

Input-Architecture Synergy in Precipitation Nowcasting: Assessing the Need for Physical Anchors using the ANDeL Framework as a Case Study

Gilbert Edwin Belson

`gebelson1@st.knust.edu.gh`

Kwame Nkrumah University of Science and Technology

Jeffrey N.A. Aryee

Kwame Nkrumah University of Science and Technology

Michael Baidu

University of Leeds

Marian A. Osei

Met Office

Patrick Davies

Kwame Nkrumah University of Science and Technology

Samuel K. Afful

Kwame Nkrumah University of Science and Technology

Mercy M. Apaw

Kwame Nkrumah University of Science and Technology

Article

Keywords: Advancing Nowcasting with Deep Learning Techniques (ANDeL), Precipitation Nowcasting, Deep Learning, Implicit Regularization, Catastrophic Drift, Land-Atmosphere Interactions, Autoregressive Models, Multi-source Data Fusion, West Africa.

Posted Date: October 22nd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11233323/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Title: Input-Architecture Synergy in Precipitation Nowcasting: Assessing the Need for Physical Anchors using the ANDeL Framework as a Case Study.

Authors: Gilbert Edwin Belson^{1*}, Jeffrey N.A. Aryee¹, Michael Baidu², Marian A. Osei³, Patrick Davies¹, Samuel K. Afful^{1,4}, Mercy M. Apaw¹

¹ Climate Diagnostics, Air Quality & AI (CDAI) Lab, Department of Meteorology and Climate Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana.

² Institute for Climate and Atmospheric Science, School of Earth and Environment, University of Leeds, Leeds, UK.

³ Met Office, FitzRoy Road, Exeter, EX13PB, UK.

⁴ Department of Computer Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana.

****Corresponding author:** Gilbert Edwin Belson. **Email:** gebelson1@st.knust.edu.gh

Abstract

High-resolution precipitation nowcasting in West Africa requires forecasting approaches that can represent rapidly evolving convective rainfall while using information from atmospheric and land-surface variables, yet it remains unclear whether the relative performance of autoregressive (AR) and non-autoregressive (NA) deep-learning architectures depends on the atmospheric and land-surface information provided as input. This study examines whether degradation in AR forecasts depends on input composition rather than being an inherent property of recursive forecasting. Using a 17-configuration ablation experiment, we systematically compare AR and NA models across precipitation-only, atmospheric, land-surface and combined input configurations. We found AR performance decreased substantially for several configurations containing highly variable atmospheric or the full multivariate inputs, NA models exhibited greater robust performance to these configurations suggesting that their non-recurrent forecasting structure may be less sensitive to the accumulation of input-related errors. Conversely, configurations incorporating slowly varying soil moisture or static land-surface information produced some of the strongest AR results, with the precipitation plus soil moisture configuration achieving the highest mean CSI (0.2087) among the configurations evaluated. For heavy rainfall, the soil-moisture AR configuration also maintained higher spatial skill than its NA counterpart across the evaluated lead times, coinciding with reduced spatial spreading in the forecast examples. The results therefore support a data-aware approach to architecture selection in which the usefulness of AR and NA forecasting depends not only on forecast horizon but also on the composition and temporal characteristics of the available inputs.

Keywords: Advancing Nowcasting with Deep Learning Techniques (ANDeL); Precipitation Nowcasting; Deep Learning; Implicit Regularization; Catastrophic Drift; Land-Atmosphere Interactions; Autoregressive Models; Multi-source Data Fusion; West Africa.

1. Introduction

High-resolution rainfall nowcasting (0-6 hours) remains a critical challenge in West Africa as it forms the backbone for agricultural planning and disaster management. While numerical weather prediction (NWP) models have historically struggled with the “spin-up” time required for these short horizons, Deep Learning (DL) has emerged as a powerful alternative for capturing non-linear spatiotemporal dynamics (Shi et al., 2015; Ravuri et al., 2021). However, a fundamental architectural debate persists in the DL forecasting community: should forecasting models treat time as a sequential recurrence (Autoregressive, AR) or as a simultaneous snapshot (Non-Autoregressive, NA)?

Current literature at the intersection of computer vision and meteorology presents a dichotomy. Autoregressive models, such as the Convolutional LSTM (ConvLSTM) and Trajectory GRU (TrajGRU), theoretically offer superior capacity for capturing temporal evolution. Classical implementations achieve this by explicitly feeding predictions back as inputs for subsequent timesteps (Shi et al., 2017), while modern Sequence-to-Sequence (Seq2Seq) variants achieve this implicitly by propagating and updating an internal spatial memory (hidden state) across the forecast horizon (Shi et al., 2015; Srivastava et al., 2015). However, although these modernized architectures avoid the direct error feedback of classical autoregression, they still suffer from long-term spatial degradation. As the forecast horizon extends, the unanchored hidden state becomes increasingly uncertain, causing the model to generate spatially average forecasts (Sun et al., 2026). This produces blurred outputs and the unphysical dissipation of convective features at longer lead times (Shi et al., 2015; Ayzel et al., 2020). In contrast, non-autoregressive models, often based on U-Net or Convolutional Neural Network (CNN) architectures, mitigate this compounding error by predicting future frames independently or simultaneously (Agrawal et al., 2019; Trebing et al., 2021). While NA models frequently yield sharper images, they often lack temporal consistency, struggling to maintain the trajectory of moving systems (Franch et al., 2020).

For operational systems, model selection has historically relied on static benchmarks in the search for a single 'winner' based on average metrics. This approach fails to capture regime-dependent performance, rendering it insufficient for assessing operational value (Ayzel et al., 2020; Franch et al., 2020; Ravuri et al., 2021). Recent studies have begun to explore multi-source input fusion to enhance these models, integrating satellite imagery with radar and atmospheric variables (Zhang et al., 2021). However, the interaction between input composition and forecasting architecture remains insufficiently characterized. In particular, it is unclear whether

auxiliary atmospheric and land-surface variables affect autoregressive and non-autoregressive forecasting architectures in systematically different ways.

This study examines whether AR forecast degradation depends on input composition rather than being an inherent limitation of recursive forecasting. We hypothesize that slowly varying or spatially persistent variables, including topography, land use/land cover (LULC), and soil moisture, provide stable spatial context that may improve AR forecast evolution, these variables may help reduce the sensitivity of the recurrent latent representation to rapidly varying atmospheric inputs and the spatial drift observed in some precipitation-only AR forecasts (Gao et al., 2022). We refer to this proposed effect as implicit temporal regularization. Using the ANDeL early fusion deep-learning architecture variant, we test this hypothesis indirectly through a systematic input-ablation experiment. The experiment compares the predictive skill, lead-time behavior, and spatial forecast evolution of AR and NA models across configurations with and without persistent land-surface information.

This paper is structured to elevate the AR vs. NA debate from a performance contest to a generalizable design principle, following three analytical phases:

1. **Multivariate Input Diagnostics:** We quantify the influence of various static and dynamic input variable configurations on predictive skill, comparing these multi-source configurations relative to precipitation-only baseline models, establishing the foundation for evaluating the implicit-temporal-regularization hypothesis.
2. **Stratified Regime Assessment:** We evaluate the relative skill differences among the input variable configurations across rainfall intensity thresholds. This analysis identifies whether the effects of auxiliary variables differ between light, moderate, and heavy rainfall events, including convective conditions associated with extreme convective events.
3. **Temporal Evolution and Architectural Synergy:** We compare AR and NA predictive skill across forecast lead times and rainfall-intensity classes. We also examine spatial forecast evolution for selected convective events to identify differences in the location, extent, intensity, and persistence of predicted rainfall. This analysis assesses whether the relative performance of AR and NA architectures changes with lead time, rainfall regime, and input configuration.

Overall, this work evaluates a data-aware framework for precipitation nowcasting in West Africa in which the relative usefulness of AR and NA architectures may depend on the composition and temporal characteristics of the available input variables. The findings provide evidence that can inform future model-design and input-selection decisions rather than identifying one universally optimal nowcasting architecture.

2. Data and Methods

2.1. Study Domain

The study domain covers Sub-Saharan West Africa between latitudes 4° N and 20° N and longitudes 17° W and 20° E, spanning approximately 8 million square kilometers from the Sahara Desert to the Atlantic Ocean (Sylla et al., 2016). The region features distinct topography, including the highlands and plateaus of Guinea and Nigeria alongside the river and lake systems of Niger and Ghana (Sarr et al., 2018). This landscape defines a gradual north-to-south transition of climatic zones, from the Saharan arid desert and Sahelian semi-arid belt to the Sudanian Savannah and southern Guinean coast (Leroux et al., 2014; Mendes et al., 2025).

Seasonal migration of the West African Monsoon (WAM) and the Inter-Tropical Convergence Zone (ITCZ) governs the regional rainfall cycle (Nicholson 2013; Akinsanola et al., 2014; Yamba et al., 2023) across three distinct zones. In the northern Sahelian zone (12° N– 20° N), a short unimodal wet season from June to September yields 150 to 600 mm of rainfall (peaking in August), characterized by intense, short-lived Mesoscale Convective Systems (MCSs) and squall lines driven by the mid-tropospheric (600–700 hPa) African Easterly Jet (Nicholson 2013; Akinsanola et al., 2015; Mendes et al., 2025; Osei et al., 2026). Further south, the Sudanian Savannah (8° N– 12° N) experiences a longer unimodal season from April/May to October with 600 to 1,200 mm of rain; this region acts as the primary zone of MCS genesis and westward propagation, shaped by the abrupt northward shift of the rain belt (the "monsoon jump") and coastal orographic enhancement (Akinsanola et al., 2015; Amekudzi et al., 2015; Yamba et al., 2023). Finally, the humid Guinea Coast (4° N– 8° N) exhibits a bimodal rainfall cycle with typical annual totals of 1,200 to 2,200 mm. Driven by monsoonal wind flow and the migration of the Intertropical Discontinuity, the region features a major wet season from March to July and a minor season in September and October with a relatively dry spell in August, known as the "Little Dry Season" (Aryee et al., 2025; Mendes et al., 2025). The spatial extent of the study domain is shown in Figure 1.

