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ARTICLE

Impact of Climate Change on the Streamflow in the Region of the Proposed Pwalugu Hydropower Plant

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ABSTRACT

Climate change has increased the frequency of extreme precipitation and temperature events, significantly affecting the environment. This study examines the impact of climate change on streamflow in the region allocated for the Pwalugu Hydropower Plant. This study employed SSP2-4.5, SSP3-7.0, and SSP5-8.5 across three temporal frameworks: the near future (2015–2043), the mid future (2044–2072), and the far future (2073–2100) with a reference period (1984–2014). A comparative analysis of three distinct machine learning models—ANN, LSTM, as well as SVM—was performed using statistical metrics including NSE, PBias, as well as R^2. The forecast of climate change indicates an increase in both frequency as well as intensity in the coming decades, potentially presenting a persistent threat to the advancement of hydropower as precipitation levels and patterns become increasingly erratic. Equally, the projections anticipated a decrease in streamflow under SSP2-4.5 for all three periods. Compared to the streamflow under the SSP3-7.0 and SSP5-8.5. It is noticed that SSP5-8.5 has the highest projections, especially in near and far future periods. As a result, it is advisable for decision-makers to implement measures aimed at mitigating risk and vulnerability, fortifying resilience, improving

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well-being, and developing the capacity to effectively anticipate and address the challenges presented by climate change in the vicinity of the proposed Pwalugu Hydropower Plant. The administration of water resources within the region would not only benefit the proposed Pwalugu Hydropower Plant but would significantly contribute to the sustainability of both agricultural and domestic endeavors.

Keywords: Pwalugu; Hydropower; Climate Change; Floods; Streamflow Shared Socio-Economic Pathways

1. Introduction

Based on the various forecasts from the Intergovernmental Panel on Climate Change (IPCC), it is anticipated that climate change will impact every facet of human activity: agriculture, energy, infrastructure, and water security. IPCC [1] assert that the ongoing release of global greenhouse gases, such as methane, carbon dioxide, as well as nitrous oxide, has led to significant alterations to the climate. The alterations in climate exert a profoundly detrimental influence on the environment, particularly affecting developing nations. The implications of climate change on streamflow have led to flooding, resulting in loss of life, property, and significant economic repercussions in numerous nations worldwide. A study conducted by IPCC [2] revealed that approximately 178 million individuals across Africa and Asia would face vulnerability to water stress as a consequence of changes in the climate. Furthermore, the study conducted by Obuobie et al. [3], Chinowsky and Arndt [4] suggests that changes in the climate are poised to adversely affect water resources in African nations, thereby placing considerable strain on the systems for water supply and management.

A variety of researchers throughout Africa have studied the effects of changes in the climate on streamflow through diverse methodologies. As an illustration, Ndhlovu and Woyessa [5] conducted a simulation of streamflow within the Zambezi River Basin located in Southern Africa, focusing on the climate scenarios of RCP 4.5 as well as RCP 8.5. The findings demonstrate an 85%, 6% increase in annual streamflow and less than 3% under RCP 4.5. Chakilu et al. [6] estimated an upsurge in the streamflow of the Lake Tana sub-basin, located in the upper Blue Nile basin of Ethiopia, with anticipated rises of 5.89%, 5.63%, 4.92%, and 4.87% in the Ribb, Gumara, Megech, and Gilgel Abay rivers, correspondingly. Orkodjo et al. [7] observed a rise in temperature, accompanied by a significant decline in both precipitation levels and streamflow within the Omo-Gibe basin in Ethiopia. The findings indicate that the range of precipitation varies from 10.77%–13.11% under RCP 4.5 and from 11.10%–13.86% under RCP 8.5. The evaluation of climate change's influence on the streamflow of the Ganjiang River catchment through LSTM-based models conducted by Deng et al. [8] indicated that mean annual precipitation as well as temperature have risen by 3.0–6.2% and 8.3–13.4%, correspondingly. It has been forecasted that streamflow will experience a reduction ranging from 1.5%–16.5% during the period of 2026–2075 across all SSP scenarios. The research conducted by Kartal et al. [9] indicates a notable decline in the volume of water traversing the region's rivers and streams in the forthcoming decades. The works of Xia et al. [10] reveals that a significant majority of rivers are witnessing a reduction in streamflow within the arid alpine regions.

1.1. Impacts of Changes in Climate on the Streamflow in Ghana

The study conducted by Kankam-Yeboah et al. [11] examines the effect of climate change on the streamflow within the White Volta basin. Research shows a projected decrease in streamflow within the basin, estimated at approximately 50% by the year 2050. The studies conducted by Obuobie et al. [3] and Mccartney et al. [12] similarly forecasted reductions in streamflows within the same basin. In their recent study, Smits et al. [13] undertook a comprehensive flood risk assessment and explored adaptation strategies in the context of a changing climate affecting the agrarian system in Ghana, specifically focusing on the White Volta Basin. Their findings suggest that the risk of flooding will rise by 79.1%, exhibiting significant spatial variability during wet periods. Their analysis suggests that the flood risk within the catchment area is projected to rise by 19.3% by the conclusion of the twenty-first century. In the Vea catchment of Ghana, Arfasa et al. [14] forecasted an average temperature rise ranging from 2.10 to 3.5 °C as well as from 2.7 to 4.15 °C under

