CMCC WEBINAR

November 13, 2018 - h.3.00 pm CET

Machine learning and cloud process parameterization for weather and climate models

Christopher S. Bretherton - Presenter
University of Washington – USA

Giovanni Aloisio - Moderator
Fondazione CMCC - Euro-Mediterranean Center on Climate Change

To investigate and model our **climate system** and its interactions with **society** to provide reliable, rigorous, and timely **scientific results**, which will in turn stimulate sustainable growth, protect the **environment**, and **develop science driven** adaptation and **mitigation policies** in a **changing climate**

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Advanced Scientific Computing (ASC)

Climate Simulation and Prediction (CSP)

Economic analysis of Climate Impacts and Policy (ECIP)

Impacts on Agriculture, Forests and Ecosystem Services (IAFES)

Ocean modeling and Data Assimilation (ODA)

Ocean Predictions and Applications (OPA)

Risk Assessment and Adaptation Strategies (RAAS)

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TOPICS

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Machine Learning and Cloud Process Parameterization for Weather and Climate Models

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Noah Brenowitz

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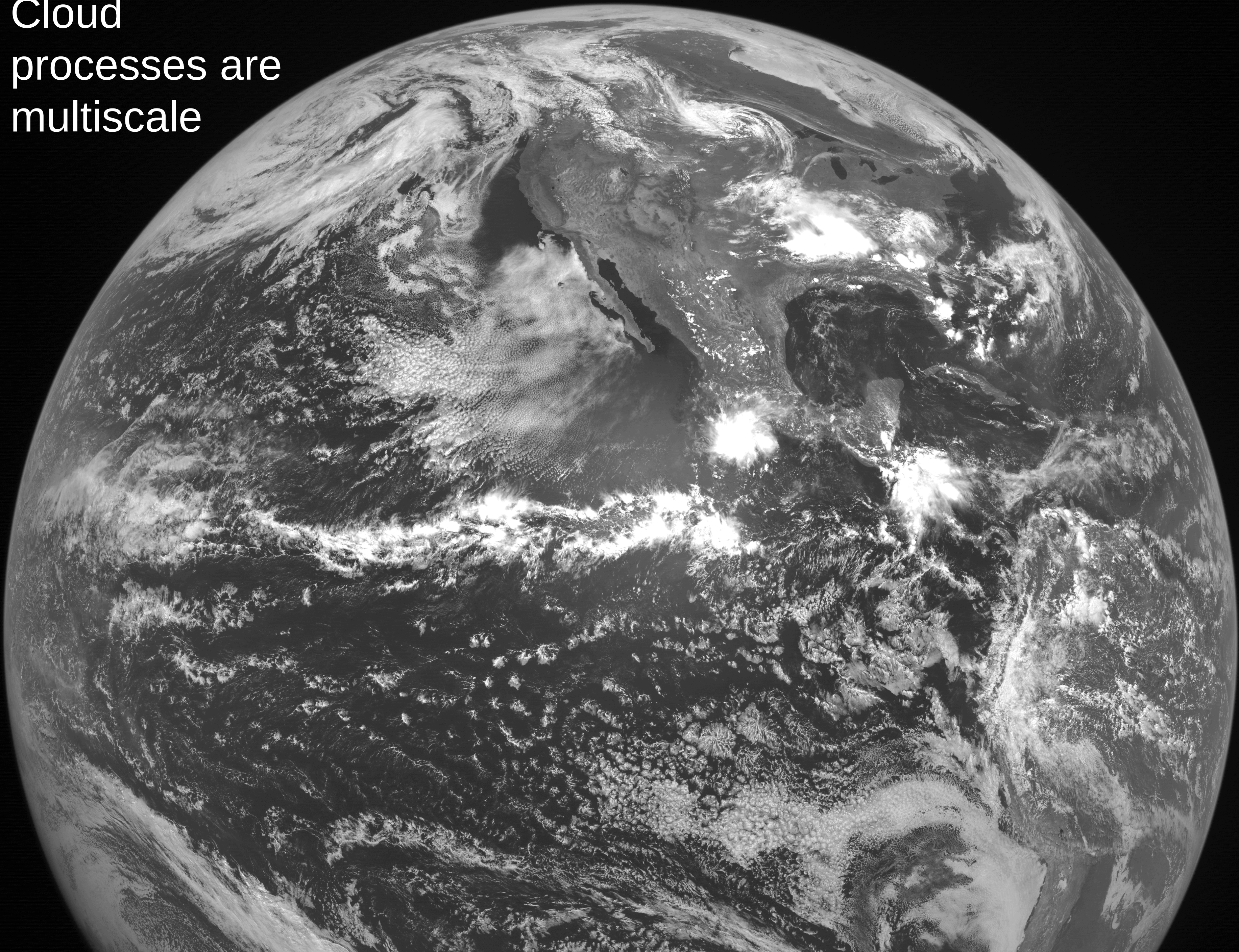
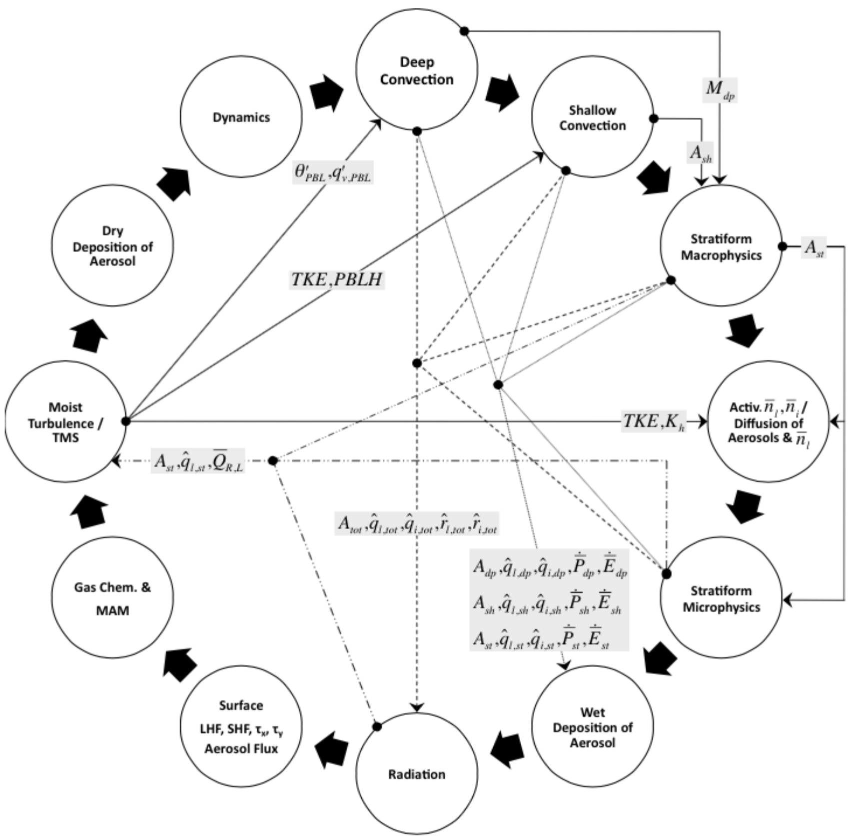
Atmospheric Sciences
University of Washington

