# Wildfire modeling with E3SM and machine learning techniques

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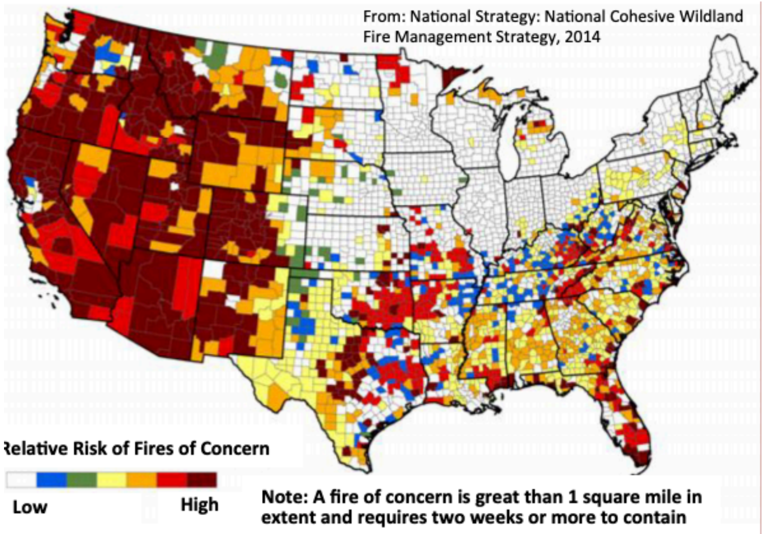
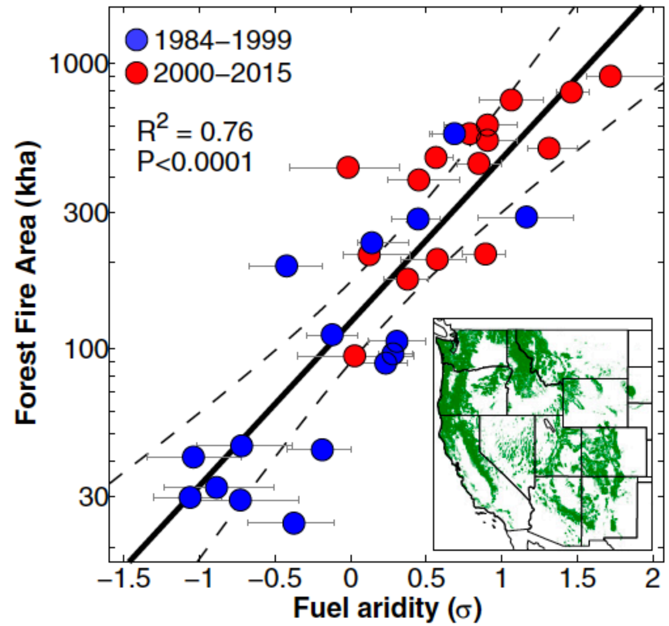


