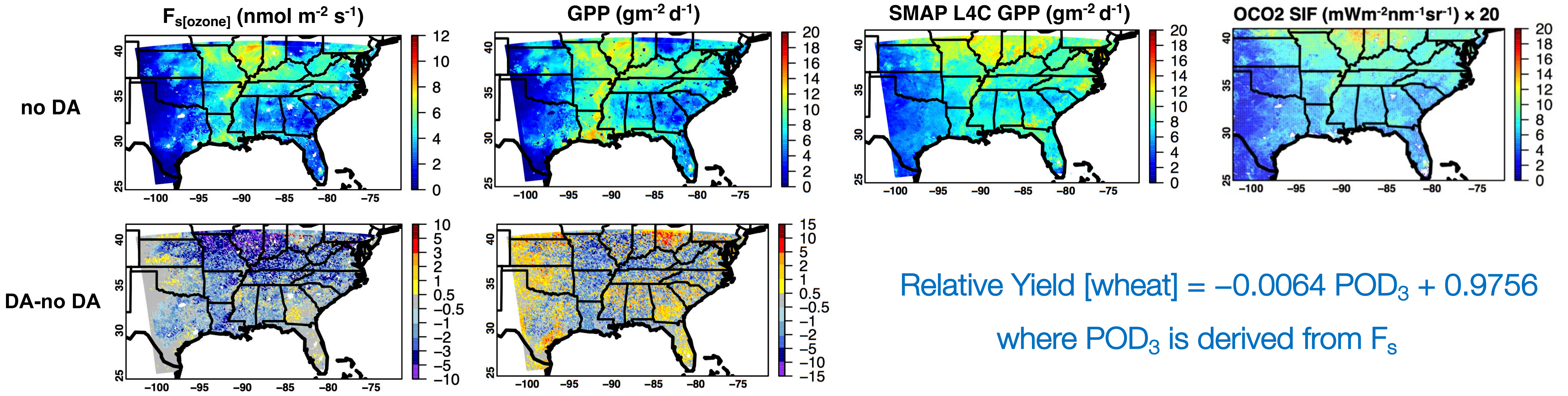
Stomatal: $\frac{1}{r_{s,i}} = m\frac{A_i}{c_{air}}\frac{e_{air}}{e_{sat}(T_v)}P_{air} + g_{min}$

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

i for sunlit & shaded leaves accounting for water stress, leaf area index, CO_2…

- Assimilated SMAP soil moisture into Noah-MP
- Estimated O_3 vegetation impacts using model-based O_3 metrics and land cover/crop specific dose-response functions

Impact assessment based on modeled stomatal O_3 flux, which correlates with GPP and SIF



Relative Yield [wheat] = −0.0064 POD_3 + 0.9756

where POD_3 is derived from F_s

- Wheat relative yield loss due to O_3, estimated based on modeled (with dynamic dry deposition scheme and SMAP assimilation) POD, is ~4% on average.
- Flux-based metrics are more biologically relevant and preferred for O_3 vegetation impact assessments. The performance of modeled O_3 fluxes is hard to assess due to very sparse measurements but may be inferred by model performance on carbon fluxes (e.g., GPP) which can be derived from satellite data. Hourly SIF data from the newly launched TEMPO are of interest.

Follow-up study: dynamically modeling O_3 impact on vegetation for 2018-2022 over NE US

- Applied F_{pO3} and F_{cO3} to photosynthesis and stomatal conductance rates, respectively *(Lombardozzi et al., 2015)*

