Neural-network parametrization of subgrid momentum transport learned from a high-resolution simulation

Janni Yuval and Paul O'Gorman

Massachusetts Institute of Technology

Part of the M²LInES project

We also thank the NSF and the MIT Environmental Solutions Initiative

Parameterizations are simplified representations of unresolved processes and they introduce inaccuracies to climate models

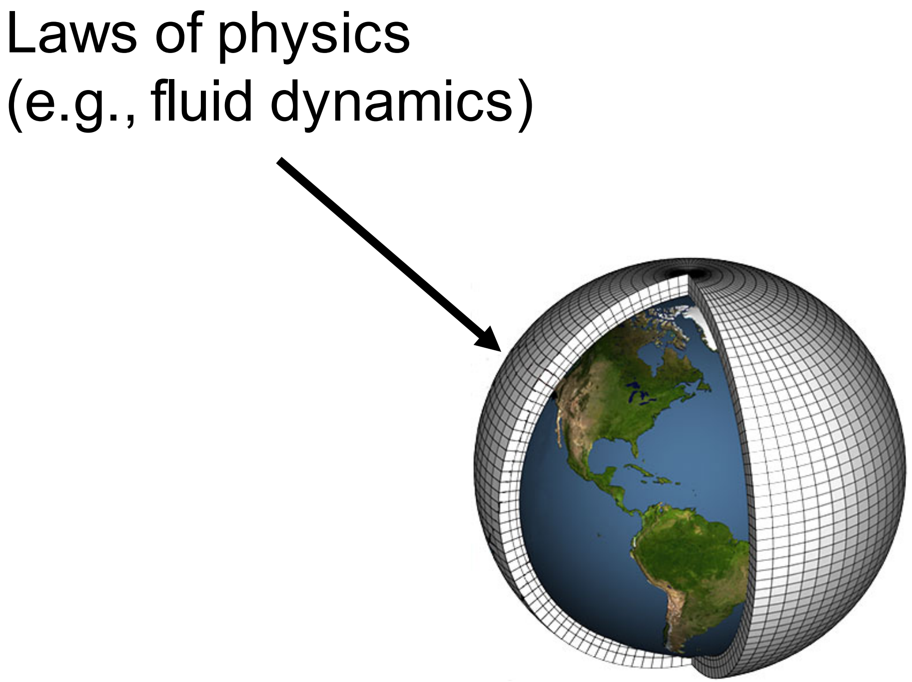
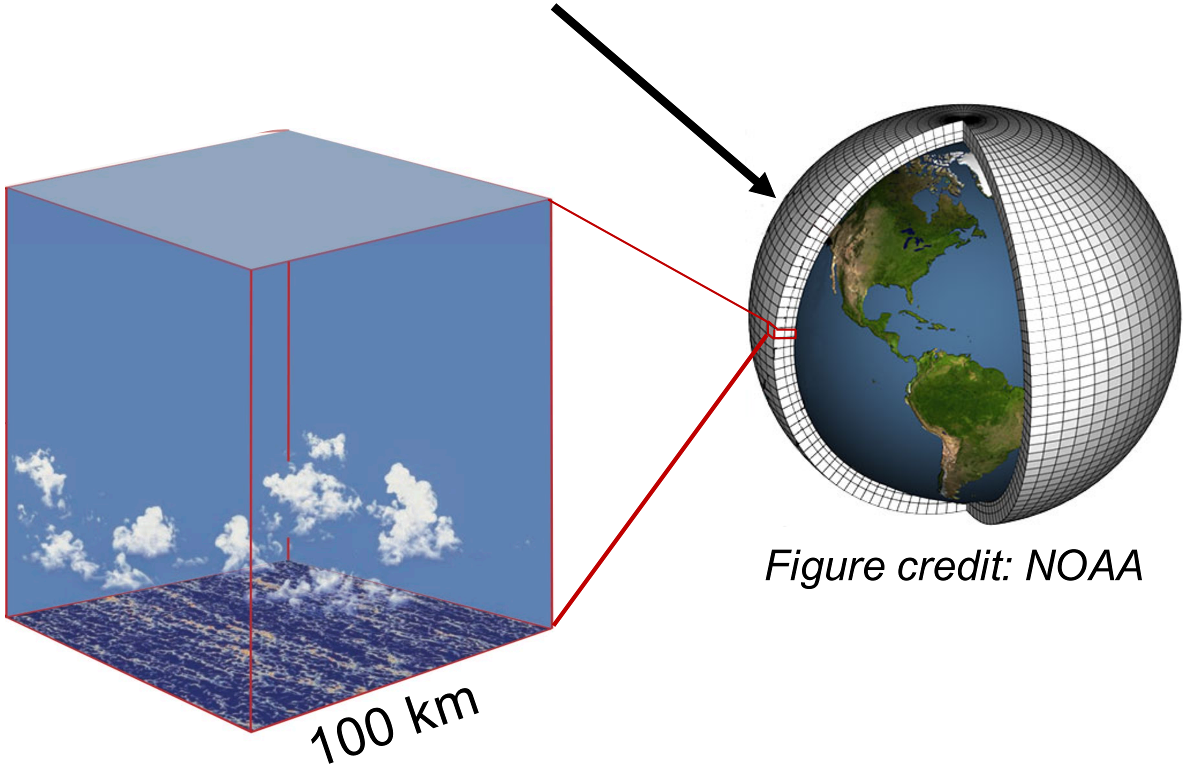


Figure credit: NOAA

Parameterizations are simplified representations of unresolved processes and they introduce inaccuracies to climate models

Laws of physics
(e.g., fluid dynamics)



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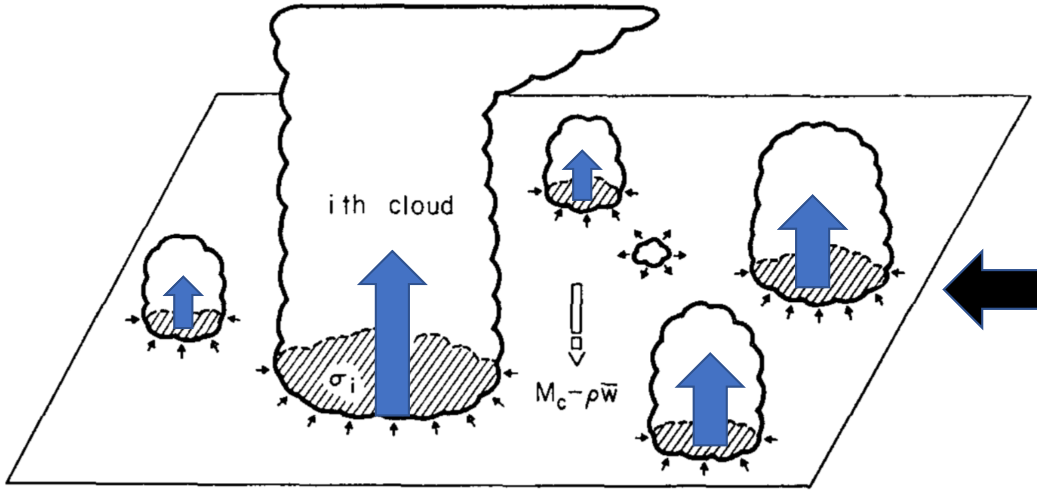
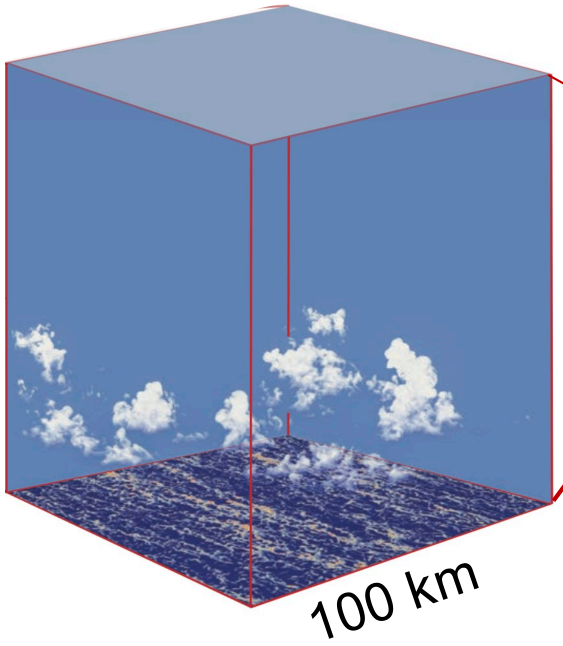
Schneider et al. (2017)

Parameterizations are simplified representations of unresolved processes and they introduce inaccuracies to climate models

Parameterization



Arakawa and Schubert (1974)



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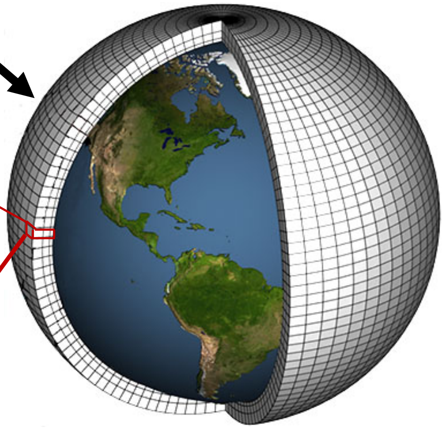

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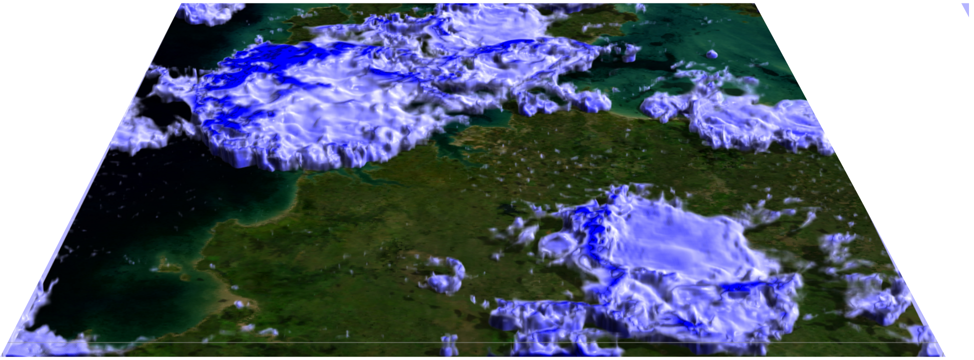
A different approach to parameterization: Use machine learning to create new parameterizations trained on high-resolution models

High resolution model



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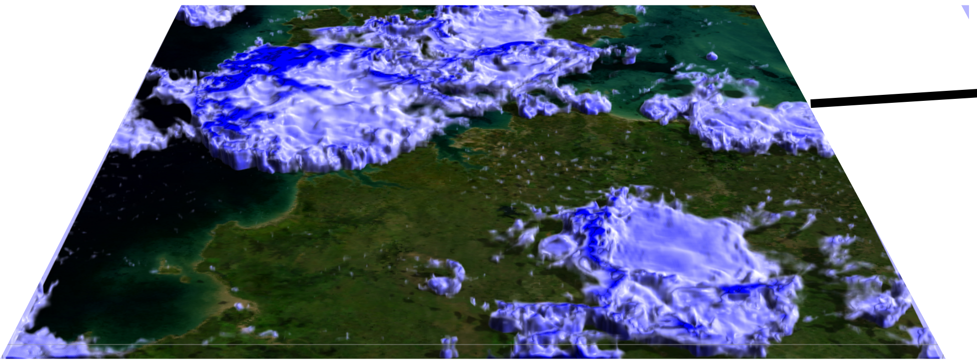
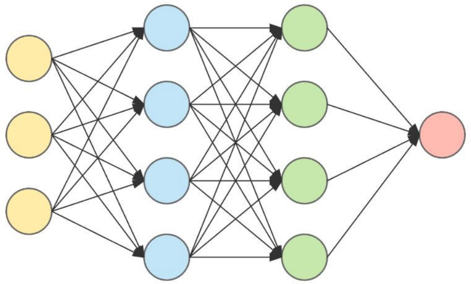


Machine learning parameterization



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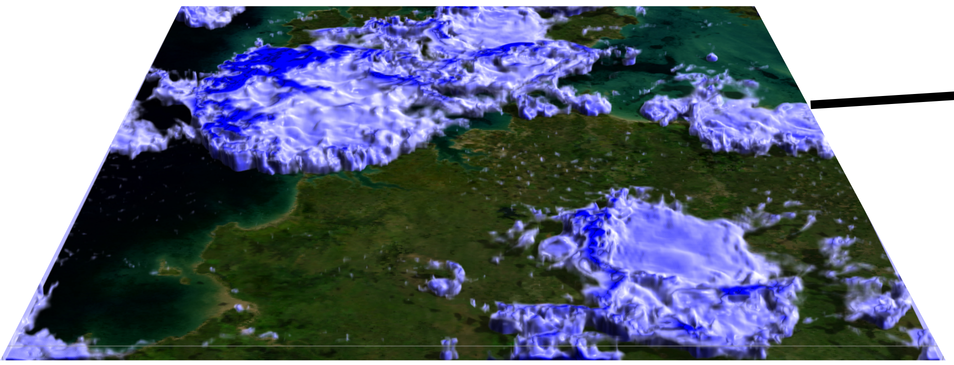

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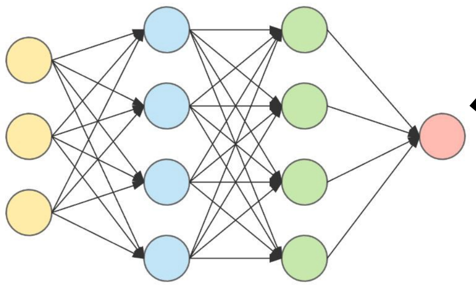

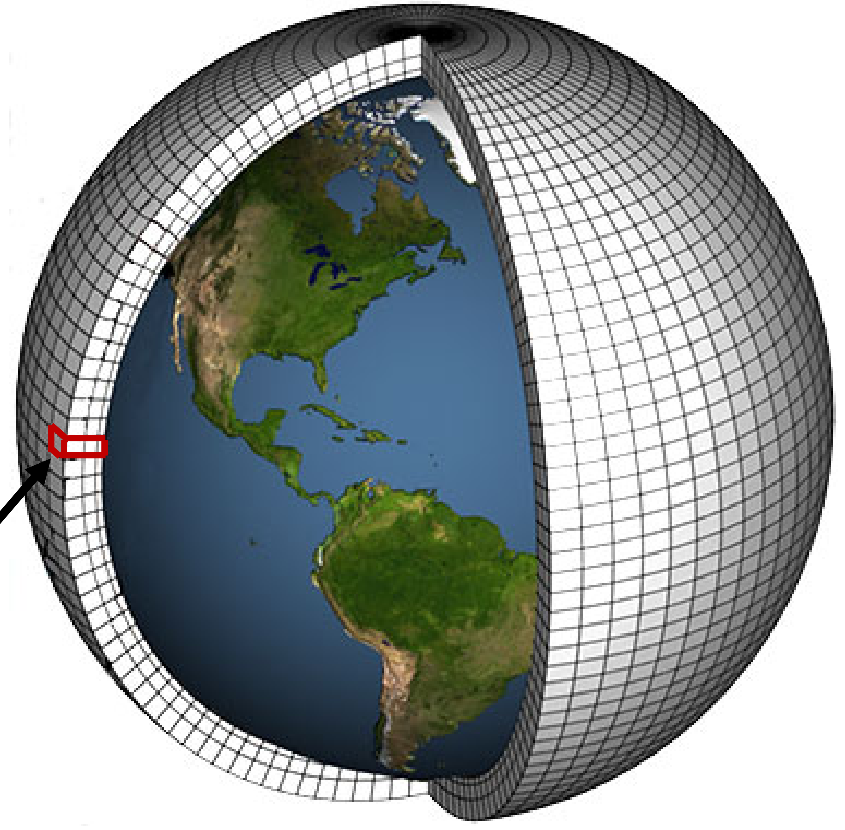

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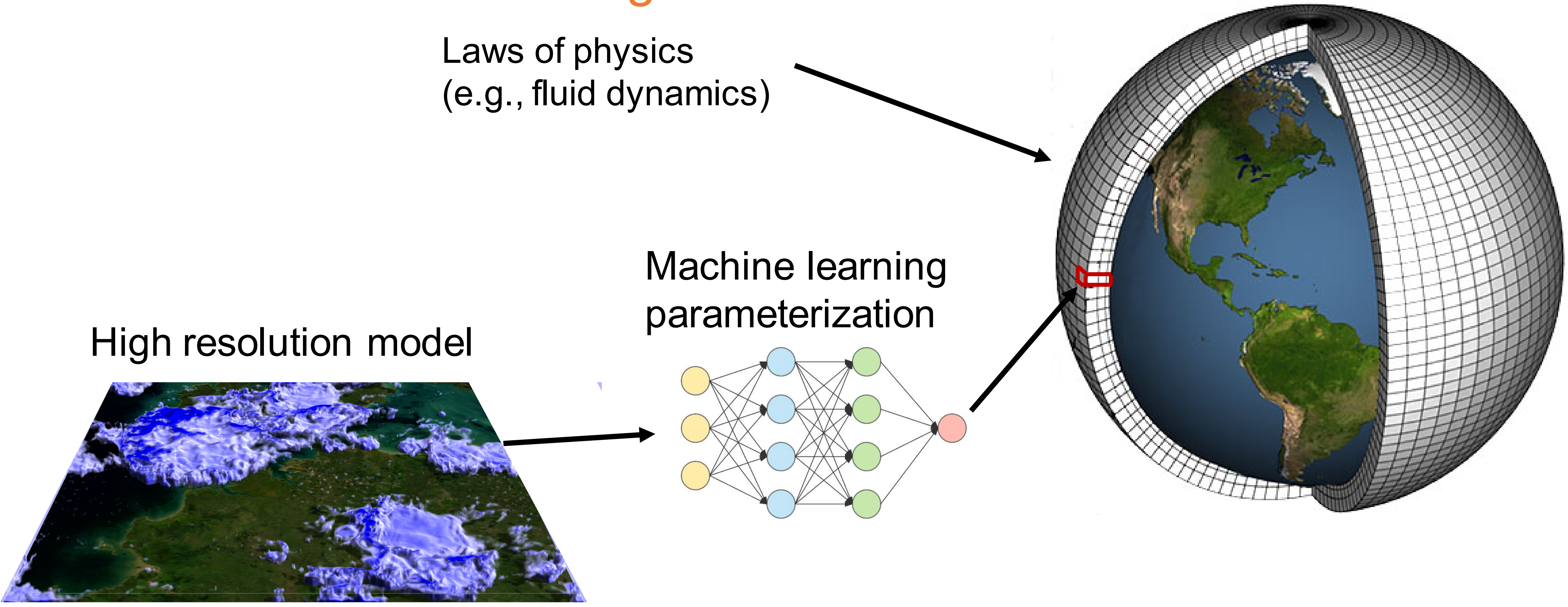

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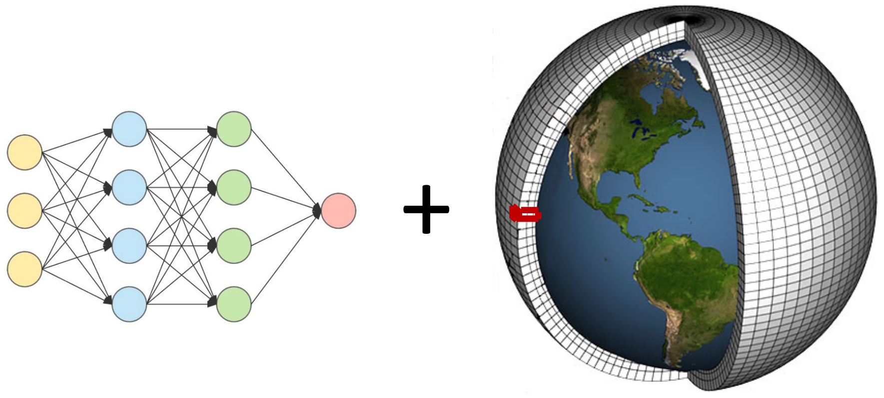
Recent attempts at machine learning parameterizations had some success but were not always stable, energy conserving and without climate drift



E.g., Rasp et al. 2018, O'Gorman & Dwyer 2018 , Brenowitz & Bretherton (2018,2019), Brenowitz et al. (2020)

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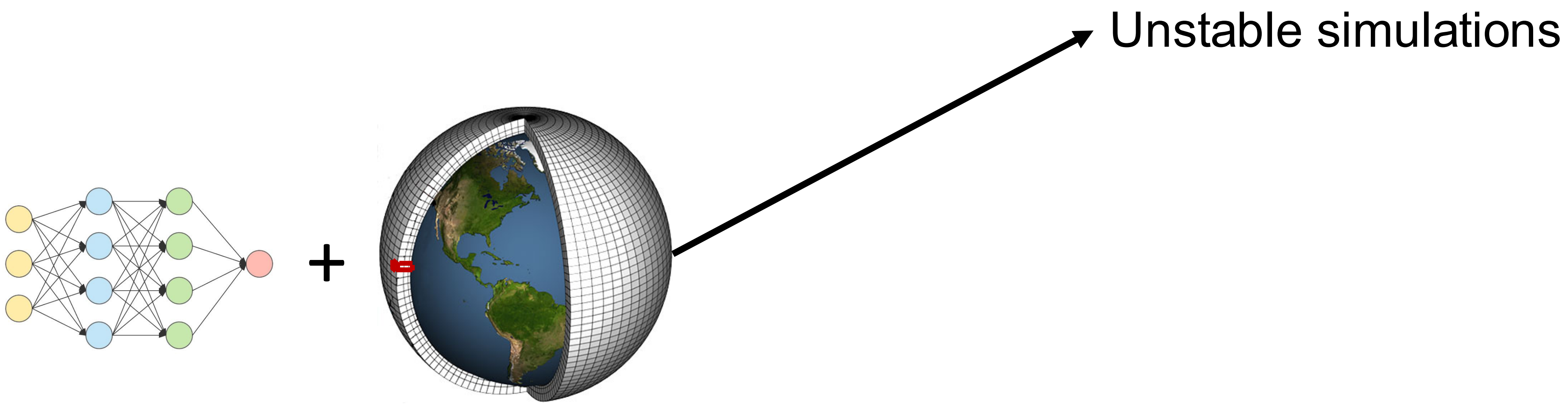