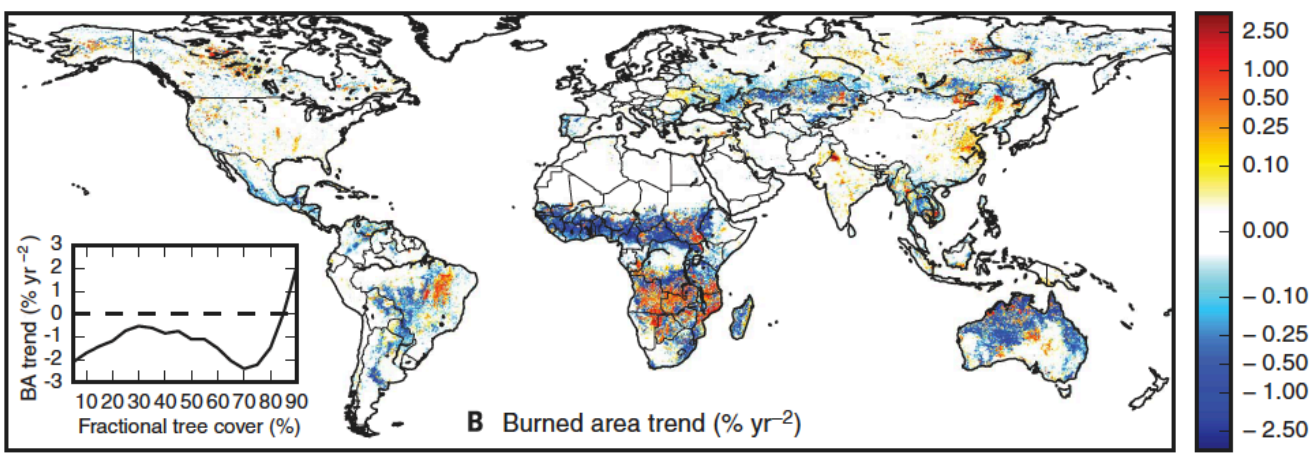

NOAA




Drier climate

Higher fire risk

Abatzoglou 2016



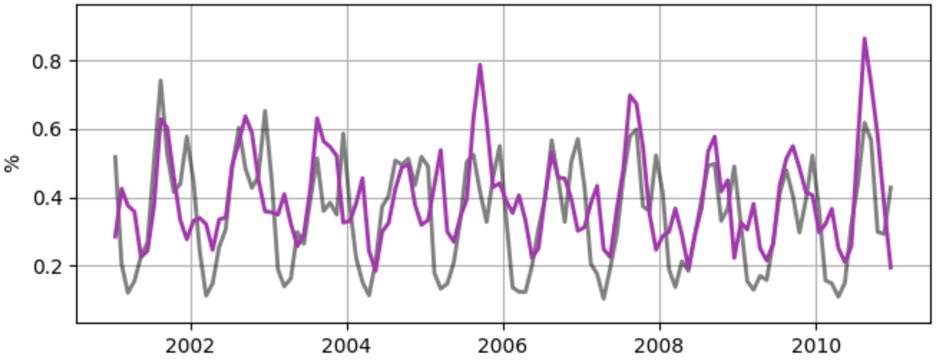

Denser population

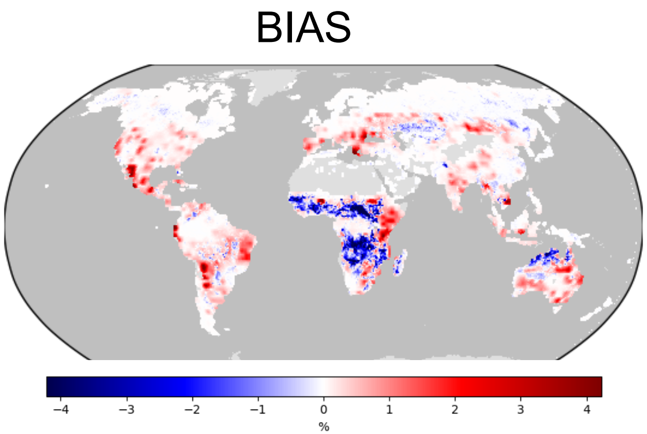
Lower burn area

Andela 2017

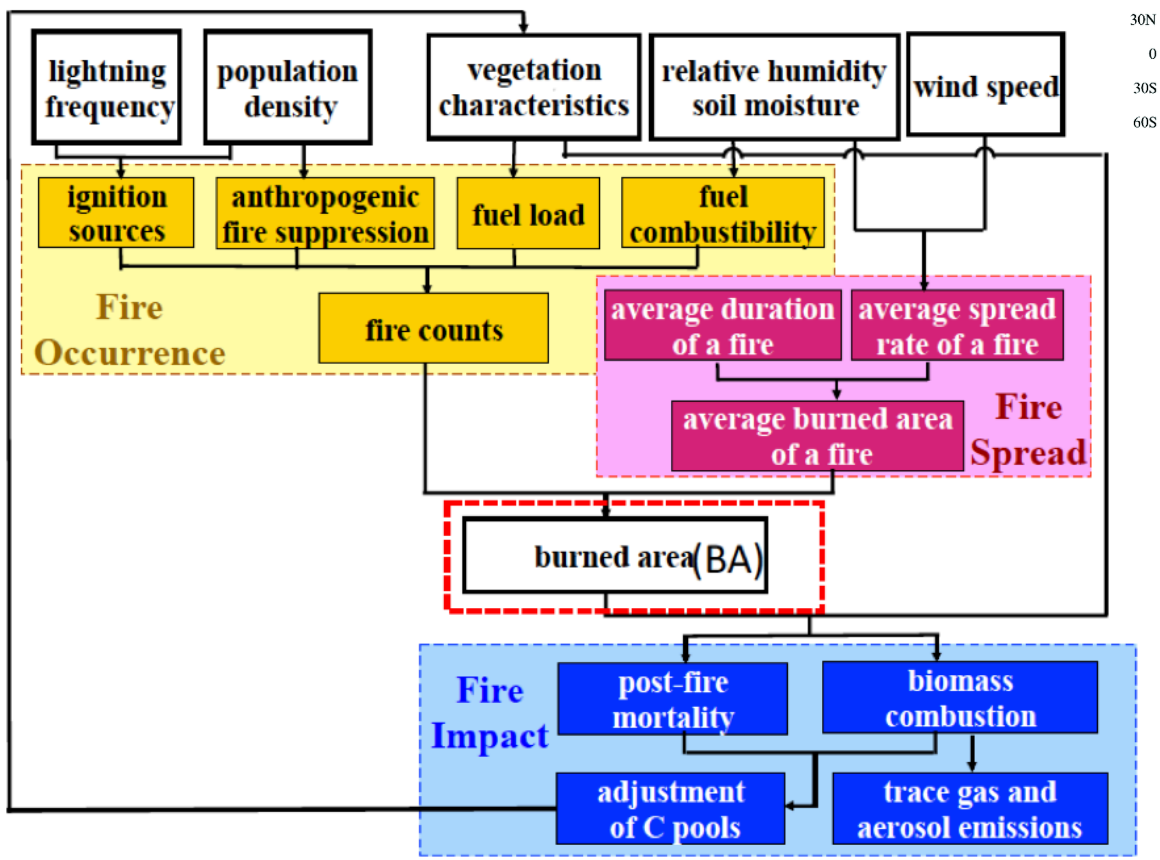
# Science Questions

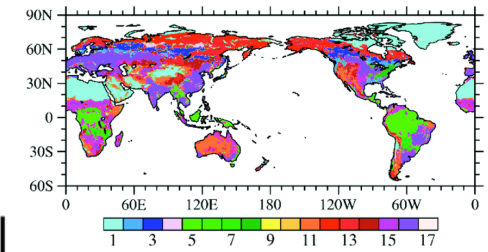
- How accurate is the current E3SM fire model in simulating burn area?
- How could machine learning help fire model parametrization?

