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ARTICLE

Deep Learning-based Flood Risk Prediction for Climate Resilience Planning in Malawi

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ABSTRACT

Climate change resilience in Malawi faces an institutional gap because most institutions often fail to prioritize risk data when dealing with climate extremes such as floods. This unfortunate gap forces many Malawians to fend for themselves during times of climate extremes. This situation is also heightened by a few studies that utilize Time Series Analysis (TSA) and Deep Learning Models (DLM) to predict climate extremes for decision-making processes. Therefore, this study focused on flood risk prediction and assessment in six selected districts of Malawi: Chikwawa, Blantyre, Phalombe, Zomba, Rumphi, and Karonga. Traditional Time Series Models (ARIMA) and Semantic Convolution Deep Learning Analysis were used for this purpose. Data were retrieved from the database of the US National Aeronautics and Space Administration (NASA). The results revealed frequent and significant precipitation peaks in Blantyre and Chikwawa, particularly during the rainy season, suggesting that the areas are at a higher risk of flooding, with a high

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probability of infrastructural damage and economic losses. Karonga and Phalombe revealed cyclical trends with prominent spikes in rainfall. In contrast, Rumphi and Zomba exhibit less pronounced trends, though there are still significant fluctuations in rainfall patterns, suggesting an increasing likelihood of flood risk in future climate extremes. This study situates its policy implications by emphasizing that residents, institutions, government, partners, and NGOs need to take a problem-focused approach towards climate resilience planning, including updating flood risk maps, designing flood protection infrastructure, and preparing emergency response plans tailored to the specific needs of each district in Malawi.

Keywords: Vulnerability Assessment; Floods; Climate Change; Lilongwe City; Karonga; Malawi

1. Introduction

Climate change (CC) has induced the occurrence and magnitude of floods across the globe [1], and it is making it hard for vulnerable countries in the global south to break the cycle of risk/vulnerability. In Malawi, the loss and damage from the impacts of climate change are unprecedented in sectors of agriculture, water, sanitation and hygiene (WASH), infrastructure, and livelihoods [2]. Yet, Malawi has a contribution of less than 0.01% cumulative global carbon, the country is extremely vulnerable to climate change extremes. Therefore, projecting climate extremes such as floods alongside climate change resilience is an important strategic option with which research can provide data needed for resilience building, including minimizing loss and damage to climate extreme events in Malawi and other vulnerable regions. It is also an approach that may help to address the institutional gaps, which often fail to prioritize proactive interventions aimed at building the resilience of communities to climate change events. While many factors may exist, significantly, climate change in Malawi matters due to three interrelated factors. The first one is the physical position of the country. The physical position makes many parts of Malawi prone to natural hazards with varying degrees of risk and vulnerability [3]. For example, Malawi is ranked with a high vulnerability (0.542) with a low readiness to respond to climate change impacts [4]. This higher vulnerability makes the majority of Malawians live below the national poverty line and experience acute food insecurity. The second factor is that most Malawians depend on natural resources (i.e., farming, fishing, forest products, wildlife) as a source of livelihood for survival, which are heavily affected by climate change events. The third factor is the high risk of transboundary hazards. Malawi faces numerous climate extremes resulting from transboundary hazards, including those from neighbouring countries such as Mozambique and Tanzania. These factors suggest that climate extremes, in this context, necessitate an analysis of floods to determine their trends, frequency, and seasonality for effective preparedness, mitigation, and response mechanisms.

The Malawi Government (GOM), in collaboration with the Civil Society Organisation, and Local and International Organisations, has envisioned the adoption of various strategies aimed at strengthening the resilience and adaptation of communities to climate risks. Climate Risk Reduction Frameworks, Policies, and Acts have been developed to assist the implementation of climate change adaptation and resilience measures. The National Climate Change Policy (2016) has been developed to promote climate change adaptation, mitigation, technology transfer, and capacity building for sustainable livelihoods through Green Economy measures for Malawi. Efforts such as enhancement of capacity building and strengthening regulatory frameworks have been made to address climate extreme challenges. Collaboration between government authorities, climate change experts, urban planners, engineers, and community stakeholders has been strengthened and promoted for an effective response to climate change adaptation. Regardless of all these efforts, the majority of Malawians, precisely in rural communities and urban informal settlements, are victims of climate risks [5–7]. The National Disaster Recovery Framework (NDRF) Policies, which were developed in 2015, emphasize a decentralization approach (from village to national level) and community participation in mitigating climate risks. However, for all these approaches to be effective, there is a need to understand climate change risk because this provides a basis for understanding the interaction between hazard and vulnerability. It is argued that while it is not easy to stop hazards, the vulnerability of people to climate change is manageable [8].

Flood risks under climate change in Malawi offer insight into at least three valuable topics. Firstly, in Malawi, an institutional gap in community disaster and climate risk reduction (DCRR) has left communities to fend for themselves, which means communities have been forced to innovate resilience and adaptive solutions without institutional support. This unfortunate gap offers an opportunity to assess flood risks to provide data that can support climate change resilience building, as well as decision-making processes. Secondly, as a relatively rural country, Malawi is an excellent case for studying climate change resilience because of its fragile economic systems in terms of the price of food, alternative sources of income, etc. The economic linkages between urban and rural areas are essential to understanding the capacity of communities to recover after a disaster influenced by climate extremes. As sites of economic opportunity, urban areas commonly received the economically vulnerable seeking new sources of income. This economic motive dominates to such a degree that individuals accept living in areas vulnerable to disaster and climate change risks. While relocation of people living in vulnerable areas has been the dominant government-endorsed adaptation approach, relatively little is known about how communities respond to this approach. Therefore, the need to identify initiatives that may serve as alternatives to the relocation of vulnerable communities or ease the costs caused by relocation is required. This need can be achieved by linking climate change trajectories and climate extremes that consider the application of TSA and DLM in risk assessments. Lastly, without nationally enforced construction standards, the resilient construction of housing has been a challenge in Malawi. Despite these challenges, communities continue to build and rebuild in disaster-prone areas. The question remains whether there are any scientific initiatives that seek to manage disaster and climate change risks in Malawi. If there are such initiatives, this research has contributed to identifying strategies that can be adopted to minimize the unique climate change risks associated with flooding through the application of TSA and DLM.

