An ML parameterization of clouds in a coarse climate model for unbiased radiation

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Clouds and radiation in climate modeling

- Cloud feedbacks on climate change are largest driver of uncertainty in climate sensitivity to GHG
- Clouds have diverse, complex spatial structures; developing climate model cloud subgrid parameterizations is hard
- ML cloud parameterizations from coarsened fine-grid model or observations: Grundner et al. (2022, 2023); Chen et al. (2023)
- How do ML clouds behave in terms of atmospheric radiation?

https://earthobservatory.nasa.gov/images/76261/crepuscular-rays-india

ML cloud parameterization and radiation

1. Can coarsened fine-grid model clouds produce unbiased radiation in a coarse-grid climate model?
2. Can an ML parameterization of cloud fields (fractional cover, cloud mixing ratios) produce unbiased radiation as well?

Models and data setup

Fine-grid reference model:

- GFDL X-SHiELD 10-day 3km resolution global storm-resolving simulation (e.g., Kwa et al. 2023)
- Cloud and radiation fields coarsened to 200km resolution

Coarse-grid ML testbed model:

- GFDL FV3GFS 200km simulation; winds, temperature, humidity nudged to fine-grid reference

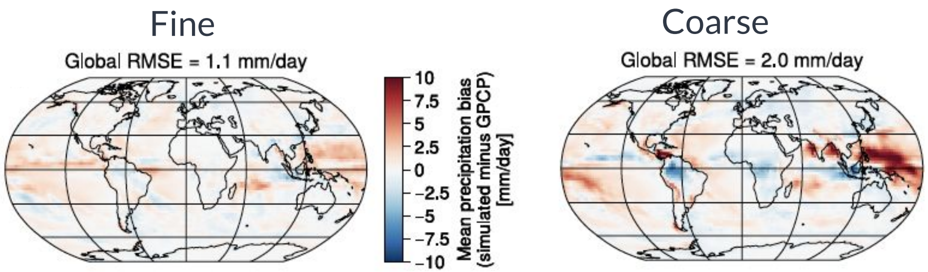
Model similarities:

- FV3 dycore, RRTMG radiation scheme, GFDL microphysics scheme

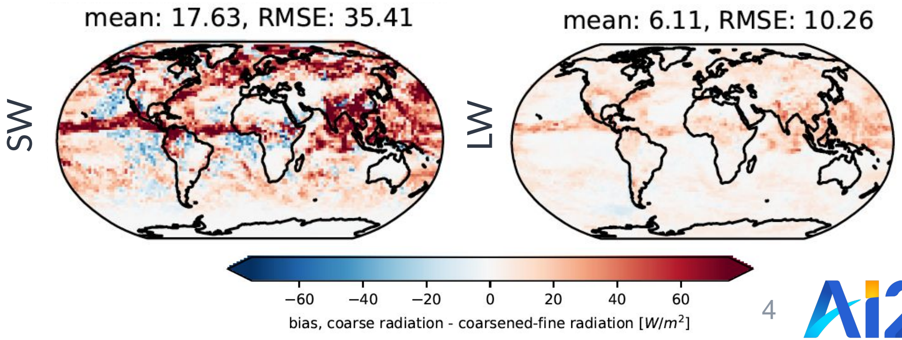
Model differences:

- Differences: resolution and timestep, coarse model has deep convection parameterization on

