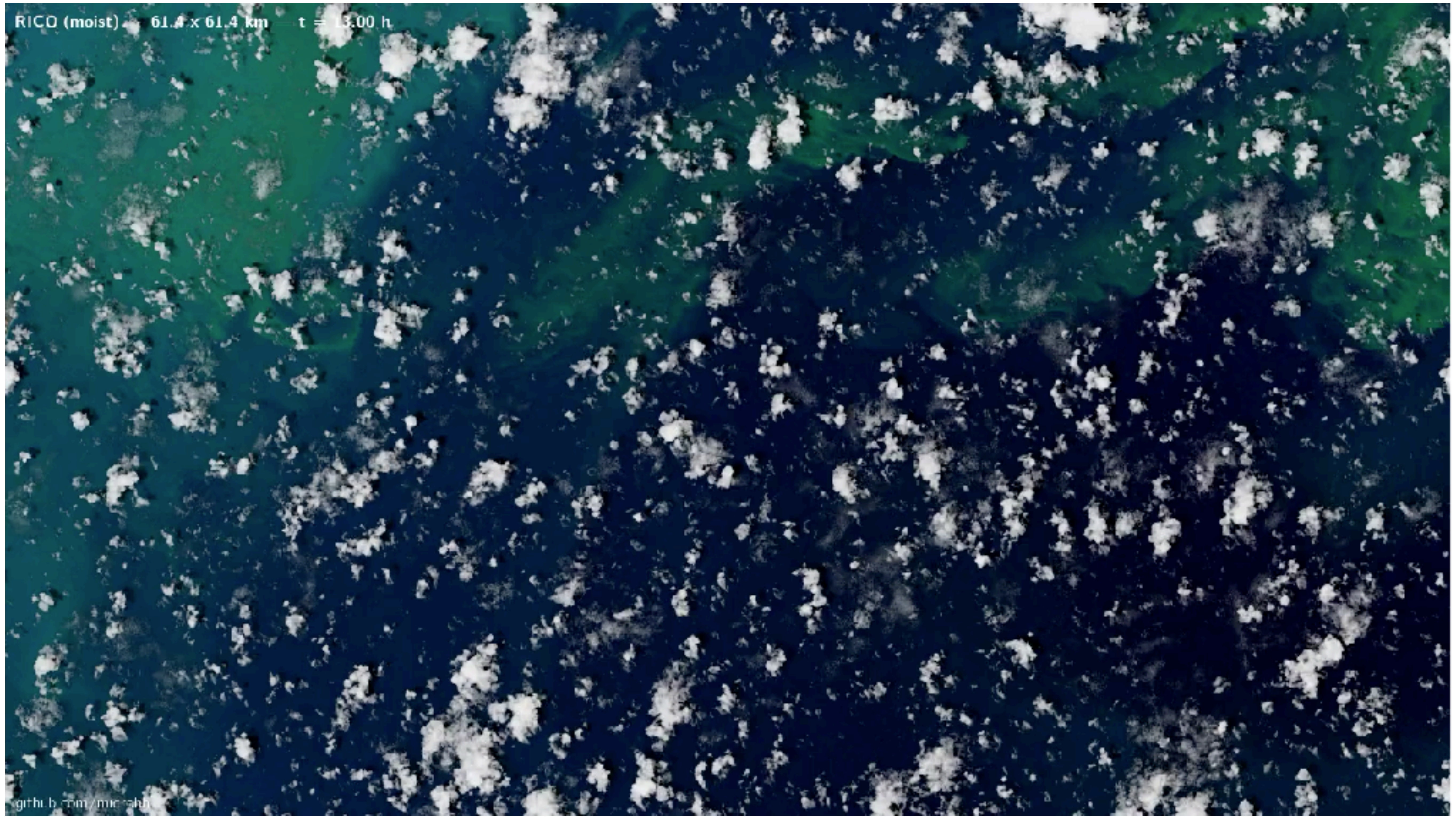
Machine-learned turbulence in next-generation weather models

Robin Stoffer, Caspar van Leeuwen, Damian Podareanu, Menno Veerman, ***Chiel van Heerwaarden***



Deep learning for science workshop - ISC 2019

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The need for accurate weather forecasts is constantly increasing

- Weather forecasts are important to anticipate on extreme weather

Drought in Summer 2018

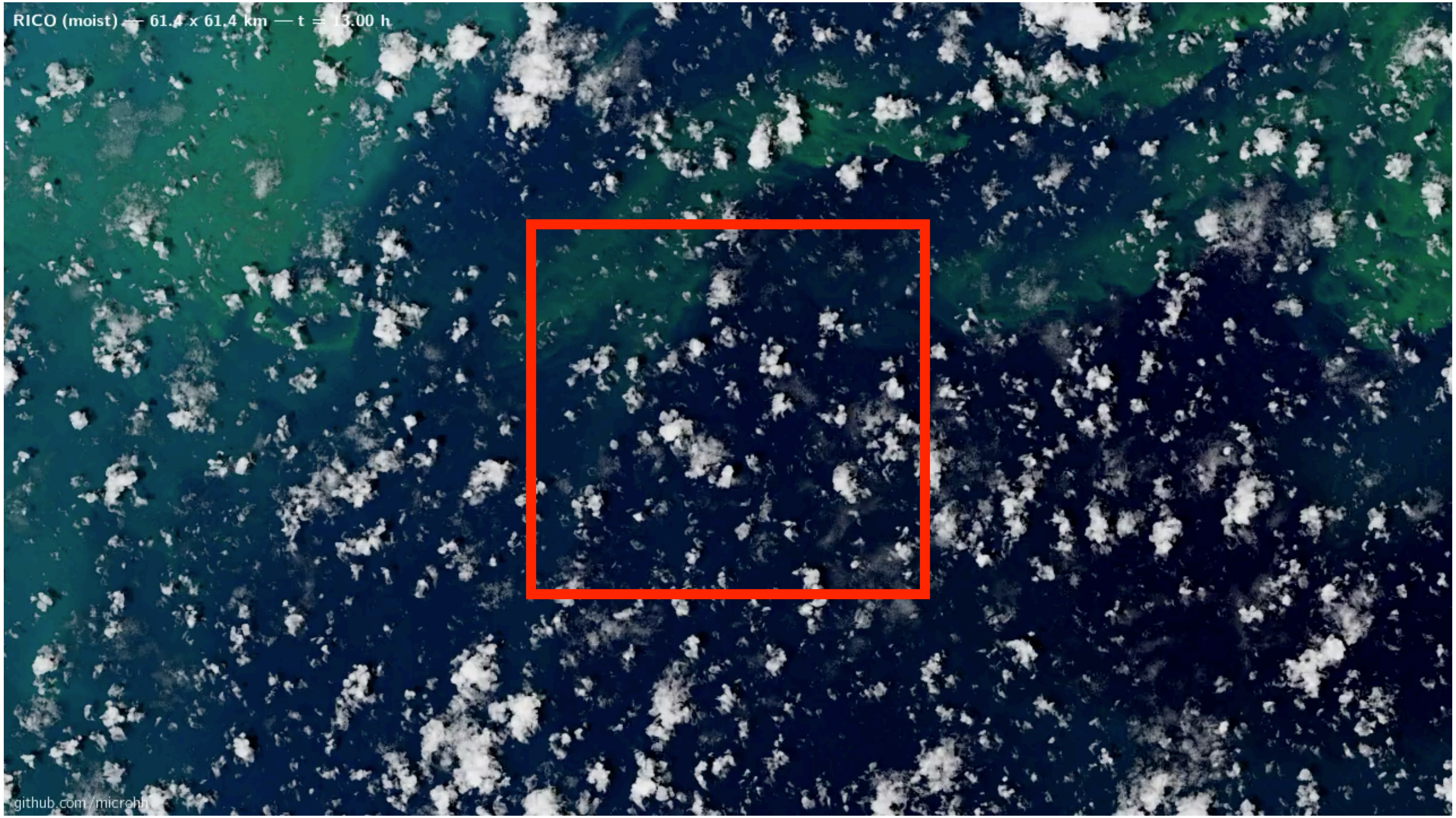
Texelse Courant, 22 July 2018, © Pieter de Vries

Extreme precipitation in Summer 2018

© De Gooi- en Eemlander, 5 September 2018

- The need for accurate and detailed weather models is increasing

Weather models are slowly moving towards cloud-resolving grid spacings (dx ~ 10 m)



vimeo.com/channels/microhh

The computational barrier of increasing resolution

- We cannot keep on increasing resolution
- Increasing the global weather forecast from 10 km to 1 km grid spacing
  - ~ 5,000 x more power consumption
  - ~ 10,000 x more computer cores
- With regional models ~100 m is potentially possible in the next decade…
- …but we need smart solutions to accelerate models
- Machine learning provides unique opportunities

