Radiation/Cloud ML

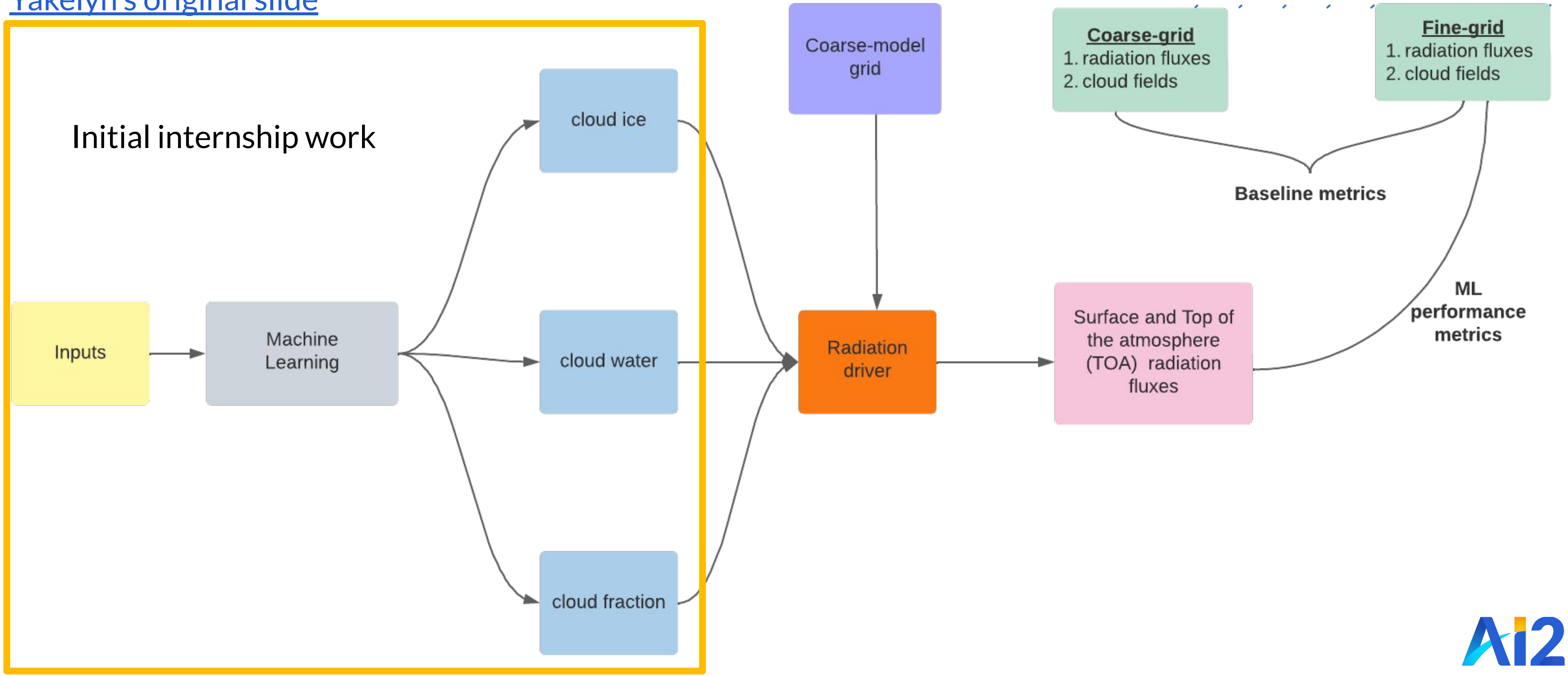
AI2CM Topic Talk
2022-12-02

Radiation/Cloud ML

- Project spanning Yakelyn's internship, conceptualization and guidance from Chris, Noah, and others
- Initial scoping from this doc:
  - "neither our N2F or fine-only methods attempts to accurately predict cloud distribution"
  - "train ML on the 3D fine-grid output to predict condensate PDF (including fraction of zero condensate) within the cell"
  - "predict vertically resolved condensate profiles and couple them to the GFS radiation scheme"
  - "try to use the ML-predicted condensate profiles, plus the T and q profiles, to predict surface and TOA longwave and shortwave fluxes. This could be done ... using the model's radiation parameterization and its implicit assumptions about vertical cloud overlap"
  - "can coarse-grained cloud fields reproduce coarse-grained radiation fields?"
  - "improve surface radiative biases in baseline FV3GFS"

