Machine learning for gravity waves in a climate model

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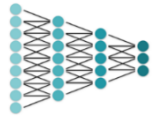
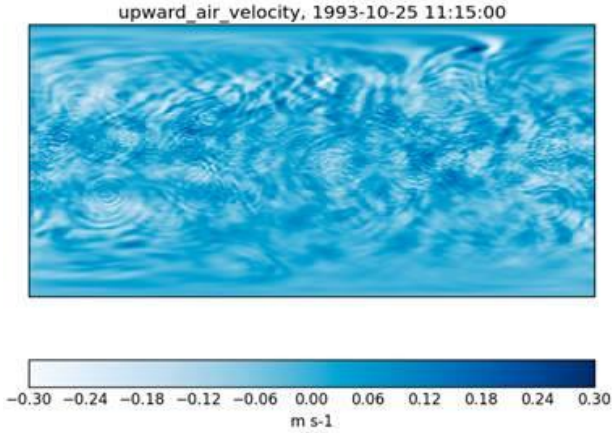
Five-year international project, funded by the Virtual Earth System Research Institute (VESRI), to enhance and improve gravity wave representation in climate simulations using machine learning.



- Gravity wave forcing must be parametrized in global climate simulations
- Parametrizations involve approximations which affect model accuracy (column based / simple source)
- Use machine learning to improve on parameterization scheme
- May improve the connections between stratospheric variability and surface climate



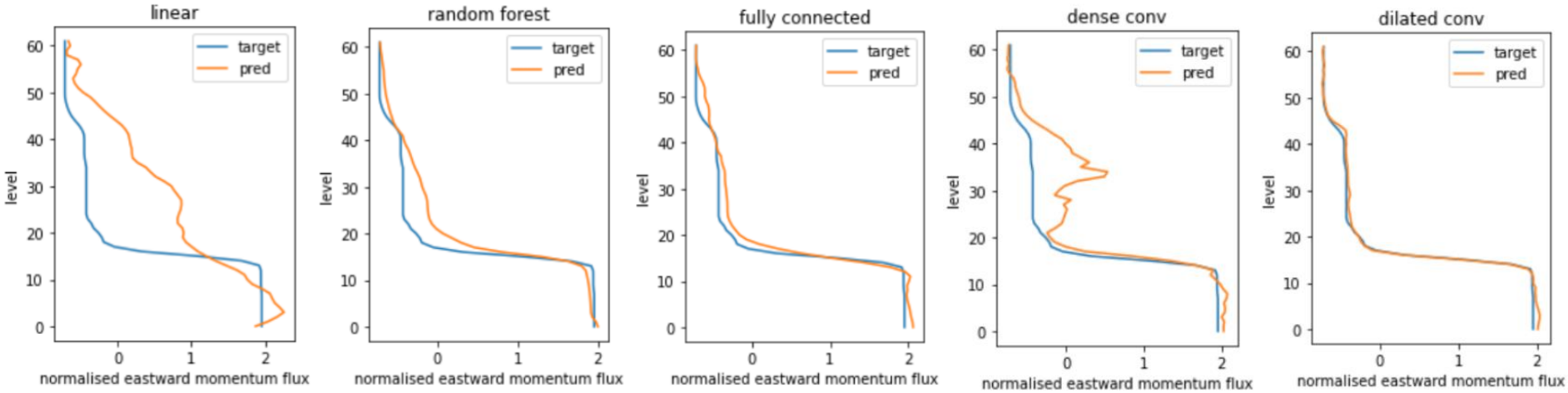
Gravity waves seen in the vertical velocity field of the Met Office climate model

Aim to:

- emulate existing non-orographic gravity wave scheme
- improve on existing scheme (i.e. descent of the QBO – a common and important bias in climate models).