Cloud processes are multiscale

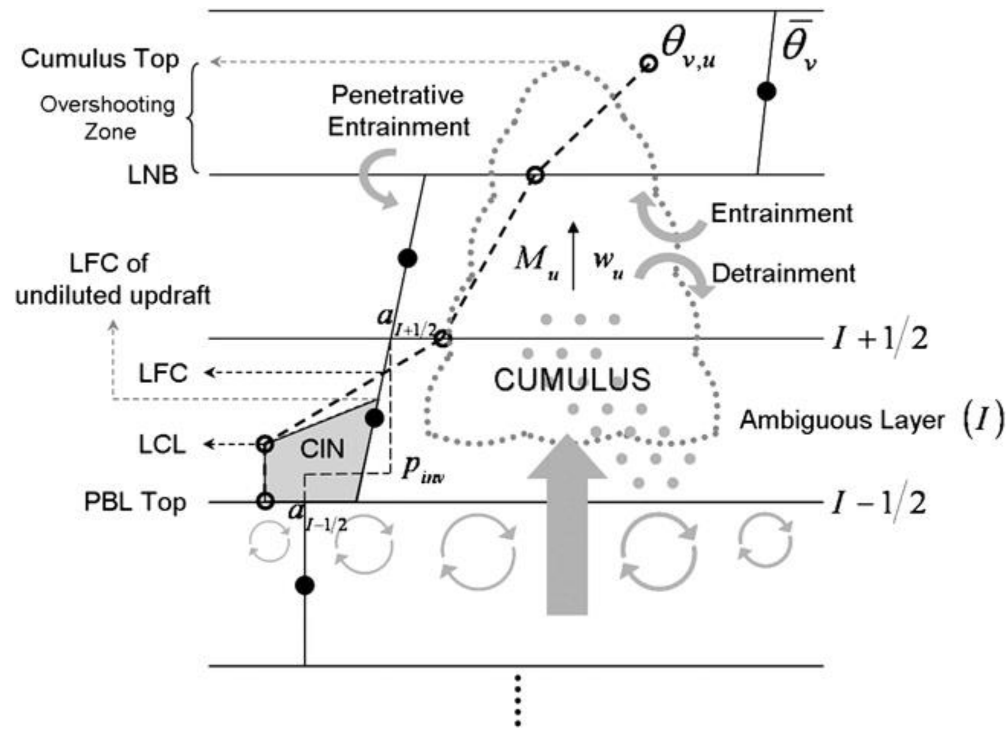



A single grid column of a global climate model (100 x 100 km)

Representing such unresolved variability is challenging



Park et al. 2014

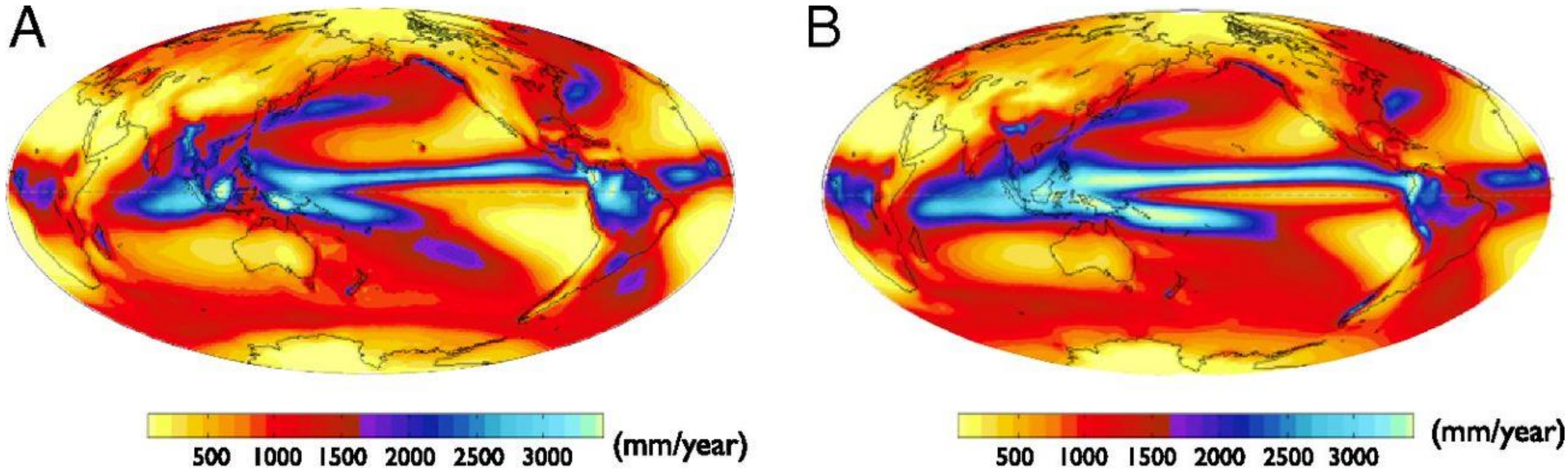


Park and Bretherton 2009

…so 'parameterizations' of moist physics are difficult to develop, subjective and work imperfectly.

