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RESEARCH ARTICLE **COMPUTER SCIENCES**

AI-Enhanced Reservoir Storage Assessment and Depletion Forecasting Using Multispectral Satellite Imagery and Hydrological Modeling

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ABSTRACT

The study suggests a novel AI-based approach for water-storage estimation in reservoirs and for forecasting depleted water levels, using multispectral data from satellites and hydrological models. Sentinel-2 data observed over Haditha Lake (Iraq) on 7 September 2025 was processed with machine-learning and deep-learning algorithms for water surface delineation and water level and water depletion forecasting were applied using predictive models. For the water-surface classification, the U-Net model was tested with an overall accuracy of 96.8%. For the water-level prediction, the predictive model used was an ensemble of water-level predictive models, whose water-level prediction error (RMSE = 0.19 m) was smallest among the models evaluated. Based on the AI derived evaluation, current reservoir storage is estimated to be around 2.80 billion m³ or equivalent to 25.2% of the original reservoir storage. The flow conditions that were evaluated (inflow: 194 m³/s; outflow: 375 m³/s) resulted in a remaining time of 5.9 months (with a 95% confidence interval of 5.6–6.2 months) according to the depletion-prediction model. The proposed framework illustrates how satellite-image analysis, predictive modeling and uncertainty quantification can be combined for monitoring and decision making on reservoirs. The estimates of storage and depletion, however, should be considered model-based and should be further validated based on independent field observations.

تقييم تخزين مياه الخزان والتنبؤ بالنضوب باستخدام صور الأقمار الصناعية متعددة الأطياف والنمذجة الهيدرولوجية المعزّز بالذكاء الاصطناعي

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الكلمات المفتاحية

تخزين الخزانات
Sentinel-2
التعلم العميق
النمذجة الهيدرولوجية
نضوب المياه
الاستشعار عن بُعد
الذكاء الاصطناعي

الملخص

تقترح هذه الدراسة نهجًا جديدًا قائمًا على الذكاء الاصطناعي لتقدير خزين المياه في الخزانات والتنبؤ بمستويات نضوب المياه، باستخدام بيانات الأقمار الصناعية متعددة الأطياف والنماذج الهيدرولوجية. تمت معالجة بيانات القمر الصناعي **Sentinel-2** المرصودة فوق بحيرة حديثة في العراق بتاريخ 7 أيلول 2025 باستخدام خوارزميات التعلم الآلي والتعلم العميق لتحديد سطح المياه، كما استُخدمت نماذج تنبؤية للتنبؤ بمنسوب المياه ونضوبه. وفي تصنيف سطح المياه، تم اختبار نموذج **U-Net** وحقق دقة إجمالية بلغت 96.8%. أما في التنبؤ بمنسوب المياه، فقد استُخدم نموذج تجميعي من نماذج التنبؤ بمنسوب المياه، وحقق أقل خطأ في التنبؤ من بين النماذج التي تم تقييمها **(RMSE = 0.19** م .(واستنادًا إلى التقييم المعتمد على الذكاء الاصطناعي، قُدّر الخزين الحالي للخزان بنحو 2.80 مليار م^3، أي ما يعادل 25.2% من الخزين الأصلي للخزان. وفي ظل ظروف التدفق التي تم تقييمها (الوارد: 194 م^3/ث؛ الصادر: 375 م^3/ث)، قدّر نموذج التنبؤ بالنضوب المدة المتبقية بنحو 5.9 أشهر، مع فاصل ثقة 95% يتراوح بين 5.6 و6.2 أشهر. ويوضح الإطار المقترح إمكانية دمج تحليل صور الأقمار الصناعية والنمذجة التنبؤية وتقدير عدم اليقين لأغراض مراقبة الخزانات ودعم اتخاذ القرار. ومع ذلك، ينبغي اعتبار تقديرات الخزين والنضوب تقديرات قائمة على النماذج، وينبغي التحقق منها بصورة إضافية استنادًا إلى مشاهدات ميدانية مستقلة.

