AQUA ALERT - AI POWERED EARLY WATER SCARCITY ALARMING SYSTEM

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Certificate

This is to certify that the project titled **"Aqua Alert - AI Powered Early Water Scaricity Alarming System"** is submitted by **Shreeya Arora** (Roll no.2210110569), **Harshit Yadav** (Roll no.2210110298) and **Umang Dwivedi** (Roll no.2210110633),Computer Science and Engineering, Shiv Nadar IOE in the partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science and Engineering**. This work was completed under the supervision of Dr. Suchi kumari. No part of this dissertation/report has been submitted elsewhere for award of any other degree.

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Regards,

Harshit Yadav
Shreeya Arora
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CONTENTS

1 ABSTRACT

AquaAlert is an early warning framework designed to forecast state-level Water Stress Index (WSI) and support proactive water-resource management. The system develops four distinct WSI formulations—equal-weighted, entropy-weighted, PCA-based, and a hybrid SPEI-style index—to capture multiple dimensions of hydrological stress. 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. Each model is trained to predict next-month WSI values, and its performance is evaluated using standardised validation procedures and model-specific evaluation artefacts, including time series plots, error summaries, and state-wise prediction analyses. The repository further includes processed datasets, trained model weights, and supporting scaler files to ensure reproducibility.

Across experiments, the analysis highlights the strengths of individual model–index combinations and demonstrates that integrating insights from multiple WSI formulations improves robustness, reduces false alerts, and enhances early-detection reliability. The AquaAlert framework thus offers a scalable and data-driven foundation for issuing timely water scarcity alerts and aiding decision-making for utilities, planners, and policymakers.

2 INTRODUCTION

2.1 Background

Water scarcity is increasingly becoming a critical global concern, exacerbated by rising demand, climate variability, and uneven resource distribution. Traditional water management strategies rely heavily on historical observations, manual measurements, and static threshold-based assessments that often fail to capture the dynamic and nonlinear nature of hydrological systems. Although various hydrological indices, such as drought indicators and supply–demand ratios, provide useful insights, they frequently overlook the multidimensional interactions that drive real-world water stress. Moreover, inconsistent data availability, regional variability, and the absence of integrated monitoring frameworks limit the effectiveness of conventional prediction methods.

Advancements in data-driven modelling have introduced machine learning and deep learning approaches that are capable of learning complex temporal patterns. In particular, sequence models such as RNNs, GRUs, and LSTMs have demonstrated strong performance in forecasting environmental time-series data. However, many existing studies focus on single-index predictions and lack comparative analyses across diverse formulations of water stress. AquaAlert addresses these gaps by integrating four complementary Water Stress Index (WSI) formulations, equal-weighted, entropy-weighted, PCA-based, and SPEI-inspired, with recurrent neural models to forecast future WSI values. This unified framework offers a comprehensive and scalable foundation for early water scarcity detection, enabling more timely alerts and informed decision-making for resource planning.

2.2 Motivation

Accurate water scarcity forecasting is challenging due to variable climatic conditions and fluctuating consumption trends, while traditional assessment methods relying on limited indicators often lack reliability. This project, AquaAlert, seeks to address these limitations by integrating multiple Water Stress Index (WSI) formulations with a range of sequence-based models—RNN, GRU, and LSTM—to enhance the precision and timeliness of predictions. This combined approach aims to strengthen early-warning capability and support more effective water resource management.

2.3 Contributions

This work presents two primary contributions toward reliable early water scarcity forecasting:

- **Multi-Index Water Stress Formulation**
  We construct and analyse four complementary Water Stress Index (WSI) variants—equal-weighted, entropy-weighted, PCA-based, and an SPEI-inspired hybrid. This multi-index framework captures diverse dimensions of hydrological stress, enabling more comprehensive and resilient forecasting compared to single-index approaches.

