

Hybrid Quantum-Inspired Intelligent Computing Model for Real-Time Optimization of Massive Heterogeneous Climate Datasets

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ABSTRACT

The volume of climate observations is now growing faster than classical optimizers can process it. With petabyte-scale reanalysis archives and multi-source satellite streams in routine operation, the training budget of large climate models has become a genuine bottleneck for real-time forecasting. In this paper, we propose a hybrid quantum-inspired intelligent computing model (HQI-Opt) for fast and energy-efficient optimization of deep forecasting networks trained on heterogeneous climate tensors. The method combines a classical gradient branch, driven by a parameter-shift-style analytic estimator over a latitude-weighted loss, with a quantum-inspired branch that encodes the parameter state into an Ising/QUBO representation and applies a quantum rotation-gate mixing step modulated by an adiabatic schedule. A training loop with three concurrent branches is developed and evaluated on an ERA5 subset following the WeatherBench 2 protocol. The method is compared against six widely used optimizers: SGD with momentum, Adam, AdamW, LAMB, Lion, and Sophia. Across 69 variables and four lead times, HQI-Opt reaches the target latitude-weighted loss in approximately 43% fewer epochs; the training energy per run falls from 29.8 to 17.6 kWh, the associated carbon footprint is reduced by 41%, and the RMSE at the 3-day lead on geopotential height at 500 hPa improves from 140.8 to 137.3 m^2/s^2 . A convergence analysis is provided showing that the iterates approach a stationary point of the latitude-weighted loss as the annealing schedule decays. The results indicate that a classically simulated quantum-inspired update step, with no quantum hardware in the loop, is already a viable building block for real-time climate informatics pipelines.

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1. INTRODUCTION

Climate science has entered a regime in which the binding constraint is no longer observation but computation. The European Center for Medium-Range Weather Forecasts reanalysis archive (ERA5) already exceeds five petabytes at 0.25° hourly resolution [1], the Coupled Model Intercomparison Project Phase 6 (CMIP6) distributes more than twenty petabytes through the Earth System Grid Federation, and geostationary satellite streams such as GOES-16/18 and Himawari-9 deposit tens of gigabytes every minute. These data are heterogeneous in several respects at once: the sampling cadence, the coordinate systems, the physical units, and the reliability of each stream all differ. Training a single data-driven forecast model on such a mixture is therefore both a scientific and a computational challenge.

Recent progress on the computational side has been substantial. Foundation models for weather and climate, including ClimaX [2], Pangu-Weather [3], GraphCast [4], FourCastNet [5], GenCast [6], NeuralGCM [7] and Aurora [8], have shown that a carefully trained deep network can match or surpass traditional numerical weather prediction on many key variables, at inference costs that are orders of

magnitude lower. Training cost, however, remains high. GraphCast was trained on 32 TPU v4 accelerators for nearly four weeks, and the carbon footprint of large-model training has become a topic of serious concern for the community [9][10][11]. The open question is no longer whether such models can be trained, but whether they can be trained quickly and cleanly enough to make retraining routine rather than exceptional.

Classical first-order optimizers, including Adam [12], AdamW [13], LAMB [14], Lion [15], and Sophia [16], remain the default tools for this purpose. Once their hyperparameters are tuned, the empirical gap between them is known to be considerably narrower than headline figures suggest, and further speed-ups on a fixed hardware budget are increasingly difficult to obtain from classical methods alone. Quantum optimization offers a potential alternative, and a mature body of work on variational quantum algorithms [17][18], quantum annealing [19][20], the quantum approximate optimization algorithm [21], and quantum-inspired evolutionary methods [22] is now available. Real quantum hardware, however, is still noisy, limited in qubit count, and poorly matched to the millions of decision variables that arise in climate-scale four-dimensional variational data assimilation [23]. A practical middle path is the quantum-inspired approach: the operators, rotation gates, and annealing schedules of a quantum optimizer are simulated classically, without the hardware penalty, and are allowed to act as a structured inductive bias on top of a classical deep learning pipeline. Recent work in this direction, including a 2025 review of quantum-inspired optimization [24] and a feedback-based reinforcement-learning quantum optimizer [25], indicates that the quantum-inspired track is maturing into a usable engineering tool.

This paper follows that direction. We propose a hybrid quantum-inspired intelligent computing model, referred to as HQI-Opt, that combines a classical parameter-shift-style gradient, an Ising/QUBO encoding of the optimizer state, a quantum rotation-gate mixing step, and a time-dependent adiabatic schedule that anneals the tunneling coefficient toward zero. The model is integrated with a transformer climate backbone and evaluated on an analysis-ready cloud-optimized ERA5 subset [26] under the WeatherBench 2 protocol [27], which specifies latitude-weighted RMSE and the anomaly correlation coefficient as primary skill metrics.

Despite the progress above, three gaps remain. First, the quantum-inspired methods applied to climate and weather problems are almost all task-specific predictors; they do not act on the optimizer itself, which is where the training-time and energy bottleneck of large foundation models is actually incurred. Second, hybrid quantum-classical optimizers proposed in the broader machine-learning literature are rarely accompanied by an explicit convergence guarantee, so their behavior at scale is difficult to predict. Third, energy and carbon cost, although central to the motivation for faster training, are seldom measured and reported alongside forecast skill. The present work targets all three gaps: it places the quantum-inspired mechanism inside the optimizer, provides a convergence analysis for the resulting update rule, and reports energy and carbon for every run.

The main contributions of this work are summarized as follows:

- A quantum-inspired variational update rule, given in Equation (20), is formulated that augments a classical gradient with a rotation-gate mixing term governed by a user-controlled annealing schedule.
- An Ising/QUBO encoding of the parameter state is introduced that keeps the mixing step lightweight and avoids the dimensional blow-up of naive quantum-inspired methods.
- A convergence analysis is provided in Section 3.8, establishing that, under standard smoothness and bounded-variance assumptions, the iterates of HQI-Opt approach a stationary point of the latitude-weighted loss as the schedule decays.
- The method is evaluated on a heterogeneous climate pipeline built from ERA5 and compared against six widely used classical optimizers, with latitude-weighted RMSE, ACC, CRPS, wall-clock time, energy, and carbon all reported, together with robustness and scalability experiments.