Feeds into weather/climate model biases & uncertainties

Example: Double-ITCZ rainfall bias in climate models



GPCP
(observations)

CMIP5
(models)

Subgrid parameterization improvements have come more through ‘targeted tweaking’ than from fundamental advances.

Big Science = Big Headaches or Big Opportunities?

Big Data

- 1 km and finer global satellite data on radiation, clouds, precipitation, surface characteristics, aerosols, ice…
- High-resolution global simulation of weather (5-10 km) and climate (25-100 km). Yet finer-grid regional models.

Big Problems

- Models still need parameterizations and optimization. Current approach is not reducing intermodel spread in climate sensitivity or regional precipitation trends.

Can machine learning (ML) enable:

More accurate parameterizations?

Better use of the data we have?

Use of ultrafine models that resolve cloud processes?

Applications of machine learning to weather and climate

- Detect extreme weather events in model output
  [Liu et al. 2016]
- Emulate parameterizations to speed them up
  [Chevalier 1998; Krasnopolsky et al. 2005; O'Gorman and Dwyer 2018]
- Automatically optimize adjustable parameters
  [Ollinaho et al. 2013]
- Automatically learn from data or reanalysis
  [Dueben and Bauer 2018]
- **Make coarse-grid parameterizations from fine-grid models.**
  [Krasnopolsky et al. 2013; Brenowitz and Bretherton 2018; Rasp et al. 2018]

Issues:

1) Machines only beat human learning if trained with **lots** of data
2) Shouldn't extrapolate out of training climate regime

(ML using present observations not good for a warmer climate)

Cloud processes are better simulated on fine grids

Giga-LES (*Khairoutdinov et al. 2009*)
100x100 km with 100 m grid

1 km global simulations are (briefly) possible

MIYAMOTO ET AL.: CONVECTION IN A SUB-KM GLOBAL SIMULATION

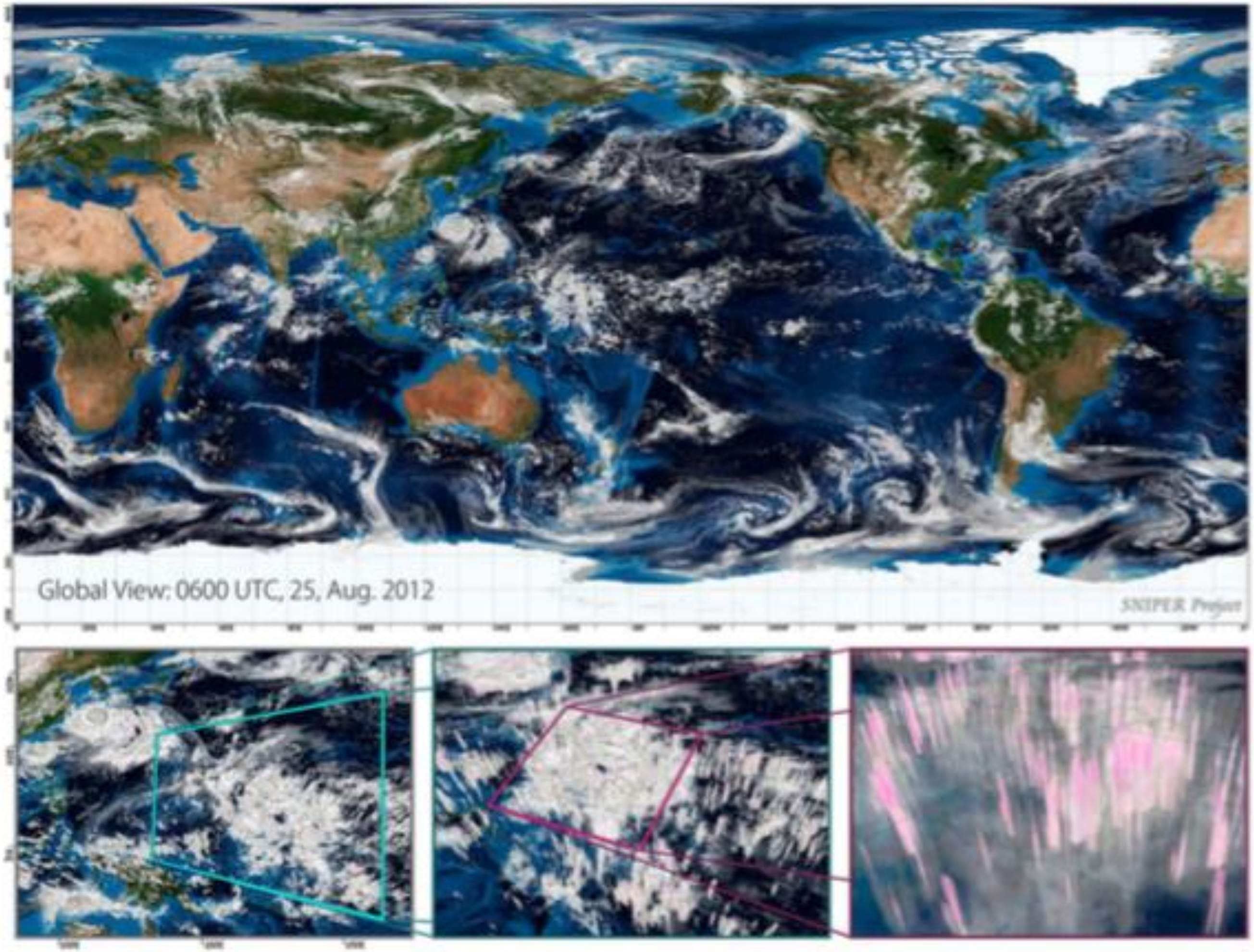


Figure 1. (top) Horizontal view of the total mixing ratio of condensed water contents in Δ0.87, (bottom left) close-up view of the northwestern Pacific, (bottom middle) a further close-up view for a cloud cluster, and (bottom right) an extreme close-up of an active convection region. The pink color indicates the hydrometeor density larger than 2 g kg^{-1}. Topography and bathymetry are Blue Marble (August) by Reto Stöckli, NASA Earth Observatory.