Emulate existing NOGWD scheme

First choose the best type of machine learning algorithm:

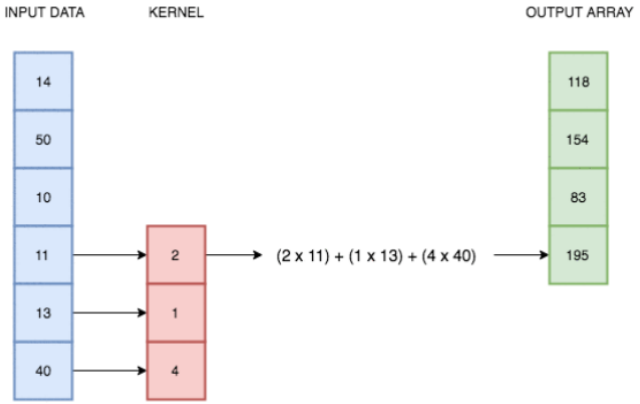


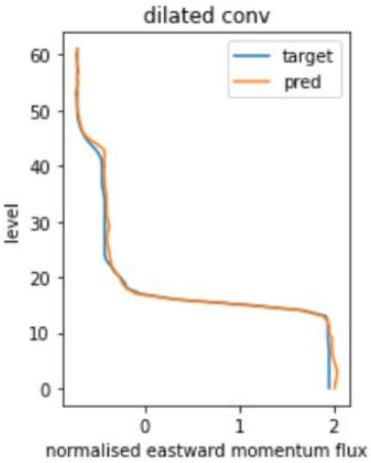
test MSE
linear: 0.1876
dense convolution: 0.0962
random forest: 0.0380
fully connected: 0.0238
dilated convolution: 0.0092

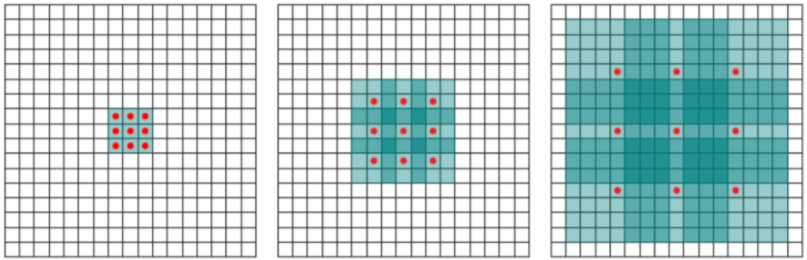
Trained convolutional neural network to output non-orographic GW acceleration, with zonal wind as input.

Dilated convolutional neural network

Compared with fully connected NNs, convolutional NNs identify and extract the key features from the data and have fewer parameters to train.





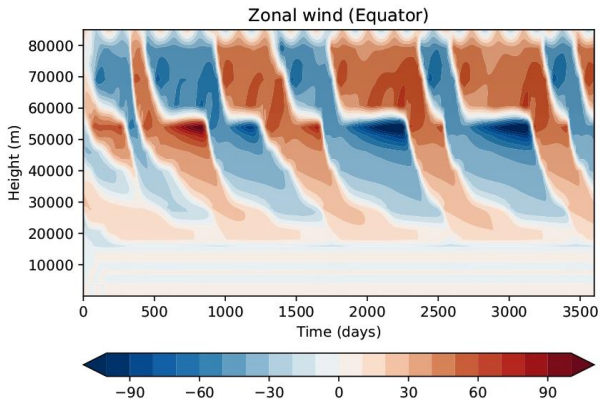


Dilated convolution involves skipping, so covers a larger area of the input than convolution.

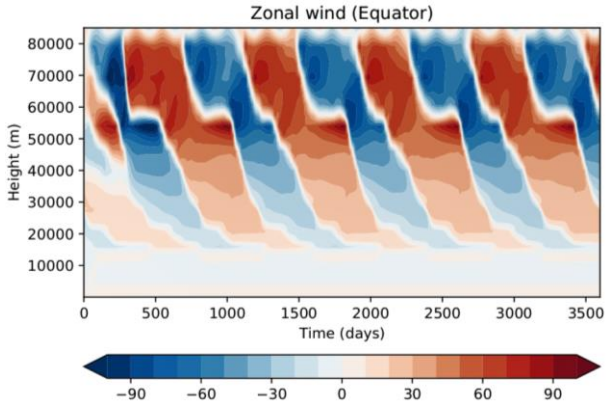
Simulating a QBO

- Simulate QBO in simple 1D model
  - enables us to optimize the network
  - gives hope that scheme will work when coupled to climate model
- Train on two years of data, containing QBOE and QBOW phases, and NH winter stratosphere with SSW and strong polar vortex.

- Neural net coupled to 1D model reproduces a QBO with correct period, amplitude and structure.



QBO simulated by offline NOGWD scheme coupled to 1D model.



QBO simulated by neural network coupled to 1D model.

