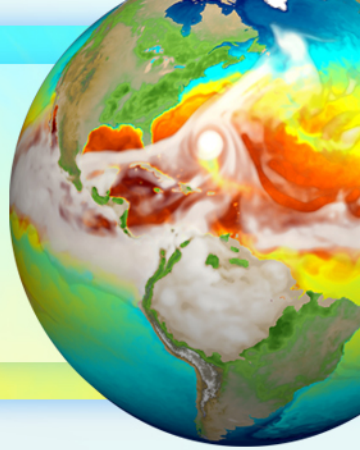


Process-based and machine learning fire representations in E3SM and interactions with the atmosphere

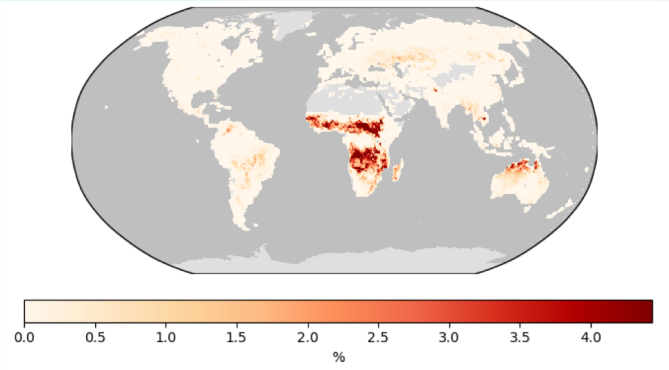
Qing Zhu[1], Li Xu[2], James T. Randerson[2], William J. Riley[1], Yang Chen[2], Natalie Mahowald[3], Katherine Mackey[2], Adam Pellegrini[4]

[1] Earth and Environment Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, CA.
[2] Department of Earth System Science, University of California, Irvine, CA.
[3] Department of Earth and Atmospheric Sciences, Cornell University, Ithaca, NY.
[4] Department of Earth System Science, Stanford University.

Science questions

- How does wildfire affect AOD, surface climate, and the carbon cycle?
- Can we improve the E3SM fire model, and what are the implications for the carbon cycle?

GFED observed burned area



MISR smoke plume height during fire peak seasons

remote sensing

MDPI

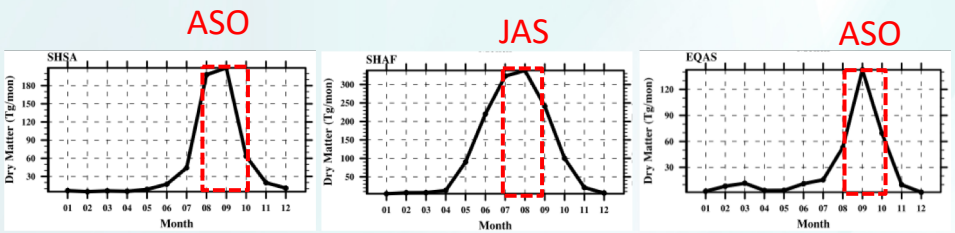
Article

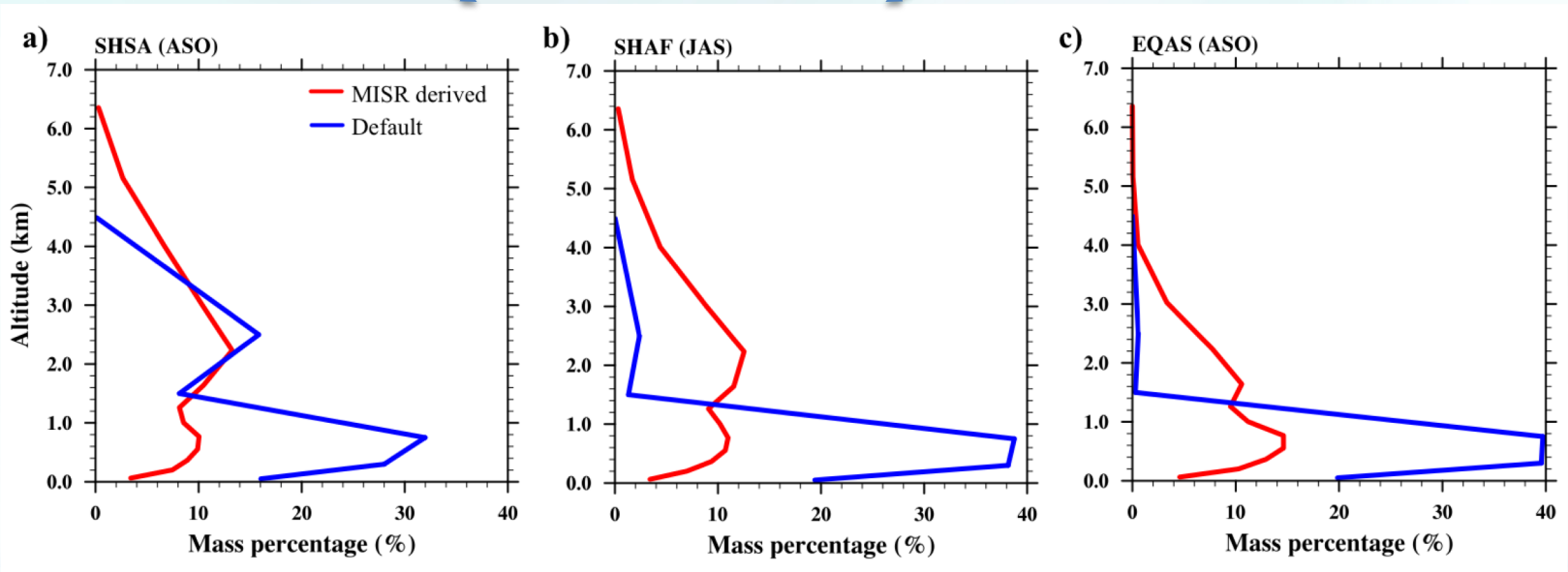
A Global Analysis of Wildfire Smoke Injection Heights Derived from Space-Based Multi-Angle Imaging

MariaVal Martin [1,†,*], Ralph A. Kahn [2,†] and Mika G. Tosca [3,4]

