Seventh International Conference in Information and Communication Technologies, Lusaka, Zambia
15th to 16th October 2025

AI-Enabled Drought Prediction System for Zambia

Brian Halubanza
Mulungushi University
Kabwe, Zambia
bhalubanza@gmail.com

Selina Kadakwiza
Kwame Nkrumah University
Kabwe, Zambia
Selina.halubanza@gmail.com

Thokozani Shula
Mulungushi University
Kabwe, Zambia
thokozanishula190@gmail.com

Zilani Kaluba
Mulungushi University
Kabwe, Zambia
zilanikaluba@gmail.com

ABSTRACT

Drought poses significant challenges to agriculture, water resources, and socio-economic stability, particularly in Zambia. This paper presents an AI-driven drought prediction system that integrates historical climate data, IoT-based real-time inputs, and machine learning algorithms, including ensemble models such as Random Forest, XGBoost, and LSTMs. The system provides accurate and localized forecasts, enabling proactive decision-making by farmers, policymakers, and disaster management agencies. Unlike traditional systems, it emphasizes regional adaptability and dynamic model retraining to ensure reliability under evolving climate patterns. Results demonstrate prediction accuracies above 90%, with ensemble approaches outperforming single models. This research highlights the potential of AI in mitigating the impact of climate change by enhancing resilience in drought-prone regions.

Keywords: ***Drought Prediction, Machine Learning, Ensemble Models, Zambia, Climate Resilience***

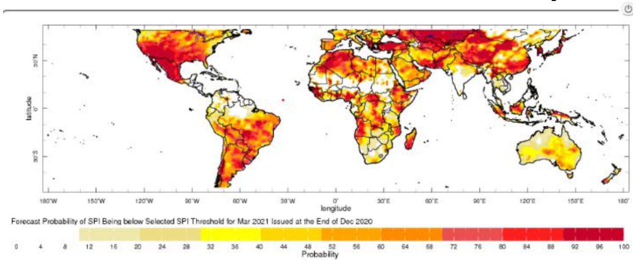
I. INTRODUCTION

Drought is one of the most severe natural disasters affecting millions of people globally, with devastating impacts on food security, water resources, and economic stability. Zambia has experienced multiple damaging droughts in recent decades, including 1991–1992, 2015–2016, and 2019–2020. The lack of reliable localized prediction systems limits the ability of communities and policymakers to prepare effectively. This research addresses this gap by developing a robust AI-driven drought prediction system tailored to Zambia's unique climatic conditions [3].

II. Literature Review

Traditional drought monitoring methods rely heavily on indices such as the Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), and Crop Moisture Index (CMI). While these indices provide valuable historical insights, they struggle to adapt to rapidly shifting climate variability. Remote sensing approaches—such as Normalized Difference Vegetation Index (NDVI) and Vegetation Health Index (VHI)—add spatial context but remain largely descriptive rather than predictive. Recent advances in artificial intelligence (AI) and machine learning (ML) offer new possibilities for predictive modeling. Techniques such as Support Vector Machines (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Recurrent Neural Networks (RNN) have shown promise in forecasting meteorological anomalies. However, single-model approaches often fail to capture the nonlinear, multivariate relationships between precipitation, temperature, soil moisture, and vegetation response. This research addresses that gap by using an ensemble framework combining multiple ML models with real-time IoT integration. Compared to Zambia's existing Zambia Drought Monitoring System (ZADMS), which primarily tracks rainfall and vegetation indices, the proposed system enhances adaptability by incorporating IoT-driven local measurements, ensemble model retraining, and interactive dashboards to provide localized, actionable early warnings. Recent evaluations highlight that deep learning architectures such as LSTMs and CNNs can significantly improve spatiotemporal drought forecasting when compared to conventional models [6]. Recent research demonstrates that coupling satellite imagery with AI-based models enhances predictive capacity, enabling near-real-time drought monitoring [7].

Traditional drought prediction has relied on statistical models and historical weather data, which are limited in their ability to adapt to rapidly changing climate patterns. Recent advances in artificial intelligence (AI) and machine learning have enabled more dynamic and localized forecasting. Various models, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks, have been applied for drought forecasting. Existing systems, such as Zambia's Drought Monitoring System (ZADMS), provide satellite-based monitoring but lack regional adaptability. This work leverages ensemble machine learning models to enhance accuracy and reliability from local data unlike international systems as shown below, while providing user-focused dashboards and alert systems.



