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# “CARAMEL”

## Cloud-resolving model machine learning (CRMML)

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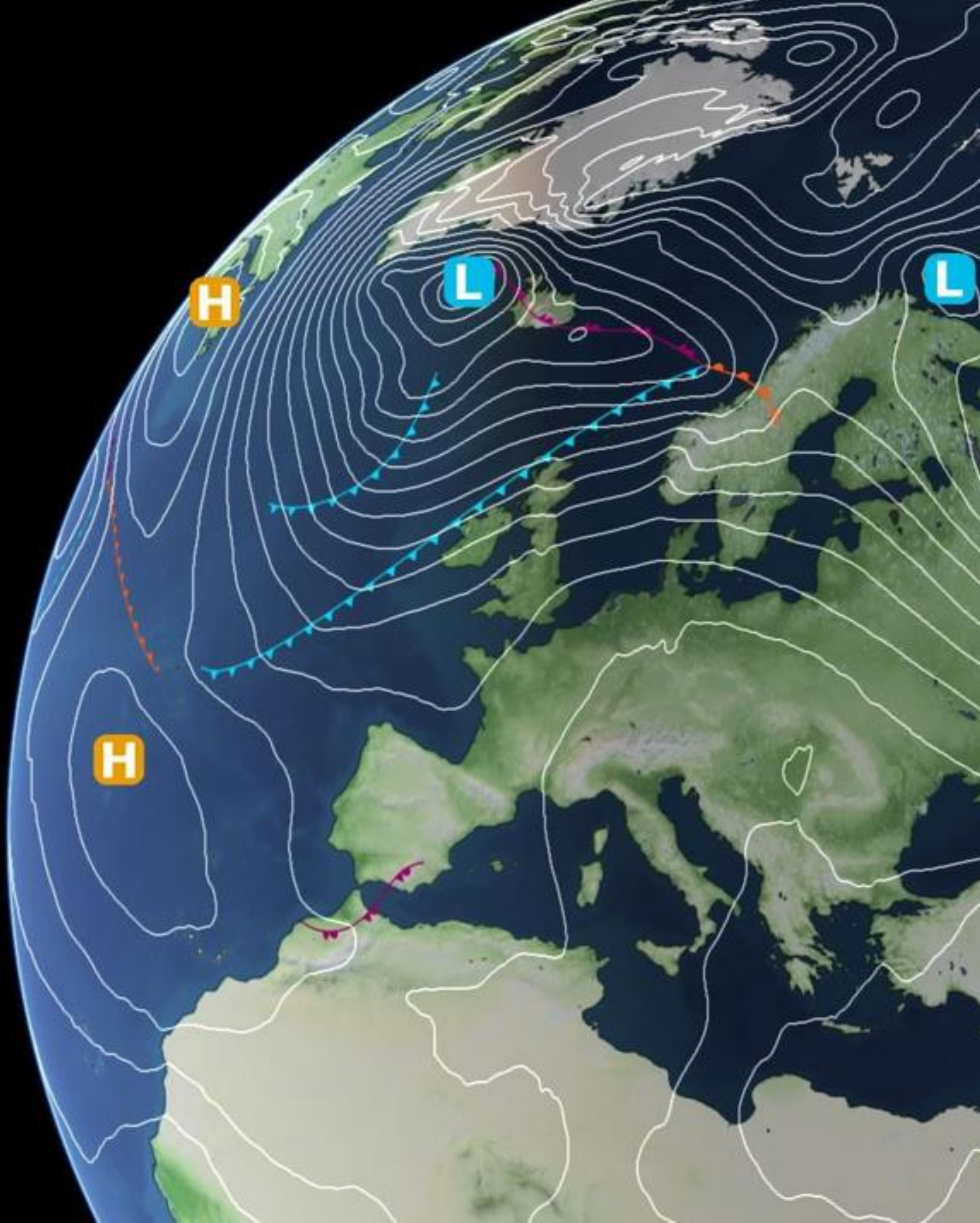

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This talk is NOT about using AI/ML to make forecasting *faster* !

This talk is about using AI/ML to make the model *better* !

Kilometre-scale models are better at predicting clouds.

Going from a global climate model with dx=100 km to dx=1km
would lead to needing 100^3=1,000,000 more compute.

If we can get some of the benefit for less than that, that is still a massive WIN!

So not faster as such, perhaps slower even, but faster than what an increase in resolution would cost!

