Using neural networks to predict atmospheric optical properties for radiative transfer computations

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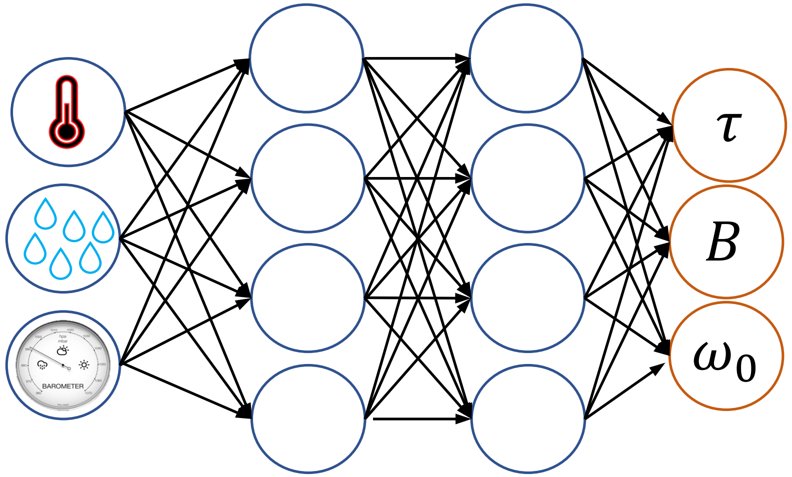

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Interactive radiation is important, but computationally expensive

- Longwave: cloud top cooling (e.g. Wood, 2012; Klinger et al., 2017)
- Shortwave: surface shading (e.g. Horn et al., 2015; Gronemeier et al., 2017)

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- Typical approximations in weather and climate models:
  - Coarsened horizontal grid in radiation computations (Morcrette, 2000)
  - Temporal sampling: infrequent radiation calls (Morcrette, 2000)
  - Spectral sampling (Pincus & Stevens, 2009)

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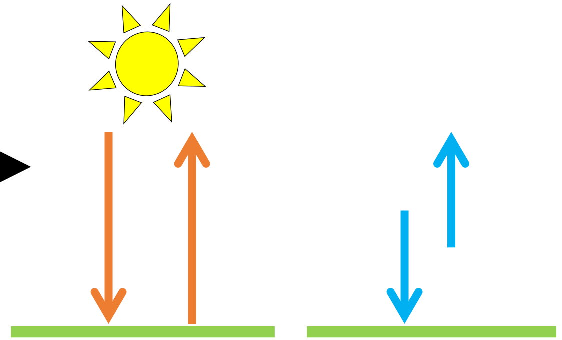
Alternative: machine learning

- ➢ Emulating a full radiative transfer parametrization (e.g. Chevallier et al., 1998; Krasnopolsky et al., 2005)
- ➢ **Emulating part of a radiative transfer parametrization**

Optical properties & radiative transfer

$$\begin{bmatrix} Temperature \\ Pressure \\ H_2O \\ O3 \\ \vdots \end{bmatrix} \longrightarrow \begin{bmatrix} \tau \\ w_0 \\ B \end{bmatrix} \longrightarrow$$