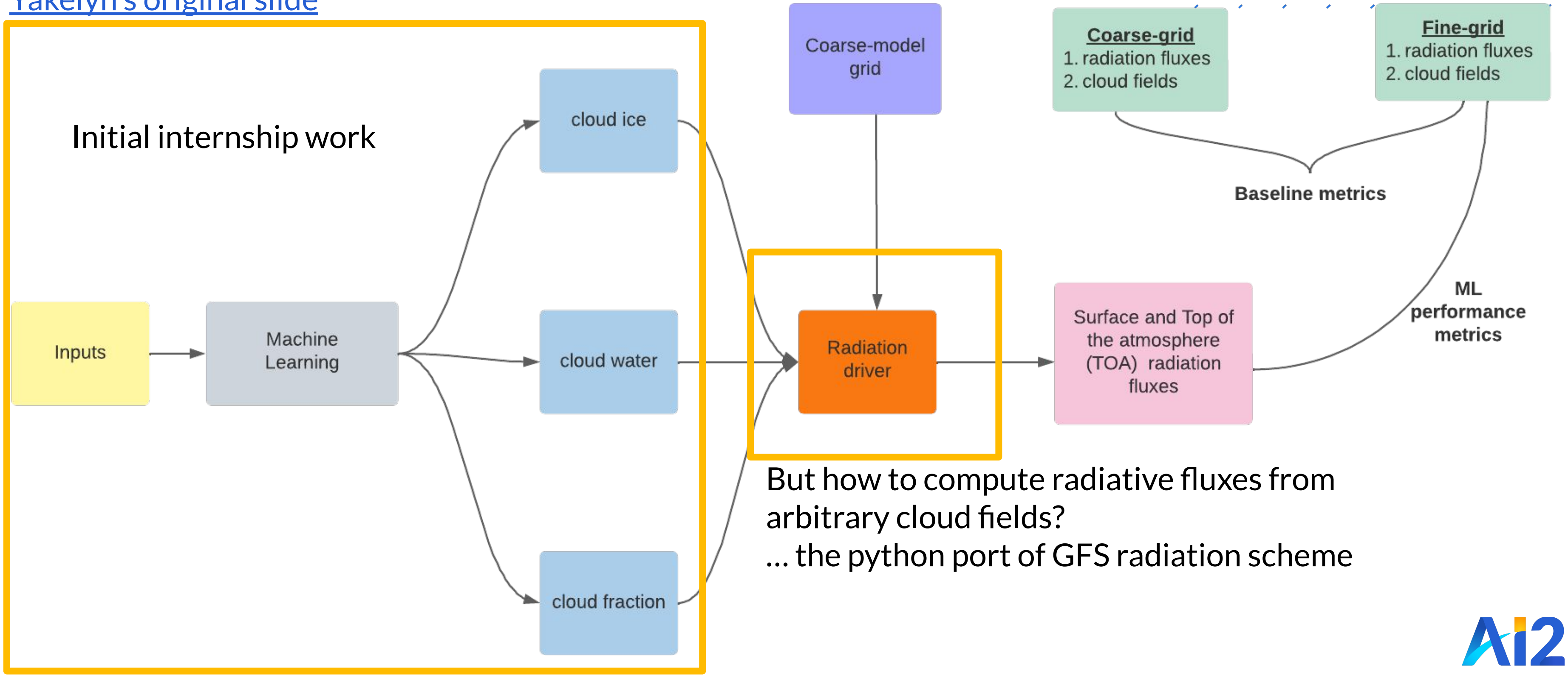
Radiation/Cloud ML - Yakelyn’s work

Yakelyn’s original slide



Radiation/Cloud ML - Yakelyn’s work

Yakelyn’s original slide

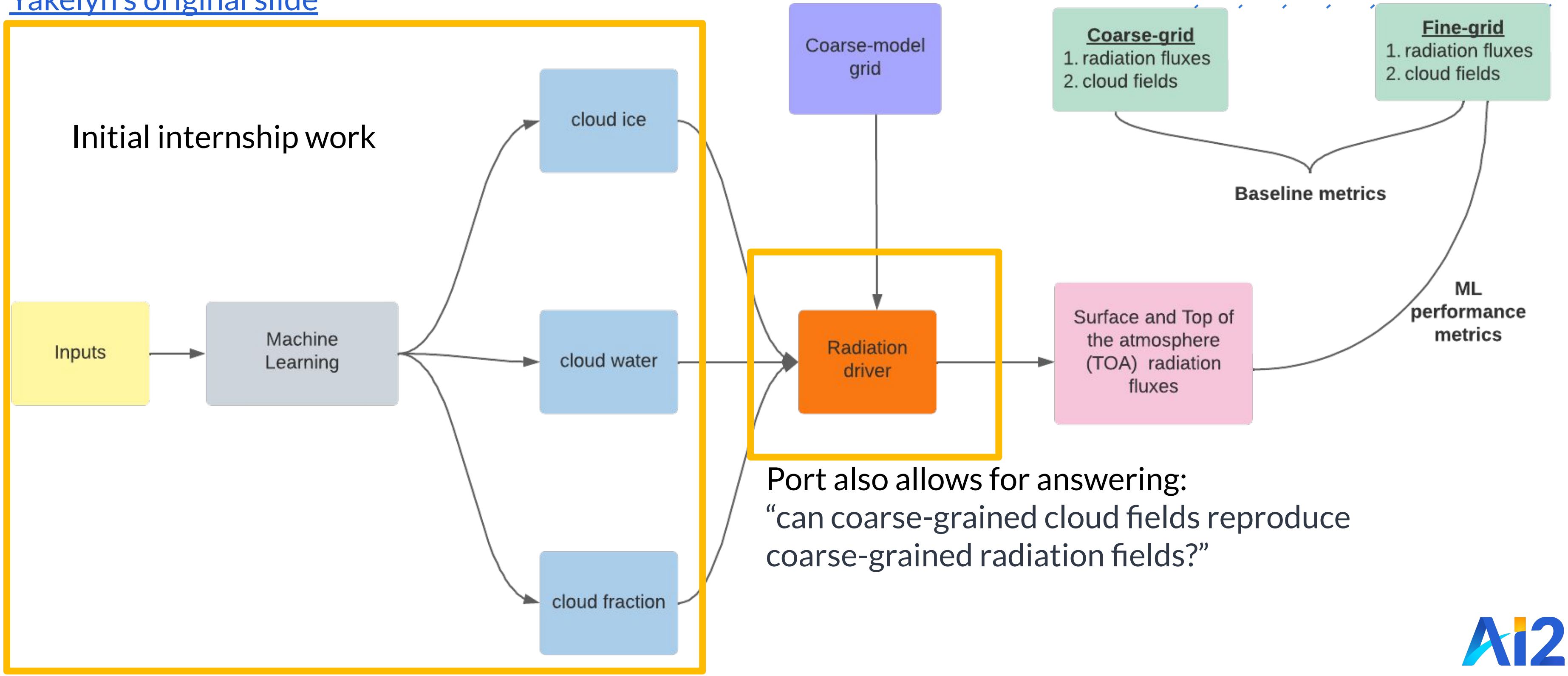


But how to compute radiative fluxes from arbitrary cloud fields?

… the python port of GFS radiation scheme

Radiation/Cloud ML - Yakelyn's work

[Yakelyn's original slide]



Port also allows for answering:
"can coarse-grained cloud fields reproduce coarse-grained radiation fields?"

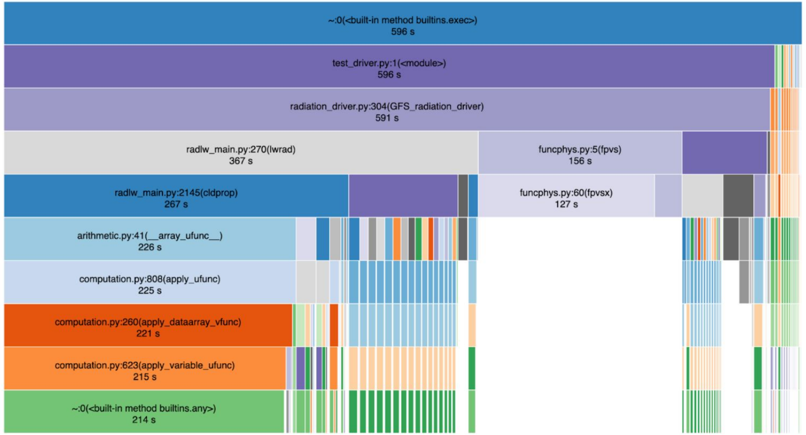
Radiation/Cloud ML - Yakelyn's work

Much performance and validation work

Speed up radiation-physics-standalone

This code has a test_driver.py that validates 24 columns of 63 k levels between the fortran and python code.

It takes about 7 minutes for a total of 144 columns



Radiation/Cloud ML - Yakelyn's work

Much performance and validation work

Tasks accomplished (software development + ML)

1. Speedup the standalone python radiation port by 50x.
    a. 1 full timestep (6-tiles) takes about 8-10 minutes.
    b. There is room for a further improvement =)
2. Validation (fv3gfs-fortran vs the rad port): **longwave** fluxes validates for offline and online setups.
3. Standalone radiation driver is a fv3net package
    a. located in external/radiation
    b. Hopefully the tools located in fv3net can help to find out why shortwave fluxes are not validating
4. Offline ML
    a. *MLclouds impacts on longwave radiative fluxes (today's talk)*
5. Online ML (#todo)

[From internship final presentation]()

Radiation/Cloud ML - Yakelyn’s work

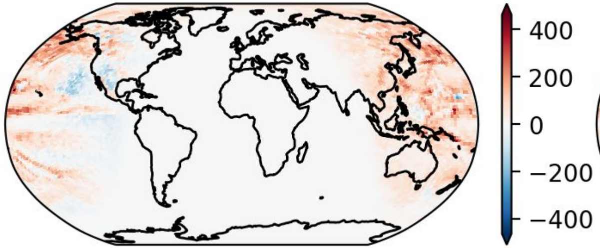
In position to answer questions:

1. “can coarse-grained cloud fields reproduce coarse-grained radiation fields?”
2. “can ML-predicted cloud profiles, plus the T and q profiles, predict surface and TOA longwave and shortwave fluxes?”

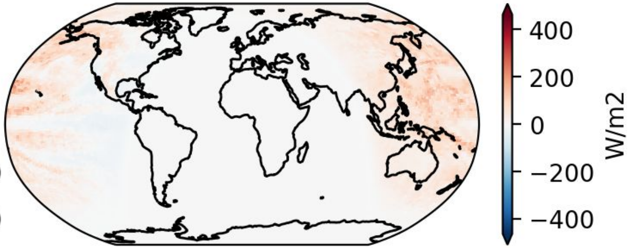
Radiation/Cloud ML - Yakelyn’s work

1. Can coarse-grained cloud fields reproduce coarse-grained radiation fields?

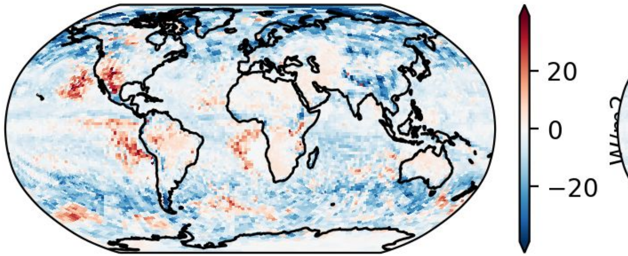
sfc. down SW bias - nudged baseline
mean +22 W/m^2



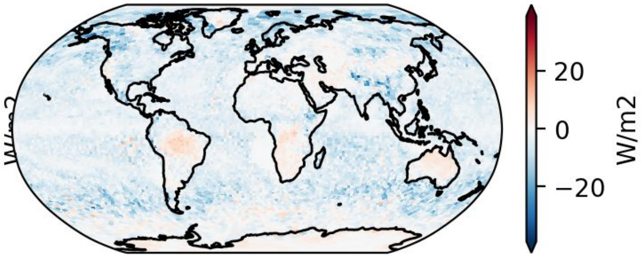
sfc. down SW bias - coarse-grained fine clouds
mean +17 W/m^2



sfc. down LW bias - nudged baseline
mean -5 W/m^2



sfc. down LW bias - coarse-grained fine clouds
mean -3 W/m^2

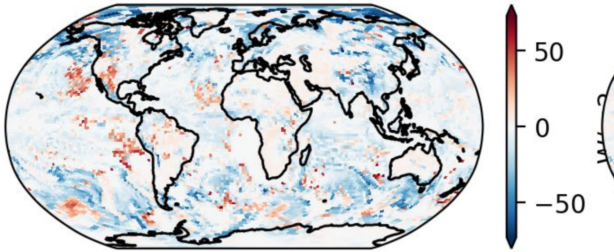


[Final report]

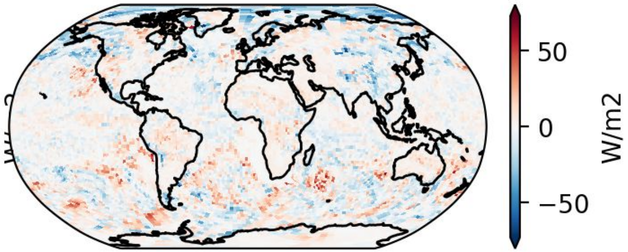
Radiation/Cloud ML - Yakelyn's work

2. Can ML-predicted cloud profiles, plus the T and q profiles, predict surface and TOA longwave and shortwave fluxes?

sfc. down LW bias - nudged baseline
mean -5 W/m^2



sfc. down LW bias - RF fine clouds
mean -3 W/m^2



[Final report]

Radiation/Cloud ML - Yakelyn’s work

In position to answer questions:

1. “can coarse-grained cloud fields reproduce coarse-grained radiation fields?”