Martin et al. 2018; Zhu et al., 2018

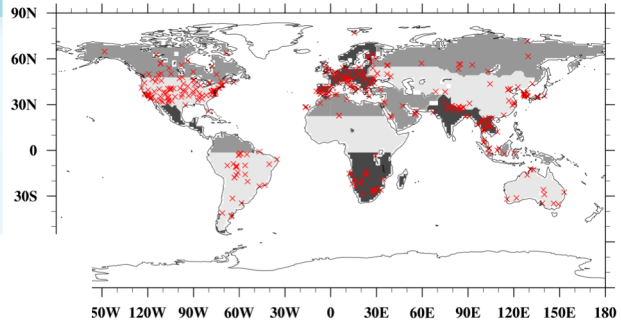
GFED4s Dry Matter Emission



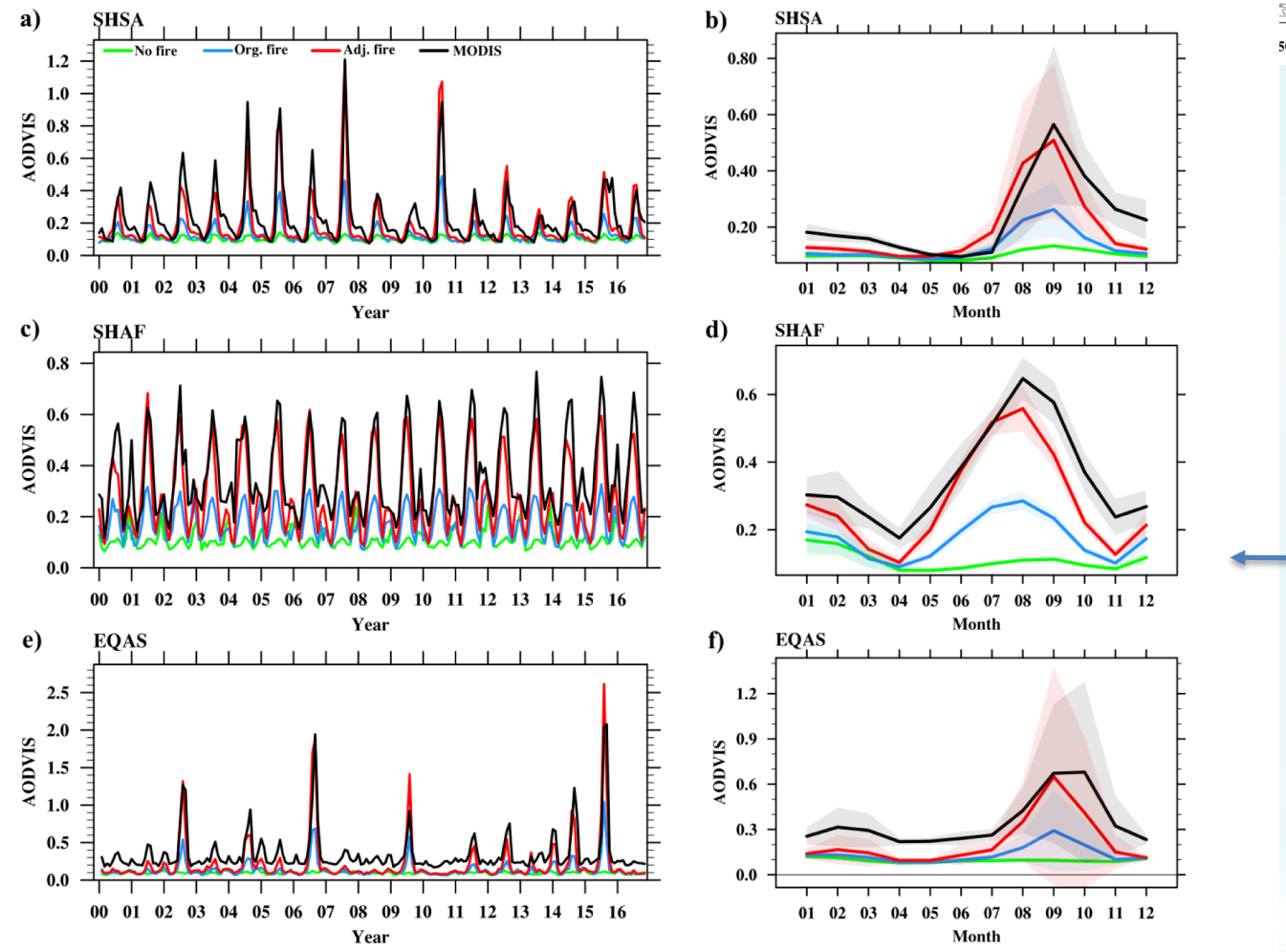


Xu et al., 2019 *in preparation*

Adjust Fire Emission Based on Observations



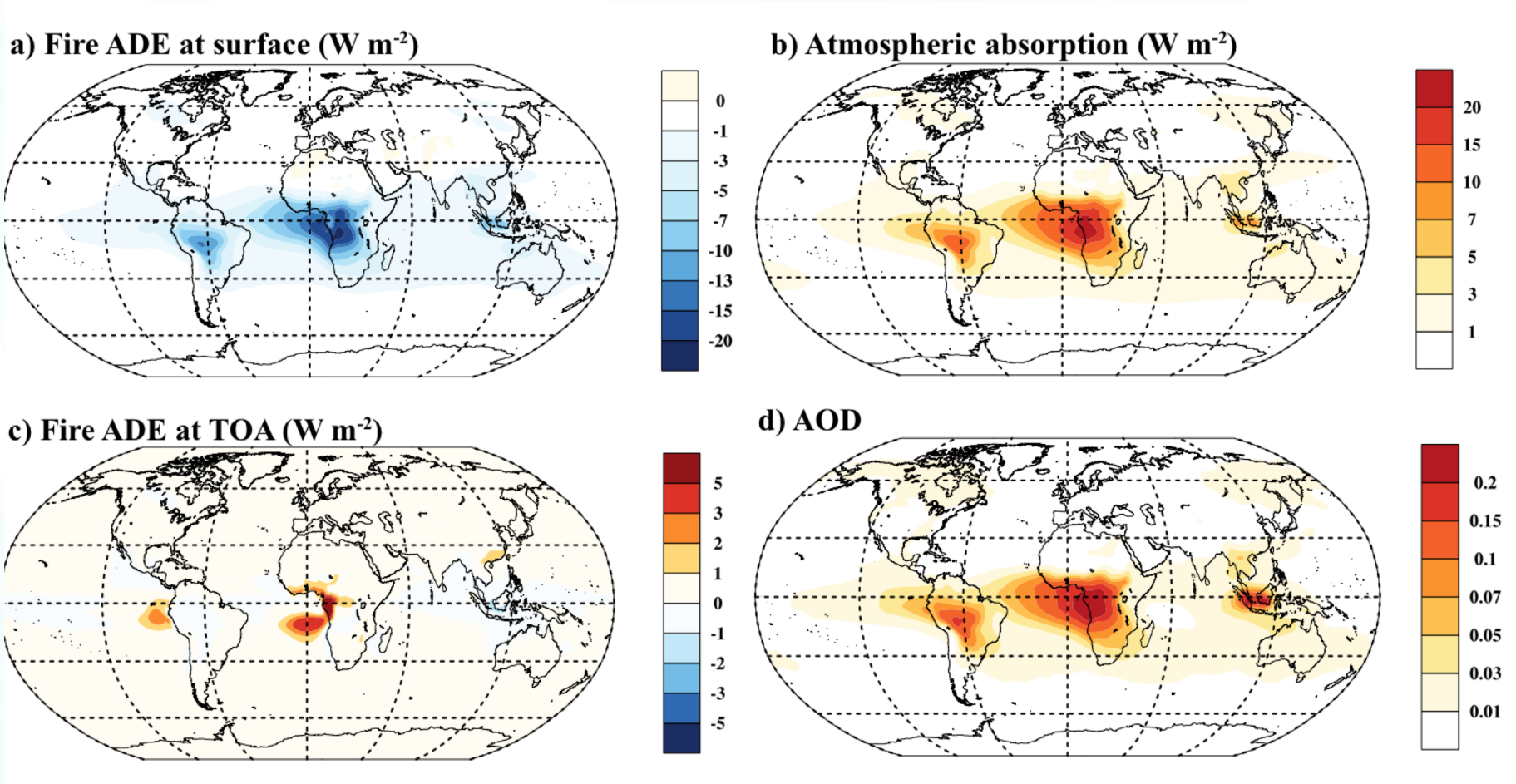
Location of AERONET sites chosen for the adjustment



Use MODIS AOD product to evaluate the adjustment

Xu et al., 2019 *in preparation*

Fire aerosols significantly affect AOD in the tropics, induce intense atmospheric absorption, and cause strong cooling at surface

