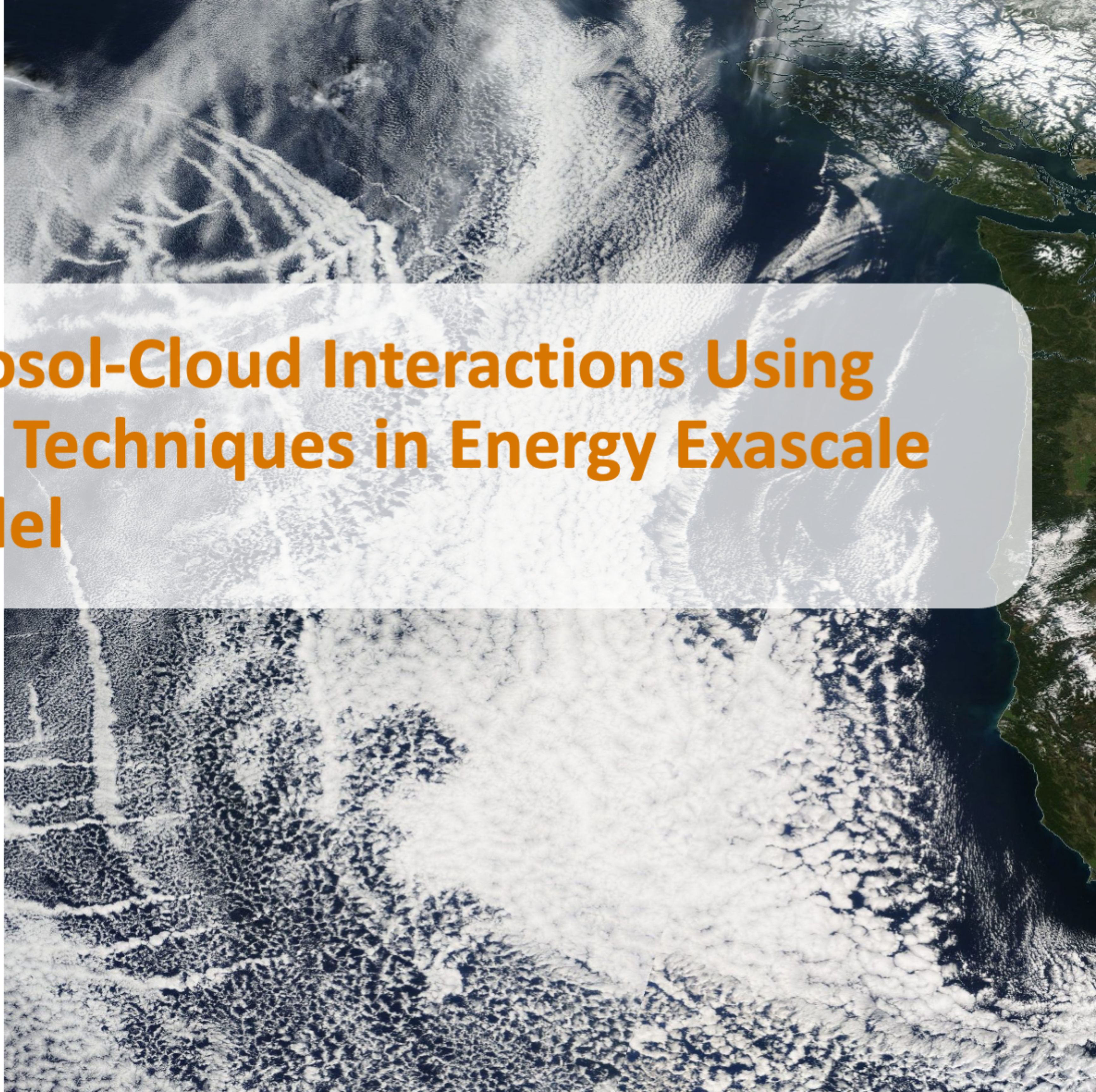
Representing Aerosol-Cloud Interactions Using Machine Learning Techniques in Energy Exascale Earth System Model