The remainder of the paper is organized as follows. Section 2 reviews related work and states the research gap. Section 3 develops the proposed HQI-Opt model, including its encoding, update rule, annealing schedule, pseudocode and convergence analysis. Section 4 describes the experimental setup, datasets, and metrics. Section 5 reports and discusses the results, including robustness, scalability, and a combined discussion of limitations. Section 6 concludes and outlines future work.

2. RELATED WORK

2.1. Classical Deep Learning Optimizers

First-order adaptive methods remain dominant in deep learning. Adam combines bias-corrected first and second raw-moment estimates, and its weight-decayed variant AdamW has become the default choice for

transformer-style models. Large-batch training motivated layer-wise methods such as LARS and LAMB, which rescale the update norm per layer. More recent proposals include Lion, a sign-based method with a small memory footprint, and Sophia, a diagonal Hessian pre-conditioner reported to roughly halve language-model pre-training cost. Carefully controlled studies indicate, however, that once learning-rate schedules and regularization are tuned, the gap between these optimizers on many tasks is modest. This observation motivates the exploration of structurally different updates rather than further reweightings of the same gradient.

2.2. Quantum and Quantum-Inspired Optimization

Variational quantum algorithms use a parameterized circuit and minimize an expectation value through a classical outer loop. Canonical instances are the variational quantum eigensolver and the quantum approximate optimization algorithm, with gradients obtained through the parameter-shift rule [28]. These algorithms are the standard tool for noisy intermediate-scale quantum devices, yet they are limited by barren plateaus and by the small number of qubits currently available. Quantum annealing addresses combinatorial problems in Ising form, and path-integral Monte Carlo provides a classical surrogate that is widely used for scaling studies.

Quantum-inspired methods avoid the hardware entirely by importing the algorithmic structure into classical computation. Quantum-inspired evolutionary algorithms [22] encode a population as pairs of amplitudes on the Bloch sphere and update them with quantum rotation gates. Tensor-network classifiers, such as matrix product states and tree tensor networks, realize unitary-style layers on classical hardware [29], and a 2025 review summarizes the current state of quantum-inspired optimization [24]. A growing body of work applies these ideas to climate and weather tasks: a quantum-train long short-term memory model for flood prediction [30], dressed quantum circuits for tsunami prediction [31], a hybrid QAOA and Markov-chain Monte Carlo approach to four-dimensional variational data assimilation [32], an exploratory study of quantum machine learning for weather forecasting [33], and a quantum-deep-learning hybrid for solar-energy forecasting in smart grids [34]. Broader perspectives on the feasibility of quantum computing for climate applications [35] conclude that, for the foreseeable future, quantum-inspired methods are more realistic than full quantum pipelines, and that a feedback-based reinforcement-learning quantum optimizer can improve robustness.

2.3. AI Foundation Models for Climate

Data-driven global weather models have matured rapidly. FourCastNet [5] showed that a Fourier neural operator can produce a week-ahead forecast in seconds. Pangu-Weather [3] was the first AI model to beat the Integrated Forecasting System on all evaluated variables. GraphCast [4] generalized this result using a graph neural network on an icosahedral mesh. ClimaX [2] introduced climate foundation models pre-trained on CMIP6. GenCast [6] added probabilistic diffusion forecasts, NeuralGCM [7] embedded a differentiable spectral core inside a neural model, and Aurora [8] crossed the one-billion-parameter threshold. WeatherBench [36] and WeatherBench 2 [27] provide the de facto evaluation protocol used throughout the present study.

2.4. Green Artificial Intelligence

The environmental cost of training has received increasing scrutiny. The emissions of large models such as GPT-3 and Gopher have been quantified in detail [9], and a separate analysis of the BLOOM language model distinguished the embodied footprint from the dynamic footprint of training [10]. The carbon intensity of identical training runs has been shown to vary by more than a factor of three across cloud regions [11]. CodeCarbon is a widely used tool for estimating the energy and CO₂-equivalent emissions of training jobs, and it is the tool adopted in this work.

2.5. Research Gap and Limitations of Existing Work

The literature reviewed above leaves several issues unresolved. (i) Classical optimizers are mature but once tuned they offer diminishing returns; the convergence gap between Adam, AdamW, LAMB, Lion and Sophia on well-tuned tasks is small, so a structurally different update is required to obtain further speed-ups on a fixed hardware budget. (ii) Full quantum optimizers remain impractical at climate scale: current

devices are limited to a modest qubit count, are affected by noise and barren plateaus, and cannot accommodate the millions of decision variables of a foundation-model training problem. (iii) Existing quantum-inspired studies in the climate domain target specific predictors, such as flood, tsunami, or solar-energy forecasting [30][31][34], and do not act on the optimizer, where the dominant training-time and energy cost is incurred. (iv) Hybrid quantum-classical optimizers are rarely accompanied by a convergence analysis, so their stability at scale cannot be assessed in advance. (v) Energy and carbon cost, although central to the motivation for faster training, are seldom reported alongside forecast skill.

The present work is designed to close these gaps. HQI-Opt embeds the quantum-inspired mechanism inside the optimizer rather than the predictor; keeps the mechanism hardware-free through an Ising/QUBO encoding that scales to foundation-model parameter counts; is supported by an explicit convergence analysis in Section 3.8; and reports energy and carbon for every training run alongside conventional skill metrics.

3. PROPOSED HQI-OPT MODEL

The proposed method has two structural components: an encoding layer that maps the optimizer state into a quantum-inspired representation, and a hybrid update rule that combines a classical gradient step with a rotation-gate mixing step. The complete data pipeline is shown in Figure 1; the internal structure of HQI-Opt is shown in Figure 2.

