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Climate Change Impact on Hydropower: A Comparative Study of SWAT and BiLSTM-Based River Discharge Forecasting in the Sunkoshi River Basin, Nepal

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Abstract: Hydropower is a significant renewable energy source for Nepal, contributing to its electricity generation and economic development. However, climate change-induced fluctuations in river discharge concerns long-term hydropower sustainability. This study investigates the effects of climate change on the hydropower potential of Nepal's Sunkoshi basin using a physically based hydrological approach (SWAT) compared with a machine-learning method (Bi-directional LSTM). In the face of increasing global energy consumption and calls for sustainable development, the paper utilizes long historical hydrological records (1980–2015) and future climates in the simulation of river flow for the period of 2024–2050. While the physically realistic data-driven SWAT approach captures physical watershed processes, the BiLSTM exploits the pattern of historical flow for future flow forecast. Both models forecast a nearly 48% reduction in the average flow in the historical period, with significant rises in the duration of low flow with total hydrological variability. Although the correlation coefficient ($r = 0.99$) for the relationship between the two approaches in predicting the yields of hydropower energy is very high, the results in the forecast of events at extremes conflict: while the SWAT overestimates the peak flows, the BiLSTM offers smoother curves. The paper emphasizes the contribution of multi-model approaches towards hydrological forecasting and highlights the importance of planning for adaptation in the face of changing climatic conditions, for the requirement of adaptation measures, investment in resilient infrastructure, as well as updating policies to maximize the utilization of hydropower in the face of changing climatic conditions. The SWAT model achieved strong calibration performance with $R^2 = 0.91$ and Nash-Sutcliffe Efficiency (NSE) = 0.82, while the BiLSTM model demonstrated superior short-term accuracy with Test MSE = 0.0006, MAE = 0.0099, and RMSE = 0.0246. Energy output projections suggest hydropower generation could decline significantly, emphasizing the need for resilient infrastructure, adaptive policy reforms, and hybrid renewable energy integration. This study underscores the necessity of multi-model approaches for hydrological forecasting and provides critical insights for climate-resilient hydropower planning in Nepal. The findings are instrumental for policymakers, engineers, and researchers aiming to enhance energy security and sustainable development. In this study, the rationale for selecting SWAT lies in its strength to interpret physical watershed processes, while BiLSTM was chosen for its ability to capture short-term temporal dependencies in hydrological time series. The regional significance of this study is emphasized by Nepal's reliance on hydropower for over 90% of electricity, making accurate discharge forecasting vital for national energy security.

Keywords: hydropower; climate change; SWAT model; BiLSTM; forecasted discharge; sustainable energy

1. Introduction

The increasing global population and urbanization have heightened the need for sustainable energy solutions. According to the International Energy Agency, an investment of $26 trillion in energy is required from 2008 to 2030, with electricity demand rising by 2.5% annually [1]. In response to these issues, the UN launched the Sustainable Energy for All initiative in 2011 and adopted SDG7 in 2015 [2]. Nepal has integrated these efforts into its national strategies, such as the National Climate Change Policy 2019, the National Energy Efficiency Strategy 2018, and the Renewable Energy Subsidy Policy 2016 [3,4]. Key objectives include boosting household electricity access from 74% in 2015 to 99% by 2030 and cutting traditional biomass use for cooking from 75% to 30% [5,6].

Nepal's energy resources are divided into traditional, commercial, and modern renewables, with further classification into renewables (fuelwood, biomass, hydro, solar, wind) and non-renewables (coal, petroleum) [7]. Fuelwood remains a significant energy source, with forests covering 40.36% of Nepal's land, supplying around 12.16 million tons of fuelwood each year. Agricultural residue is another traditional energy source, with approximately 26 million tons available in 2021, producing about 442 million GJ of energy. The Nepal Electricity Authority (NEA) had an installed electricity capacity of 626.7 MW in 2022, generating 3242.5 GWh of energy, with peak demand reaching 1748 MW. In FY 2078/79, Nepal exported 493.6 GWh of electricity. The country depends on petroleum imports managed by the Nepal Oil Corporation (NOC), which stored 68,427 kiloliters of petroleum products in 2021. Petroleum sales, excluding kerosene, saw a significant rise in 2022. Coal production in Nepal varied, peaking at 11,303.9 tons in FY 2077/78 but dropping to 6927.04 tons in FY 2078/79, mainly for brick manufacturing. Micro/pico hydro plants, vital for rural electrification, increased their capacity to 37,734 kW in 2022. The potential for biogas includes 1.9 million households, with 439,547 systems installed by 2022. Nepal has an estimated 2100 MW potential for on-grid solar PV, with 974,000 solar PV systems installed by 2022. Despite a 3000 MW potential for wind energy, it remains underdeveloped, with only 113.6 kW installed by 2018 [7]. Previous studies have applied SWAT in Himalayan catchments (Bhattarai et al., 2024) [8] and LSTM-based models for short-term forecasting, but few works have compared process-based and deep learning approaches under climate change scenarios in Nepal. This research addresses this gap by providing a dual-model comparison in the Sunkoshi Basin, highlighting novelty and scientific contribution.

In 2022, Nepal's total energy consumption was 640 PJ, with 64.17% from traditional sources, 28.35% from commercial fuels, 4.96% from electricity, and 2.52% from renewables [7]. The country's energy intensity remains high, although the per capita residential sector intensity decreased from 14 GJ in 2019 to 13.3 GJ [7]. The energy mix is still dominated by traditional biomass (64.17%), but the share of renewable energy is on the rise (7.48%) [7].

Nepal's energy supply and demand scenario for several fuel sources is traditional, commercial, and modern renewable resources. These resources can be divided into two categories: non-renewables (coal and petroleum products) and renewables (fuelwood, agricultural residue, and other biomass, animal waste, hydro, solar, and wind power generation) [7].

1.1. Short Literature Review

The impacts of climate change on the forecast of river discharge and hydropower have also been the focus of recent works. Though Kratzert et al. (2018) [9] demonstrated the promise of the use of LSTM networks in rainfall–runoff modelling, Bhattarai et al. (2022) [10] discussed the expected decline in discharge in Himalayan basins due to climate change. Works such as Liu et al. (2013) [11] also outline the sustainability concerns in the development of hydropower. The SWAT modelling was applied in more recent works of Bhattarai et al. (2024) [8] to assess hydropower in the river basins of Nepal. Additionally, the studies by Thapa et al. (2025) [12] and Silewu et al. (2025) [13] reflect the significance of the use of machine learning in enhancing the precision of forecasting and in ensuring safer decision-making in the field of civil engineering study.

