



HAL
open science

A comparison of AI methods for Groundwater Level Prediction in Burkina Faso

Abdoul Aziz Bonkougou, Souleymane Zio, Rodrique Kafando, Abdoul-Kader Kabore, Aminata Sabané, Tégawendé F. Bissyandé

► **To cite this version:**

Abdoul Aziz Bonkougou, Souleymane Zio, Rodrique Kafando, Abdoul-Kader Kabore, Aminata Sabané, et al.. A comparison of AI methods for Groundwater Level Prediction in Burkina Faso. 2024. hal-04425413

HAL Id: hal-04425413

<https://hal.science/hal-04425413>

Preprint submitted on 30 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

A comparison of AI methods for Groundwater Level Prediction in Burkina Faso

Abdoul Aziz Bonkougou^{*1,3}, Souleymane Zio³, Rodrique Kafando¹, Abdoul-Kader Kabore¹, Aminata Sabané², Tégawendé F. Bissyandé^{1,2}

¹Centre d'Excellence CITADEL, Université Virtuelle du Burkina Faso

²Département d'Informatique, UFR/SEA, Université Joseph KI-ZERBO, Burkina Faso

³Institut du Génie Informatique et Télécoms, Ecole Ploytechnique de Ouagadougou

*E-mail : abbonkounkougou@gmail.com

Abstract

Groundwater serves as a valuable resource to supplement surface water, and its extensive utilization underscores the importance of precise groundwater level predictions. Burkina Faso confronts a critical challenge in the domain of sustainable groundwater resource management, underscoring the need for accurate forecasts of groundwater levels to enable efficient resource allocation and ensure long-term sustainability. This study introduces a robust framework that uses state-of-the-art Artificial Intelligence methodologies to predict groundwater levels across six strategically located piezometers in Burkina Faso's Central Plateau region. The dataset combines piezometric Measurements, Rainfall, and vegetation indices that serves as a multi-faceted feature space for model training. We systematically evaluated the performance of three specific machine learning models—NeuralProphet, XGBoost, and Long Short-Term Memory to determine which machine learning model offers the most robust predictions, enabling more effective and sustainable groundwater management. We observe that the XGBoost model outperforms its counterparts in terms of predictive accuracy. The findings of this study offer critical insights into the temporal variations in groundwater levels, thereby contributing to the formulation of more efficient water resource management strategies and facilitating data-driven decision-making processes in the target region.

Keywords

Groundwater level prediction, XGBoost, LSTM, NeuralProphet, Satellite Time-Series Imagery

I INTRODUCTION

In Burkina Faso, a Sahelian country, groundwater is used extensively to make up for the shortage of surface water [4]. Groundwater is used for agriculture, livestock breeding, mining, drinking, etc[9]. Nevertheless, rapid population growth, improved living standards and increased water demand linked to economic activities are exerting growing pressure on groundwater reserves [6]. This growing need calls for efficient and sustainable management of groundwater resources [5]. Groundwater levels are a direct indicator of the availability of groundwater resources [8]. Variations in groundwater levels can directly influence groundwater resource management strategies [1]. Effective groundwater management therefore depends on control of the water table. This control requires the ability to predict these level fluctuations. To achieve this

goal, two main approaches have emerged: numerical methods and Machine Learning methods, each with its advantages and disadvantages. Numerical methods offer a detailed representation of hydrological processes, but can be complex to implement and require precise data on subsurface properties [3]. Previous studies have shown that ML models outperform numerical methods in terms of prediction performance [2, 3, 7].

The problem at the core of this study is the need for accurate predictions of groundwater levels, which are vital for effective resource allocation and long-term sustainability. To tackle this issue, We apply three advanced Machine Learning algorithms—NeuralProphet, Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM)—each rigorously evaluated using performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The rationale behind this choice was driven by the effectiveness of these models in predicting groundwater levels observed in the literature review. This research aims to determine which machine learning model offers the most robust predictions, enabling more efficient and sustainable groundwater management in Sahelian contexts. We focus on six strategically selected piezometers in the Central Plateau region of Burkina Faso. These piezometers are contextualized by auxiliary variables such as Rainfall and enhanced vegetation index (EVI).