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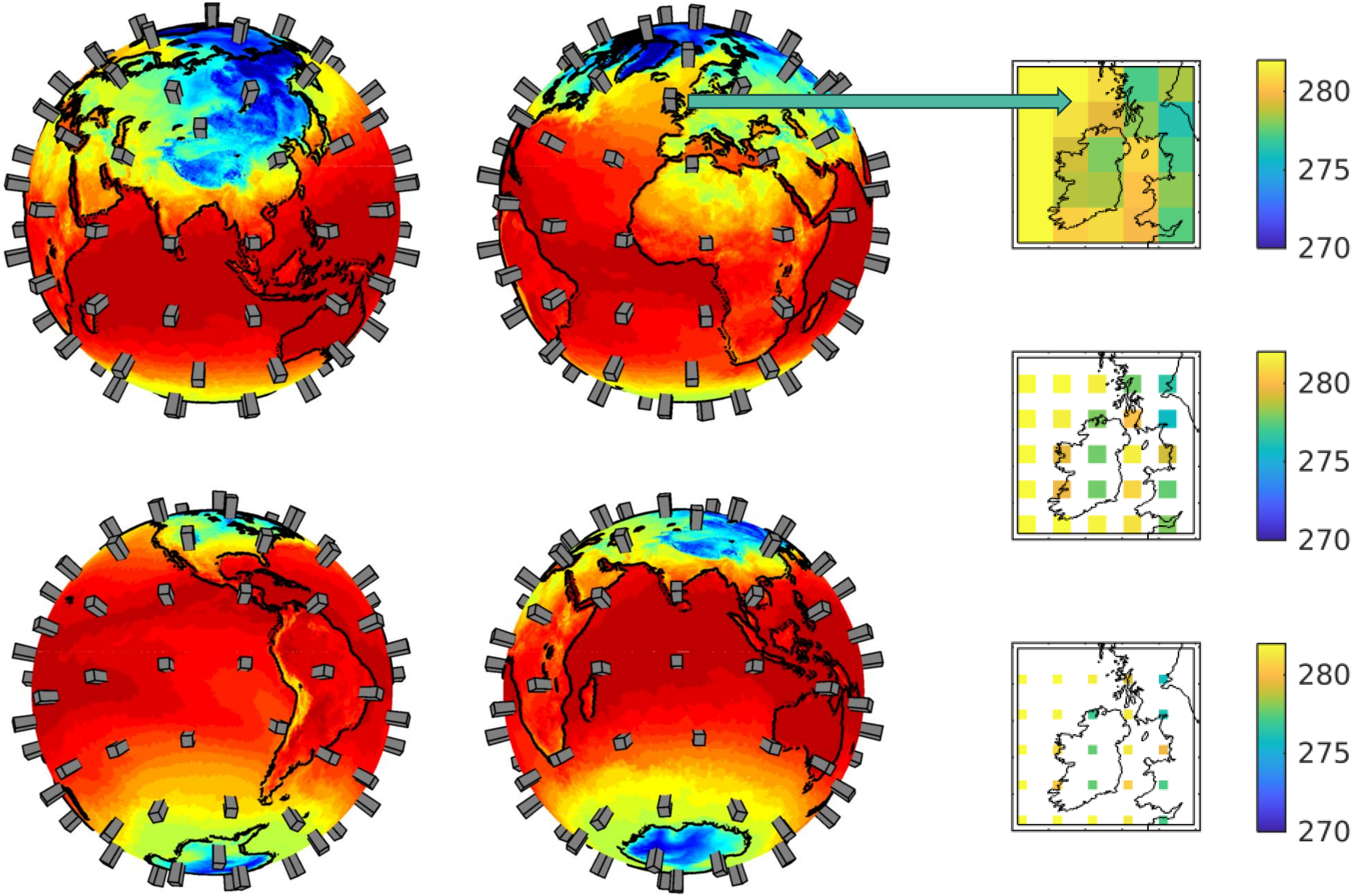
80 nested models, each running 1.5 km simulations with 512x512 grid-points