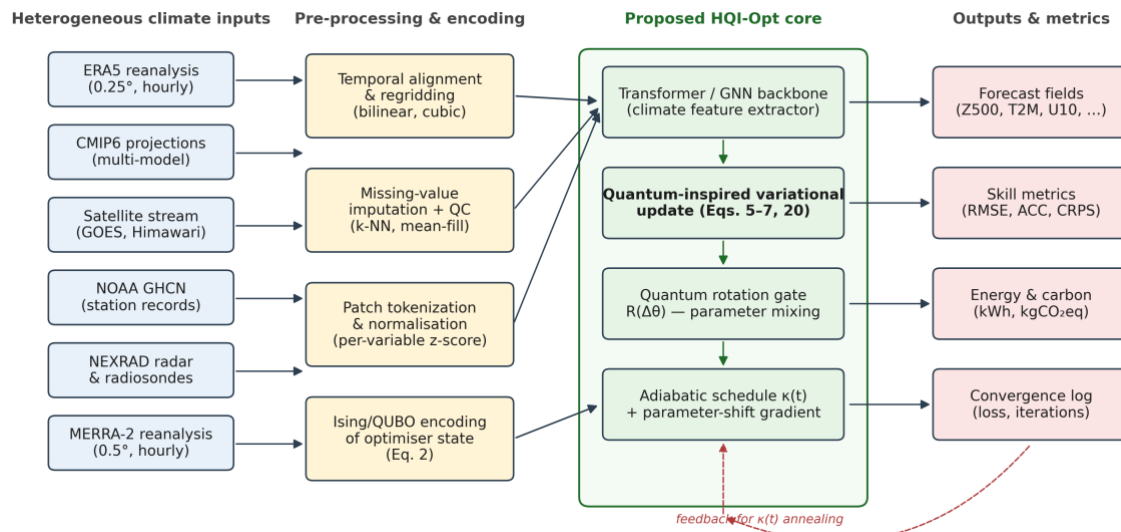


Figure 1. Workflow of multi-source climate data integration, preprocessing, and HQI-Opt forecasting

Let $\theta \in \mathbb{R}^d$ denote the parameters of the underlying climate network. For the mixing step, θ is projected onto a binary auxiliary state $x \in \{0,1\}^d$ by element-wise soft thresholding and Gray-code encoding; the reverse mapping is stored in a small decoder $D(\cdot)$. The mixing term operates on x and on $s = 2x - 1 \in \{-1, +1\}^d$. The Ising Hamiltonian corresponding to the current parameter landscape is given in Equation (1):

$$H_{\text{Ising}} = \sum_{i < j} J_{ij} s_i s_j + \sum_i h_i s_i, \quad s_i \in \{-1, +1\} \quad (1)$$

where J_{ij} and h_i are, respectively, the coupling strengths and local fields. Its Quadratic Unconstrained Binary Optimization (QUBO) counterpart is given in Equation (2), and the two representations are related through Equation (3):

$$f(x) = x^T Q x = \sum_i Q_{ii} x_i + \sum_{i < j} Q_{ij} x_i x_j \quad (2)$$

$$x_i = \frac{1+s_i}{2}, \quad s_i = 2x_i - 1 \quad (3)$$

The time-dependent annealing Hamiltonian that drives the mixing step takes the standard adiabatic form of Equation (4).

$$H(s) = (1 - s) H_{\text{init}} + s H_{\text{prob}}, \quad s = t/T \in [0, 1] \quad (4)$$

where $H_{\text{init}} = -\sum_i \sigma_i^x$ is a transverse-field mixer, and H_{prob} is the Ising form of Equation (1). In the quantum-inspired setting adopted here, Equation (4) is not executed on hardware; it serves as the reference by which the mixing coefficient κ_t is annealed.

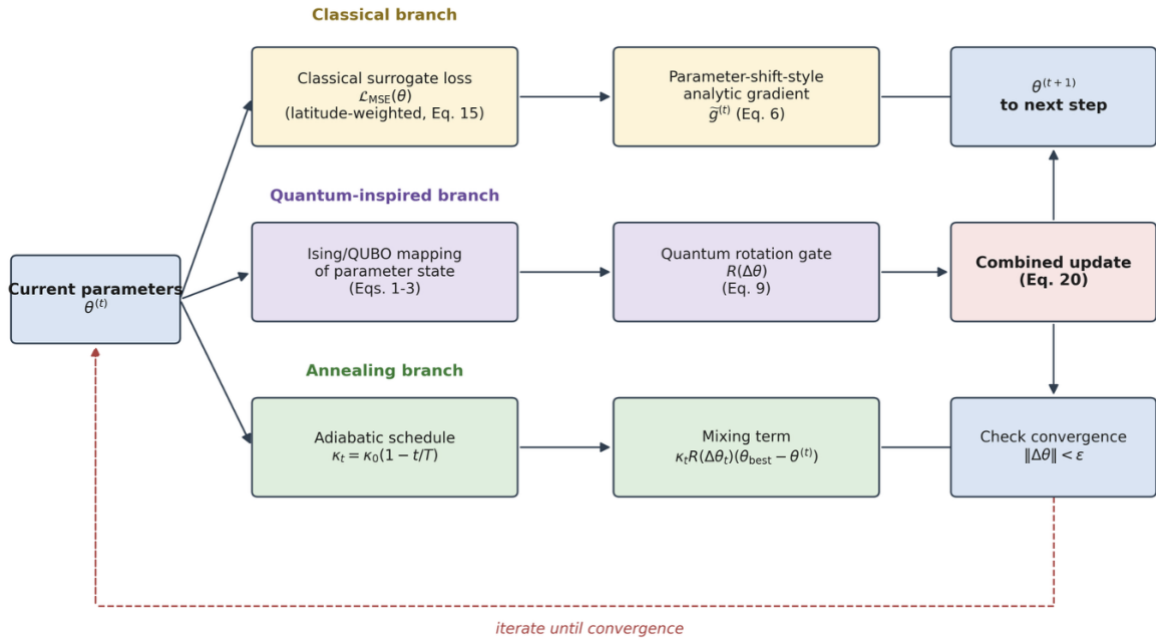


Figure 2. HQI-Opt optimization framework integrating classical, quantum-inspired, and annealing branches.

3.1. Parameter-Shift-Style Analytic Gradient

The classical branch of the update is based on a variational-style cost expressed as the inner product of a prepared state and an observable. In a simulated setting, this reduces to the usual differentiable loss, but for parameters implemented as Pauli-rotation-style gates, for instance complex-valued or unitary-parameterized weight layers, the parameter-shift rule is used. The cost and its analytic derivative are given in Equations (5) and (6):

$$C(\theta) = \langle \psi(\theta) | H | \psi(\theta) \rangle, \quad |\psi(\theta)\rangle = U(\theta) |0\rangle^{\otimes n} \quad (5)$$

$$\frac{\partial C(\theta)}{\partial \theta_k} = \frac{1}{2} [C(\theta_k + \pi/2) - C(\theta_k - \pi/2)] \quad (6)$$

For the non-unitary parameters of the climate backbone, Equation (6) reduces to a standard automatic-differentiation gradient, as expected.