1.2. Energy Policies and Planning

Nepal's energy strategies prioritize the development of hydropower, the promotion of renewable energy, and ensuring energy security. The National Rural Energy Programme (NREP) is instrumental in enhancing energy access and efficiency. In 2018, the Ministry of Energy, Water Resources, and Irrigation (MOEWRI) released a white paper with ambitious goals to boost hydropower generation capacity to 15,000 MW within a decade. The Low Carbon Economic Development Strategy (LCEDS) focuses on expanding renewable energy and reducing greenhouse gas emissions [7]. Nepal's revised Nationally Determined Contribution (NDC) sets a target to increase energy production to 15,000 MW, with 5–10% sourced from renewables, and aims to introduce electric cookstoves in 25% of households by 2025 [7]. The Energy Vision 2050 outlines long-term objectives for hydropower, aiming for a capacity of 31,000 MW by 2050 [7]. Hydropower Potential and Challenges Nepal, a landlocked country with a population of 29.16 million, has significant hydropower potential due to its mountainous landscape. As of February 2024, the total power output from 162 projects is 2639.485 MW, representing only 3% of Nepal's estimated 83,000 MW hydropower potential and 6% of the economically viable 50,000 MW [10,14,15]. However, the development of hydropower is hindered by various challenges, including technical, environmental, social, and political issues [7,8]. Despite these obstacles, Nepal's renewable energy sector is expanding, with hydropower being a key component of its sustainable energy future [8–11].

2. Prospect of Hydropower Development in Nepal

2.1. Background

Nepal experiences an average yearly rainfall of about 1530 mm [16] and is rich in water resources. The nation is home to approximately 6000 rivers, both large and small, including significant river systems like the Koshi, Gandaki, and Karnali, as well as border rivers such as the Mechi in the east and the Mahakali in the west [17]. Some rivers have their origins in the High Himalayas and Tibet, while others, like the Kankai, Kamala, Bagmati, Rapti, and Bheri, begin in the Mahabharata mountains. The Churia hills are the source of many smaller, rain-fed seasonal streams.

Between June and September, during the monsoon season, Nepal receives about 60–90% of its annual rainfall, which accounts for 55–80% of the total runoff; the rest is stored as snow and groundwater, feeding rivers during the dry season [18]. Annually, Nepal produces an estimated 225 billion cubic meters of runoff, including contributions from the Tibetan watershed [17]. The country spans 885 km from east to west and 145–248 km from north to south, with elevations ranging from 60 masl to 8848 masl, providing substantial potential for hydropower development.

A previous study estimated Nepal's economically feasible hydropower potential at around 45,610 MW [17–19], with a gross potential of 83,500 MW [20]. More recent evaluations suggest a run-of-the-river (ROR) hydropower potential of 53,836 MW at 40% dependable flow [21].

2.2. Hydrological & Meteorological Data

Since the 1960s, the Department of Hydrology and Meteorology (DHM) in Nepal has been tasked with collecting hydrometeorological data. Currently, DHM monitors river flow at about 100 stations, but with around 6000 rivers and streams, hydrometric stations are still sparse. River gauging stations are mainly located in mid-hill regions, with fewer in the Terai due to frequent river channel changes and in the Himalayas due to their remoteness. DHM also gathers meteorological data from roughly 300 sites, including information on precipitation, air temperature, solar radiation, humidity, and wind speed. For this study, DHM provided average monthly discharge and rainfall data.

2.2.1. Average Monthly Rainfall Data

Nepal's monsoon, which lasts from mid-June to late September, accounts for 79.58% of the annual precipitation, often leading to flash floods, landslides, soil erosion, and sedimentation in mountainous areas, as well as flooding in the plains. Understanding rainfall patterns is vital for hydrological studies and evaluating climate change impacts. This study uses average monthly rainfall data from operational meteorological stations from their inception until December 2014.

2.2.2. Average Monthly Discharge Data

DHM supplies river discharge data from selected monitoring stations, which reflect seasonal variations and long-term hydrological trends crucial for assessing hydropower feasibility.

2.3. History of Hydropower in Nepal

In the past, hydropower in Nepal was mainly utilized to mill grain. The country's first hydropower station, a 500-kW plant in Pharping, was built in 1911, followed by a 600-kW facility in 1934. Initially, access to hydropower was restricted to the ruling class, with the general public gaining access only in 1965 through the 2.4 MW Panauti project. After this, the development of hydropower began to accelerate**.** The trend of hydropower installations in Nepal since the early 20th century is illustrated in Figure 1. The political changes in 1990 led to new policies that encouraged private sector involvement; however, the sector experienced a nearly decade-long stagnation due to ambiguous regulations and political turmoil. Despite challenges, such as the cancellation of the Arun III (404 MW) project due to environmental concerns and the Maoist conflict, projects like Khimti (60 MW) and Bhotekoshi (36 MW) were completed in 2000, followed by Middle Marsyangdi (70 MW) in 2002 and Kali Gandaki A (144 MW) in 2008.

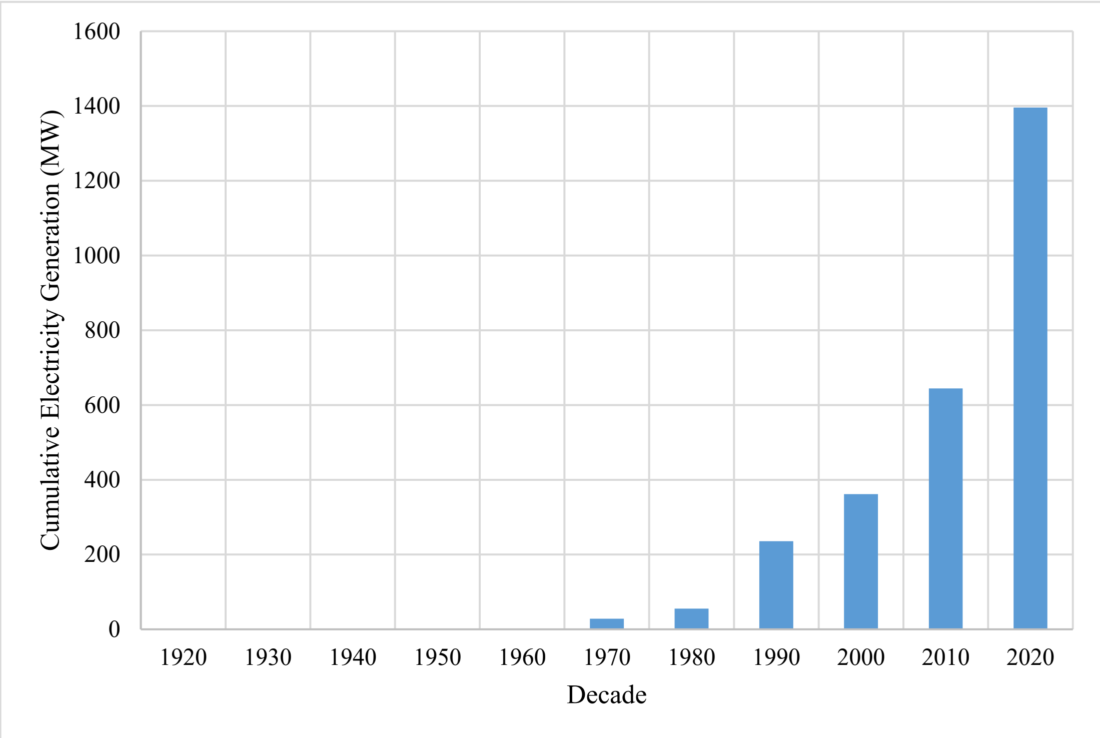

Figure 1. Trend of hydropower installations in Nepal [22].