- **Comparative Evaluation of Sequence Models**
  We implement and evaluate three recurrent neural architectures—RNN, GRU, and LSTM—for next-month WSI prediction. By comparing their performance across all WSI formulations, we identify model–index pairings that offer improved temporal learning, reduced false alerts, and enhanced predictive stability.

To further refine the system, AquaAlert integrates standardised preprocessing, feature scaling, and state-wise temporal validation procedures. The repository includes processed datasets, trained model weights, and evaluation artefacts, ensuring reproducibility and clear comparative analysis. Together, these contributions establish a scalable and structured foundation for issuing early and reliable water scarcity alerts.

2.4 Significance of the Work

Our results show that combining multiple WSI formulations with recurrent neural models significantly improves the accuracy and stability of water scarcity forecasting. LSTM models, particularly when paired with PCA-based and entropy-weighted indices, deliver the most reliable predictions with fewer false alerts. Overall, AquaAlert offers a scalable, data-driven framework that strengthens early warning capabilities and supports more informed water resource management.

3 LITERATURE SURVEY

3.1 Composite indices for water stress

Composite indices are commonly deployed to quantify multi-dimensional water scarcity by integrating hydrometeorological and demand-driven indicators into a single metric [1], [9]. A widely used climatic drought indicator, the Standardised Precipitation–Evapotranspiration Index (SPEI), standardises the difference between precipitation and potential evapotranspiration, making it sensitive to climate-induced water imbalance [1].

To enhance objectivity in index construction, data-driven techniques such as Shannon Entropy and Principal Component Analysis (PCA) are applied. Entropy-weighting

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij}), \qquad w_j = \frac{1 - e_j}{\sum_j (1 - e_j)}.$$

assigns weights based on information variability, where highly informative parameters receive greater influence [6], [11].

Similarly, PCA extracts dominant variance-explaining components and constructs an index using principal loadings (formula placeholder here) [7], [12]. These approaches have shown improved robustness in environmental modelling, helping capture groundwater decline, climatic variability, and consumption pressures more accurately than single-indicator methods.

3.2 Time-Series Forecasting Models

Recurrent neural architectures have demonstrated strong proficiency in modelling temporal dependencies within hydrological datasets [14]. However, classical Recurrent Neural Networks (RNNs) suffer from vanishing gradients, limiting their long-term memory capabilities [4].

Long Short-Term Memory (LSTM) networks introduce gated memory units

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \qquad h_t = o_t \odot \tanh(c_t),$$

allowing them to retain seasonal and multi-year patterns essential for drought evolution [2], [5].

Gated Recurrent Units (GRUs) simplify the gating mechanism using **two gates** — update and reset — defined as:

$$z_t = \sigma(W_z[h_{t-1}, x_t])$$

$$r_t = \sigma(W_r[h_{t-1}, x_t])$$

These gates allow GRUs to retain or forget historical information efficiently, giving performance comparable to LSTMs while being computationally lighter [3], [5]. Empirical studies have consistently shown that LSTM and GRU outperform classical models such as ARIMA in water-resource forecasting scenarios [10], [14].

3.3 Machine Learning Baselines and Ensemble Approaches

Tree-based ensemble models — including Random Forest and Gradient Boosting — effectively capture non-linear feature interactions and are often used as comparison baselines in water resource modelling [8], [10]. Hybrid architectures combining deep learning and ensemble predictions have shown improved robustness against climatic irregularities and outlier-driven disturbances [8], [15]. These strategies also enhance reliability when deployed in operational drought forecasting systems requiring rapid and stable decision-making support.

3.4 Early-Warning Systems and Thresholding Strategies

Effective early-warning systems depend on converting continuous predictions into interpretable alert classes through threshold-based decision rules [17]. Multi-index fusion, aggregating climatic, groundwater, and demand patterns, reduces false alarms and enables stronger situational awareness [9], [15].

Regional calibration, consistency checks, and multi-source validation are critical components of reliable deployment [16], ensuring alerts align with real-world hydrology.

