Makerere University

SPATIOTEMPORAL PHYSICS-INFORMED MACHINE LEARNING MODEL FOR WEATHER PREDICTION

by

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List of Acronyms

AFNOs	Adaptive Fourier Neural Operators
AI	Artificial Intelligence
AIST	Advanced Institute of Science and Technology
AMS	American Meteorological Society
ARIMA	AutoRegressive Integrated Moving Average
ASCC	Asian Science and Computing Conference
CNN	Convolutional Neural Network
CRPS	Continuous Ranked Probability Score
DL	Deep Learning
FNOs	Fourier Neural Operators
GAN	Generative Adversarial Network
GIS	Geographic Information System
GNN	Graph Neural Net- works
ICAML	International Conference on Artificial Intelligence and Machine Learning
ICCSA	International Conference on Computational Science and its Applications
ICECA	International Conference on Electronics, Communication, and Aerospace Technology
ICLR	International Conference on Learning Representations
ICMLA	International Conference on Machine Learning and Applications
IEEE	Institute of Electrical and Electronics Engineers
IT	Information Technology
KNN	K-Nearest Neighbors
KPI	Key Performance Indicator

LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
MSE	Mean Squared Error
NASA	National Aeronautics and Space Administration
NM	Numerical Methods
NWP	Numerical Weather Prediction
PDE	Partial Differential Equation
PINN	Physics-Informed Neural Network
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RFR	Random Forest Regressor
RMSE	Root Mean Squared Error
SLR	Systematic Literature Review
UNMA	Uganda National Meteorological Authority
WMO	World Meteorological Organization
WRF	Weather Research and Forecasting Model

Chapter 1

Introduction

1.1 Background of the Study

Extreme weather events are increasingly being influenced by global climate change [1]. The frequency and intensity of wildfires, heavy rainfall, severe floods, prolonged droughts, record-breaking heat waves on land and in water, and catastrophic flooding during hurricanes are all rising [2, 3]. In 2023, heatwaves, torrential rains, floods, tropical cyclones, and prolonged droughts struck various parts of the Globe [4–6]. Several countries in the Horn of Africa and north-western Africa have endured multi-year droughts, while others have faced devastating floods, leading to loss of life and economic disruption [7–9]. These climate-induced disasters have had severe consequences on communities, causing displacement, destruction of infrastructure, and long-term socio-economic challenges [10].

Uganda is already experiencing the impacts of climate change, marked by an increased frequency and intensity of disasters such as droughts, floods, and landslides [11, 12]. The proportion of drought extremes and rainfall events is rising, negatively affecting agriculture by reducing crop yields and leading to livestock losses. This has significant implications for food security and rural livelihoods [13, 14]. Additionally, Lake Victoria, a vital economic and food source for nearly 30 million people in Uganda, Kenya, and Tanzania, has become increasingly hazardous due to shifting weather patterns [15]. Cyclical midnight thunderstorms, driven by complex meteorological interactions over the lake, claim the lives of an estimated 3,000 to 5,000 fishermen annually, underscoring the urgent need for improved weather prediction systems [16].

Given these challenges, accurate weather forecasting is essential for mitigating the adverse effects of extreme weather and supporting key sectors such as agriculture, energy, military, transportation, and disaster management [17–19]. Traditional forecasting methods, primarily based on Numerical Weather Prediction (NWP) models, rely on complex physical equations to simulate atmospheric dynamics [20, 21]. While these models have played a fundamental role in meteorology, they often struggle with computational demands and sensitivity to initial conditions, limiting their precision and reducing the reliability of long-term forecasts. As climate change continues to intensify weather extremes, improving forecasting techniques becomes increasingly crucial for resilience and disaster preparedness [22].

In recent years, the integration of machine learning (ML) techniques into weather forecasting has gained significant attention. ML models excel at identifying intricate patterns within vast datasets, offering a data-driven approach to prediction [23–25]. However, purely data-driven models may lack the ability to enforce physical laws, potentially resulting in forecasts that violate fundamental atmospheric principles [26, 27]. To address this, hybrid models have been developed that combine the strengths of both physics-based and ML approaches [28] [29]. These hybrid models aim to improve the accuracy of the prediction by leveraging the computational efficiency and pattern recognition capabilities of ML while adhering to the physical constraints inherent in atmospheric processes [17] [30]. For instance, studies have demonstrated the effectiveness of integrating soil physics with ML models to improve predictions of soil moisture dynamics, thereby enhancing the applicability and reliability of forecasts in real-world settings [31] [32].