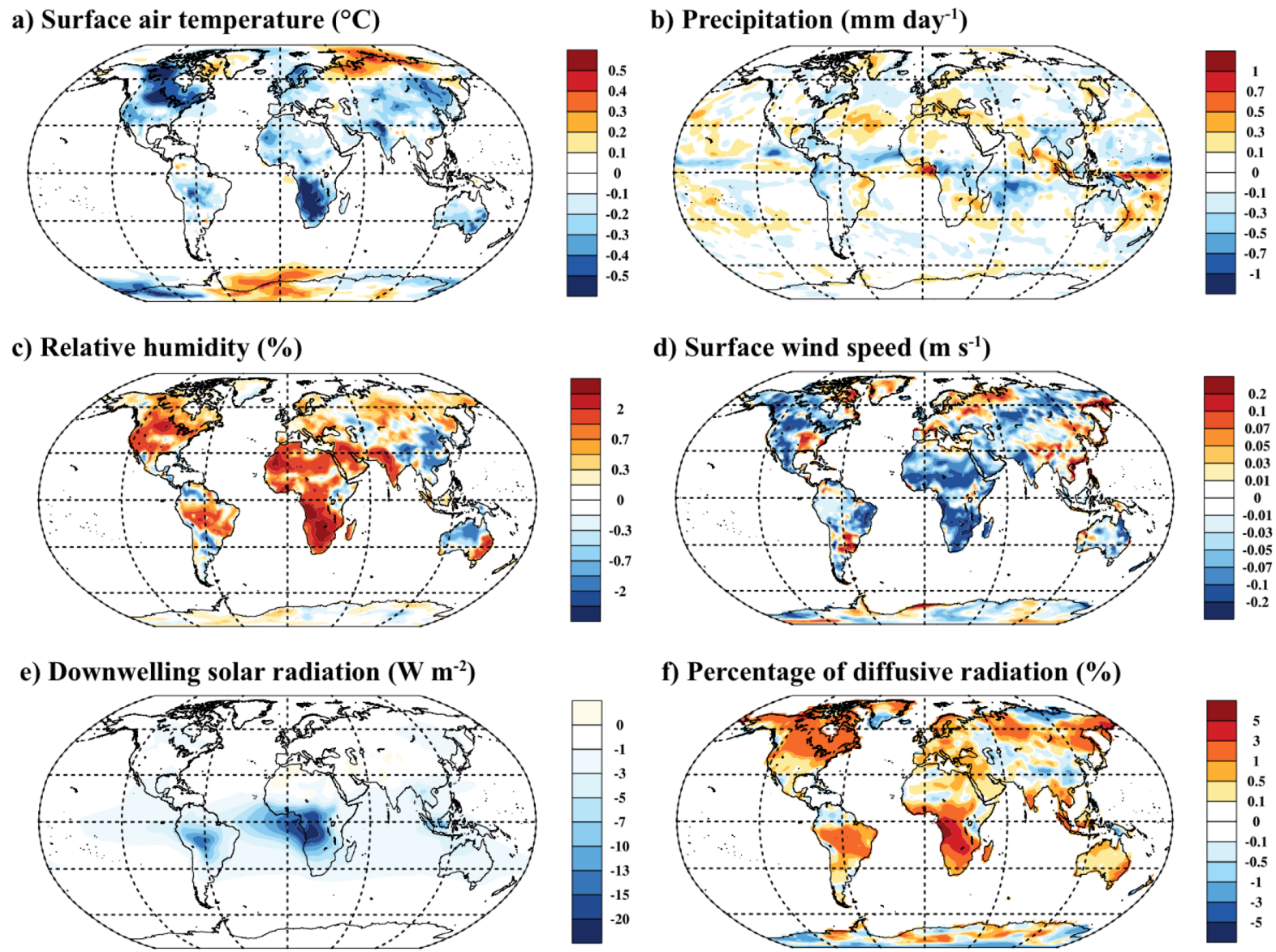


Xu et al., 2019 *in preparation*

E3SM Energy Exascale Earth System Model

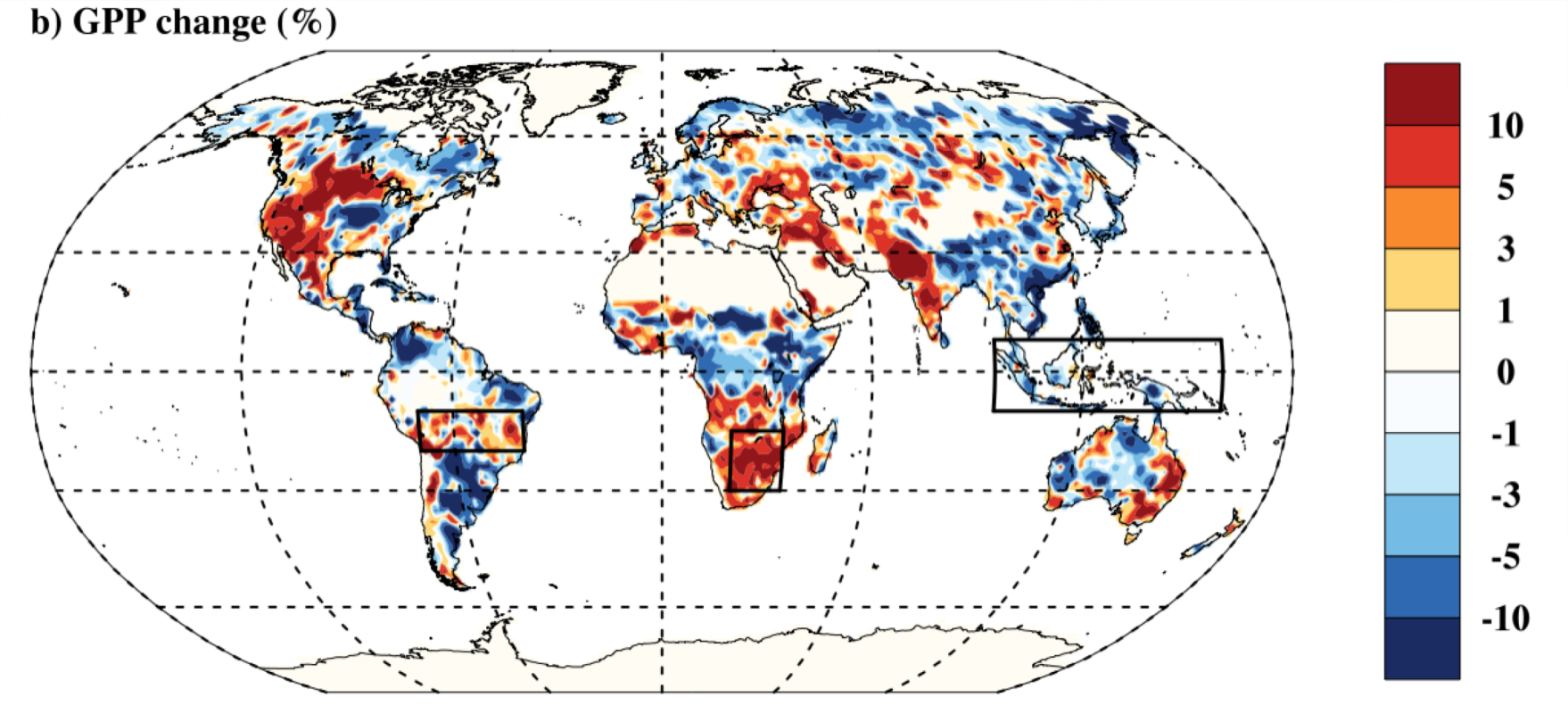
U.S. DEPARTMENT OF ENERGY

Fire aerosols affect near-surface climate



Xu et al., 2019 *in preparation*

Fire aerosols affect GPP: increases in South America and South Africa and decreases in equatorial Asia