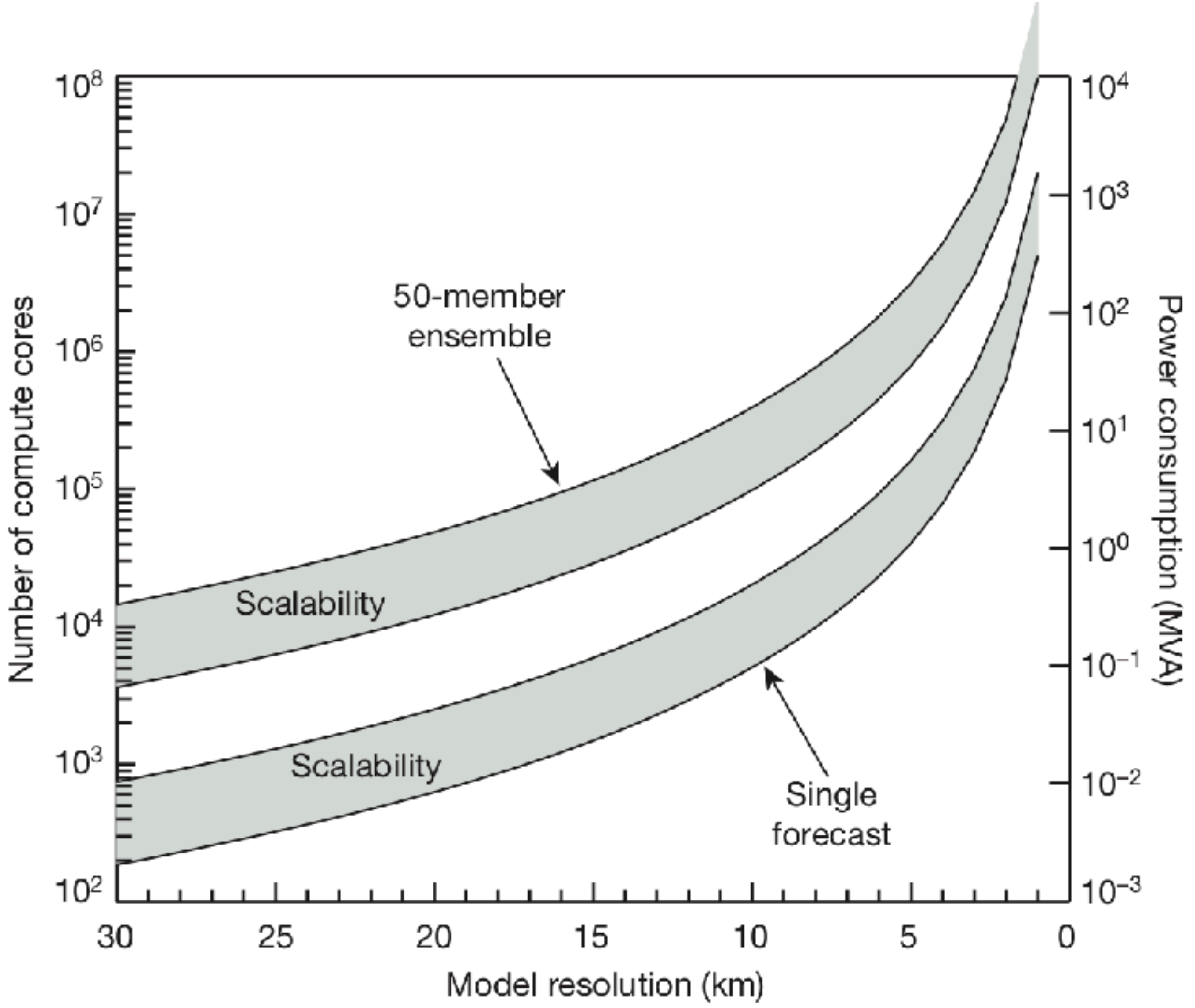
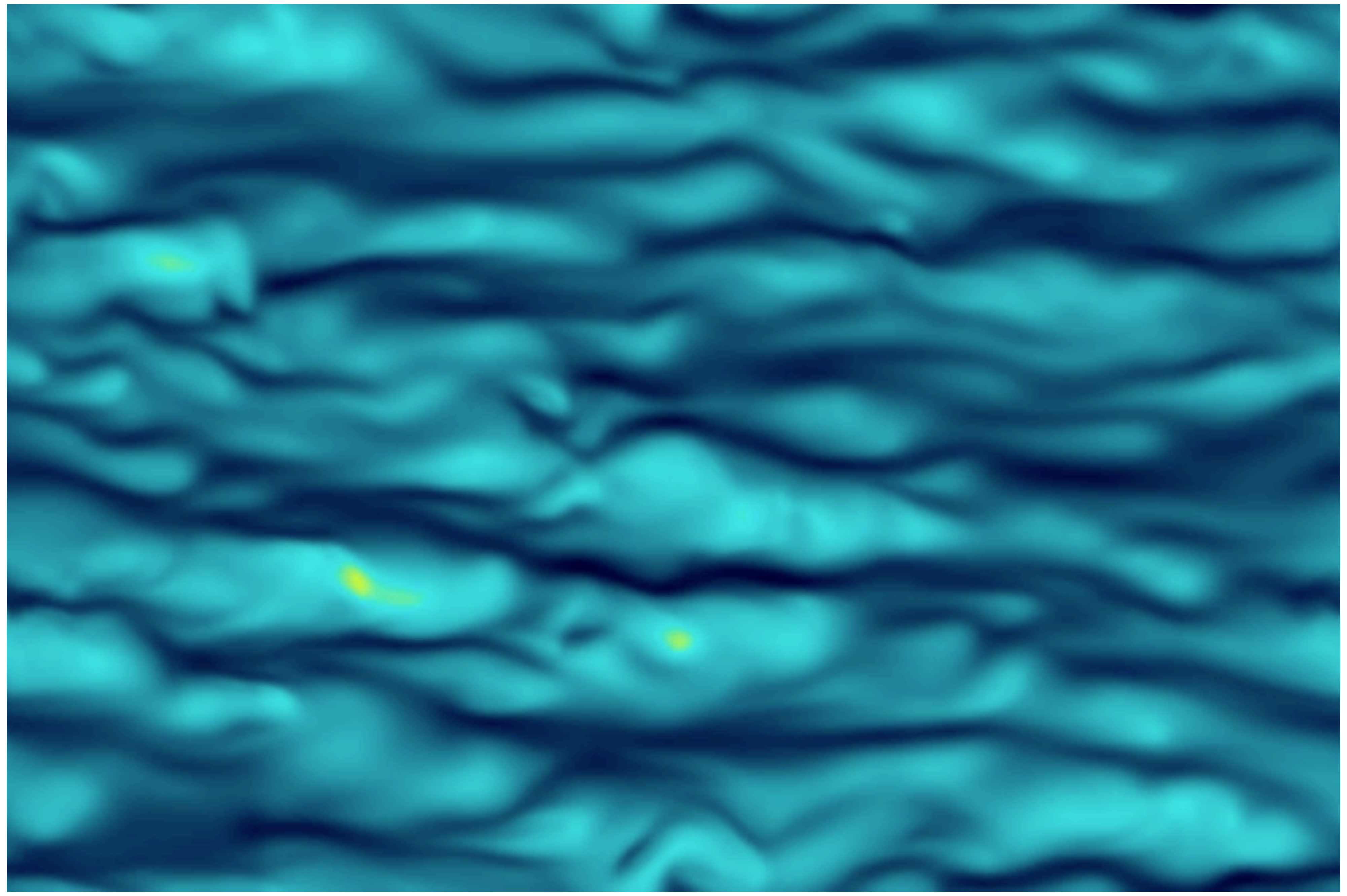


Figure 5 | CPU and power requirements as a function of NWP model resolution. Simplified illustration of the number of compute cores (left *y*-axis) and power (in units of megavolt amps, MVA, right *y* axis) required for single 10-day model forecast (lower curves) and 50-member ensemble forecast (upper curves) as a function of model resolution, given today's model code and compute technology. The shaded area indicates the range covered when assuming perfect scaling (bottom curve) and inefficient scaling (top curve), respectively. Today's single global forecasts operate at around 15 km while ensembles have around 30 km resolution.

Bauer et al. (2015, Nature)

Machine learning can provide smart solutions for computation of physics

- Physical processes happening at scales smaller than the grid can be computationally very expensive
- Atmospheric radiation (Menno Veerman's talk earlier today)
  - Transfer of solar and thermal energy through the atmosphere
- Microphysical processes
  - Processes that make water droplets and ice crystals
- **Turbulent transport**
  - Mixing caused by turbulence
  - Friction
  - Dispersion of pollutants
  - Water transport



Simulated wind patterns at 2 m height (black is no wind, yellow 4 m/s)
Domain is ~3000 x 2000 m