The emergence of physics-informed machine learning models represents a promising advancement in weather forecasting. By embedding physical laws into the learning process, these models can produce predictions that are both data-driven and physically consistent. Research has shown that such hybrid approaches can outperform traditional NWP models in certain scenarios, particularly in capturing complex, nonlinear interactions within the atmosphere. For example, hybrid hydroclimatic forecasting systems that blend climate predictions with AI models have been recognized for their potential to enhance the prediction skill of meteorological variables and events. This integration of physics and machine learning holds the potential to revolutionize weather forecasting, offering more accurate and timely predictions that are essential for informed decision-making in the face of a changing climate [33] [34].

1.2 Research Motivation

Accurate and reliable weather prediction is crucial for Uganda, where agriculture, water resources, and disaster management heavily depend on timely and precise forecasts. However, traditional NWP models face challenges such as high computational costs, sensitivity to initial conditions, and limited accuracy in data-scarce regions. ML has emerged as a promising alternative, offering data-driven forecasting capabilities. However, pure ML models often struggle with generalization, physical consistency, and interpretability. This study aims to bridge this gap by integrating spatiotemporal ML techniques with physics-informed neural networks (PINNs) to enhance weather prediction accuracy and reliability.

By incorporating physics-based constraints, such as the Navier-Stokes equations and energy conservation laws, into deep learning architectures like Graph Neural Networks (GNNs), Fourier Neural Operators (FNOs), and Long Short-Term Memory (LSTM) networks, this research seeks to develop a robust hybrid model. This approach will improve generalization in data-scarce environments, reduce forecasting errors, and provide interpretable predictions aligned with meteorological principles. Ultimately, the study contributes to advancing weather forecasting in Uganda by leveraging spatiotemporal data, remote sensing, and hybrid AI techniques to support decision-making in agriculture, disaster preparedness, and climate resilience.

1.3 Problem Statement

Accurate weather prediction is essential for mitigating climate-related risks, supporting agriculture, and enhancing disaster preparedness in Uganda. However, existing weather forecasting approaches face significant challenges. Traditional NWP models, such as the Weather Research and Forecasting (WRF) model, require extensive computational resources and often struggle with local-scale accuracy due to the region's sparse observational data. On the other hand, purely data-driven ML models can capture complex patterns but lack physical consistency, leading to unrealistic predictions and poor generalization in data-scarce environments.

To address these limitations, there is a need for a hybrid forecasting approach that integrates spatiotemporal deep learning models with PINNs. By incorporating physical constraints such as the Navier-Stokes equations, moisture balance, and energy conservation, this approach can enhance prediction accuracy, ensure physically consistent forecasts, and improve generalization in low-data regions. However, the application of such hybrid models in Uganda remains underexplored. This research seeks to bridge this gap by developing a Spatiotemporal Physics-Informed Machine Learning Model tailored for Uganda's unique meteorological conditions, leveraging remote sensing, reanalysis data, and in-situ observations to enhance weather prediction capabilities.

1.4 Research Objectives

1.4.1 Main Objective

The main objective of this research is to develop a Spatiotemporal Physics-Informed Machine Learning (PINN) model for weather prediction in Uganda by integrating deep learning architectures with physical constraints to enhance forecast accuracy, generalization, and interpretability in data-scarce environments.

1.4.2 Specific Objectives

The specific objectives of this study are to:

i. Systematically review ML algorithms for weather forecasting, focusing on their data sources.

ii. Develop a hybrid Spatiotemporal Physics-Informed Machine Learning (PINN) model that integrates deep learning architectures with physical constraints for improved weather prediction.

iii. Evaluate the performance of the proposed model against traditional Numerical Weather Prediction (NWP) models and pure data-driven ML models in terms of forecast accuracy, generalization, and physical consistency

Chapter 2

Literature Review

2.1 Introduction

The literature review explores existing research on weather forecasting, emphasizing the importance of accurate predictions in mitigating the impacts of extreme weather events. It first examines traditional forecasting methods, such as NWP models, and their inherent limitations, particularly in data-scarce regions. Recognizing these challenges, the review then delves into the integration of ML and artificial intelligence (AI) techniques, which offer promising improvements in forecast accuracy but often lack physical consistency. To address this, advancements in PINNs and hybrid models that blend deep learning with physical constraints are explored. By analyzing past studies, this chapter identifies gaps in current methodologies and establishes the foundation for the development of a hybrid physics-informed machine learning model tailored for weather forecasting in Uganda.