Coarse-grain 1.5 km data to a range of size from 144 km to 12 km



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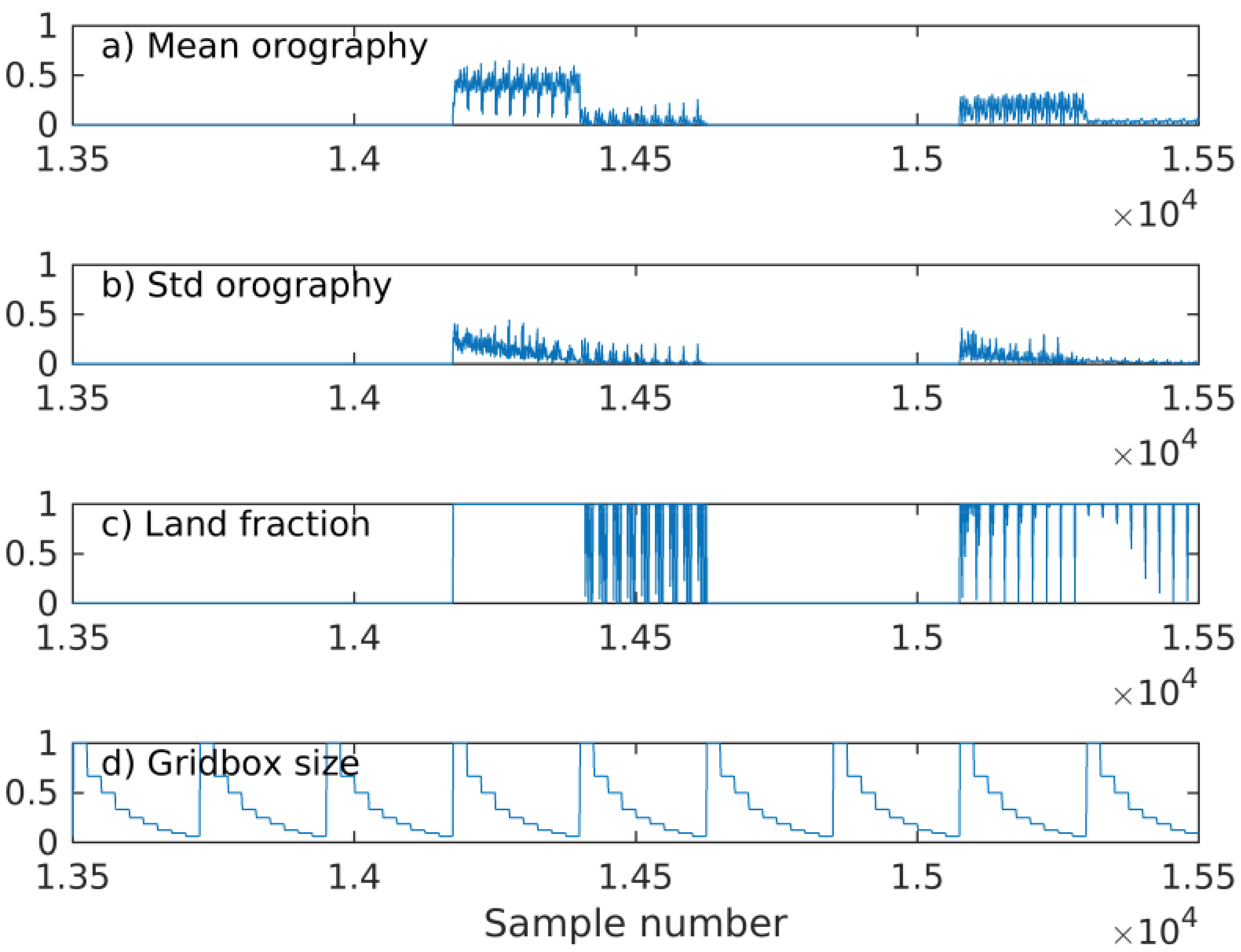
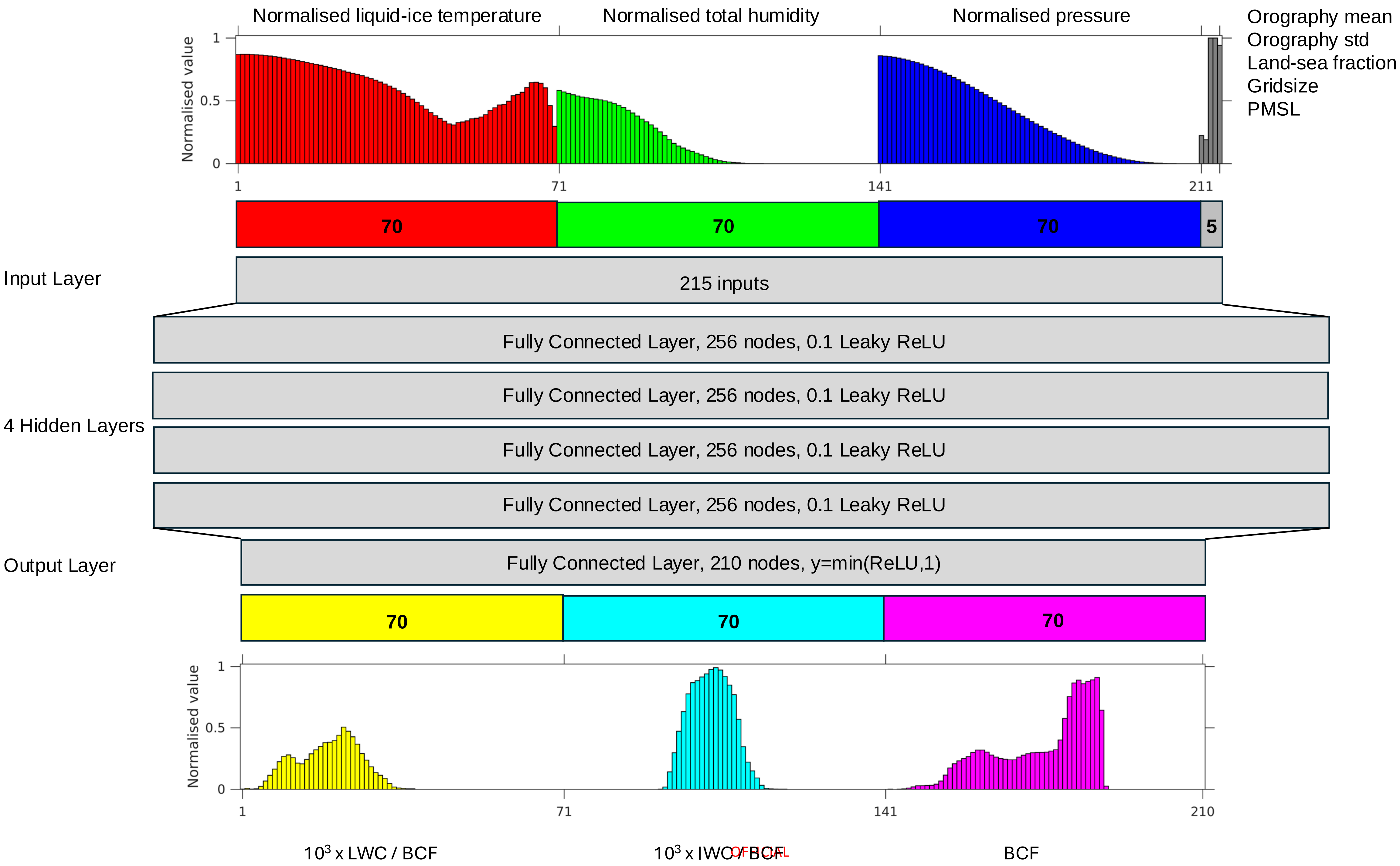