The paper is structured as follows: Section II provides an overview of the study area, data sources, and methodological approach, setting the stage for the research. Section III delves into an in-depth analysis and discussion of the results, with an emphasis on the comparative assessment of the models using RMSE and MAE metrics. Section IV wraps up with the study’s conclusions, underscoring the significance of our findings for the sustainable management of water resources in Burkina Faso.

II MATERIALS AND METHODS

2.1 Study Area and Data Collection

2.1.1 Study Area

The Central Plateau is a region of Burkina Faso characterized by relatively flat terrain and moderate altitudes. The climate of the Central Plateau is Sahelian, meaning that it has a short but crucial rainy season, extending from June to September. Annual Rainfall is limited, creating a semi-arid environment. However, despite these climatic constraints, the Central Plateau is an important agricultural region for Burkina Faso. The region’s vegetation is adapted to Sahelian conditions, with wooded and grassy savannahs. Figure 1 show the plateau central region. Figure 2 displays the study area and the locations of the piezometers. We have a total of 6 piezometers distributed across the following localities: Barago, Boussé, and Mogtédó, with two piezometers per locality. The proximity of the piezometers within the same locality can create the illusion of having 3 piezometers instead of 6 due to their close proximity.

The data used in this study come from daily groundwater level records in six piezometers located in the Central Plateau region. These data were supplied by the Direction Générale des Ressources en Eau (DGRE).

In addition to piezometric Measurements, we integrated other factors such as Rainfall and the enhanced vegetation index (EVI). Rainfall data were collected from the National Meteorological Department. These data come from weather stations located in the same localities as the



Figure 1: Burkina Faso Plateau Central Region

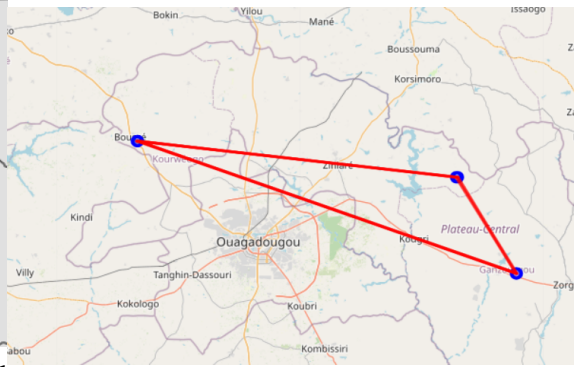


Figure 2: Study area

piezometers studied. As for vegetation, we retrieved the enhanced vegetation index from satellite images. Using javascript code and images provided by the Landsat 7 satellite, we were able to extract the enhanced vegetation index for each piezometer using the google earth engine. The Enhanced Vegetation Index (EVI) is an improved vegetation index used to assess the health and vigor of vegetation on Earth. It is a quantitative measure of greenness and plant photosynthesis, based primarily on satellite data and hyperspectral imagery. The EVI was developed to overcome some of the limitations of conventional vegetation indices, such as the Normalized Difference Vegetation Index (NDVI). The EVI takes into account atmospheric scattering, ground reflection and other factors that can influence the accuracy of vegetation assessment. It is calculated from Measurements of light reflectance at different wavelengths, allowing us to correct for distortions caused by the atmosphere and obtain more accurate estimates of vegetation density and health. The experimental dataset utilized in this study consists of time-series Measurements, encapsulating piezometric levels, Rainfall statistics, and the Enhanced Vegetation Index (EVI), all of which were systematically collected over the timeframe of 2010 to 2021.

2.2 Methods

The methodology involves standard machine learning processes, which include data preprocessing, the division of data into training and testing sets, model training, and concluding with model evaluation. For a comprehensive view of our modeling framework, please refer to the architectural diagram presented in the figure 3. Regarding data preprocessing, the input data undergoes normalization using MinMax scaling. This scaling method standardizes values to a specified range, typically within 0 and 1. The models undergo training using various combinations of columns, namely "Measurement +EVI+Rainfall" "Measurement+EVI", "Measurement+Rainfall", and "Measurement." These combinations are employed as input features for the models to predict the target feature, "Measurement." This approach allows for an assessment of each column's contribution to the predictive accuracy of the models. As the objective of this research is to conduct a comparative analysis of the effectiveness of these three machine learning algorithms: XGBoost, Neural-Prophet, and LSTM, the subsequent section outlines these tree models and their application in this research. To assess the model performance, we employed two widely recognized metrics: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). These metrics offer valuable insights into the disparity between the predicted and actual groundwater level values, allowing us to gauge the overall accuracy of our models.

