

AI-Driven Atmospheric Modeling and Environmental Prediction for Sustainable Climate Management

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Abstract

The increase in extreme weather events and environmental degradation demands new computational approaches for accurate forecasting and green management. Traditional numerical weather prediction (NWP) models are computationally expensive and struggle with resolution and data assimilation, despite being effective and high capacity. The proposal in this work is an Artificial Intelligence (AI) hybrid framework featuring machine learning (ML) and deep learning (DL) models with atmospheric and climate datasets to improve forecast accuracy, reduce computing costs and improve temporal-spatial resolution of environmental simulation. The framework consists of transformer models, spatiotemporal neural networks, and physics-constrained AI models to forecast weather events, air quality indices, and greenhouse gas (GHG) levels. Our project develops an extensible and sustainable AI pipeline that continuously learns from satellite images, sensor networks, and community open climate data sources (e.g., NASA EarthData, Copernicus). Expected outcomes are improved accuracy of short-term forecasts, reduced computational energy costs, and actionable insights for strategic decision making by policy-makers and intelligent city infrastructure planners.

Key words: AI for climate modeling, Atmospheric prediction, Deep learning, Environmental sustainability, Spatiotemporal forecasting, Green computing

Climate change is now one of the most critical challenges of the 21st century, undermining ecosystems, economies, and health. The growing intensity and frequency of extreme weather events - floods, hurricanes, droughts, and heat waves - demonstrate that the climate system of the Earth is becoming more and more unpredictable. Climate change has emerged as one of the most pressing global challenges of the twenty-first century, exerting profound impacts on natural ecosystems, human societies, and economic systems across the world. Rapid industrialization, urbanization, deforestation, and the excessive emission of greenhouse gases such as carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O) have significantly altered the Earth's climate system. As a consequence, global temperatures are rising at an unprecedented rate, leading to severe environmental disturbances and increasing climatic variability. The growing scientific consensus indicates that anthropogenic activities are the primary drivers of contemporary climate change, with far-reaching implications for environmental sustainability and human well-being.

One of the most alarming manifestations of climate change is the increasing frequency and intensity of extreme weather events, including floods, hurricanes, droughts, cyclones, heat waves, and unseasonal rainfall. These events not only disrupt ecological balance but also threaten agricultural productivity, food security, water resources, infrastructure, and public health. Heat waves have become more prolonged and

severe in many regions, causing increased mortality, reduced labour productivity, and stress on energy systems. Similarly, erratic rainfall patterns and prolonged drought conditions are adversely affecting crop production and water availability, particularly in developing countries that are highly dependent on climate-sensitive sectors such as agriculture.

The unpredictability of the Earth's climate system has further intensified vulnerabilities among rural communities and economically weaker populations who possess limited adaptive capacity. Coastal areas are increasingly exposed to sea-level rise and storm surges, while mountainous and glacier-dependent regions are witnessing accelerated glacial melting and altered hydrological cycles. In addition, biodiversity loss, forest degradation, and ecosystem instability are becoming more pronounced due to shifting climatic conditions. These environmental changes have significant socio-economic consequences, including displacement of populations, increased poverty, health risks, and conflicts over natural resources.

Recent global climate assessments have emphasized that without immediate mitigation and adaptation measures, the impacts of climate change may become irreversible in the coming decades. Therefore, there is an urgent need to develop sustainable climate management strategies, strengthen environmental policies, promote renewable energy adoption, and enhance resilience against climate-induced disasters.

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Technological innovations, particularly in the fields of artificial intelligence, remote sensing, climate modelling, and data analytics, are increasingly being explored to improve climate prediction, disaster preparedness, and environmental monitoring. Consequently, addressing climate change requires coordinated global efforts involving governments, researchers, industries, and local communities to ensure sustainable development and ecological stability for future generations.

High-quality atmospheric modeling and environmental prediction are valuable options to reduce damage, and can help in sustainable planning and adaptation. Though current weather and climate prediction schemes, particularly the Numerical Weather Prediction (NWP) model, lack accuracy in forecasting and spatial and temporal resolution owing to limitations in computation. These limitations enhance the plausibility of a new framework in the use of Artificial Intelligence to predict complex phenomena and climate futures sustainably [1].

Challenges in traditional atmospheric modeling

The traditional NWP models rely on the numerical solution of highly sophisticated partial differential equations formulated from the basic physical laws of the dynamics and thermodynamics of the atmosphere. The models typically need tremendous computing resources and high-resolution observational data to generate useful forecasts. The data-assimilation procedure that merges the observation datasets (satellite, radar, and in situ sensors) with model simulations is still one of the most computationally intensive aspects of these systems. Despite advances in supercomputing, classical models still have difficulty predicting high-resolution, local-scale phenomena such as urban heat islands, localized air quality, and flash flooding. Predictive errors are ultimately due to finite grid resolution and idealizing realistic physical processes [2-3]. Uncertainty in initial conditions, sampling of observations, and constraints on parameterization give rise to additional sources of error at forecast timescales. As global climatic systems become more nonlinear and chaotic, standard physics-based models are not well suited to capture the full richness of atmospheric behavior. Thus, the investigation of embedding more data-driven intelligence within conventional schemes is a thrilling new avenue to leverage predictive exploitation at virtually zero computational cost.