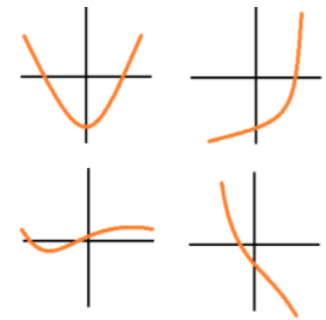


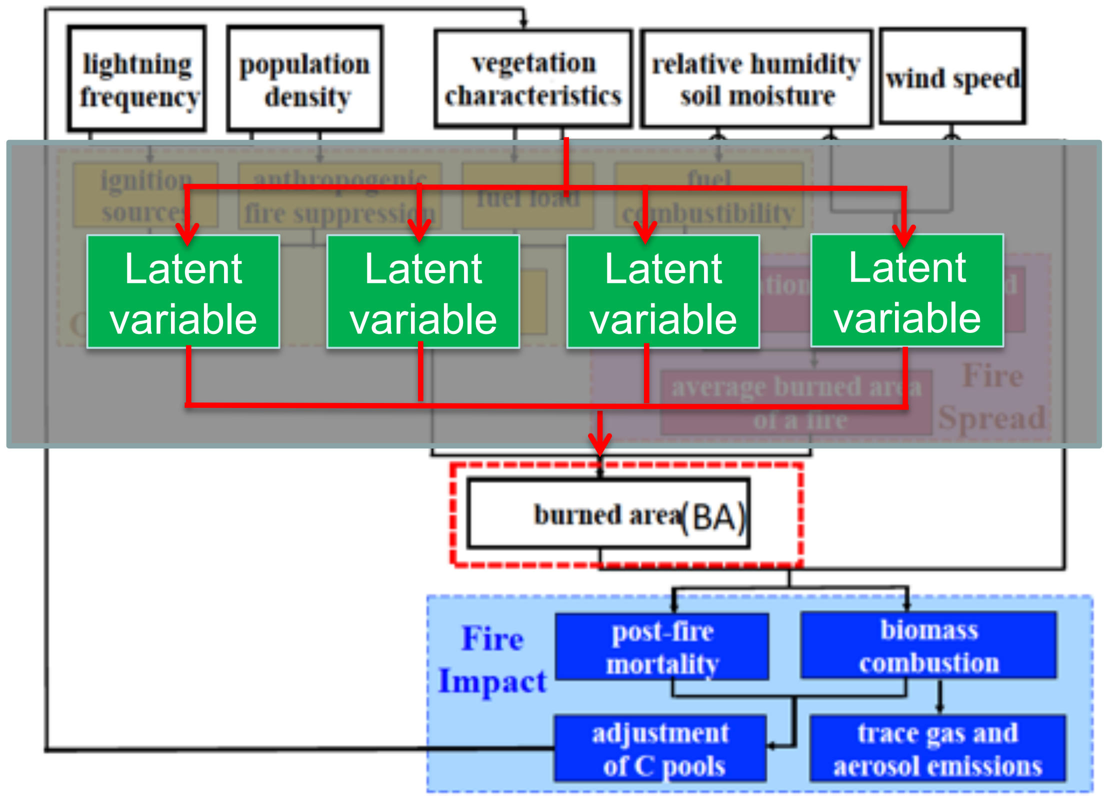
# E3SM fire model

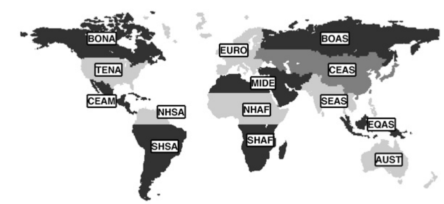


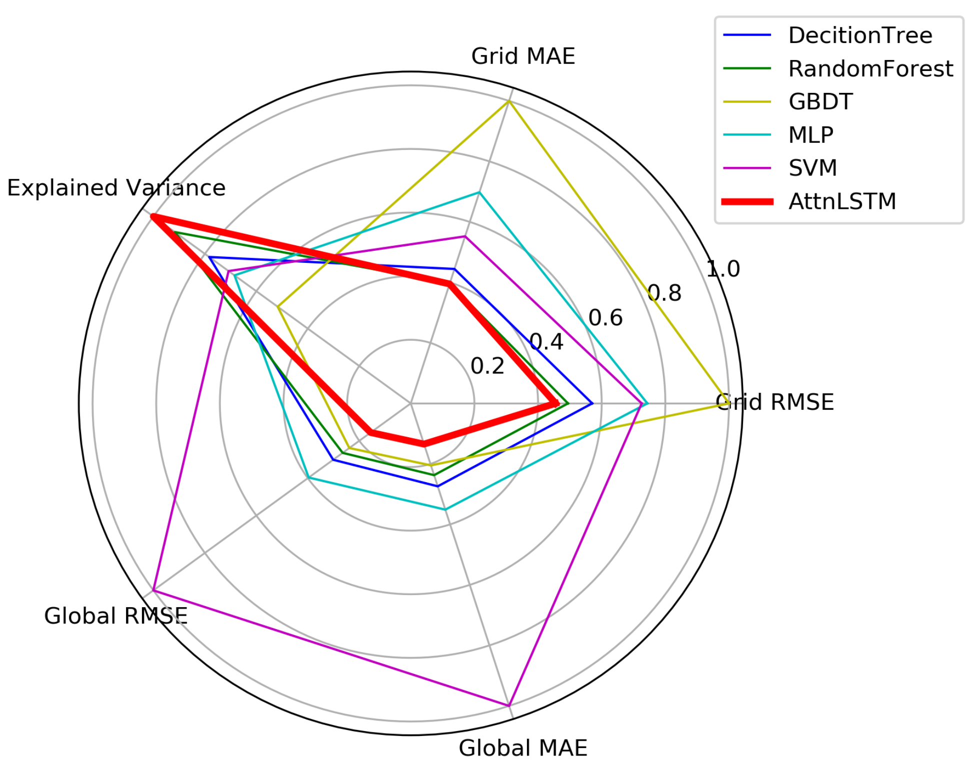



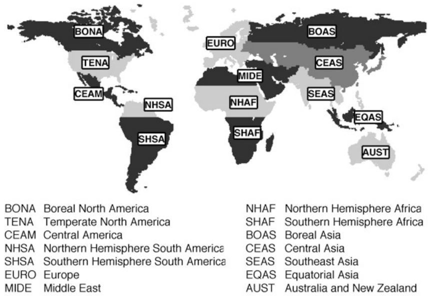
# Development of a Machine Learning Fire Model in E3SM




BONA Boreal North America
TENA Temperate North America
CEAM Central America
NHSA Northern Hemisphere South America
SHSA Southern Hemisphere South America
EURO Europe
MIDE Middle East
NHAF Northern Hemisphere Africa
SHAF Southern Hemisphere Africa
BOAS Boreal Asia
CEAS Central Asia
SEAS Southeast Asia
EQAS Equatorial Asia
AUST Australia and New Zealand




| Model | Grid RMSE | Grid MAE | Global RMSE | Global MAE | Global Explained Variance |
|---|---|---|---|---|---|
| DecitionTree | 0.064337 | 0.00897 | 27.282946 | 24.113867 | 0.618629 |
| RandomForest | 0.055752 | 0.008004 | 23.945963 | 20.859749 | 0.724087 |
| GBDT | 0.112835 | 0.020174 | 21.605206 | 18.018206 | 0.408553 |
| MLP | 0.083888 | 0.014080 | 35.889773 | 30.894498 | 0.541029 |
| SVM | 0.081880 | 0.011141 | 90.508528 | 87.970343 | 0.55925 |
| AttnLSTM | 0.051353 | 0.007965 | 14.100684 | 11.831382 | 0.790124 |