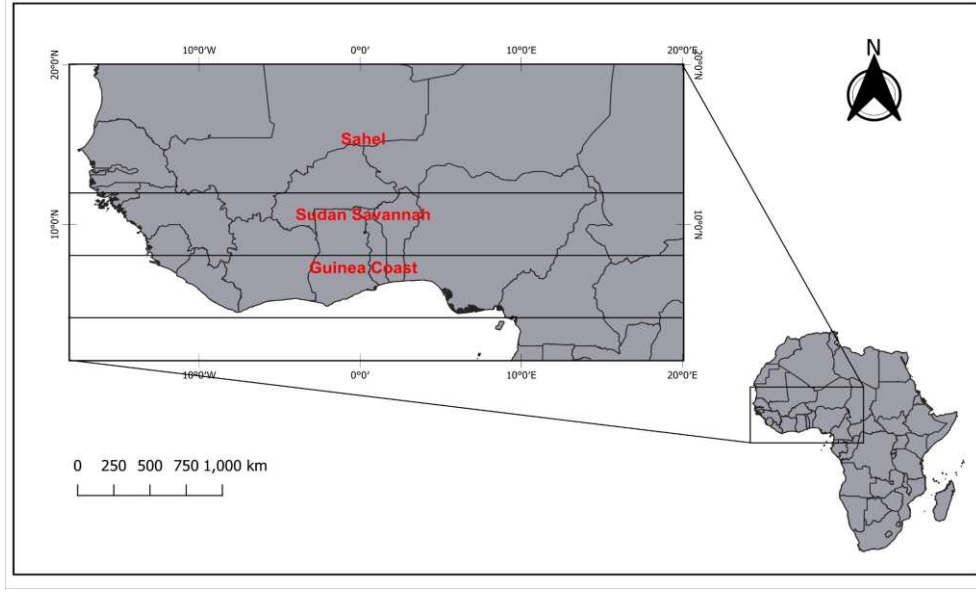


Figure 1: The Study Domain of Sub-Saharan West Africa. The region spans from 4°N to 20°N and 17°W to 20°E, encompassing distinct climatic transitions from the semi-arid Sahel in the north to the humid Guinea-coast in the south.

2.2. Data

The study used a suite of datasets to allow the models to learn from the observed precipitation dynamics and the underlying environmental conditions of the region.

The primary precipitation data for this study was the Integrated Multi-satellitE Retrievals for GPM (GPM-IMERG) from NASA. We specifically selected the Early Run product, a near-real-time (NRT) estimate to simulate an operational nowcasting environment. This dataset provides a spatial resolution of $0.1^\circ \times 0.1^\circ$ and a temporal resolution of 30 minutes of precipitation estimates over the study domain (Huffman et al., 2023), serving as the target variable of these models.

The ERA5 reanalysis dataset from European Centre for Medium-Range Weather Forecasts (ECMWF) was also used to provide atmospheric state information to our models. ERA5 provides a globally complete and consistent climate record at a spatial resolution $\sim 31\text{km}$ (0.25°) at an hourly temporal frequency (Hersbach et al., 2020). For this study, we selected key variables known to influence convective processes such as: Total Column of Water Vapor (TCWV), 2-meter dewpoint temperature (d2m), Convective Available Potential Energy (CAPE), and wind components (u and v) at relevant atmospheric pressure levels (925, 850, and 600 hPa). To ensure compatibility with the IMERG data, the ERA5 data was subjected to a two-step preprocessing pipeline. First, they were temporally interpolated to a 30-minute resolution to match the IMERG frequency, and subsequently spatially regridded from their native 0.25° resolution to the 0.1° IMERG grid using bilinear interpolation technique, a commonly used grid-to-grid interpolation method (Rajulapati et al., 2021).

To capture the effect of land-atmosphere interactions on convective initiation, we incorporated surface soil moisture data from the NASA Soil Moisture Active Passive (SMAP) Level 4 (L4) Global Surface and Root Zone Soil Moisture Analysis Update (SPL4SMGP, Version 8). This product provides 3-hourly global estimates of surface (0–5 cm) and root-zone (0–100 cm) soil moisture at a 9 km spatial resolution, generated by assimilating SMAP L-band brightness temperatures into the NASA Catchment land surface model (Reichle et al., 2017). To harmonize this data with the IMERG temporal resolution, we applied the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) technique (He et al., 2024). This method interpolates the 3-hourly estimates to a 30-minute frequency to preserve the shape of the moisture signal and prevent overshooting, which is a common artifact in standard interpolation techniques (He et al., 2024). Spatially, the data was regridded from the EASE-Grid 2.0 to the $0.1^\circ \times 0.1^\circ$ IMERG grid.

To account for the influence of surface characteristics on precipitation patterns, two static datasets were incorporated. Topographical information was derived from the NASA Digital Elevation Model (NASADEM) Global 1 arc second ($\sim 30\text{m}$) product, which is a successor to the original Shuttle Radar Topography Mission (SRTM) DEM data. NASADEM provides a global, void-free DEM data using improved algorithms and incorporating ancillary data such as ICESat/GLAS (Crippen et al., 2016; Uuemaa et al., 2020). Land Use and Land Cover data was obtained from the ESA WorldCover 2021 product, which provides eleven distinct land cover classifications at a ten meters spatial resolution (Zanaga et al., 2022). Both datasets were accessed and spatially regridded to the common $0.1^\circ \times 0.1^\circ$ IMERG grid using the Google Earth Engine (GEE) platform, utilizing mode aggregation for the categorical LULC data and mean aggregation for the elevation data. These static variables provide crucial context on geographical and surface characteristics that physically force precipitation dynamics.

3. Model Architectures

3.1 The Early-Fusion Architecture

The Early Fusion model was designed to integrate both static and dynamic data sources at the initial stage of the network, allowing the model to learn complex interactions between them. This architecture (Figure 2) is a sophisticated encoder-forecaster structure utilizing a residual prediction mechanism coupled with an attention-based baseline. The model’s structure can be deconstructed into four main components: a temporal attention-based (precipitation baseline), a static feature extractor, a main ConvLSTM expert (sequence processing), and a residual prediction head. The model is designed to accept two distinct inputs: a dynamic input of time-varying sequence of meteorological observations (Precipitation, TCWV, d2m, CAPE, u, and v) and a static input of time-invariant geographical features (Elevation and Land Use and Land Cover).

First, an attention-based sub-network generates baseline prediction utilizing only the precipitation channel of the dynamic input sequence. The precipitation sequence is processed through a series of 3D convolutional layers (Conv3D) to generate spatio-temporal attention scores. These scores are normalized using a softmax function over the time axis to create attention weights, which signify the relative importance of each historical timestep. These weights are then used to compute a time-weighted average precipitation field, serving as an intelligent, dynamically weighted persistence baseline for the subsequent forecasting steps.

Subsequently, the static input is processed by a dedicated Static feature Extractor composed of two 2D convolutional layers (Conv2D) paired with batch normalization. This component extracts relevant geospatial and environmental drivers that influence regional rainfall patterns. Crucially, these extracted static features are tiled along the temporal dimension of the dynamic input sequence and concatenated with the dynamic variables along the channel axis.

The core of the “early fusion” strategy occurs within the main sequence processing module. The concatenated dynamic and static fused data are fed into a stack of two Convolutional Long Short-Term Memory (ConvLSTM) layers. These layers are tasked with capturing and propagating spatio-temporal dependencies. By forcing the recurrent hidden states to continuously condition on the tiled static features at every timestep, this architecture mechanically facilitates the “implicit Temporal Regularization” hypothesized to anchor the model and mitigate long-term error drift. Regularization is applied through batch normalization and dropout to prevent data overfitting.

Finally, rather than directly predicting absolute future precipitation fields directly, the model employs a residual prediction head to forecast the deviations from the attention-weighted precipitation-based baseline. For each future lead time, a dedicated head comprising Conv2D layers receives the latent representations produced by the ConvLSTM module and predicts a residual precipitation field. This final forecast is generated by adding the predicted residual sequence to the tiled attention baseline. This residual formulation allows the model to learn changes relative to a dynamically weighted precipitation reference rather than reconstructing the full precipitation field independently at every lead time. This may simplify optimization by focusing model capacity on the evolving components of the precipitation field.

This early-fusion design, combined with the attention mechanism and residual prediction strategy, creates a robust architecture tailored to fully leverage both stable environmental anchors and atmospheric drivers in convective rainfall nowcasting.

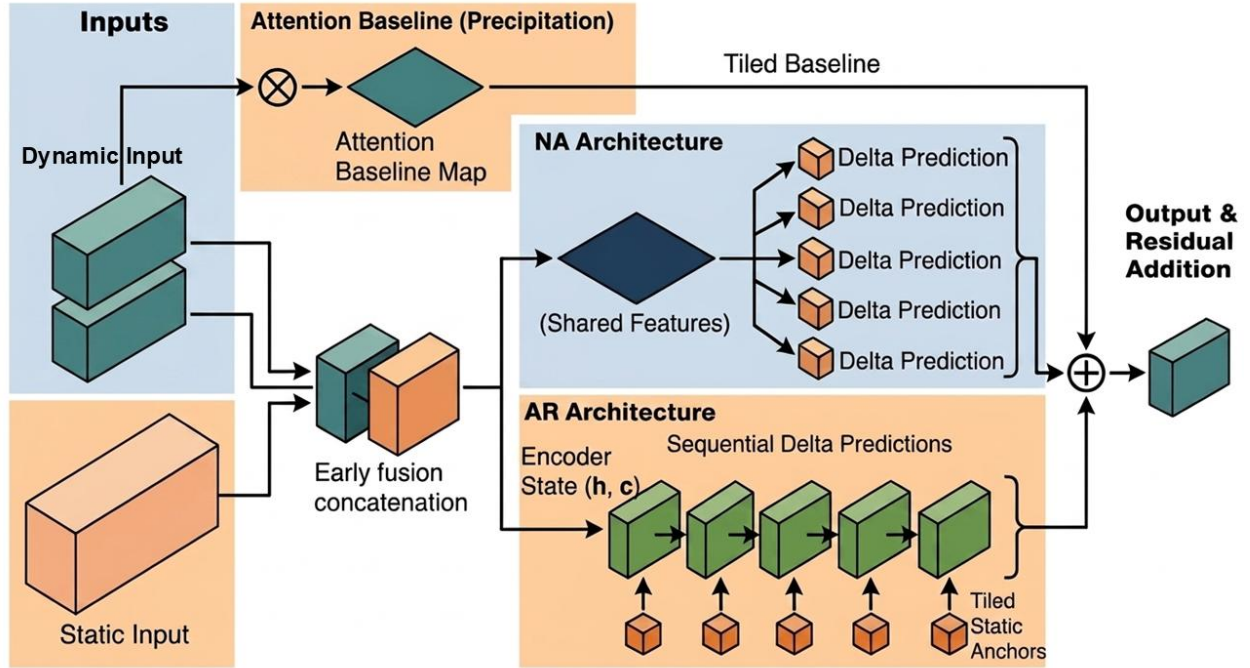


Figure 2: Schematic of the Early Fusion Deep Learning Architecture. The architecture features four primary components: 1) A temporal attention sub-network that isolates the precipitation channel to generate an additive baseline map; 2) An Early Fusion module that concatenates dynamic atmospheric variables with static boundary conditions; 3) A bifurcated sequence processing module evaluating both Non-Autoregressive (NA) parallel mapping from shared features, and Implicitly Autoregressive (AR) Seq2Seq mapping; and 4) A residual prediction head. Crucially, the AR pathway illustrates the "Implicit Temporal Regularization" mechanism, where tiled static anchors are continuously fed into the evolving hidden state (h, c) at every timestep to prevent catastrophic drift.