3.5 Evaluation Metrics for Water Scarcity Forecasting

Environmental forecasting accuracy is assessed using both continuous error metrics, such as RMSE, MAE:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}, \qquad \mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|.$$

and event-based drought-detection performance measures such as precision, recall, and false-alarm rates [9], [10], [14]. Best practice in literature recommends multi-metric evaluation to ensure models not only minimise numerical error but also generate trustworthy scarcity alerts for policymakers and utilities.

3.6 Conclusion

Recent research strongly supports the use of combined predictive models and multi-index drought indicators to enhance robustness in water scarcity forecasting [8], [14], [15]. Ensemble decision-making — where agreement among indicators strengthens drought classification — is increasingly viewed as essential for practical water-security applications [9], [17].

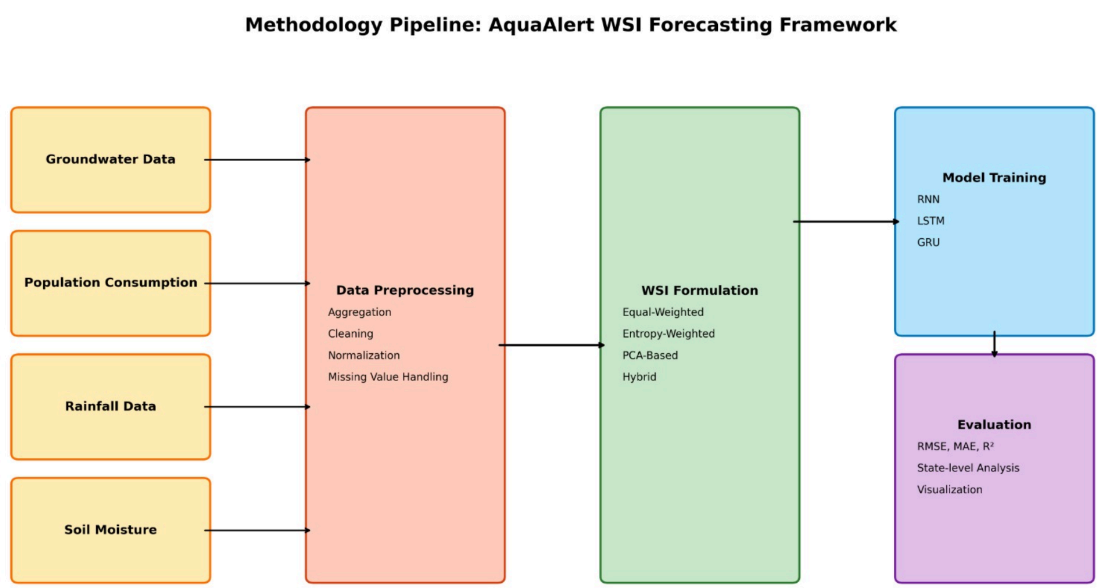
AquaAlert aligns directly with these modern recommendations by evaluating **four WSI formulations** across **three recurrent deep-learning models**, enabling a scientifically grounded, operationally reliable early-warning framework.

4 METHODOLOGY

4.1 Proposed Method

The proposed AquaAlert framework follows an end-to-end pipeline that integrates multi-source environmental and demographic datasets to generate reliable Water Stress Index (WSI) forecasts. The process begins with the acquisition of rainfall, groundwater depth, soil moisture, and population consumption data from state-level repositories. Because these inputs vary in scale, completeness, and temporal resolution, a comprehensive preprocessing stage is implemented. This includes aggregation, cleaning, normalisation, and missing-value handling, ensuring consistency across all indicators before they enter the modelling pipeline.

The process is briefly illustrated in Figure 1



Following preprocessing, the system constructs four complementary WSI formulations—Equal-Weighted, Entropy-Weighted, PCA-Based, and SPEI-style climatic WSI. Each formulation captures a distinct dimension of water stress: equal weighting provides interpretability, entropy weighting assigns higher importance to informative variables, PCA extracts dominant statistical patterns, and the SPEI-inspired method models climatic anomalies using precipitation–evapotranspiration balance. These multi-perspective indices act as parallel stress representations and provide a richer, more holistic foundation for forecasting compared to single-index approaches.