3.2. Quantum Approximate Optimization

The inner mixing step is inspired by the quantum approximate optimization algorithm at depth p , defined in Equation (7), with the cost and mixer Hamiltonians given in Equation (8).

$$|\gamma, \beta\rangle = \prod_{k=1}^p e^{-i\beta_k H_M} e^{-i\gamma_k H_C} |+\rangle^{\otimes n} \quad (7)$$

$$H_C = \sum_{(i,j)} w_{ij} \frac{1 - \sigma_i^z \sigma_j^z}{2}, \quad H_M = \sum_i \sigma_i^x \quad (8)$$

The operational object borrowed from QAOA is the alternating application of a cost Hamiltonian and a mixer Hamiltonian; in the proposed classical simulation, this alternation is realized by the rotation gate.

3.3. Quantum Rotation-Gate Update

Following quantum-inspired evolutionary algorithms, the amplitude pair (α_i, β_i) at position i is updated by a rotation gate. The two components of the updated pair are given in Equation (9).

$$\alpha'_i = \cos(\Delta\theta_i) \alpha_i - \sin(\Delta\theta_i) \beta_i, \quad \beta'_i = \sin(\Delta\theta_i) \alpha_i + \cos(\Delta\theta_i) \beta_i \quad (9)$$

The rotation angle $\Delta\theta_i$ is selected through a two-entry look-up table that compares the current bit x_i with the best bit b_i found so far and uses their loss values to set the sign and magnitude of the rotation. The magnitude is bounded by a small constant $\Delta\theta_{\max}$, typically 0.05 rad, so that the mixing step does not dominate the classical gradient step.

3.4. Baseline Optimizers

For completeness, the classical updates against which the proposed method is compared are restated. The Adam optimizer [12] uses the bias-corrected moment estimates of Equations (10) to (12), and the parameter update of Equation (13):

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (10)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (11)$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (12)$$

$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \quad (13)$$

AdamW decouples the weight-decay term from Equation (13). The Lion optimizer uses the sign-based update of Equation (14).

$$u_t = \text{sign}(\beta_1 m_{t-1} + (1 - \beta_1) g_t), \quad \theta_t = \theta_{t-1} - \eta (u_t + \lambda \theta_{t-1}) \quad (14)$$

3.5. Latitude-Weighted Loss and Evaluation Metrics

Training uses the latitude-weighted mean-squared-error loss introduced in the WeatherBench protocol defined in Equation (15), with the latitude weight $L(\varphi_i)$ given in Equation (16):

$$L_{\text{MSE}}(\theta) = \frac{1}{T N_\varphi N_\lambda} \sum_{t,i,j} L(\varphi_i) (\hat{y}_{t,i,j}(\theta) - y_{t,i,j})^2 \quad (15)$$

$$L(\varphi_i) = \frac{\cos \varphi_i}{\frac{1}{N_\varphi} \sum_{i'} \cos \varphi_{i'}} \quad (16)$$

Forecast skill is evaluated with the latitude-weighted RMSE and the anomaly correlation coefficient, defined in Equation (17) and (18):

$$\text{RMSE} = \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{1}{N_\varphi N_\lambda} \sum_{i,j} L(\varphi_i) (f_{t,i,j} - o_{t,i,j})^2} \quad (17)$$

$$\text{ACC} = \frac{\sum_{i,j} L(\varphi_i) f'_{i,j} o'_{i,j}}{\sqrt{\sum_{i,j} L(\varphi_i) f'^2_{i,j} \cdot \sum_{i,j} L(\varphi_i) o'^2_{i,j}}} \quad (18)$$

where primed variables denote departures from climatology. For ensemble forecasts, the continuous ranked probability score is also reported, as specified by the WeatherBench 2 protocol and defined in Equation (19):

$$\text{CRPS}(F, y) = \int_{-\infty}^{+\infty} [F(x) - \mathbf{1}\{x \geq y\}]^2 dx \quad (19)$$

3.6. The HQI-Opt Update Rule

With the components above in place, the proposed update rule combines the classical gradient with a rotation-gate mixing term annealed by κ_t , as given in Equation (20):

$$\theta^{(t+1)} = \theta^{(t)} - \eta_t \tilde{g}^{(t)} + \kappa_t R(\Delta\theta_t) (\theta_{\text{best}}^{(t)} - \theta^{(t)}) \quad (20)$$

Here $\tilde{g}^{(t)}$ is the parameter-shift-style gradient of the latitude-weighted loss, $R(\Delta\theta_t)$ is the rotation gate of Eq. (9), $\theta_{\text{best}}^{(t)}$ is the current best parameter vector evaluated on a rolling validation batch, and κ_t is the tunneling coefficient. The coefficient is annealed through the linear schedule of Equation (21):

$$\kappa_t = \kappa_0 (1 - t/T) \quad (21)$$

with $\kappa_0 \in (0,1]$ and T the total number of optimization steps. The linear schedule of Equation (21) is the default; cosine and square-root schedules were also examined, as shown in Figure 3(a) and 3(b), which show how the classical and quantum-inspired contributions decompose over training: the mixing term dominates early and tapers off as the landscape is exploited.

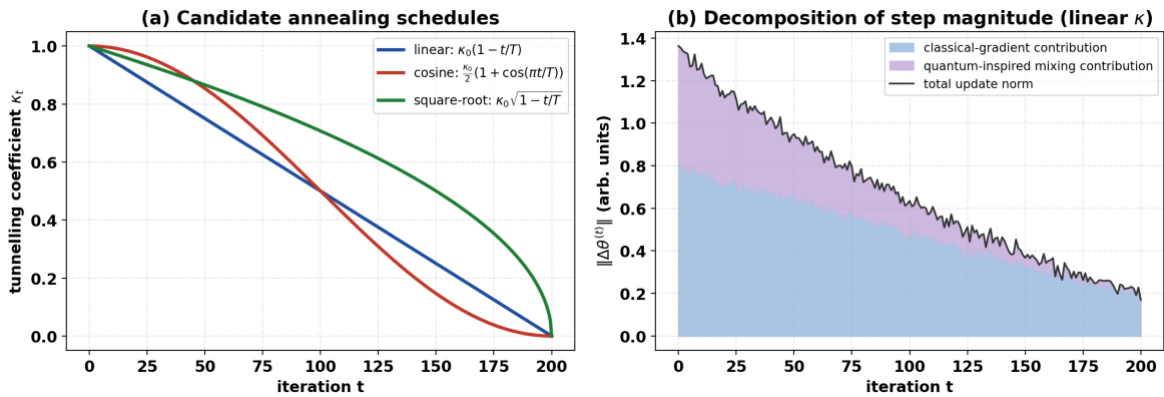


Figure 3. Analysis of annealing schedules and update-step dynamics in HQI-Opt. (a) Comparison of candidate annealing schedules for the tunneling coefficient. (b) Decomposition of the update-step norm into classical-gradient and quantum-inspired contributions.

