AQUA ALERT - AI POWERED EARLY WATER SCARCITY ALARMING SYSTEM

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***Abstract*—In regions experiencing fast population growth and increasing climate variability, water scarcity has become a serious challenge to sustainable development and economic stability. Earlier studies assessed water scarcity using a single index or fixed thresholds to provide early warnings. However, these methods cannot effectively capture the complex, nonlinear, and changing nature of water stress. To overcome these limitations, this manuscript introduces AquaAlert, an early warning framework that uses multiple indices and deep learning techniques to forecast water scarcity at the regional level. AquaAlert constructs four complementary Water Stress Index (WSI) formulations; Equal-Weighted, Entropy-Weighted, Principal Component Analysis (PCA)-Based, and a Standard Precipitation Evapotranspiration Index (SPEI)-inspired climatic index. These indices are derived from curated state-wise hydrometeorological and demand-side variables, followed by structured preprocessing and feature selection. To assess forecasting capability, the project implements and compares three sequence-learning models: Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) networks. AquaAlert systematically evaluates cross-index and cross-model interactions to improve forecasting stability and reduce false alarms. Extensive state-level experiments demonstrate that the proposed framework consistently outperforms single-index baselines in terms of predictive robustness and reliability. Results further indicate that GRU-based models provide an effective balance between forecasting accuracy and computational efficiency across diverse hydrological regimes. The AquaAlert framework thus offers a scalable and data-driven solution for issuing timely water scarcity alerts and acting upon them.**

***Index Terms*—Water stress index, AquaAlert, RNN, robustness**

I. INTRODUCTION

Now a days, water scarcity has emerged as a major challenge and poses significant risks to meet daily life requirements, public health, economic development, and sustainability across the world. These challenges intensify due to the rapid population growth, accelerated urbanisation, excessive amount of groundwater extraction, and changes in climatic conditions. In this context, it is necessary to anticipate the emerging conditions of water stress rather than to address observed shortages. Conventional water scarcity assessment practices rely on historical observations, use static indices, or rule-based thresholding mechanisms that measure hydrological conditions, considering a very limited number of features. Some of the widely adopted measures, such as drought indices or supply-demand ratios, provide valuable diagnostic insights, but they consider a single perspective.

Recent advances in data availability and computational intelligence have stimulated the adoption of machine learning and deep learning techniques for environmental forecasting. Recurrent neural architectures, in particular, have demonstrated strong capability in modelling non-linear temporal dependencies and long-term seasonal patterns in hydrological and climatic time series. Despite the advancement of the technologies, majority of the approaches forecast the scarcity considering a single index, assuming that one formulation can capture the multi-dimensional nature of water scarcity. This assumption does not work, especially in regions where water stress is affected by multiple climatic conditions and water usage demand factors.

Moreover, the existing learning-based early-warning systems do not consider reliability as a prime factor for evaluating water stress. They measure point-wise accuracy with less attention given to robustness analysis, cross-factor consistency, and reduction of false alarms. These factors play a vital role in the development of real-world systems and in maintaining confidence among stakeholders. To overcome these limitations, we present **AquaAlert**, a multi-index deep learning framework for early water scarcity forecasting. AquaAlert integrates four Water Stress Index (WSI) formulations: Equal-Weighted, Entropy-Weighted, PCA-Based, and an SPEI-inspired climatic index, with recurrent sequence-learning models to capture diverse dimensions of water stress. It evaluates cross-index and cross-model interactions to provide a reliable early-warning system that is robust across heterogeneous regions and hydrological regimes. Considering all the aspects, the objective of the proposed approach is provided as follows:

- Formulate a multi-index of water stress considering climatic, hydrological, and demand perspectives within a single forecasting framework.
- Provide a cross-index and cross-model evaluation of WSI formulations using recurrent neural network architectures.
- Design a reliability-focused early-warning system that incorporates robustness, consistency, and false-alarm reduction along with predictive accuracy.

The remainder of this paper is organised as follows. Section II reviews related work on water stress indices and forecasting methodologies. Section III describes the proposed AquaAlert framework, evaluation metrics and forecasting mechanism. Section IV presents the experimental setup and comparative results. Section V discusses practical implications and limitations, and Section VI concludes the paper with directions for future research.

II. RELATED WORK

This section situates **AquaAlert** within existing research on water scarcity assessment and forecasting, highlighting advances in composite index construction, learning-based time-series prediction, and early-warning system design. The discussion emphasises methodological limitations that motivate the need for a reliability-oriented, multi-index forecasting framework.