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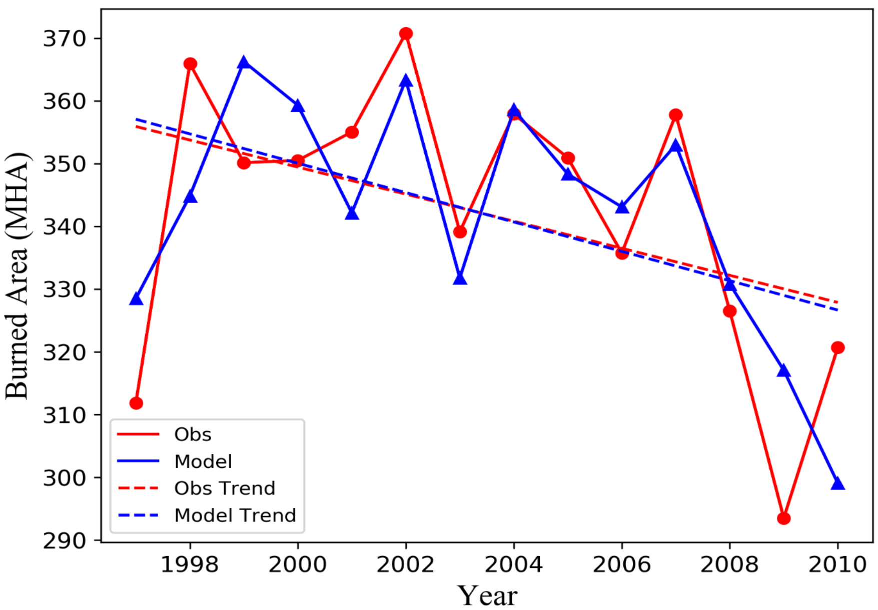
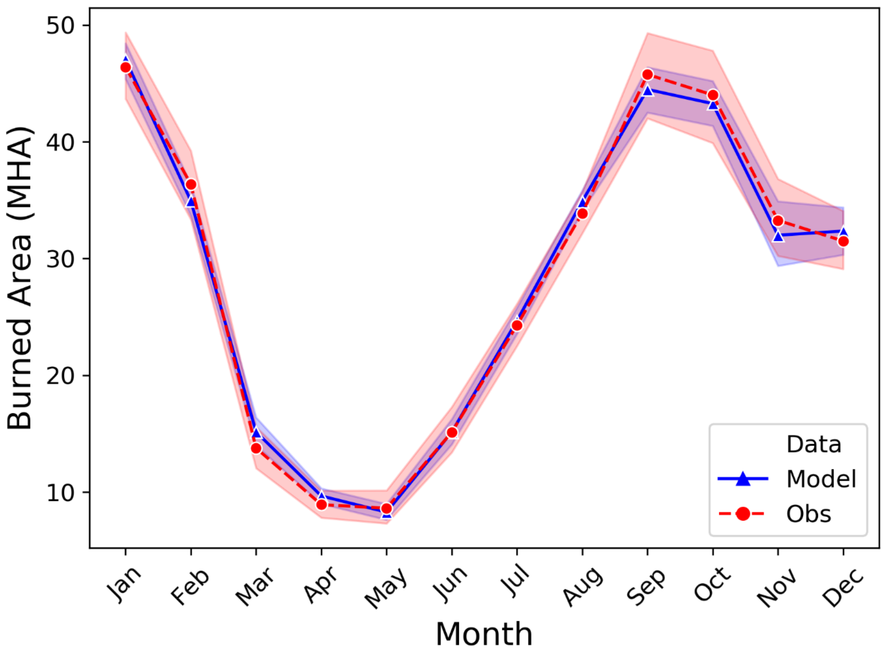
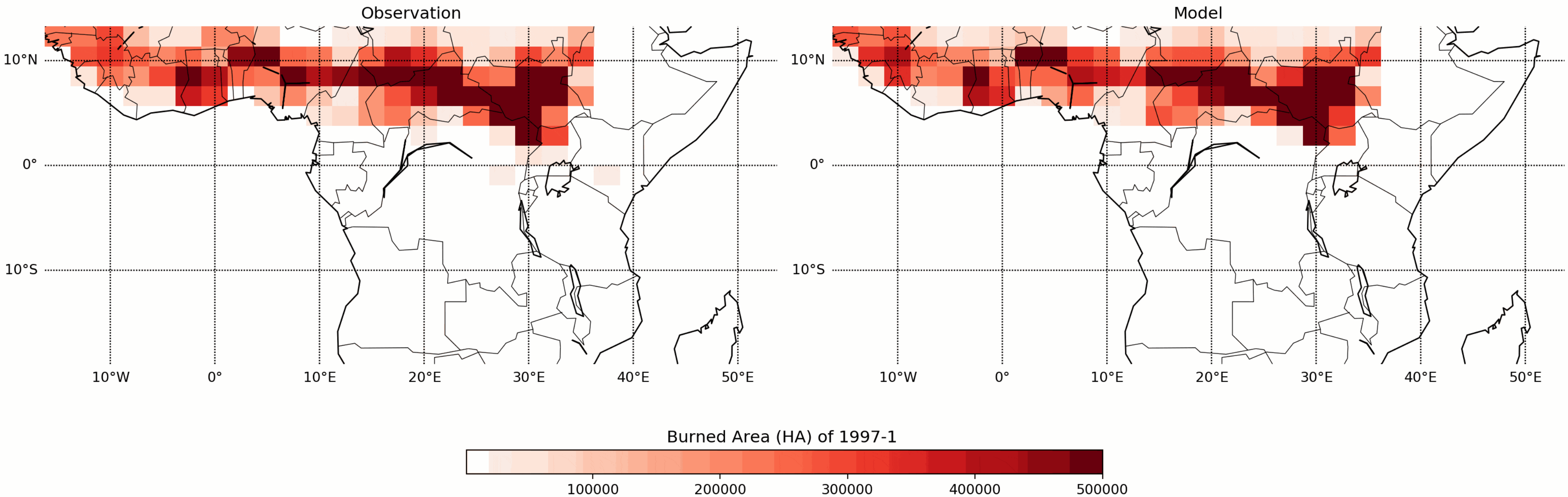