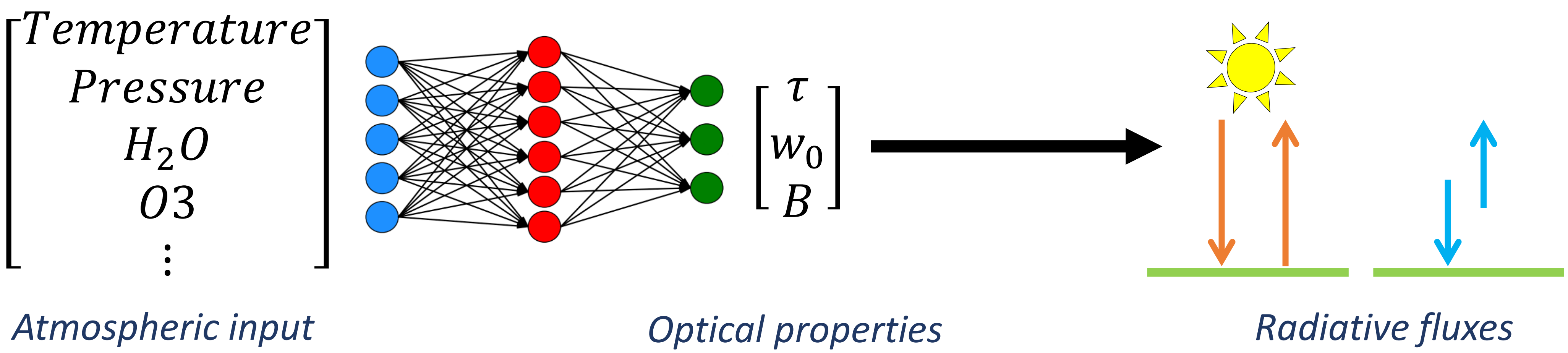
Atmospheric input

Optical properties

Radiative fluxes

τ	Optical depth
ω_0	Single scattering albedo
B	Planck source function

Optical properties & radiative transfer



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Neural network emulator of RRTMGP

- Neural networks are trained against RRTMGP[1] (Pincus et al., 2019)
  - Gaseous optical properties only
  - Input: pressure, temperature, water vapour, ozone (per grid cell)
  - Output: Optical properties for all 224 (SW) or 256 (LW) g-points (per grid cell)

- 3 sets of training (95%) and testing (5%) data:
  - **Pseudo-random perturbations of the 100 atmospheric profiles from RFMIP[2] (Pincus et al, 2016)**
  - Random atmospheric profiles within the p/T/q-parameter space of an RCEMIP[3] Large-Eddy Simulation (LES) (Wing et al., 2018)
  - Random atmospheric profiles within the p/T/q-parameter space of an LES simulation of developing shallow cumulus grassland near Cabauw, the Netherlands

[1]*RRTM for General circulation model application – Parallel*
[2]*Radiative Forcing Model Intercomparison Project*
[3]*Radiative Convective Equilibrium Model Intercomparison Project*

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- Computational costs versus accuracy
  - ➢ Multiple neural network architectures
  - ➢ "LES-specific" training

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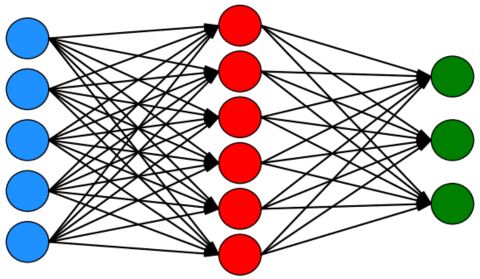
Neural network architecture is quite straightforward



- Multilayer perceptrons
  - 1 hidden layer of 32 neurons
  - 1 hidden layer of 64 neurons
  - 2 hidden layers of 32 neurons
  - 2 hidden layers of 64 neurons
  - 3 hidden layers of 32, 64 and 128 neurons, respectively
  - <u>Small networks are required for performance</u>

- Two separate neural networks per optical property (8 in total)
  - Solar/shortwave (SW): τ_{sw} , ω_0
  - Thermal/longwave (LW: τ_{lw} , B
  - $p > 100$ hPa & $p < 100$hPa

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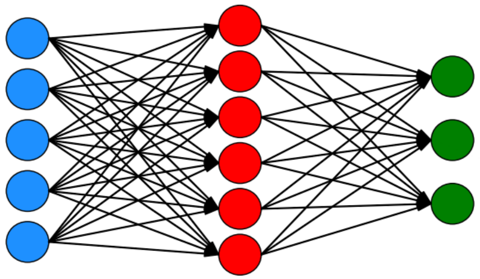

