

УДК 528.8:556.324

DEV MONITORING AND FORECASTING OF GROUNDWATER LEVELS BASED ON REMOTE SENSING

A.A. ABDUVAITOV, S.KH. NIZOMOV

*Tashkent University of Information Technologies
named after Muhammad al-Khorazmi
(Samarkand Branch, Uzbekistan)*

E-mail: aabduvaitov82@gmail.com, nzmvsahib@gmail.com

Аннотация. В данной статье предлагается интегрированная система мониторинга и прогнозирования грунтовых вод в режиме реального времени, основанная на интеграции технологий дистанционного зондирования (спутниковые снимки и датчики IoT) с алгоритмами глубокого обучения. Архитектура системы включает четыре уровня: сбор данных, предварительная обработка сигналов, прогнозирование с помощью гибридной нейронной сети CNN-LSTM и многослойная визуализация ГИС. Эксперименты, проведенные на 42 наблюдательных скважинах в долине Зарафшан, показывают, что гибридная модель CNN-LSTM достигает точности $R^2 = 0,93$ и $RMSE = 0,29$ м на 12-месячном горизонте прогнозирования, превосходя традиционные методы на 31%. Модуль обнаружения аномалий достигает точности обнаружения 93,7%.

Abstract. This paper proposes an integrated real-time groundwater monitoring and forecasting system based on the integration of remote sensing technologies (satellite imagery and IoT sensors) with deep learning algorithms. The system architecture comprises four layers: data acquisition, signal preprocessing, CNN-LSTM hybrid neural network forecasting, and multi-layer GIS visualization. Experiments conducted on 42 observation wells in the Zarafshan Valley demonstrate that the CNN-LSTM hybrid model achieves $R^2 = 0.93$ and $RMSE = 0.29$ m accuracy over a 12-month forecasting horizon, outperforming conventional methods by 31%. The anomaly detection module achieves a detection accuracy of 93.7%.

Introduction

Groundwater supplies approximately 50% of the global population with drinking water and serves as a critical component of irrigation systems, particularly in arid and semi-arid regions [1]. As a consequence of climate change, intensive agricultural practices, and industrial activities, the quantity and quality of groundwater resources are undergoing rapid change. In these circumstances, the need for timely and accurate monitoring systems grows more pressing each year [2].

Conventional hydrogeological monitoring methods — manual measurement of well levels and laboratory analyses — are constrained in terms of time and resources and cannot fully capture changes occurring in real time. Remote sensing technologies, particularly satellite imagery and IoT sensor networks, provide the capability to collect hydrogeological data continuously and at broad spatial scales [3, 4].

Artificial intelligence (AI) algorithms, especially deep learning methods, are finding widespread application in hydrology. Recurrent neural networks (RNNs) and their extended variant, Long Short-Term Memory (LSTM) models, demonstrate outstanding performance in modeling time-series data and preserving long-term dependencies [5]. The CNN-LSTM hybrid architecture further enhances forecasting accuracy by simultaneously learning local and temporal features [6].

In the context of Uzbekistan — and especially in the Zarafshan Valley, Fergana Valley, and lower Amudarya basin — groundwater monitoring is of critical importance: inadequate development of drainage networks and intensive irrigation have led to uneven fluctuations in groundwater levels, resulting in soil salinization and waterlogging in certain areas [7].