The foregoing discussion points to a need to start encompassing time series and deep learning models when dealing with these climate extremes. However, while studies conducted in Malawi have attempted to quantify and analyze climate change extremes in the aspects of exposure, susceptibility, and resilience [3,5–7], the application of TSA and DLM to predict flood risks has been neglected. Moreover, studies focusing on flood risk assessment under climate change resilience have been dominated by either socio-economic surveys or GIS tools, lacking the attributes of machine learning tools capable of stimulating various environmental parameters. Studies that incorporate TSA and DLM provide data that can assist in strengthening institutional capacity and support decision-making processes regarding climate change risks because of their contrasts with traditional flood risk assessments as GIS and remote sensing-based studies. For example, Ngongondo et al. carried out a study on the evaluation of integrated impacts of climate and land use change on the river regime in the Wamkulumadzi River basin in Malawi [9]. This study assessed how the CC and LUC affect the flow regime of Wamkulumadzi. The study used both remotely sensed imagery using a supervised image classification system and the Soil Water Assessment Tool (SWAT). The study used images from 1984 to 2015 on part of understand land use changes and gauged data from the same years to understand the hydro climatology. The results of the supervised classification of Landsat images from the years 1989, 1999, and 2015 demonstrated a lot of land use changes in the Wamkulumadzi catchment. The results showed that agricultural land had covered 30.66% in 1989 but had decreased to 7.62% in 1999 before increasing to 15.14% [9]. It further revealed that urban areas increased rapidly between 1989 and 1999, followed by a slight decrease in 2015. What is not clear from this analysis is whether the changes in land use were due to flooding, because the occurrence of flooding was not predicted using TSA and DLM.

TSA and DLM provide data that can be used to identify flood-prone areas, including predicting and forecasting flood occurrence, intensity, and trends. Knowledge of these parameters is critical for understanding mitigation and adaptation measures that can strengthen the resilience of communities to climate change extremes. Sankaranayanan carried out a study in India on flood and drought risk assessment using TSA and MLD [10]. The study found that most of the systems employed an artificial neural network (ANN) with a single hidden layer for the prediction of floods using parameters such as rainfall, temperature, water flow, water level, and humidity. In this study, it was argued that flood risk assessment using such parameters allows for the proper formulation of flood risk control measures. Similarly, Jamshed et al. carried out a study in Pakistan, specifically by assessing the vulnerability and capacity of flood-affected communities in Punjab, Pakistan, in the Districts of Jhang and Muzaffargarh using time series analysis [11]. The study found that the vulnerability of immovable assets (infrastructure, houses, water quality, etc.) has increased or remained constant, and for certain assets lack of physical infrastructure reduces the capacity to cope and adapt to climate extremes. In Malawi, a study by Mulumphwa was carried out to model and forecast Lake Malawi water level fluctuations using stochastic models as part of machine learning [12]. This study found that the forecast for Lake Malawi water levels showed a drop in water levels by 0.15 masl as compared to the mean water levels recorded in the previous years. The study pointed out that there would be negative implications for the use of Lake Malawi and the Shire River that flows out of it for irrigation, pumping of water for domestic use, and hydroelectric power generation, among others. Atashi et al. carried out a study in the United States of America (USA), specifically by forecasting water level using deep learning and time-series analyses [13]. The study found that the deep learning method, the LSTM method, achieved better results and was more accurate for the prediction performance than the SARIMA and RF methods. SARIMA is effective at modeling linear data, whereas the other statistical machine-learning models are superior at modeling nonlinear data. These findings suggest that the application of TSA and DLM is crucial to provide data for management and monitoring climate extremes.

Other hydrological studies have used artificial neural networks (ANN) in flood modelling [14]. ANN helps to solve problems of uncertainty in inputs and produce outputs from incomplete data [15]. This method uses rainfall and run-off parameters as the input and output [14]. However, this method can take other factors to assess the causes of floods [16]. It has been noted that studies that used ANN in flood risk analysis might predict similar values by using hydrological data records [17]. However, while ANN has the potential to be applied in flood risk estimation, it is part of deep learning models, which have been understudied in Malawi. This study therefore used TSA and DLM methods to conduct a flood risk assessment to explain the variability of flood risk in six districts of Malawi.

2. Materials and Methods

2.1. Study Area

This Study was carried out in six districts of Malawi (**Figure 1**). Malawi has over 50% of its population living below the national poverty line, and about 15% of its population experiencing acute food insecurity [18]. The country has contributed less than 0.01% of cumulative global carbon dioxide emissions associated with human activities, but is extremely vulnerable to climate impacts. This is partly because Malawi's economy is heavily reliant on the agriculture sector, which employs up to 80% of the population [19]. Around 90% of people live in rural areas and are mostly reliant on rain-fed and smallholder farming, which is vulnerable to changes in rainfall patterns and extreme weather.

In Malawi, floods are the most frequent natural hazards, causing devastating impacts in both rural and urban areas. Between 2015 and 2023, about four major floods induced by extreme tropical cyclones have affected communities. The most destructive were floods of 11-13 March 2023, influenced by tropical cyclone Freddy (TCF), which was developed in the Western Indian Ocean and moved eastwards [20]. The TCF caused multiple flash floods and landslides, which killed about 679 people, injured 2178 people, displaced 563,602 people, and about 511 people were reported missing, including causing several other damages and losses in sectors such as agriculture, infrastructure, food security, and health [20]. The response to this catastrophe, including the previous floods, was tailored more to rescue and relief operations [21]. While these are critical to save lives and to provide immediate relief and short-term support, they cannot provide long-term solutions for addressing current and future climate change impacts. As such, the need to use TSA and DLM can provide practical indicators for programming current and future flood mitigation measures that consider long-term climate change resilience measures.