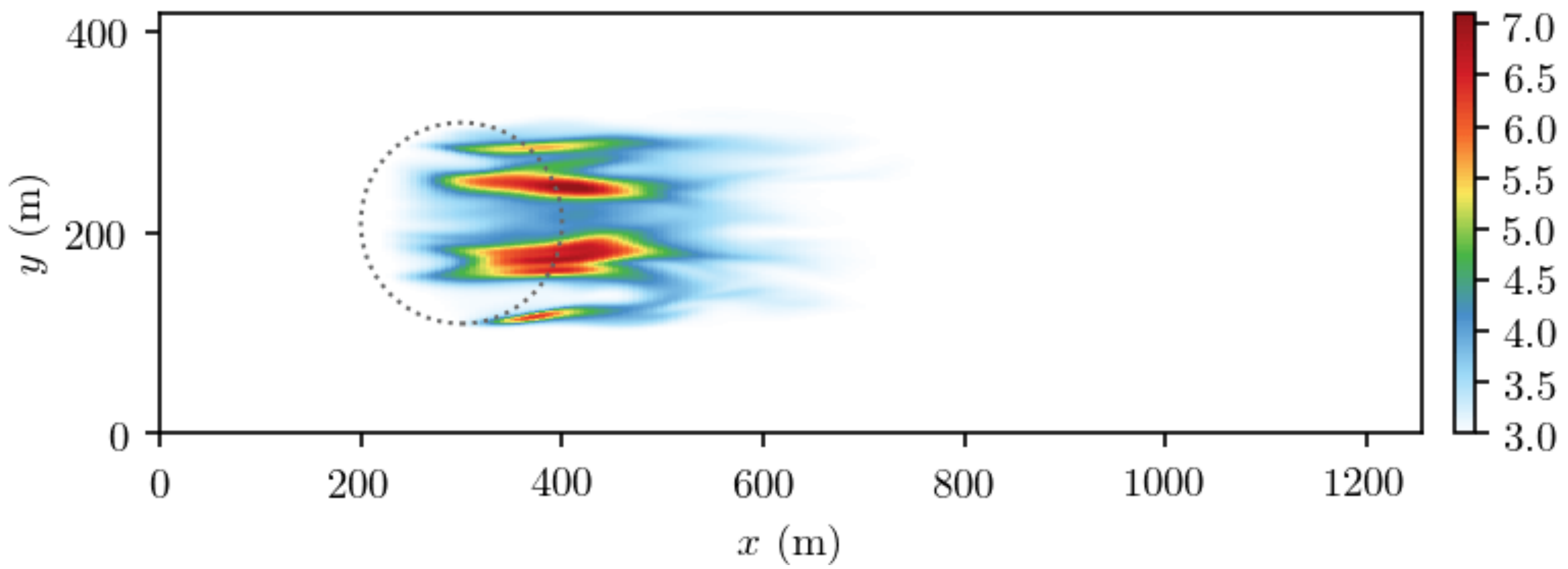
Where do fine scale flow characteristics matter: a case study of irrigation in the desert

- Next-generation weather models can better predict estimations of evaporation in irrigated regions
- Strong spatial variation in relative humidity near the land surface regulates evaporation of water

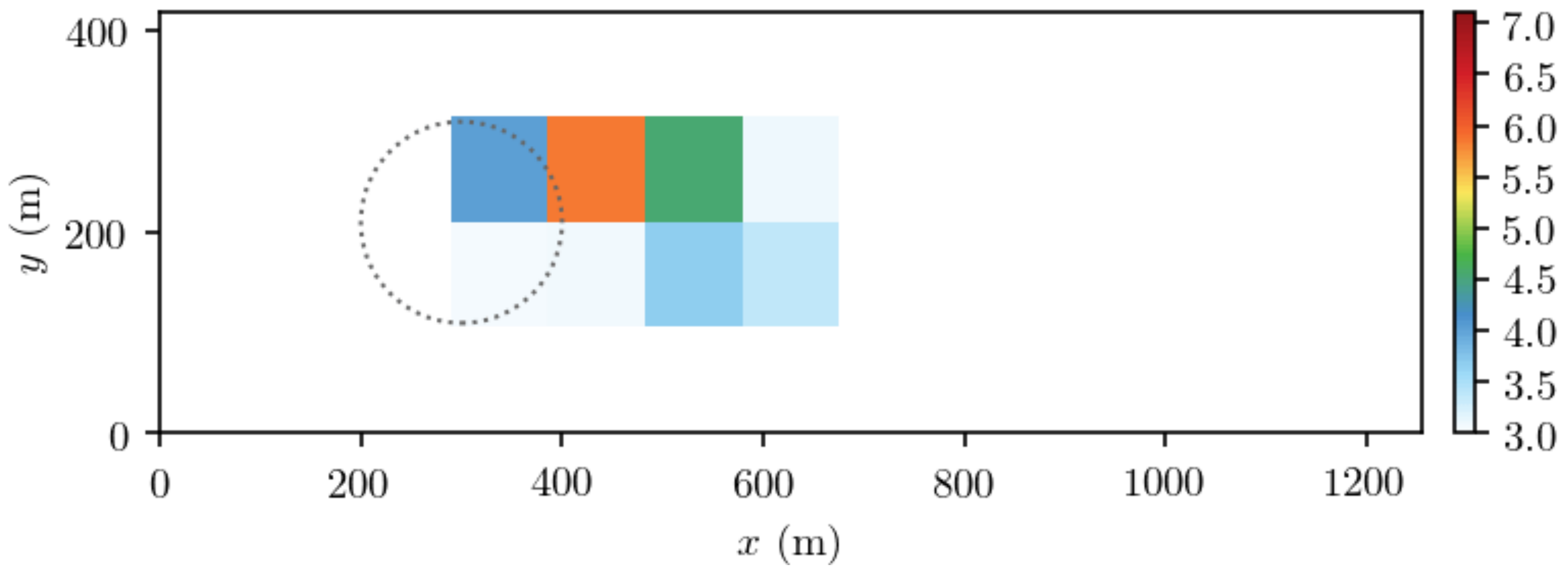
Irrigation in semi-arid and arid regions leads to fascinating landscape patterns (Saudi-Arabia)
[MET-P: Machine-learned evapotranspiration prediction over irrigated agriculture]

Simulation of water transport: where are we and where do we want to go?

- Current weather models do not pick up the structure of the irrigation structures
  - Unrealistic representation of near-surface atmosphere
- In the ideal world, we make simulations that capture all the physics (~1 m grid)
  - Unfeasible in terms of computational power
- The challenge: the middle way (~100 m grid)
  - Make 100 m resolution models produce the correct water transport
  - Make 100 m resolution models produce the correct surface fluxes



Atmospheric water content at 2 m height in the atmosphere.
***Top** is the simulation detail that we want.*
***Bottom** is what can achieve in 10 years operationally.*



MicroHH as the simulation tool (www.microhh.org)

- MicroHH is a CFD code for 3D simulation of the near-surface atmosphere at very high resolution (~1 m)
- Written in modern C++
- It has a NVIDIA CUDA mode for fully GPU-resident simulations (1 Tesla V100 ~ 300 cores of SURFsara Cartesius)
- Versatile code: from simple fluid dynamical problems to deep moist convection

Model description paper 28 Aug 2017

MicroHH 1.0: a computational fluid dynamics code for direct numerical simulation and large-eddy simulation of atmospheric boundary layer flows

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The mathematical problem to solve

- The advection term in the one dimensional Navier-Stokes equation is

$$\frac{\partial u}{\partial t} + \frac{\partial uu}{\partial x} = \ldots$$

- If we take a perfectly resolved field and filter this to a coarser field, we get

$$\frac{\partial \overline{u}}{\partial t} + \frac{\partial \overline{uu}}{\partial x} = \ldots$$

- Problem, we do not know the $\overline{uu}$ term

- We can define a new quantity, which we define the unresolved transport

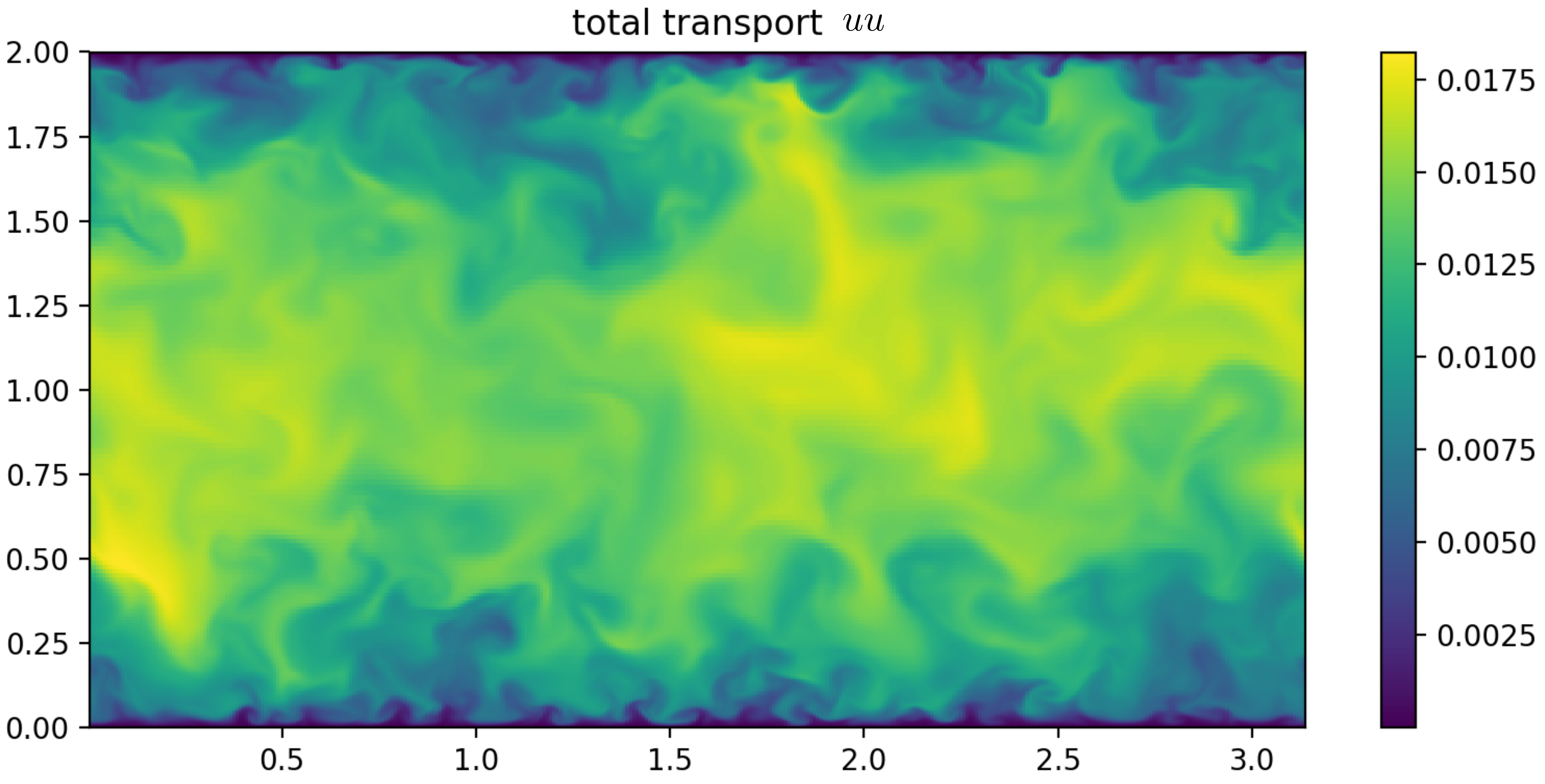
$$\tau \equiv \overline{uu} - \overline{u}\,\overline{u}$$