SSP4.5 and SSP8.5, respectively. Nonetheless, a decrease in the yearly average precipitation is estimated to be between 12.34 and 13.1% for SSP4.5, whereas SSP8.5 forecasts a decline of 12.6–13.6%. Ofosu et al.[15] also conducted a thorough investigation into the impacts of anthropogenic activities, altered land use, as well as climatic fluctuations on the hydrologic regimes of the Densu River basin, utilizing the SWAT in conjunction with GIS technology. Between 1986 and 2005, there was a notable decrease in dense forest cover, which fell from 69% to roughly 26%. In contrast, open forest cover saw a significant rise, increasing from approximately 16% to about 52%. The primary water cycle events in the Densu basin were notably affected by curve-number (CN2), groundwater-delay-time (GW_Delay), and base flow-alpha-factor (Alpha_BF). The performance metrics for model time steps revealed that the PBIAS, as well as Nash-Sutcliffe Efficiency outcomes, were categorized as satisfactory. Afrifa et al.[16] conducted an evaluation of the impacts of changes in climate on fluctuations in groundwater levels. This study presents an innovative approach for forecasting fluctuations in groundwater levels, employing three distinct datasets: historical groundwater level data alongside climatic variables, including precipitation and temperature, which influence the dynamics of groundwater. The findings from the deep learning models reveal a Root Mean Square Error varying from 2.20 to 12.40, alongside a coefficient of determination (R^2) that spans from 0.84 to 0.99. This illustrates a significant improvement in Root Mean Square Error and Mean Absolute Error within the testing and validation categories in comparison to current leading methodologies.

The works of Assefa et al.[17] utilized the SWAT model to assess the hydrology and water resource impacts of additional irrigation in the Upper Offin sub-basin of Ghana. The study employed advanced spatial data in conjunction with field survey data to develop models that depict baseline conditions during dry seasons as well as irrigation scenarios for cocoa farms characterized by gentle slopes (2%). This offers important insights into achieving a balance between cocoa yield and water conservation. The findings indicate that supplemental irrigation from the shallow water table is capable of sustaining irrigation for up to 5% of the cocoa area (4760 ha) without negatively impacting groundwater flow. The proposal entails the expansion of irrigation to cover 30% of the cocoa area, which amounts to 28,540 hectares, all while ensuring a negligible decrease in catchment water yield.

1.2. Hydrological Model

A multitude of hydrological models have been employed worldwide, with the SWAT model being particularly prominent in the analysis of hydrological processes within river basins. The use of the SWAT model can be found in studies, such as Awotwi et al., Li et al., Wang, et al. Yan et al., Kim et al., Vu et al., and Abbaspour et al.[18–24]. The work of Waseem et al.[25] assert that the SWAT model is favored by numerous researchers due to its capability to intricately model the desired hydrological processes and its superior ability to replicate streamflow compared to alternative hydrological models. While widely utilized by numerous researchers, the findings of Nasir et al.[26] suggest that the SWAT model, along with other physically based models, requires considerable input data and various physical characteristics of the catchment area. Consequently, scholars worldwide have focused their efforts on "data-driven" models that possess the ability to extrapolate based on the relationship between input and output data. A notable example of a contemporary approach grounded in empirical evidence is the utilization of machine learning algorithms, which have exhibited superior performance when compared to traditional physically based models. For example, the research conducted by Koycegiz et al.,[27] analyzed the comparative performance of SWAT, Artificial Neural Network, as well as Support Vector Machine in the headwaters of the Carsamba River. The findings suggest that both the Support Vector Machine as well as Artificial Neural Networks have outperformed the SWAT model. Pradhan et al.[28] conducted an examination of the efficacy of three Artificial Neural Network models alongside the SWAT model. Their findings demonstrated that Artificial Neural Network models yield more precise estimates in comparison to SWAT. In a similar vein, Rahman et al.[29] conducted an evaluation and comparison of the SWAT model's performance against that of machine learning-based Multi-Layer Perceptron models for the simulation of streamflow in the Upper Indus Basin. Employing statistical metrics including percent bias (Pbias), Mean Absolute Percentage Error (MAPE), Nash–Sutcliffe efficiency (NSE), as well coefficient of determination (R^2), the findings reveal the comparatively subpar performance of the SWAT model in relation to the Multi-Layer Perceptron model. Due to the benefits that machine learning presents compared to traditional hydrological models, Katsekpor et al.[30] also employed machine learning models, particularly Random Forest as well as Long Short-Term Memory, to analyze data on temperature, precipitation, evapotranspiration as well as soil moisture. The objective was to predict the streamflow at intervals of 1, 5, as well as 10 days within the White Volta basin. Their approach encompassed the utilization of Long Short-Term Memory as well as Random Forest techniques to predict future streamflow, drawing upon data from the CMIP6 SSP5–8.5 scenario. The analysis utilizes Kling-Gupta Efficiency, Mean Bias Error, as well as Mean Absolute Error, demonstrating significant variations in streamflow. Both models effectively captured these variabilities; however, Long Short-Term Memory demonstrated a superior ability to capture peak flows, while Random Forest offered reliable long-term forecasts for periods extending up to 10 days. The models skillfully capture the effectiveness of streamflow, including seasonal patterns as well as peaks, thus enabling them to deliver accurate forecasts that support efficient mitigation and flood risk management within the basin. Future projections indicate significant variations in streamflow, suggesting a heightened probability of both flooding and drought scenarios within the White Volta basin. Their conclusion led to a recommendation for the application of such models in analogous basins, thereby creating a repeatable as well as sustainable framework for proactive flood early warning.