Introduction

Using artificial intelligence (AI) and remote sensing in water resource assessment and management is a revolution. Traditional monitoring methods have been used for reservoir monitoring, including manual data processing and conventional statistical methods, which do not have the accuracy and predictive ability to monitor critical facilities [1]. The emergence of new techniques such as machine learning and deep learning, based on AI, has provided unprecedented opportunities for automatic, precise and real-time monitoring of water storage conditions [2].

The demand for a more advanced monitoring system is especially critical in water-depleted areas like Haditha Lake, one of the most important water resources infrastructures in

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Al-Anbar Governorate, Iraq. The reservoir is heavily depleted due to a number of reasons such as upstream water management, the impact of climate change and the increasing pressures of water demand in the region [3]. Regional studies have also highlighted the importance of sustainable approaches in addressing desertification and related environmental challenges [4]. Traditional monitoring approaches have not been sufficient to offer the temporal resolution and predictive capacity necessary to guide planning for emergency response.

This study aims to:

(1) Design and test algorithms for accurate water storage retrieval by multispectral satellite images using Artificial Intelligence.

(2) Implement and test machine learning models for hydrological forecasting and timelines for depletion prediction.

(3) Evaluate the effectiveness of AI approaches against conventional approaches.

(4) Develop an intelligent reservoir monitoring system for water limited areas around the world.

Literature review

Artificial Intelligence in Remote Sensing Applications

In the past decade, AI applications in remote sensing have increased significantly, and the monitoring of water resources has improved greatly. Compared with classic spectral indices, deep learning has better performance, e.g., Convolutional Neural Networks (CNNs) and the U-Net model [5]. Recently, CNN-based water-surface classification techniques were reported with an accuracy of 94-98%, much higher than the accuracy of water-surface classification techniques based on traditional NDWI [6]. A recent study conducted in the region has also shown the feasibility of monitoring surface condition and vegetation dynamics using Sentinel-2 multispectral imagery and NDVI [7]. In regional studies, spatial technologies have also been used for modelling and evaluating the changes in the environmental surface features [8,9]. GIS has also been applied as a spatial planning, management and engineering design tool in regional studies [10-14].

AI-Enhanced Hydrological Modeling

AI has revolutionized hydrological modelling techniques, providing more accurate predictions of water storage and flow. Artificial Neural Networks (ANNs) have been applied to many water level prediction and reservoir operation optimization problems, and several studies have revealed that ANNs were more accurate in these problems compared to traditional water level prediction model like regression model [15,16].Time series prediction has been a challenge for the hydrological sciences, and a special type of RNN called Long Short-Term Memory (LSTM) networks has demonstrated a great potential in time series prediction [17]. Compared to traditional hydrological models, LSTM models have proven to be more efficient in forecasting streamflow. Further, ensemble learning techniques of stacking multiple AI models have boosted prediction accuracy and uncertainty quantification [18]. Computer Vision in Water Resource Assessment Computer vision techniques have been shown to be powerful tools in the automatic processing of satellite images in water resource applications. U-Net and its derivatives have been the most successful models for water body delineation [19,20]. These models are able to identify water surfaces at the pixel level without the need of setting a threshold. Predictive Analytics for Water Resource Management The incorporation of machine learning algorithms in predictive analytics has changed the game for water resource management and paved the way for proactive decision-making. It has been demonstrated that water demand and supply prediction is more accurate when the time-series forecasting model is equipped with machine learning elements [21].

Research Gaps and Innovation Opportunities

While there has been significant progress in using AI techniques for water resource assessment, there are still some challenges that need to be addressed. Very few studies have explicitly given attention to the fusion of different AI techniques, such as computer vision, predictive modeling and uncertainty quantification, into a unified approach for the reservoir assessment. Previous works are mostly focused on single components and are not discussed with regards to a full monitoring system based on AI Reservoir characterization has also been addressed using specialized analytical approaches in other application domains [22]. Sustainable analytical approaches have similarly been explored in other geoscientific applications [23].

