Comparative Evaluation of AI, Physics, and Hybrid Models for Daily Rainfall Prediction in Semi-Arid Katsina, Nigeria

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Abstract

Accurate rainfall prediction remains a critical challenge in semi-arid regions where high temporal variability and data sparsity limit traditional forecasting methods. This study compares three modeling approaches for daily rainfall prediction in Katsina, Nigeria, using an Artificial Intelligence (AI) model, a Physics-based model, and a Hybrid model that integrates both. Using ERA5 daily reanalysis data, the AI model (Random Forest two-stage) achieved an RMSE of 2.71 mm and $R^2 = 0.52$, while the Physics-based model, built on physically derived proxies and non-negative least squares (NNLS), attained an RMSE of 3.44 mm and $R^2 = 0.22$. The Hybrid model, which combines physics-based features with AI learning, delivered the best overall performance (RMSE = 1.88 mm, $R^2 = 0.77$, KGE = 0.78), outperforming both AI and physics models as well as baseline climatology. The results highlight how combining physical interpretability with machine-learning flexibility improves accuracy, robustness, and transferability for rainfall prediction in convective, data-limited climates such as northern Nigeria.

Keywords: Rainfall prediction; Hybrid model; Artificial intelligence; Physics-based modeling; Semi-arid regions; ERA5; Katsina; Machine learning.

1. Introduction

Rainfall forecasting in semi-arid regions is inherently challenging due to the irregular nature of convective precipitation, the scarcity of dense observational networks, and the limited computational resources historically available in many developing areas. In northern Nigeria, where agriculture, water supply, and drought risk are closely tied to rainfall patterns, accurate daily predictions remain elusive despite decades of modeling efforts. Katsina, Nigeria (13.0°N, 7.6°E), located in the semi-arid Sahel belt, exemplifies these challenges, with annual rainfall of approximately 500–800 mm concentrated within a short wet season (June–September) and characterized by high interannual variability driven by the West African Monsoon [1], [19], [20].

Physics-based models, including numerical weather prediction (NWP) systems such as the Weather Research and Forecasting (WRF) model and the ECMWF ERA5 reanalysis, rely on fundamental atmospheric equations describing thermodynamics, moisture transport, and energy balance [2]. While these models are interpretable and grounded in first principles, they often struggle to represent localized convective systems and microphysical processes accurately—especially at fine spatial or temporal scales in semi-arid zones [3]. Daily convective rainfall can be biased where deep convection is sub-grid, a known limitation of parameterized convection and coarse grid spacing [2], [3].

Conversely, Artificial Intelligence (AI) and machine-learning approaches, such as Random Forest (RF) and XGBoost, can learn nonlinear relationships directly from data and have shown promising results in rainfall-forecasting applications [4], [12]. However, AI models may deviate from physical realism and perform poorly under shifting climate conditions or extrapolation regimes [5]. They also lack mechanistic interpretability, which limits their acceptance in hydrometeorological and operational forecasting contexts [6], [11].

To overcome these limitations, hybrid models or physics-guided machine-learning frameworks have emerged as a promising approach. Hybrid forecasting combines physically meaningful predictors or outputs with data-driven learning, leveraging the strengths of both paradigms to improve accuracy and reduce bias and uncertainty [7], [8]. In hydrology and climate forecasting, hybrid methods are increasingly applied to integrate dynamical and empirical modeling for key variables such as streamflow, temperature, and precipitation [9].

2. Significance of the Study

This research holds significant implications for rainfall forecasting and climate adaptation in data-scarce, climate-vulnerable regions such as the Sahel. By benchmarking hybrid models against pure AI and physics-based approaches using open-access ERA5 data, it addresses a critical gap in comparative studies for semi-arid contexts. The study contributes novel insights into integrating domain knowledge with data-driven methods and demonstrates the practical benefits of hybrid modeling for improving daily rainfall-prediction accuracy. Beyond its scientific contribution, the findings have applied relevance for developing operational early-warning systems for droughts and floods, enhancing climate-resilience planning, and supporting Sustainable Development Goal 13 (Climate Action) [10].