    → Actually not that well (!?)

2. “can ML-predicted cloud profiles, plus the T and q profiles, predict surface and TOA longwave and shortwave fluxes?”

    →Yes, can beat nudged baseline. But given answer to 1., is this actually well posed?

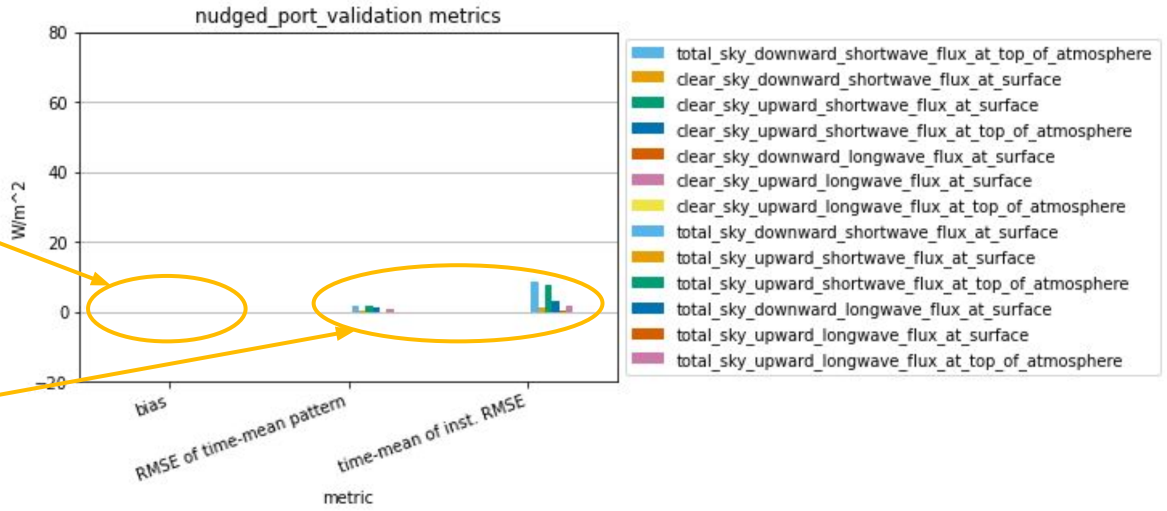
Work since mid-Sept.

Radiation port implementation and validation

- Radiation port implemented in external fv3net package, and made accessible via a wrapper in the prognostic run
  - Wrapper abstracts port API into something simpler
  - Improved configuration management and testing
- Radiation port validation against Fortran GFS radiation:

Port is unbiased against Fortran fluxes

Port total sky fluxes are not exactly the same as Fortran, but this is largely attributable to stochastic scheme

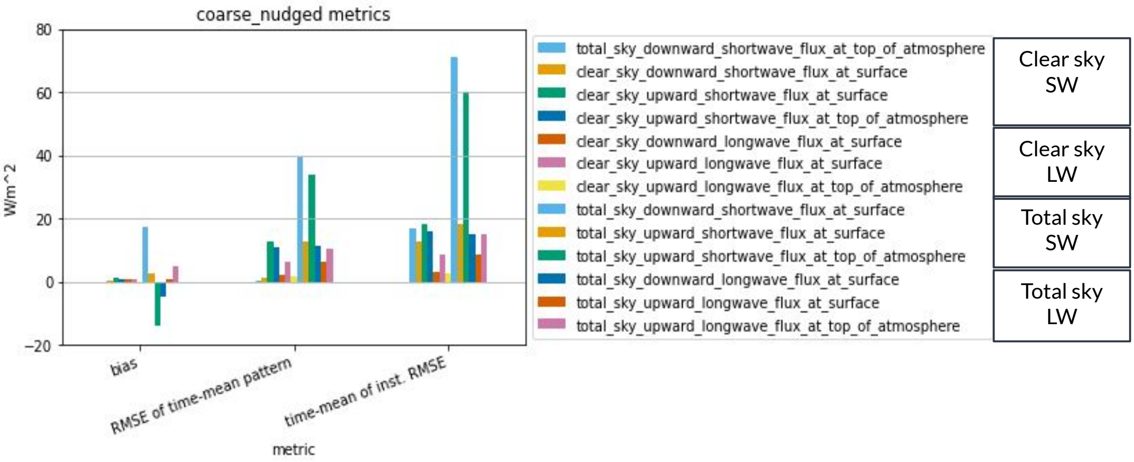


Baseline radiative fluxes

Coarse nudged time-mean errors:

notebook

- Total-sky biases of ~17 W/m^2 in SW (too much gets to surface, too little reflected) and ~5 W/m^2 in LW (too little downward at surface, too much outgoing)
- RMSEs of time-mean ~40W/m^2 SW and ~10 W/m^2 LW



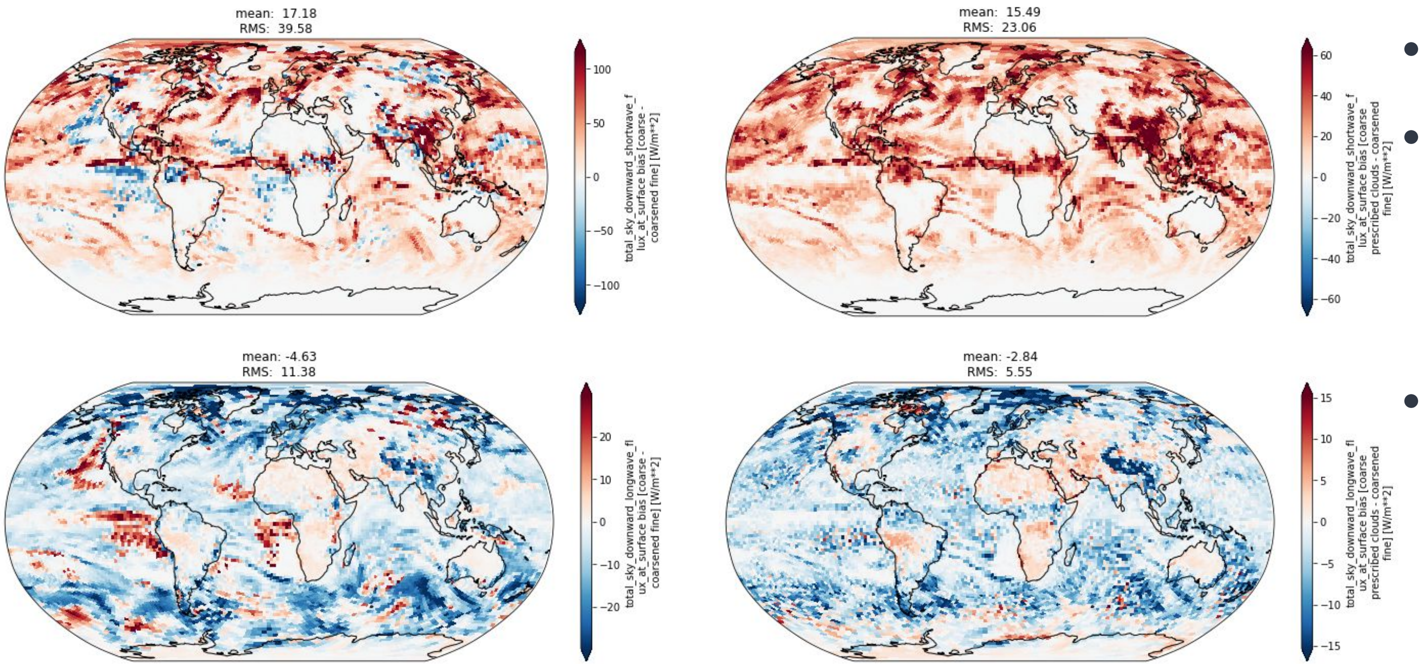
Coarse-grained clouds == coarse-grained fluxes?

Prescribed clouds errors over 1d - downward surface flux bias

[notebook]

SW

LW



Coarse nudged baseline

Prescribed clouds

- Note different color scales
- Prescribed clouds struggle with areas of deep convection/ moisture conv.
- Prescribed clouds eliminate bias from missing shallow stratocumulus

Coarse-grained clouds == coarse-grained fluxes?

Why didn’t the coarse-grained fine clouds, when prescribed as inputs to the coarse radiation scheme, produce unbiased coarse radiative fluxes?