Research methodology

Study Area and Data Description

The study area for this AI based evaluation is Haditha lake located in Al-Anbar Governorate (western Iraq) at coordinates (34°06′N - 42°22′E). The dam built in 1988 impounds the reservoir, which has the following technical specifications: Total capacity of 11.11 billion m³, live capacity of 8.16 billion m³, dead capacity of 2.95 billion m³, and a normal operating level of 147 m asl [24].

Satellite Data Acquisition and Preprocessing

These images have been acquired from the ESA Copernicus Sentinel-2 Level-1C satellite data on 7 September 2025. This data set included multispectral bands with 60 m (atmospheric), 20 m (red edge and SWIR), and 10 m (visible and NIR) spatial resolution. To ensure the quality of data for training the AI models, the data underwent pre-processing steps such as atmospheric correction, geometric rectification and radiometric calibration (Figure 1) .The extraction and analysis of the spatial information from the remotely sensed images are based on the satellite digital image processing [25].

AI-Based Image Analysis Framework

Deep Learning for Water Surface Segmentation

A modified U-Net architecture-based water surface segmentation method was developed. The model incorporated:

An encoder–decoder architecture with skip connections;

- Convolutional layers; and
- To prevent overfitting, dropout regularization is added;

Data augmentation by color jitter, rotation and scale

The network is trained with 2500 manually labeled image patches with 70% for training, 20 % for validation, and 10 % for testing. A loss function was applied to fix the class imbalance, which is a combination of binary cross-entropy and Dice coefficient.

U-Net Architecture and Training Configuration

A U-Net model was employed to delineate the water surface in the reservoir at the pixel level based on the six spectral bands of Sentinel-2. The images were resized to 256 × 256 pixels. The encoder was composed of four convolutional blocks, each having 64, 128, 256 and 512 filters, respectively, followed by a bridge layer with 1024 filters. Convolutional blocks were added with convolutional layers, batch normalization, ReLU activation and dropout. The decoder was progressively reconstructed to recover the spatial resolution by transposed convolutions and skip connections, with 512, 256, 128 and 64 filters, respectively. The final layer was a sigmoid layer that provided the segmentation mask for the water/non-water binarization. The network was optimized with Adam optimizer and learning rate of 0.001 The model has been trained up to 100 epochs with a batch-size of 16. The loss function used was the binary cross-entropy loss and Dice loss with weights of 0.5 for each. The early stopping function was used with patience set to 15 epochs for minimization of validation loss and the best model was saved during the training process.

