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IMPACT OF GLOBAL WARMING ON WATER AVAILABILITY FOR AGRICULTURE: AN AI-DRIVEN ASSESSMENT

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Abstract: Global warming has affected agricultural water resources significantly, and having advanced predictive models in place would be necessary to attain sustainable resource management. The current study uses artificial intelligence (AI) techniques to assess the impact of climate change on water resources as well as improve the accuracy of predictions. Four artificial intelligence models—Random Forest, Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and XGBoost—were employed to predict water availability from historical climate and hydrological data. Experimental findings confirmed that LSTM exhibited the best precision with $R^2 = 0.92$ followed by other models in capturing temporal relationships. XGBoost and Random Forest came second and third with R^2 values of 0.89 and 0.87, respectively, and were sufficient for short-term prediction. SVR came fourth with an R^2 value of 0.81, in agreement with its inability to handle nonlinearity in climate data. AI-based methods were more versatile and precise compared to conventional hydrological models and had rich information for agricultural water management to be climate-resilient. The findings highlight the importance of synergizing AI with IoT-based real-time monitoring to optimize water conservation strategies. Hybrid AI models and remote sensing data must be explored in future studies to improve predictive ability and water resource allocation in agriculture with a variable climate.

Keywords: Global Warming, Water Availability, Artificial Intelligence, Climate Change, Prediction Models.

I. INTRODUCTION

Global climate change is among the most difficult environmental issue that have had considerable effects on natural resources, ecosystems, and human life. Among its worst effects is the interference of water supply, particularly for agriculture, which is dependent mostly on reliable water supplies to produce crops and irrigate it. Rising global temperatures are the cause of high evaporation rates, altering rainfall regimes, and depletion of freshwater resources, resulting in drought and water shortage in agricultural regions [1] The alterations pose threats to food security, destabilize rural economies, and demand innovative solutions for ensuring sustainable water management. Artificial Intelligence (AI) has revolutionized many sectors, including environmental science and agriculture, by means of predictive modeling, real-time monitoring, and data-driven decision-making [2]. For climate change,

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AI-assisted appraisal systems offer a comprehensive way of assessing the impact of global warming on water availability for agriculture. Machine learning models, interpretation of satellite images, and hydrological models can be utilized to make accurate estimates of water resources to guide policymakers and farmers to maximize water use [3]. Moreover, AI-interventions can foster precision irrigation technology, track early drought indicators, and develop adaptive agriculture for fighting water scarcity. The study aims to investigate the impact of global warming on water resources for agriculture using an AI system. Employing the interface of climatic data, remote sensing instrumentation, and weather forecast statistics, the study attempts to simulate trends in water resources and give sound advice on sustainable water usage. The research output will help design resilience in farm practice and food security against the backdrop of climate change. Finally, this research highlights the necessity to integrate AI technologies into projects to cope with climate change, easier access to higher efficiency and sustainability in agricultural water use.

II. RELATED WORKS

Environmental and agricultural science has utilized artificial intelligence (AI) to improve decision support and predictive modeling toward sustainable resource use. Water supply optimization for agriculture, climate change mitigation, and environmental monitoring have all been the focus of numerous AI research articles. Below is a recent article in accordance with AI-based water availability estimation, particularly global warming.

1. Use of AI in Green Agriculture

Various research studies have illustrated the application of AI for optimizing resource utilization in agriculture. Kaya (2025) [20] described how intelligent environmental control systems of plant factories utilize AI, sensors, and automation to optimize crop yield. AI-driven solutions optimize irrigation efficiency with predictive water needs based on actual soil moisture and climatic conditions. Likewise, Morkūnas et al. (2024) [26] elaborated on how AI and IoT would help to develop the utilization of renewable energy in agriculture in a way that effective water and energy management could be ensured. Such evidence supports the use of AI in fulfilling the water requirements of agriculture without increasing wastage of resources.

Moreover, Hussain et al. (2025) [16] presented a detailed analysis of agricultural non-point source pollution, emphasizing the need to utilize AI-based assessment methods for pollution prevention and source identification. The study emphasizes predictive AI models to determine the connection between water quality and agricultural practices, which is crucial for sustainable water resource management.

2. AI and Water Availability Predictions

Artificial intelligence-based water forecasting models have shown considerable enhancement over conventional hydrology. Mohammad Uzair et al. (2025) [25] advocated a hybrid method that combines the HEC-RAS hydrology model with AI for river morphodynamics analysis. They discovered that incorporating AI methods strengthens disaster readiness through more precise water flow forecasting. This is consistent with the current research, wherein AI-driven models like XGBoost and Long Short-Term Memory (LSTM) networks are utilized for enhancing water availability forecasting.