Po-Lun Ma

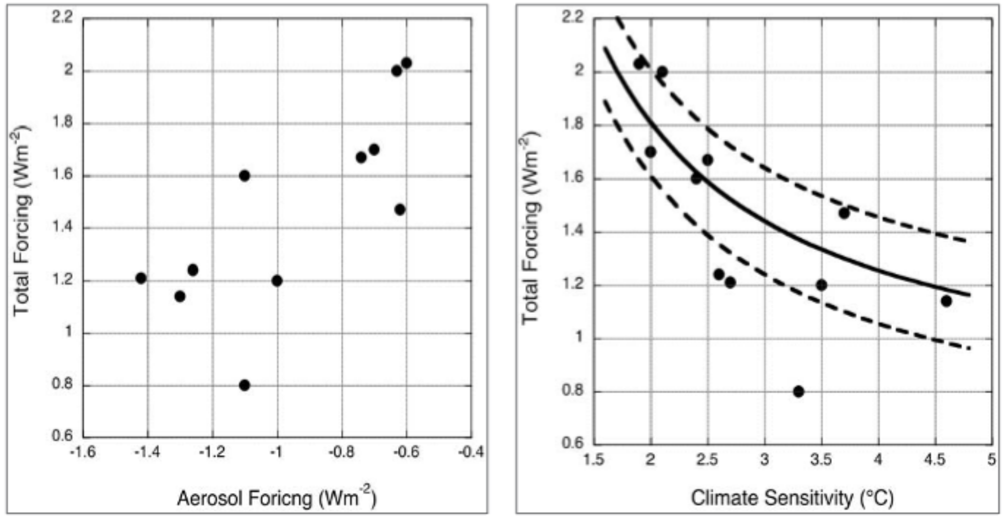
October 1, 2020



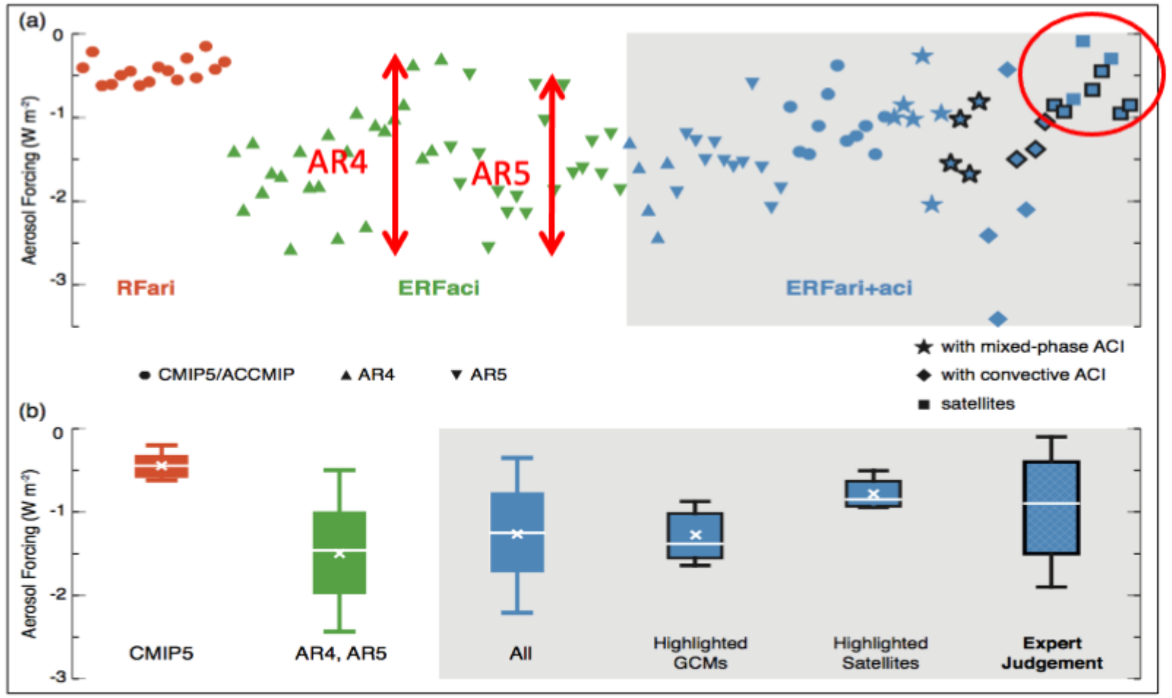
PNNL is operated by Battelle for the U.S. Department of Energy

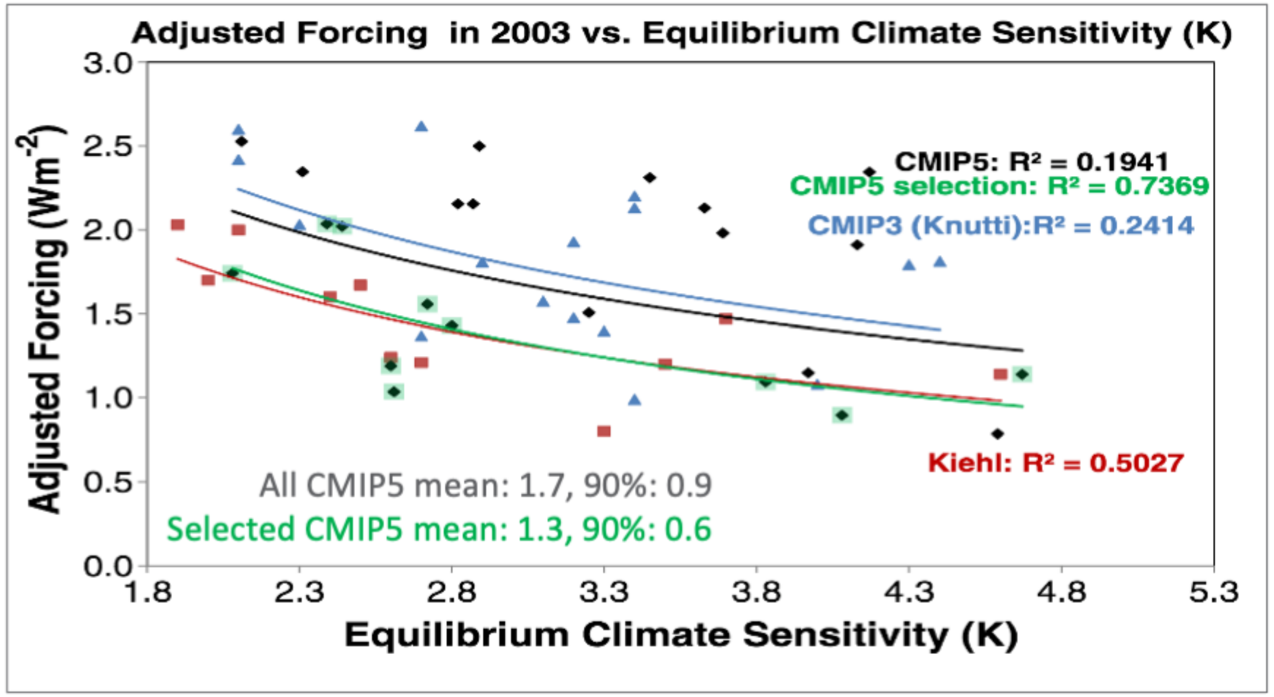
Aerosol effect is a major source of uncertainty

Kiehl (2007)



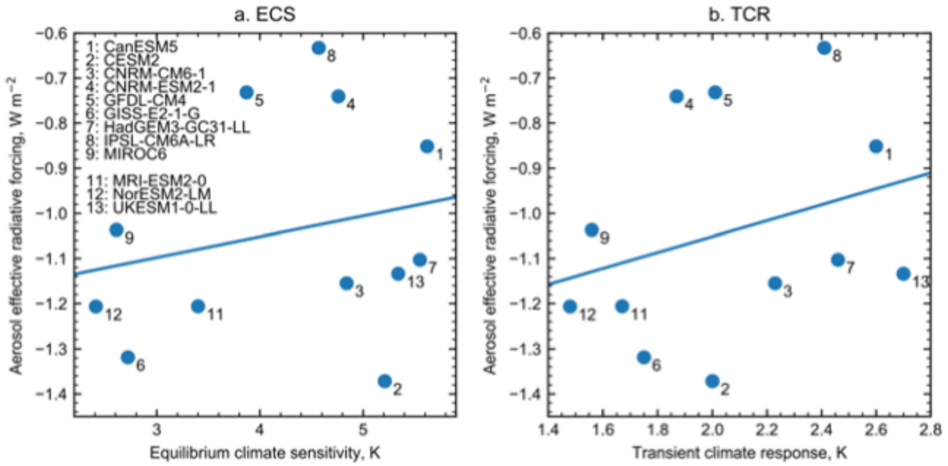
IPCC AR5 (2014)





