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Research Paper Title :Physics-Informed Stochastic Neural Operators for Climate and Earth-System Prediction

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Abstract:

Climate and Earth-system prediction requires simultaneous representation of nonlinear multiscale dynamics, uncertain initial and boundary conditions, incomplete observations, and physical conservation laws. Data-driven forecasting can capture large-scale statistical structure, yet long forecast horizons and rare events expose difficulties associated with physical consistency and calibrated predictive distributions. This paper develops a Physics-Informed Stochastic Neural Operator for Earth-System Prediction (PISNO-Earth), a proposed framework that maps observed spatiotemporal states and forcing fields to distributions of future climate states while explicitly penalizing governing-equation residuals and conservation violations. The methodology integrates a conditional neural operator, stochastic latent forcing, discretization-aware differential operators, and multi-objective estimation of predictive, dynamical and probabilistic losses. It specifies an observation-alignment protocol, temporal and geographic holdouts, ensemble evaluation, and stratified diagnostics for tropical cyclones, heavy precipitation and subseasonal anomalies. A closed-form diffusion problem supplies an independently reproducible numerical benchmark: at a normalized forecast horizon of 0.10, its leading-mode amplitude is approximately 0.3727 relative to the initial amplitude, illustrating how a conservation-compatible decay constraint can be checked without asserting an unmeasured forecasting gain. The proposed architecture makes physical consistency, uncertainty reliability, and resolution transfer jointly testable, rather than treating them as interchangeable performance criteria. The principal contribution is a falsifiable and implementation-oriented modelling specification with explicit ablations, evaluation metrics, and operational safeguards. Large-scale forecasting benefits remain hypotheses until the proposed system is trained and evaluated on independently sourced Earth observations and reanalysis archives.

Keywords: neural operators; physics-informed learning; stochastic partial differential equations; climate prediction; Earth-system modelling; Bayesian uncertainty; probabilistic forecasts; conservation constraints; spectral operators; subseasonal prediction; extreme precipitation; ensemble calibration; resolution transfer; causal forcing.

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1. Introduction

Climate prediction is a coupled inference problem across atmosphere, ocean, land and cryosphere. Predictors must reconcile heterogeneous observation streams with transport, energy exchange and forcing processes. Recent data-driven weather and subseasonal research demonstrates sustained interest in learned forecast systems, while physically structured downscaling and process-specific models highlight the value of embedding domain knowledge (Allen et al. 2025; Guan et al. 2026; Francies et al. 2026). These strands invite a system that produces coherent distributions without abandoning physical diagnostics.

An operator-learning perspective models the map between input fields and future solution fields, potentially permitting reuse over multiple resolutions. A stochastic construction is important because uncertain boundary fluxes, unresolved convection, observation error and intrinsic variability cannot be reduced to one deterministic trajectory. Operational assessment must also be sensitive to the forecasting setting: tropical cyclone tracks, subseasonal rainfall and evapotranspiration impose different event definitions and error costs (Choy et al. 2026; Cong et al. 2025; Gyamfi and Chung 2026).

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1.1 Research Problem

The core research problem is how to couple flexible field-to-field forecasting with governing equations and predictive uncertainty while maintaining computational tractability. A low pointwise error alone cannot establish conservation, calibration or resilience under distribution shift. Physics penalties can themselves be misleading when forcing fields are incompletely observed or the numerical discretization does not preserve the intended invariants.

1.2 Research Questions

• Can physical residual constraints improve out-of-region and long-horizon consistency relative to an otherwise identical stochastic neural operator?

• Which stochastic parameterization yields calibrated ensembles for precipitation and temperature anomalies?

• How do conservation penalties interact with skill at sharp fronts and infrequent extremes?

• Does performance persist under changes in spatial resolution and external forcing?
• What failure thresholds and governance controls are required for operational use?

1.3 Research Objectives

• Specify a conditional stochastic neural operator and a compatible physical constraint system.
• Define a realistic data acquisition, sampling and leakage-prevention protocol.
• Design comparable deterministic, stochastic and physics-informed ablations.
• Establish an uncertainty, skill, physical-consistency and computational evaluation suite.
• Translate model outcomes into auditable climate-risk decision support.

