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

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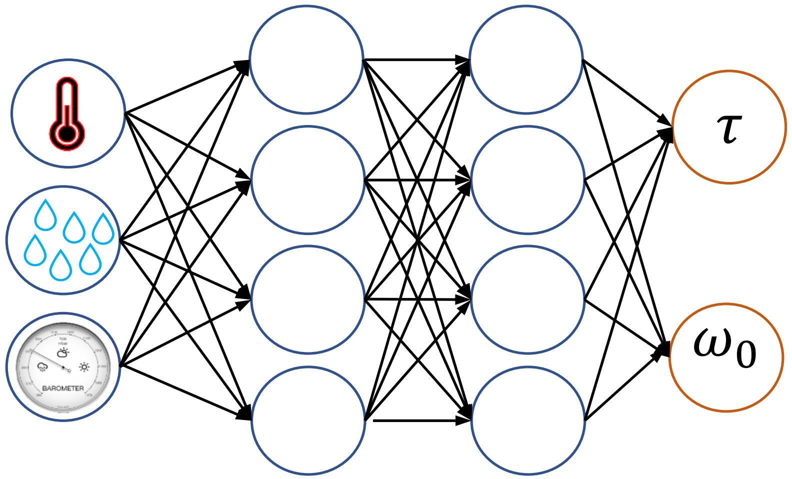

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A constant need for rapid radiative transfer

- Radiative transfer is computationally very expensive
- First step: spectral integration with correlated *k*-method (e.g. Fu & Liou, 1992)
  - ➢ $\sim 10^6 \rightarrow \sim 10^2$ spectral integration points

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

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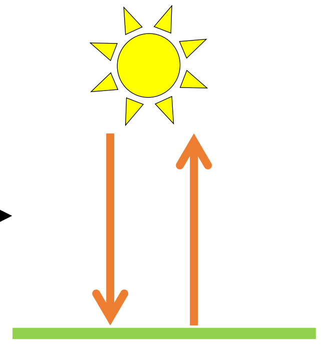
- Alternative approach: machine learning
  - Emulating/replacing a full radiative transfer parametrization (e.g. Chevallier et al., 1998; Krasnopolsky et al., 2005)
  - **Emulating part of a radiative transfer parametrization**

Optical properties & radiative transfer

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



Atmospheric input ***Optical properties*** ***Radiative fluxes***

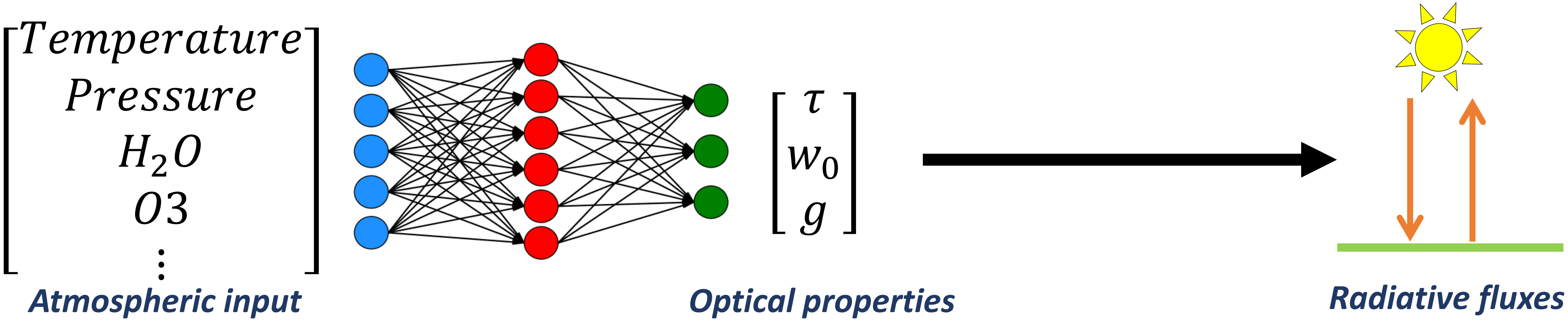
τ Optical depth

ω_0 Single scattering albedo

g Asymmetry parameter

B Planck source function

Optical properties & radiative transfer



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Only gaseous optical properties!