Despite these advancements, the demand for electricity in Nepal has surpassed the supply, resulting in significant load-shedding. In December 2008, the government announced a "national energy crisis" as winter power outages reached 16 h per day. These outages continued, peaking at 14 h daily during 2011–2012.

2.4. Hydropower Potential

Nepal's rugged terrain and plentiful water resources present enormous hydropower potential. The often-cited estimate of 83,500 MW [23] remains a standard, though technological progress calls for updates. A recent study using hydro-meteorological data, GIS, and hydropower modeling estimates Nepal's ROR potential at 53,836 MW, with an annual generation capacity of 346,538 GWh at Q40% flow exceedance and 80% efficiency. Major river basins like Narayani, Saptakoshi, and Karnali significantly contribute, with potential capacities of 17,800 MW, 17,008 MW, and 15,661 MW, respectively. This updated analysis highlights Nepal's vast untapped hydropower resources, stressing the importance of sustainable investments and optimized use for both national and regional energy security.

3. Materials and Methods

3.1. Study Area

The study focuses on the Sunkoshi River basin in the Sindhupalchok district in Nepal (Figure 2) which plays a vital role in hydropower generation. The Sunkoshi River, also spelled Sunkosi, is a major tributary of the Koshi (Saptkoshi) River system in Nepal. It originates from two primary sources: one within Nepal at Choukati and the other, a more significant tributary, flowing from Nyalam County in the Tibet region of China [24]. The river's headwaters can be traced to the Zhangzangbo Glacier in Tibet [25].

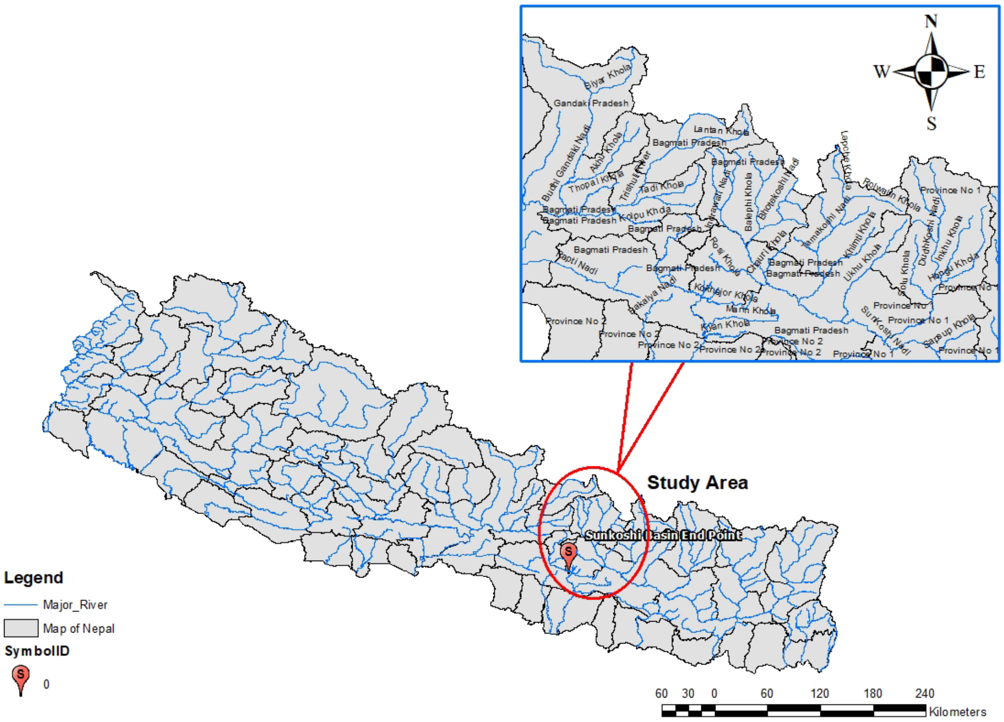

Figure 2. Study area; Sunkoshi River Basin.

Geographically, the Sunkoshi River catchment is defined by longitudes ranging from 6°19′28.41″ E to 85°26′40.76″ E and latitudes from 28°29′51.54″ N to 27°31′34.39″ N. The elevation within the basin varies from 588 m to 7945 m above sea level.

Climatically, temperatures in the basin fluctuate, reaching up to 33 °C in summer and dropping below 4 °C in winter. The basin covers an area of approximately 3394 km^2, within which 2007 km^2 is within Tibet and 1387 km^2 is within Nepal [24]. Morphologically, the basin has a leaf-shaped structure, with a mean area length of 110 km and a width of 66 km [8].

3.2. Data

This research utilized two primary categories of data: spatial data and time-series data. The spatial data included three key components: (i) a digital elevation model (DEM) from USGS Earth Explorer (30 m resolution) to characterize the terrain; (ii) land use/land cover (LULC) information from the Global Map of Land Use/Land Cover Areas (GMLULCA) and IWMI's Global Map of Irrigated Areas (GMIA) to assess surface characteristics; and (iii) soil data sourced from the FAO Global Soil Database to analyze soil types and compositions.

The time-series data consisted of (i) weather parameters, including precipitation, solar radiation, temperature, wind velocity, and relative humidity; and (ii) daily discharge data, which was crucial for calibrating and validating the hydrological model. The sources of all these data sets are detailed in Table 1.

Before model execution, the gathered data were extensively preprocessed: the datasets are cleaned to handle missing values and outliers, normalized and scaled for model suitability, and enhanced through feature engineering to develop additional predictors, including the introduction of lag variables and the use of moving averages. The data span an extensive period—from 1980 to 2015—and are recorded at suitable timescales (daily or monthly), allowing for the detection of both short-term fluctuations and long-term trends. This robust, multidimensional data

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coverage is crucial for providing the Bi-directional LSTM and SWAT models with reliable, high-quality inputs, ultimately enabling a meaningful comparison of their energy forecasting capabilities.

Table 1. Source of dataset.

Category	Data Type	Data Source
Climate	Precipitation and temperature	Department of Hydrology and Metrology (DHM), Nepal
Topography	DEM 30m resolution	Shuttle Radar Topography Mission (SRTM)
Soils	Soil properties map	FAO Digital Soil Map
Physical Infrastructure	Hydropower site	International Centre for Integrated Mountain Development (ICIMOD) and Department of Hydrology and Metrology (DHM)
Discharge	Daily discharge	Department of Hydrology and Metrology (DHM), Nepal

3.3. Overview of SWAT Model

The Soil and Water Assessment Tool (SWAT) [26,27] is a physically based, semi-distributed hydrological model designed to assess the impact of land management practices on water, sediment, and agricultural chemical yields in large and complex watersheds. Originally developed by the United States Department of Agriculture—Agricultural Research Service (USDA-ARS), SWAT is a public domain model widely used for hydrological and environmental studies across the globe.