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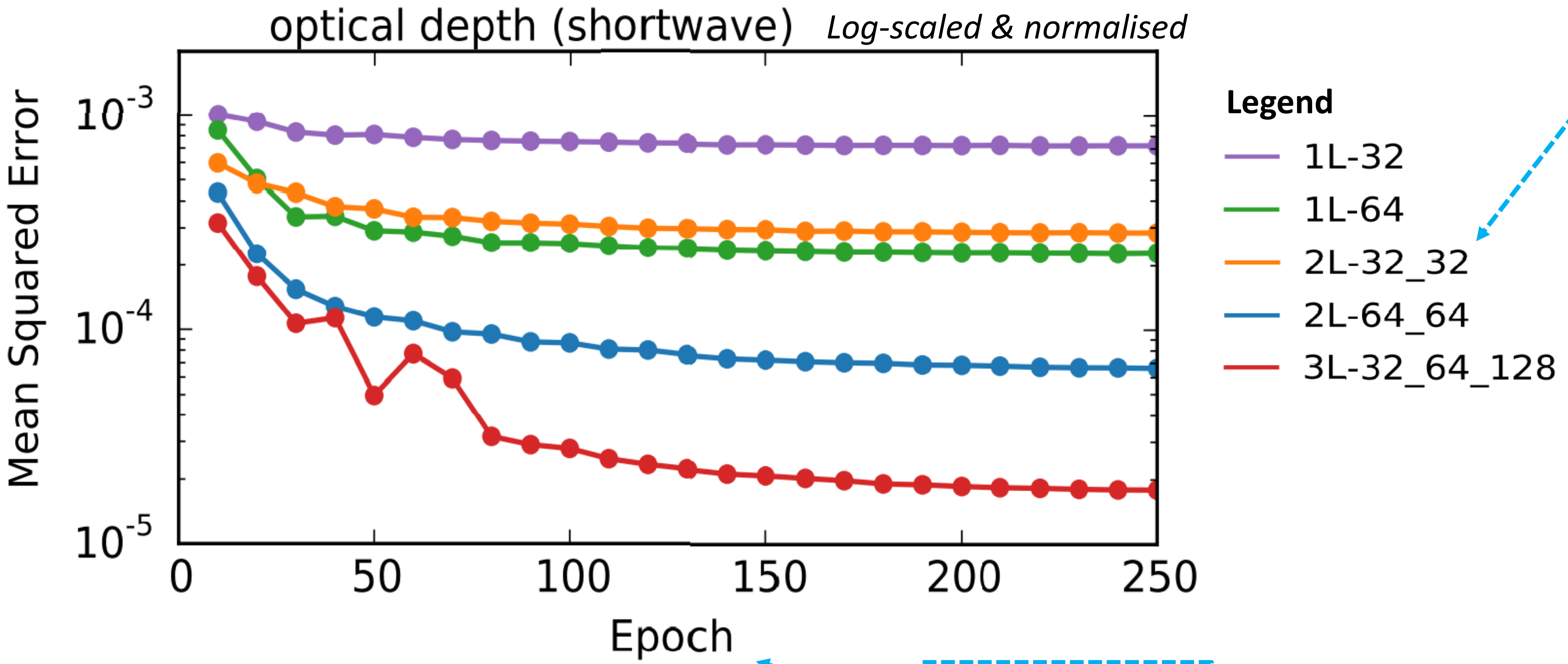
- Other hyperparameters:
  - Mean Squared Error (MSE) loss function
  - Leaky ReLU $(\alpha = 0.2)$ activation function
  - Adam optimizer (Kingma, 2014)

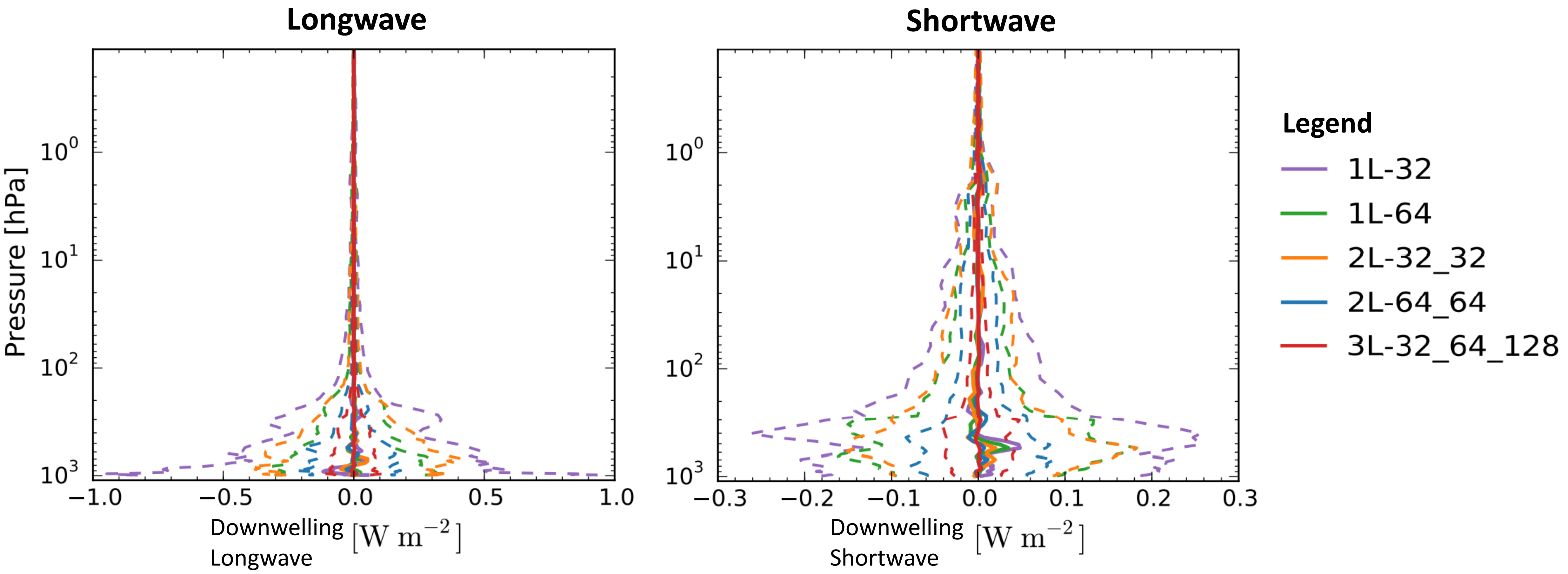
Larger networks clearly have higher prediction skills



