Past studies on machine-learned parameterizations have used feed-forward neural networks (FNNs). Unlike FNNs, recurrent networks can directly propagate information through a column, and are shown to work better for radiation and moist physics.

A recurrent neural network approach to more accurately parameterize sub-grid processes in weather and climate models

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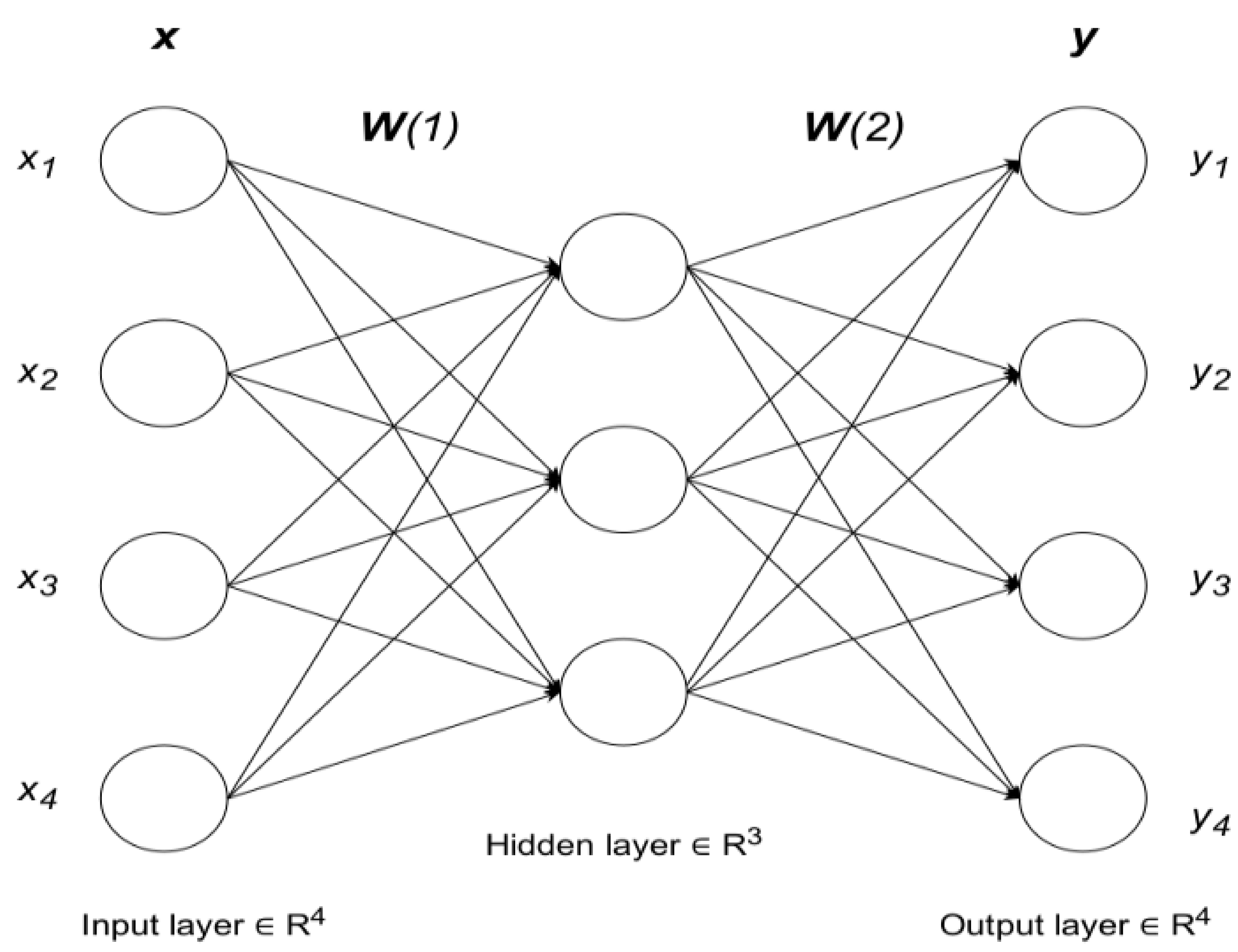
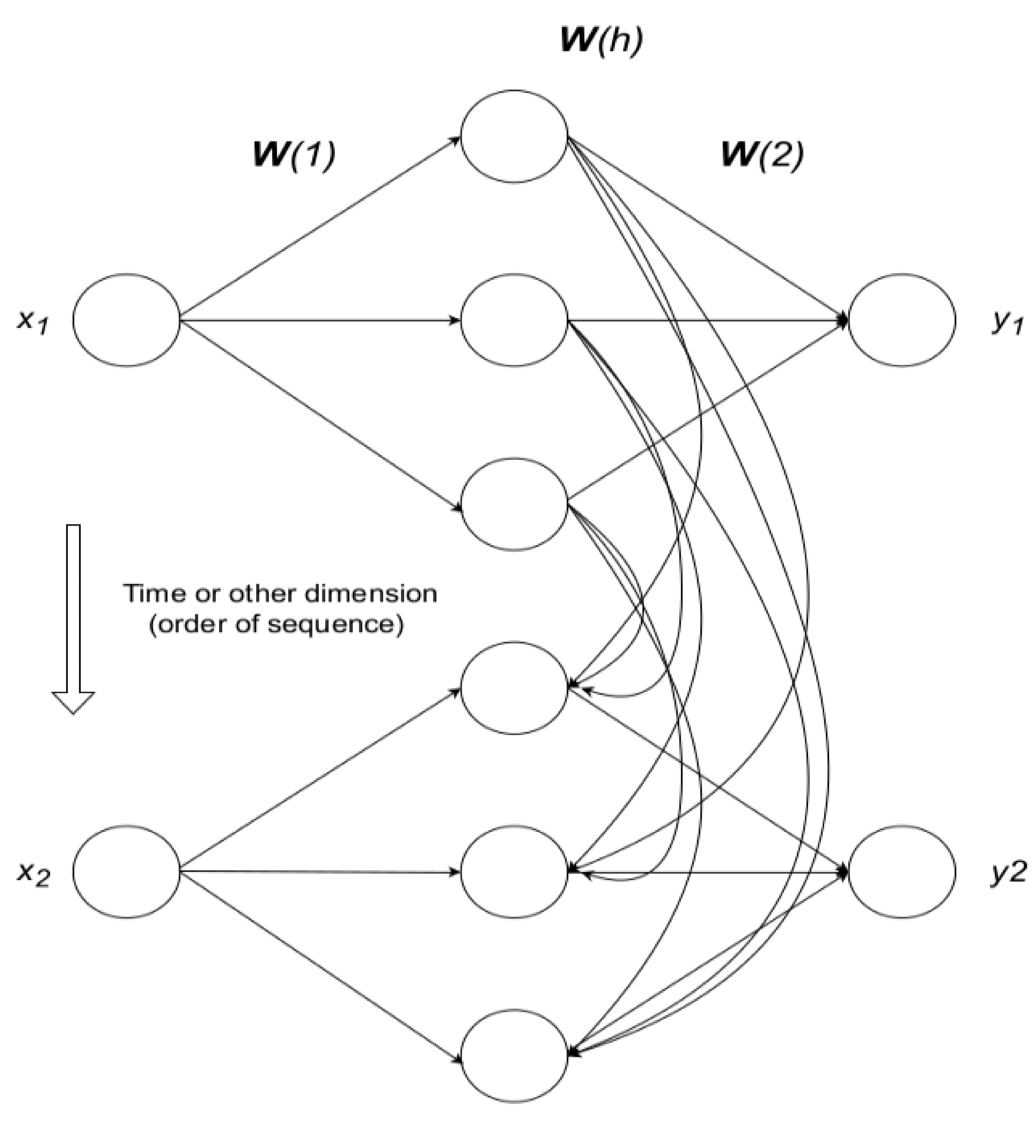
1 Intro