Xu et al., 2019 *in preparation*

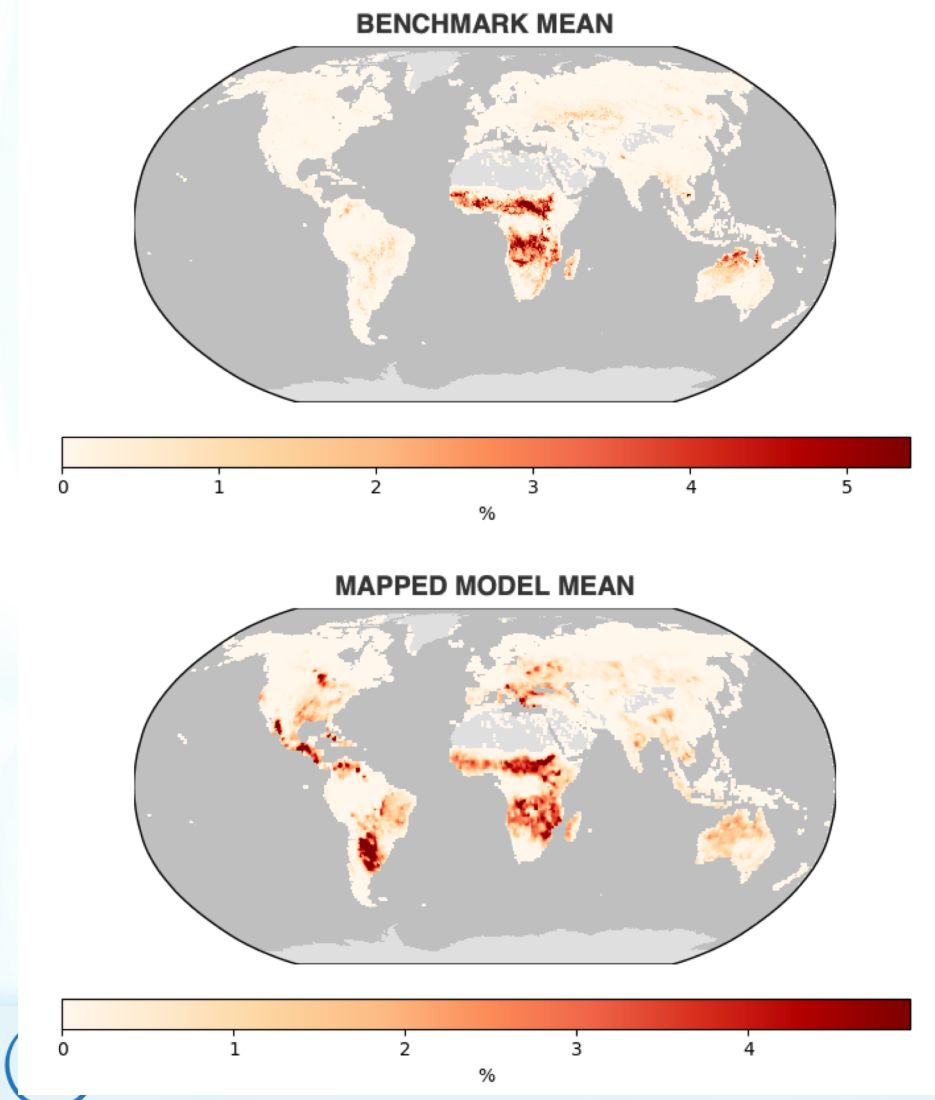
Quick summary

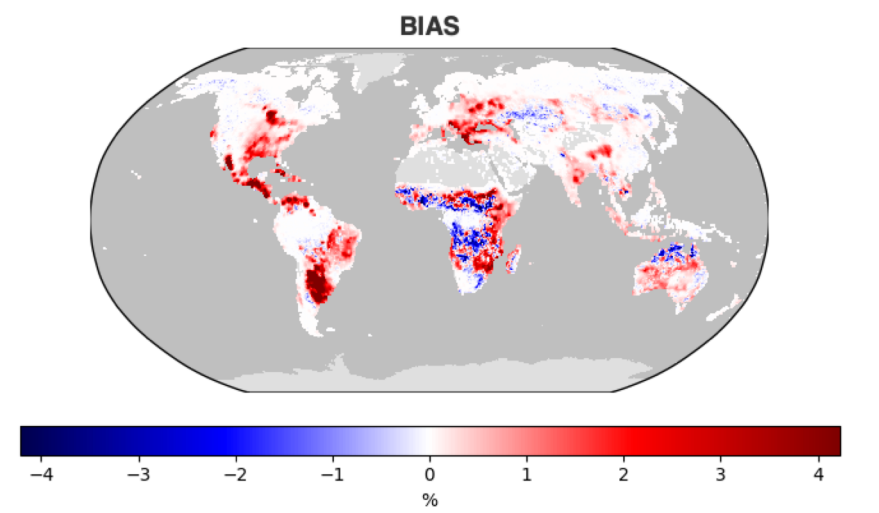
- Adjusted fire emissions better represent observed aerosol optical depth particularly during fire peak season in tropical fire regions.
- Fire aerosols induce the strong surface cooling through both scattering and absorption of sunlight.
- GPP responses to fire aerosols are complex and appears most sensitive to surface air temperature, relative humidity and available sunlight condition.

Science questions

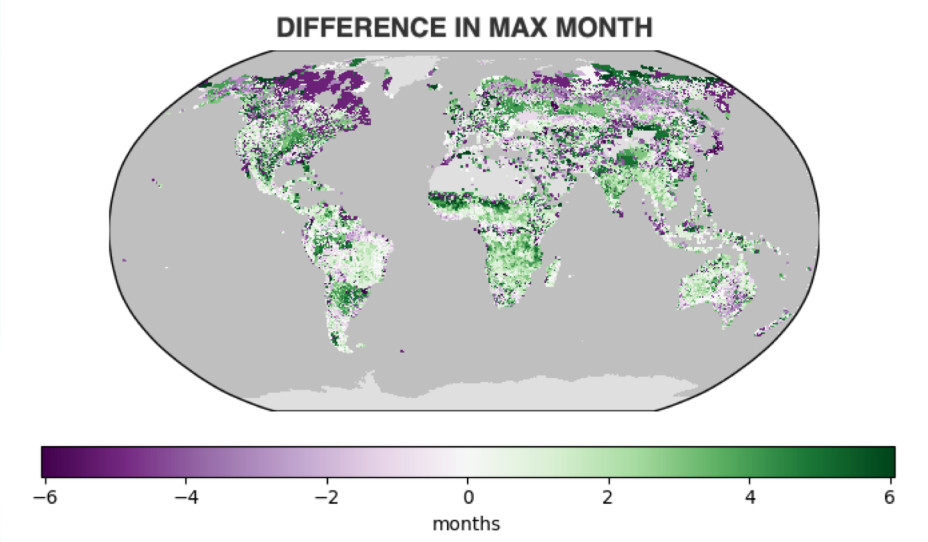
- How accurate is the current E3SM fire model in simulating emissions?
- How could machine learning help fire model parametrization?

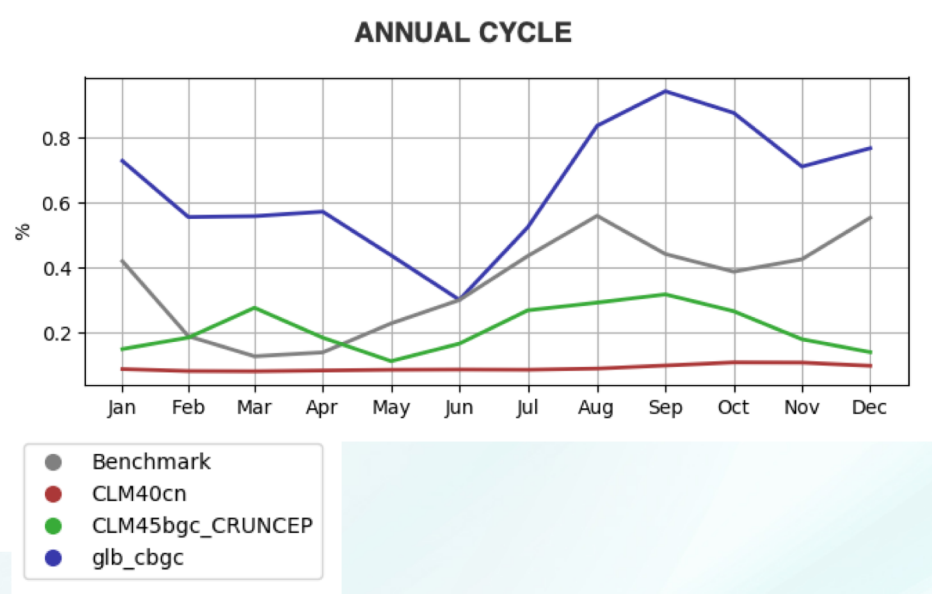
Coupled BGC experiment fire estimates





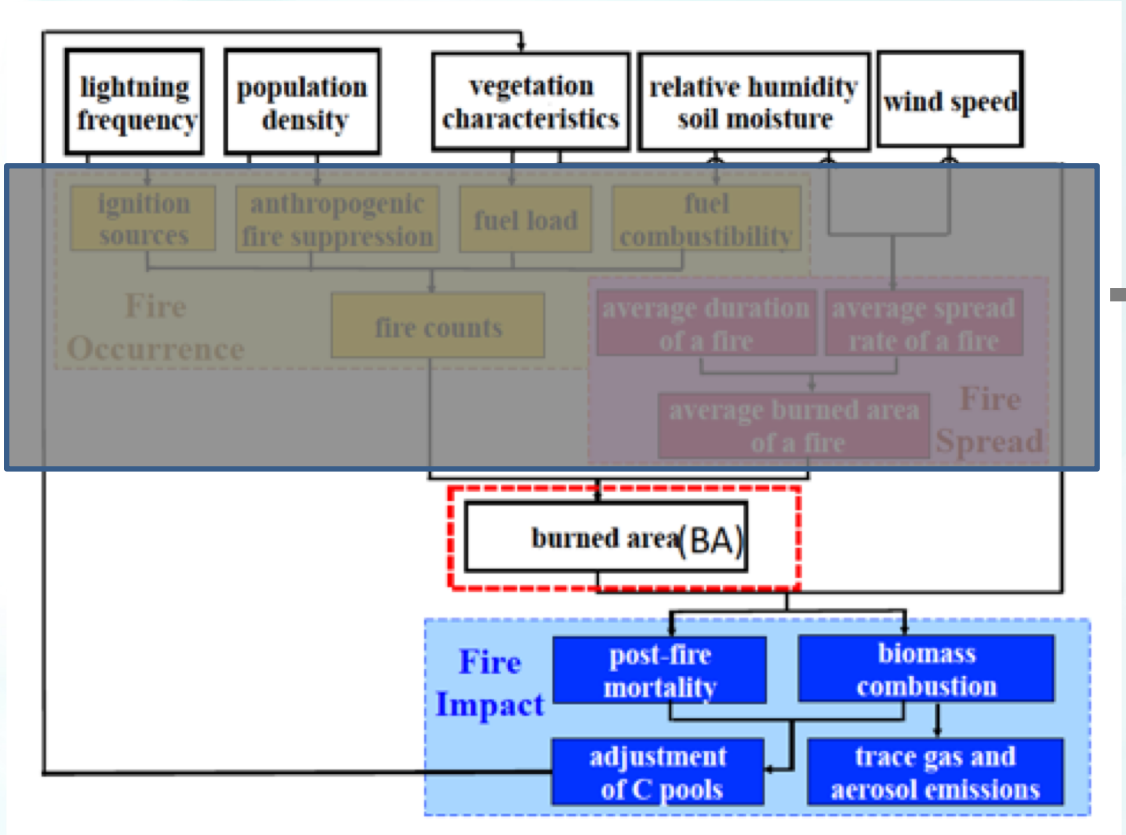
Coupled BGC experiment: Difference in month of maximum fire area