This evaluation presently draws upon data from three distinct Shared Socio-Economic Pathway scenarios: SSP2-4.5, SSP3-7.0, as well as SSP5-8.5, employing machine learning algorithms for analysis. This research represents a notable evolution in methodological approach through the adoption of the Shared Socio-Economic Pathways (SSPs), in contrast to previous studies that relied on the Representative Concentration Pathways, e.g., Dill et al.[31]. The Shared Socio-Economic Pathways integrate a range of socioeconomic factors, such as demographic expansion, economic advancement, and technological innovation, whereas the Representative Concentration Pathways focus predominantly on the patterns of greenhouse gas concentrations. Experts employ the Shared Socio-Economic Pathways to ascertain the impact of diverse societal choices on mitigation and adaptation strategies, thereby providing valuable insights that aid policymakers in making informed decisions in a timely manner.

1.3. Justification and Objectives of the Study

The influence of climate change on water resources has been the subject of extensive research, not only in Ghana but worldwide. Prior research by Ahialey et al.[32] have demonstrated that water resources have been greatly affected by changes in climate and this varies significantly across different regions and locations. Consequently, the alterations differ across various locales, each carrying its own implications. As climatic variations manifest differently across regions and locales, nations persist in grappling with unpredictable rainfall and temperature fluctuations, alongside recurrent droughts and floods. The alterations prompted by climate change significantly affect river flow and hydrological patterns. Therefore, the prediction of streamflow is essential, as it significantly contributes to the sustainable development of the region. Consequently, an investigation into the impacts of climate change on streamflow within the vicinity of the proposed Pwalugu Hydropower Plant is warranted. The findings will elucidate the mechanisms through which climate change affects streamflow in the vicinity of the proposed Pwalugu Hydropower Plant. This understanding would aid effective planning as well as management of surface water and also help Governments and policymakers take steps to alleviate the impact of climate change on the proposed Pwalugu Hydropower Plant, humans and other structures. This would further assist managers of Ghana's water resources in embracing more sustainable development approaches that align with Sustainable Development Goals (SDGs) 11, 13, and 15. This research is being undertaken as the Government of Ghana takes steps to initiate the triad project encompassing solar, irrigation, and hydroelectric components. In pursuit of the stated aims, the study's objectives are follows: **(i)** to forecast the variations in mean yearly maximum as well as minimum temperatures under SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios; **(ii)** to anticipate future changes in seasonal precipitation as well as temperature for the dry season (November to April) and the rainy season (May to October); **(iii)** to evaluate machine learning algorithms for streamflow predictions by employing Percent Bias (PBias), Nash–Sutcliffe Efficiency (NSE), as well as Mean Squared Error (MSE) metrics.

2. Materials and Methodology

2.1. Description of the Study Area

The study area is covered with Guinea Savannah forest with thin, small deciduous trees and grassy ground flora Ghana Statistical Service [33]. As a result, the area is densely forested with trees such as acacia, baobab, dawadawa, and sheanuts Ghana Statistical Service [33]. Ahialey et al. [34] discovered that crops such as corn, onions, beans, cassava, cabbage, carrots, guinea corn, rice, Sorghum, millet, and mangoes are cultivated in the catchment area. The crops are either irrigated or rain-fed. Previous work by Ahialey et al. [34] discovered five land use classes (cropland, grassland, settlement/bareland, waterbody and Others). Out of the five, grassland has increased from 9%, 20%, and 40% whilst the remaining four (4) classes experienced diverse variations over the 30-year period. Ahialey et al. [34] assigned population growth, changes in climate, deforestation and the decline of water bodies during this thirty-year period as key factors responsible for the variations in the land use.

The site for the proposed Pwalugu Hydropower Plant is situated on the White Volta River, approximately 30 kilometers to the southwest of Bolgatanga. This site is situated between the North East and Upper East Regions of Ghana. The proposed Pwalugu Hydropower Plant is situated upstream of the Bagré dam in Burkina Faso, while the Akosombo and Kpong dams are positioned downstream. The area in question typically experiences flooding during the month of August. It also has two distinct climatic seasons: the rainy season as well as the dry season. The period characterized by rainfall extends beginning May to October, while the dry season commences in November and lasts until April [33]. Presented below is the map of the study area, illustrated in **Figure 1**.