Neural network emulator

- 2 neural networks per optical property (upper/lower atmosphere)
  - Shortwave (solar): τ_{sw} , ω_0
  - Longwave (thermal): τ_{lw} , B

- Training against RRTMGP (Pincus et al., 2019) → same input/output
  - Input: pressure, temperature, water vapour, (ozone) (per grid cell)
  - Output: 224/256 optical properties (spectral integration) (per grid cell)

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- Optimising the speed-accuracy trade-off:
  - Multiple neural network architectures
  - LES-specific training

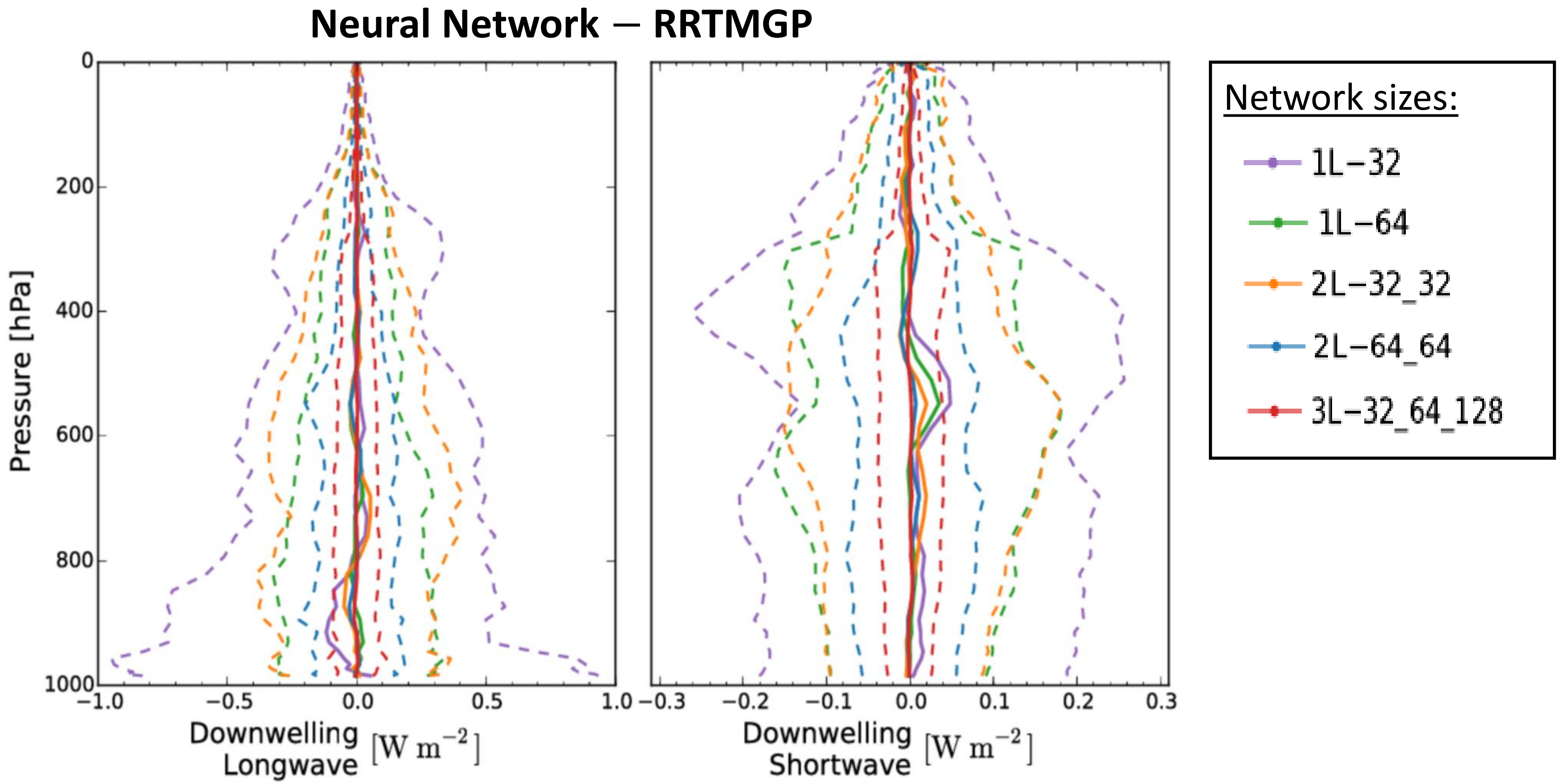
Neural network set-up

- Multilayer perceptons
    - 1 layer of 32 neurons
    - 1 layer of 64 neurons
    - 2 layers of 32 neurons
    - 2 layers of 64 neurons
    - 3 layers of 32, 64 and 128 neurons, respectively