The computed WSI time series are then used to train deep sequence-learning models, namely RNN, GRU, and LSTM networks. These architectures are well-suited for hydrological forecasting due to their ability to capture temporal dependencies, seasonality, and long-term climatic variation. Each model processes a sliding window of historical WSI values to predict the next-month stress level. Model performance is evaluated using RMSE, MAE, and R^2 metrics, and the best-performing configurations—primarily GRU with equal-weighted WSI—form the operational backbone of AquaAlert. The final step maps predicted WSI values to low, moderate, or high scarcity categories using thresholding and cross-index consistency checks, enabling the system to provide actionable early-warning signals for policymakers, water authorities, and communities.

4.2 Overall Workflow and Execution Control

The AquaAlert system operates through a structured, end-to-end workflow managed by a central execution module. This module oversees data ingestion, preprocessing, index computation, model initialisation, forecasting, evaluation, and final alert generation. Each stage is executed sequentially to ensure reproducibility and stability across the forecasting pipeline.

4.2.1 Data Collection

The methodology begins with the acquisition of monthly hydrometeorological and demographic datasets from authenticated sources such as governmental climate repositories and statistical departments. The collected dataset typically includes:

- Rainfall and precipitation
- Groundwater or reservoir storage
- Soil moisture and climatic water balance
- Population-based demand indicators

These variables collectively represent the supply–demand dynamics required for constructing a comprehensive water stress indicator.

4.2.2 Data Preprocessing

The raw dataset undergoes systematic preprocessing to ensure consistency and suitability for analysis. This stage includes:

- **Missing-value imputation** using statistical interpolation
- **Outlier detection and correction** to eliminate anomalous data points
- **Temporal alignment** to standardise all indicators to monthly intervals
- **Dataset restructuring** for time-indexed forecasting compatibility

Preprocessing ensures that the dataset is continuous, reliable, and free from structural distortions that could degrade model performance.

4.2.3 Normalisation

All hydrological and climatic indicators vary in scale and magnitude. To ensure balanced contribution during WSI computation, AquaAlert normalises the variables using Min–Max scaling or Z-score normalisation:

$$\tilde{x}_t = \frac{x_t - \mu}{\sigma}$$

This transformation enhances numerical stability and prevents parameters with large ranges from disproportionately influencing the index.

4.3 Water Stress Index (WSI) Construction

A central component of AquaAlert is the computation of four complementary WSI formulations. Each formulation provides a unique analytical perspective on water scarcity, capturing statistical, climatic, and demand-driven factors.

4.3.1 Equal-Weighted WSI

This formulation assigns uniform weights to all normalised indicators, providing a straightforward and interpretable measure of water stress. It is defined as:

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

4.3.2 Entropy-Weighted WSI

Entropy-based weighting identifies the most informative indicators by assigning a higher weight to variables with greater variability. The entropy for each feature is computed as:

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

and the weight:

$$w_j = \frac{1 - e_j}{\sum_j (1 - e_j)}$$

4.3.3 PCA-Based WSI

Principal Component Analysis (PCA) reduces dimensionality and extracts orthogonal components that capture maximum variance.

The WSI is computed using the loadings of the first principal component:

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

where αj\alpha_jαj are PCA loadings.

4.3.4 SPEI-Style Climatic WSI

Inspired by the Standardised Precipitation Evapotranspiration Index (SPEI), this formulation uses a climate-driven water balance:

$$D_t = P_t - PET_t$$

The series is standardised to reflect anomalous climatic stress.

Together, these four indices provide a multi-angle assessment of hydrological and climatic stress.

