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Assessment of Climate Change Impacts on Water Scarcity in Semajid Watershed, Pamekasan, East Java

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ABSTRACT The increase in global temperature has caused climate change, resulting in changes in the distribution of rainfall patterns, seasonal shifts, changes in water availability, and water scarcity. At present, water scarcity in Semajid watershed in Pamekasan Regency is increasing with climate change. Water scarcity will be increasingly difficult to predict due to highly complex dynamics of atmospheric circulation and local climate phenomena such as El Niño-Southern Oscillation (ENSO). This research aims to develop an assessment model to evaluate the impact of climate change on water scarcity using the Semajid watershed of Pamekasan Regency as a case study. The prediction of water scarcity is based on atmospheric circulation dynamics data from the General Circulation Model (GCM-MIROC5) under different climate change scenarios namely Representative Concentration Pathways (RCP). A statistical downscaling model was developed to overcome the limited resolution of the GCM output. The rainfall prediction model was developed using a deep learning-based downscaling model i.e. Long-Short Term Memory (LSTM), while streamflow or water availability prediction was conducted using the Soil Water Assessment Tools (SWAT) model. The Standardized Precipitation Index (SPI) and the Water Scarcity Index (WSI) were used to assess water scarcity. The results showed that the LSTM-based downscaling model provided satisfactory rainfall predictions under different climate change scenarios (RCP) with a reliability average of R^2 = 0.741. The SWAT model results also provided satisfactory predictions of water availability with an average reliability of R^2 = 0.668. The assessment of water scarcity using SPI and WSI indices showed that water scarcity ranged from moderate to high levels and coincided with the occurrence of El Niño events. Overall, this study demonstrates that the integration an LSTM-based rainfall downscaling model and the SWAT hydrological model can be used as an effective tool to predict water scarcity in the Semajid watershed.

KEYWORDS Water scarcity; Downscaling; GCM-MIROC5; LSTM; SWAT.

1 INTRODUCTION

The increase in greenhouse gas emissions is a major factor contributing to climate change problems in different parts of the world. Human activities and industrialization over several decades have caused an increase in CO_2 emissions that affect the state of the Earth's surface temperature. The global average temperature change will continue to increase by approximately 1°C during the period 2016-2035 (Intergovernmental Panel on Climate Change (IPCC), 2013). The increasing temperature trend has affected components of the hydrological cycle, such as changes in precipitation patterns that vary at local and global scales (Santidrián Tomillo et al., 2015). Climate change has also affected the frequency and intensity of extreme events such as droughts (Halik et al., 2022), flood disaster (Ikhwali et al., 2022) and the availability of water resources (Wubneh et al., 2023).

The Semajid watershed, administratively located in Pamekasan, East Java, Indonesia, is a critical area for water availability. Extreme rainfall events in this region have tended to decrease significantly and consistently (Supari et al., 2012). In addition, the conditions of the El Niño-Southern Oscillation (ENSO) phenomenon influences most of the spatial and temporal rainfall variability in Indonesia (Aldrian and Dwi Susanto, 2003). Based on a study by the National Disaster Management Agency (BNPB) in 2023, the Semajid watershed is classified as having moderate to high hazard, while the drought risk is classified as moderate. These conditions can significantly affect water management in the basin. In addition, local climate phenomena and dynamic climate conditions make predicting water availability critical for understanding future trends under climate change scenarios.

The General Circulation Model (GCM) output data can be used to predict water availability under climate change conditions (Halik et al., 2015; Shekar et al., 2023; Wang, Zhang, Wang and Hossain, 2024). Many researchers have explored the use of climate model or GCM output data in climate change impact studies, including drought analysis (Halik et al., 2022), streamflow estimation (Zhou et al., 2015), reservoir inflow prediction (Halik et al., 2015), temperature prediction (Adeyeri et al., 2020), and irrigation water demand estimation (Saputra et al., 2021). GCM data are mathematical representations of surface processes involving the atmosphere, oceans, and land surface, including data on various climate variables. One of the drawbacks of GCM output data is their coarse resolution due to their global nature, which can introduces systematic biases when applied to small spatial scales such as watersheds (Sundaram and Radhakrishnan, 2023). Systematic biases cause conceptual imperfections in spatial grids that make direct use of GCM data outputs unreliable in climate change studies (Ghimire et al., 2019). Therefore, empirical functions are needed to establish the relationship between global and local climate (Mendez et al., 2020). One approach to address this gap is using statistical downscaling techniques (Das et al., 2022).