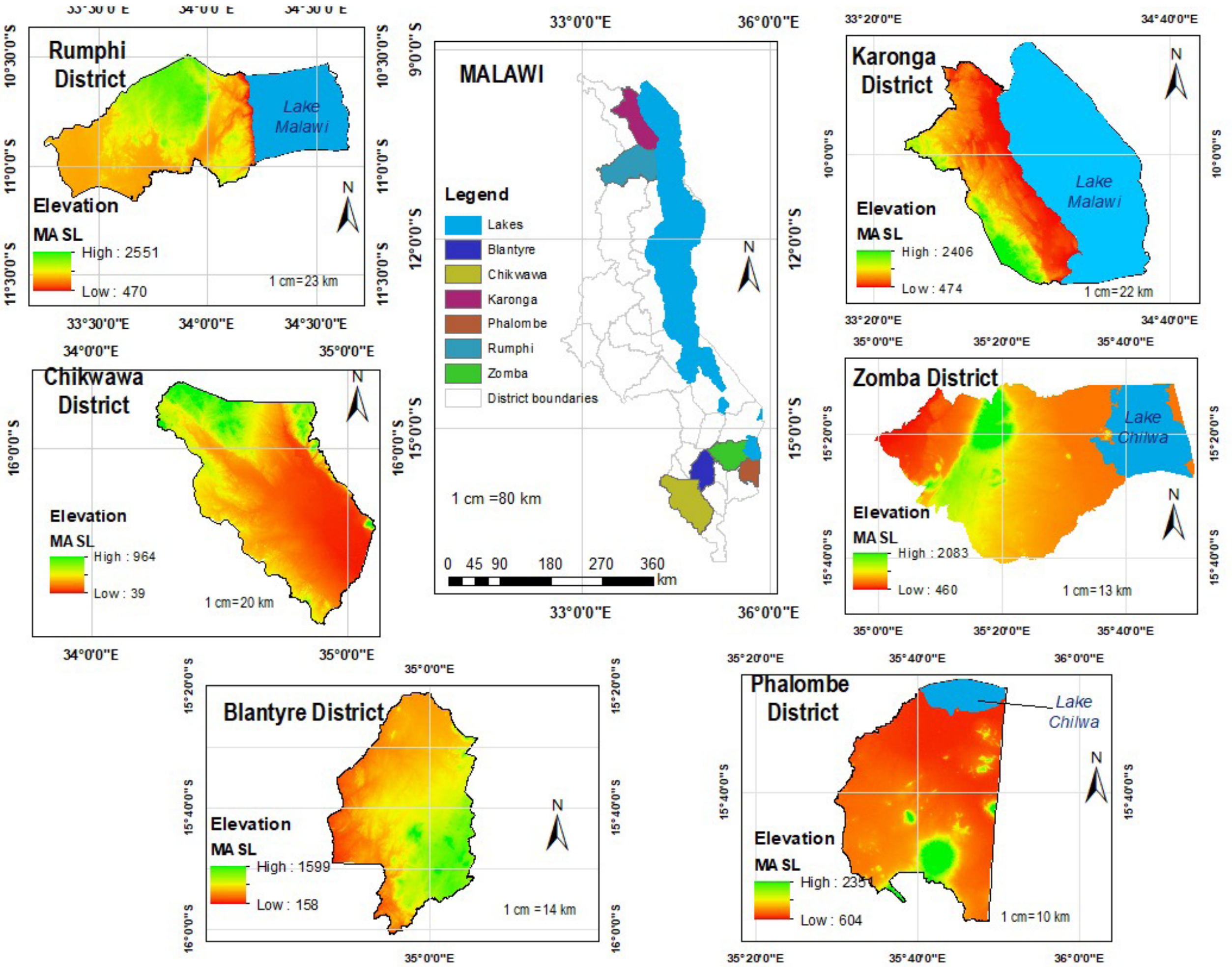

Figure 1. Map of Malawi with Six Selected Districts.

2.2. Study Approach

This study adopted a quantitative analysis approach using two-phase methods for predicting flood risk. The first method involved using Time Series Analysis (TSA) (**Figure 2**). TSA is used as a descriptive analysis of the time series data to understand trends, seasonality, and autocorrelation of the subject under investigation [22]. It also uses modeling through traditional time series models (ARIMA) to establish trends and identify any underlying patterns in flood risk and vulnerability over time. The second involved using Deep Learning Models (DLMs). DLM applied semantic convolution analysis to capture long-term land cover and land use and convolutional neural networks with LSTMs.

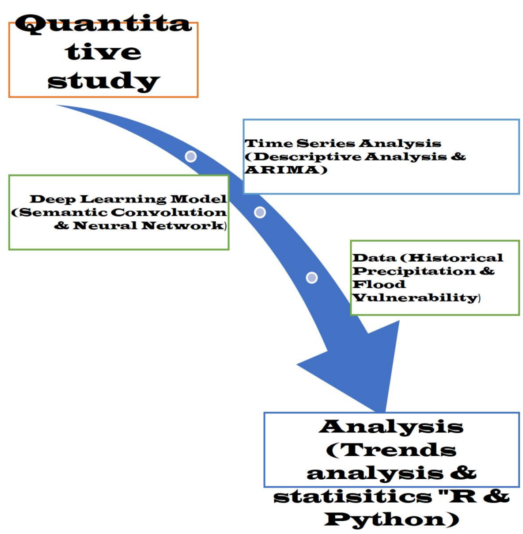

Figure 2. Methodology Flow Chart.

The deep learning model was developed using Python, with key libraries including TensorFlow/Keras for model construction and training, pandas for data preprocessing, and scikit-learn for scaling, splitting, and performance evaluation. The data were partitioned into training (80%) and testing (20%) sets using a randomized split to ensure independent model evaluation. Within the training data, 20% was further reserved as a validation set to monitor training progress and mitigate overfitting through internal validation during each epoch. Model performance was assessed using standard classification metrics—accuracy, precision, recall, F1 score, and Matthew's correlation coefficient (MCC)—to provide a robust evaluation of the model's effectiveness in predicting flood events.