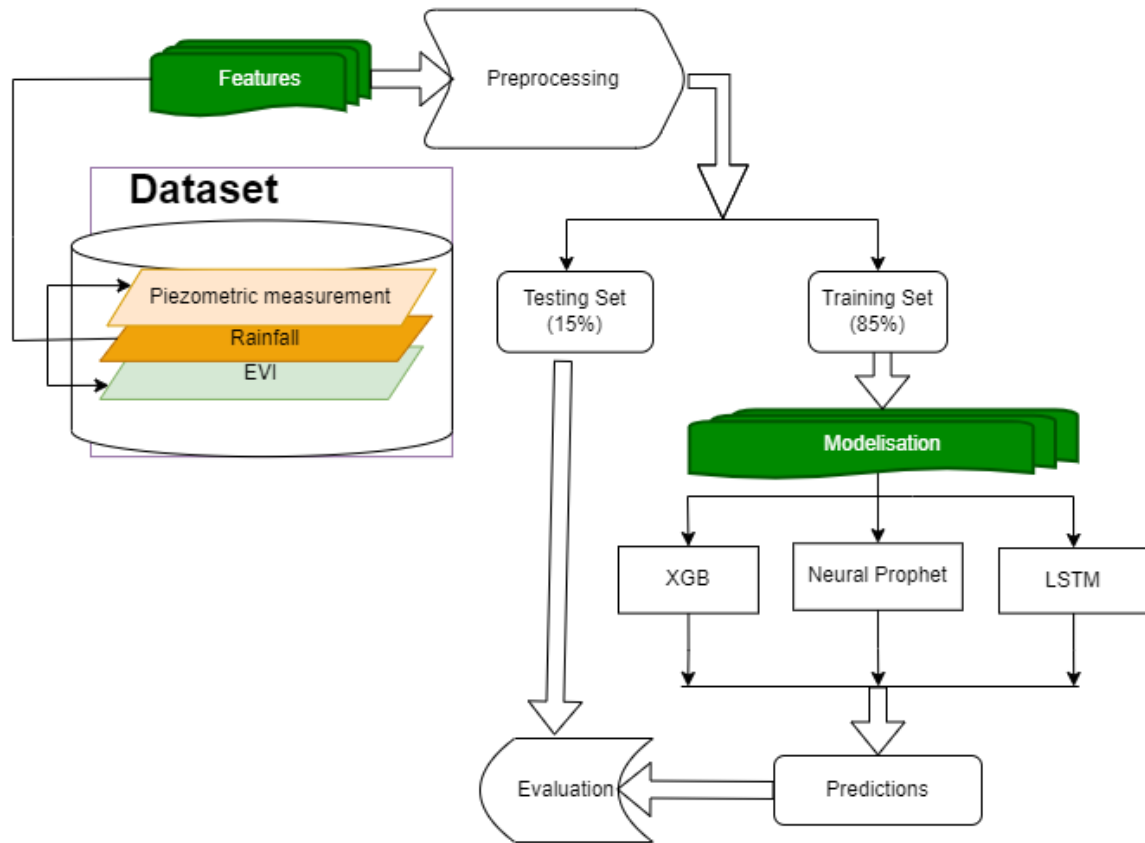


Figure 3: Model architecture

III RESULTS AND DISCUSSION

3.1 LSTM Results Analysis

Table 1 offers a comprehensive insight into the RMSE and MAE values associated with LSTM models, implemented with various combinations of input columns. This table serves as a valuable resource for understanding the model's performance across diverse feature configurations.