Statistical downscaling is a method that provides a relatively efficient and less computationally demanding way to formulate statistical relationships between GCM output climate variables and local climate compared to dynamic downscaling methods. Statistical methods for downscaling climate model outputs, both simple and complex, have been widely developed and can bridge the relationship between global and local climate (Das et al., 2022; Nourani et al., 2023). One of them is bias correction methods, such as linear scaling and quantile mapping, which have been tested and shown to reduce systematic bias of climate model outputs (Usman et al., 2022). In other words, these methods assume that historical simulation models maintain a stable statistical relationship with observations, even though the distribution may change. Therefore, high spatial resolution GCM outputs are needed to improve the evaluation of studies predicting water availability due to climate change.

In recent years, deep learning using Long-Short Term Memory (LSTM) has demonstrated significant success in modeling complex natural phenomena, including hydrological modeling. LSTM has shown promising potential in various hydrological applications, including: rainfall forecasting (Rampal et al., 2022) and streamflow prediction (Kheir et al., 2023). The LSTM model also provides better temperature and rainfall prediction when compared to traditional Statistical Downscaling Model (SDSM) (Manfouo et al., 2023). Furthermore, the LSTM model can be effective as a transformation model for separating baseflow and predicting runoff (Wang, Wang and Zhao, 2024). In addition, rainfall-runoff modeling with LSTM model can provide better accuracy than conceptual rainfall-runoff model with the Water Partition and Balance (WAPABA) model (Clark et al., 2024).

Meanwhile, global temperature is predicted to increase due to the increase in greenhouse gas concentrations. The Intergovernmental Panel on Climate Change in Assessment Report 5 (IPCC-AR5) defines climate change scenarios based on temperature increase in 2100, namely: RCP 4.5 (1.8°C), RCP 6.0 (2.2°C) and RCP 8.5 (3.7°C) (Intergovernmental Panel on Climate Change (IPCC), 2013). This temperature increase will significantly impact water availability and water scarcity (Siabi et al., 2021).

The objective of this study is to assess water scarcity based on general atmosphere circulation and climate Phenomena related to ENSO in the Semajid watershed using IPCC AR5 climate model output data. The methodological approach integrates LSTM-based rainfall downscaling and the SWAT hydrological models. Water scarcity is investigated using meteorological drought indices using Standardized Precipitation Index (SPI) and water scarcity indices with Water Stress Index (WSI). This research aims to provide an overview of water scarcity projections under different climate change scenarios.

2 METHODS

The assessment of the impact of climate change on water scarcity was conducted in the Semajid watershed in Pamekasan Regency, Madura, East Java, Indonesia. This location was chosen as a case study because the Semajid watershed is an area that has a dry climate. The research site is shown in Figure 1.

Meanwhile, the climate variables were obtained from the global climate model GCM-MIROC5. GCM-MIROC5 is developed by the Japanese Climate Agency, and the Indonesian Agency for Meteorology, Climatology and Geophysics (BMKG) uses this model in simulating future rainfall projections. The selection of GCM predictors was analyzed using a correlation test against observed rainfall. The statistical performance indicators of the downscaling model was tested using the coefficient of determination (R^2).

The atmospheric circulation predictor data obtained from GCM-MIROC5, including precipitation water, relative humidity (500 hPa and 850 hPa), specific humidity (500 hPa and 850 hPa), zonal wind (surface and 850 hPa), meridional wind (surface and 850 hPa) and climate phenomena related to ENSO i.e. Sea Surface Temperature (SST) on a monthly time scale. At the same time, the prediction target was monthly rainfall. The model testing period was conducted from 2006 to 2023.