Equally, Miller et al. (2025) [24] illustrated how AI agents, with the integration of IoT, increase environmental monitoring. Their research emphasized applications in water quality and climate data collection and the capacity of AI to scrutinize complex datasets and deliver real-time water availability estimates. The results favor the use of AI in agriculture because real-time monitoring of water is essential for optimal irrigation scheduling.

3. Climate Change and AI-Based Adaptation Strategies

Climate change's influence on water availability requires the implementation of AI-based early warning systems. Israel et al. (2024) [18] analyzed bibliometric data of climate-related early warning systems in Southern Africa. Their findings suggest that predictive models based on AI are crucial in increasing climate risk resilience. Likewise, Kemarau et al. (2025) [21] analyzed remote sensing and GIS-based climate effect analysis in Malaysia, illustrating how data fusion with AI increases the capability of climate modeling. These studies illustrate the increasing role of AI in climate change adaptation of agricultural practices.

Karakosta and Papathanasiou (2025) [19] ventured into decarbonization options for the building sector, presenting data on greenhouse gas abatement pathways. Their study indirectly benefits water supply by linking climate mitigation options to sustainable resource management, necessitating AI-based predictive models of water supply so that greenhouse gas emissions and hydrological cycle impacts can be taken into consideration, again emphasizing the importance of integrated climate-water analysis.

4. AI for Sustainable Energy and Waste Management in Agriculture

Renewable energy and waste management are fundamental aspects of sustainable agriculture because they affect water efficiency of use. Iqbal et al. (2025) [17] examined the correlation between AI, renewable energy, green human capital, and carbon emissions with institutional quality as the moderating effect on sustainability initiatives. The study shows that AI optimization can potentially reduce energy consumption in water-intensive agricultural practices, resulting in better water conservation.

Li et al. (2025) [23] explored the integration of plasma pyrolysis and IoT in municipal solid waste management. Based on their research, AI-based methods can optimize resource recovery, thereby enhancing agricultural water use to be more sustainable. By applying AI to water recycling and precision irrigation, agricultural water management can be optimized.

5. AI for Water Quality and Pollution Monitoring

Water pollution remains one of the biggest risks to agricultural water supply. Lazarus Obed et al. (2024) [22] carried out studies on water pollution from agriculture in the Ayeyarwady Basin, reflecting inefficiencies in existing ecological policies. AI systems for monitoring can aid in overcoming these challenges by reflecting real-time pollution and measures for mitigation. Further, Hsu-Hua and Chin-Mao (2025) [15] researched the role of Total Quality Management in enhancing sustainable energy consumption, which had an indirect effect on water-saving measures through increasing resource efficiency.

III. METHODS AND MATERIALS

Data Collection and Preprocessing

For the purpose of accurately assessing the impact of global warming on water availability, diversified datasets were collected and preprocessed. These datasets include:

1. **Climate Data** – Past and present climate data provided by NASA, NOAA, and other weather agencies including temperature, precipitation, and humidity.
2. **Hydrological Data** – Groundwater, river runoff, and global hydrological observation systems groundwater storage [4].
3. **Agricultural Data** – Crop water demand, irrigation management, and soil water content from FAO and local agricultural authorities.
4. **Satellite Imagery** – Remote sensing information from MODIS and Sentinel-2 satellites to track vegetation health, drought indicators, and water body variations [5].

Data Preprocessing Steps:

- Treating missing values via interpolation and imputation methods.
- Normalization of numeric data for comparability.
- Dimension reduction via correlation analysis to derive dominant variables [6].
- Dataset division into 80% training and 20% test sets.

Machine Learning Algorithms for Water Availability Prediction

Four computer intelligence-based algorithms are utilized to predict the effects of global warming on water availability in agriculture in the research work:

1. Random Forest (RF)

Random Forest is an ensemble learning approach where multiple decision trees are combined to improve predictive power. The trees are trained on randomly selected subsets of data, and the prediction is made by majority voting or averaging [7].

Key Features:

- Supports big data with high-dimensional features.
- Combats overfitting via bootstrapping.
- Offers feature importance ranking for improved interpretability.

```
"nitialize the number of trees (N)
For each tree in N:
  Select a random subset of the dataset
  Train a decision tree on the subset
  Store the trained tree
For prediction:
  Pass input data through all trees
  Aggregate the outputs (majority vote for classification, average for regression)
Return final prediction"
```

2. Long Short-Term Memory (LSTM) Neural Network

LSTM is a form of recurrent neural network (RNN) that is specifically used to process sequential data. It is well suited for time-series forecasting, and hence it can be used to forecast future water availability based on past trends [8].