The performance of LSTM exhibits notable variability, contingent on both the chosen feature combinations and the specific piezometer in consideration. For instance, optimal results for piezometers like Barago SE6 and Boussé SE1G are attained through the combination of "Measurement" and "EVI." Conversely, in the case of Barago SE1 and Boussé SE5G piezometers, the most effective feature combination involves "Measurement" and "Rainfall." Interestingly, for Mogtedo SE3 and Mogtedo SE5B piezometers, the utilization of solely the "Measurement" feature yields the best results. A deep dive into LSTM's results underscores the profound impact of feature combinations on its overall efficacy. The inclusion of the "Rain" column notably reduces the mean RMSE and MAE, and the incorporation of "EVI" further strengthens its performance. However, it is crucial to note that the features "EVI" and "Rainfall" do not contribute significantly to the improvement of the overall results, as observed in the detailed examination of the outcomes.

Table 1: RMSE and MAE values for LSTM with different column combinations

Columns used	Barago SE1	Barago SE6	Boussé SE1G	Boussé SE5G	Mogtedo SE3	Mogtedo SE5B
RMSE						
Measurement, EVI, Rainfall	1.0036	1.0166	0.3330	0.3176	0.0369	0.1346
Measurement, EVI	0.6275	0.4023	0.2431	0.2895	0.1020	0.2179
Measurement, Rainfall	0.3779	0.9237	0.6509	0.2772	0.03102	0.1670
Measurement	0.5470	1.0035	0.3442	0.3409	0.0146	0.1279
MAE						
Measurement, EVI, Rainfall	0.8936	0.9326	0.2756	0.2642	0.0350	0.1224
Measurement, EVI	0.557	0.3245	0.2082	0.2389	0.0881	0.2013
Measurement, Rainfall	0.2633	0.8610	0.5787	0.2284	0.02443	0.1427
Measurement	0.4831	0.8689	0.3125	0.2838	0.0121	0.1056

3.2 NeuralProphet Results Analysis

Table 2 highlights RMSE and MAE values for NeuralProphet across various piezometers, revealing fluctuations in the model's performance depending on the specific monitoring point. The performance of the NeuralProphet model is diverse, showcasing notable success for certain piezometers, such as "Mogtedo SE3" and "Mogtedo SE5B." However, challenges arise with increased errors observed for other locations, including "Barago SE1" and "Barago SE6." On the other hand, for the "Boussé SE1G" and "Boussé se5" piezometers, the NeuralProphet model shows intermediary performance. It is noteworthy that, in this model, the sole predictor utilized is the piezometric level.

Table 2: RMSE and MAE values for NeuralProphet

Column	RMSE	MAE
Barago SE1	2.1591	1.9191
Barago SE6	1.6002	1.4423
Boussé SE1G	0.7295	0.6611
Boussé SE5G	0.5100	0.4616
Mogtedo SE3	0.0425	0.0349
Mogtedo SE5B	0.1313	0.1180

3.3 XGBoost Results Analysis

Table 3 presents a comprehensive overview of RMSE and MAE values for XGBoost across different combinations of input columns. **Columns Used** provides detailed explanations for each combination of input features. XGBoost consistently exhibits outstanding performance across all piezometers, showcasing remarkably low average RMSE and MAE values. Its predictions particularly excel for piezometers such as "Mogtedo SE3", and it maintains commendable accuracy for "Boussé SE1G". While there is a slight deviation in performance for piezometers like "Barago SE1", this appears to be more of an exception than a prevailing trend. Notably, the influence of input feature combinations on XGBoost's performance is relatively modest; the average RMSE and MAE values remain relatively stable across various configurations. This observation suggests that auxiliary columns such as "EVI" and "Rain" have minimal impact on influencing the outcomes of XGBoost. The use of the "measure" column consistently shows lower RMSE values for all data sets. Thus, its use as a primary input feature generally results in reduced RMSE and MAE values, suggesting its effectiveness as a predominant predictor.