The rainfall downscaling model uses the LSTM model (Figure 2). The LSTM network consists of an input layer, one or more hidden layers, and an output layer. The layers are connected by a set of updatable weights, with the same weights applied to all time steps of the data. Memory cells are located within each node in the hidden layer, storing important information over long periods of time. Each node in the input layer repre-

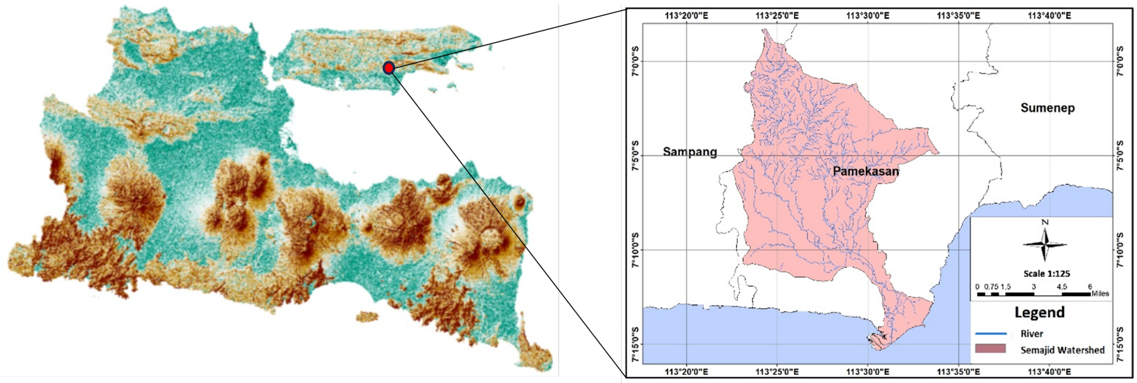

Figure 1. Research site

sents a variable from the input data (Shrestha et al., 2023). After the forward propagation step, the backpropagation algorithm is applied to update the optimal model parameters. In the study, observed rainfall data were used as targets to evaluate the performance of the LSTM networks.

The inputs of the LSTM model consist of atmospheric circulation dynamics data from GCM-MIROC5 and climate phenomena related to ENSO, while model outputs are monthly rainfall. The rainfall predictions were also generated under different climate change scenarios (Representative Concentration Pathways - RCP). Meanwhile, rainfall-runoff modeling uses the SWAT hydrological model.

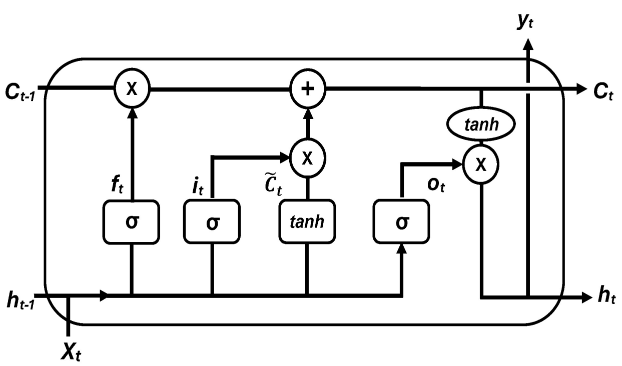

Figure 2. LSTM Architecture

Where: i_t (input gate); f_t (forget gate); and o$_t$ (output gate); h_{t-1} (the output of each previous block); X_t (input); C_t (cell state at t); C_{t-1} (cell state of each previous block); $\tilde{C}_t$ (candidate for cell state); h_t (the output of each next block); tanh (the hyperbolic tangent function); and σ (the sigmoid function).

The SWAT model is a physically based hydrological model for rainfall-runoff developed by the United States Department of Agriculture (USDA) Research Service. This model represents the interaction processes of hydrological components within a watershed, including: elevation class, soil type, land use, and meteorological data. The SWAT model provides a strong conceptual and physical representation of watershed interaction processes and parameter interpretation (Shrestha et al., 2023). Several studies have successfully applied SWAT in watershed with various characteristics (Halik et al., 2022; Shrestha et al., 2023; Zhou et al., 2015). The implementation of the SWAT model requires calibration and validation to obtain optimal watershed parameters.