a) Mean orography
b) Std orography
c) Land fraction
d) Gridbox size
1
0.5
0
1.35
1.4
1.45
1.5
1.55
×10^4
Sample number


Normalised liquid-ice temperature
Normalised total humidity
Normalised pressure
Orography mean
Orography std
Land-sea fraction
Gridsize
PMSL
Normalised value
1
0.5
0
1
71
141
211
70
70
70
5
Input Layer
215 inputs
4 Hidden Layers
Fully Connected Layer, 256 nodes, 0.1 Leaky ReLU
Fully Connected Layer, 256 nodes, 0.1 Leaky ReLU
Fully Connected Layer, 256 nodes, 0.1 Leaky ReLU
Fully Connected Layer, 256 nodes, 0.1 Leaky ReLU
Output Layer
Fully Connected Layer, 210 nodes, y=min(ReLU,1)
70
70
70
Normalised value
1
0.5
0
1
71
141
210
10^3 x LWC / BCF
10^3 x IWC / BCF
BCF

We trained some models

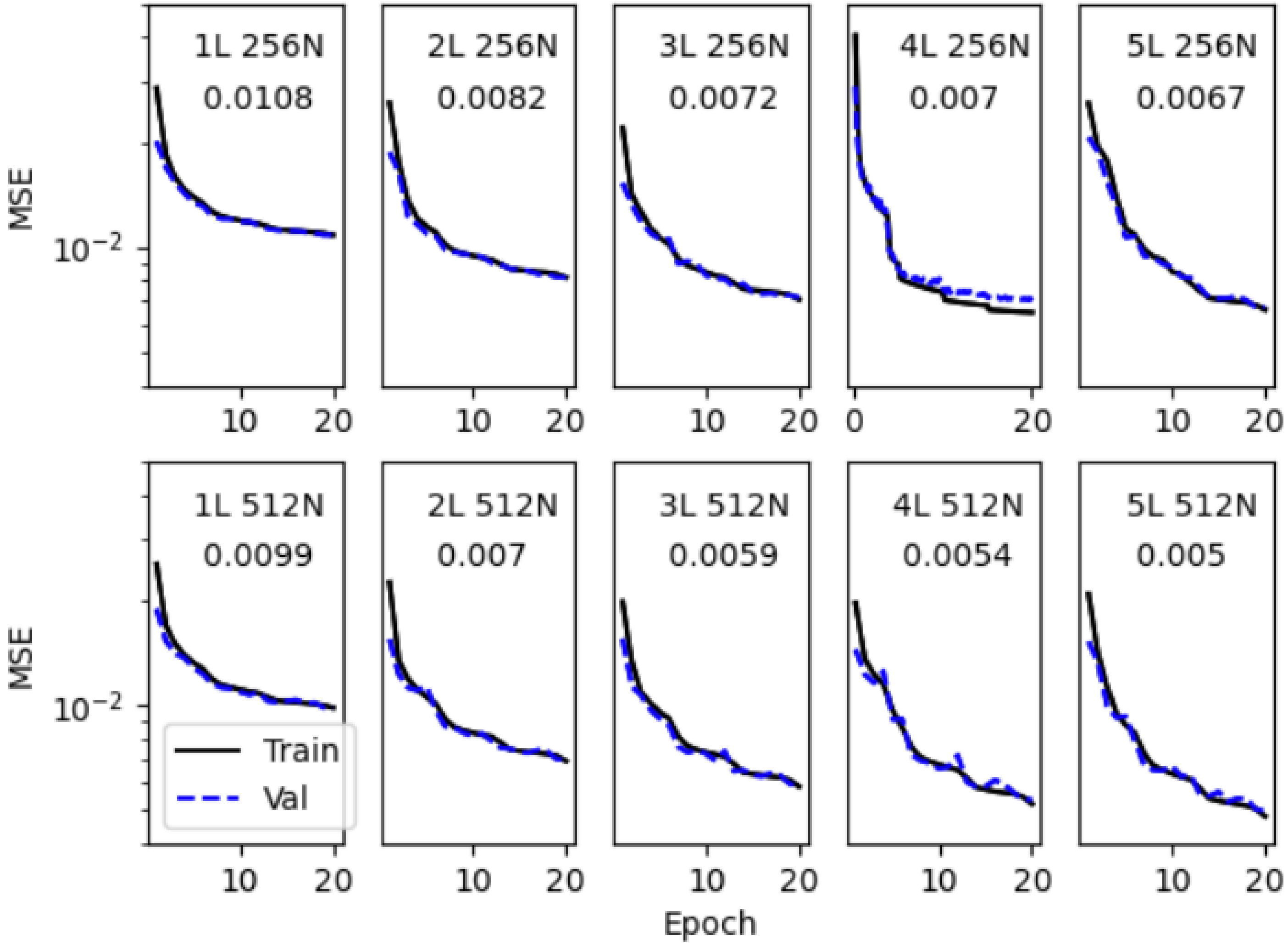



**Figure 5.** Training and validation curves showing the evolution of mean-squared error (MSE) as a function of epochs for multi-layer perceptrons with 1 to 5 hidden layers (L) each with 256 or 512 nodes (N). The MSE after 20 epochs appears on each panel.

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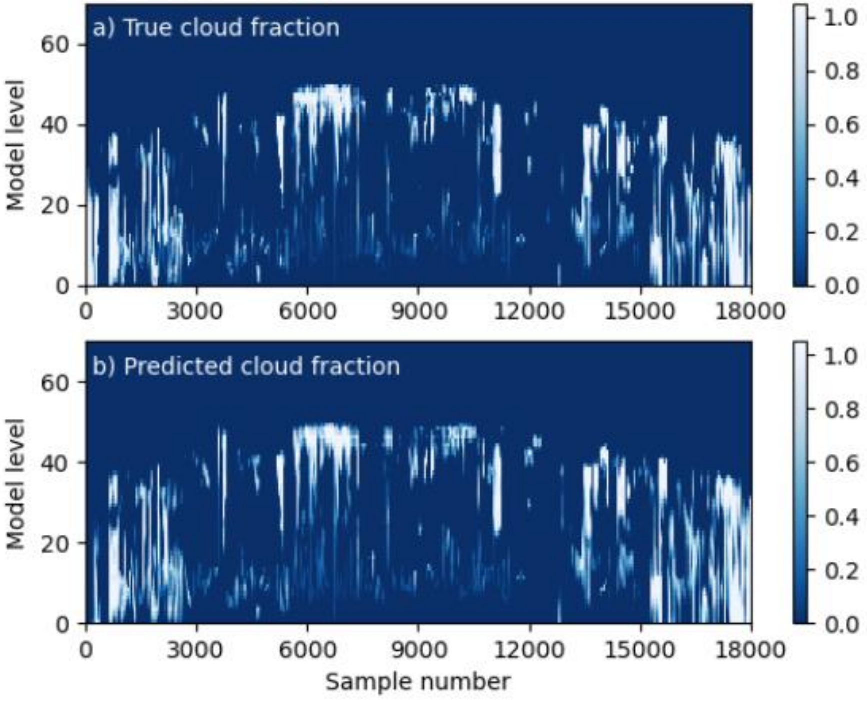