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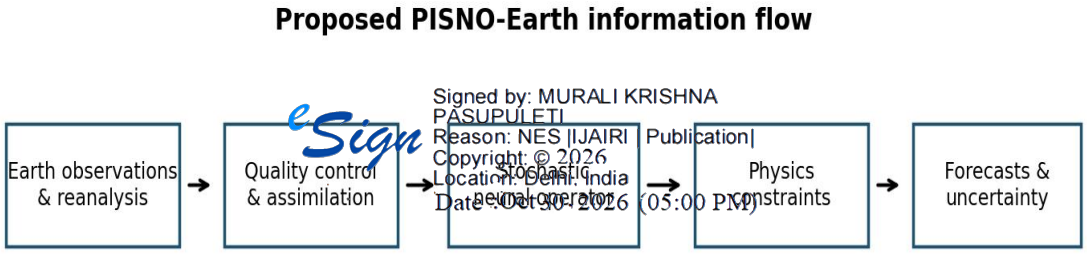
2. Literature Review

The provided literature spans end-to-end weather learning, subseasonal prediction, physics-informed architectures, stochastic operator systems, and operational forecasting. Allen et al. (2025) and Guan et al. (2026) are directly relevant to learned temporal forecasting; Francies et al. (2026) addresses physically informed and topology-aware urban downscaling. Gyamfi and Chung (2026) links ENSO dynamics to physics-informed graph models, providing a motivation to incorporate structured climate drivers. Lee and Chang (2026) treats modular physical coupling for urban flood modelling, while Resifi et al. (2026) addresses probabilistic regional subseasonal downscaling.

The distinction between weather forecast skill and deployable risk assessment is significant. Choy et al. (2026) discusses operational AI forecast experience for tropical cyclones; Esmaili et al. (2022) concerns satellite sounders and cyclone environments. The stochastic neural-operator methodology in Liu et al. (2025), although developed for bridge dynamics rather than climatology, offers a transferably relevant modelling concept. Earth-observation data management is a separate systems problem emphasized by Chen et al. (2026). These studies do not, by themselves, verify the PISNO-Earth architecture proposed here.

2.1 Conceptual Framework

Let atmospheric/oceanic state X, resolved forcing F, observation mask M and static geography G form the information set at time t. A conditional operator maps this information and stochastic latent variable Z to a future field. Physics residuals represent the incompatibility between each generated field and discretized dynamics; uncertainty diagnostics quantify distributional correspondence to held-out observations. Forecast utility is determined jointly by accuracy, tail-event detection, physical coherence, calibration and operational cost.



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Figure 1. Proposed PISNO-Earth modelling pipeline (conceptual schematic).

2.2 Prior-art Search Matrix

Source	Research focus	Direct relevance	Unresolved question for this paper
Allen et al. (2025)	Data-driven weather prediction	Learned forecasts	Physics / ensemble compatibility
Guan et al. (2026)	Subseasonal machine learning	Extended horizons	Cross-region reliability
Francies et al. (2026)	Physics-informed downscaling	Constraint design	General-purpose stochastic coupling
Gyamfi and Chung (2026)	ENSO-aware graph model	Climate drivers	Uncertainty calibration
Resifi et al. (2026)	Probabilistic regional forecasts	Distributional downscaling	Conservation across scale
Liu et al. (2025)	Stochastic-load	Stochastic operator	Transfer to Earth-

	neural operators	concepts	system equations
Choy et al. (2026)	Operational cyclone forecasting	Deployment context	Robustness thresholds

2.3 Research Gap

The theoretical gap concerns simultaneous conditional stochastic mapping and explicitly testable conservation under incomplete forcings. The methodological gap concerns identical-data ablations that disentangle the gains and costs of stochastic sampling, physics regularization and resolution transfer. The empirical gap concerns consistent out-of-time, out-of-region and extreme-event evaluation. The sectoral gap is the translation of model outputs into flood, water and cyclone workflows; the policy gap is transparent reporting of reliability, limitations and failure triggers (Lee and Chang 2026; Makgati et al. 2026).

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3. Methodology

This is a prospective modelling study with a deterministic analytic check, not a report of a fitted empirical model. The planned experiment would combine publicly licensed atmospheric reanalysis, satellite-derived observations and station observations with compatible timestamps, coordinate systems and measurement definitions. Operational protocols would record versions, spatial interpolation, quality-control flags, imputation decisions and provenance. Data subsets must be separated by forecast initialization time, region and severe-event episode; overlapping forecast windows must not cross the train–test split.