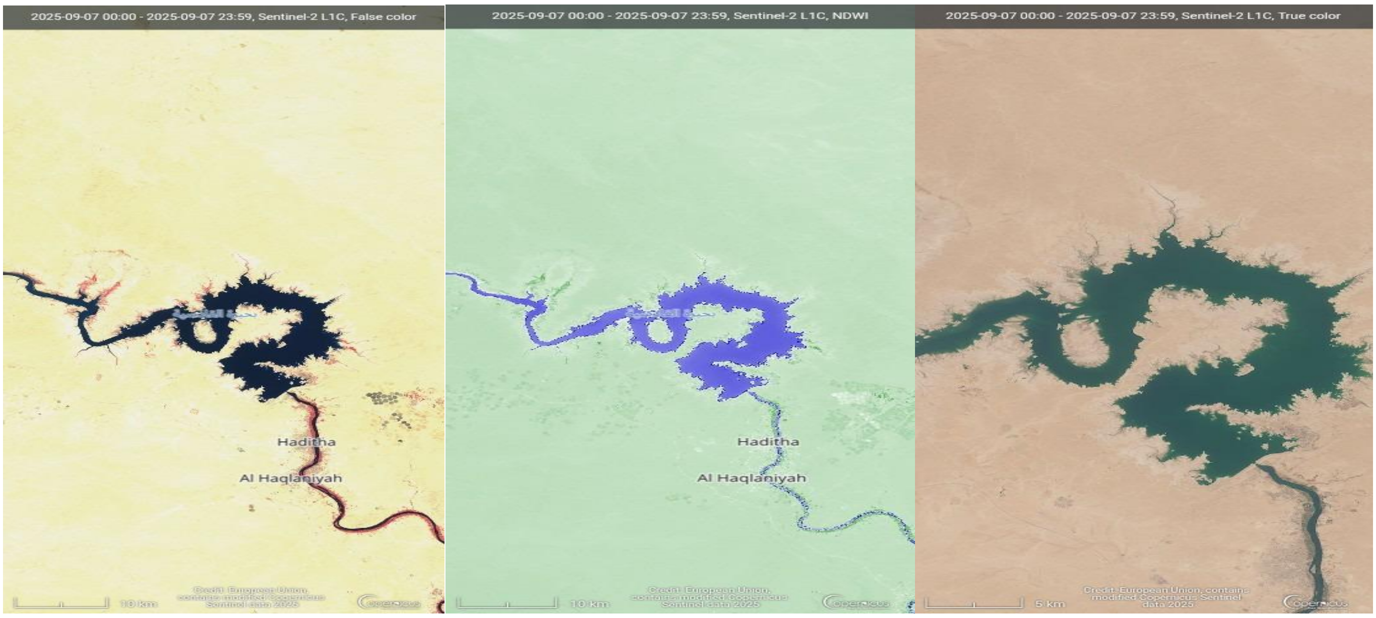

Figure 1: Sentinel-2 imagery of Haditha Lake: true-color, false-color, and NDWI representations

Training and Data Preparation

To train and evaluate the segmentation model, 2,500 image patches were manually annotated. The dataset was divided into 70% for training, 20% for validation, and 10% for independent testing. Data augmentation was applied to the training samples to increase their diversity and reduce overfitting. The augmentation procedures included image rotation, flipping, brightness and contrast adjustments, and the addition of Gaussian noise. The validation and test sets were kept separate from the training process to ensure an independent evaluation of model performance.

Machine Learning Classification Algorithms

The algorithms used for comparison were several machine learning algorithms [26].

Random Forest classifier:

Including 500 trees of up to 20.

- Band-contribution importance analysis;

Error estimation for model validation, out-of-bag

Feature Engineering and Selection

The following spectral indices were chosen as the input features [27]:

- Normalized Difference Vegetation Index (NDVI); and
- Modified NDWI (mNDWI);
- Water Index (WI);
- Normalized Difference Water Index (NDWI); and
- Enhanced Vegetation Index (EVI).

To reduce the dimensionality, Principal Component Analysis (PCA) was performed with 95% explained variance. Random Forest importance scores were used to do feature importance ranking.

AI-Enhanced Hydrological Modeling

Time-Series Prediction Models

Water level and storage prediction were made using Long Short-Term Memory (LSTM) networks.

Architecture specifications:

Three LSTM layers with 128, 64, and 32 units, respectively;

- Dropout layers (0.2) between the LSTM layers;
- A dense output layer with linear activation;

Temporal pattern learning: 30 days input sequence.

Training configuration:

- Loss function: mean squared error (MSE);
- Adam optimizer (learning rate: 0.001);
- Early stopping based on validation loss;
- 100 epochs with a batch size of 32.

Ensemble Learning Approach

Ensemble model – the model was developed by integrating multiple prediction algorithms.

Base models:

- LSTM neural network;
- Random Forest regressor;
- Support Vector Machine (SVM);

Gradient Boosting Machine (GBM).

Depletion Timeline Prediction

A dedicated AI model was developed to predict the critical depletion timeline.