The use of **machine learning (ML) for parameterizing sub-grid processes** is a popular research topic. A typical approach as been to generate training data with cloud-resolving simulations, and flatten the vertical profiles of variables such as temperature and humidity into large input and output columns of a feed-forward neural network (FNN). In the figure below, consider x_i an input variable at model level i.

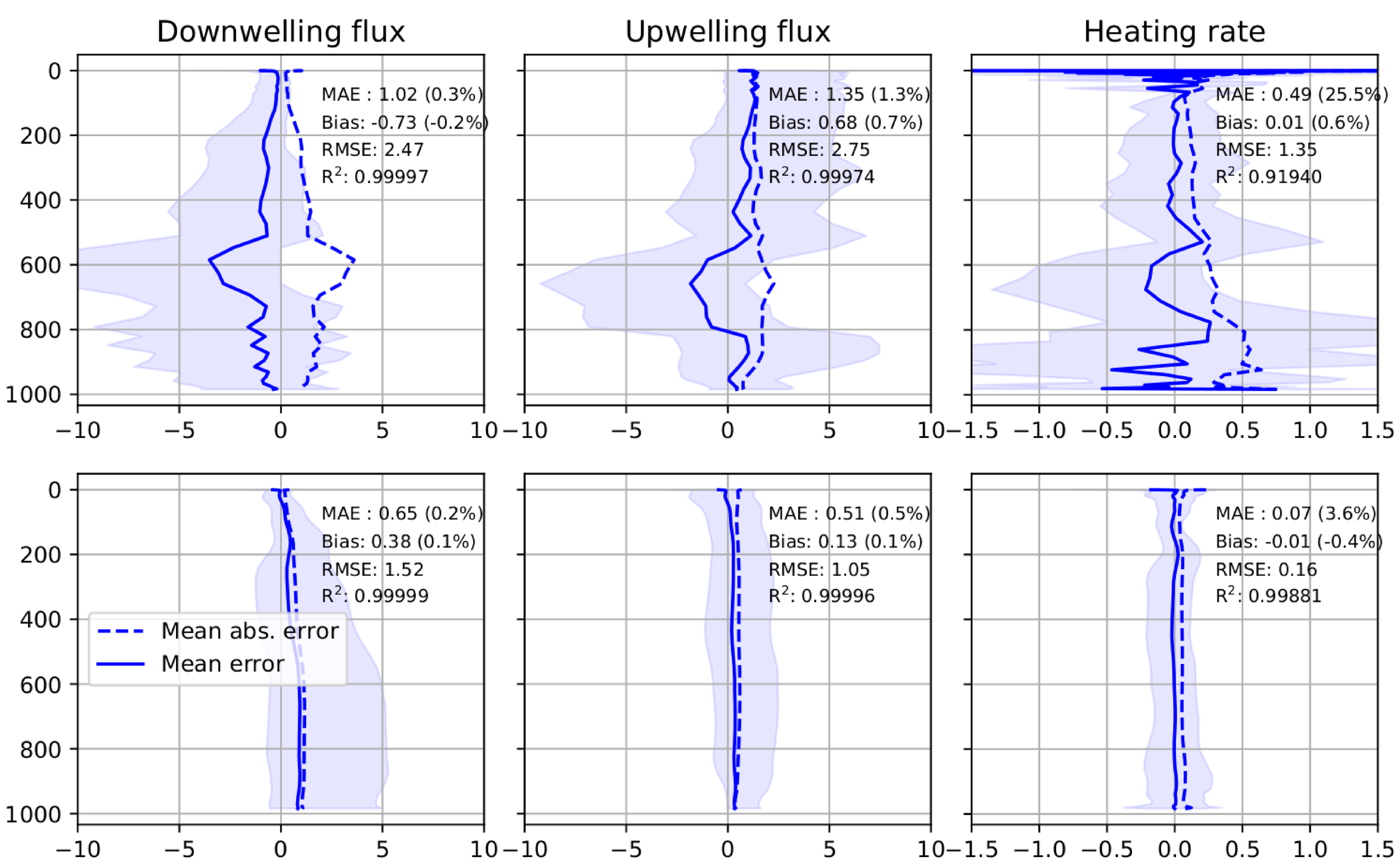


But how appropriate are these models? **Sub-grid processes such as convection and radiation are vertically non-local. In the FNN, there are no vertical connections between nodes to directly propagate information in this direction.** Why not instead **treat the vertical column as a sequence**, and iterate through it one level at a time, like you would in a radiative transfer equation or to keep track of a rising plume? **Recurrent neural networks (RNNs)** are able to process sequential data, and reapply the same weights to different points in the sequence, which makes sense for emulating sub-grid processes because the laws of physics do not change by height.



2 Application to shortwave radiation

The RNN approach was introduced in Ukkonen [2022] for emulating a shortwave radiation scheme. A bidirectional RNN with 5,600 model parameters (bottom row) achieved an order of magnitude better accuracy in heating rates than a FNN model with 100,000 parameters (top row):



3 Application to moist physics

In climate models, **moist physics parameterizations are the main source of biases in simulated precipitation and atmospheric circulation**. In Han et al. [2020], a new moist physics parameterization based on complex NNs (residual convolutional networks, or ResNet) was developed by using data from a superparameterized GCM. In prognostic validation using a single-column model, ResNet was able to reproduce the timing and intensity of convective events in midlatitude summer land convection as well as tropical monsoon convection. Obtaining a subsample of their data, I briefly tested training a bidirectional RNN on it. **The RNN model with 70,000 parameters achieved a similar offline accuracy as the 1-million-parameter ResNet**, with R^2 values of $\sim$ 0.88 for diabatic moistening rates and $\sim$ 0.94 for diabatic heating rates.

References

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