4.4 Statistical Similarity of WSI to SPEI (Ground Truth)

To evaluate how closely each Water Stress Index (WSI) aligns with established drought conditions, all four WSI variants were statistically compared against the Standardised Precipitation–Evapotranspiration Index (SPEI). Pearson correlation and Spearman's rank correlation were used to assess linear and monotonic relationships, respectively.

Table: Correlation of WSI Indices with SPEI

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

Key Insight

Among the four 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.

4.5 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 kkk:

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

This framing enables the model to learn:

- Seasonal trends
- Long-term climatic cycles
- Short-term fluctuations

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

4.6 Forecasting Next-Month WSI

AquaAlert employs three recurrent neural architectures—RNN, GRU, and LSTM—to forecast next-month WSI values. These models were selected due to their ability to handle sequential dependencies and long-range temporal patterns.

- **RNNs** capture short-term patterns using recurrent feedback loops.

$$h_t = \sigma(W_h h_{t-1} + W_x X_t + b)$$

- **GRUs** introduce update and reset gates to manage long-term dependencies with reduced computational overhead.

  Update gate:

$$z_t = \sigma(W_z X_t + U_z h_{t-1})$$

Reset gate:

$$r_t = \sigma(W_r X_t + U_r h_{t-1})$$

Hidden state:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tanh(W_h X_t + U_h(r_t \odot h_{t-1}))$$

- **LSTMs** use input, forget, and output gates, along with a memory cell, to maintain information over extended sequences.

$$f_t = \sigma(W_f[X_t, h_{t-1}] + b_f)$$

$$i_t = \sigma(W_i[X_t, h_{t-1}] + b_i)$$

$$o_t = \sigma(W_o[X_t, h_{t-1}] + b_o)$$

LSTM update equations include:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t, \qquad h_t = o_t \cdot \tanh(c_t)$$

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.

4.7 Scarcity Level Classification

Once the next month's WSI is predicted, AquaAlert categorises the value into predefined scarcity levels

- Low Stress < 40
- 40 < Moderate Stress < 60
- 60 < High Stress

A smoothing filter is applied to stabilise predictions:

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

This reduces sudden fluctuations and prevents false alarms arising from short-lived anomalies.

4.8 Reference Index Check

To ensure reliability and robustness, predicted WSI values undergo a reference index validation step. This includes:

- Cross-verifying predictions across all four WSI formulations
- Comparing predicted trends with historical behaviour
- Applying deviation limits to prevent unrealistic jumps
- Ensuring consistency in month-to-month predictions

If multiple WSI variants confirm a rising stress level, the alert is strengthened. If discrepancies occur, additional checks prevent the generation of misleading warnings.

Methodology Summary

The AquaAlert methodology integrates multi-source data, four complementary WSI formulations, advanced recurrent neural forecasting, and structured alert-generation to deliver a reliable early-warning system for water scarcity. Its multi-index, multi-model framework ensures high accuracy, reduced false alarms, and improved decision-making for water resource management. By leveraging robust preprocessing, statistical weighting methods, temporal modelling, and validation checks, AquaAlert provides a comprehensive and scalable solution for predicting water stress across states.

5 EXPERIMENTATION AND RESULTS

5.1 Overview

This section presents a detailed overview of the experiments conducted to evaluate the performance of AquaAlert's multi-index, multi-model forecasting framework. The system was designed to predict monthly water stress conditions across Indian states using sophisticated machine learning approaches coupled with diverse index formulations.

The experimental framework encompasses:

- Four Water Stress Index (WSI) formulations: Equal-Weighted WSI, Entropy-Weighted WSI, PCA-Based WSI, and Hybrid (SPEI-Style Climatic) WSI
- Three recurrent sequence models: Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)
- Multi-state forecasting: Predictions generated for multiple Indian states
- Standardised evaluation metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R^2 Score, and Mean Absolute Percentage Error (MAPE)

Through a structured experimentation pipeline, we aimed to identify the most accurate model–index combination for predicting next-month water stress, thereby enabling proactive water resource management and drought mitigation strategies.