3.2 Experimental Settings

To systematically evaluate the impact of variable selection on architectural stability, we implemented an additive ablation strategy. This design isolates the marginal contribution of specific dynamic atmospheric variables and static boundary conditions against a baseline precipitation-only model.

Models were trained on seventeen (17) distinct input configurations (Table 1), categorized into three tiers: Baseline; Single-Variable Addition and Synergistic Combinations, culminating in a Full Model containing all available inputs.

Table 1: Experimental Design Input Variable Configurations.
A summary of the seventeen (17) distinct feature combinations used to train the Autoregressive and Non-Autoregressive models. The configurations are systematically categorized to isolate the marginal contribution of dynamic atmospheric variables (e.g., Wind at 850hPa, TCWV) and static boundary conditions (Elevation, LULC) against the precipitation-only control.

Category	Input Configuration	Expected Theoretical Contribution
Baseline	Precipitation Only (P)	Provides a precipitation-based reference representing temporal persistence and information contained in the recent precipitation state alone (Holloway and Neelin, 2010; Huang et al., 2024; Horvath-Makkos and Minhas, 2026).
Single-Variable Inclusion	P + TCWV	Provides information on the total atmospheric moisture content, helping characterize the moisture reservoir available for precipitation development (Holloway and Neelin, 2010; Liu et al., 2022; Kim et al., 2024).
	P + D2M	Provides near-surface moisture information relevant to characterizing low-level humidity and moisture availability (Pumo et al., 2021; Liu et al., 2023; Zhang et al., 2026).
	P + CAPE	Provides information on atmospheric buoyancy and convective potential, helping characterize environments favourable for convective development and intensity (Liu et al., 2023; Agyekum et al., 2023; Küçük and Dabernig, 2024).
	P + Wind @ 925hPa	Provides information on very low-level atmospheric motion, helping represent moisture transport, low-level convergence and near-surface circulation effects (Osei et al., 2023; Kim et al., 2024; Zhang et al., 2026).
	P + Wind @ 850hPa	Provides lower tropospheric flow

	information, helping represent moisture transport, convergence, and convective-system organization (Li et al., 2018; Osei et al., 2023; Zhang et al., 2026).
P + Wind @ 600hPa	Provides mid-tropospheric steering flow information, helping characterize the evolution and propagation of organized convective systems and flow associated with the African Easterly Jet (AEJ) (Baidu et al., 2022; Osei et al., 2023; Raj et al., 2026).
P + Wind Shear (925-600 hPa)	Provides information on vertical wind shear, helping characterize convective storm structure, organization and propagation (Klein and Taylor, 2020; Baidu et al., 2022; Osei et al., 2023).
P + All Winds (925, 850, 600 hPa)	Provides a multi-level representation of atmospheric motion, allowing the representation of variations in wind structure, transport, steering, and circulation across selected pressure levels (Osei et al., 2023; Liu et al., 2023; Song et al., 2025).
P + Soil Moisture	Provides land-surface moisture information, allowing representation of land-atmosphere coupling, surface fluxes, and antecedent moisture conditions (Klein and Taylor, 2020; Koukoula et al., 2021; AlNasser et al., 2026).
P + Elevation	Provides topographic information supporting the characterization of orographic lifting and terrain-related spatial variations in precipitation (Nisi et al., 2014; Küçük et al., 2024; Baig et al., 2025).
P + LULC	Provides information on land-surface characteristics that influence surface roughness, energy exchange and evapotranspiration (Rajeswari et al., 2021;

		Shadmehri Toosi et al., 2025; Ma et al., 2026).
Synergistic Combinations	P + Elev + LULC	Combines topographic and land-surface information to represent the interacting effects of terrain and surface characteristics on precipitation (Ter Maat et al., 2013; Freitag et al., 2018).
	P + Wind @ 850hPa + Elev	Combines lower-tropospheric flow and topographic information to represent the interaction between moisture transport/convergence and orographic effects (Wang et al., 2013; Li et al., 2022; Xu et al., 2026).
	P + Wind @ 850hPa + LULC	Combines lower-tropospheric flow and land-surface characteristics to represent the interaction between moisture transport, surface roughness and land-surface exchange (Rajeswari et al., 2021; Ma et al., 2026).
	P + Wind @ 850hPa + Elev + LULC	Combines lower-tropospheric flow, topography, and land-surface characteristics to represent their interacting influences on precipitation evolution (Freitag et al., 2018; Cui et al., 2026).
Full Model	All Available Variables	Combines complementary atmospheric, thermodynamic, land-surface and topographic information to provide a comprehensive representation of the interacting physical processes influencing precipitation evolution (Ciu et al., 2026; Jin et al., 2026; Qu et al., 2026).

For each configuration, AR and NA model variants were trained to compare the architectural response to different input compositions. The following sections describe the two modeling frameworks:

1. **Non-Autoregressive (NA):** An architecture where the input sequence is compressed by the encoder into a single, frozen spatial feature map (Peng et al., 2023). All future timesteps are predicted independently and simultaneously from this shared latent representation, with no temporal communication between the output steps.
2. **Recurrent Autoregressive (AR):** A sequence-to-sequence encoder-decoder architecture. The encoder compresses the historical input sequence into spatiotemporal memory states. The decoder (a ConvLSTM module) subsequently generates future timesteps sequentially (Shi et al., 2015). Unlike a classical output-feedback autoregressive model, the decoder does not explicitly feed its previously predicted precipitation fields into the next prediction step. Instead, temporal dependence is maintained through the evolving ConvLSTM hidden and cell states, which propagate information across the forecast sequence (Srivastava et al., 2015). The static variables are tiled to the forecast dimensions and fed into this decoder at each prediction step, thereby constraining the evolving memory states to remain grounded by the physical landscape (Xiaoyang, 2025). We hypothesize that this repeated contextual input may reduce spatial degradation at longer lead times. However, this interpretation is evaluated indirectly through forecast skill metrics and spatial-output analysis rather than a direct examination of the internal recurrent states.

All model variants were trained using the ANDeL early-fusion architecture and a contiguous dataset covering 1 January – 31 December 2020. This 2020 dataset was partitioned chronologically with the first 80% used for training and the remaining 20% used for validation, preserving temporal ordering and avoiding random temporal mixing. The validation set was used to monitor convergence and assess potential overfitting during training. Input sequences were generated using a sliding window approach with one timestep (30 minutes) stride, with each sample containing 9 historical input timesteps. To ensure consistency across all configurations, each model was trained for 10 epochs using the RMSProp optimizer with a learning rate of 3.09×10^{-4} . The entire 2021 calendar year was excluded from model development and was not used for training, validation, hyperparameter tuning, checkpoint selection, or performance evaluation. Final performance, however, was evaluated using an unseen and independent test data covering 1 January to 31 December 2022.

To address the sparsity of high-intensity rainfall events, standard loss functions often converge to a trivial solution of predicting zero prediction. To prevent this, we employed a Balanced Mean Absolute Error (Balanced MAE) loss function. This function explicitly partitions the domain, independently calculating the MAE for raining pixels (≥ 0.872 mm/hr) and non-raining/light-raining pixels (< 0.872 mm/hr), and subsequently averages them. This ensures the model is equally penalized for missing convective initiation as it is for over-predicting drizzle.

Model performance was assessed over a 2.5-hour forecast horizon (5 timesteps x 30 mins). We utilized standard deterministic and spatial meteorological skill scores to evaluate performance

across three discrete rainfall intensity thresholds: Light ($< 2.5\text{mm/hr.}$), Moderate ($2.5 \leq R < 10\text{ mm/hr.}$), and Heavy ($\geq 10\text{ mm/hr.}$).

To calculate the categorical metrics, predictions and observations were binarized at these thresholds to compute Hits (H), False Alarms (FA), Misses (M), and Correct Negatives (CN). The deterministic scores evaluated include Critical Success Index (CSI), Probability of Detection (POD), False Alarm Ratio (FAR) and the Heidke Skill Score (HSS):

$$CSI = \frac{H}{H + FA + M}$$

$$POD = \frac{H}{H + M}$$

$$FAR = \frac{FA}{H + FA}$$

$$HSS = \frac{(H + CN) - E}{Total\ Count - E}$$

$$where\ E = \frac{(H + M) \cdot (H + FA) \cdot (CN + M) \cdot (CN + FA)}{Total\ Count}$$

To evaluate the spatial accuracy and mitigate the “double penalty” effect common in high-resolution forecasting, we utilized the Fractions Skill Score (FSS) evaluated over a set of neighborhood windows of 3 x 3, 5 x 5, and 8 x 8 corresponding to approximately 30, 50 and 80 km at low latitudes)

$$FSS = 1 - \frac{Fraction\ Brier\ Score}{Fraction\ Brier\ Score_{worst}}$$

Finally, overall magnitude accuracy was evaluated using the Mean Absolute Error (MAE), with lower values approaching 0 indicating higher accuracy:

$$MAE = \frac{1}{n} \sum_{i=1}^n |Observed_i - Predicted_i|$$

To isolate the specific value added by the supplementary variables, we calculated the relative percentage improvement in the Critical Success Index (ΔCSI). This metric normalizes the performance gains against the precipitation-only control model. It is calculated as follows:

$$\Delta CSI = \frac{CSI_{config} - CSI_{baseline}}{CSI_{baseline}} \times 100$$

Positive values indicate that the added variables improved forecast skill, while negative values indicate performance degradation relative to the baseline. To facilitate the interpretation and comparison of these performance metrics, their theoretical ranges and recommended thresholds are defined as follows: CSI, POD, and FSS are bounded between 0 and 1, where 1 represents a perfect forecast and 0 indicates no skill. For FAR, the optimal value is 0; it also ranges from 0 to 1. The HSS ranges from -1 to 1, where 1 represents a perfect forecast, 0 indicates no skill beyond random chance, and negative values indicate performance worse than a random forecast (Kondal et al., 2024). Following Roberts and Lean (2008), FSS = 0.5 was used as a reference level for scale-selective usefulness, while recognizing that the interpretation of FSS depends on spatial scale and event frequency.

4. Results

4.1. Multivariate Input Diagnostics (Phase 1)

To quantify the effect of static and dynamic input configurations on predictive skill, an input variable ablation study was conducted. Figure 3 shows that the precipitation-only baseline (P_Only_Baseline) produced different CSI values for the two architectures. The AR precipitation-only baseline achieved a mean CSI of 0.1944, compared with 0.1732 for the NA precipitation-only baseline. This AR baseline therefore exceeded the NA baseline by +0.0212 CSI units.