2.2 Traditional Weather Prediction Techniques

TraditionalNWP models describe essential physical processes in the atmosphere, at the surface, and in the soil, incorporating their impact on key meteorological variables such as pressure, temperature, wind, water vapor, clouds, and precipitation. However, many atmospheric processes, such as cloud formation and solar radiation interactions, occur at spatial scales too small to be explicitly resolved by NWP models [35]. These models rely on differential equations governing the spatiotemporal evolution of physical variables like wind velocity, temperature, air density, and pressure, alongside specific masses of tracers such as water vapor and rain [36]. In addition to NWP models, traditional statistical models, such as the Autoregressive Integrated Moving Average(ARIMA) model, have been employed for time-series forecasting of temperature, achieving high accuracy by automatically tuning model parameters [37]. However, both NWP and statistical models face limitations in handling highly complex and nonlinear weather patterns, necessitating the exploration of alternative approaches.

2.3 Integration of Machine Learning Models in Weather Prediction and Forecasting

The growing availability of vast datasets from satellites, remote sensing, and weather stations has facilitated the integration of ML in weather forecasting, offering data-driven solutions to overcome the shortcomings of NWP models.

Several studies have examined the performance of different ML algorithms in weather forecasting. For instance, [38] evaluated the effectiveness of Gradient Boosting, AdaBoost, Artificial Neural Networks, and ensemble models in predicting precipitation and temperature patterns using a 20-year dataset from a single weather station in Dhaka. Meanwhile, [39] developed an ML-based support vector machine (SVM) model for drought prediction, achieving an accuracy range of 0.85 to 0.95 but revealing sensitivities to parameter settings and data quality.

ML models have also been employed in flood risk management. [40] integrated ML, deep learning (DL), IoT, and crowdsourcing to create a flood prediction and mitigation system with an accuracy exceeding 0.70, highlighting the role of community-driven data collection in disaster risk reduction. Additionally, [41] proposed a hybrid ensemble neural network model that reduced redundancy in weather predictions by employing mutual information to optimize correlation between variables. These studies underscore the potential of ML in weather forecasting while pointing to areas for further refinement, such as enhancing interpretability and integrating additional data sources.

Deep learning architectures have demonstrated significant advancements in capturing spatiotemporal dependencies within weather data. Models such as Long Short-Term Memory (LSTM) networks and Random Forest Regressors (RFR) have outperformed operational forecasting systems, reducing root mean squared error (RMSE) by up to 83% in temperature predictions [42]. Additionally, ML-based real-time monitoring systems like WeathCast have leveraged logistic regression, decision trees, and support vector machines for improved weather predictions [43].

Further advances in deep learning architectures have introduced Graph Neural Networks (GNNs), Fourier Neural Operators (FNOs), and Transformers for weather prediction. Platforms like ClimateLearn have facilitated benchmarking, demonstrating that models such as ResNet and U-Net outperform conventional approaches in downscaling and forecasting tasks [44]. Moreover, high-resolution models like FourCastNet leverage Adaptive Fourier Neural Operators (AFNOs) to achieve accuracy comparable to state-of-the-art NWP models while significantly reducing computational costs [34].These ML models enhance predictive accuracy, particularly in regions with limited observational data. However, they often lack physical consistency, resulting in unrealistic predictions. To mitigate these issues, researchers have investigated physics-informed approaches that embed physical laws into ML models to improve generalization and interpretability.

2.4 Physics-Informed Neural Networks (PINNs) in Weather Forecasting

To address the limitations of purely data-driven ML models, physics-informed neural networks (PINNs) incorporate governing physical laws, such as the Navier-Stokes equations, into neural networks. This approach enhances interpretability and generalization, particularly in regions with sparse data. Studies have demonstrated that physics-informed constraints can improve prediction accuracy; for example, incorporating physical constraints in wind speed forecasting led to a 29.24% reduction in Mean Squared Error (MSE) [45]. Similarly, ClimODE, a physics-inspired neural advection PDE model, has been shown to improve long-term stability in forecasting [46].

Recent research has emphasized hybrid models that integrate ML with NWP outputs to leverage the strengths of both methodologies. For instance, a hybrid ML-NWP model combining XGBoost and neural networks for rainfall prediction demonstrated a 25% improvement over conventional NWP models [17]. Additionally, the ClimateLLM framework introduced a frequency-aware large language model that integrates Fourier-based frequency decomposition with ML, enhancing spatial and temporal predictions [47]. These hybrid approaches highlight the potential of combining physical knowledge with data-driven techniques to balance computational efficiency with physical accuracy.