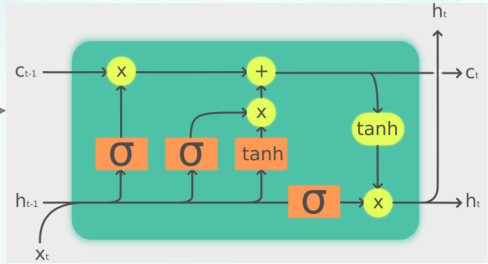


Conclusion: There are large biases in current model estimates of burned area and timing

Development of a Machine Learning Fire Model in E3SM



Surrogate fire model using recurrent neural network



Accuracy improvement: 50-90%

Parameterization time save: 99%

Inputs for ML fire model

Fuel condition

- fuel availability (live biomass and litter)
- fuel combustibility (soil wetness)

Climate

- Weather (air temperature, air relative humidity, pressure)
- Wind speed (fire spread and geometry)

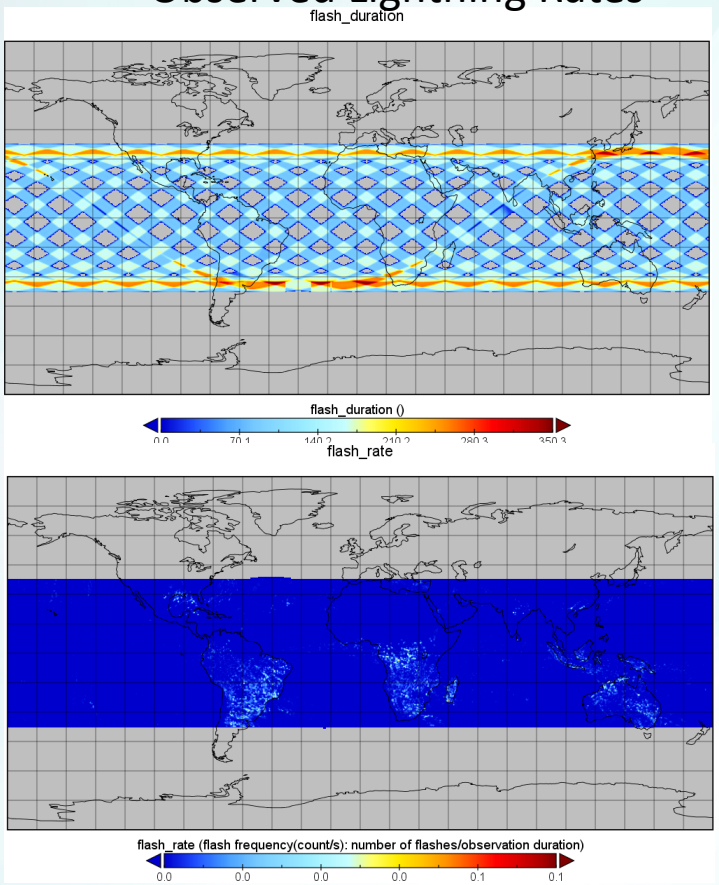
Nature ignition

- natural ignition (lighting density)

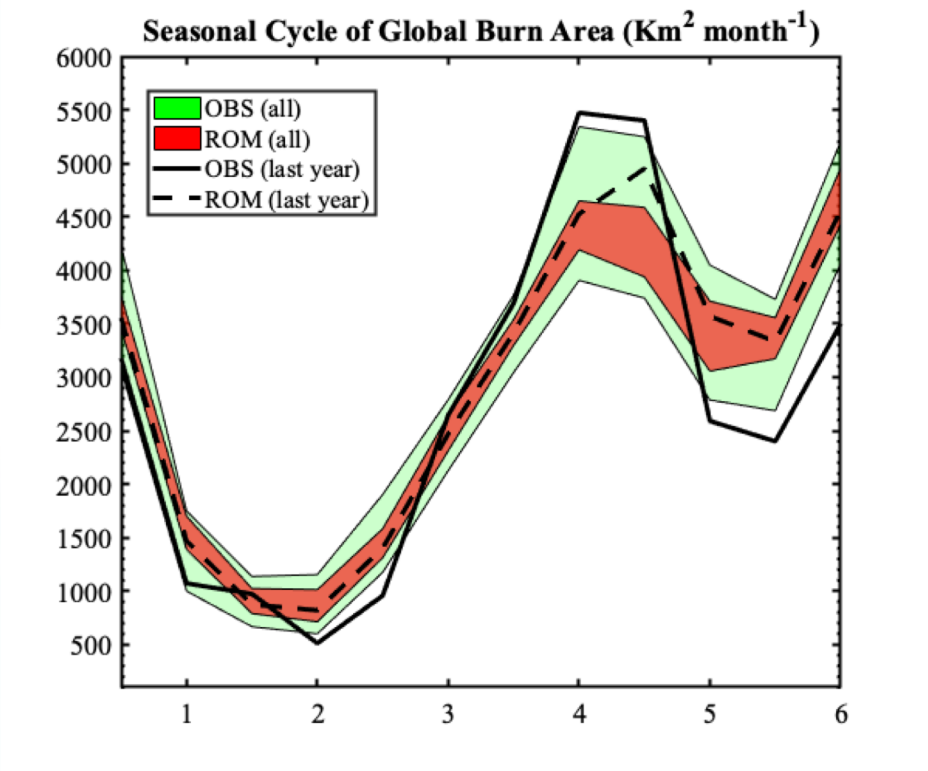
Anthropogenic

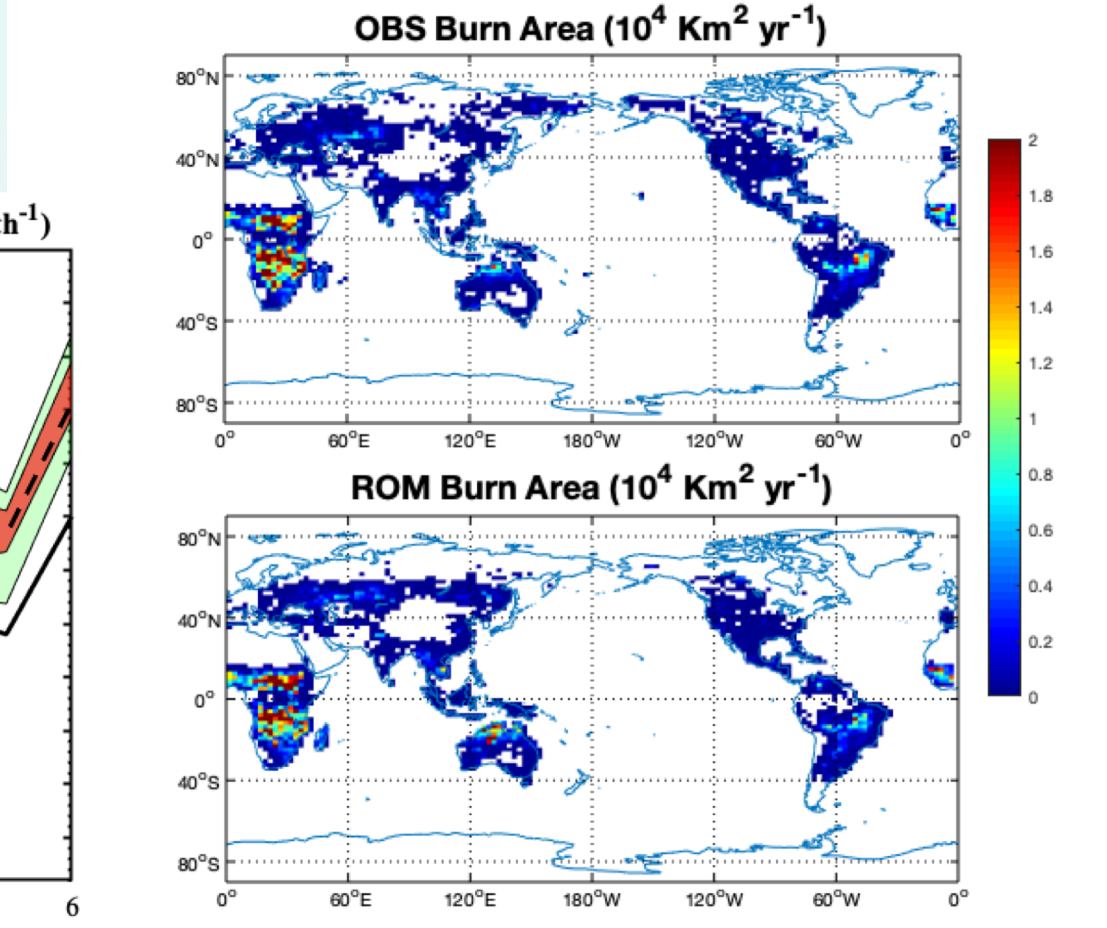
- Seasons (for agricultural fire)
- land surface classification (grass, tree, crop); Land use
- Demographic impacts (population density)