The inclusion of auxiliary variables produced different performance responses in the AR architecture across input configurations. The precipitation-plus-soil-moisture (P + SMa) and precipitation-plus-land-use/land-cover (P + LULC) configurations achieved the highest AR CSI values, with scores of 0.2087 and 0.2020, respectively. In comparison, the precipitation-plus-dew-point configuration (P + D2M) achieved a CSI of 0.1292, while the Full Model achieved a CSI of 0.1263. Both values were lower than the precipitation-only AR baseline (CSI = 0.1944).

The Full Model achieved a mean CSI of 0.1860, ranking fourth among the NA configurations. The highest-performing NA configuration was precipitation plus 850-hPa wind and elevation (P + Wind@850 hPa + Elev), which achieved a CSI of 0.1959. This score was lower than the CSI values obtained by the highest-performing AR configurations, including P + SMa (CSI = 0.2087) and P + LULC (CSI = 0.2020).

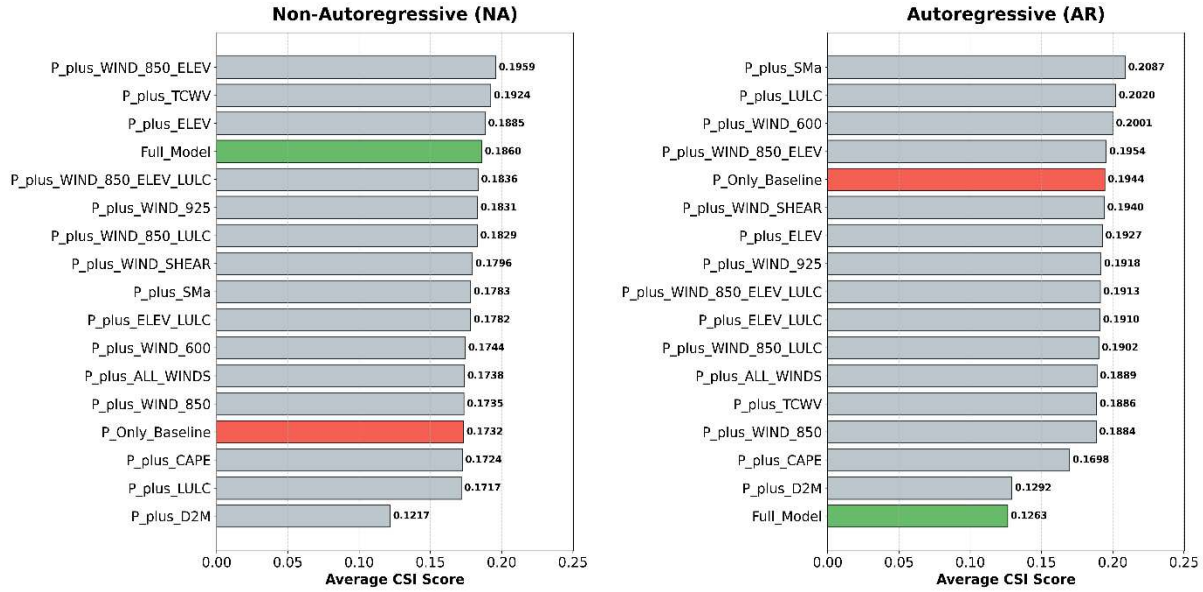


Figure 3: Comparative ranking of AR and NA architectures by average Critical Success Index (CSI). A ranking of the impact of auxiliary variables on the overall prognostic skill of Non-Autoregressive (left) and Autoregressive (right) models. The red bar indicates the precipitation-only baseline, green bar indicates the full model (all variables) and grey bars indicate isolated/synergistic variable combination.

4.2. Stratified Regime Assessment (Phase 2)

To evaluate the regime-dependent behavioral response of these architectures to input variables, a baseline-relative percentage improvement analysis was conducted across distinct rainfall intensity thresholds (Figure 4). The results expose a profound architectural asymmetry in how deep learning models process atmospheric volatility versus stable boundary conditions.

During Light and Moderate Rain events (top and middle rows), the Non-Autoregressive (NA) approach consistently extracts marginal predictive gains across the majority of variable configurations. The Autoregressive (AR) architecture, however, exhibits high sensitivity to input expansion: most multi-variable configurations trigger performance degradation (negative red bars) compared to the AR baseline. The notable exception is the integration of the soil moisture anchor (P_plus_SMa), which bucks this trend and yields consistent positive improvements for AR across both light (~10%) and moderate (~5%) regimes.

During Heavy Rain events (bottom row), the architectural difference is more pronounced. NA models better capture the rapid, complex changes in high-dimensional data. Configurations such as dew-point (P_plus_D2M) and the all-inclusive Full_Model yield staggering relative improvements for the NA architecture, exceeding +230% and +200%, respectively. In stark

contrast, these exact same volatile configurations trigger catastrophic predictive collapse in the AR model, resulting in significant degradations of $\sim -50\%$ and $\sim -30\%$.

Crucially, the AR architecture only unlocks massive positive gains during heavy convective regimes when strictly paired with stable physical anchors. The introduction of Soil moisture (P_plus_SMa) triggers a $\sim +100\%$ performance spike for the AR model, while combinations involving stable topographic features (e.g., P_plus_ELEV_LULC) yield $\sim +70\%$ improvements.

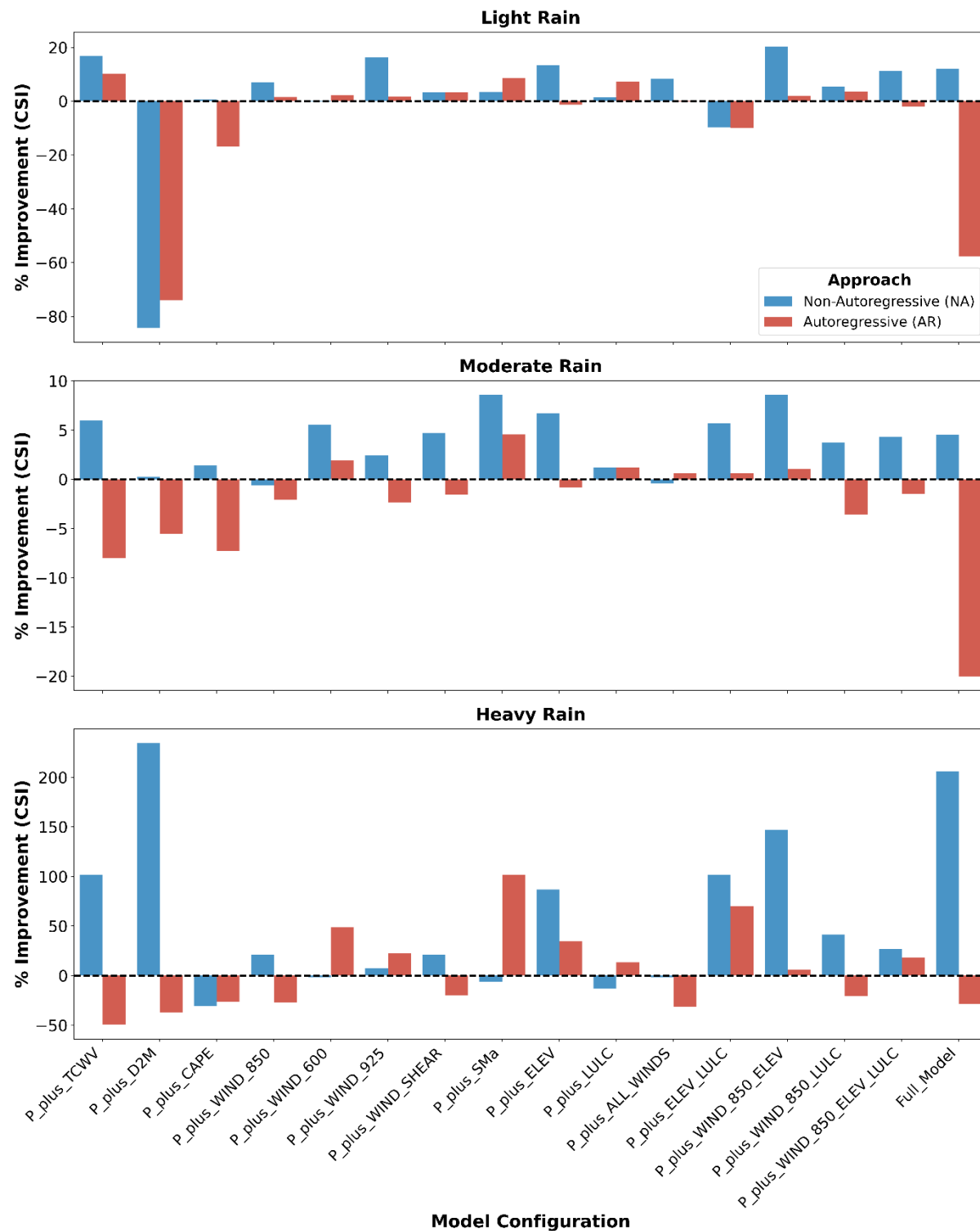


Figure 4: Percentage improvement in Critical Success Index (CSI) for AR and NA architectures. Relative percentage improvement in CSI over the baseline for the Autoregressive (red bars) and Non-Autoregressive (blue bars) configurations across Light (top), Moderate (middle), and Heavy (bottom) rain intensities.

4.3. Temporal Evolution and Architectural Synergy

To examine changes in relative spatial skill across forecast lead times, we conducted a differential Fractions Skill Score (ΔFSS) analysis that compares performance as function of lead time, rain intensity and input configuration (Figure 5). The results demonstrate that AR or NA superiority is not governed by a static temporal rule, but rather varies with lead time, rainfall intensity, and input variable configuration.

An architectural crossover in relative spatial skill emerges distinctly in partially anchored, mixed-variable configurations such as the precipitation plus wind at 850 hPa combined with elevation or LULC (P_plus_WIND_850_ELEV and P_plus_WIND_850_LULC). In these scenarios, the NA approach exhibits superior spatial accuracy at immediate lead times ($t=1,2,3$; ≤ 90 minutes) for heavy rainfall regimes, evidenced by negative ΔFSS values. However, as forecast horizons extend ($t=4,5$; 120–150 minutes), the AR architecture crosses the zero-threshold, outperforming the NA model as it captures long-term structural propagation.

Crucially, this architectural crossover vanishes at the absolute extremes of the input volatility spectrum. For the highly volatile configurations such as Full_Model, Total Column Water Vapour (TCWV), and dew-point (P_plus_D2M), the ΔFSS remains negative across all lead times and heavy intensity, indicating that the AR architecture fails to recover from the initial drift induced by high-dimensional noise. Conversely, when the AR architecture is inputted with the slowly varying soil moisture input (P_plus_SMa), the crossover is suppressed in favour of sustained AR performance. Here, the ΔFSS remains positive across virtually all lead times and intensities (light, moderate, and heavy), indicating that a robust physical anchor completely mitigates the early-step blurring typically associated with recursive AR forecasting, allowing it to maintain superior spatial accuracy from initiation through to extended dissipation.