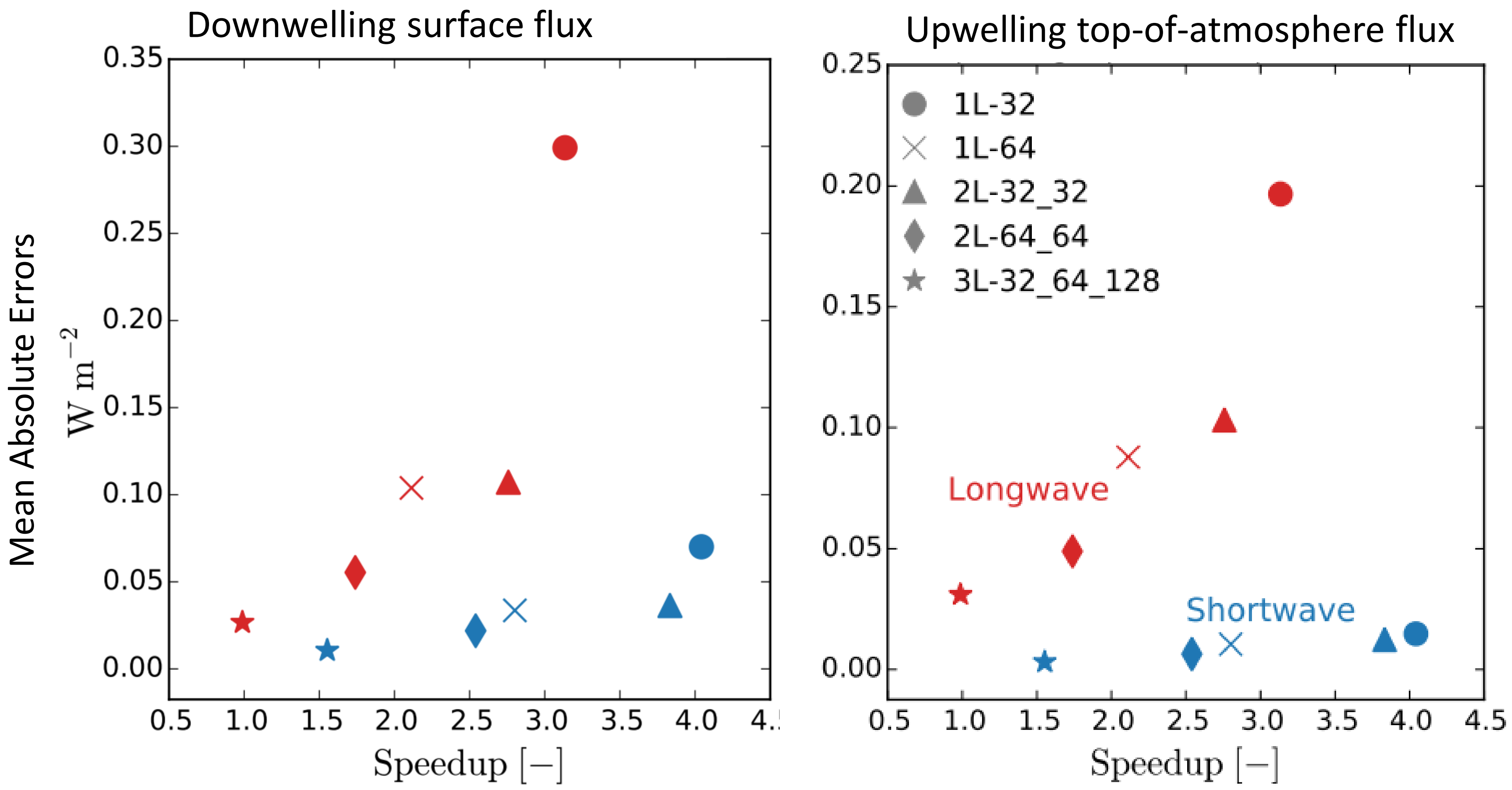
2 hidden layers of 32 neurons

1 full cycle through the training data