Observed Lightning Rates



Surrogate fire model in E3SM: evaluation





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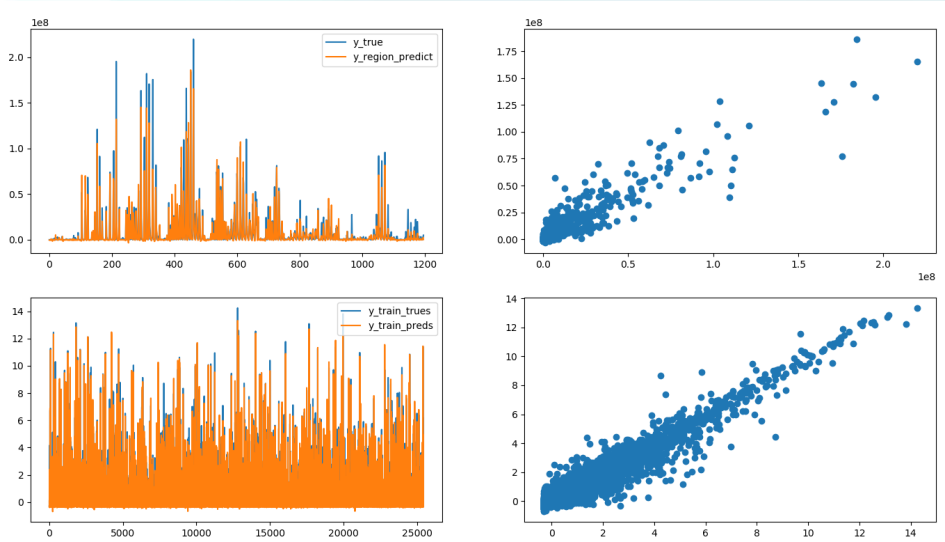
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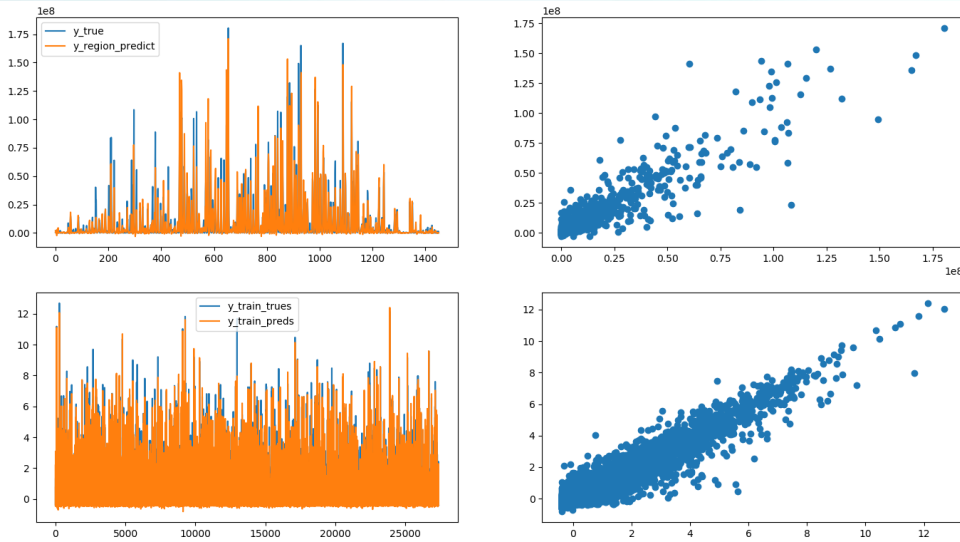
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One ML model for all regions

GFED Region	NHSA	SHSA	NHAF	SHAF
correlation coefficient	0.539	0.543	0.873	0.896

ML models for individual region

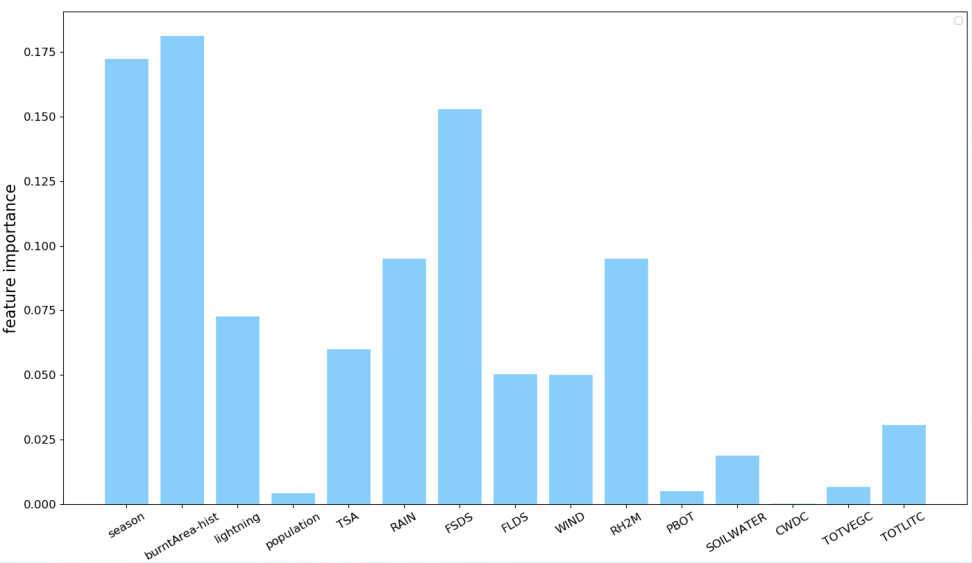
GFED Region	NHSA	SHSA	NHAF	SHAF
correlation coefficient	0.826	0.679	0.848	0.855

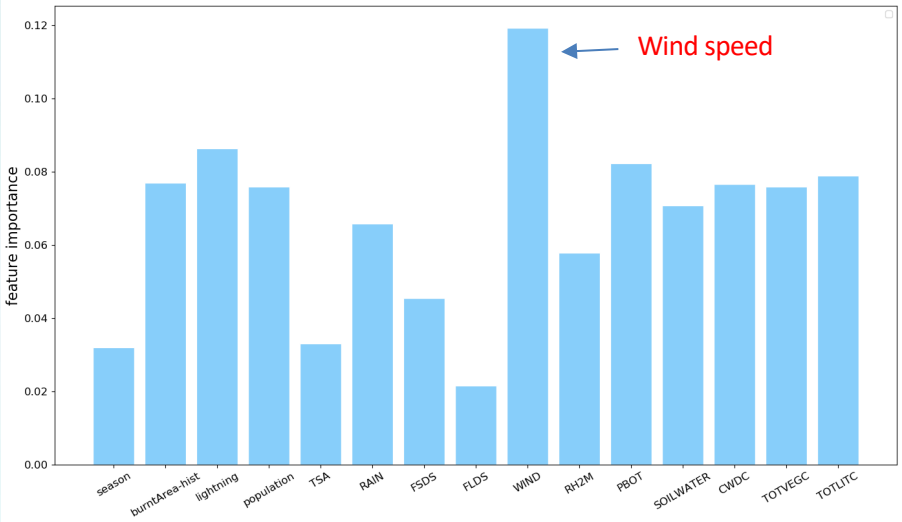
Analytic capability: Attention mechanism

Case Study: *a wildfire event*

True burnt area: **611,997** hectares
Predicted burnt area: **613,250** hectares

Informs most important forcing variables





Quick summary

- Machine Learning surrogate fire module produced high accuracy wild fire burned area
- Parameterization time could be reduced from ~weeks to ~minutes
- Powerful analytic capability with Attention mechanism