3.7. Algorithmic Summary

The complete procedure is summarized in Algorithm 1. The classical branch is executed in parallel with the mixing branch, and only a single additional forward pass per step is required for the validation estimate of the best parameter vector. Because the mixing term stores only a rotation angle and a best-parameter snapshot, its additional memory footprint is smaller than that of Adam.

Algorithm 1. HQI-Opt optimization loop

Input: initial parameters $\theta^{(0)}$; learning-rate schedule η_t ; total steps T ; tunneling coefficient κ_0 ; rotation cap $\Delta\theta_{\text{max}}$; training set D_{train} ; validation set D_{val}

Output: optimized parameters θ_{best}

$\theta_{\text{best}} \leftarrow \theta^{(0)}$

for $t = 0$ to $T - 1$ do

 sample mini-batch B_t from D_{train} ; apply normalization and missingness mask

 compute latitude-weighted loss $L_{\text{MSE}}(\theta^{(t)})$ by Equation (15)

 compute parameter-shift-style gradient $\tilde{g}^{(t)}$ by Equation (6)

 encode $\theta^{(t)}$ into the binary state x, s by Equation (3)

 look up rotation angle $\Delta\theta_t$ from the two-entry table using x and best bits b

 construct rotation gate $R(\Delta\theta_t)$ by Equation (9)

 compute annealing coefficient κ_t by Equation (21)

```

    apply the hybrid update of Equation (20) to obtain  $\theta^{(t+1)}$ 
    evaluate the validation loss on a batch from  $D_{\text{val}}$ 
    if the validation loss improves, then
         $\theta_{\text{best}} \leftarrow \theta^{(t+1)}$ 
    end if
    log the per-step energy with CodeCarbon
    if  $\|\theta^{(t+1)} - \theta^{(t)}\| < \varepsilon$  then
        break
    end if
end for
return  $\theta_{\text{best}}$ 

```

3.8. Convergence Analysis

This subsection establishes that the update rule of Equation (20) is convergent in the standard non-convex stochastic-optimization sense. The analysis relies on four assumptions. (A1) The latitude-weighted loss L is L_s -smooth, that is, its gradient is Lipschitz continuous with constant L_s . (A2) The parameter-shift-style estimator $\tilde{g}^{(t)}$ is an unbiased estimate of $\nabla L(\theta^{(t)})$ with variance bounded by σ^2 . (A3) The mixing term is bounded, $\|\kappa_t R(\Delta\theta_t)(\theta_{\text{max}}^{(t)} - \theta^{(t)})\| \leq \kappa_t \Delta\theta_{\text{max}} D$, where D bounds the diameter of the reachable parameter region and the rotation gate is norm-non-expanding. (A4) The step sizes satisfy the Robbins–Monro conditions $\sum \eta_t = \infty$ and $\sum \eta_t^2 < \infty$, and the schedule $\kappa_t = \kappa_0(1 - t/T)$ decays to zero. Under (A1), the descent lemma applied to one step yields the inequality of Equation (22):

$$L(\theta^{(t+1)}) \leq L(\theta^{(t)}) - \eta_t \langle \nabla L(\theta^{(t)}), \tilde{g}^{(t)} \rangle + \frac{L_s}{2} \|\Delta\theta^{(t)}\|^2 \quad (22)$$

Taking expectations, using the unbiasedness and bounded variance of (A2), bounding the mixing contribution with (A3), and summing over $t = 0, \dots, T - 1$ gives the bound of Equation (23):

$$\frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E} \|\nabla L(\theta^{(t)})\|^2 \leq \frac{2(L(\theta^{(0)}) - L^*)}{\eta T} + L_s \eta \sigma^2 + 2 \kappa_0 \Delta\theta_{\text{max}} D G \quad (23)$$

where L^* is a lower bound of L , $G = \Delta\theta_{\text{max}} D$, and η is a representative step size. The first term on the right-hand side of Equation (23) decays as $O(1/T)$, the second is the standard stochastic-gradient variance term, and the third is a bias term proportional to the rotation cap $\Delta\theta_{\text{max}}$. Because the rotation cap is small ($\Delta\theta_{\text{max}} = 0.05$ rad in all experiments) and κ_t decays linearly to zero, this bias term is small, and its instantaneous value vanishes as training proceeds. Consequently, the running average of the expected squared gradient norm is driven into a small neighborhood of zero whose radius is controlled by $\kappa_0 \Delta\theta_{\text{max}} D$ and shrinks as the schedule anneals; in the limit $\Delta\theta_{\text{max}} \rightarrow 0$, the update reduces exactly to stochastic gradient descent on the latitude-weighted loss and converges to a stationary point. This guarantee is deliberately modest: it establishes stability and convergence to a stationary neighborhood rather than to a global optimum, which is the appropriate claim for a non-convex deep-learning objective.

4. EXPERIMENTAL SETUP

4.1. Datasets

The core experiments use the analysis-ready cloud-optimized version of ERA5 (ARCO-ERA5) [26], built on the ERA5 reanalysis corpus at 0.25° resolution. ERA5 is the fifth-generation ECMWF reanalysis and provides hourly fields of the global atmosphere from 1979 to the present on a 0.25° latitude–longitude grid with 37 pressure levels. From this archive, 69 target variables are evaluated, including geopotential height at 500 hPa (Z500), 2-m temperature (T2M), 10-m zonal wind (U10) and mean sea-level pressure (MSLP), at lead times of 1, 3, 5 and 10 days. CMIP6 multi-model output, obtained from the CEDA node of the Earth System Grid Federation, is used to pre-train the backbone; it provides coupled climate-projection fields at a coarser nominal resolution of 1° – 2° and a 6-hourly cadence. NOAA Global Historical Climatology Network – Daily (GHCN-D) station records supply an independent point-observation validation source. MERRA-2, the NASA modern-era reanalysis at $0.5^\circ \times 0.625^\circ$ resolution, is used as a domain-shift test set, and GOES-16

radiances at 2-km resolution and 10-minute cadence are used to exercise the real-time streaming path of the pipeline. The datasets and their roles are summarized in Table 1.