Simulating a QBO

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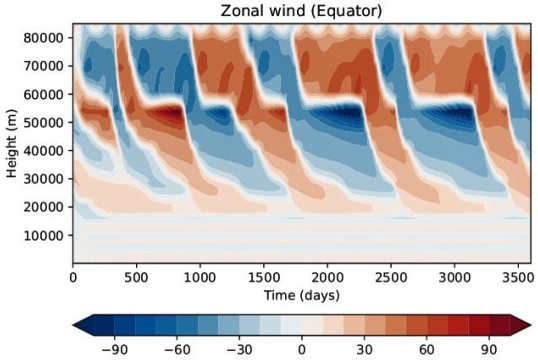

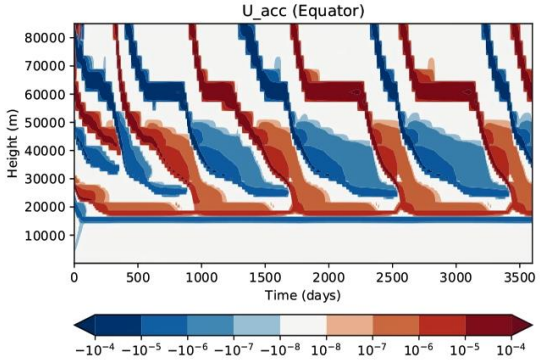

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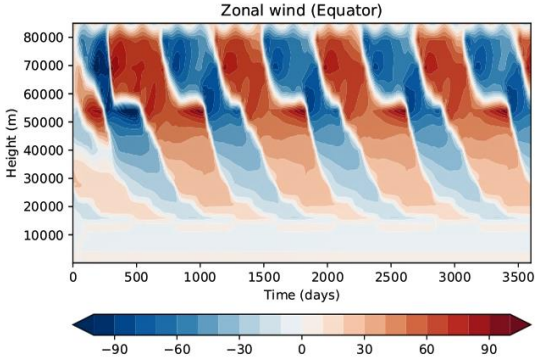
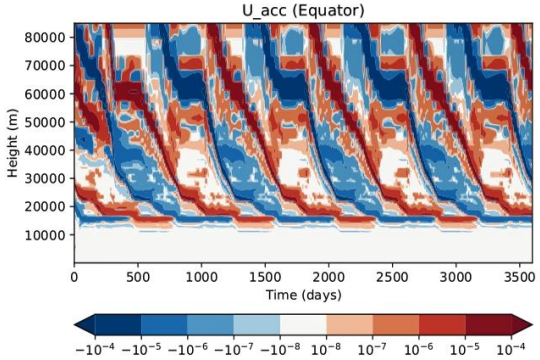




- Acceleration is concentrated around transition periods for parametrisation scheme and neural network

SSW/Strong vortex GW simulation

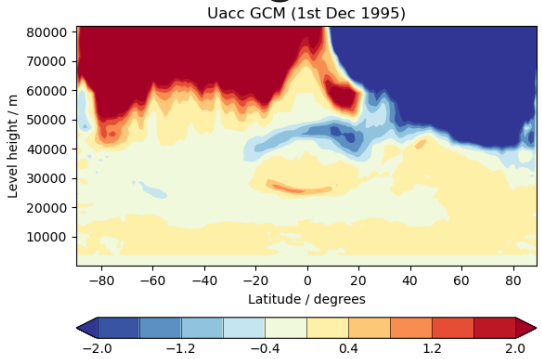
An initial look at the extratropics shows the neural net correctly captures the different features in NOGWD between periods with strong and weak vortex