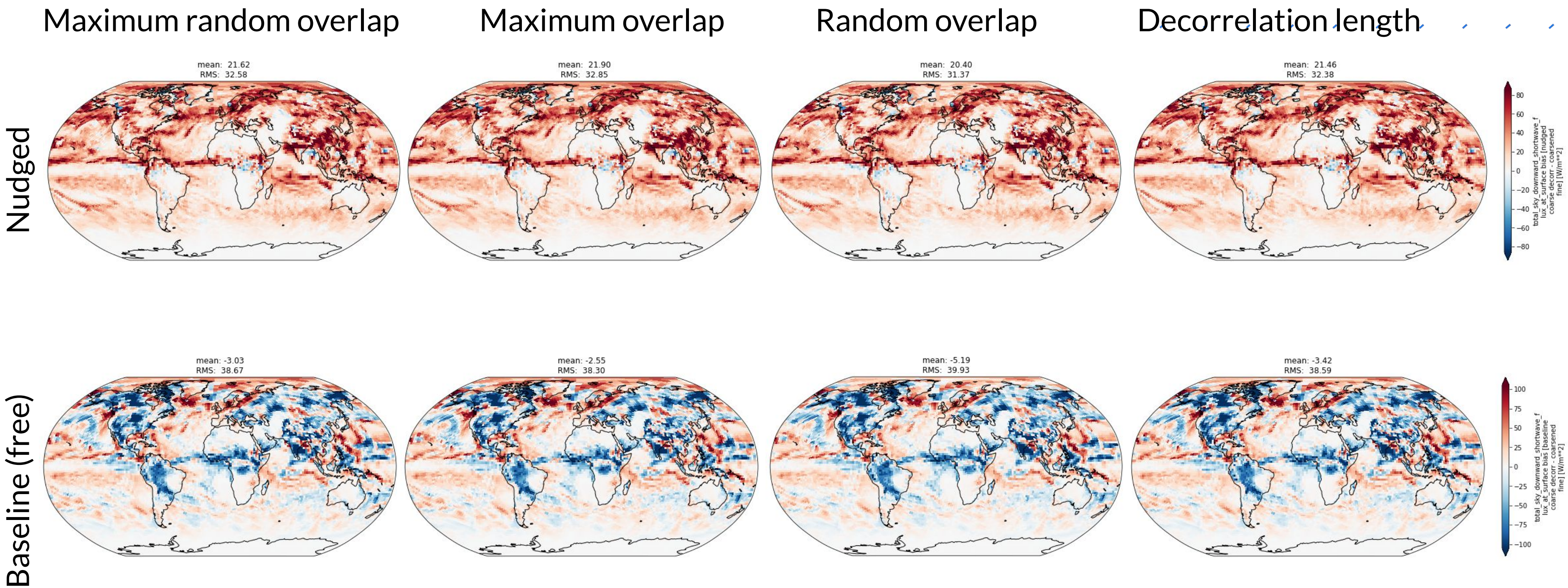
- Something to do with overlap not being preserved properly in coarsened radiation scheme?
- Try an overlap namelist sensitivity experiment with the nudged and baseline coarse runs (using Fortran radiation output – port lacked these options)

Coarse-grained cloud overlap exploration

A bit of background on the MCICA (Monte Carlo Independent Column Approximation) cloud overlap scheme used in GFS radiation:

- Does not simulate separate subgrid spatial “columns”
- Instead, uses spectral discretization (g-points) as proxy for spatial subgrid heterogeneity
- For each spectral band, uses independent random numbers to simulate how correlated the clouds are vertically
- Greater vertical overlap allows more transmittance/less reflection for a column with partial cloud coverage
- Namelist default is “maximum-random”; tends to have high overlap

Coarse-grained cloud overlap exploration: SW down at surface 5-day mean bias

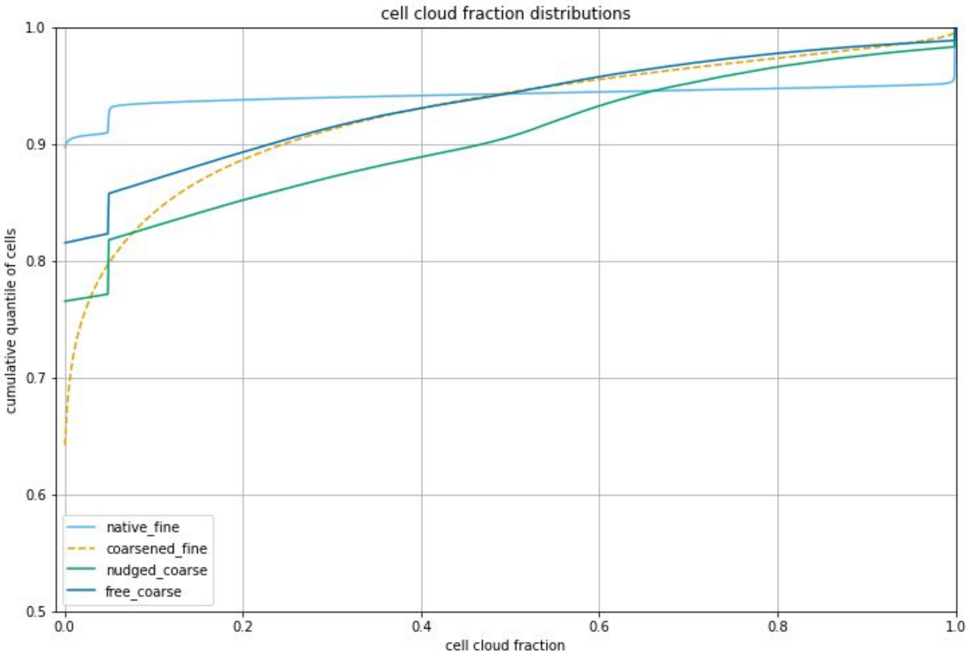


Doesn't seem like there is much sensitivity at all, but this was a bit of a red herring.

Coarse-grained cloud overlap exploration

In fact, native GFS cloud fractions (whether free-running or nudged) have very different distributions than coarse-grained cloud fractions

- Far more fractional cloud cells in coarse-grained fields
- Needed to add the different overlap options to the port to test their effects correctly



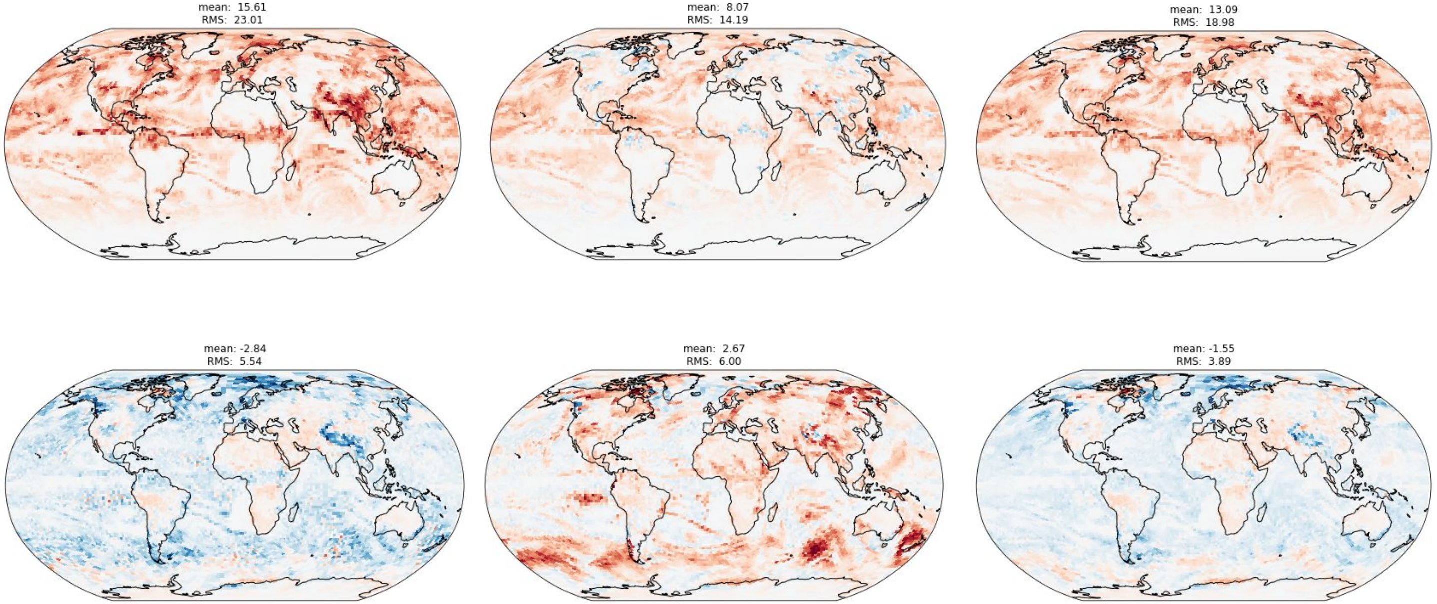
Coarse-grained cloud overlap exploration