2.5 Research Gaps

Despite significant advancements in weather forecasting, existing approaches exhibit notable limitations that hinder their effectiveness, particularly in data-scarce regions like Uganda. Traditional NWP models, while grounded in physical laws, require extensive computational resources and struggle with high-resolution, short-term predictions due to inherent uncertainties in parameterization and data assimilation. On the other hand, ML models have demonstrated improved forecasting accuracy by leveraging large datasets, yet they often lack physical interpretability and generalization beyond training conditions, leading to unrealistic predictions in unseen scenarios.

Several challenges remain. Existing ML models face difficulties in capturing extreme weather events and generalizing across diverse climate zones, as highlighted in the ClimateLLM study, which emphasized the need for physics-informed techniques to enhance long-range forecasting capabilities [47]. Additionally, the lack of standardized datasets and evaluation benchmarks impedes reproducibility, as noted in the Climate-Learn study [44]. Integrating physical constraints into ML models remains an open challenge, as demonstrated in studies on constrained GANs for weather modeling [48].

Hybrid approaches, such as PINNs, have emerged to bridge this gap by integrating physical constraints into ML models. However, most existing hybrid models are tailored for regions with abundant meteorological data and are not optimized for data-sparse environments like Uganda. Furthermore, current spatiotemporal forecasting techniques, including Graph GNNs and FNOs, have shown promise but require further exploration in the context of regional weather prediction.

This research aims to address these limitations by developing a hybrid physics-informed ML model that integrates deep learning architectures with fundamental atmospheric physics (Navier-Stokes equations, energy conservation, and moisture balance) to improve forecast accuracy, generalization, and interpretability in Uganda's unique climatic conditions.

2.6 Conclusion

The literature review highlights the evolution of weather forecasting methodologies, from traditional NWP and statistical models to modern ML-based and physics-informed techniques. While ML models offer improved accuracy, their reliance on purely data-driven approaches limits their physical consistency. PINNs and hybrid ML-NWP models address these limitations by integrating physical laws into data-driven frameworks, enhancing interpretability and generalization. The insights gained from this review inform the development of a hybrid physics-informed machine learning model for weather forecasting in Uganda, leveraging the strengths of deep learning and physical constraints to improve predictive accuracy in data-scarce environments.