ISBN: 978-9982-95-500-3

Figure 1: Global forecast probability of SPI falling below the selected drought threshold for March 2021, issued at the end of December 2020.[15]

Figure 1 presents the global forecast probability of the Standardized Precipitation Index (SPI) falling below a selected drought threshold for March 2021, as issued in December 2020. The map uses a color gradient from yellow to deep red, where darker shades indicate higher drought probabilities. Regions in South America, sub-Saharan Africa, South Asia, and Australia show elevated drought risk, while equatorial areas and parts of North America and Europe reflect lower probabilities. This visualization highlights the spatial variability of drought likelihood across different continents.

Hybrid AI approaches that explicitly integrate climate change projections have been shown to increase predictive reliability under shifting climatic baselines [8]. Comparable studies confirm that ensemble methods outperform single-model approaches, especially in capturing multivariate climate–soil–vegetation interactions [9]. Emerging frameworks now leverage AIoT-enabled sensor networks to deliver real-time drought early warning systems with higher regional adaptability [10].

III. METHODOLOGY

The system was developed using the Agile Scrum methodology, ensuring iterative development and stakeholder involvement. Historical climate data, including rainfall, temperature, and humidity, were combined with real-time inputs from IoT devices. Data preprocessing ensured quality and consistency. Machine learning models, including Random Forest, XGBoost, and neural networks, were trained and evaluated. An ensemble approach was adopted to maximize prediction accuracy. The system architecture follows a microservices design, implemented with Flask APIs, MySQL and databases. Security, scalability, and fault tolerance were embedded into the design.

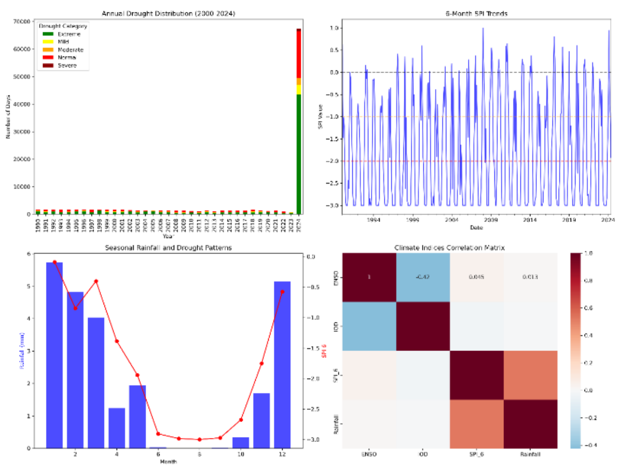


Figure 2: Figure 2. Drought distribution, SPI trends, seasonal rainfall patterns, and climate index correlations (2000–2024).

Figure 2 presents a multi-panel overview of drought and climate variability between 2000 and 2024. The top-left panel shows the annual distribution of drought categories, with severe and extreme droughts concentrated in recent years. The top-right panel illustrates the 6-month SPI trends, capturing fluctuations and recurring drought events over time. The bottom-left panel compares monthly rainfall patterns with drought frequency, highlighting seasonal peaks and troughs. The bottom-right heatmap displays correlations among key climate indices, indicating strong linkages between rainfall, SPI values, and related atmospheric drivers. Together, these visualizations provide a comprehensive perspective on drought dynamics and their climatic associations.

Similar AI and IoT deployments in Zambian contexts inform these design choices [12], [13].