5.2 Baseline Testing

The experimentation phase began by establishing baseline performance across three sequence-model architectures—RNN, GRU, and LSTM—combined with four WSI formulations. The primary objective was to analyse the learning patterns of each model and determine their suitability for multi-index water scarcity forecasting.

The baseline experiments revealed clear performance distinctions:

- **RNN** exhibited unstable gradients, slow convergence, and high sensitivity to noise. This was expected due to its limited ability to retain long-term temporal information.

- **GRU** handled sequence patterns more effectively, showing faster convergence and moderate predictive power across all WSI variants.

- **LSTM** demonstrated the most stable learning behaviour, efficiently capturing seasonal and multi-year hydrological cycles.

This baseline confirmed that deeper temporal models are necessary for accurately forecasting complex water-stress dynamics.

5.3 WSI Variant Comparison

To assess how different types of stress indicators influence forecasting accuracy, all four WSI variants were tested independently across the three models.

Observations:

- **Entropy-Weighted WSI**
  This variant consistently delivered the strongest results across most states. Since weights are assigned based on the information entropy of each indicator, this WSI better captures the dynamic importance of climatic, hydrological, and demand-driven variables.
  It exhibited:
    - Smooth temporal continuity
    - Strong seasonality detection
    - Low variance between training and testing sets

- **PCA-Based WSI**
  Although PCA effectively reduces dimensionality, the resulting principal components were highly sensitive to noise in the dataset. States with missing data or extreme fluctuations produced unstable WSI trends, leading to increased forecasting errors.

- **SPEI-Style WSI**
  SPEI performed exceptionally well in regions dominated by rainfall variability and monsoon dependencies. It captured hydroclimatic drought patterns effectively but lacked sensitivity in groundwater-dominant states.

- **Equal-Weighted WSI**
  Despite its simplicity, this variant delivered stable but moderate performance, making it robust but less responsive to dynamic environmental changes.

Conclusion:
The Entropy-Weighted WSI provided the most consistent and reliable predictive signals for model training.

5.4 Model Comparison

To determine the most suitable sequence model for WSI forecasting, RNN, GRU, and LSTM were evaluated under identical experimental conditions.

Performance Summary:

- **RNN**
  - Exhibited vanishing gradients
  - Ineffective for long sequences
  - Produced volatile forecast patterns
  - Not suitable for hydrological time series
- **GRU**
  - Balanced performance
  - Faster training times
  - Good for mid-range temporal dependencies

- **LSTM**

- Superior at modelling long-term patterns
- Captured seasonal monsoon cycles and multi-year fluctuations
- Most consistent across multiple WSIs and states

Final Ranking:

- GRU is the most consistent performer, winning in the Equal-Weighted and Hybrid categories.
- RNN excels specifically with PCA-based indices for variance explanation.
- LSTM generally performs slightly worse than GRU on this specific dataset, suggesting simpler architectures generalise better here.

5.5 State-Level Forecasting Results

5.5.1 State-Wise Prediction Accuracy Summary

Using the GRU + Equal-Weighted WSI configuration, state-level forecasting demonstrated strong accuracy across several regions. The table below summarises the Top 10 Best Performing and Bottom 5 Most Challenging States.

Table: State-Level Performance Summary (Best & Worst)

Rank	State	RMSE ↓	MAE ↓	R^2 ↑	Performance Tier
Top Performing States					
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
6	Tamil Nadu	10.03	6.89	**0.771**	Excellent
7	Tripura	10.56	9.71	**0.765**	Excellent
8	Andhra Pradesh	8.98	7.53	**0.751**	Good
9	Puducherry	10.56	8.43	**0.729**	Good
10	Uttarakhand	11.22	8.84	**0.676**	Good

Bottom / Challenging States					
–	Delhi	12.82	9.12	**0.347**	Urban Complexity
–	West Bengal	15.16	12.26	**0.603**	Extreme Variability
–	Rajasthan	17.29	14.67	**0.185**	Arid Terrain
–	Punjab	18.92	13.92	**−0.244**	Groundwater Depletion