For the prescribed coarse-grained cloud fluxes, there is substantial sensitivity to overlap scheme

Max-random overlap | Random overlap | Decorrelation length overlap

Surface downward SW bias

Surface downward LW bias



Coarse-grained cloud overlap exploration

Overlap sensitivity part of the reason why coarse-grained clouds didn't produce coarse-grained radiative fluxes:

- Default namelist setting of maximum-random overlap has "too much" overlap for cloud fields with many fractional cells → too much transmittance
- Random and decorrelation length overlap have effectively less overlap and are a better fit
- They don't get to zero bias alone, however

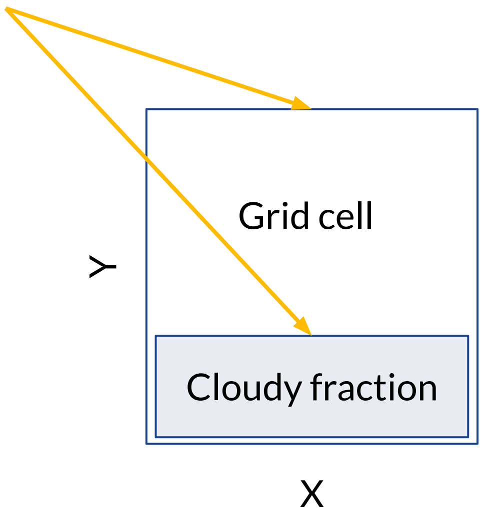
Cloud-fraction scaled condensate

Cloud water and ice (condensate) mixing ratios are reported as grid-cell averages in diagnostics/restarts.

But for radiation calculations, it is more physically correct to assume cloud condensate is inside cloudy fraction.

`ccnorm` namelist flag makes this assumption when `True`, but default is `False`. (This probably doesn't matter much when almost all cells are either 0 or 1 cloud fraction.)

Cloud water mixing ratio reflects which area?



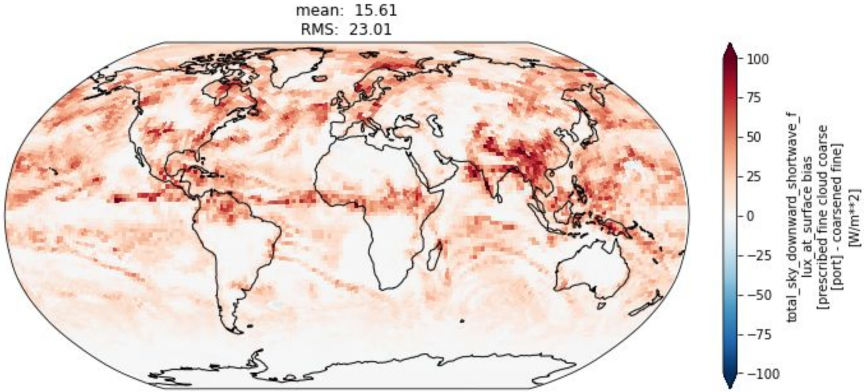
Cloud-fraction scaled condensate

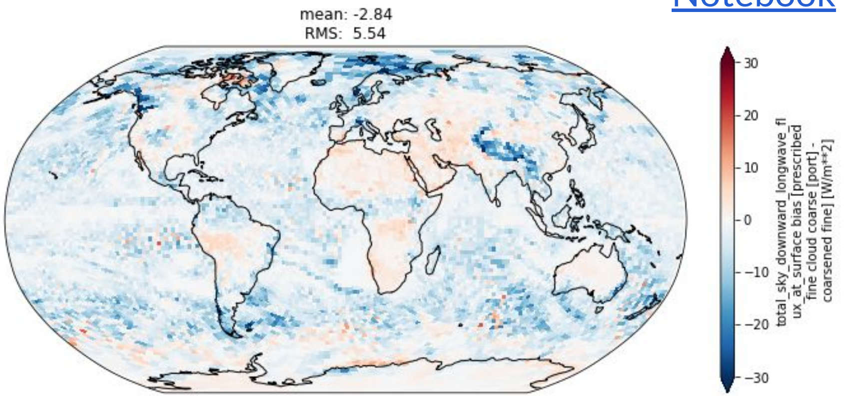
SW bias

LW bias

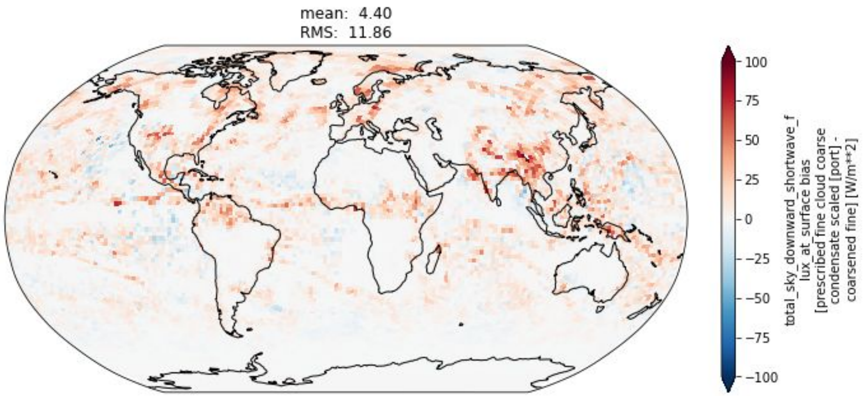
[Notebook]

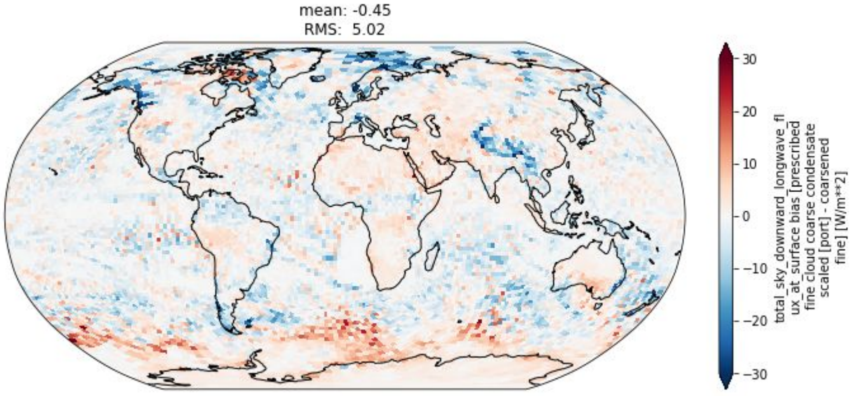
Prescribed cloud





Prescribed cloud +
condensate scaling

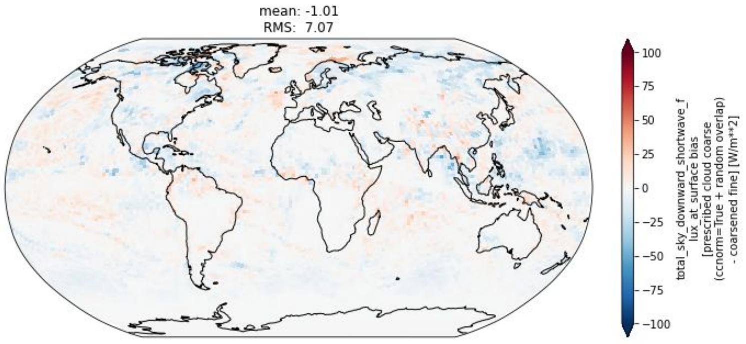




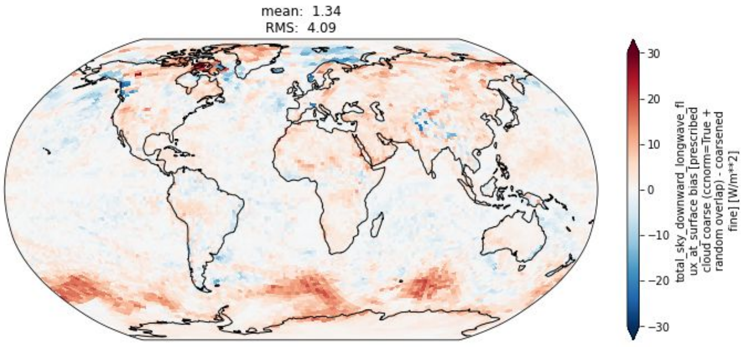
Cloud-fraction scaled condensate

- Coarse-grained cloud radiation is sensitive to condensate scaling assumption; scaling by cloud fraction reduces excessive transmittance bias
- Putting it all together:
    - With physically sensible overlap and condensate scaling namelist choices, we can get unbiased (~1 W/m^2) radiative fluxes from coarse-grained fine cloud fields
    - The ML problem is not ill-posed, assuming we can make ML work with this namelist

SW bias



LW bias



Fine-cloud ML and prescribed cloud radiation

Context: Now have a namelist scheme that produces ~unbiased radiation fluxes with prescribed coarsened-fine clouds. Pivot to ML to predict those clouds.