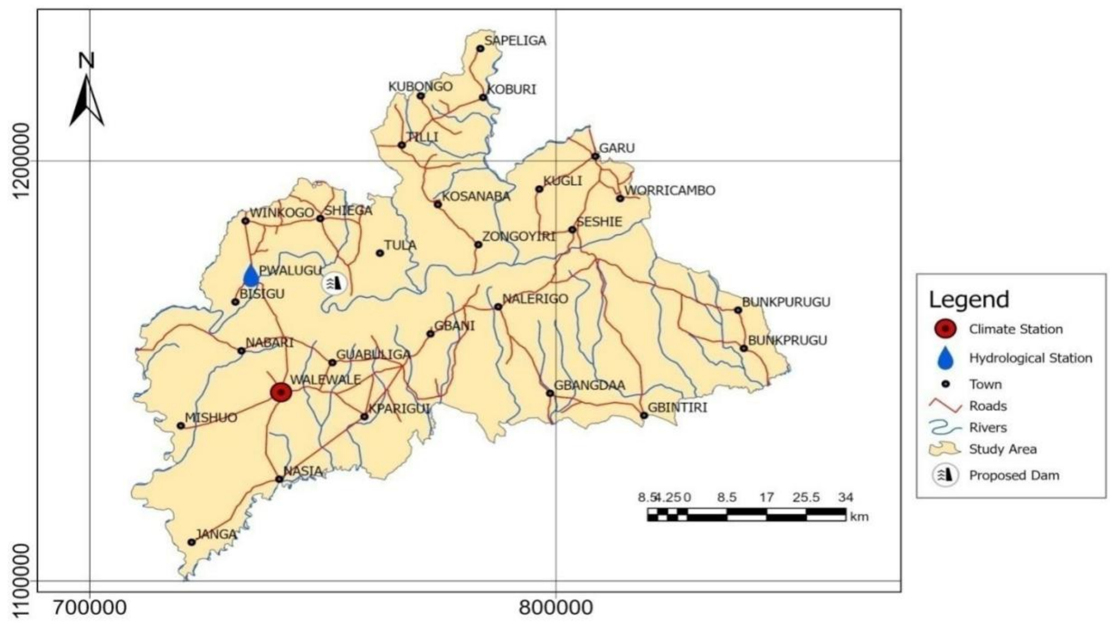


Figure 1. Study area showing climate and Hydrological stations as well as major towns.

2.2. Data Preparation and Downscaling

Historical meteorological data in the form of precipitation, temperature were collected in addition to the observed streamflow data for the study area. One global climate models (GCMs) and one future projection under different Shared Socioeconomic Pathways (SSPs). The Shared Socio-Economic Pathways were derived from global circulation model (GCMs), specifically the Canadian Earth System Model version 5 (CanESM5), which was retrieved from the Earth System Grid Federation (ESGF) website during the period of March 26th to 28th, 2022.

Using the linear scaling method, the daily Shared Socio-Economic Pathways data was therefore bias-corrected using the nearest station's climate data with the **C**limate **M**odel Data for **H**ydrologic **M**odelling (CMhyd) tool. This action was taken to lessen the discrepancy between the observed and simulated climate variables. It is also to enable the corrected simulated climate data to match simulations using observed climate data. Three distinct machine learning models (Long Short-Term Memory, Support Vector & Artificial Neural Network) were selected after an extensive literature review. These chosen models were trained using the historical, downscaled climate data as inputs and the observed streamflow data as the targeted output. Standard statistical metrics, including R-squared (R^2), Nash-Sutclife Efficiency (NSE), and Per cent Bias (PBias), were used to evaluate the model's performance. The use of the metrics was to ensure the choice as well as the outcome accurately represent the historical relationship between climate and streamflow.

Three distinct temporal phases were examined: the near future (2015–2043), the mid future (2044–2072), as well as the far future (2073–2100) against a reference period of 1984–2014 in order to evaluate the implications of climate change on streamflow within the region designated for the proposed Pwalugu Hydropower Plant. The specific research methodologies and theoretical frameworks employed in this study are illustrated in **Figure 2**.