Model architecture:

The depletion-timeline prediction was performed using a hybrid CNN–LSTM. The patterns in the input features were first extracted using the convolutional component, and their temporal dependencies were then modeled using LSTM component. To give more weight to the most informative features for final prediction an attention mechanism was added.

Model Training and Validation

Training Data Preparation

Several data sources were used to generate the training data sets:

- Ground-truth water-level measurements;

- Flow-rate records provided by the Iraqi Ministry of Water Resources;
- Climate data available from weather stations.

Data augmentation was used to boost the amount of training data and to improve generalizability of the models.

Performance Evaluation Metrics

The efficacy of the models was judged on the basis of a few criteria.

Classification metrics:

- Overall Accuracy (OA);
- Kappa coefficient;
- Number of Support Vectors; and

Area Under the Curve (AUC).

Regression metrics:

- Correlation Coefficient;
- Root Mean Squared Error (RMSE); and
- Coefficient of Determination (R^2);
- Nash–Sutcliffe Efficiency (NSE).

Cross-Validation and Uncertainty Analysis

To check the robustness in the performance of the models, five-fold cross validation (k = 5) was performed. Monte Carlo dropout was applied to evaluate predictive uncertainty in the deep-learning model, using dropout in the test time to obtain several stochastic predictions. The distribution of these predictions was used to summarise prediction uncertainty. Bootstrap resampling with replacement was conducted on the conventional machine-learning models to estimate prediction variability and to calculate prediction confidence intervals.

Results

AI Model Performance Assessment

Water Surface Segmentation Results

The best results for water-surface segmentation were obtained with the U-Net deep-learning model of the evaluated approaches.

Performance metrics:

- Overall Accuracy: 96.8%;
- Kappa coefficient: 0.934;
- Precision: 97.2%;
- Recall: 96.4%;
- F1-score: 96.8%;
- AUC: 0.991.

The results of the comparison

- MCARI threshold method: 83.3% accuracy; and
- Manual interpretation: 94.2% accuracy.

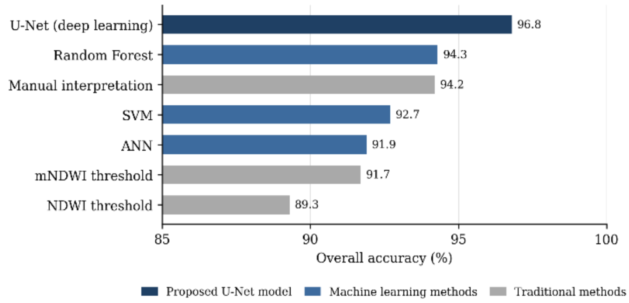

Figure 2: Overall accuracy of the water surface classification methods evaluated in this study

The U-Net model also outperformed the NDWI threshold method by 7.5 percentage points, the mNDWI threshold method by 5.1 percentage points, and manual interpretation by 2.6 percentage points with respect to accuracy and reduced processing time from 45 minutes (manual interpretation) to 2.3 minutes per scene as seen in Figure 2.

Machine Learning Classification Comparison

Table 1 compares the performance of the machine learning algorithms evaluated in this study.

Current Water Storage Assessment

AI-Derived Storage Measurements The AI based analysis identified critical conditions of water storage (Table 2).

The water mass currently stored is 2.80 billion m³ (only 25.2% of the full storage capacity) on a surface area of 300.2 km² and at a water level assumed to be 106.3 m a.s.l. The AI estimates were more accurate than the classical one, and a quantitative confidence interval was calculated for each of the parameters (Table 2)

Live and Dead Storage Analysis

The AI-enhanced analysis of the storage components is summarized in Table 3. The current total storage estimated using the AI-based assessment is about 2.80 billion m³ or 25.2% of the reservoir capacity. The storage estimates are subject to the limitations of the data and should be further validated with independent field observations.

