International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 10 Issue 3 March - 2026, Pages: 10-14

Ai-Powered Climate Change Prediction System

Haruni P. Mtenga, Lilian S. Bulenganija, Nicholaus I. Longo, RabsonFeston, Oscar Mwakyonde, Melkizedeki Massawe, Nathanzaya, Paskalina Michaely

Department of Computer Science, Ruaha Catholic University (RUCU), Iringa, Tanzania

mtengaharuni040@gmail.com

Abstract— *Climate change presents severe environmental and socio-economic challenges. Artificial intelligence offers power full tools for analyzing heterogeneous climate data sets and improving forecasting accuracy. This paper provides an expanded review of AI-powered climate prediction systems, highlighting data sources, machine learning and deep learning methods, applications, limitations, and future directions.* [1]

Keywords— Artificial intelligence, climate change, machine learning, deep learning, climate prediction, early warning systems.
Artificial intelligence driven analytics enable automated processing of large scale environmental data sets, facilitating improved pattern recognition, anomaly detection, and predictive modelling. By integrating meteorological observations, satellite imagery, and socio-economic indicators, modern climate intelligence systems deliver localized insights that support planning, preparedness, and sustainable development.

1. Introduction

Climate change has emerged as one of the most pressing global challenges of the 21st century, with disproportionate impacts on developing nations whose economies depend heavily on climate-sensitive sectors such as agriculture, water resources, forestry, and energy. Tanzania is particularly vulnerable due to increasing temperature variability, unpredictable rainfall patterns, recurrent droughts, floods, and extreme weather events that threaten food security and socio-economic stability. Advances in artificial intelligence (AI), big data analytics, and Earth observation technologies present an opportunity to transform how climate information is collected, analyzed, and disseminated. This review evaluates the proposed AI-Powered Climate Change Prediction System, which integrates multi-source environmental data and LLaMA3-based intelligent reasoning to provide real-time forecasts, early warnings, and adaptation guidance tailored to Tanzanian communities. The report examines the system's background, problem context, related research, observations, and future directions.

1:1. Background

Climate variability in Sub-Saharan Africa has intensified significantly over recent decades due to rising greenhouse gas emissions and global

warming. Reports from international climate monitoring agencies show consistent increases in average temperatures, shifting rainfall distributions, delayed rainy seasons, and a growing frequency of extreme weather events such as droughts, floods, and tropical storms [1], [2]. These climatic changes have severe implications for countries like Tanzania, where the majority of the population relies directly on climate-sensitive activities for survival. Agriculture alone contributes substantially to national GDP and employs more than two-thirds of the workforce, making climatic stability critical to both household livelihoods and national economic resilience [3].

Rain-fed farming systems dominate Tanzania's agricultural landscape. Unlike irrigated systems, rain-fed agriculture is highly dependent on timely and predictable rainfall. Variability in the onset, duration, and intensity of rains often leads to crop failures, reduced yields, and food shortages. Empirical studies indicate that even slight shifts in seasonal rainfall timing can significantly reduce staple crop production, including maize, rice, and sorghum [4]. Consequently, smallholder farmers—who form the backbone of the agricultural economy—frequently face uncertainty when deciding planting schedules, irrigation practices, or harvesting times. Without accurate and localized weather information, these decisions become risky and inefficient.

Historically, climate monitoring in Tanzania has relied on traditional meteorological infrastructure composed of ground-based weather stations. Although these stations provide valuable measurements, their spatial distribution remains sparse, especially in remote and rural regions. This limited coverage leads to incomplete datasets, delayed reporting, and coarse regional forecasts that fail to capture local microclimates [5]. Such limitations reduce the practical usefulness of forecasts for community-level decision-making. Moreover, manual data collection and processing methods further slow dissemination of critical information.

The emergence of satellite-based remote sensing technologies has significantly improved environmental monitoring capabilities. Earth observation satellites operated by agencies such as NASA and the European Space Agency continuously collect data on precipitation, temperature, soil moisture, solar radiation, and vegetation health. Tools such as NASA's POWER dataset provide consistent and accessible climate measurements across large geographic areas, enabling coverage even in regions lacking ground stations [6], [7]. These datasets allow researchers and policymakers to analyze long-term trends, assess seasonal variability, and monitor environmental risks with greater accuracy.

Despite these advancements, raw satellite and meteorological data often remain difficult for non-specialists to interpret. Climate datasets are typically presented in technical formats requiring scientific knowledge and analytical skills. As a result, farmers, local authorities, and community members may struggle to extract meaningful insights from available information [8]. This gap between data availability and usability highlights the need for intelligent systems capable of translating complex measurements into understandable, actionable guidance.