$$\frac{\partial \overline{u}}{\partial t} + \frac{\partial \overline{u}\,\overline{u}}{\partial x} + \frac{\partial \tau}{\partial x} = \ldots$$

- Current *subgrid-scale models* to predict the unresolved transport are expensive or/and inaccurate

An illustration of the math: simulation in the high resolution model

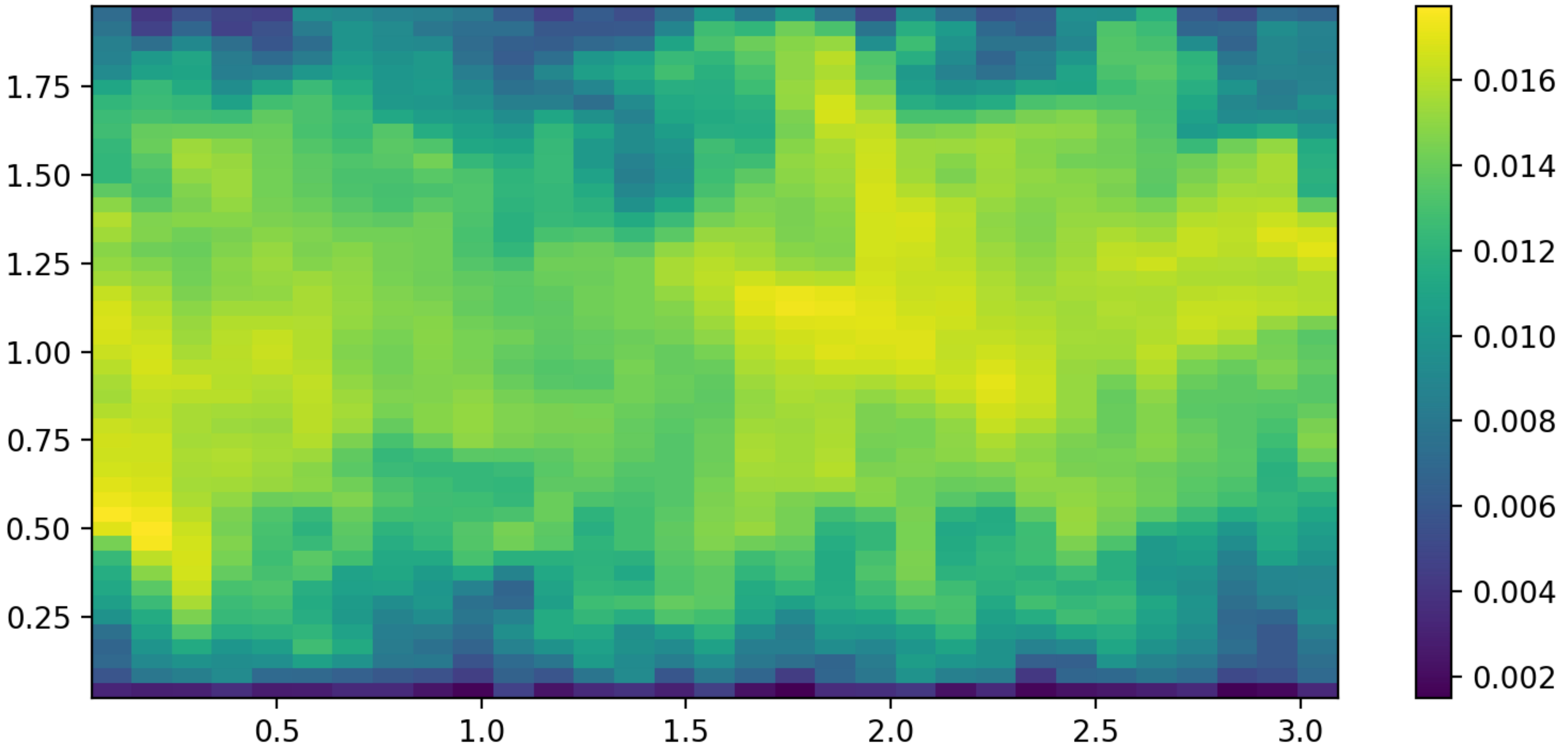
$$\frac{\partial u}{\partial t} + \frac{\partial uu}{\partial x} = \dots$$



An illustration of the math using a cross section of the channel flow

$$\frac{\partial \overline{u}}{\partial t} + \frac{\partial \overline{uu}}{\partial x} = \dots$$

coarsened total $\overline{uu}$



An illustration of the math using a cross section of the channel flow

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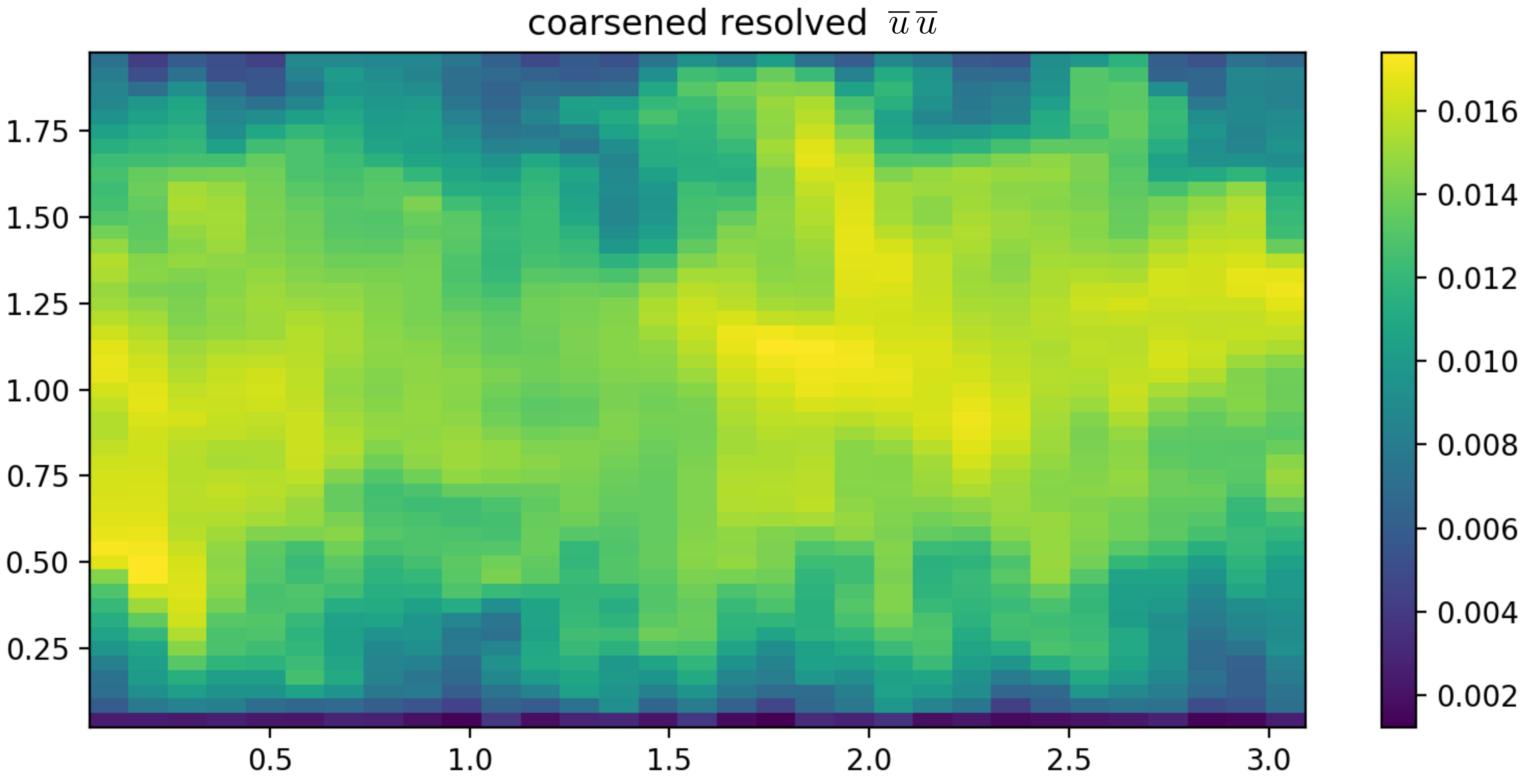