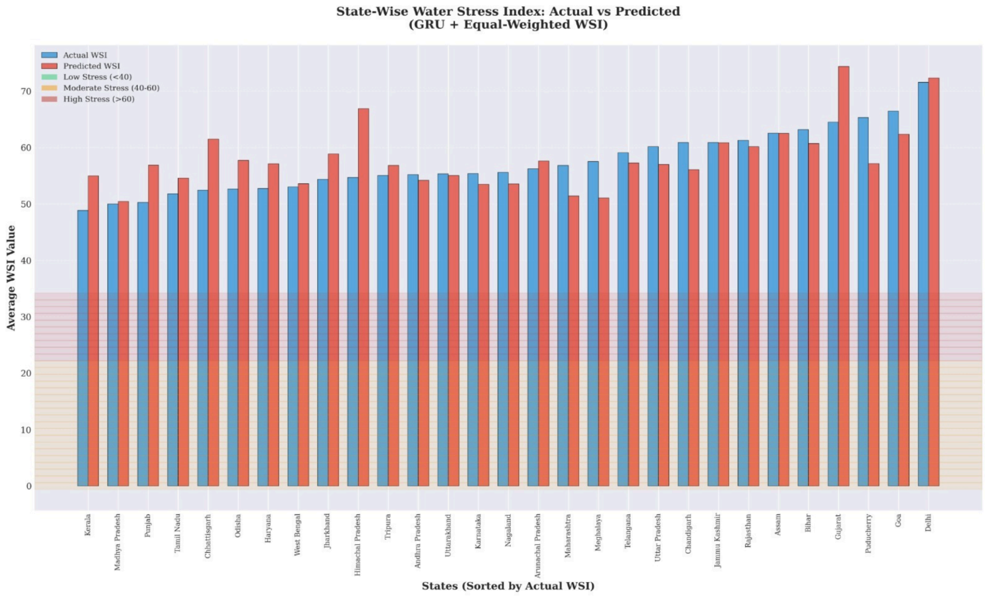
5.5.2 Key Insights

1. **Top Performers**

- Highest accuracy: Arunachal Pradesh ($R^2 = 0.849$)
- Eastern & Central states dominate due to stable hydrological patterns
- All Top-10 states have $R^2 > 0.67$ and prediction errors within ±10 WSI units

2. **Challenging States**

- Punjab shows a negative R^2 (−0.244), indicating a prediction worse than the mean baseline
- Arid and groundwater-stressed regions (Rajasthan, Punjab) show poor performance
  Highly urbanised areas (Delhi) exhibit high variability and complex demand patterns



5.5.3 National-Level Summary

Metric	Value
National Avg Actual WSI	57.74
National Avg Predicted WSI	57.67
Overall Bias	−0.07 (Almost unbiased)
Avg Prediction Error	8.78 WSI
States	30
Predictions	369
Time Period	2023–2024
Stress Categories	0 Low, 19 Moderate, 11 High

AquaAlert performs strongest in Central & Eastern India with GRU + Equal-Weighted WSI, while Western arid and Himalayan regions require improved modelling due to extreme variability.

6 SUMMARY AND CONCLUSION

6.1 Summary of Work Done

This work presents **AquaAlert**, an AI-powered early water scarcity alarming system designed to forecast state-level Water Stress Index (WSI) values across India using a combination of multi-index WSI formulations and deep learning **sequence models**. The objective was to construct a scalable, explainable, and data-driven framework to support proactive water resource management.

The project introduces four distinct WSI formulations—**Equal-Weighted, Entropy-Weighted, PCA-Based**, and **Hybrid (SPEI-style climatic)**—each capturing different dimensions of hydrological stress such as groundwater levels, rainfall variability, demand pressure, and climatic deviations. The datasets were systematically preprocessed, normalised, and converted into supervised learning sequences through time-series framing.