Figure 6 shows the spatiotemporal evolution of a severe convective event over the 150-minute forecast horizon. In the Full Model configuration, the AR nowcasts degrade rapidly with time producing a broad precipitation field covering nearly the entire domain by T+150 min while obscuring the discrete convective structures. The NA architecture is comparatively more stable, retaining more distinct storm clusters, although low-intensity precipitation gradually expands and spatially becomes smoother at longer lead times. Under the Soil moisture (SMa) configuration, the NA model remains relatively stable but shows a progressive weakening and loss of some localized convective intensity cores, particularly from T+120 min onward. In contrast, the AR SMa configuration effectively preserves both the spatial organization and several high-intensity convective cores across the forecast horizon.

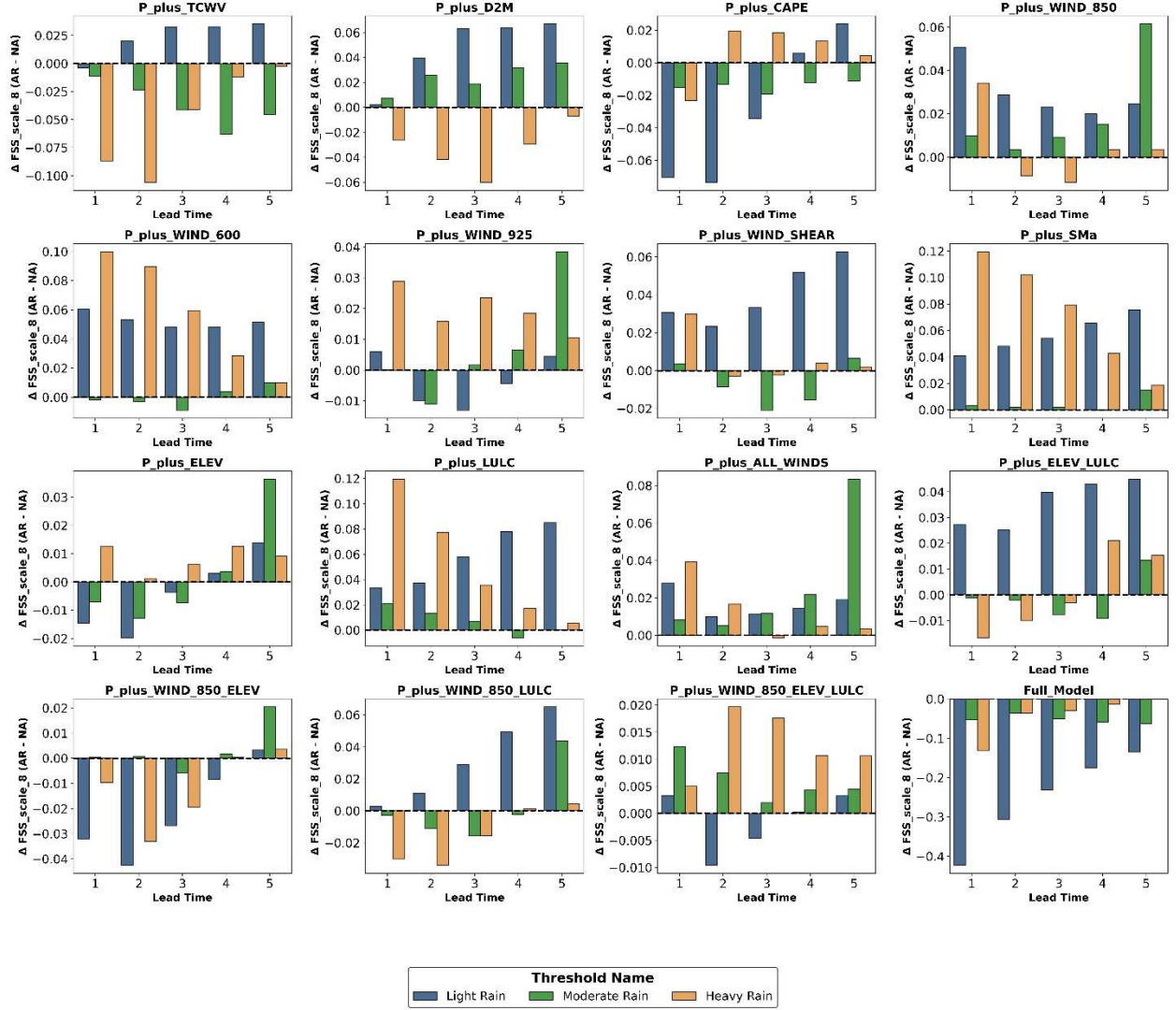


Figure 5: Differential Fractions Skill Score (ΔFSS) across lead times 1-5 (30-150 minutes). Plots show $\Delta FSS (FSS_{AR} - FSS_{NA})$ evaluated at an 8 x 8 pixel (~80 km) spatial scale across five forecast lead times. Positive values indicate AR superiority; negative values indicate NA superiority.

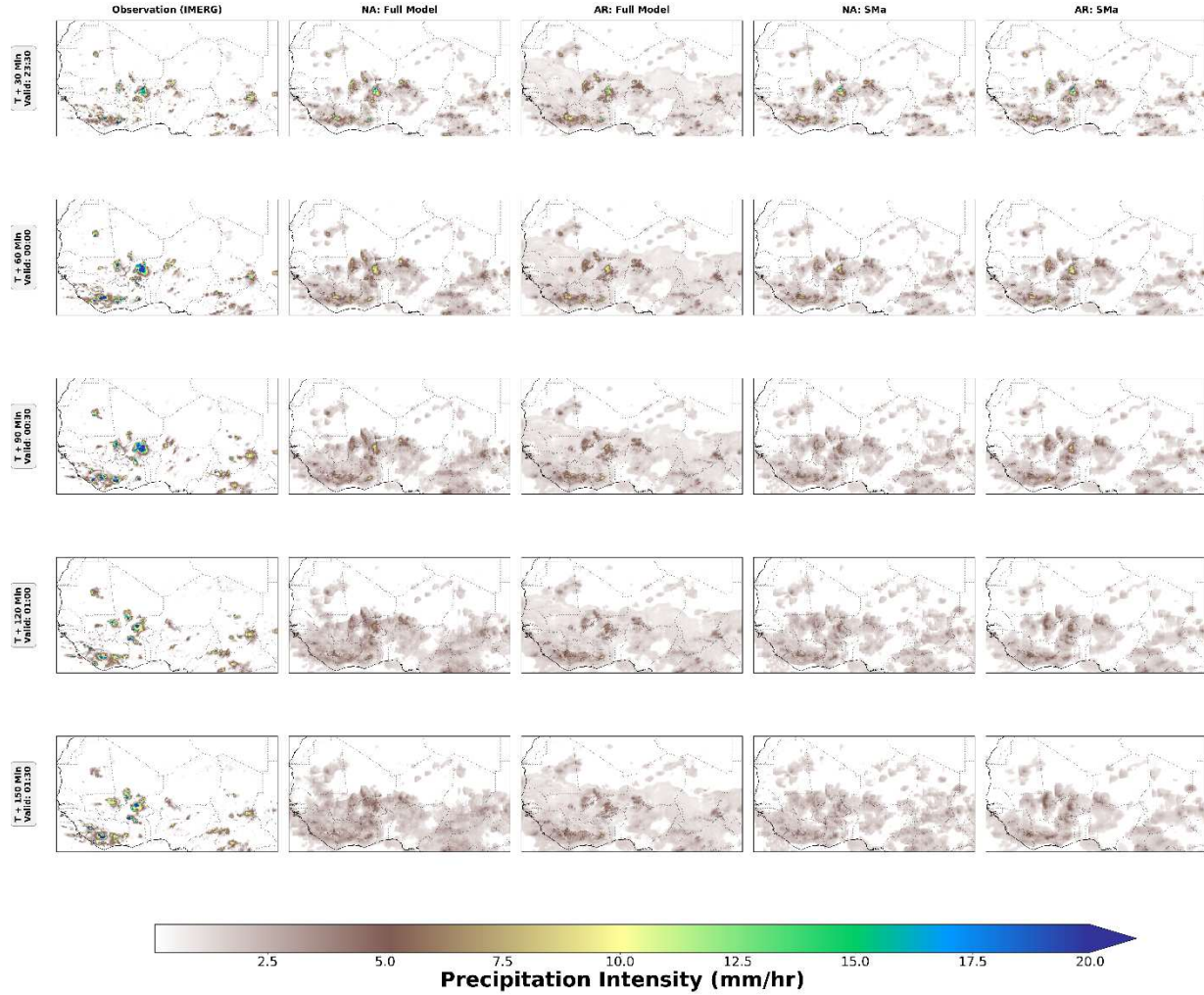


Figure 6: Spatiotemporal evolution of observed and forecast precipitation for a representative high-rainfall event. Rows show successive forecast lead times from T+30 to T+150 min. Columns show the IMERG precipitation estimate, followed by Non-Autoregressive (NA) and Autoregressive (AR) forecasts using the Full Model configuration, and NA and AR forecasts using the precipitation-plus-Soil moisture (SMa) configuration.

5. Discussion

5.1 Multivariate Input Diagnostics

The study demonstrates that input variable configurations exert a measurable influence on the predictive skill of both modeling approaches, supporting our initial hypothesis with a notable architectural nuance. While absolute CSI values in the 0.12-0.21 range reflect the inherent forecasting difficulty of chaotic tropical convection, point-by-pixel metrics are also notoriously constrained by the well-documented “double-penalty” effect (Smith et al., 2024). Consequently, rather than claiming absolute predictive mastery, our analysis evaluates relative rank advantage.

In this context, the results validate the "Implicit Temporal Regularization" mechanism, where the integration of static and slowly varying variables (specifically Soil moisture and Land Use and Land Cover) serves as physical anchors for the Autoregressive (AR) framework. By grounding the recursive hidden state with low-volatility spatial contexts, these anchors demonstrate strong potential to elevate forecasting scores, prevent the model from generating unphysical convective drift and help achieve the highest relative performance observed in the study.

Crucially, the ablation analysis uncovered a distinct input-architecture synergy, providing a mechanical rationale for why AR models are frequently characterized as inherently unstable. The pronounced degradation observed for AR configurations incorporating rapidly varying atmospheric variables (e.g., dew point temperature) or unconstrained, high-dimensional datasets (the Full Model) is consistent with a heightened sensitivity of recurrent forecasting structures to input perturbations across successive prediction steps. Because the present experiments do not directly track hidden-state dynamics, this mechanism should be interpreted as a plausible explanation rather than a definitively demonstrated causal pathway. Nevertheless, this observation aligns with the stability and "hallucination" challenges recently identified in generative nowcasting models, where unconstrained algorithms produce physically inconsistent precipitation patterns when exposed to volatile inputs outside standard training distributions (Franch et al., 2025).