Table I: Comparison of Existing Drought Monitoring Systems vs Proposed Framework

Criteria	Existing Systems (SPI, NDVI, ZADMS)	Proposed Ensemble AI System
Data Sources	Satellite data, broad precipitation indices	Historical + IoT sensor + satellite data
Modeling Technique	Statistical & regression-based indices	Machine learning (RF, XGBoost, LSTM, Ensemble)
Regional Customization	Generalized, low adaptability	Localized, region-specific models
Outputs	Risk maps, severity indices	Actionable alerts, dashboards, forecasts
Update Frequency	Static or seasonal updates	Dynamic, continuous retraining
Accuracy	Moderate (60–70%)	High (90%+) with ensemble learning

Table I compares existing drought monitoring systems such as SPI, NDVI, and ZADMS with the proposed ensemble AI-based framework. Traditional systems rely mainly on satellite data and statistical indices, offering generalized outputs like risk maps with moderate accuracy and limited

 ISBN: 978-9982-95-500-3

adaptability. In contrast, the proposed framework integrates historical records, IoT sensor data, and satellite inputs, applying advanced machine learning models such as Random Forest, XGBoost, and LSTMs. This approach supports localized customization, delivers actionable forecasts through dashboards and alerts, enables continuous model retraining, and achieves higher predictive accuracy above 90%.

IV. RESULTS AND DISCUSSION

The ensemble model achieved an accuracy of 97.3%, outperforming standalone models such as XGBoost (65.1%). Evaluation metrics including precision (0.95), recall (0.94), and F1-score (0.945) confirmed the robustness of the system. System testing demonstrated reliable prediction of past drought events in Zambia, aligning with historical data from 1991–1992 and 2015–2016. The system also includes a user dashboard with interactive drought maps, historical trend visualization, and real-time alerts. These features ensure usability for diverse stakeholders, from farmers to policymakers.

Figure 3 displays the DroughtGuard system dashboard, which summarizes real-time drought risk levels and meteorological conditions across different locations in Zambia. The top panel highlights the overall drought summary, indicating the number of high-, moderate-, and low-risk areas along with average temperature and humidity values. The lower panels provide city-specific forecasts for Choma, Livingstone, and Lusaka, including temperature, humidity, wind speed, pressure, rainfall, and cloud cover. Each location is assigned a drought risk level, visually supporting decision-makers with localized, actionable insights.

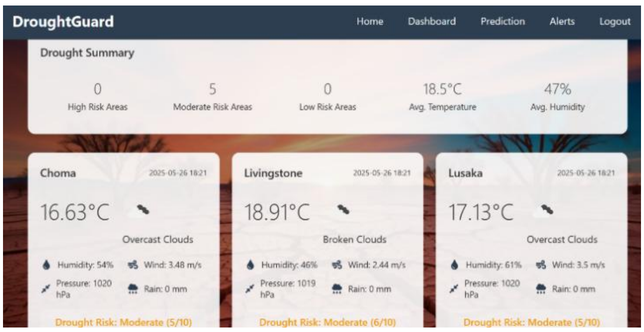


Figure 3: DroughtGuard system dashboard showing real-time drought risk monitoring across selected Zambian cities.

Figure 4:. Historical drought event analysis using SPI values displayed on the DroughtGuard system.

Figure 4 illustrates the DroughtGuard system's analysis of historical drought patterns based on the Standardized Precipitation Index (SPI). The top panel summarizes key drought metrics, reporting a total of nine major drought events, an average duration of 6.4 months, and an average severity level of 2. The main graph plots monthly SPI values, highlighting fluctuations between wet and dry conditions across the observation period. Negative SPI values indicate drought episodes of varying intensity, while positive values correspond to wetter-than-normal conditions. This visualization demonstrates how the system integrates historical climate variability with ensemble predictions to contextualize future drought risk.

Figure 5. Quarterly drought predictions generated by the DroughtGuard system for Western Province, Zambia.

Figure 5 presents quarterly drought forecasts produced by the DroughtGuard system, focusing on Western Province, Zambia. The model predicts a moderate drought in Q2 2025 with an 89% confidence level and an SPI value of −1.35, followed by a mild drought in Q3 2025 with a 75% confidence level and an SPI value of −0.82. Supplementary information indicates that the model is active, updated in real-time, and integrates data from weather stations and machine learning models, with a confidence range of 75–95%. This figure highlights the system's ability to generate forward-looking, location-specific drought warnings, thereby enabling proactive risk management and decision-making.