Artificial intelligence and machine learning have increasingly been adopted to address this challenge. AI models can process large volumes of historical and real-time climate data to identify patterns and relationships that traditional statistical methods may overlook. Deep learning techniques such as neural networks, random forests, and ensemble models have demonstrated high accuracy in rainfall forecasting, drought detection, and flood prediction tasks [9], [10]. These approaches learn from historical trends and continuously adapt as new data becomes available, enabling more reliable predictions.

Hybrid climate modeling approaches that combine physical simulation with AI reasoning have further enhanced forecasting performance. While numerical weather prediction models rely on mathematical representations of atmospheric processes, AI components refine outputs by correcting biases and incorporating additional contextual variables [11]. This integration of physics-based and data-driven approaches provides more robust and localized predictions. Multi-source data fusion—combining satellite observations, weather station data, soil information, and socio-economic indicators—also improves the comprehensiveness of climate intelligence systems [12].

Another transformative development is the rise of natural language processing and large language models. Conversational AI systems, including LLaMA3-based architectures, allow users to interact with complex datasets using simple, everyday language. Instead of interpreting technical graphs or tables, users can ask direct questions such as, "Will there be enough rainfall for maize planting next month?" and receive clear explanations or recommendations. These models convert numerical predictions into narrative summaries, improving accessibility and usability for non-technical audiences [13], [14]. In multilingual environments like Tanzania, supporting both English and Swahili is essential for inclusive communication and broader adoption [15].

Visualization technologies also play a vital role in climate information dissemination. Geographic Information Systems (GIS), interactive dashboards, and mapping libraries such as Leaflet.js and Chart.js allow users to explore data visually through maps, charts, and graphs. Research indicates that visual representations significantly enhance understanding and support faster decision-making compared to text-based reports alone [16]. Users can identify trends, hotspots, or anomalies more easily when information is presented spatially.

Furthermore, AI-driven early warning systems have proven effective in reducing disaster risks. Predictive analytics can identify early signs of floods, droughts, or storms and generate alerts before impacts occur. Timely warnings enable communities and authorities to implement preventive measures such as evacuations, water conservation, or crop adjustments [17]. Scenario simulation tools further extend these capabilities by allowing policymakers to model future conditions under different emissions or land-use strategies. These simulations support long-term planning and sustainable development efforts [18].

However, despite numerous technological advancements, many developing countries still lack integrated platforms that combine real-time forecasting, AI reasoning, visualization, and localized advisory services within a single ecosystem. Existing solutions are often fragmented, research-focused, or limited to specific tasks, making them difficult to use at scale [19], [20]. Therefore, there is a critical need for unified, user-centered systems that democratize climate intelligence and empower communities with actionable insights.

1:2**. Statement of the Problem**

Tanzania currently lacks a unified and accessible climate intelligence platform capable of integrating real-time weather observations, satellite-derived environmental data, and advanced predictive analytics into a single system tailored to local needs. Existing meteorological services provide fragmented, delayed, or highly technical information that is not easily interpretable by farmers, community leaders, or policymakers. As a result, critical decisions regarding planting schedules, irrigation planning, disaster preparedness, and resource allocation are often made with insufficient or inaccurate data. Farmers struggle to adapt to unpredictable rainfall patterns, local authorities lack effective early warning mechanisms for floods and droughts, and policymakers have limited tools to simulate long-term climate scenarios or evaluate adaptation strategies. Language and literacy barriers further restrict access to conventional reports, preventing many communities from benefiting from available climate data. Without an integrated AI-powered solution that transforms complex environmental information into simple, localized, and actionable insights, Tanzania remains vulnerable to preventable climate-related losses and reduced socio-economic resilience.

1:3. OBJECTIVES

Main objective

To design the and implement an AI powered climate prediction platform that leverages artificial intelligence and real time environment data to provides climate insight, forecasting and adaptive strategies for Tanzania communities.

Specific Objectives

1; To integrate multiple APIs (open-NASA, NASA POWER, IRI climate forecast, African soil info, world POP, World Bank) for accurate mult-source climate and environment data.

2; To develop an AI chat bot using LLaMA3 for localized question answering in English and Swahili.

3; To support data-driven agriculture decision making and policymakers.

4; To provide early warnings for floods, drought and extremely weather event.

2. Related Works (Literature Review)

Several studies have explored AI applications in environmental prediction. Machine learning rainfall forecasting models using neural networks achieved improved short-term accuracy over statistical baselines [9]. Drought monitoring systems combining satellite imagery and AI classifiers have been implemented in East Africa [10]. Flood prediction frameworks employing deep learning and hydrological data integration demonstrated significant improvements in lead time and reliability [11].