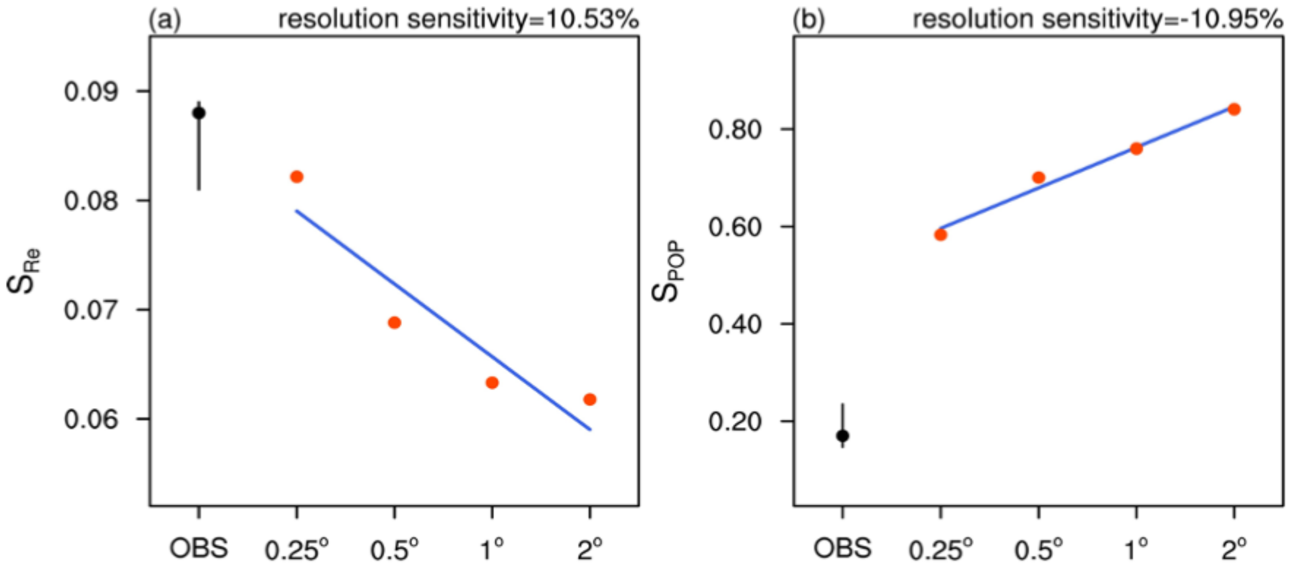
Forster et al (2013)

Smith et al (2020)

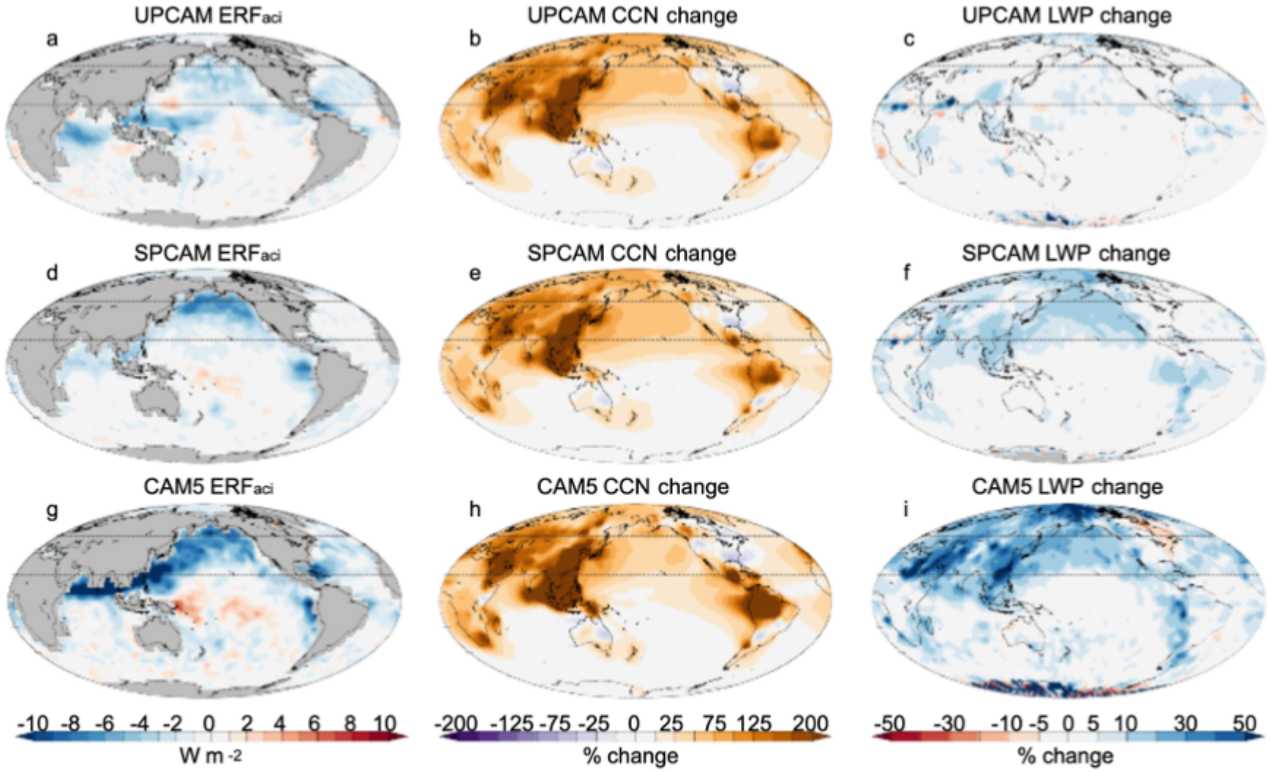


- CMIP3-5: Stronger aerosol effects lead to weaker total forcing and higher climate sensitivity
- CMIP6: New (no?) relationship

Increase resolution improves agreement between model and observational estimates of ACI



Ma et al. (2015)



Terai et al. (2020)

- Increasing resolution improves small-scale meteorological features critical for aerosol-cloud interaction, increasing the agreement of cloud and precipitation susceptibility with observations even though the same physical parameterizations are used.
- Weaker ERFaci is caused by a combination of weaker increase in LWP in non-raining clouds and a smaller fraction of raining clouds in UPCAM