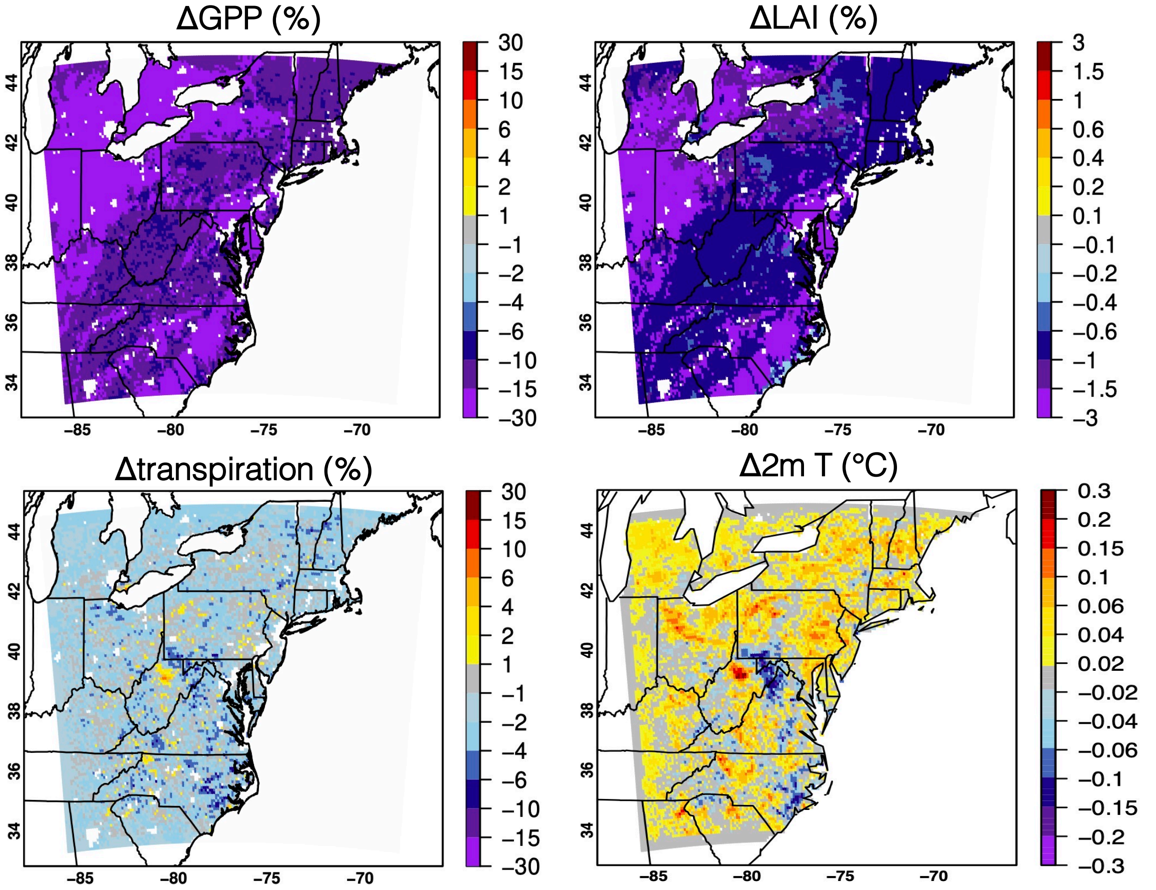
$$F_{\mathrm{pO3}} = a_p \times \mathrm{CUO} + b_p$$
$$F_{\mathrm{cO3}} = a_c \times \mathrm{CUO} + b_c$$

CUO: cumulative O_3 uptake
a, b: land cover dependent

- Biogenic emission schemes (VOC, NO, HONO) were also updated

- O_3 impacts GPP more strongly than transpiration and ET, reducing plants' water use efficiency.

6-19 July 2022 daytime



- This result is based on “coupled” simulations. LIS/Noah-MP offline simulations may also be set up to help understand links between O_3 impacts and climate change at larger spatiotemporal scale while at lower computational costs.

Biogenic emissions schemes updated: Now sensitive to multiple environmental stresses

Soil NO emissions *(Hudman et al., 2012)*
Biome-based emission factors adjusted by soil temperature T and water-filled pore space θ (SM/porosity)

