Mila

Environment and Climate Change Canada
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ClimART

Emulating Atmospheric Radiative Transfer in Weather and Climate Models

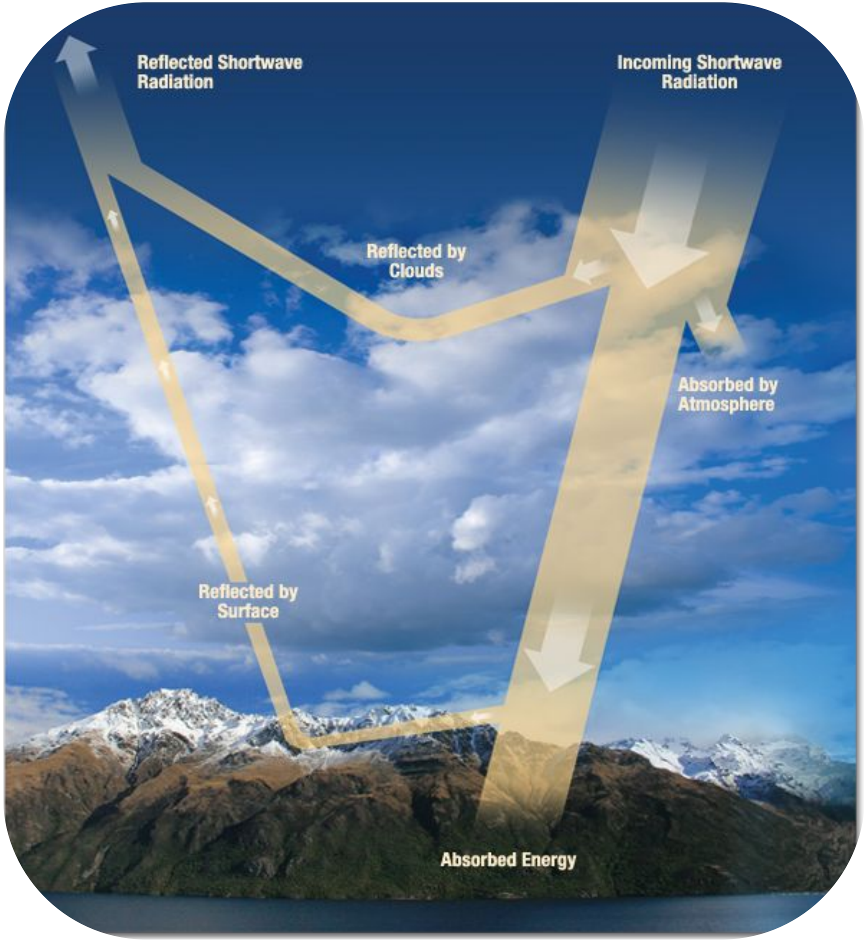
Dataset paper:
ClimART: A Benchmark Dataset for Emulating Atmospheric Radiative Transfer in Weather and Climate Models
Salva Rühling Cachay*, Venkatesh Ramesh*, Jason N. S. Cole, Howard Barker, and David Rolnick.
In Thirty-fifth Conference on Neural Information Processing Systems (NeurIPS) Datasets and Benchmarks Track, 2021.
Code: https://github.com/RolnickLab/climart **Arxiv**: https://arxiv.org/abs/2111.14671

