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

Janni Yuval, Paul O’Gorman and Peidong Wang

Support from Houghton-Lorenz Fellowship

MIT Environmental Solutions Initiative and the NSF

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

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

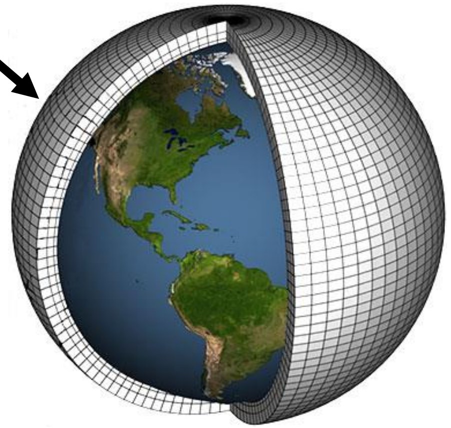

Figure credit: NOAA

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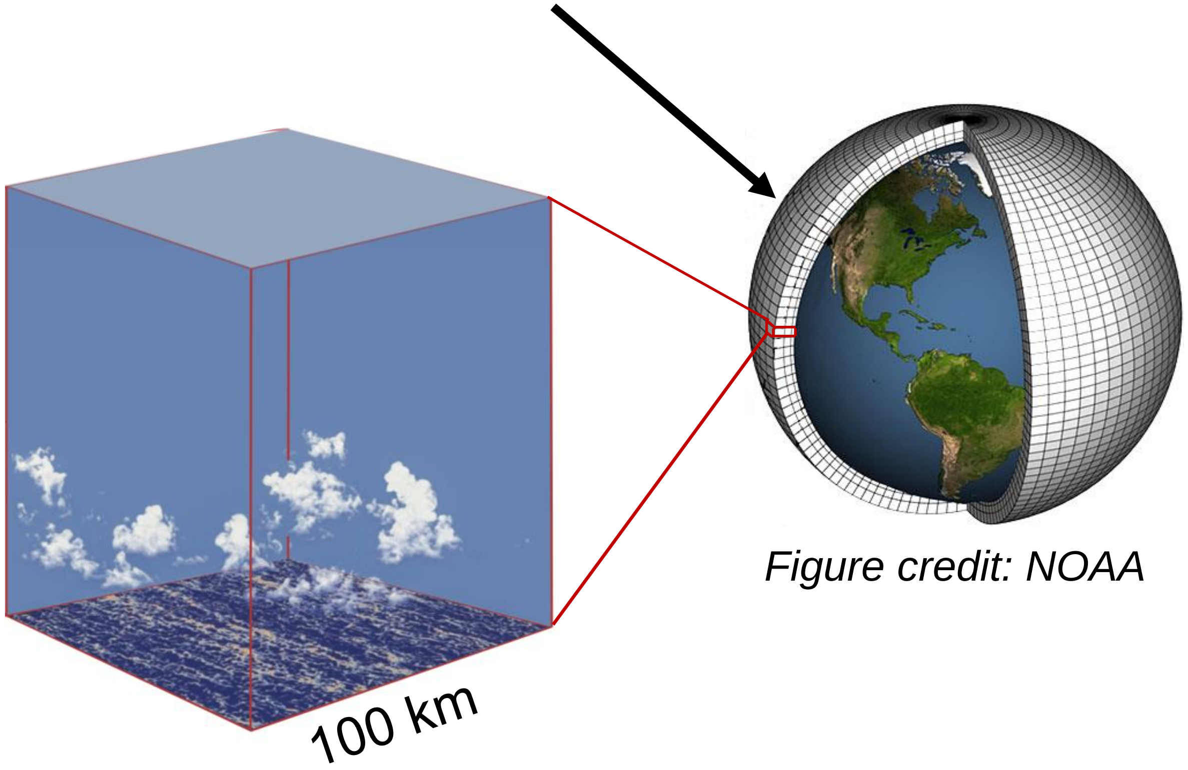

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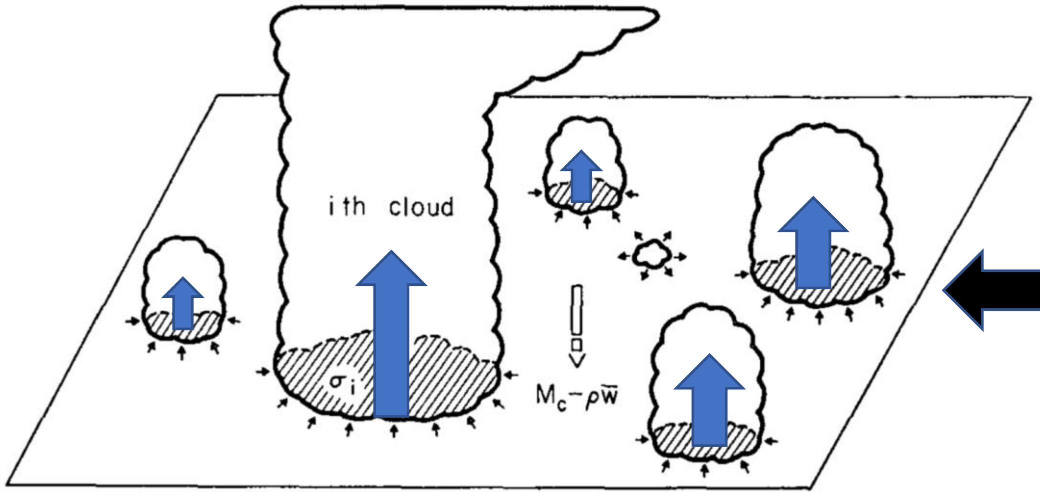
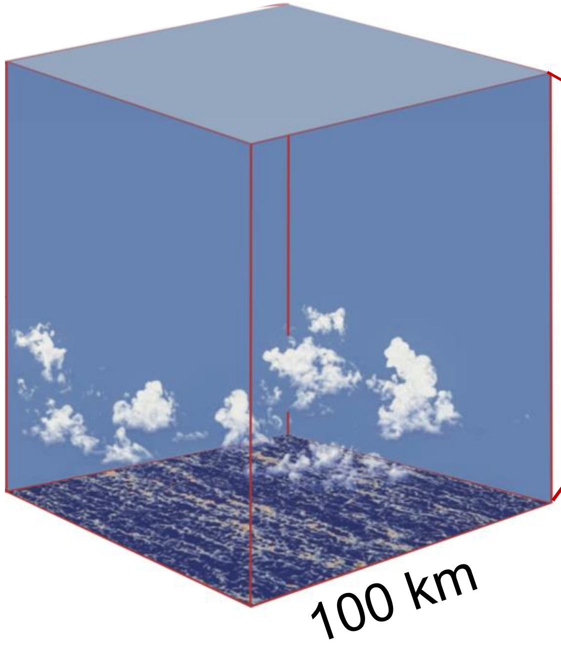
Schneider et al. (2017)

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

Parameterization



Arakawa and Schubert (1974)



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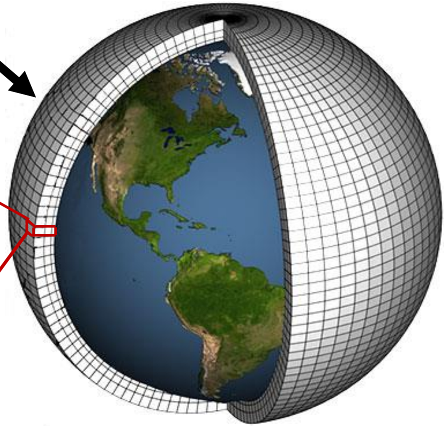

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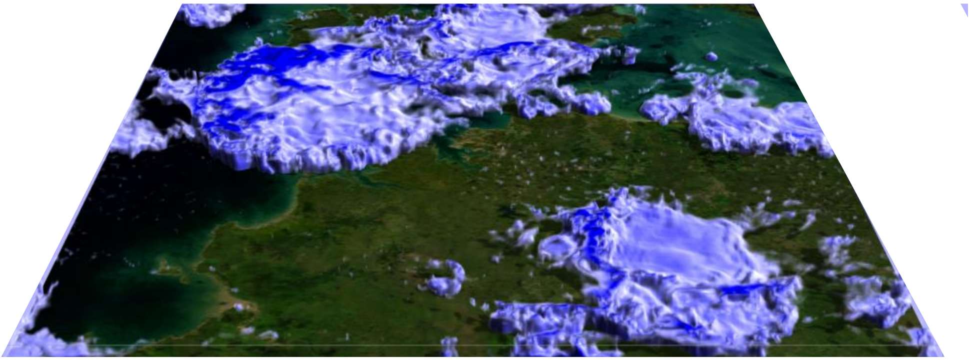
A different approach to parameterization: Use machine learning to create new parameterizations trained on high-resolution models

High resolution model



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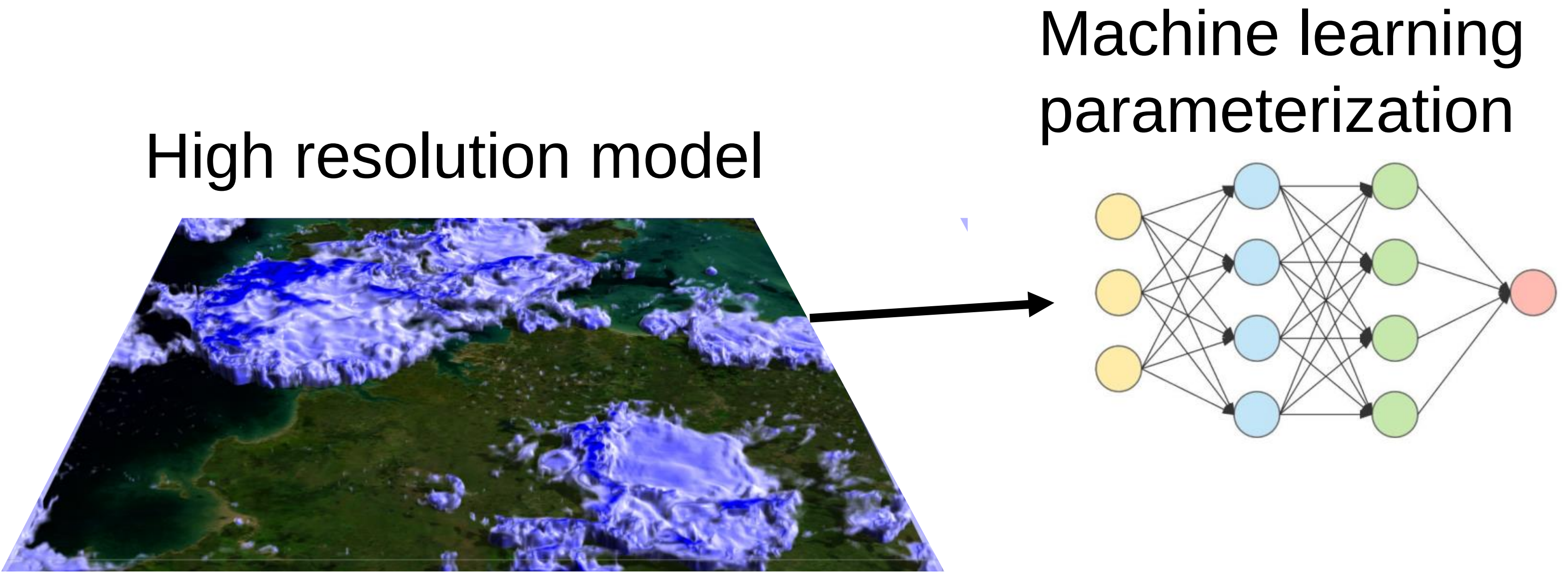

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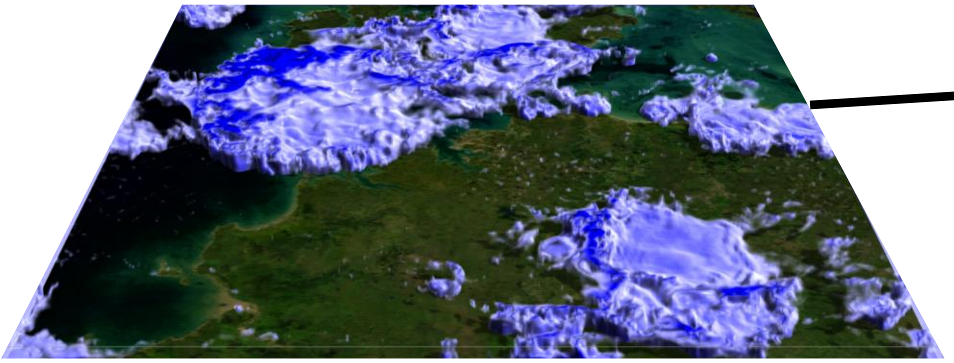

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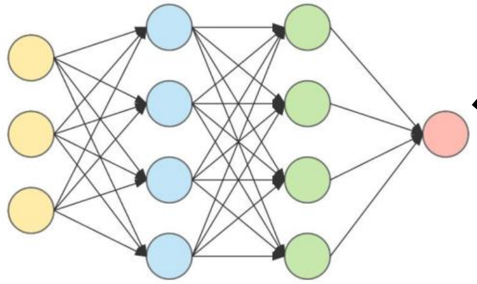
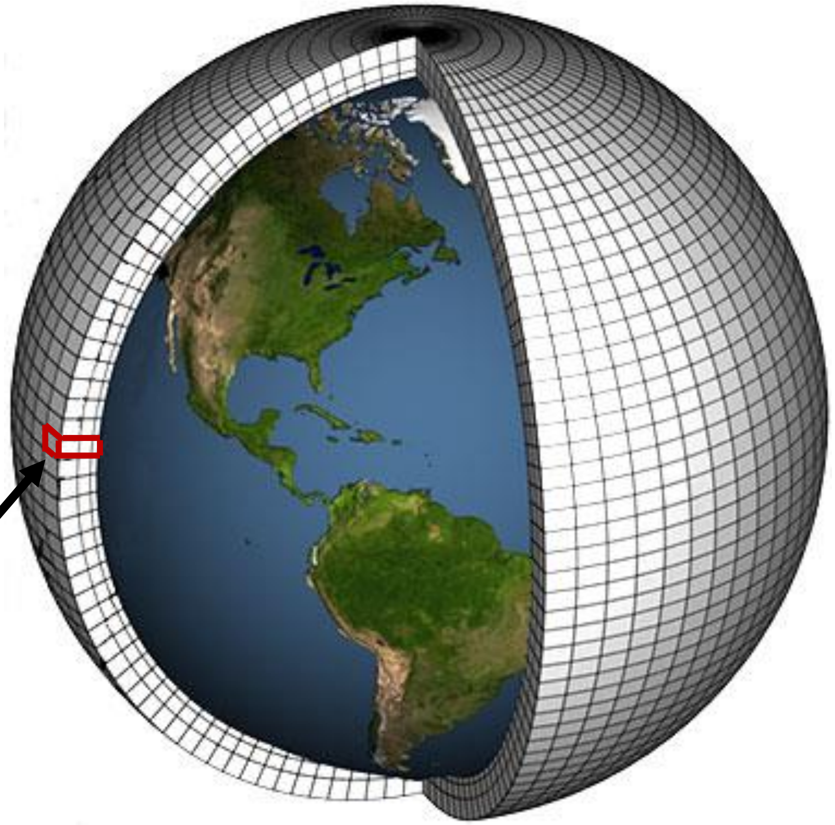
Machine learning parameterization





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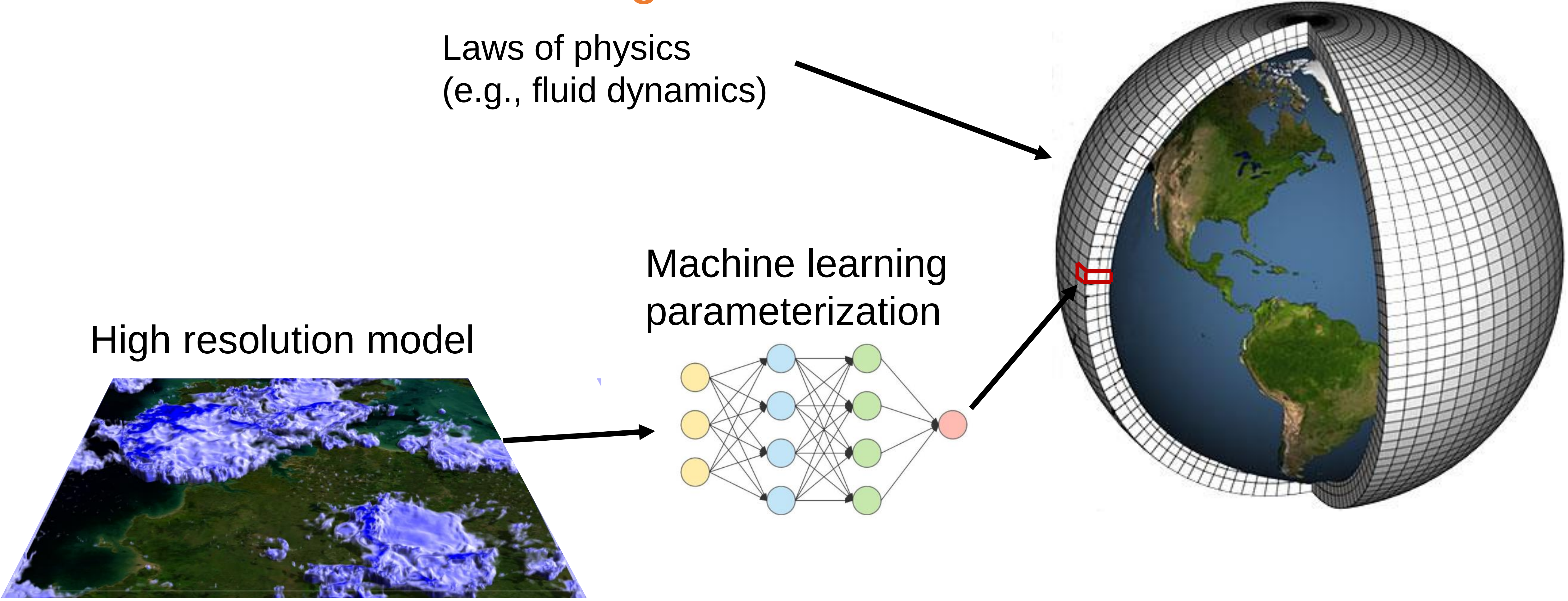

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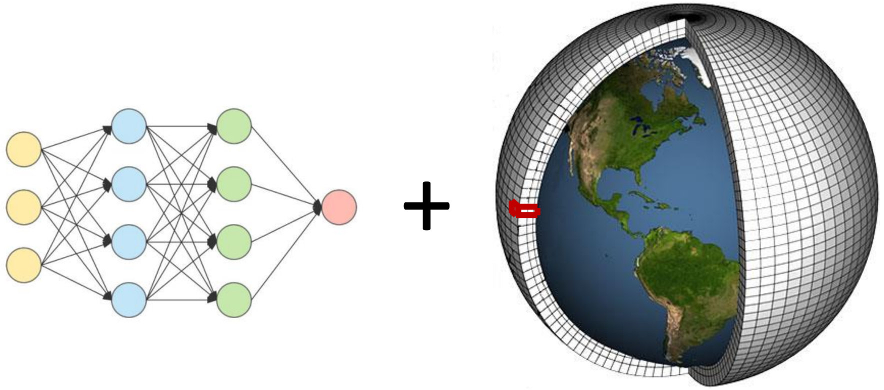
Recent attempts at machine learning parameterizations had some success but were not always stable, energy conserving and without climate drift



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

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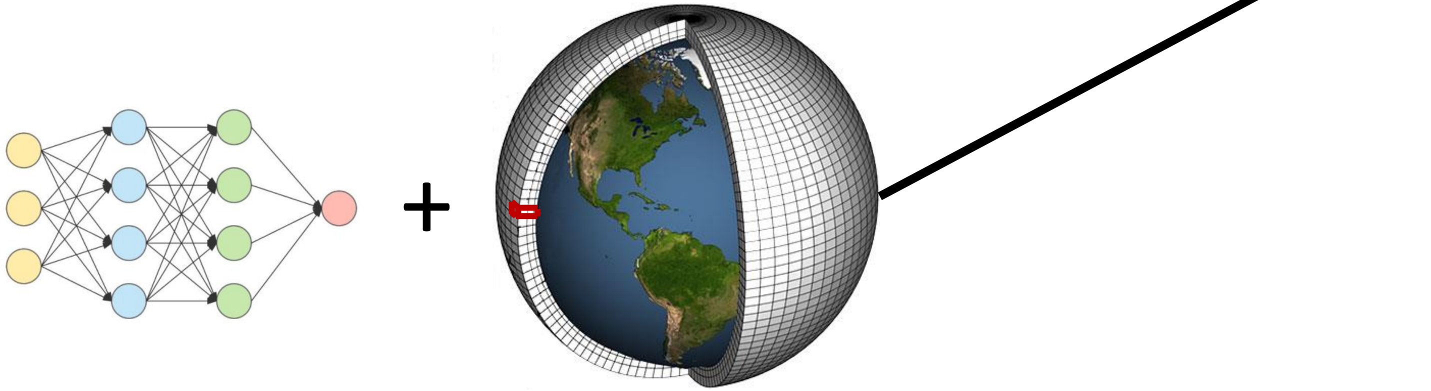