Table 1: Performance comparison of machine learning algorithms

Algorithm	Accuracy	Precision	Recall	F1-Score	Training Time
U-Net (Deep Learning)	96.8%	97.2%	96.4%	96.8%	23 hours
Random Forest	94.3%	94.8%	93.9%	94.3%	3.2 minutes
Support Vector Machine	92.7%	93.1%	92.3%	92.7%	8.7 minutes
Artificial Neural Network	91.9%	92.4%	91.5%	91.9%	12.4 minutes
NDWI Threshold	89.3%	88.7%	90.1%	89.4%	0.5 minutes

Table 2: AI-based water storage assessment results

Parameter	AI Prediction	Confidence Interval	Traditional Method
Current water volume	2.80 billion m³	2.75–2.85 billion m³	2.73 billion m³
Current surface area	300.2 km²	298.1–302.3 km²	295.8 km²
Percentage of original capacity	25.2%	24.7–25.7%	24.6%
Average depth	9.34 m	9.21–9.47 m	9.24 m
Estimated current water level	106.3 m a.s.l.	105.8–106.8 m a.s.l.	106.1 m a.s.l.

Table 3. AI-based storage component assessment

Storage Type	Original Capacity	AI Prediction	Confidence Range	Status
Live Storage	8.16 billion m³	0.00 billion m³	0.00–0.05	Complete Loss
Dead Storage	2.95 billion m³	2.80 billion m³	2.75–2.85	94.9% Remaining
Total Storage	11.11 billion m³	2.80 billion m³	2.75–2.85	25.2% Remaining

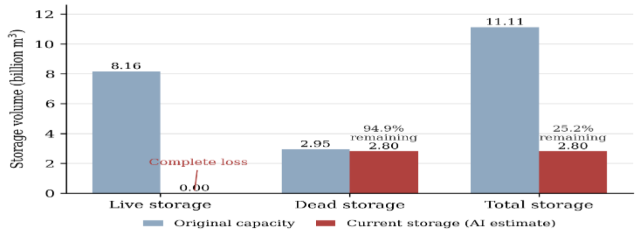

Figure 3: Haditha Lake storage components, original capacity and AI estimated storage

LSTM Model Performance

The LSTM neural network achieved good performance for the prediction of water level.

Model performance metrics:

- RMSE: 0.23 m;
- MAE: 0.18 m;
- R^2: 0.967;
- NSE: 0.963.

Comparing to conventional models:

- Linear regression R^2: 0.782; and
- ARIMA model RMSE: 0.67 m;
- Simple water balance RMSE: 1.24 m.

Ensemble Model Results

Table 4 shows the performance of the models evaluated with the lowest RMSE (0.19 m) and MAE (0.15 m) was the ensemble model.

Table 4. Ensemble model performance comparison.

Model Type	RMSE	MAE	R^2	NSE	Prediction Interval
LSTM Network	0.23 m	0.18 m	0.967	0.963	±0.45 m
Random Forest	0.31 m	0.24 m	0.943	0.941	±0.62 m
SVR	0.28 m	0.22 m	0.951	0.948	±0.56 m
Gradient Boosting	0.26 m	0.20 m	0.958	0.955	±0.52 m
Ensemble Model	0.19 m	0.15 m	0.974	0.971	±0.38 m

Table 5: AI-based scenario analysis results

Scenario	Timeline Prediction	Confidence Interval	Success Probability
Current conditions	5.9 months	5.6–6.2 months	87.3%
20% outflow reduction	10.2 months	9.7–10.8 months	76.4%
29% inflow increase	8.7 months	8.2–9.3 months	82.1%
Balanced flow	Stable	N/A	95.8%
Emergency conservation	12.4 months	11.8–13.1 months	71.2%