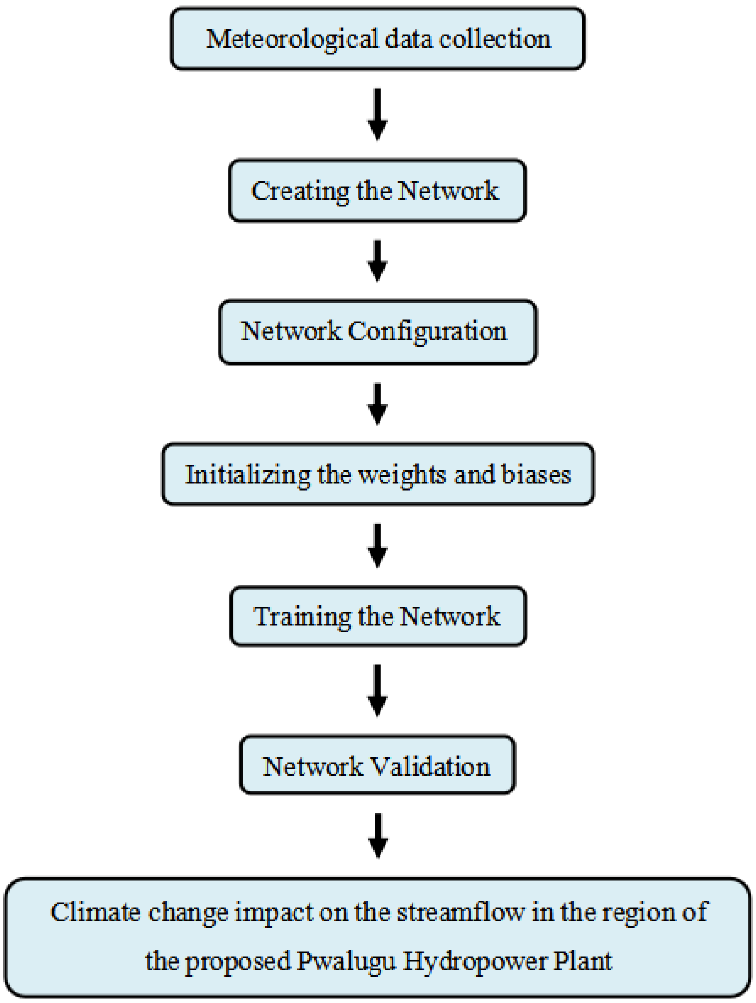


Figure 2. A flow chart of climate change impact on the streamflow in the region of the proposed Pwalugu Hydropower Plant.

3. Results and Discussion

As previously noted, the objective was to appraise the influence of climate change on the streamflow within the region of the proposed Pwalugu Hydropower Plant, utilizing the Shared Socio-Economic Pathways as a framework for analysis. The input data for the machine learning algorithm comprised weather data, climate scenarios from Shared

Socio-Economic Pathways 2, 3, and 5, as well as hydrological data.

3.1. Maximum and Minimum Temperature Projections

under SSP2-4.5, SSP3-7.0, and SSP5-8.5 As illustrated in **Figure 3**, projections for maximum temperature and minimum temperature across the three future periods indicate a steady increase. The maximum temperature is anticipated to rise by 0.7, 1.0, and 1.3 °C in the near future, followed by increases of 1.5, 1.7, and 2.0 °C in the mid future, and 2.0, 2.3, and 2.5 °C in the far future, corresponding to SSP2-4.5, SSP3-7.0, as well as SSP5-8.5 scenarios, respectively. The minimum temperature for the respective scenarios is anticipated to increase by 0.5, 0.7, and 0.9 °C (near future), followed by increases of 1.0, 1.4, and 1.6 °C (mid future), and ultimately 1.7, 2.0, as well as 2.5 °C (far future). As anticipated, the most significant alterations in maximum temperature as well as minimum temperature were forecasted under the SSP5-8.5 scenario, with particularly profound changes expected between 2073 and 2100. Once more, the forecast for maximum temperature as well as minimum temperature depicted in **Figure 3** has surpassed 2 °C threshold in the distant future (2073–2100), particularly under the SSP5-8.5 scenario.