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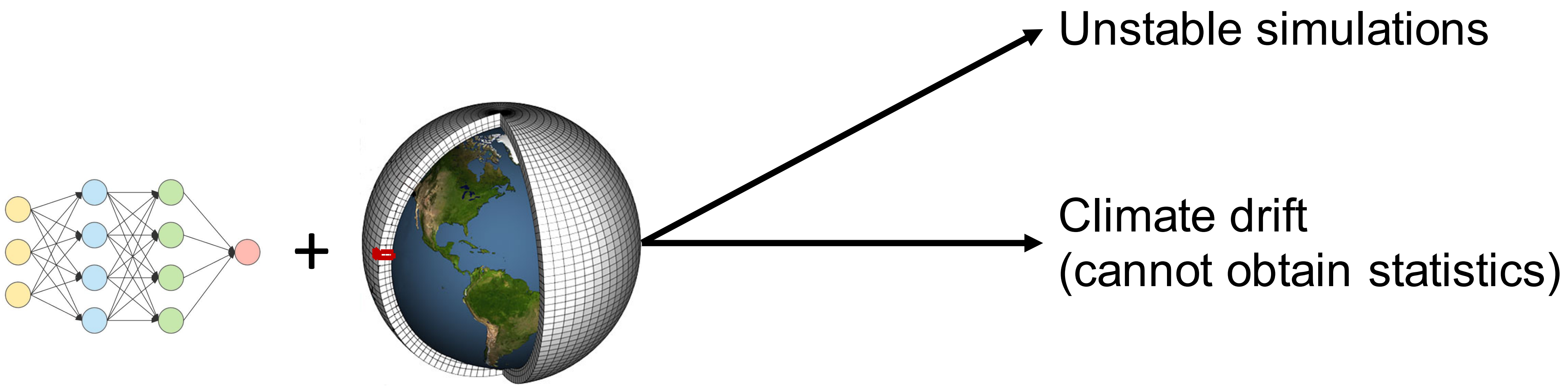

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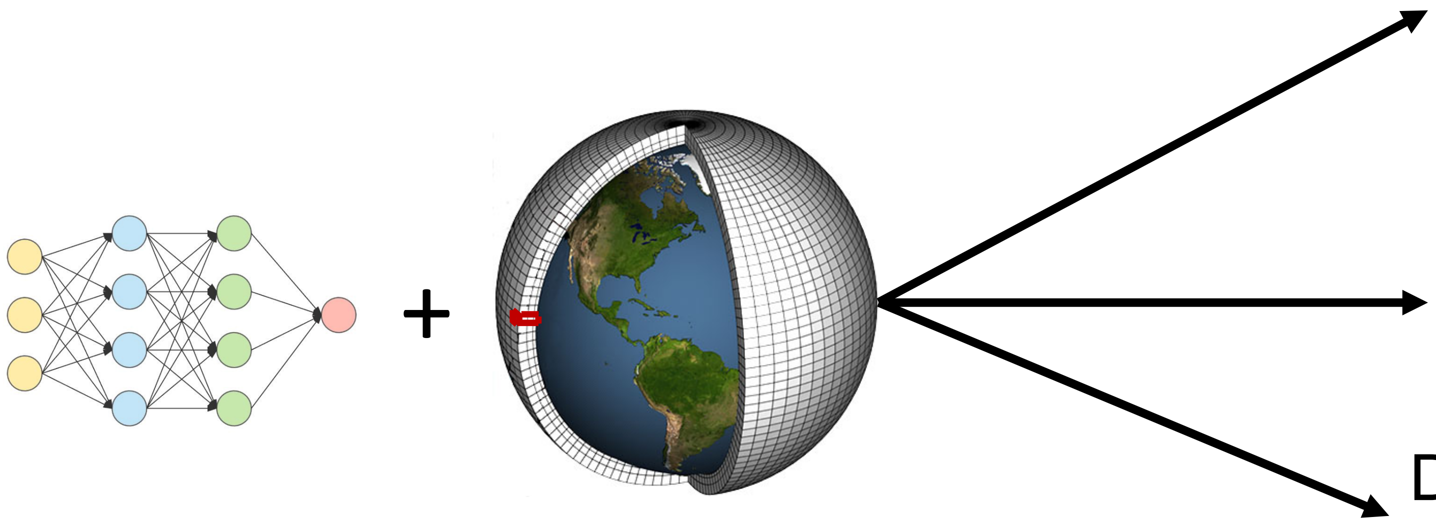

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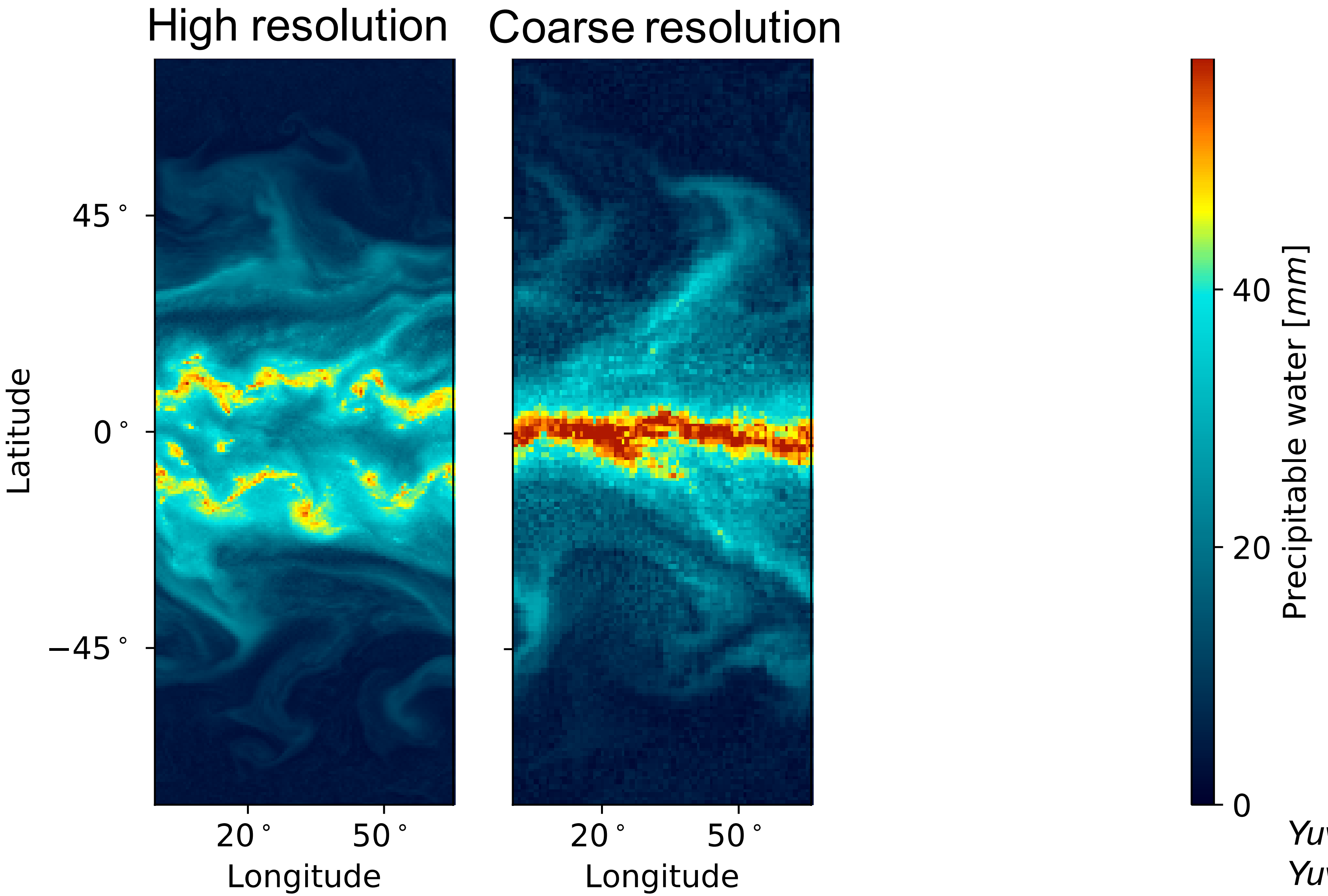

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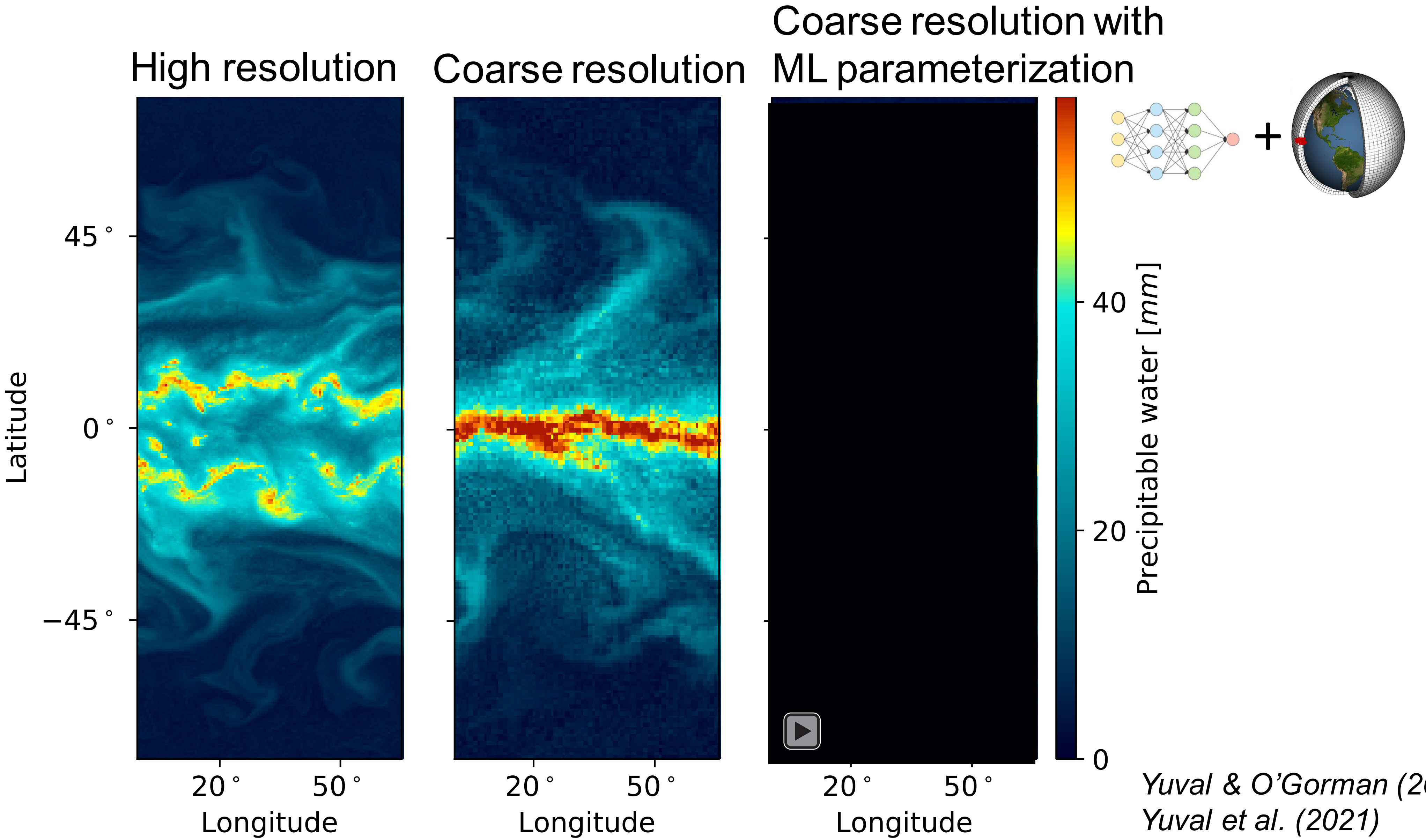

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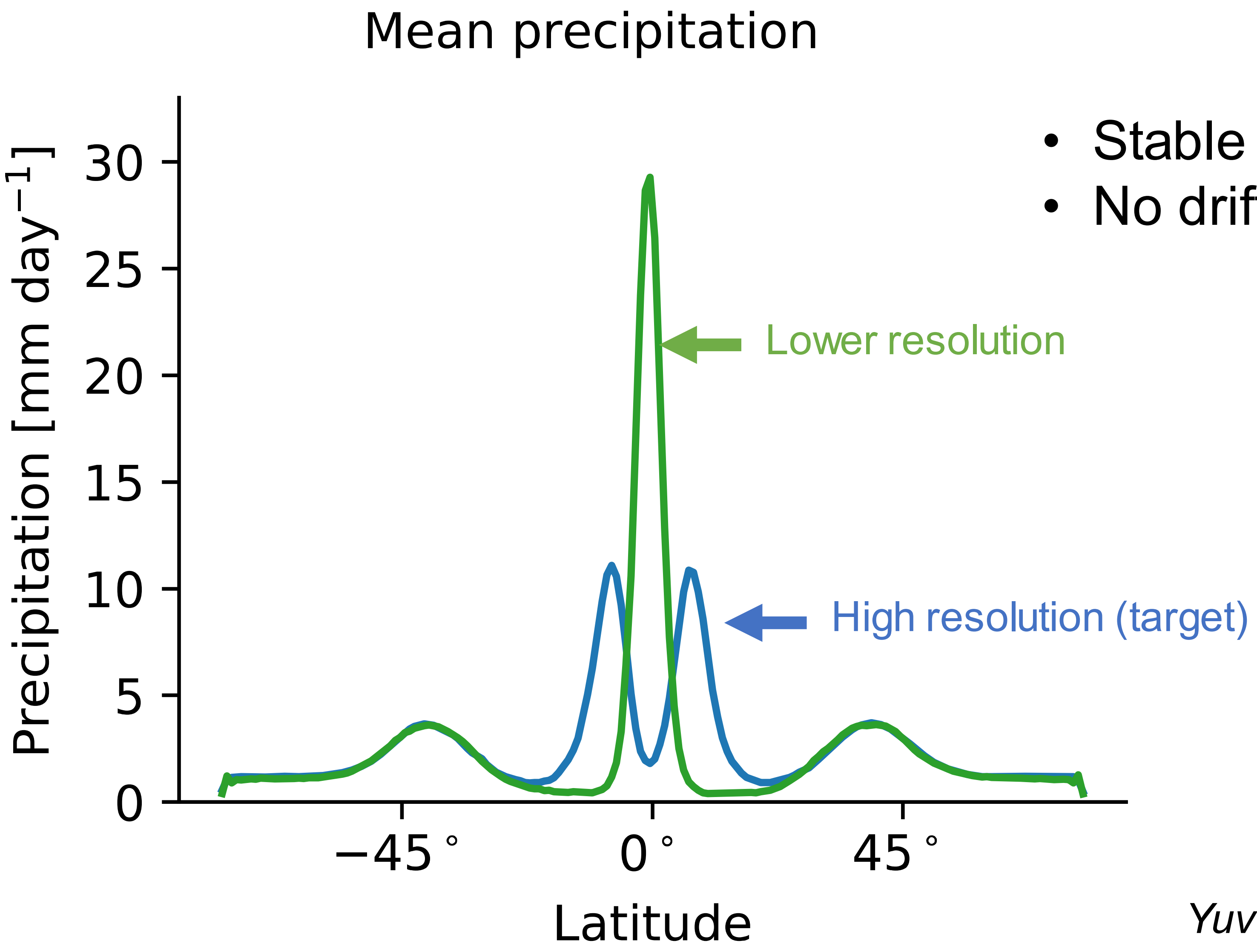
Neural network parameterization leads to accurate simulation of **mean precipitation**



- Stable simulation
- No drift

Yuval et al. (GRL, 2021)

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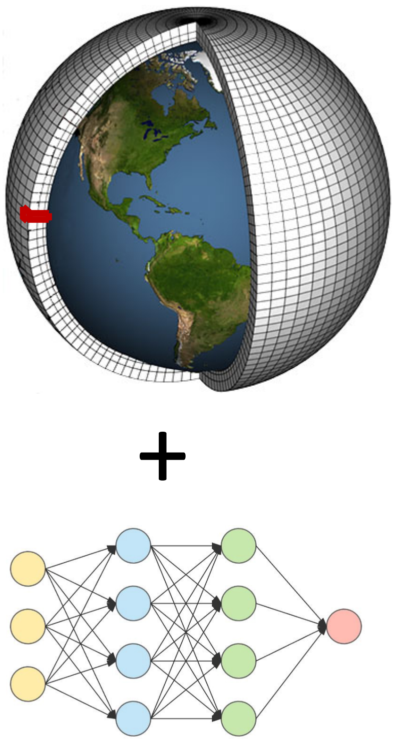

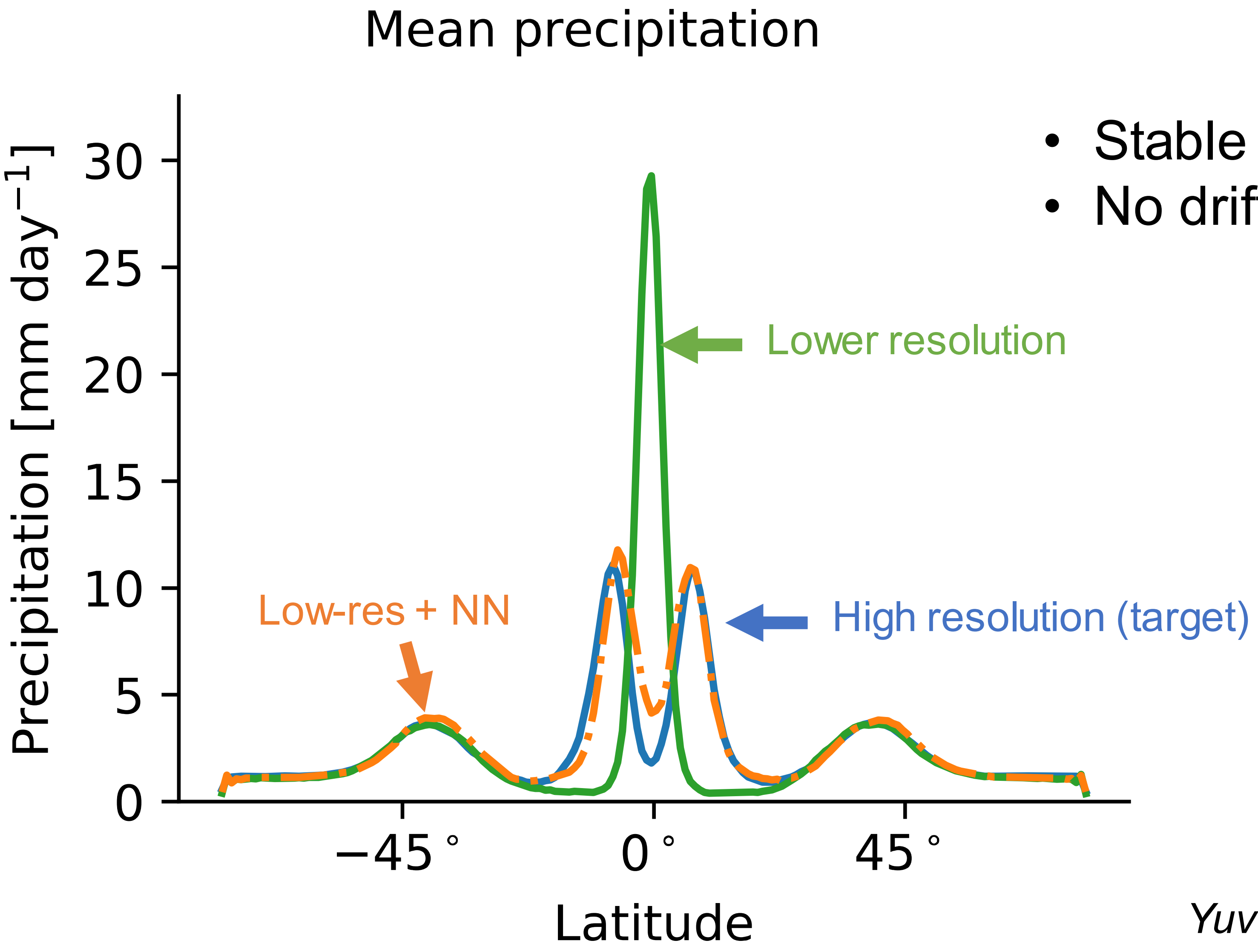

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Goal: to use machine learning to develop physically-consistent **subgrid momentum parameterization** from a fully 3D high-resolution simulation