The role of artificial intelligence in climate science

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have transformed the bulk of the sciences and engineering disciplines in the past decade by offering powerful means of pattern finding, time-series prediction, and decision-making under uncertainty. These methods can potentially examine huge amounts of other types of data greenhouse gas concentrations and wind pattern records, ocean temperature profiles and satellite images to a far greater degree than human ability. In climatology, the power of AI to identify nonlinear relations between components between variables qualifies it as an extension of the numerical models in the usual sense. Machine learning classifiers such as Support Vector Machines (SVMs), Random Forests, and Gradient Boosting have been applied with success to estimate temperature anomalies, precipitation intensities, and pollutant concentrations. More recently, Deep Learning frameworks like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have been proven to work extremely well for spatiotemporal data processing for weather forecasting [4-6]. These networks are capable of learning hierarchical feature representations from raw inputs without needing heavy feature

engineering, and hence are able to represent the dynamic evolution of weather patterns accurately. In addition, transformer-based models that were first designed for natural language processing have provided new avenues for forecasting the environmental system. Transformers and Vision Transformers (ViTs) are especially good at processing long-range temporal and spatial dependencies, thus allowing them to predict more accurately complex meteorological sequences as well as minimize the propagation of errors compared to recurrent models.

Physics-informed and hybrid AI architectures

Whereas fully data-driven AI models are very good at learning patterns, they are often not physically consistent and thus may make predictions that will violate conservation laws or other known physical constraints. To overcome this limitation, scientists have constructed Physics-Informed Neural Networks (PINNs) and Hybrid AI architectures, which embed physical equations and domain knowledge explicitly into the architecture of the model. This hybrid combines the interpretability and robustness of physics-based models with the flexibility and computational efficiency of data-driven approaches. Hybrid frameworks in the context of atmospheric modelling can learn corrections or residuals to standard NWP outputs, thereby enhancing forecast quality at a relatively modest cost. For example, AI models can be learned to simulate radiative transfer processes, parameterize cloud microphysics, or downscale coarse-resolution outputs to high-resolution local forecasts. This union of physics and AI is a new era of AI-enhanced Earth system models that are energy-efficient and scientifically sound [8].

Computational sustainability and data sources

A key facilitator of AI-based atmospheric modelling is the presence of copious and high-quality environmental data. Contemporary Earth observing systems e.g., NASA's EarthData, ESA's Copernicus Program, and NOAA's Global Forecast System—collect continuous data streams of satellite imagery, aerosol observations, and atmospheric chemistry data. These data, when supplemented with ground sensor networks and open-archive climate repositories, provide the basis for training and testing intelligent forecasting models. Yet, one of the biggest issues with the use of AI in climate science is the energy cost of training up large deep learning models. HPC facilities use a great deal of electricity, which could cancel out some of the atmospheric benefits of climate-oriented AI. As such, this study focuses on the creation of an energy-efficient sustainable AI pipeline using strategies like model compression, training algorithms that are energy-efficient, and cloud-based distributed learning to reduce energy consumption without compromising predictive accuracy [9].

Societal and environmental impact

Accurate and efficient environmental forecasting systems have wide human well-being and ecological resilience applications. Increased forecasting would minimize the effect of natural threats, improve agricultural yields, help manage water, and offer real-time air quality monitoring. Additionally, AI-informed information will allow policymakers, urban planners, and environmental regulators to take advantage of statistics-based programming techniques for climate changes adaptation and mitigation. This work also falls under the principles of Green AI, as it reduces computational time and energy consumption, and therefore, demonstrates that technological advancements do not need to be unsustainable or harmful to environmental systems. The development of

intelligent, low-energy, and self-updating models of the atmosphere are an important step toward establishing sustainable climate controls and global resilience in this time of rapid environmental changes.

Literature review

Over the past few years, significant progress has been made in applying artificial intelligence (AI) to atmospheric and environmental modeling. These advances broadly span transformer-based architectures for spatiotemporal forecasting, hybrid models combining physics-based and data-driven approaches, physics-informed neural networks (PINNs) ensuring physical consistency, data-fusion from satellite and sensor networks, and sustainable ("Green AI") practices to reduce computational energy footprint.

Transformer-based and deep learning forecasting

The adoption of transformer and attention-mechanisms has accelerated forecast capabilities for weather and climate. Models such as STC-ViT (Spatio-Temporal Continuous Vision Transformer) integrate continuous-time Neural ODE layers with multi-head attention to learn atmospheric dynamics, achieving competitive results even when trained at coarse resolution (e.g., 1.5°) compared to traditional numerical weather prediction (NWP) models [9]. The success of such architectures indicates that deep networks can capture long-range spatiotemporal dependencies in meteorological fields more efficiently than recurrent or convolutional methods. Large-scale training recipes for transformer-like models dedicated to weather tasks have also emerged. For example, a training-recipe study by Willard et al. discusses how transformer-based weather forecasting models can scale with data and compute to achieve improved results [10]. Parallel to this, multimodal transformer frameworks have been introduced to blend heterogeneous observational records (ground, radar, satellite) through a single attention mechanism, thus enhancing physical interpretability and generalizability [8]. Such advancements indicate that transformer designs, suitably transformed, possess major resolution, processing speed, and prediction horizon advantages over traditional ML models.