An illustration of the math using a cross section of the channel flow

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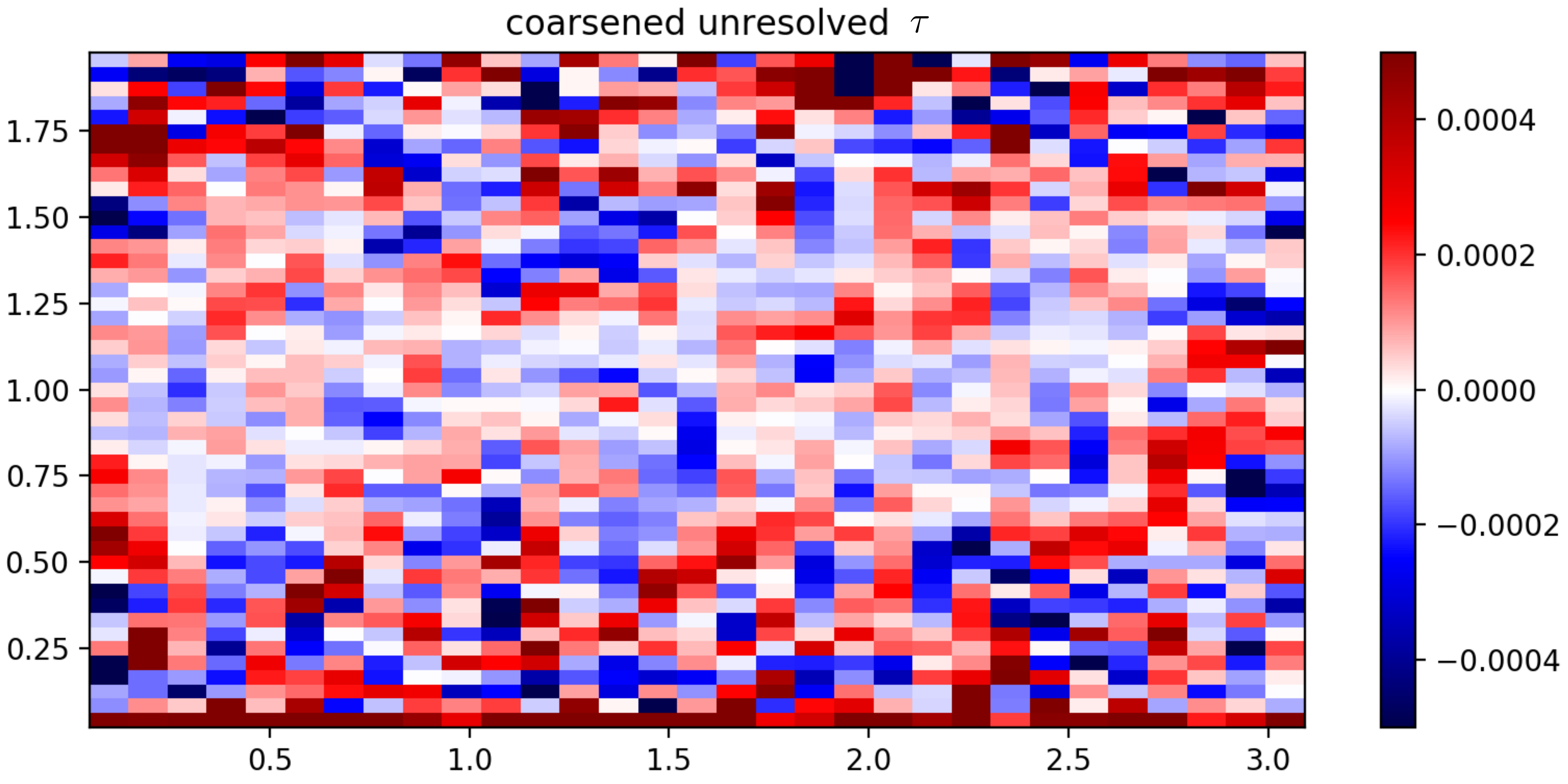


Can ***neural networks*** *predict the* ***unresolved transport*** *as a function of the* ***resolved transport****?*

or

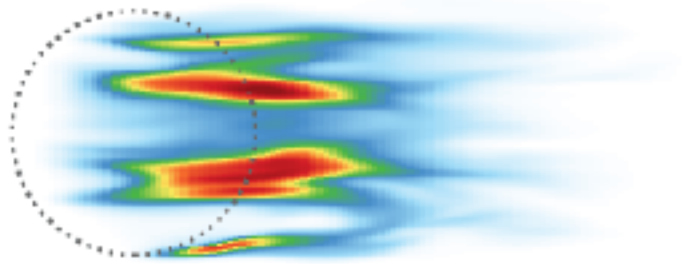
Can we ***train*** *a* ***coarse-resolution model*** *to be as good as a* ***fine-resolution model****?*

Using deep learning to make the 100-m simulation as accurate as the 1 m resolution

- We train the **100 m resolution** simulation to be as accurate as the **1 m resolution**

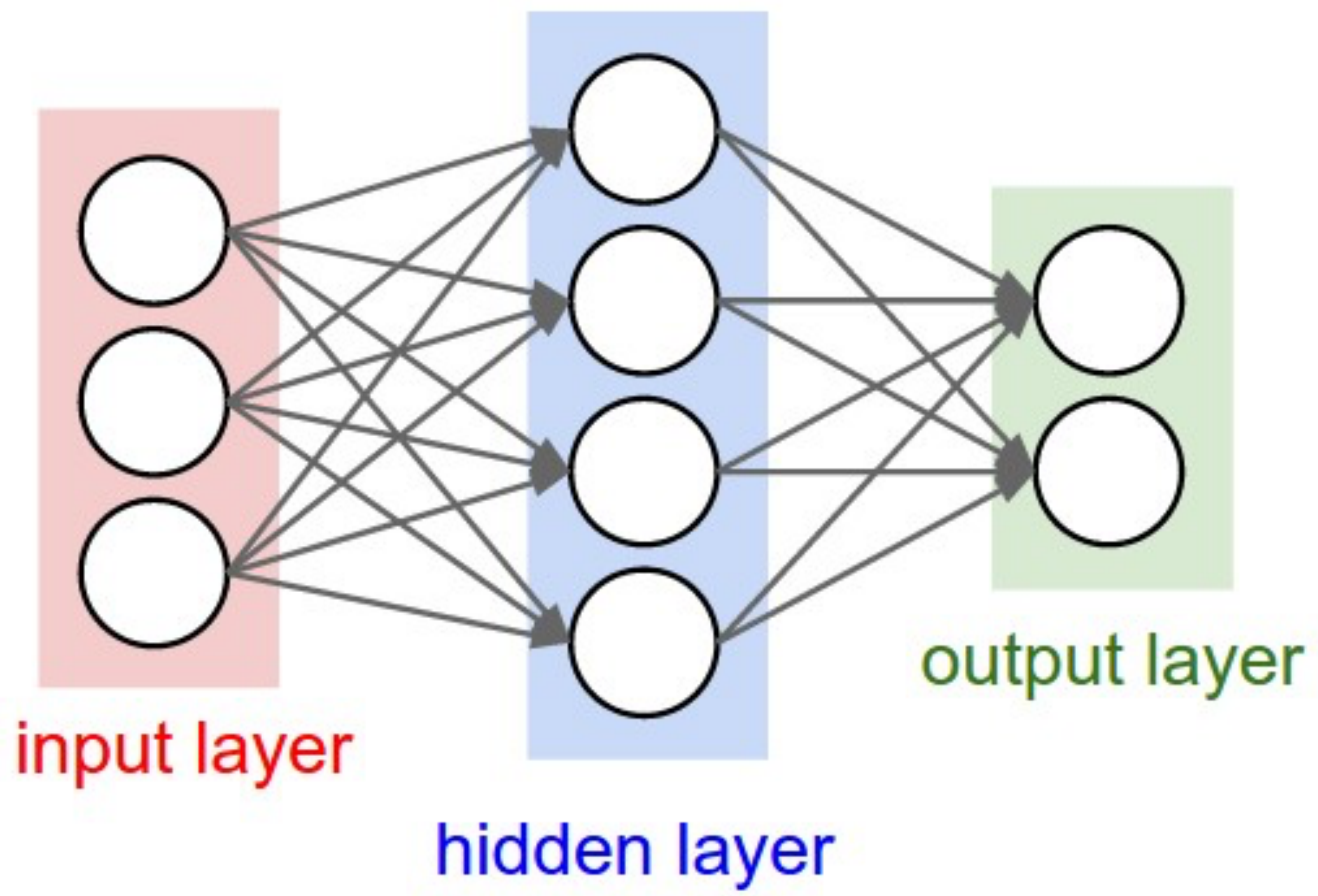
Input: *flow, temperature, and moisture field at 100 m resolution*

Training: *flow, temperature, and moisture field at 1 m resolution*



Output: *unresolved transport at 100 m*

We aim to let the network predict the unresolved transport as a function of the 100 m resolution flow field