Rainfall and water availability are also used to assess water scarcity. Several water scarcity indicators have been used, including the meteorological drought index using Standardized Precipitation Index (SPI) (Edwards and McKee, 1997) and the Water Stress Index (WSI) (Falkenmark et al., 1989). The equations SPI and WSI are as follows:

$$SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 + d_2 t^2 + d_3 t^3}\right) \quad \text{for } 0 < H(x) \leq 0.5 \tag{1}$$

$$SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 + d_2 t^2 + d_3 t^3}\right) \quad \text{for } 0.5 < H(x) \leq 1.0 \tag{2}$$

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \quad \text{for } 0 < H(x) \leq 0.5 \tag{3}$$

$$t = \sqrt{\ln\left(\frac{1}{(1.0 - H(x))^2}\right)} \quad \text{for } 0.5 < H(x) \leq 1.0 \tag{4}$$

$$WSI = \frac{\text{water demand}}{\text{water availability}} \tag{5}$$

Where c_0 = 2.515517; c_1 = 0.802853; c_2 = 0.010328; d_1 = 1.432788; d_2 = 0.189269 and d_3 = 0.001308, $H(x)$ is the cumulative probability, t is the time series. Water demand includes domestic water demand and irrigation water demand, while water availability is represented by river discharge.

SPI is designed to measure rainfall deficits across multiple time scales. A positive SPI indicates conditions greater than the median of the rainfall data, while a negative SPI indicates conditions less than the median of the rainfall data used. A drought event occurs when the negative SPI index persists and reaches an intensity of -1.0 or below. SPI with a time scale of 6 (SPI-6) can be used to monitor drought disasters in East Java (Malini et al., 2021).

The SPI index values are categorized into extreme drought (SPI < -2), very dry (-1.99 < SPI < -1.50), and dry (-1.0 < SPI < -1.49). WSI is the ratio of water demand to water availability. The level of water scarcity WSI is grouped into: no water scarcity (WSI < 0.20); low water scarcity (0.2 < WSI < 0.4); moderate water scarcity (0.4 < WSI < 0.7); and high or extreme water scarcity (WSI > 0.7).

3 RESULTS

3.1 Rainfall Modelling

The results of rainfall downscaling modeling using a deep learning type Long-Short Term Memory (LSTM) under various climate change scenarios are shown in Figure 3 through Figure 5. The optimal parameters of LSTM architecture are shown in Table 1.

Table 1. The Optimal Parameter of LSTM Architecture

RCPs	Node	Hidden Layer	Optimizer	Drop-out	Batch Size	Epochs
4.5	20	1	adam	0.20	12	2,000
6.0	15	1	adam	0.15	12	1,500
8.5	20	1	adam	0.20	12	2,000

The results of monthly rainfall downscaling modeling with LSTM under different climate change scenarios (RCP) show different rainfall patterns. However, the model output exhibits a pattern that is closely aligned with the observed rainfall pattern. The reliability of the LSTM model under different climate change scenarios is: R^2 = 0.718 (RCP-4.5); R^2 = 0.784 (RCP-6.0); R^2 = 0.722 (RCP-8.5). The rainfall prediction model generally provides better accuracy under the RCP-6.0 climate change scenario compared to the RCP-4.5 and RCP-8.5 scenarios.

3.2 Water Availability Modeling

Rainfall-runoff or water availability modeling was conducted using SWAT model. The input model consists of a digital elevation model or topography, land use or land cover, soil type, and meteorological data. The output model is discharge or water availability. In this study, the SWAT model parameters were calibrated using a trial and error approach. The optimal SWAT parameters are shown in Table 2.

Table 2. The optimal SWAT Parameters

Code	Parameter	Optimal Value
CN2	Curve Number	72.5
GW-Delay	Ground Water Delay	85
ESCO	Soil Evaporation Coeff.	0.95
GWQMN	Threshold Depth of Water in Swallow Aquifer	105
CH-K2	Hydraulic Conductivity	42
CH-N2	Manning Value for Main Channel	0.015

The results of rainfall predictions under different climate change scenarios were subsequently used as input to predict discharge or water availability. The discharge predictions under different climate change scenarios are shown in Figure 6 through Figure 8.