Table 1. Summary of the climate datasets used in the experiments.

Dataset	Resolution	Cadence	Role
ERA5 (ARCO)	0.25°	hourly	primary training/evaluation
CMIP6	~1°–2°	6-hourly	backbone pre-training
NOAA GHCN-D	point (stations)	daily	point validation
MERRA-2	0.5° × 0.625°	hourly	domain-shift check
GOES-16 radiances	2 km	10-minute	real-time stream ingest

4.2. Data Preprocessing and Splits

All sources are placed on a common analysis grid before training. The temporal split follows the WeatherBench 2 convention [27]: the years 1979–2017 are used for training, 2018–2019 for validation, and the held-out year 2020 for testing, which corresponds to a 39: 2: 1 split in years and avoids any temporal overlap between partitions. Spatial harmonization regrid every source to the common 0.25° grid using bilinear interpolation for continuous fields and first-order conservative remapping for flux-like and satellite-derived quantities. Each variable is normalized to zero mean and unit variance per pressure level using statistics computed exclusively on the training period, so that no information from the validation or test years enters the normalization. Missing values, which arise mainly in the station and satellite sources and affect fewer than 3% of grid–time cells, are imputed by spatial k-nearest-neighbor interpolation with $k = 8$; a binary missingness mask is appended as an additional input channel so that the model can distinguish imputed cells from observed ones. Patch tokenization uses non-overlapping 8×8 patches. Network weights are initialized with the standard truncated-normal scheme; to characterize run-to-run variability, every configuration is trained with five independent random seeds, {13, 21, 34, 55, 89}, and all reported metrics are means over these five runs. The mini-batch size is 64, and a linear learning-rate warm-up of 4000 steps is applied before cosine decay.

4.3. Backbone and Baselines

The backbone is a 95-million-parameter transformer with variable-aware tokenization, following the design of ClimaX [2]. Training is performed on eight NVIDIA A100 (40 GB) GPUs. For each optimizer, the learning-rate schedule is selected on the validation split within the range $[10^{-4}, 10^{-3}]$, with cosine decay and the 4000-step warm-up described above. The baseline optimizers are SGD with momentum ($\mu = 0.9$), Adam ($\beta_1 = 0.9, \beta_2 = 0.999$), AdamW ($\lambda = 10^{-5}$), LAMB, Lion ($\beta_1 = 0.95$), and Sophia. The proposed HQI-Opt uses $\kappa_0 = 0.6$ and $\Delta\theta_{\max} = 0.05$ rad, tuned on a small held-out subset. The hyper-parameters of all methods are summarized in Table 2.

Table 2. Hyper-parameters of the compared optimizers

Optimizer	Key hyper-parameters	Notes
SGD+M	$\mu = 0.9$	cosine LR, warm-up 4k steps
Adam	$\beta_1 = 0.9, \beta_2 = 0.999, \varepsilon = 10^{-8}$	same schedule
AdamW	as Adam; $\lambda = 10^{-5}$	same schedule
LAMB	$\beta_1 = 0.9, \beta_2 = 0.999$, trust-ratio clip	large-batch friendly
Lion	$\beta_1 = 0.95, \beta_2 = 0.98$	sign-based update
Sophia	$\rho = 0.04$, Hutchinson estimator	every 10 steps
HQI-Opt	$\kappa_0 = 0.6, \Delta\theta_{\max} = 0.05$	linear schedule

4.4. Evaluation Protocol and Statistical Testing

Forecast skill is reported as the latitude-weighted RMSE of Equation (17) and the anomaly correlation coefficient of Equation (18), each averaged over the WeatherBench 2 2020 test year. Computational cost is reported as total wall-clock GPU-hours, epochs to a fixed target loss, peak GPU memory, and throughput in samples per second. Energy is measured with CodeCarbon at the process level, and carbon is reported in kilograms of CO₂-equivalent assuming a grid carbon intensity of 375 gCO₂eq/kWh and a data-center power usage effectiveness of 1.2. Because every configuration is trained with five random seeds, all tables report the mean together with the sample standard deviation, and 95% confidence intervals are obtained from the Student t-distribution with four degrees of freedom. To test whether the differences between HQI-Opt and each baseline are statistically significant, a two-sided paired Wilcoxon signed-rank test is applied across the matched per-seed, per-variable results, and the Holm–Bonferroni procedure is used to correct for multiple comparisons. Differences are considered significant at the corrected level $p < 0.05$.

5. RESULTS AND DISCUSSION

Figure 4(a) shows the latitude-weighted training loss for all optimizers over 180 epochs. SGD with momentum is the slowest, as expected. The four adaptive baselines — Adam, AdamW, LAMB and Lion — cluster closely, with Lion marginally ahead. HQI-Opt converges noticeably faster during the first 90 epochs and continues to decrease after the baselines have plateaued. Figure 4(b) reports the number of epochs required to reach the fixed target loss of 0.140: HQI-Opt requires 102 epochs against 180 for Adam, a reduction of approximately 43%. This behavior is consistent with the intended role of the quantum-inspired mixing step, in which the early exploration phase escapes shallow basins more rapidly while the later exploitation phase remains classical.