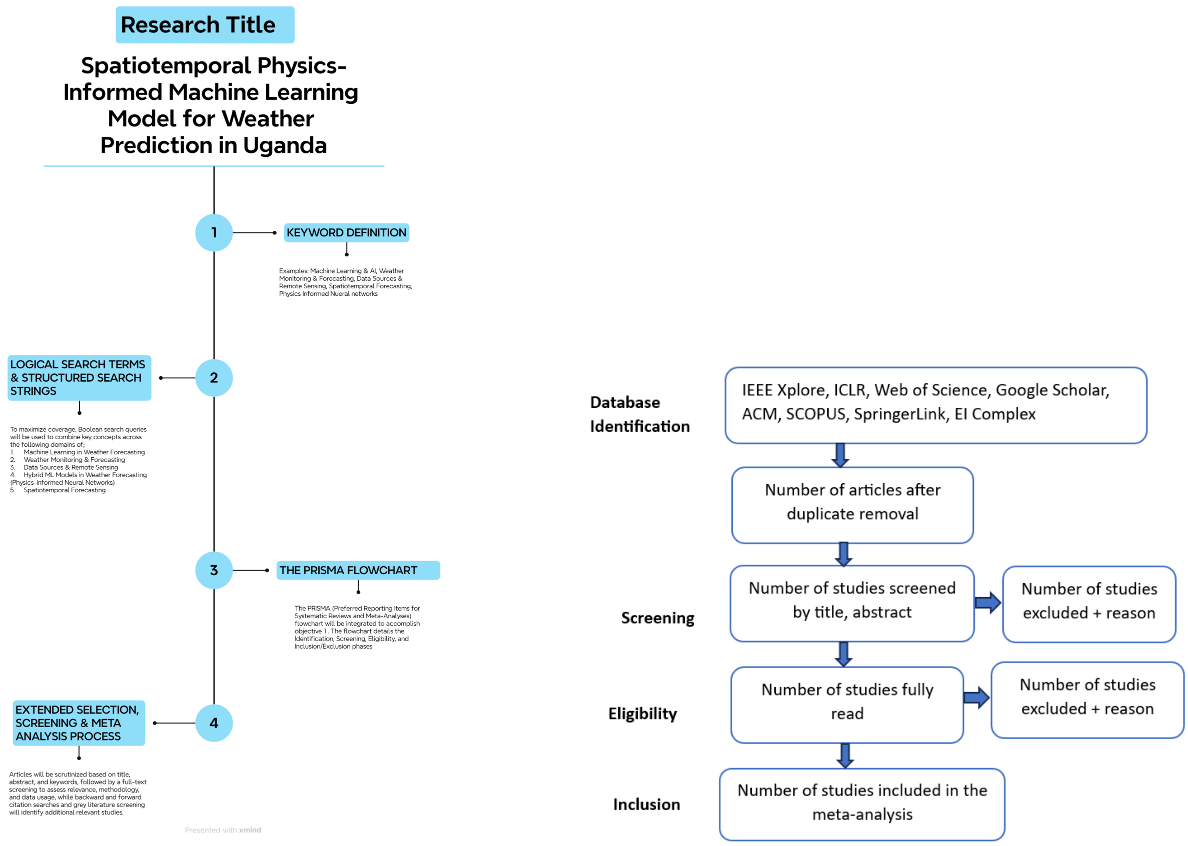
Chapter 3

Proposed Methodology

This section explains the structured methodology to systematically address all research objectives mentioned in section 1.4 above. To achieve these objectives, the research will be divided into three key methodological phases. First, a systematic literature review (SLR) will be conducted to analyze existing ML models, spatiotemporal forecasting techniques, and the integration of physics-informed approaches in weather prediction. This phase will provide a foundation for identifying research gaps and designing an improved forecasting model. Second, a data-driven experimental approach will be employed, leveraging satellite data, reanalysis datasets, and in-situ weather station observations from the Uganda National Meteorological Authority (UNMA) and other global repositories. Third, the study will develop and evaluate a hybrid physics-informed ML model, integrating deep learning architectures (e.g., CNNs, LSTMs, GNNs, and FNOs) with physical constraints (e.g., Navier-Stokes equations, moisture balance, and energy conservation). The model's performance will be benchmarked against conventional NWP models and purely data-driven ML approaches using standard meteorological evaluation metrics.

3.1 Systematic Literature Review Methods

To achieve the research objective one, a systematic literature review will be conducted to analyze existing ML and Physics informed models The SLR will establish a theoretical foundation by analyzing existing weather forecasting models, identifying gaps, and informing the proposed approach. A systematic literature review will be conducted to analyze recent advancements in physics-informed deep learning, NWP, and data-driven forecasting models. Research articles, conference papers, and technical reports from IEEE, Springer, Elsevier, and arXiv will be reviewed. The review will focus on spatiotemporal modeling techniques, challenges in data-scarce environments, and hybrid approaches combining physics with machine learning. Special attention will be given to studies on Navier-Stokes equations, moisture balance, and energy conservation laws in weather prediction. The insights gained will help refine the proposed model architecture and highlight best practices for improving model accuracy, robustness, and interpretability. To conduct a comprehensive SLR, phases of; Title/Research question refinement, keywords selection, search string formation, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method, and extended selection, screening & meta-analysis are followed as shown in figure 3.1.



(a) SLR Architecture (b) The PRISMA Flowchart

Figure 3.1: Integrated SLR Architecture

3.1.1 Phase 1: Research Title/Question Refinement & Keywords Identification

The journey will begin with Phase 1, where a clear research question and title are defined, setting the foundation for focused exploration. The refined title is 'Spatiotemporal Physics-Informed Machine Learning Model for Weather Prediction in Uganda'

Concept Identification method will used to extract core ideas and themes directly from the research title to pinpoint the fundamental elements that define the scope of the study. The relevant keywords like "Machine Learning," "Weather Forecasting," "Spatiotemporal Forecasting, " and "Physics-Informed Neural Networks" will be identified to guide the search process.

3.1.2 Phase 2: Search String Formation and Search Criteria

In Phase 2, structured and logical search strings will be developed that combine advanced terms such as "Machine Learning", "Weather Forecasting", "Spatiotemporal Forecasting," and "Physics-Informed Neural Networks" ensuring the inclusion of diverse concepts. To expand the identified concepts, synonyms, related terms, and variations of the identified keywords will be considered. These multiple keywords will later be combined using Boolean operators like AND, OR, and NOT to create structured search strings such as;

i. Machine Learning in Weather Forecasting

Machine Learning **OR** AI **OR** Deep Learning **OR** Neural Networks **OR** Hybrid Machine Learning **OR** Long Short-Term Memory **OR** Convolutional Neural Networks **OR** Automated Learning **OR** Computational Learning **OR** AI Learning **OR** Statistical Learning **OR** Data-Driven Learning **OR** Algorithmic Learning **OR** Predictive Modeling