NICAM

3.5-14 km (mo-yr)
Tomita et al. 2005

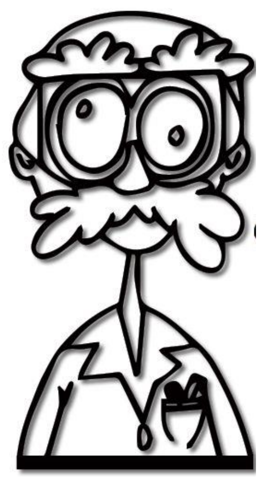
0.9 km (for 24 hr):
Miyamoto et al. 2013

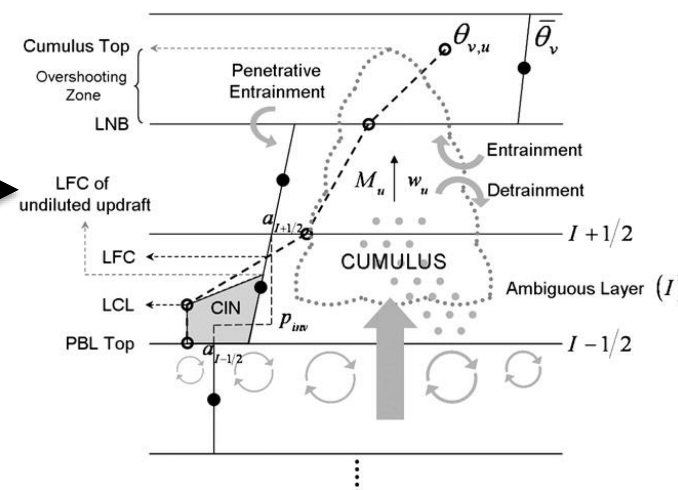
Can hi-res simulations help subgrid parameterizations?

- Cloud-resolving models (CRMs) advancing faster than moist physics parameterizations in global climate models (GCMs)
- Unlike in GCMs, CRM cloud properties and air velocity don’t vary much within a grid cell.
- CRMs must still parameterize smaller-scale processes (e. g. cloud droplets a few microns wide, complex ice crystals, turbulence, aerosols). Like other models, they are works in progress needing constant testing vs. observations.
- CRM simulations (dx < 5 km for cumulonimbus, dx < 250 m for shallow clouds) provide realistic reference datasets for parameterizing subgrid cloud processes.

The human bottleneck

- Since 1992, GCSS/GASS program has used this approach
- Improved parameterizations of cumulus convection, turbulence, and cloud microphysics have been implemented in leading weather and climate models
- But progress has been slow, and the uptake of new insights from hi-res modelling and new observations is difficult because humans concoct parameterizations.





Cloud parameterization using machine learning

- Increasingly large and comprehensive training datasets from high-resolution CRM simulations.
- A ‘hybrid’ coarse-graining problem: With variables predicted by the coarse grid model (temperature, moisture and wind profiles), use the fine-grid model to return needed quantities to the coarse-grid model (e. g. rainfall, vertical profiles of cloud cover, turbulence, atmospheric heating and drying), which advects T,q, u, v around.
- Ideally, the needed quantities should be stochastic - sampled from the pdf of internal fine-grid variability consistent with the coarse-grid variables.
- Could machine learning techniques help?