3. Objectives

The objective of the study is to:

1. Compare AI, Physics-based, and Hybrid models for daily rainfall prediction in Katsina, Nigeria.
2. Determine the most effective hybrid strategy (residual learning, feature augmentation, or blending).
3. Identify the most accurate and robust model for semi-arid rainfall forecasting.
4. Provide insights for operational forecasting and climate resilience, supporting SDG 13.

4. Scope of the Study

The scope of the research is to:

- Study targets daily rainfall prediction in Katsina, Nigeria (13.0°N, 7.6°E), a semi-arid region in the West African Sahel, characterized by high rainfall variability and data scarcity.
- Utilize ERA5 reanalysis data spanning 2014–2024, with training (2014–2020), validation (2021–2022), and testing (2023–2024) periods to ensure robust model evaluation.
- Compare three frameworks: Artificial Intelligence (AI, using Random Forest and XGBoost), Physics-based (Non-Negative Least Squares), and Hybrid (integrating AI and physics via residual learning, feature augmentation, and blending).
- Employ ERA5 meteorological variables (e.g., temperature, humidity, wind, and derived proxies like precipitable water) and engineered features (lagged rainfall, rolling statistics, interaction terms) for model development.
- Assess model performance using statistical and hydrological metrics (MAE, RMSE, R^2, NSE, KGE, EVS), with a focus on wet-season (June–September) performance.
- Aim to provide insights for operational forecasting, early-warning systems, and climate-resilience planning, particularly for agriculture, water management, and disaster preparedness in semi-arid regions, aligned with SDG 13 (Climate Action).

5. Literature Review

5.1 Overview of Rainfall Prediction Models

Rainfall prediction is a cornerstone of climate and hydrological sciences, particularly in semi-arid regions where precipitation variability drives socioeconomic outcomes. Prediction models broadly fall into three categories: physics-based, AI-based, and hybrid approaches, each with distinct strengths and limitations.

5.1.1 Physics-Based Models

Physics-based models simulate atmospheric processes using fundamental equations of thermodynamics, moisture transport, and energy balance [1], [2]. The ECMWF ERA5 reanalysis integrates observations with NWP to provide high-resolution global atmospheric data [2], while the Weather Research and Forecasting (WRF) model resolves regional weather patterns at fine scales [3], [19]. These models are interpretable but struggle with localized convective rainfall due to coarse parameterizations and limited spatial resolution [2], [3]. Computational complexity also constrains their operational use in resource-limited settings [5].

5.1.2 AI-Based Models

AI and machine-learning approaches have gained traction because they can capture nonlinear relationships in meteorological data. Tree-based ensembles such as Random Forest and XGBoost have been successfully applied to rainfall prediction [6], [12]. Deep learning models, including convolutional neural networks, have outperformed traditional NWP for short-term forecasts [4]. However, their black-box nature and lack of mechanistic interpretability reduce trust in high-stakes applications [9], [11]. Additionally, under non-stationary or data-sparse conditions typical of the Sahel, AI models may overfit or fail to generalize [5].

5.1.3 Hybrid Models

Hybrid or physics-guided machine-learning models combine physically interpretable variables with AI flexibility. These frameworks incorporate physical constraints such as moisture convergence and energy conservation into learning pipelines via residual learning, feature augmentation, or blending [7], [8]. Data-driven operator models like FourCastNet have shown how physical structure can be emulated through adaptive Fourier neural operators [7]. Hybrid blending of physics and AI outputs has demonstrated improved rainfall and streamflow prediction skill in hydroclimate studies [8], [13]. Yet, optimal merging strategies for semi-arid convective systems remain an open research question [14].