Unstable simulations

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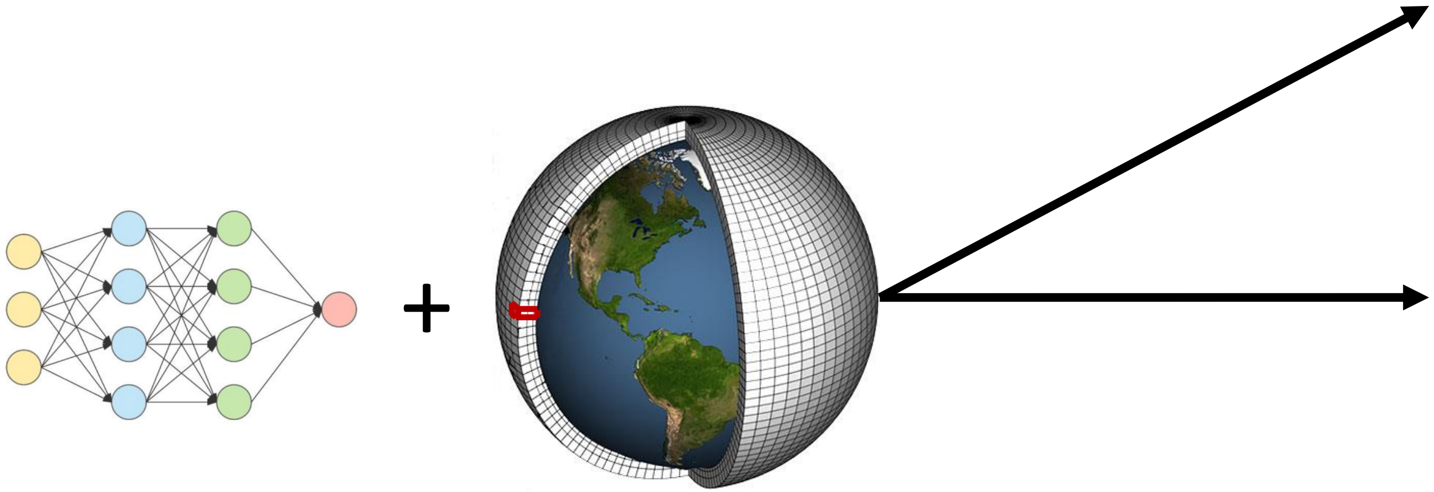

Unstable simulations

Climate drift
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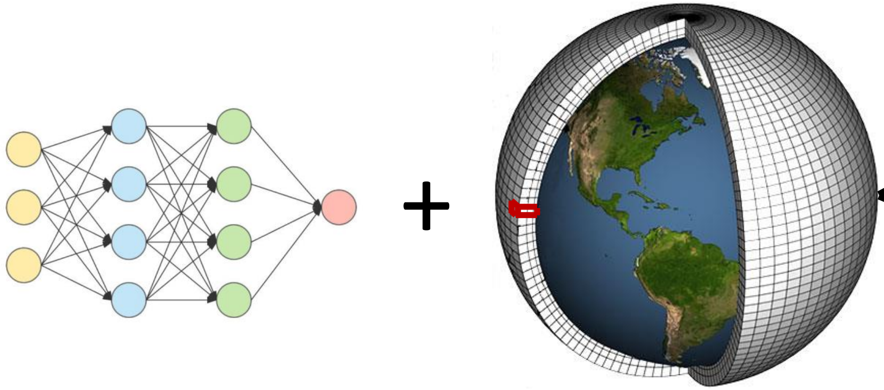


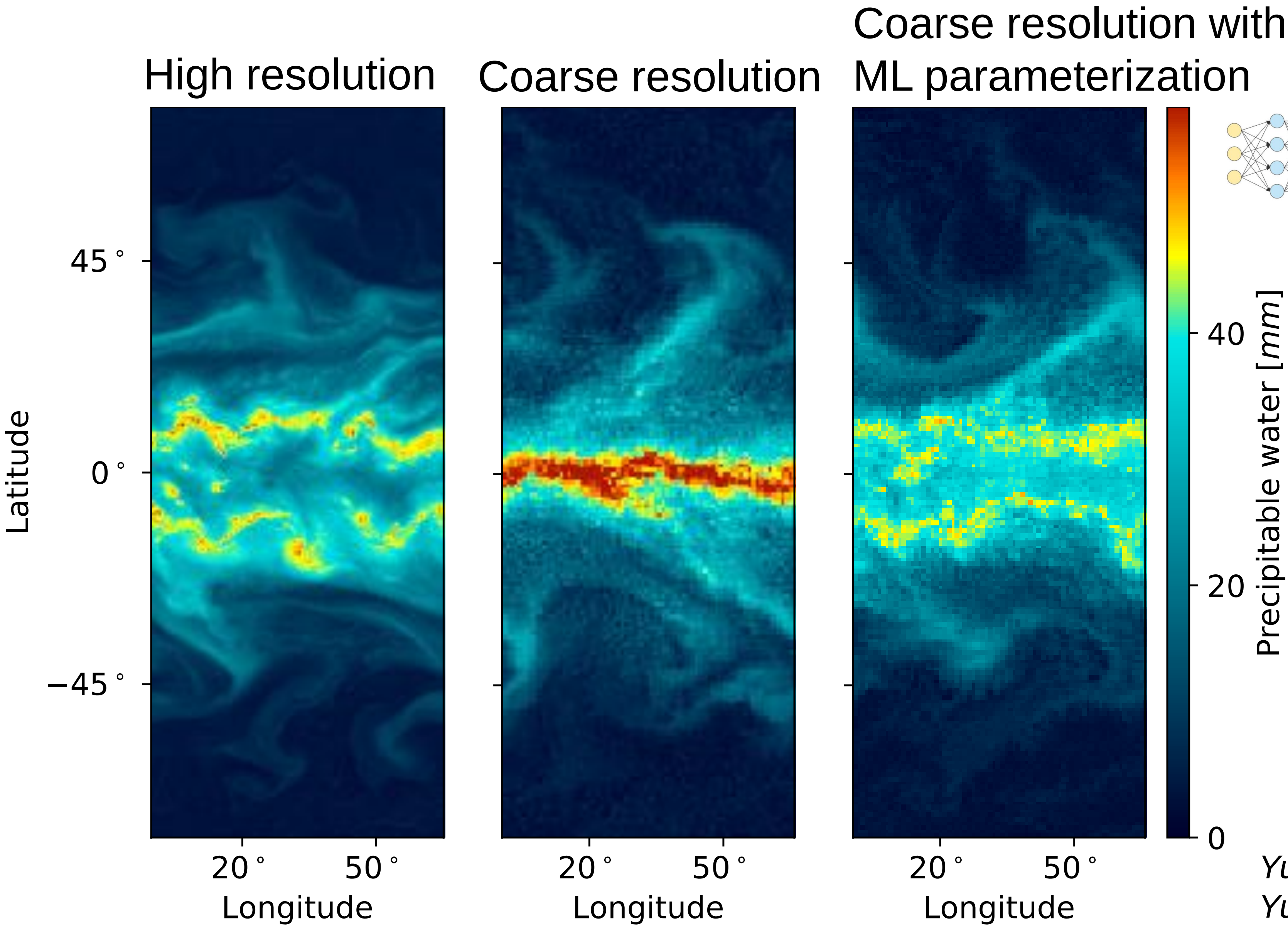
Unstable simulations

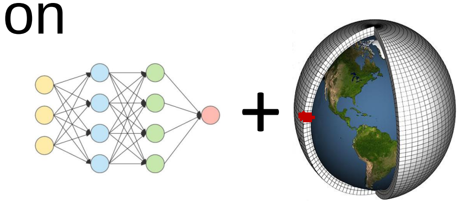
Climate drift
(cannot obtain statistics)

Do not obey physical
constraints

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

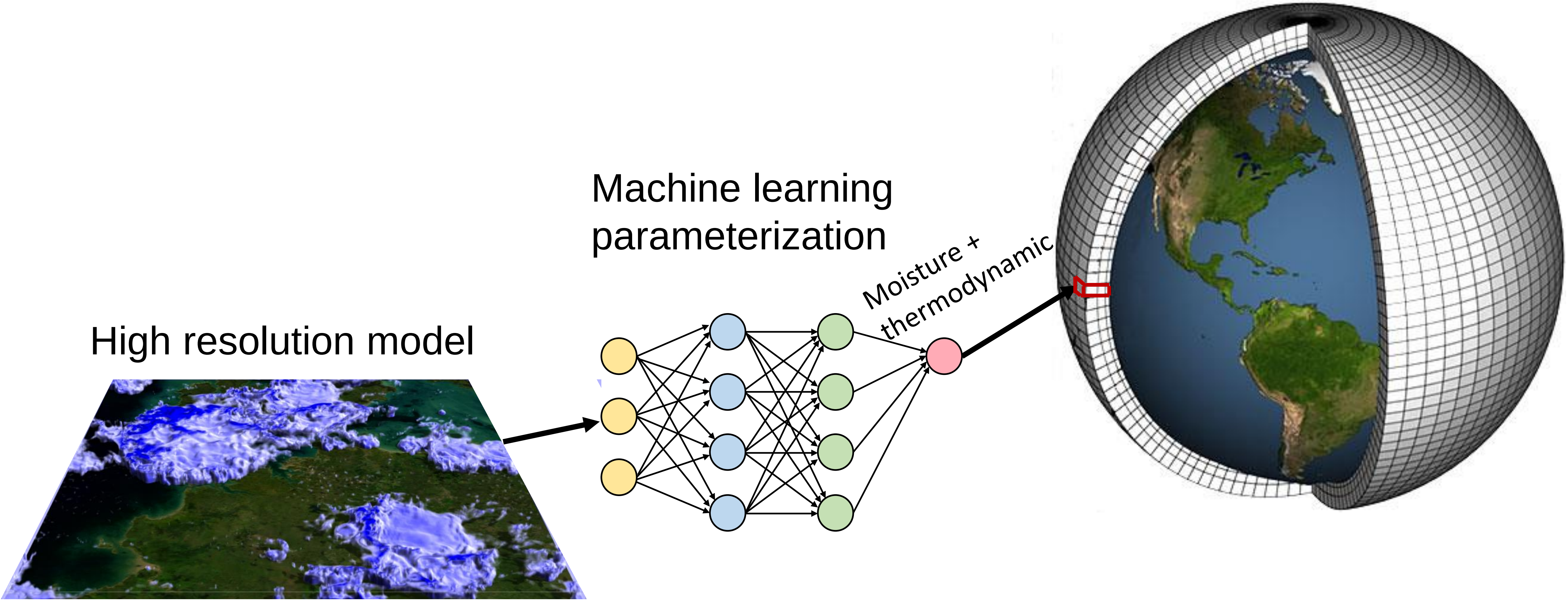
Previous study: we achieved physically consistent parameterization that leads to stable and accurate simulations





Yuval & O'Gorman (2020),
Yuval et al. (2021)

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



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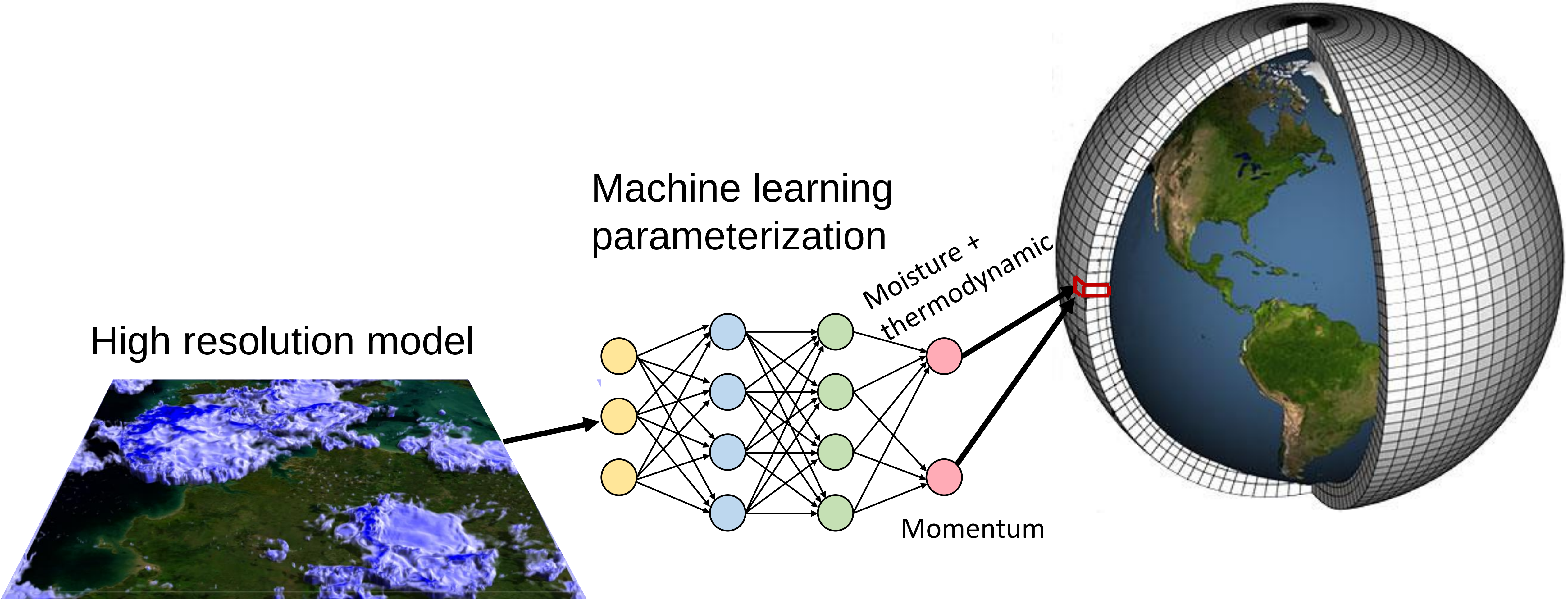

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Subgrid processes such as convection and gravity waves transport horizontal momentum in the vertical

Convective momentum transport

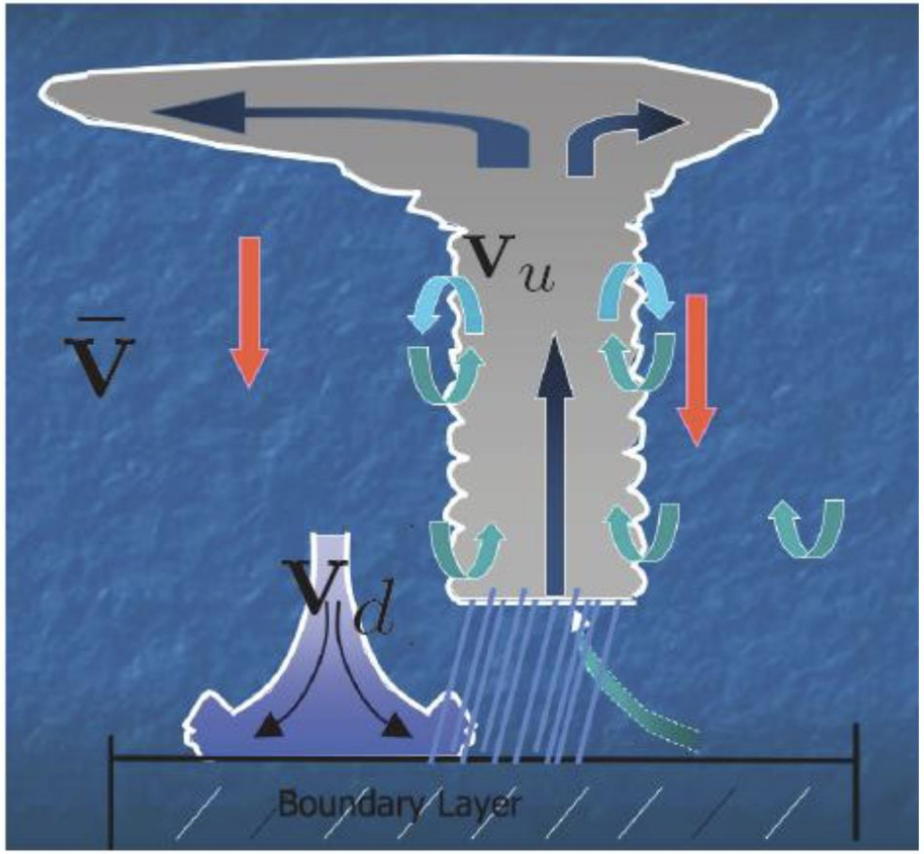

Image credit: Joe Tribbia presentation

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

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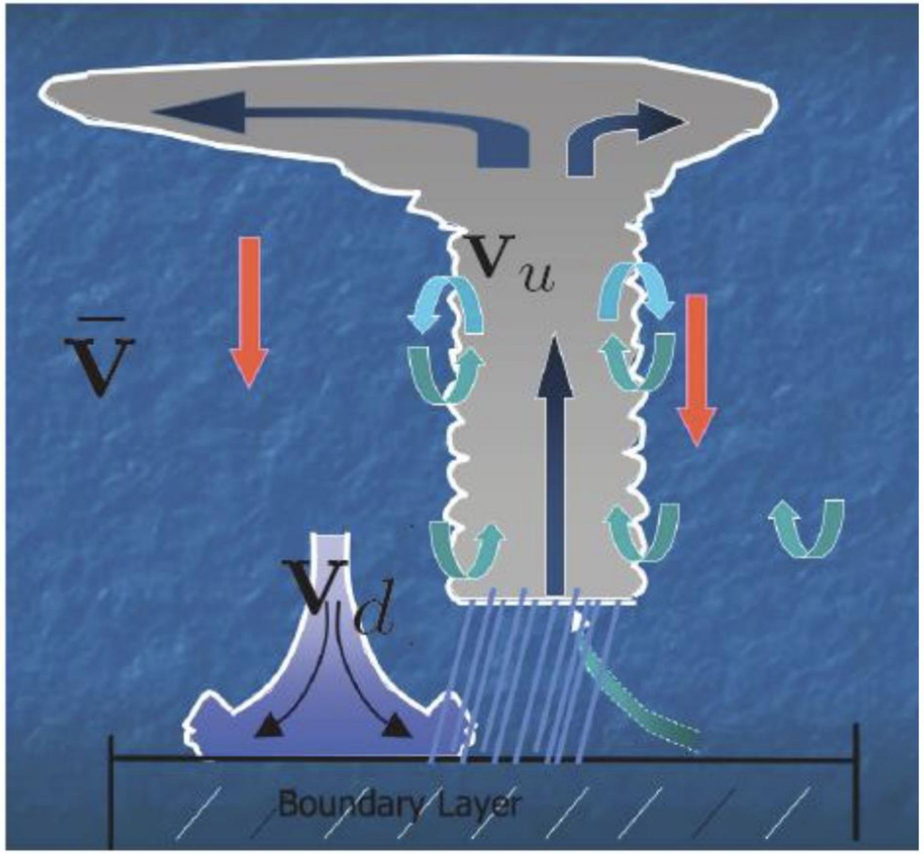

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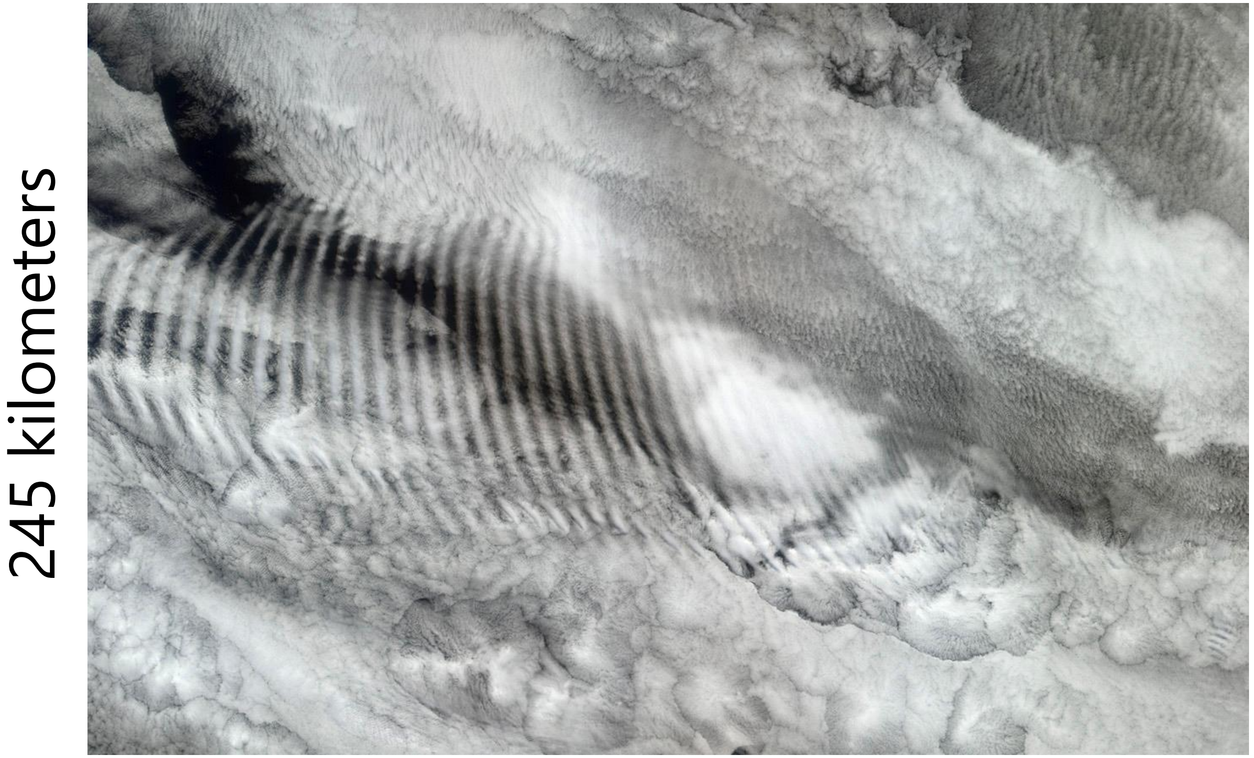
Gravity waves above the Indian Ocean