On the other hand, NA architecture, which maps simultaneous spatiotemporal snapshots, lacks the recurrent feedback mechanism that drives sequential error accumulation. As a result, the NA models showed comparatively smaller performance degradation under the expanded input configurations, suggesting greater robustness to the additional variability introduced by the full multivariate input set. Although the model was trained for only 10 epochs under a constrained computational budget, the consistent relative performance improvements suggest that the extensive spatiotemporal dataset (utilizing a full-year sliding window) partially compensated for limited training duration. This comprehensive data exposure enabled the architectures to capture underlying physical constraints when appropriately anchored. These findings provide empirical support for the potential of land-surface integration (specifically soil moisture and LULC) to mitigate temporal decay, indicating that future model selection must be carefully aligned with input data volatility.

5.2. Stratified Regime Assessment

By evaluating the percentage improvement in predictive skill on an intensity basis, this study empirically validates the "Implicit Temporal Regularization" mechanism, demonstrating that its necessity scales with convective extremity. The findings reveal that deep learning architectures possess fundamentally different sensitivity profiles to input dimensionality and volatility during heavy rainfall events.

The NA architecture's ability to achieve >200% performance improvements when fed highly volatile data (e.g., dew-point) or unconstrained datasets (the Full Model) highlights its capacity to act as a robust noise filter. Because NA models generate predictions via discrete simultaneous mapping, they avoid recursive error compounding, allowing them to indiscriminately ingest complex thermodynamics to boost baseline performance during extreme events.

The AR architecture exhibits a noticeable vulnerability to input volatility. The sharp decline in AR performance under the full multivariate and dew point configurations suggests that, absence of invariant physical constraints, the recursive loop amplifies dynamic atmospheric noise, thereby destabilizing the hidden state trajectory. However, when paired with the slowly varying soil moisture configuration, the AR model achieves an approximate 100% relative improvement in heavy precipitation. This result provides empirical support for the proposed role of stable boundary variables in providing the physical regularization necessary to constrain AR latent representations, thereby mitigating divergent drift during chaotic, high-intensity convective regimes.

While these findings align with recent literature advocating for multimodal frameworks to capture extreme rainfall (Ampas et al., 2025; Mazumder et al., 2025), they introduce a critical operational caveat: multimodal inputs must be architecturally curated. Furthermore, a persistent nuance remains. Even as anchored AR approaches and robust NA configurations significantly improve extreme event capture, deep learning models still battle an inherent "upper limit" when predicting the absolute peak intensities of convective cores. This is widely attributed to the smoothing effect of mathematical regularization in high-dimensional spaces (Tan et al., 2024; Zhang et al., 2025). Acknowledging this inherent ceiling underscores the absolute necessity of strategically pairing specific physical anchors with appropriate architectural priors to push the performance boundary of heavy rainfall prediction as far as mathematically possible.

5.3. Temporal Evolution and Architectural Synergy

The assessment of temporal degradation and differential spatial skill strongly refines our hypothesis regarding the conditional nature of AR and NA approaches. The findings establish that the temporal crossover between NA and AR superiority is not a structural inevitability, but a highly fluid boundary dictated by the presence of exogenous physical anchors.

In mixed-variable configurations, we observe the traditional temporal trade-off: NA models maintain localized advantages in early-horizon heavy rains ($t \leq 90$ minutes) by avoiding the error propagation common in early recursive steps (Diab & Al Kobaisi, 2025). As the system evolves, the anchored AR model's ability to track spatial persistence over time eventually outweighs NA's discrete, independent estimations.

However, our most profound finding is the complete suppression of this temporal crossover at the extremes of the input spectrum. When overwhelmed by unconstrained multi-source data (the

Full Model), the AR hidden state destabilizes so severely that NA models permanently dominate spatial accuracy. However, the addition of soil moisture improves the AR performance, enabling it to outperform the NA models at heavy rain predictions across all lead times ($t=1$ through $t=5$). This indicates that slowly evolving land surface states are so superiorly integrated into recursive prediction processes that they eliminate the AR architecture's traditional "spin-up" lag, supporting recent observations regarding land-surface predictability in the Sahel (Taylor et al., 2022). It is worth noting, however, that the relationship between satellite-detected rainfall and soil moisture in the African Savanna can occasionally be complicated by phenomena such as virga, where precipitation evaporates before reaching the ground (Estébanez-Camarena et al., 2023) which warrants consideration in operational deployments.

Ultimately, these results necessitate a paradigm shift in operational nowcasting design. The optimal framework is not a static choice between AR and NA, nor is it a simple lead-time-based switch. Future research must prioritize the development of dynamic, "data-aware" gated architectures. Such systems would evaluate incoming data volatility in real-time: delegating forecasts to robust NA modules when relying on noisy, high-dimensional atmospheric variables, while dynamically transitioning to AR modules when high-quality static and slowly-varying boundary anchors are available to maintain extended-horizon structural coherence (Zhang et al., 2025).

The spatial evolution shown in Figure 6 provides qualitative support for the proposed input-architecture synergy. In the Full Model, the AR nowcasts exhibit a rapid broadening of the precipitation field and a loss of intensity cores with an increase in lead times. This severe spreading is primarily caused by highly volatile dynamic inputs overwhelming the recurrent hidden state, which leads to spatial drift. Once this drift creates spatial uncertainty, the Balanced MAE loss function acts as a secondary factor. Because this loss heavily penalizes missed rain events, the uncertain model predicts broad, light rainfall over a massive area to minimize errors. The NA nowcasts however avoid this recursive error accumulation as it effectively filters the high-dimensional noise to retain more organized patterns, although they still smooth spatially at longer lead times although the convective cores become smoother and spatially expanded at longer lead time. In contrast, the AR P+SMA configuration shows less artificial spreading of light rainfall, whereas the NA nowcasts show a greater weakening of convective cores at extended lead times. The improved AR performance is consistent with the hypothesis that slowly varying soil moisture provides stable spatial context that reduces forecast degradation in the recurrent model. This configuration maintains more coherent convective cells, preserves dry areas, and sustains high-intensity cores over extended lead times while limiting widespread low-intensity rainfall.

6. Conclusion

This study demonstrates that the performance degradation of autoregressive (AR) precipitation-nowcasting models is not uniform across input configurations. Instead, the magnitude and direction of the performance gap between AR and non-autoregressive (NA) architectures depend heavily on the auxiliary information supplied. By evaluating the "Implicit Temporal Regularization" hypothesis across three distinct analytical phases: multivariate input diagnostics, a stratified regime assessment, and an evaluation of temporal evolution, our findings reveal a profound asymmetry in how these deep learning models process atmospheric and land-surface data.

The integration of static and slowly varying variables provided the physical regularization required to constrain the recursive hidden state of the AR models. Specifically, isolated configurations incorporating either soil moisture or Land Use and Land Cover (LULC) yielded the highest performance among all evaluated AR variants, achieving mean Critical Success Index (CSI) values of 0.2087 and 0.2020, respectively. For heavy precipitation events, the precipitation plus soil moisture configuration produced an approximate 100% relative increase in CSI over the precipitation-only AR baseline, rising from a baseline CSI of 0.1944 to 0.2087.

This physically constrained the model and mitigated the divergent error accumulation observed when the AR architecture relied on highly volatile dynamic inputs such as dew point temperature or the unconstrained, high-dimensional full multivariate dataset, both of which induced predictive collapse. In contrast, the NA architecture demonstrated inherent robustness to input volatility, showing comparatively smaller performance degradation under the expanded input configurations and achieving relative CSI improvements exceeding 200% during heavy rain events under the identical multivariate conditions that degraded AR performance.

Evaluating model performance over time revealed that the architectural crossover in relative spatial skill is driven by the volatility of the atmospheric inputs rather than a fixed forecast lead time. In mixed-variable configurations, the NA approach achieved superior spatial accuracy for short- to medium-lived heavy rain events ($t \leq 90$ minutes), while the anchored AR architecture avoided long-term structural blurring to dominate at extended lead times. However, at the extremes of the input spectrum, this crossover vanished entirely: anchored AR models utilizing soil moisture maintained superior spatial accuracy across all lead times, whereas highly volatile environments resulted in sustained NA superiority.

Ultimately, these results indicate that the primary operational challenge in deep learning nowcasting is no longer a binary architectural selection between AR and NA approaches, but rather the strategic implementation of "data-aware" synergistic frameworks. Future work must prioritize investigating the persistence of this anchoring mechanism at extended 2.5–6-hour horizons. Furthermore, a natural next step is to design and test adaptive forecasting systems that

dynamically select or weight AR and NA modules according to measurable characteristics of the available input fields, such as temporal persistence or input data volatility. Such systems could balance the short-term robustness of NA models during highly volatile atmospheric regimes with the long-term forecast integrity and terrain-influenced spatial propagation of anchored AR configurations.

Acknowledgements

This research is an outcome of the Advancing Nowcasting using Deep Learning techniques (ANDeL) project, which received earlier cloud credits from ORACLE for Research and further financial support from Google. We appreciate all the generous support from our funders, including the World Meteorological Organization (WMO) for their endorsement of the ANDeL project and further support for the 6-month extension phase of ANDeL (known as ANDeLx). The authors gratefully acknowledge National Aeronautics and Space Administration (NASA), the European Space Agency (ESA), and the European Centre for Medium-Range Weather Forecasts (ECMWF) for providing the IMERG, SMAP, NASADEM, WorldCover, and ERA5 datasets, respectively. We used the Google Earth Engine platform for spatial data processing.

Author Contributions

G.E.B. and J.N.A.A. conceptualized the study. G.E.B. developed the deep learning architectures, performed the data analysis, and wrote the original manuscript. J.N.A.A., M.B., M.O., and P.D. provided critical scientific insights, reviewed the methodology, and contributed to the editing and refinement of the manuscript. S.K.A. and M.M.A. provided scientific insights and reviewed the manuscript. All authors reviewed and approved the final manuscript.

References

- Agrawal, S., Barrington, L., Bromberg, C., Burge, J., Gazen, C., & Hickey, J. (2019). Machine learning for precipitation nowcasting from radar images. *arXiv preprint arXiv:1912.12132*. <https://doi.org/10.48550/arXiv.1912.12132>
- Agyekum, J., Amekudzi, L. K., Stein, T., Aryee, J. N., Atiah, W. A., Adefisan, E. A., & Danuor, S. K. (2023). Verification of satellite and model products against a dense rain gauge network for a severe flooding event in Kumasi, Ghana. *Meteorological Applications*, 30(5), e2150. <https://doi.org/10.1002/met.2150>
- Akinsanola, A., Ajayi, V., Adefisan, E., and Ogunjobi, K. (2014). Diagnostic evaluation of precipitation over west africa using three of the cordex-africa simulations. In International Conference Proceedings of the Nigerian Meteorological Society, Makurdi, Nigeria.