The SWAT model is a continuous, long-term watershed simulation tool designed to operate on a daily time step. It predicts the effects of land management on water resources, sediment transport, and crop chemical production. As a physically based and computationally efficient model, SWAT can process extensive spatial data by dividing the watershed into multiple sub-watersheds. Its core components include hydrology, weather, and soil, along with temperature, plant growth, nutrient cycles, pesticide dynamics, and land management practices. The model has been validated for various watersheds.

In SWAT, a watershed is divided into multiple sub-watersheds, which are further subdivided into hydrologic response units (HRUs) characterized by unique soil and land-use properties. The water balance within each HRU is represented by four storage components: snow, soil profile (0–2 m), shallow aquifer (typically 2–20 m), and deep aquifer (>20 m). Flow generation, sediment yield, and non-point source loadings from each HRU within a sub-watershed are aggregated and routed through channels, ponds, and reservoirs to the watershed outlet. The hydrologic processes in SWAT are governed by the water balance equation and are systematically represented in Figure 3.

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw})$$

where,

SW_t = Final soil water content (mm)
SW_0 = Initial soil water content (mm)
R_{day} = Amount of precipitation on day i (mm)
Q_{surf} = Surface runoff (mm)
E_a = Evapotranspiration (mm)
W_{seep} = Water seeping into the vadose zone (mm)
Q_{gw} = Groundwater flow contribution to streamflow (mm)

This equation represents the hydrological balance of a watershed, accounting for inputs (precipitation) and outputs (runoff, evapotranspiration, infiltration, and groundwater movement). The model uses this balance to simulate the flow of water through various environmental compartments, helping researchers estimate water resource availability and sustainability.

The Soil and Water Assessment Tool (SWAT) include basic elements that simulate hydrological processes in a watershed system. The climate module provides basic meteorological information, including variables like precipitation, temperature, and humidity, which are essential in controlling water cycle processes, such as evapotranspiration and runoff. The hydrology module describes the water movement in two phases: the land phase, which includes infiltration, surface runoff, and retention of soil moisture, and the routing phase, which simulates riverine flow, groundwater input, and the ability of reservoir storage [28].

The soil and land use component influences hydrology by incorporating soil properties and land cover, affecting runoff, infiltration, and water retention. SWAT also includes a sediment and nutrient transport component, tracking erosion, nutrient movement, and pollution sources to assess water quality. Additionally, the groundwater component models shallow and deep aquifer interactions, determining baseflow contributions and long-term recharge.

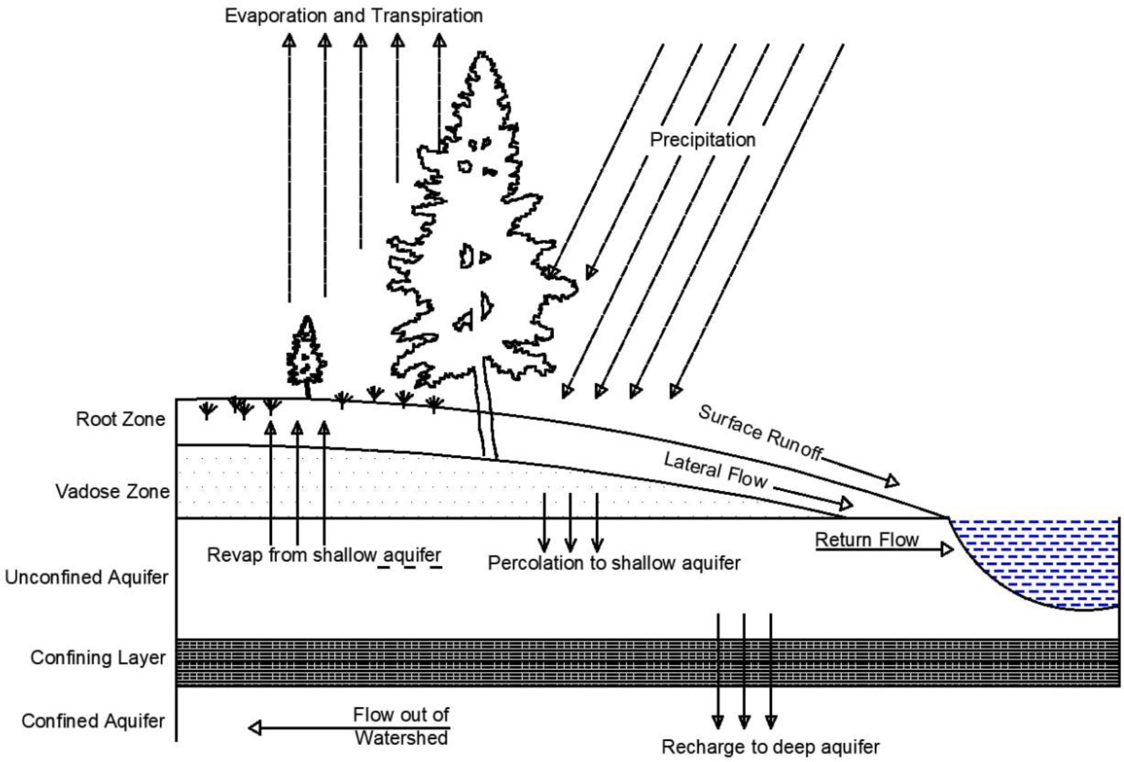

Figure 3. Systematic representation of the hydrologic cycle.

3.4. Discharge Forecasted Using SWAT Model

The discharge prediction made using the Soil and Water Assessment Tool (SWAT) model entailed the use of past daily discharge records obtained from the Department of Hydrology and Meteorology (DHM) of Nepal, between 1980 and 2015. The discharge forecasted by the SWAT model for the period 2024–2050 is shown in Figure 4. The dataset was used as the input for both the calibration and validation stages of the SWAT model, thus confirming its effectiveness in simulating river discharge under varying hydrological conditions. In the calibration stage, the Sequential Uncertainty Fitting (SUFI-2) [29] algorithm was used to minimize the differences between the simulated and observed discharge values, thus improving the model's precision for future predictions. The calibration performance of the model was evaluated using key statistical parameters, yielding values of p-factor = 0.18, r-factor = 0.09, R^2 = 0.91, and Nash-Sutcliffe Efficiency (NSE) = 0.82, indicating a high level of accuracy in discharge simulation. Future climate data were obtained from CMIP6 models, specifically GCMs under RCP4.5 and RCP8.5 scenarios [30]. The starting year of 2024 was chosen due to unavailability and incompleteness of observed discharge data between 2016–2023.

Using the calibrated SWAT model, river discharge was modeled for the period between 2024 and 2050, using future climatic data to estimate future hydrological trends. The model accounted for key hydrological processes such as precipitation, surface runoff, evapotranspiration, groundwater recharge, and river flow dynamics [27]. By coupling climate predictions with land use changes, the estimates provide useful information on future changes in water availability, seasonality of discharge, and the impact of climate change on river systems.

The results of the discharge forecasting during the period from 2024 to 2050 indicate probable trends in the dynamics of river flow, which are critical to the management of water resources, hydropower project planning, flood risk evaluation, and sustainable development. The findings can help policymakers and engineers develop adaptive measures to mitigate water-related problems, ensuring the optimal utilization of Nepal's river systems in the next decades.