Free running precipitation errors: fine more accurate



Nudged-coarse radiation error against fine



ML fine-grid cloud and radiation

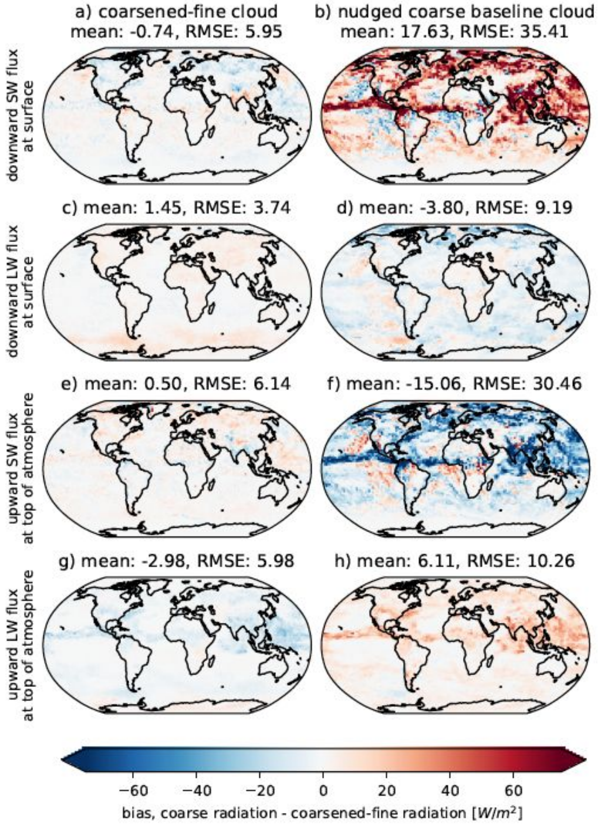
1. **Can coarsened fine-grid model clouds produce unbiased radiation in a coarse-grid climate model?**
2. Can an ML parameterization of cloud fields (fractional cover, cloud mixing ratios) produce unbiased radiation as well?

Coarsened-fine cloud in coarse model

Use a python port of the RRTMG radiation scheme running “piggybacked” (diagnostically offline) with the coarse FV3GFS model, to allow for evaluating arbitrary cloud fields’ radiation while keeping the temperature, humidity, etc. the same

- i.e., “prescribe” coarsened-fine fractional cloud cover and cloud liquid and ice mixing ratios on the coarse model grid
- run the radiation scheme with these prescribed clouds

Coarsened-fine cloud in coarse model



- Coarsened-fine clouds produce **±3 W/m^2** global-mean radiation biases (upward at TOA + downward at sfc., for shortwave and longwave)
- Easily provides more skillful radiative fluxes than the nudged coarse model's own fluxes
- BUT requires some appropriate radiation scheme assumptions…

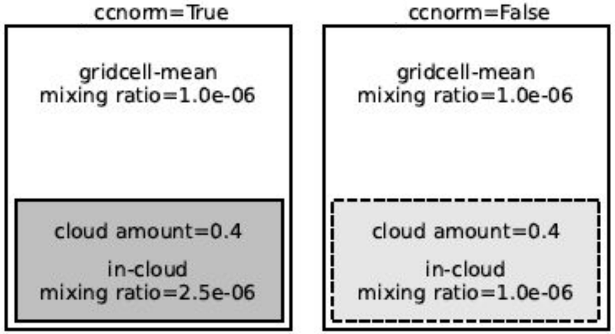
Coarsened-fine cloud in coarse model

Overlap and fractional cover assumptions matter!
Prescribed-cloud radiation biases sensitive to:

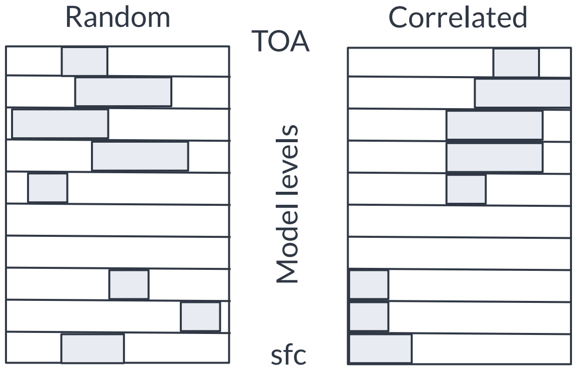
- Whether cloud condensate occupies entire horizontal area, or just fractionally cloud portion (latter works best)
- Cloud overlap assumption of grid cells in same column: Pure random? Maximally overlapped? Correlated within some length scale? (latter works best)