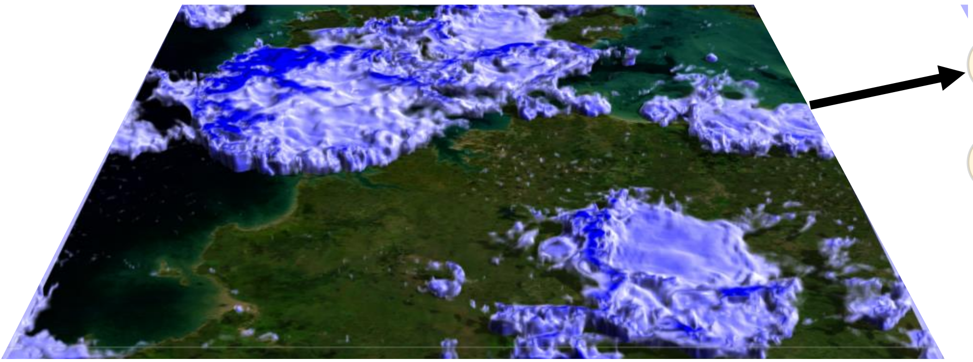
378 kilometers

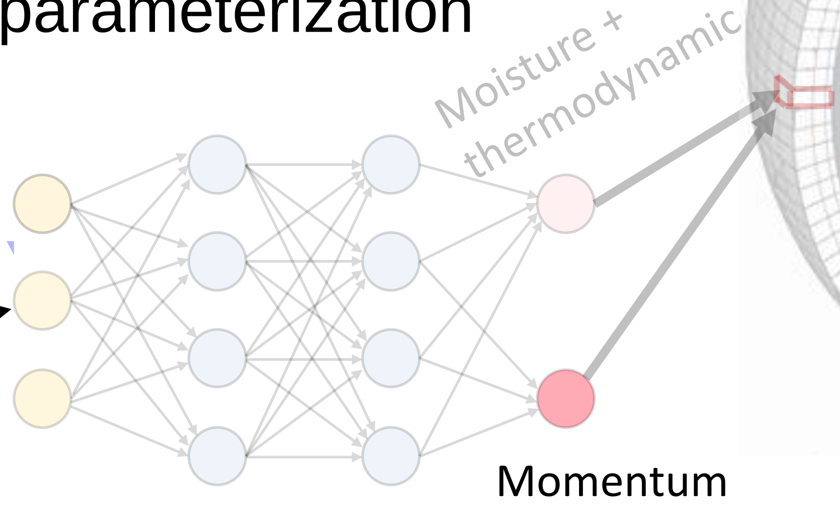
Image credit: NASA/GSFC/LaRC/JPL, MISR TEAM

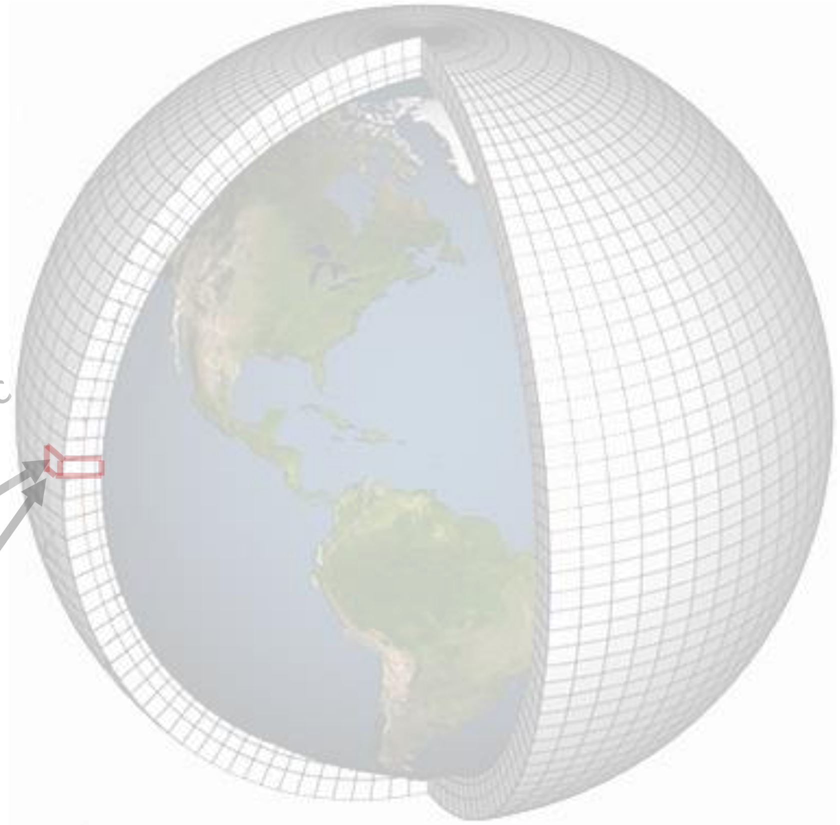
E.g., Dunkerton (1997), Ray et al. (1998), Orr et al. (2010)

Machine learning
parameterization

High resolution model







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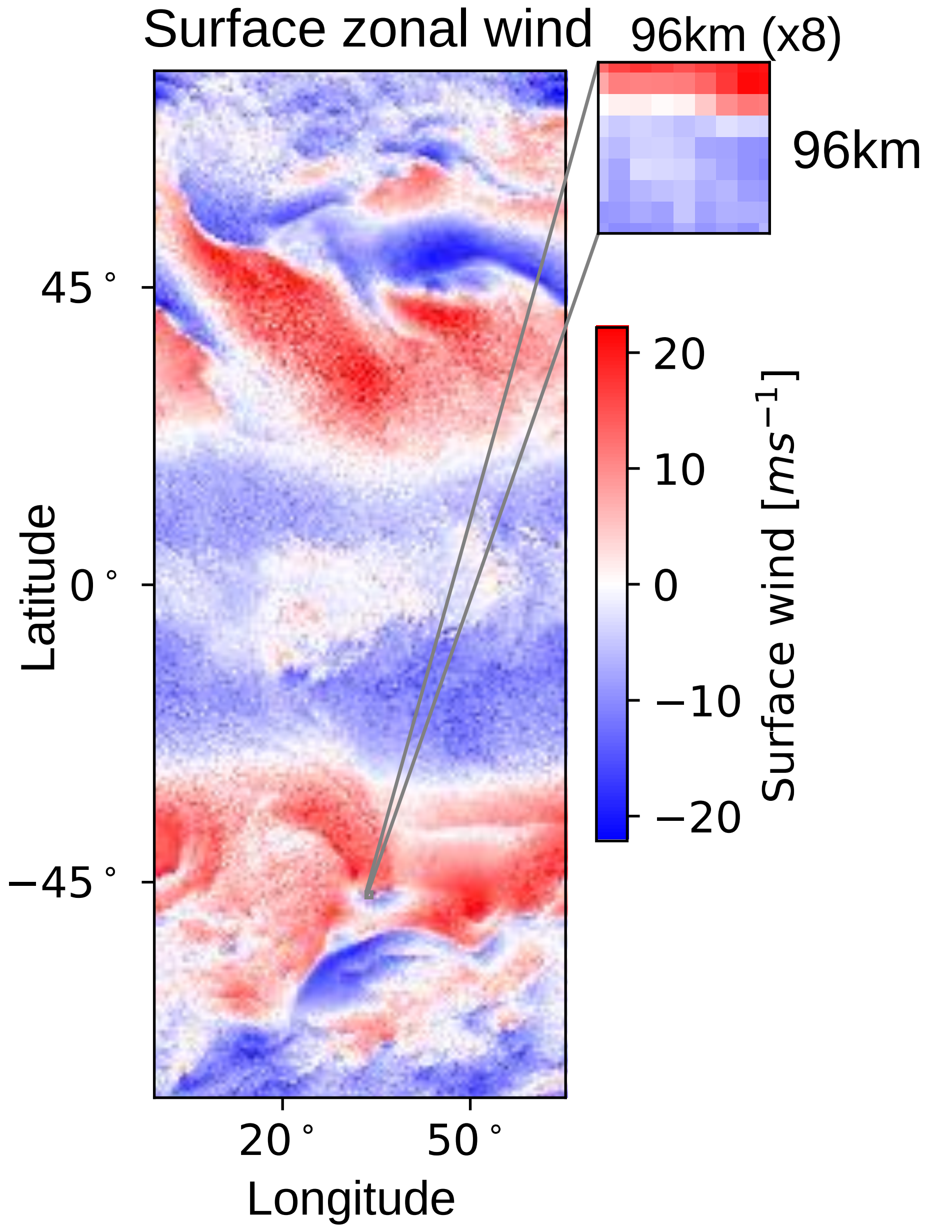
We coarse-grain high-resolution simulation to calculate the contribution of subgrid momentum transport



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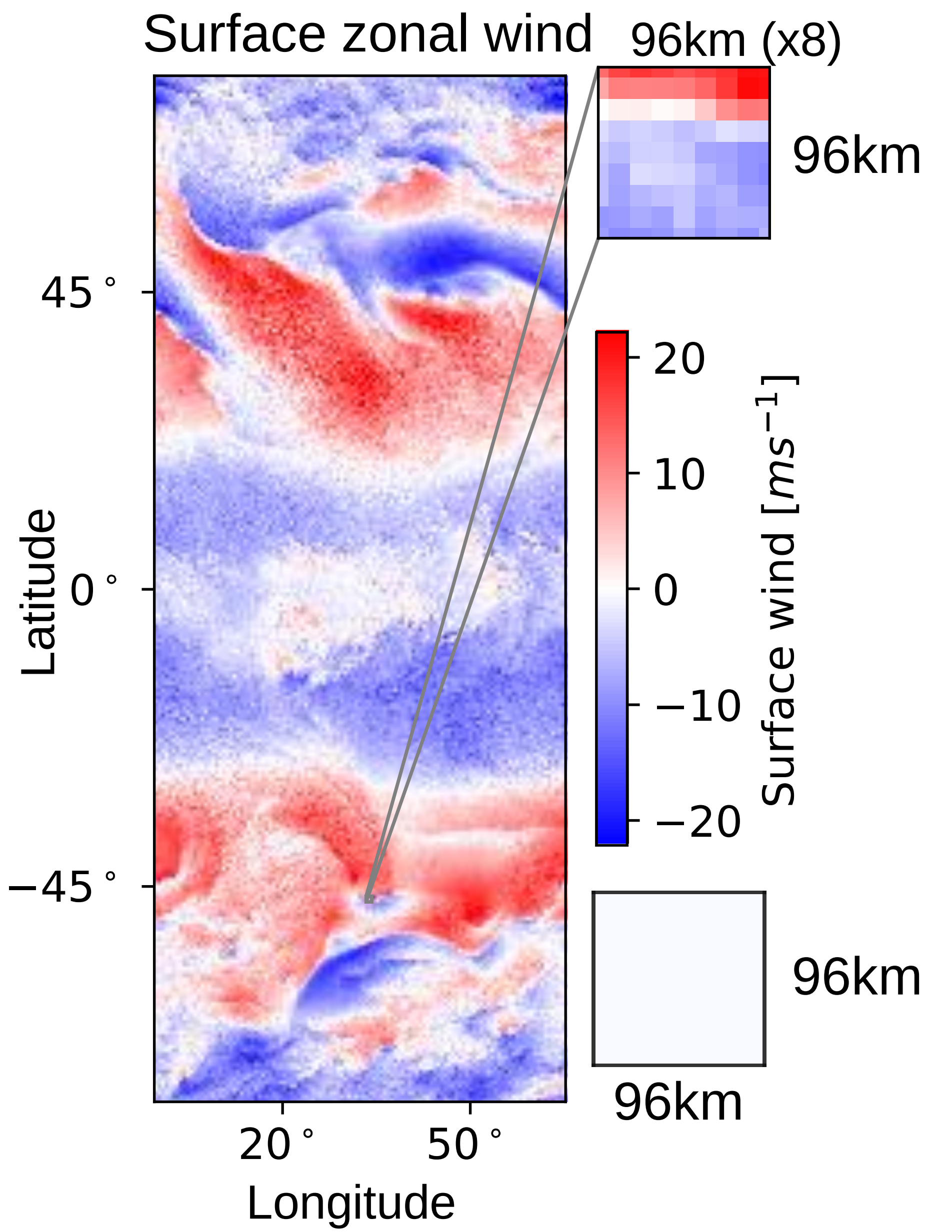

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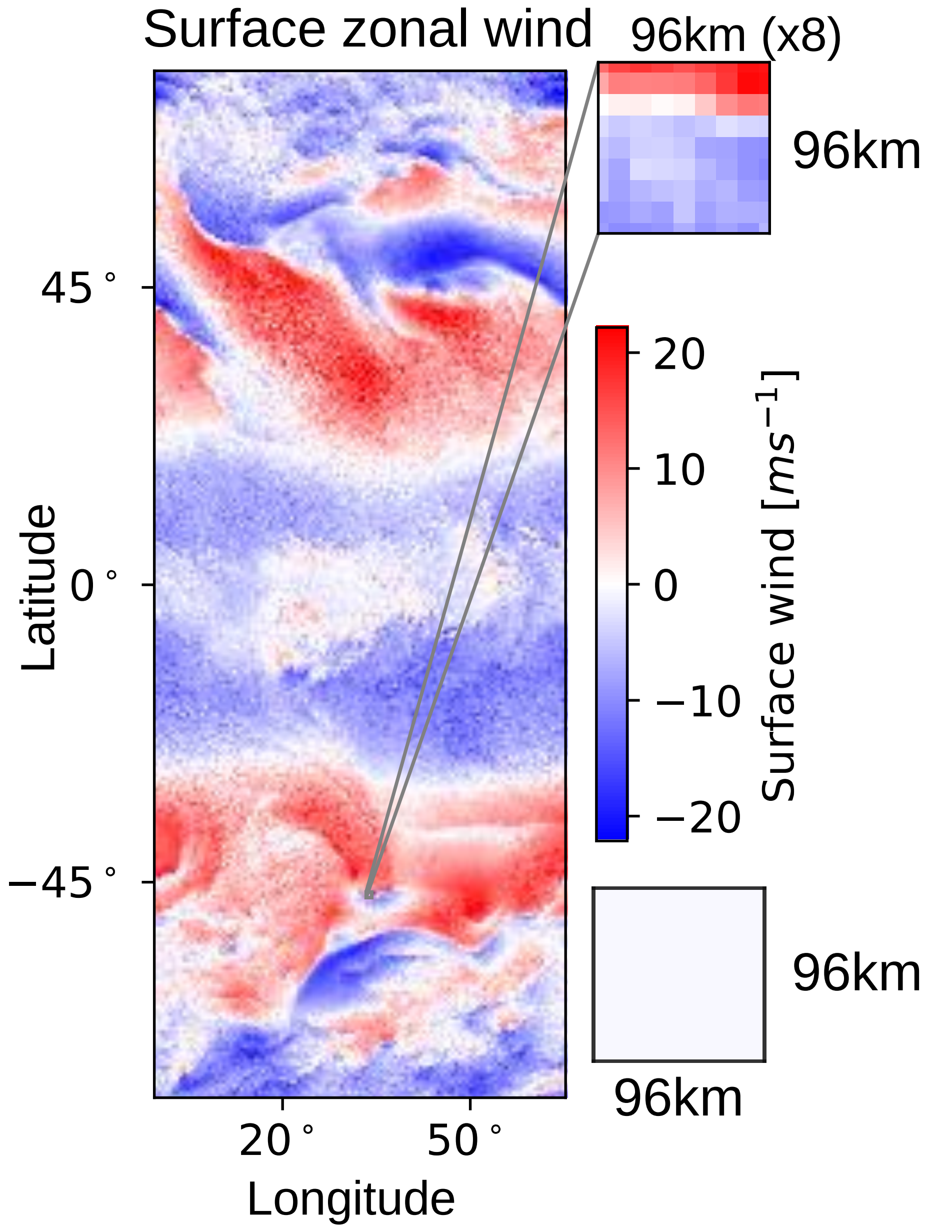

$$\overline{wu}$$

Coarse grained momentum flux from high resolution simulation

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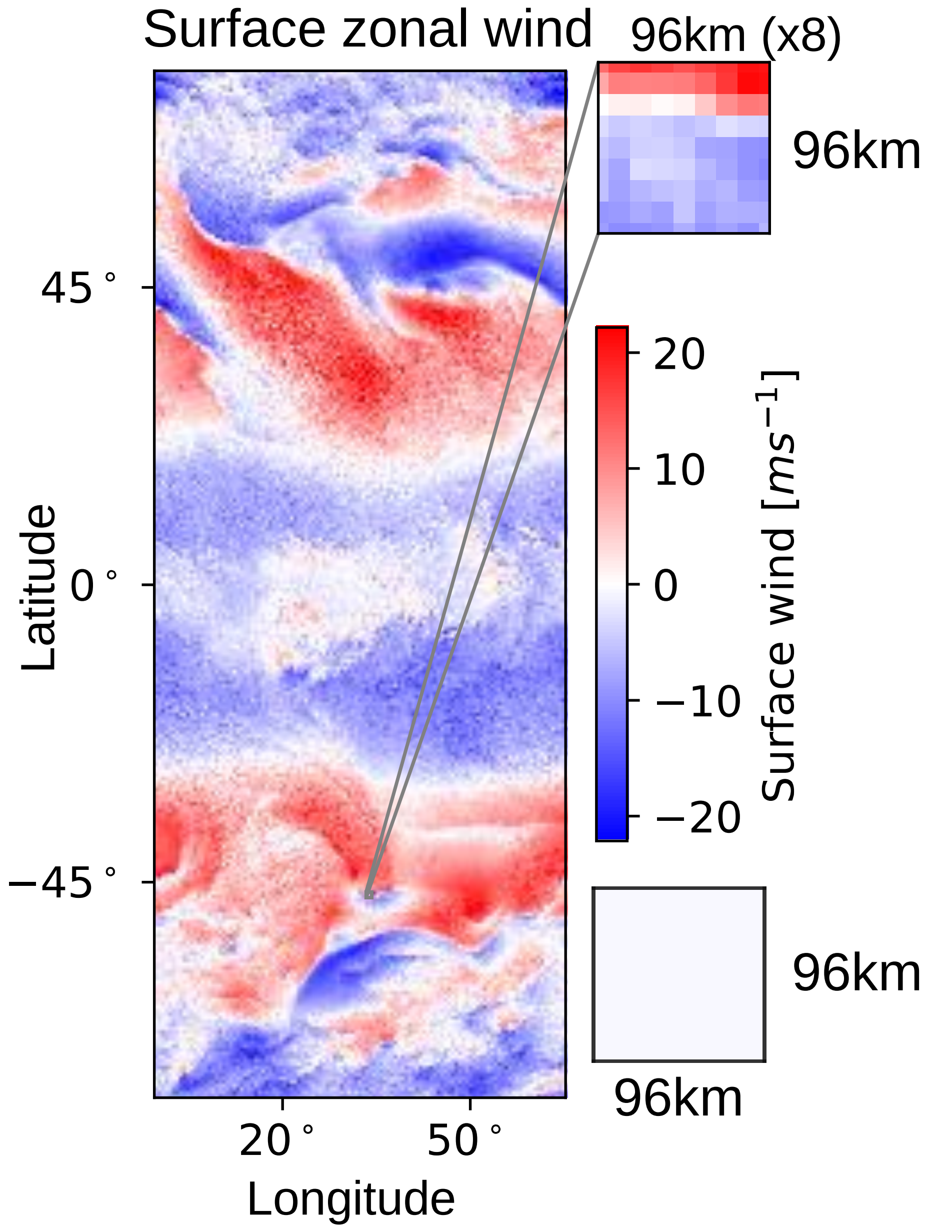