Resolution

Physics

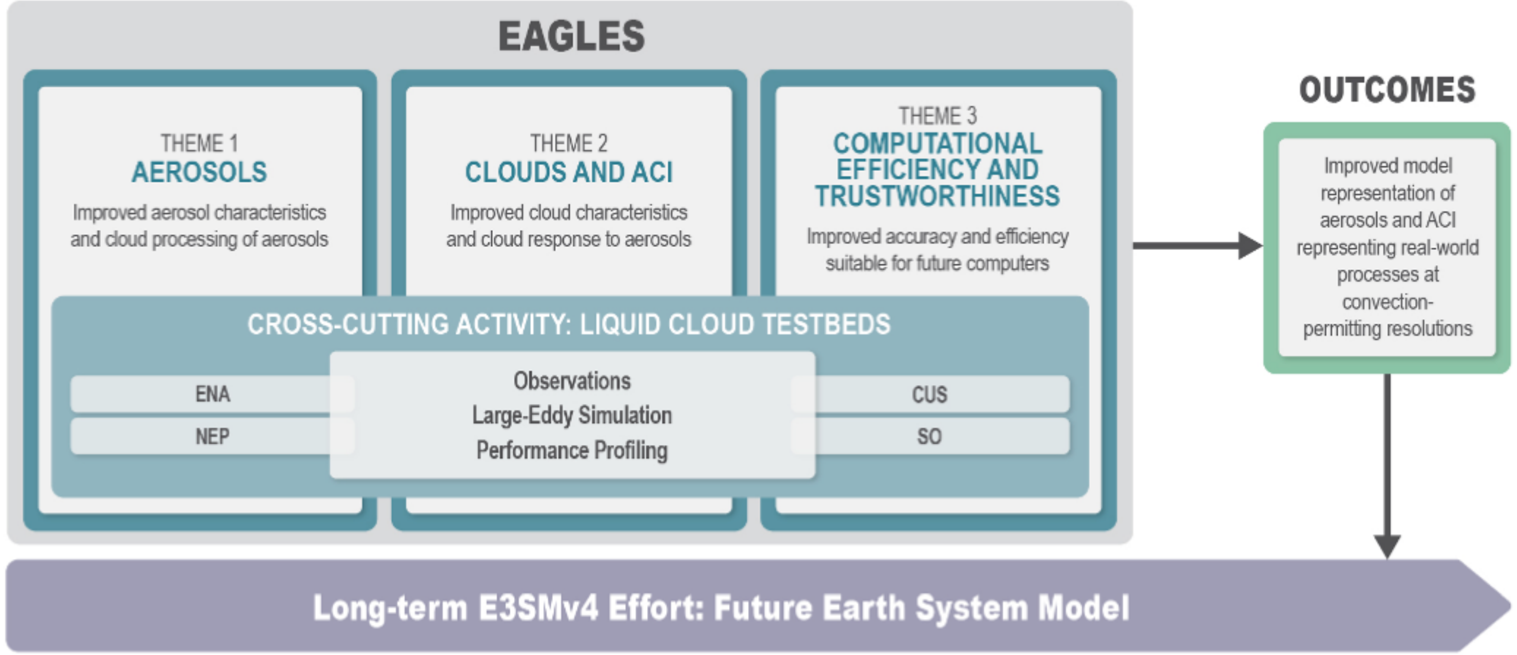
Computation

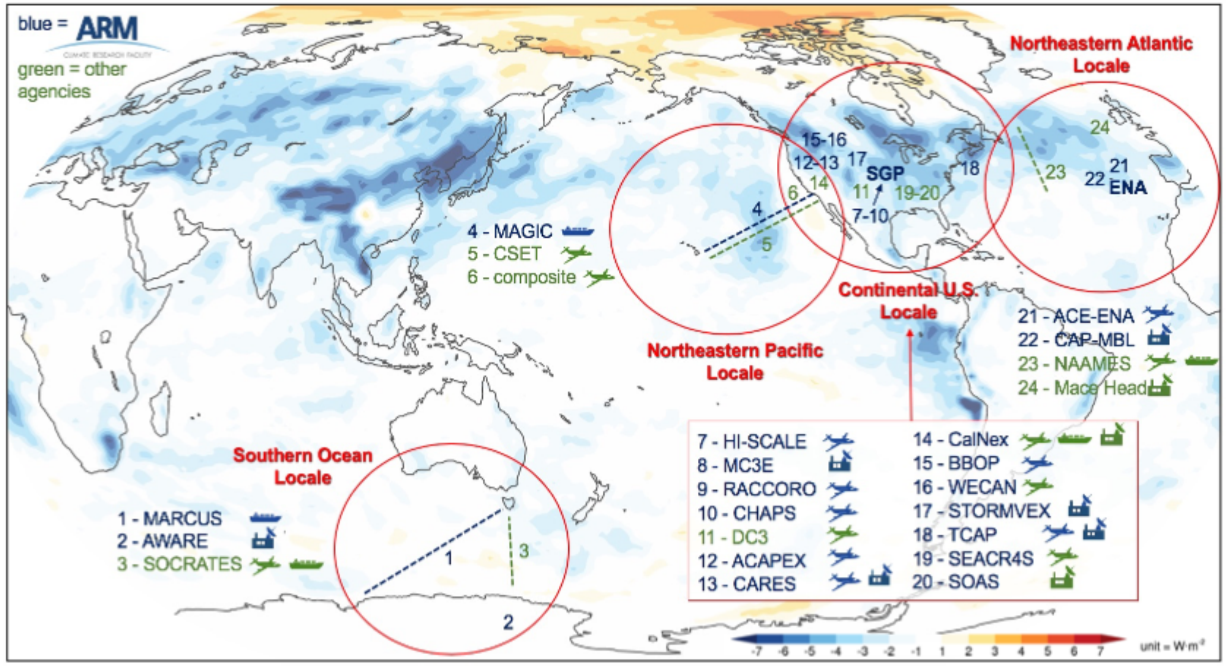
Energy balance

EAGLES

3 model development themes (Aerosol, Clouds, Computation)
1 cross-cutting activity (Testbeds)
Deliver improved representation to run on DOE's GPU-based computers