Radiative transfer

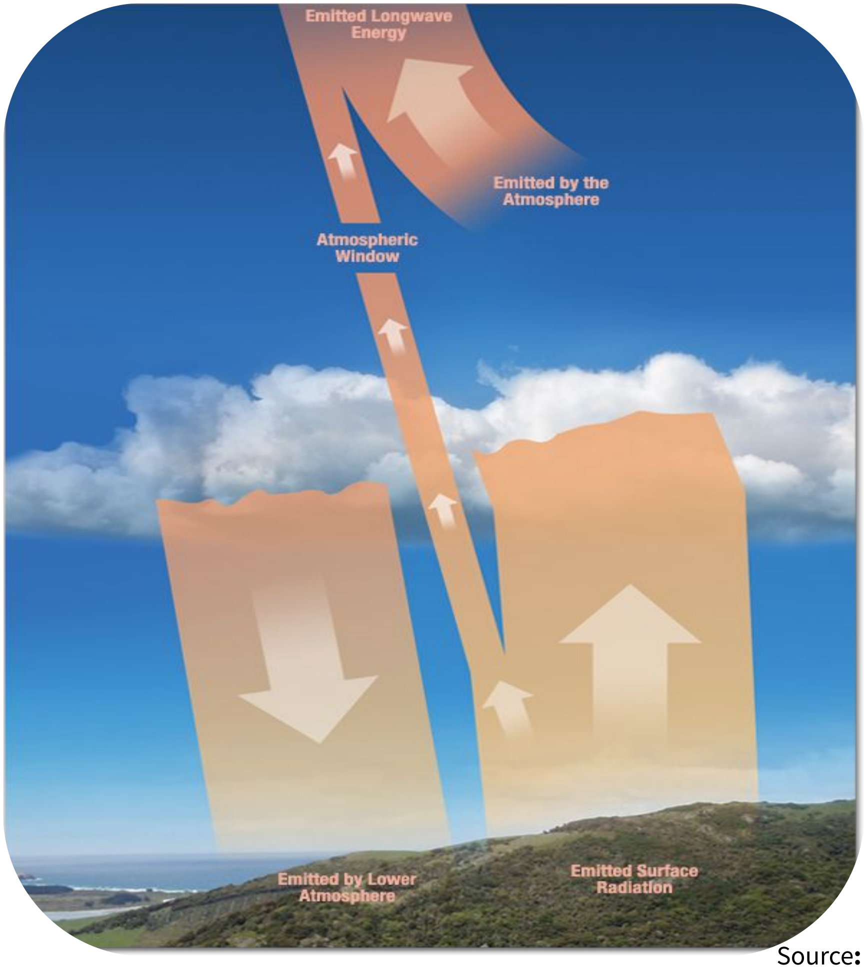
= Propagation of radiation

(through the atmosphere, in our case)

Longwave radiation = emitted by the Earth



Shortwave radiation = emitted by the sun



Source: **Nasa**

Goal: ***Speed-up computationally slow component of climate & weather models***

Why?

→ Allow for more simulations.

→ Improve simulations (e.g.: run at more simulation steps).

→ Run at higher spatial and/or temporal resolution.

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→ Better understand & adapt to the impacts of climate change

→ Motivate stakeholders towards mitigating actions

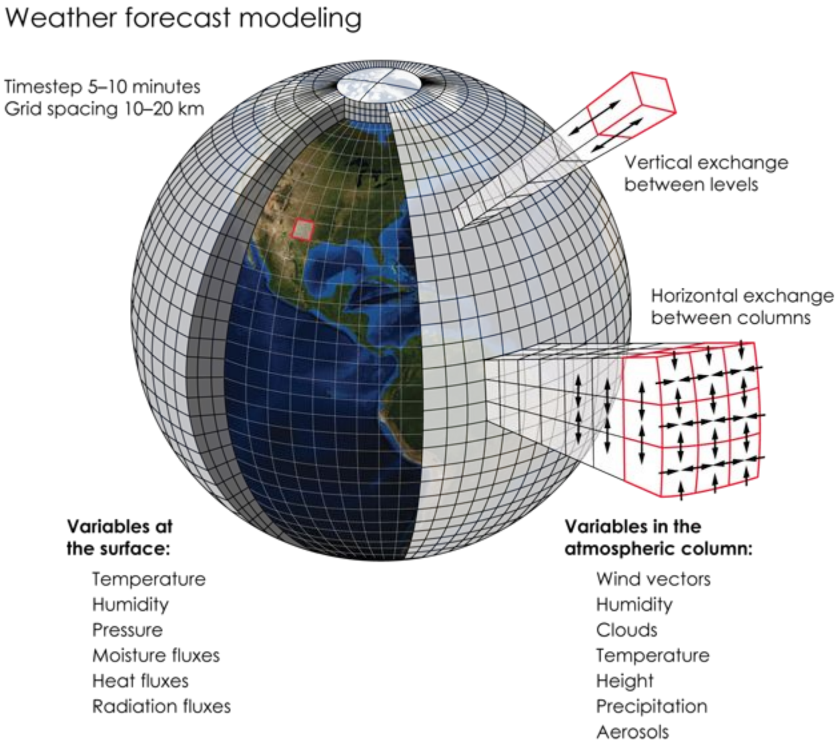
ClimART dataset

→ *Based on input-output pairs drawn from the RT physics scheme of CanESM5*

→ *Follows independent column assumption (McICA)*

→ *Only pristine and clear-sky conditions*

Atmospheric Data Format



Source: SERC/Carleton College

Large-scale

> 10 million data points
& “ML-ready”

- Allow ML model failure analysis
- Standardize dataset, training setup (1979-2004), and evaluation (2007-14)

Comprehensive

Multiple data subsets with distributional shifts

- Historical conditions (1850-52)
- Future conditions (2097-99)
- Anomalies due to volcanic eruptions (eg. Mt. Pinatubo, 1991)

Challenging

Many promising directions for improving on our baselines

- Out-of-distribution generalization
- Complex underlying physics
- Accuracy ← → inference speed trade-off

Experiments

Baselines

As in prior work:

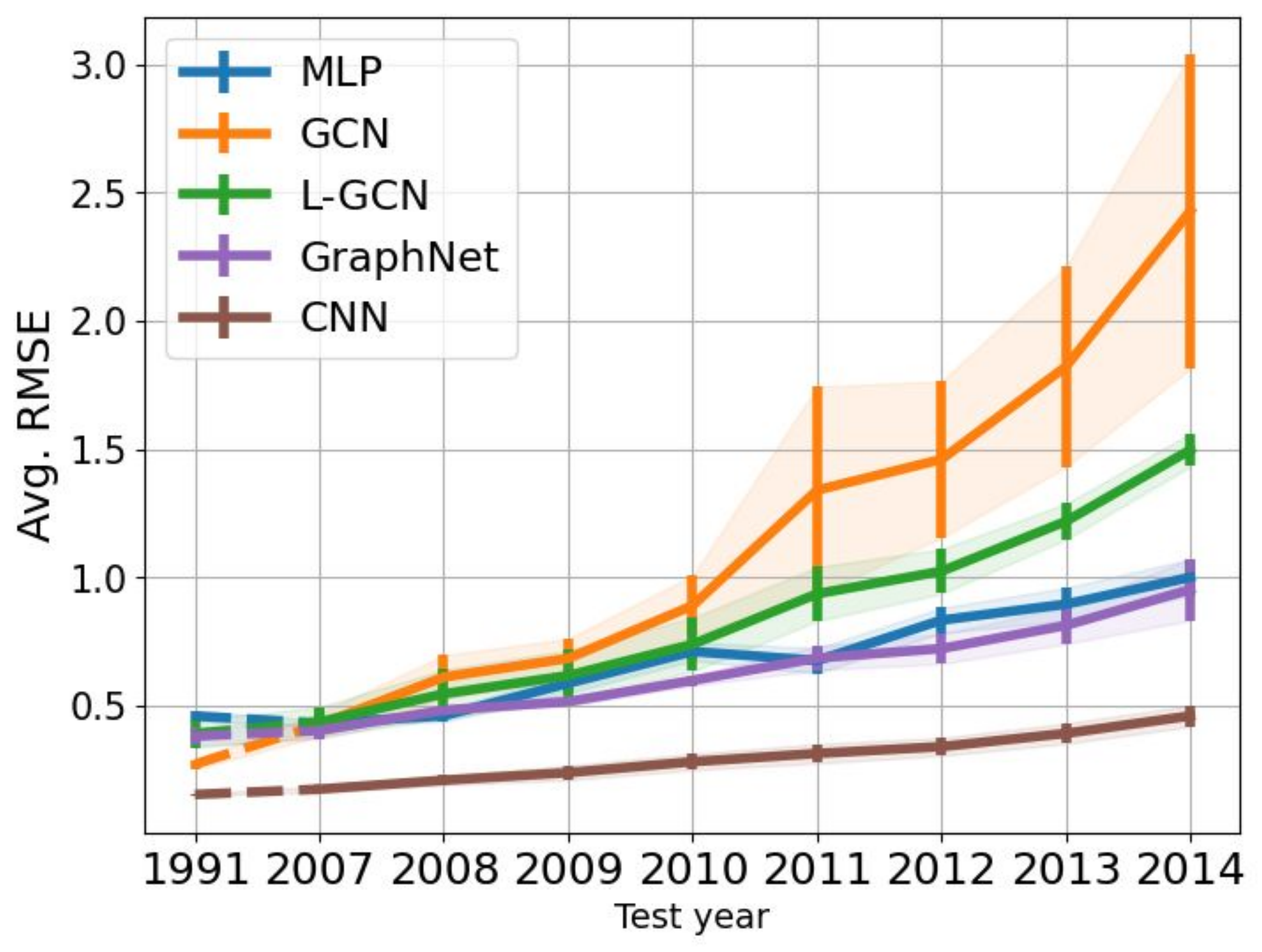
- Fully-connected net (MLP),

  as well as more structured models that we newly propose:

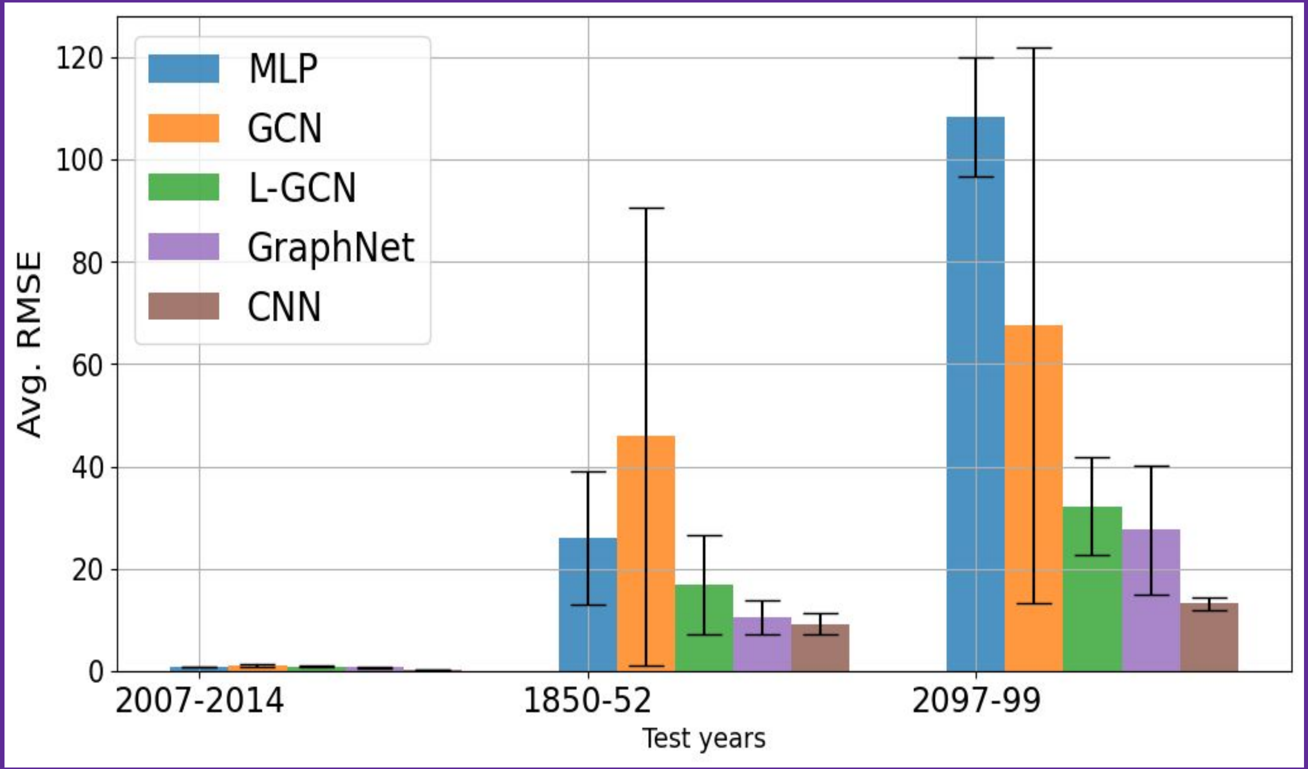
- Graph-based GCN and GraphNet
- Convolutional neural net (CNN)

Performance worsens as test year is farther away from training period

(1990, 1999, 2003)