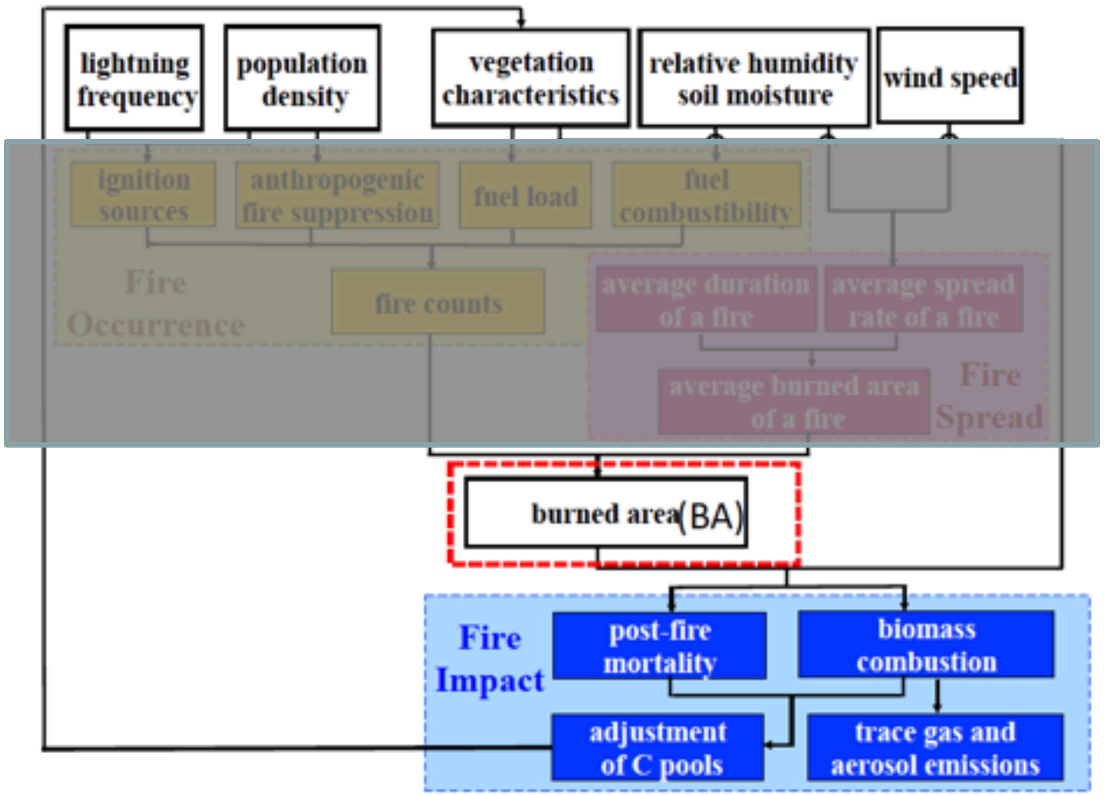



# Critical fire zone

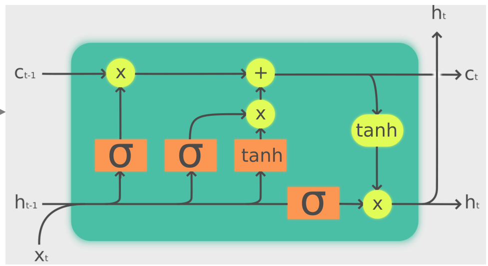

| | | | |
|---|---|---|---|
| BONA | Boreal North America | NHAF | Northern Hemisphere Africa |
| TENA | Temperate North America | SHAF | Southern Hemisphere Africa |
| CEAM | Central America | BOAS | Boreal Asia |
| NHSA | Northern Hemisphere South America | CEAS | Central Asia |
| SHSA | Southern Hemisphere South America | SEAS | Southeast Asia |
| EURO | Europe | EQAS | Equatorial Asia |
| MIDE | Middle East | AUST | Australia and New Zealand |