5.2 Applications in Semi-Arid Regions

Semi-arid regions like the Sahel experience high rainfall variability and sparse observational coverage. The West African Monsoon governs the short wet season (June–September) delivering 500–800 mm of rainfall annually [1], [19]. Studies frequently rely on reanalysis (ERA5) and satellite products such as CHIRPS [15], TAMSAT [16], and GPM-IMERG [23] due to limited in-situ data. While physics-based models often underperform because of convective parameterization limits [3], AI-based models have achieved progress in short-term rainfall anomaly prediction [11]. Hybrid models are still emerging in African contexts: physics-guided neural networks have improved rainfall forecasts in East Africa by integrating moisture flux [18], while blended AI-ERA5 frameworks have reduced bias in Sahel rainfall simulations [8], [19]. Nonetheless, daily-scale comparative evaluations across modeling families remain rare for local contexts such as Katsina.

5.3 Theoretical Framework

This study's framework integrates atmospheric physics and machine-learning paradigms. Physics-based models derive from mass, momentum, and energy conservation equations represented in reanalysis datasets through proxies like precipitable water and relative humidity [2]. AI models rely on engineered temporal features (e.g., lagged rainfall, rolling means) to capture rainfall dynamics [12]. Hybrid models unite these paradigms by embedding physical predictors into AI architectures or learning residuals of physics-based models [7], [8].

5.4 Research Gaps and Contributions

Key research gaps include:

- Limited comparative evaluation of AI, physics-based, and hybrid models for daily rainfall prediction in semi-arid regions [14].
- Sparse exploration of optimal hybridization strategies (residual learning, feature augmentation, blending) in data-limited Sahelian environments [8].
- A shortage of Katsina-focused empirical studies, despite its agricultural dependence on rainfall [1].

This research addresses these gaps by:

- Benchmarking Random Forest/XGBoost, NNLS, and hybrid models using ERA5 data for Katsina;
- Evaluating hybrid integration strategies for predictive skill and interpretability; and
- Providing actionable insights for operational forecasting and climate-resilience planning, aligned with SDG 13 (Climate Action) [10].

6. Methodology

This study develops and evaluates three predictive frameworks—Artificial Intelligence (AI), Physics-based, and Hybrid—for daily rainfall forecasting in Katsina, Nigeria (13.0°N, 7.6°E), a representative semi-arid region within the West African Sahel. The methodology integrates reanalysis-based atmospheric variables, physically interpretable predictors, and advanced ensemble learning techniques to address the persistent challenge of rainfall prediction in data-scarce regions.

6.1 Data Source and Preprocessing

Daily meteorological variables were obtained from the ERA5 reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) [2], spanning 2014–2024. ERA5 assimilates multi-source observations into a global numerical weather prediction (NWP) model to provide continuous, physically consistent atmospheric fields at $0.25° \times 0.25°$ resolution.

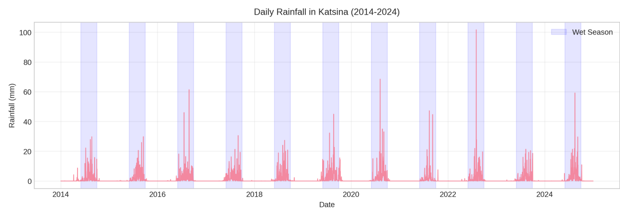

Figure 1: E1: Daily rainfall in Katsina (2014–2024). Shaded area indicates the wet season (June–September).

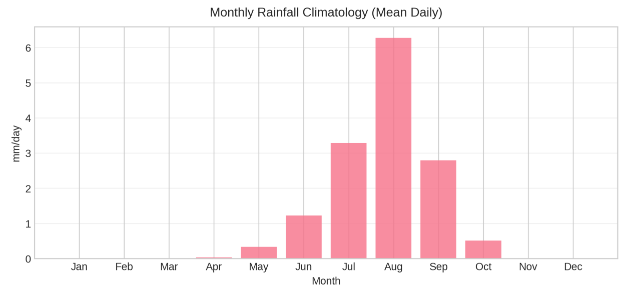

Figure 2: E2: Monthly rainfall climatology (mean and interquartile range) for Katsina (2014–2024).