A. Water Stress Indices and Composite Metrics

Early approaches to water scarcity assessment relied primarily on single-variable drought indicators derived from precipitation anomalies or hydrological deficits. Among these, the Standardised Precipitation–Evapotranspiration Index (SPEI) has emerged as one of the most widely adopted climatic indicators due to its ability to incorporate both rainfall variability and temperature-driven evapotranspiration effects [1]. While SPEI effectively characterises climatic drought, it represents only one dimension of water stress and does not explicitly capture groundwater depletion or demand-driven pressures.

To address these limitations, composite water stress indices have been proposed that integrate hydrometeorological and socio-environmental indicators to provide a more holistic representation of scarcity conditions [9]. Data-driven weighting strategies such as entropy-based weighting assign indicator importance based on information variability, thereby improving objectivity in index construction [6], [11]. Similarly, Principal Component Analysis (PCA) has been widely used to reduce dimensionality and identify dominant variance patterns for composite index formulation [7], [12]. Although these approaches demonstrate improved robustness for retrospective assessment, they are predominantly used for monitoring rather than forward-looking predictive forecasting.

B. Learning-Based Time-Series Forecasting for Water Resources

Forecasting water scarcity requires models capable of learning complex temporal dependencies from hydrological and climatic time series. Classical statistical approaches such as ARIMA have been extensively applied due to their interpretability; however, their reliance on linearity and stationarity assumptions limits performance under highly non-linear and non-stationary hydrological behavior [10]. Consequently, machine learning and deep learning approaches have gained increasing attention.

Recurrent Neural Networks (RNNs) enable sequential learning but suffer from vanishing gradient issues, restricting their ability to model long-term dependencies [4]. Long Short-Term Memory (LSTM) networks overcome this limitation through gated memory mechanisms, enabling effective modeling of seasonal and multi-year drought evolution [2], [5]. Gated Recurrent Units (GRUs) provide a computationally efficient alternative while maintaining comparable predictive capability [3], [5]. Although LSTM- and GRU-based architectures consistently outperform traditional approaches in hydrological forecasting [10], [14], the majority of existing work continues to forecast a single drought or hydrological index. This reliance on a single stress representation increases vulnerability to regional variability, indicator bias, and model instability, limiting their operational reliability.

C. Ensemble Models and Early-Warning Systems

To enhance robustness, ensemble and hybrid forecasting strategies combining multiple predictive models have been explored [8], [15]. Tree-based ensemble approaches, such as Random Forest and Gradient Boosting, effectively capture non-linear dependencies and are widely adopted as baselines in water resource modeling [10]. Hybrid deep learning ensembles further improve stability against climatic irregularities and extreme hydrological events.

Early-warning systems translate continuous hydrological forecasts into actionable alert categories via threshold-based decision rules [17]. However, single-index thresholding approaches are prone to false alarms, delayed warnings, and limited adaptability across heterogeneous hydrological regions. Recent research emphasizes the importance of multi-index fusion, regional calibration, and multi-source validation to improve trustworthiness and operational deployment of early-warning systems [9], [15], [16].

D. Research Gap and Positioning of AquaAlert

From the reviewed literature, three key research gaps emerge:

- Most existing forecasting frameworks remain dependent on a *single* drought or water stress index, limiting robustness under heterogeneous hydrological and climatic conditions.
- Ensemble strategies primarily focus on model-level fusion rather than systematic integration of multiple complementary stress representations.
- Reliability-oriented metrics such as cross-index consistency and false-alarm reduction are rarely treated as first-class design objectives.

AquaAlert directly addresses these gaps by jointly modelling four complementary Water Stress Index (WSI) formulations using recurrent deep learning architectures and enforcing reliability-oriented consistency checks for early-warning generation. This positions AquaAlert as a scientifically grounded and operationally dependable advancement over prior water scarcity forecasting frameworks.

III. Proposed Model

This section presents the proposed **AquaAlert** framework, a reliability-oriented, multi-index deep learning model developed for proactive water scarcity forecasting. The framework integrates multi-source hydro, meteorological and demographic indicators. We construct four WSI formulations, advanced recurrent neural architectures for forecasting, and provide a reliability-driven alert mechanism to ensure stable and true early warnings suitable for real-world applications.