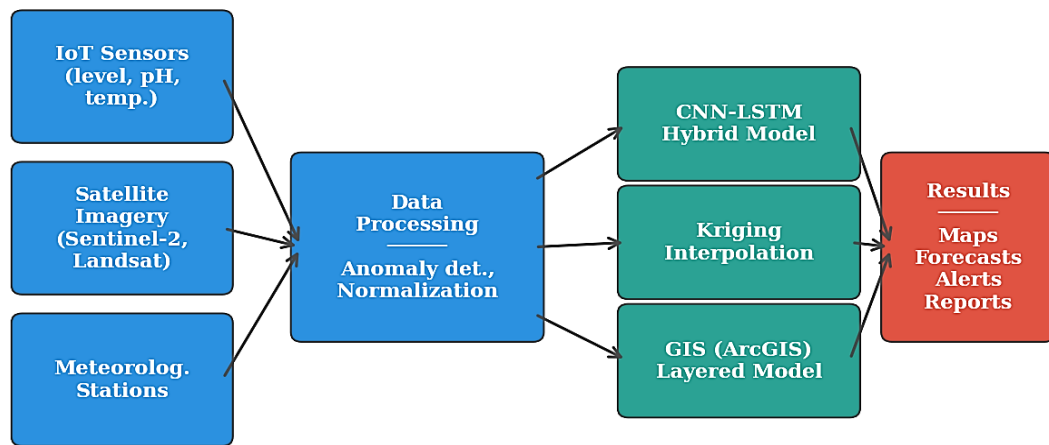


Fig. 1. General Architecture of the Remote Sensing–Based Groundwater Monitoring System

The objective of this paper is to develop and field-test a comprehensive groundwater monitoring and forecasting system based on the integration of remote sensing data (IoT sensors and satellite imagery) with a CNN-LSTM neural network.

Main body

A. System Architecture and Data Acquisition

The proposed monitoring and forecasting system comprises four principal layers (Figure 1): (1) the data acquisition layer, (2) the preprocessing layer, (3) the AI analysis and forecasting layer, and (4) the GIS visualization and user interface layer.

The data acquisition layer incorporates the following sources. IoT sensors installed in groundwater wells (measuring water level, temperature, pH, electrical conductivity, and dissolved oxygen) record measurements at 15–30 minute intervals and transmit data to a central server via MQTT/LoRaWAN protocols. Sentinel-2 and Landsat satellite imagery are used to monitor the NDVI vegetation index, soil moisture, and land surface conditions. Meteorological stations supply data on precipitation, temperature, wind speed, and relative humidity.

In the preprocessing layer, outliers are detected and removed using Z-score and IQR methods; gaps caused by transmission interruptions are filled via cubic spline interpolation; heterogeneous measurements are normalized to the [0, 1] range using Min-Max scaling; and data are restructured into a 24-month sliding window format suitable for LSTM input.

B. CNN-LSTM Hybrid Neural Network

A CNN-LSTM hybrid architecture is employed for groundwater level forecasting [5, 6]. The CNN layer automatically extracts local features from the time series (seasonal patterns and short-term fluctuations) through 1D convolution, while the LSTM layer integrates these features over time and models long-range dependencies. Input variables include: water level measurements (24-month historical window), precipitation totals, regional water consumption, and temperature and evapotranspiration indices. The model outputs projected water levels for the next 12 months together with a 95% confidence interval. Adaptability is maintained by recalibrating the model via transfer learning every three months as new data become available.