$$\overline{wu}$$

Coarse grained momentum flux
from high resolution simulation

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

Resolved momentum flux
When running a low resolution simulation

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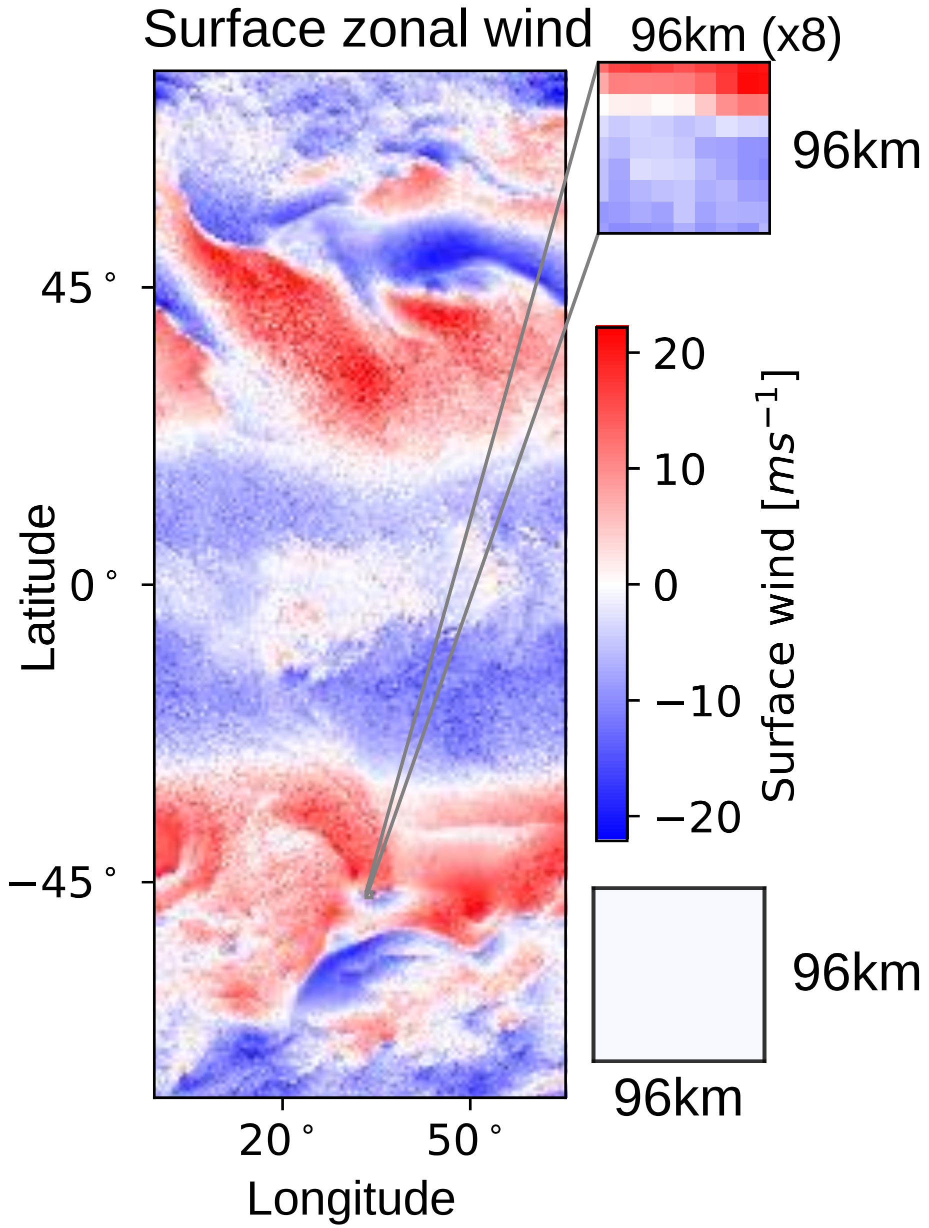

$$\overline{wu}$$

Coarse grained momentum flux
from high resolution simulation

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

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

Resolved momentum flux
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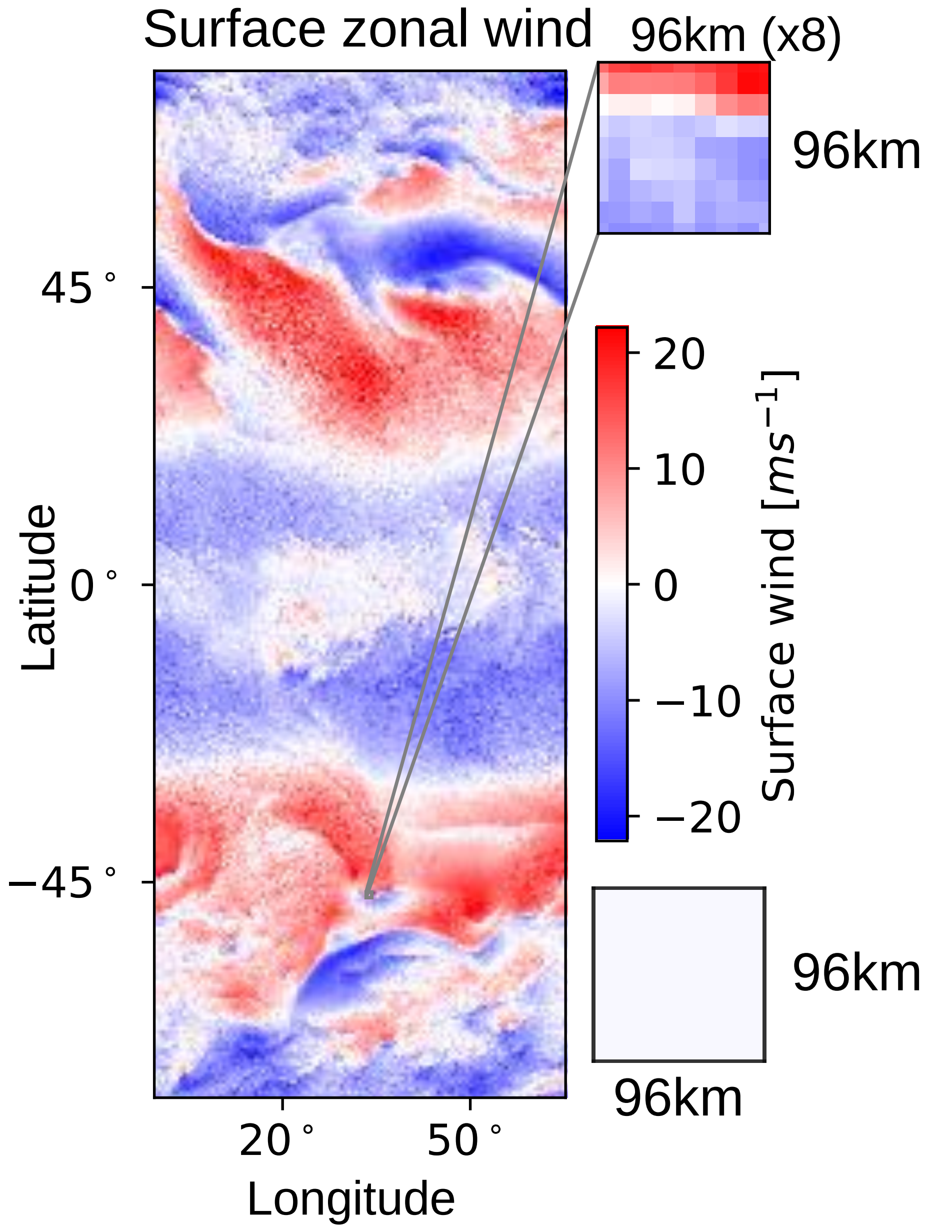

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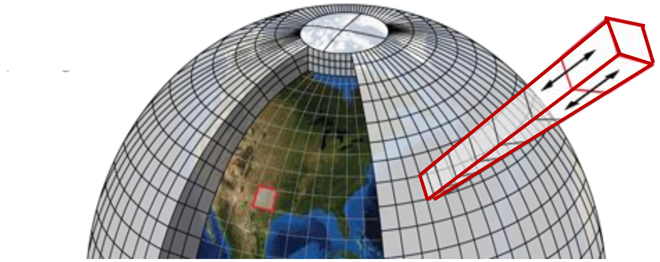

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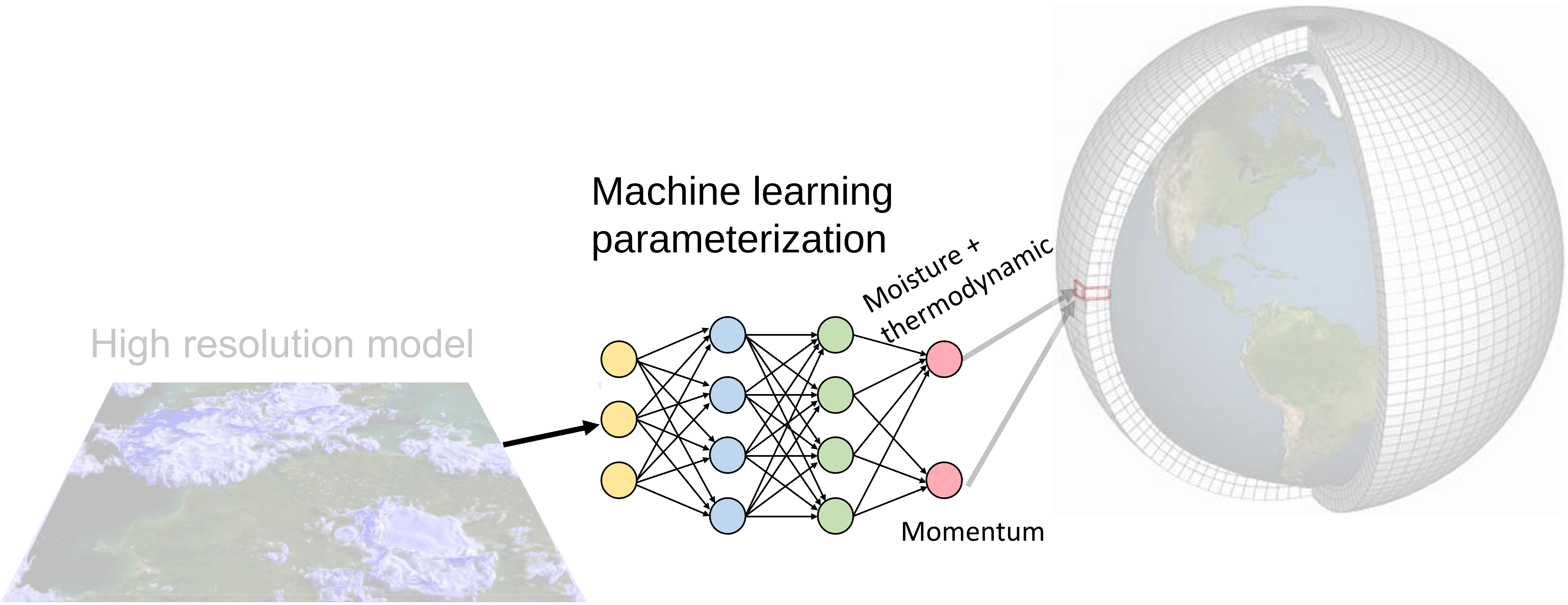
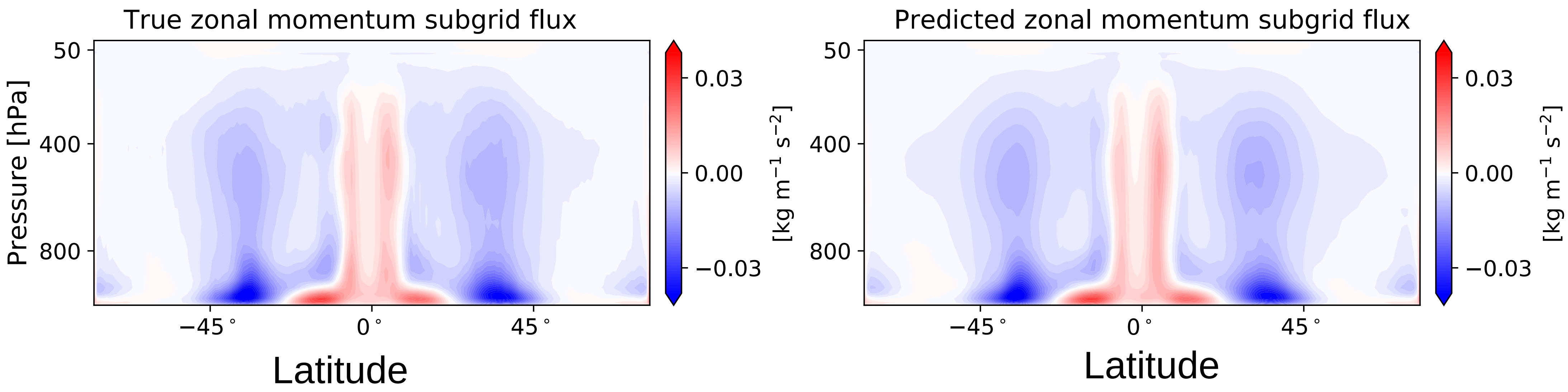


Figure credit: NASA

Figure credit: NOAA

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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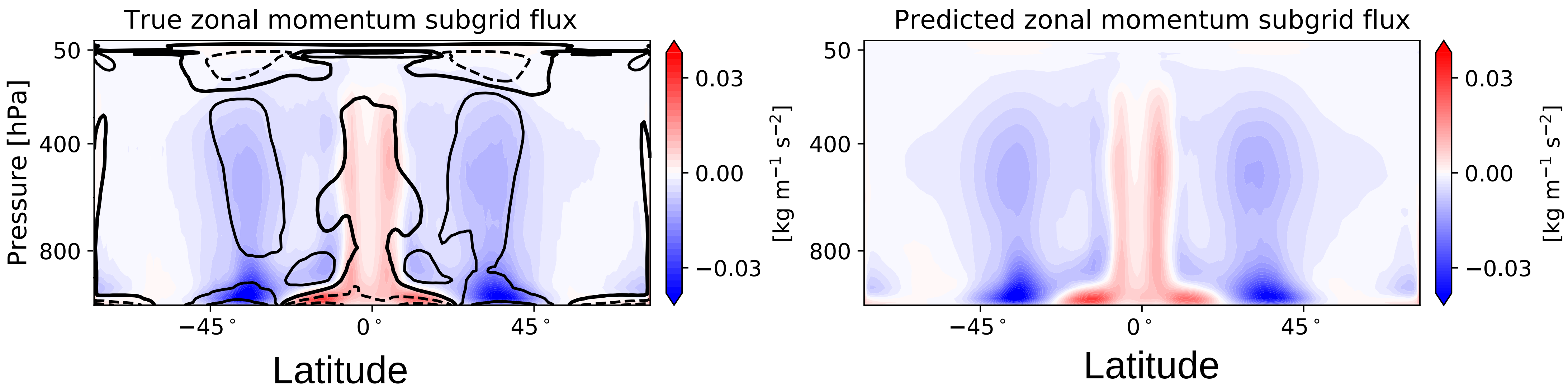
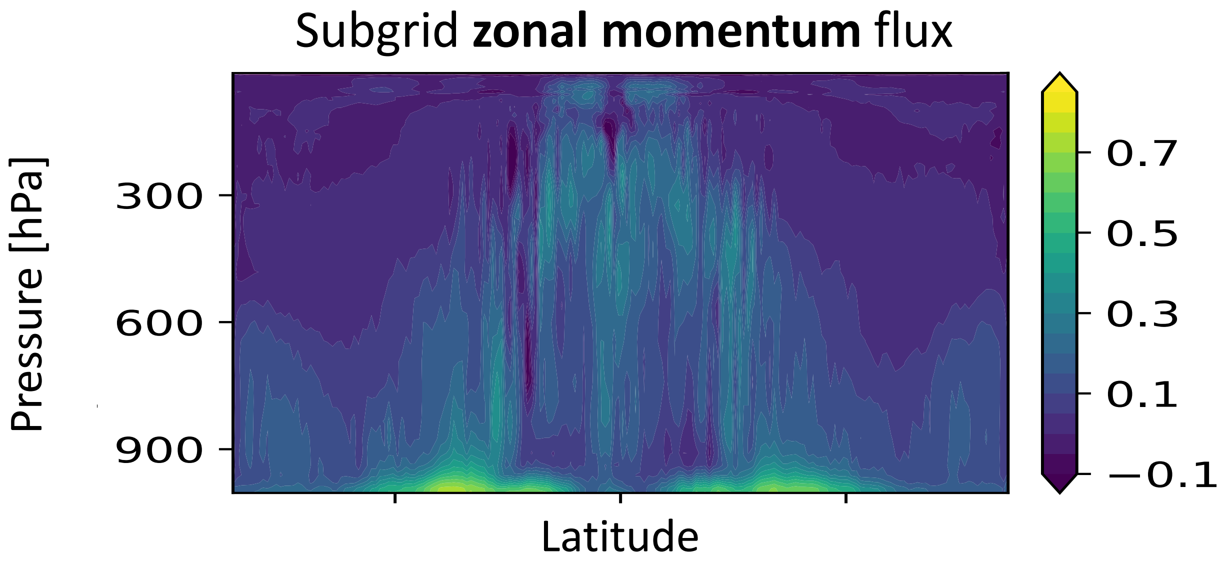


Wind shear shown in contours

Yuval and O'Gorman (ESSOAr preprint)

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

Offline performance



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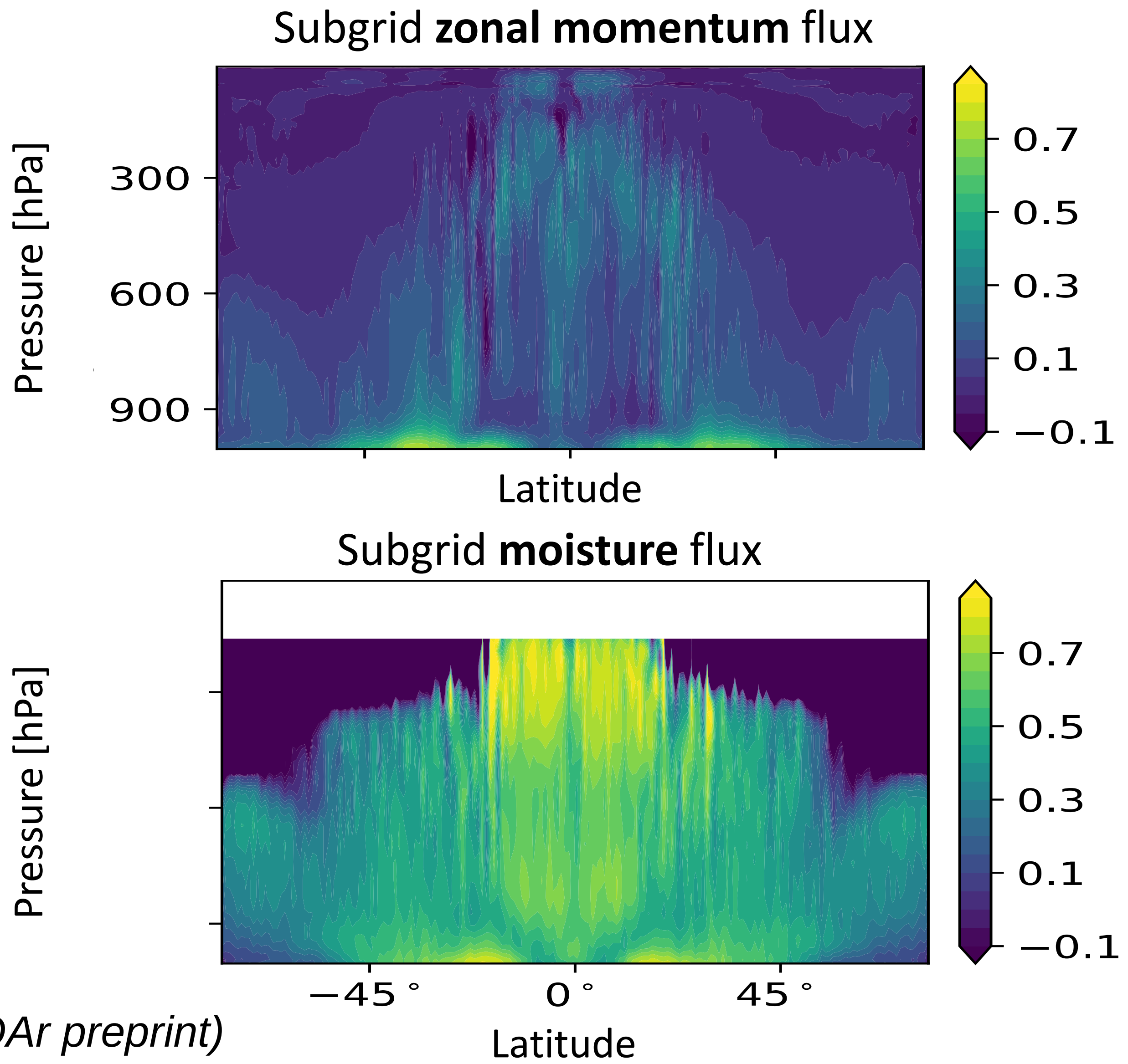
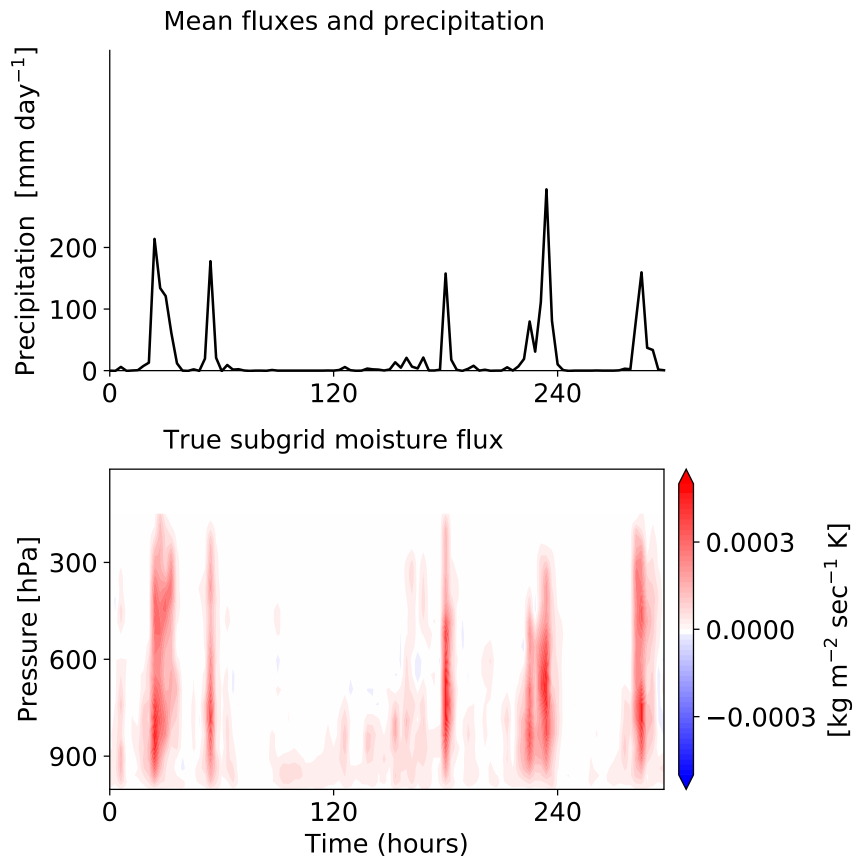