We present our work on an example application…

Geophysical Research Letters

RESEARCH LETTER
10.1029/2018GL078510

Prognostic Validation of a Neural Network Unified Physics Parameterization

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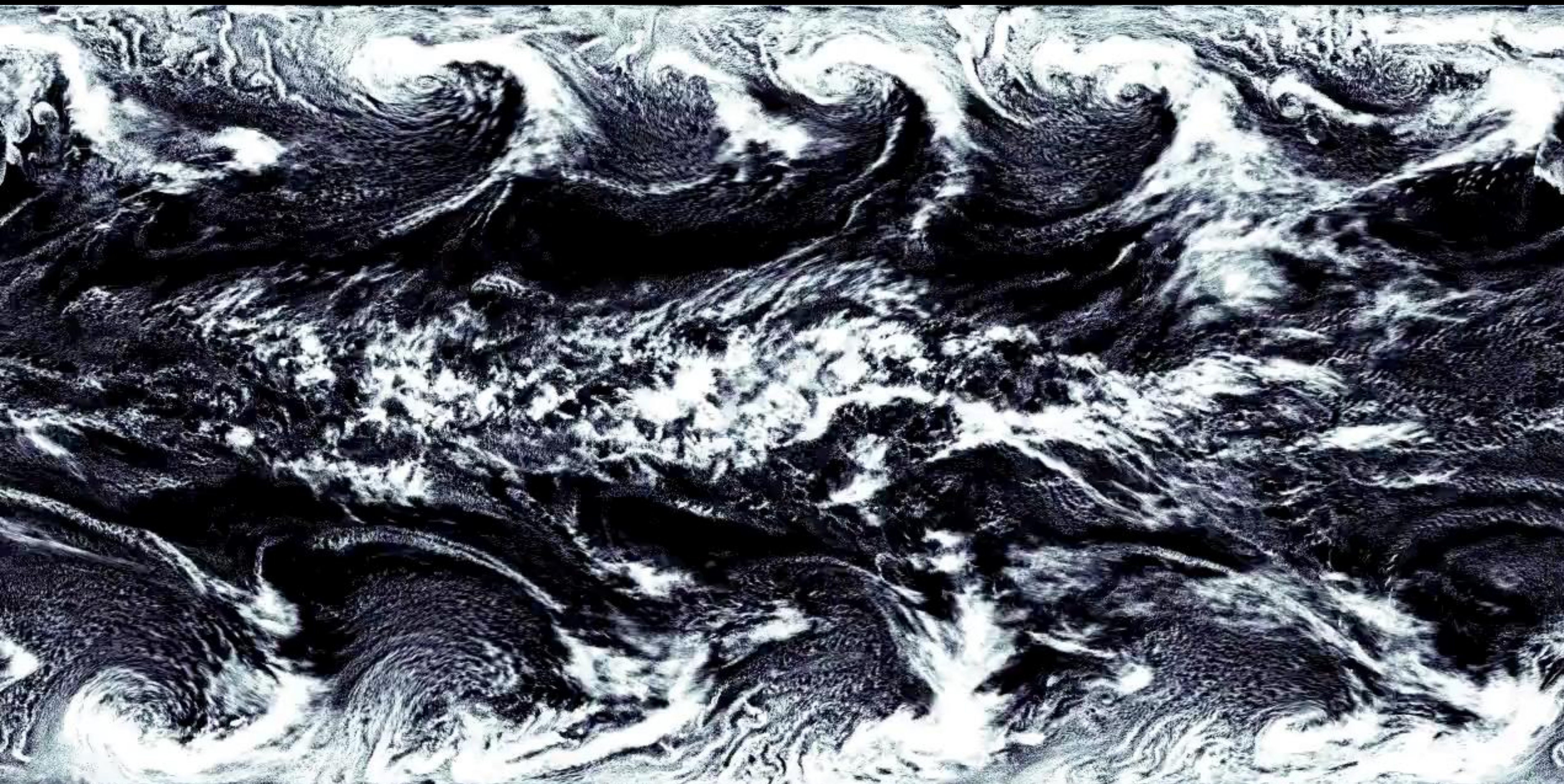
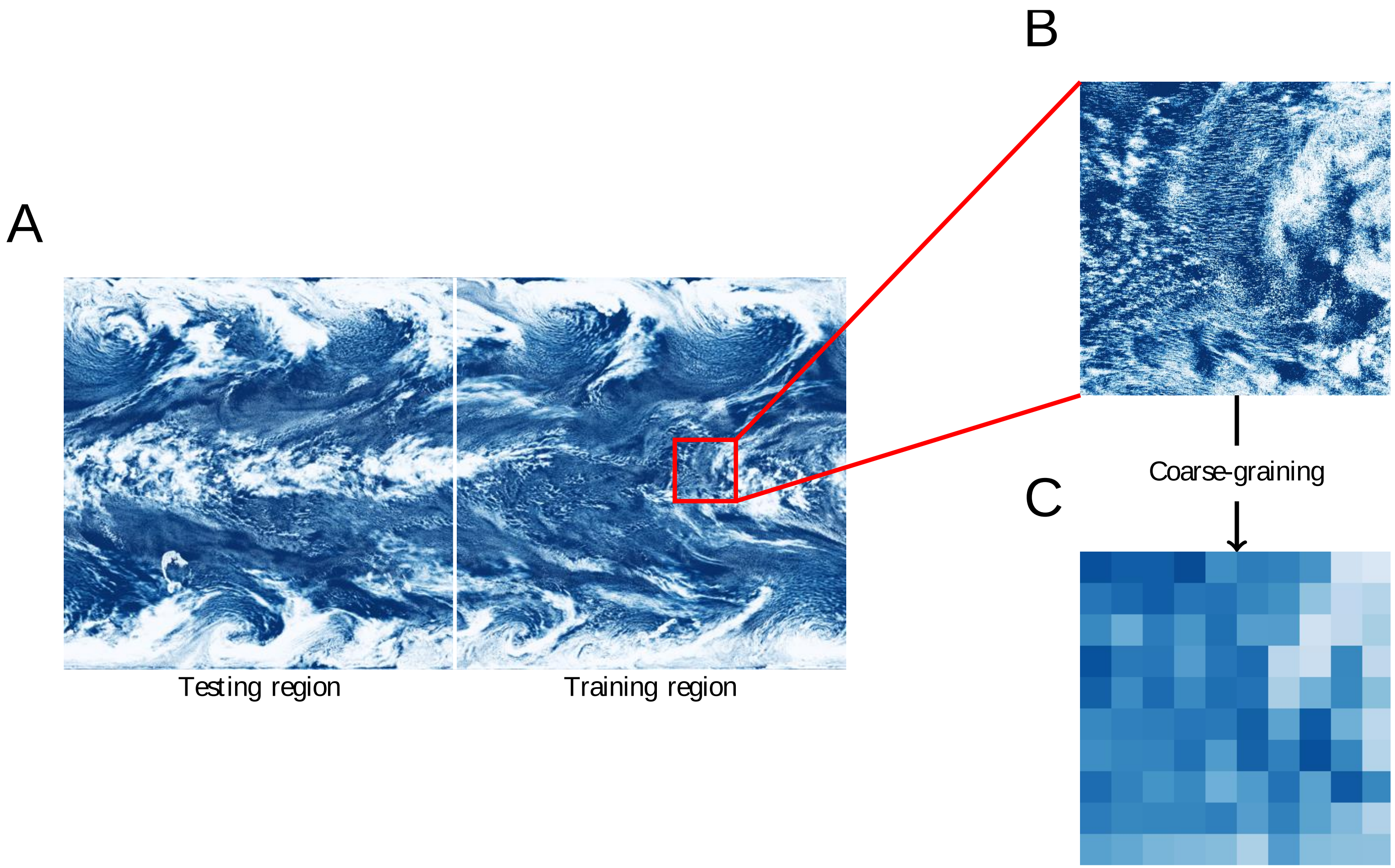
Key Points:
- A neural network-based unified physics parameterization is trained on a near-global aqua-planet simulation from a cloud-resolving model
- A numerically stable scheme is trained