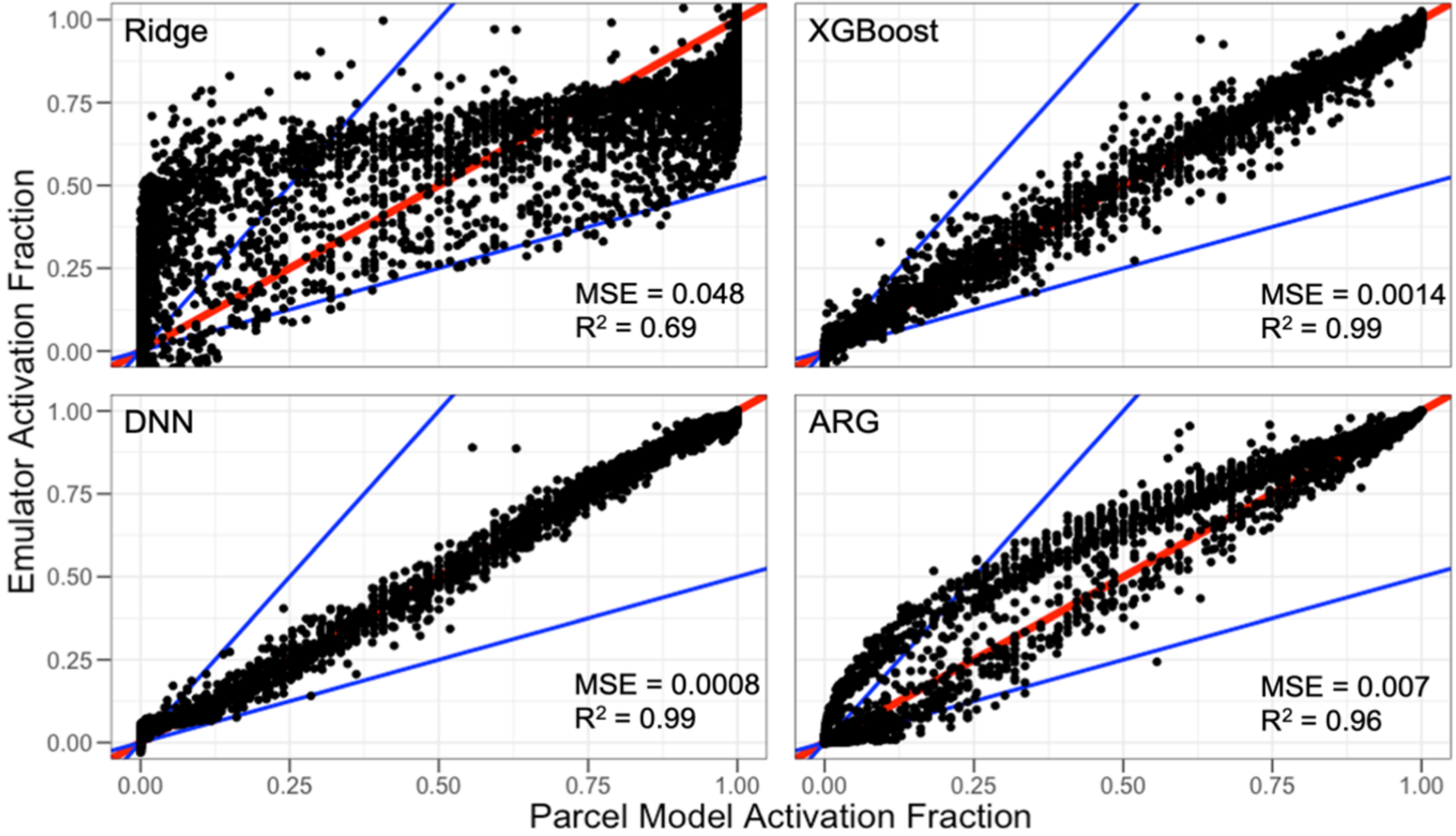
Vision: To increase confidence in and understanding of the role of aerosols and aerosol-cloud interactions in the evolution of the Earth system using new modeling techniques that are scientifically robust and computationally efficient for global convection-permitting simulations





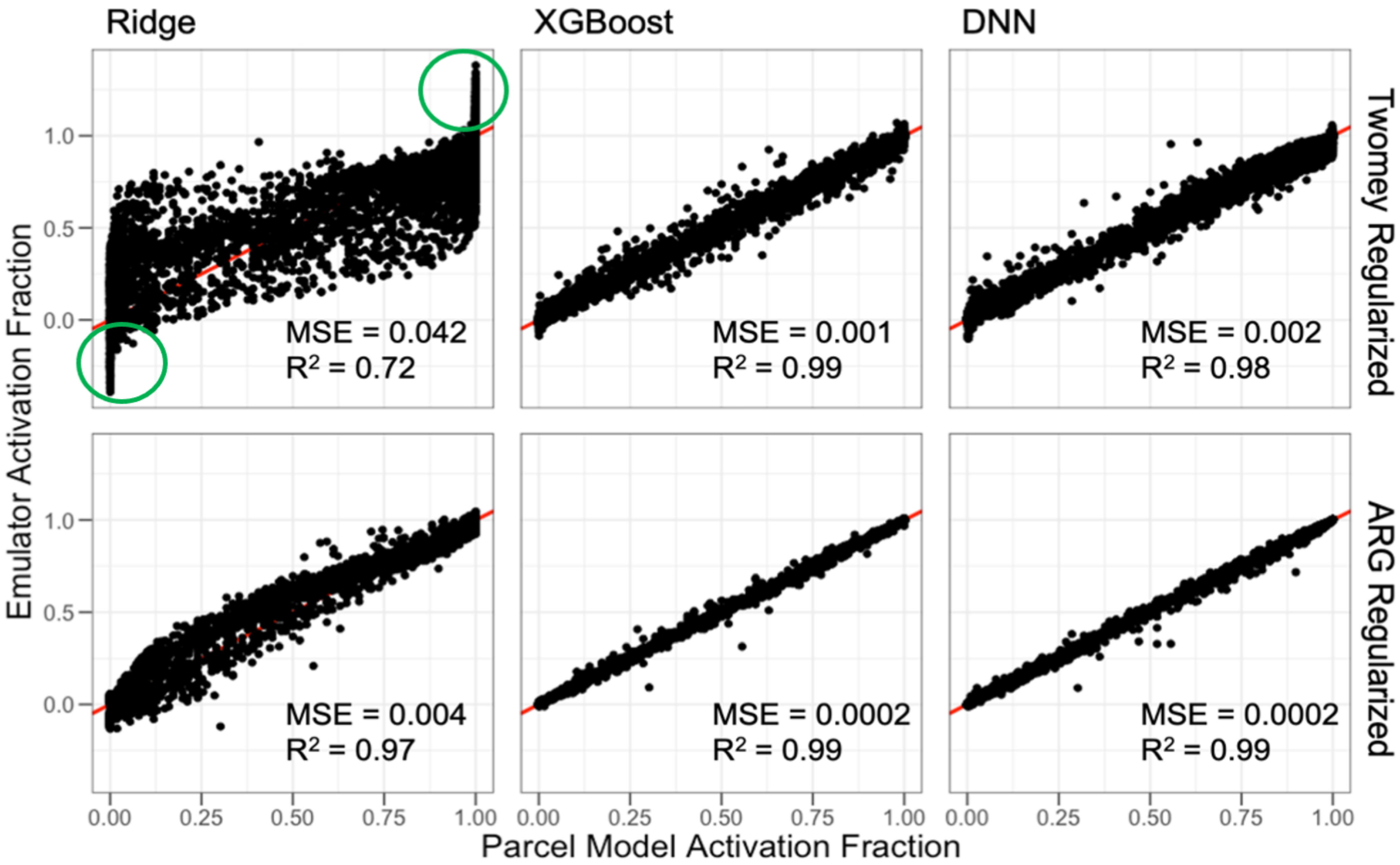
Activation emulation

Silva et al.