The suggested unit of evaluation is a forecast initialization with fixed lead times (1–10 days, 2–6 weeks where available) and spatial grids defined prior to training. A multi-year chronological holdout, an independent region holdout, and stress tests for unusually warm, wet and cyclone-active periods are needed. Training can optimize the model using gradient methods; baselines must share preprocessing and compute constraints.

3.1 Mathematical Framework

$$X(t + \Delta t) = S\theta[X(t), F(t{:}t + \Delta t), G, Z] \tag{1}$$

X denotes the prognostic state field, Δt the lead interval, F resolved forcing, G geographic covariates, Z a stochastic latent variable, Sθ the learned conditional operator, and θ its parameters.

$$\partial t\, X = -\nabla \cdot \Phi(X) + Q(X,F) + \Xi \tag{2}$$

Φ denotes physical flux, Q deterministic source/sink terms, and Ξ an unresolved stochastic tendency. The formula is a process template and must be instantiated separately for each target variable.

$$R\theta = D\Delta t\, X\theta + \nabla \mathrm{h} \cdot \Phi(X\theta) - Q(X\theta,F) \tag{3}$$

Rθ is the discretized dynamical residual, DΔt and ∇h are time and spatial discrete differentiation operators. Xθ denotes a sampled forecast.

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$$L\mathrm{phys} = E[\, \|R\theta\|^2 W\,] + \lambda c\, E[\, \|C(X\theta)\|^2\,] \tag{4}$$

W is a positive weighting operator and C is a specified integral conservation defect; λc is a nonnegative conservation weight.

$$X\theta(t + \Delta t) = \mu\theta(X,F,G) + B\theta(X,F,G)\, Z \tag{5}$$

μθ is the conditional central prediction; Bθ maps latent perturbations Z into spatially structured forecast uncertainty.

$$LCRPS = (1/N)\, \Sigma i\, CRPS(P\theta,i, yi) \tag{6}$$

CRPS is the continuous ranked probability score, yi a withheld realized outcome, Pθ,i the predictive distribution, and N the number of valid targets.

$$Ltotal = Ldata + \alpha\, L\mathrm{phys} + \beta\, LCRPS + \gamma\, Lspec \tag{7}$$

Ldata is an observation-based proper predictive loss, Lspec spectral consistency penalty, and α, β, γ nonnegative selected weights. Avoid adding CRPS twice when it already defines Ldata.

$$C(X) = \int\Omega\, X(x,t)\, dx - \int\Omega\, X(x,0)\, dx - \int_0{}^t\int\Omega\, Q\, dx\, ds + \int_0{}^t\int\partial\Omega\, \Phi\cdot n\, dA\, ds \tag{8}$$

C(X̂) expresses an integrated budget defect; Ω is the domain and n its outward normal. Each scientific variable needs appropriate units and budget terms.

The notation above is a design specification. In production, flux-form losses should use matching boundary conditions and conservative gridding; otherwise apparently small residuals can conceal physically significant discretization errors.

3.2 Numerical Model for Better Insight

To provide a reproducible independent check without uncollected observations, consider the one-dimensional nondimensional heat equation on $0 \leq x \leq 1$, homogeneous zero boundaries, diffusivity $\kappa = 1$, and initial state $\sin(\pi x)$. This benchmark is mathematically exact and tests whether a proposed operator can respect exponential mode damping. It is not evidence of weather forecasting skill.

$$\partial t\, u = \kappa\, \partial xx\, u; \quad u(0,t) = u(1,t) = 0 \tag{9}$$

u is the normalized scalar field and κ the diffusivity.

$$u(x,t) = exp(-\kappa\pi^2 t)\, sin(\pi x) \tag{10}$$

For $\kappa = 1$, the exact first-mode amplitude A(t) is $\exp(-\pi^2 t)$, which can be compared with model-generated amplitudes.