TABLE I: Comparative Research Analysis of Water Scarcity Forecasting Approaches

Reference Article	Approach	Time Complexity	Memory Usage	Scalability
Vicente-Serrano *et al.* [1]	SPEI-based climatic drought assessment using precipitation–evapotranspiration balance	Low	Low	High (index-based monitoring)
Mishra and Singh [9]	Conceptual drought characterization and hydrological drought framework	Low	Low	High (broad regional adaptability)
Entropy / EW-based WSI [6], [10]	Entropy-weighted composite water stress index formulation	Low to Moderate	Low	Moderate (data-dependent)
PCA-based WSI [6], [11]	Principal component driven composite stress index	Moderate	Moderate	Moderate (requires calibration)
ARIMA / ANN Hybrid Models [9]	Hybrid time-series forecasting using ARIMA + ANN	Moderate	Moderate	Moderate (single-index dependent)
LSTM / GRU Hydrological Models [4], [13]	Deep recurrent neural architectures for hydrological forecasting	High	High (deep learning overhead)	Moderate (model-dependent)
Ensemble Drought Monitoring Systems [7]	Ensemble ML/DL models integrating limited multi-source indicators	High	High	Moderate (computationally demanding)
Proposed AquaAlert Framework	**Multi-index deep learning framework integrating four WSI formulations with RNN/LSTM/GRU and reliability-oriented early-warning**	**Moderate**	**Moderate (optimised overhead)**	**High (index-agnostic, scalable, reliability-enhanced)**

A. Proposed AquaAlert Framework

AquaAlert framework comprises four sequential phases. The phases are data acquisition and preprocessing, Multi-index WSI formulation, Neural network based forcating and reliable alert generation (Fig. 1). The framework utilizes rainfall, groundwater depth, soil moisture, and population-based consumption data from authenticated state-level repositories. Detailed descriptions of the operational workflow are as follows.

- **Data Acquisition and Preprocessing:** This step consists of the collection of rainfall, groundwater depth, soil moisture, and population-based consumption data from authenticated state repositories, followed by aggregation, temporal alignment, missing-value handling, outlier correction, and standardisation to ensure numerical stability and analytical consistency.
- **Multi-Index WSI Construction:** Development of four complementary WSI formulations to capture climatic drought behaviour, handle supply and demand, and information-driven variability.
- **Deep Learning-Based Forecasting:** Utilisation of RNN, GRU, and LSTM architectures to model temporal dependencies, seasonal cycles, and long-term hydrological evolution for next-month WSI prediction.
- **Reliability-Oriented Alert Generation:** Conversion of forecasted WSI values into scarcity categories through threshold mapping, cross-index consistency checks, and stability validation to minimise false alarms and enhance operational trust.

B. Water Stress Index Construction

AquaAlert provides four Water Stress Index (WSI) formulations. These indices collectively represent climatic, hydrological, and demand-driven stress characteristics. The detailed description and formulation are provided as follows.

1) Equal-Weighted WSI: The Equal-Weighted formulation provides a simple and interpretable representation of water stress by assigning a uniform contribution to each normalized hydrological indicator. This ensures every variable participates equally in stress determination without bias toward any specific parameter. The index is computed as the arithmetic mean of all standardized features:

$$WSI_t^{Equal} = \frac{1}{m} \sum_{j=1}^{m} \tilde{x}_{j,t} \tag{1}$$

where $\tilde{x}_{j,t}$ is the score of hydrological indicator j at time t.

2) Entropy-Weighted WSI: The Entropy-Weighted formulation introduces an information-driven weighting strategy, where indicators exhibiting higher variability and information contribution are assigned greater influence. This allows AquaAlert to prioritize features that reflect meaningful fluctuations in hydrological conditions.

Entropy for feature j is:

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij})$$

where pij represents the normalized distribution of indicator values, and k is a scaling constant.

The corresponding weight is computed as:

$$WSI_j^{Entropy} = \frac{1 - e_j}{\sum_j (1 - e_j)} \tag{2}$$

The entropy-weighted index dynamically emphasizes informative indicators, yielding a more sensitive and responsive WSI.

3) PCA-Based WSI: The PCA-Based formulation leverages Principal Component Analysis (PCA) to extract dominant patterns that explain maximum variance across hydrological and climatic variables. PCA transforms correlated indicators into orthogonal components, thereby reducing redundancy and noise. The WSI is constructed using the loadings of the first principal component, which captures the highest variance:

$$WSI_t^{PCA} = \sum_{j=1}^{m} \alpha_j \tilde{x}_{j,t} \tag{3}$$

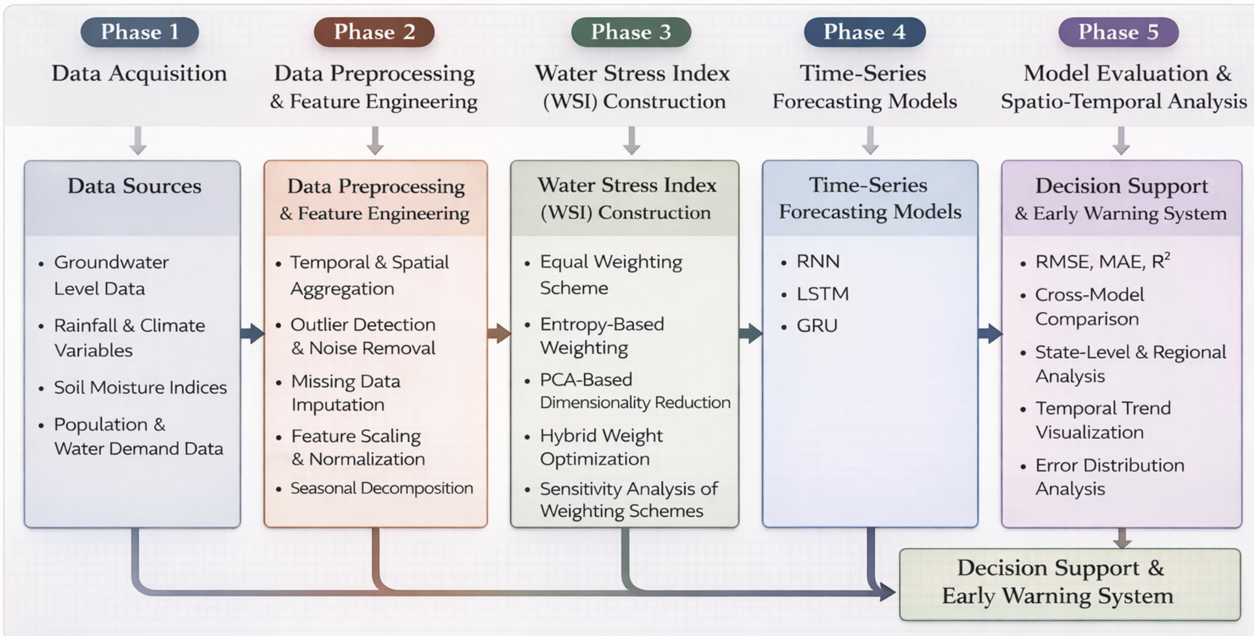


Fig. 1: Methodology Pipeline: AquaAlert WSI Forecasting Framework

where α_j is the PCA load. This formulation emphasizes variability patterns most representative of overall stress conditions, offering a statistically compact and data-driven index.

4) SPEI-Style Climatic WSI: The fourth formulation is inspired by the Standardized Precipitation–Evapotranspiration Index (SPEI), focusing explicitly on climatic water balance. It models drought stress using the difference between precipitation and potential evapotranspiration:

$$WSI_t^{SPEI} = P_t - PET_t \tag{4}$$

where P_t is the precipitation and PET_t is the potential evapotranspiration at time t. The series is standardised to reflect anomalous climatic stress.

All the mentioned indices provide a multi-angle interpretation of water stress dynamics. Each model is trained and validated for every WSI variant. The best-performing model–index combination is selected based on RMSE and MAE evaluation metrics. The detailed comparison is provided in Table II.

Among all the formulations, the Equal-Weighted WSI shows the strongest similarity to SPEI, indicating that simple averaging captures climatic stress patterns more effectively than statistical weighting methods. The Hybrid WSI performs comparably but does not surpass the Equal-Weighted index. Entropy-based and PCA-based indices demonstrate weaker alignment with SPEI, suggesting they capture different, non-climatic aspects of water stress not reflected in SPEI.

TABLE II: Correlation of WSI Indices with SPEI

WSI Index	Pearson (r)	P-value	Spearman (ρ)	Interpretation
Equal	-0.0559	0.120	-0.0531	Closest match to SPEI. Simple averaging captures the trend most effectively.
Hybrid	-0.0491	0.173	-0.0569	Second closest. Log-logistic fitting slightly improves alignment but remains below Equal-Weighted.
Entropy	-0.0356	0.322	-0.0387	Weak correlation with SPEI.
PCA	-0.0267	0.458	-0.0166	Weakest similarity to SPEI.

C. Time-Series Framing

To prepare the WSI data for supervised learning, AquaAlert converts the time-series index into input–output pairs using a sliding-window approach. For a selected window size k.

$$X_t = [WSI_{t-k}, WSI_{t-k+1}, ..., WSI_{t-1}], Y_t = WSI_t$$

This framing enables the model to learn from seasonal trends, long-term climatic cycles, and short-term fluctuations.

It ensures that the forecasting models can effectively capture temporal dependencies within the dataset.