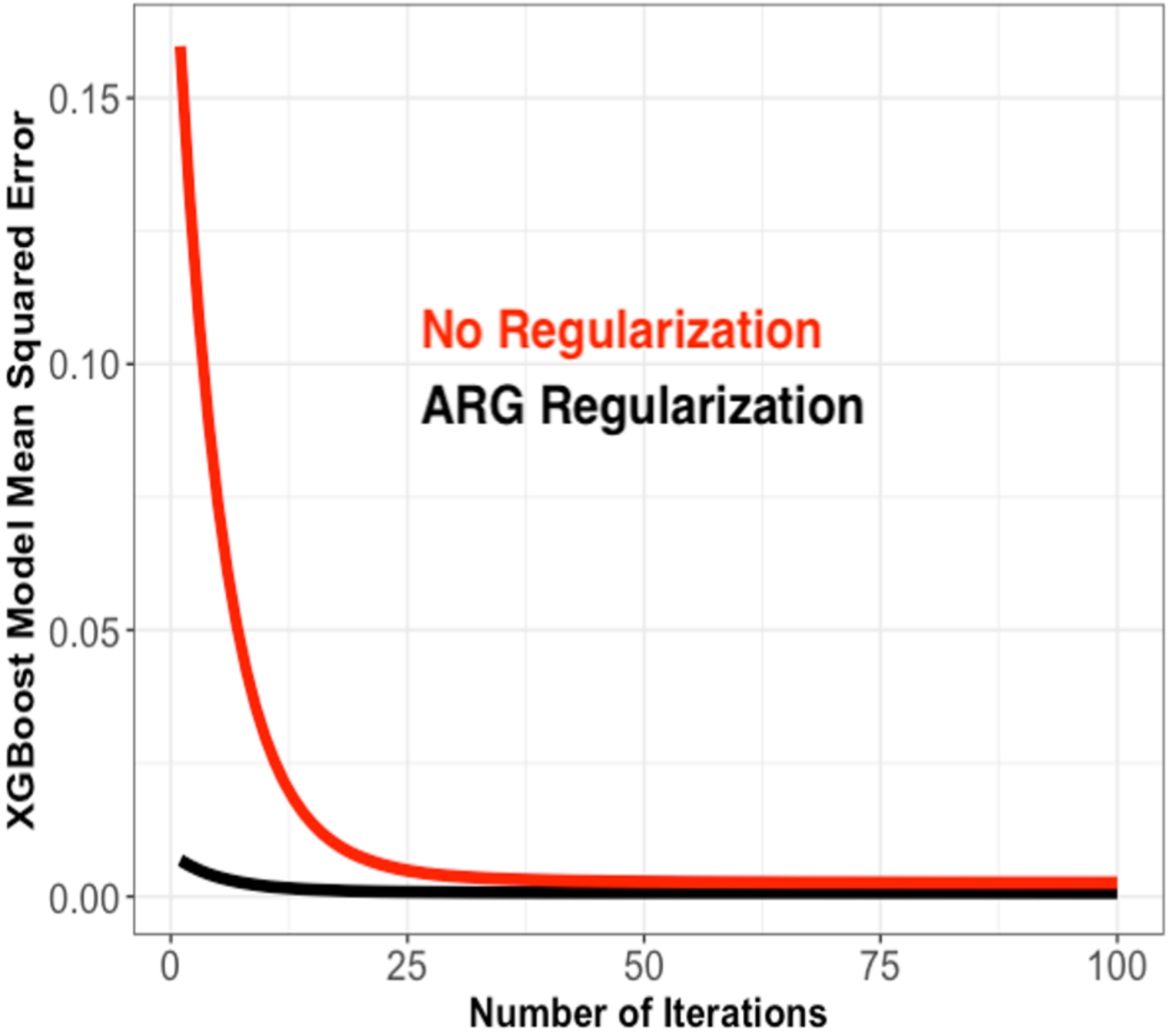
Use physics to regulate the emulator

Silva et al.



Physics regularization: reducing emulator complexity

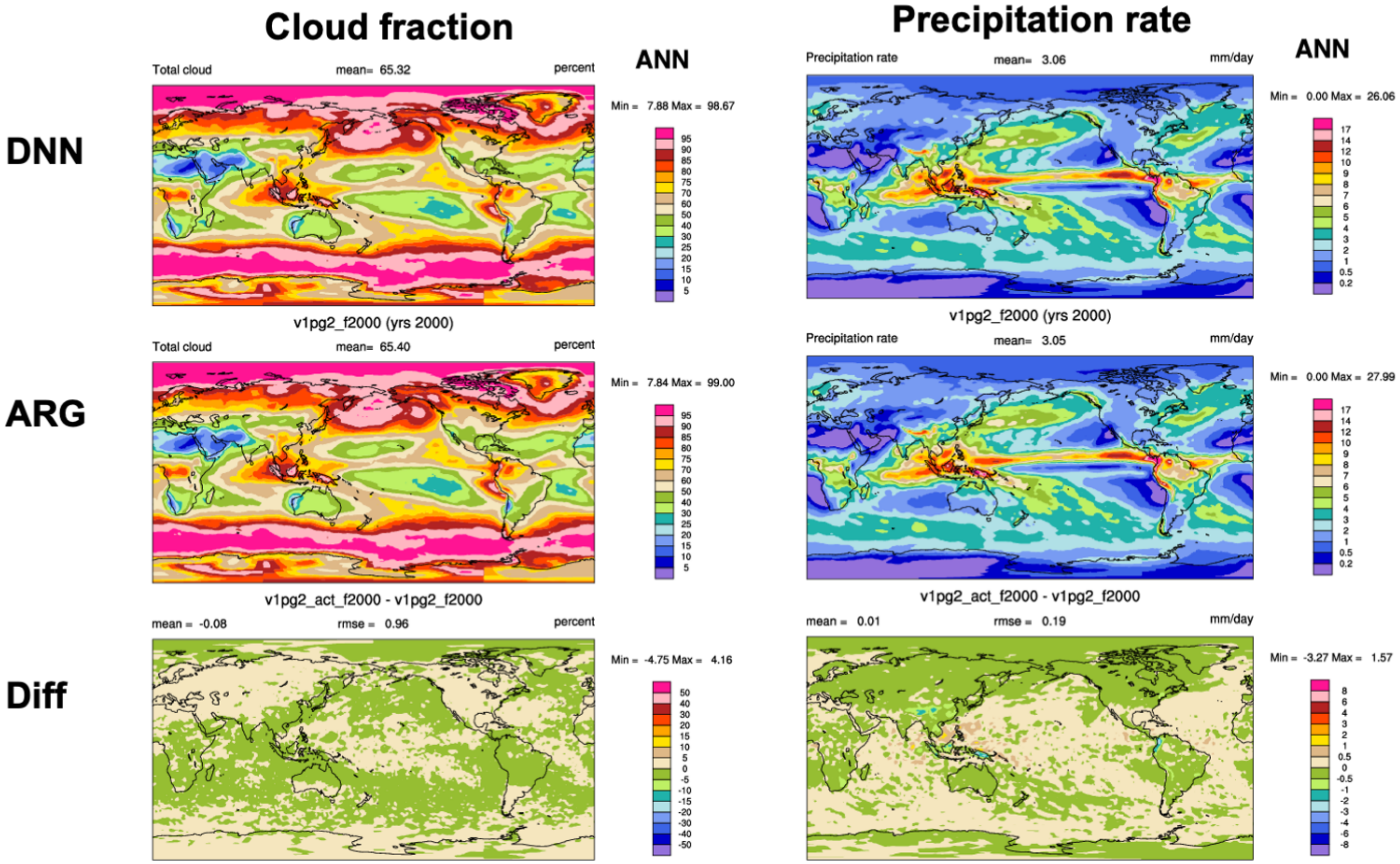
Silva et al.