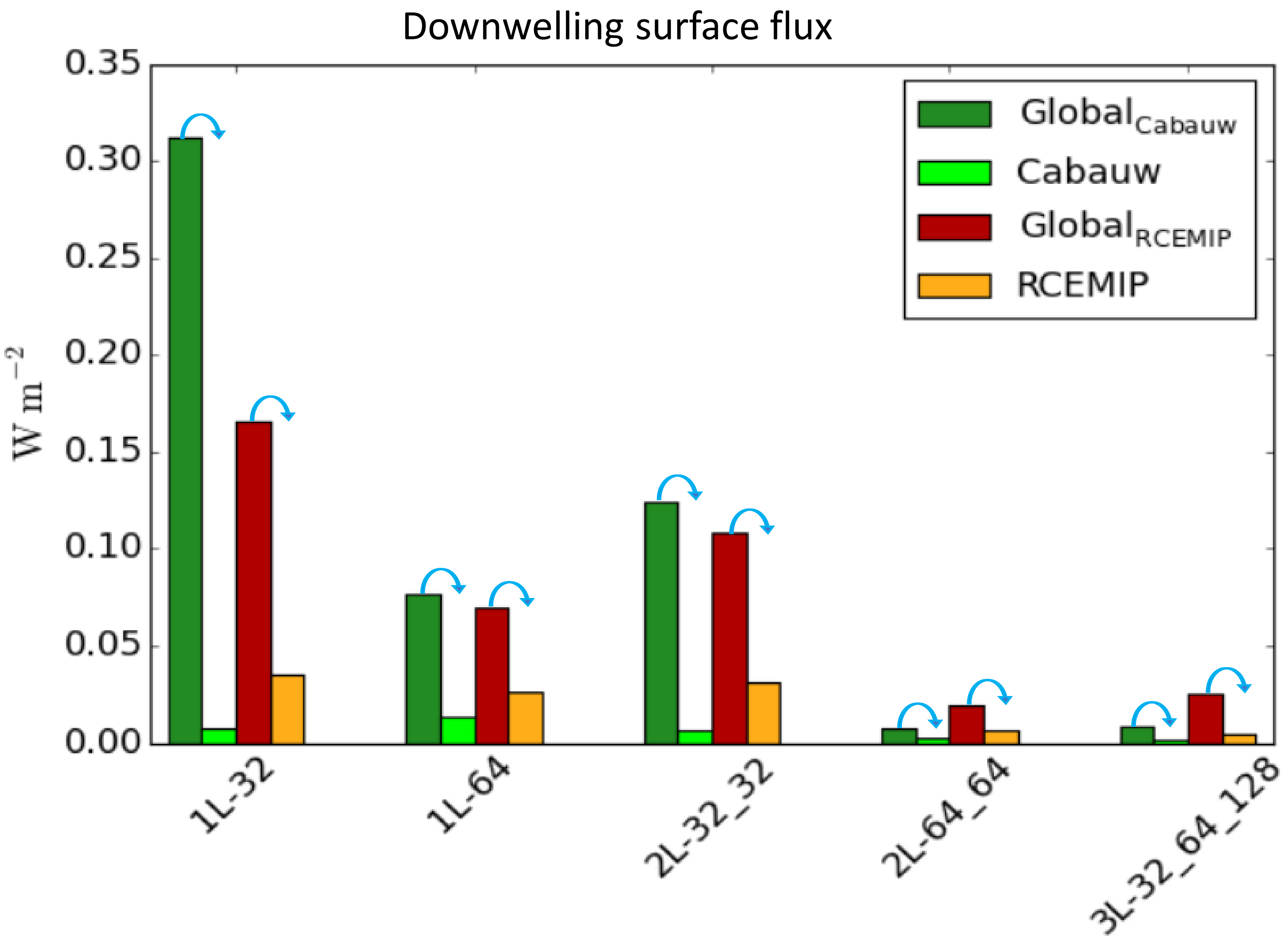
Better predictions give more accurate radiative fluxes