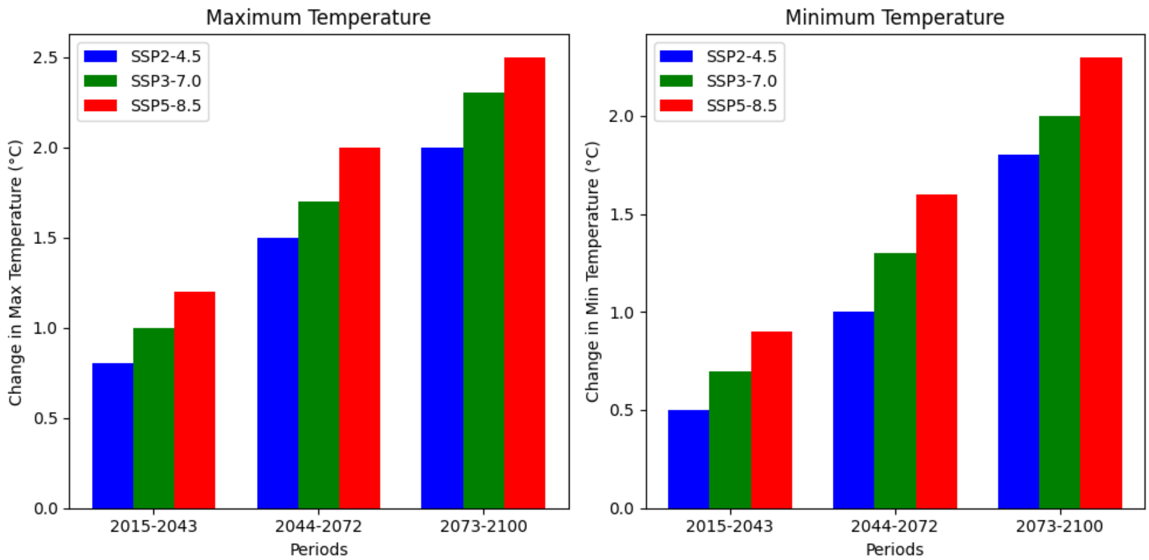


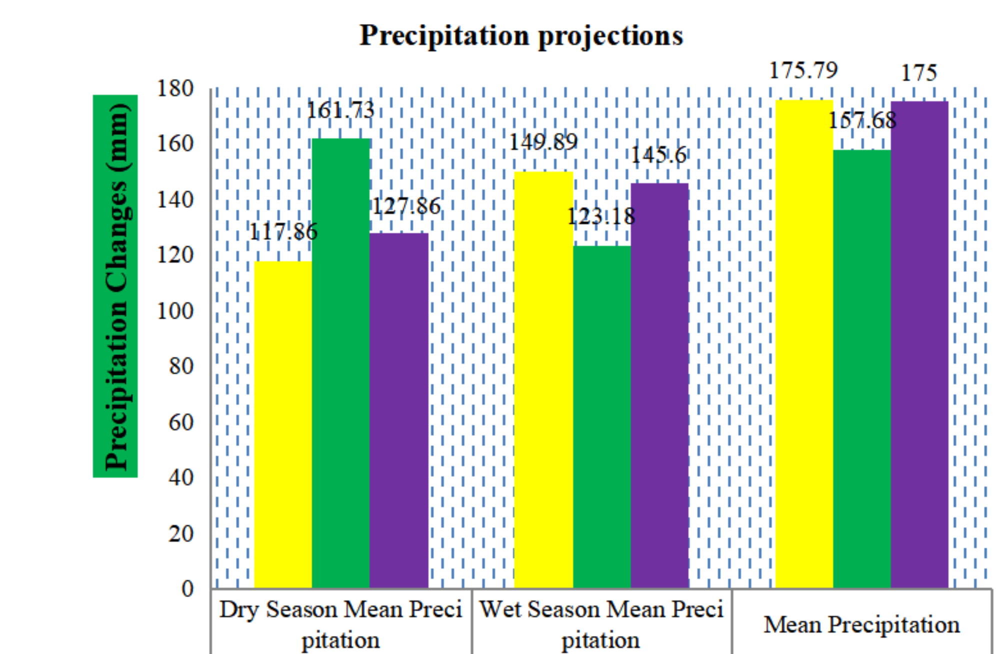
Figure 3. Maximum and minimum temperature projections for the three future periods: Near future (2015–2043), Mid-far future (2044–2072) and Far future (2073–2100).

As the upper and lower bounds of temperature under each Shared Socio-Economic Pathways persist in their ascent, additional reductions in streamflow are anticipated. The rise in maximum temperature as well as minimum temperature is set to enhance evapotranspiration, thereby elevating the demand for water. Consequently, the findings suggest that climate change will have detrimental impacts on the proposed Pwalugu Hydropower Plant. This discovery highlights the pressing need to confront climate change as well as its possible ramifications for ecosystems, communities, and economies in the climate-affected area of the proposed Pwalugu Hydropower Plant. It underscores the pressing necessity for proficient management of water resources in the area designated for the proposed Pwalugu Hydropower Plant. The results align with the prior research conducted by Koycegiz et al. [27].

3.2. Projected Precipitation and Temperature Changes for the Dry and Raining Seasons

According to Ahialey et al. [32], temperature and precipitation changes are the manifestation of climate change. As a result, climate change projections in this study are based on precipitation and temperature. The projections of precipitation for the two seasons under SSP2-4.5, SSP3-7.0, as well as SSP5-8.5 in the area designated for the proposed

Pwalugu Hydropower Plant are illustrated in **Figures 4** and **5**. As previously indicated, the Northern sector of the country accommodates the proposed Pwalugu Hydropower Plant, which experiences a singular rainy season that commences in May and extends through September/October. The mean precipitation during the wet season (May to September) under the SSP2-4.5 scenario is the highest at 149.89 mm, followed closely by the SSP5-8.5 scenario at 145.60 mm, as in **Figure 4**. The peak dry season, observed from **Figure 4**, occurs under SSP3-7.0 with a measurement of 161.73 mm, closely followed by SSP5-8.5 at 127.86 mm. Concurrently, the average maximum temperature for the three scenarios is recorded as 27.78, 27.48, 26.72 °C for SSP2-4.5, SSP3-7.0, as well as SSP5-8.5, correspondingly indicated in **Figure 5**. The observed rise in both precipitation and temperature in this study is consistent with the findings presented by Nasir et al.[26] and Ullah et al.[35]. The dry season in the Northern region of the country commences from November to April, and projections suggest a probable increase in the number of dry days throughout this timeframe in the forthcoming years, as indicated by the SSP3-7.0 scenario. The findings presented through the three scenarios suggest a significant increase in mean daily precipitation is expected from May to September/October. This phenomenon is especially evident across all three scenarios, yet it is more pronounced in the SSP2-4.5 relative to the SSP3-7.0 and SSP5-8.5.



	Dry Season Mean Precipitation	Wet Season Mean Precipitation	Mean Precipitation
SSP2-4.5	117.86	149.89	175.79
SSP3-7.0	161.73	123.18	157.68
SSP5-8.5	127.86	145.6	175

Figure 4. Seasonal precipitation projections.

The dry season is likely to experience momentous challenges related to streamflow reduction under SSP5-8.5, predominantly in the distant future, as a result of fluctuations in both maximum and minimum temperatures. The wet season seems to diminish under SSP3-7.0, while experiencing a slight rise under SSP5-8.5. This would impose a significant burden due to diminished streamflow, especially in the arid season of the distant future. In this context, a comprehensive approach to water resources management is indispensable for the effective regulation of water availability derived from river basins, predominantly in light of the challenges posed by climate change.