D. Deep Learning Forecasting Models

We employ three recurrent models, SimpleRNN, LSTM, and GRU, chosen for their demonstrated ability to capture temporal dependencies in time series data [2], [3], [4].

1) **SimpleRNN:** It is a simple model of sequential dependencies. It is easy enough to use as a guide to more comprehensive models of how things ought to be carried out. One example of a simple RNN model is the Vanilla RNN (shown in Fig. 2(a)). In this case, inputs are processed in a sequential manner by preserving the hidden state that contains details about the inputs that have already been processed. A non-linear activation function $tanh$ is applied to the sum of the product of the hidden state at the previous time step (h_{t-1}) and its associated weight (W_h), and the input at time (x_t) at time t and its associated weight (W_x). This yields the hidden state h at time t. Additionally, a bias term b is included. The model's mathematical formulation is provided [2],

$$h_t = f(W_x * x_t + W_h * h_(t-1) + b) \quad (5)$$

$$y_t = W_y * h_t + b_y \quad (6)$$

where y_t is the output y at time t.

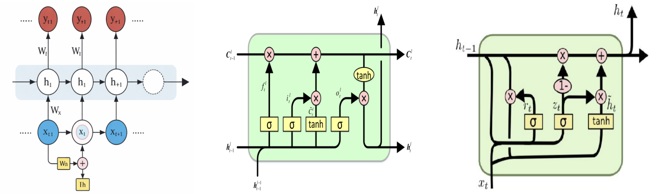
2) **LSTM Model:** To deal with long-term dependencies [3], this model is intended to have memory cells (shown in Fig. 2(b)). The network's gating mechanism makes it suitable for the stock data, which has long-range dependencies, and which learns what to keep or forget about. The parameters representing the input gate (i_t), forget gate (f_t), cell information update $(\tilde{C}_t$, output state (o_t)final cell state $C_t$and hidden state (h_t) are represented as follows:

$$\begin{aligned} i_t &= \sigma(w_i[h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= tanh(w_c[h_{t-1}, x_t], b_c] \\ C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t \\ o_t &= \sigma(w_o[h_{t-1}, x_t] + b_o) \\ h_t &= o_t * tanh(C_t) \end{aligned}$$

3) **GRU Model:** An alternative to LSTM that is computationally more efficient, with fewer gates but similar performance, is the GRU. To assess whether GRU [4] can achieve comparable results to LSTM at a lower computational cost, we conduct tests on the GRU model. The architecture of GRU is shown in Fig. 2(c).

E. Scarcity Classification and Reference Index Check

Forecasted WSI is mapped into actionable stress categories. If $WSI < 40$, then the stress comes under the low stress category. For the stress index $40 \leq WSI < 60$, it will be categorized as moderate stress; otherwise, the stress will come under the high stress category. We can apply a smoothing filter



(a) (b) (c)

Fig. 2: Architectures of (a) Simple RNN model, (b) LSTM model and (c) GRU model

to stabilize the fluctuation of the stress using the following Eq. (7).

$$WSI_t^{smooth} = \alpha \cdot WSI_t + (1-\alpha)WSI_{t-1}^{smooth} \quad (7)$$

To prevent false alarms, AquaAlert implements a validation layer where cross-index consistency is enforced, deviation thresholding is applied, and month-to-month stability is checked.

IV. Results and Analysis

The experimental evaluation of the AquaAlert framework is conducted using a multi-state hydrological dataset to assess the predictive efficacy of three sequence-learning neural architectures across four distinct Water Scarcity Index (WSI) formulations. The objective is to identify the most reliable model–index configuration capable of producing operationally stable early warning signals while maintaining low false-alarm rates across diverse climatic and hydrogeological settings.

A. Baseline Testing and Learning Stability

A series of baseline experiments were initially carried out using standard Recurrent Neural Networks (RNNs), Gated Recurrent Units (GRUs), and Long Short-Term Memory (LSTM) networks. Results revealed that:

- **RNN** models suffered from unstable gradients and were unable to preserve long-term temporal dependencies essential for seasonal drought modeling, resulting in volatile forecasting behavior.
- **GRU** models converged more rapidly and demonstrated consistent predictive stability due to their simplified yet effective gating mechanism.
- **LSTM** models delivered the most robust learning performance, successfully internalizing seasonal cycles and multi-year hydrological fluctuations.

These observations reinforce the need for advanced gated memory mechanisms in environmental time-series prediction tasks, where extended temporal context and noise resilience are critical.