Following Yakelyn's approach, train ML to predict:

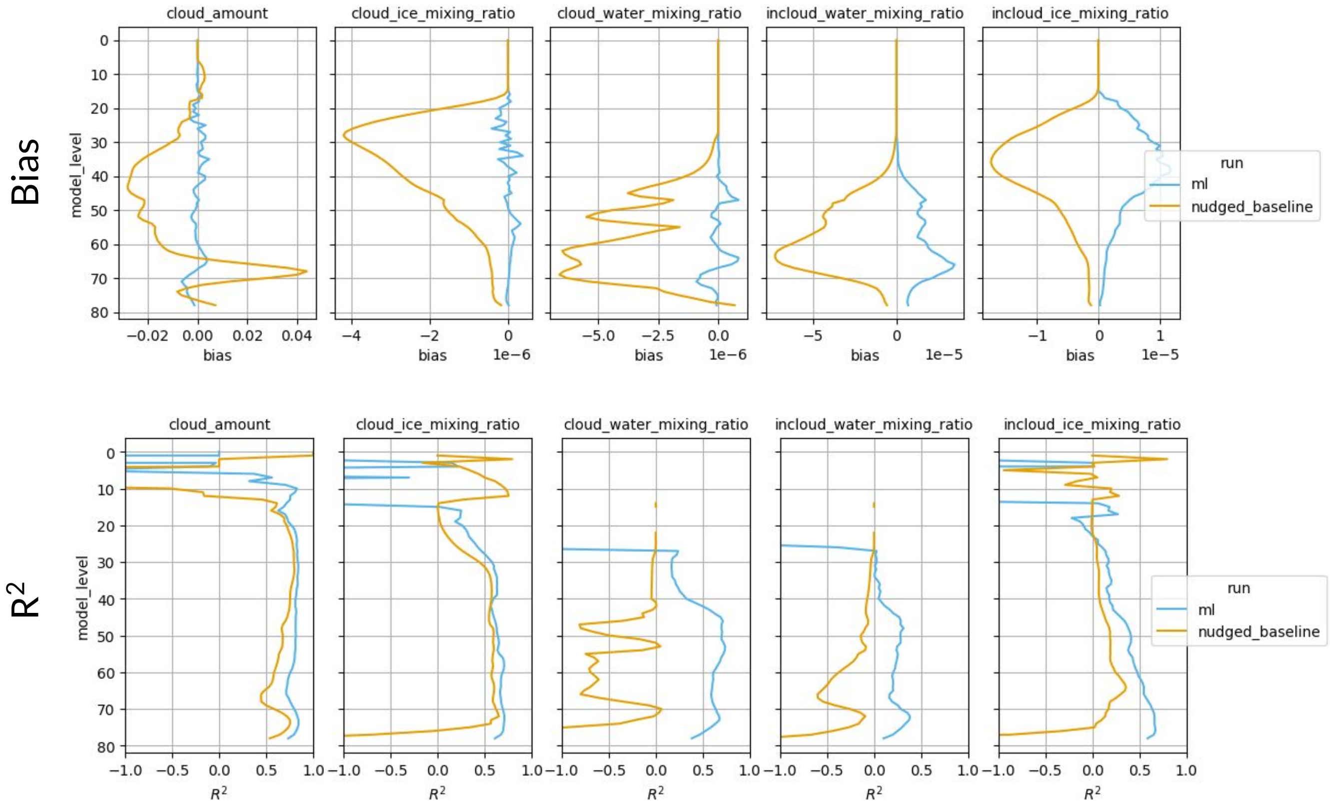
- Cloud water, cloud ice, cloud amount

From grid-cell local:

- Air temperature, relative humidity, pressure, coarse physics cloud ice

Architecture: ~~local dense (grid-cell based not column); simple MLP of 3 hidden layers and width 64~~ Random Forest

Fine-cloud ML and prescribed cloud radiation



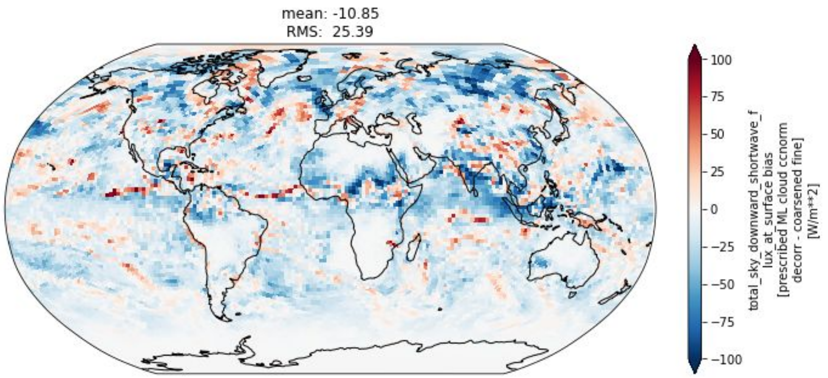
Offline ML performance on cloud fields:

- RF is unbiased for cloud amount, grid-cell mixing ratios
- Beats nudged baseline almost everywhere

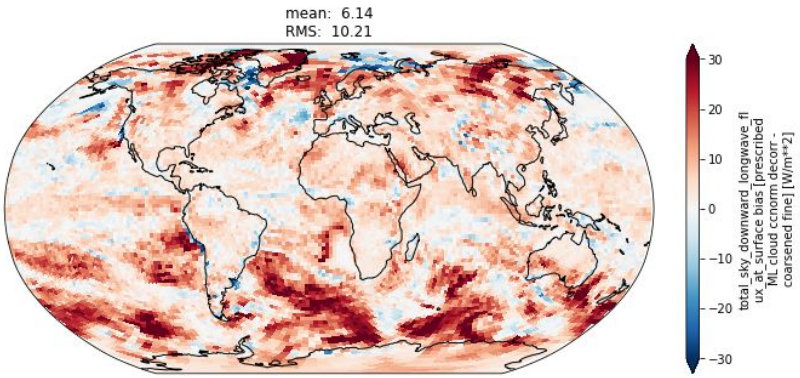
Fine-cloud ML and prescribed cloud radiation

But, radiative fluxes from these ML fields have significant biases (too little transmittance/too opaque)

SW bias



LW bias



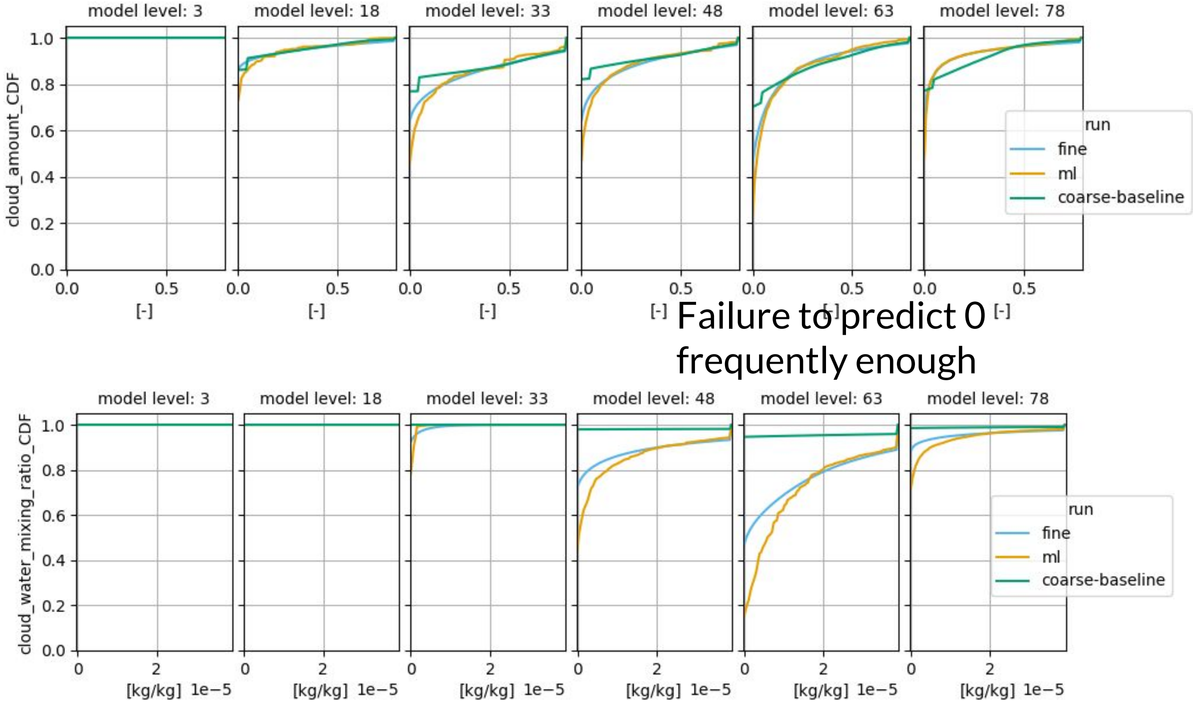
Note, however, that in-cloud mixing ratios were not unbiased. Why?