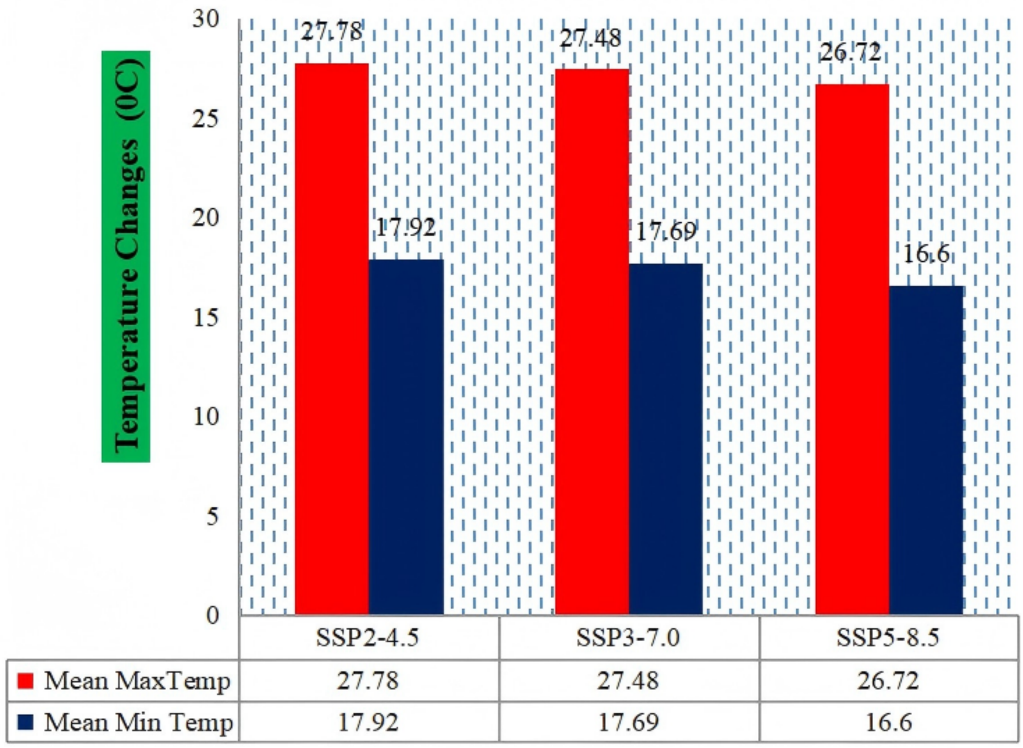


Figure 5. Temperature projections for the dry seasons.

3.3. Comparison of Machine Learning Models in the Projection of Streamflow

The data presented offers a proportional analysis of the performance of three distinct machine learning models: Long Short-Term Memory, Support Vector, as well as Artificial Neural Network utilizing statistical indicators including R-squared (R^2). Nash-Sutclife Efficiency (NSE), and Percent Bias (PBias). In the context of each machine learning algorithm, the dataset was partitioned into two segments: the testing data, comprising 30% of the total dataset, and the training data, which constituted the remaining 70%. Utilizing the NSE as a metric for assessing the predictive accuracy of the models reveals that a value approaching 1 signifies superior predictive performance. The Artificial Neural Network demonstrates a training NSE of 0.9695 and a testing NSE of 0.9023, reflecting robust efficacy in both stages. The Long Short-Term Memory exhibits diminished values, with a training NSE of 0.9236 and a testing NSE of 0.8727, indicating a decline in performance. In a manner akin to Long Short-Term Memory, the Support Vector Machine demonstrates a training NSE of 0.9381 and a testing NSE of 0.9008. The Percent Bias (PBias) reflects the average inclination of predictions to exceed or fall short of the observed values. Consequently, values approaching 0 indicate predictions that are well-balanced. The Artificial Neural Network exhibits a minimal training bias of 0.03 and a slightly negative testing bias of −1.37, indicating commendable performance. The Long Short-Term Memory demonstrates a pronounced negative bias in both training (−0.76) and testing (−7.12), suggesting challenges related to underestimation. Conversely, the SVM exhibits a minor negative training bias of −0.11, accompanied by a more pronounced negative testing bias of −1.95. The R-squared (R^2) denotes the fraction of variance in the dependent variable that is elucidated by the model. Values approaching 1 suggest a more optimal alignment. The Artificial Neural Network attains a training R^2 of 0.9695 and a testing R^2 of 0.9023, both of which are elevated figures that suggest a commendable fit. However, the training R^2 for the Long Short-Term Memory is 0.9236, while the testing R^2 stands at 0.8727, indicating a satisfactory fit yet demonstrating inferior performance compared to the Artificial Neural Network. Conversely, the Support Vector Machine demonstrates comparable efficacy to Long Short-Term Memory, exhibiting a training R^2 of 0.9381 and a testing R^2 of 0.9008. In conclusion, the Artificial Neural Network exhibits superior performance compared to Support Vector Machines as well as Long Short-Term Memory regarding training and testing metrics, especially in predictive accuracy (NSE) and explained variance (R^2). Conversely, both Support Vector Machine and Long Short-Term Memory show marginally lower performance, characterized by a tendency for underestimation as reflected in their PBias metrics. This result is consistent with the earlier studies conducted by [28–30]. In these investigations, scholars employed Artificial Neural Networks to evaluate and forecast the effects of climate change on streamflow dynamics.