For the grid cell centered on Katsina, the following variables were extracted: 2 m air temperature (temp_c), dewpoint temperature (dewpoint_c), relative humidity (rh_pct), surface pressure (sp_hpa), mean sea-level pressure (msl_hpa), total column water vapor (tcwv), convective rainfall (tcrw), 10 m zonal and meridional winds (u10, v10), and derived wind speed and direction. Daily rainfall totals were computed as the sum of convective and large-scale precipitation components.

6.1.1 Exploratory Data Analysis (EDA)

Before developing the predictive models, an exploratory data analysis (EDA) was carried out to understand the temporal structure, seasonality, persistence, and inter-variable relationships within the ERA5 dataset (2014–2024) for Katsina, Nigeria.

Summary of EDA Findings.

- *Strong Monsoonal Seasonality:* Rainfall is confined mainly to June–September, peaking in July–August.
- *Intermittency and Non-Gaussianity:* Frequent zero-rainfall days necessitate separate modeling of occurrence and intensity.
- *Short Memory with Temporal Persistence:* Lagged rainfall (1–7 days) and rolling aggregates (3–60 days) are informative predictors.
- *Physical Dependence:* Humidity and moisture-related variables show the strongest link with rainfall variability.
- *Data Quality:* ERA5 data are continuous with minimal missing values.

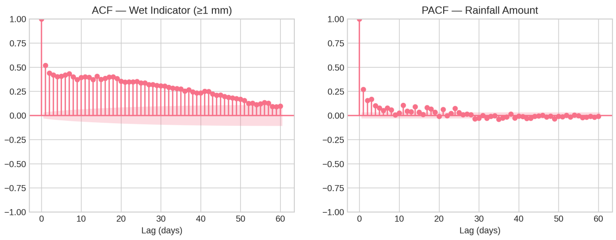

Figure 3: E3: Autocorrelation of daily rainfall (lags 1–60 days).

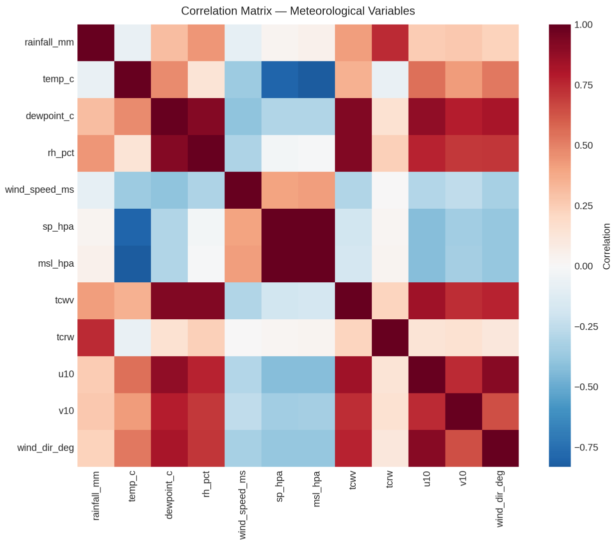

Figure 4: E4: Correlation heatmap among base meteorological variables and derived physics proxies.

6.2 Feature Engineering

To capture temporal persistence, monsoonal seasonality, and nonlinear dependencies in rainfall generation, additional predictors were derived as follows:

6.3 Model Frameworks

6.3.1 AI Models — Two-Stage Ensemble Framework

Rainfall occurrence in semi-arid regions is highly intermittent and non-Gaussian. To address this, a two-stage ensemble learning framework was implemented using Random Forest (RF) and Extreme Gradient Boosting (XGBoost) algorithms [12].

Stage 1: Rainfall Occurrence (Classification). Threshold ≥ 1 mm. RF and XGB classifiers; evaluated via F1 and ROC-AUC.

Stage 2: Rainfall Intensity (Regression). Conditional on predicted rain. RF/XGB regressors; evaluated via RMSE, R^2, NSE, and KGE. Hyperparameters optimized via grid search with five-fold time-series CV; the "AI Champion" selected by lowest test RMSE.