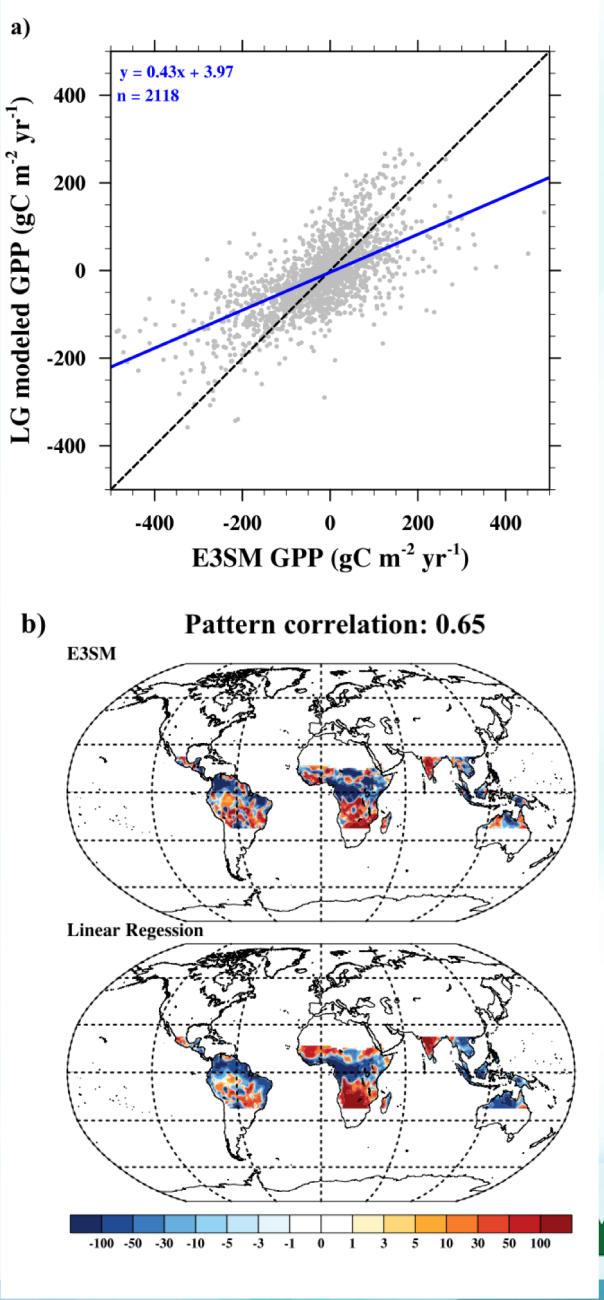
Extras

Experiments

Experiment	Description
No fire	Includes all aerosol and trace species default in the E3SM model except black carbon, primary organic matter, secondary organic aerosol precursor gases, SO_2(gas) from fires.
Org. fire	Includes all aerosol and trace species default in the E3SM model with fire-emitted black carbon, primary organic matter, secondary organic aerosol precursor gases, SO_2(gas) from the original GFED4s emission data.
Adj. fire	Includes all aerosol and trace species default in the E3SM model with adjusted fire emissions of black carbon, primary organic matter, secondary organic aerosol precursor gases, SO_2(gas).

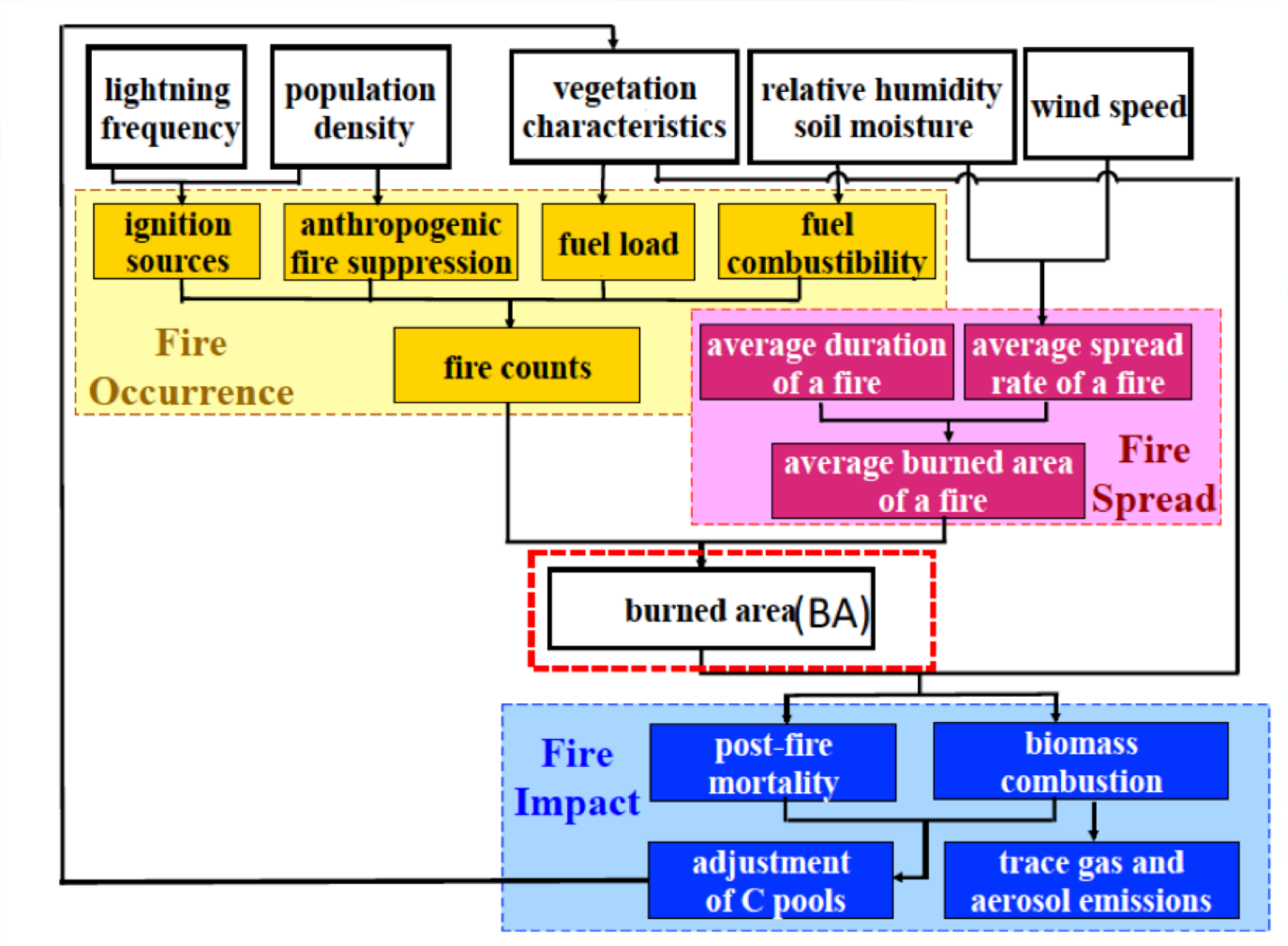
Multivariate Linear regression model of near-surface climate in tropics

Variables	Contribution (%)
Surface air temperature	30
Relative humidity	27
Downward shortwave radiation	17
Surface wind speed	11
Diffusive radiation fraction	8
Surface soil water	4
Precipitation	4