ii. Weather Monitoring & Forecasting

Weather Prediction **OR** Weather monitoring **OR** Weather Forecasting **OR** Climate Prediction **OR** Meteorological Data **OR** Climate Forecasting **OR** Climate Change **OR** Meteorological Forecasting **OR** Atmospheric Forecasting **OR** Weather Projection **OR** Weather Outlook **OR** Numerical Weather Prediction **OR** Extreme Weather Events

iii. Data Sources & Remote Sensing

Satellite Data **OR** Remote Sensing **OR** Reanalysis Data **OR** Geospatial Analysis **OR** Weather Station Data **OR** Time Series Forecasting **OR** Data Assimilation **OR** Satellite Imagery **OR** GIS **OR** Spatial Interpolation **OR** Weather Data Fusion **OR** Climate Model Data **OR** Numerical Weather Prediction **OR** Hydrometeorological Data **OR** Land Surface Data **OR** Topography Data **OR** Oceanic Climate Data **OR** ENSO Index

iv. Hybrid ML Models in Weather Forecasting (Physics Informed Nueral networks)

Hybrid machine learning **OR** Physics-informed neural networks **OR** Physics-guided neural networks **OR** Physics-inspired neural networks **OR** Hybrid Machine Learning **OR** Physics-Guided AI **OR** Physics-Constrained **OR** Science-Informed **OR** Mechanics-Guided **OR** Theory-Driven

v. Spatiotemporal Forecasting

Spatiotemporal Forecasting **OR** Graph Neural Networks **OR** Fourier Neural Operators

3.1.3 Phase 3: The PRISMA Method

Moving forward, Phase 3 incorporates the PRISMA flowchart [49] and the its different steps as displayed in figure 3.1. The PRISMA flowchart will be followed to meet the end detailing the Identification, Screening, Eligibility, and Inclusion phases. It involves selecting authoritative databases like IEEE Xplore, Web of Science, and Google Scholar, which provide access to high-quality peer-reviewed literature. It also includes the inclusion and exclusion criteria shown in Table 3.1 emphasizing recent, peer-reviewed, and high-quality studies while filtering out irrelevant or low-impact work.

3.1.4 Phase 4: Extended Selection, Screening & Meta-analysis

Finally, in Phase 4, a thorough review of titles, abstracts, and keywords will be conducted to identify articles that focus on the intersection of Machine Learning, Physics-Informed Neural Networks (PINNs), and weather forecasting, while also expanding the scope to include valuable grey literature and conference proceedings.

Table 3.1: Article Selection Criteria

Criteria	Inclusion	Exclusion
Publication Type & Quality	Peer-reviewed journal articles, conference papers	Non-peer-reviewed, preprints without validation, low-impact journals
	Reputable preprints (arXiv, ICLR, AMS)	Short abstracts, editorials, tool demos, and workshop papers
Relevance to Study	Studies on ML for weather monitoring, forecasting, and hybrid ML-NWP models	ML research unrelated to weather forecasting
	Spatiotemporal forecasting with GNNs, Fourier Neural Operators	Statistical models (e.g., ARIMA) without ML components
Data Relevance	Research using satellite data, reanalysis datasets, and weather station observations	Studies without a clear methodology or valid dataset
Publication Date	Preferably published in the last 5-10 years (2015 - Present)	Older than 2015 unless fundamental to theoretical background
Article Availability	Full-text available in scientific databases	Not available, paywalled without institutional access
Article Language	English	Non-English publications

3.2 The Model Development phase

To achieve specific objective 2, the method will integrate data-driven deep learning techniques with fundamental atmospheric physics laws to improve weather forecasting accuracy and generalization. The model will be structured as an encoder-decoder architecture in figure 3.2, where the encoder (E) extracts spatiotemporal features from input weather data, maps them to a latent representation (Z), and the decoder (D) reconstructs future weather states while ensuring coherence with physical laws.

3.2.1 Data Encoding & Latent Representation

The input meteorological data, denoted as X_t undergoes feature extraction through multiple deep learning components:

i. CNNs: Extract spatial features from gridded weather data.

ii. LSTMs: Capture temporal dependencies in sequential weather patterns.

iii. GNNs: Model spatial relationships between different weather stations or grid points.

iv. Fourier Neural Operators (FNOs): Learn continuous spatiotemporal functions in the latent space.