Prescribing coarsened-fine clouds in coarse model with incompatible assumptions can yield global-mean radiation biases, at sfc. and TOA relative to coarsened-find radiation, of **±15 W/m²** (SW), **±10 W/m²** (LW)

Grid cell (plan view)



Column (profile view)



ML cloud parameterization and radiation

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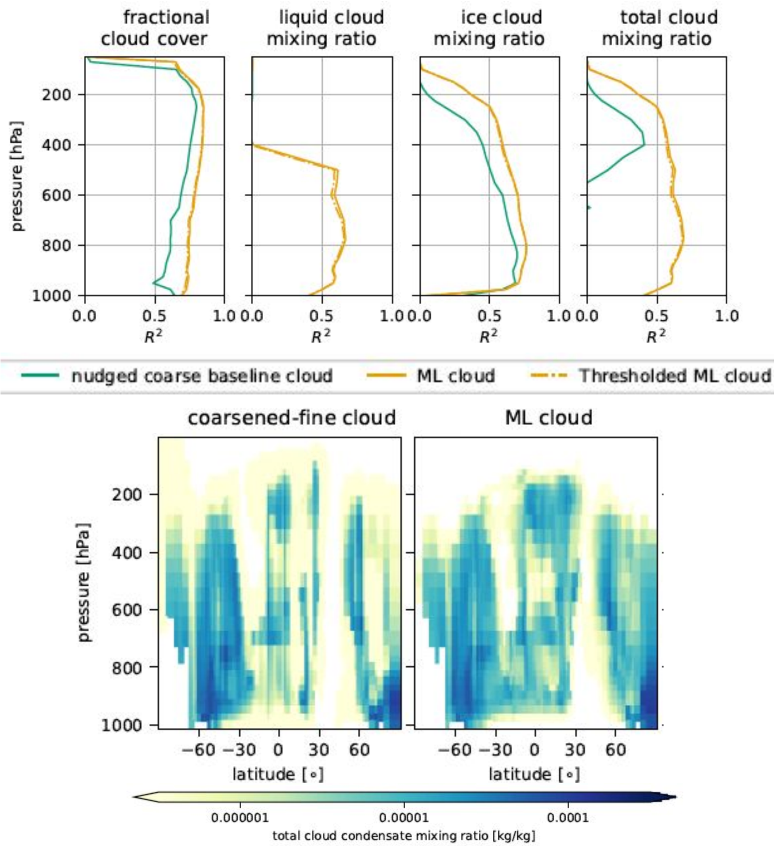
Coarse ML parameterization of fine cloud