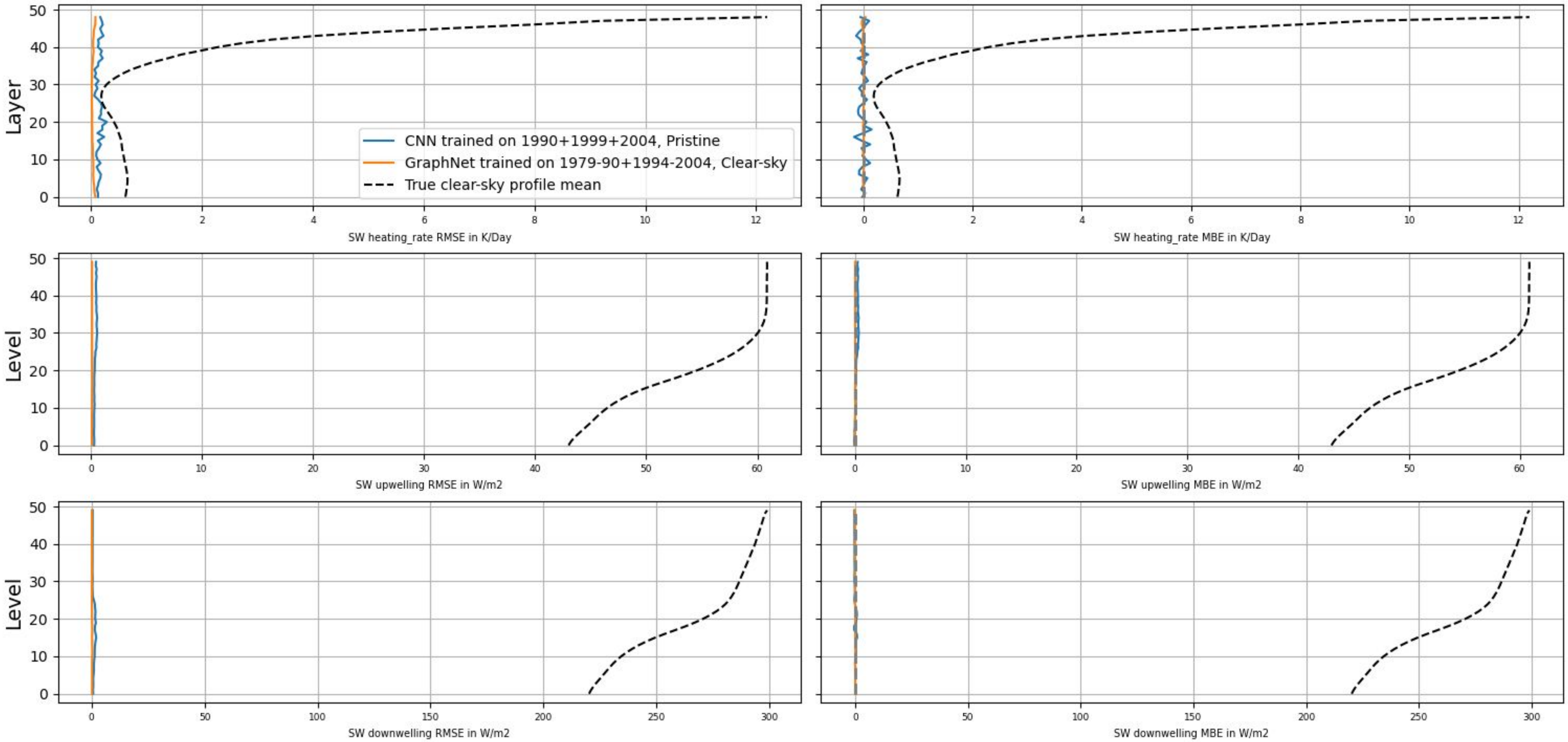


Historical and future climate conditions pose a challenge



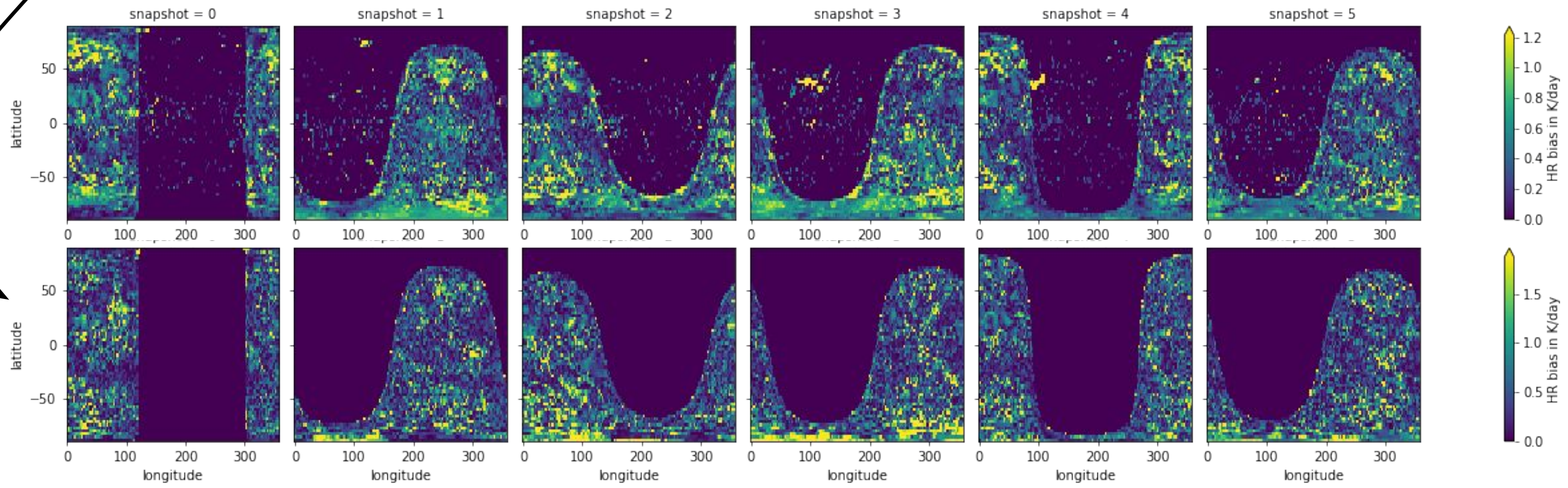
More training data is key!