# Development of a Machine Learning Fire Model in E3SM

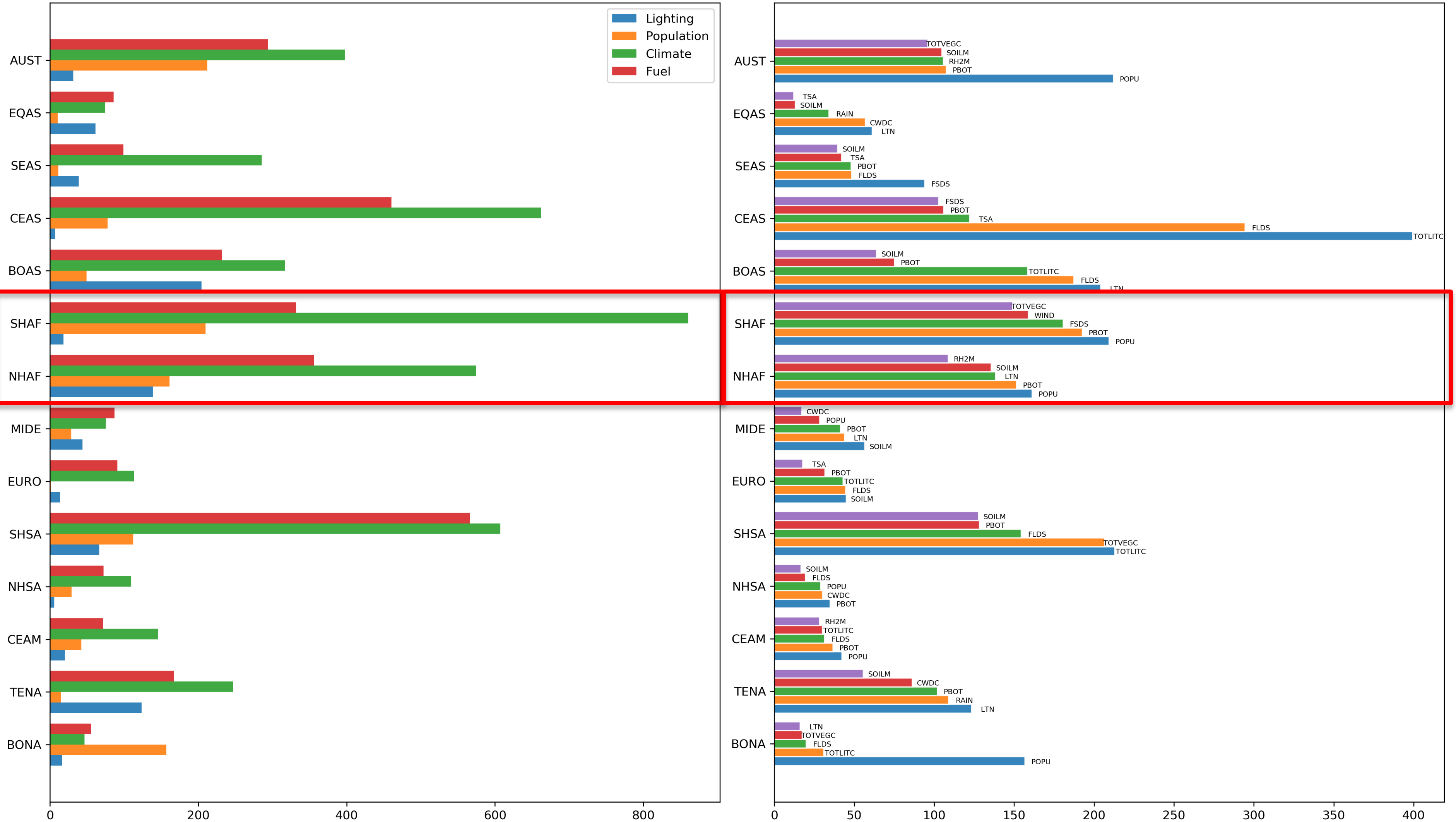



Surrogate fire model using recurrent neural network




Accuracy improvement: **50-90%**

Parameterization time save: **>99%**


Lighting
Population
Climate
Fuel
AUST
EQAS
SEAS
CEAS
BOAS
SHAF
NHAF
MIDE
EURO
SHSA
NHSA
CEAM
TENA
BONA
0
200
400
600
800
TOTVEGC SOILM RH2M PBOT POPU
TSA SOILM RAIN CWDC LTN
SOILM TSA PBOT FLDS FSDS
FSDS PBOT TSA FLDS TOTLITC
SOILM PBOT TOTLITC FLDS LTN
TOTVEGC WIND FSDS PBOT POPU
RH2M SOILM LTN PBOT POPU
CWDC POPU PBOT LTN SOILM
TSA PBOT TOTLITC FLDS SOILM
SOILM PBOT FLDS TOTVEGC TOTLITC
SOILM FLDS POPU CWDC PBOT
RH2M TOTLITC FLDS PBOT POPU
SOILM CWDC PBOT RAIN LTN
LTN TOTVEGC FLDS TOTLITC POPU
0
50
100
150
200
250
300
350
400

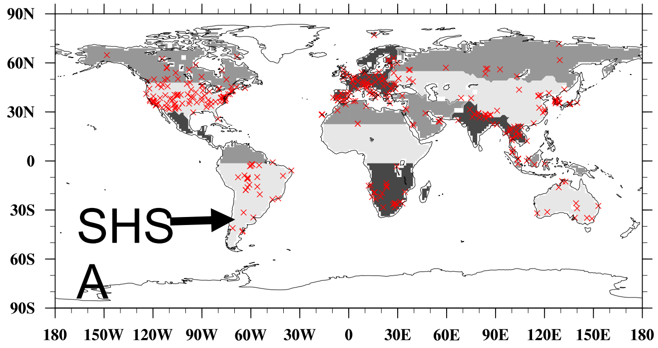
# summary

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

## Simulation experiments

| Experiment | Sources of carbonaceous aerosol and sulfate |
|---|---|
| No fire | Non-fire sources |
| Org. fire | Non-fire sources + fire emission from the original GFED4s data |
| Adj. fire | Non-fire sources + fire emission from the optimized GFED4s data |