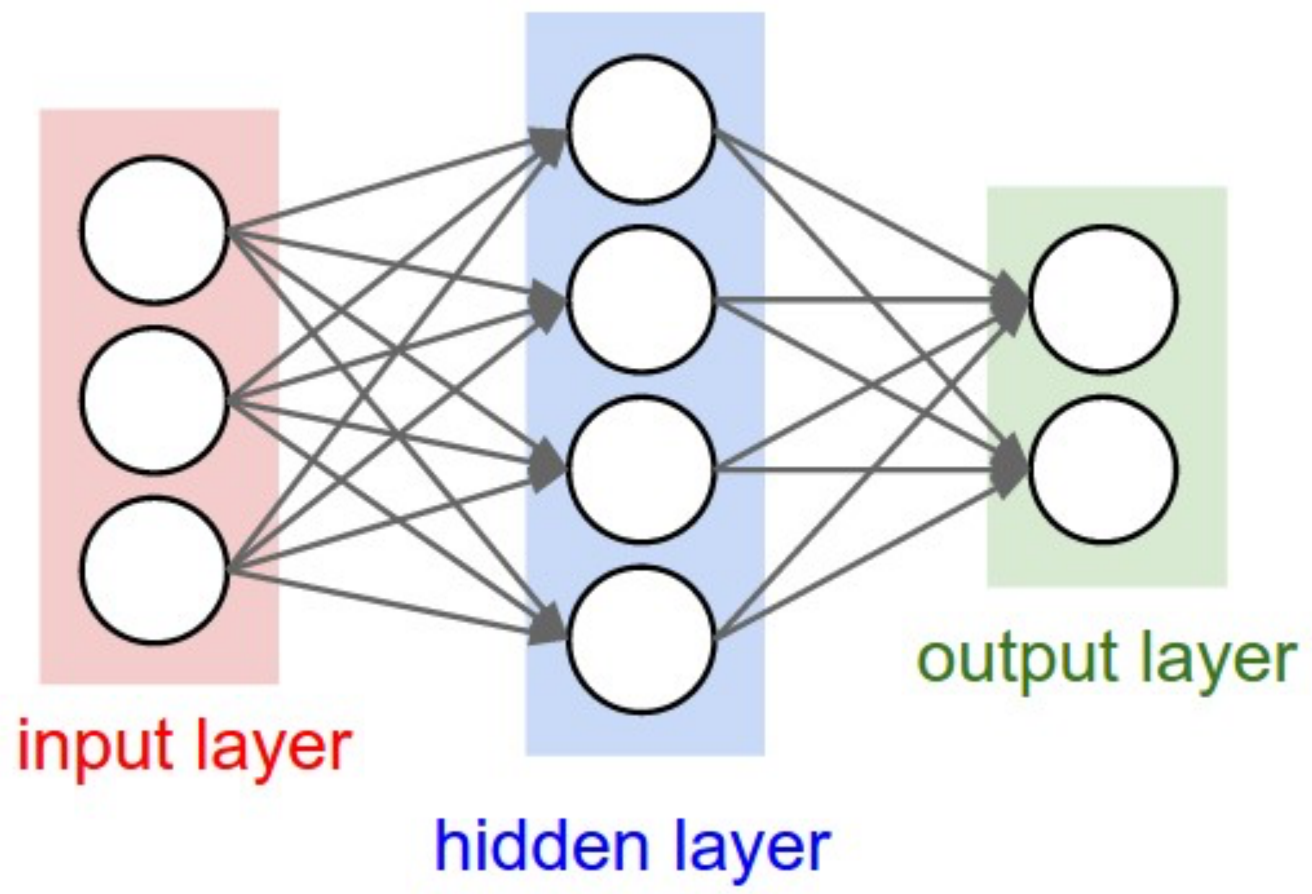


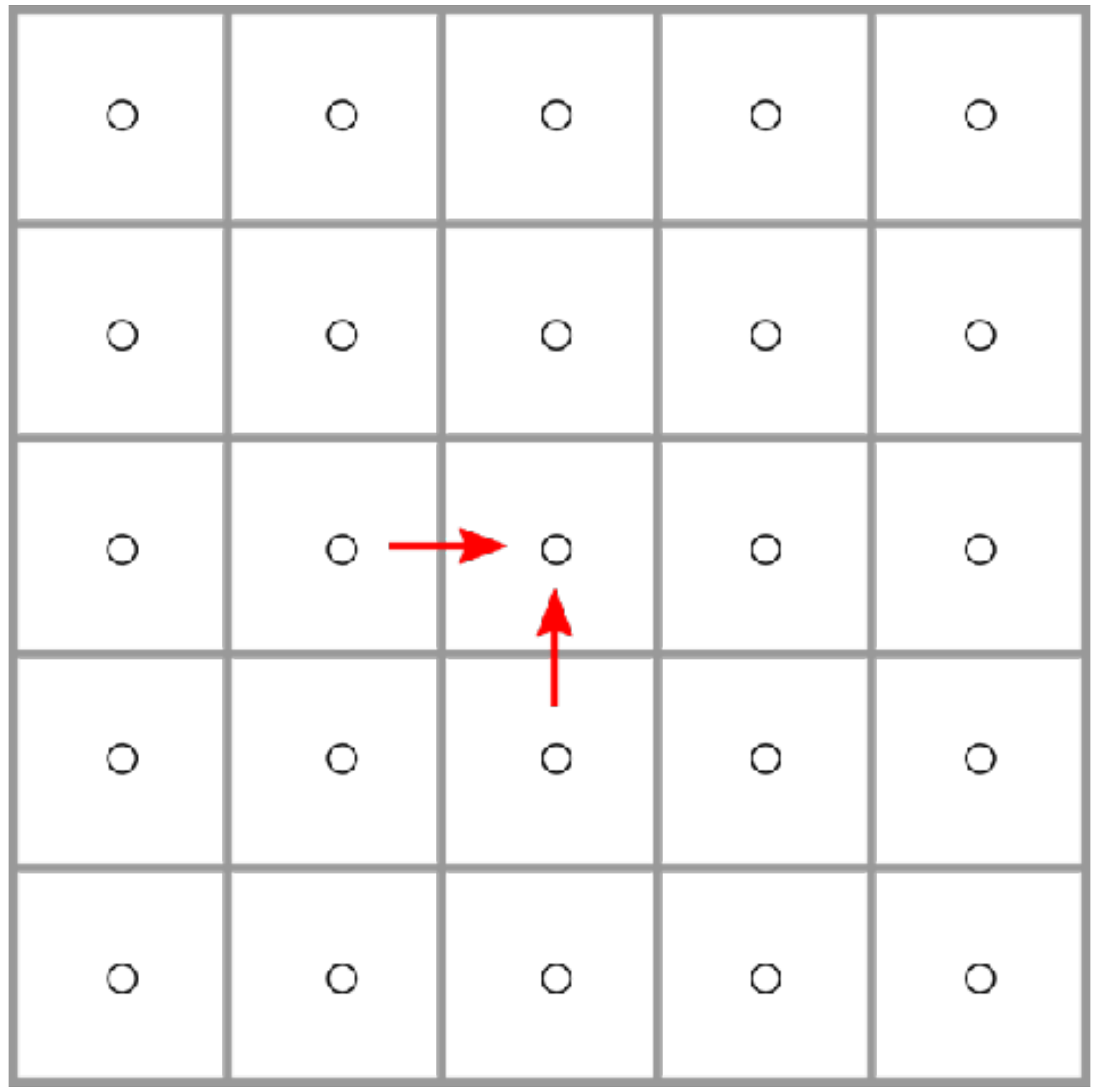
SURF Open Innovation Lab
provides expertise in deep learning

$$\frac{\partial \overline{u}}{\partial t} + \frac{\partial \overline{u}\,\overline{u}}{\partial x} + \frac{\partial \tau}{\partial x} = \dots$$

Multilayer perceptron as a neural network

- Network takes 3 3D dimensional blocks (5 x 5 x 5 grid points)
  - Three wind components
- Network predicts 9 unresolved fluxes (tensor)
  - Three wind components in three directions
- One densely-connected layer of 80 nodes