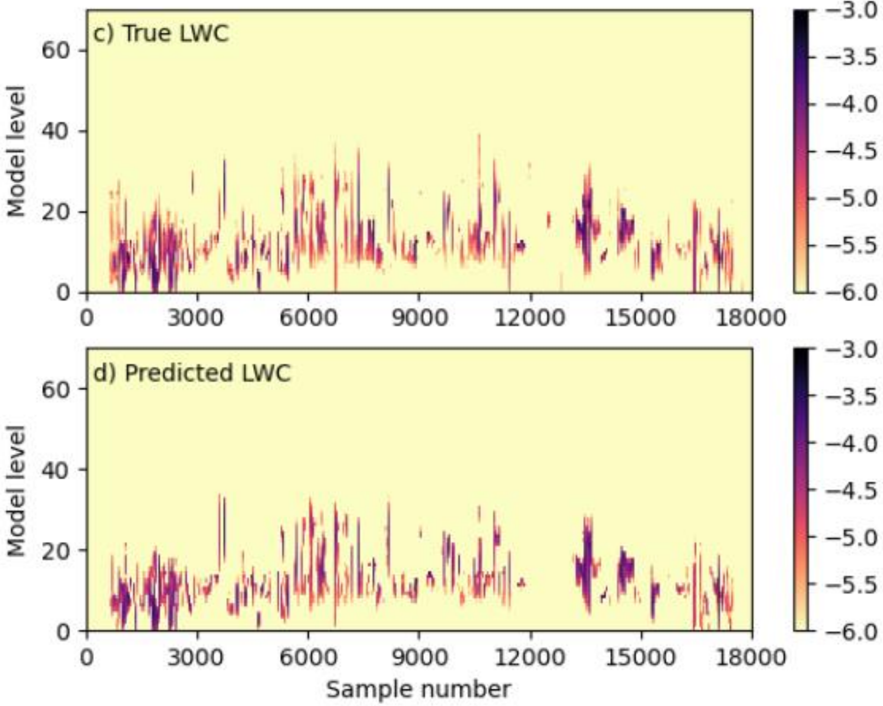


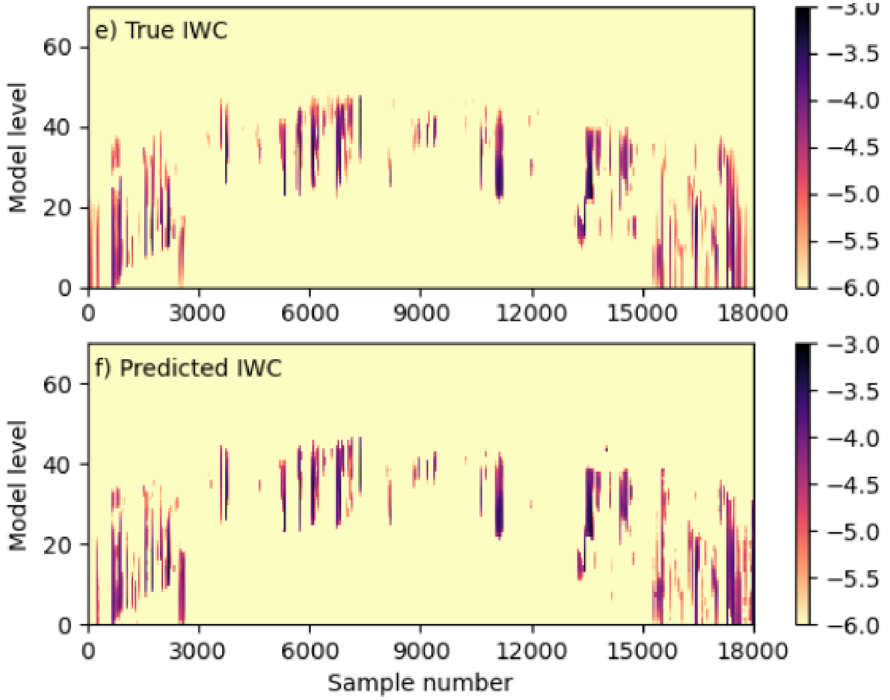


Validation against not-used-in-training data

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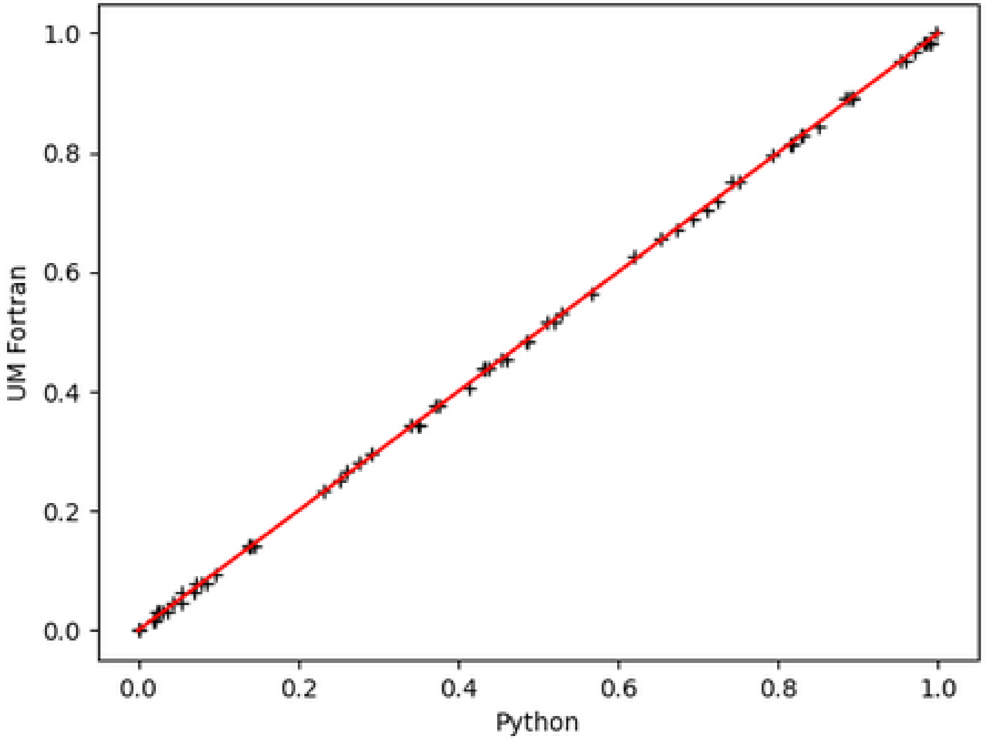
Coupling of Python-trained Neural Networks to the Unified Model written in Fortran.