Training dataset: 3-hourly 3D snapshots from

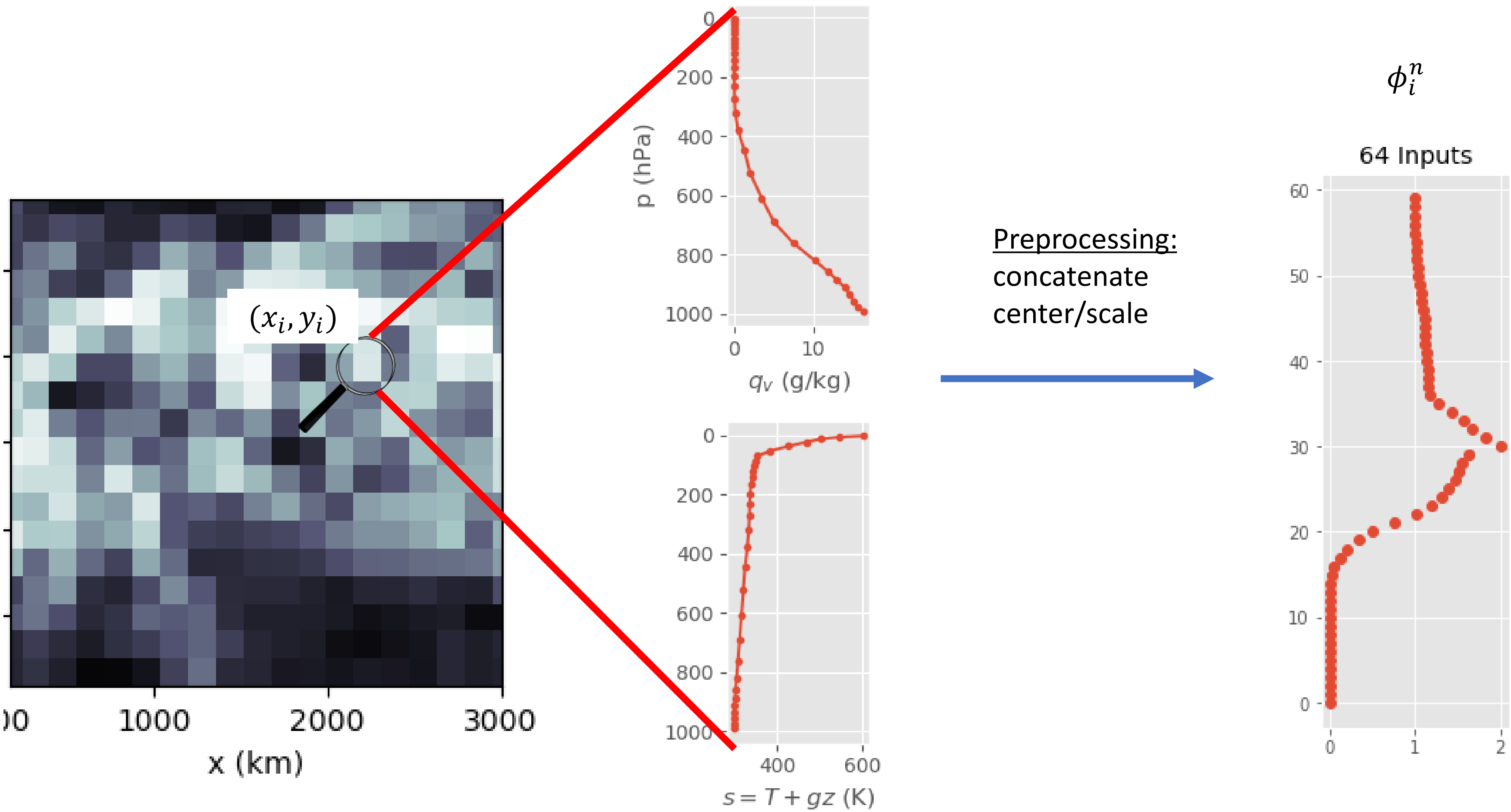
Near-global aqua-planet (NGAqua) simulation generated by the System for Atmospheric Modeling ($\Delta x = 4$km)



Coarse-grain data to 160 km boxes



Machine learning inputs



Training

1. Use finite differences to compute residual ‘physics’ tendencies

$$\frac{\partial \overline{s_L}}{\partial t} + \overline{\mathbf{v}} \cdot \overline{\nabla} \overline{s}_L = Q_1 \qquad \text{apparent heating}$$

$$\frac{\partial \overline{q_T}}{\partial t} + \overline{\mathbf{v}} \cdot \overline{\nabla} \overline{q}_T = Q_2 \qquad \text{apparent drying}$$

2. Train neural network over all coarse-grid tropical columns

   (80 days x 8/day x 16 lats x 128 lons = 1.3x10^6 samples)

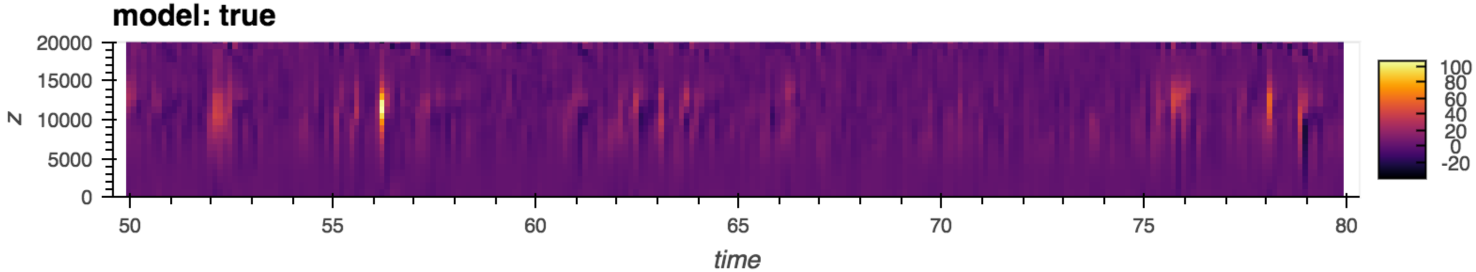
$q_T(z)$, $s_L(z)$, SHF, LHF, TOA → Neural Network → $Q_1(z)$, $Q_2(z)$

(1 layer of 256 nodes ≅ 70,000 parameters)

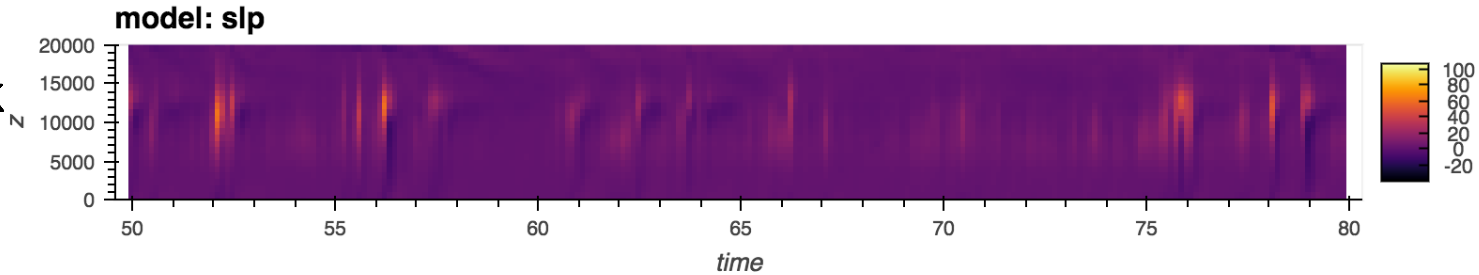
Results

✓ The diagnostic performance is good!