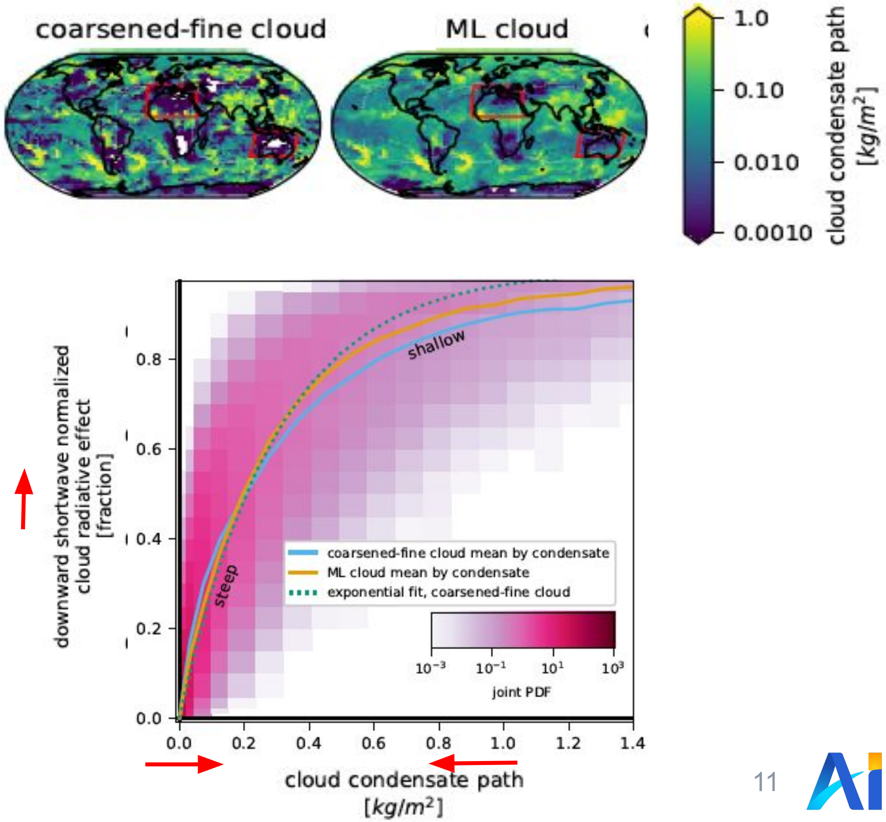
- ML is a small gridcell-local dense neural network (MLP):
  - A few layers deep, about 60k parameters
  - *Inputs*: coarse gridcell-local **air temperature**, **pressure**, and **relative humidity** + coarse-physics deep convective ice mixing ratio
  - *Targets*: coarsened-fine model gridcell-local **fractional cloud cover**, **liquid and ice cloud mixing ratios**
- ML performance:
  - Captures about 60% of variance on validation, exceeding nudged coarse baseline
  - Predicted cloud fields look acceptable, though a bit smeared out



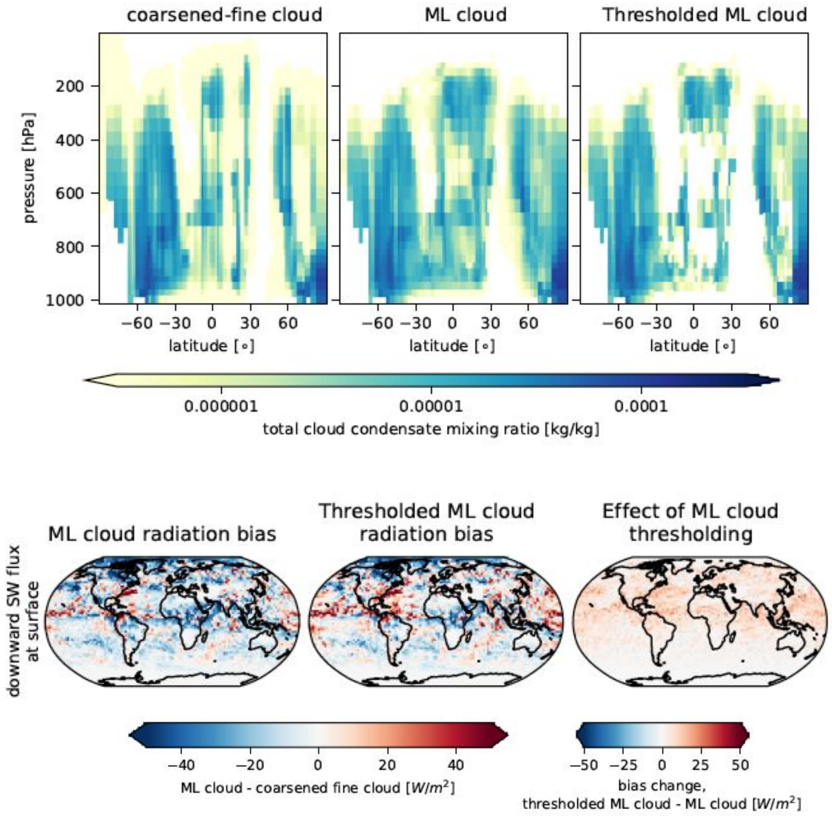
Coarse ML parameterization of fine cloud

