Modeling Climate Change using Quantum Physics-Informed Neural Networks

Hubert Kołcz[1], Amardeep Singh[2], Santiago Maza[3], Montasir Jim[4], Wasif Ahmed, and Muhammad Al-Zafar Khan[6]

[1]Warsaw University of Technology, [2]University of Toronto, [3]Stanford University, [4]Technical University of Munich, [6]Zayed University

Introduction

Quantum sensors, particularly those using cold atom interferometry for gravitational field mapping, can detect subtle variations in Earth's gravitational field that are directly linked to climate change indicators, such as ocean water mass movement or polar ice mass changes. Among standard approaches, like Burgers' equations and vector flow components, these processes are described by Advection-Diffusion (A-D) equations with stochastic noise terms, reflecting potential measurement disturbances from the environment.

Methodology

Selecting an appropriate diffusion model is crucial for accurately capturing noise effects, depending on problem scale and reference frame. This research uses the A-D equation to model scalar field evolution under advection and diffusion, with the analytical solution:

$$u(x,t) = \frac{1}{\sqrt{4\pi Dt}} \exp\left(-\frac{(x-Vt)^2}{4Dt}\right)$$

where D is diffusion and V is advection velocity.

Model	Equation
Classical A-D	$\frac{\partial C}{\partial t} + \mathbf{u}\cdot\nabla C = D\,\nabla^2 C$
Stochastic (Fokker–Planck)	$d\mathbf{X}(t) = \mathbf{u}\,dt + \sqrt{2D}\,d\mathbf{W}(t)$
Quantum (Lindblad)	$\frac{d\rho}{dt} = -i[H,\rho] + \mathcal{D}[\rho]$

Table 1:Advection-diffusion models: classical, stochastic, and quantum.

To reflect exemplary environments, we implemented selected stochastic noise terms in the A-D equation, modelling different scales of impact.

Noise Type	A-D Equation with Noise
Additive	$\frac{\partial C}{\partial t} + \mathbf{u}\cdot\nabla C = D\nabla^2 C + \eta(\mathbf{x},t)$
Random Advection	$\frac{\partial C}{\partial t} + [\mathbf{u}+\boldsymbol{\eta}(\mathbf{x},t)]\cdot\nabla C = D\nabla^2 C$
Multiplicative Diffusion	$\frac{\partial C}{\partial t} + \mathbf{u}\cdot\nabla C = [D+\xi(\mathbf{x},t)]\,\nabla^2 C$

Table 2:Stochastic noise models for the A-D equation.

hubert.kolcz.dokt@pw.edu.pl | MPQCQL2025 - Porquerolles, France

We investigate Quantum Physics-Informed Neural Networks (QPINNs) for solving advection–diffusion equations relevant to climate modeling, benchmarking both qubit-based, continuous-variable (CV), and hybrid D-Wave quantum architectures against classical PINNs. Our numerical experiments on stochastic advection–diffusion scenarios show that QPINN models achieve 30–50× lower mean squared error (MSE) than classical PINNs for the same problem, with up to 90% fewer trainable parameters. Specifically, QPINN (qubit), QPINN (CV), and hybrid D-Wave models reach MSEs of 1.05–1.97, compared to 51–59 for classical PINNs. While quantum and hybrid approaches are currently limited by hardware access and QUBO encoding, these results demonstrate the practical potential of quantum-enhanced PINNs for accurate and efficient climate-relevant PDE modelling.

(Q)PINNs Formulation

PINN (Classical): Approximates $u(x,t)$ using a neural network:

$$u(x,t,\boldsymbol{\theta}) \approx \mathrm{NN}(x,t;\boldsymbol{\theta})$$

The loss combines PDE residual and initial/boundary conditions:

$$\mathcal{L}_{\mathrm{PINN}} = \mathcal{L}_{\mathrm{data}} + \lambda\,\mathcal{L}_{\mathrm{physics}}$$

QPINN (Qubit): Approximates $u(x,t)$ as

$$u(x,t,\boldsymbol{\theta}) = \mathrm{post}\left(\langle 0|U(x,t,\boldsymbol{\theta})^\dagger O U(x,t,\boldsymbol{\theta})|0\rangle\right)$$

where U is a parameterized qubit circuit. The loss

$$\mathcal{L}_{\mathrm{QPINN}} = \mathcal{L}_{\mathrm{data}} + \lambda\,\mathcal{L}_{\mathrm{physics}}$$

combines PDE residual and initial/boundary conditions. Training uses parameter-shift and backpropagation.

QPINN (CV, Master Equation): Encodes the solution as a CV quantum circuit expectation:

$$u(x,t,\boldsymbol{\theta}) = \langle\psi|U_{\mathrm{CV}}(x,t,\boldsymbol{\theta})^\dagger O U_{\mathrm{CV}}(x,t,\boldsymbol{\theta})|\psi\rangle$$

with gates parameterized by $x, t, \boldsymbol{\theta}$. The same loss is minimized, with gradients via finite differences or classical updates.