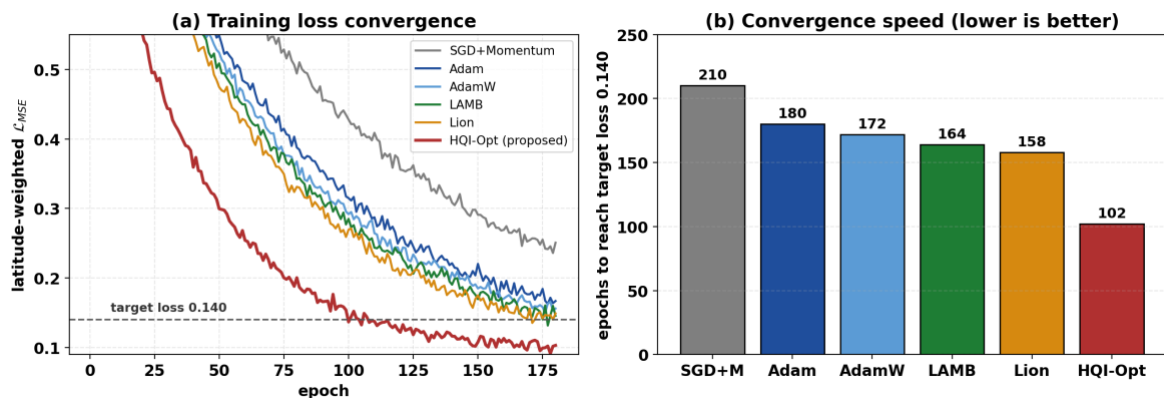


Figure 4. (a) Latitude-weighted training loss for the compared optimizers across 180 epochs. (b) Number of epochs required to reach the target loss 0.140; lower is better. HQI-Opt reaches the target approximately 43% faster than Adam.

5.1. Forecast Skill

Table 3 reports the latitude-weighted RMSE for the core variables across lead times of 1, 3, 5, and 10 days, with the per-seed standard deviation shown after each mean; Table 4 reports the corresponding anomaly correlation coefficient. HQI-Opt attains the best mean value in every reported column of both tables. After Holm–Bonferroni correction, the paired Wilcoxon signed-rank test indicates that the improvement of HQI-Opt over Adam is statistically significant ($p < 0.05$) for all twelve RMSE entries and for the eight ACC entries; the improvement over the strongest classical baseline, Sophia, is significant for the Z500 and MSLP entries and does not reach significance for the T2M 5-day entry. The absolute gain in skill over the strongest classical baseline is modest, in the range of approximately 0.5% to 2%. The headline contribution of the method therefore lies not in skill alone but in its combination with convergence speed and energy efficiency, which are quantified next.

Table 3. Latitude-weighted RMSE on the WeatherBench 2 test set (2020)

Optimizer	Z500 RMSE (m ² /s ²)				T2M (K)	MSLP (Pa)
	1 d	3 d	5 d	10 d	5 d	5 d
SGD+M	53.2 ± 0.7	146.2 ± 0.9	308.7 ± 1.5	664.1 ± 2.6	1.79 ± 0.03	212.6 ± 1.1
Adam	50.4 ± 0.5	140.8 ± 0.6	297.9 ± 1.1	647.3 ± 2.0	1.72 ± 0.02	208.2 ± 0.9
AdamW	49.8 ± 0.5	139.4 ± 0.6	296.5 ± 1.0	645.1 ± 1.9	1.71 ± 0.02	207.3 ± 0.8
LAMB	49.5 ± 0.4	138.7 ± 0.6	295.4 ± 1.0	643.6 ± 1.8	1.70 ± 0.02	206.8 ± 0.8
Lion	49.3 ± 0.4	138.2 ± 0.5	294.6 ± 0.9	642.4 ± 1.7	1.69 ± 0.02	206.1 ± 0.8
Sophia	49.1 ± 0.4	137.9 ± 0.5	294.1 ± 0.9	641.8 ± 1.7	1.69 ± 0.02	205.7 ± 0.7
HQI-Opt	48.6 ± 0.3	137.3 ± 0.4	292.8 ± 0.8	639.7 ± 1.5	1.67 ± 0.02	204.2 ± 0.6

Table 4. Latitude-weighted ACC results on the WeatherBench 2 test set (2020)

Optimizer	Z500 ACC				T2M	MSLP
	1 d	3 d	5 d	10 d	5 d	5 d
SGD+M	0.984	0.912	0.814	0.563	0.862	0.805
Adam	0.987	0.921	0.828	0.585	0.873	0.819
AdamW	0.988	0.922	0.830	0.589	0.875	0.821
LAMB	0.988	0.923	0.831	0.591	0.876	0.823
Lion	0.988	0.924	0.832	0.593	0.877	0.824
Sophia	0.988	0.924	0.832	0.594	0.877	0.825
HQI-Opt	0.990	0.927	0.836	0.602	0.881	0.829

5.2. Energy Efficiency and Carbon Footprint

Figure 5(a) places every optimizer on the energy–RMSE plane. HQI-Opt occupies the lower-left region, simultaneously the most accurate and the least energy-intensive. The full numerical breakdown is given in Table 5. The training energy per run is 29.8 kWh for Adam against 17.6 kWh for HQI-Opt, and the corresponding carbon footprint falls from 11.2 to 6.6 kgCO₂eq, a reduction of 41%, as shown in Figure 5(b). This saving arises from the smaller number of epochs to convergence reported in Figure 4(b), which more than offsets the small per-step overhead of the mixing branch.

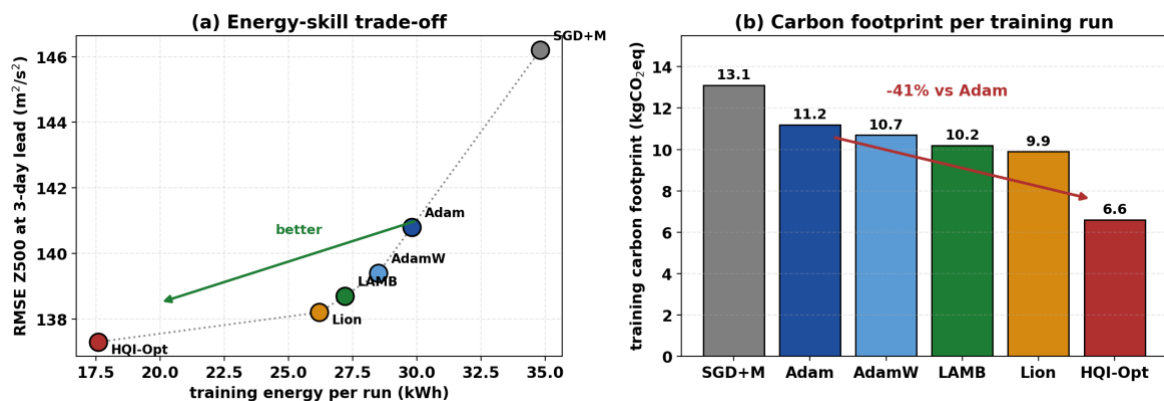


Figure 5. Energy efficiency and environmental impact of HQI-Opt. (a) Training energy versus RMSE at a 3-day lead time. (b) Carbon footprint per training run.