But while ML-predicted cloud is unbiased and reasonably skillful, radiation from ML clouds is biased (too opaque)

Why? ML skill limitations with tails of distributions, such that very clear (and very cloudy) columns are too close to “mean cloudiness”



“Thresholded” ML parameterization



Apply post-processing step of zeroing out cloud fields where predicted fractional cloud cover is less than a “threshold” (6.5% here), to reduce radiation biases

If we could backpropagate directly through the radiation scheme and make its fluxes ML targets, this step would not be needed

Coarse ML parameterization of fine cloud

Metric		Cloud dataset		
		coarse nudged baseline	ML cloud	Thresholded ML cloud
Validation bias [W/m^2]	SW down at sfc.	18.37	-6.15	-1.53
	LW down at sfc.	-5.24	2.74	1.40
	SW up at TOA	-15.56	4.80	0.86
	LW up at TOA	9.09	-4.33	-2.77

Raw ML clouds' radiation is more skillful than coarse nudged baseline, but with thresholding the biases (<±3W/m^2) and random errors are smaller

ML cloud parameterization and radiation

- Original questions:
  - Can coarsened fine-grid model clouds produce unbiased radiation in a coarse-grid climate model? **Yes, much less biased than nudged coarse model's radiation**
  - Can an ML cloud parameterization of cloud fields (fractional cover, cloud mixing ratios) produce unbiased radiation as well? **Yes, ML can predict coarsened-fine clouds as functions of coarse model state to produce less-biased radiation as well**
- Suggests biases in computationally-cheap coarse climate models could be reduced with ML cloud parameterization
- Caveat:
  - ML cloud parameterization and radiation are computed in an "offline piggybacked" manner, i.e., no feedbacks with coarse model state
  - Vertically-resolved radiative heating rates would need to be sufficiently skillful to actually replace existing scheme in online manner

ML cloud parameterization and radiation

Henn et al., “A machine learning parameterization of clouds in a coarse-resolution climate model for unbiased radiation”, submitted to *JAMES*. https://essopenarchive.org/doi/full/10.22541/essoar.169402955.59735956

Also see my teammate Andre Perkins’ talk on emulating cloud microphysics in the same FV3GFS model later in this session