Vertical profile errors over the test year 2014



Incorporating physics knowledge

- Predict flux profiles → physical equation → get heating rate profile
    - And add a loss component for the resulting heating rates!
- Normalize the shortwave fluxes by the incident/downwelling flux at TOA
    - Incident downwelling flux need not be predicted/is a boundary condition



Important considerations

- Trade-off between accuracy/model complexity and speed
- Trained ML emulator needs to also be validated *on-line*, running jointly with the host weather/climate model
- Weather models require little random errors, but tolerate more bias errors
- Climate models require little bias errors, but tolerate more random errors

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Thanks!

Code: https://github.com/RolnickLab/climart

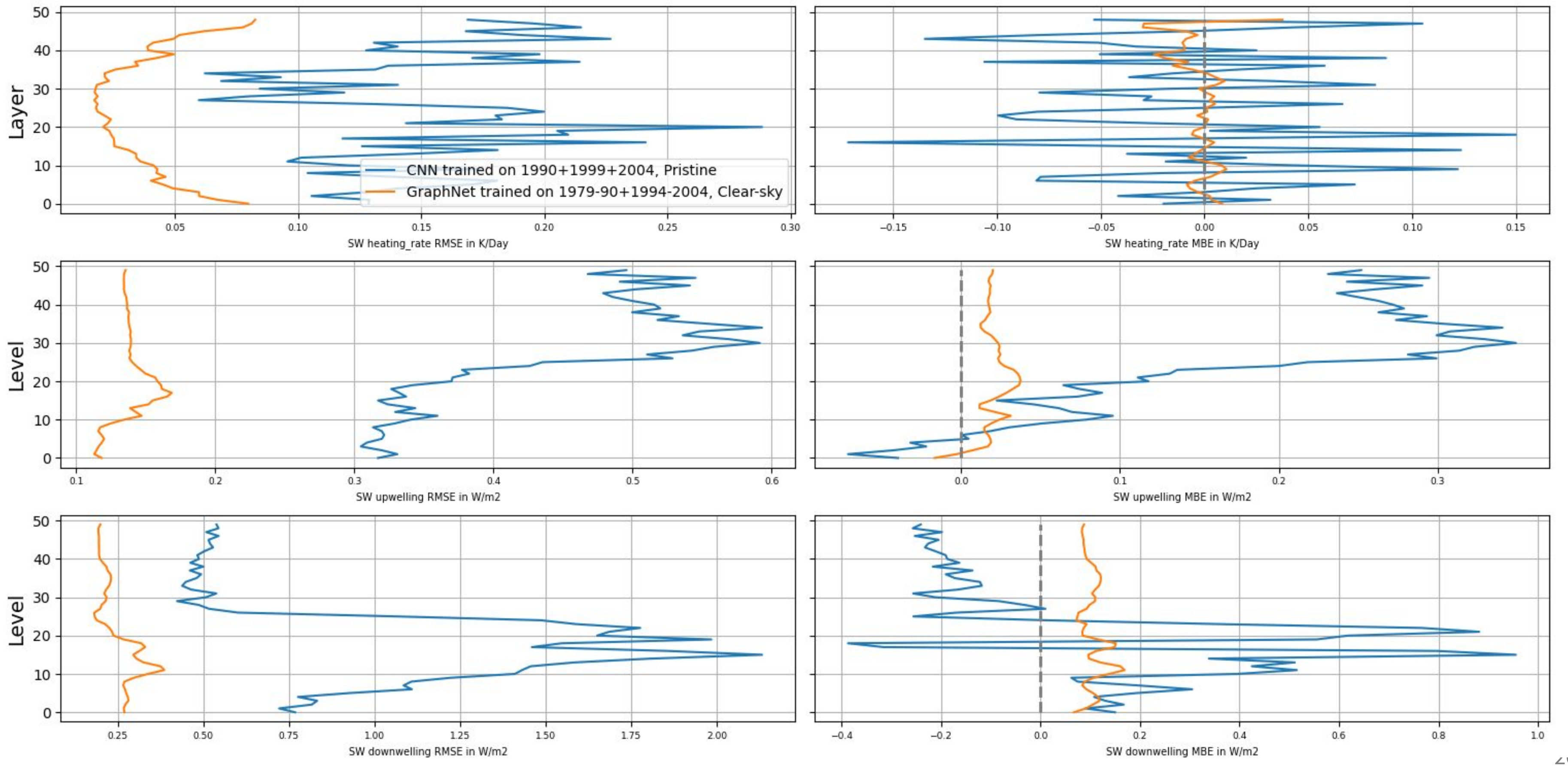
Dataset Paper: https://arxiv.org/abs/2111.14671

Contacts: salvaruehling@gmail.com and venka97@gmail.com

Vertical profile errors over the test year 2014 for:

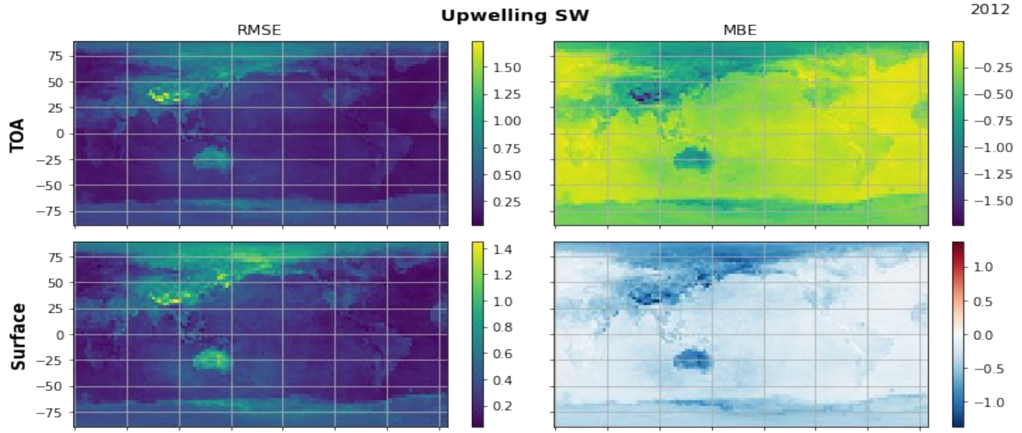
CNN: best model trained on *3y* for the *simpler* pristine-sky