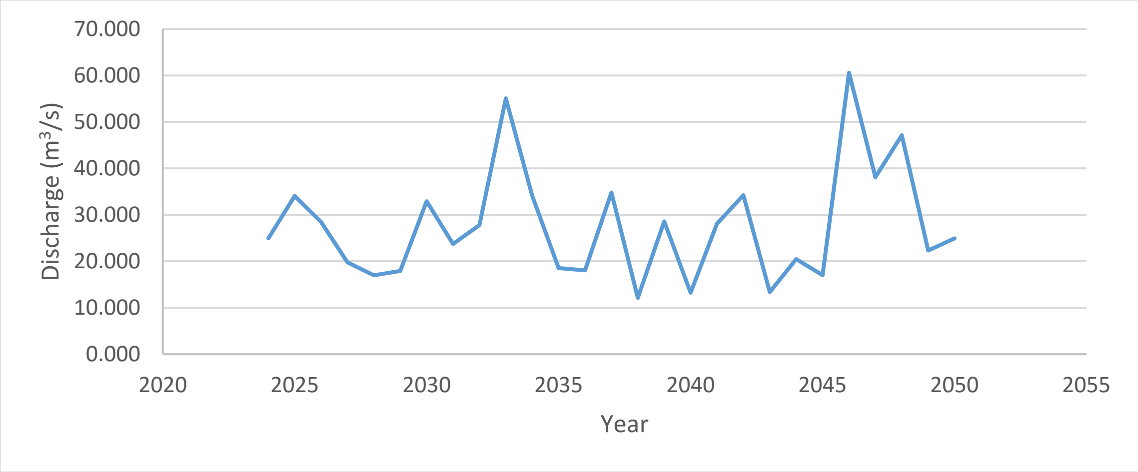

Figure 4. Forecasted discharge by SWAT model.

3.5. Discharge Forecasted by Bi-directional LSTM

Bi-directional LSTMs, a powerful tool, augment the LSTM models that have been established by passing the input data through two LSTMs. The input sequence undergoes LSTM application in the initial round, corresponding to the forward layer. The LSTM model receives the input sequence in its reversed form during the second round, also known as the backward layer. Two applications of the LSTM enhance the model's accuracy by facilitating the learning of long-term dependencies. Recurrent neural networks (RNNs) that operate in both directions are bidirectional RNNs. At each time increment, this architecture enables the networks to possess both forward and backward knowledge of the sequence. The bidirectional operation executes inputs within, specifically from the past to the future and from the future to the past, respectively. In contrast to the unidirectional approach, this method preserves information from the future while the LSTM operates in reverse. Combining the two concealed states makes retaining data from the past and the future possible at any given moment, thereby significantly improving the model's predictive capabilities. The working principles diagram of the model is shown in Figure 5 below.

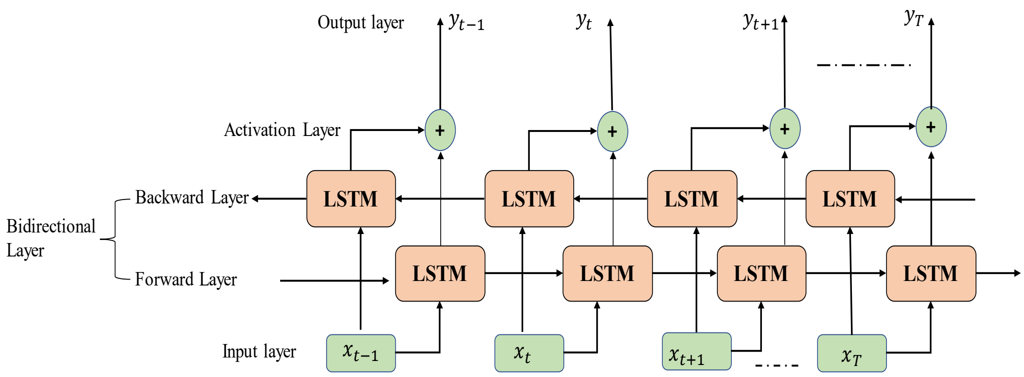

Figure 5. Architecture of BiLSTM.

The Bi-directional Long Short-Term Memory (BiLSTM) model is a sophisticated deep learning technique used for river discharge forecasting based on patterns extracted from historical data. Unlike traditional machine learning techniques, the BiLSTM can recognize temporal dependencies in both the forward and backward directions of a time series, thus improving its performance in hydrological forecasting. Figure 5 illustrates the two LSTM layers of the BiLSTM model, one processing data in the forward direction and the other in the reverse direction. The model architecture is composed of two LSTM layers; one layer processes data in the forward direction, while the other processes data in the reverse direction, allowing for the preservation of both past and future information before prediction. The BiLSTM architecture used in this study consisted of two hidden layers with 64 nodes each, ReLU activation, a dropout of 0.2 to prevent overfitting, and the Adam optimizer with a learning rate of 0.001. The model was trained for 200 epochs with a batch size of 32. Preprocessing included normalization, lag features, and incorporation of precipitation and temperature as external predictors.

To forecast river discharge using BiLSTM, the first step is to preprocess historical discharge data. The preprocessing process includes normalization of data, handling missing values, and dividing the dataset into training and test sets. During training, sequential discharge data is fed into the model, enabling the learning of patterns associated with changes in streamflow due to both seasonal and climatic factors. Other features, such as precipitation, temperature, and previous discharge values, can be added to improve the accuracy of forecasts. The model is then optimized using loss functions, in this case, Mean Squared Error (MSE), and further tuned using algorithms like the Adam optimizer.

Following the training process, the BiLSTM model is utilized to forecast future discharge using recent discharge information combined with climatic parameters. The future discharge values forecasted by the BiLSTM model for the period 2024–2050 are shown in Figure 6. The future discharge values forecasted between the years 2024 and 2050 are of major importance for hydropower planning, flood hazard prevention, and water resource allocation. Compared to traditional hydrological models like SWAT, BiLSTM exhibits greater accuracy in short-term predictions; however, it might require significant data and computational capacity. The integration of BiLSTM with physically-based models has the capability to increase the accuracy of predictions regarding long-term water management strategies.

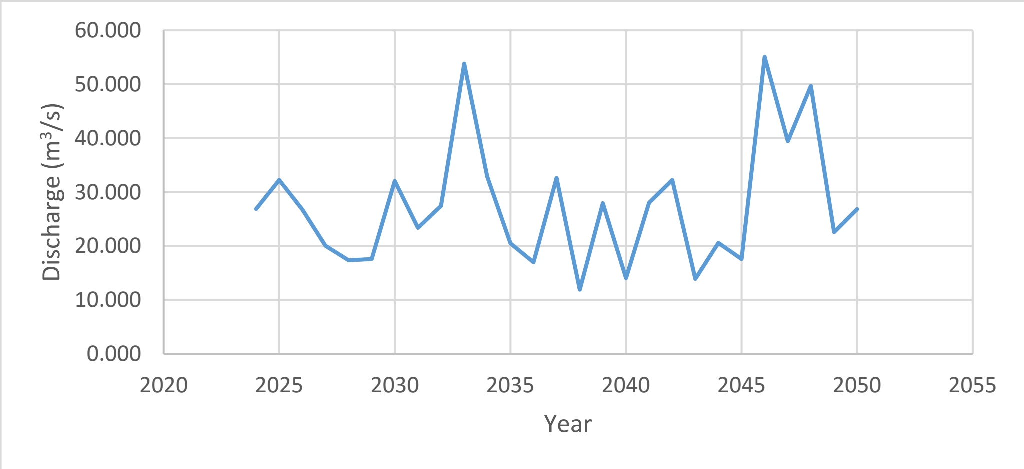

Figure 6. Forecasted discharge by BiLSTM.