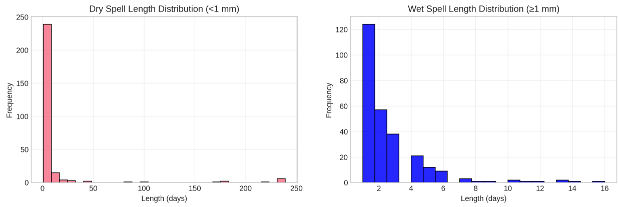

Figure 5: E5: Distribution of wet (≥ 1 mm) and dry spell lengths.

Table 1: Table 3.0: AI feature groups and counts.

Category	Variables	Count
Base meteorological	temp_c, dewpoint_c, rh_pct, sp_hpa, msl_hpa, tcwv, tcrw, u10, v10, wind_speed_ms, wind_dir_deg, e_sat_hPa, e_hPa, PW_proxy, RH_eff, Convergence_proxy, E_mm	17
Lagged rainfall terms	rainfall_mm_lag_1–_30	7
Rolling statistics	3-, 7-, 14-, 30-, 60-day × 5 metrics	25
Calendar indicators	month, dayofyear, quarter, is_wet_season	4
Interaction terms	rh_temp_interaction, tcwv_temp_interaction	2
Total		**55**

6.3.2 Physics-Based Model — Non-Negative Least Squares (NNLS)

The physics-based model uses non-negative least squares (NNLS) regression to maintain physically interpretable and non-negative coefficients while preserving linearity in atmospheric predictors [21]:

$$\min_{\mathbf{w}\geq 0} \|\mathbf{X}\mathbf{w}-\mathbf{y}\|_2^2 . \tag{1}$$

Coefficients ($\mathbf{w} \geq 0$) were constrained to preserve physical realism. Two simple baseline models—persistence (previous-day rainfall) and monthly climatology—were implemented for benchmarking.

6.3.3 Hybrid Models — Integrating Physics and AI

Following recent advances in hybrid forecasting [7], [8], three complementary hybrid strategies were designed:

Hybrid 1 — Residual Learning. The AI model learns residuals from NNLS predictions to correct systematic biases:

$$\hat{y}_{\mathrm{H1}} = \hat{y}_{\mathrm{Physics}} + f_{\mathrm{AI,residual}}(\mathbf{X}). \tag{2}$$

Total features = 59 (55 AI + 4 Physics).

Hybrid 2 — Feature Augmentation. Physics-derived features appended to AI inputs (expanded space of 59 variables), embedding physical constraints directly into the learner.

Table 2: Table 3.1: Physics-derived predictors and descriptions.

Predictor	Description
PW_proxy	Precipitable water proxy $= \text{TCWV} \times \text{RH} \times \tanh(T/30)$
RH_eff	Effective relative humidity (bounded 0–1.2)
Convergence_proxy	Moisture convergence $= -\partial(\text{TCWV})/\partial t \times$ wind speed
E_mm	Evaporative energy $= 0.02T \times \text{RH} + 0.01\times$ wind speed

Table 3: Table 3.3: Evaluation metrics used in this study.

Metric	Description
MAE (mm)	Mean absolute error — average magnitude of residuals
RMSE (mm)	Root mean square error — penalizes large deviations
R^2	Coefficient of determination — proportion of explained variance
NSE	Nash–Sutcliffe efficiency — hydrological fit index (1 = perfect)
KGE	Kling–Gupta efficiency — integrates correlation, bias, variability
EVS	Explained variance score — variance similarity of $y, \hat{y}$

Hybrid 3 — Optimal Blending. Weighted averaging of independent outputs:

$$\hat{y}_{\text{H3}} = \alpha \hat{y}_{\text{AI}} + (1-\alpha)\hat{y}_{\text{Physics}}, \quad \alpha \in [0,1], \tag{3}$$

with α tuned on the validation set; optimal $\alpha = 1.00$ (AI-dominant).