Yuval and O'Gorman (ESSOAr preprint)

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



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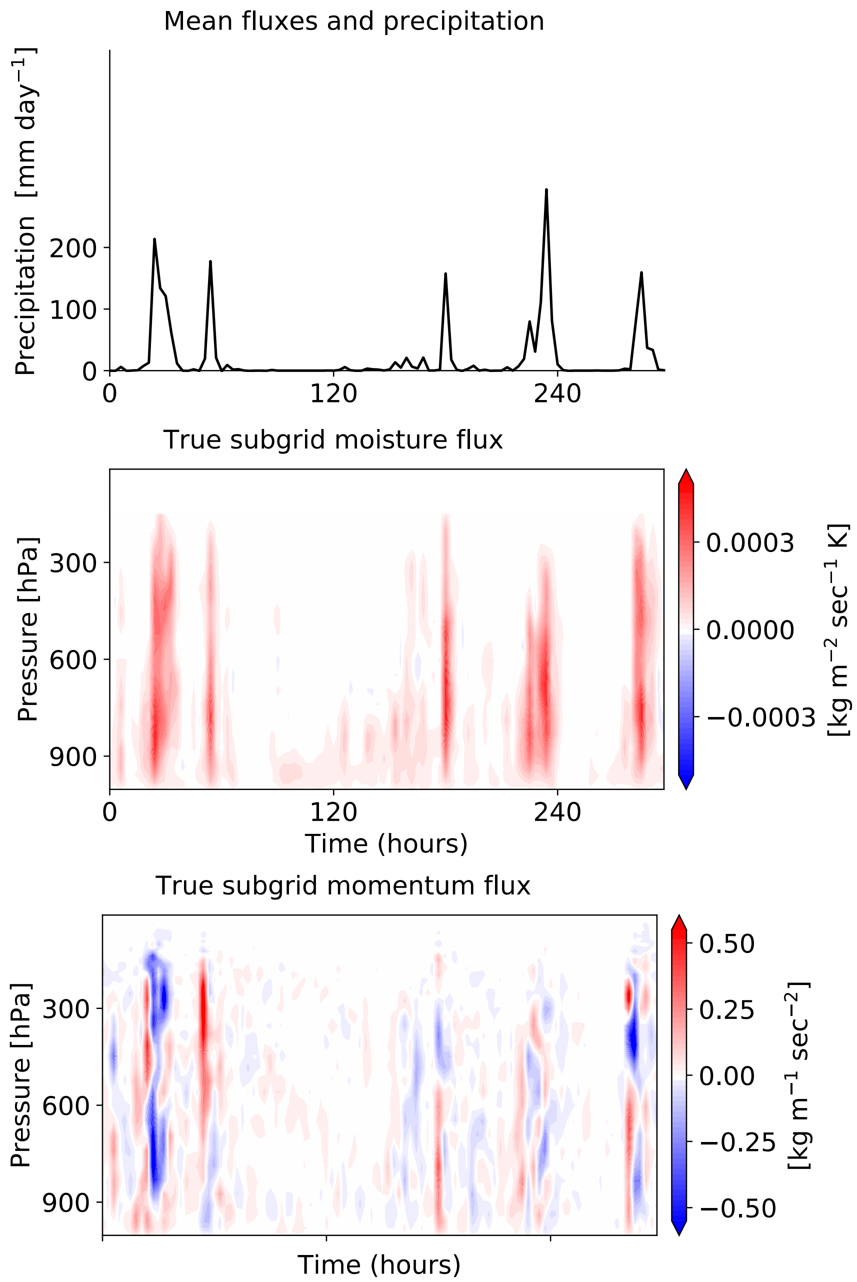

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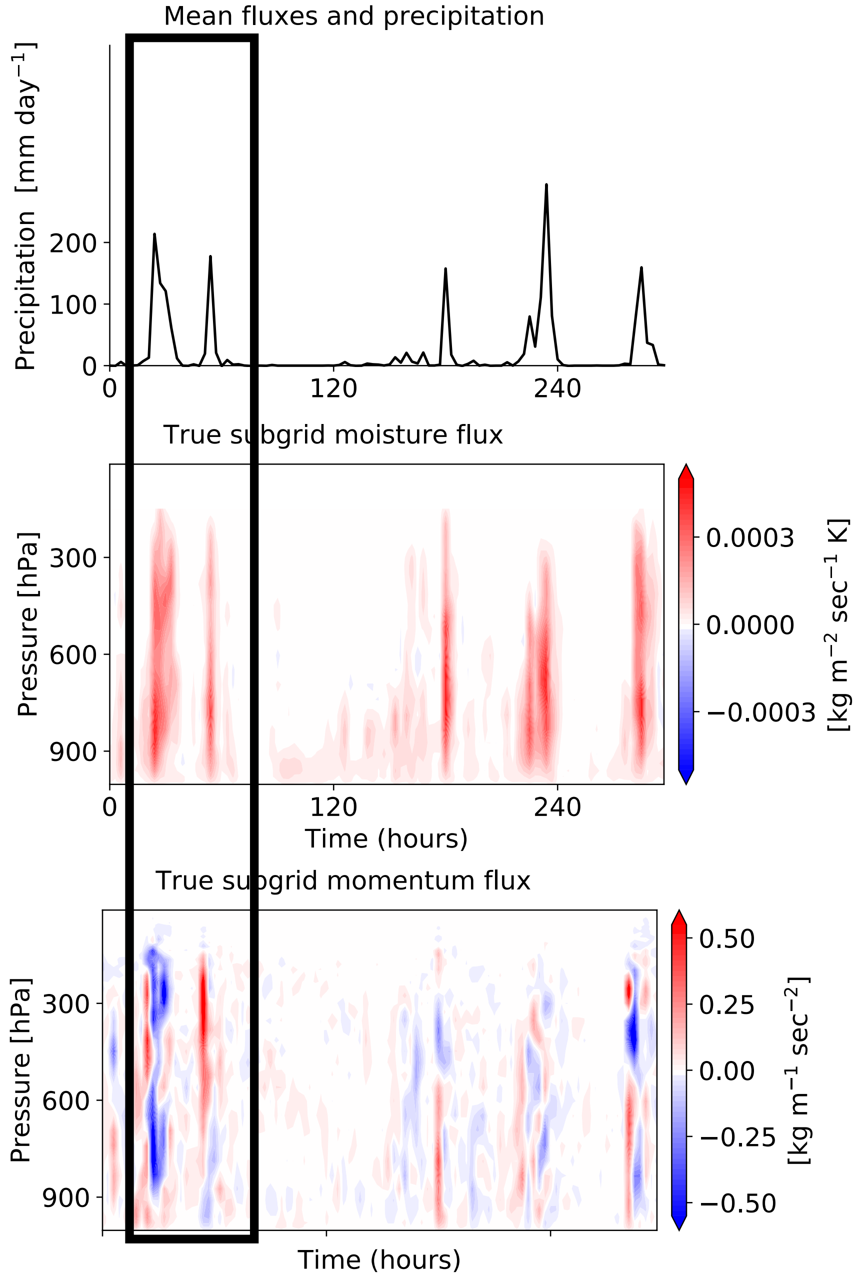

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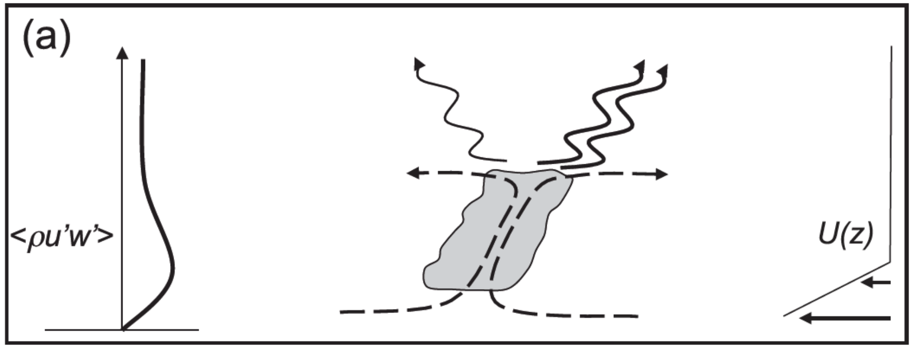
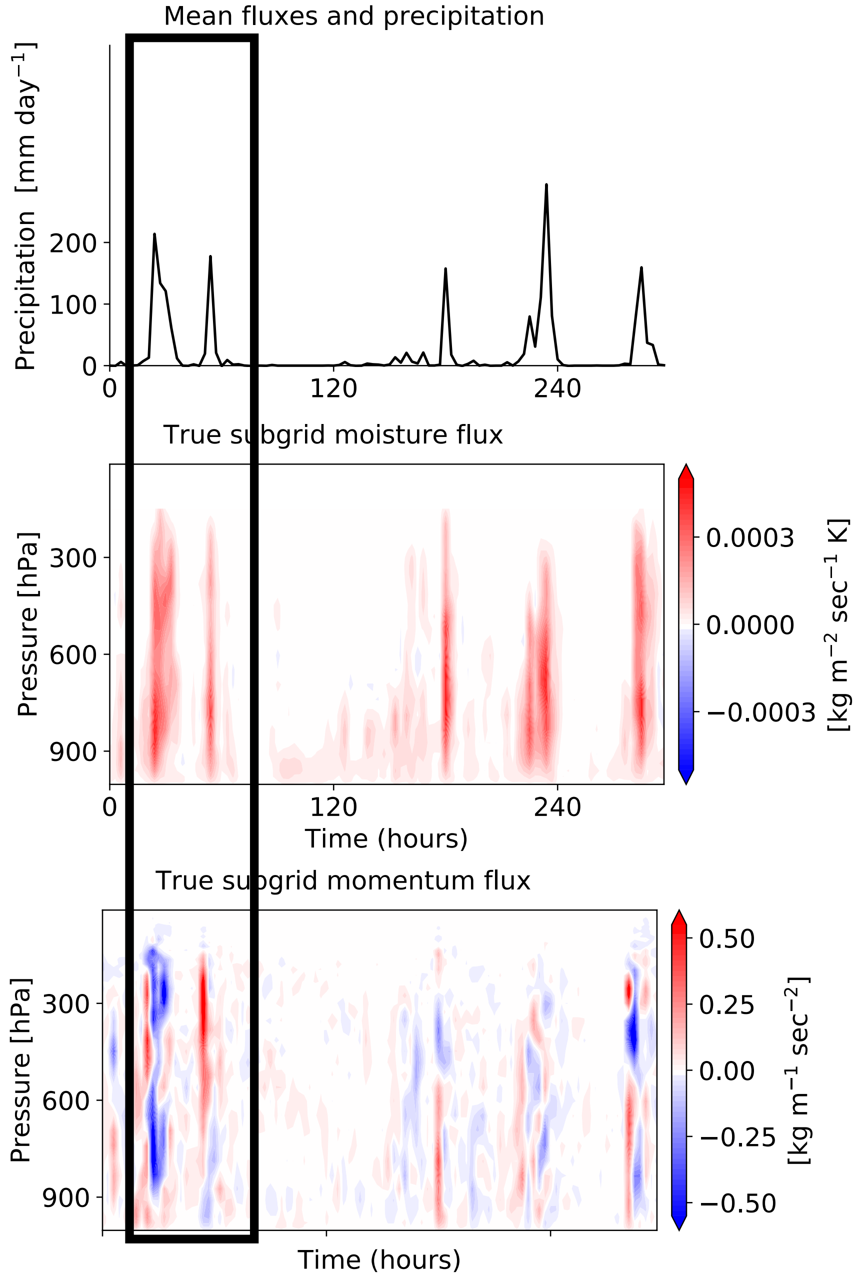


Lane and Moncrieff (2010)

Convective momentum transport can be negative or positive



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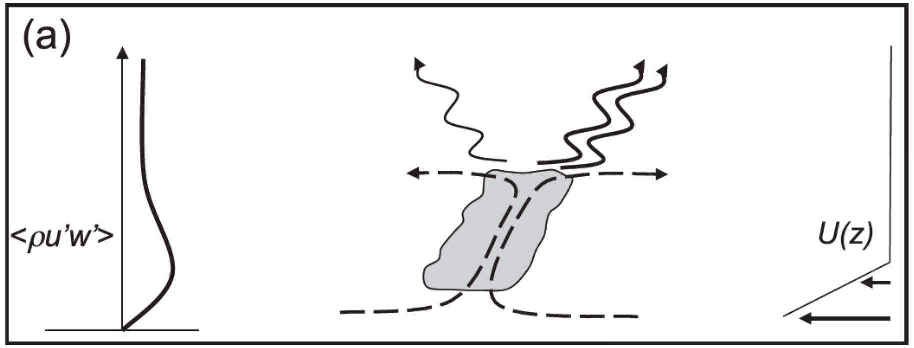

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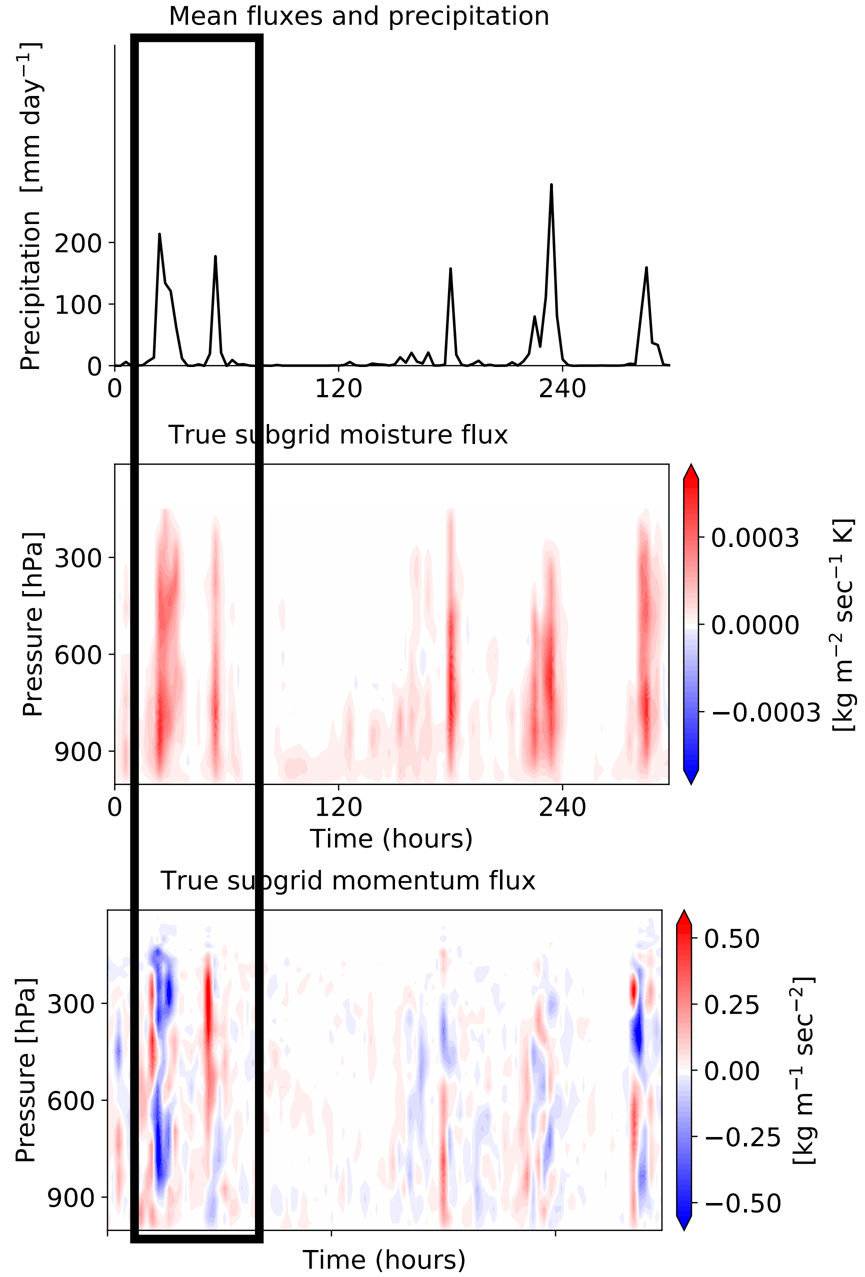
For (linear) gravity waves:

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

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



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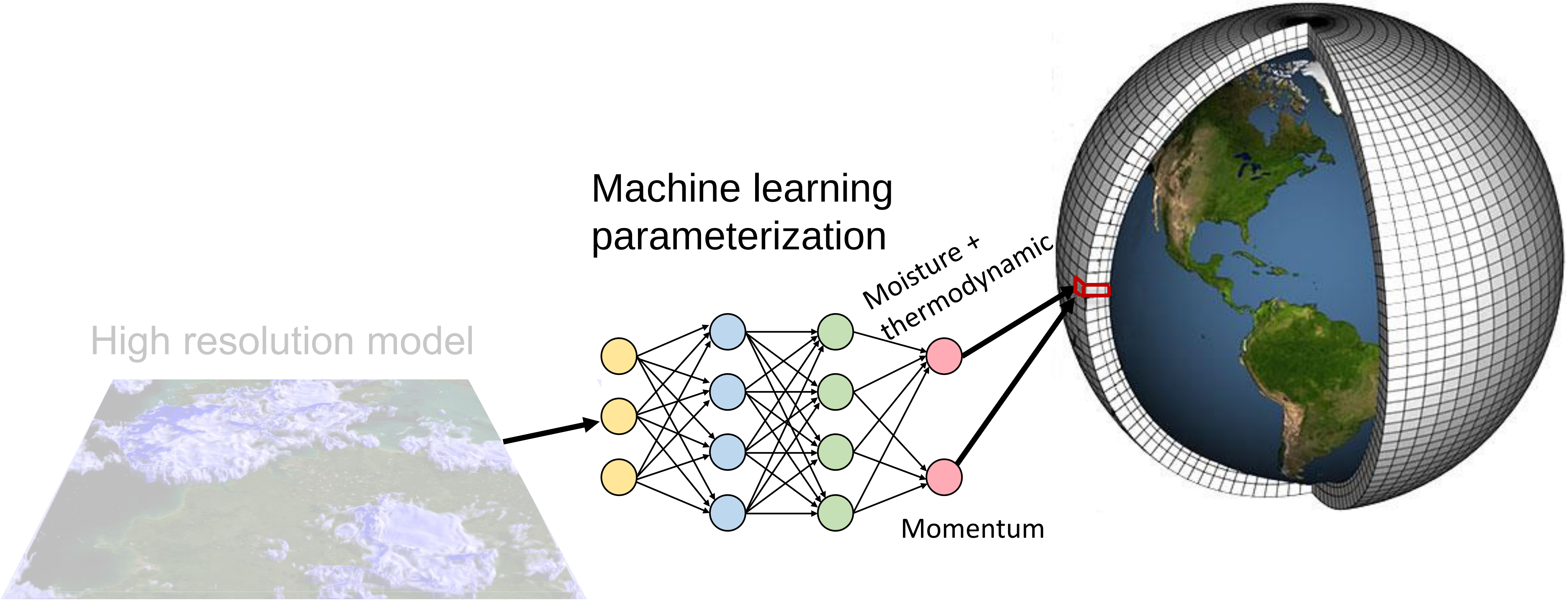