The BiLSTM model's performance evaluation reveals strong predictive accuracy for river discharge forecasting. With a low Mean Squared Error (MSE) of 0.0006, the model exhibits minimal deviation from actual values, ensuring reliable predictions. The Mean Absolute Error (MAE) of 0.0099 and Root Mean Squared Error (RMSE) of 0.0246 further confirm its robustness in capturing streamflow variations. Additionally, the RMSE of 0.3057 and MAE of 0.2625 highlight its effectiveness in detecting fluctuations in river discharge. The training loss versus validation loss for the BiLSTM model is depicted in Figure 7.

The validation loss stabilizes over time, demonstrating good generalization without severe overfitting. A slight gap between training and validation loss suggests some variance, but overall, the model remains stable and accurate, making it a valuable tool for hydrological forecasting and water resource management.

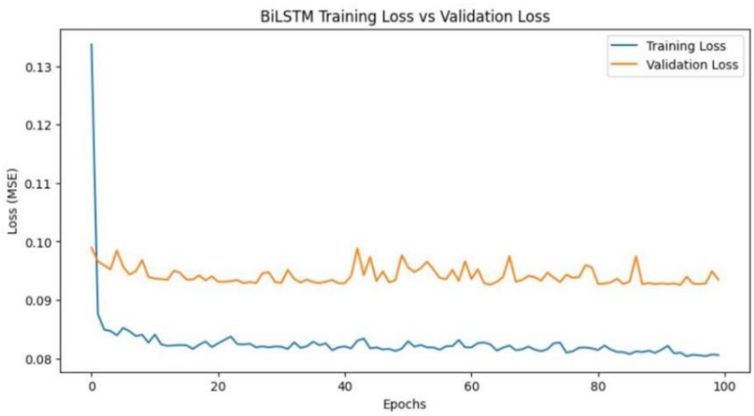

Figure 7. Training loss vs. validation loss.

3.6. Energy Calculation by Using Forecasted Discharge

Hydropower generation is primarily dependent on the availability of water discharge and the effective utilization of hydraulic heads. The potential power output of a hydroelectric plant can be estimated using the fundamental equation:

$$P = \eta * \gamma * Q * H$$

where, η = overall efficiency of hydropower plant, γ = Unit weight of water (9.81 kN/m^3), Q = Flow discharge (m^3/s), H = Net head (m).

For Bhotekoshi Hydropower, the overall efficiency (η) is determined by considering the efficiency of key components, including the generator, transformer, and turbine, which results in an efficiency of 90.2%.

The flow discharge used for power calculation was forecasted separately using both the Soil and Water Assessment Tool (SWAT) model and a machine learning (ML) method. The predicted discharge from both methods was then used to calculate the hydroelectric potential power using the given equation. Subsequently, the total hydroelectric potential energy was determined by multiplying the calculated power with time. The results obtained from the SWAT and ML methods were compared to evaluate the accuracy and reliability of each approach in forecasting river discharge for hydropower generation. This comparative analysis helps in understanding the impact of different forecasting techniques on energy estimation, ultimately contributing to improved hydropower planning and management.

4. Result and Discussion

4.1. Comparative Analysis of Forecasted Hydropower Potential Energy by SWAT Model and BiLSTM

These findings are consistent with Bhattarai et al. (2022) [10], who projected similar declines in discharge for Himalayan basins [9]. However, our dual-model approach provides additional robustness by integrating both physical and data-driven insights.

In this study, both the machine learning (ML) model and the SWAT model simulated the hydropower potential energy. The 1980 to 2015 daily hydrological discharge records from the Nepal Department of Hydrology and Meteorology were employed to parameterize the SWAT model, but the historical pattern was employed to train the ML model. The annual energy outputs were simulated from 2024 to 2050, and the average annual energy (GW.h) was achieved using both models.

The SWAT and ML models project closely aligned hydropower potential energy outputs from 2024 to 2050, with a near-perfect Pearson correlation coefficient of 0.99, indicating robust agreement. Statistically, SWAT forecasts a slightly higher mean energy output (23.33 GW.H) compared to ML (23.27 GW.H), while both exhibit comparable variability (standard deviations of 10.82 GW.H for SWAT and 10.21 GW.H for ML). SWAT predicts a broader range of outcomes, with a maximum of 53.29 GW.H in 2046 and a minimum of 10.75 GW.H in 2038, whereas ML's forecasts are more restrained, peaking at 48.36 GW.H (2046) and bottoming out at 10.56 GW.H (2038). Figure 8 illustrates that both models project closely aligned hydropower potential energy outputs, although SWAT forecasts slightly higher peaks in some years, as seen in 2046.

Both models identify similar cyclical patterns, but key differences emerge in extreme events. SWAT consistently forecasts higher peaks, such as the 53.29 GW.H in 2046 (10% above ML's estimate), likely due to its process-based sensitivity to extreme hydrological events like sudden rainfall or snowmelt. Conversely, ML produces smoother transitions between wet and dry phases, reflecting its training on historical data to mitigate outliers. Notable divergences occur in 2035, where ML predicts 18.18 GW.H (10% higher than SWAT's 16.42 GW.H), and in 2046, underscoring SWAT's tendency to amplify extremes. Low-energy phases, such as 2038, align closely between models, with both predicting critical minima near 10.5–10.7 GW.H, signaling periods demanding alternative energy sources or storage solutions.

While SWAT and ML agree strongly on mid-term hydropower trends, their divergences in extremes and volatility underscore the value of multi-model approaches. Policymakers must prioritize infrastructure resilience and adaptive energy policies to mitigate risks from declining outputs and erratic generation, ensuring stability in future energy grids.