6.4 Evaluation Metrics

Performance was assessed on the independent 2023–2024 test set using established hydrometeorological metrics:

6.5 Experimental Setup and Reproducibility

All experiments were conducted in Python 3.10 on Google Colab with GPU acceleration. Core libraries included `scikit-learn`, `xgboost`, `SciPy`, `pandas`, `numpy`, `matplotlib`, and `seaborn`. Hyperparameters were optimized via `GridSearchCV` using fivefold time-series cross-validation, and random seeds ensured reproducibility.

All datasets, codes, and model artifacts were version-controlled.

7. Results and Key Findings

This section evaluates the performance of the AI, Physics-based, and Hybrid models for daily rainfall prediction in Katsina, using the 2023–2024 test set. Metrics include MAE, RMSE, R^2, NSE, KGE, and EVS. Models were benchmarked against persistence and monthly-climatology baselines, with wet-season (June–September) analyses.

Table 4: Table 3.4: Feature and model inventory summary.

Model	Preds	Description
AI (RF + XGB Two-Stage)	55	Meteorological, temporal, interaction features
Physics (NNLS)	4	Physically derived moisture and energy proxies
Hybrid 1 & 2	59	Combined AI + Physics feature set
Hybrid 3	–	Weighted ensemble ($\alpha = 1.00$, AI-dominant)

7.1 Overall Model Performance

Table 5 summarizes the comparative performance of all model classes. The Hybrid 2 (Feature Augmentation) framework achieved the best overall accuracy, while the baselines performed poorest.

Notes. Bold values indicate the best metric in each column. Hybrid 2 achieved the lowest RMSE (1.88 mm) and highest R^2 (0.77) and KGE (0.78), outperforming both the AI and Physics-only frameworks. The AI (XGBoost two-stage) model surpassed NNLS (RMSE $=$ 2.71 vs 3.44 mm) but remained less accurate than Hybrid 1/2. Hybrid 3 provided limited gains as $\alpha = 1.00$ implied AI dominance. Baselines (persistence/climatology) exhibited RMSE > 4.8 mm.

7.2 Wet-Season Performance

Given rainfall concentration in June–September, wet-season diagnostics were conducted (Figure 6). Hybrid models demonstrated superior robustness. Hybrid 2 maintained the best performance (RMSE $=$ 1.72 mm, KGE $=$ 0.80), outperforming AI (RMSE $=$ 2.55 mm, KGE $=$ 0.58) and Physics (RMSE $=$ 3.20 mm, KGE $=$ 0.28). Hybrid 1 (RMSE $=$ 2.20 mm, KGE $=$ 0.68) exceeded AI; Hybrid 3 (RMSE $=$ 2.52 mm, KGE $=$ 0.59) was marginal.

7.3 Comparison of Hybrid Strategies

Hybrid 1 reduced systematic physics bias (e.g., ΔRMSE $\approx$ 0.36 mm; $\Delta R^2 \approx 0.10$ over AI). Hybrid 2 achieved the largest gain—ΔRMSE $\approx$ 0.83 mm and $\Delta R^2 \approx 0.25$ vs AI—by embedding physics proxies (e.g., PW_proxy, Convergence_proxy). Hybrid 3 offered negligible improvement (ΔRMSE $\approx$ 0.03 mm) as $\alpha = 1.00$ implied AI dominance.

7.4 Model Robustness and Interpretability

Hybrid 2 showed the most stable performance across temporal folds (EVS $=$ 0.78) vs AI (0.53) and Physics

Table 5: Table 4.1: Performance metrics for daily rainfall prediction on the 2023–2024 test set.