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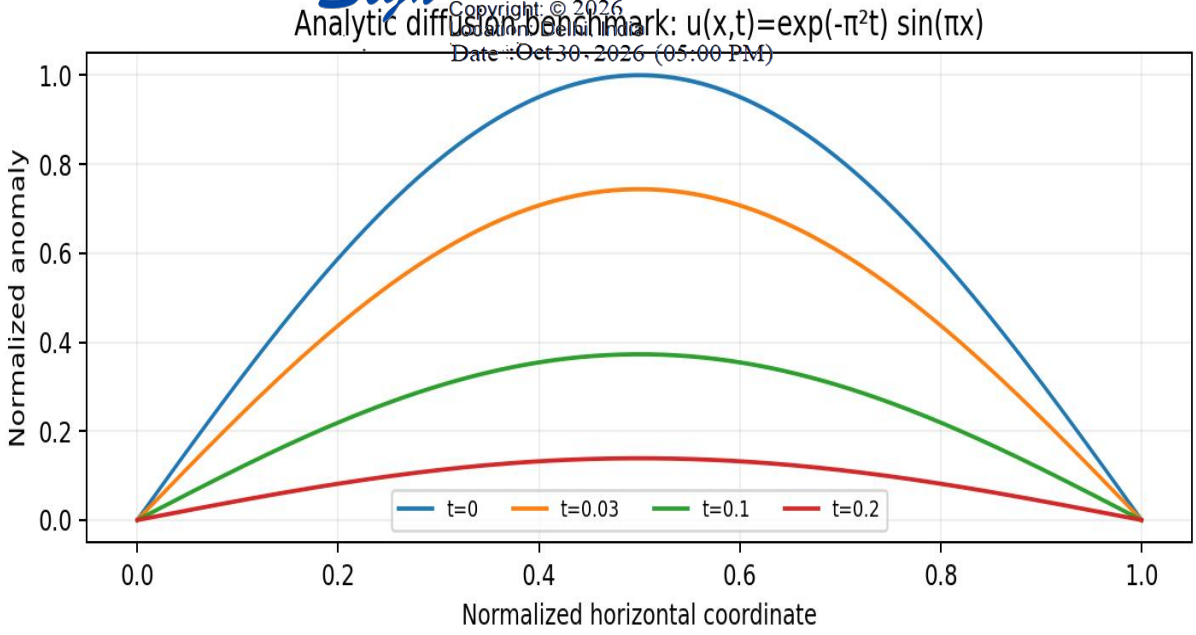


Figure 2. Exact analytic benchmark at four normalized lead times; no measured data are used.

Table 2. Reproducible analytic benchmark for the first diffusion mode.

Lead t	Amplitude A(t)	Decay from initial	Status
0.00	1.0000	0.0%	Analytic exact value
0.03	0.7437	25.6%	Analytic exact value
0.10	0.3727	62.7%	Analytic exact value

0.20	0.1389	86.1%	Analytic exact value
0.30	0.0518	94.8%	Analytic exact value

For t = 0.10 the exact amplitude is 0.3727, a reduction of 62.7% relative to t = 0.00. A candidate method that produces a materially increasing first-mode amplitude under these source-free conditions would violate the specified benchmark. No calibrated ensemble, error advantage or performance improvement is inferred from these values.

3.3 Data and Variables

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Table 3. Proposed variables and operational measurement conventions.

Variable	Definition / measurement	Scale	Expected model relevance
T2m	Near-surface air temperature; K	Continuous grid	State and verification
P	Accumulated precipitation; mm day−1	Nonnegative, skewed	Extremes and probabilistic skill
U,V	Horizontal winds; m s−1	Signed vectors	Advection and dynamics
SLP	Sea-level pressure; hPa	Continuous field	Storm dynamics
SST	Sea surface temperature; K	Continuous field	Boundary forcing
ENSO index	Standardized oscillation metric	Continuous temporal	Long-range climate state
M	Availability/quality mask	Binary / categorical	Observation provenance
Z	Latent random draw	Continuous vector/field	Ensemble spread
C	Integral budget defect	Physical units / normalized	Conservation compliance

3.4 Novel Architecture

PISNO-Earth includes (i) a gridded observation encoder, (ii) a multiresolution latent operator with local and global interactions, (iii) a latent stochastic driver with independent ensemble seeds, (iv) flux- and budget-aware differentiable residual modules, and (v) a distributional forecast head. The system stores input provenance alongside generated forecast ensembles. Loss terms are masked where observations are unavailable and weighted using variable-specific normalizers to avoid an arbitrary preference for fields with larger numerical magnitudes.

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The central design choice is to evaluate physical residuals on every stochastic sample, not solely on the ensemble mean: the latter can mask incompatible trajectories whose errors cancel on averaging. Physics losses must be relaxed when boundary fluxes are genuinely unknown, with that relaxation recorded and analyzed as a source of uncertainty.