2.2.1. Vulnerability Assessment

Wisner et al. indicate that vulnerability involves a combination of underlying factors that determine the degree to which life, livelihoods, property, and other assets are put at risk by a discrete, identifiable event in nature and society [23]. Iloka maintains that vulnerability is the combination of numerous factors that determine the level of risk to people's lives and livelihoods [24]. Ndanusa et al. highlight that assessment of flood vulnerability has not been holistically conducted. Studies have assessed flood vulnerability either using physical or social components [25]. Therefore, this study indicates that the physical, social, economic, and environmental factors in which an individual, a household, or a community lives can increase (or decrease) the degree to which life, livelihoods, property, and assets are put at risk. Hence, any flood risk prediction needs to take into account flood vulnerability assessment for proper resilience planning. Mwalwimba et al., in a study of flood vulnerability assessment in rural and urban informal settlements in Malawi observed that the determinants of households' flood vulnerability are place of settlement, low-risk knowledge, communication accessibility, lack of early warning systems, and limited access to income of household heads [7]. The study further found that the vulnerability of households to floods in rural and urban informal settlements is high because of proximity to catchments and limited communication due to a lack of advanced flood risk prediction. Msasa et al. conducted a study to assess the physical vulnerability of buildings to floods in low-income areas of Biwi and Kawale 1 in Lilongwe City [26]. The study focused on building exposure and vulnerability and the effectiveness of household protection measures. The study found that exposure factors variably influenced the physical vulnerability of individual building types, and that building typology and floodwater depth were important factors. Elias et al. conducted a study with a focus on valuating the flood vulnerability of Bahir Dar City, Ethiopia [27], using an indicator-based method that considered physical, social, and economic factors. GIS-based tools were used to create vulnerability maps that showed the spatial distribution of flood risk and priority areas for intervention. The study revealed that the city is highly vulnerable to flooding due to heavy rainfalls, insufficient infrastructure, and poor maintenance. All these studies attest that flood vulnerability assessment is an important component in flood risk prediction for resilience planning. Therefore, this study used the flood vulnerability data to assess potential changes in flood risks.

2.3. Data Collection

This study involved, first, the collection of precipitation data. Historical precipitation data for the regions of Blantyre, Karonga, Chikwawa, Phalombe, Rumphi, and Zomba were collected. The data collected were records of rainfall intensity and frequency, essential for identifying trends and seasonal patterns. Second-order autocorrelation plots for precipitation values were generated to examine how precipitation values at different time lags correlate with past values. This helped in identifying recurring seasonal patterns and improving flood prediction accuracy. Third, flood vulnerability data across the six districts were analyzed. This includes past flood events, their frequency, and intensity. Forecast data indicating future flood vulnerability was also used to assess potential changes in flood risk. Further, Deep Learning Model Performance Metrics. Performance metrics of a deep learning model used for flood prediction were reviewed. Metrics included accuracy, precision, recall, F1 score, and the Matthews correlation coefficient (MCC), which are critical for evaluating the model's effectiveness in predicting flood events. Google Earth Engine was used for supervised machine learning to make a classification of land use land cover (LULC) to produce maps for each district. The NOAA Optimum

Interpolation Sea Surface Temperature (SST) V2.1 dataset (NOAA/CDR/OISST/V2_1) was selected as the data source for sea surface temperature. The data offered daily global SST values on a 0.25° grid from satellite, ship, and buoy observations. The temporal scope of the data spanned from January 1990 to December 2024, with data aggregated to monthly means to enhance clarity and manageability.

2.4. Data Analysis

Five levels were performed to analyze the data. The first level utilized Precipitation Trend Analysis (PTA), which involved undertaking the following steps: Firstly, data visualization. This used a graphical representation of precipitation trends over time for each district. This visualization highlighted seasonal fluctuations and identified periods of increased flood risk. Secondly, trend identification. In this, patterns of precipitation in terms of significant peaks and increasing trends were analyzed to assess their impact on flood risk. The second level used Autocorrelation Analysis by employing autocorrelation plots and pattern analysis. Autocorrelation plots were generated to examine how current precipitation values are related to past values over different time lags. Significant spikes in plots were used to indicate recurring seasonal patterns. Pattern Analysis was used to determine the periodicity of precipitation and its implications for predicting flood events. The third level involved flood vulnerability assessment (FVA) using historical data and forecast analysis. On the one hand, historical flood vulnerability data were examined to identify variability in flood risk across different years and regions. On the other hand, forecast analysis analyzed future flood vulnerability to understand potential changes in flood risks. This involved comparing historical data with forecasted trends to assess future flood risks. The fourth level used model performance evaluation by applying both metric calculation and model reliability. The deep learning model's performance metrics, including accuracy, precision, recall, F1 score, and MCC, were calculated to evaluate its effectiveness in predicting flood events. Reliability assessment was assessed based on its ability to correctly classify flood events and its overall predictive accuracy. The last level applied statistical and analytical tools. Tools such as R and Python were used for statistical analysis and generating autocorrelation plots. These tools facilitated the examination of data trends and patterns. Deep learning frameworks like TensorFlow or PyTorch were employed for developing and evaluating the deep learning model. These frameworks provided the infrastructure for training, validating, and testing the model. Data Visualization Tools: Software such as Matplotlib and ggplot was used to create visual representations of precipitation trends, autocorrelation plots, and flood vulnerability data. These visualizations helped in interpreting complex data and identifying key patterns. In data processing, daily SST imagery was filtered by time and region, monthly averages were computed, and the regional mean SST was extracted using reduce Region () with a 25 km resolution. These monthly values were stored as a time series in a Feature Collection. For visualizatio**n**, a line chart was created using GEEs in Chart Feature, depicting SST trends over time.

2.5. Limitations of the Study

Though the application of deep learning models has promising performance, several limitations are likely to be encountered. To begin with, the input data may lack sufficient spatial and temporal granularity, potentially overlooking local-scale or short-duration flood events. Additionally, encoding location as categorical variables may not fully capture the geospatial relationships between regions, which may exhibit results that are not spatially localized for effective risk management. The model's generalizability is constrained by the scope and representativeness of the training data, raising concerns about performance on unseen or extreme climatic conditions. For future work, efforts should focus on integrating real-time data streams (e.g., satellite rainfall estimates, river gauge sensors), enhancing geospatial modeling through techniques like convolutional or graph neural networks, and implementing early warning systems for operational use. Incorporating climate projections and broader environmental variables could further strengthen the model's predictive power and applicability in dynamic flood risk management contexts.

3. Results and Discussion

3.1. Trends and Seasonality

The results (**Figure 3**) offer a detailed view of precipitation trends across several locations in Malawi, including Blantyre, Karonga, Chikwawa, Phalombe, Rumphi, and Zomba. Each district displays distinct patterns in rainfall over time, with noticeable seasonal fluctuations that are crucial for understanding and predicting flood risks.

