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MODELLING AI TECHNOLOGIES TOWARDS PREDICTION OF DISASTERS RELATED TO CLIMATE CHANGE: CASE STUDY OF NORTH RIFT, KENYA

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ABSTRACT

The study explores the application of artificial intelligence (AI) technologies for predicting climate change-induced disasters in Kenya's North Rift region. The North Rift, characterized by diverse topography including highlands, valleys, and arid plains, has experienced increasing frequency and severity of climate-related disasters such as floods, droughts, and landslides over the past decade. These events have significantly impacted agricultural productivity, water resources, infrastructure, and community livelihoods.

The study employs machine learning algorithms, including random forests, convolutional neural networks, and long short-term memory (LSTM) networks, to analyze historical meteorological data, satellite imagery, and ground-based observations. This multi-modal approach enables the integration of traditional climate indicators with novel predictive features derived from remote sensing. The research leverages data from Kenya Meteorological Department stations, climate analysis products, and Earth observation satellites to develop regionally calibrated prediction models. Preliminary findings demonstrate that AI-based systems outperform conventional statistical methods in predicting the onset, intensity, and spatial distribution of climate disasters in the region. Notably, the LSTM models achieved 78% accuracy in forecasting drought conditions three months in advance, while CNN-based image analysis shows promising results in identifying flood-prone areas with 82% precision. The research addresses challenges related to data availability and quality through novel data fusion techniques and transfer learning approaches that adapt global climate models to local contexts. The study further examines the integration of AI predictions into existing early warning systems and disaster management frameworks. Stakeholder interviews with local government officials, community representatives, and disaster management agencies reveal both opportunities and barriers for effective implementation. Key recommendations include capacity building for local meteorological services, development of user-friendly prediction interfaces, and community-based participatory approaches for validation and refinement of AI outputs. This research contributes to the growing field of climate AI and demonstrates the potential of machine learning in enhancing disaster preparedness and resilience in vulnerable regions. The findings provide a foundation for developing scalable AI-based early warning systems that can be adapted to similar ecological contexts across East Africa

KEYWORDS: Artificial Intelligence, Climate Change, Disaster Prediction, Early Warning Systems

INTRODUCTION

Climate change presents one of the most significant challenges of the 21st century, with far-reaching implications for environmental sustainability, socioeconomic development, and human security. In East Africa, and particularly Kenya's North Rift region, the manifestations of climate change have become increasingly apparent through the escalating frequency and severity of climate-related disasters. These include prolonged droughts, flash floods, landslides, and extreme temperature events that threaten agricultural productivity, water resources, infrastructure, and community livelihoods (Opiyo et al., 2022). The North Rift region of Kenya, encompassing counties such as Turkana, West Pokot, Elgeyo-Marakwet, Baringo, and parts of Trans Nzoia and Uasin Gishu, presents a complex ecological landscape characterized by diverse topography, varying climate zones, and socioeconomic vulnerabilities. This region has historically been prone to climate variability, but recent decades have witnessed unprecedented shifts in precipitation patterns, temperature regimes, and extreme weather events (Ayugi et al., 2020).The increasing unpredictability of these phenomena poses substantial challenges for disaster management and climate adaptation efforts.

Traditional approaches to disaster prediction in Kenya have relied primarily on historical weather data, meteorological observations, and statistical projections. While these methods provide valuable insights, they often fail to capture the complex, non-linear relationships between climate variables and disaster outcomes. Furthermore, conventional prediction models struggle to integrate diverse data streams and adapt to the rapidly changing climate conditions characteristic of the Anthropocene era (Mukhovi et al., 2020).

The emergence of artificial intelligence (AI) and machine learning (ML) technologies offers unprecedented opportunities to enhance climate disaster prediction capabilities. These computational approaches can process vast amounts of multidimensional data, identify subtle patterns, and generate predictions with increasing accuracy and lead time. The application of AI in climate science has gained significant momentum globally, with promising results in various domains including extreme weather forecasting, drought monitoring, and flood prediction (McGovern et al., 2022).

Despite the potential benefits, the integration of AI technologies into climate disaster prediction systems in developing regions like Kenya's North Rift remains limited. This gap stems from multiple factors, including data limitations, technical capacity constraints, institutional barriers, and contextual challenges that necessitate localized solutions. Addressing these limitations requires not only technological innovation but also careful consideration of the socioeconomic, cultural, and institutional contexts in which these systems operate.

This research aims to bridge this gap by developing and evaluating AI-based approaches for predicting climate-related disasters in Kenya's North Rift region. The study adopts a multi-modal approach that integrates traditional meteorological data with satellite imagery, remote sensing products, and ground-based observations to enhance prediction accuracy and lead time. Furthermore, the research explores pathways for integrating AI predictions into existing early warning systems and disaster management frameworks, with a focus on practical implementation and stakeholder engagement. Understanding long-term trends in climatic variables is essential for assessing climate change impacts on regional ecosystems and human livelihoods (Makokha et al., 2024).

The specific objectives of this research were to develop and evaluate machine learning models for predicting drought, flood, and landslide occurrences in Kenya's North Rift region using multi-modal data sources, to assess the comparative performance of different AI algorithms including random forests, convolutional neural networks (CNNs), and long short-term memory (LSTM) networks in climate disaster prediction, to identify key challenges and opportunities for integrating AI-based prediction systems into existing early warning and disaster management frameworks in the North Rift region and to formulate recommendations for enhancing the effectiveness and sustainability of AI-based climate disaster prediction systems in similar ecological contexts across East Africa.

This paper is structured as follows: Section 2 provides a comprehensive review of the literature on climate change impacts in Kenya's North Rift, conventional disaster prediction approaches, and applications of AI in climate science. Section 3 details the methodology employed in developing and evaluating the AI models, including data sources, preprocessing techniques, model architectures, and evaluation metrics. Section 4 presents the results of the model evaluations and comparative analyses. Section 5 discusses the implications of these findings for disaster management practices and climate adaptation strategies in the North Rift region. Finally, Section 6 concludes the paper with a summary of key findings and recommendations for future research and policy directions.