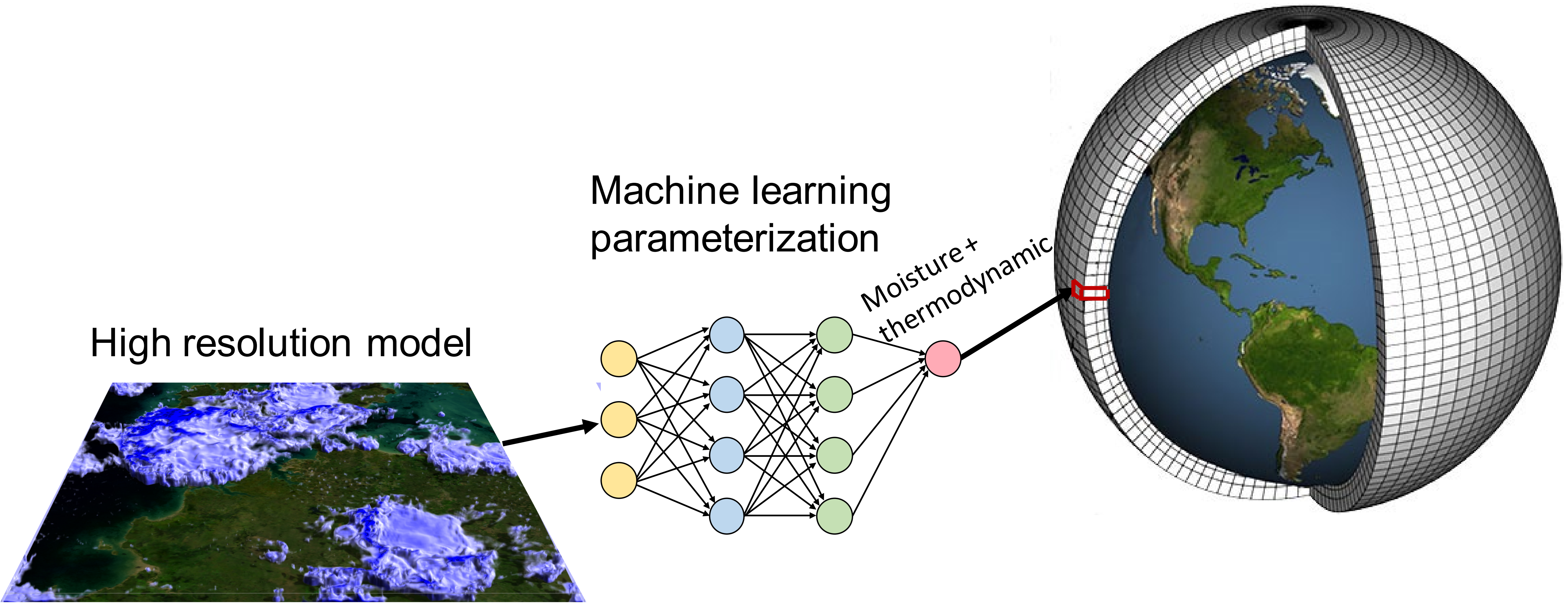

Figure credit: NASA

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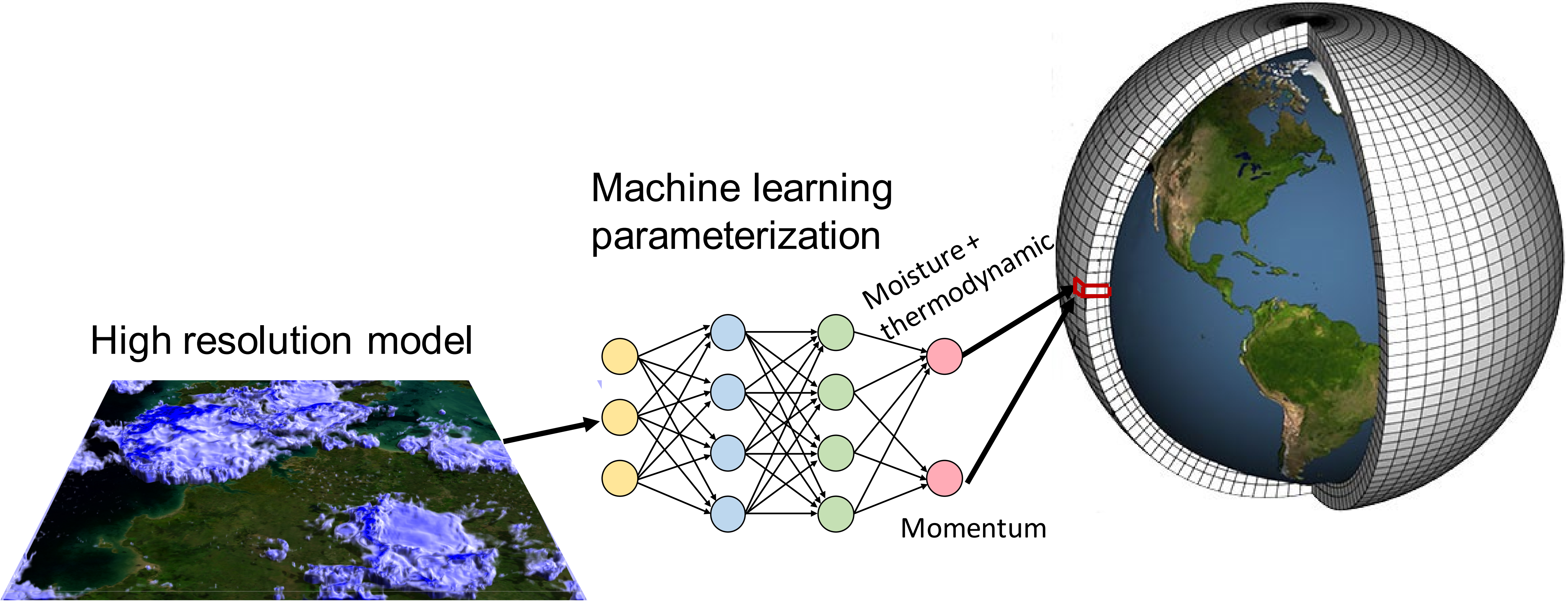

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Subgrid processes such as convection and gravity waves transport horizontal momentum in the vertical

Convective momentum transport

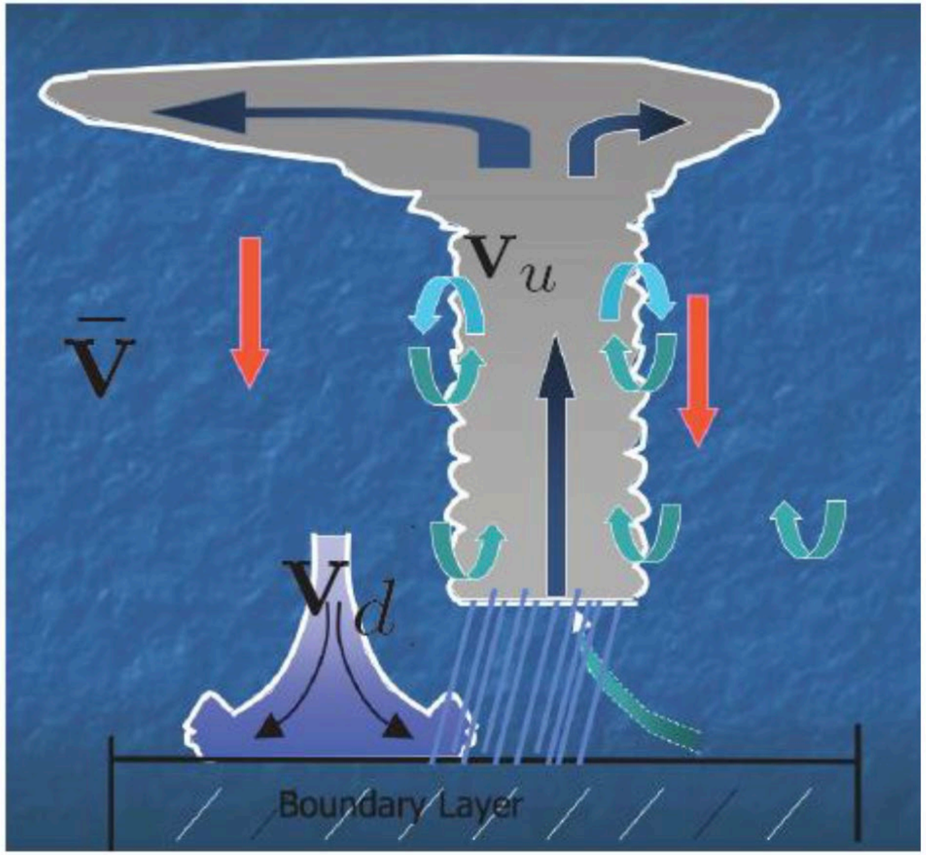

Image credit: Joe Tribbia presentation

E.g., Wu et al. (2007), Song et al. (2008), Woelfle et al. (2018)

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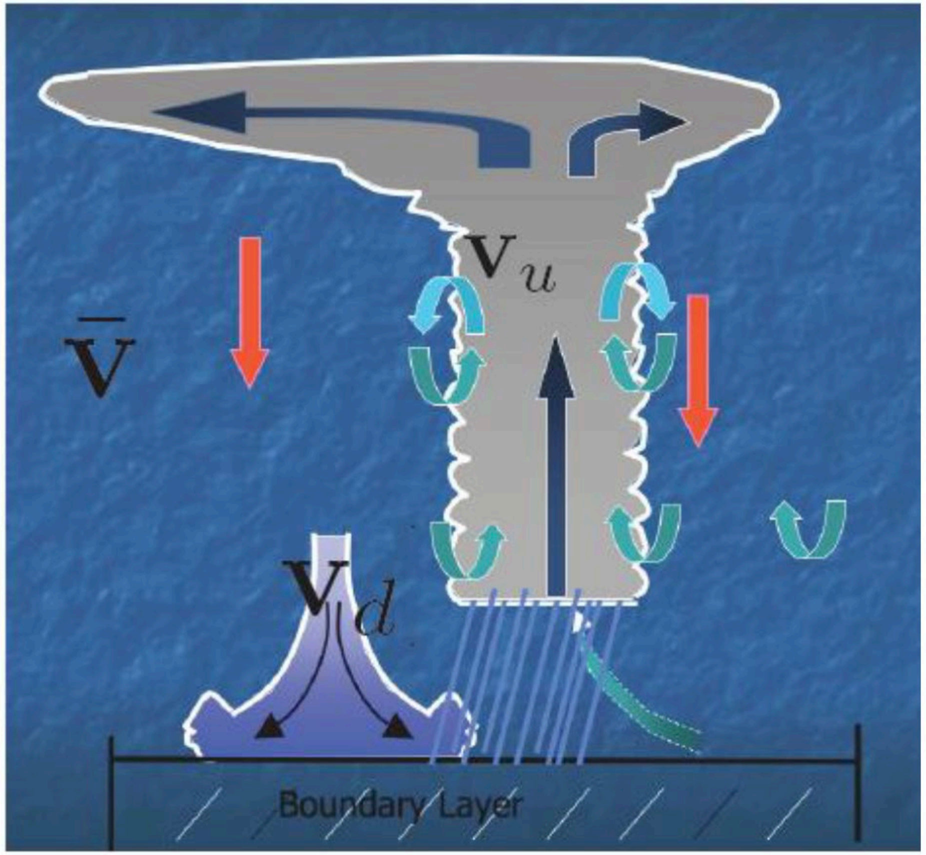

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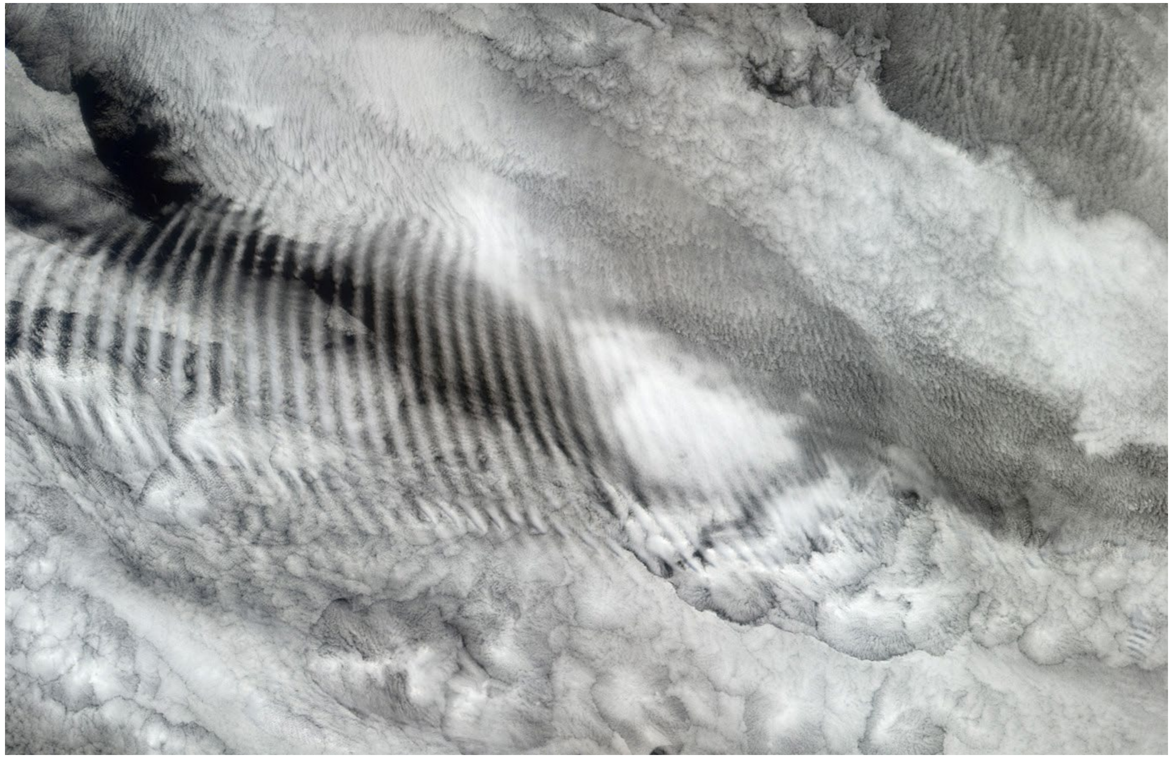
Gravity waves above the Indian Ocean

245 kilometers



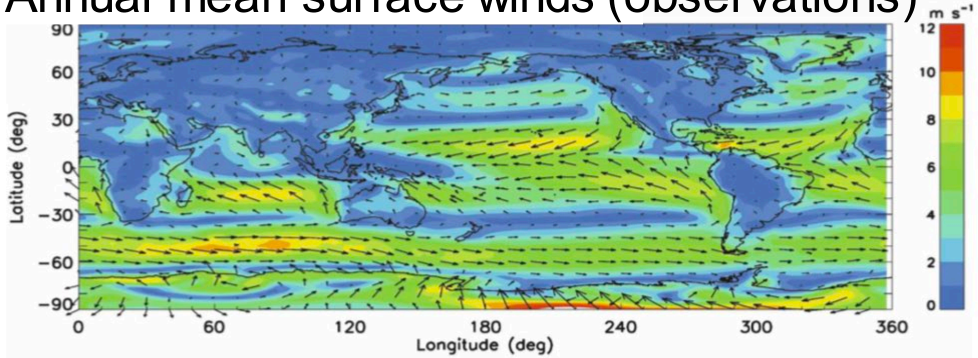
378 kilometers

Image credit: NASA/GSFC/LaRC/JPL, MISR TEAM

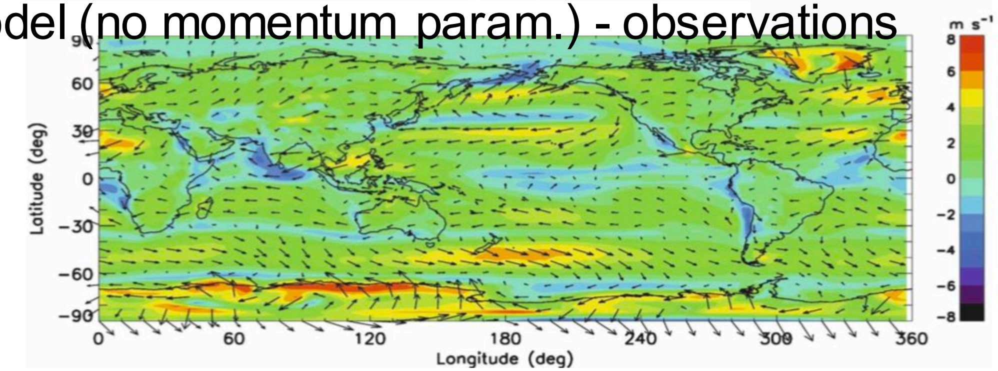
E.g., Dunkerton (1997), Ray et al. (1998), Orr et al. (2010)

Convective momentum transport has large consequences for the tropical atmospheric circulation and precipitation

Annual mean surface winds (observations)



Model (no momentum param.) - observations



Richter and Rasch (2007)

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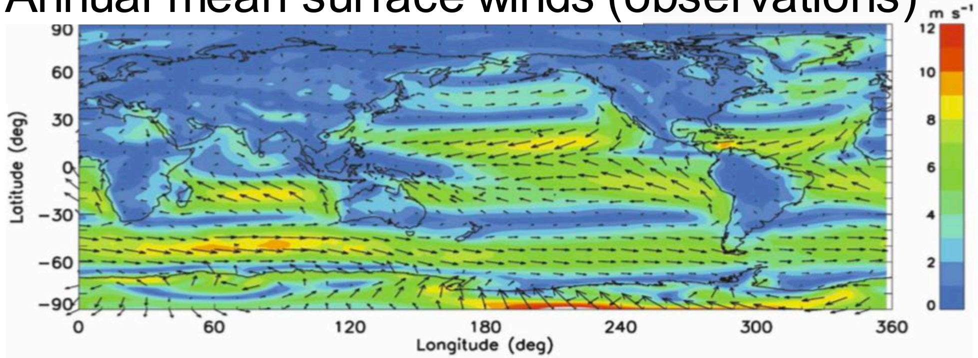

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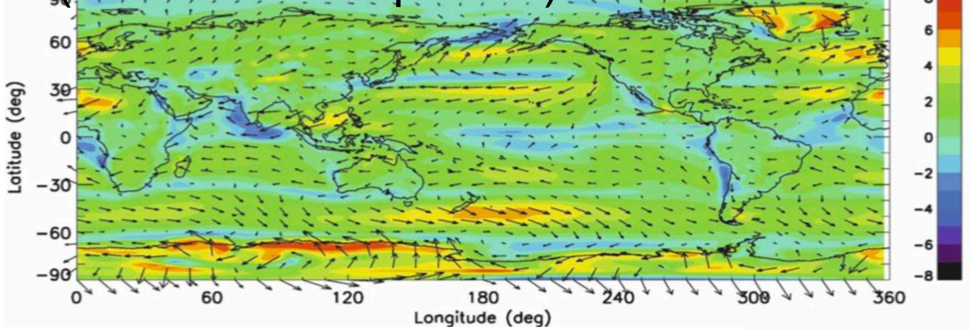
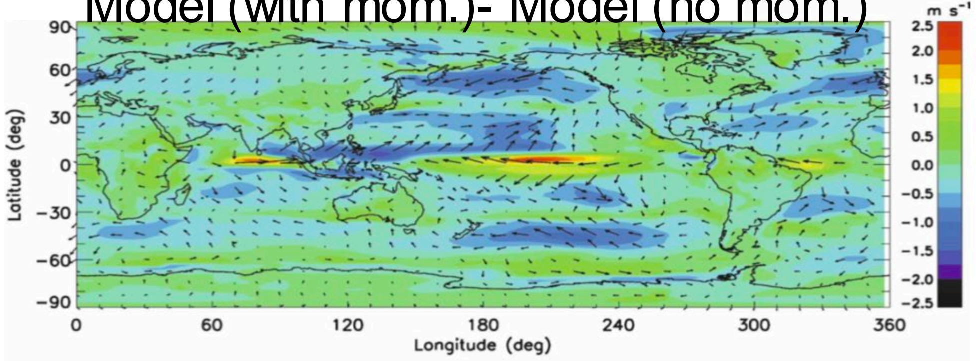


Model (with mom.)- Model (no mom.)



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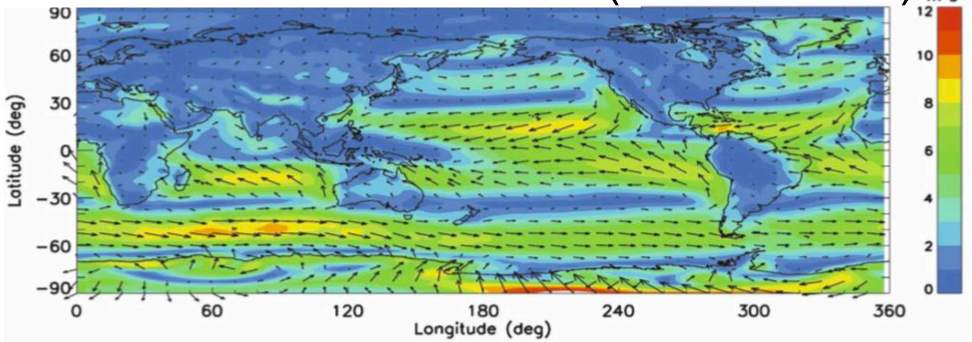

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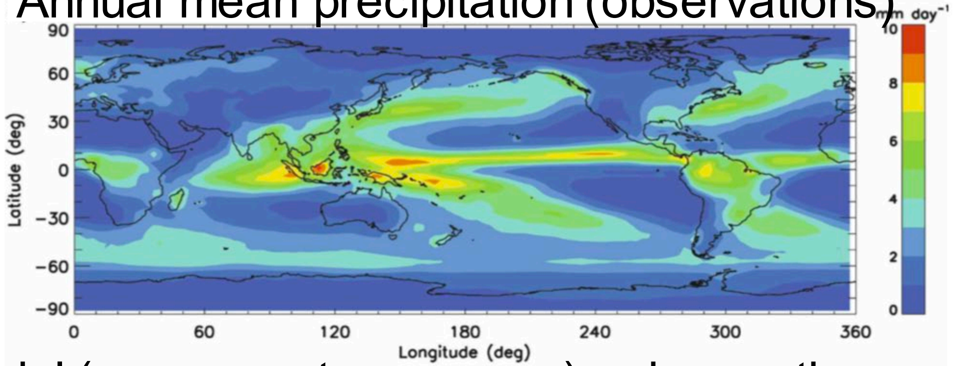

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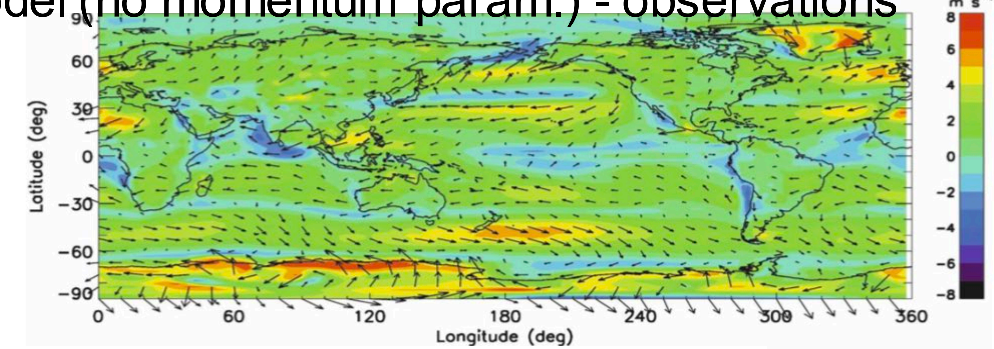

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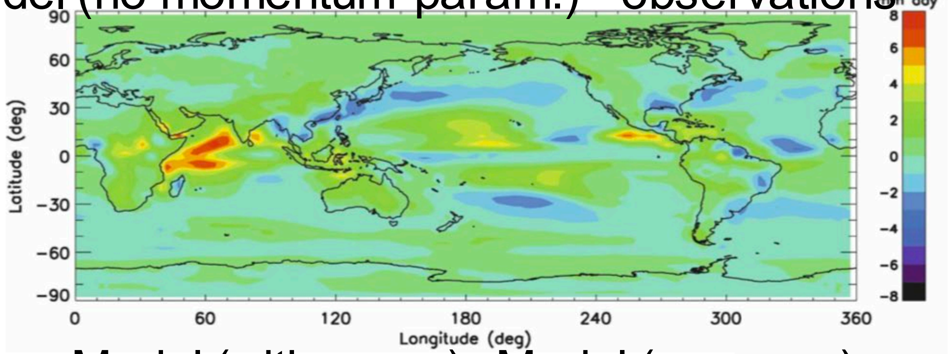