## Optimized fire emission




$$AOD_{AERONET} = \beta AOD_{nofire}$$

$$AOD_{AERONET} = \beta AOD_{nofire} + \alpha AOD_{fire}$$

| Region | Fire emission scalar ($\alpha$) |
|---|---|
| SHSA | 2.79 |

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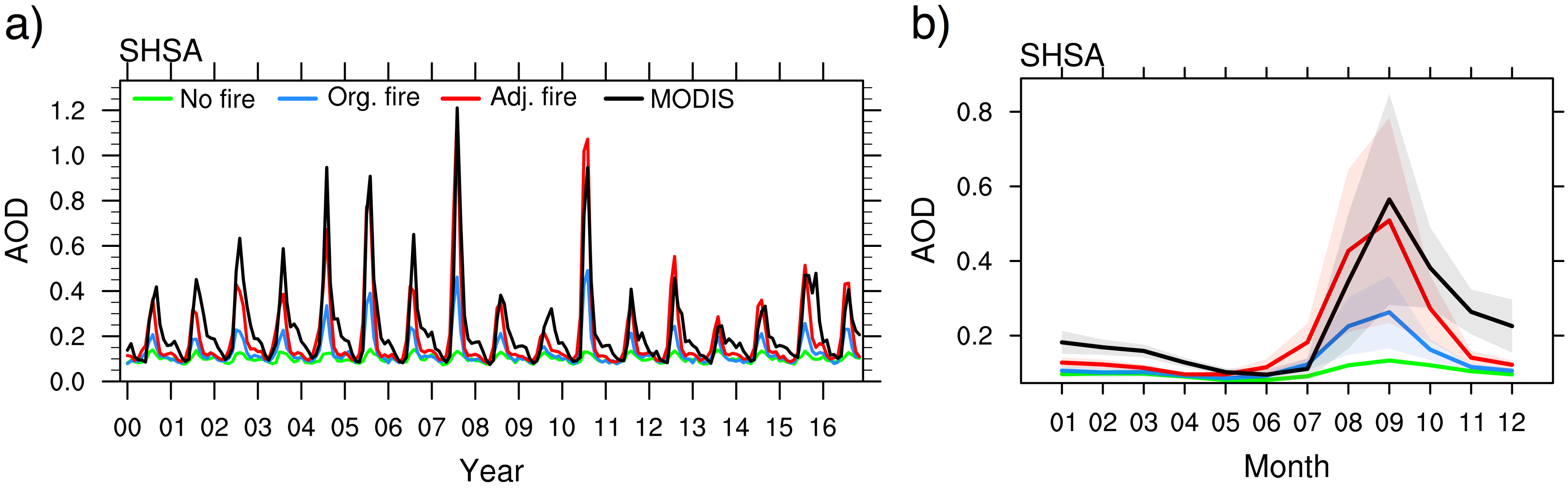
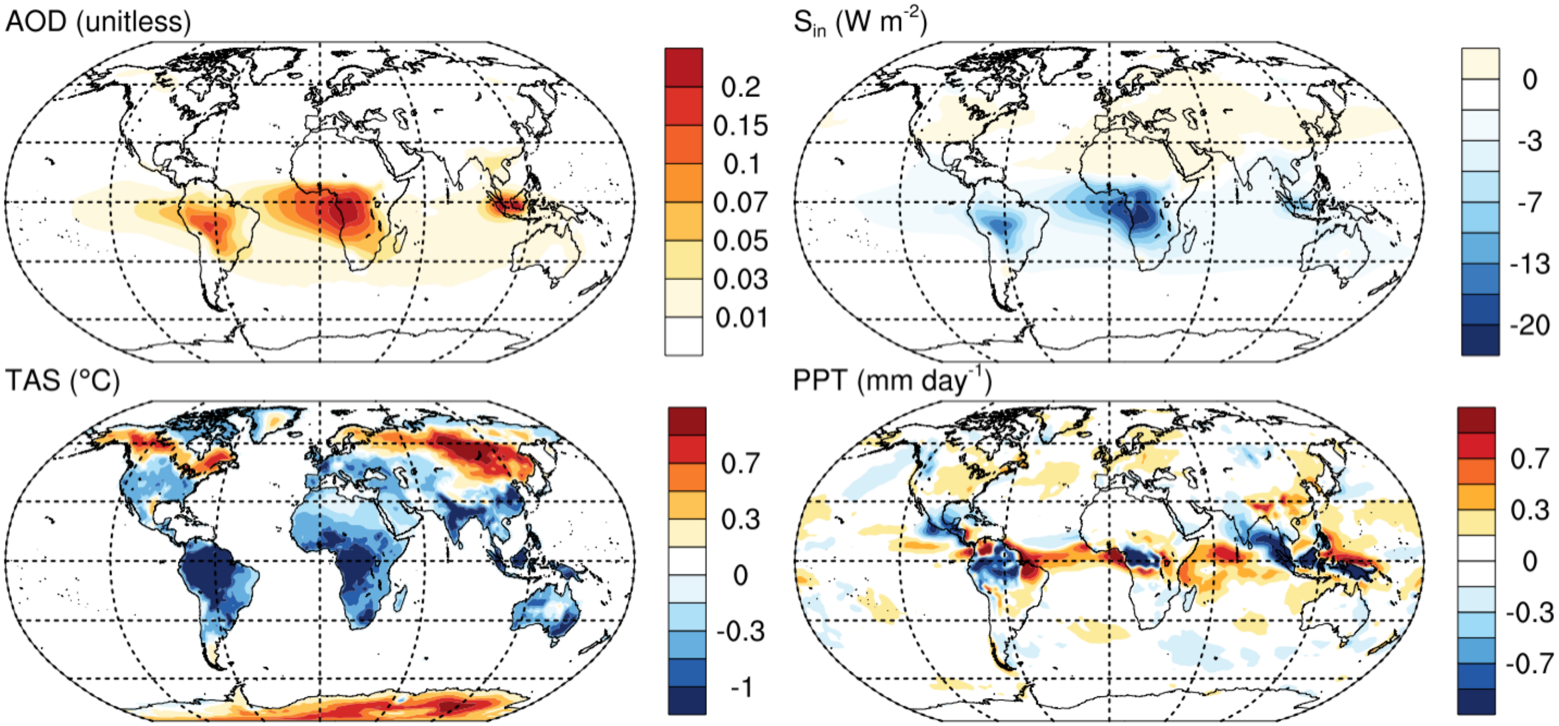
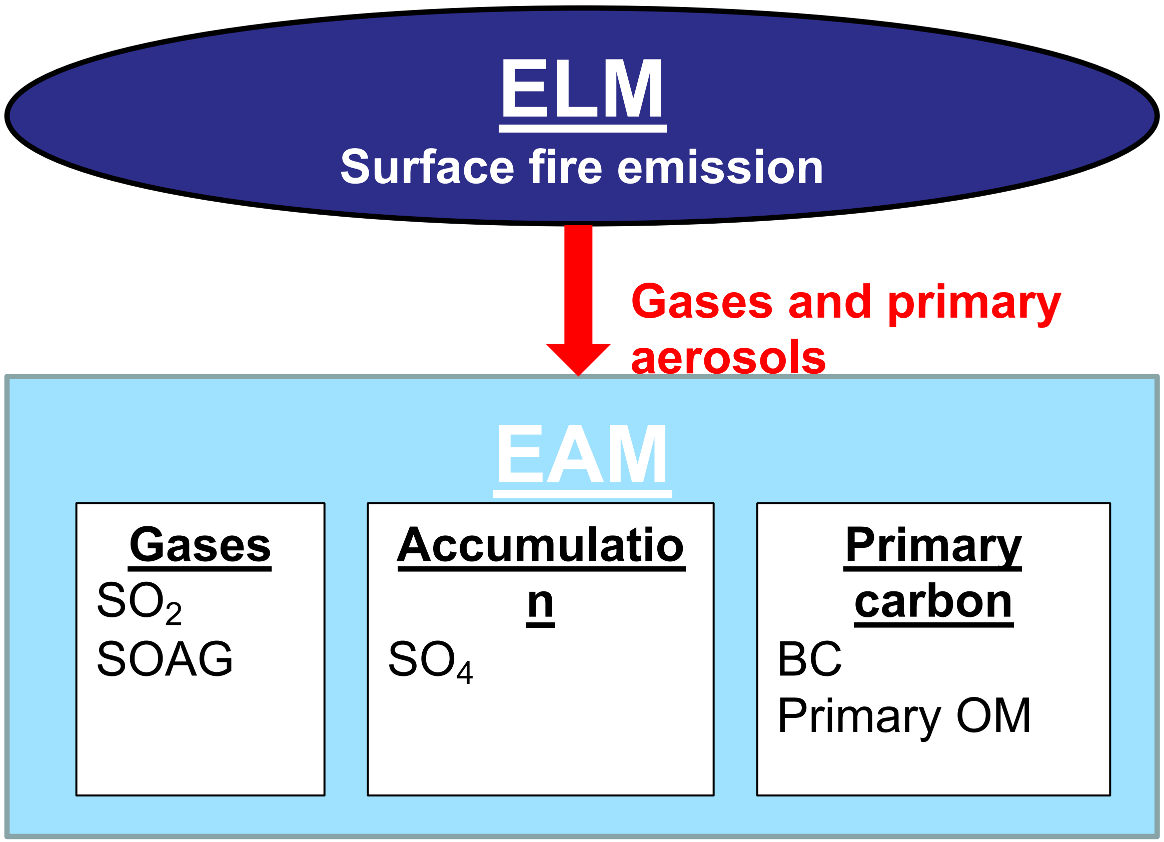
The modeled aerosol optical depth from the optimized fire emission simulation has better agreement with the MODIS AOD