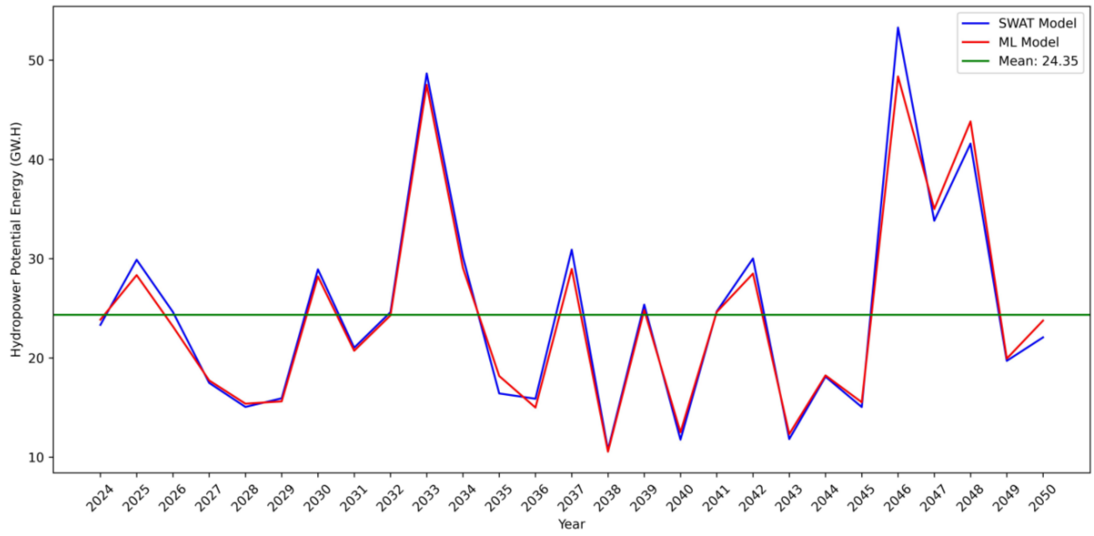

Figure 8. Forecasted potential energy by SWAT and ML model.

Figure 9 compares hydropower potential energy (GW.H) projections from 2024 to 2050 using the SWAT model (physics-based) and the ML model (data-driven). The SWAT model shows a gradual increase, starting at 23.327 GW.H in 2024, peaking at 53.289 GW/H in 2046, and ending at 22.069 GW.H in 2050. The ML model, however, predicts more dynamic trends, beginning at 23.854 GW/H in 2024, reaching 48.364 GW/H in 2046, and concluding at 23.762 GW/H in 2050. While both models align closely in some years (e.g., 2028: SWAT 15.061 GW/H vs. ML 15.389 GW/H), they diverge in others (e.g., 2046: SWAT 53.289 GW.H vs. ML 48.364 GW.H), reflecting the ML model's ability to capture non-linear patterns. Supported by strong performance metrics (RMSE: 0.3057, MAE: 0.2625, Test MSE: 0.0006), the ML model excels in short-term accuracy, while SWAT's interpretability aids long-term environmental planning. As shown in Figure 9, the SWAT model predicts a more gradual increase in energy output compared to the ML model, which captures more dynamic trends. Together, they provide complementary insights for sustainable hydropower strategies. Together, they provide complementary insights for sustainable hydropower strategies.

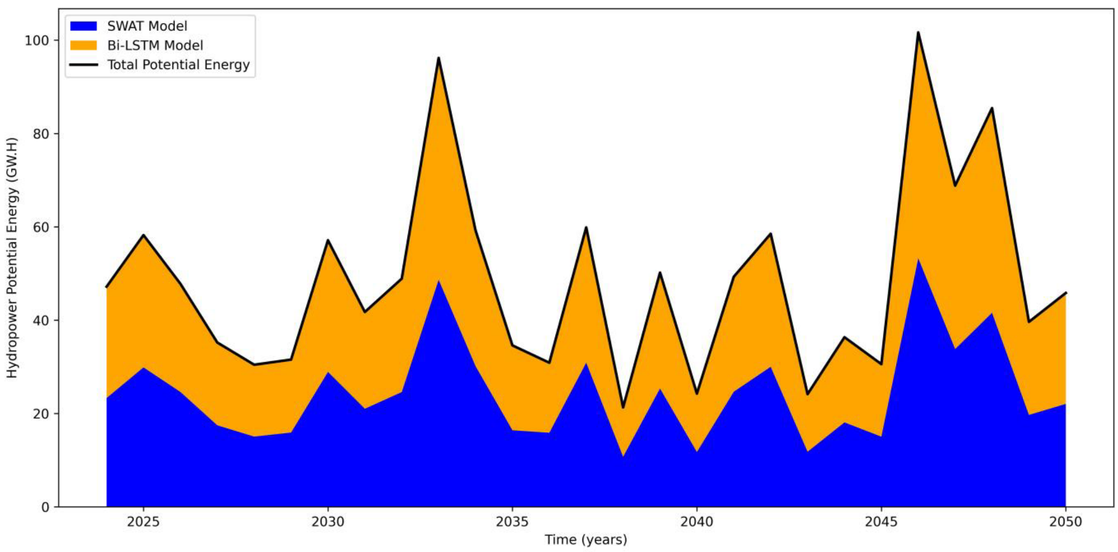

Figure 9. Potential hydropower energy comparison.

4.2. Comparative Analysis between Current Discharge and Probable Future Discharge

To assess the temporal dynamics in the river discharge, the current discharge values were further compared to the future predicted discharge within the 2024–2050 time frame based on both the SWAT model projections and machine learning-based projections. The historical baseline was taken to be the 1980–2015 records of the discharge, while the future trends in the discharge were predicted based on hydrological models and climate models.

The comparative analysis of historical (1980–2015) and forecasted (2024–2050) river discharge reveals significant shifts in hydrological patterns, underscoring potential challenges for water resource management and ecosystem sustainability. Figure 10 illustrates the stark decline in discharge magnitude predicted by both models compared to historical data, highlighting potential challenges for water resource management. Historically, the watershed exhibited a mean discharge of 55.12 m^3/s, characterized by moderate to high flows with notable interannual variability. Peaks such as 79.26 m^3/s (2013) and 74.72 m^3/s (1985) highlighted periods of intense runoff, likely linked to heavy monsoon rains or snowmelt events. Conversely, low-flow phases, such as 36.42 m^3/s (1992), were infrequent and rarely dipped below 40 m^3/s. These patterns reflect a dynamic but relatively stable hydrological regime, with cyclical fluctuations but no dominant long-term trend.

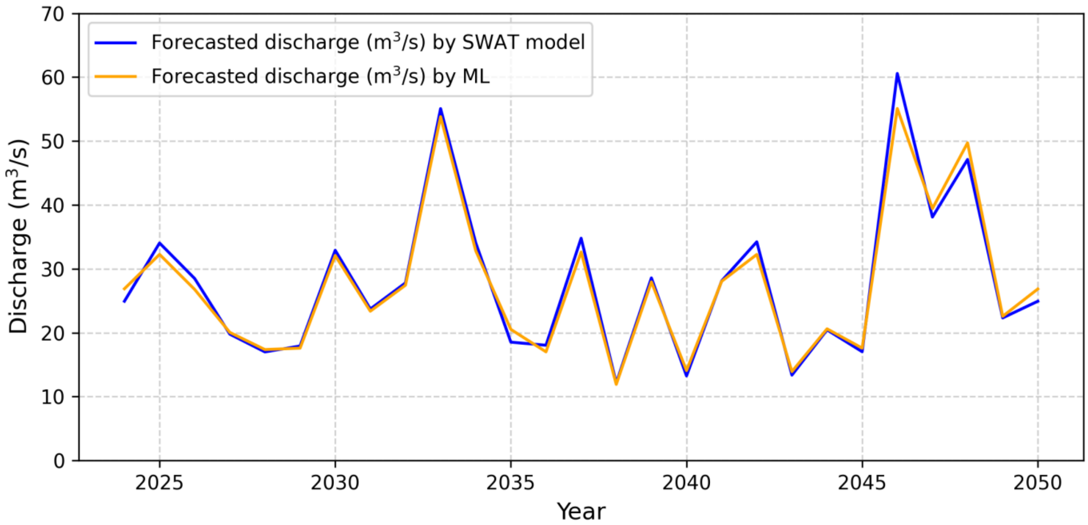

Figure 10. Forecasted discharge by SWAT and ML model.