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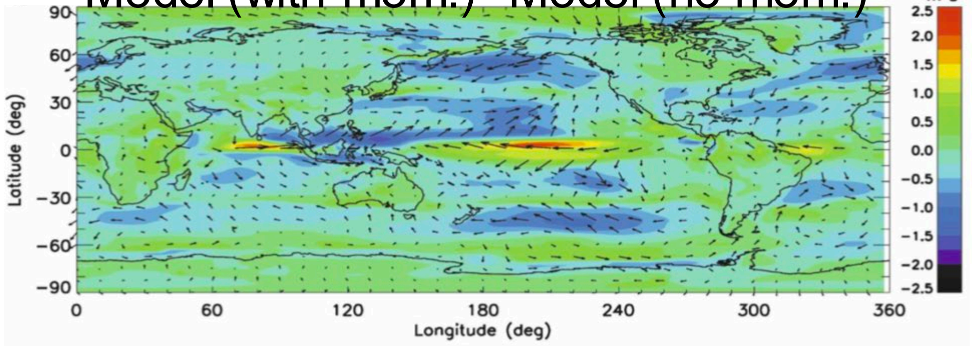

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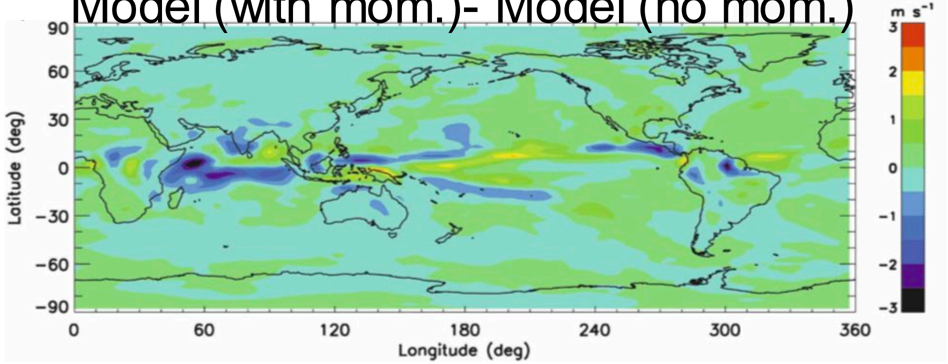

Richter and Rasch (2007)

Machine learning parameterization

High resolution model

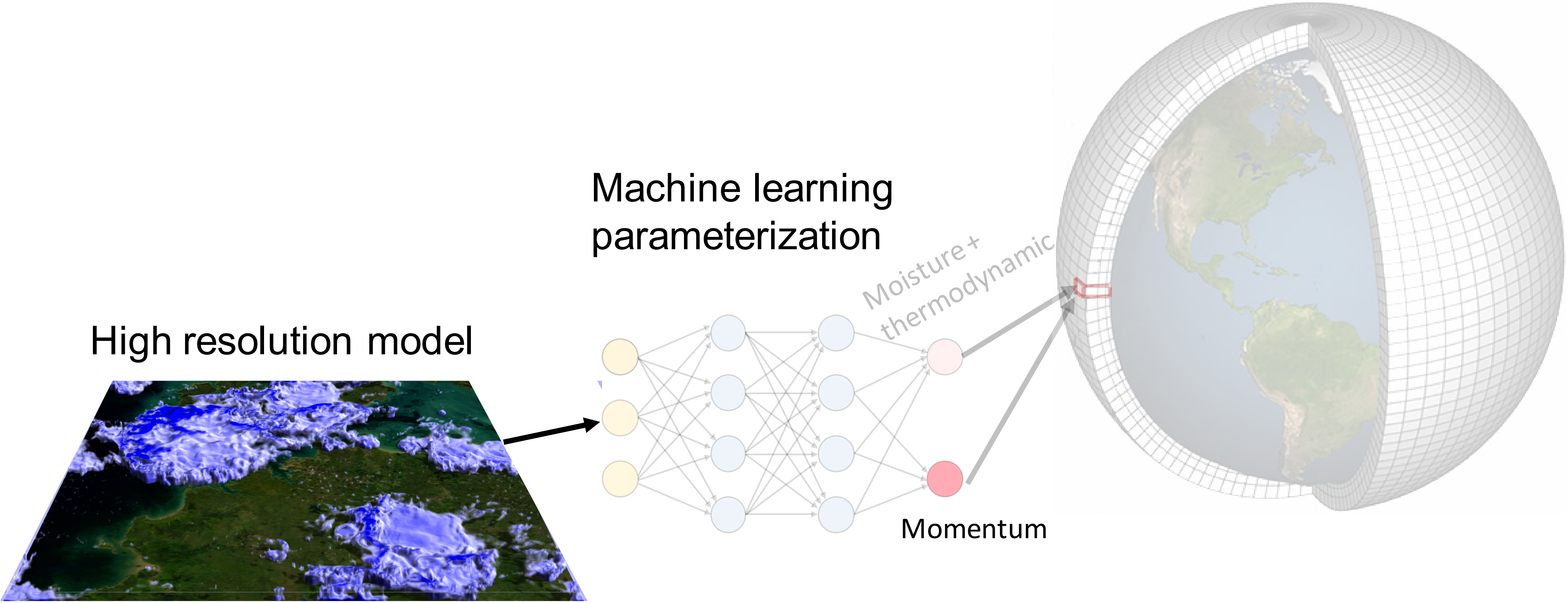

Figure credit: NASA

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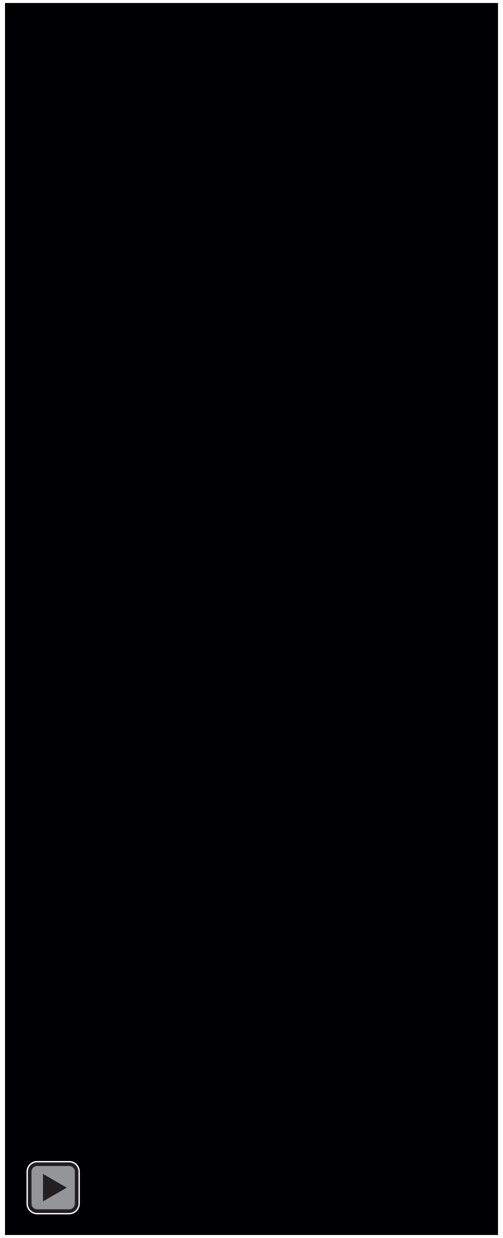
We learn from a high-resolution simulation of the atmosphere in a quasi-global domain



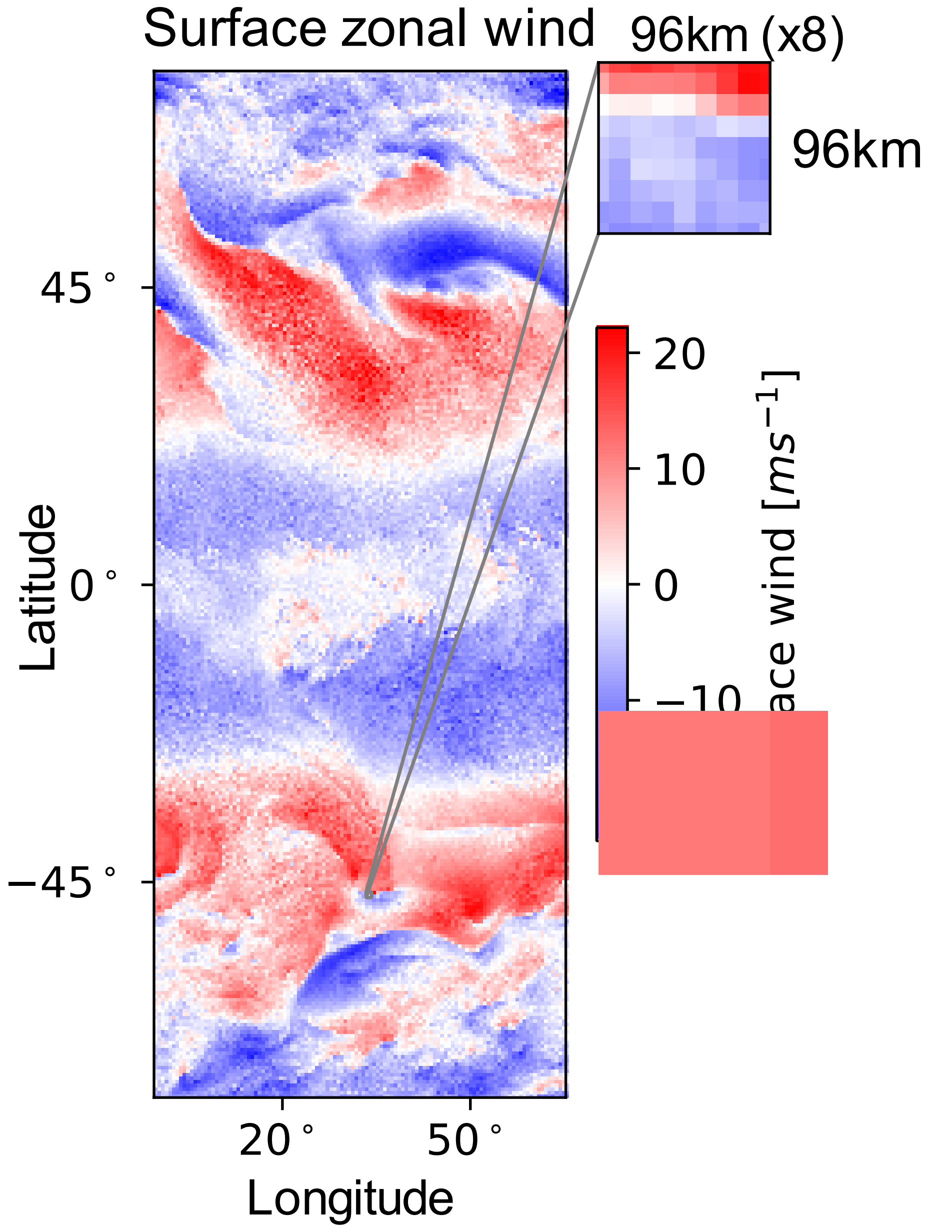
Outgoing longwave radiation shown

- SAM model with hypohydrostatic rescaling (grid spacing 12km, effective 3km)

- Prescribed sea-surface temperature distribution that is symmetric about the equator

SAM model: Khairoutdinov et al 2003
Hypohydrostatic/DARE: e.g. Kuang et al 2005
Original simulations thanks to Bill Boos and Alexey Federov

We coarse-grain high-resolution simulation to calculate the contribution of subgrid momentum transport



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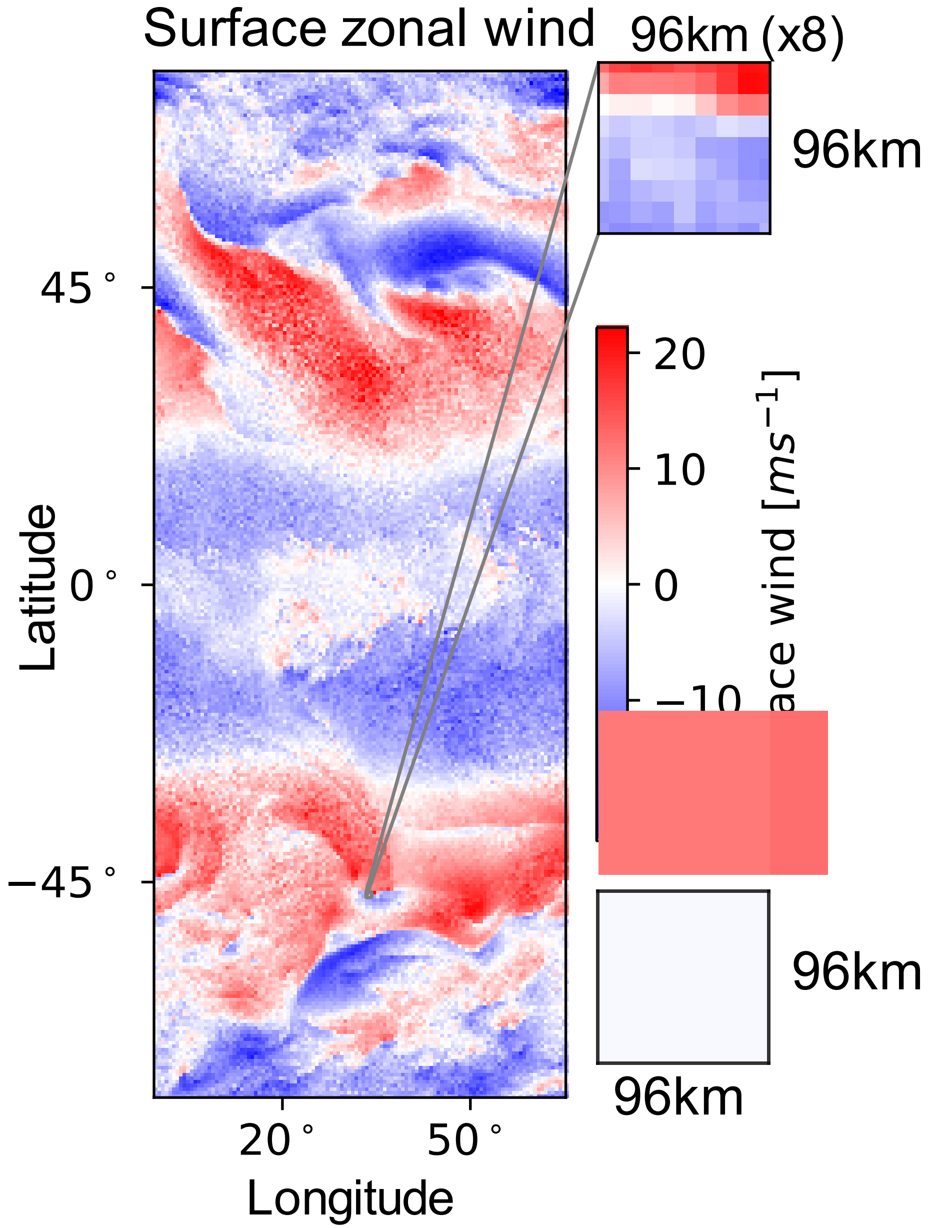

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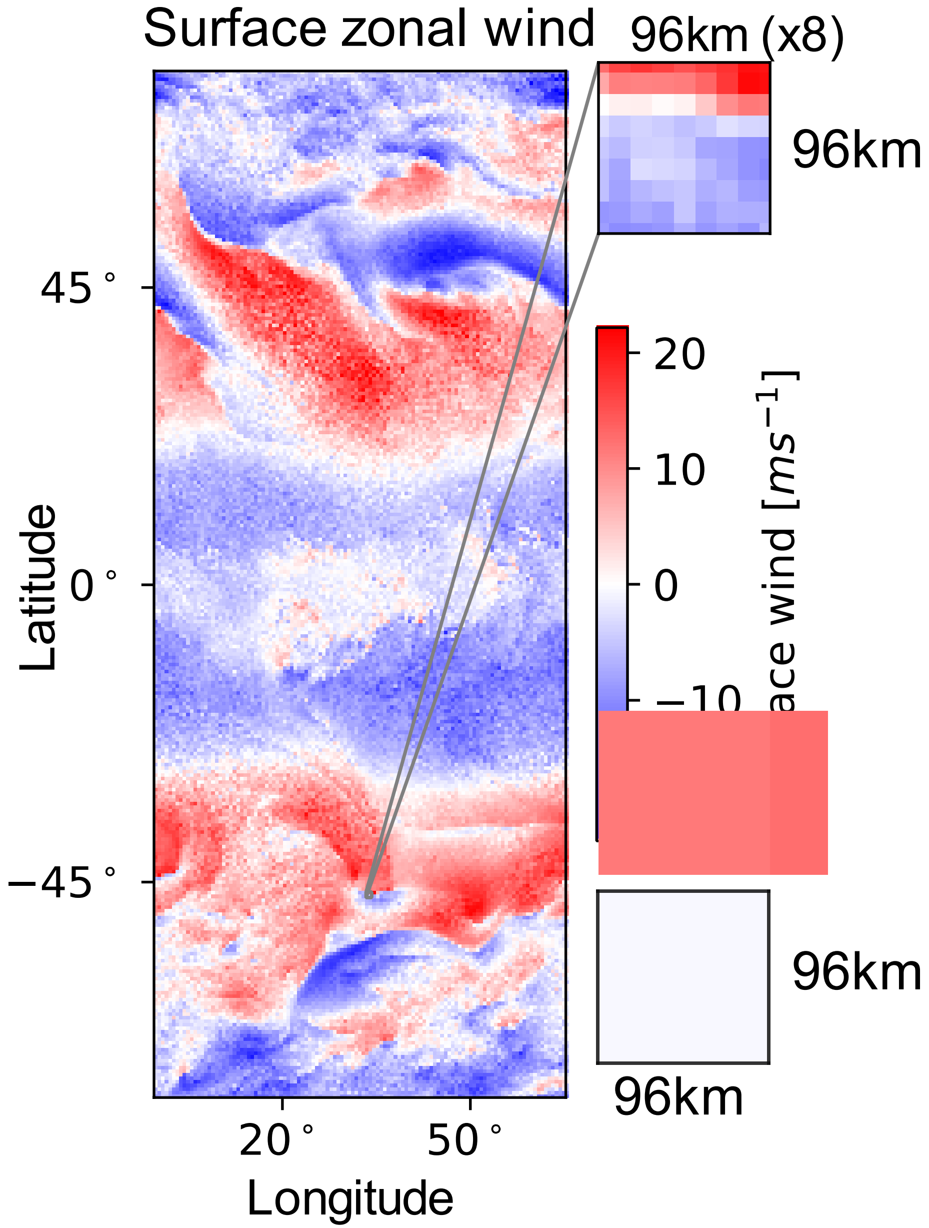

$$\overline{wu}$$

Coarse grained momentum flux from high resolution simulation

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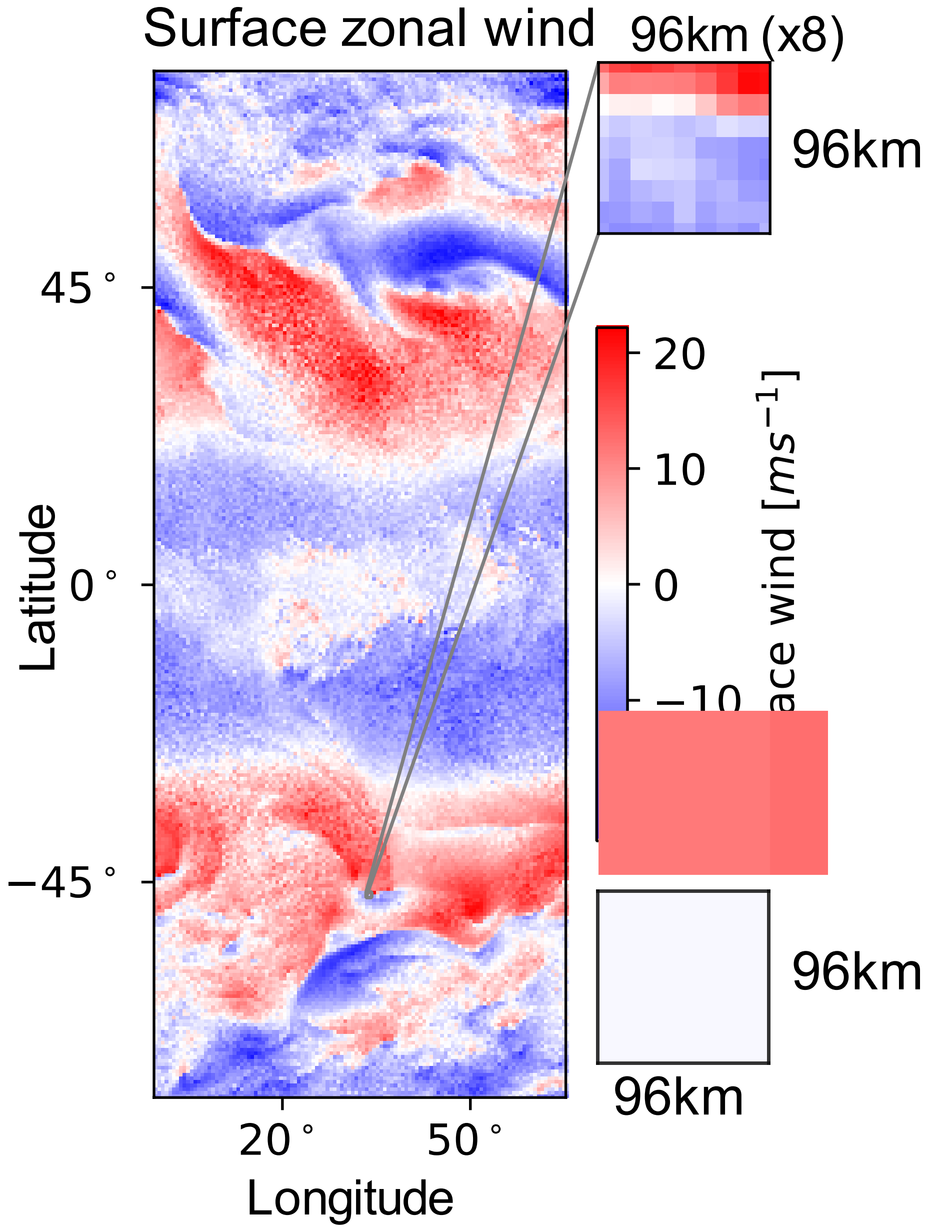