NGAqua $Q_1(z, t)$ in a tropical column



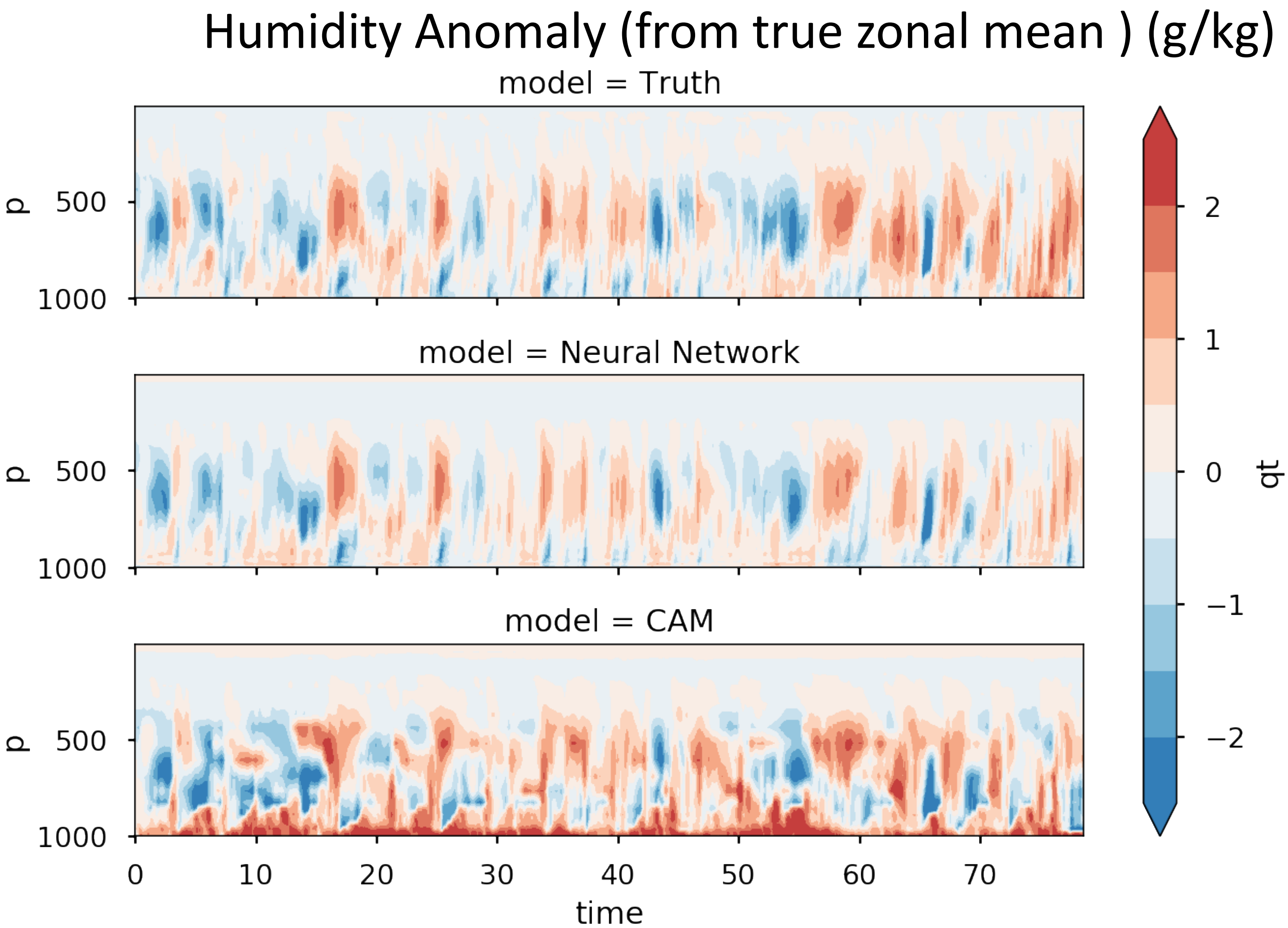
Neural Network
$R^2 \approx .50$



✗ …but method blows up within a day when evolution of a typical tropical grid column is prognosed with NN + advective tendencies.

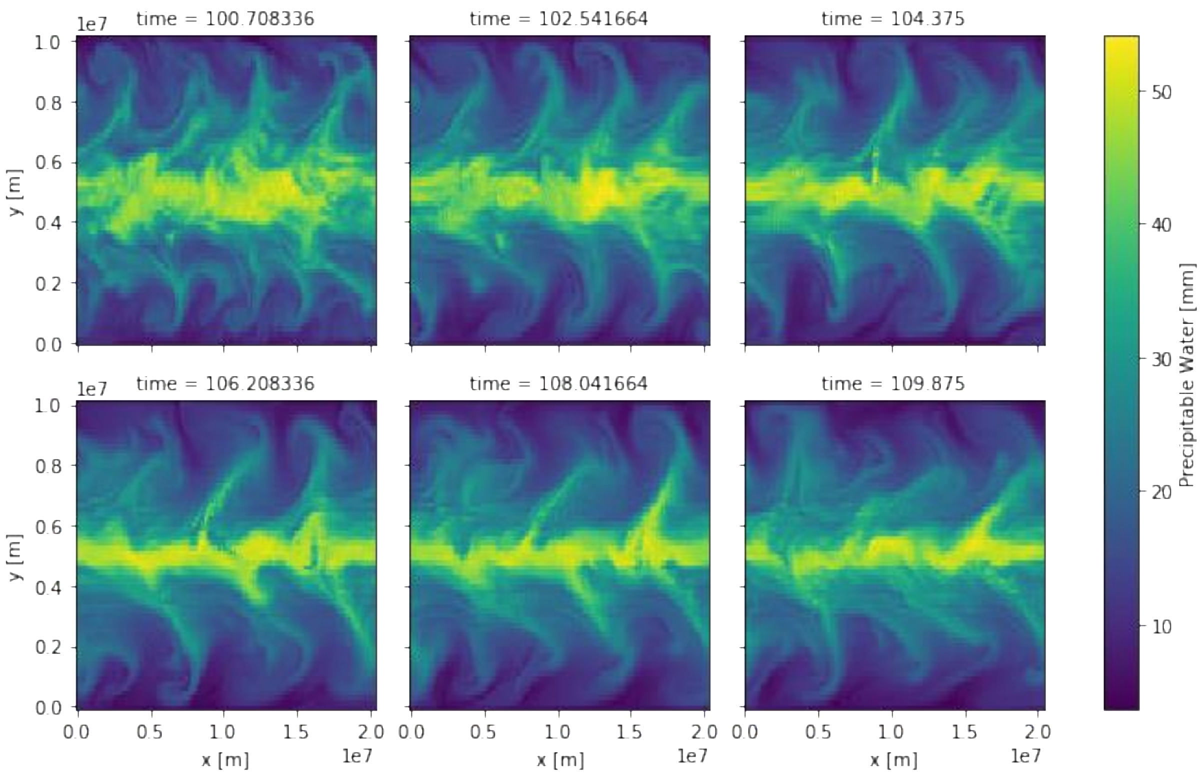
✓ Solution: Enforce accuracy over 10 (rather than 1) 3-hour timesteps. This selects a NN which is as accurate but is also stable.