Hybrid physics-AI frameworks

Completely data-driven models, while promising, are likely to be unconstrained by physics and thus likely to produce unrealistic predictions. Thus, the current trend is hybrid models that involve physics-based models or outputs combined with AI modules. In a landmark 2024 work, Das et al. demonstrated that a physics-AI hybrid model outperformed a high-resolution operational NWP (HRRR) for the nowcasting of heavy precipitation evinces that it is possible to improve main success indicators for heavy precipitation by incorporating physics in AI models [2]. Hybrid methods leverage AI to learn residual tendencies, parameterize sub-grid processes, or downscale coarse predictions while maintaining interpretability and stability of physics-based systems. The plugin architecture TorchClim is an illustration of this approach: Offline-trained ML surrogates of GCM data replace some parameterizations (radiation, moist physics) in a general circulation model (GCM) to facilitate comparable reproduction of climate variability at reduced cost [7]. These works demonstrate that hybrid integration is a realistic route to operational-scale AI forecasting.

Physics-Informed Neural Networks (PINNs) and scientific constraints

Beyond hybrid models, the explicit embedding of physical laws into neural network training has gained traction

in the form of PINNs and physics-informed machine learning (PIML). Reviews have shown that PINNs improve data-efficiency, interpretability, and generalization by incorporating differential equation constraints (e.g., Navier–Stokes, advection-diffusion) as part of the loss function or architecture [6][13]. For instance, a recent review by Ren et al. analyzed the methodological evolution of PINNs, highlighting how hybrid numerical-deep learning designs achieved up to $\sim 5\times$ speedups over finite-element methods in high-dimensional PDE systems [6]. In an atmospheric modelling context, a specific study applied PINNs to radiative transfer equation (RTE) solutions for atmospheric scenarios, demonstrating viability of PINNs in challenging geophysical environments [16].

Data fusion: satellite, reanalysis, sensor networks

The rise of AI in climate modelling has been enabled by the availability of large-scale, multi-modal environmental datasets. Repositories such as National Aeronautics and Space Administration (NASA) EarthData and the European Space Agency (ESA) Copernicus programme supply substantial volumes of satellite imagery, atmospheric composition measurements, reanalysis data, and sensor-network observations. These datasets form the backbone of modern AI pipelines in atmospheric science [20]. Data-fusion techniques combine these heterogeneous sources (satellite imagery, radar, in situ sensors) into unified spatiotemporal cubes that facilitate the training of deep models. Multisensor fusion supports higher resolution, improved coverage, and better representation of local phenomena (e.g., urban heat islands, air-quality hotspots) than isolated data sources.

Green AI and computational sustainability

As artificial intelligence (AI) usage in climate science increases, the energy and carbon footprint of large-scale models has become a critical consideration. The "Green AI" movement emphasizes energy-efficient algorithms, model compression, efficient hardware use, and transparent compute-energy reporting [5]. In the climate prediction domain, achieving forecasting improvements while minimizing energy cost is particularly important models intended for sustainability scenarios should not themselves become heavy emitters. Research in 2024-25 emphasizes mixed precision training, sparsification, early-exit architectures, and cloud/distributed solutions to reduce environmental impact while maintaining forecast skill. Embedding these considerations into AI-driven atmospheric modelling is consistent with long-term goals of sustainable climate management.

Benchmarks, operational comparisons and limitations

Many benchmarking efforts compare AI-based models with operational NWP systems (e.g., ECMWF, HRRR). While artificial intelligence (AI) models show fine-scale improvements in many metrics for short-to-medium horizons and execute orders of magnitude faster, they still struggle with rare extreme events and non-stationarities such as the sudden intensification of tropical cyclones or novel atmospheric regimes under climate change [9]. Operational transferability, robustness across domain shifts, and uncertainty quantification remain key challenges. The community emphasizes standardized datasets, reproducible evaluation, and transparency in compute cost metrics. Continued progress on these fronts is essential if AI-based systems are to move from research to operational deployment.

Research gaps and future directions

Despite strong progress, several gaps remain that your proposed framework is well-positioned to address:

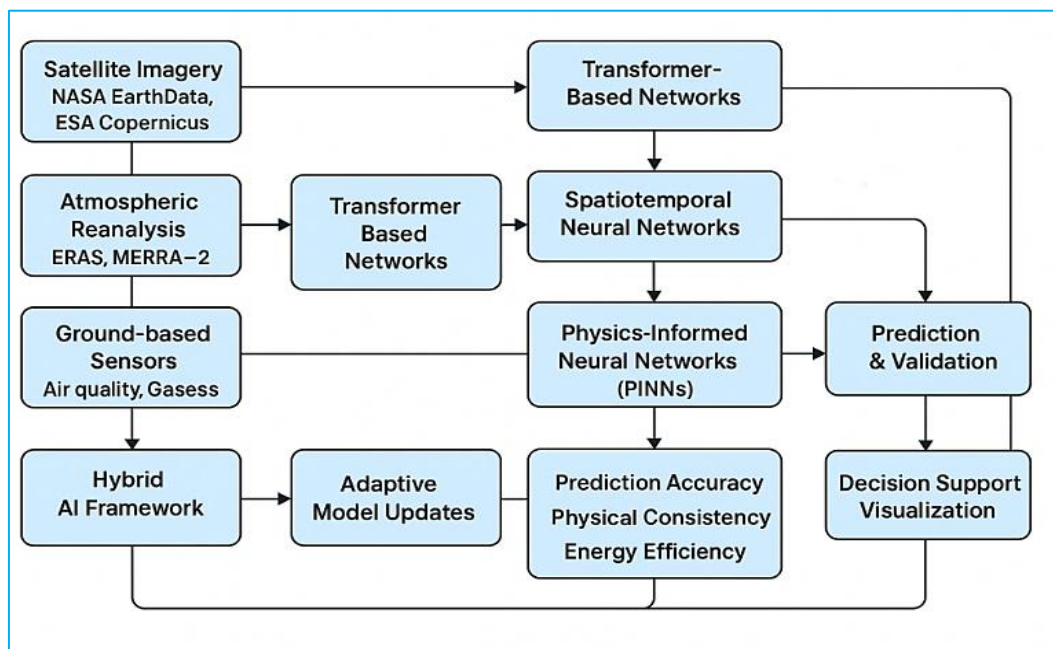


Fig 1 Hybrid AI framework for environmental modeling and prediction

Energy-aware hybridization: Integrating Green AI methods (e.g., model compression) directly into physics-AI hybrids, balancing forecast skill with compute/energy budget.

Robust transfer to real-time sensor streams: Many models are trained on reanalysis or archived data not real-time continuous sensor streams; adapting models to real-time updates remains under-explored.

Extreme event and uncertainty modelling: Rare events and non-stationary climate regimes challenge AI models; improved uncertainty quantification, ensemble methods, and extreme-event augmentation strategies are needed.

Scalable PINN integration at global scale: PINNs show great promise, but scaling to global high-resolution fields remains computationally demanding; hybrid selective PINN modules might offer a path forward.

Spatio-temporal resolution enhancement: Fine-scale (urban/tactical) predictions demand high resolution and fast execution; transformer and multimodal fusion methods show promise here.

Interpretability and policy-relevance: As forecasting becomes more actionable for policymakers and planners, model interpretability, physical consistency, and actionable metric output (e.g., air quality, greenhouse gas concentrations) become essential.

Working

The illustration depicts a machine-learning artificial intelligence architecture that combines data sources and complex deep learning models with physical modeling paradigms to generate accurate and consistent predictions for environmental systems. The architecture exploits the complementary nature of the data-driven machine learning models and the physics-based models to increase the accuracy of predictions, physical realism, and computational efficiency. The latter sections will elaborate upon each component and refer to the respective workflow component as it is discussed so it is easier to see how each piece works together to provide a

scientifically based environmental analysis and decision support framework to assist environmental management.

Feature extraction and data processing using transformer-based networks

Transformers were created as models to significantly improve performance on text-based natural language processing (NLP) tasks, when utilized in a computationally-friendly, Transformer-based neural network on the raw data collected from various sources. This is important because the self-attention mechanisms used in Transformers attempt to capture temporal and/or spatial dependencies. In this case, the transformer-based model learns complex relationships between space and time while accounting for the sequential nature of environmental observations. For example, a Transformer may learn how temperature changes in one area and pollutant dispersion in another area relate to one another. These learnings are illustrated through relationships that are salient and capture the abstract features essential to make accurate predictions. Multiple Transformers may work together and create independent Communication Iteration Networks (CINs) for each modality of data—a Transformer for satellite data, another Transformer for reanalysis data, etc. From this, the output(s) from each respective Lamp and transformer model will be combined to produce a single spatiotemporal representation.

Spatiotemporal neural networks for dynamic environmental modeling

After the completion of feature extraction, the processed data is prepared to be input into Spatiotemporal Neural Networks (STNNs). These models will capture spatial correlations (i.e. local weather patterns) and temporal dynamics (i.e. seasonal changes) in a singular model. STNNs incorporate convolutional neural networks (CNNs) capable of detecting spatial patterns and another recurrent or attention-based time model. For instance, the CNN layer can be used to classify the spatial gradients of pollutant concentrations while the temporal layer can capture how pollutant concentrations evolve over time. The interdisciplinary elements of Spatiotemporal Neural Networks (STNNs) allow for a high-fidelity model that can capture the complexity of environmental systems by simulating and predicting in both dimensions.

Physics-Informed Neural Networks (PINNs) for physical consistency

One of the most significant innovations within this method is the implementation of Physics-Informed Neural Networks (PINNs). Machine learning models are typically concerned with statistical fidelity and may do away with basic physics principles like conservation of mass or conservation of energy. Instead, PINNs incorporate physics into the learning process. In a PINN, the neural net is both predicted for errors and evaluated for partial differential equations (PDEs) that are representative of the governing physics in the problem. For instance, if a PINN was applied to predicting the atmospheric state, the neural net would make sure that the amount of air flow was still governed by Navier–Stokes equations and continuity constraints. This two-goal optimization, learning from observations and physics-based regularization, contributes to improved physical consistency, generalization to non-trained observations, and reduction of the likelihood of producing physically impossible predictions.