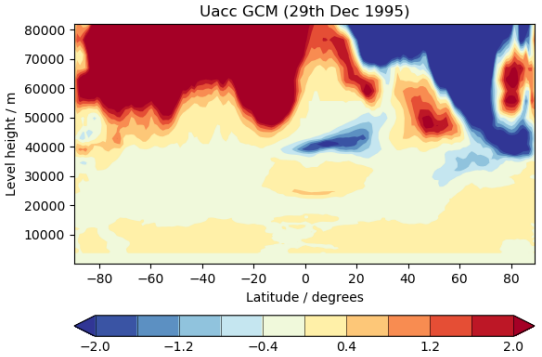
Strong vortex

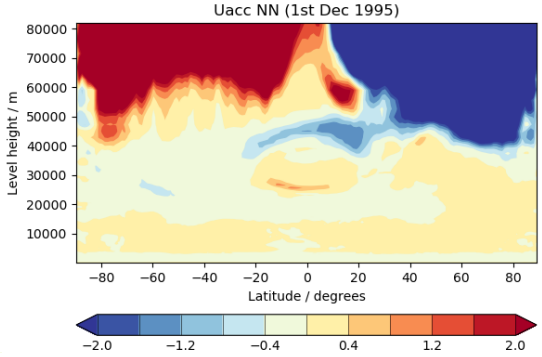
SSW

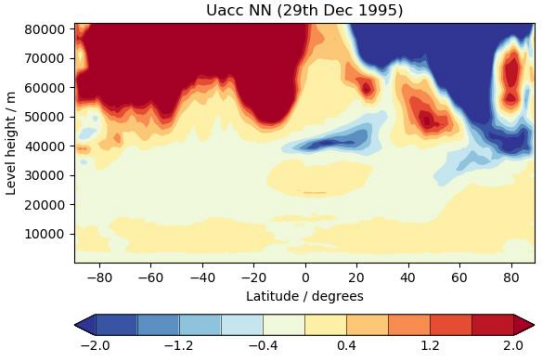
GCM

NN

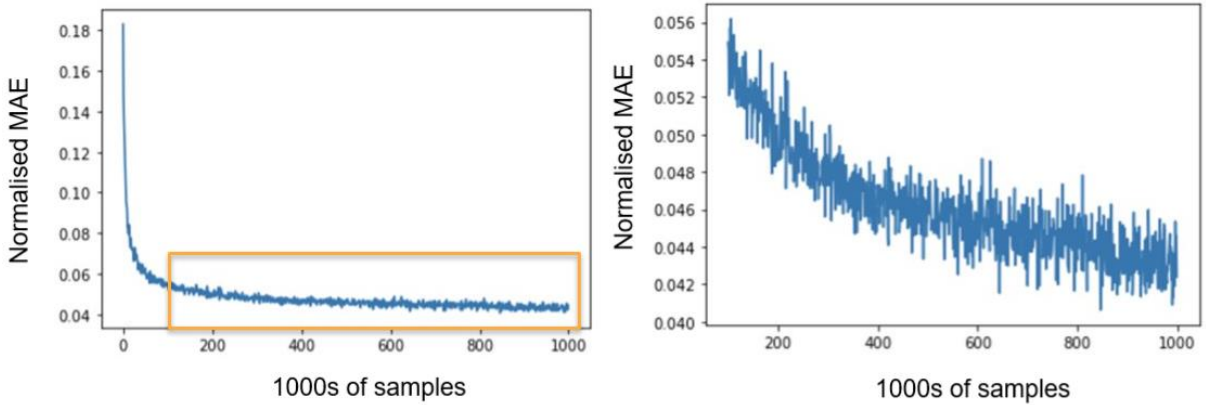








Training sample size



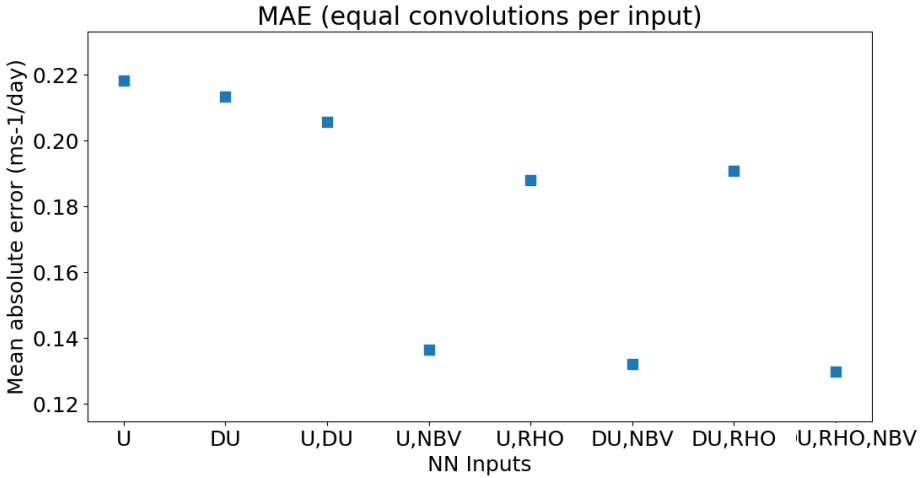
- Normalised error converges for around 300-400 randomly chosen input samples.