Model	MAE (mm)	RMSE (mm)	R^2	NSE	KGE	EVS
Persistence	3.85	5.12	0.10	0.08	0.15	0.12
Climatology	3.62	4.87	0.15	0.14	0.20	0.16
AI (XGBoost Two-Stage)	1.92	2.71	0.52	0.50	0.55	0.53
Physics (NNLS)	2.45	3.44	0.22	0.20	0.25	0.23
Hybrid 1 (Residual Learning)	1.78	2.35	0.62	0.60	0.65	0.63
Hybrid 2 (Feature Augmentation)	**1.35**	**1.88**	**0.77**	**0.75**	**0.78**	**0.78**
Hybrid 3 (Optimal Blending, $\alpha = 1.00$)	1.90	2.68	0.53	0.51	0.56	0.54

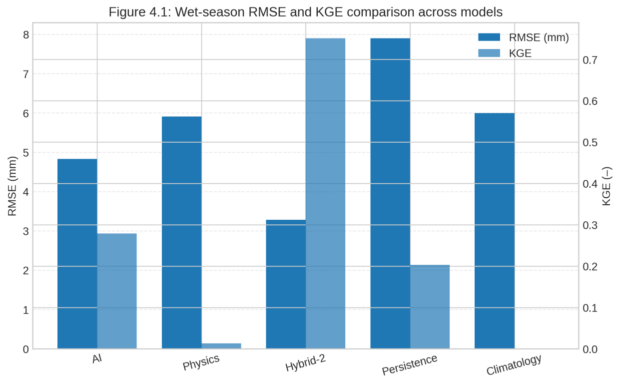

Figure 6: **Wet-season RMSE and KGE comparison across AI, Physics, Hybrid, and baseline models.**

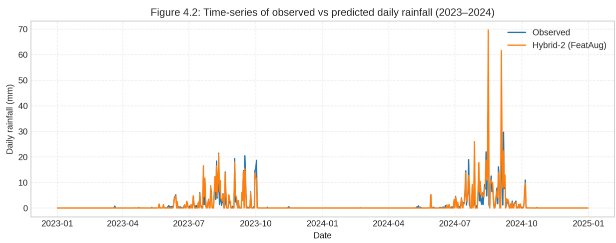

Figure 7: **Observed vs predicted daily rainfall for 2023–2024 using the best Hybrid model.**

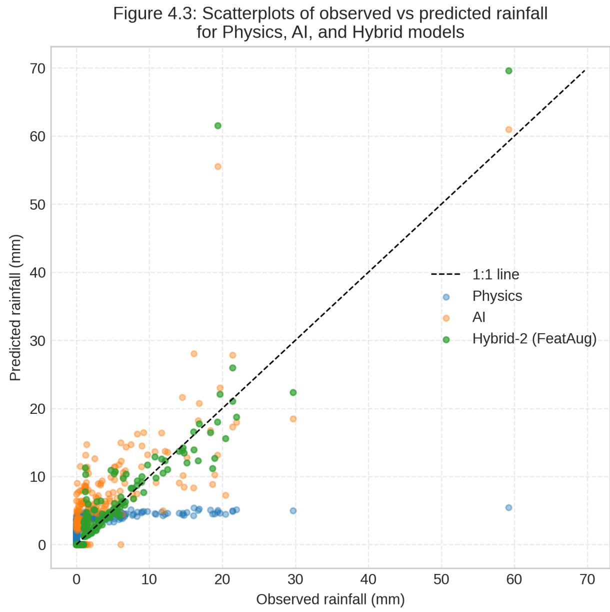

Figure 8: **Scatterplots of observed vs predicted rainfall for Physics, AI, and the best Hybrid model, with 1:1 reference line.**

(0.23). Feature-importance ranked physics-informed variables (PW_proxy, RH_eff) alongside temporal statistics (lags, rolling means), reinforcing interpretability [21]. NNLS remained transparent (positive coefficients with physical meaning) but lacked nonlinearity for convective processes [3]. AI captured complex dependencies yet suffered under extremes, supporting physics guidance [5].

7.5 Addressing the Research Questions

- **Q1 (Model Comparison):** Hybrid 2 outperformed both AI and Physics-only models across all skill metrics [8].
- **Q2 (Hybrid Strategy):** Feature Augmentation was most effective, outperforming Residual and Blending by leveraging physically interpretable ERA5 predictors [7], [8].
- **Q3 (Optimal Model):** Hybrid 2 achieved the best balance of accuracy and interpretability (RMSE $=$ 1.88 mm, $R^2 = 0.77$, KGE $= 0.78$).