$$e^{0.103T} \times a\theta e^{-b\theta^2}$$

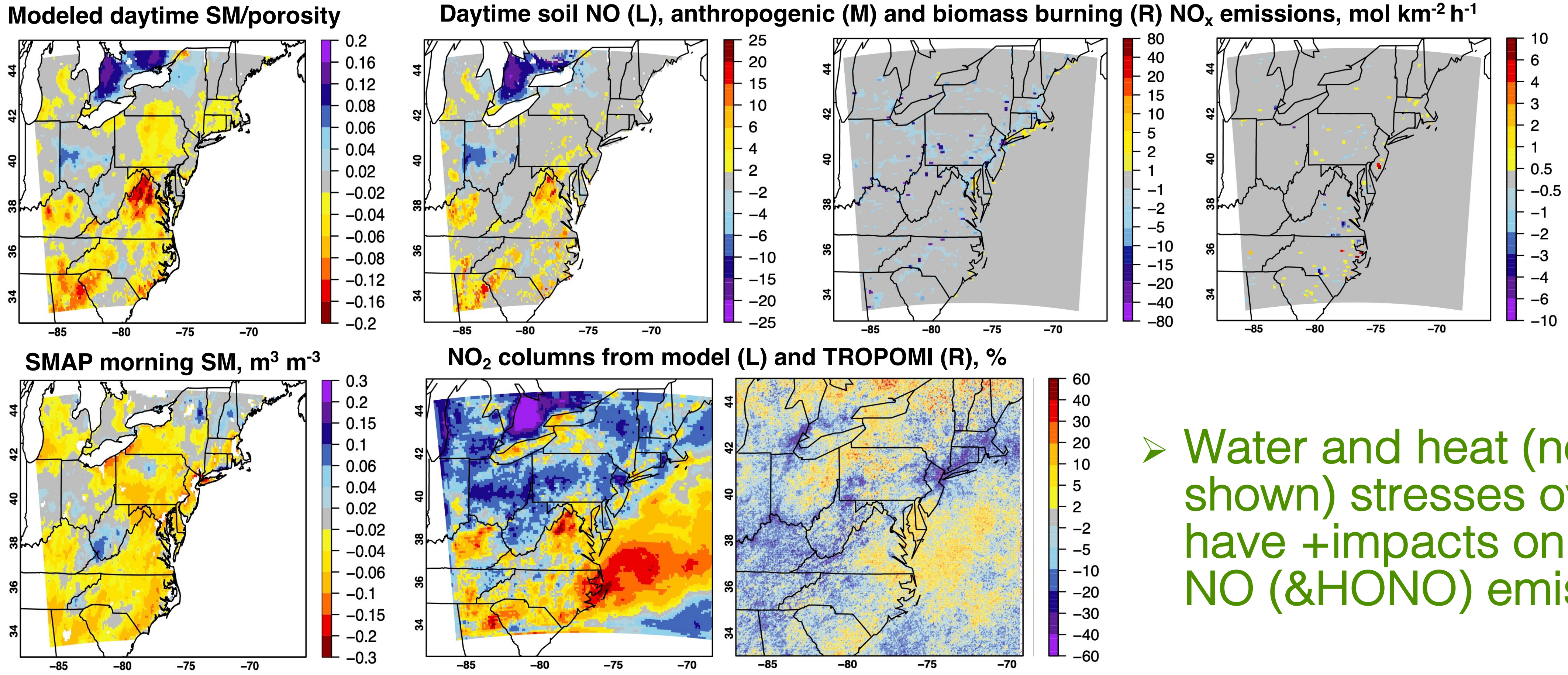
Soil HONO emissions
Derived from soil NO emissions and biome dependent scaling factors

MEGAN biogenic VOC emissions: Introduced a drought stress activity factor γ_d *(Jiang et al., 2018)* depending on the SM factor controlling stomatal resistance (β) and maximum carboxylation rate (V_{cmax})

$$\gamma_{d,\ \mathrm{isoprene}} = 1\ (\beta_t > 0.6)$$

$$\gamma_{d,\ \mathrm{isoprene}} = V_{cmax}/\alpha\ (\beta_t < 0.6,\ \alpha = 37)$$

Model helps connect interannual variability (MJJ 2022-2018) of NO_2 fields with emissions

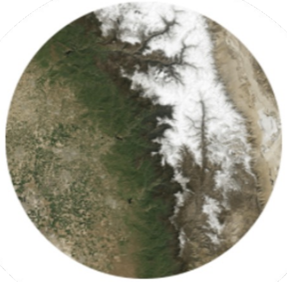


- Water and heat (not shown) stresses overall have +impacts on soil NO (&HONO) emissions.

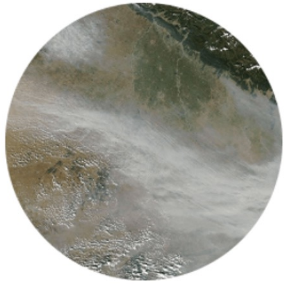
- Temporal changes in biogenic emissions, along with other (e.g., fire, anthropogenic, lightning) emissions and processes, contribute to interannual differences of NO_2 columns from model, that are overall qualitatively consistent with TROPOMI-based.
- Model uncertainty can be reduced by parameter/input tuning and land DA.

Summary and thoughts on future directions

- Three Noah-MP (“traditional” model structure) applications were presented, that advance our understanding of the connections between atmospheric chemistry and land surface conditions. In these studies, Noah-MP results were evaluated/improved by satellite data. Changes were made to Noah-MP related code/table as well as routines (e.g., emissions, deposition) in WRF-Chem.
- Interested in including nitrogen dynamics, which exists in other land models such as JULES and CLM for long. Cai et al. (2016) started to add such capability where the magnitude and spatiotemporal variability in nitrogen inputs (from deposition, fertilizer) may be better represented.


Water Availability


Vegetation Health


Air Quality


Water Quality

Figure source: GSFC food security site