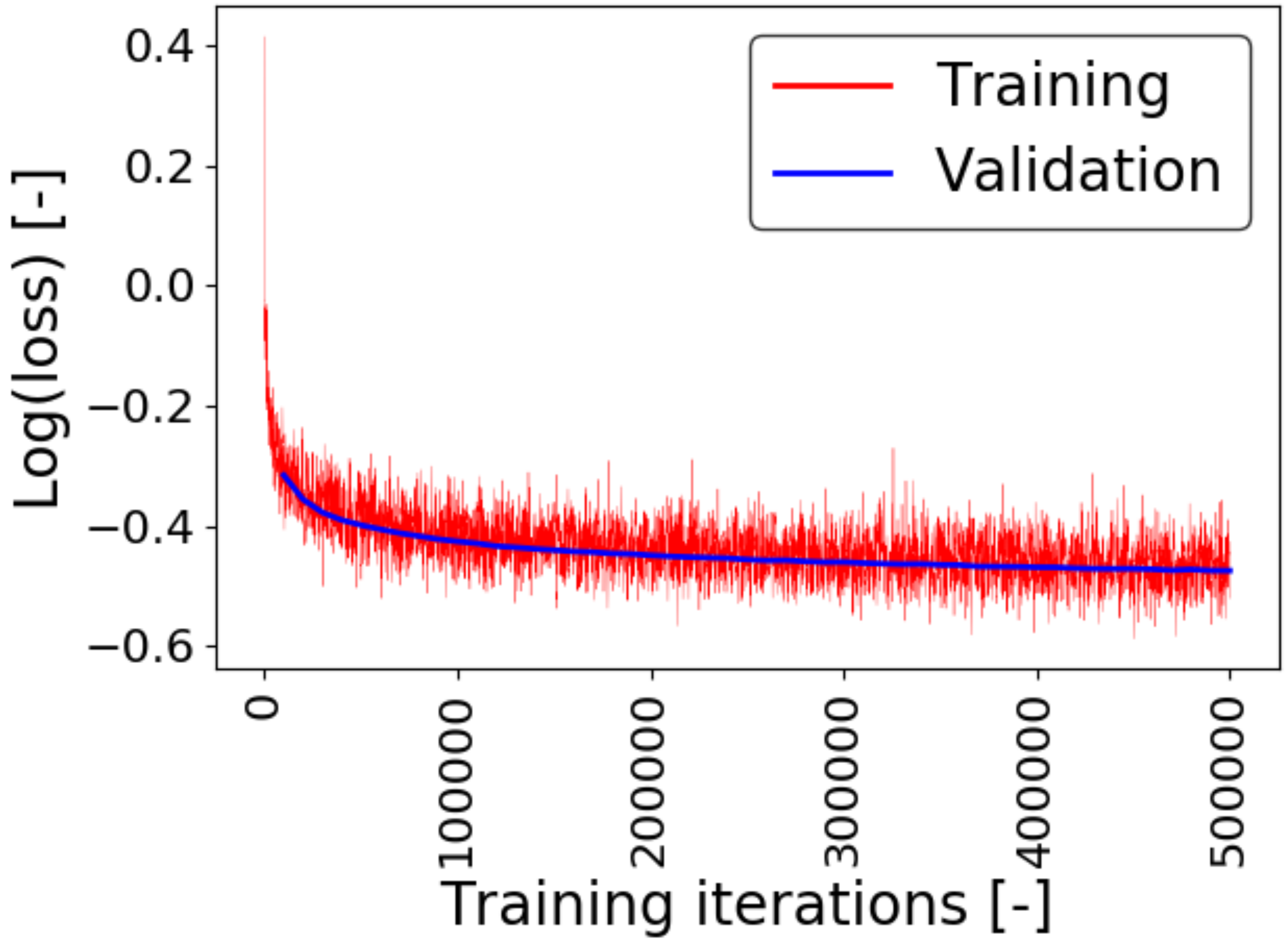




Coarse resolution fields
$\overline{u}, \overline{v}, \overline{w}$
are input to acquire unresolved fluxes

Showing the training in action

- ~300,000 training samples from 3D simulations
- TensorFlow is used for network training
- The loss is the MSE (Adam optimizer)
- The 500,000 iterations comprise 63 epochs
- Batch size 1000
- Learning rate 0.0001
- Distributed training using TensorFlow + Horovod



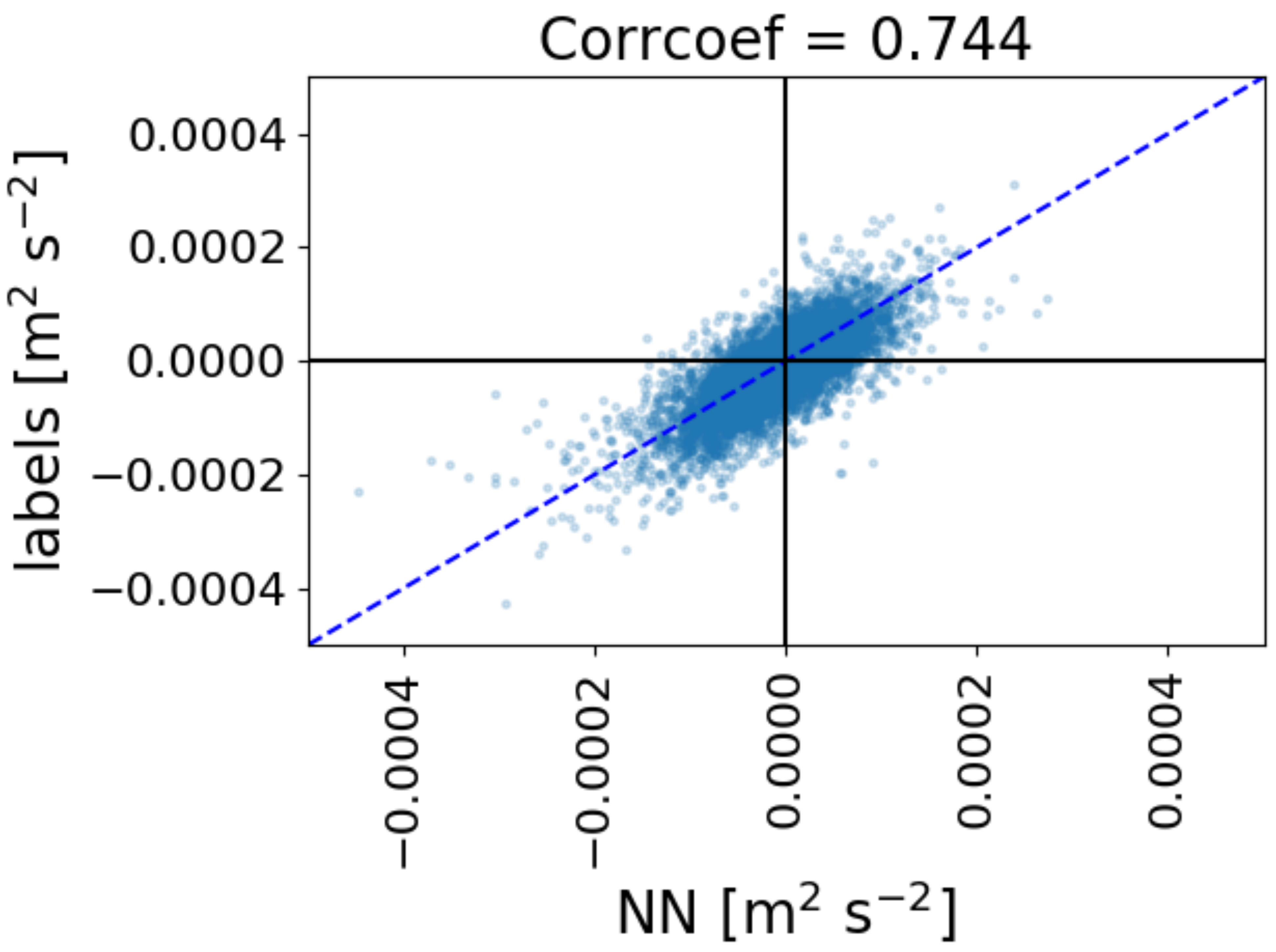
Quality of the network in predicting unresolved transport

- The neural network is very well able to predict the unresolved transport

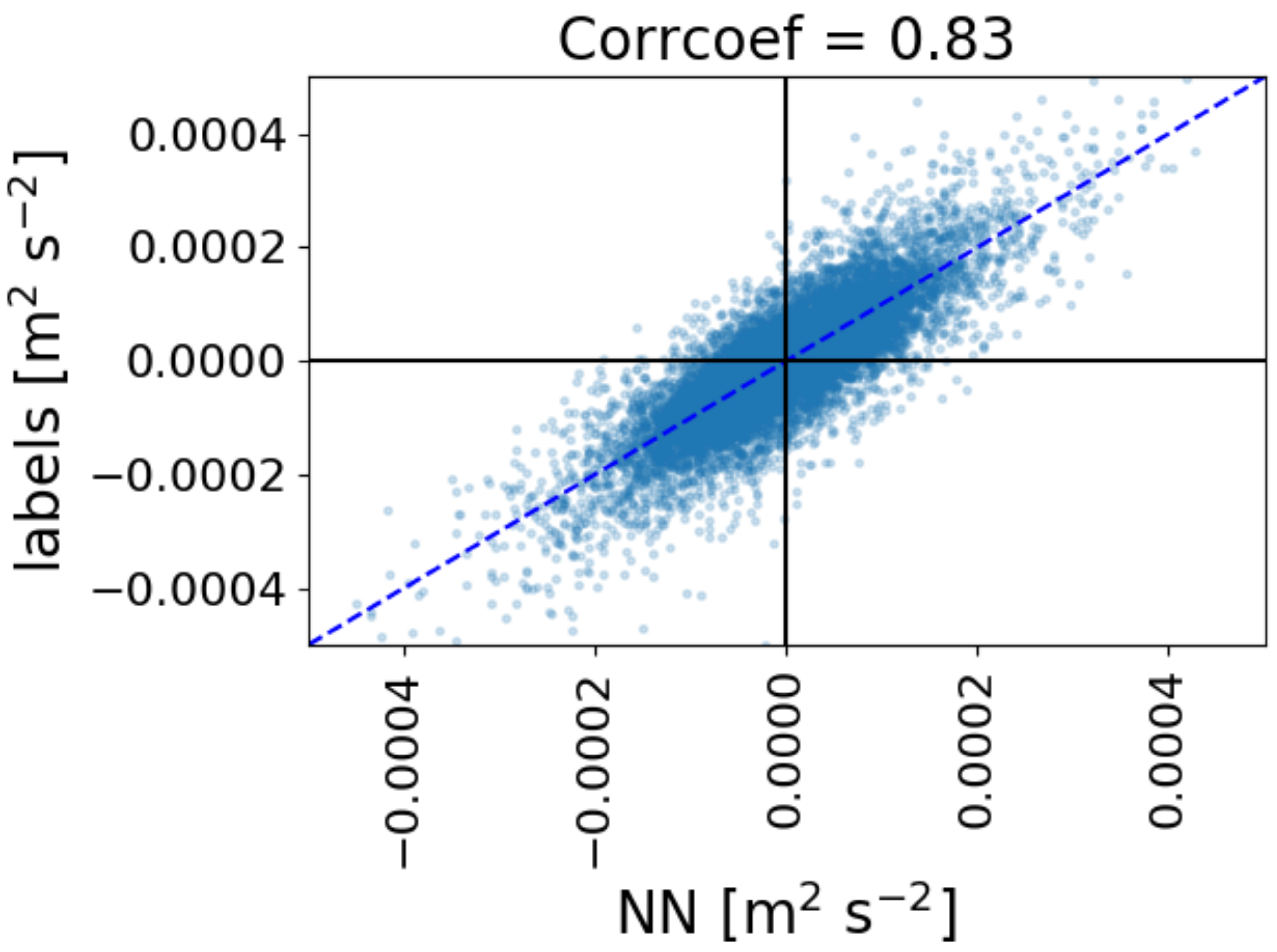
$$\frac{\partial \overline{u}}{\partial t} + \frac{\partial \overline{u}\,\overline{u}}{\partial x} + \frac{\partial \tau}{\partial x} = \dots$$