The results of monthly streamflow modeling using the SWAT model under different climate change scenarios (RCP) provide different streamflow patterns. The SWAT model output shown a pattern that is closely aligned with the observed streamflow pattern. The reliability of the SWAT model under different climate change scenarios is as follows: RCP-4.5 (R^2 = 0.657), RCP-6.0 (R^2 = 0.716), and RCP-8.5 (R^2 = 0.630). The streamflow or water availability prediction model in the RCP-6.0 climate change scenario provides better accuracy than the RCP-4.5 and RCP-8.5 scenarios. Meanwhile, water availability in RCP-8.5 provides a higher level of vulnerability compared to RCP-4.5 and RCP-6.0.

In general, it can be stated that the SWAT hydrological model provides accurate predictions of runoff at low and moderate flows; however, the SWAT model shows limitations in accurately predicting high flows (Figure 6-Figure 8). The integration of the LSTM model and the SWAT model can therefore be applied to predict water availability in the analysis of dependable flow for water allocation purposes.

3.3 Water Scarcity Assessment

The assessment of water scarcity in the Semajid watershed in Pamekasan Regency, East Java, was conducted using several water scarcity indicators, including SPI and WSI. In addition, these water scarcity indices were correlated with climatic phenomena such as ENSO to determine the degree of pattern correspondence. Plots

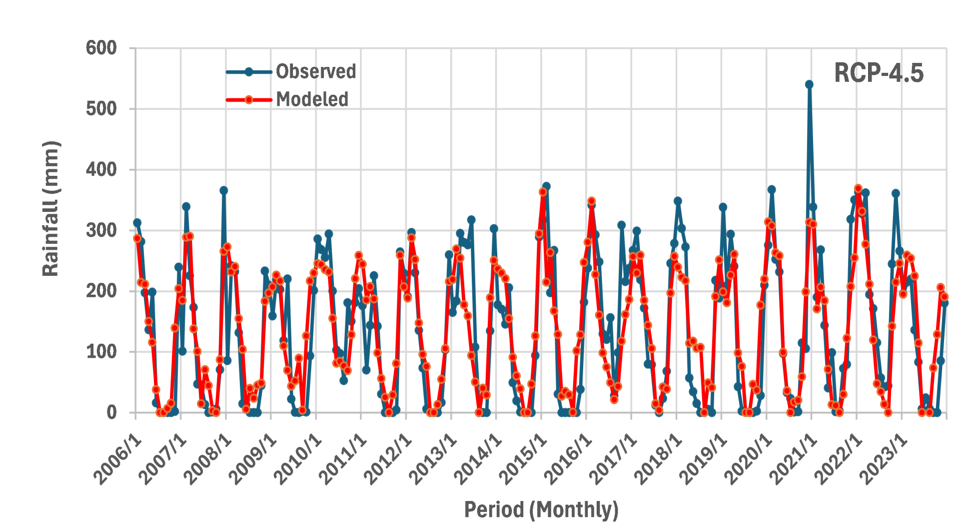

Figure 3. Predicted Rainfall under the RCP-4.5.

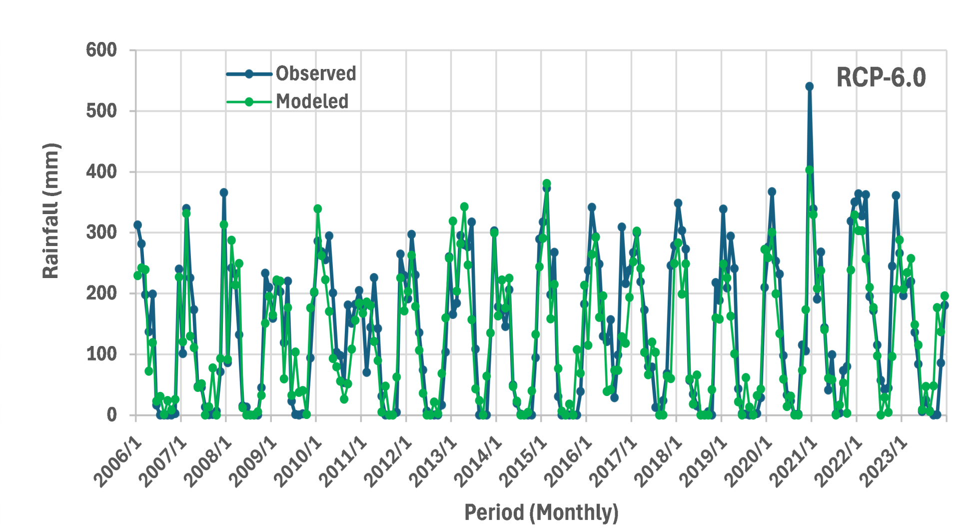

Figure 4. Predicted Rainfall under the RCP-6.0.