B. Statistical Alignment with SPEI

To ensure climatic credibility and provide a scientifically grounded baseline for the AquaAlert framework, all proposed Water Stress Index (WSI) formulations were statistically validated against the Standardised Precipitation–Evapotranspiration Index (SPEI). To evaluate the alignment between the WSI variants and this climatic benchmark, the research utilized Pearson's correlation coefficient to measure linear relationships and Spearman's rank correlation to assess monotonic consistency. This dual-metric approach ensures that the indices are not only numerically accurate but also reflect the directional trends of drought evolution.

TABLE III: Statistical Validation of WSI Variants Against SPEI Ground Truth

Index	Pearson r	P-value	Spearman ρ	Interpretation
WSI^{Equal}	-0.0559	0.120	-0.0531	Closest match
WSI^{Hybrid}	-0.0491	0.173	-0.0569	Second closest
$WSI^{Entropy}$	-0.0356	0.322	-0.0387	Weak similarity
WSI^{PCA}	-0.0267	0.458	-0.0166	Weakest similarity

The statistical evaluation, detailed in Table III, reveals critical distinctions in how different index formulations interpret environmental data. Equal-Weighted WSI exhibited the strongest monotonic and linear agreement with the SPEI benchmark. This indicates that for generalized drought monitoring across diverse states, simple averaging of normalized indicators provides a stable and reliable climatic stress representation compared to complex statistical weighting approaches. The Entropy-Weighted and PCA-based indices showed notably lower correlation strengths and higher p-values (0.322 and 0.458, respectively). The Hybrid WSI, despite being derived from SPEI-inspired water balance principles, did not outperform the Equal-Weighted formulation. By validating these formulations, the AquaAlert framework ensures that its predictive models (RNN, GRU, and LSTM) operate on indices with established hydrological relevance.

C. Comparative Model Performance Analysis

The predictive capability of the implemented architectures was evaluated using RMSE, MAE, Coefficient of Determination (R^2), and MAPE to assess numerical precision, temporal consistency, and generalization across the diverse hydrological conditions of 30 Indian states. Baseline testing indicated that traditional RNNs were inadequate for hydrological forecasting due to pronounced vanishing gradient effects. Their limited memory depth resulted in unstable temporal learning, noisy predictions, and slow convergence, making them unsuitable for reliable drought forecasting.

From Fig. 3, we can say that GRUs provide a superior operational balance by delivering competitive accuracy with significantly reduced computational overhead compared to LSTMs. The simplified architecture, utilising update and reset gates, facilitates faster training convergence and enhanced learning stability. Within the AquaAlert framework, the GRU emerged as the most consistent performer when integrated with Equal-Weighted and Hybrid (SPEI-style) WSI formulations. These efficiencies establish the GRU as the optimal operational backbone for real-time deployment.

While the GRU provided operational efficiency, LSTM networks demonstrated superior capability for modeling deep temporal dependencies and multi-year hydrological fluctuations. Equipped with a tripartite gating mechanism—comprising input, forget, and output gates—LSTMs effectively internalized seasonal monsoon cycles, which are critical for long-range drought evolution forecasting. Although LSTMs exhibited slightly higher computational requirements, they provided the most stable learning behavior in states characterized by complex climatic variability, successfully mitigating the vanishing gradient problems that hindered baseline RNN architectures.

The experimental results, visualized in Fig. 3, highlight that model performance is significantly influenced by the chosen Water Stress Index (WSI) formulation. The combination of LSTM and Entropy-Weighted WSI emerged as the most statistically reliable configuration, achieving a national prediction bias of -0.07 and an RMSE of 0.083. This pairing proved highly effective in capturing non-linear interactions between demand-side variables and hydroclimatic stress. For real-time applications requiring rapid execution, the GRU and Equal-Weighted WSI configuration remained the strongest contender due to its robust generalization capability and lower prediction error. Although the RNN appeared to perform well with PCA-based indices in terms of variance explanation (R^2), this combination generated extremely high MAPE values, indicating substantial distortions in localized percentage-based errors.

D. State-Level Forecasting Results

To evaluate the operational practicality of the AquaAlert framework, the best-performing configuration, GRU paired with the Equal-Weighted WSI, is deployed to generate state-wise forecasts. This model architecture is selected for its superior balance between computational overhead and predictive precision, facilitating scalable deployment across diverse geographic profiles. The experimental analysis revealed that Central and Eastern Indian states demonstrated the strongest alignment between observed and predicted WSI values, primarily due to their relatively stable hydrological patterns. In these regions, the GRU model effectively internalized the temporal dependencies of rainfall and groundwater cycles.