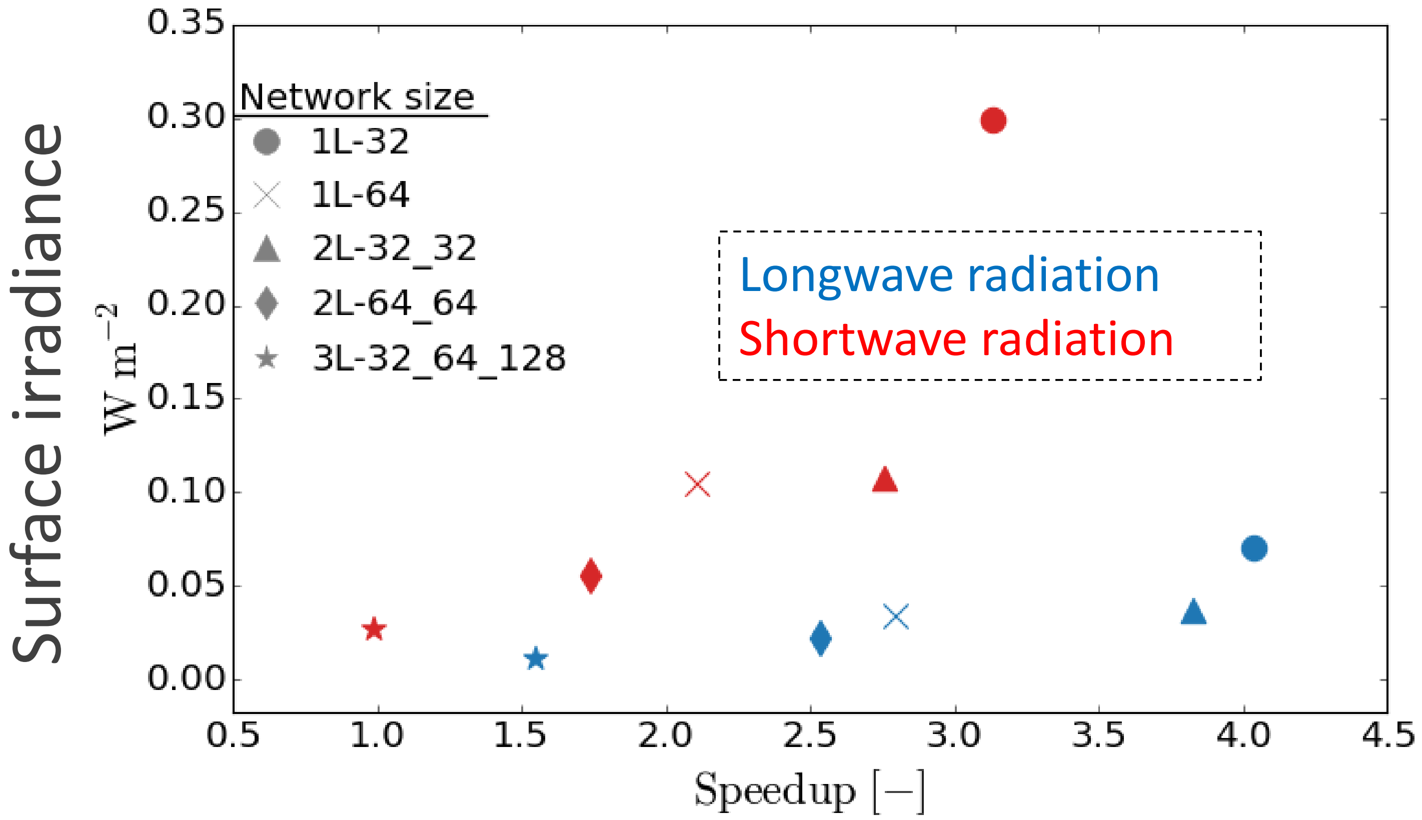
- Activation function: Leaky ReLU ($\alpha = 0.2$)
- Optimizer: Adam
- Loss: Mean Squared Error (MSE)

- <u>Training/testing data:</u> random perturbations of the 100 atmospheric profiles from RFMIP (Pincus et al, 2016), with a random 5% reserved for testing.