In Blantyre and Chikwawa, the data reveal frequent and significant peaks in precipitation, particularly during the rainy season, suggesting that these areas are at a higher risk of flooding. The higher risk of flooding is also an indicator of the explicit potential probability of more households being affected by floods. This further implies that more infrastructure (such as bridges, schools, power supply transmission and distribution networks, and livelihoods) and livelihoods (crops, businesses, and other assets) are at risk and vulnerable to floods. This outcome confirms the findings that most physical infrastructures, roads (0.443), houses (0.551), and bridges (0.708) have higher risk/vulnerability to floods in Malawi [5]. There is also an observable increase in the intensity or frequency of these peaks in recent years, potentially indicating the impact of climate change, which could heighten flood risks in these regions. These results support the fact that flooding in Blantyre District is a frequent and known hazard that requires measures to build the resilience of communities to mitigate its risks. This proposition is an indication that the vulnerability of Blantyre District to flooding due to its position and topographical characteristics makes most residents prone to floods [28]. These identified factors in the assessed areas further point to the need to focus on place-based oriented risk reduction measures because each place displays its distinctive features, leading to flood risk and vulnerability under the changing climate. Similarly, Karonga and Phalombe show cyclical trends with prominent spikes in rainfall, underscoring the likelihood of seasonal flooding in these areas as well. These spikes suggest that these regions are vulnerable during specific months when precipitation levels reach their highest. These results also suggest a higher probability of flood hazard in future climate extreme scenarios. Therefore, if measures to build the resilience of communities are not properly done, the consequential outcome would be more damage to infrastructure and economic losses within the society.

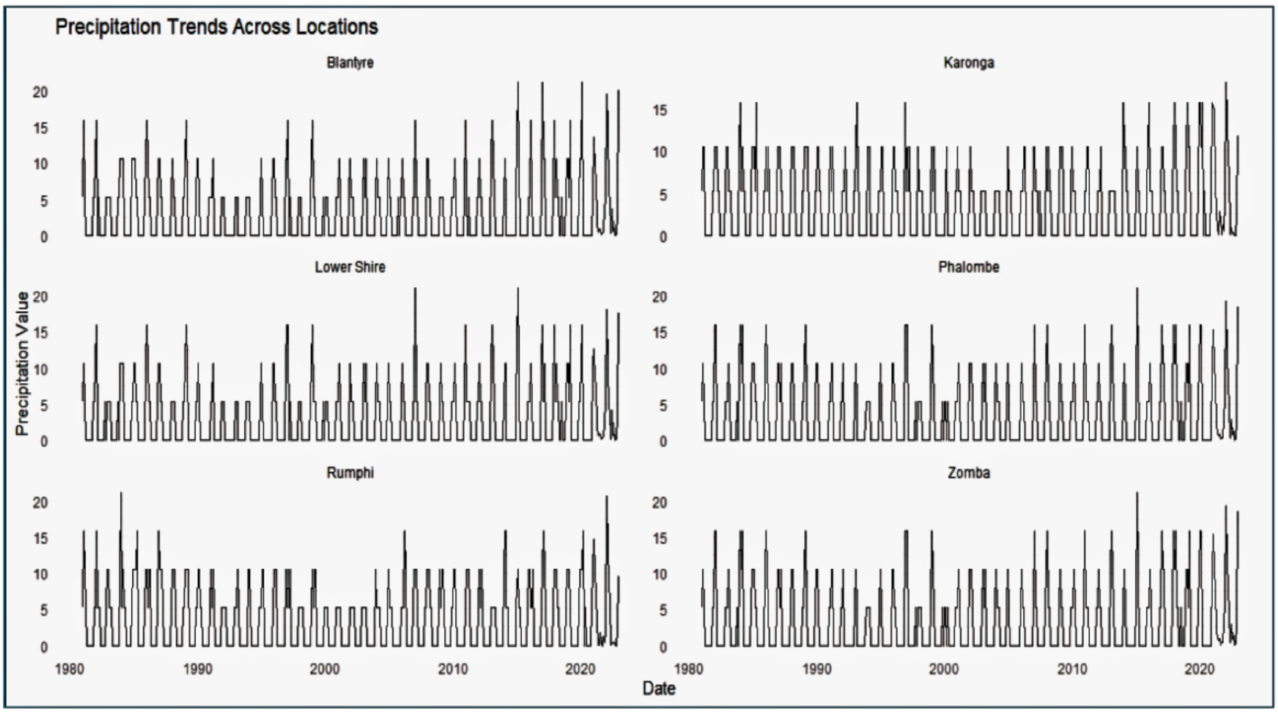

Figure 3. Graph of Trends and Seasonality.

In contrast, Rumphi and Zomba exhibit less pronounced trends, though there are still significant fluctuations in rainfall. While these regions might not experience flooding as frequently as the others, the variability in their precipitation data indicates that they remain susceptible during years with particularly intense rainfall. The cyclical nature of these trends suggests a strong seasonal component to the weather patterns in these locations. This seasonality can be instrumental in predicting floods, especially if the timing of these peaks aligns with historical flood events. Additionally, any observed increase in the frequency or intensity of these peaks in recent years may point to changing climate patterns, necessitating updates to flood prediction models to accommodate potential increases in flood risk. Understanding these precipitation patterns is essential for effective flood management and planning in Malawi. By identifying high-risk periods and regions, resources can be allocated more efficiently to mitigate the impacts of flooding. Continuous monitoring and updates to predictive models are crucial to account for the evolving climate patterns and their potential effect on flood frequency and severity. Moreover, this information can help to make warning systems targeted, focused, and inclusive to deal with climate risks.

3.2. ACF and PACF

For rainfall data, the plots (**Figure 4**) suggest that rainfall patterns exhibit temporal dependencies, where current rainfall levels are influenced by recent rainfall events (as indicated by significant autocorrelation at lower lags in the ACF plot). The PACF plot suggests that these dependencies are strongest at specific lags, implying that past rainfall data can be used to predict future rainfall levels. This further has implications for flood risk, as persistent or high-intensity rainfall over consecutive periods can increase the likelihood of flooding. Understanding these patterns can help improve rainfall forecasting and flood preparedness, allowing for more effective early warning systems and resource planning.

