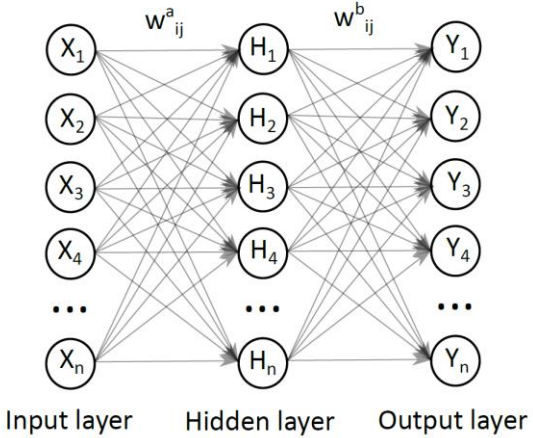
LES subgrid modelling using neural networks

Robin Stoffer[1], Caspar van Leeuwen[2], Damian Podareanu[2], Valeriu Codreanu[2], Menno Veerman[1], Martin Janssens[1], Oscar Hartogensis[1], Chiel van Heerwaarden[1]

[1]Meteorology and Air Quality Group, Wageningen University, The Netherlands

[2]SURFsara, Amsterdam, The Netherlands





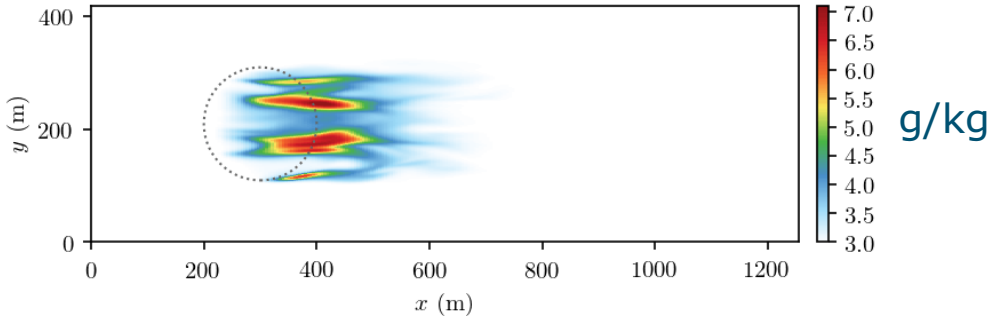
EMS Annual Meeting, 5th September 2022

Publication: Stoffer, R., van Leeuwen, C. M., Podareanu, D., Codreanu, V., Veerman, M. A., Janssens, M., Hartogensis, O. K., and van Heerwaarden, C. C.: Development of a large-eddy simulation subgrid model based on artificial neural networks: a case study of turbulent channel flow, Geosci. Model Dev., 14(6), 3769-3788, https://doi.org/10.5194/gmd-14-3769-2021*, 2021*

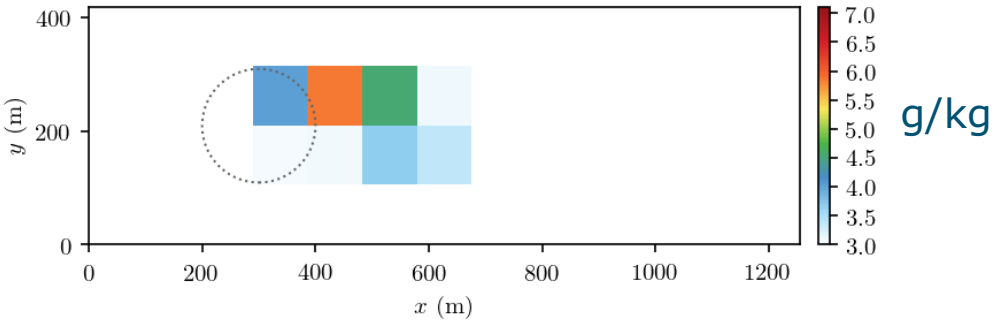
Contact: robin.stoffer@wur.nl

Motivation

Computationally expensive, high-fidelity DNS



Computationally affordable, lower-resolution LES





Picture: George Steinmetz, 2016

Problem:
Traditional LES subgrid models (e.g Smagorinsky) need *strong assumptions*

Idea:
Use instead artificial neural networks (ANNs) that are *trained on high-fidelity data*

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RQ: Can traditional LES subgrid models be replaced with neural networks learning from high-fidelity data?