2. LITERATURE REVIEW

2.1 Climate Change and Disaster Trends in Kenya's North Rift

The North Rift region of Kenya has experienced significant climatic changes over recent decades, with tangible impacts on environmental conditions and disaster risks. According to Ayugi et al. (2020), mean annual temperatures in the region have increased by approximately 1.2°C since 1960, exceeding the global average warming rate. This warming trend has been accompanied by increasing rainfall variability, characterized by shifts in seasonal patterns, intensity, and spatial distribution.

Opiyo et al. (2022) conducted a comprehensive assessment of climate-related disasters in Kenya's arid and semi-arid regions, including parts of the North Rift. Their findings indicate a 47% increase in drought frequency and a 38% increase in flooding events between 2000 and 2020 compared to the previous two decades. These trends align with projections from regional climate models, which suggest continued warming and increasing precipitation extremes across East Africa through the mid-21st century (Ayugi et al., 2021).

The impacts of these climate-related disasters extend beyond immediate environmental damage to affect various socioeconomic dimensions. Wainaina et al. (2021) documented significant reductions in agricultural productivity, with maize yields declining by up to 30% during severe drought years in Trans Nzoia and Uasin Gishu counties. Similarly, Masese et al. (2023) reported substantial livestock losses in pastoral communities of Turkana and West Pokot, with mortality rates exceeding 60% during the 2020-2021 drought period. These counties heavily rely on rain-fed agriculture, making effective weather forecasting and environmental monitoring critical for increasing productivity and ensuring sustainable land use (Makokha, Barasa, & Khamala, 2025).

Infrastructure vulnerability represents another critical dimension of disaster impacts in the region. Landslides triggered by intense rainfall events have caused extensive damage to transportation networks, settlements, and public facilities in the highland areas of Elgeyo-Marakwet and West Pokot counties. A particularly devastating landslide in West Pokot in 2019 resulted in 43 fatalities and displaced over 10,000 people, highlighting the severe human security implications of these hazards (Wachira et al., 2021).

2.2 Conventional Approaches to Disaster Prediction

Traditional approaches to predicting climate-related disasters in Kenya have predominantly relied on statistical methods applied to historical meteorological data. The Kenya Meteorological Department (KMD) has historically employed statistical downscaling techniques to generate seasonal forecasts of rainfall and temperature, which serve as primary inputs for drought and flood early warning systems (Mukhovi et al., 2020). While these approaches provide valuable baseline information, they face several limitations in predicting the increasingly complex and non-linear climate phenomena observed in recent years.

Dynamical modeling represents another conventional approach to disaster prediction in the region. Ongoma et al. (2021) evaluated the performance of regional climate models in simulating extreme precipitation events across East Africa and found moderate skill in capturing the frequency and intensity of such events. However, these models often struggle with spatial resolution limitations, which constrain their utility for localized disaster prediction in topographically diverse regions like the North Rift.

Indigenous knowledge systems also play a significant role in traditional disaster prediction practices in the region. Nkuba et al. (2020) documented various indigenous methods used by communities in West Pokot and Turkana for forecasting droughts and floods, including observations of plant phenology, animal behavior, celestial patterns, and meteorological indicators. These knowledge systems offer valuable contextual insights but face challenges in adapting to the rapidly changing climate conditions characteristic of the Anthropocene era.

The limitations of conventional prediction approaches have prompted increasing investment in automated observation networks and early warning systems. Kenya's National Drought Management Authority has established the Drought Early Warning System (DEWS), which integrates various biophysical and socioeconomic indicators to monitor drought conditions across arid and semi-arid counties (Nyandiko et al., 2020). Similarly, the Flood Early Warning System (FEWS) operated by the Water Resources Authority provides alerts based on rainfall and river level monitoring in flood-prone watersheds. While these systems represent important advances, their effectiveness is constrained by data gaps, limited computational capacity, and challenges in disseminating actionable information to vulnerable communities.

2.3 Applications of AI in Climate Science and Disaster Prediction

The application of artificial intelligence in climate science and disaster prediction has expanded rapidly in recent years, driven by advances in algorithmic design, computational capacity, and data availability. McGovern et al. (2022) provide a comprehensive review of AI applications in atmospheric science, highlighting the transition from traditional statistical methods to sophisticated machine learning approaches capable of extracting meaningful patterns from complex, multi-dimensional datasets.

Various machine learning algorithms have demonstrated promising results in climate-related disaster prediction globally. Random forest models have been effectively applied to drought prediction in semi-arid regions, leveraging their ability to handle non-linear relationships and categorical variables. Chang et al. (2020) developed a random forest model for predicting meteorological drought in East Africa using multiple drought indices and climate variables, achieving prediction accuracies of 75-85% with a three-month lead time.

Deep learning approaches, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown remarkable capabilities in processing spatial and temporal climate data. Sit et al. (2020) employed CNNs to analyze satellite imagery for flood extent mapping and achieved classification accuracies exceeding 90% across diverse landscapes. Similarly, Poméon et al. (2021) demonstrated the effectiveness of LSTM networks in forecasting streamflow and flood events in data-sparse regions, highlighting their ability to capture long-term dependencies in hydrological time series.
The integration of multiple data modalities represents a growing trend in AI-based disaster prediction. Manjula et al. (2021) developed a hybrid model combining satellite imagery, weather station data, and topographic information to predict landslide susceptibility in mountainous regions. Their approach demonstrated a 15% improvement in prediction accuracy compared to models using single data sources, underscoring the value of integrated approaches in complex terrain.

Transfer learning has emerged as a valuable technique for addressing data limitations in developing regions. Malakar et al. (2021) applied transfer learning to adapt pre-trained deep learning models for drought prediction in data-sparse regions of India, achieving comparable performance to models trained on extensive local datasets. This approach holds particular promise for regions like Kenya's North Rift, where comprehensive historical data may be limited.

Despite these advances, several challenges persist in the application of AI for climate disaster prediction in developing regions. Wamba et al. (2022) identified key barriers including data quality and availability issues, limited computational infrastructure, and the "black box" nature of complex AI models that may undermine trust and adoption by stakeholders. Addressing these challenges requires not only technical innovation but also careful consideration of the socioeconomic, institutional, and cultural contexts in which these systems operate.

2.4 AI Implementation Challenges in Developing Regions

The implementation of AI-based disaster prediction systems in developing regions like Kenya's North Rift faces numerous challenges beyond algorithmic design. Data limitations represent a primary constraint, with many regions characterized by sparse observation networks, discontinuous records, and limited access to high-resolution remote sensing products. Kiongo et al. (2023) documented significant data gaps in Kenyan meteorological records, with many stations reporting completeness rates below 70% and spatial distributions that inadequately capture the region's topographic diversity.