Use the **ENNUF** frame-work.

Includes sanity check that NN in Fortran reproduces known good output (KGO) from version in Python.




ENNUF

(ENNUF also works in LFRic)

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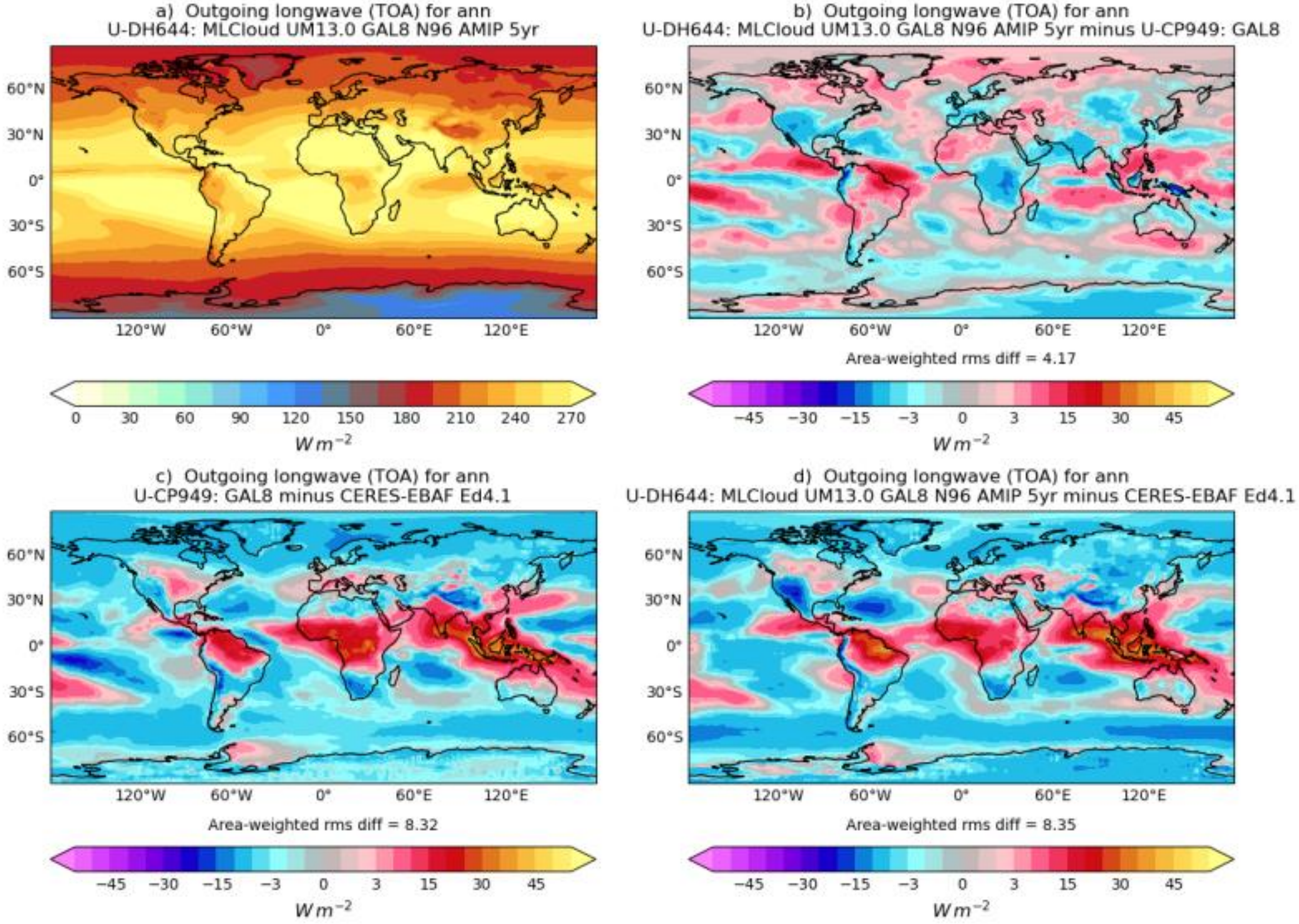
Replace the PC2 cloud scheme in the climate model with the ML one.

Runs stably for many years.