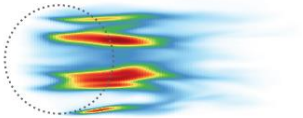
Input

Large eddy simulation (LES)



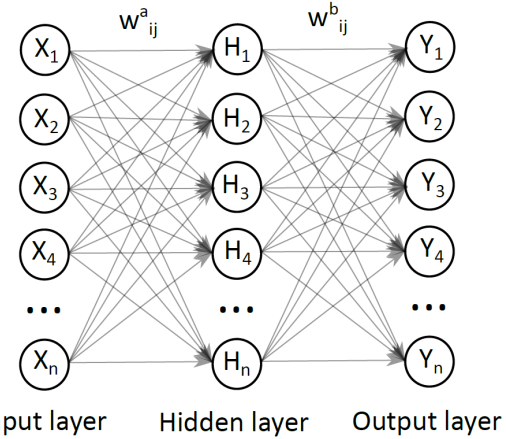
Training

Direct numerical simulation (DNS)



Output

Correction terms Navier-Stokes momentum eq. τ_{ij}



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Key novelty: derive & predict alternative τ_{ij} that also accounts for interpolation errors in a staggered finite-volume grid

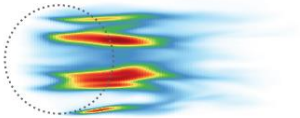
Input

Large eddy simulation (LES)



Training

Direct numerical simulation (DNS)



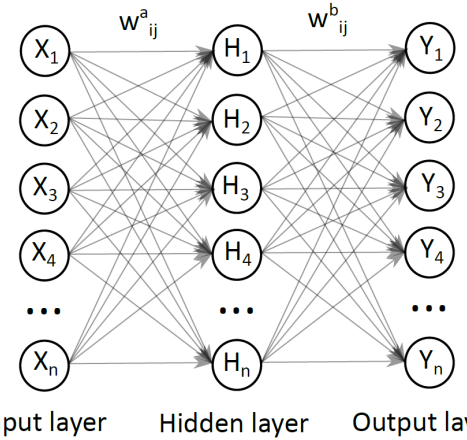
Output

τ_{ij}

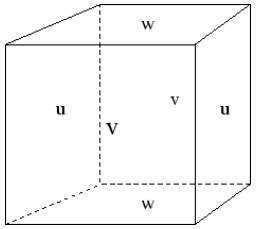
Unresolved physics

+

Compensation interpolation errors



Considered LES grid:
Staggered finite-volume



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Test case: turbulent channel flow simulated with MicroHH

- Turbulent channel flow with Re_τ = 590 (Moser et al.,1999):
  - Horizontal flow bounded by walls
  - No temperature/humidity effects
  - Represents simplified dry, neutral ABL

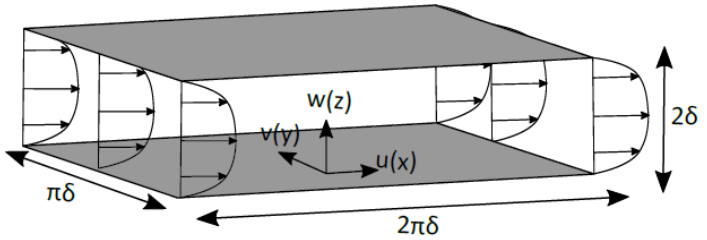
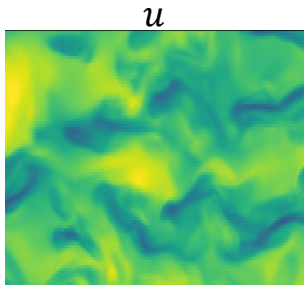


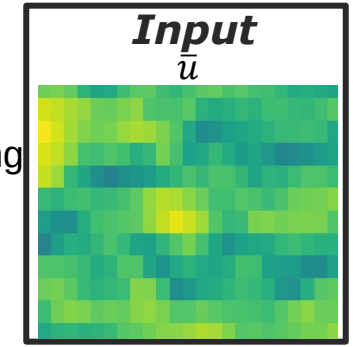
Figure 1. Sketch of simulated turbulent channel flow. Here, δ [m] refers to the channel-half width.