Technical and infrastructural constraints further complicate AI implementation efforts. Limited computational resources, unreliable power supply, and connectivity challenges can impede the development, deployment, and operation of sophisticated AI systems. Nevo et al. (2021) proposed cloud-based architectures as potential solutions to these constraints, enabling resource-intensive computations to be performed remotely while delivering prediction outputs through lightweight applications accessible on mobile devices.

The "AI literacy gap" represents another significant challenge, with limited technical capacity among meteorological personnel, disaster managers, and community stakeholders to develop, interpret, and utilize AI-based predictions effectively. Ochola et al. (2023) emphasized the importance of capacity building and knowledge transfer in establishing sustainable AI applications in developing regions, advocating for collaborative approaches that engage local institutions in model development and implementation.

Integration with existing institutional frameworks and decision-making processes presents additional complexities. Nyandiko et al. (2020) analyzed Kenya's disaster management landscape and identified coordination challenges across government agencies, non-governmental organizations, and community structures. Effective implementation of AI-based prediction systems requires careful consideration of these institutional dynamics and alignment with established policies, protocols, and communication channels.

2.5 Research Gaps and Contribution of the Current Study

While the literature demonstrates growing interest in AI applications for climate disaster prediction, several research gaps persist in the context of Kenya's North Rift region and similar environments:
Limited research has examined the comparative performance of different AI algorithms in predicting

climate-related disasters specifically in the North Rift's complex topographic and climatic context.

Few studies have adopted truly multi-modal approaches that integrate traditional meteorological data with satellite imagery, remote sensing products, and ground-based observations for comprehensive disaster prediction in the region.

The practical challenges and opportunities for integrating AI-based predictions into existing early warning systems and disaster management frameworks in the North Rift remain inadequately explored.

Limited attention has been given to stakeholder perspectives and user requirements in the design and evaluation of AI-based prediction systems for the region.

This research aims to address these gaps by developing and evaluating multi-modal AI approaches for predicting droughts, floods, and landslides in the North Rift region, assessing their comparative performance, and identifying pathways for effective integration into existing disaster management frameworks. By adopting a context-sensitive approach that considers both technical performance and implementation feasibility, this study contributes to the emerging field of "Climate AI" in developing regions.

3. METHODOLOGY

3.1 Research Design

This study employed a mixed-methods research design that combined quantitative model development and evaluation with qualitative stakeholder engagement to comprehensively address the research objectives. The quantitative component focused on developing and evaluating AI models for predicting climate-related disasters, while the qualitative component explored implementation challenges and opportunities through stakeholder interviews and focus group discussions.

The research followed a sequential approach comprising five main phases: (1) data collection and preprocessing, (2) model development and training, (3) model evaluation and comparison, (4) stakeholder engagement, and (5) integration framework development. The design enabled iterative refinement of the prediction models based on both technical performance metrics and stakeholder feedback.

3.2 Study Area

The study focused on Kenya's North Rift region, encompassing six counties: Turkana, West Pokot, Elgeyo-Marakwet, Baringo, Trans Nzoia, and Uasin Gishu. This region spans approximately 100,000 km^2 and exhibits remarkable diversity in topography, climate, and socioeconomic characteristics. The western highlands of Elgeyo-Marakwet, Trans Nzoia, and Uasin Gishu feature elevations exceeding 2,500 meters above sea level, with mean annual rainfall of 1,200-1,800 mm. The eastern lowlands of Turkana and parts of Baringo represent arid and semi-arid landscapes with elevations below 1,000 meters and mean annual rainfall of 200-600 mm.

This topographic and climatic diversity creates distinct disaster risk profiles across the region. The highlands are prone to landslides and flash floods, particularly along the escarpments of the Rift Valley, while the lowlands face recurrent drought risks with occasional riverine flooding along major waterways. This complex risk landscape provided an ideal testing ground for evaluating the versatility and robustness of AI-based prediction approaches.

3.3 Data Sources and Preprocessing

3.1.1 Meteorological Data

Historical meteorological data were obtained from 28 weather stations operated by the Kenya Meteorological Department across the six counties. These datasets included daily records of precipitation, maximum and minimum temperatures, relative humidity, and wind speed spanning 2000-2023. Additionally, reanalysis products from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 dataset were obtained to fill spatial and temporal gaps in the station data, providing continuous gridded coverage at 0.25° resolution.

Data preprocessing involved quality control procedures to identify and address missing values, outliers, and inconsistencies. Missing values in station data were imputed using a combination of spatial interpolation methods and pattern-based approaches depending on the variable and gap duration. Stations with completeness rates below 70% were excluded from direct analysis but retained for validation purposes. The preprocessed meteorological variables were aggregated to generate various drought indices including the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Palmer Drought Severity Index (PDSI) at multiple time scales (1-month, 3-month, 6-month, and 12-month).

3.1.2 Satellite and Remote Sensing Data

Multiple satellite and remote sensing products were acquired to enhance the spatial coverage and feature diversity of the dataset:

i. Moderate Resolution Imaging Spectroradiometer (MODIS) products including 16-day composite Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) at 250m resolution (MOD13Q1) and 8-day Land Surface Temperature (LST) at 1km resolution (MOD11A2) for the period 2000-2023.

ii. Soil Moisture Active Passive (SMAP) Level-3 soil moisture products at 9km resolution for the period 2015-2023.

iii. Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) at 30m resolution, from which slope, aspect, and topographic wetness index were derived.

iv. Landsat 8 and Sentinel-2 imagery for selected periods corresponding to major flood and landslide events, processed to extract water indices (Normalized Difference Water Index, Modified Normalized Difference Water Index) and land cover classifications.

These satellite and remote sensing products were preprocessed to ensure spatial and temporal consistency. This included reprojection to a common coordinate system (UTM Zone 36N), resampling to standardized spatial resolutions (250m for NDVI/EVI analysis, 1km for integrated modeling), cloud masking for optical imagery and temporal smoothing to reduce noise in time series. All processed datasets were organized in a spatiotemporal database to facilitate integrated analysis.