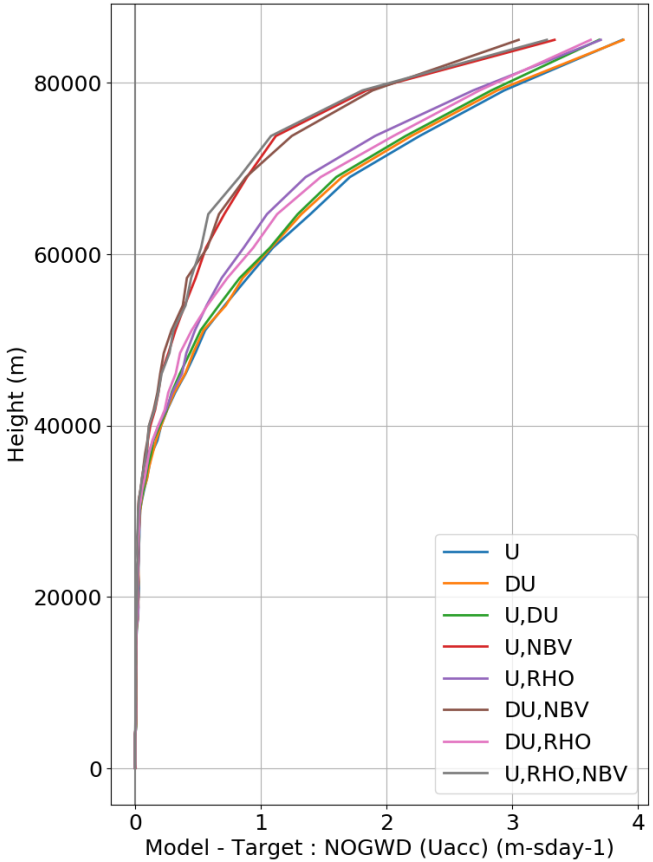
- Have also demonstrated that two years of training data is sufficient, whereas one month is not.

Optimize network: Input variables

- Don’t need all the inputs to the NOGWD scheme
- Using u (or du/dz) gives most of the signal
- Adding density helps a bit
- Adding buoyancy frequency (nbv) helps a lot

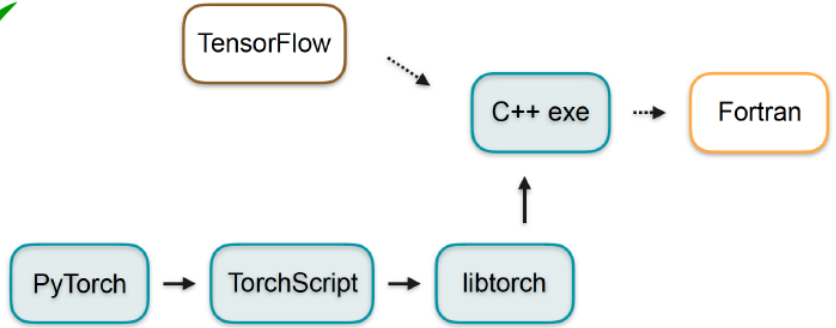
- (u, nbv) appears sufficient





Coupling ML components to the GCM

- Compile PyTorch models using libtorch ✓
- Write C++ to load and run model ✓
- Verify outputs match Python version ✓
- Test build libtorch on HPC ✓
- Select PyTorch / libtorch versions (1.6?)
- Write Fortran bindings



Bonus:

We get the ability to train the model in C++

Could use this to train ML components natively in the GCM

Summary and further work

Summary

- Dilated convolutional neural network is best machine learning algorithm to emulate existing NOGWD scheme
- When trained with 2 years of model data, neural net coupled to 1D model reproduces a QBO with correct period, amplitude and structure
- 1D model allows us to test QBO dependence on neural net inputs, depth, size, stride etc.
- Zonal wind and buoyancy frequency may be sufficient input variables

Current work

- Work on implementing a potential approach for coupling the neural network to the Met Office climate model.

Future work

- Use high resolution model data as NN input → improved model features (esp. lower stratosphere QBO)?
- Also emulate (and improve on?) OGWD scheme.