Table 3: RMSE and MAE values for XGBoost with different column combinations

Columns used	Barago SE1	Barago SE6	Boussé SE1G	Boussé SE5G	Mogtedo SE3	Mogtedo SE5B
RMSE						
Measurement, EVI, Rainfall	0.07521	0.048285	0.00128	0.00167	0.00285	0.00091
Measurement, EVI	0.07531	0.0481	0.0013	0.00157	0.00297	0.00091
Measurement, Rainfall	0.0749	0.0483	0.001301	0.00157	0.00190	0.00091
Measurement	0.0748	0.0482	0.0013	0.00157	0.00175	0.00097
MAE						
Measurement, EVI, Rainfall	0.05531	0.02968	0.0010	0.00108	0.00220	0.00074
Measurement, EVI	0.0554	0.02954	0.00107	0.00106	0.00229	0.00074
Measurement, Rainfall	0.0549	0.0295	0.001049	0.00104	0.00142	0.00074
Measurement	0.0549	0.0295	0.00106	0.00104	0.00123	0.00079

3.4 Comparative study

The piezometers "Mogtedo SE3" and "Mogtedo SE5B" consistently present lower error metrics, underscoring their notable superiority in predictive accuracy. This steadfast performance suggests a robust modeling capability for these specific monitoring points. On the contrary, "Barago SE1" and "Barago SE6" consistently exhibit elevated error metrics across various feature combinations, indicating a comparatively higher level of discrepancy between the predicted values and the actual observations.

Meanwhile, the piezometers "Boussé SE1G" and "Boussé SE5G" demonstrate results in the intermediate range, reflecting a moderate level of prediction accuracy. This mid-range positioning suggests that the models applied to these piezometers achieve a satisfactory but not exceptionally precise level of forecasting.

The observed variability in results among the different piezometers may potentially be attributed to the unique data patterns or inherent characteristics specific to each monitoring point.

It is important to highlight that the inclusion of additional features, "EVI" and "Rainfall," does not significantly enhance the predictive outcomes for both XGBoost and LSTM models. Therefore, we use their results derived exclusively from the Measurement feature for comparison with the results obtained using NeuralProphet.

Upon conducting a comprehensive evaluation of the three models side by side, XGBoost consistently emerges as the leading performer across all piezometers, as depicted in Table 4. This trend underscores the robust predictive capabilities of XGBoost in comparison to LSTM and NeuralProphet across the specified monitoring points.

It combines robustness with efficiency, consistently delivering low errors across the majority of piezometers. Thus, for those seeking steadfast and precise predictions, XGBoost stands as the recommended choice due to its unwavering performance caliber.

IV CONCLUSIONS

In the context of Burkina Faso, a Sahelian country facing increasing challenges linked to limited access to surface water, effective management of groundwater resources is of crucial importance. This study centers on predicting groundwater levels, a crucial approach for gaining deeper insights into these invaluable resources. Our research delves into predictions of water levels in six strategically placed piezometers within the Central Plateau region in Burkina

Table 4: Models comparison

Piezometers	NeuralProphet	LSTM	XGBoost	Comparison
Barago SE1	2.1591	0.4831	0.0748	NeuralProphet < LSTM < XGBoost
Barago SE6	1.6002	0.8689	0.0482	NeuralProphet < LSTM < XGBoost
Boussé SE1G	0.7295	0.3125	0.0013	NeuralProphet < LSTM < XGBoost
Boussé SE5G	0.5100	0.2838	0.00157	NeuralProphet < LSTM < XGBoost
Mogtedo SE3	0.0425	0.0121	0.00175	NeuralProphet < LSTM < XGBoost
Mogtedo SE5B	0.1313	0.1056	0.00097	NeuralProphet < LSTM < XGBoost

Faso. The objective was to perform a comparative analysis among three different Machine Learning methods predictive accuracy: XGBoost, NeuralProphet, and LSTM, with the aim of identifying the most effective method for sustainable groundwater resource management. The results revealed that the XGBoost model outperformed the others, demonstrating exceptional performance with remarkably low RMSE and MAE values for all piezometers. These findings provide valuable information to guide groundwater resource management decisions and strategies, enabling more efficient use of these precious resources and better preparation for future challenges.

For the improvement of this research, the following recommendations are proposed:

- **Incorporation of Additional Features:** Expanding the dataset to include more relevant features, such as geological data and land use information, holds the potential to enhance prediction accuracy significantly.
- **Real-Time Monitoring:** The development of a real-time monitoring system that seamlessly integrates predictive models with real-time data collection on the ground would enable a more dynamic and adaptive approach to groundwater management.