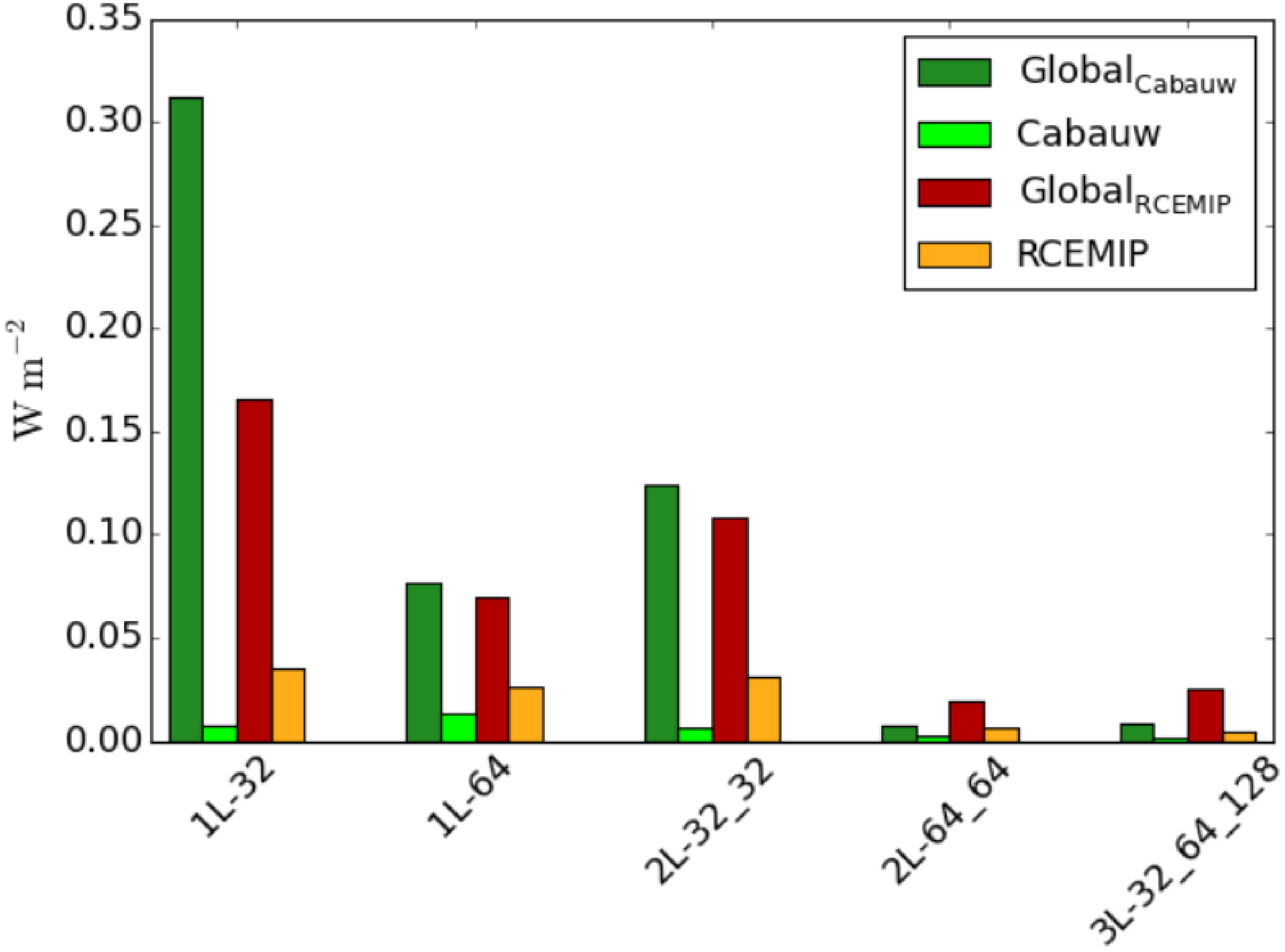
Validation: from optical properties to fluxes



Prediction accuracy comes at a cost



LES tuning allows smaller networks



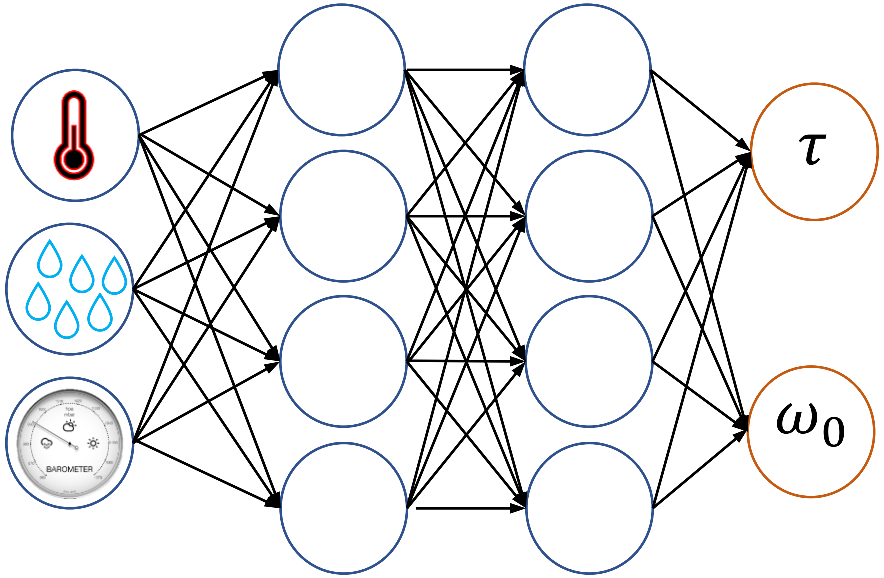
2-3 times faster

Conclusions

- Neural networks can predict optical properties with high accuracy
  - ➢ Resulting surface irradiance errors are largely within 1.0 W m^{-2} (<1%)

- Neural network-based parametrisation is up to 4 faster than RRTMGP

- LES-specific tuning shows great potential



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