Fine-cloud ML and prescribed cloud radiation

Note, however, that in-cloud mixing ratios were not unbiased. Why?

Cloud fraction

Cloud water



Failure to predict 0 frequently enough

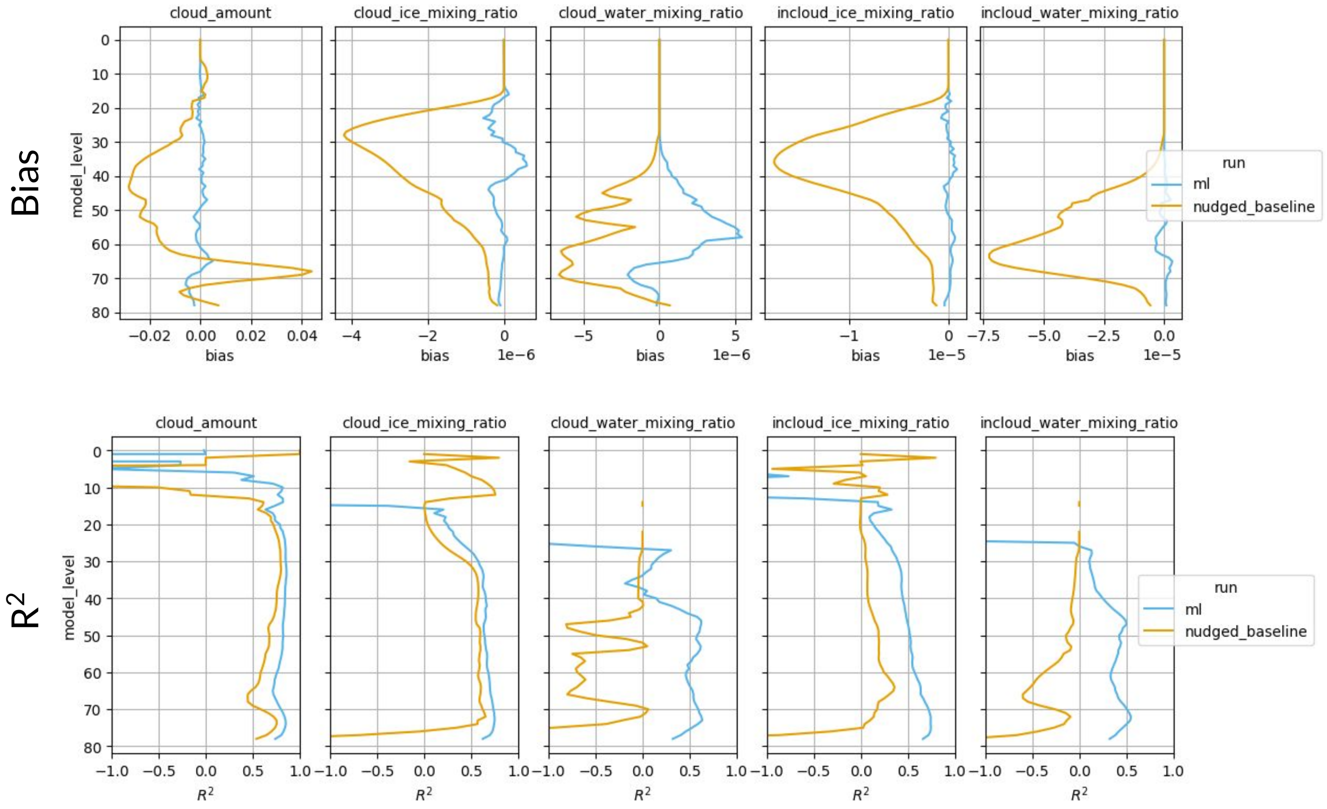
Fine-cloud ML and prescribed cloud radiation

Instead, train RF to predict

- *In-cloud water*, *in-cloud ice*, cloud amount

Then translate predictions into grid-cell cloud water and ice using predicted cloud fractions. The goal is that with `ccnorm: True`, in-cloud prescribed condensate will be most accurate.

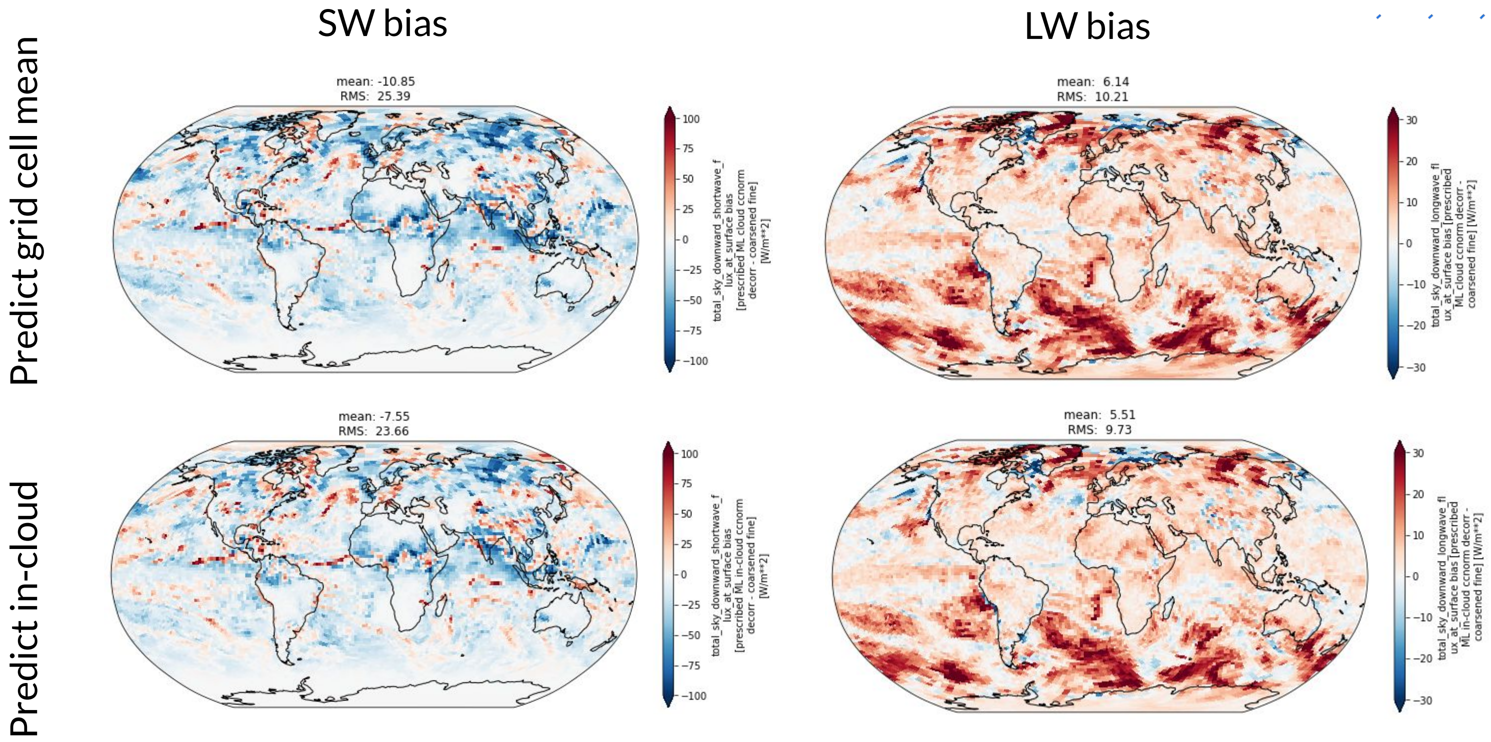
Fine-cloud ML and prescribed cloud radiation



Offline ML performance on cloud fields:

- Now RF is unbiased for *in-cloud* condensate

Fine-cloud ML and prescribed cloud radiation



This gives some improvement, but still not unbiased.