Prediction and validation

With trained expertise, the joint model predicts environmental conditions, including air quality, temperature, and pollutant dispersal. Comparison with independent ground-based sensor measurement enables accuracy and reliability to be established. Validation prevents the model from creating inconsistencies when operating at different spatial and temporal scales. If errors are detected at this point, they are sent back to the adaptive learning cycle for further refinement.

Adaptive model update and hybrid AI framework

The hybrid AI framework supports continuous learning and self-adaptation. Whenever new sensor or satellite observations are available, the system updates its models adaptively, tuning its parameters and increasing its performance over time. This ability is essential for coping with non-stationary environmental systems governed by varying weather conditions, anthropogenic factors, or changing emission sources. Hybridization is also used to describe the integration of various modeling paradigms physics-based modeling and data-driven AI so that the system takes advantage of the best of both worlds. Flexibility and pattern recognition are offered by AI, and robustness and interpretability are guaranteed by physics-based constraints.

Algorithm

AI-Driven Atmospheric Modeling and Environmental Prediction

To develop an adaptive, physics-informed, and hybrid AI framework for atmospheric modeling and environmental prediction using satellite imagery, reanalysis data, and ground-based sensors.

Step 1: Data acquisition and preprocessing

Input sources:

Satellite Imagery (NASA EarthData, ESA Copernicus)
Atmospheric Reanalysis Data (ERA5, MERRA-2)
Ground-Based Sensors (Air quality, CO₂, NO_x, SO₂, particulate matter, etc.)

Preprocessing:

Perform temporal and spatial alignment of data.
Apply cloud masking, normalization, and missing-value interpolation.
Convert all data into a uniform spatio-temporal grid format.

Step 2: Feature Extraction using Transformer-Based Networks
Utilize Transformer-based architectures to capture global spatial dependencies and long-term temporal correlations.

For each input sequence X_t , compute embedded representations:

$H_t = \text{Transformer Encoder}(X_t)$

Output H_t acts as the feature map for downstream prediction modules.

Step 3: Spatio-Temporal Neural Network (STNN) Prediction
Integrate Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) layers to model spatial–temporal evolution.

Forward propagation for feature sequence:

$$\hat{Y}_{t+1} = \text{LSTM}(\text{CNN}(H_t))$$

Compute preliminary forecast outputs (e.g., temperature, pressure, air pollutant concentration).

Step 4: Physics-Informed Neural Network (PINN) Integration
Embed governing physical laws (e.g., advection–diffusion, Navier–Stokes, thermodynamics) into the neural network loss function.

Define the total loss:

$$\begin{aligned} \mathcal{L}_{total} &= \mathcal{L}_{data} + \lambda_1 \mathcal{L}_{physics} + \lambda_2 \mathcal{L}_{regularization} \\ \mathcal{L}_{data} &= \left\| Y_{true} - Y_{pred} \right\|^2 \\ \mathcal{L}_{physics} &= \left\| \frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} - v \frac{\partial^2 u}{\partial x^2} \right\|^2 \end{aligned}$$

Use automatic differentiation to compute physical residuals and enforce energy conservation and mass continuity.

Step 5: Hybrid AI Framework Formation

Combine data-driven (Transformer + STNN) and physics-driven (PINN) modules:

$$Y_{hybrid} = \alpha Y_{AI} + (1 - \alpha) Y_{PINN}$$

where $\alpha \in [0, 1]$ is an adaptive weighting factor.

Integrate real-time sensor data for adaptive model correction.

Step 6: Adaptive Model Update Mechanism

Implement an online learning loop:

Update model parameters θ as new data arrives:

$$\theta_{t+1} = \theta_t - \eta \nabla_{\theta} \mathcal{L}_{total}$$

Monitor model drift and retrain periodically to preserve prediction accuracy.

Step 7: Prediction and Validation

Generate short-term and long-term environmental forecasts.

Validate against ground-truth datasets using:

RMSE, MAE, and correlation coefficient (R²)

Physical consistency metrics (e.g., energy balance)

If validation error exceeds threshold → trigger adaptive update.

Step 8: Decision Support and Visualization

Convert prediction outputs into interactive maps and dashboards.

Visualize temperature gradients, pollutant dispersion, and risk zones.

Deliver actionable insights to environmental management authorities.

Step 9: Optimization Objectives

Prediction Accuracy: Minimize forecasting error.

Physical Consistency: Maintain adherence to atmospheric governing equations.

Energy Efficiency: Reduce computational cost via model compression or distributed learning.