3.3. Autocorrelation

The autocorrelation plots for precipitation values across six locations in Malawi—Blantyre, Karonga, Chikwawa (Lower Shire), Phalombe, Rumphi, and Zomba—illustrate distinct patterns in how precipitation values correlate with past values over time (lags) (**Figure 5**). In each location, the significant spikes in autocorrelation at specific lags suggest recurring seasonal patterns in precipitation. The presence of positive and negative correlations at various lags across all locations implies that precipitation tends to be periodic, with certain time intervals showing higher predictability based on past values. These patterns are critical for flood prediction, as understanding the temporal structure of rainfall in these areas can enhance the accuracy of predictive warnings to be more effective. This information could be important to shift away from the business-as-usual basis for dealing with climate risks in Malawi. Similarly, the information provides a basis for the need to prioritize climate risk assessment as a matter of build back better for potentially affected sectors.

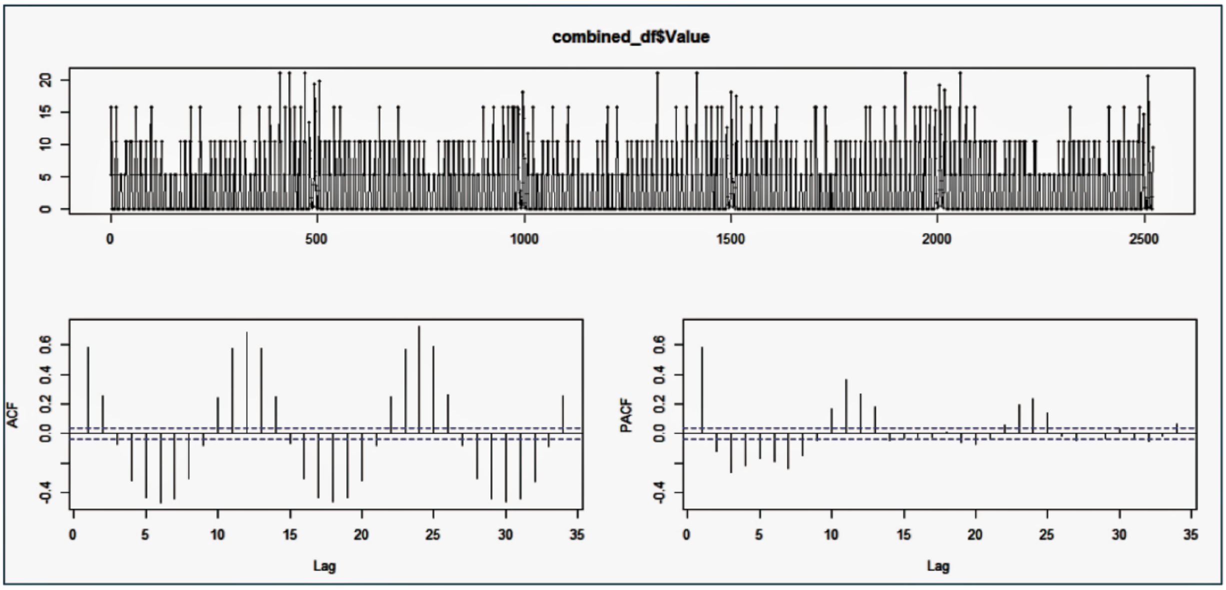

Figure 4. Graph of ACF and PACF.

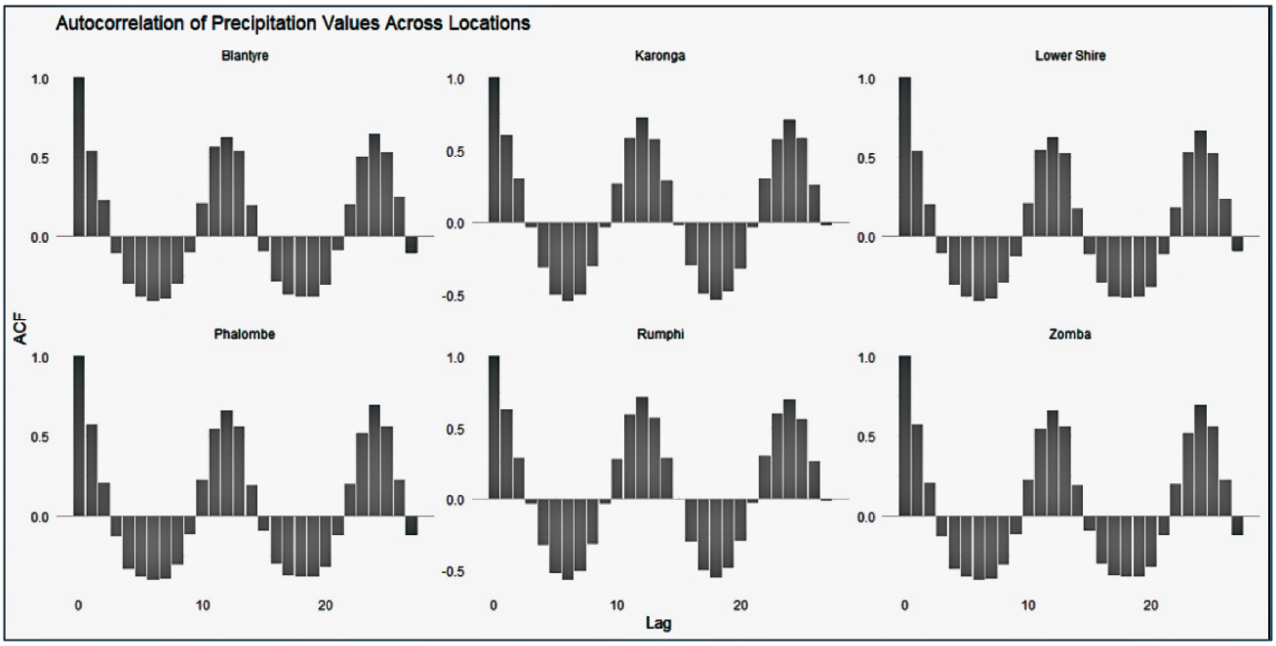

Figure 5. Graph of Autocorrelation.