- Akinsanola, A., Ogunjobi, K., Gbode, I., and Ajayi, V. (2015). Assessing the capabilities of three regional climate models over cordex africa in simulating west african summer monsoon precipitation. *Advances in Meteorology*, 2015(1):935431. <https://doi.org/10.1155/2015/935431>
- AlNasser, F., Gianotti, D., & Entekhabi, D. (2026). Soil moisture impact on convective initiation. *Water Resources Research*, 62(7), e2025WR042329. <https://doi.org/10.1029/2025WR042329>
- Amekudzi, L. K., Yamba, E. I., Preko, K., Asare, E. O., Aryee, J., Baidu, M., & Codjoe, S. N. (2015). Variabilities in rainfall onset, cessation and length of rainy season for the various agro-ecological zones of Ghana. *Climate*, 3(2), 416-434. <https://doi.org/10.3390/cli3020416>
- Amoakowaah Osei, M., Klein, C., Taylor, C. M., Parker, D. J., & Baidu, M. (2026). Covariance of the intertropical discontinuity and African easterly jet in Sahelian wet and dry years. *Quarterly Journal of the Royal Meteorological Society*, 152(777), e70123. <https://doi.org/10.1002/qj.70123>
- Ampas, H., Refanidis, I., & Ampas, V. (2025). Hybrid Hydrological Forecasting Through a Physical Model and a Weather-Informed Transformer Model: A Case Study in Greek Watershed. *Applied Sciences*, 15(12), 6679. <https://doi.org/10.3390/app15126679>
- Aryee, J. N. A., Quagraine, K. T., Davies, P., Afrifa, F. O. T., Agyapong, G., Annor, E. G., ... & Poku, L. P. (2025). Spatial and temporal rainfall patterns in the little dry season over the Guinea Coast: Case assessment of historical observations, associated drivers and future projections. *Meteorological Applications*, 32(6), e70125. <https://doi.org/10.1002/met.70125>
- Ayzel, G., Scheffer, T., & Heistermann, M. (2020). RainNet v1. 0: a convolutional neural network for radar-based precipitation nowcasting. *Geoscientific Model Development*, 13(6), 2631-2644. <https://doi.org/10.5194/gmd-13-2631-2020>
- Baidu, M., Schwendike, J., Marsham, J. H., & Bain, C. (2022). Effects of vertical wind shear on intensities of mesoscale convective systems over West and Central Africa. *Atmospheric Science Letters*, 23(8), e1094. <https://doi.org/10.1002/asl.1094>
- Baig, F., Ali, L., Faiz, M. A., Chen, H., & Sherif, M. (2025). From bias to accuracy: Transforming satellite precipitation data in arid regions with machine learning and topographical insights. *Journal of Hydrology*, 653, 132801. <https://doi.org/10.1016/j.jhydrol.2025.132801>
- Crippen, R., Buckley, S., Agram, P., Belz, E., Gurrola, E., Hensley, S., ... & Tung, W. (2016). NASADEM global elevation model: Methods and progress. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 41, 125-128. <https://doi.org/10.5194/isprs-archives-XLI-B4-125-2016>
- Cui, H., Yu, H., Zuo, X., & Wu, G. (2026). Impacts of orography and urbanization on extreme precipitation event in Beijing during 2023. *Weather and Climate Dynamics*, 7(2), 743-765. <https://doi.org/10.5194/wcd-7-743-2026>
- Diab, W., & Al Kobaisi, M. (2025). Temporal neural operator for modeling time-dependent physical phenomena. *Scientific Reports*, 15(1), 32791. <https://doi.org/10.48550/arXiv.2504.20249>
- Estébanez-Camarena, M., Taormina, R., van de Giesen, N., & ten Veldhuis, M.-C. (2023). The Potential of Deep Learning for Satellite Rainfall Detection over Data-Scarce Regions, the West African Savanna. *Remote Sensing*, 15(7), 1922. <https://doi.org/10.3390/rs15071922>
- Franch, G., Maggio, V., Coviello, L., Pendesini, M., Jurman, G., & Furlanello, C. (2020). TAASRAD19, a high-resolution weather radar reflectivity dataset for precipitation nowcasting. *Scientific Data*, 7(1), 234. <https://doi.org/10.1038/s41597-020-0574-8>

Freitag, B. M., Nair, U. S., & Niyogi, D. (2018). Urban modification of convection and rainfall in complex terrain. *Geophysical Research Letters*, 45(5), 2507-2515. <https://doi.org/10.1002/2017GL076834>

Gao, Z., Shi, X., Wang, H., Zhu, Y., Wang, Y. B., Li, M., & Yeung, D. Y. (2022). Earthformer: Exploring space-time transformers for earth system forecasting. *Advances in Neural Information Processing Systems*, 35, 25390-25403. <https://doi.org/10.48550/arXiv.2207.05833>

He, J., Yuan, L., Lei, H., Wang, K., Weng, Y., & Gao, H. (2024). A novel piecewise cubic hermite interpolating polynomial-enhanced convolutional gated recurrent method under multiple sensor feature fusion for tool wear prediction. *Sensors*, 24(4), 1129. <https://doi.org/10.3390/s24041129>

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., ... & Thépaut, J. N. (2020). The ERA5 global reanalysis. *Quarterly journal of the royal meteorological society*, 146(730), 1999-2049. <https://doi.org/10.1002/qj.3803>

Holloway, C. E., & Neelin, J. D. (2010). Temporal Relations of Column Water Vapor and Tropical Precipitation. *Journal of the Atmospheric Sciences*, 67(4), 1091-1105. <https://doi.org/10.1175/2009JAS3284.1>

Horvath-Makkos, L., & Minhas, F. (2026). Interpretable rainfall modelling reveals rapid reorganisation of Amazonian rainfall under vegetation loss. *arXiv preprint arXiv:2605.10948*. <https://doi.org/10.48550/arXiv.2605.10948>

Huang, C., Mu, P., Bai, C., & Watson, P. A. (2024). TCP-diffusion: A multi-modal diffusion model for global tropical cyclone precipitation forecasting with change awareness. *arXiv preprint arXiv:2410.13175*. <https://doi.org/10.48550/arXiv.2410.13175>

Huffman, G. J., Bolvin, D. T., Joyce, R., Kelley, O. A., Nelkin, E. J., Portier, A., ... & West, B. J. (2023). IMERG V07 release notes. Goddard Space Flight Center: Greenbelt, MD, USA, 1140. <https://gpm.nasa.gov/resources/documents/imerg-v07-release-notes>

Jin, X., Yang, Z., Shu, S., Dong, M., Xu, H., Zhang, C., ... & Shen, H. (2026). Improving FY-4B Satellite Precipitation Retrieval over Coastal Complex Terrain of Eastern China: Deep Learning Approaches with Multi-Source Underlying Surface Data. *Remote Sensing*, 18(14), 2397. <https://doi.org/10.3390/rs18142397>

Klein, C., & Taylor, C. M. (2020). Dry soils can intensify mesoscale convective systems. *Proceedings of the National Academy of Sciences*, 117(35), 21132-21137. <https://doi.org/10.1073/pnas.2007998117>

Kim, W., Jeong, C. H., & Kim, S. (2024). Improvements in deep learning-based precipitation nowcasting using major atmospheric factors with radar rain rate. *Computers & Geosciences*, 184, 105529. <https://doi.org/10.1016/j.cageo.2024.105529>

Kondal, A., Hegewisch, K., Liu, M., Abatzoglou, J.T., Adam, J.C., Nijssen, B. and Rajagopalan, K., 2024. Seasonal forecasts have sufficient skill to inform some agricultural decisions. *Environmental Research Letters*, 19(12), p.124049. <https://doi.org/10.1088/1748-9326/ad8bde>

Koukoulas, M., Schwartz, C. S., Nikolopoulos, E. I., & Anagnostou, E. N. (2021). Understanding the impact of soil moisture on precipitation under different climate and meteorological conditions: A numerical sensitivity study over the CONUS. *Journal of Geophysical Research: Atmospheres*, 126(23), e2021JD035096. <https://doi.org/10.1029/2021JD035096>

Küçük, Ç., Atencia, A., & Dabernig, M. (2024). Integrated nowcasting of convective precipitation with transformer-based models using multi-source data. *arXiv preprint arXiv:2409.10367*. <https://doi.org/10.48550/arXiv.2409.10367>

- Li, H., Hu, Y., Zhou, Z., Peng, J., & Xu, X. (2018). Characteristic features of the evolution of a Meiyu frontal rainstorm with Doppler radar data assimilation. *Advances in Meteorology*, 2018(1), 9802360. <https://doi.org/10.1155/2018/9802360>
- Li, S., Yang, S., & Ran, L. (2022). Impacts of changes in land cover and topography on a heavy precipitation event in Central Asia. *Atmospheric and Oceanic Science Letters*, 15(4), 100207. <https://doi.org/10.1016/j.aosl.2022.100207>
- Liu, Y., Yao, Y., & Zhao, Q. (2022). Real-time rainfall nowcast model by combining CAPE and GNSS observations. *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1-9. <https://doi.org/10.1109/TGRS.2022.3206459>
- Liu, Q., Lou, X., Yan, Z., Qi, Y., Jin, Y., Yu, S., ... & Xia, J. (2023). Deep-learning post-processing of short-term station precipitation based on NWP forecasts. *Atmospheric Research*, 295, 107032. <https://doi.org/10.1016/j.atmosres.2023.107032>
- Ma, Y., Liu, K., Wang, Q., Wang, J., Gao, C., Song, S., & Xu, Y. (2026). Impacts of urbanization on precipitation and thermodynamic–dynamic mechanisms of typhoon. *Journal of Hydrology: Regional Studies*, 64, 103190. <https://doi.org/10.1016/j.ejrh.2026.103190>
- Mazumder, S. I., Kumar, M., & Khan, A. (2025). Learning Regional Monsoon Patterns with a Multimodal Attention U-Net. arXiv preprint arXiv:2509.23267. <https://doi.org/10.48550/arXiv.2509.23267>
- Mendes, O., Correia, E., & Fragoso, M. (2025). Variability and trends of the rainy season in West Africa with a special focus on Guinea-Bissau. *Theoretical and Applied Climatology*, 156(5), 242. <https://doi.org/10.1007/s00704-025-05471-6>
- Osei, M. A., Aryee, J. N., Agyekum, J., Ashong, J., Ansah, S. O., Ahiataku, M. A., ... & Lamptey, B. (2023). Environment of severe storm formations over West Africa on the 26-28 June 2018. *Meteorological Applications*, 30(1), e2109. <https://doi.org/10.1002/met.2109>
- Nicholson, S. E. (2013). The west african sahel: A review of recent studies on the rainfall regime and its interannual variability. *International Scholarly Research Notices*, 2013(1):453521. <https://doi.org/10.1155/2013/453521>
- Nisi, L., Ambrosetti, P., & Clementi, L. (2014). Nowcasting severe convection in the Alpine region: The COALITION approach. *Quarterly Journal of the Royal Meteorological Society*, 140(682), 1684-1699. <https://doi.org/10.1002/qj.2249>
- Peng, Y., Zhang, G., Shi, J., Li, X. and Zheng, L., 2023. MRGTraj: A novel non-autoregressive approach for human trajectory prediction. *IEEE Transactions on Circuits and Systems for Video Technology*, 34(4), pp.2318-2331. <https://doi.org/10.1109/TCSVT.2023.3307442>
- Pumo, D., & Noto, L. V. (2021). Exploring the linkage between dew point temperature and precipitation extremes: A multi-time-scale analysis on a semi-arid Mediterranean region. *Atmospheric Research*, 254, 105508. <https://doi.org/10.1016/j.atmosres.2021.105508>
- Qu, Y., Feng, X., Luo, L., Deng, X., Kang, R., Lv, G., ... & Li, Z. (2026). A Bio-Inspired Weather-System Sensing Framework for Physically Constrained Precipitation Nowcasting Correction. *Biomimetics*, 11(8), 526. <https://doi.org/10.3390/biomimetics11080526>
- Raj, J., Mohino, E., Rodríguez-Fonseca, B., Losada, T., Rackow, T., & Becker, T. (2026). Projected changes in African Easterly Waves and rainfall events in West Africa with kilometre-scale global coupled simulations. *EGUsphere*, 2026, 1-36. <https://doi.org/10.5194/egusphere-2026-2879>