3.5 Proposed Model / Framework

$$PISNO{-}Earth\text{: } P\theta(Xt{+}\tau \mid Xt, F, G) = Law[S\theta(Xt,F,G,Z)] \tag{11}$$

Pθ is the conditional predictive distribution, τ the forecast horizon and Law[·] the distribution induced by independently sampled latent Z.

$$\theta^{*} = argmin\theta \{ E[Lforecast] + \alpha E[Lphys] + \beta E[Lcal] \} \tag{12}$$

Lforecast evaluates observed field skill, Lcal is a calibration-sensitive score distinct from the selected forecast loss, and weights are chosen exclusively using validation data.

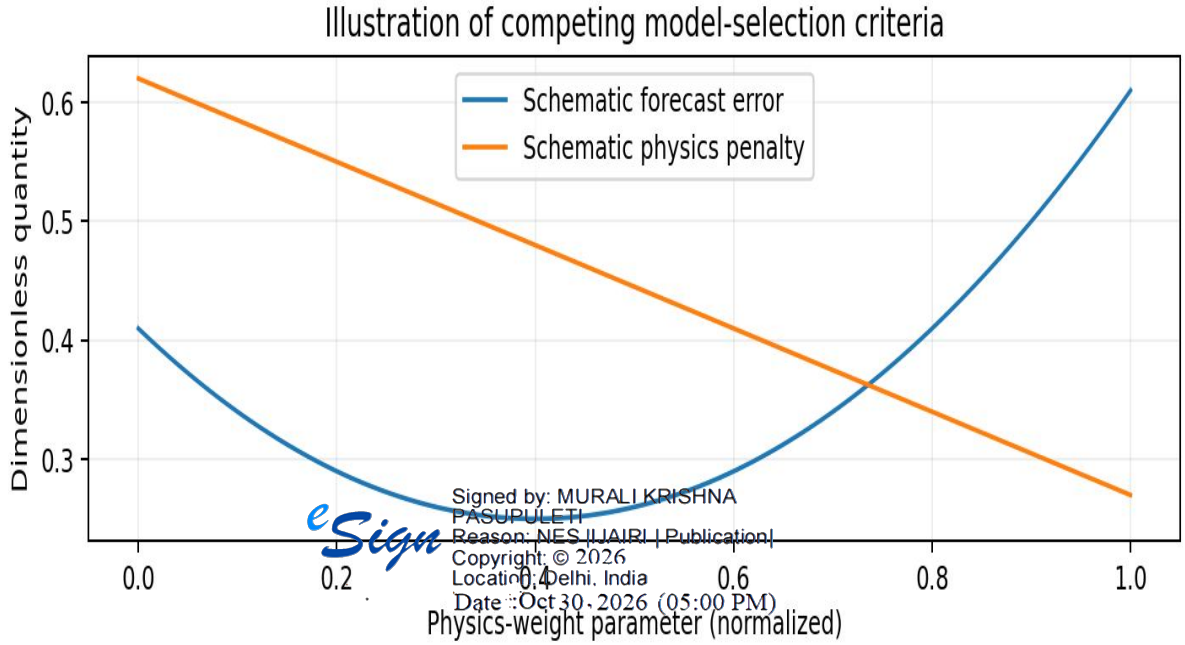


Figure 3. Schematic hyperparameter trade-off curves. Values are conceptual, not empirical comparisons.

3.6 Research Implementation

Implementation should proceed through a documented pipeline: (1) obtain licensed observations and reanalysis; (2) establish audit-ready variable definitions; (3) fit deterministic operator and standard numerical forecasts as baselines; (4) introduce latent stochastic sampling; (5) incorporate flux and conservation terms one at a time; (6) select hyperparameters on validation years only; (7) evaluate fixed lead times and predeclared extremes; (8) release code, configuration, dataset provenance and metric definitions where licensing permits. Model checkpoints and data assimilation times must be frozen before evaluation.

The comparison plan includes consistent-resolution skill and resolution-transfer tests. High-resolution regions should be excluded from training in geographic transfer experiments. A serious operational assessment further needs latency, energy use, forecast availability and reproducibility under model reruns.