3.4. Trends and Underlying Patterns in Flood Vulnerability Over Time

Figure 6 presents the flood vulnerability over time across six districts in Malawi: Blantyre, Karonga, Lower Shire, Phalombe, Rumphi, and Zomba. The black bars represent historical data, while the red dashed lines indicate forecasts for future flood vulnerability. The consistent pattern of vulnerability across all districts shows variability in flood risk, with certain years exhibiting higher vulnerability levels. The forecasted data suggests that flood vulnerability is expected to continue, with fluctuations that may reflect seasonal patterns or other contributing factors. This time series analysis highlights the ongoing risk of flooding in these districts, emphasizing the need for continued monitoring and proactive flood management strategies to mitigate future impacts. The predictive trends can inform policymakers and emergency response teams to allocate resources effectively and prepare for potential flood events.

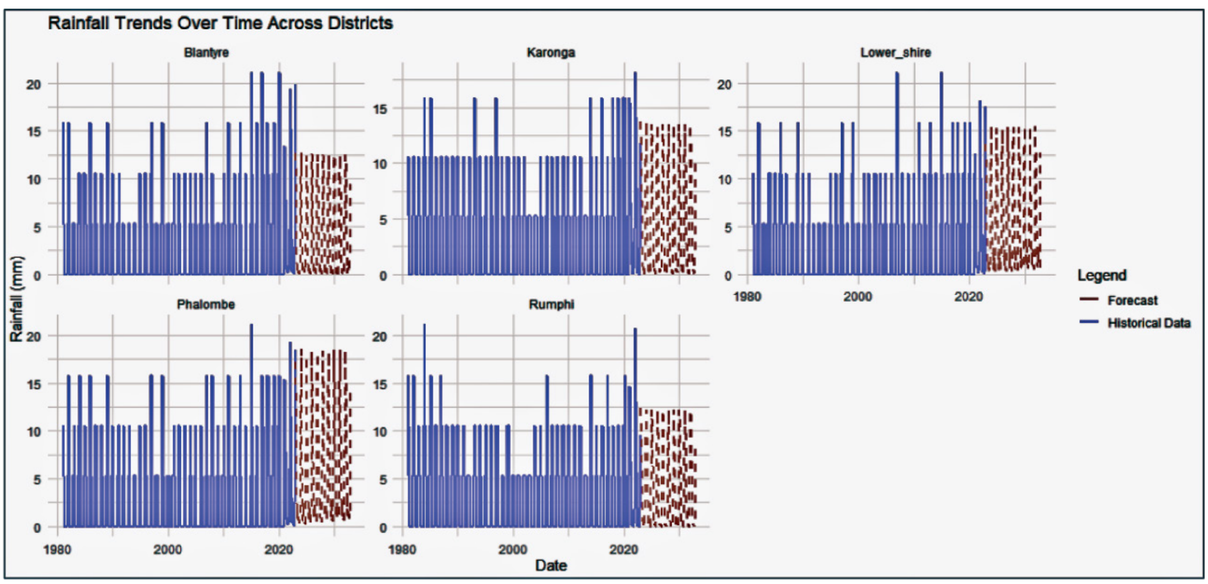

Figure 6. Trends and Underlying Patterns in Flood Vulnerability Over Time.

3.5. DNN Performance Metrics

Different machine learning algorithms, such as deep neural networks, are employed to compute the prediction accuracy to predict the pre-processed dataset. The prediction accuracy results and related metrics for each algorithm are given in **Table 1**.

Table 1. DNN Performance Metrics.

Detailed accuracy terms	Value
Accuracy	99.83%
Precision	1.00
Recall	1.00
F1 Score	1.00
MCC	1.00

The performance metrics for the deep learning model applied to flood prediction in flood-prone areas of Malawi indicate exceptional accuracy. With an overall accuracy of 99.83%, the model demonstrates near-perfect classification of flood events. The precision, recall, and F1 score all being 1.00 suggest that the model is not only precise in its predictions (with no false positives) but also highly sensitive, accurately identifying all true flood occurrences (with no false negatives). The Matthews correlation coefficient (MCC) of 1.00 further supports the model's robustness, indicating a perfect correlation between the predicted and actual outcomes. These results suggest that the model is highly reliable for flood prediction in the targeted regions.

3.6. Sea Surface Temperature (SST) in the Indian Ocean

Figure 7 shows the monthly Sea Surface Temperature (SST) trends in the Indian Ocean from 1990 to 2024. The results reveal a clear upward trend in SST over time, as indicated by the red regression line. The increasing SST—rising by approximately 0.0062°C per month—suggests gradual ocean warming. This trend is critical because warmer sea surface temperatures contribute to the formation and intensification of tropical cyclones. As the Indian Ocean continues to warm, it creates more favorable conditions for cyclones to develop, become stronger, and travel further. For Malawi, this implies a heightened risk of experiencing more frequent and intense cyclones originating from the Indian Ocean, potentially leading to increased climate extremes such as flooding and strong winds. These extremes are likely to increase infrastructural damage and disruption to livelihoods, especially in vulnerable districts of the Southern part of Malawi. This underscores the importance of strengthening climate adaptation and disaster preparedness strategies in Malawi.

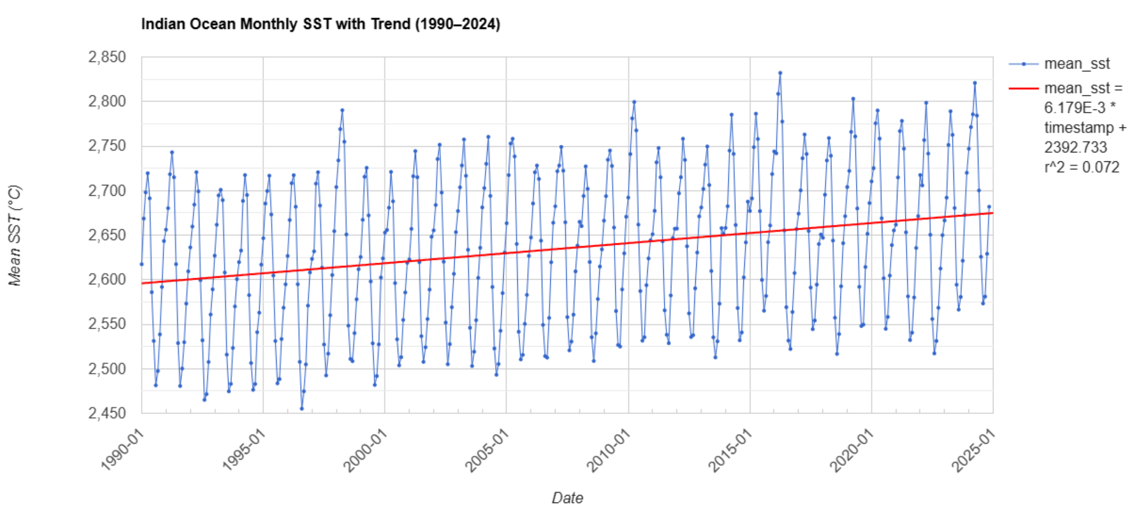

Figure 7. Graph of Sea Surface Temperature Trends in the Indian Ocean.