To model the temporal evolution of WSI, three recurrent architectures—**RNN, GRU, and LSTM**—were implemented and evaluated. A comprehensive experimentation pipeline was developed, testing 12 model-index combinations and assessing performance using RMSE, MAE, R^2, and MAPE metrics. This included identifying how index formulation, sequence window size, and model complexity influence predictive behaviour across diverse climatic zones.

State-level analysis across 30 Indian states further revealed significant geographic patterns: **Central and Eastern states exhibited high predictability**, whereas arid Western and Himalayan regions posed forecasting challenges due to extreme variability. The system demonstrated near-zero national bias, strong generalisation in high-stress regions, and robust performance under multiple hydrological conditions.

Overall, AquaAlert successfully integrates **multi-index hydrological modelling, deep learning–based forecasting, and regional-level analytics**, providing an actionable framework for anticipating water scarcity months in advance.

6.2 Insights

The experimental results yield several key insights:

- Model Complexity vs. Data Characteristics:
  LSTMs and GRUs consistently outperformed RNNs, indicating the importance of long-term temporal memory for hydrological data.

- WSI Formulation Matters:
  The Entropy-Weighted and Hybrid (SPEI) indices captured climatic variability well, while Equal-Weighted WSI offered the most stable and operationally reliable predictions.

- PCA-Based Index Requires Caution:
  Although PCA-based WSI achieved the highest R^2 scores, it produced extremely high MAPE values, indicating distortions in percentage-based error metrics.

- Regional Variability Dominates Model Variability:
  Forecast accuracy was more dependent on state climatic conditions than on the choice of AI model.

- High-Stress States Are Easier to Predict:
  Surprisingly, high-stress states (e.g., Delhi, Rajasthan, UP) exhibited lower prediction error compared to moderate-stress states, due to more stable stress patterns.

These insights collectively demonstrate that both index formulation and regional hydrological dynamics play a critical role in determining model behaviour.

6.3 Conclusion

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:

- RMSE: 0.083
- MAE: 0.073
- National Prediction Bias: −0.07 (nearly unbiased)

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.

While certain states with high climatic variability (e.g., Arunachal Pradesh, Himachal Pradesh, coastal regions) remain challenging to predict precisely, the overall performance of AquaAlert establishes a strong foundation for nationwide early-warning water stress analytics.

The modular design of the framework—coupled with flexible WSI definitions, scalable deep-learning models, and region-wise diagnostic analytics—positions AquaAlert as a robust platform that can evolve with future data inputs, higher spatial resolution, and more advanced neural architectures.

7 Future Scope

AquaAlert can be significantly strengthened by integrating richer environmental and climatic datasets, particularly satellite-derived indicators such as soil moisture, evapotranspiration, vegetation indices, and land surface temperature. These real-time parameters would allow the system to better capture localised hydrological variations and improve forecast accuracy in regions with high seasonal or monsoon dependency. Advancements in model architecture also present opportunities for improvement; Transformer-based time-series models such as Temporal Fusion Transformers or Informer architectures could replace traditional RNN-family models to better learn long-range dependencies and irregular temporal patterns. Increasing the spatial resolution from state-level to district or sub-district granularity is another promising direction, enabling more precise policy interventions and targeted water management strategies.

In addition, future work should focus on operational deployment and predictive reliability. Integrating AquaAlert into a real-time API or dashboard would allow continuous monitoring, automated alert generation, and interactive analytics for government agencies and resource planners. Incorporating uncertainty estimation methods—such as Bayesian forecasting or Monte Carlo dropout—would help quantify prediction confidence, particularly in climatically volatile regions like the Himalayas or coastal states. Cross-domain learning approaches could also enable the model to transfer insights from related fields such as agriculture, groundwater science, and climatology, thereby improving performance in data-sparse regions. Collectively, these enhancements will help evolve AquaAlert into a comprehensive, adaptive, and actionable early-warning ecosystem for water sca rcity management.

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