GraphNet: best model trained on *23y* for clear-sky conditions

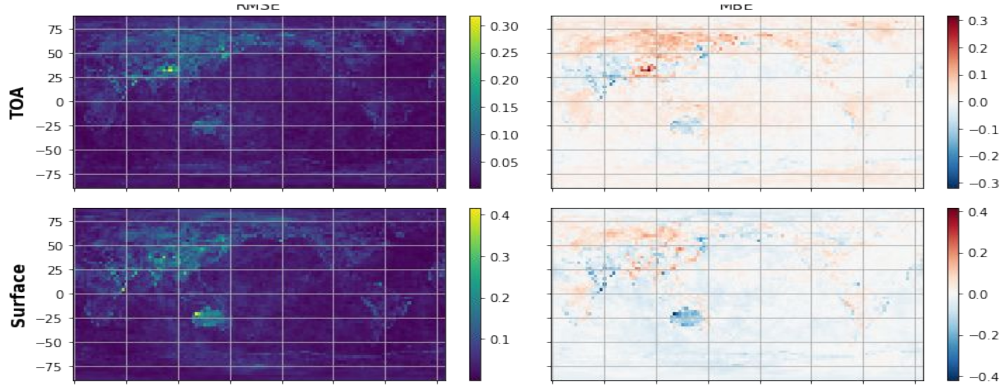


From ClimART paper: A GraphNet trained on 1990+1999,+2004

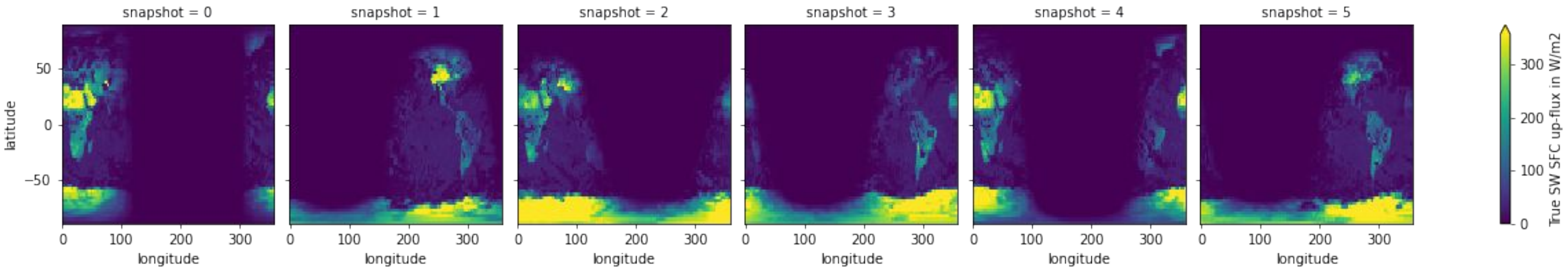
Test year: 2012



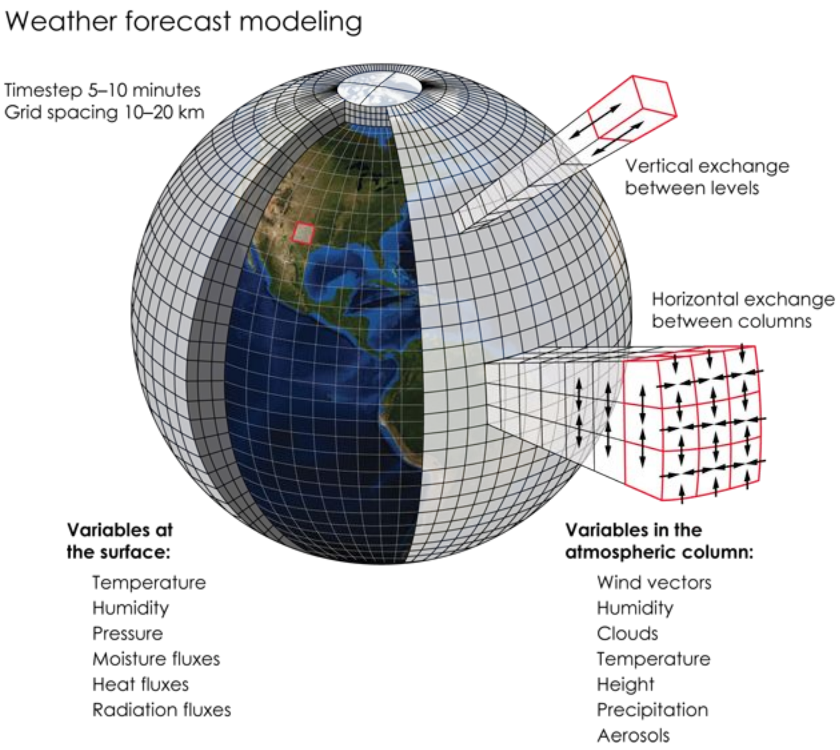
The same GraphNet trained on 1979-90 + 1994-2004

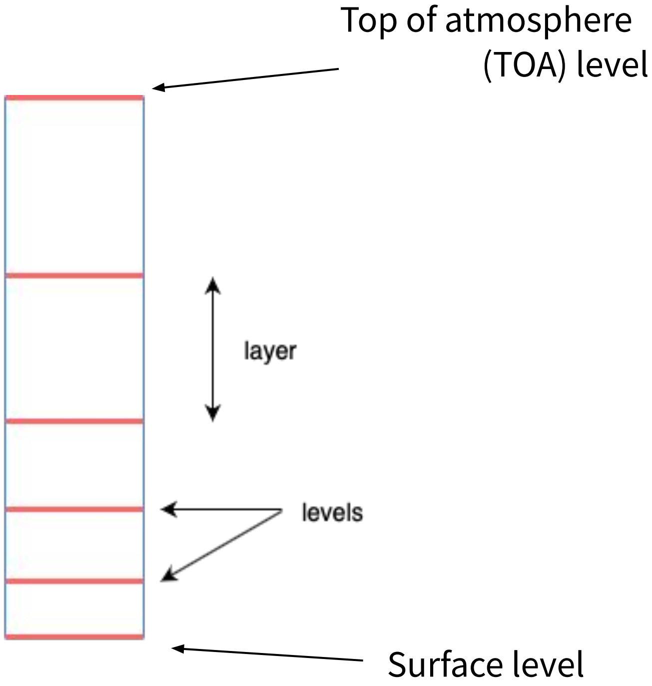


Looking at the data…



Atmospheric Data Format





Lateral view of a profile/column

Source: SERC/Carleton College

Inputs

Non-spatial information

Surface Variables	
emisrot	Surface emissivity for each surface tile
gtrot	Surface temperature for each surface tile
farerot	Fraction of grid of each surface tile
salbrot	All-sky surface albedo for each surface tile
csalrot	Clear-sky surface albedo for each surface tile
gtrow	Grid-mean surface temperature
pressg	Surface pressure

1D vertical profiles of the atmospheric state

Layer/Level Variables	
shtj	Eta coordinate at layer interface
tfrow	Temperature at layer interfaces
shj	Eta coordinate at layer mid-point
dshj	Layer thickness in eta coordinate
dz	Geometric thickness of the layer
tlayer	Temperature at layer mid-point

Gas Variables	
ozphs	Ozone
qc	Water vapour
co2rox	CO2 concentration
ch4rox	CH4 (Methane) concentration
n2orox	N2O concentration
f11rox	CFC11 concentration
f12rox	CFC12 concentration

Potential targets

→ Pristine-sky (neither clouds nor aerosols) or clear-sky (aerosols, but no clouds) conditions

→ Long- and short-wave radiative fluxes as well as heating rates

Output Variables	
rldc	Downward thermal (longwave) flux profile
rluc	Upward thermal flux profile
rsdc	Downward solar (shortwave) flux profile
rsuc	Upward solar flux profile
hrsc	Solar heating rate profile
hrlc	Thermal heating rate profile