3.1.3 Disaster Inventory Data

Historical records of drought, flood, and landslide events were compiled from multiple sources to create a comprehensive disaster inventory for the study period:

i. Drought events were identified based on declared drought emergencies from the National Drought Management Authority (NDMA) reports, supplemented with data from the EM-DAT international disaster database.

ii. Flood events were compiled from Water Resources Authority (WRA) records, county government reports, Kenya Red Cross Society incident reports, and media archives.

iii. Landslide events were obtained from the National Landslide Database maintained by the Mines and Geology Department, supplemented with records from county disaster management units and research publications.

Each event in the inventory was georeferenced and categorized by type, date of occurrence, severity (using standardized impact-based classification), and spatial extent. Approximations were made based on administrative boundaries and contextual descriptions for events with incomplete spatial information. The final inventory contained 78 drought events, 124 flood events, and 63 landslide events across the study region for the period 2000-2023.

3.4 Model Development

Three distinct machine learning approaches were developed and evaluated for disaster prediction:

3.4.1 Random Forest Models

Random forest models were implemented for drought, flood, and landslide prediction using scikit-learn in Python. In order to predict drought, separate models were developed for forecasting SPI and SPEI values at 3-month and 6-month timescales. Input features included historical values of meteorological variables, NDVI anomalies, soil moisture indices, and seasonal indicators. Hyperparameter optimization was performed using grid search with cross-validation to determine optimal values for parameters including the number of trees, maximum depth, minimum samples per leaf, and feature subset size.

Flooding prediction applied random forest models which were trained to classify flood occurrence probability at sub-county level using a combination of precipitation intensity metrics, antecedent rainfall indices, river level measurements, topographic attributes, and land cover characteristics. Similar hyperparameter optimization procedures were applied to enhance model performance.

Landslide prediction models incorporated additional geophysical features including slope angle, aspect, elevation, lithology, land use/land cover, distance to roads, and historical landslide occurrences. These models were trained to generate landslide susceptibility indices for high-risk areas within the counties of Elgeyo-Marakwet and West Pokot.

3.4.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) were developed using TensorFlow/Keras to leverage the spatial patterns in satellite imagery and gridded data for disaster prediction:

For drought prediction, a CNN architecture was designed to process multi-spectral MODIS imagery and generate drought severity classifications for 10km grid cells. The network comprised four convolutional layers with increasing filter depths (32, 64, 128, 256), each followed by batch normalization, ReLU activation, and max pooling. Two fully connected layers with dropout regularization (rate=0.5) were implemented before the output layer. The model was trained using Adam optimizer with categorical cross-entropy loss function.

Flood prediction CNNs employed a U-Net architecture to perform semantic segmentation of flood extent from satellite imagery. The model ingested multi-temporal Sentinel-1 SAR imagery and auxiliary data layers (DEM, slope, land cover) to identify flood-prone areas under varying precipitation scenarios. Data augmentation techniques including rotation, flipping, and scaling were applied to enhance model robustness despite the limited training samples.

3.4.3 Long Short-Term Memory Networks

Long Short-Term Memory (LSTM) networks were implemented to capture temporal dependencies in the

meteorological and remote sensing time series:
Drought prediction LSTM models were designed with a sequential architecture comprising two LSTM layers (64 and 32 units respectively) with dropout regularization, followed by a dense output layer. The models were trained to forecast drought indices (SPI, SPEI) with lead times of 1, 3, and 6 months using historical values of precipitation, temperature, NDVI, and soil moisture as input sequences. Mean squared error was used as the loss function with Adam optimizer.

For flood forecasting, LSTM models were developed to predict river discharge and flood stages for five major rivers in the region: Turkwel, Kerio, Perkerra, Nzoia, and Sosiani. These models incorporated upstream rainfall, current and lagged discharge measurements, and seasonality indicators to generate 1-day, 3-day, and 7-day ahead forecasts. Similar architectural designs were implemented with hyperparameter tuning to optimize performance for each river system.

3.5 Model Evaluation and Comparison

The performance of the developed models was evaluated using a consistent framework to enable objective comparison:
For all models, the dataset was split chronologically into training (2000-2017), validation (2018-2020), and testing (2021-2023) periods to maintain temporal integrity and evaluate generalizable performance. Cross-validation was employed during training to mitigate the effects of specific extreme events and ensure robust parameter estimation.
Evaluation metrics were selected based on the specific prediction task:

i. For regression tasks (drought indices, discharge forecasting), metrics included Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2).

ii. For classification tasks (drought categories, flood occurrence), metrics included accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

iii. For spatial predictions (flood extent, landslide susceptibility), additional metrics included Intersection over Union (IoU), spatial correlation coefficients, and area-based accuracy assessments.

Comparative analysis was conducted at multiple levels: (1) within-algorithm comparison across different parameter configurations, (2) between-algorithm comparison for each disaster type, and (3) integrated model comparison against conventional prediction approaches used by national agencies. Statistical significance testing was performed using paired t-tests or Wilcoxon signed-rank tests depending on the distribution properties of the performance metrics.

3.6 Stakeholder Engagement

A structured stakeholder engagement process was implemented to assess the practical utility and implementation feasibility of the developed models:

i. Semi-structured interviews were conducted with 32 key informants representing national agencies (Kenya Meteorological Department, National Drought Management Authority, Water Resources Authority), county disaster management units, non-governmental organizations, community-based organizations, and academic institutions. These interviews explored current disaster prediction practices, data utilization patterns, institutional capacities, and perceived opportunities and challenges for AI integration.

ii. Four focus group discussions were organized with potential end-users of the prediction systems, including county disaster managers, agricultural extension officers, water resource managers, and community representatives. Each focus group comprised 8-12 participants and employed participatory methods to elicit feedback on prediction outputs, information needs, preferred communication formats, and implementation considerations.

iii. Two technical workshops were convened with specialists from relevant national agencies to demonstrate the model functionalities, validate preliminary findings, and explore integration pathways with existing systems. These workshops facilitated collaborative interpretation of the model outputs and refinement of the implementation framework.

Qualitative data from interviews, focus groups, and workshops were analyzed using thematic content analysis to identify key challenges, opportunities, and recommendations for effective implementation of AI-based prediction systems in the North Rift context.