As for future work, two potential avenues have been identified:

- **Real-Time Monitoring System :** Our plan involves the creation of a real-time monitoring system, applying the insights gleaned from this study to enhance dynamic resource allocation.
- **Policy Formulation:** Collaboration with policymakers and stakeholders is vital to integrating research findings into actionable policies for the sustainable management of groundwater resources.

By addressing these recommendations and embarking on future work, we can contribute to more effective and sustainable resource allocation, not only in Burkina Faso but in regions facing similar challenges worldwide.

REFERENCES

Publications

- [1] T. Abiye, K. Masindi, H. Mengistu, and M. Demlie. “Understanding the groundwater-level fluctuations for better management of groundwater resource: A case in the Johannesburg region”. In: *Groundwater for Sustainable Development* 7 (Sept. 1, 2018), pages 1–7. ISSN: 2352-801X.

- [2] M. Malekzadeh, S. Kardar, and S. Shabanlou. “Simulation of groundwater level using MODFLOW, extreme learning machine and Wavelet-Extreme Learning Machine models”. In: *Groundwater for Sustainable Development* 9 (Oct. 1, 2019), page 100279. ISSN: 2352-801X.
- [3] C. Chen, W. He, H. Zhou, Y. Xue, and M. Zhu. “A comparative study among machine learning and numerical models for simulating groundwater dynamics in the Heihe River Basin, northwestern China”. In: *Scientific Reports* 10.1 (Mar. 3, 2020). Number: 1 Publisher: Nature Publishing Group, page 3904. ISSN: 2045-2322.
- [4] A. P. Belemtougri, A. Ducharne, F. Tazen, L. Oudin, and H. Karambiri. “Understanding key factors controlling the duration of river flow intermittency: Case of Burkina Faso in West Africa”. In: *Journal of Hydrology: Regional Studies* 37 (Oct. 1, 2021), page 100908. ISSN: 2214-5818.
- [5] I. Fathy, A. Ahmed, and H. F. Abd-Elhamid. “Integrated management of surface water and groundwater to mitigate flood risks and water scarcity in arid and semi-arid regions”. In: *Journal of Flood Risk Management* 14.3 (2021). _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/e12720>. ISSN: 1753-318X.
- [6] M. B. Kafando, M. Koïta, M. Le Coz, O. R. Yonaba, T. Fowe, C. O. Zouré, M. D. Faye, and B. Leye. “Use of Multidisciplinary Approaches for Groundwater Recharge Mechanism Characterization in Basement Aquifers: Case of Sanon Experimental Catchment in Burkina Faso”. In: *Water* 13.22 (Jan. 2021). Number: 22 Publisher: Multidisciplinary Digital Publishing Institute, page 3216. ISSN: 2073-4441.
- [7] A. Najafabadipour, G. Kamali, and H. Nezamabadi-pour. “Application of Artificial Intelligence Techniques for the Determination of Groundwater Level Using Spatio–Temporal Parameters”. In: *ACS Omega* 7.12 (Mar. 21, 2022), pages 10751–10764. ISSN: 2470-1343.
- [8] H. Tao, M. M. Hameed, H. A. Marhoon, M. Zounemat-Kermani, S. Heddami, S. Kim, S. O. Sulaiman, M. L. Tan, Z. Sa’adi, A. D. Mehr, M. F. Allawi, S. I. Abba, J. M. Zain, M. W. Falah, M. Jamei, N. D. Bokde, M. Bayatvarkeshi, M. Al-Mukhtar, S. K. Bhagat, T. Tiyasha, K. M. Khedher, N. Al-Ansari, S. Shahid, and Z. M. Yaseen. “Groundwater level prediction using machine learning models: A comprehensive review”. In: *Neurocomputing* 489 (June 7, 2022), pages 271–308. ISSN: 0925-2312.
- [9] H. M. D. Gramont. “DIAGNOSTIC SUR LES EAUX SOUTERRAINES”. In: ().