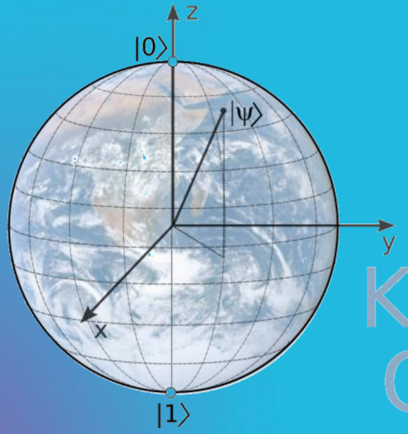
DLR **QCI**



KLIM-QML

Quantum Machine Learning-based parameterizations for Earth System Models

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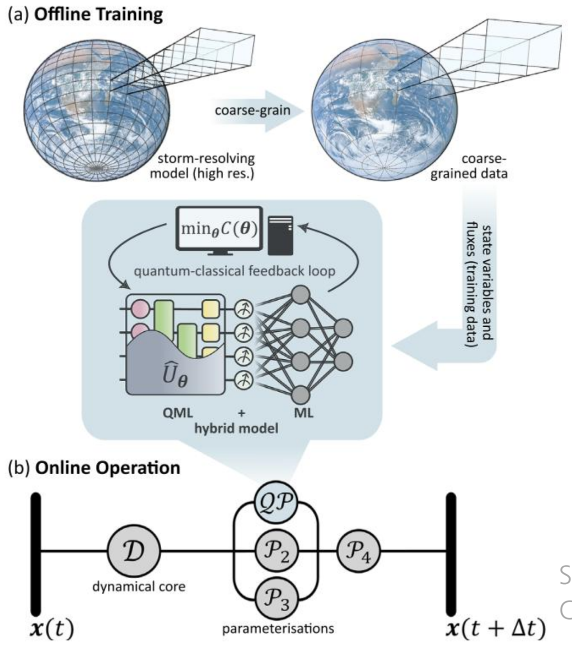
DLR

Quantum Machine Learning-based parameterizations for Earth System Models

Progress in quantum computing is accelerating, important to explore its potential for climate modelling

Parameterizations:

Describe subgrid-scale (unresolved) processes, not very accurate, could be improved by training QML models on high-resolution data



Schwabe (2025a)
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Training QML models with high-resolution Earth system model (ESM) simulations

- Short high-res simulation as training data
- Calculate target variables at coarse (earth system models resolution) scale
- Train hybrid ML-QML model
- Finally couple QML-based parameterization to earth system models

Implemented QML-based parameterizations:

- Cloud cover[1] (Pastori et al., 2026)
- Cloud microphysics (Herbort et al., 2026)
- Atmospheric boundary layer height[2] (Rodriguez Garrido, 2026)
- Atmospheric boundary layer turbulence[1] (Dogra, Klamt et al., 2026)

QML models are often competitive to classical models of same size

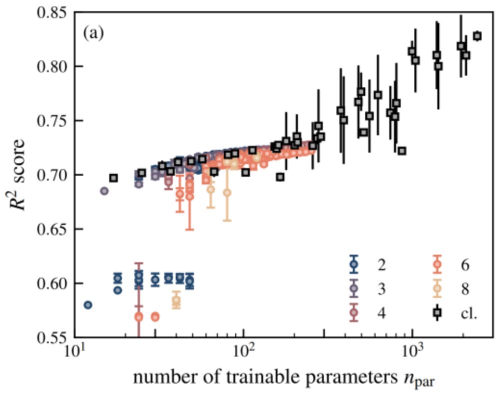
[1]More stable feature importances for quantum models

[2]lower seed-to-seed variability

Quantum Machine Learning-based parameterizations…

… for atmospheric boundary layer turbulence

- QNN and classical NNs achieve similar performance and generalization skills
- Feature importance is more stable for QNN



(Dogra, Klamt et al., 2026)
Validation *R*2 score for all models, as a function of their numbers of trainable parameters, error bars are standard deviations over 10 trainings with different initial conditions. The colors indicate the number of qubits of the QNN, while the classical NN are shown as black squares.

…. for atmospheric boundary layer height (Rodriguez Garrido 2026)

- Compression of 76 input features to eight features using interpretable feature engineering
- Comparison of QNN to MLP architecture:
  - MLP: slightly better RMSE,R2,MAE
  - QNN: lower seed-to-seed variable, bias closer to zero

… coupled to the Earth System Model

- Evaluations so far only offline, without coupling to the earth system model
- Limited hardware availability

  → Coupling of simulator (computationally expensive)

  → Coupling of shadow model/ classical surrogate

Shadow models: (Jerbi et al., 2024)

- For quantum circuit $f_Q\,(x,\theta^\star)$ find a classical model $f_C(x)$, s.t. $f_Q\,(x,\theta^\star) \approx f_C(x)$

  → classical inference possible
- Methods e.g.
  - quantum Fourier model
  - tensor networks
  - Gaussian processes
- Closely related to dequantization

  → shadowfiability might imply classical simulatability

Quantum Machine Learning-based parameterizations for Earth System Models

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