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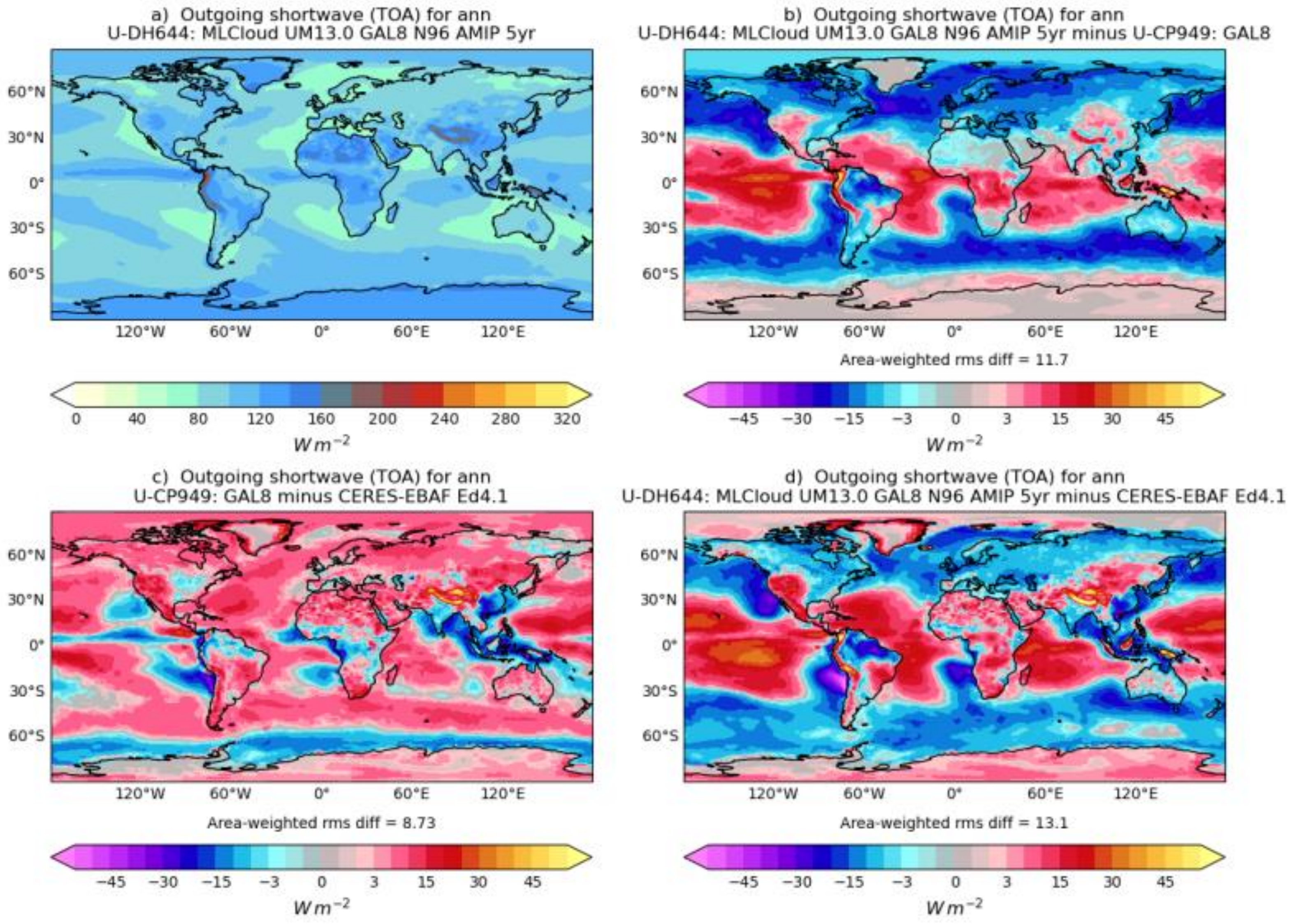
a) Outgoing shortwave (TOA) for ann
U-DH644: MLCloud UM13.0 GAL8 N96 AMIP 5yr
b) Outgoing shortwave (TOA) for ann
U-DH644: MLCloud UM13.0 GAL8 N96 AMIP 5yr minus U-CP949: GAL8
Area-weighted rms diff = 11.7
c) Outgoing shortwave (TOA) for ann
U-CP949: GAL8 minus CERES-EBAF Ed4.1
Area-weighted rms diff = 8.73
d) Outgoing shortwave (TOA) for ann
U-DH644: MLCloud UM13.0 GAL8 N96 AMIP 5yr minus CERES-EBAF Ed4.1
Area-weighted rms diff = 13.1
60°N
30°N
0°
30°S
60°S
120°W
60°W
0°
60°E
120°E
0
40
80
120
160
200
240
280
320
−45
−30
−15
−3
0
3
15
30
45
W m⁻²

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We have blazed a path:

from UM convective-scale simulations via
coarse-graining,
normalisation,
NN training & validation and
grafting into the UM

to show that convective-scale information can be machine-learnt and put back into the global model!

So convective-scale modelling is useful in itself (of course!)…

but it is also useful as a source of high-res data to improve the coarse model.

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In a world where big-tech can mine ERA5 and produce global weather forecast emulators at the 25 km scale… and beyond.

Q: What is our unique selling point?

A: The ability to develop/run/improve physics-based kilometre-scale models with better clouds/rain/extremes either to use in themselves or as a source of data for training the next generation of emulators.