4. Study Implications for Policy and Practice in Malawi

Based on the findings of this study, it is important to indicate that strategic directions need to be suggested to influence policy and practice to narrow down the institutional gap in disaster and climate risks in Malawi. The first implication of this study in policy and practice is the suggestion that residents and institutions, government, partners, and NGOs need to take a problem-focused approach to deal with climate risks. This approach is immediate and cost-effective to prevent or reduce climate risks. The problem-focused coping could be implemented at the individual, household, community, district, and national levels. The measures could include changing the farming systems, crop diversification, developing construction standards, evacuation to safer places, adjusting behaviours to current situations, etc. The problem-focused coping is not capital-intensive; it requires undertaking measures that are feasible within one's risks. The second implication is that Government of Malawi in collaboration with partners should embark on developing long term protective behaviours to climate extremes to build community resilience: The protective behaviours should focus on both structural (material) methods of protection, such as a barrier, zoning, land use planning, human occupancy, relocation/resettlement, adaptive capacity and non-structural methods, such as raising awareness of risk, developing early warning systems, and disasterpreparedness training and education should be intensified, but in medium- and long-term approaches. The protective behaviour is largely capital-intensive and therefore requires more planning, investment, and commitment of various integrated government sectors, partners, and institutions. The third implication is that government institutions like the Department of Climate Change and Meteorological Services (DCCMS) should strengthen knowledge dissemination. This can further improve the verification of the effectiveness of early warning systems provided to communities through forecast information. It would be further used as a preparedness and response tool for the communities to better develop their coping mechanisms to impending disasters. Lastly, the findings imply the need for the government of Malawi to develop construction standards, supported by a land sealing policy, both in rural and urban areas. Malawi lacks a nationally enforced construction standard, and the lack of this policy has led to human occupancy along the river channels, including sealing the land with interlocking, which locks the soil, and encourages high run-off, resulting in short lag time with high probability of flooding in most of the catchments.

5. Conclusions

This study focused on flood risk assessment for climate change resilience in Malawi using time series and deep learning. These two methods provide a comprehensive analysis of precipitation trends, autocorrelation patterns, and flood vulnerability to provide a solid foundation for understanding and predicting flood risks in six districts of Malawi. The observed results of increasing precipitation intensity and frequency offer an insight into enhancing climate models to better understand and explore scenarios with varying potential impacts on flood frequency and severity in the area. While the current deep learning model demonstrates exceptional accuracy, ongoing advancements in machine learning techniques to predict flood risks. This also points to the potential of exploring measures of building climate resilience. Real-Time Data Integration: Incorporating real-time weather and hydrological data into predictive models can improve the timeliness and accuracy of flood forecasts. Future research should explore the integration of real-time monitoring systems to provide dynamic updates and early warnings. Broader Geographic Scope: Extending the analysis to include additional regions within Malawi or neighbouring countries could offer a more comprehensive understanding of regional flood patterns and risks. This expanded scope can help in identifying cross-border flood risks and facilitate regional cooperation in flood management. Socioeconomic Impact Studies: Investigating the socioeconomic impacts of flooding, including effects on communities, infrastructure, and economies, can provide valuable insights for developing targeted flood mitigation strategies. Future research should assess how different flood risk levels affect various aspects of society and inform policies accordingly.

In line with the aim of this study, it is imperative to indicate that information embedded in the findings could be used to develop and implement proactive flood risk management strategies, including updating flood risk maps, designing flood protection infrastructure, and preparing emergency response plans tailored to the specific needs of each district in Malawi. The study further provides data needed for professionals associated with disaster and climate change risk management who are at the forefront of addressing flood risks with limited understanding of risks and vulnerabilities. More specifically, the information may help to strengthen flood monitoring systems by investing in and enhancing in flood monitoring infrastructure across the identified flood-prone areas, including upgrading weather stations, river gauges, and other monitoring tools to ensure timely and accurate data collection to build resilience of communities to climate extremes Relatedly, the information should foster implementation of proactive flood risk management strategies by utilize the predictive insights gained from this study to develop and implement proactive flood management strategies. In this case, this should involve updating flood risk maps, designing flood protection infrastructure, and preparing emergency response plans tailored to the specific needs of each district, including strengthening institutional capacity to deal with flood risks. Finally, this study provides information that should guide flood prediction to ensure that there is a regular update with the latest data and advancements in machine learning. Continuous improvement and validation of these models are essential for maintaining their accuracy and reliability. Similarly, institutions and stakeholders should utilize this information to promote community awareness and preparedness through conducting public awareness campaigns and educational programs to inform communities about flood risks and preparedness measures. This should also facilitate engaging local populations in flood risk management to enhance resilience and response capabilities in the life cycle of disaster risk management. Finally, the findings point to the notion that the government should aim to allocate resources based on detailed risk assessments and predictive forecasts to prioritize investments in high-risk areas and ensure that resources are distributed effectively to mitigate potential impacts of climate extremes.

Author Contributions

Conceptualization, I.M.K., M.M. and C.N.; methodology, I.M.K. and B.K.; formal analysis, I.M.K. and B.K.; investigation, I.M.K.; validation, I.M.K. and C.N.; writing—original draft preparation, I.M.K.; visualization, I.M.K. and V.K.; project administration, I.M.K., V.M., V.K. and C.N.; writing—review and editing, C.C. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest

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