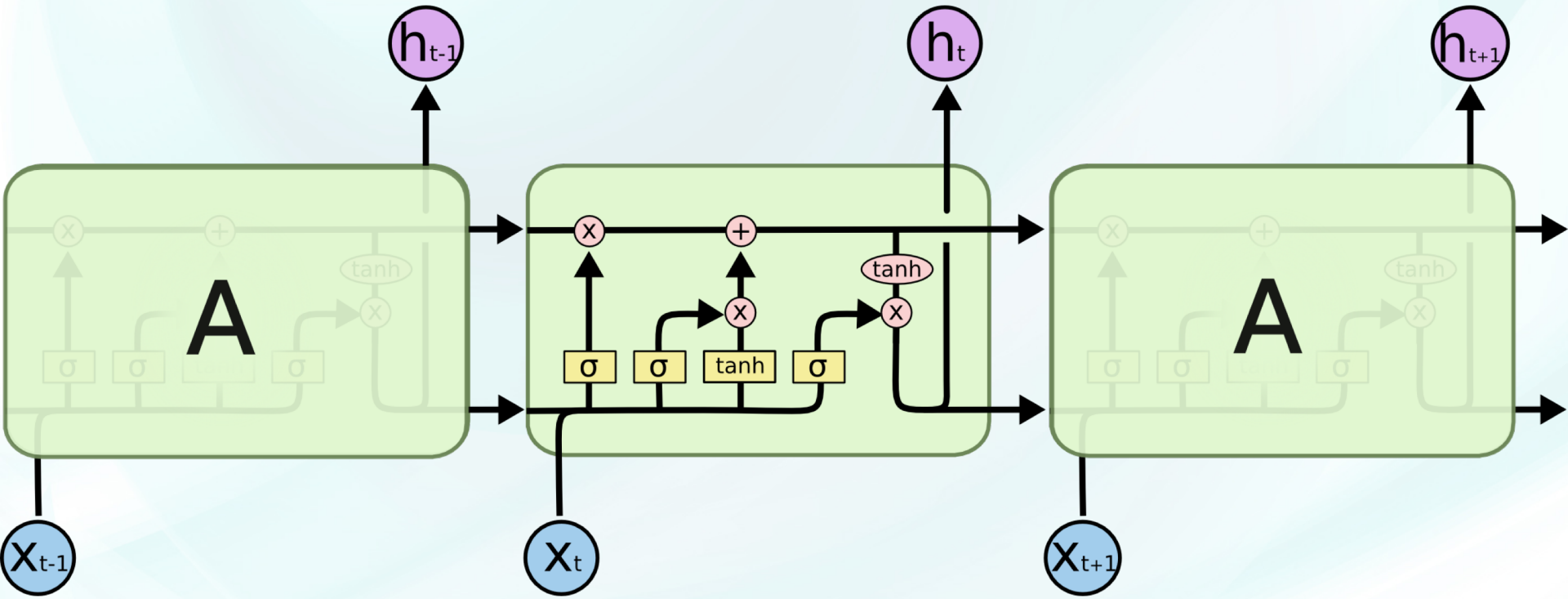


Xu et al., 2019 *in preparation*

E3SM fire model



Surrogate fire model in E3SM: model structure



Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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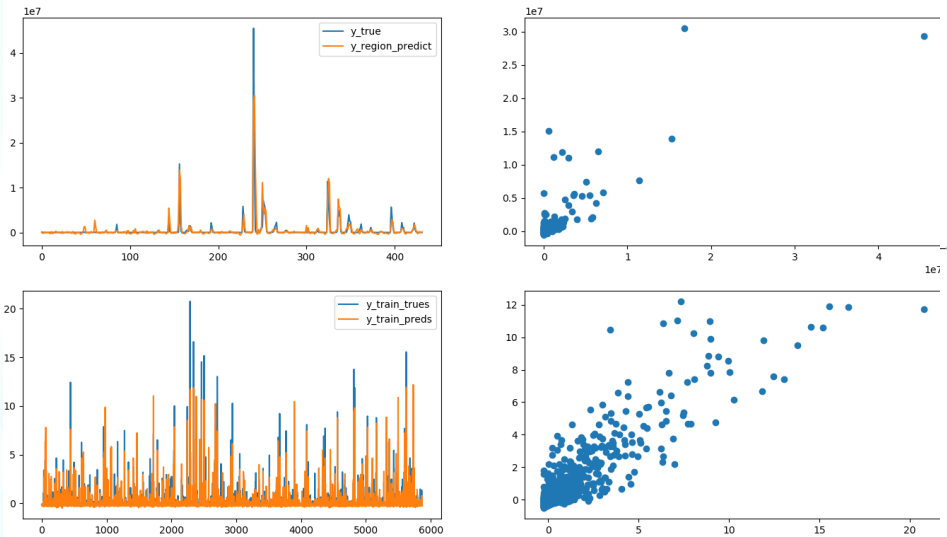
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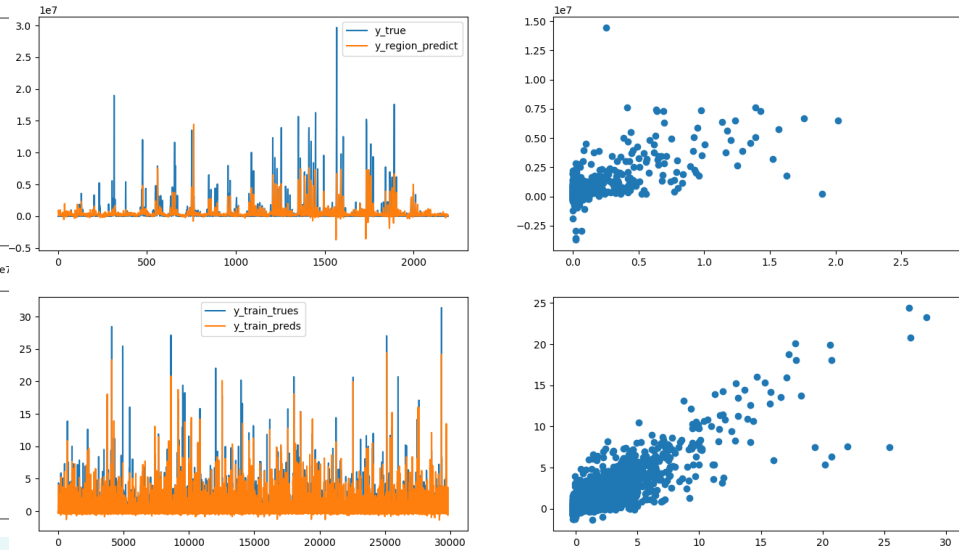
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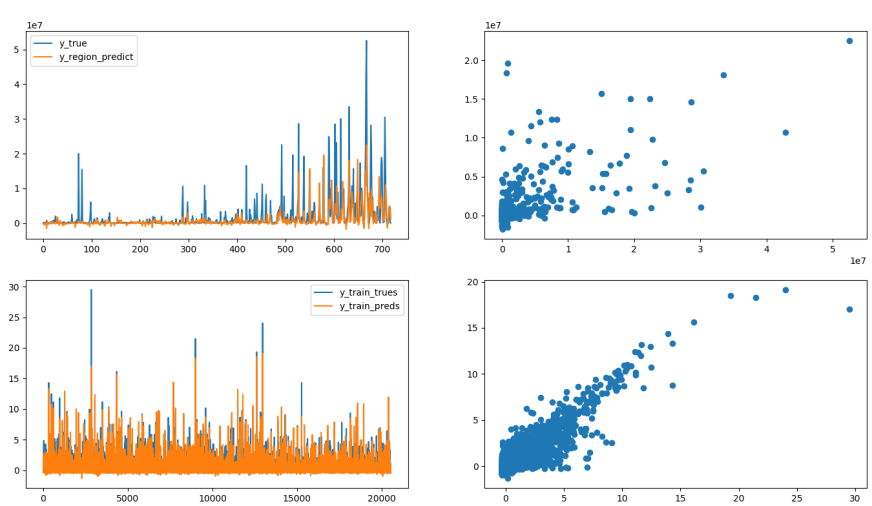
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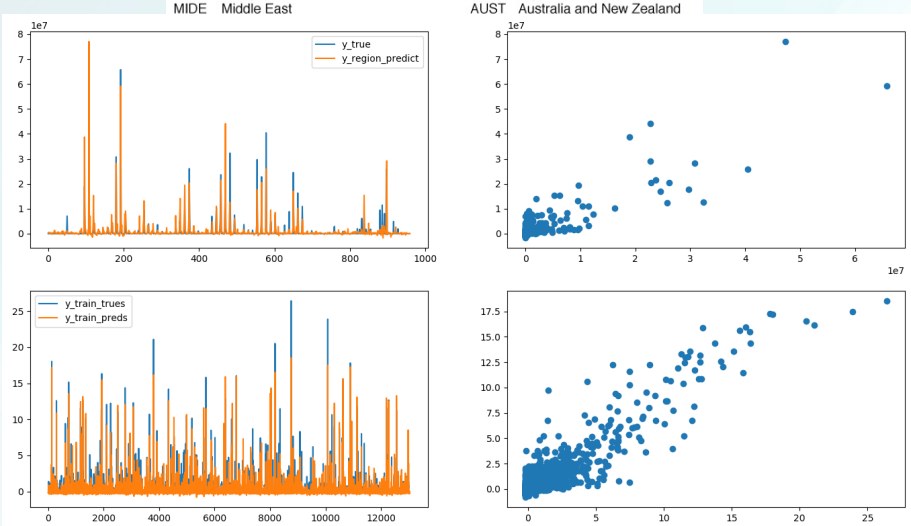
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y_train_preds

One model for all six regions

n	NHSA	SHSA	NHAF	SHAF	SEAS
icient	0.539	0.543	0.873	0.896	0.753
ance	0.120	0.269	0.749	0.686	0.534

n	NHSA	SHSA	NHAF	SHAF	SEAS
icient	0.826	0.679	0.848	0.855	0.624
ance	0.675	0.273	0.719	0.723	0.384