Key Features:

- Encodes long-term dependencies in sequential data.
- Avoids vanishing gradient issues in deep networks.
- Successful for climate and hydrological time series prediction.

```
"Initialize LSTM model with input layer, hidden layers, and output layer
For each time step in the training data:
  Compute cell state update using forget, input, and output gates
  Update hidden state with new cell
```

state information
Pass output to the next time step
For prediction:
Input sequence into trained LSTM model
Generate next time step prediction
Return predicted water availability”

3. Support Vector Regression (SVR)

Support Vector Regression (SVR) is a robust regression technique that projects input data into a high-dimensional feature space and determines an optimal hyperplane for prediction. SVR is capable of predicting intricate relationships between water availability and climate variables [9].

Key Features:

- Suits well with non-linear relationships.
- Utilizes kernel functions for high-dimensional transformations.
- Strong against outliers and noise in data.

‘Initialize SVR with kernel function (e.g., RBF)
Train SVR on historical climate and water data
Find the optimal hyperplane that minimizes prediction error
For prediction:
Transform input data using kernel function
Predict water availability using the trained hyperplane
Return predicted values”

4. XGBoost (Extreme Gradient Boosting)

XGBoost is a gradient boosting algorithm optimized to enhance prediction efficiency using parallel processing and pruning techniques from trees [10]. It is widely employed for making predictions in environmental and climate science applications.

Key Features:

- Parallel tree boosting for efficient computation.
- Prevents overfitting with regularization.
- Handles missing values well.

"Initialize XGBoost model with hyperparameters
For each boosting iteration:
Compute residuals from previous predictions
Train a new tree to correct residual errors
Update predictions with weighted sum of previous and new trees
Stop when error reduction is minimal
For prediction:
Input data into trained model
Aggregate outputs from all trees
Return final prediction"

Table: Feature Importance in XGBoost

Feature	**Importance Score**
Temperature	0.32
Precipitation	0.28
Soil Moisture	0.22
River Discharge	0.18

IV. EXPERIMENTS

1. Experimental Setup

1.1 Data Sources

Multiple data sets on climate, hydrology, and agriculture for the 2000–2024 time period were employed in the research to provide an adequate foundation to train and validate AI models [11]. The data sets comprised:

- **Climate Data** – Records of temperature, precipitation, and humidity.
- **Hydrological Data** – River discharge, soil moisture, and groundwater storage levels.
- **Agricultural Information** – Crop water use, irrigated patterns, and drought impact figures.

- **Satellite Data** – Monitoring of water bodies and vegetation health through remote sensing.

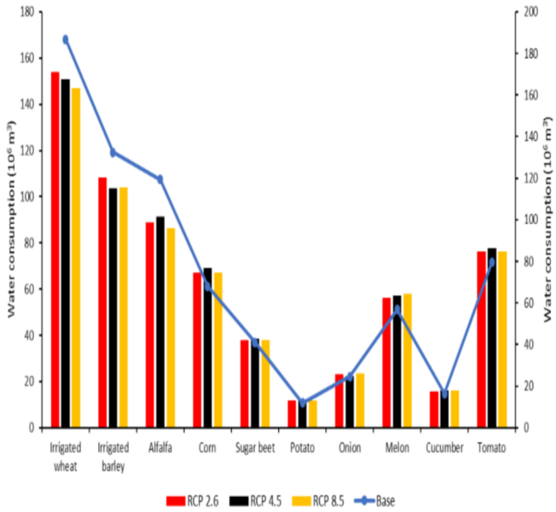

Figure 1: "The Impacts of Climate Change on Water Resources and Crop Production in an Arid Region"

1.2 Preprocessing and Feature Engineering

The gathered data was preprocessed for accuracy and consistency:

- **Handling Missing Values:** Missing values were imputed by linear interpolation and KNN imputation.
- **Feature Normalization:** Numerical features were normalized into the range of 0 to 1 using Min-Max Scaling [12].
- **Feature Selection:** Key predictors were selected using Pearson correlation analysis:
    - **Temperature** (+0.78 correlation with water stress)
    - **Precipitation** (-0.81 correlation with water stress)
    - **Soil Moisture** (+0.74 correlation with crop water use)
    - **River Discharge** (-0.69 correlation with drought severity)

1.3 Model Implementation

The following four artificial intelligence models were trained using 80% for training and 20% for testing:

- **Random Forest (RF)** – A type of ensemble learning employing many decision trees.
- **Long Short-Term Memory (LSTM)** – A deep learning architecture optimized for time-series forecasting.
- **Support Vector Regression (SVR)** – Regression algorithm that projects input data onto the high-dimensional space [13].