The encoded representation Z_t at time t is formulated as:

$$Z_t = E(X_t) = f_{CNN}(X_t) + f_{LSTM}(X_t) + f_{GNN}(X_t) + f_{FNO}(X_t) \tag{3.1}$$

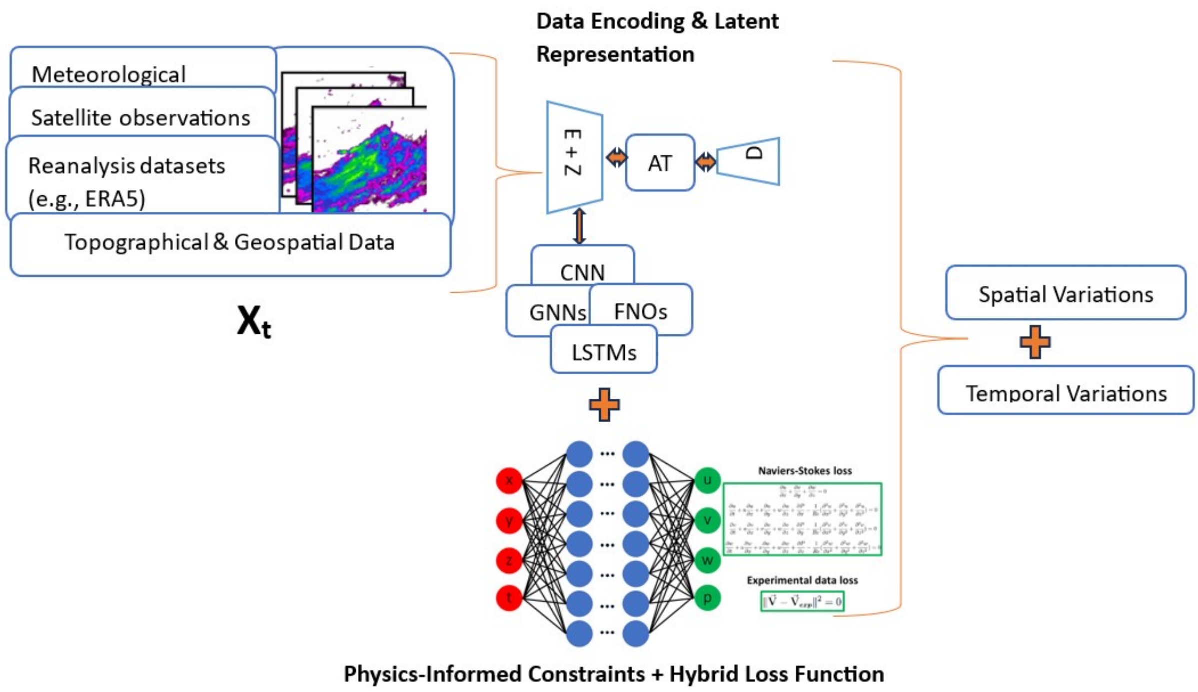


Figure 3.2: Model Architecture

where f_{CNN},f_{LSTM}, f_{GNN}, f_{FNO} are transformation functions of the respective network layers.

3.2.2 Physics-Informed Constraints

To ensure physically consistent predictions, the model integrates fundamental meteorological governing equations as regularization terms. The key physical constraints include:

i. **Navier-Stokes Equations (Momentum Conservation)**

   The Navier-Stokes equations describe atmospheric motion based on conservation of momentum:

$$\frac{\partial \mathbf{v}}{\partial t} + (\mathbf{v} \cdot \nabla)\mathbf{v} = -\frac{1}{\rho}\nabla p + \nu \nabla^2 \mathbf{v} + \mathbf{F} \tag{3.2}$$

   Where:

   - $\mathbf{v}$ = velocity field (wind components: u, v, w)
   - p = atmospheric pressure
   - ρ = air density
   - ν = viscosity coefficient
   - $\mathbf{F}$ = external forces (e.g., Coriolis force, gravity)

   This equation ensures that predicted wind patterns adhere to physical momentum constraints.

ii. **Energy Conservation Equation**

The model also incorporates energy balance principles, ensuring realistic temperature evolution:

$$\frac{\partial \mathbf{T}}{\partial t} = -(\mathbf{v} \cdot \nabla T) + \frac{Q}{\rho c_p} \tag{3.3}$$

Where:

- T = temperature
- Q = radiative and latent heat flux
- c_p = specific heat capacity of air
- ρ = air density
- $\mathbf{v}$ = velocity vector

This term ensures that predicted temperature changes are physically realistic.

iii. **Moisture Balance Equation**

$$\frac{\partial \mathbf{T}}{\partial t} + (\nabla \cdot \ \mathbf{v}q) = S \tag{3.4}$$

Where:

- q = specific humidity
- S = moisture source/sink term (e.g., evaporation, condensation)

This equation ensures that the predicted humidity and precipitation follow physical water cycle constraints.