Figure 6 illustrates the anticipated impacts of climate change on streamflow within the region designated for the proposed Pwalugu Hydropower Plant across three future timeframes, utilizing the scenarios SSP2-4.5, SSP3-7.0, as well as SSP5-8.5. All chosen climate scenarios suggest a consistent rise across the near, mid, then distant future timeframes. The examination indicates that precipitation is projected to rise across the near, mid, as well as far future periods, with a notable escalation under SSP3-7.0 and SSP5-8.5 for all three intervals. In contrast, the forecasts indicated a decrease in streamflow under SSP2-4.5 across all three periods. The most significant decrease observed under SSP2-4.5 occurs in the distant future, falling below 160 m^3/s compared to the streamflow associated with SSP3-7.0 and SSP5-8.5. Observations indicate that SSP5-8.5 presents the most elevated projections, particularly in both the near then distant future timeframes.

The results indicate that the region exhibits a significant degree of susceptibility and vulnerability to both floods and droughts. It is clear that climate change will adversely affect the water resources in the area of the proposed Pwalugu Hydropower Plant, placing significant strain on the water supply and management systems. Such an outcome necessitates the development of comprehensive strategies for the long-term management of water resources. It also signifies that current strategies ought to be reinforced to effectively tackle the repercussions of climate change in the region.

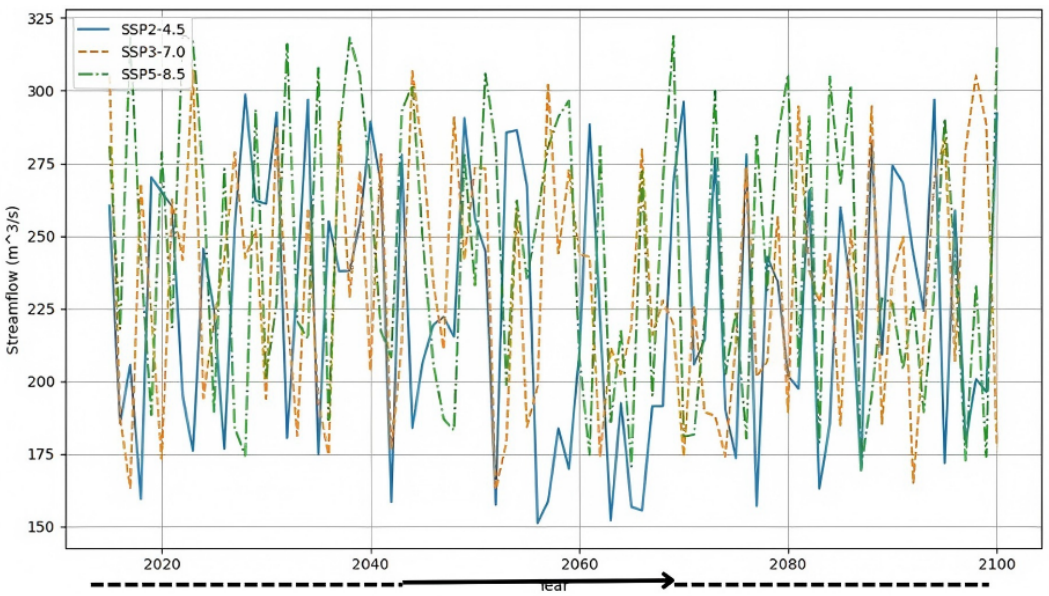


Figure 6. Projection of the climate change impact on the streamflow for the three Shared Socio-Economic Pathways and future periods.

4. Conclusions

The evaluation of climate change's influence on streamflow within the area designated for the proposed Pwalugu Hydropower Plant was conducted utilizing the Shared Socio-Economic Pathways and employing the Artificial Neural Networks algorithm. Among the three machine learning algorithms employed, the artificial neural network algorithm adeptly forecasts daily streamflow utilizing solely climatic data such as precipitation, as well as maximum and minimum temperature. The Artificial Neural Networks algorithm exhibits impressive performance metrics throughout its training then testing phases, affirming the dependability of machine learning algorithms as essential instruments for understanding hydrology. The results of this study indicate the necessity for formulating extensive long-term plans for managing water resource; alongside enhancing current approaches help alleviate the impacts of climate change in the region designated for the proposed Pwalugu Hydropower Plant. Given the anticipated rise in precipitation across the near, mid, and far future periods, particularly under the SSP3-7.0 and SSP5-8.5 scenarios, it is probable that the hydrological regime will undergo significant alterations. This will be marked by increased seasonal unpredictability and a heightened likelihood of extreme occurrences as a result of substantial warming and increased moisture in the forthcoming periods. The observations underscored the pressing necessity for focused mitigation and adaptation options to address the challenges of water scarcity that may arise, predominantly throughout the dry season and in the mid-- to distant future. The results indicated variations in streamflow projections across the examined periods. This necessitates a critical enhancement of financing for climate-resilient water infrastructure by policymakers, alongside the implementation of a drought early warning system. The proposal advocates for the adoption of optimal management strategies alongside the execution of a robust water resource management framework to mitigate the adverse impacts of drought and enhance resilience to address the issues presented by climate change in the region.

Author Contribution

Conceptualization, formal analysis, writing and editing, E.K.A; conceptualization and review A.T.K.-b; review, S.G. All authors have read and agreed to the published version of the manuscript.

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Not applicable.

Data Availability Statement

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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