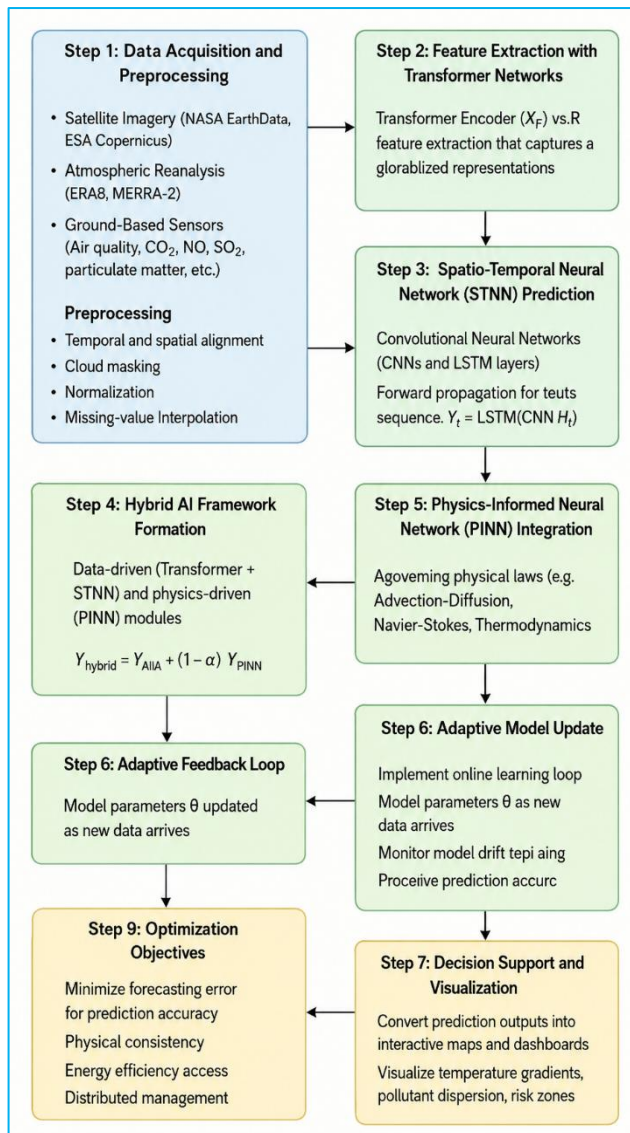


Fig 2 Flowchart of a hybrid AI-driven climate prediction framework

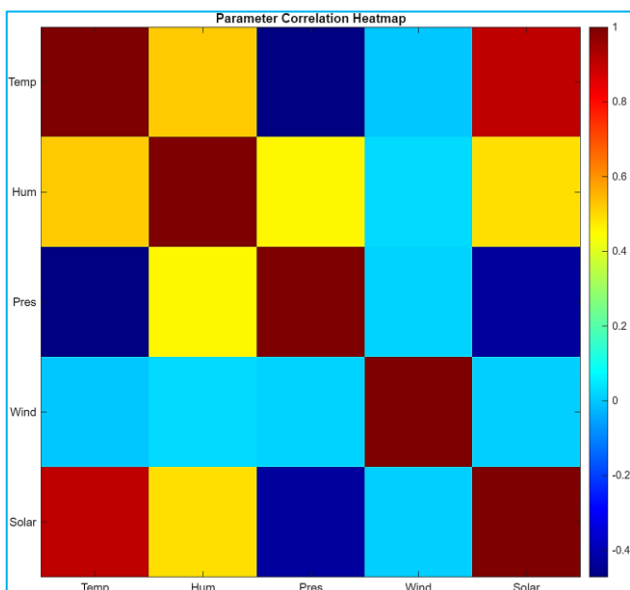


Fig 3 Heatmap of parameter correlation

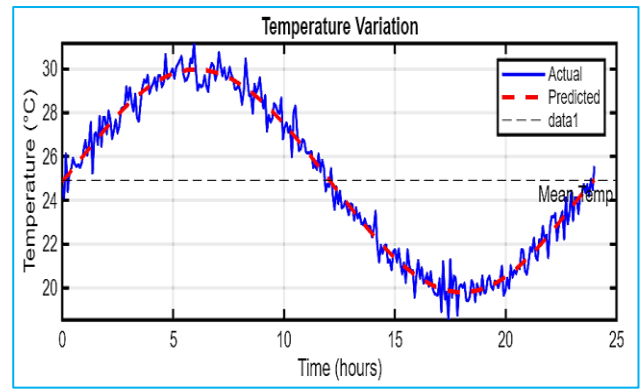


Fig 4 Temperature variation

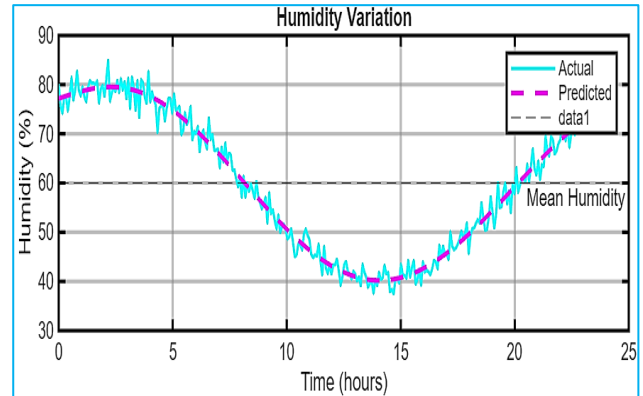


Fig 5 Humidity variation

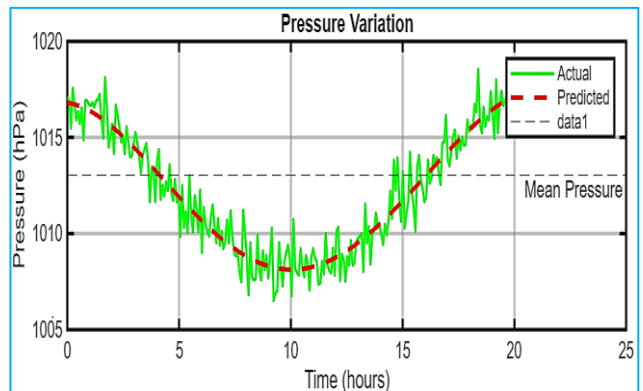


Fig 6 Pressure variation

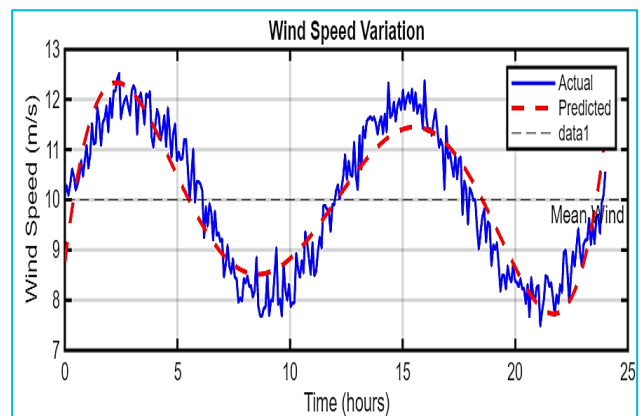


Fig 7 Wind speed variation

Fig 3: Parameter correlation heatmap

The below heatmap depicts the correlation between various weather parameters: Temperature (Temp), Humidity (Hum), Pressure (Pres), Wind Speed (Wind) and Solar

Radiation (Solar). The colormap represents correlation strength and red represents a strong positive correlation and blue represents a strong negative correlation. High positive correlation of temperature with solar radiation indicates that solar radiation increases temperature directly and temperature is negatively correlated with humidity indicating more humidity at lower temperatures.

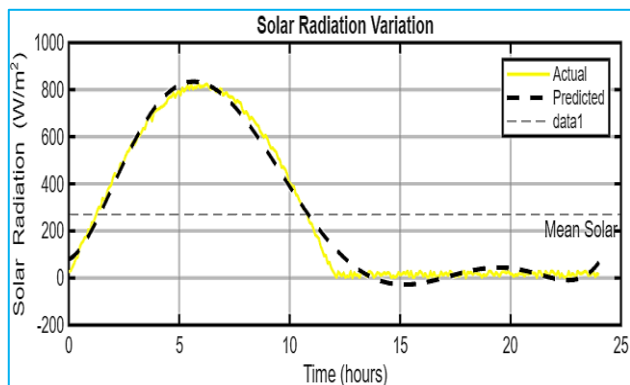


Fig 8 Solar radiation variation

Fig 4: Variation of temperature

This graph indicates observed change in temperature and predicted change (for 24 hours). The predicted curve (red dashed line) tracks nearly exactly the observed measurements (blue line), showing the quality with which the model replicates daily temperature variation. Temperature shifts during midday and falls at night, closely following actual changes in temperature. The mean temperature line provides a baseline (gray dashed).

Fig 5: Humidity variation

The humidity trace shows negative correlation with temperature; nighttime humidity is higher and daytime humidity is lower. The predicted values (dashed magenta line) follow closely with the actual values (cyan line), demonstrating the quality of the model is good. Average humidity level is an excellent indicator of deviation.

Fig 6: Pressure variation