- Rajeswari, J. R., Srinivas, C. V., Yesubabu, V., Hari Prasad, D., & Venkatraman, B. (2021). Impacts of urbanization, aerodynamic roughness, and land surface processes on the extreme heavy rainfall over Chennai, India. *Journal of Geophysical Research: Atmospheres*, 126(10), e2020JD034017. <https://doi.org/10.1029/2020JD034017>
- Rajulapati, C. R., Papalexiou, S. M., Clark, M. P., & Pomeroy, J. W. (2021). The Perils of Regridding: Examples Using a Global Precipitation Dataset. *Journal of Applied Meteorology and Climatology*, 60(11), 1561-1573. <https://doi.org/10.1175/JAMC-D-20-0259.1>
- Ravuri, S., Lenc, K., Willson, M., Kangin, D., Lam, R., Mirowski, P., ... & Mohamed, S. (2021). Skilful precipitation nowcasting using deep generative models of radar. *Nature*, 597(7878), 672-677. <https://doi.org/10.1038/s41586-021-03854-z>
- Reichle, R. H., De Lannoy, G. J., Liu, Q., Koster, R. D., Kimball, J. S., Crow, W. T., ... & Smith, E. B. (2017). Global assessment of the SMAP Level-4 surface and root-zone soil moisture product using assimilation diagnostics. *Journal of hydrometeorology*, 18(12), 3217-3237. <https://doi.org/10.1175/JHM-D-17-0130.1>
- Roberts, N.M. and Lean, H.W., 2008. Scale-selective verification of rainfall accumulations from high-resolution forecasts of convective events. *Monthly Weather Review*, 136(1), pp.78-97. <https://doi.org/10.1175/2007MWR2123.1>
- Sarr, A. B., Camara, M., and Diba, I. (2018). Multi-model analysis of the west african monsoon: seasonal evolution and the monsoon onset. *Journal of Scientific Research and Reports*, 20(2):1-17. <https://doi.org/10.9734/JSRR/2018/43311>.
- Shadmehri Toosi, A., Batelaan, O., Shanafield, M., & Guan, H. (2025). Land use-land cover and hydrological modeling: A review. *Wiley Interdisciplinary Reviews: Water*, 12(2), e70013. <https://doi.org/10.1002/wat2.70013>
- Shi, X., Chen, Z., Wang, H., Yeung, D. Y., Wong, W. K., & Woo, W. C. (2015). Convolutional LSTM network: A machine learning approach for precipitation nowcasting. *Advances in neural information processing systems*, 28. <https://doi.org/10.48550/arXiv.1506.04214>
- Shi, X., Gao, Z., Lausen, L., Wang, H., Yeung, D. Y., Wong, W. K., & Woo, W. C. (2017). Deep learning for precipitation nowcasting: A benchmark and a new model. *Advances in neural information processing systems*, 30. <https://doi.org/10.48550/arXiv.1706.03458>
- Smith, J., Birch, C., Marsham, J., Peatman, S., Bollasina, M. and Pankiewicz, G., 2024. Evaluating pySTEPS optical flow algorithms for convection nowcasting over the Maritime Continent using satellite data. *Natural Hazards and Earth System Sciences*, 24(2), pp.567-582. <https://doi.org/10.5194/nhess-24-567-2024>
- Sønderby, C. K., Espeholt, L., Heek, J., Dehghani, M., Oliver, A., Salimans, T., ... & Kalchbrenner, N. (2020). Metnet: A neural weather model for precipitation forecasting. *arXiv preprint arXiv:2003.12140*. <https://doi.org/10.48550/arXiv.2003.12140>
- Srivastava, N., Mansimov, E., & Salakhudinov, R. (2015, June). Unsupervised learning of video representations using lstms. In *International conference on machine learning* (pp. 843-852). PMLR. <https://doi.org/10.48550/arXiv.1502.04681>
- Sun, J., Wei, H., Liu, J., Xu, M., Shi, J., & Gao, M. (2026). FusionFormer: A Multi-Source Data Fusion Transformer for Precipitation Nowcasting. *Expert Systems*, 43(3), e70199. <https://doi.org/10.1111/exsy.70199>

- Sylla, M. B., Nikiema, P. M., Gibba, P., Kebe, I., and Klutse, N. A. B. (2016). Climate change over west africa: Recent trends and future projections. *Adaptation to climate change and variability in rural West Africa*, pages 25–40. https://doi.org/10.1007/978-3-319-31499-0_3
- Tan, J., Huang, Q., and Chen, S.: Deep learning model based on multi-scale feature fusion for precipitation nowcasting, *Geosci. Model Dev.*, 17, 53–69, <https://doi.org/10.5194/gmd-17-53-2024>, 2024.
- Taylor, C. M., Klein, C., Dione, C., Parker, D. J., Marsham, J., Abdoulahat Diop, C., Fletcher, J., Saidou Chaibou, A. A., Nafissa, D. B., Semeena, V. S., Cole, S., and Anderson, S.: Nowcasting Tracks of Severe Convective Storms in West Africa from Observations of Land Surface State, *EGU General Assembly 2022*, Vienna, Austria, 23–27 May 2022, EGU22-2915, <https://doi.org/10.5194/egusphere-egu22-2915>, 2022.
- Ter Maat, H. W., Moors, E. J., Hutjes, R. W. A., Holtslag, A. A. M., & Dolman, A. J. (2013). Exploring the impact of land cover and topography on rainfall maxima in the Netherlands. *Journal of Hydrometeorology*, 14(2), 524-542. <https://doi.org/10.1175/JHM-D-12-036.1>
- Trebing, K., Stańczyk, T., & Mehrkanoon, S. (2021). SmaAt-UNet: Precipitation nowcasting using a small attention-UNet architecture. *Pattern Recognition Letters*, 145, 178-186. <https://doi.org/10.1016/j.patrec.2021.01.036>
- Uuemaa, E., Ahi, S., Montibeller, B., Muru, M., & Kmoch, A. (2020). Vertical accuracy of freely available global digital elevation models (ASTER, AW3D30, MERIT, TanDEM-X, SRTM, and NASADEM). *Remote Sensing*, 12(21), 3482. <https://doi.org/10.3390/rs12213482>
- Wang, D., Miao, J., & Tan, Z. (2013). Impacts of topography and land cover change on thunderstorm over the Huangshan (Yellow Mountain) area of China. *Natural Hazards*, 67(2), 675-699. <https://doi.org/10.1007/s11069-013-0595-0>
- Xiaoyang, C. (2025). Explainable dual LSTM-autoencoders with exogenous features for anomaly detection and supply chain forecasting. *Scientific Reports*, 15(1), 42371. 1| <https://doi.org/10.1038/s41598-025-26449-4>
- Xu, Y., Li, G., Zhang, X., Dong, Y., & Wang, K. (2026). Synergistic mechanisms of gravity waves and windward slopes in intensifying regional rainstorms: A Sichuan Basin case study. *Atmospheric Research*, 109028. <https://doi.org/10.1016/j.atmosres.2026.109028>
- Yamba, E. I., Aryee, J. N., Quansah, E., Davies, P., Wemegah, C. S., Osei, M. A., ... & Amekudzi, L. K. (2023). Revisiting the agro-climatic zones of Ghana: A re-classification in conformity with climate change and variability. *PLoS Climate*, 2(1), e0000023. <https://doi.org/10.1371/journal.pclm.0000023>
- Zanaga, D., Van De Kerchove, R., Daems, D., De Keersmaecker, W., Brockmann, C., Kirches, G., ... & Arino, O. (2022). ESA WorldCover 10 m 2021 v200. <https://pure.iiasa.ac.at/18478>
- Zhang, F., Wang, X., Guan, J., Wu, M., and Guo, L. (2021). Rn-net: A deep learning approach to 0–2 hour rainfall nowcasting based on radar and automatic weather station data. *Sensors*, 21(6):1981. <https://doi.org/10.3390/s21061981>
- Zhang, Y., Long, M., Chen, K., Xing, L., Jin, R., Jordan, M. I., & Wang, J. (2023). Skilful nowcasting of extreme precipitation with NowcastNet. *Nature*, 619(7970), 526-532. <https://doi.org/10.1038/s41586-023-06184-4>
- Zhang, Z., Song, Q., Duan, M., Liu, H., Huo, J., & Han, C. (2025). Deep Learning Model for Precipitation Nowcasting Based on Residual and Attention Mechanisms. *Remote Sensing*, 17(7), 1123. <https://doi.org/10.3390/rs17071123>

Zhang, R., Shangguan, W., Dong, W., Shi, Y., Huang, F., & Huang, L. (2026). An explainable deep learning framework for torrential rainfall forecasting in Guangdong: Accuracy gains and physical insights. *Journal of Hydrology: Regional Studies*, 67, 103848. <https://doi.org/10.1016/j.ejrh.2026.103848>