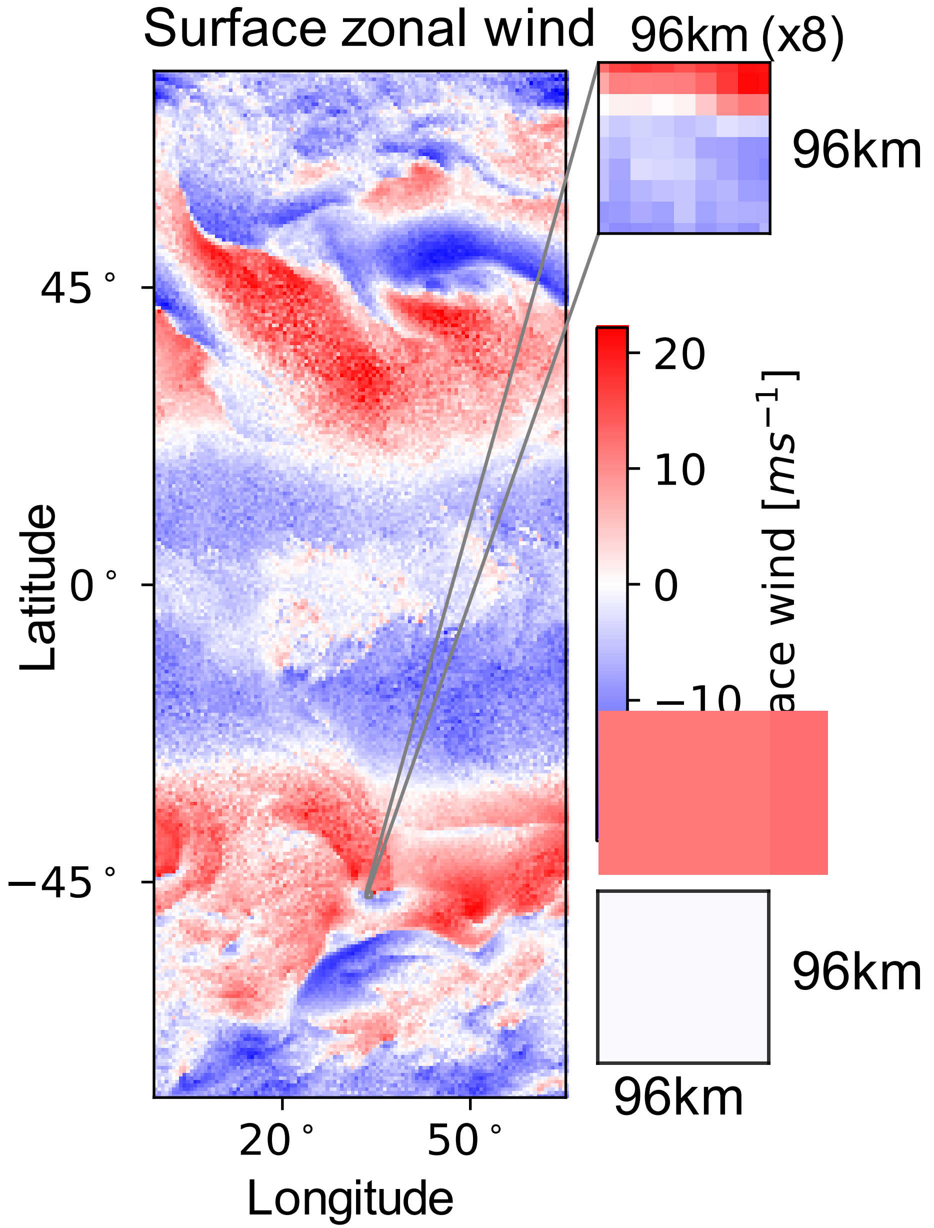
$$\overline{wu}$$

Coarse grained momentum flux
from high resolution simulation

$$\overline{w}\,\overline{u}$$

Resolved momentum flux
When running a low resolution simulation

We coarse-grain high-resolution simulation to calculate the contribution of subgrid momentum transport



$$\overline{wu}$$

Coarse grained momentum flux
from high resolution simulation

Subgrid flux = $\overline{wu} - \overline{w}\,\overline{u}$

$$\overline{w}\,\overline{u}$$

Resolved momentum flux
When running a low resolution simulation

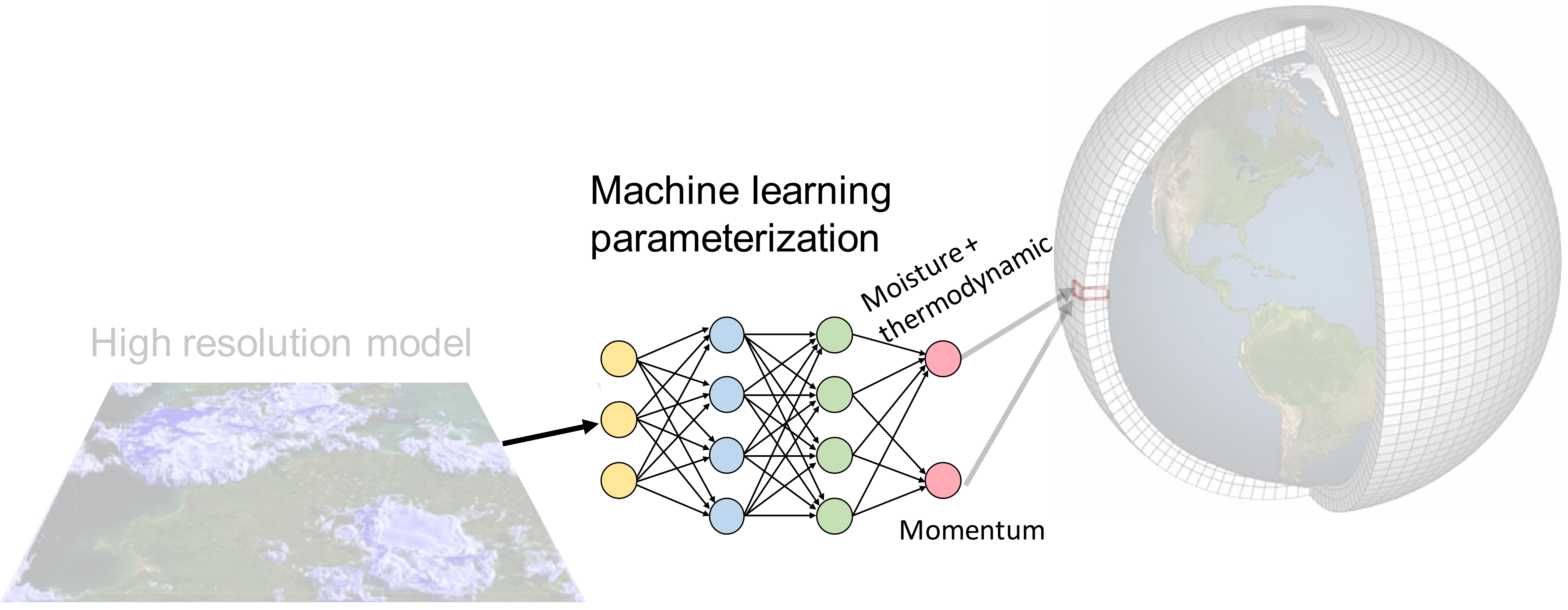
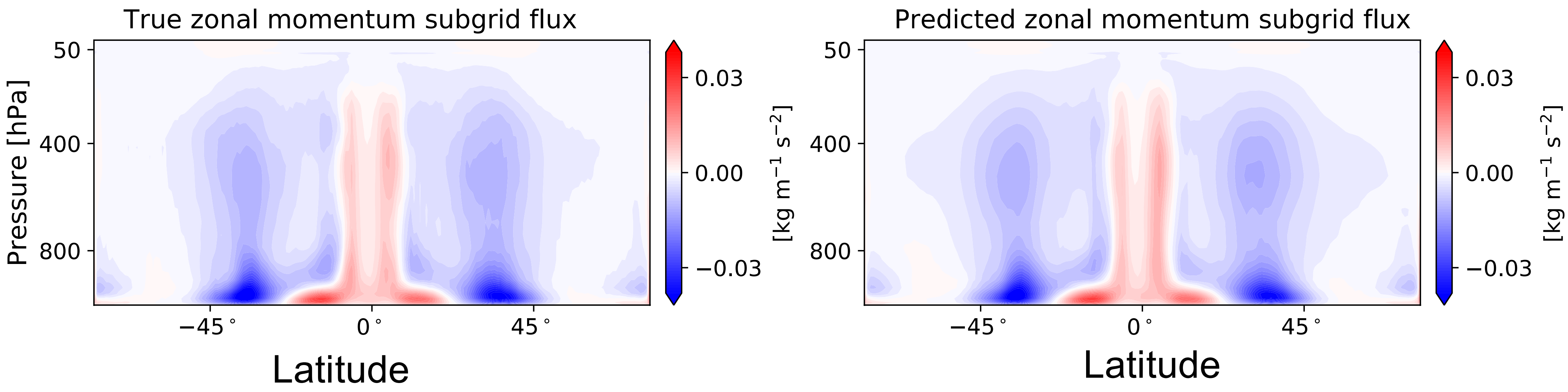


Figure credit: NOAA

Figure credit: NASA

Mean subgrid momentum fluxes are downgradient and the neural network approximates well the mean fluxes

Offline results



Yuval and O'Gorman (ESSOAr preprint)

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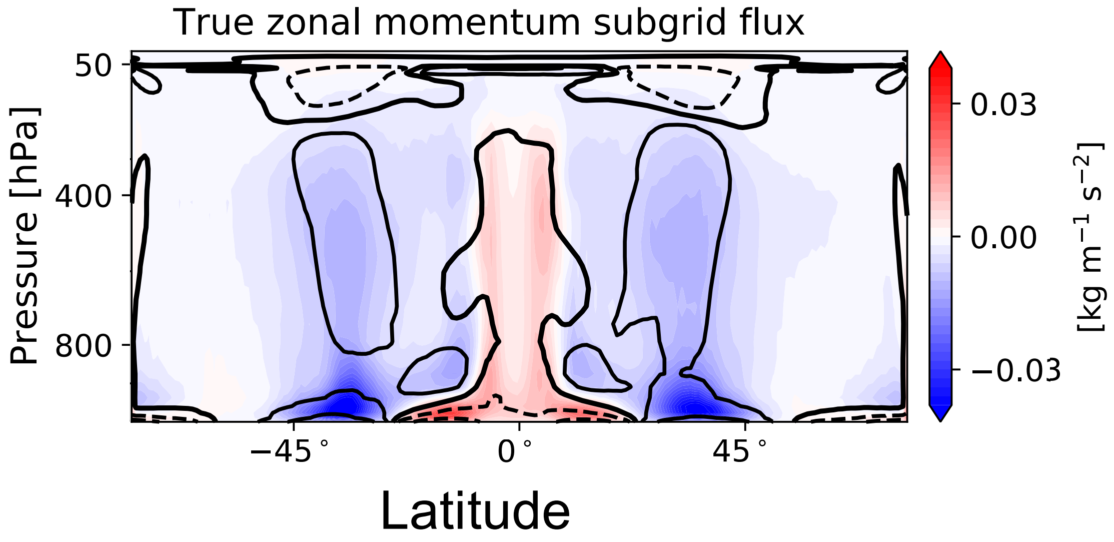
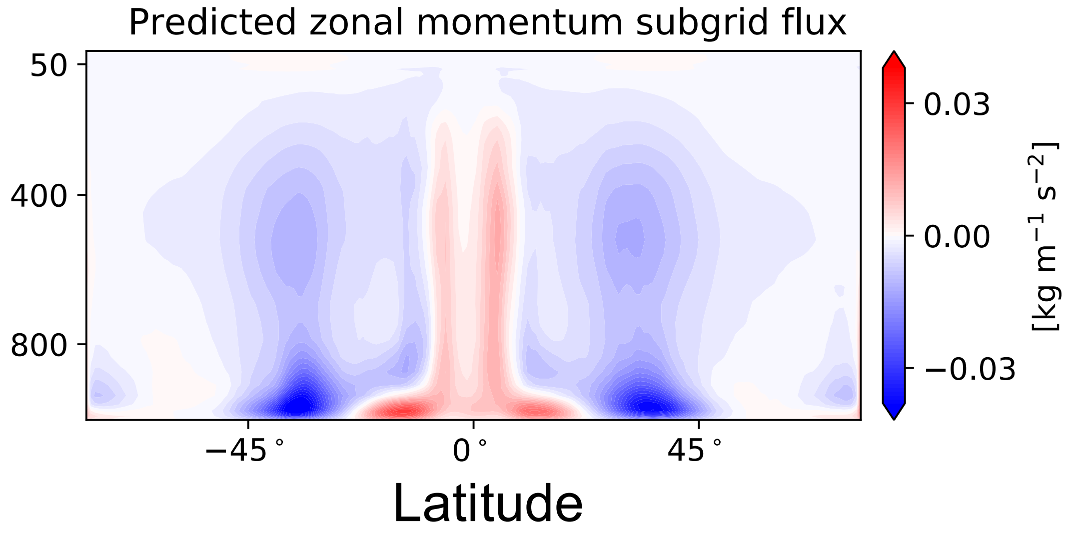




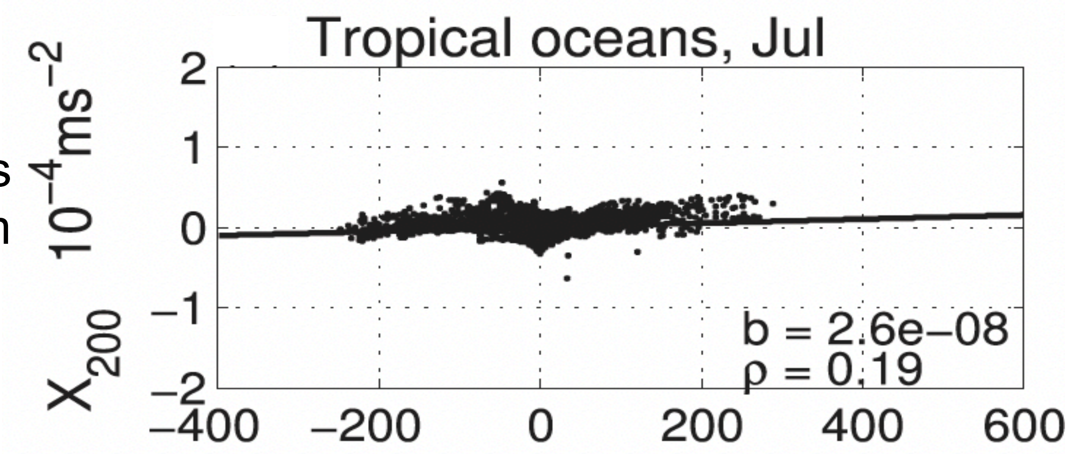
Wind shear shown in contours

Yuval and O'Gorman (ESSOAr preprint)

Calculated fluxes are similar to a simplified parameterization that was fit to reanalysis, and NN accurately predict the mean fluxes

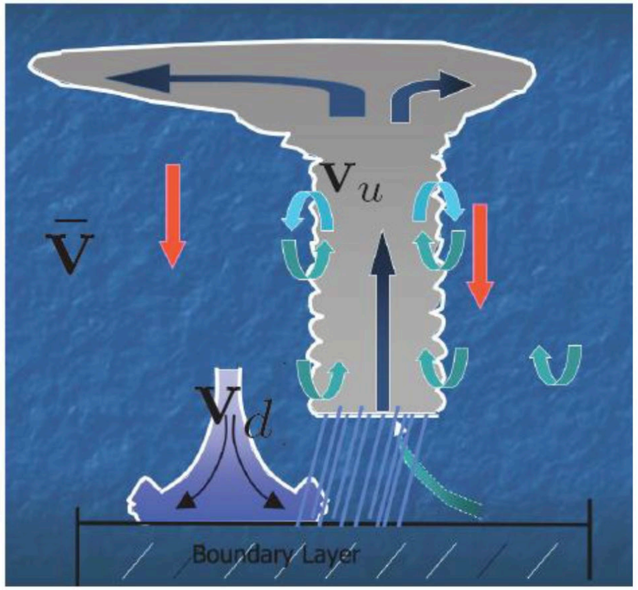
Reanalysis: mean residual momentum tendency scales like a simple momentum convection parameterization

Reanalysis momentum residual



Simple parameterization: $\mathrm{prcp}^*(\overline{u}_{925} - \overline{u}_{200})$

Yang et al. (2013)



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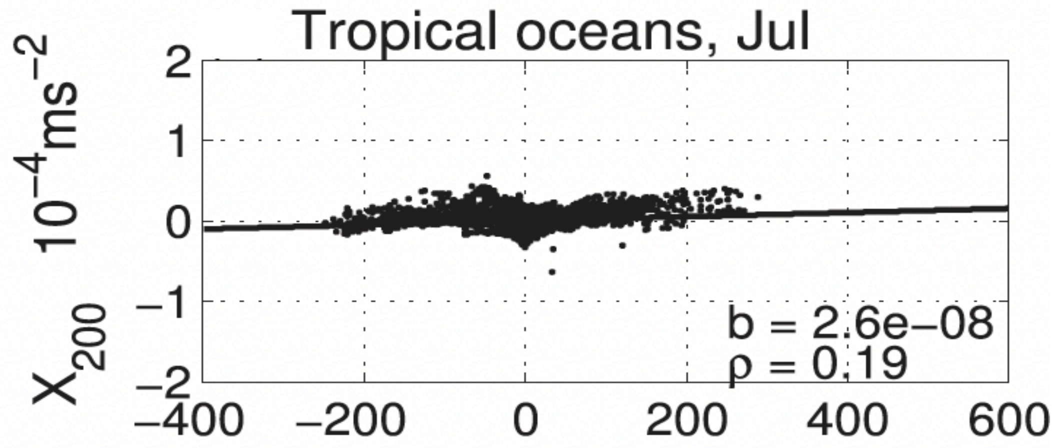

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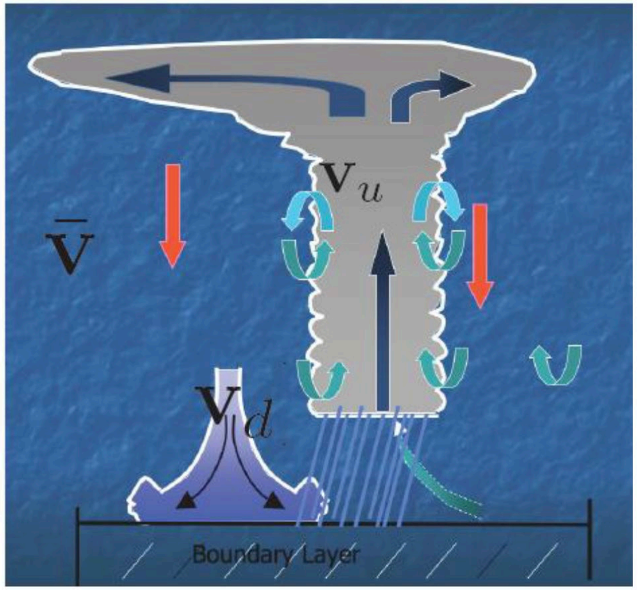
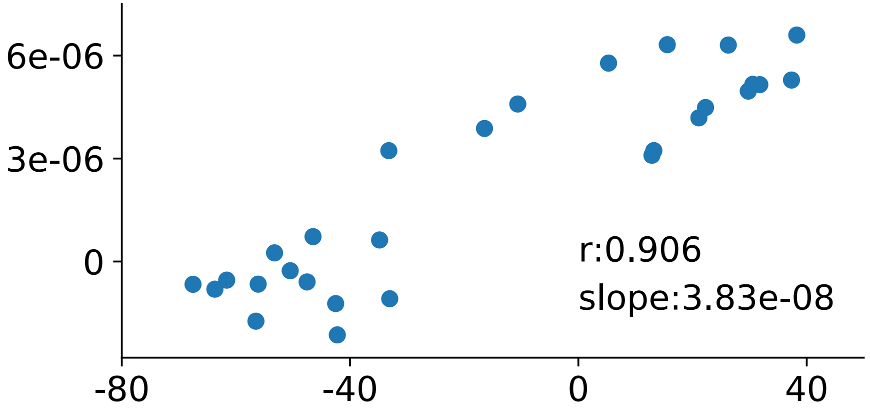


Subgrid momentum from hi-res



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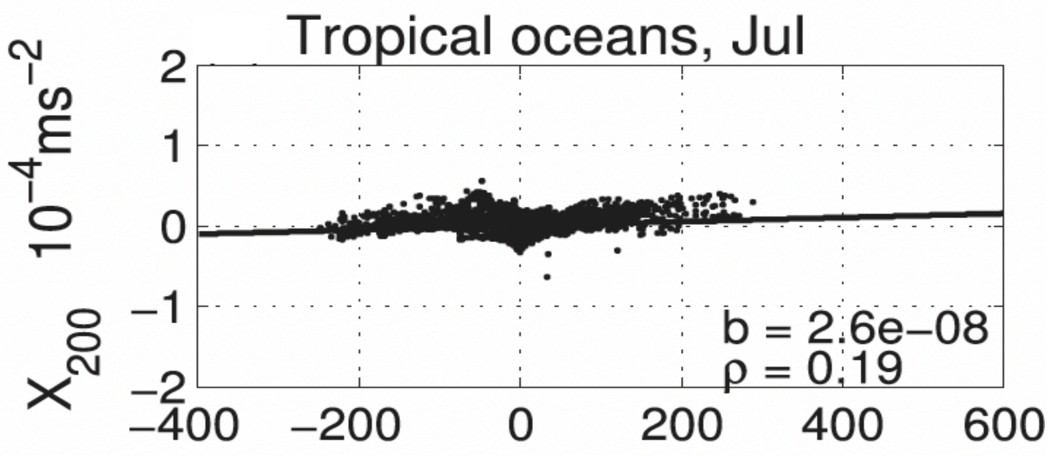

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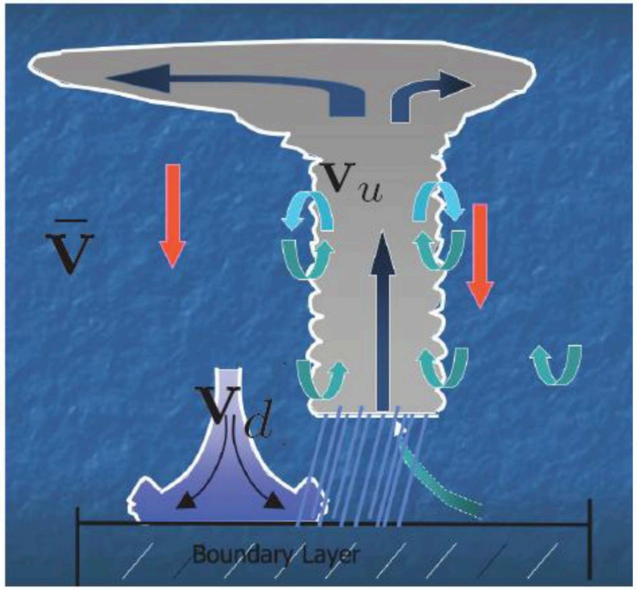