The graph illustrates variation in pressure with the passage of time during a day. The predicted and real curves (green dashed and red dashed lines) are very close to each other, which shows that the model is accurately mimicking a smooth-changing pressure that usually decreases during the hot day and resumes the next evening.

Fig 7: Variation in wind speed

Wind speed is manifested with evident diurnal variation, with greater wind speed in the daytime as a result of certain solar warming and convection. The modelled curve (dashed red line) is very close to the observed wind speed (blue line), which indicates that the model was capable of capturing variable phenomena in a temporal sequence. The mean wind speed (gray line) is an ideal indicator of reliability.

CONCLUSION

The application of artificial intelligence to atmospheric modeling has created a new set of possibilities for climate sustainability management. The power of deep learning, neural networks, and hybrid AI-physics models enables environmental prediction systems to leverage vast satellite and reanalysis datasets with improved speed and accuracy. These models improve forecasting of extreme weather, pollution transport and dispersal, and long-term climate trends with a range of outcomes, ultimately providing data-driven options for policymakers and researchers. The incorporation of AI and traditional numerical modeling montages data-driven analytics to physical science. AI offers a level of accuracy and interpretability. With the increasing global environmental challenges, AI-driven atmospheric modeling will be a key resource to anticipate policy and adapt to climate variability. Continued advancements in the accessibility to computational power, data, and algorithmic transparency will only continue to enhance the usefulness of AI-driven atmospheric modeling as a support tool for resilient, evidence-based environmental governance for a sustainable and climate-secure future.