But at what computational cost?



LES tuning allows for smaller networks



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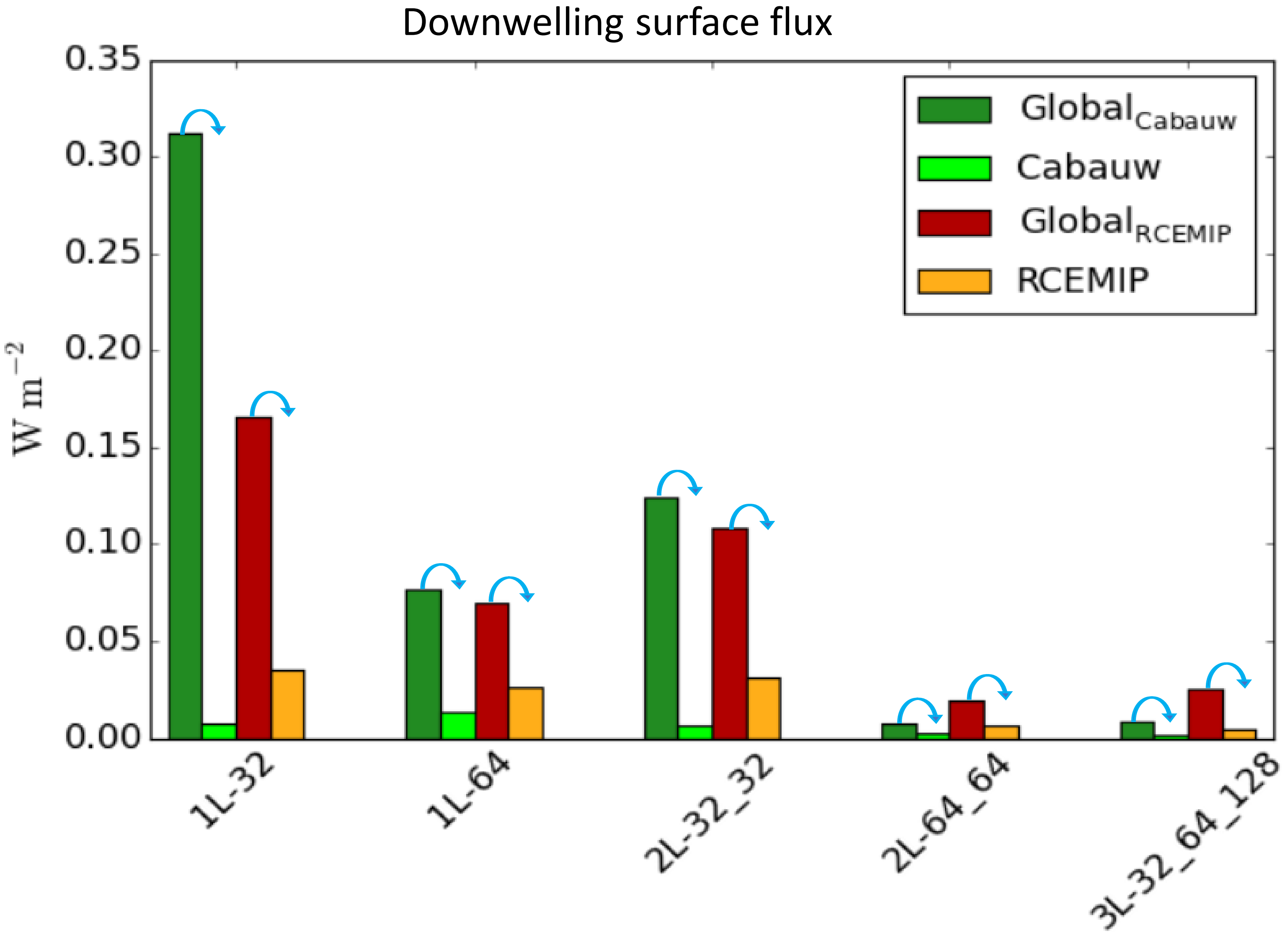
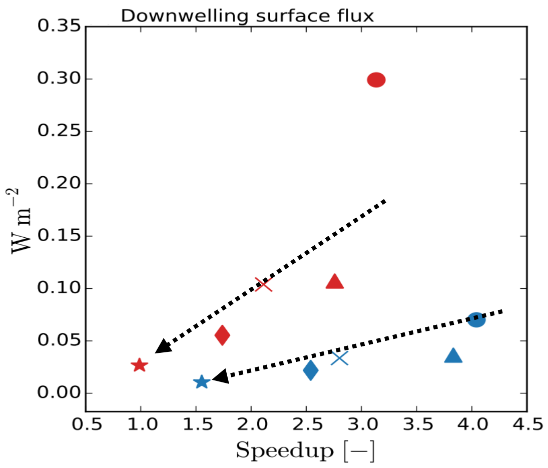
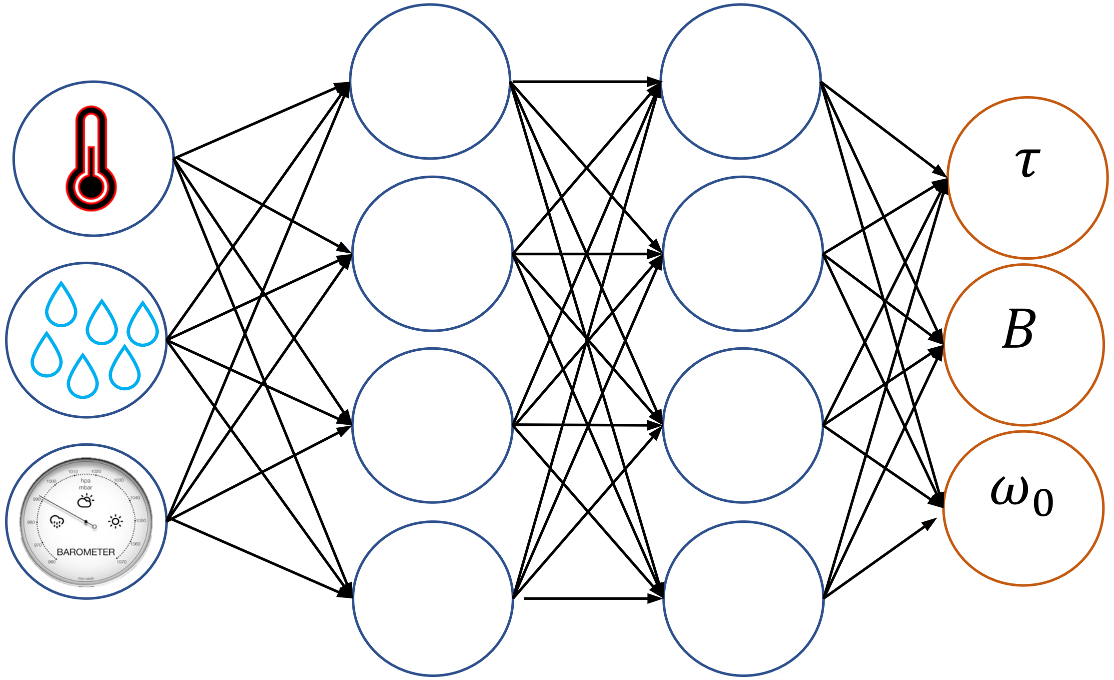




Summary

- Neural network-based emulator of RRTMGP's gaseous optical predictions
  - Predicted optical properties have high accuracy
  - Resulting irradiance errors are largely within 1.0 W m^{-2} (<1%)
  - Parametrization is up to 4x faster than RRTMGP
  - LES-specific tuning shows great potential



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