## Fire aerosols significantly impact aerosol optical depth, induce strong cooling at surface and cause changes in surface temperature and precipitation, particularly at tropics



# Coupled fire emission module in E3SM

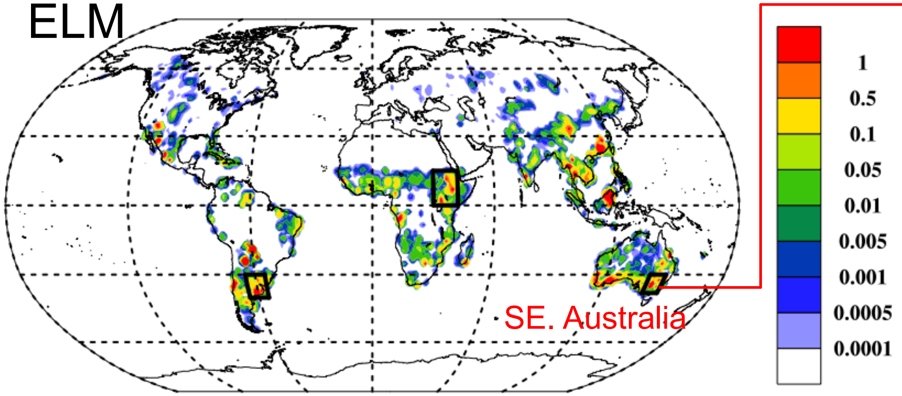


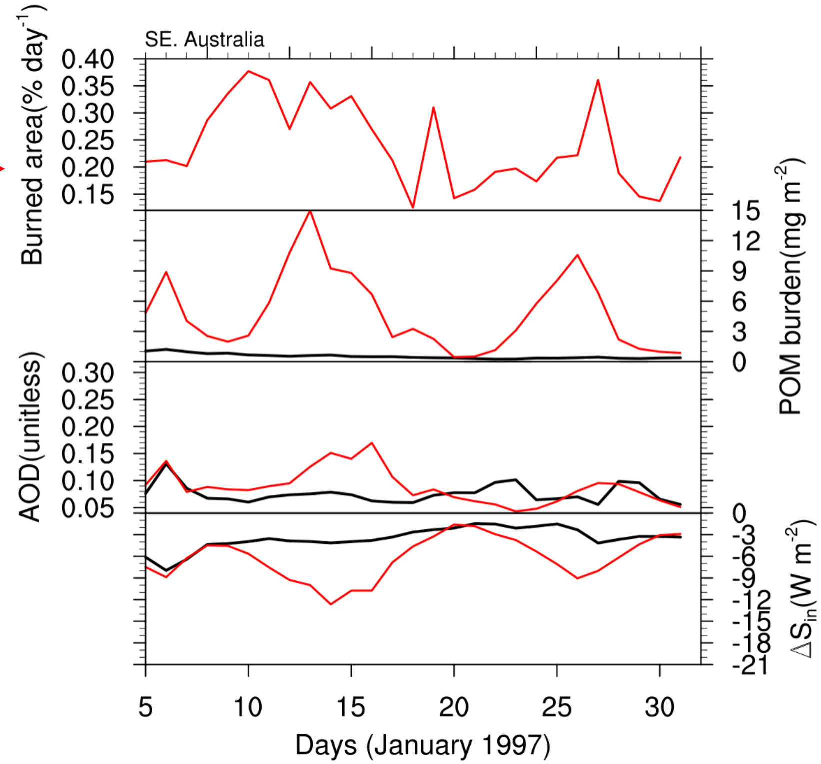

- PFT-dependent emission factor for each species
- Consideration of peat fire emission factor in the equatorial Asia
- Choice of surface or vertical fire emission in EAM

The coupled fire emission simulation

- instantaneously emits the fire-associated carbonaceous aerosols into the atmosphere
- produce a day-to-day variability of aerosol optical depth and aerosol radiative effects

POM fire emission (g $m^{-2}$ $month^{-1}$) from ELM



# summary

- Adjusted fire emissions better represent observed AOD during fire peak season in tropical fire regions.
- Fire aerosols induce the strong surface cooling through both scattering and absorption of sunlight.
- Fire-associated aerosols species are instantaneously emitted into the atmosphere.

# Thanks!

Model Settings

| Model | Settings |
|---|---|
| *Decision Tree* | *Minimum leaf sample: [3,6,9]*<br>*Maximum depth: 150* |
| *Random Forest* | *Minimum leaf sample: [3,6,9]*<br>*Number of trees: [20,30,40]* |
| *Gradient Boosting Decision Tree (GBDT)* | *Learning rate: 0.01*<br>*Maximum depth: [3,4,5]*<br>*Number of trees: 100* |
| *MLP* | *Learning rate: 0.001*<br>*Batch size: 32*<br>*Tow hidden layers with 10 and 5 neuro units*<br>*Optimizer: SGD* |
| *SVM* | *Maximum iteration: 10,000*<br>*Kernel: [‘rbf’,’linear’]* |
| *AttnLSTM* | *Learning rate: 0.001*<br>*Batch size: 32*<br>*Hidden dimension: 16*<br>*Sequence length: 12*<br>*Optimizer: SGD* |