QPINN (D-Wave Hybrid): Uses a neural network with a binary output layer optimized on D-Wave:

$$\mathcal{L}_{\mathrm{QPINN}} = \mathcal{L}_{\mathrm{data}} + \lambda\,\mathcal{L}_{\mathrm{physics}}$$

This loss is minimized by alternating classical (backprop) and quantum (QUBO) updates for the binary layer.

Results and Key Findings

Variant	Per-epoch time (900 pts)	100 epochs	Notes
Classical PINN	<1 s (CPU)	∼1–2 min (Fastest, highly scalable)	linear in batch size
QPINN (Qubit)	10–30 s (CPU)	30–60 min (Much slower due to quantum simulation)	exponential scaling with qubits/circuit depth
QPINN (CV)	1.5 min (CPU, 30 epochs)	∼45 min (slowest, not scalable)	linear in batch, slow CV sim.
Hybrid PINN (D-Wave)	1–5 s (incl. QPU latency)	∼1.5–8 min (QPU access, hybrid)	QPU latency, hybrid classical/quantum, QUBO overhead

Table 3:Computational time and scaling comparison for each neural network variant in the benchmark (batch size 900, 100 epochs).

Metric	Classical PINN	QPINN (Qubit)	QPINN (CV)	Hybrid PINN (D-Wave)
MSE	51–59	1.05–1.24	1.95	1.97
L_2 error	1×	0.57×	0.57×	0.57×
Params (%)	100	10–20	10–20	5–10
T time	Fast	Slow	Slow	Moderate

Table 4:Comparison of classical PINN, QPINN (qubit-based), QPINN (CV-based), and Hybrid PINN (D-Wave) approaches for 8–10 epochs.

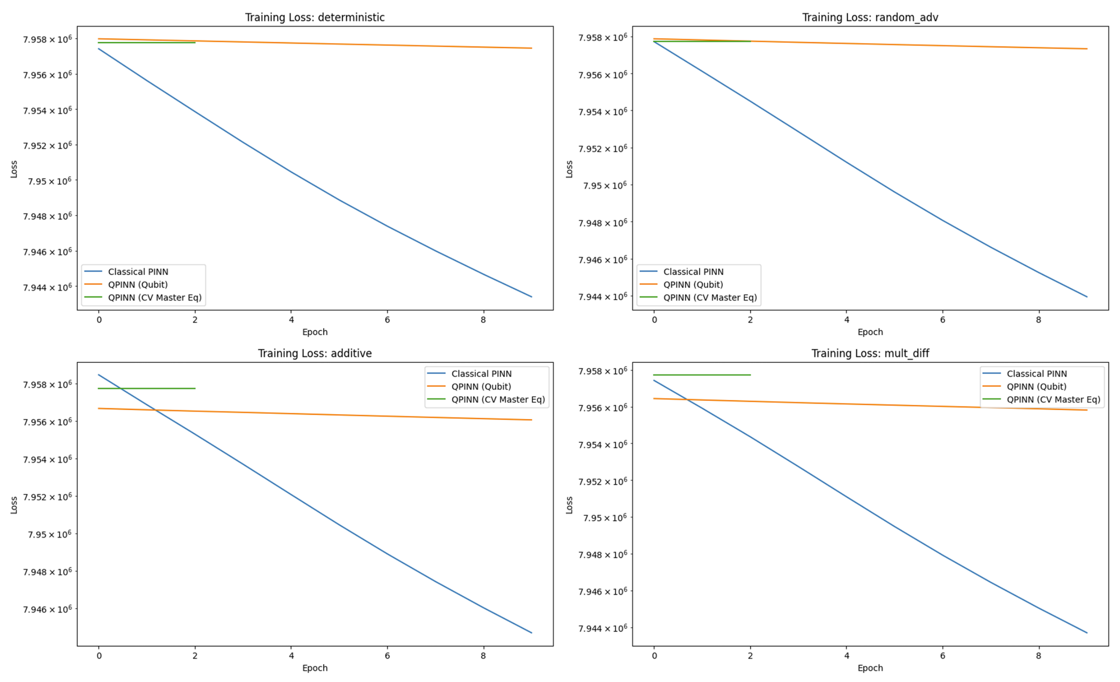

Figure 2:Numerical simulations results - training loss.

Conclusion

The presented methods enable modelling environmental impacts using the advection-diffusion model for both climate change and qubit decoherence. Method efficiency depends strongly on internal parallelisation and linear algebra optimisation. Related approaches include neural operators, constraint learning, and PINO. In addition to neural network-based methods, established techniques such as DFT and Laplace transforms are also common.

References

[1] M. Raissi et al.
Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear pdes.
J. Comput. Phys., 378:686–707, 2019.

[2] Afrah Farea, Saiful Khan, and Mustafa Serdar Celebi.
Qcpinn: Quantum-classical physics-informed neural networks for solving pdes.
arXiv preprint arXiv:2503.16678, 2024.

[3] Hubert Kołcz, Amardeep Singh, Santiago Maza, Montasir Jim, Wasif Ahmed, and Muhammad Al-Zafar Khan.
Qpinns-for-climate-change, 2025.
GitHub repository, version 2.0.

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