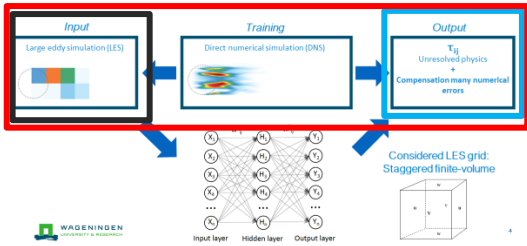
- MicroHH: an open-source flow simulation model for the near-surface atmosphere (Van Heerwaarden et al., 2017)
  - Is able to run both on high- (DNS) and lower-resolutions (LES)

Generation training data: spatial filtering procedure

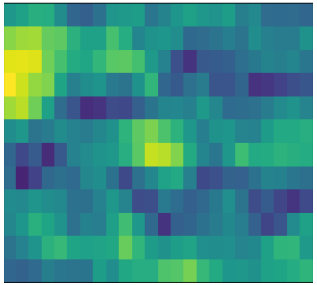


1. Coarse-graining

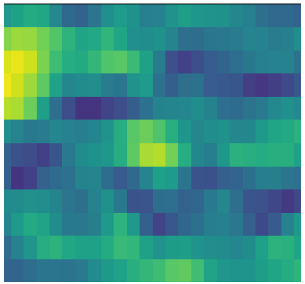


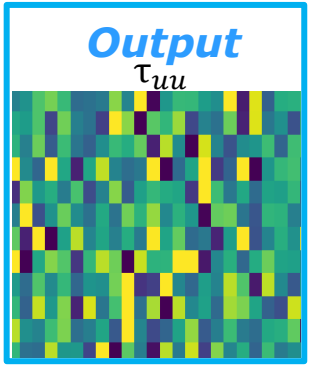


2. Calculate *full* Navier-Stokes terms