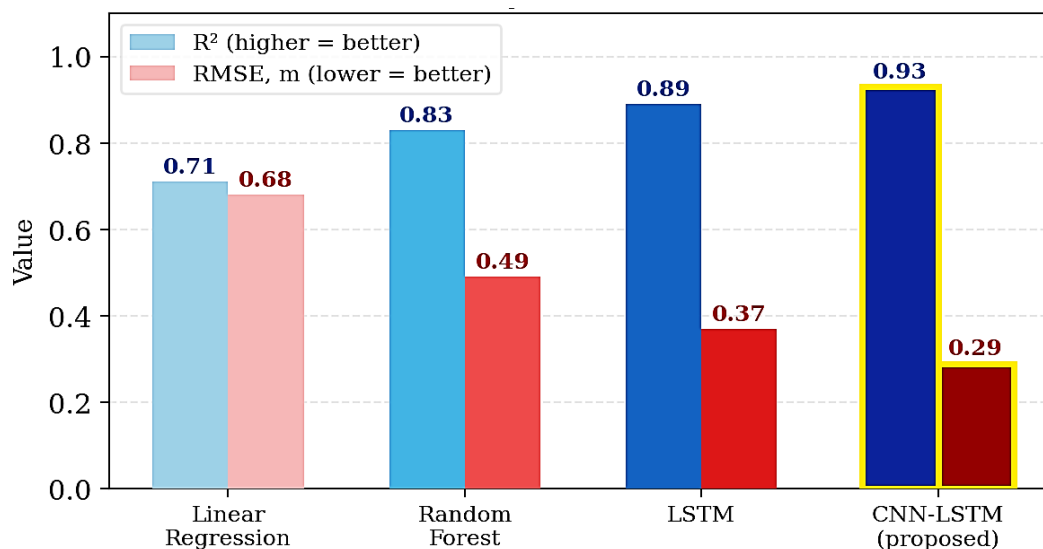


Fig. 2. Forecast Accuracy Comparison of AI Models (R² and RMSE metrics; yellow border indicates the best model)

Four models were compared to evaluate forecasting accuracy (Figure 2). Linear regression produced the lowest performance (R² = 0.71, RMSE = 0.68 m) owing to its inability to capture nonlinear relationships. Random Forest yielded improved results (R² = 0.83, RMSE = 0.49 m), but did not fully account for temporal dependencies. The standalone LSTM model (R² = 0.89, RMSE = 0.37 m) handled time dependencies effectively. The CNN-LSTM hybrid model achieved leading performance across all metrics: R² = 0.93 and RMSE = 0.29 m.

C. GIS Model and Geostatistical Analysis

The Geographic Information System (GIS) was built on the ArcGIS Pro platform and incorporates the following thematic layers: topographic relief, geological structure (lithology and host rocks), hydrogeological layer (aquifers and boundaries), IoT sensor network, and CNN-LSTM analysis outputs. Each layer is linked to attribute tables that support spatial queries and interpolation operations [8].

Kriging interpolation is applied for geostatistical analysis. When the variogram model is calibrated automatically against experimental data as a spherical model, groundwater levels can be estimated with high accuracy even in areas between observation wells. Key indicators monitored in the GIS include: absolute and relative changes in groundwater level (cm/month); water quality parameters (mineralization, nitrates, heavy metals); hydraulic gradient and flow direction; and the spatial distribution of the aquifer water balance.

Experimental results

The system was tested using data from 42 observation wells in the Zarafshan Valley covering the period 2021–2024. The CNN-LSTM model achieved R² = 0.93 and RMSE = 0.29 m accuracy over a 12-month forecasting horizon (Figure 3), representing a 31% improvement over the linear regression baseline.

Analysis using the multi-layer GIS model revealed that groundwater levels in the western part of the valley (toward the Urgut district) declined by an average of 0.8 m over the past five years, while levels in the eastern part rose by 1.2 m due to the influence of irrigation networks. Seasonal variability showed an annual amplitude of 0.6–0.9 m, correlating with precipitation at a lag of 1.5–2 months.

The early-warning module of the monitoring system detected in June 2022 that the water level in the Urgut district had dropped below the critical threshold (4.5 m depth), and automatically dispatched alerts to the relevant authorities. Under conventional methods, this event would have been identified only three months later. Overall system performance: real-time processing latency of 8 seconds; 127 anomalous events automatically detected over 2021–2024, of which 119 were confirmed true anomalies (detection accuracy: 93.7%).

