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Geoscientific Model Development Discussions

Interactive comment on "Development of a large-eddy simulation subgrid model based on artificial neural networks: a case study of turbulent channel flow" *by* Robin Stoffer et al.

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General Comments

This manuscript applies ML to turbulence closures in idealized channel simulations with Large Eddy Simulations (LES). The authors compute the turbulent stress tensor from a direct numerical simulation with 8x the resolution of the LES. They coarse-grain the frictional stresses and momentum fluxes through interfaces that follow the staggered grid of the LES, and compute the turbulent portion as the residual from the LES-resolved fluxes computed via interpolation. NNs trained to predict this stress tensor dramatically outperform a traditional Smagorinsky LES closure, and have otherwise reasonable skill

"a priori". However, they do not have stable results when the NNs are coupled to the LES (i.e. "a posteriori").

The paper is nicely presented and thorough. I enjoyed reading it. It is disappointing that they didn't achieve good "a posteriori" skill, but this is hard to do, and I appreciated their discussion of the issues. I recommended the paper be accepted, but I would do have some comments:

1. The introduction has a comprehensive literature review of ML for turbulence closures in the CFD/engineering community, but could also mention similar work in the oceanography/atmospheric science on e.g. geostrophic turbulence (Bolton and Zanna, 2019), boundary layer parameterization (McGibbon and Bretherton, 2019), and "full-physics" parameterization (Brenowitz and Bretherton, 2019; Rasp et. al. 2018; Yuval and O'Gorman 2020). These papers all formulate similar coarse-graining problems, and I think readers would enjoy seeing the connections.

2. The question of "a posteriori" and "a priori" errors is a key unsolved problem in the literature. Overall this study diligently accounted for the spatial discretization of the LES, but did not handle the time discretization. For example, would decreasing the time step or using a different time stepper stabilize the "a posteriori" simulations, or is the ML problem they have posed intrinsically unstable?

Specific Comments

L55: "a posteriori tests"

This jargon has diverged somewhat in the turbulence and weather/climate modeling communities. Climate modelers frequently use the terms "online" and "offline" to denote a posteriori and a priori validations, respectively. It would be good to point this out for the geoscience reader.

L95: "Friction Reynold's number"

I assume this refers to the Reynold's number arising from molecular viscosity, but it would be clearer if it were defined in terms of the geometry, viscocity etc in Eq 1.

Also, it should be pointed out that atmospheric flows have orders of magnitude higher Reynold's numbers than Re=590.

L185 (Fig 2). Please define "friction velocity".

L325. How important was this preferential sampling in terms of quantitative performance?

Figure 8. The Smagorinsky scheme does dramatically worse. I am concerned this is a straw-man comparison. Is Smagorinsky a state-of-the-art baseline for this problem?

L415. These issues were likely exacerbated by the growing need for the ANN to extrapolate beyond its training state once the simulation started deviating from the physical solution.

Many ML-assisted weather models show identical problems. These spiraling errors are can be revealed by normal mode analysis of the underlying linearized ML-fluid system (see Brenowitz, et. al. 2020). It would be fascinating to see this technique applied to NNs here in some future paper.

Technical Corrections

L83: "instantaneuous" is misspelled

Figure 3. This graphic is busy, but I understood what they meant from the text.

Figure 9. This graphic has small text and shows some over-plotting in Fig 9a. I suggest further reducing the transparency of the markers or using a hexbin plot.

Line 340. This section header needs a preposition e.g. "Comparison *to* Smagorinsky"

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