4. Results and Analysis

The only computed numerical values in this manuscript arise from the exact diffusion benchmark in Section 3.2. Forecast skill, confidence intervals, cyclone outcomes and

calibration statistics are unmeasured pending execution of the empirical protocol. Consequently, this section reports logical deductions and prespecified evaluation endpoints rather than presenting hypothetical measurement as an experiment.

Table 4. Preregistered comparative model ablations (outcomes remain to be measured).

Model	Stochastic forecast	Physics loss	Primary comparison
A. Deterministic operator	No	No	Point-forecast baseline
B. Stochastic operator	Yes	No	Probabilistic calibration
C. Physics-informed deterministic	No	Yes	Budget consistency and point skill
D. PISNO-Earth	Yes	Yes	Joint skill, uncertainty and physics
E. PISNO-Earth minus budget	Yes	Residual only	Effect of integral constraint

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Table 5. Operational evaluation protocol and interpretation.

Metric	Evaluation	Meaning / caution
RMSE / MAE	Per target, lead and region	Central forecast error, not calibration
CRPS / log score	All held-out ensemble forecasts	Proper distributional accuracy
Coverage / PIT	Nominal intervals and rank histograms	Over- or under-dispersion
Brier / reliability	Threshold-defined extremes	Probability quality at rare events
Budget closure error	Area-integrated relevant fluxes	Physical consistency conditional on known boundary
Spectral energy error	Wavenumber bands	Cross-scale behaviour

Inference latency	Identical hardware and batch	Operational feasibility

A robust result would require improvements on independently held-out cases with uncertainty intervals across initialization episodes, not merely point estimates on correlated grid cells. Statistical comparisons should bootstrap by weather event or initialization cluster rather than treating neighboring pixels as independent samples. Improvement in conservation error without corresponding probability skill should be reported as a trade-off rather than an overall gain.

4.1 Discussion

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The framework links operator learning to stochastic differential systems and explicit budget checks. Conceptually, the principal advantage is falsifiability: the deterministic benchmark, empirical ablations, and operational failure criteria are separable. Physics constraints can be especially important in water and energy planning where implausible global or regional budgets undermine confidence, but they are not a substitute for observing missing forcing terms (Francies et al. 2026; Lee and Chang 2026).

For industry users, outputs can support cyclone preparedness, drainage planning and climate-sensitive infrastructure risk only when forecasts are appropriately calibrated and domain-tested. Policy agencies should require provenance, uncertainty summaries, threshold-specific verification and a fallback numerical forecast. Ethical concerns include geographic representation, exposure to unequal observation density, model drift, resource use and the danger of presenting a single precise forecast as a certain outcome (Choy et al. 2026; Esmaili et al. 2022).

5. Conclusion

This paper specifies PISNO-Earth, a conditional stochastic neural-operator framework for coupled Earth-system forecasting with explicit physical-residual, conservation and probabilistic verification. The architecture integrates data, forcing and geometry with ensemble generation and provides a transparent protocol for ablation, geographic transfer, tail-event assessment and deployment auditing. Its analytic diffusion benchmark yields exact expected amplitudes and demonstrates a concrete physics-

consistency check; it does not establish empirical climate forecasting superiority. Future value depends on rigorous cross-region experiments, complete boundary-condition accounting, independent forecast verification and controlled operating procedures.

5.1 Limitations

No original climate dataset, trained network or operational forecast has been produced for this manuscript. The analytic diffusion equation cannot represent atmospheric moist convection, coupled ocean processes, turbulence, regime switching or spatially heterogeneous climate feedbacks. Physical budgets may contain unavailable sources and uncertain boundary flows. Neural operators can be sensitive to data-resolution changes, rare-event sparsity and bias in assimilated observations; computational and calibration costs remain unspecified until implementation. The provided bibliography was deduplicated and selected for thematic relevance, but publication metadata and DOIs should be verified against publisher records before submission.

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5.2 Future Research Directions

• Coupled atmosphere–ocean–land stochastic operators with cross-domain flux closure.
• Conformal or distribution-free forecast calibration across shifting climate regimes.
• Adaptive mesh and spectral transfer with budget-preserving interpolation.
• Rare-event conditional generation for compound heat–rainfall–wind hazards.
• Differentiable data assimilation with heterogeneous station and satellite uncertainty.
• Mechanistic teleconnection conditioning and interpretable climate-driver sensitivity.
• Independent operational trials of model fallback, latency and alert thresholds.
• Energy-aware ensemble design and transparent lifecycle impact accounting.