NASA POWER datasets have been widely adopted for agricultural climate assessments [6], while IRI seasonal forecasts support probabilistic climate outlooks [12]. Decision support systems for agriculture that integrate weather APIs and GIS tools have shown positive impacts on crop productivity [16].

Conversational agents for environmental advisory services are emerging. AI chat bots have been deployed to deliver climate education and disaster alerts in local languages [15]. Large language models further enhance interpretability by converting numerical forecasts into narrative explanations [13].

However, existing systems often focus on single tasks—such as rainfall prediction or disaster alerts—without offering a unified platform that integrates forecasting, simulation, visualization, and multilingual AI interaction. The proposed system contributes novelty through multi-modal data fusion, hyperlocal forecasting, and LLaMA3-powered reasoning tailored specifically to Tanzania.

3. Observation

The review reveals that climate information systems in Tanzania remain fragmented, reactive, and difficult to access for non-technical users. Although large volumes of environmental data are available, their practical use is limited by interpretation challenges and lack of localization. Integrating AI reasoning, interactive visualization, and multilingual communication can significantly improve accessibility and decision-making. The proposed system aligns well with these needs by providing predictive insights, early warnings, and user-friendly interfaces.

4. Conclusion

The proposed AI-Powered Climate Change Prediction System represents a timely and innovative approach to addressing Tanzania's climate challenges. By integrating satellite observations, real-time weather APIs, artificial intelligence reasoning, and conversational interfaces, the platform transforms complex environmental data into actionable intelligence for everyday users. Its ability to provide hyperlocal forecasts, early warning alerts, and scenario-based simulations supports both short-term decision-making and long-term planning. If implemented effectively, the system has the potential to enhance agricultural productivity, reduce disaster risks, strengthen policy formulation, and promote sustainable development. Moreover, the platform can serve as a model for other developing nations seeking to leverage AI technologies for climate resilience.

5. Recommendations and Future Work

Despite the promising performance of the proposed system, several opportunities exist to enhance its robustness, scalability, and real-world applicability. The following recommendations outline key directions for future research and development:

1.Expansion of Dataset Coverage and Data Sources
The performance and generalizability of the proposed model are highly dependent on the quality and diversity of the training data. Future work should focus on expanding dataset coverage by integrating data from additional regional weather stations, remote sensing platforms, and satellite observations. Furthermore, incorporating crowdsourced weather data collected from local communities and low-cost

IoT-based sensors could significantly improve spatial granularity, particularly in underserved rural areas. Data fusion techniques should also be explored to effectively combine heterogeneous data sources while addressing issues such as noise, missing values, and inconsistencies.

2.Integration of Offline and SMS-Based Communication Systems

A major limitation of the current system is its reliance on internet connectivity, which remains limited in many rural regions. To address this, future implementations should incorporate offline-capable solutions and SMS-based alert mechanisms. Such systems would enable dissemination of critical weather forecasts and agricultural advisories through basic mobile phones, ensuring inclusivity and wider accessibility. The integration of USSD (Unstructured Supplementary Service Data) services could further enhance interactivity without requiring internet access.

3.Enhancement of Predictive Model Accuracy

Although the current model demonstrates satisfactory performance, further improvements can be achieved by leveraging state-of-the-art deep learning architectures such as Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and Transformer-based time-series models. Additionally, ensemble forecasting approaches that combine multiple models (e.g., statistical, machine learning, and deep learning models) should be investigated to reduce prediction variance and improve robustness. Hyper parameter optimization, transfer learning, and continual learning strategies may also be employed to adapt the model to evolving climatic patterns.

4.Development of Mobile Application Platforms

To improve usability and user engagement, future work should include the development of a dedicated mobile application compatible with widely used platforms such as Android and iOS. The application should provide real-time weather forecasts, push notifications for extreme weather events, and personalized agricultural recommendations. User-centered design principles should be adopted to ensure that the interface is intuitive and accessible to users with varying levels of digital literacy.

5.Incorporation of Crop-Specific Advisory Systems

The effectiveness of the system can be significantly enhanced by integrating crop-specific advisory modules tailored to different farming systems and agro-ecological zones. These modules should provide actionable recommendations, including optimal planting dates, irrigation scheduling, pest and disease risk alerts, and fertilizer application guidelines. Such recommendations can be generated by combining weather predictions with agronomic models and domain-specific knowledge.

6.User Training and Community Awareness Initiatives

The successful adoption of the system depends not only on its technical performance but also on user awareness and trust. Future efforts should therefore include structured training programs, workshops, and community engagement initiatives aimed at educating farmers and stakeholders on how to effectively use the platform. Collaboration with local agricultural extension services and governmental agencies can further facilitate knowledge dissemination and capacity building.