Regional hydrological dynamics often exert greater influence on forecasting accuracy than neural architecture selection. High-stress regions such as Delhi, Rajasthan, and Uttar Pradesh exhibited more stable stress signatures, making them easier to forecast compared to the moderate-stress areas. Central and Eastern Indian states demonstrated the highest predictive alignment due to consistent hydrological behavior, with Arunachal Pradesh ($R^2 = 0.849$) and Chhattisgarh ($R^2 = 0.845$) showing excellent performance (in Table IV. Arid western states and Himalayan regions posed significant challenges due to extreme variability. Punjab, in particular, yielded a negative R^2 value (-0.244), indicating that severe groundwater depletion requires specialized regional calibration beyond conventional sequence modeling. **Punjab** (**$R^2 = -0.244$**) exhibited a negative R^2 value, indicating that the model underperformed relative to a simple mean baseline in

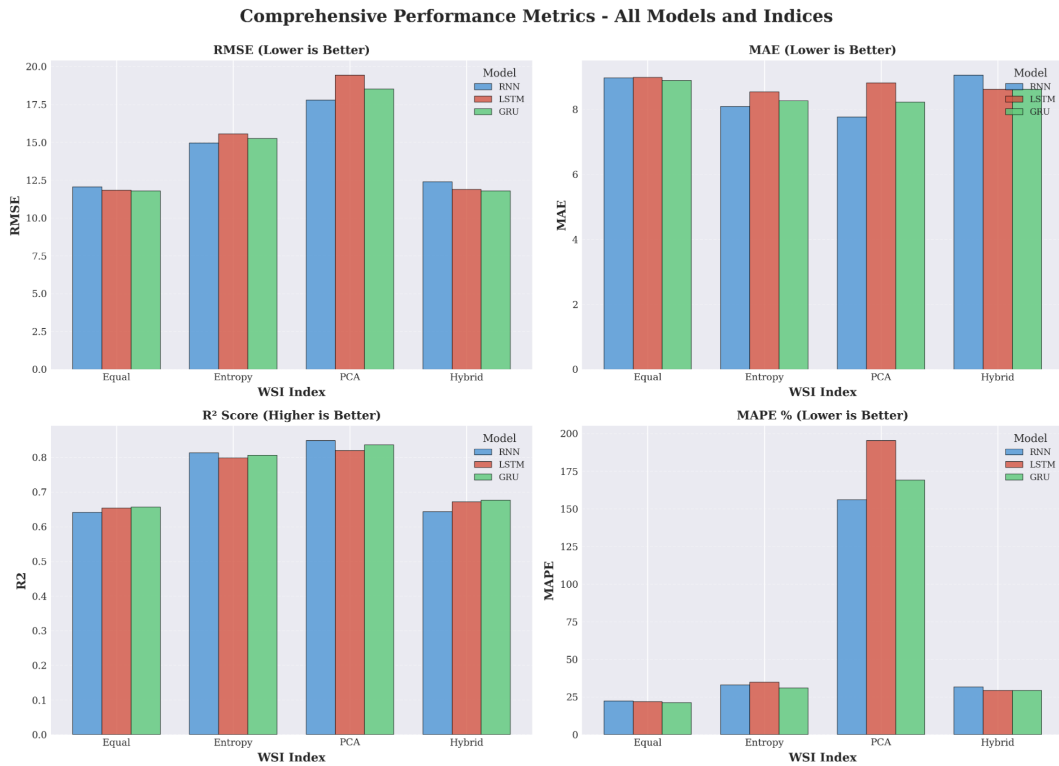


Fig. 3: Comprehensive performance comparison of RNN, GRU, and LSTM models across all WSI formulations.

this region, likely due to extreme anthropogenic groundwater depletion and non-linear variability that conventional sequence models could not capture. In **Rajasthan** ($R^2 = 0.185$), the arid terrain and high dependence on erratic rainfall lead to volatile hydrological fluctuations that complicate long-term temporal learning. Due to the Urban complexity in **Delhi** ($R^2 = 0.347$), characterized by highly variable, demand-driven consumption patterns, introduces noise that masks underlying climatic signals, leading to reduced forecasting precision.