References

Allen, A., Markou, S., Tebbutt, W., Requeima, J., Bruinsma, W.P., Andersson, T.R., Herzog, M., Lane, N.D., Chantry, M., Hosking, J.S. and Turner, R.E. (2025) 'End-to-end data-driven weather prediction', Nature, 641(8065), pp. 1172–1179. doi:10.1038/s41586-025-08897-0.

Chen, B., Gavriilidis, H., Gaedicke, L., Bök, T.E., Boehm, M., Abedjan, Z., Demir, B. and Markl, V. (2026) 'Demonstrating EarthLake: A Model Lake System for Earth Observation Foundation Model Management', Proceedings of the VLDB Endowment, 19(12), pp. 4610–4613. doi:10.14778/3827998.3828078.

Choy, C.W., He, Y.H., Wong, W.K., Lee, T.C., Ho, C.K., Law, H.F., Lui, Y.S. and Chan, P.W. (2026) 'Operational Experience of Using Artificial Intelligence Global Models for Tropical Cyclone Forecasting in the Western North Pacific and the South China Sea', Tropical Cyclone Research and Review, 15(3), pp. 339–347. doi:10.1016/j.tcrr.2026.05.001.

Cong, T., Ha, T.-H.-G., Vu, G.-L., Bui, H.-N., Dao, N.-Q.-H., Le, M.-H., Dinh, C.-M., Cong, M.-P. and Doan, Q.-V. (2025) 'Advancing Subseasonal Extreme Rainfall Forecasting in Vietnam Using Machine Learning', SOLA, 21, pp. 273–282. doi:10.2151/sola.2025-034.

Esmaili, R., Barnet, C., Dunion, J., Folmer, M. and Zawislak, J. (2022) 'Evaluating Satellite Sounders for Monitoring the Tropical Cyclone Environment in Operational Forecasting', Remote Sensing, 14(13), p. 3189. doi:10.3390/rs14133189.

Francies, M.L., Khalil, A.T., Amer, H.M. and Ata, M.M. (2026) 'A trustworthy deep learning framework for urban climate downscaling via physics-informed diffusion and topology-aware graph neural operators', Expert Systems with Applications, 331, p. 133361. doi:10.1016/j.eswa.2026.133361.

Guan, H., Mouatadid, S., Orenstein, P., Cohen, J., Dong, H., Ni, Z., Berman, J., Flaspohler, G., Lu, A., Schloer, J., Talib, J., Weyn, J.A. and Mackey, L. (2026) 'Advancing subseasonal forecasting with machine learning', Nature, 658(8137), pp. 951–957. doi:10.1038/s41586-026-11126-x.

Gyamfi, K.A. and Chung, E.-S. (2026) 'Integrating ENSO dynamics into physics-informed Graph Neural Networks for extreme evapotranspiration prediction under climate change', Agricultural and Forest Meteorology, 389, p. 111427. doi:10.1016/j.agrformet.2026.111427.

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Lee, B.J. and Chang, Y.-S. (2026) 'A modular coupled physics-informed neural network framework for urban flood prediction', Journal of Water and Climate Change, 17(2), pp. 426–439. doi:10.2166/wcc.2026.311.

Liu, Y., Chen, S., Han, Y. and Xiong, Z. (2025) 'Modularized Physics-Driven Dynamic Response Prediction of Long-Span Bridge and Traffic System Subjected to Stochastic Loads Based on Neural Operators', Journal of Bridge Engineering, 30(10). doi:10.1061/jbenf2.beeng-7551.

Makgati, L.N., Bopape, M.-J.M., Phaduli, E., Rambuwani, G., Maisha, R. and Reason, C.J.C. (2026) 'Improvements in tropical cyclone forecasting using CCAM compared with the operational Unified Model: A case study of tropical cyclone Idai', Natural Hazards, 122(8). doi:10.1007/s11069-026-08032-w.

Resifi, S., Al Aawar, E., Luong, T. and Hotet, J. (2026) 'HiResCastNet: A 3D Deep Learning Model for Probabilistic Regional High-Resolution Subseasonal Forecasting Through Downscaling', Journal of Geophysical Research: Machine Learning and Computation, 3(6). doi:10.1029/2026jh001400.

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