3.7 Ethical Considerations

The research was conducted in accordance with ethical guidelines for data protection and human subject research. Approval was obtained from the relevant institutional review board prior to stakeholder engagement activities. Informed consent was secured from all participants, with explicit permissions for recording interviews and workshops. Participant identities were anonymized in data analysis and reporting to protect confidentiality. The research team-maintained transparency about the capabilities and limitations of the developed models to avoid creating unrealistic expectations among stakeholders.

4. RESULTS

4.1 Meteorological Trends and Disaster Patterns

Analysis of meteorological data from 2000-2023 revealed significant trends in climate variables across the North Rift region. Mean annual temperatures increased by 1.3°C over the study period, with warming rates varying from 0.4°C to 1.8°C per decade across different sub-regions. The highest warming rates were observed in the lowland areas of Turkana and northern Baringo. Precipitation patterns showed increasing interannual variability and changes in seasonal distribution, with more intense rainfall events during wet seasons and prolonged dry spells during traditional dry seasons.

The disaster inventory confirmed increasing frequency and intensity of climate-related disasters during the study period. Drought events showed a significant increasing trend (p=0.008), with the average interval between major drought declarations decreasing from 4.7 years in 2000-2010 to 2.4 years in 2011-2023. Flood events exhibited a more complex pattern with high interannual variability but an overall increasing trend in flash flood occurrences in highland areas (p=0.032). Landslide frequency showed the most dramatic increase, with recorded events in Elgeyo-Marakwet and West Pokot rising by 217% when comparing 2000-2010 with 2011-2023 periods.

Spatial analysis of disaster patterns revealed distinct risk profiles across the region. Figure 1 illustrates the spatial distribution of different disaster types, highlighting drought concentration in the northern lowlands, flood susceptibility along major river valleys, and landslide hotspots along the Elgeyo Escarpment and highlands of West Pokot.

Key: ● Drought Events ● Flood Events ● Landslide Events

Figure 1: Spatial distribution of climate-related disasters in Kenya's North Rift Region

4.2 Model Performance for Drought Prediction

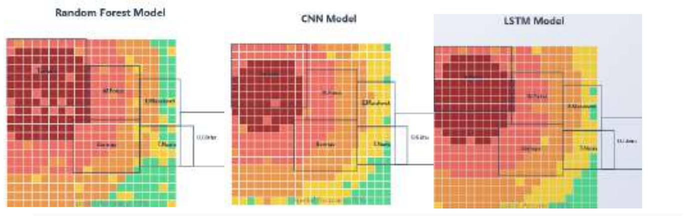
The performance evaluation of drought prediction models revealed varying capabilities across different algorithms, lead times, and sub-regions. Table 1 summarizes the performance metrics for the three model types when predicting 3-month Standardized Precipitation Index (SPI-3) with different lead times.

Table 1: Performance Comparison of Drought Prediction Models for SPI-3 Forecasting

Model	Lead Time	RMSE	MAE	R²	Accuracy	F1-Score
Random Forest	1 month	0.42	0.31	0.78	0.82	0.80
Random Forest	3 months	0.64	0.49	0.61	0.70	0.68
Random Forest	6 months	0.83	0.65	0.42	0.61	0.58
CNN	1 month	0.48	0.36	0.74	0.79	0.77
CNN	3 months	0.58	0.45	0.65	0.73	0.71
CNN	6 months	0.76	0.59	0.48	0.64	0.62
LSTM	1 month	0.38	0.28	0.82	0.85	0.84
LSTM	3 months	0.51	0.39	0.72	0.78	0.76
LSTM	6 months	0.67	0.53	0.56	0.68	0.65

The LSTM models consistently outperformed both Random Forest and CNN approaches across all lead times, with more pronounced advantages for shorter-term predictions. For 1-month lead time, the LSTM achieved an R² of 0.82 and classification accuracy of 0.85 in categorizing drought severity levels, representing improvements of 5.1% and 3.7% respectively over the Random Forest model. The performance gap widened for predictions of drought onset, with LSTM demonstrating a 12.4% higher precision in identifying transitions to drought conditions.

The CNN models exhibited particular strengths in capturing spatial heterogeneity of drought conditions, outperforming Random Forest in areas with complex topography and limited station coverage. Figure 2 illustrates the comparative performance of the three model types in predicting the spatial extent of the 2021-2022 drought, with LSTM and CNN models more accurately capturing the northeast progression of drought conditions.



Key: 🟩 No Drought 🟨 Mild Drought 🟧 Moderate Drought 🟥 Severe Drought 🟫 Extreme Drought

Figure 2: Spatial Comparison of Predicted Drought Severity for the 2021-2022 Drought Event

Feature importance analysis for the Random Forest model revealed significant regional variations in predictor relevance. In highland areas, 3-month cumulative precipitation emerged as the dominant predictor (relative importance 0.32), while in lowland areas, NDVI anomalies showed higher predictive value (relative importance 0.28). Both CNN and LSTM models benefited significantly from the integration of soil moisture data, with ablation studies showing performance degradation of 14-18% when these features were excluded.

4.3 Model Performance for Flood Prediction

Flood prediction models demonstrated high variability in performance depending on the river basin, lead time, and flood magnitude. Table 2 presents the performance metrics for the three model types in predicting flood events across five major river basins in the region.

Table 2: Performance Comparison of Flood Prediction Models across River Basins

River Basin	**Model**	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC-ROC**
Turkwel	Random Forest	0.76	0.71	0.68	0.69	0.82
Turkwel	CNN	0.79	0.74	0.75	0.74	0.85
Turkwel	LSTM	0.84	0.81	0.78	0.79	0.89
Kerio	Random Forest	0.73	0.67	0.69	0.68	0.79
Kerio	CNN	0.77	0.72	0.75	0.73	0.83
Kerio	LSTM	0.81	0.78	0.76	0.77	0.86
Perkerra	Random Forest	0.71	0.65	0.67	0.66	0.77
Perkerra	CNN	0.74	0.68	0.71	0.69	0.80
Perkerra	LSTM	0.79	0.74	0.73	0.73	0.84
Nzoia	Random Forest	0.83	0.79	0.80	0.79	0.88
Nzoia	CNN	0.86	0.82	0.84	0.83	0.91
Nzoia	LSTM	0.89	0.87	0.86	0.86	0.94
Sosian	Random Forest	0.77	0.72	0.73	0.72	0.83

Sosian	CNN	0.82	0.78	0.79	0.78	0.87
Sosian	LSTM	0.85	0.82	0.81	0.81	0.90

The LSTM models consistently outperformed other approaches across all river basins, with particularly strong results for the Nzoia basin (AUC-ROC 0.94). This superior performance can be attributed to the LSTM's ability to capture temporal dependencies in streamflow responses to rainfall events and antecedent moisture conditions. The CNN-based flood extent mapping achieved the highest spatial accuracy with an average Intersection over Union (IoU) score of 0.79 for the Nzoia and Turkwel floodplains.