3. Calculate *resolved* Navier-Stokes terms

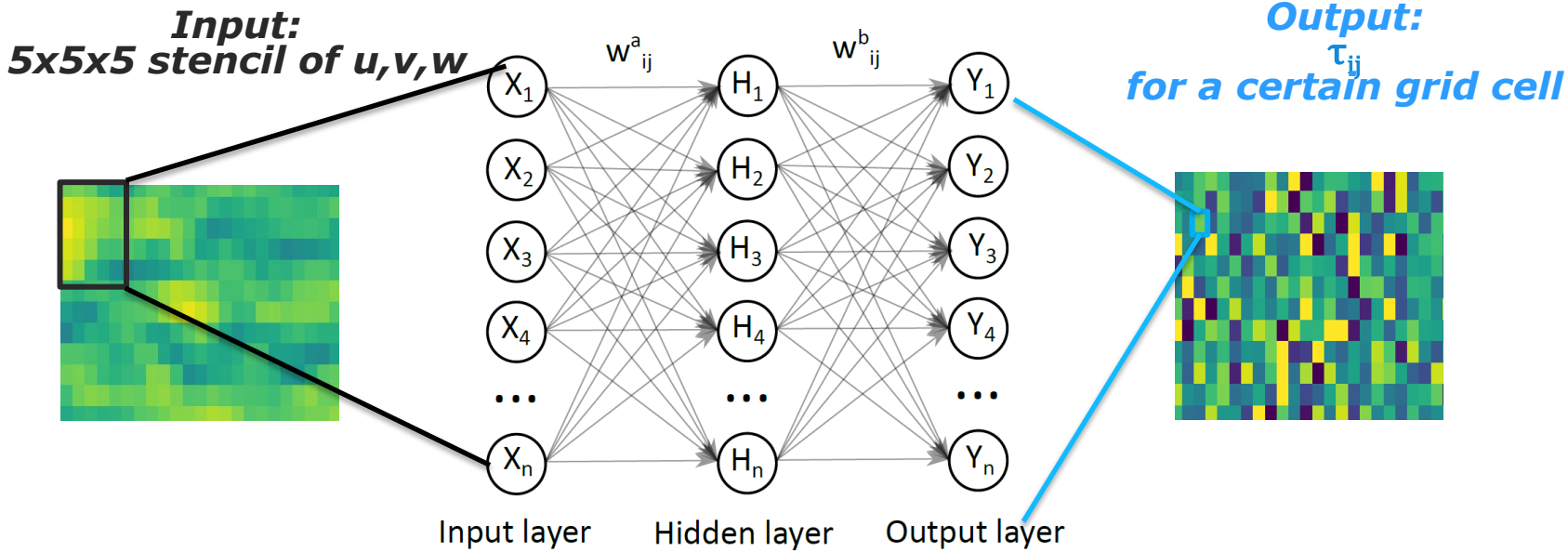




4. Calculate correction terms

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Basic component of our ANN design:
multi-layer perceptrons (MLPs) working locally in the grid domain



Advantages of simple architecture:

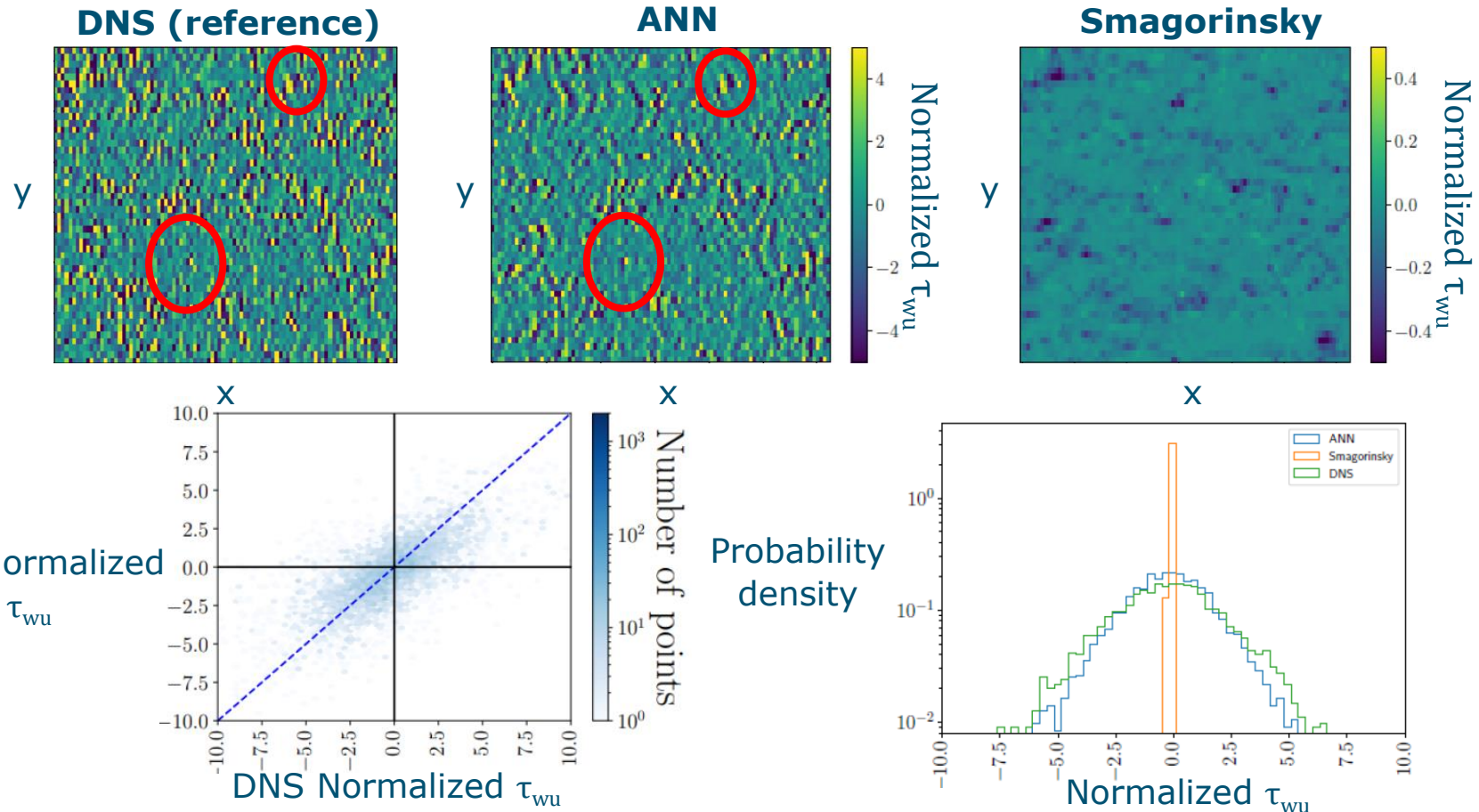
- Relatively simple to implement in existing code
- Computationally cheap to evaluate