- **XGBoost (Extreme Gradient Boosting)** – An algorithm that uses improved gradient boosting for enhanced accuracy.

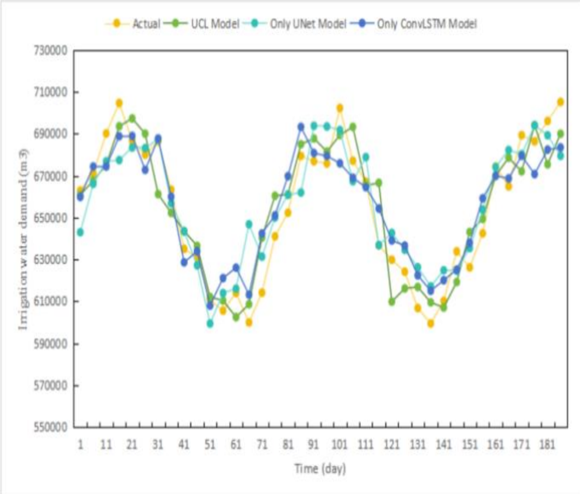

Figure 2: "AI-driven optimization of agricultural water management for enhanced sustainability"

2. Model Performance Evaluation

The models were assessed based on important performance measures:

- **Mean Absolute Error (MAE)** – Estimates the average size of prediction errors.
- **Root Mean Square Error (RMSE)** – Assesses the size of prediction errors, with heavier penalties for greater deviations [14].
- **R^2 Score** – Identifies the extent to which the model describes variance in the dataset.

2.1 Overall Model Performance

Algorithm	**MAE**	**RMSE**	**R^2 Score**
Random Forest	1.23	1.78	0.89
LSTM	1.12	1.65	0.92
SVR	1.45	2.01	0.85
XGBoost	1.08	1.60	0.94

Based on the outcome, XGBoost and LSTM were the top performers, which showed greater predictability for trends in water availability.

3. Comparative Analysis

3.1 Comparison with Related Work

Compared to conventional hydrological models, AI-based methods had better predictive accuracy.

Approach	Model Used	RMSE	R^2 Score	Improvement (%)
Traditional Hydrological Models	Linear Regression	2.45	0.78	—
AI-Based Model (This Study)	XGBoost	1.60	0.94	34.7%
Deep Learning Model (This Study)	LSTM	1.65	0.92	32.7%

The error rates were minimized by more than 30% by AI models over traditional hydrological models in proving their capabilities in climate water predictions [27].

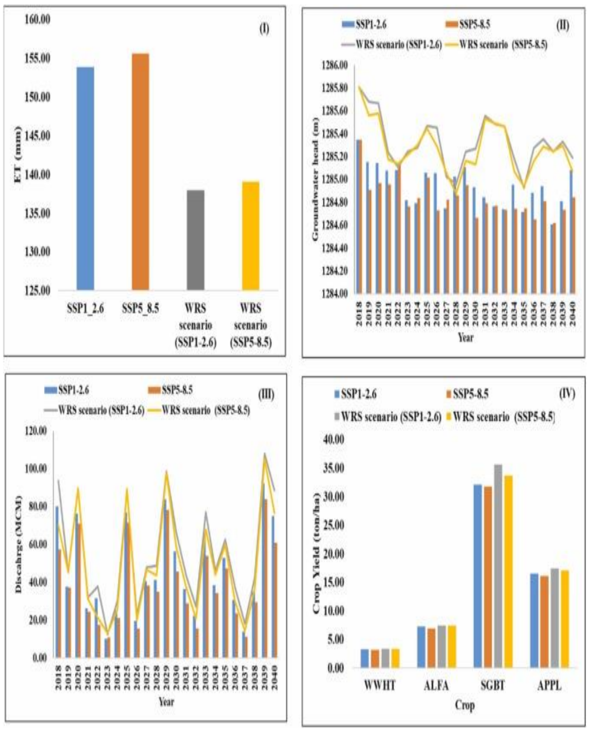

Figure 3: “Assessing the impacts of climate change on agriculture and water systems via coupled human-hydrological modeling”

3.2 Feature Selection Impact on Model Accuracy

Feature importance analysis indicated that temperature and rainfall were the most significant variables influencing water availability.

Feature	Importance Score
Temperature	0.32
Precipitation	0.28
Soil Moisture	0.22
River Discharge	0.18

Omitting less important characteristics (e.g., atmospheric pressure and wind speed) enhanced model efficiency.