3.2.3 Hybrid Loss Function

The model training is guided by a hybrid loss function combining:

$$L = \lambda_d L_{\text{data}} + \lambda_p L_{\text{physics}} + \lambda_a L_{\text{adv}} \tag{3.5}$$

Where:

- L_{data} = Data-driven loss (e.g., Mean Squared Error (MSE) or Mean Absolute Error (MAE) on observed weather data)
- L_{physics} = Physics consistency loss (penalizing deviations from physical equations)
- L_{adv} = Adversarial loss from GAN-based discriminators ensuring realistic spatiotemporal structure
- $\lambda_d, \lambda_p, \lambda_a$ = Hyperparameters controlling the influence of each term

The physics consistency score η evaluates the model's adherence to atmospheric constraints:

$$\eta = \|L_{\text{physics}}\|_2 \tag{3.6}$$

A lower η indicates better compliance with physical principles, improving generalization and interpretability.

3.2.4 Hybrid Loss Function

The trained model is evaluated using:

- RMSE, MAE, and CRPS to compare forecast accuracy with baseline models.
- Ablation studies to assess the impact of different deep learning components.
- Uncertainty quantification (e.g., Bayesian inference, Monte Carlo dropout) to estimate prediction confidence.

The final model is deployed for real-time weather forecasting using cloud-based infrastructure with explainability tools like SHAP values for feature importance analysis.

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Appendix A

Time Framework/Work Plan

Deliverable	Key Result Areas (KRAs)	Key Performance Indicator (KPI)	Timeline
Phase 1: Understanding the Research Dynamics	Conduct background study of the research topic	Summary report of related works	Month 1-4
	Undertaking relevant self-paced ML courses (Deep learning (MIT channel), Udemy, Neuromatch)	Progress presentation	
	Seminar series (monthly)	AfriClimate AI Seminar	Monthly
Phase 2: Proposal Development & Systematic Literature Review (SLR)	Conduct a systematic literature review and identify research gaps to refine the study's methodology.	A well-defined research problem, a comprehensive literature review document summarizing existing techniques and key research gaps, and a structured research framework outlining the study's novelty and approach.	Month 5-6
	Develop the proposal, submit the proposal for review, and make necessary revisions based on feedback.	A complete and well-structured proposal draft, revised and approved for research execution.	
	Write a review Paper (1st paper)	A review paper ready to be submitted	Month 7
Phase 3: Data Collection & Preprocessing	Identify and acquire datasets, clean, preprocess, and integrate datasets	Raw & Processed datasets	Month 8-9

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Deliverable	**Key Result Areas (KRAs)**	**Key Performance Indicator (KPI)**	**Timeline**
	Perform Exploratory Data Analysis, select relevant features and engineer new ones	Data insights and visualization, Feature selection documentation	
	Store and manage datasets for modeling	Ready-to-use dataset	
Phase 4: Model Development (Functional hybrid physics-informed ML model)	Develop baseline ML models (LSTMs, CNNs, GNNs, FNOs) and a hybrid physics-informed neural network (PINN)	Initial ML models, PINN prototype	Month 11-13
	Integrating physics constraints into the model followed by model training and hyperparameter tuning, and finally, comparing performance with traditional forecasting methods (WRF, NWP).	Fully functional hybrid model, optimized model, and model benchmarking results.	Month 14-17
	Write a journal paper to a major peer-reviewed journal (2nd paper)	Research paper ready to be submitted	Month 18-19
Phase 4: Experimentation & Evaluation	Design experiments for model validation, evaluate model performance (accuracy, generalization, robustness)	Experiment plan, Evaluation results	Month 20-21
	Refine the model, conduct sensitivity analysis	Model improvements, Robustness validation	
	Compare results with existing forecasting models	Comparative performance report	
	Write a journal paper to a major peer-reviewed journal (3rd paper)	Research paper ready to be submitted	Month 23-24
Phase 5: Thesis Writing & Defense	Write research findings and methodology chapters	Draft thesis chapters	Month 25-27
	Revise thesis based on supervisor feedback	Finalized thesis draft	
	Conduct internal PhD progress presentation	Progress defense	Month 28-29
	Submit thesis for review	Thesis submission	
	Address reviewer comments and finalize thesis	Final approved thesis	Month 30-34
	Defend PhD thesis	PhD defense and completion	Month 35-36