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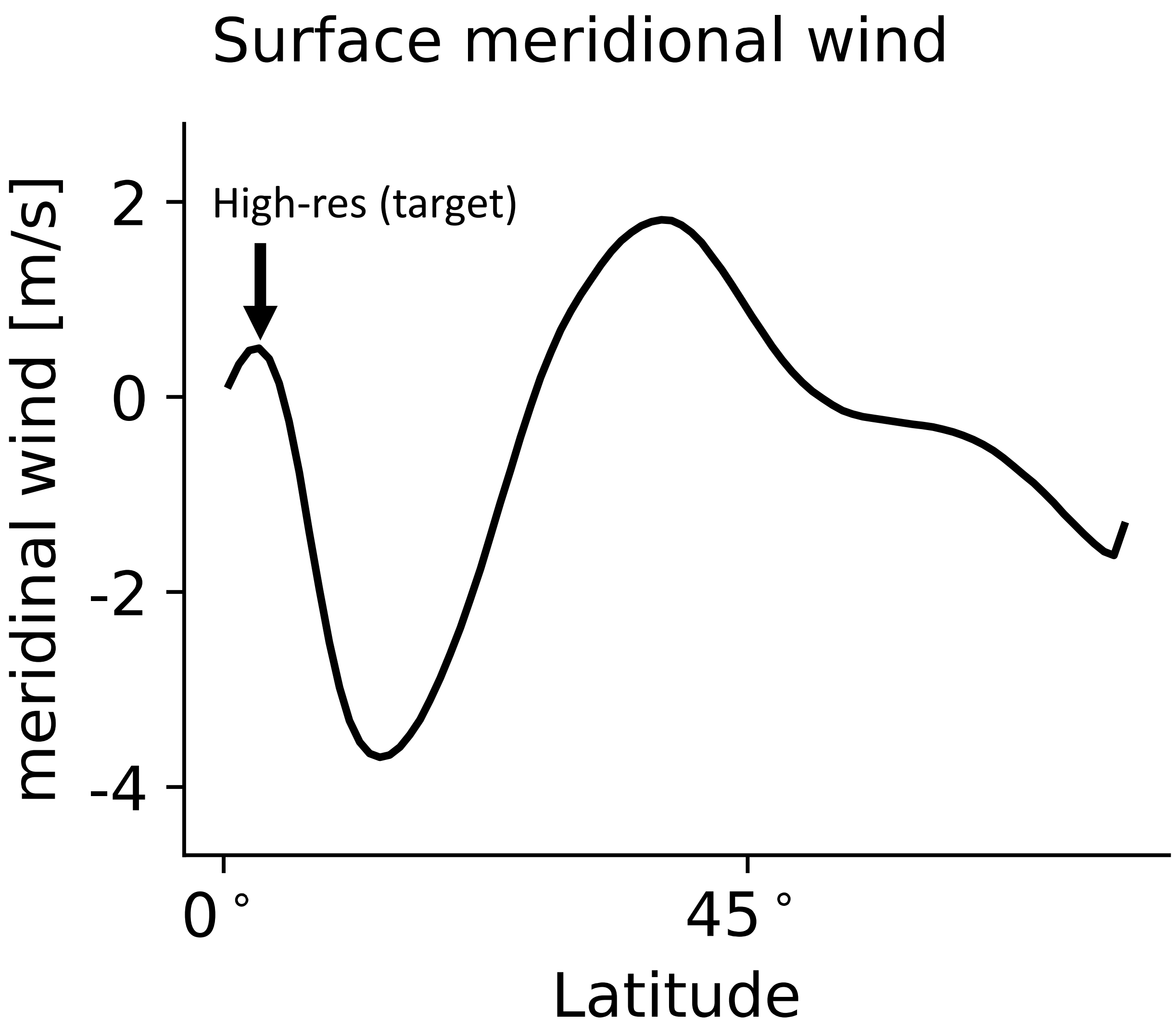
Neural network parameterization of subgrid momentum transport improves some characteristics of the atmospheric circulation



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

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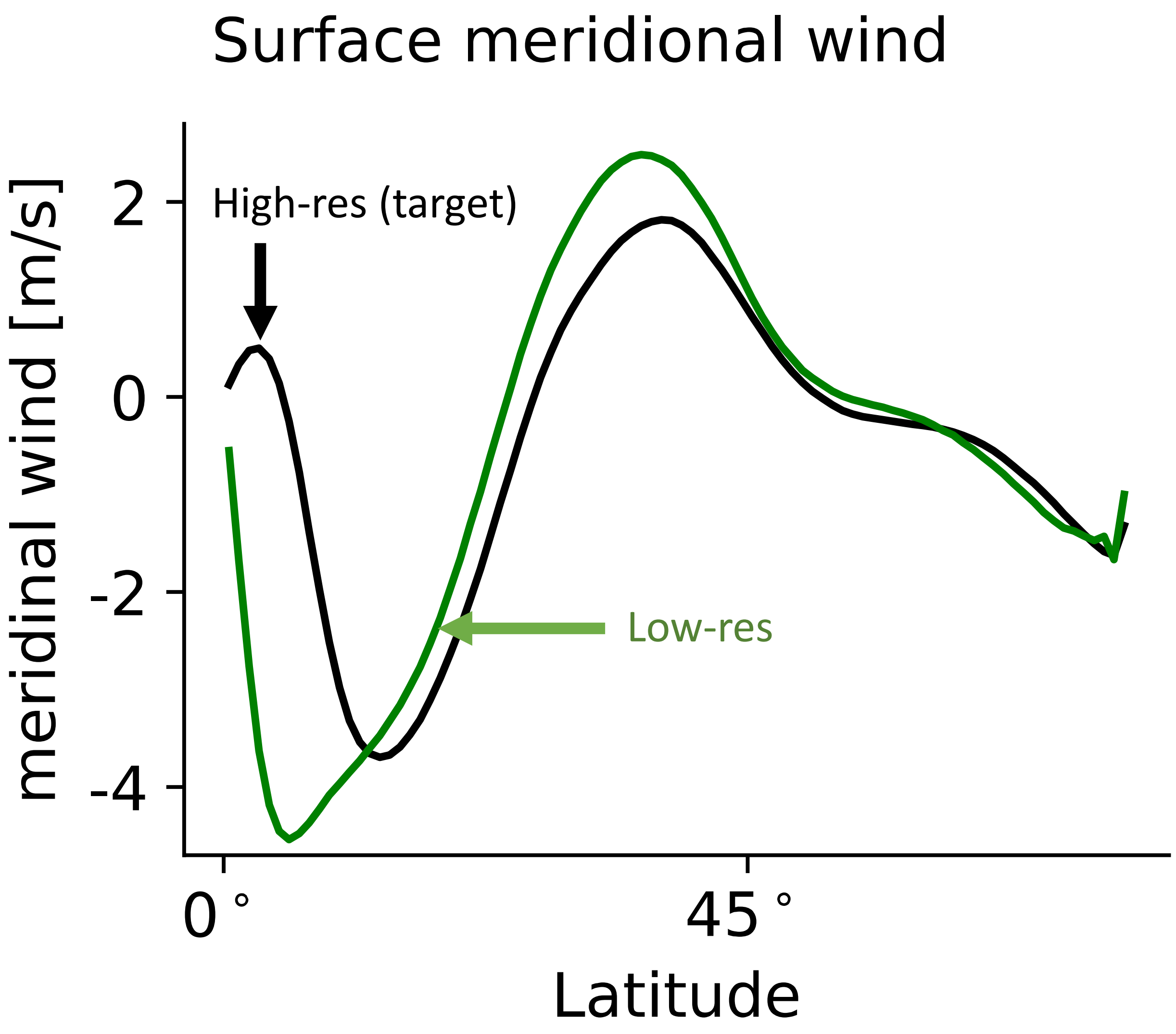

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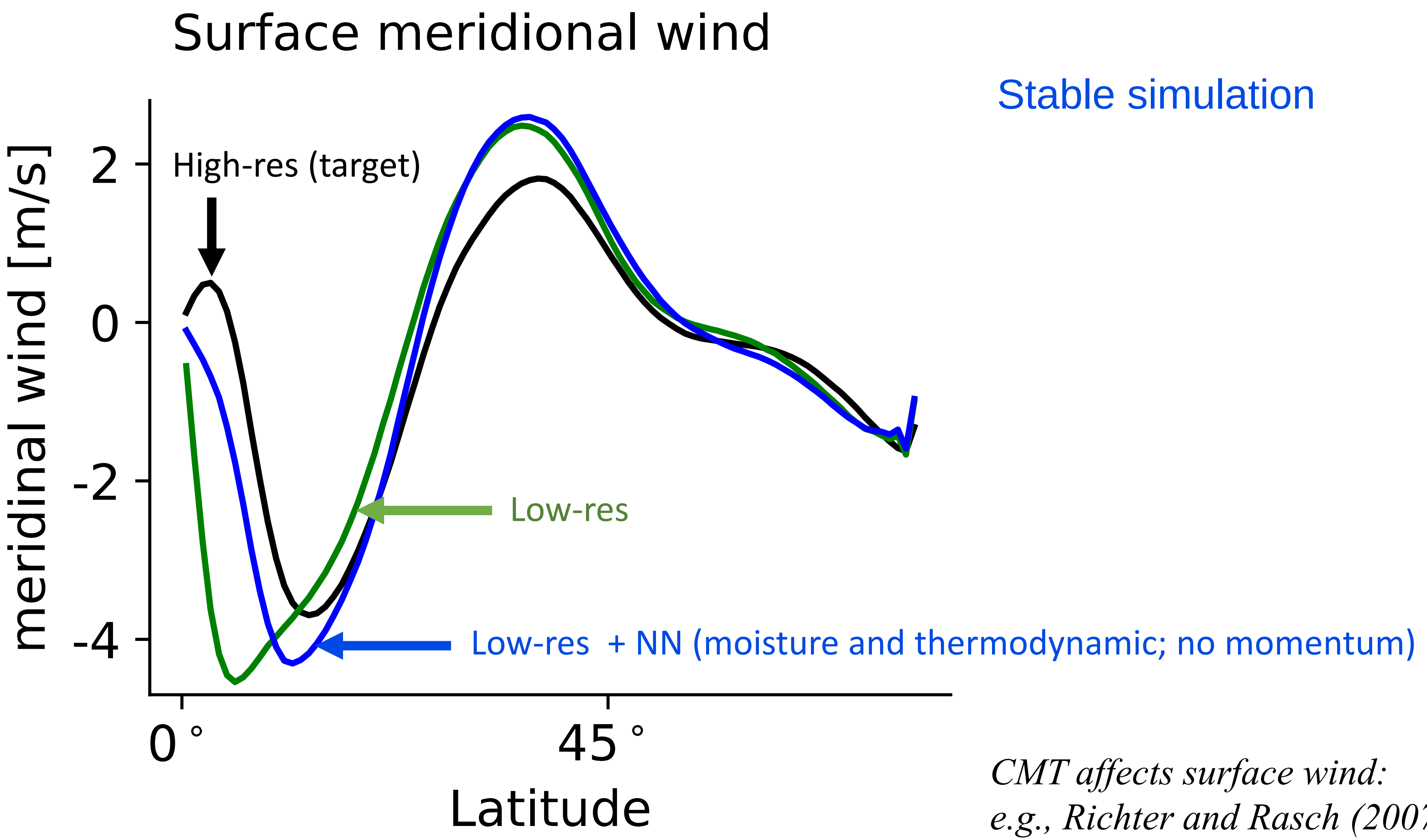
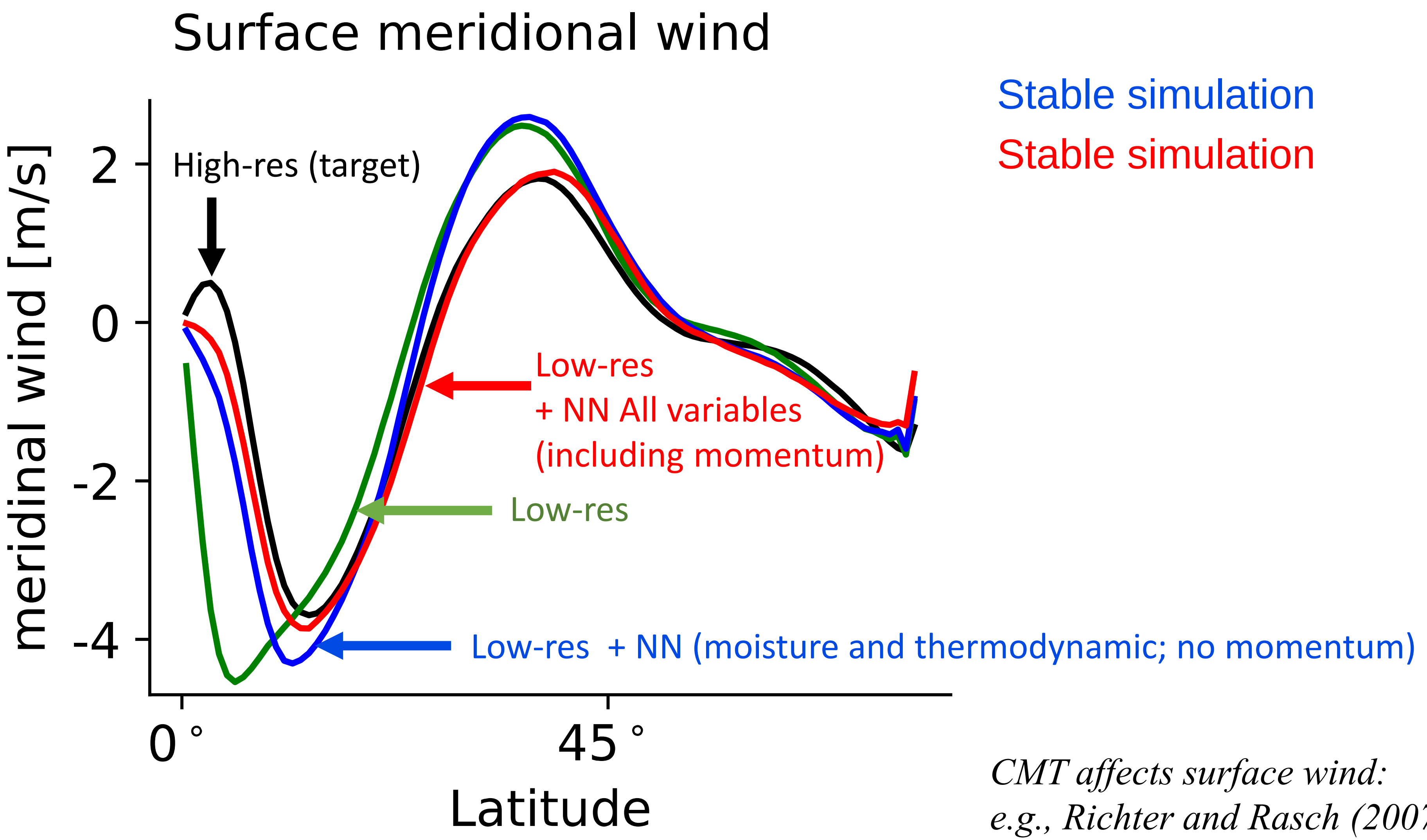


Stable simulation

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

Yuval and O'Gorman (ESSOAr preprint)

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



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Yuval and O'Gorman (ESSOAr preprint)

Certain subgrid processes might be predicted better when using the 3D spatial structure of large scale fields

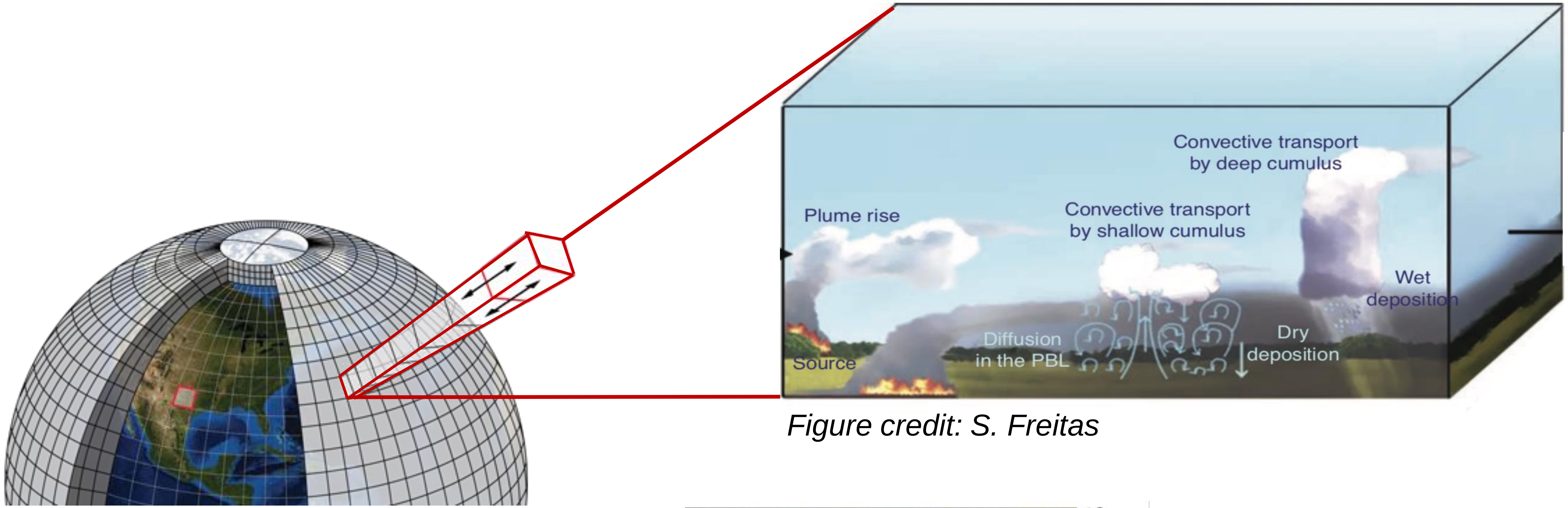

Figure credit: S. Freitas

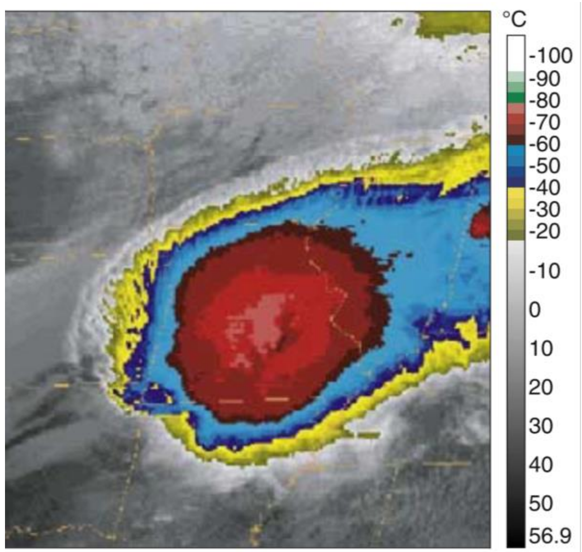

Figure credit: J. Moore

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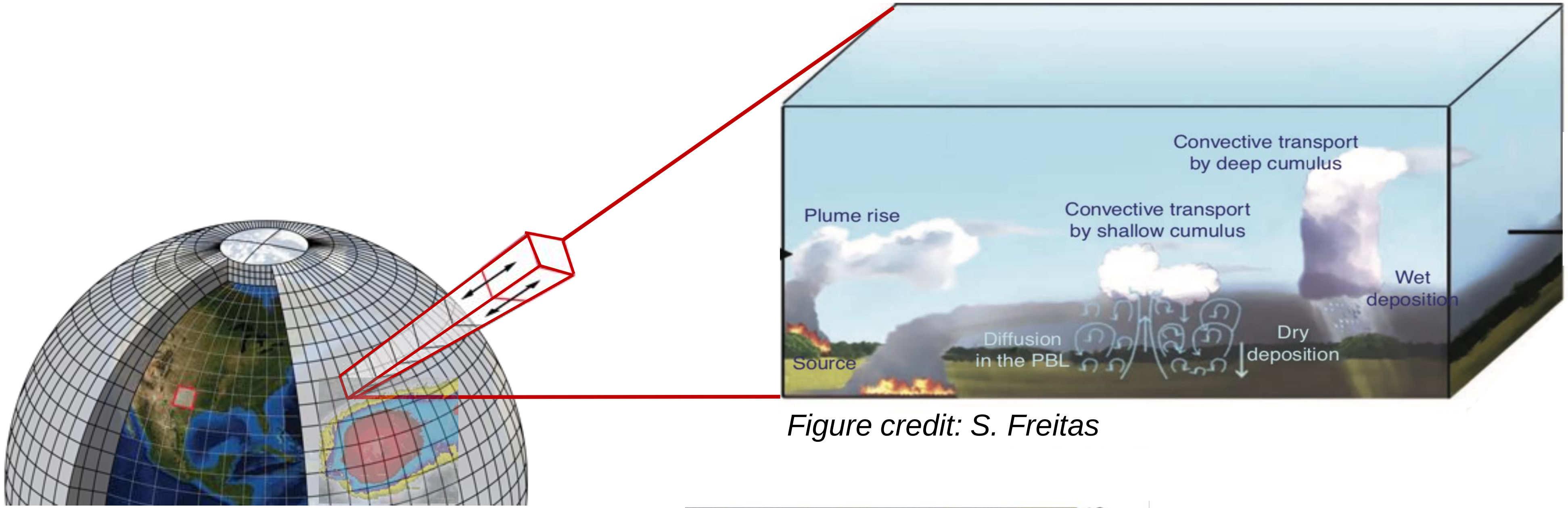