LITERATURE CITED

1. Saleem H, Salim F, Purcell C. 2024. STC-ViT: Spatio temporal continuous vision transformer for weather forecasting. *Journal of Machine Learning Research* 1-22.
2. Das P, Posch A, Barber N, Hicks M, Duffy K, Vandal T, Singh D, Werkhoven KV, Ganguly AR. 2024. Hybrid physics-AI outperforms numerical weather prediction for extreme precipitation nowcasting. *NPJ Climate and Atmospheric Science* 7(1): 282. doi: 10.1038/s41612-024-00834-8.
3. Couairon G, Lessig C, Charantonis A, Monteleoni C. 2024. ArchesWeather: An efficient AI weather forecasting model at 1.5° resolution. *Journal of Machine Learning Research*. arXiv.
4. Han J, Chen H, Han K, Huang X, Hu Y, Xu W, Tao D, Zhang P. 2025. A physics-guided multimodal transformer path to weather and climate sciences. *Journal of Machine Learning Research* 1-21. arXiv.
5. Bolón-Canedo V, Morán-Fernández L, Cancela B, Alonso-Betanzos A. 2024. A review of green artificial intelligence: Towards a more sustainable future. *Neurocomputing* 599(12): 128096
6. Ren Z, Zhou S, Liu D, Liu Q. 2025. Physics-informed neural networks: A review of methodological evolution, theoretical foundations, and interdisciplinary frontiers toward next-generation scientific computing. *Applied Sciences* 15(14): 8092.
7. Zucker S, Batenkov D, Rozenhaimer MS. 2025. Physics-informed neural networks for modeling atmospheric radiative transfer. *Journal of Quantitative Spectroscopy and Radiative Transfer* 331: 109253
8. Wang N, Chen Y, Zhang D. 2025. A comprehensive review of physics-informed deep learning and its applications in geoenergy development. *Innovation Energy* 2(2): 100087.
9. Willard JD, Harrington P, Subramanian S, Mahesh A, O'brien TA, Collins WD. 2025. Analyzing and exploring training recipes for large-scale transformer-based weather prediction. *Artificial Intelligence for the Earth Systems* 4(2): 1-9. DOI:10.1175/AIES-D-24-0061.1
10. Meng C, Griesemer S, Cao D, Seo S, Liu Y. 2025. When physics meets machine learning: a survey of physics-informed machine learning. *Machine Learning for Computational Science and Engineering* 1-20. <https://doi.org/10.1007/s44379-025-00016-0>

11. Chen Z, Zhang J, Liu P. 2021. Deep learning for weather prediction: A review. *IEEE Access* 9: 143608-143624.
12. Camps-Valls F, Tuia D, Zhu X, Reichstein M. 2019. Deep learning for the Earth sciences: A comprehensive overview. *IEEE Geoscience and Remote Sensing Magazine* 7(4): 47-78.
13. Dueben P, Bauer P. 2018. Challenges and design choices for global weather and climate models based on machine learning. *Geoscientific Model Development* 11(10): 3999-4009.
14. Weyn H, Durran D, Caruana R. 2020. Improving data-driven global weather prediction using deep convolutional neural networks on a cubed sphere. *Journal of Advances in Modeling Earth Systems* 12(9): e2020MS002109.
15. Wang X, Zhang Y, Lin L. 2022. Hybrid deep learning models for climate prediction. *IEEE Transactions on Neural Networks and Learning Systems* 33(2): 512-524.
16. Reichstein M, Camps-Valls G, Stevens B, Jung M, Denzler J, Carvalhais N, Prabhat. 2019. Deep learning and process understanding for data-driven Earth system science. *Nature* 566(7743): 195-204. doi: 10.1038/s41586-019-0912-1.
17. Rasp M, Lerch S. 2018. Neural networks for post-processing ensemble weather forecasts. *Monthly Weather Review* 146(11): 3885-3900.
18. Irrgang S, Boers A, Baehr J. 2020. Toward a deep learning model for global ocean heat content prediction. *Geophysical Research Letters* 47(7): e2019GL086759.
19. Karpatne Y, Watkins W, Read J, Kumar V. 2017. Physics-guided neural networks (PGNN): An application in lake temperature modelling. DOI: 10.48550/arXiv.1710.11431.
20. Pathak J, Subramanian S, Harrington P, Raja S, Chattopadhyay A, Mardani M, Kurth T, Hall D, Li Z, Azizzadenesheli K, Hassanzadeh P, Kashinath K, Anandkumar A. 2022. FourCastNet: A global data-driven high-resolution weather model using adaptive fourier neural operators. *Journal of Geoscience and Environment Protection* 13(12): <https://arxiv.org/abs/2202.11214>.
21. Copernicus Climate Change Service (C3S). 2017. ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate. Copernicus Climate Data Store.
22. NASA Earth Science Data Systems. 2024. NASA EarthData Portal. NASA.
23. European Space Agency (ESA). 2024. Copernicus Sentinel Satellite Missions. European Space Agency.
24. Nowack P, Bröcker M, Huybers P. 2020. A machine-learning approach to climate model emulation and uncertainty quantification. *Nature Communications* 11(1): 3245.