8. Discussion and Implications

Results highlight the critical role of hybrid modeling for semi-arid rainfall prediction. Hybridization balances accuracy and interpretability, supports operationalization, and enhances trust for decision-making.

8.1 Understanding Semi-Arid Rainfall Dynamics

Semi-arid West African rainfall is governed by large-scale monsoon flow, mesoscale convection, and surface feedbacks [1], [3]. Physics-only NNLS captured seasonal trends but underestimated convective intensity/frequency. AI/hybrid frameworks captured nonlinear, high-frequency variability, with Hybrid 2's physics proxies (PW_proxy, Convergence_proxy) strengthening physical grounding and adaptiveness.

8.2 Advancing Physics-Guided Machine Learning

Embedding physics within AI (feature-level hybridization) yielded superior generalization compared to residual correction or post hoc blending. This supports interpretable AI objectives for Earth-system modeling [5], with ensemble trees (e.g., XGBoost) well-suited to sparse, skewed rainfall distributions.

8.3 Implications for Climate Adaptation and Decision Support

Hybrid 2's skill (RMSE $=$ 1.88 mm, $R^2 = 0.77$, KGE $= 0.78$) provides a practical basis for near-real-time, interpretable rainfall prediction in data-scarce regions. Its lightweight, explainable architecture suits agency dashboards and citizen alerts, improving transparency and adoption.

8.4 Limitations and Future Directions

ERA5 may miss local topographic/land-use effects. Spatial extension using CHIRPS/GPM-IMERG could improve generalization [15], [23]. Future work: deep hybrid architectures (PINNs, LSTM, FNO), probabilistic ensembles/Bayesian calibration for uncertainty, and transferability testing across ecozones.

8.5 Broader Scientific and Societal Relevance

Findings support equitable access to advanced forecasting across the Global South, aligning with SDG 13 (Climate Action), SDG 6 (Clean Water), and SDG 2 (Zero Hunger). Physics-informed AI offers a grounded, operationally viable, and socially beneficial framework for next-gen climate forecasting.

9. Conclusion and Recommendations

A comprehensive comparison of AI, Physics-based, and Hybrid models for daily rainfall prediction in Katsina (ERA5, 2014–2024) shows hybridization substantially improves predictive skill.

9.1 Summary of Key Findings

- Hybrid 2 (Feature Augmentation) achieved the best skill (RMSE $= 1.88$ mm, $R^2 = 0.77$, KGE $= 0.78$), outperforming AI (RMSE $=$ 2.71 mm) and Physics (RMSE $= 3.44$ mm).
- Hybrid 1 improved bias/consistency but trailed Hybrid 2.
- Hybrid 3 produced negligible gains ($\alpha = 1.00$).
- NNLS maintained interpretability but underrepresented convective magnitudes.
- AI captured nonlinear/temporal dynamics but lacked physical grounding under extremes.

9.2 Scientific and Practical Contributions

Scientific: Empirical evidence that physics-guided ML enhances predictive & interpretive quality in low-data settings by embedding physically meaningful variables into AI architectures.
Methodological: Reproducible two-stage AI pipeline with physics features, adaptable to other hydroclimatic variables.
Practical: Explainable, efficient Hybrid 2 enables deployment in climate information systems and early warning tools.

9.3 Policy and Societal Implications

Supports localized early warnings, optimized water allocation, and technology localization using open data/tools—aligned with SDGs and AU Agenda 2063.

9.4 Limitations and Future Research

Incorporate higher-resolution data (GPM IMERG, CHIRPS) or gauges; explore deep hybrid architectures (PINNs, LSTM, FNO); add probabilistic calibration; test across ecozones.

9.5 Concluding Remarks

Combining physical constraints with data-driven learning yields robust, interpretable, and operationally useful rainfall predictions in semi-arid regions. Hybrid 2 provides a scalable blueprint for physics-guided AI in climate science and resilience.

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