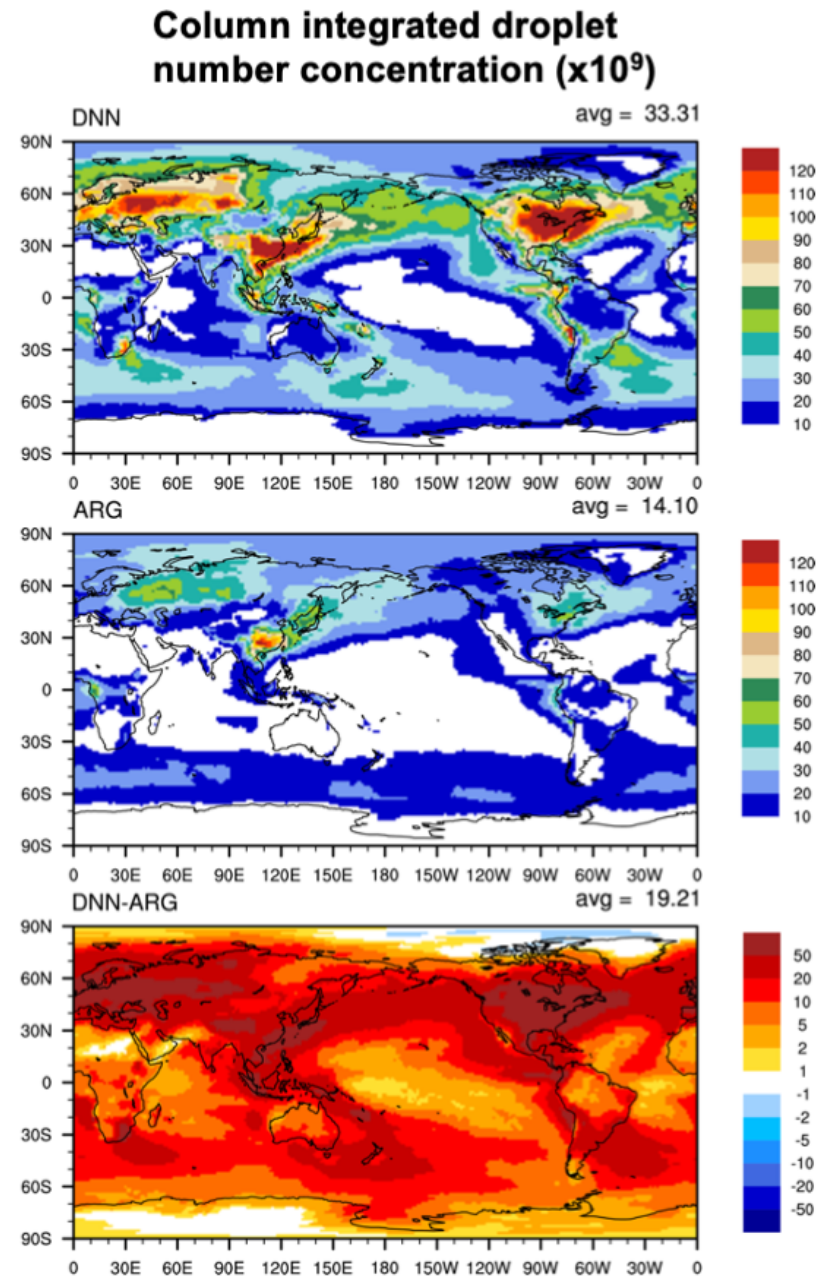
Pacific Northwest
NATIONAL LABORATORY

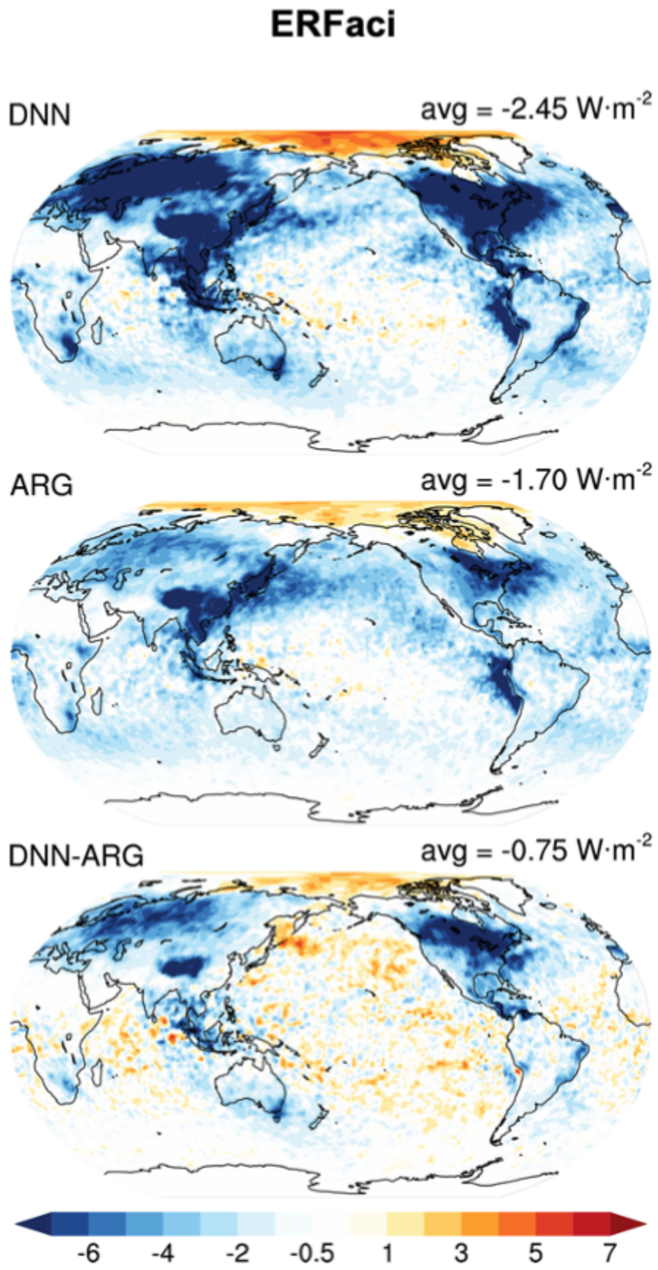
New DNN-based activation in E3SM runs smoothly