Fine-cloud ML and prescribed cloud radiation

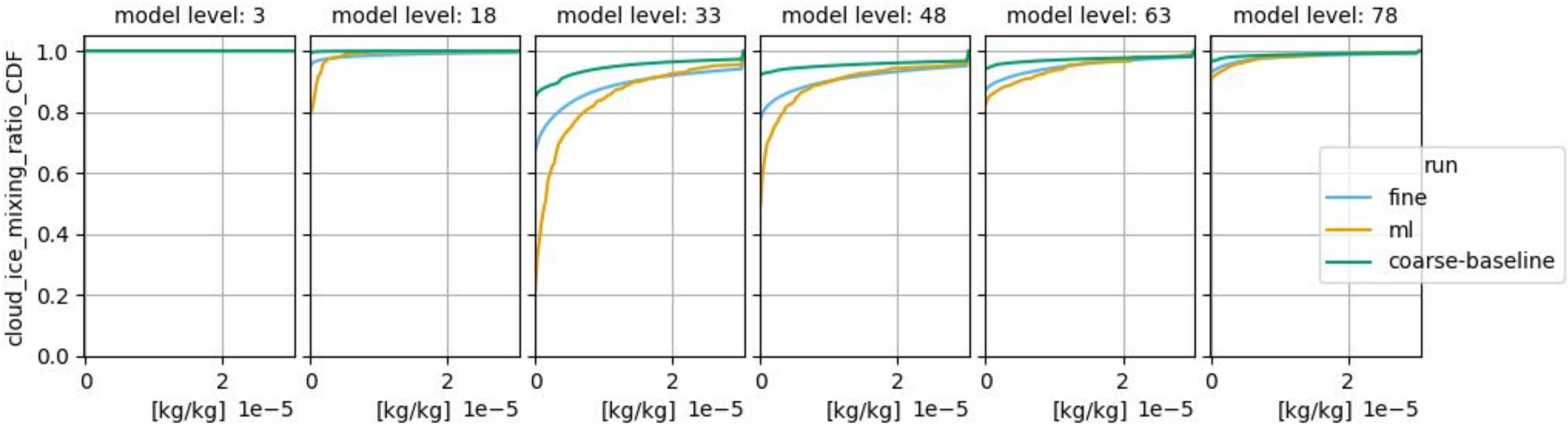
Takeaways:

- Fine-cloud ML is getting close to predicting cloud fields that clearly beat the coarse-nudged baseline
- Still an issue with predicting small values instead of 0 (even with RF), leading to too many non-clear/non-dry cells
- Further ML architecture approaches probably warranted

Additional slides

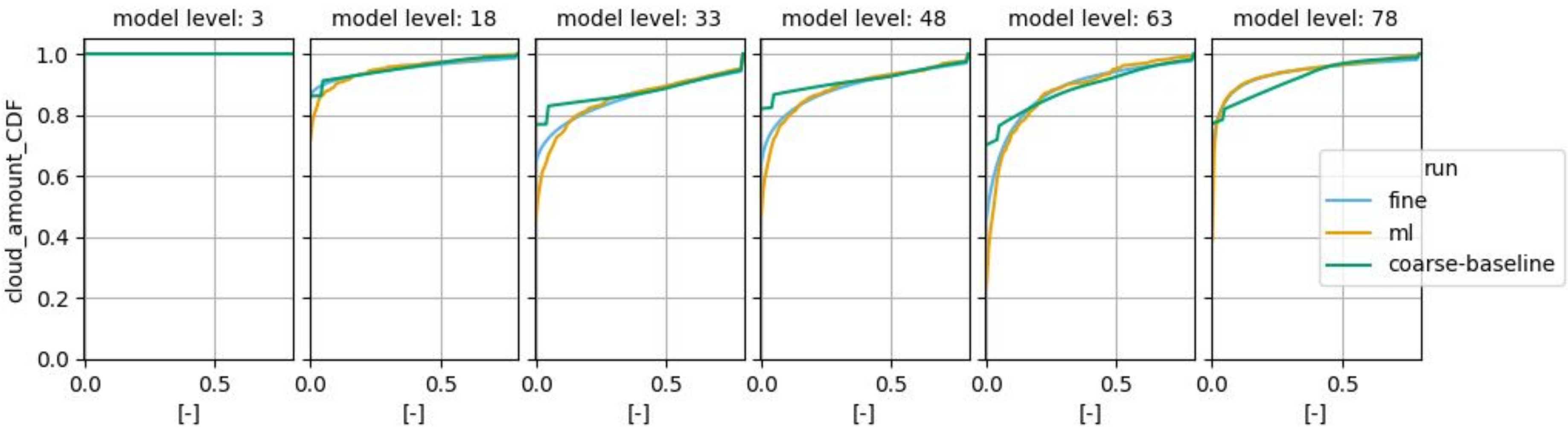
Fine-cloud ML and prescribed cloud radiation

In-cloud RF, grid-cell cloud ice CDFs



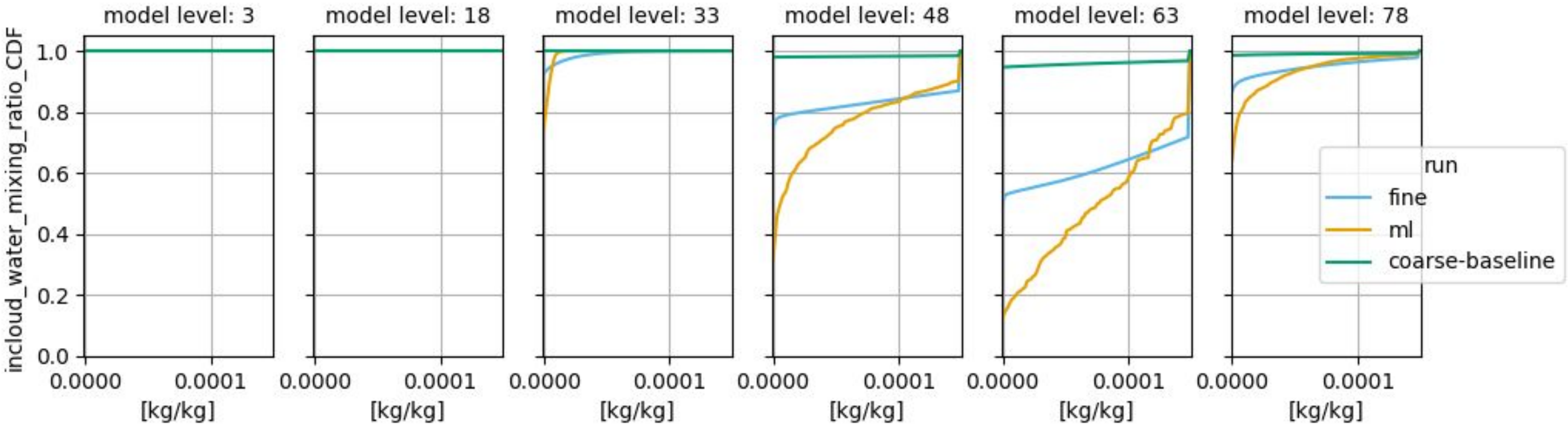
Fine-cloud ML and prescribed cloud radiation

In-cloud RF, cloud amount CDFs



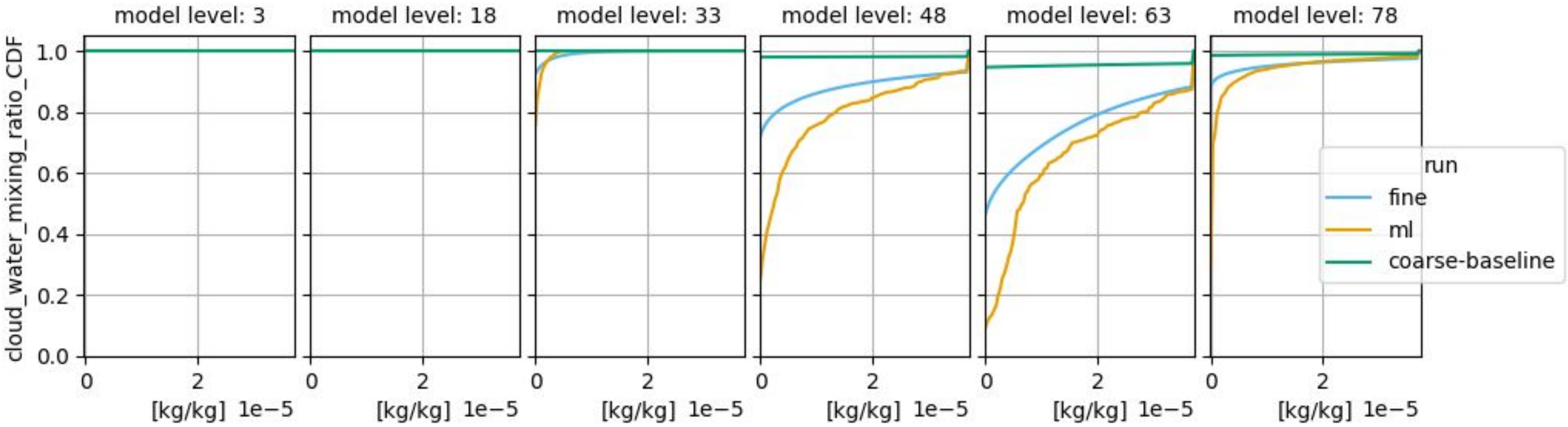
Fine-cloud ML and prescribed cloud radiation

In-cloud RF, in-cloud water CDFs



Fine-cloud ML and prescribed cloud radiation

In-cloud RF, grid-cell cloud water CDFs



Fine-cloud ML and prescribed cloud radiation

In-cloud RF, in-cloud ice CDFs