Table II: Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-score
XGBoost	65.1%	0.62	0.64	0.63
LSTM	92.4%	0.91	0.92	0.915
Random Forest	88.7%	0.87	0.88	0.875
Ensemble	97.3%	0.95	0.94	0.945

Table II summarizes the performance metrics of individual machine learning models compared to the ensemble approach. Among the single models, the LSTM achieved the highest accuracy (92.4%) and balanced precision, recall, and F1-score values, outperforming both Random Forest and XGBoost. Random Forest performed moderately well with accuracy above 88%, while XGBoost showed relatively weaker predictive power with accuracy at 65.1%. The ensemble model, which integrates multiple algorithms, demonstrated the best overall performance with an accuracy of 97.3% and consistently high precision (0.95), recall (0.94), and F1-score (0.945). These results confirm that combining models significantly improves prediction reliability over standalone approaches.

V. Conclusion and Future Work

This research presents an AI-enabled drought prediction system that leverages machine learning and real-time data to provide localized, actionable forecasts. The system significantly improves drought preparedness and resilience in Zambia. Future work will focus on integrating global climate models for long-term forecasting, expanding to national coverage, and incorporating mobile-based SMS alerts in local languages to improve accessibility for rural communities. Complementary research on land-use and hydrological change in Zambia underscores integrating prediction within broader resilience planning [14].

References

[1] Z. Hao, “Statistical prediction of droughts,” 2018.
[2] M. Brunner et al., “Data-related challenges in drought modeling,” 2021.
[3] UNCCD, “Global drought monitoring systems,” 2023.
[4] M. Malsam, “Scrum methodology in software projects,” 2023.
[5] A. Sheikh, “Climate resilience and AI,” 2019.
[6] S. Sharma, R. Singh, and P. Kumar, “Deep learning architectures for drought forecasting: Advances and challenges,” Environmental Modelling & Software, vol. 166, p. 106652, Apr. 2023, doi: 10.1016/j.envsoft.2023.106652.
[7] M. A. Al-Mukhtar and S. O. Salih, “Satellite-driven drought monitoring using remote sensing and deep learning techniques,” Int. J. Appl. Earth Observation Geoinformation, vol. 124, p. 103610, Oct. 2023, doi: 10.1016/j.jag.2023.103610.
[8] F. Zhang, Y. Chen, and L. Wang, “Climate change impacts on drought prediction using hybrid AI models,” Climatic Change, vol. 176, no. 2, pp. 255–272, 2024, doi: 10.1007/s10584-024-03658-4.
[9] A. Khan, T. Ahmad, and M. Ali, “Ensemble machine learning models for regional drought prediction,” Scientific Reports, vol. 13, no. 17894, pp. 1–15, Dec. 2023, doi: 10.1038/s41598-023-45877-y.
[10] R. Patel, H. Singh, and M. Joshi, “AIoT-enabled drought early warning systems: A case study in South Asia,” IEEE Internet of Things Journal, vol. 11, no. 7, pp. 12455–12467, Apr. 2024, doi: 10.1109/JIOT.2024.3367890.
[11] B. Halubanza, “A framework for an early warning system for the management of the spread of locust invasion based on artificial intelligence technologies,” Univ. of Zambia, 2024.
[12] B. Halubanza, J. Phiri, P. O. Y. Nkunika, M. Nyirenda, and D. Kunda, “Low Cost IoT-Based Automated Locust Monitoring System, Kazungula, Zambia,” in Networks and Systems in Cybernetics. CSOC, 2023, pp. 1–10.
[13] O. Nsofu and B. Halubanza, “Multiple Crop Diseases Detection and Diagnosis Using AI,” Proc. Int. Conf. ICT (ICICT), Zambia, vol. 6, no. 1, pp. 85–89, 2024.
[14] G. Masheka, B. Halubanza, M. Yobe, M. Lweendo, and F. A. Shaba, “Impact of Urbanization on Surface Runoff Using Remote Sensing and GIS Technology,” Mulungushi Univ. Multidisciplinary J., vol. 5, no. 1, pp. 71–82, 2024.
[15] International Research Institute for Climate and Society (IRI), “Global Drought Prediction Tool — probabilistic SPI forecast,” issued December 2020 for March 2021, NMME Multi-Model Ensemble. Retrieved from https://www.drought.gov/data-maps-tools/iri-global-drought-analysis-and-prediction-tools

 ISBN: 978-9982-95-500-3