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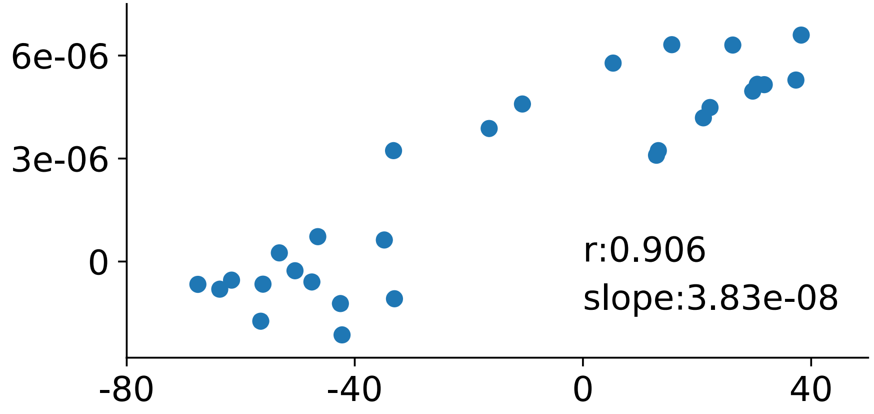

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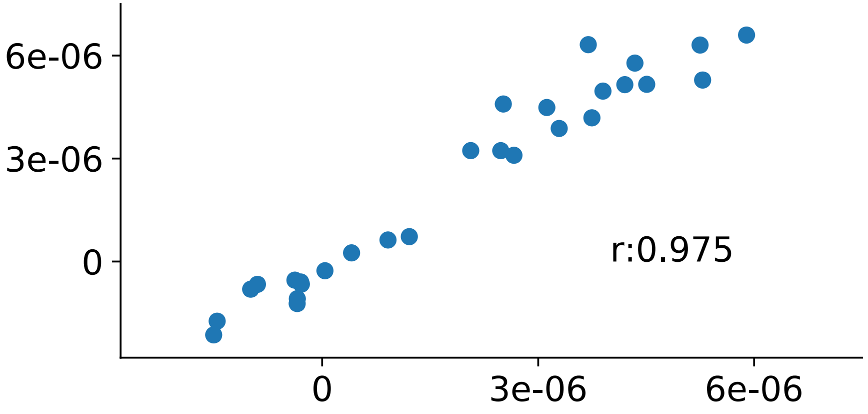
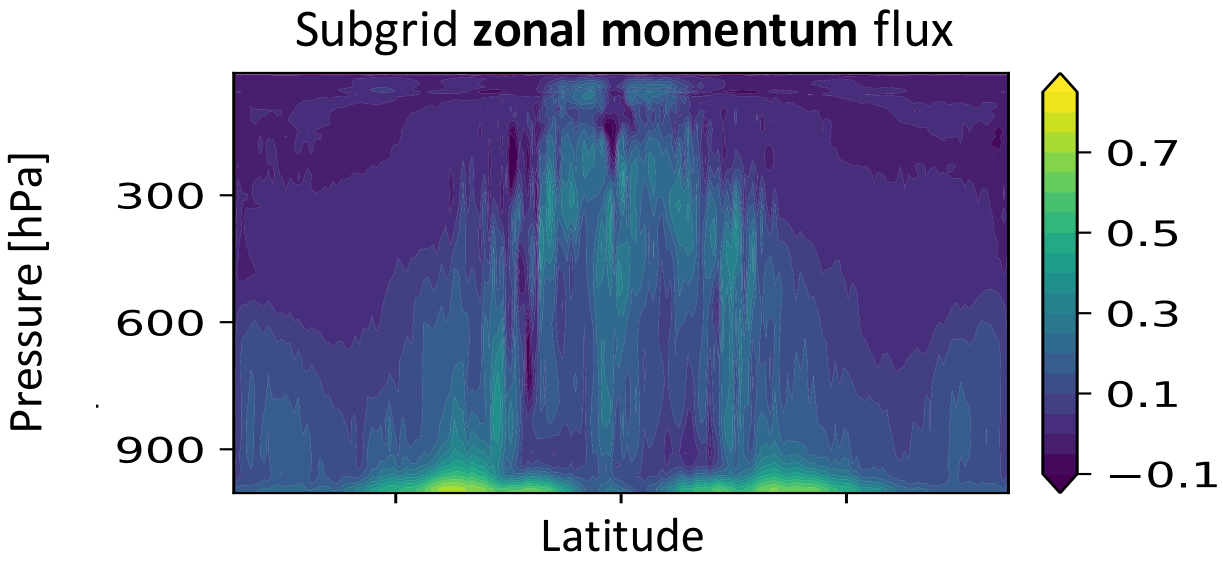


Neural network parameterization

It is more difficult to predict subgrid momentum fluxes compared to subgrid moisture fluxes

Offline performance



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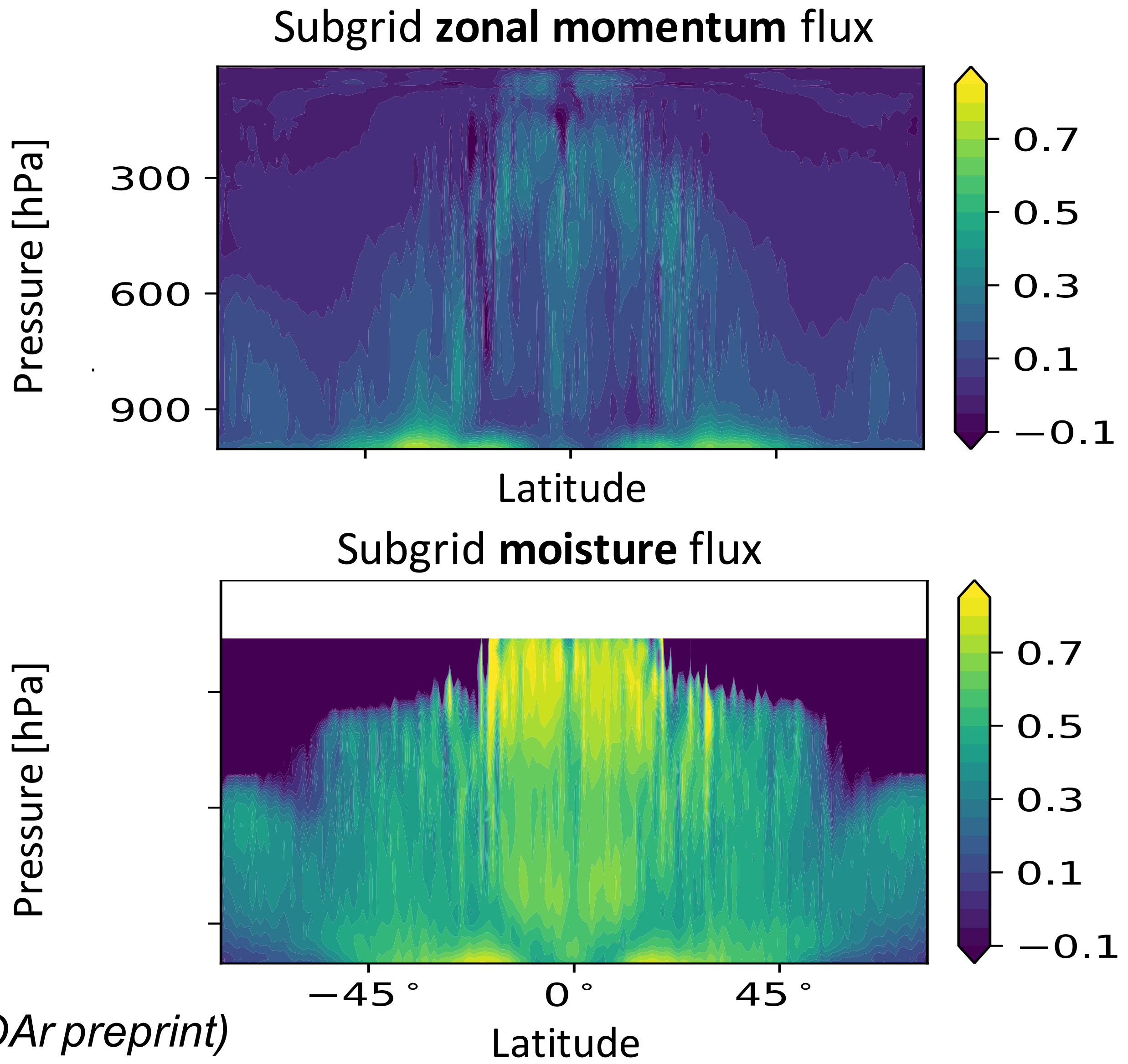
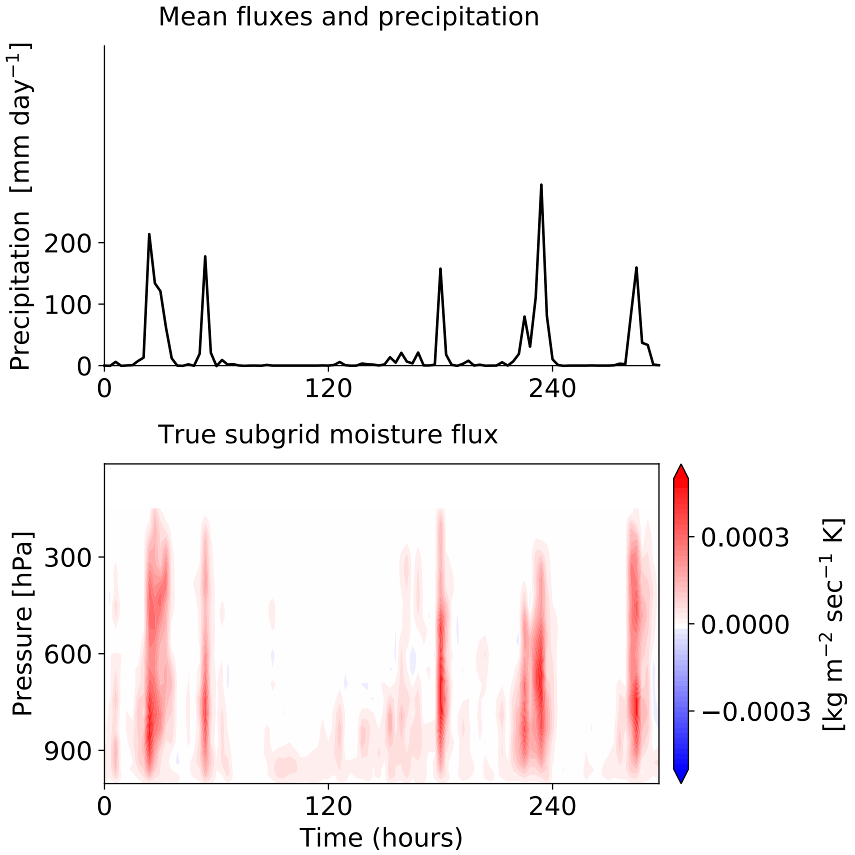
Offline performance



Yuval and O'Gorman (ESSOAr preprint)

Why is it more difficult to predict subgrid momentum fluxes compared to moisture fluxes?



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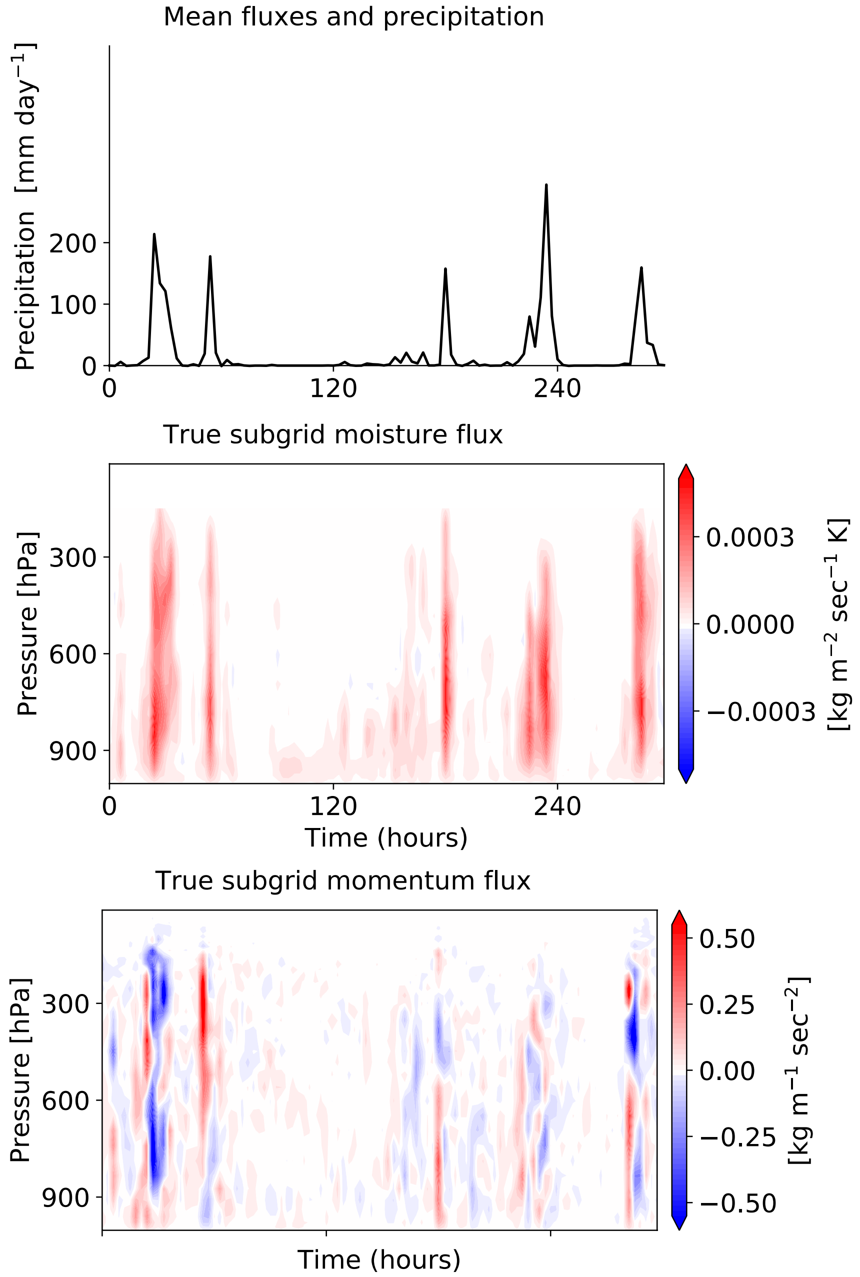

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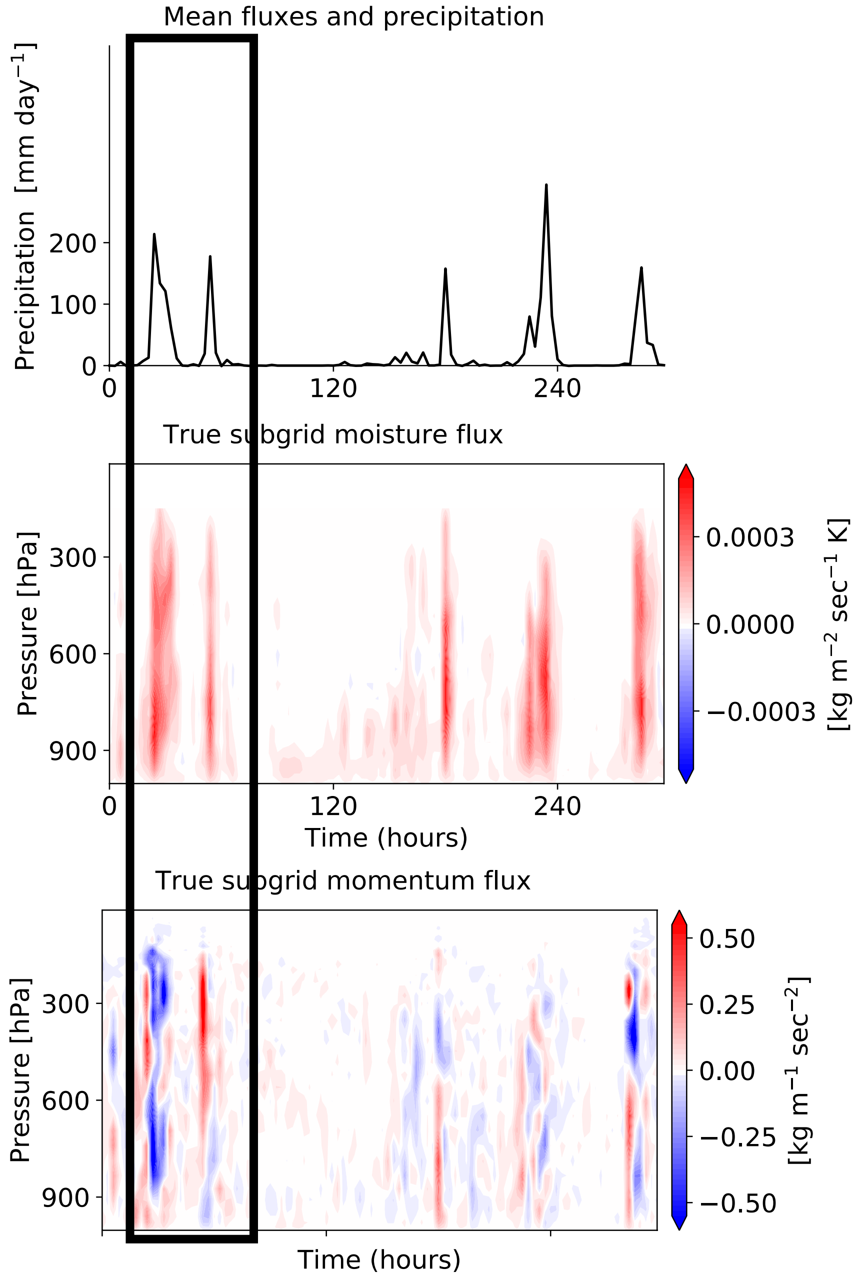

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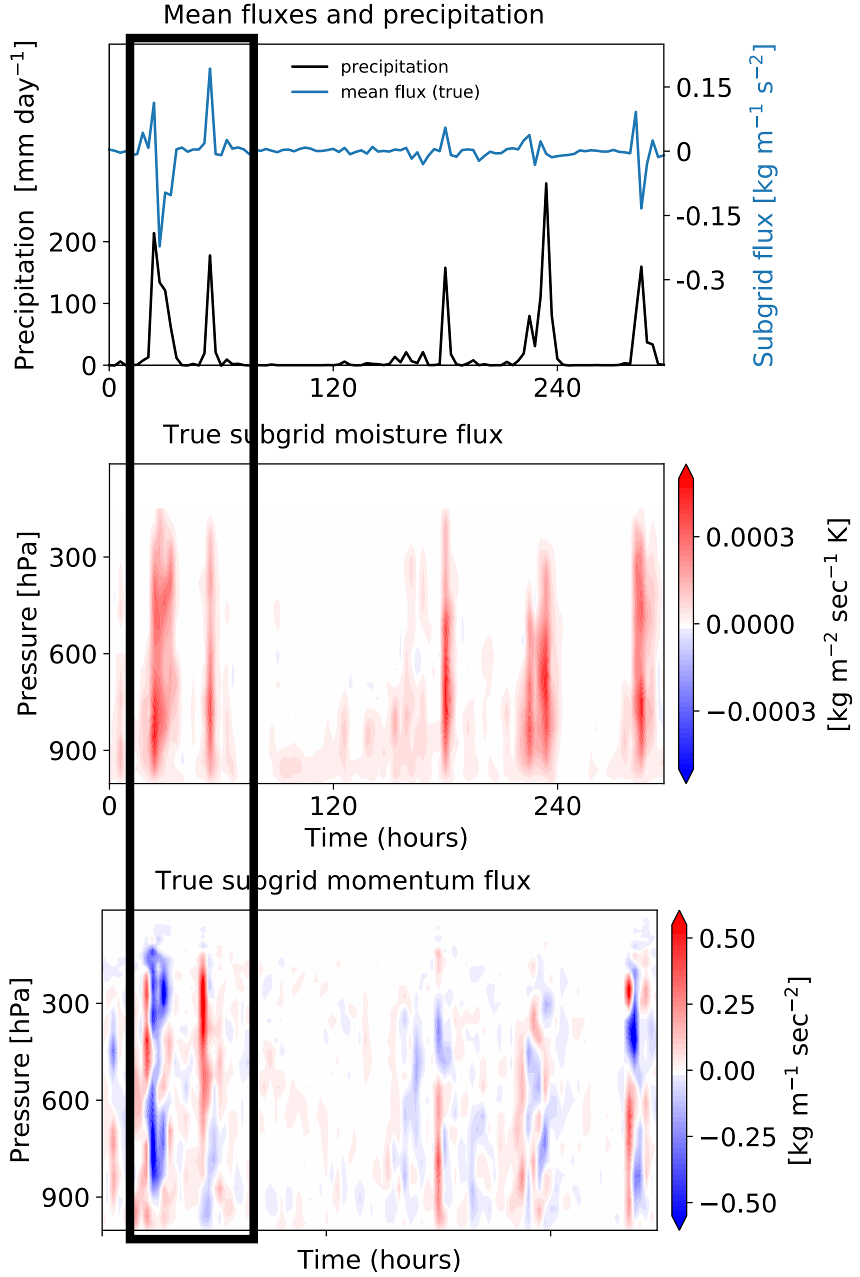