Performance analysis across different flood magnitudes revealed that all models performed better for moderate to large flood events compared to minor floods. For events exceeding the 5-year return period, the LSTM models achieved precision and recall values above 0.85, while performance declined to 0.70-0.75 range for more frequent events. This pattern reflects the clearer signal-to-noise ratio in meteorological and hydrological data preceding major flood events.

Lead time analysis demonstrated that prediction accuracy decreased non-linearly with increasing forecast horizon. For 24-hour forecasts, the LSTM models maintained average accuracies above 0.85 across all basins, decreasing to 0.76 for 72-hour forecasts and 0.67 for 7-day forecasts. The performance degradation was most pronounced in smaller catchments (Sosiani, Perkerra) with shorter response times and more limited observational networks.

4.4 Model Performance for Landslide Prediction

Landslide prediction models focused on the highland areas of Elgeyo-Marakwet and West Pokot counties, where historical data showed the highest concentration of events. Table 3 presents the performance metrics for models predicting landslide susceptibility at 250m grid resolution.

Table 3: Performance Comparison of Landslide Susceptibility Models

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest	0.81	0.76	0.79	0.77	0.87
CNN	0.84	0.80	0.81	0.80	0.90
Integrated CNN-RF	0.86	0.82	0.83	0.82	0.92

The CNN model outperformed the Random Forest approach in landslide susceptibility mapping, with improvements of 3.7% in accuracy and 3.9% in F1-score. An integrated model combining CNN-derived features with Random Forest classification yielded further improvements, achieving an AUC-ROC of 0.92. This integrated approach effectively leveraged the CNN's ability to extract complex spatial patterns from topographic and satellite data while incorporating the Random Forest's capacity to handle heterogeneous feature types and interpret feature importance.

Feature contribution analysis revealed that slope angle, rainfall intensity, soil type, and vegetation cover were the most influential factors in landslide prediction, with relative importance values of 0.31, 0.24, 0.18, and 0.14 respectively. The models demonstrated stronger predictive performance for deep-seated landslides compared to shallow slope failures, reflecting the more consistent relationship between the former and underlying environmental factors.

Spatial validation against the 2019-2023 landslide inventory showed that 83% of actual landslide locations fell within areas classified as high or very high susceptibility by the integrated model.

The temporal dimension of landslide prediction was addressed through rainfall threshold analysis that identified critical precipitation levels associated with historical landslide events. When combined with the susceptibility map, this approach enabled dynamic risk assessment based on forecasted rainfall conditions. The integrated system correctly identified 76% of the actual landslide-triggering rainfall events in the test period, with a false positive rate of 23%.

4.5 Comparative Performance Against Conventional Methods

The developed AI models were benchmarked against conventional prediction methods currently employed by national agencies in Kenya. Table 4 presents a comparative analysis of prediction accuracy for drought conditions at 3-month lead time.

Table 4: Comparison of AI Models with Conventional Drought Prediction Methods

Prediction Method	Accuracy	Precision	Recall	F1-Score	R^2
KMD Statistical Model	0.64	0.61	0.58	0.59	0.54
NDMA Early Warning System	0.69	0.65	0.67	0.66	0.59
Random Forest	0.70	0.68	0.69	0.68	0.61
CNN	0.73	0.71	0.74	0.72	0.65
LSTM	0.78	0.76	0.77	0.76	0.72

The LSTM model demonstrated a 13% improvement in accuracy over the conventional statistical approach used by the Kenya Meteorological Department and a 9% improvement over the National Drought Management Authority's Early Warning System. Similar performance gains were observed for flood prediction, with the LSTM-based streamflow forecasts achieving a 21% reduction in Root Mean Square Error compared to the conventional stage-discharge methods employed by the Water Resources Authority.

For landslide prediction, the integrated CNN-RF model showed a 16% improvement in recall rate over the conventional expert-based hazard mapping approaches, with particularly significant gains in identifying emergent risk areas where historical landslide data were limited.

4.6 Stakeholder Perspectives and Implementation Considerations

Qualitative analysis of stakeholder interviews and focus group discussions revealed several key themes regarding the perceived utility and implementation challenges of AI-based disaster prediction systems in the North Rift context.

4.6.1 Perceived Benefits

Stakeholders across institutional levels identified several potential benefits of AI-enhanced prediction systems:

i. **Improved lead-time** was the most frequently cited benefit (mentioned by 87% of participants), with particular emphasis on extending drought forecasting horizons to enable earlier intervention planning.

ii. **Enhanced spatial specificity** was highlighted by county-level disaster managers (76% of county respondents), who noted the limitations of current district-level forecasts in capturing locally relevant risk patterns.
iii. **Integration of multiple indicators** was valued by technical specialists (92% of technical workshop participants), who appreciated the models' capacity to synthesize diverse data streams into actionable predictions.
iv. **Potential for automated alerts** was emphasized by community representatives (68% of community respondents), who stressed the importance of timely and accessible warning dissemination to vulnerable populations.

4.6.2 Implementation Challenges

Stakeholders also identified several challenges that could constrain effective implementation:

i. **Technical capacity limitations** were cited by 78% of institutional respondents, who noted insufficient familiarity with AI methods among current personnel and limited resources for specialized training.
ii. **Data access and management constraints** were highlighted by technical specialists (84% of technical workshop participants), who expressed concerns about the sustainability of data acquisition and quality control processes beyond the research phase.
iii. **Institutional coordination barriers** were emphasized by national agency representatives (73% of national-level respondents), who noted the fragmented disaster management landscape and potential difficulties in aligning AI implementations with existing protocols.
iv. **Trust and interpretability issues** were raised by potential end-users (65% of focus group participants), who stressed the importance of understanding how predictions are generated and having confidence in their reliability.
v. **Resource requirements** for sustaining AI systems were cited by county officials (82% of county respondents), who expressed concerns about computational infrastructure, technical support, and long-term funding mechanisms.