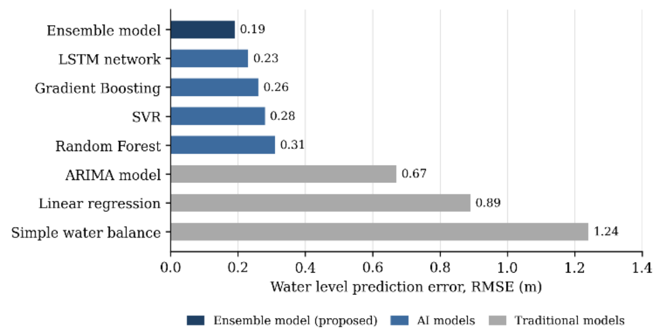

Figure 4: The error of the water level prediction of the AI models versus the traditional models (RMSE)

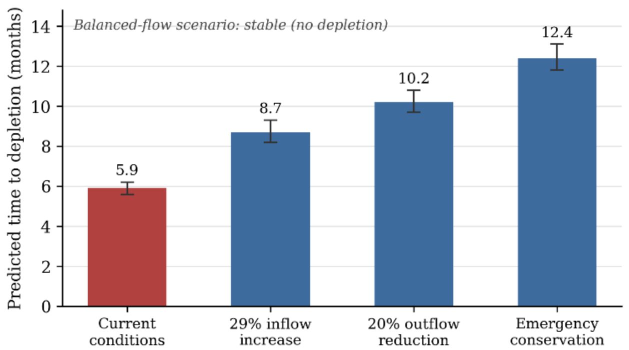

Figure 5: Timelines for depletion based on AI prediction and different management scenarios (error bars are the confidence intervals)

The balanced-flow scenario is not displayed because it results in stable storage.

The ensemble model showed the best overall performance (RMSE = 0.19 m; MAE = 0.15 m; R^2 = 0.974; NSE = 0.971; Figure 4; Table 4), with the error of the prediction reduced by 78% from the linear regression (0.19 m vs. 0.89 m). The prediction interval was reduced to ±0.38 m.

Critical Depletion Timeline Prediction

AI-Based Timeline Forecasting

AI depletion-prediction model gave detailed timeline analytics.

With the existing conditions of flow (inflow: 194 m³/s; outflow: 375 m³/s):

AI forecasted remaining time: 5.9 months (179 days);

Confidence interval: 5.6–6.2 months;

6 months probability of depletion: 87.3%;

The current water deficit is 181 m³/s, which translates to a loss of water from storage of some 15.6 million m³ per day.

Scenario Analysis with AI Predictions

The results of the AI-based scenario analysis are presented in Table 5.

Uncertainty Quantification and Risk Assessment

An extensive uncertainty analysis was realized using the available AI models.

Prediction Uncertainty

Based on the uncertainty analysis the following estimate was produced:

- Water quality uncertainty: ±10 g/L; and
- Uncertainty in estimating the water volume: ±0.05 billion m³.

Uncertainty in prediction of depletion time: ±0.3 months.

Computational Processing Time

The computational workflow took around 2.3 minutes per scene for image processing, 3.1 minutes per scene for the storage assessment and 1.7 minutes per scene for the update of the estimate of the depletion timeline. The total processing time was about 7.1 minutes with the experimental configuration in this study. These processing times suggest potential for reservoir assessment in a timely fashion within the proposed framework, but further evaluation under operational conditions and across different computing environments is required to establish real-time capability.

DISCUSSION

AI Model Performance and Advantages

The results highlight the effectiveness of the AI-based method in detecting water surfaces, outperforming the traditional methods assessed in the study. The U-Net model obtained an overall accuracy of 96.8%, surpassing by 7.5 percentage points the NDWI threshold model. The outcomes showed that segmentation using deep learning can be used to improve the consistency of delineating the water surface of the reservoir, which is essential for the following reservoir evaluation.The ensemble learning method outperformed the other models tested, with RMSE of 0.19 m, compared to 0.89 m of linear regression. Moreover, uncertainty quantification can be included in the modeling framework, thereby giving prediction intervals in addition to point estimates, which can help with risk-informed reservoir operation and decision making.This is in line with earlier research that has shown the efficacy of deep-learning techniques to hydrological and remote-sensing tasks. LSTM networks have already proven to be effective in hydrological prediction [17] and deep-learning approaches in water body extraction in remote sensing images [19]. These methods are generalized in the current research by using deep learning segmentation of water surfaces in conjunction with ensemble prediction and uncertainty quantification in a comprehensive reservoir-assessment framework.