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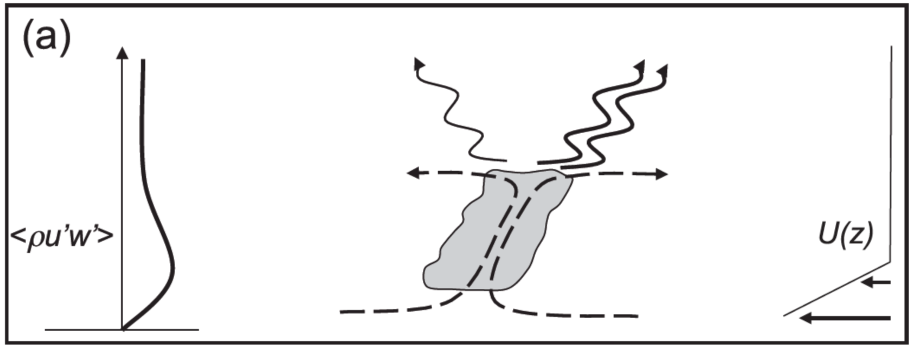
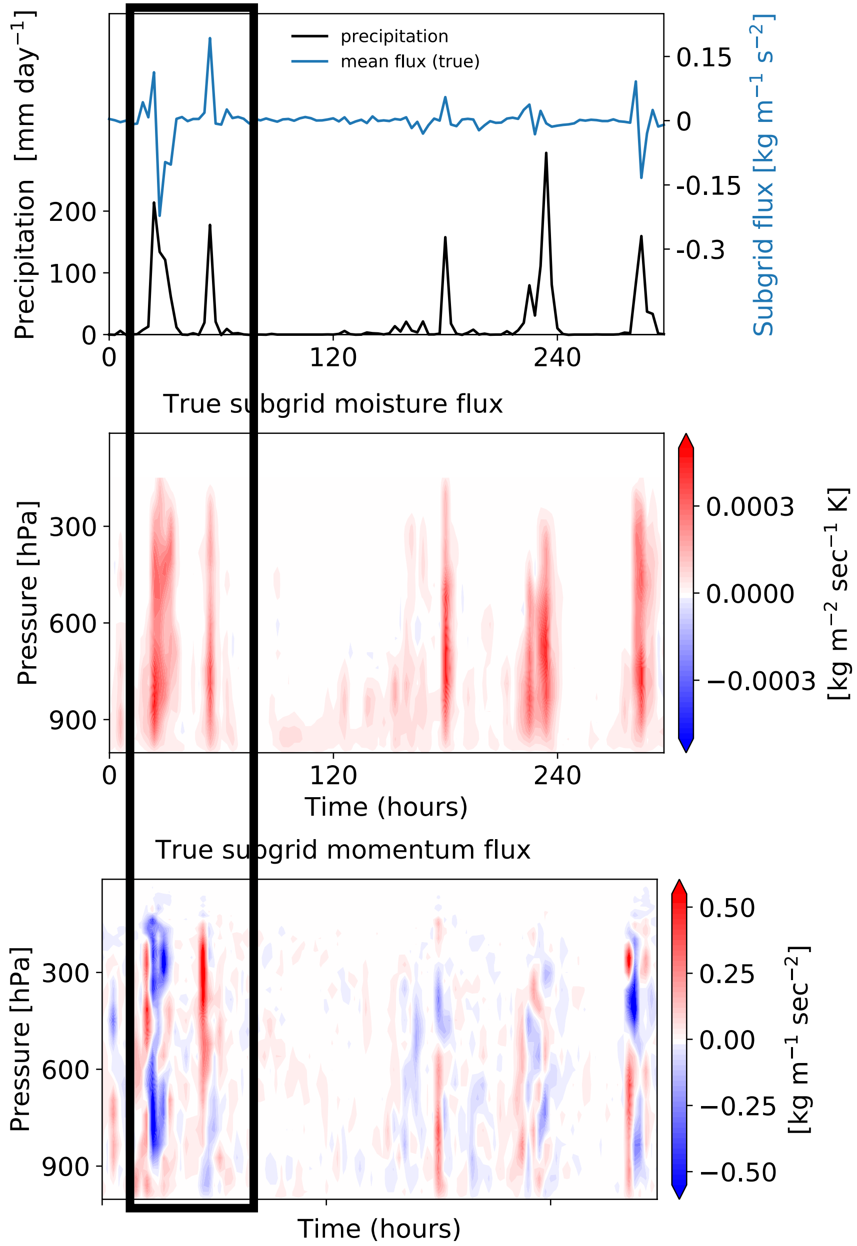


Lane and Moncrieff (2010)

Convective momentum transport can be negative or positive



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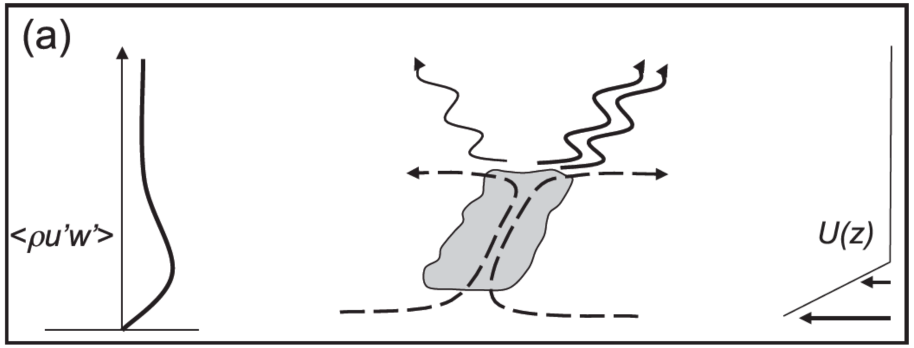

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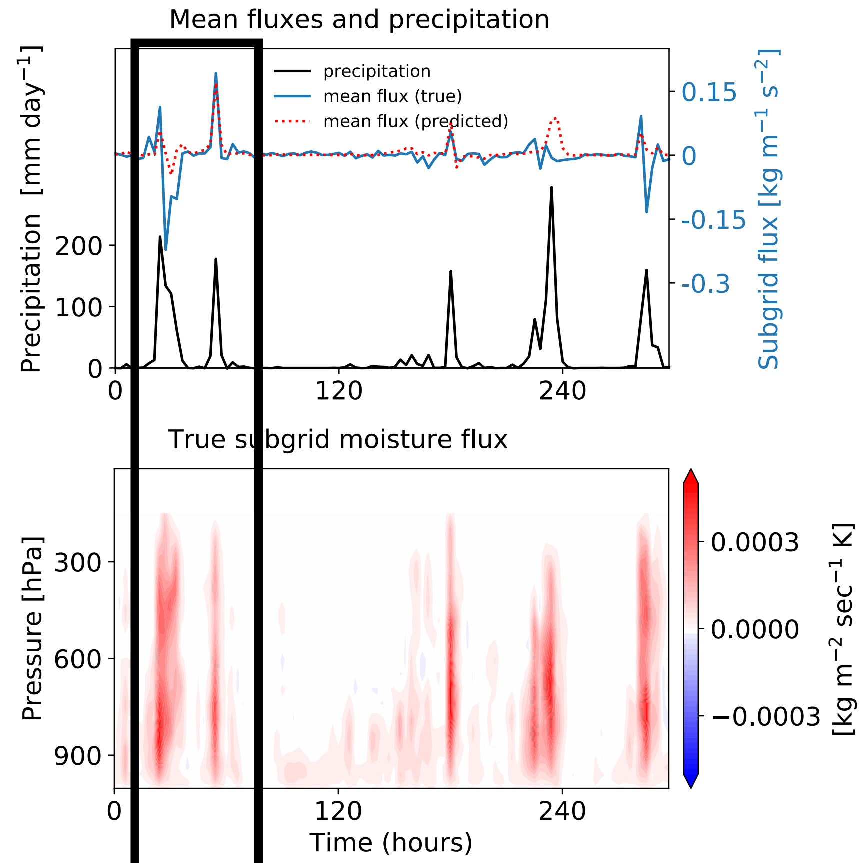

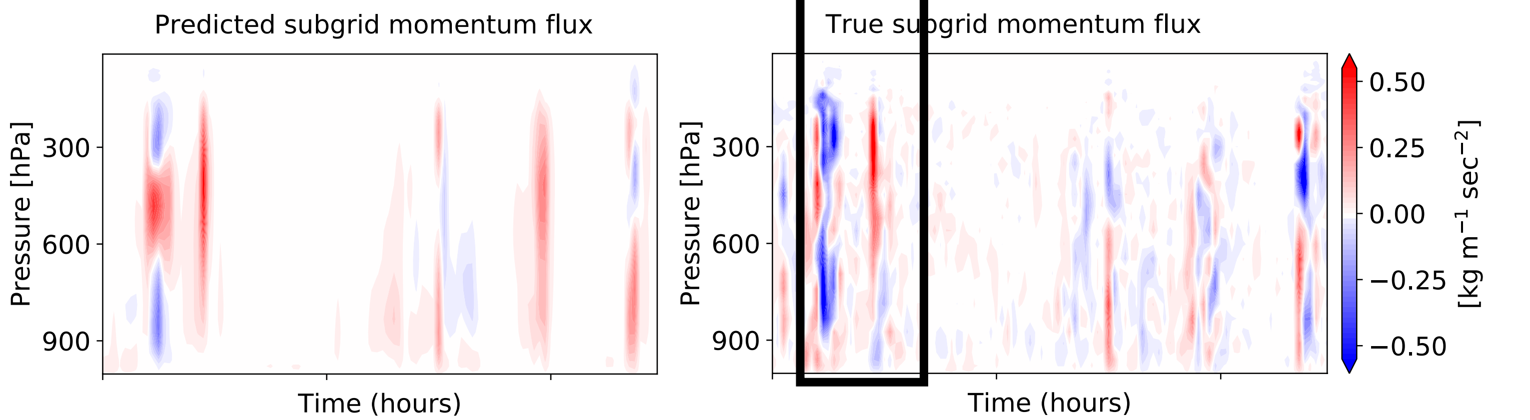

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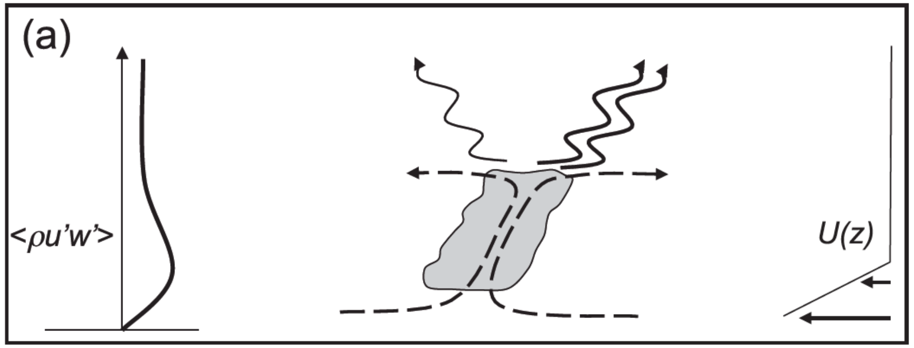

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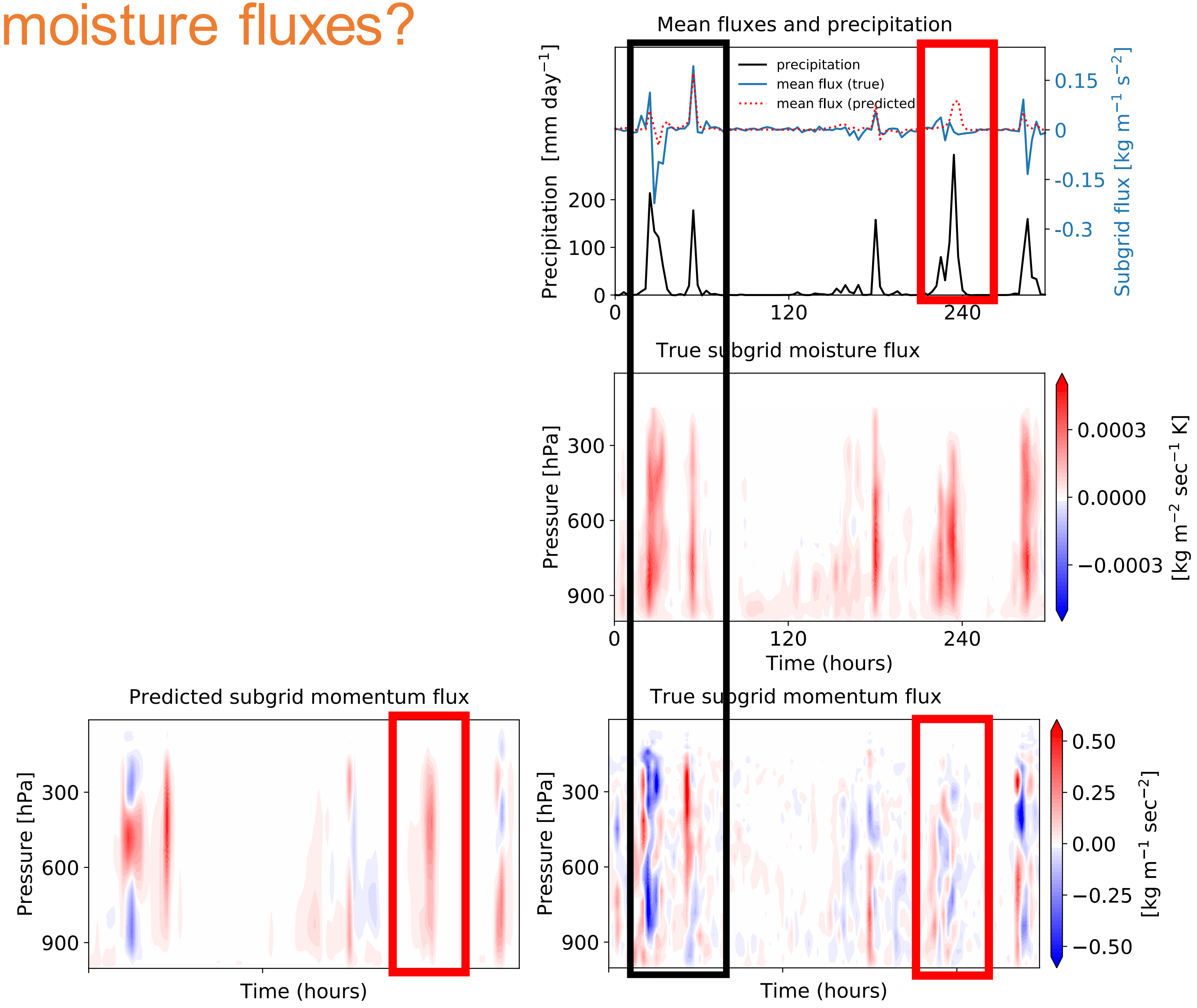

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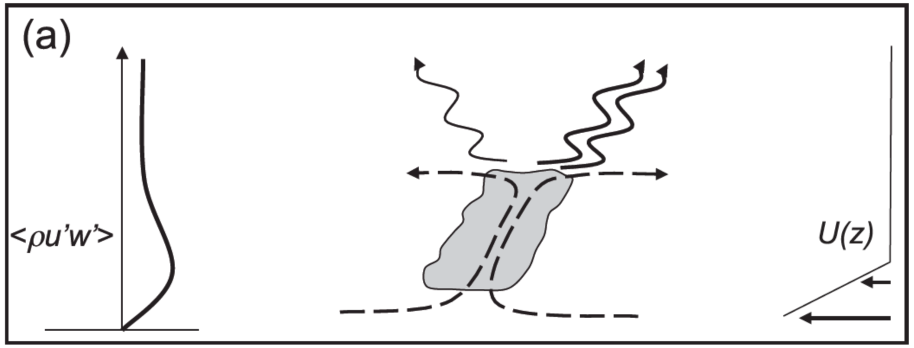

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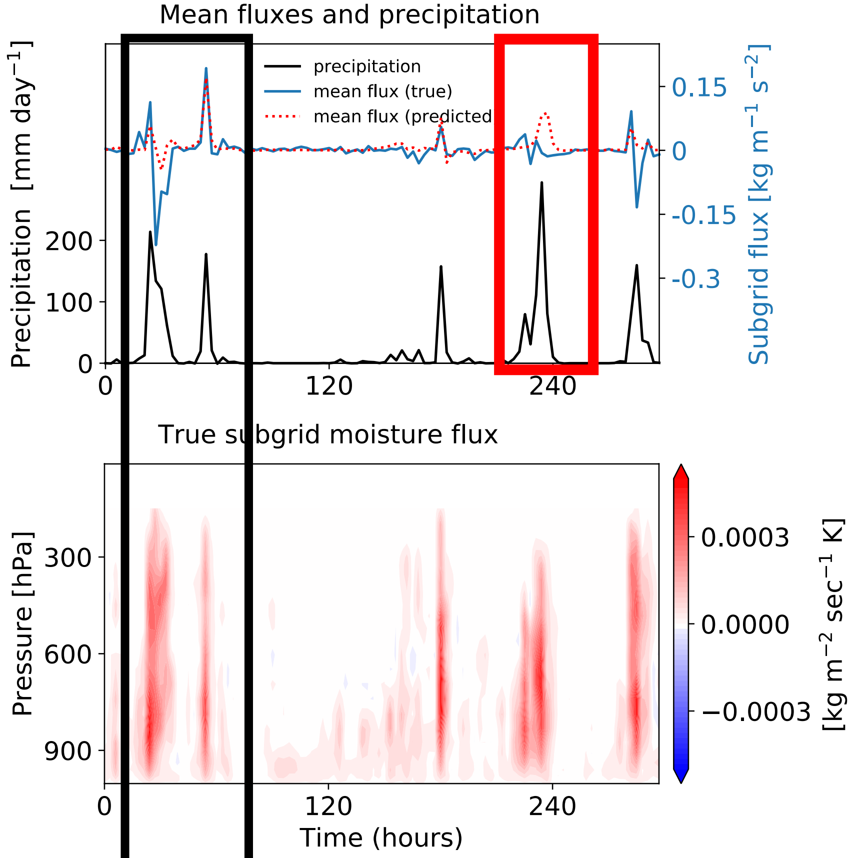
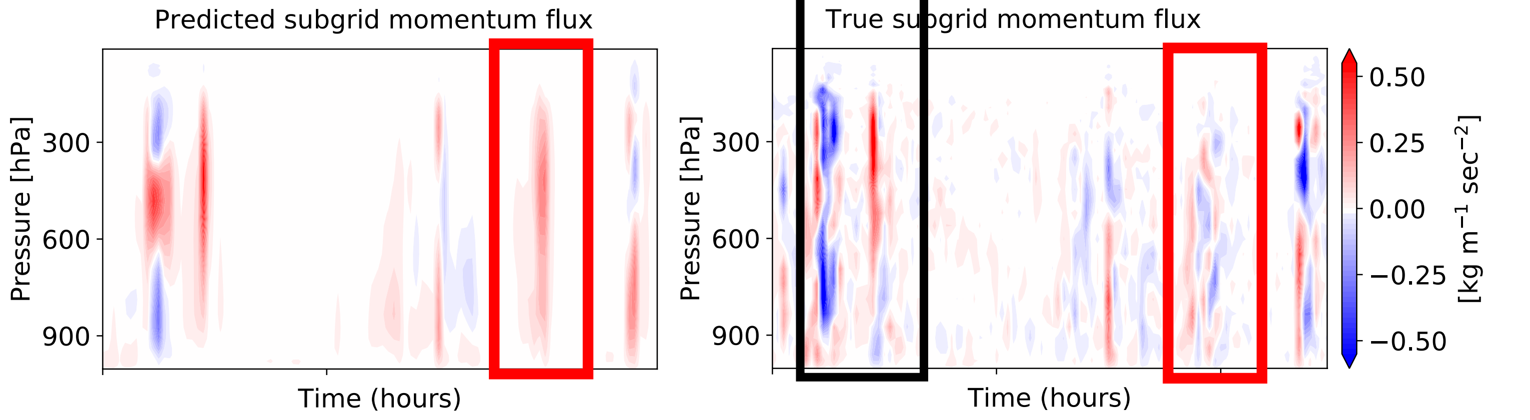
Convective momentum transport can be negative or positive