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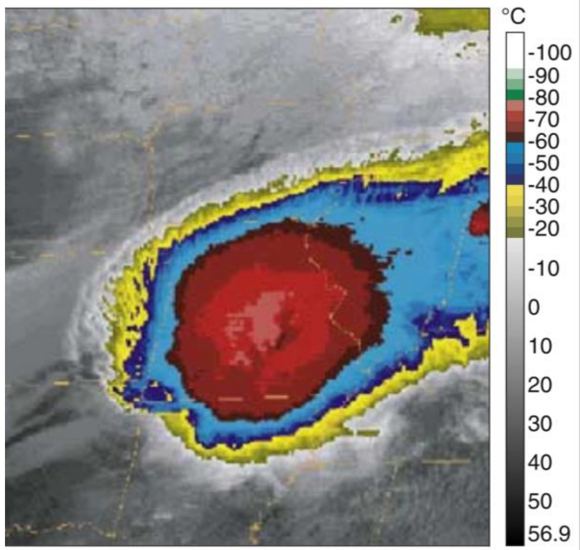

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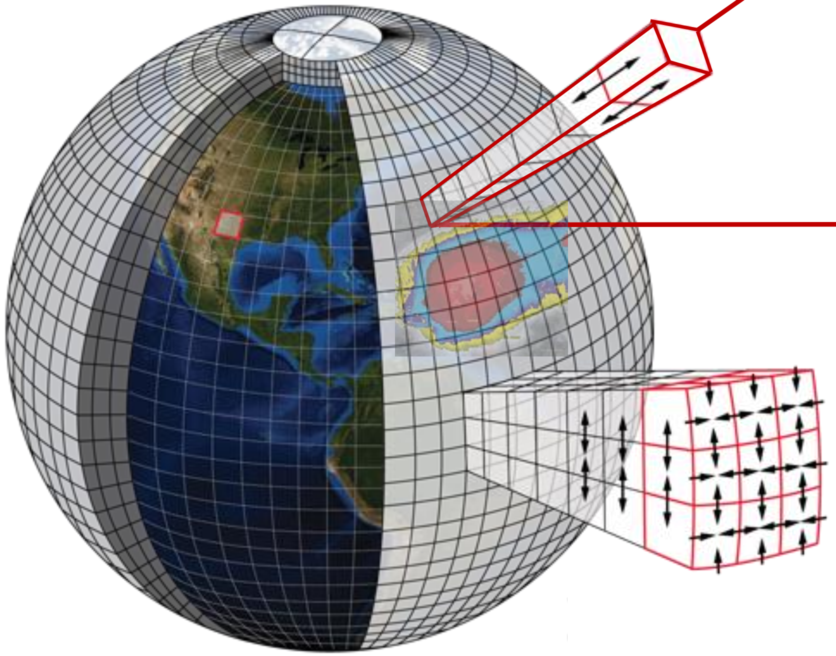

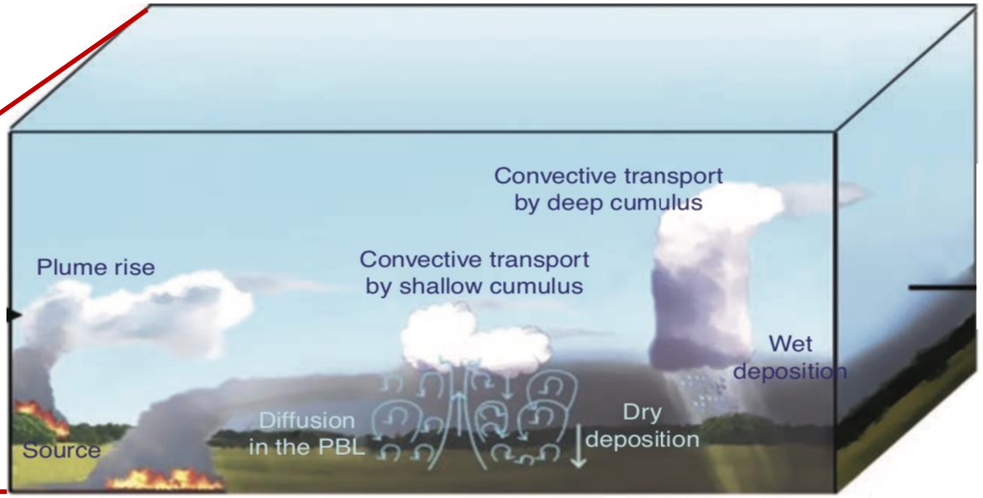

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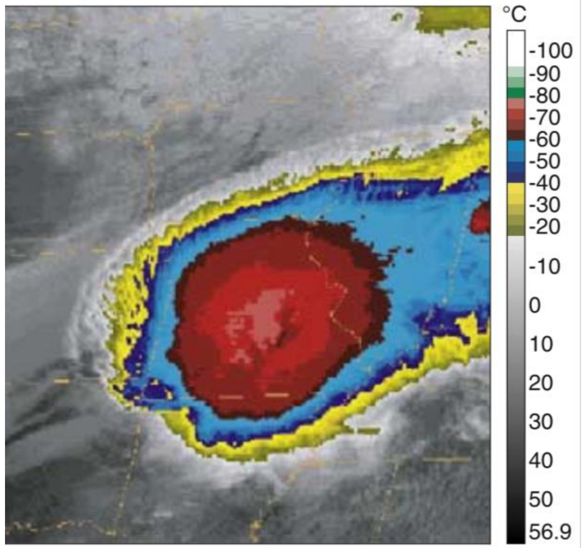
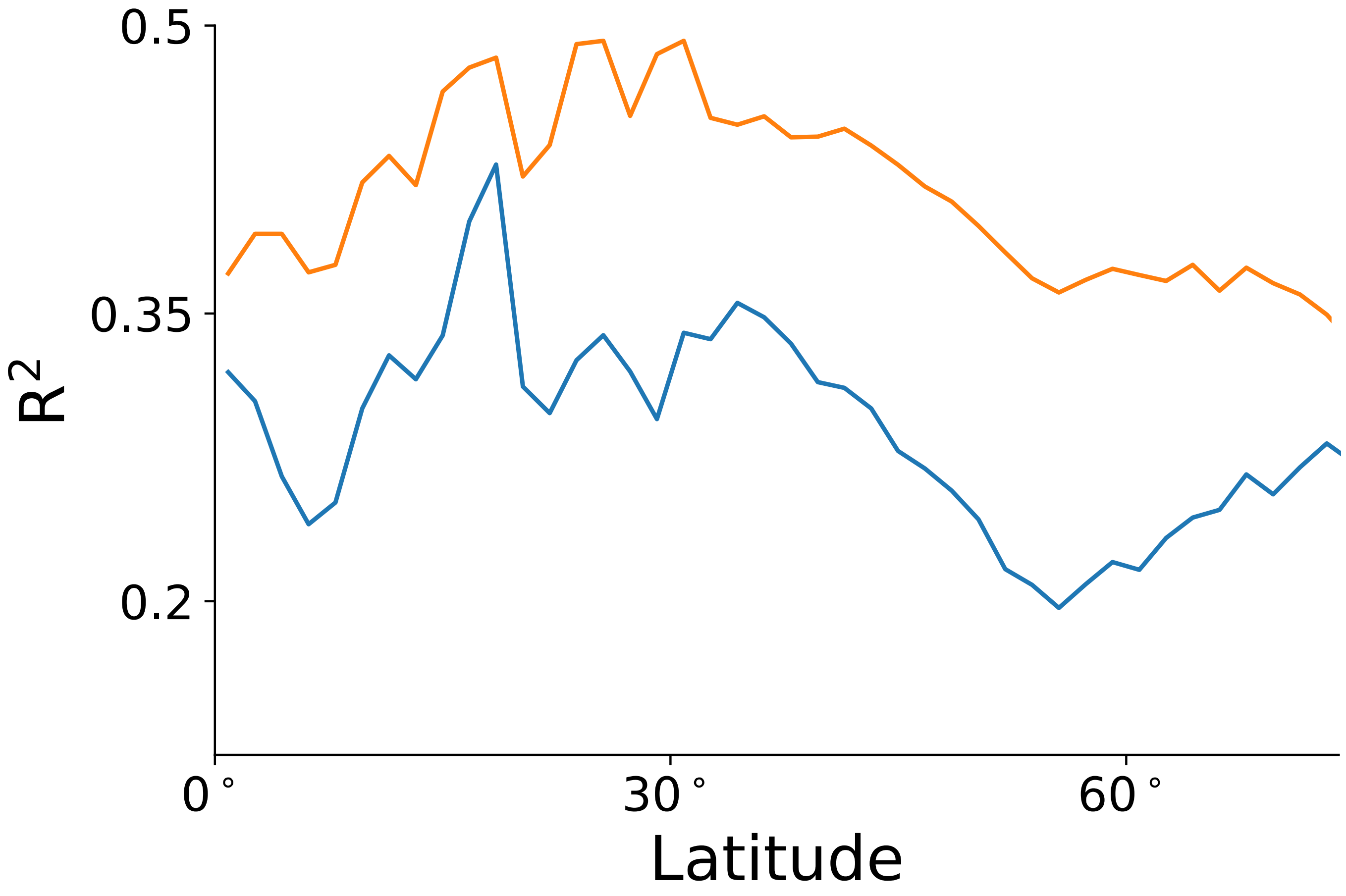
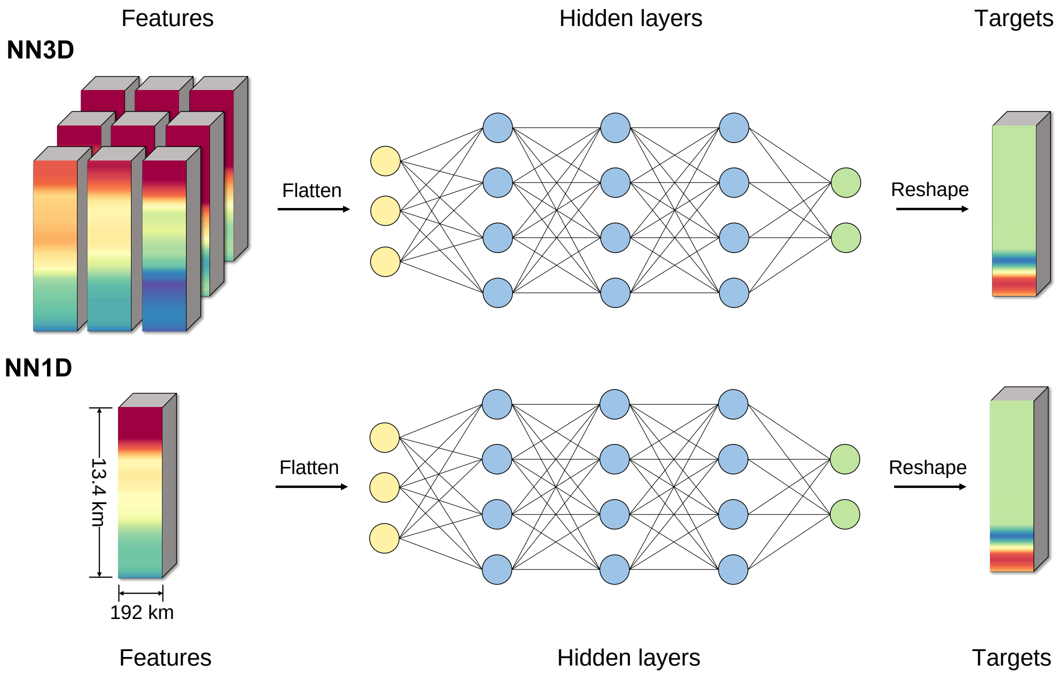


Figure credit: J. Moore

Non-local parameterization improves offline performance of the neural network parameterization



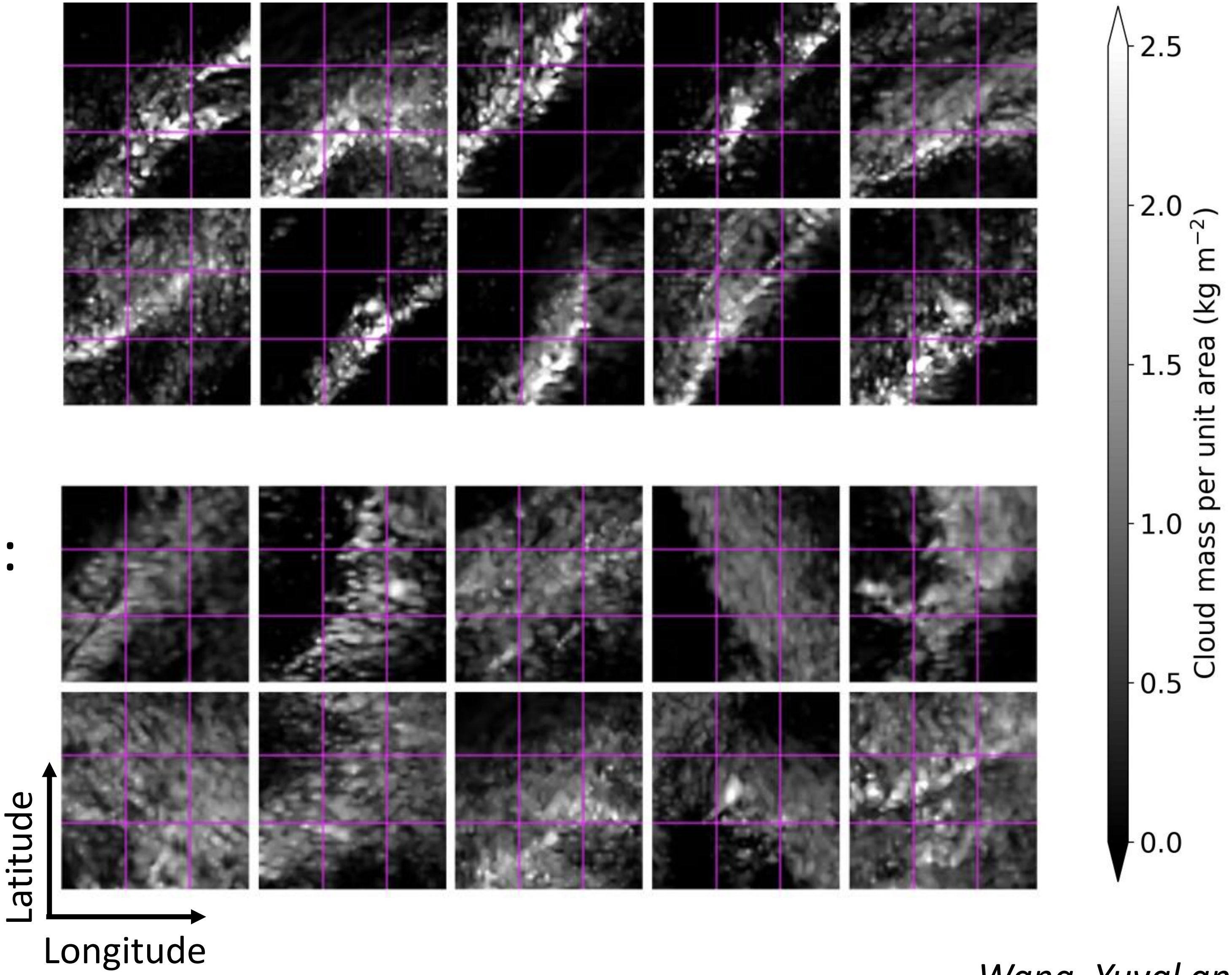


Wang, Yuval and O'Gorman (arXiv preprint)

Non-local parameterization improves the prediction of subgrid processes in fronts

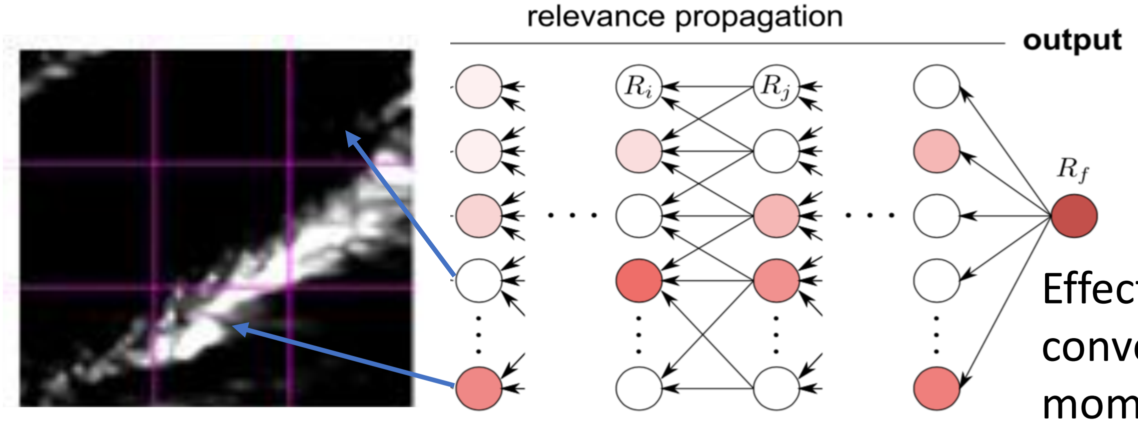
Improved:

Not improved:



Wang, Yuval and O'Gorman (arXiv preprint)

Non-local parameterization relies on non-local wind variables



Effect of convection (e.g., momentum flux)

Where the network looked to determine the effects of convection

Montavon et al. (2017)

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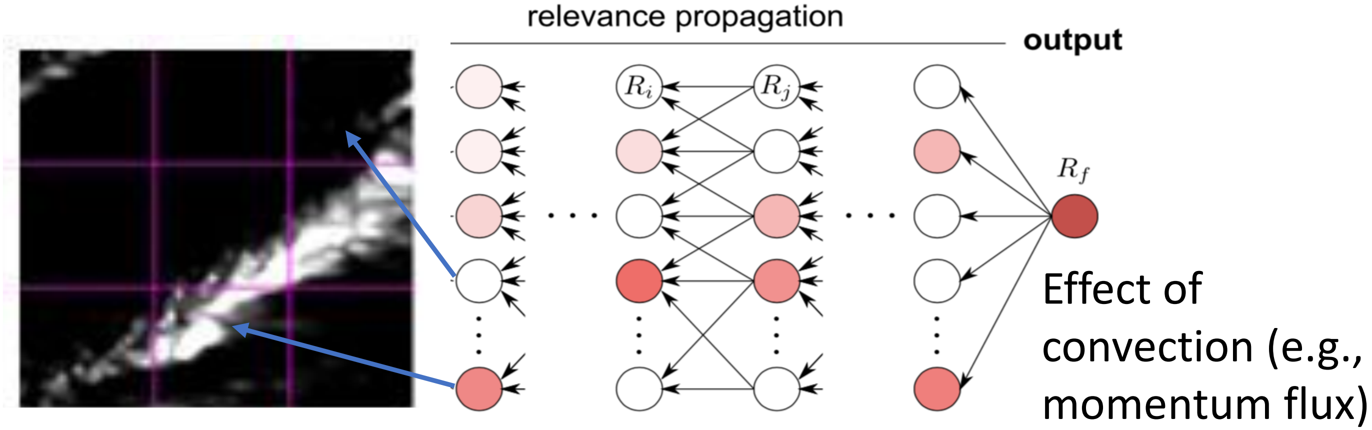
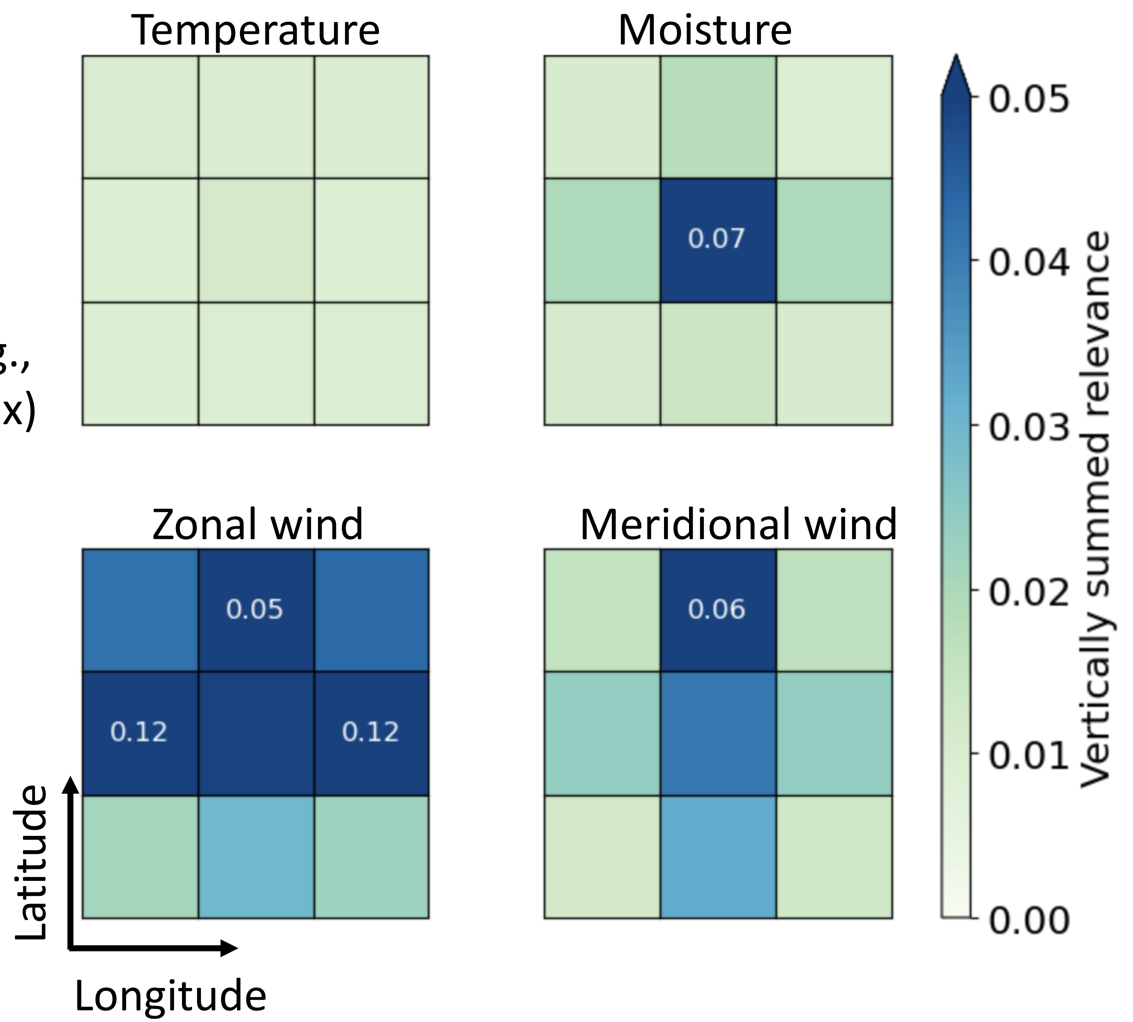