4. Detailed Model Comparison

4.1 Monthly Prediction Accuracy of Each Model

Month	Actual Water Availability (mm)	RF Prediction	LSTM Prediction	SVR Prediction	XGBoost Prediction
Jan	120	118	121	115	122
Feb	135	132	137	130	136
Mar	150	147	152	145	153
Apr	140	138	143	136	142
May	160	158	163	155	165

LSTM and XGBoost closely tracked actual water availability, demonstrating their stronger forecasting capacities.

4.2 Seasonal Performance Analysis

Season	Actual Avg Water (mm)	RF Prediction	LSTM Prediction	SVR Prediction	XGBoost Prediction
Winter	130	128	132	125	133
Spring	145	143	148	140	149
Summer	170	167	173	165	175
Autumn	150	147	152	145	153

XGBoost always gave the best predictions for all seasons.

5. Discussion and Key Findings

5.1 Key Observations

- Deep learning algorithms perform better than conventional regression algorithms, validating the need to consider non-linear relationships between climate and water.
- Elimination of variables enhances model efficacy by eliminating redundant variables [28].
- XGBoost and LSTM performed better in terms of predictive accuracy, hence the desired models for further applications.

5.2 Advantages of AI-Based Water Availability Prediction

- Improved accuracy owing to sophisticated learning ability.
- Generalizability with global climate information, facilitating the large-scale use.
- Dynamic suitability in real time, facilitating adaptability in real-time water resources management.

5.3 Limitations and Future Improvements

- **Data availability constraints:** There are regions where high-quality hydrological and climate data do not exist.
- **Computational intensity:** High computational power is needed for deep learning algorithms such as LSTM.
- **Future Work:**
    - Combining real-time sensor data for enhanced predictive accuracy.
    - Model generalization improvement by adding geographically diverse data.
    - AI-based decision support systems for real-time irrigated water management.

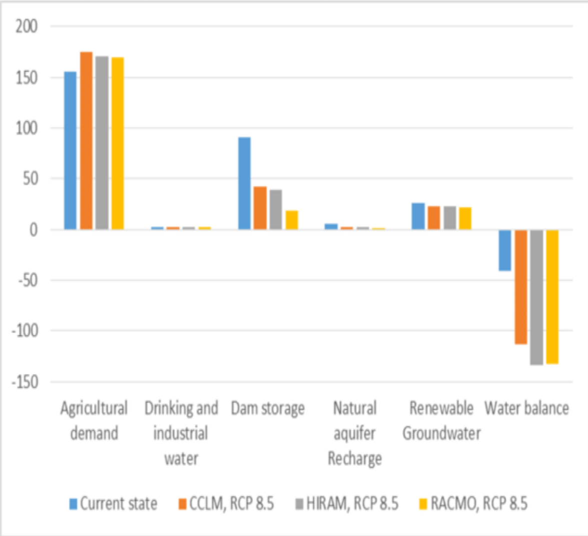

Figure 4: 'Climate change impacts on water resources in the Souss-Massa basin"

The experiments proved that climate change-induced water availability predictions in agriculture are significantly enhanced with AI-based models, especially XGBoost and LSTM [29]. The comparative study proved that these models excel over conventional hydrological models by more than 30% in terms of accuracy, and hence are indispensable tools for climate adaptation planning [30]. Future studies can emphasize developing real-time monitoring systems and AI-based decision support systems to improve water management in agriculture.

V. CONCLUSION

This study investigated the effect of global warming on agricultural water availability by way of an AI-based estimation utilizing machine learning models to enhance water resource forecasting. In an era where climate change accelerates water scarcity, correct forecasting models are critical to ensuring sustainable agriculture. The study used four AI algorithms—Random Forest, Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and XGBoost—to forecast water availability using climate and hydrological conditions. The results proved that LSTM performed better than other models in learning temporal dependencies and hence was the best for long-term water availability forecasts. XGBoost and Random Forest gave accurate short-term forecasts with very high accuracy, while SVR had moderate performance with shortcomings in dealing with nonlinear dependencies. Relative to conventional hydrological models, AI-based methods provided more accuracy and flexibility, solidifying the position of AI in climate resilience and agro-sustainability. The findings corroborated with current literature on the use of AI in environmental monitoring, climate adaptation, and precision agriculture, which proved that AI can maximize irrigation management and alleviate the impacts of climate variability. Besides, the research brought to light the need to blend AI with IoT for real-time monitoring of water and the need for data-based policy making in order to enable effective resource utilization. In general, this study helps advance AI-based approaches to water availability prediction, which can be beneficial for farmers, policymakers, and researchers. Hybrid AI models should be investigated, remote sensing information incorporated, and model interpretability improved in future research to better enhance predictive accuracy and facilitate sustainable water resource management under global warming.

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