For (linear) gravity waves:

$$\overline{w'u'} \neq 0$$

$$\overline{w'\theta'} = 0$$





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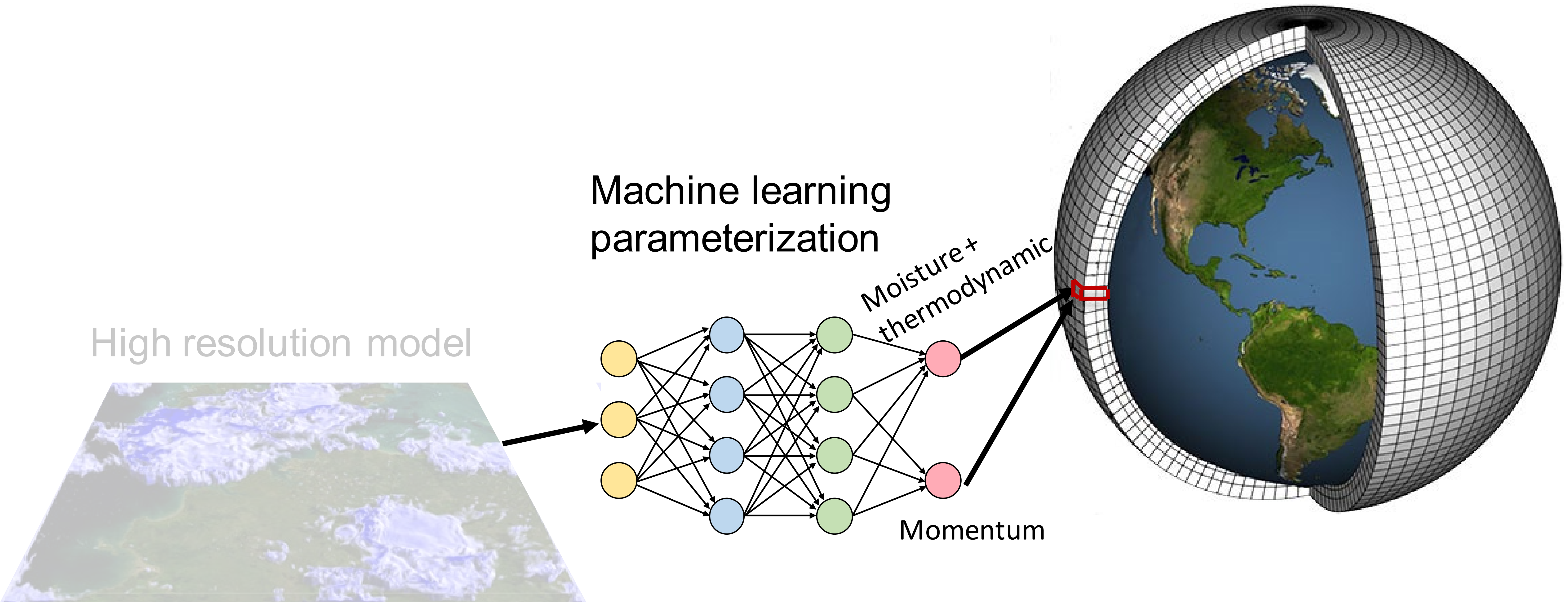
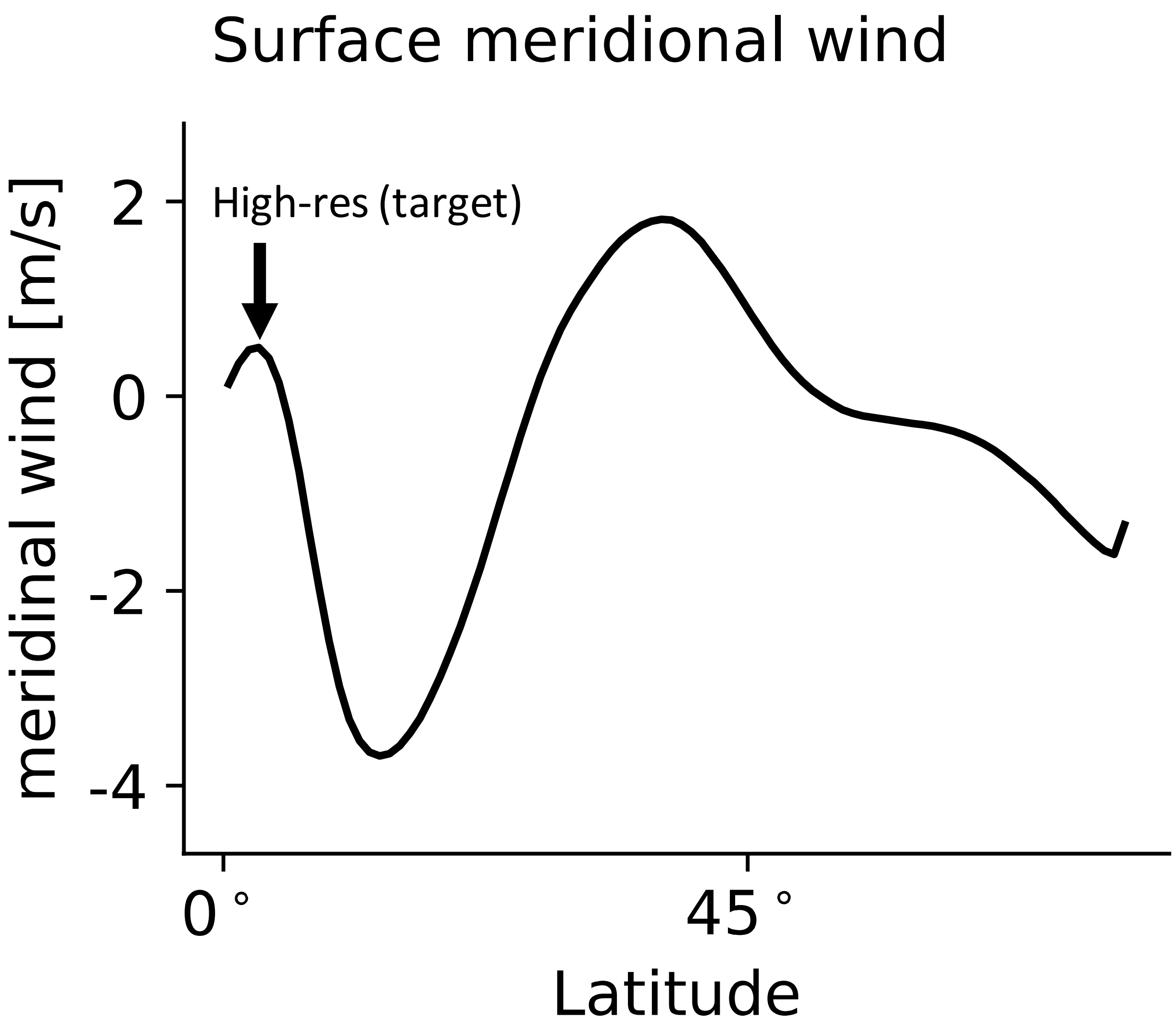


Figure credit: NOAA

Figure credit: NASA

Neural network parameterization of subgrid momentum transport improves some characteristics of the atmospheric circulation



CMT affects surface wind:
e.g., Richter and Rasch (2007),
Woelfle et al. (2018)

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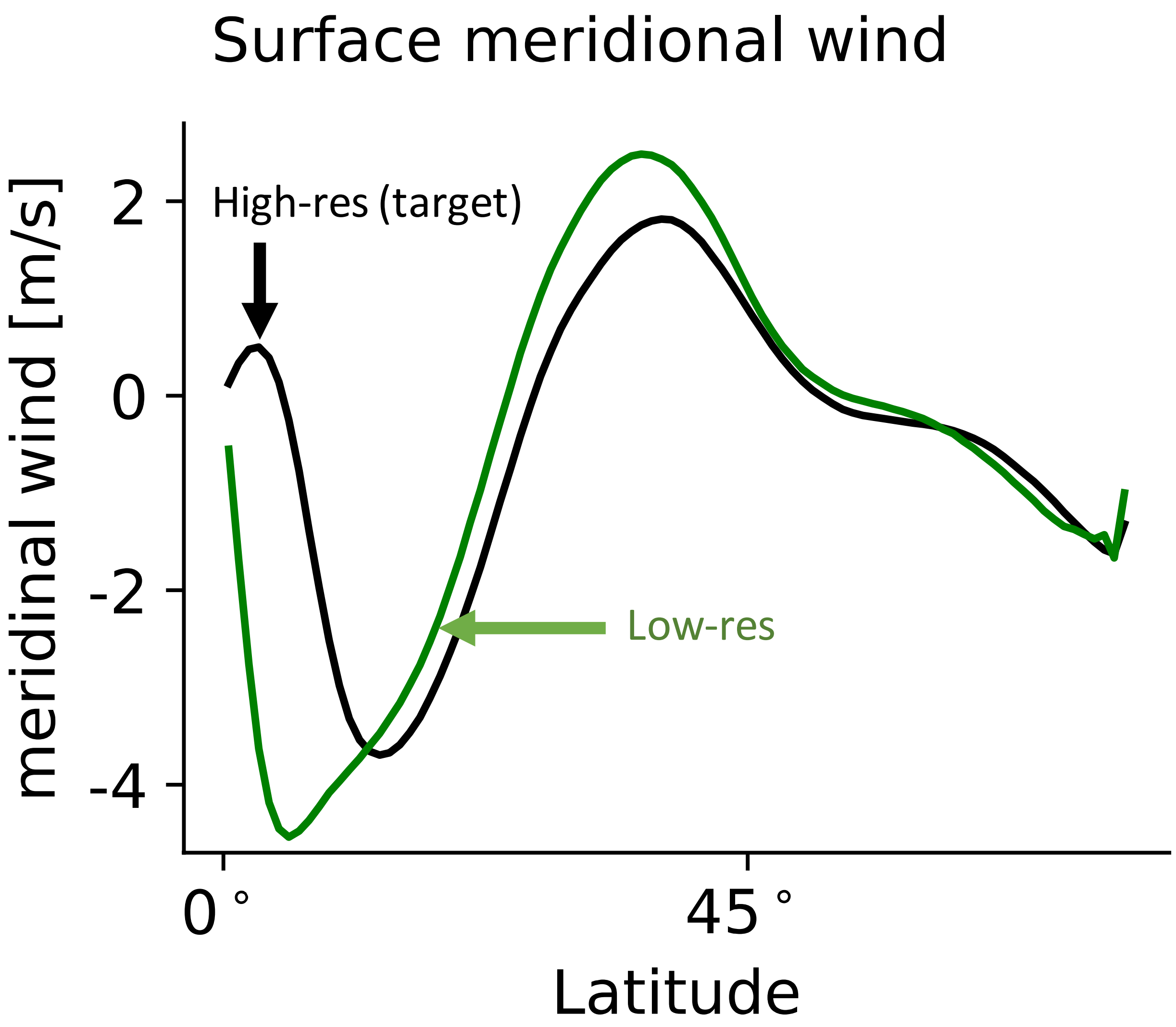

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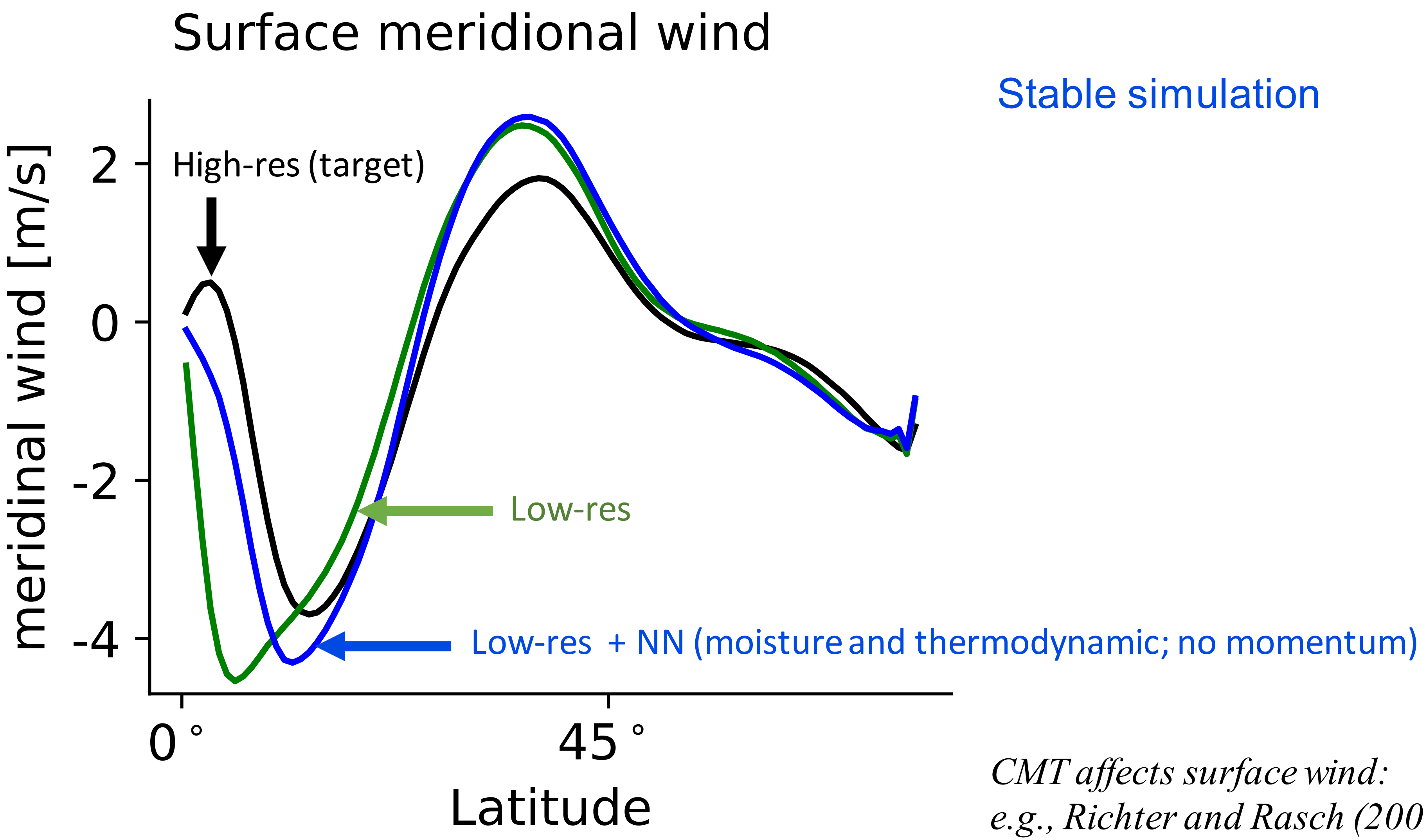

Stable simulation

CMT affects surface wind: e.g., Richter and Rasch (2007), Woelfle et al. (2018)

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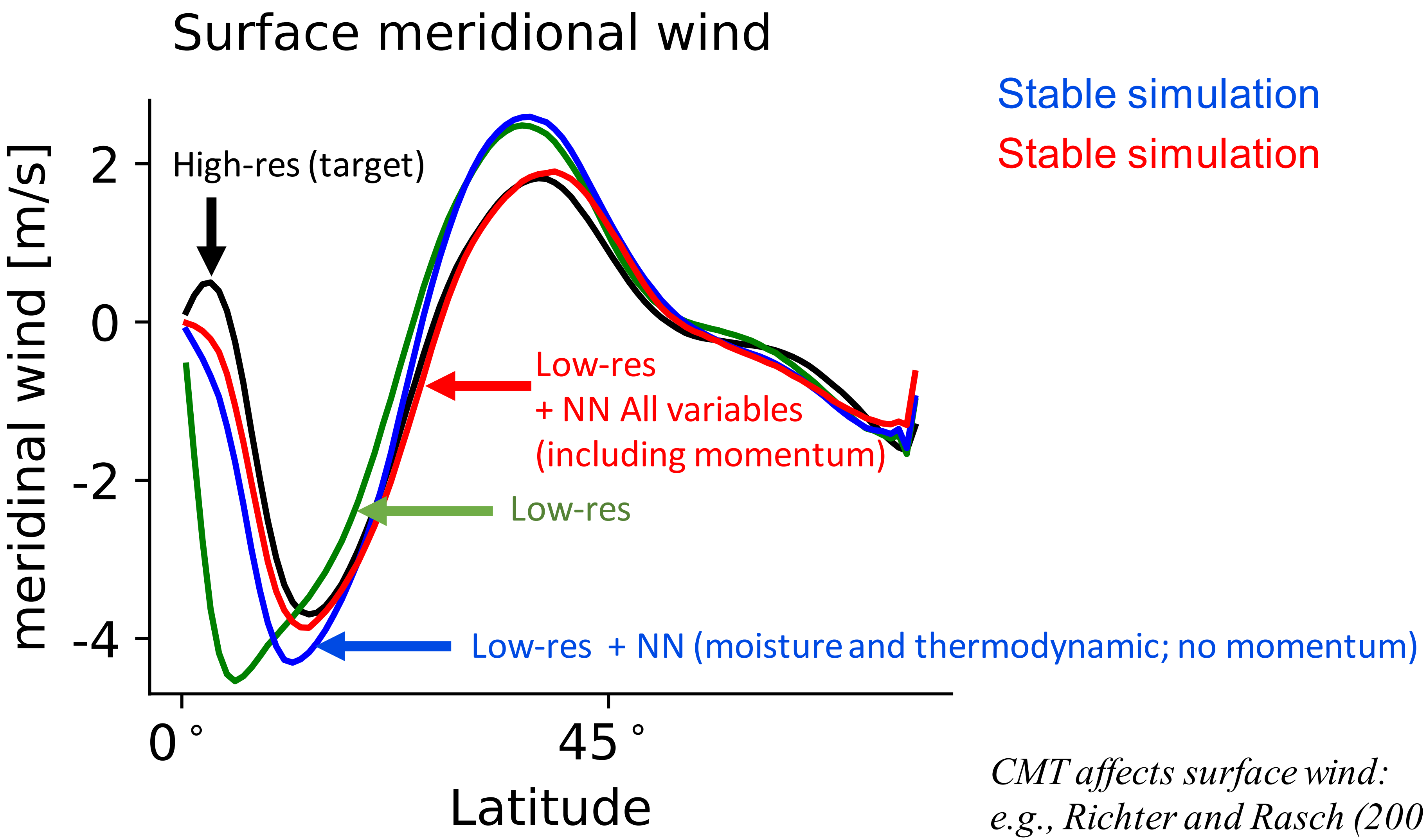

CMT affects surface wind: e.g., Richter and Rasch (2007), Woelfle et al. (2018)

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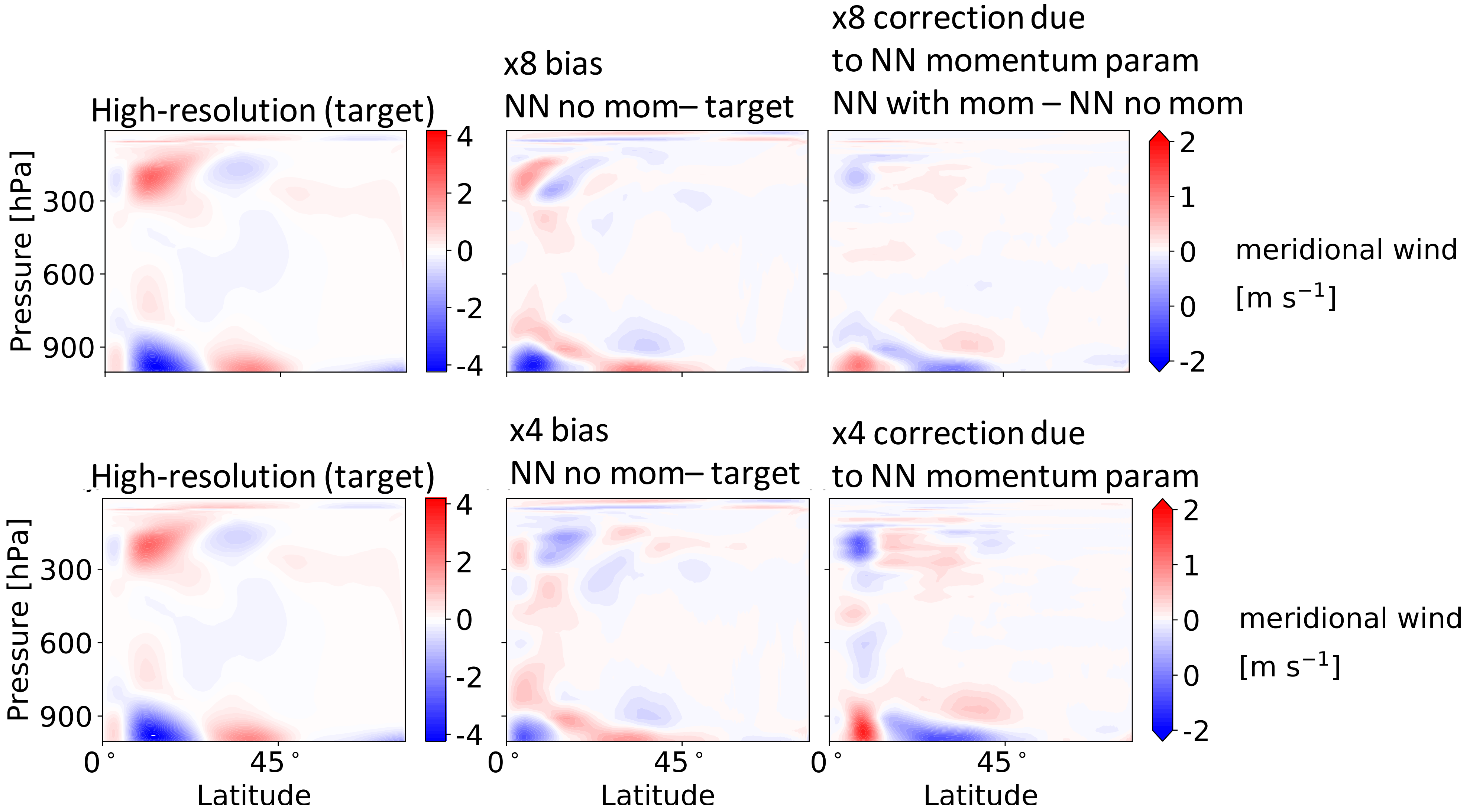
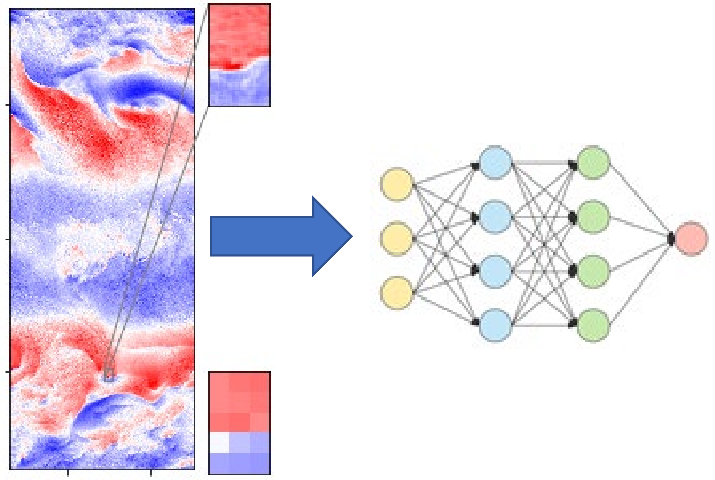
Neural network parameterization can also overestimate the effect subgrid momentum transport

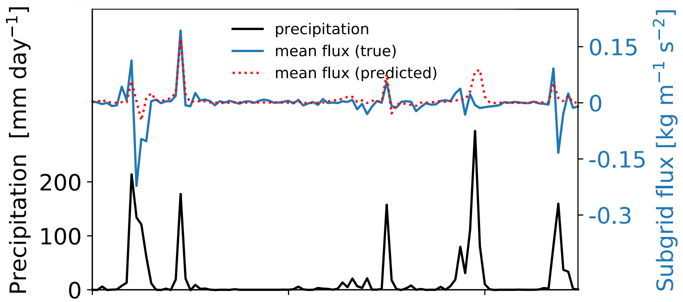


Conclusions

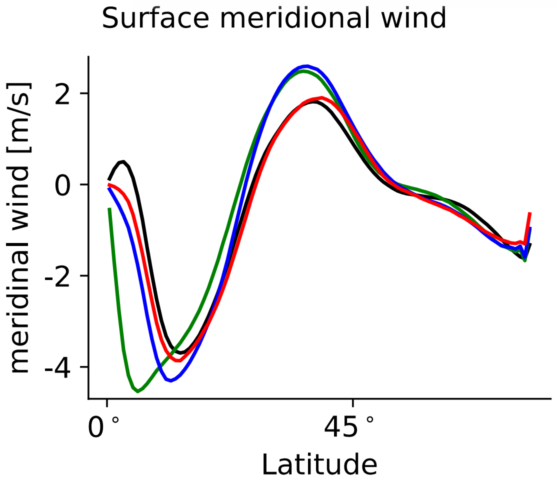
- Physically-consistent neural-network parameterization for subgrid momentum learned from fully 3-D high-resolution simulation



- It is challenging to predict subgrid momentum fluxes



- Machine-learning momentum parameterization + atmospheric model at climate-model resolution -> stable simulation and improve some characteristics of the atmospheric circulation



Substantially better performance when predicting the absolute value of momentum fluxes