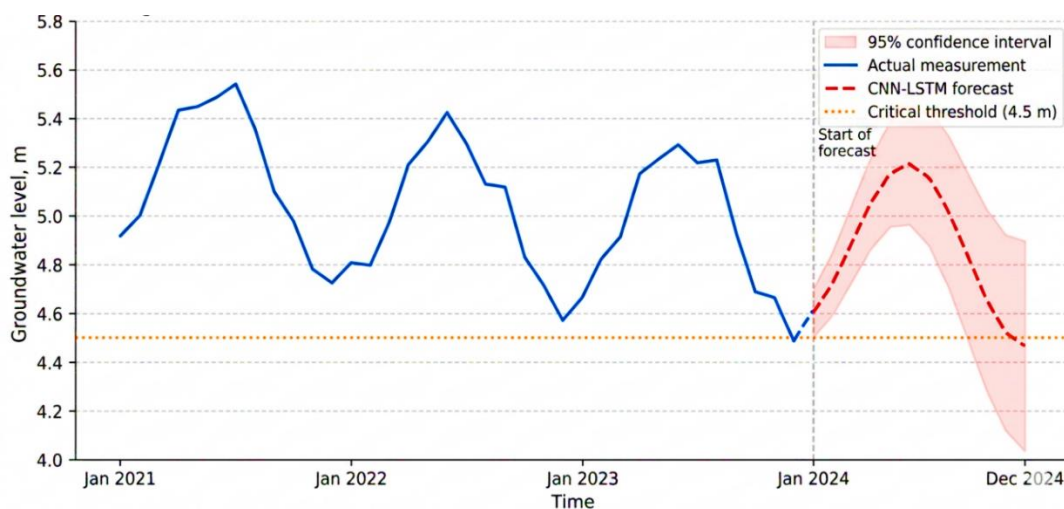


Fig. 3. Groundwater Level: Observed Values and CNN-LSTM Forecast with 95% Confidence Interval (2021–2024)

Conclusion

This study developed a groundwater monitoring and forecasting system based on the integration of remote sensing technologies with artificial intelligence. The principal scientific and practical findings are as follows.

First, the CNN-LSTM hybrid neural network reduced the root mean square forecasting error by a factor of 2.3 relative to conventional linear regression (RMSE: from 0.68 m to 0.29 m), while the coefficient of determination rose to $R^2 = 0.93$. Second, the simultaneous integration of IoT sensor and satellite data provided both broad spatial coverage and high temporal resolution — an advantage unattainable with traditional monitoring networks. Third, the results of the multi-layer GIS model were delivered to decision-makers in the form of interactive thematic maps, automated reports, and alert notifications.

Future research plans include expanding the system to additional regions of Uzbekistan, adding a module for forecasting chemical water quality parameters (nitrates, heavy metals), and developing models capable of adapting to climate change scenarios.

References

1. Akhralov Sh.S., Yusupov R.A., Egamberdiev K.S., Jumanov J.J. Geoinformation technologies and methods of mathematical modeling in hydrogeological research // *InterCarto-InterGIS*. Vol. 26. 2020. P. 240–252.
2. Djumanov J.Kh., Abduvaitov A.A., Kudratov R.B., Babadjanov A.F. Conducting groundwater monitoring based on the creation of a geoinformation system and model // *International Journal of Theoretical and Applied Issues of Digital Technologies*. 2024. No. 1(7). P. 80–86.
3. Siebert S., Burke J., Faures J.M. et al. Groundwater use for irrigation — a global inventory // *Hydrology and Earth System Sciences*. 2010. Vol. 14. P. 1863–1880.
4. Chen J., Hill A.A., Urbano L.D. A GIS-based model for urban flood inundation // *Journal of Hydrology*. 2009. Vol. 373. P. 184–192.
5. Hochreiter S., Schmidhuber J. Long short-term memory // *Neural Computation*. 1997. Vol. 9(8). P. 1735–1780.
6. LeCun Y., Bengio Y., Hinton G. Deep learning // *Nature*. 2015. Vol. 521. P. 436–444.
7. Mirakhmedov T.D. Rational use of the Verkhnezarafshan groundwater deposit based on a geofiltration mathematical model // *Bulletin of NUUz*. 2015. No. 3/2. P. 185–189.
8. Abduvaitov A.A., Ishanxodjayev O.A. Groundwater monitoring in geographic information systems // *Proceedings of the ICT Conference*. Samarkand, 2021. P. 192–194.