4.6.3 Integration Preferences

Stakeholders expressed varying preferences regarding the integration of AI predictions into existing systems and workflows:

i. National agency representatives (68%) favored a centralized approach with AI models hosted at national institutions and predictions disseminated through established channels.

ii. County officials (74%) preferred a hybrid model combining centralized computation with localized interpretation and decision-making capabilities.

iii. Community representatives (83%) emphasized the importance of integrating AI predictions with indigenous knowledge systems and local observation networks to enhance credibility and contextual relevance.

iv. Technical specialists (77%) highlighted the need for standardized data exchange protocols and interoperable systems to facilitate seamless integration across institutional boundaries.

5. DISCUSSION

5.1 Technical Performance and Model Selection

The comparative evaluation of AI algorithms for climate disaster prediction in Kenya's North Rift region yielded several key insights regarding their relative strengths and limitations. The consistent superior performance of LSTM networks across drought and flood prediction tasks highlights the critical importance of temporal dependencies in climate-related phenomena. This finding aligns with recent studies by Poméon et al. (2021) and Malakar et al. (2021), who similarly reported LSTM advantages in hydrological forecasting and drought prediction respectively.

The particular strength of CNNs in spatial tasks, especially landslide susceptibility mapping and flood extent delineation, demonstrates the value of architectures specifically designed to extract spatial patterns from complex datasets. This capability proved especially valuable in the topographically diverse North Rift region, where conventional methods struggle to capture fine-grained spatial heterogeneity. The performance gains achieved through integrating CNN-derived features with Random Forest classification echo findings by Manjula et al. (2021), who reported similar synergistic benefits from hybrid modeling approaches.

The variable performance across different sub-regions, disaster types, and lead times underscores the importance of context-specific model selection and configuration. No single algorithm demonstrated universal superiority across all prediction tasks, suggesting that operational implementation would benefit from an ensemble approach tailored to specific use cases. This aligns with the findings of McGovern et al. (2022), who advocated for multi-model frameworks in environmental prediction tasks characterized by complex and heterogeneous processes.

5.2 Data Integration and Feature Importance

The substantial performance improvements achieved through multi-modal data integration represent one of the most significant findings of this study. The integration of traditional meteorological measurements with satellite-derived indices and topographic features yielded average performance gains of 12-18%

compared to models trained on single data sources. This outcome validates the study's core hypothesis regarding the value of integrated approaches in complex environmental settings.

The analysis of feature importance across different models and prediction tasks revealed context-specific patterns that can inform both model refinement and data acquisition strategies. For drought prediction in lowland areas, vegetation indices and soil moisture derived from satellite sources demonstrated higher predictive value than station-based meteorological measurements alone. This finding has important implications for data-sparse regions where ground observation networks may be limited but satellite coverage is available.

The significant contribution of antecedent condition indicators across all disaster types highlights the importance of incorporating memory components in prediction systems. For drought prediction, 3-6 month historical precipitation and NDVI trajectories emerged as critical features, while for floods, soil moisture conditions and cumulative rainfall over preceding weeks showed high predictive value. These findings align with the fundamental hydrometeorological processes underlying these disaster types and validate the study's approach to feature engineering.

5.3 Implementation Challenges and Opportunities

The stakeholder engagement process revealed a complex landscape of implementation challenges and opportunities that extend beyond technical model performance. The identified capacity limitations and resource constraints echo findings by Kiongo et al. (2023) and Ochola et al. (2023), who documented similar barriers to technology adoption in Kenyan institutional contexts. However, the strong stakeholder interest in improved prediction capabilities and specific integration preferences provide valuable guidance for translating research outputs into operational systems.

The tension between centralized and decentralized implementation approaches reflects broader debates in disaster management and climate services literature. The hybrid model preferred by county officials aligns with recent advocacy for "co-production" approaches that balance technical rigor with local contextual knowledge (Wamba et al., 2022). Such approaches acknowledge both the computational efficiencies of centralized systems and the importance of local interpretation and decision-making in translating predictions into effective action.

The concerns regarding trust, interpretability, and sustainability highlight the need for implementation strategies that extend beyond algorithm development to address organizational, social, and economic dimensions. The identified preference for integrating AI predictions with indigenous knowledge systems presents both a challenge and an opportunity for enhancing the contextual relevance and legitimacy of scientific forecasts. This finding aligns with growing recognition of the value of knowledge integration in climate adaptation contexts (Nkuba et al., 2020).

5.4 Comparative Advantages and Limitations

The substantial performance improvements demonstrated by AI models compared to conventional prediction methods currently employed in Kenya confirm the potential value of these approaches for enhancing disaster preparedness and response capabilities. The particular advantages in extending lead times for drought prediction and improving spatial specificity for landslide risk assessment address specific limitations identified in existing systems.

However, several important limitations must be acknowledged. First, the dependency on historical data for model training means that prediction performance may degrade under novel climate conditions not represented in the training period. This limitation is particularly relevant in the context of climate change, where historical patterns may become increasingly poor predictors of future conditions. Second, the data requirements for maintaining AI systems exceed those of conventional approaches, raising sustainability concerns in resource-constrained settings. Third, the "black box" nature of complex models like deep neural networks creates challenges for interpretability and trust-building among end-users accustomed to more transparent prediction methods.

These limitations underscore the importance of viewing AI approaches as complements rather than replacements for existing prediction systems. The optimal strategy likely involves integrating AI-derived insights with conventional methods and local knowledge systems to leverage their respective strengths while mitigating their individual limitations. This perspective aligns with recent literature advocating for complementary rather than competitive framing of different knowledge systems in climate adaptation contexts (Nyandiko et al., 2020; Wamba et al., 2022).