Silva et al.



Some new problems indicates (hidden) issues in the emulator
Silva et al.





Software considerations when implementing emulators in E3SM

Singh et al.

- We use Fortran keras bridge library
  - Easy: Provide a text file, link the library, write an interface routine
  - Flexible: do not need to recompile the whole E3SM after replacing the emulator

- Numerical considerations
  - Clipping (input)
    - Assumptions made in other parts of the model: updraft velocity
    - Inconsistent bounds: minimum hygroscopicity in the emulator (10^{-4}) vs in E3SM (10^{-10})
  - Clipping (output)
    - Fraction between 0 and 1
  - Sampling of training data
    - Comprehensive (Latin Hypercube, MCMC) vs. realistic multivariate PDF

- Computational cost
  - DNN on CPU machines is slightly cheaper than the default E3SM with ARG

Autoconversion emulation

Pressel et al.

Objective

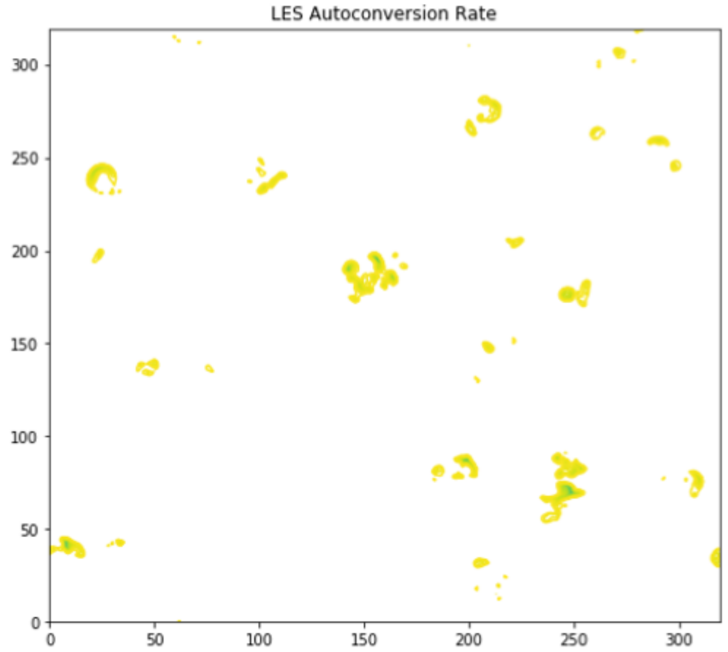
- To develop robust training data sets to be used for machine learning emulation of autoconversion rates for a diverse set of aerosol conditions and boundary layer cloud regimes

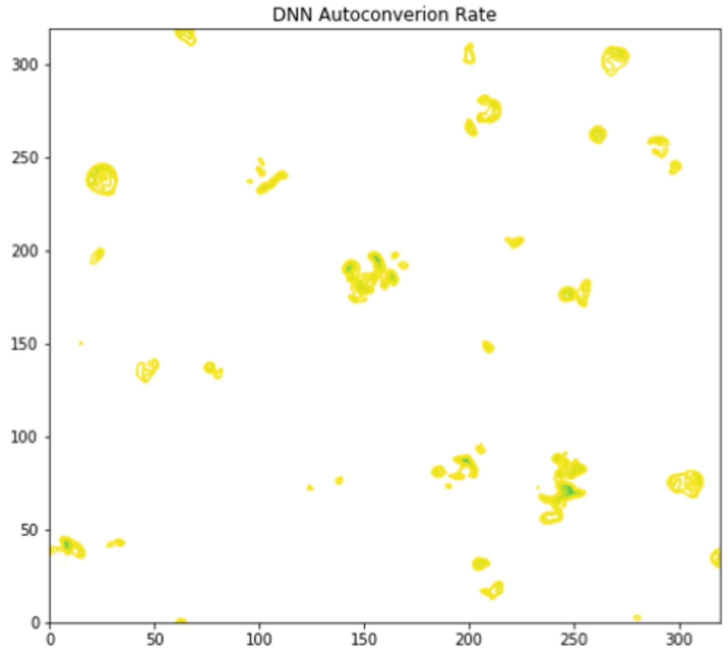
Approach

- Anew computationally efficient LES model, Predicting INteractions of Aerosol and Clouds in Large Eddy Simulation (**PINACLES**)
- Coupled with spectral bin microphysics (**SBM**) to explicitly predict autoconversion rates
- Perform a very **large LES ensemble** for a wide range of aerosol conditions and cloud types

Results

- A proof-of-concept exercise builds a reasonable emulator
- In addition to traditional variables, **meteorological variables** play a significant role in autoconversion rates and need to be included in the training





Summary

- Successful development of physically regularized DNN that outperforms all existing parameterizations
- Successful implementation of DNN-based parameterization in E3SM with ample flexibility. Computational cost is slightly reduced
- Interface routine has some numerical considerations needed for both the DNN emulator and for the E3SM
- Climate simulations are stable and reasonable, though we see new biases in droplet numbers, pointing to DNN's relatively large bias in low activation scenarios.

Lessons learned

- Tools are available for inserting a DNN-based parameterization (python-based) in a climate model (FORTRAN-based), but interface routine needs to be designed carefully.

- Emulator development requires close collaboration between domain scientists and data scientists. E3SM with the DNN-based parameterization produces reasonable climate simulations, but new biases were produced. Some iterations between emulator-building (parameterization development) and climate modeling are needed.

- What are we learning? Statistical characterization of model states and process rates or real-world physics?

Thank you.