Where the network looked to determine the effects of convection

Montavon et al. (2017)



Wang, Yuval and O'Gorman (arXiv preprint)

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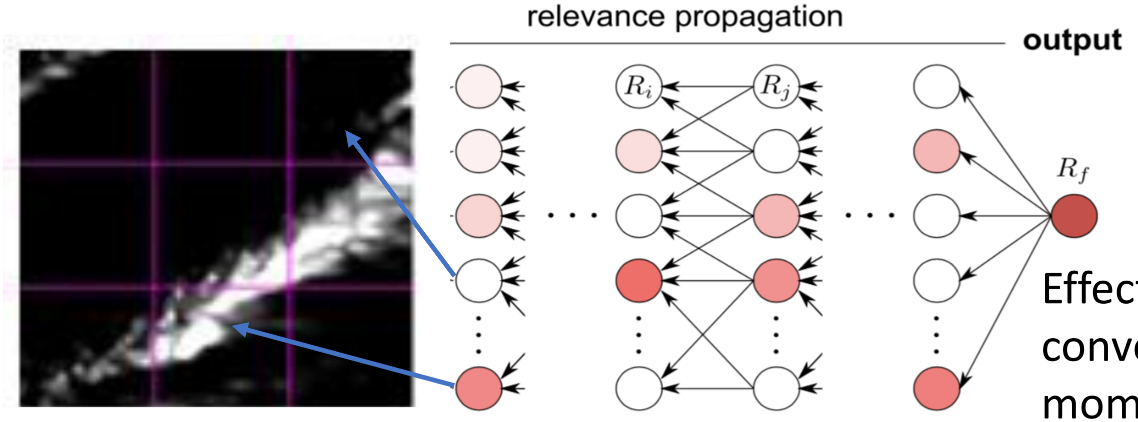

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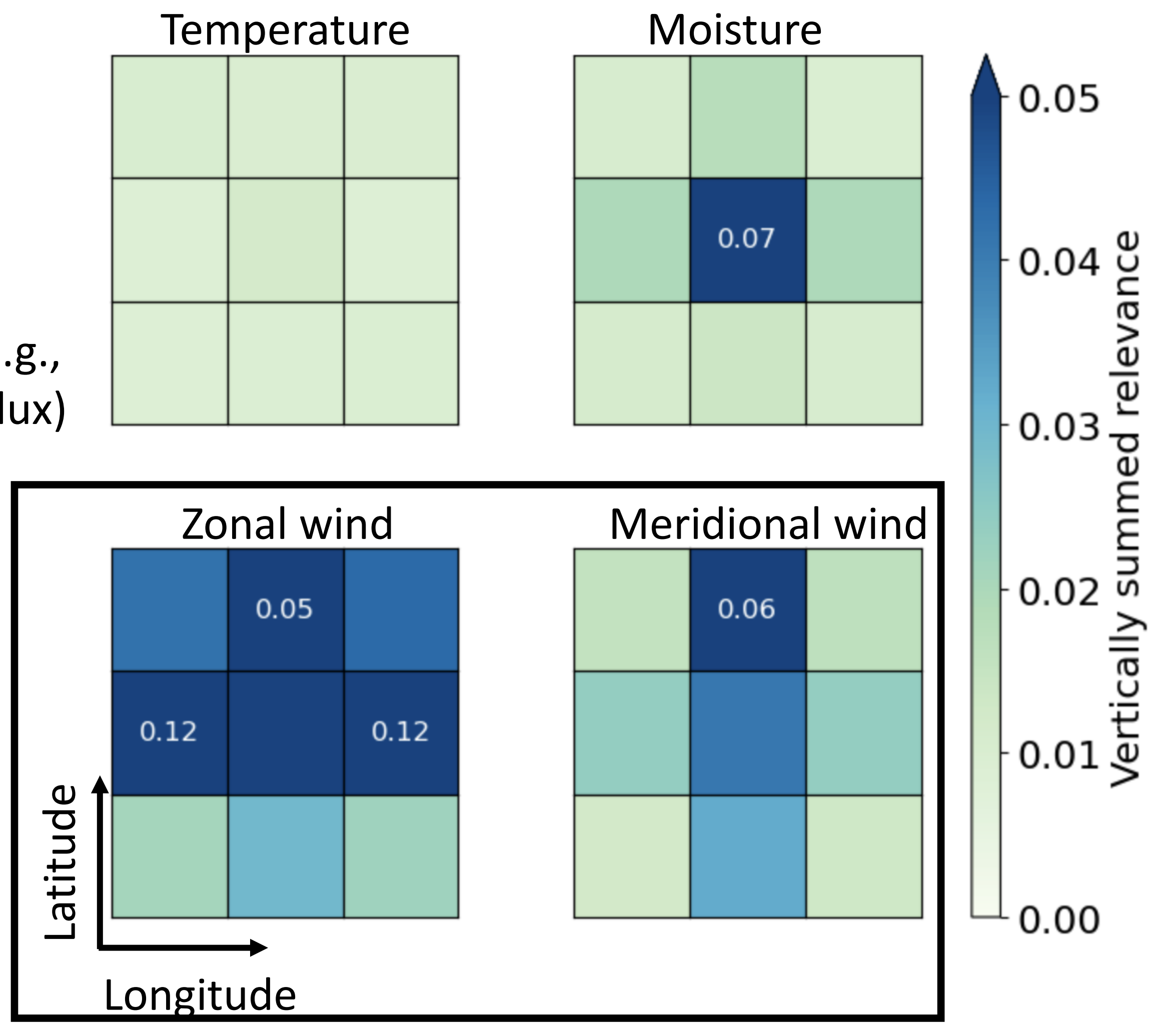
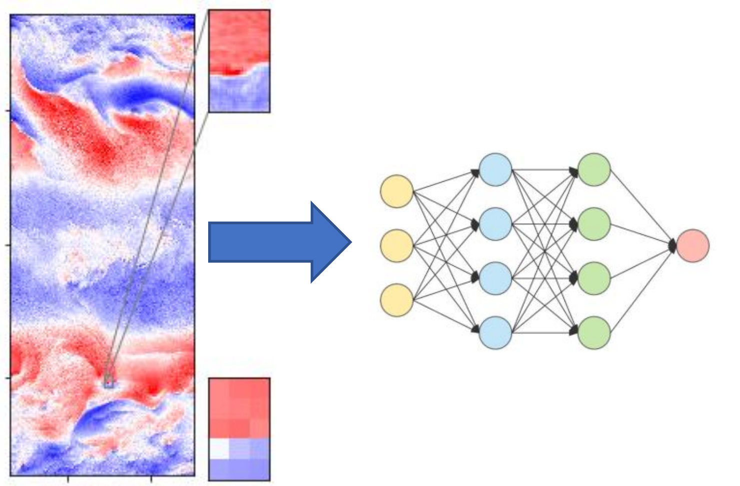
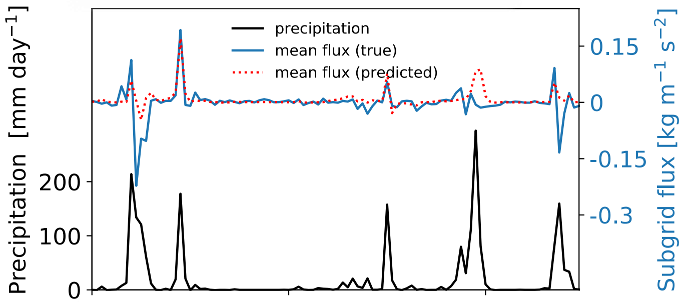


Wang, Yuval and O'Gorman (arXiv preprint)

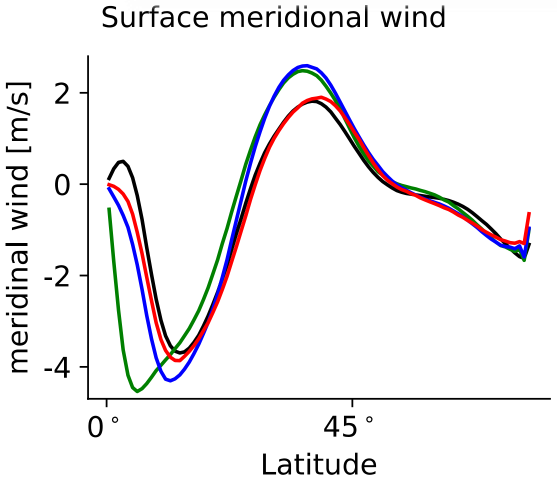
Conclusions



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

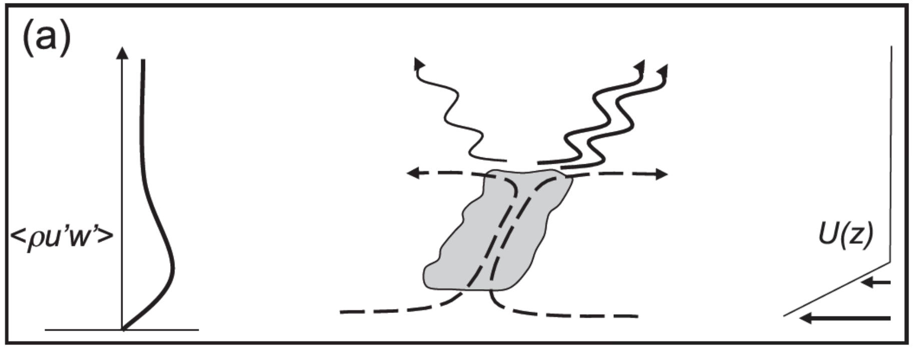


- It is challenging to predict subgrid momentum fluxes



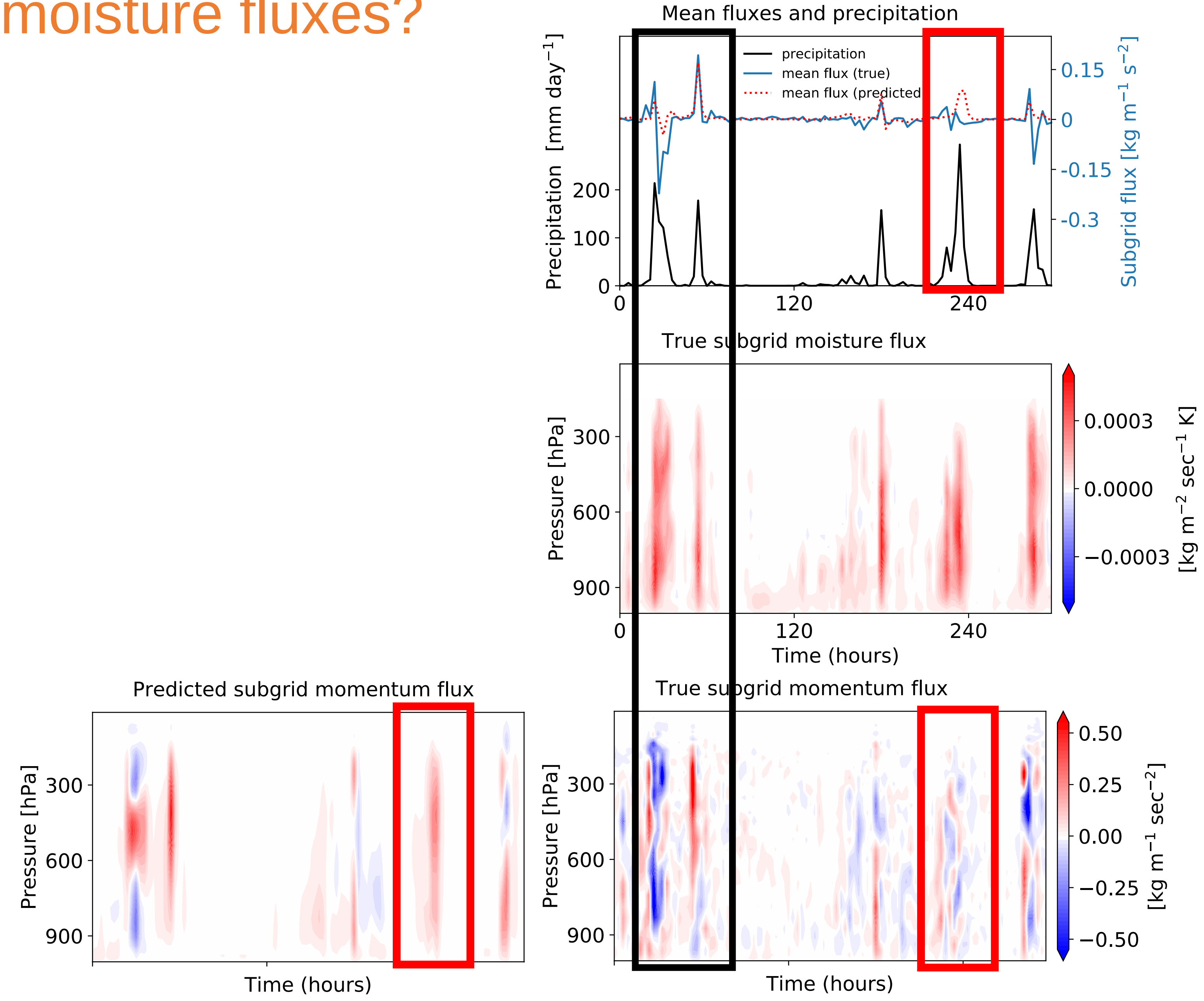
- Machine-learning momentum parameterization + atmospheric model at climate-model resolution -> stable simulation and improve some characteristics of the atmospheric circulation

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



Lane and Moncrieff (2010)

Convective momentum transport can be negative or positive



Yuval and O’Gorman (ESSOAr preprint)

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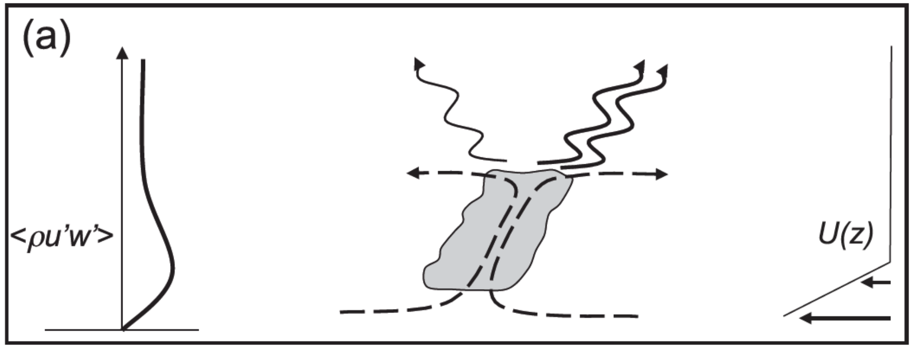


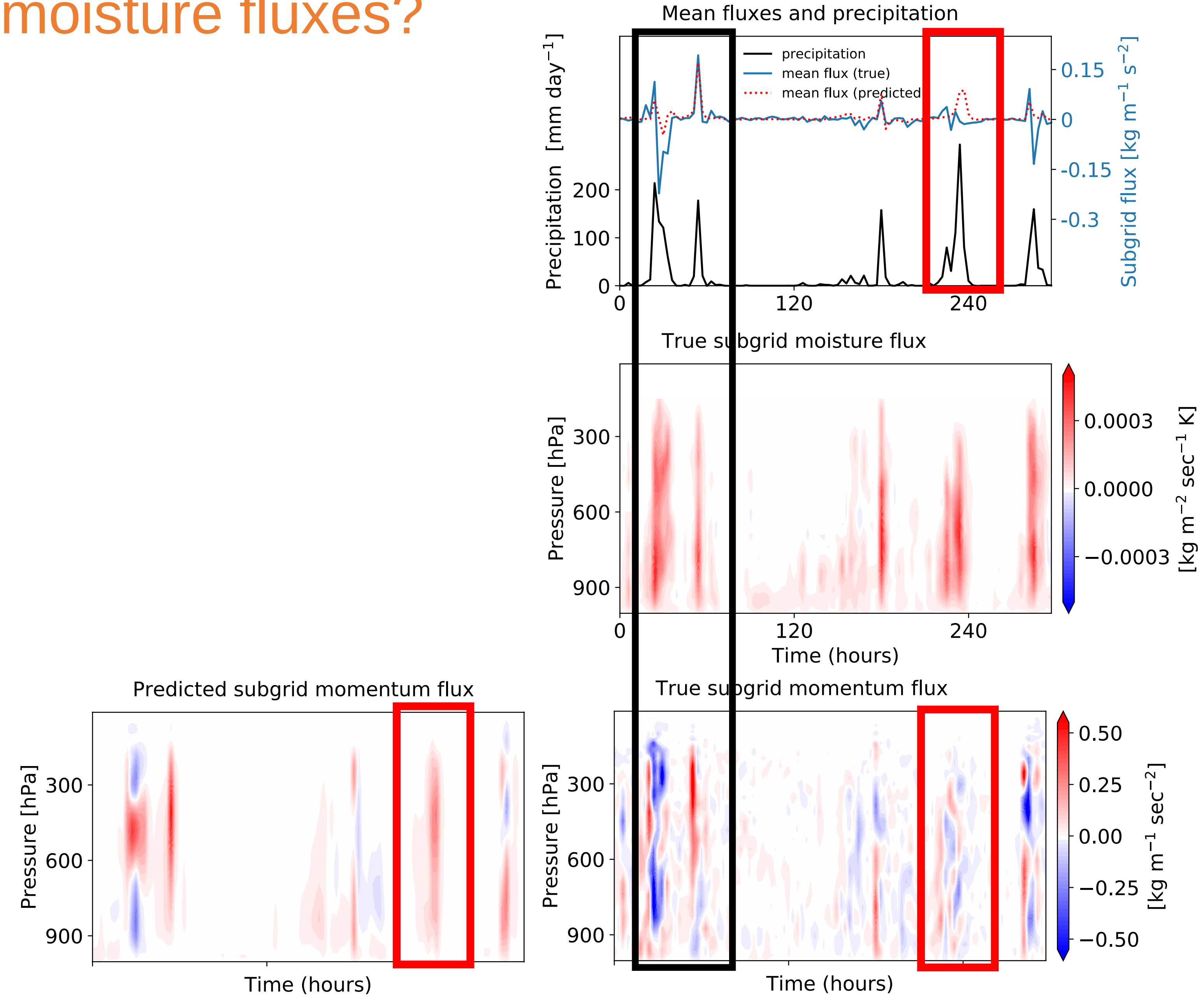
Lane and Moncrieff (2010)

Convective momentum transport can be negative or positive

For (linear) gravity waves:

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

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



Yuval and O'Gorman (ESSOAr preprint)