Additional slides

References

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ML cloud validation

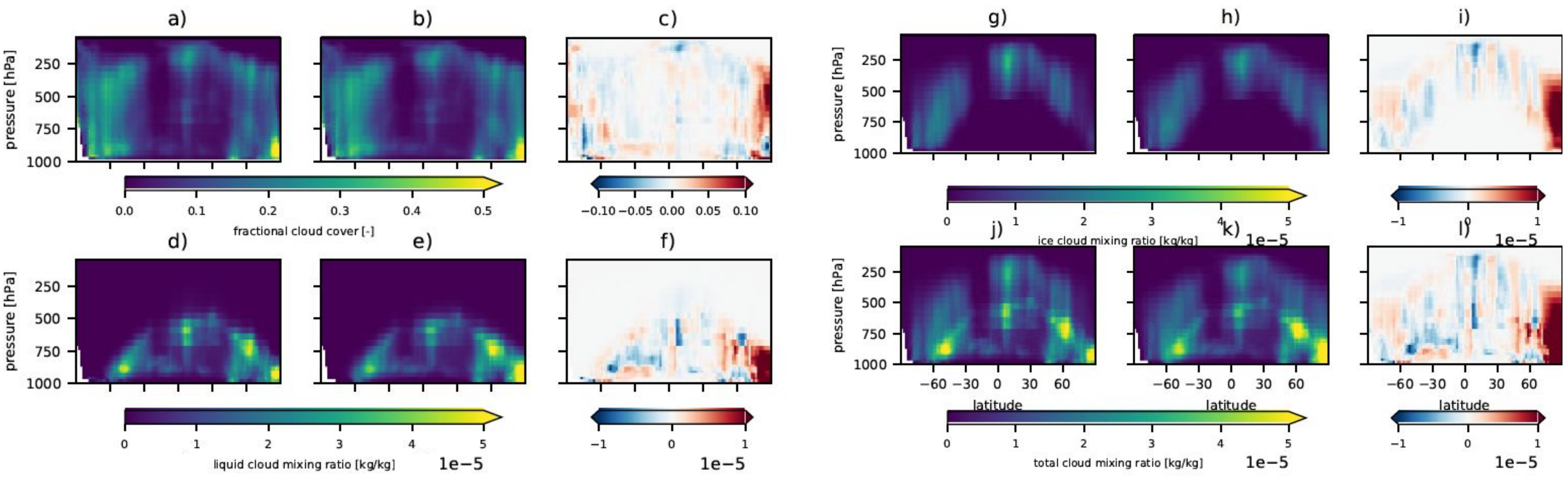

Figure S4. Time- and zonal-mean cloud variables in the coarsened-fine dataset (a, d, g, j), the ML predictions (b, e, h, k) and their differences (c, f, i, l).

ML cloud validation

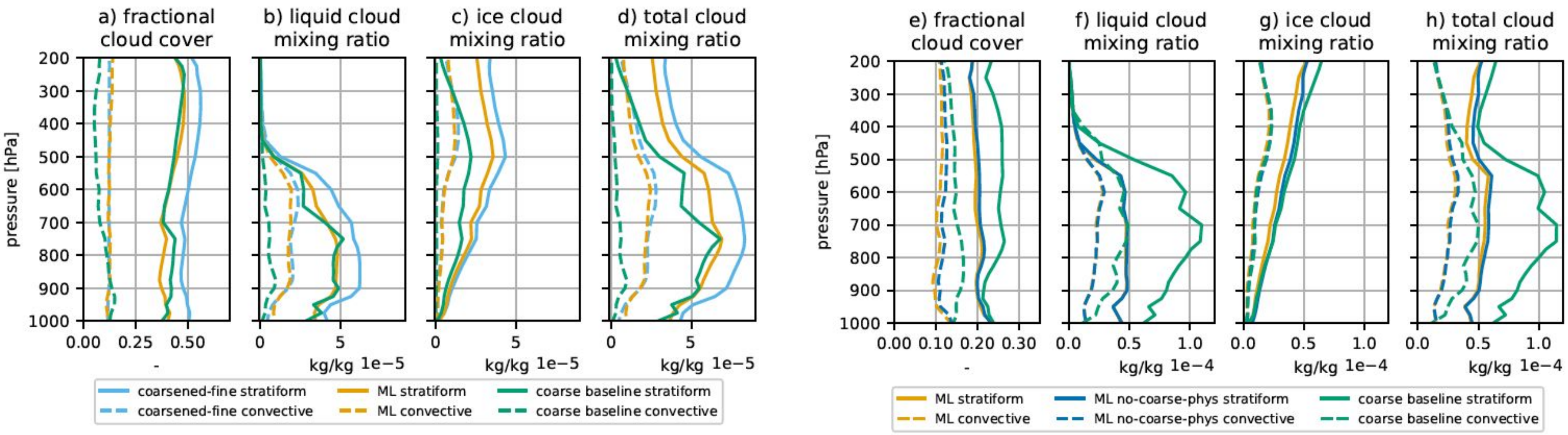

Figure S5. a) - d): Global horizontal mean cloud fields, composited by coarsened-fine fractional cloud cover. e) - h): Root-mean-squared error (RMSE). "Stratiform" cells have cloud cover > 0.2. "Convective" cells have cloud cover >= 0.065 but < 0.2.

Radiative heating rates