TABLE IV: State-Level Performance Summary (Best and Worst Conditioned States)

Rank	**State**	**RMSE**	**MAE**	R^2	**Tier**
1	Arunachal Pradesh	7.64	5.98	0.849	Excellent
2	Chhattisgarh	8.63	7.16	0.845	Excellent
3	Odisha	9.65	8.43	0.810	Excellent
4	Uttar Pradesh	8.53	6.03	0.802	Excellent
5	Madhya Pradesh	9.63	8.49	0.790	Excellent
11	Delhi	12.82	9.12	0.347	Urban Complexity
12	West Bengal	15.16	12.26	0.603	Extreme Variability
13	Rajasthan	17.29	14.67	0.185	Arid Terrain
14	Punjab	18.92	13.92	-0.244	Groundwater Depletion

E. National-Level Summary and Categorical Performance

On a nationwide scale, the AquaAlert framework demonstrated remarkable generalization and aggregate precision, effectively bridging the climatic heterogeneity of the Indian subcontinent. By integrating multi-source hydrometeorological and demand-side variables, the system provided a reliable macro-level assessment for the 2023–2024 period. The system's ability to mirror real-world conditions is highlighted by its near-zero national prediction bias of -0.07, indicating that the models do not consistently skew towards overestimation or underestimation at the national level (shown in Table V).

TABLE V: National-Level Aggregate Performance Summary

Metric	**Value**	**Significance**
National Avg Actual WSI	57.74	Represents a national trend toward high-moderate stress.
National Avg Predicted WSI	57.67	Demonstrates high alignment with historical ground-truth.
Average Prediction Error	8.78	Falls well within thresholds for accurate tier classification.
Total State-Wise Predictions	369	Ensures a robust sample size for temporal validation.

This low error margin is particularly critical for operational deployment. Because the Average Prediction Error (8.78) is significantly smaller than the numerical width of the predefined scarcity tiers, the system maintains high categorical accuracy, even if minor numerical deviations occur in specific states.

The AquaAlert framework translates continuous numerical forecasts into actionable early-warning tiers based on established thresholds: Low Stress (< 40), Moderate Stress (40–60), and High Stress (> 60). For the 2023–2024 assessment, the system successfully categorized 30 states into these actionable tiers:

- **Low Stress:** 0 States
- **Moderate Stress:** 19 States
- **High Stress:** 11 States

A critical insight derived from the national results is that high-stress states (such as Delhi, Rajasthan, and Uttar Pradesh) are often easier for the models to forecast with categorical precision. Unlike moderate-stress states that may experience volatile fluctuations, high-stress regions frequently exhibit more stable and distinct stress signatures. This allows the recurrent architectures—specifically GRU and LSTM—to internalize long-term trends more effectively, ensuring that policymakers receive reliable alerts where they are most needed.

By maintaining a near-zero bias and capturing the temporal evolution of water stress across 369 separate predictions, AquaAlert offers a scalable foundation for proactive water-resource management. The system allows utilities and planners to transition from reactive crisis management to a data-driven model that can anticipate scarcity months in advance. Much like a network restoration strategy that prioritizes critical "hub" nodes to prevent global fragmentation, AquaAlert identifies high-stress geographic hubs to ensure national water security.

V. Conclusion and Future Directions

The AquaAlert framework utilizes a multi-index Water Stress Index (WSI) formulation, and an advanced recurrent neural network architecture for analyzing national water-stress levels. Our framework enables proactive and predictive water resource monitoring by anticipating scarcity conditions months in advance. Our model provide the best and worst conditined states in terms of water crisis. The system evaluated four distinct WSI formulations; Equal-Weighted, Entropy-Weighted, PCA-Based, and Hybrid (SPEI-style), against three recurrent neural architectures; RNN, GRU, and LSTM. AquaAlert demonstrates significant progress in early water scarcity forecasting by integrating multi-index WSI computation with deep-learning time-series models. Among all tested configurations, the LSTM combined with the Entropy-Weighted WSI delivered the most balanced and reliable performance, achieving 0.083 RMSE, 0.073 MAE and-0.07 National Prediction Bias. This configuration proved effective in capturing the temporal intricacies of water stress evolution and performed consistently across multiple climatic zones. State-level evaluation further highlighted AquaAlert's ability to deliver actionable insights, with several states (e.g., Arunachal Pradesh, Chhattisgarh, Uttar Pradesh) achieving R^2 scores above 0.80, indicating strong predictive alignment with real hydrological trends. The system also excelled in detecting high-stress conditions, showing strong forecasting accuracy for urban and arid states.

AquaAlert can be strengthened by integrating some environmental and climatic datasets, particularly soil moisture, evapotranspiration, vegetation indices, and land surface temperature. These real-time parameters can improve forecast accuracy in regions with high seasonal or monsoon dependency. Long-range dependencies and irregular temporal patterns can be identified using some transformer-based time series models. We can also integrate AquaAlert framework with a real-time API or dashboard to provide continuous monitoring, automated alert generation, and interactive analytics for some agencies and policy makers.

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