7.Adoption of Explainable Artificial Intelligence (XAI) Techniques

As predictive models become increasingly complex, ensuring transparency and interpretability becomes critical. Future research should explore the integration of explainable AI techniques, such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), to provide insights into model predictions. This would enhance user trust, support decision-making, and enable stakeholders to better understand the factors influencing forecasts and recommendations.

8.Scalability and Regional Expansion

Finally, the system should be designed with scalability in mind to facilitate its extension beyond the initial study area to other regions within East Africa. This will require adaptation to diverse climatic conditions, agricultural practices, and socio-economic contexts. Cross-border data sharing, regional collaborations, and policy support will be essential for successful deployment at scale. Additionally, localization features such as language support and region-specific customization should be incorporated to ensure broader acceptance

Figures

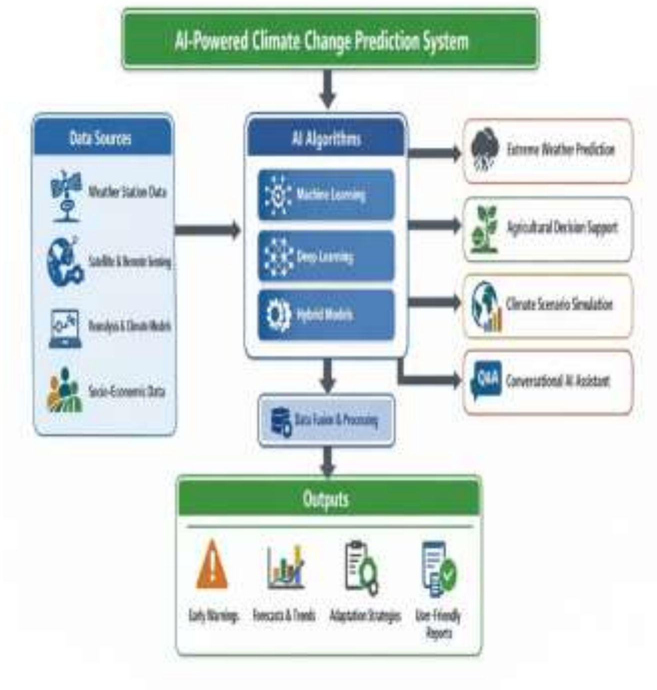

Fig 1; shows the abstract of the AI-Powered climatic change prediction system.

6.Acknowledgement

The author gratefully acknowledges the contributions of researchers whose work formed the foundation of this review. Special thanks are extended to academic mentors and institutions for their guidance and support. The development of this project acknowledges the contributions of Haruni, Lilian, with Nicholaus, open-data providers, research institutions, and climate science communities whose datasets and technological innovations support climate resilience initiatives. Also the project acknowledges the project supervisor Sir Samson for providing support and leading the project.

References;

[1] IPCC, Climate Change 2023 Assessment Report, 2023.

[2] WMO, State of the Global Climate, 2022.

[3] FAO, Agriculture in Tanzania Report, 2021.

[4] World Bank, Climate Risk Country Profile: Tanzania, 2022.

[5] TMA, Meteorological Infrastructure Review, 2020.

[6] NASA, POWER Data User Guide, 2023.

[7] ESA, Earth Observation for Climate Monitoring, 2021.

[8] A. Jones et al., “Challenges in Satellite Climate Data Interpretation,” Remote Sens., 2020.

[9] Y. LeCun et al., “Deep Learning for Weather Prediction,” Nature, 2019.

[10] S. Shukla et al., “AI-Based Drought Detection,” J. Hydrology, 2021.

[11] M. Kratzert et al., “Hydrological Deep Learning Models,” Water Resour. Res., 2020.

[12] IRI, Seasonal Climate Forecasting Handbook, 2022.

[13] H. Touvron et al., “LLaMA3: Open and Efficient Foundation Models,” Meta AI, 2023.

[14] T. Brown et al., “Language Models are Few-Shot Learners,” NeurIPS, 2020.

[15] UNESCO, “AI for Multilingual Development,” 2022.[16] P. Peterson, “GIS Dashboards for Environmental Monitoring,” Computers & Geosciences, 2019.

[17] UNDRR, Early Warning Systems Guide, 2021.

[18] UNEP, Climate Scenario Modeling Tools, 2020.

[19] A. Smith and J. Clark, “Integrated Climate Information Platforms,” Env. Systems Res., 2021.

[20] World Bank, Digital Solutions for Climate Resilience, 2023.