- Correlation of 0.7 - 0.8 is excellent for prediction of a chaotic system (inherent noise in system)

Predicted transport at a height of 10 m

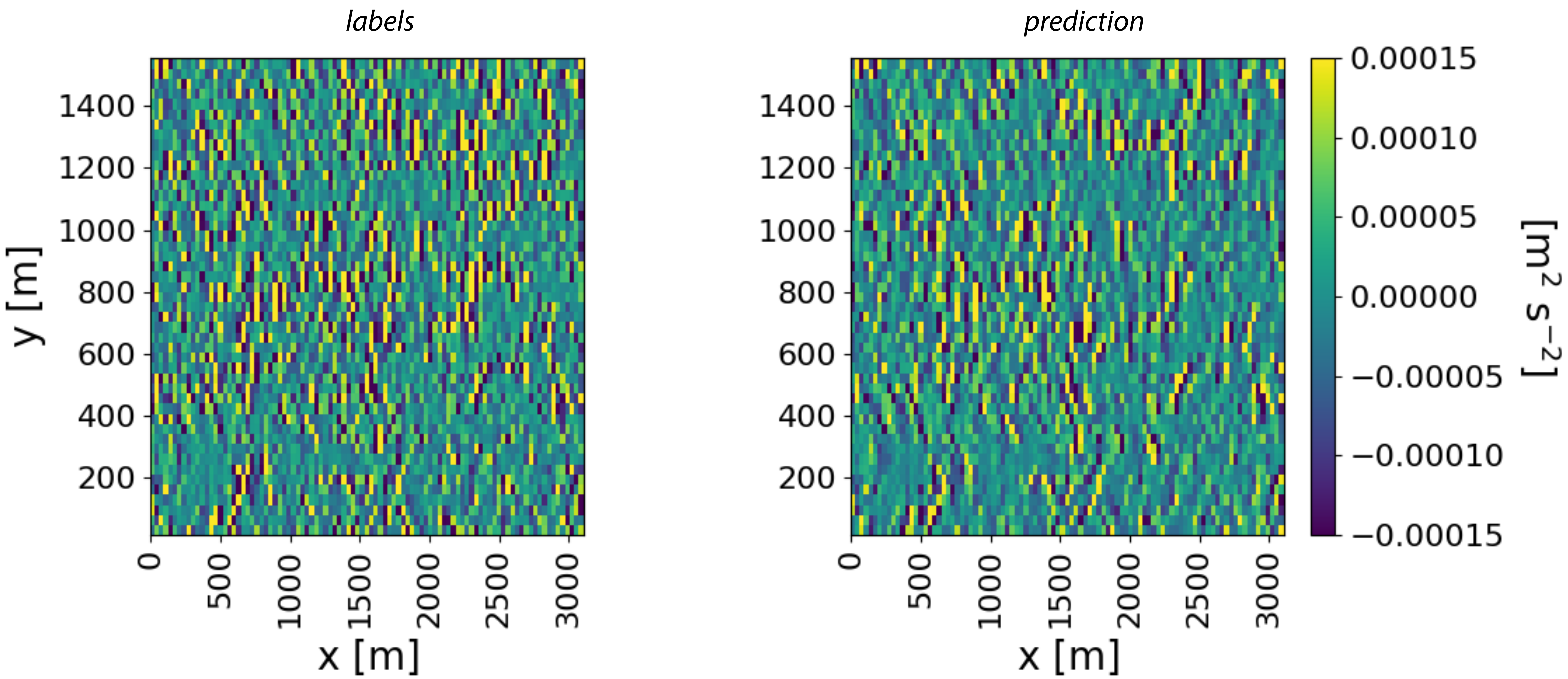


Predicted transport at a height of 100 m



Quality of the network in predicting unresolved transport in the 2D plane

- At a height of approximately 100 m in the atmosphere unresolved transport has the correct pattern



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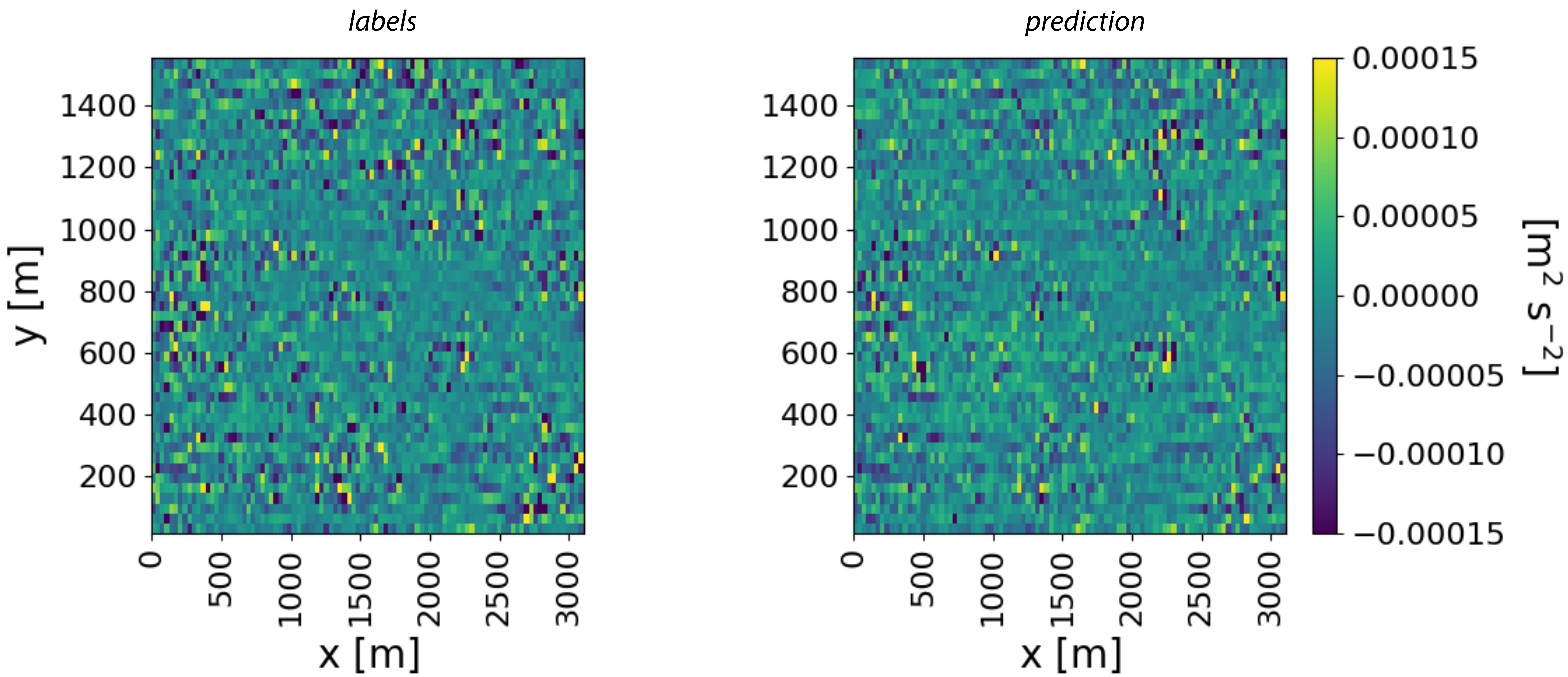

Conclusions: machine learning shows promising results to model turbulent transport

- Need for accurate weather models is higher than ever
- Exponentially increasing power usage with model resolution prohibits fast resolution increase
- Machine-learning can provide computationally cheap and accurate computations of transport by turbulence
- Our proof-of-concept for turbulent transport shows promising results
- Fast inference mode key to successful application
  - TensorRT in CUDA-enabled MicroHH
  - Data handling an open challenge