Implications of the AI-Enhanced Assessment

The AI based assessment reveals significant decreases in water storage at Haditha Lake for the conditions examined in this study. The depletion-prediction model estimated that the remaining time would be 5.9 months (with a 95% confidence interval from 5.6 to 6.2 months). These estimates give a model-based idea about the potential depletion schedule, and should be considered with regard to the data available and the requirement for additional independent validation.The results of the feature importance analysis showed that the modified NDWI and near infrared spectral information were the most significant features for water detection and should be incorporated in future water monitoring systems. This understanding can be used to select sensors and processing algorithms for operational monitoring networks.

Technological Innovation and Scalability

The framework proposed integrates computer vision, machine learning, and predictive modeling, all into a single work flow for reservoir monitoring and assessment. The integration allows for automated processing of satellite and hydrological data, a structured approach for delineating water surfaces, predicting water levels, and performs uncertainty-aware assessment.The modular design of the framework offers possibility of adaptation to other reservoir systems. The present study was however assessed for Haditha Lake only and its transferability to reservoirs with different climatic, hydrological and geomorphological characteristics needs to be independently validated. It would be useful for future studies to assess the framework over a number of reservoirs and explore transfer-learning techniques to find out if some degree of model adaptation can be accomplished using a smaller number of extra training reservoirs.

Uncertainty Quantification and Decision Support

A key element of the proposed plan is the addition of uncertainty quantification to the assessment of a model. The framework is based on prediction intervals rather than just point predictions because it captures prediction interval variability around model outputs. This information can be used to support reservoir management decisions based on risk and assist in the interpretation of model predictions in the face of hydrological uncertainty.

Operational Implementation Considerations

Potential for operational monitoring of reservoirs with the proposed AI framework through integrating satellite observations, automated image processing and predictive modelling. Linkage to frequently updated streams from satellites and hydrological data could assist in the periodic evaluation of reservoirs and assist in the timely detection of changing water conditions. But deployment in an operational environment would necessitate additional validation of computational performance, the availability of data, system robustness, as well as model transferability for other hydrological conditions.

Conclusions

The results show that the AI-based assessment also gives an idea of the current “storage at Haditha” (HWST) which is currently about 2.80 billion m³ (25.2% of the HWST). The depletion-prediction model predicts a remaining time of 5.9 months with a 95% confidence interval of 5.6–6.2 months. The estimates must be treated as provisional and need to be further verified with other field observations.

The key innovations of this study are:

1. Water-surface segmentation with deep learning (U-Net) with an overall accuracy of 96.8%.
2. An ensemble predictive model that resulted in the lowest RMSE (0.19 m) value among the models evaluated, with 0.89 m for linear regression.
3. Ensemble of uncertainty quantification into predictive framework: prediction intervals and model output risk-informed interpretation.
4. Integrated development of a model based on satellite-image analysis, machine-learning based prediction and uncertainty quantification for reservoir monitoring and assessment.

Recommendations

Following this study and its limitations, the following recommendations are suggested:

1. Use continuous monitoring from satellite to monitor changes in reservoir surface area and water conditions.
2. Field validation of reservoir storage estimates based on independent water-level and storage data.
3. Continue to update the predictive models with additional inflow, outflow, water-level and satellite observations.
4. Establish and test thresholds for early warnings based on scientific evidence to aid in reservoir management under varying hydrological conditions.

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