In contrast, projections from the SWAT and ML BI-LSTM models forecast a stark decline in discharge magnitude. The mean flow is expected to drop by 48%, averaging 29.66 m^3/s (SWAT) and 28.84 m^3/s (ML) over 2024–2050. This reduction suggests a fundamental shift in water availability, potentially driven by climate change impacts such as reduced precipitation, higher evaporation rates, or anthropogenic interventions like upstream water abstraction. Notably, future extremes are also projected to diminish. While historical peaks exceeded 70 m^3/s, the highest forecasted values—60.57 m^3/s (SWAT, 2046) and 55.08 m^3/s (ML, 2046)—are 24–30% lower, indicating attenuated flood risks but also raising concerns about diminished groundwater recharge and ecosystem vitality.

Low-flow conditions, however, are projected to intensify dramatically. Forecasted minima, such as 11.92 m^3/s (2038), are 3–4 times lower than historical lows, with recurrent dry periods between 2035 and 2045. Such prolonged low flows could strain agricultural irrigation, urban water supplies, and aquatic habitats, particularly in drought-prone regions. Temporal variability is also expected to increase post-2040, with sharp, short-lived spikes (e.g., SWAT's 60.57 m^3/s in 2046) followed by rapid declines. This heightened volatility aligns with climate models predicting erratic rainfall patterns and more frequent extreme weather events.

Both models show strong agreement ($r = 0.99$), validating their mid-term reliability, yet key divergences offer insights into their methodological strengths. SWAT, a process-based model, predicts higher peaks and lower dry-phase flows, possibly due to its sensitivity to physical watershed parameters like land use and soil moisture. In contrast, the ML BI-LSTM model, trained on historical data, produces smoother transitions and slightly higher dry-period estimates, reflecting its reliance on past patterns to mitigate extremes. These differences underscore the importance of multi-model approaches to capture uncertainties in hydrological forecasting.

4.3. Conclusions

This study provides a detailed estimation of climate change-affected hydropower potential in Nepal's Sunkoshi Basin using a dual-model framework employing SWAT hydrology and a Bi-directional LSTM machine learning model. Comparison between 2024–2050 predictions and 1980–2015 discharge history indicated a 48%

reduction in mean river discharge, with both models projecting increased volatility from 2040 and frequent low-flow events (e.g., 11.92 m^3/s minima in 2038). These correspond to a significant reduction in hydropower potential energy, with SWAT calculating marginally higher maxima (53.29 GW.H in 2046) and ML producing smoother, conservative predictions (48.36 GW.H). High correlation (r = 0.99) between models confirms their use for mid-term planning but indicates differences in extreme-event modeling, with SWAT achieving strong calibration metrics ($R^2 = 0.91$, NSE = 0.82) and BiLSTM excelling in short-term accuracy (Test MSE = 0.0006, MAE = 0.0099, RMSE = 0.0246). Both SWAT and BiLSTM models consistently confirmed approximately a 48% reduction in mean river discharge, which corresponds to a significant projected decline in hydropower output for the Sunkoshi Basin. However, the study faced several limitations, including data gaps between 2016 and 2023, limited gauging station coverage, and the absence of hybrid or ensemble modeling approaches. These constraints highlight the need for future research focusing on the development of integrated SWAT–BiLSTM frameworks, incorporation of glacial retreat data, and consideration of socio-economic factors to enhance the forecasting and sustainability of hydropower in the region.

The findings hold significant energy security significance for Nepal with a vision to achieve 15,000 MW hydropower capacity and universal access to electricity in 2030. The estimated decline in discharge has the potential to increase existing deficits in demand and supply and calls for adaptive strategies such as:

- Resilient Infrastructure: Invest in hybrid energy systems (e.g., solar-hydropower hybrid) and pumped storage technologies to hedge against dry spells.
- Policy Reforms: Increase data collection networks to fill gaps (e.g., 2016–2023 discharge data) and include hydrological predictions in-country energy plans like the Energy Vision 2050 and Low Carbon Economic Development Strategy.
- Climate Adaptation: Harmonize hydropower development with regional climate models to reflect variations in monsoon flow and glacial meltwater contribution. While the process-based character of SWAT is helpful in explaining physics in a watershed, its tendency to amplify extremes has a tendency to overestimate risks. ML's data-based character, while helpful in short-term predictions, has a tendency to underestimate nonlinear climate feedback. These limitations indicate hybrid modeling schemes and continuous real-time data-based calibration.

Nepal's current 3% out of 83,500 MW hydropower utilization rate is indicative both of opportunity and imperative for sustainable growth. By overcoming technological, environmental, and political barriers e.g., improving hydrometric station coverage and encouraging public-private partnerships the nation can use its mountainous topography to meet SDG 7 targets and reduce reliance on imported fossil fuels.

Future research should explore combining land-use transformation scenarios, glacial recession influence, and socio-economic drivers with hydrology models. This approach can be extended to other Himalayan basins and provide regional data to aid regional water management and climate resilience initiatives.

In conclusion, not only does this research contribute to scientific understanding in terms of climate-hydro-energy interactions in the Sunkoshi Basin, but it is a pragmatic handbook for Nepal to navigate itself out of energy security and sustainable development issues. With efficient utilization of potent forecasting capacity and adaptive measures, the nation can leverage its vast hydropower resources as a pillar for low-carbon growth, enhancing resilience in a changing climate.

Author Contributions

A.Y.: conceptualization, methodology, hydrological analysis and modeling, validation, visualization, data curation, project administration, writing—original draft, writing—review and editing, supervision; S.C.S.: machine learning (BiLSTM) modeling and analysis, data preprocessing, writing—review and editing; S.D.: literature review, data collection support, formatting, proofreading; P.D.: Literature Review, Minor Editing, Proofreading; D.B.: literature review, minor editing, proofreading. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Ethical review and approval were waived for this study because only secondary hydrometeorological data from the Department of Hydrology and Meteorology (DHM), Nepal were used; no human participants or animals were involved.

Informed Consent Statement

Not applicable.

Data Availability Statement

The raw hydrometeorological data were provided by the Department of Hydrology and Meteorology (DHM), Nepal, under license and are not publicly available. Processed data and model results generated during the current study are available from the corresponding author on reasonable request and subject to permission from DHM.

Conflicts of Interest

The authors declare no conflict of interest.

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