Results: *a priori* and *a posteriori* testing

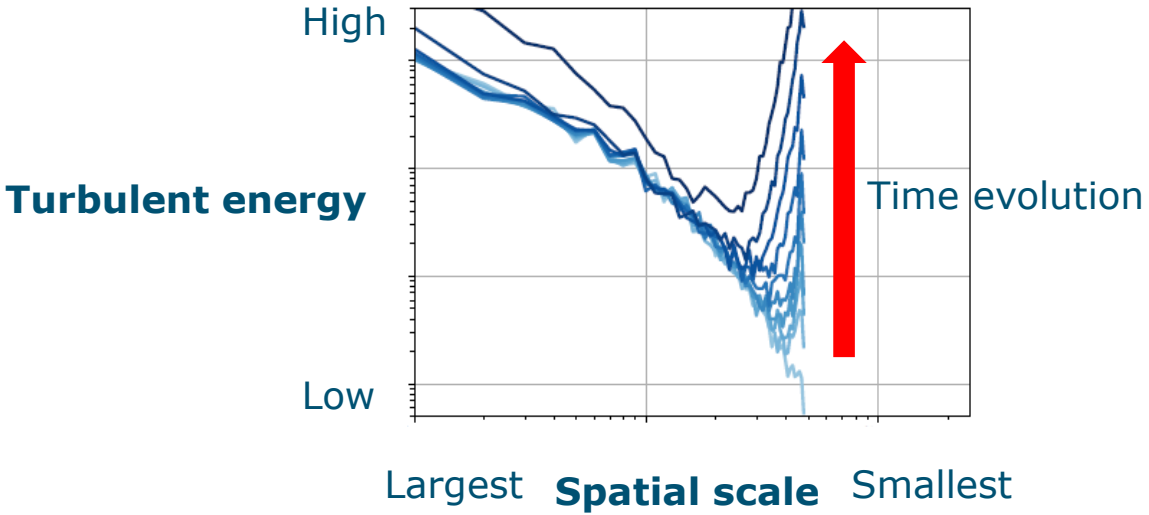
- A priori testing (offline):
  - Assess whether ANN produces **accurate correction terms**

- A posteriori testing (online):
  - Assess whether ANN improves **accuracy of the simulation as a whole**

A priori test: in general good agreement



A posteriori test: numeric instability



Our main hypothesis: error accumulation induced by the ANNs, exacerbated by compensation interpolation errors

Potential solutions include:

1. Artificially increase dissipation
2. Differentiable fluid solver (e.g. List et al., 2022)
3. (Semi-)Online learning (e.g. Rasp et al., 2019)

Can traditional LES subgrid models be replaced with neural networks learning from high-fidelity data?

- Motivation: traditional LES subgrid models require strong assumptions, and do not compensate for interpolation errors associated with staggered finite volume grids
- Approach: train ANNs using high-resolution DNS to infer the correction terms for lower-resolution LES
- Test case: turbulent channel flow with friction Re = 590
- Results:
    - A priori: ANN reproduces correction terms well
    - A posteriori: ANN causes numeric instability

Back-up slides

A priori test: generalization potential towards other horizontal coarse resolutions (f: horizontal coarse-graining factor)

$f_{hor,train}$	$f_{hor,test}$	ρ
8	12	0.624
8	8	0.758
8	4	0.526
12, 4	12	0.656
12, 4	8	0.737
12, 4	4	0.832
12, 8, 4	12	0.657
12, 8, 4	8	0.744
12, 8, 4	4	0.832