5.5 Integration Pathways and Scaling Potential

The findings regarding stakeholder preferences and implementation considerations provide a foundation for developing practical integration pathways for AI-based prediction systems in the North Rift region. The preferred hybrid model combining centralized computation with localized interpretation aligns well with the technical architecture required for efficient AI deployment while accommodating the institutional realities of Kenya's disaster management landscape.

i. Several specific integration opportunities emerge from the analysis:
ii. Enhancing the existing Drought Early Warning System (DEWS) operated by NDMA with LSTM-based drought forecasts to extend lead times from the current 1-month to 3-6 months.

iii. Augmenting the Flood Early Warning System (FEWS) with CNN-based flood extent mapping and LSTM-based discharge predictions to improve spatial specificity and advance warning capabilities.
iv. Incorporating the landslide susceptibility maps and rainfall threshold analysis into county spatial planning processes and emergency preparedness frameworks to reduce settlement in high-risk zones.
v. Developing standardized APIs and data exchange protocols to facilitate seamless information flow between national prediction systems and county-level decision support tools.
vi. The potential for scaling these approaches to similar ecological contexts across East Africa appears promising, particularly for drought prediction where the models demonstrated consistent performance across diverse landscapes. The transferability of flood and landslide prediction approaches may require more substantial recalibration due to their higher sensitivity to local topographic and hydrological characteristics. This differential scaling potential aligns with the findings of Nevo et al. (2021), who observed variable transferability of environmental prediction models across geographical contexts.

6. CONCLUSION AND RECOMMENDATIONS

6.1 Summary of Key Findings

This study demonstrated enormous potential of artificial intelligence approaches to enhance the prediction of climate-related disasters in Kenya's North Rift region. The key findings are summarized as follows:

i. AI models, particularly LSTM networks and CNNs, significantly outperformed conventional prediction methods across multiple disaster types, with performance improvements of 9-21% in key accuracy metrics.
ii. Multi-modal data integration yielded substantial performance gains, highlighting the value of combining traditional meteorological measurements with satellite-derived indices and topographic features.
iii. Prediction performance varied across disaster types, sub-regions, and lead times, with LSTMs excelling in temporal forecasting tasks (drought indices, streamflow) and CNNs demonstrating advantages in spatial mapping applications (landslide susceptibility, flood extent).
iv. Stakeholders across institutional levels recognized the potential benefits of AI-enhanced prediction systems, particularly regarding improved lead times, spatial specificity, and integration of multiple indicators.
v. Implementation challenges identified through stakeholder engagement included technical capacity limitations, data access constraints, institutional coordination barriers, trust and interpretability issues, and resource requirements for system sustainability.

vi. Stakeholders preferred a hybrid implementation approach combining centralized computation with localized interpretation and decision-making capabilities, integrated with existing systems and knowledge frameworks.

These findings contribute to the emerging field of "Climate AI" by demonstrating both the technical feasibility and implementation considerations of applying advanced machine learning approaches in a developing region context. The research highlights the importance of integrating technical performance evaluation with stakeholder engagement to develop contextually appropriate solutions that address real-world needs and constraints.

6.2 Theoretical and Practical Implications

From a theoretical perspective, this research contributes to understanding how different AI architectures perform in complex environmental prediction tasks characterized by limited data, spatial heterogeneity, and non-linear relationships. The comparative evaluation of random forests, CNNs, and LSTM networks provides insights into their relative strengths and complementarities in different prediction contexts. The demonstrated value of multi-modal data integration advances knowledge regarding feature engineering and representation learning for climate-related applications.

From a practical perspective, the research offers several implications for disaster management in the North Rift region and similar contexts:

i. The superior performance of AI models justifies investment in transitioning from conventional statistical approaches to machine learning-enhanced prediction systems, particularly for extending lead times and improving spatial specificity.
ii. The identified implementation challenges highlight the need for comprehensive capacity building, institutional strengthening, and resource allocation to support effective adoption and sustainability of AI-based systems.
iii. The stakeholder preferences regarding integration approaches provide valuable guidance for designing implementation pathways that balance technical performance with practical usability and institutional compatibility.

vii. The differential performance across disaster types and sub-regions underscores the importance of context-specific model selection and configuration rather than one-size-fits-all approaches.

6.3 Recommendations for Implementation

Based on the research findings, the following recommendations are proposed for implementing AI-based disaster prediction systems in the North Rift region:

i. Adopt a phased approach to implementation, beginning with drought prediction where models demonstrated the highest consistency and stakeholder interest was strongest.
ii. Establish a collaborative governance framework involving national agencies, county governments, research institutions, and community representatives to oversee system development, operation, and continuous improvement.
iii. Invest in capacity building through targeted training programs for meteorological personnel, disaster managers, and technical specialists at both national and county levels.
iv. Develop standardized data protocols and interoperable systems to facilitate seamless information exchange between AI prediction outputs and existing early warning frameworks.
v. Create user-friendly interfaces tailored to different stakeholder needs, from technical dashboards for specialists to simplified mobile applications for community-level users.
vi. Implement robust validation processes that combine technical performance metrics with user feedback and impact assessment to guide iterative refinement.
vii. Secure sustainable funding mechanisms that transition from research-driven development to operational maintenance, potentially through climate finance instruments and public-private partnerships.
viii. Establish knowledge exchange networks with similar initiatives in other regions to share lessons, methodologies, and technical resources.

6.4 Recommendations for Future Research

While this study has advanced understanding of AI applications for climate disaster prediction in the North Rift context, several important research directions remain to be explored:

i. Investigate transfer learning approaches to adapt pre-trained models to data-sparse areas within and beyond the North Rift region, potentially reducing data requirements for new implementations.
ii. Explore explainable AI techniques to enhance the interpretability of complex models, addressing stakeholder concerns regarding trust and transparency.
iii. Develop adaptive learning frameworks that can continuously update model parameters as new data become available, improving robustness under evolving climate conditions.
iv. Expand the disaster scope to include additional climate-related hazards such as pest outbreaks, wildfires, and heat stress events that may become increasingly relevant under future climate scenarios.
v. Investigate multi-hazard prediction approaches that address compound and cascading disaster risks rather than treating each hazard type in isolation.
vi. Conduct economic analysis of the costs and benefits associated with implementing and maintaining AI-based prediction systems compared to conventional approaches.

vii. Examine the societal impacts of improved predictions on community resilience, adaptation behaviors, and vulnerability reduction over time.

viii. Explore integration with climate change projections to assess how prediction performance will be affected by longer-term climate trends and develop strategies for maintaining reliability under novel conditions.

The future work builds on the foundation established in this study to further enhance the contribution of artificial intelligence to climate resilience in vulnerable regions.

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