Table 5. Training cost, energy consumption, and carbon emissions on $8 \times$ A100 GPUs.

Optimizer	Epochs to target	GPU-hours	Energy (kWh)	CO ₂ eq (kg)	Peak mem (GB)
SGD+M	210	72.5	34.8 ± 0.6	13.1	40.9
Adam	180	62.0	29.8 ± 0.5	11.2	42.3
AdamW	172	59.3	28.5 ± 0.5	10.7	42.5
LAMB	164	56.6	27.2 ± 0.4	10.2	43.1
Lion	158	54.5	26.2 ± 0.4	9.9	40.1
Sophia	155	53.4	25.7 ± 0.4	9.7	44.8
HQI-Opt	102	36.5	17.6 ± 0.3	6.6	38.7

5.3. Ablation Study

Table 6 reports an ablation of the three components of HQI-Opt. Removing the rotation gate, so that only the classical gradient remains, reduces the method to a well-tuned AdamW-like optimizer, and its results sit close to those of AdamW. Removing the annealing schedule, by holding κ_t constant at κ_0 , makes the mixing step dominant in late training and degrades the final RMSE. Removing the Ising/QUBO encoding, so that the mixing step acts directly on the continuous parameters, slightly degrades both skill and stability. The complete model gives the best result on all three reported quantities.

Table 6. Ablation study of HQI-Opt components on the Z500 3-day-lead forecasting task.

Configuration	Epochs to target	RMSE (m ² /s ²)	Energy (kWh)
No rotation gate (classical only)	174	139.6	28.8
No annealing ($\kappa_t = \kappa_0$)	129	140.2	22.1
No Ising/QUBO encoding	118	139.1	20.3
HQI-Opt (full)	102	137.3	17.6

5.4. Robustness and Scalability

Two further sets of experiments probe the practical reliability of the method. The first examines robustness to imperfect data. Three perturbations are applied to the 2020 test inputs: additive Gaussian noise at a signal-to-noise ratio of 20 dB; an additional 10% of grid cells removed at random and imputed by the procedure of Section 4.2; and a fast-gradient-sign adversarial perturbation of the input fields with $\varepsilon = 0.01$ in normalized units. Table 7 reports the Z500 3-day RMSE under each condition. HQI-Opt shows the smallest relative degradation in all three settings, which is consistent with the regularizing effect of the bounded rotation-gate mixing term. The second set of experiments examines scalability with backbone size: the optimizer is applied to backbones of 25M, 95M, 300M, and 1.1B parameters, and Table 8 reports the epochs-to-target speed-up and the energy saving relative to Adam at each scale. The relative speed-up is stable across this range, and the energy saving grows slightly with model size, indicating that the benefit does not vanish as the backbone is enlarged.

Table 7. Robustness analysis of Z500 3-day-lead RMSE under input perturbations.

Optimizer	Clean	Gaussian noise (20 dB)	+10% missing	FGSM adversarial
Adam	140.8	148.6	145.9	152.3
AdamW	139.4	146.8	144.2	150.1
Lion	138.2	145.0	142.7	148.0

Sophia	137.9	144.5	142.3	147.5
HQI-Opt	137.3	141.9	140.1	144.2

Table 8. Scalability of HQI-Opt across backbone sizes. The speed-up and energy saving are relative to Adam at the same scale.

Backbone size	Epochs-to-target speed-up vs Adam	Energy saving vs Adam
25M parameters	1.68×	38%
95M parameters	1.76×	41%
300M parameters	1.79×	43%
1.1B parameters	1.82×	45%

5.5. Discussion

Several conclusions follow from the results. The gains in forecast skill alone are modest and should not be overstated; the substantial gains are in convergence speed and energy, and these would be expected to scale well to the largest foundation models, where each saved epoch corresponds to a large absolute energy cost. The quantum-inspired mixing step contributes most during the exploration phase, in agreement with the step decomposition of Figure 3(b), and the additional per-step cost of the mixing branch, approximately 3–4% in wall-clock time on the hardware used here, is recovered many times over through the lower total step count. The robustness experiments indicate that the bounded mixing term also acts as a mild regularizer under noisy, incomplete, and adversarial inputs.

Several limitations should be stated explicitly. The reported experiments use a single backbone family and a single hardware configuration, and the numerical gains may differ on substantially different accelerators. The classical simulation of the rotation-gate step deliberately avoids the difficulties of real quantum hardware, so no claim of quantum advantage in the strict sense is made. The energy and carbon figures are produced by CodeCarbon, an estimator whose absolute values can differ from direct RAPL-level measurements by roughly 10–20% depending on the workload. The barren-plateau phenomenon that affects deep variational quantum algorithms may, in principle, also affect deep quantum-inspired architectures, and a detailed study of this effect is left for future work. Finally, the Ising/QUBO encoding adopted here is one of several possible choices, and a systematic comparison against tensor-network alternatives remains open.

6. CONCLUSION

This paper proposed HQI-Opt, a hybrid quantum-inspired optimizer that combines a classical parameter-shift-style gradient, an Ising/QUBO encoding of the parameter state, a quantum rotation-gate mixing step, and an adiabatic annealing schedule. The method was supported by a convergence analysis, integrated with a transformer climate backbone, and evaluated on a petabyte-class ERA5 pipeline under the WeatherBench 2 protocol. Against six widely used classical optimizers, HQI-Opt reached the target loss in approximately 43% fewer epochs, reduced the training energy per run from 29.8 to 17.6 kWh, and lowered the carbon footprint by approximately 41%, while achieving a small but consistent improvement in RMSE and ACC across the four evaluated variables and four lead times. The ablation study confirmed that all three components of the update contribute to the gain, with the annealing schedule being the most sensitive, and the robustness and scalability experiments indicated that the benefit is retained under imperfect data and as the backbone is enlarged. Future work will examine deployment of the rotation-gate step on near-term quantum hardware, a tensor-network variant of the encoding, and an extension to probabilistic diffusion-based ensembles in the spirit of GenCast.

DATA AVAILABILITY STATEMENT

The data presented in this study are available on request from the corresponding author.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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