Excellent prognostic single-column performance

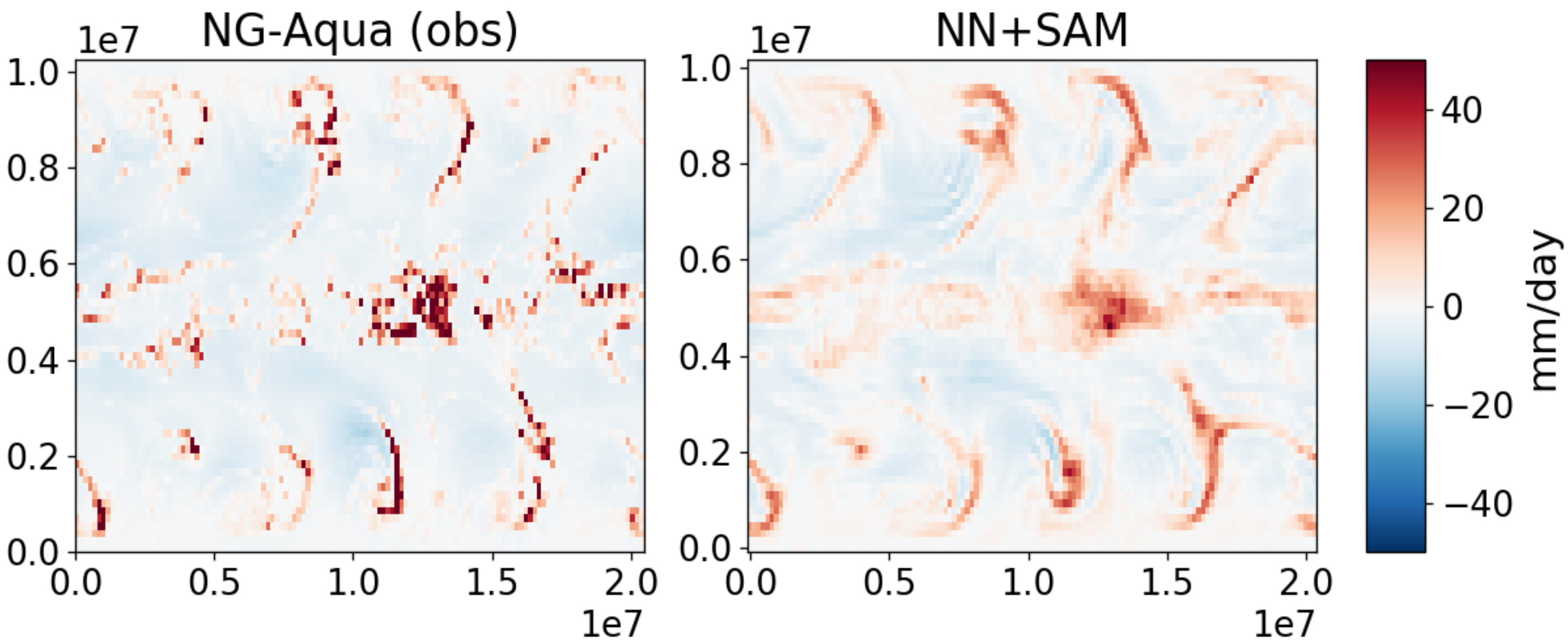


Ongoing work: testing in full 3D setting

- Generalize NN to parameterize moist physics over 46 S-46 N.
- Initialize with coarse-grained NGAqua snapshot from some time
- Run SAM on coarse grid with NN and subgrid momentum diffusion but no moist physics.
- Goal: Coarse-SAM + NN should forecast fine-grid NGAqua simulation.
- A 10-day forecast is stable but P-E drift causes ITCZ to slowly narrow.



Precipitation - Evaporation at 1 day



Neural net smooths the precipitation. For ensemble prediction, should add stochastic variability to NN.

Prospectus

- As observational and model datasets get bigger, machine learning is becoming an important tool for making forecast models better.
- Designing a machine learning scheme that works well in a within a 'hybrid' context of a larger numerical model takes expert humans.
- Several research groups are making rapid progress toward machine learning parameterizations for atmospheric convection, ocean eddy mixing, and other processes.
- Prediction: A machine learning parameterization will be included within the operational version of a numerical weather prediction or climate model within three years.

Q&A session

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Forthcoming CMCC Webinar

Low-carbon energy finance – new research results and their implications for modelers and policy makers

November 27, 2018 – h. 12:30 pm CET

Presenters: **Tobias S Schmidt,** Energy Politics Group, ETH Zurich &
Bjarne Steffen, Energy Politics Group, ETH Zurich
Moderator: **Elena Verdolini,** Senior Researcher, RFF-CMCC European Institute on Economics and the Environment, Milan

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If you have any further question about the webinar, please email: webinar@cmcc.it

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