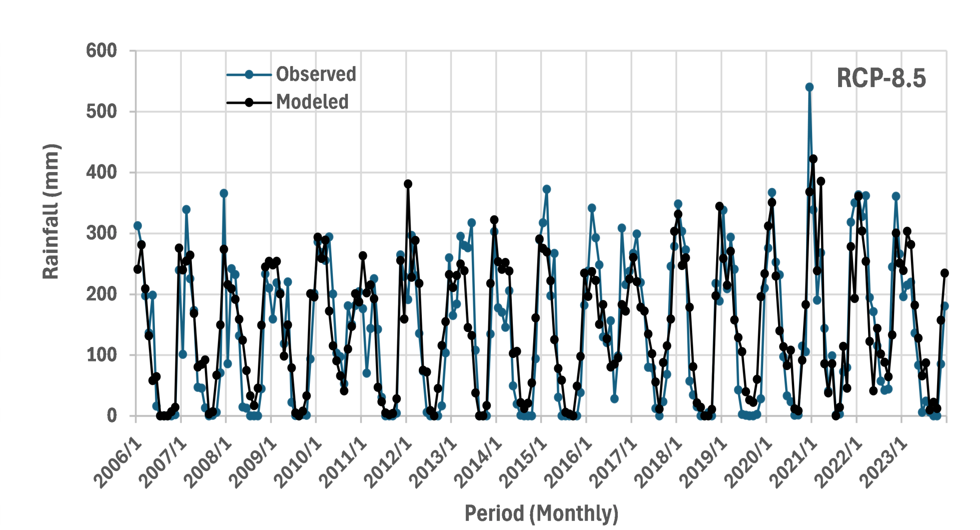

Figure 5. Predicted Rainfall under the RCP-8.5.

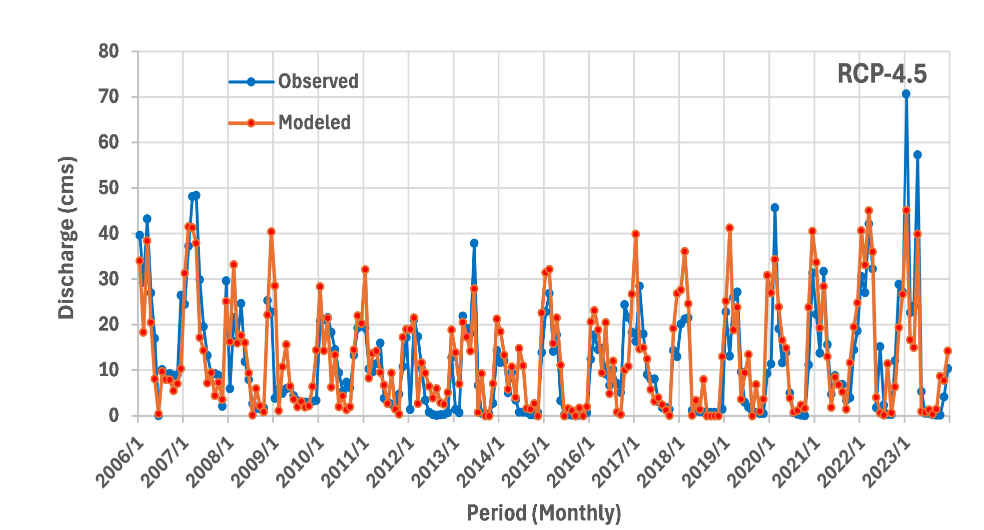

Figure 6. Predicted Discharge under the RCP-4.5.

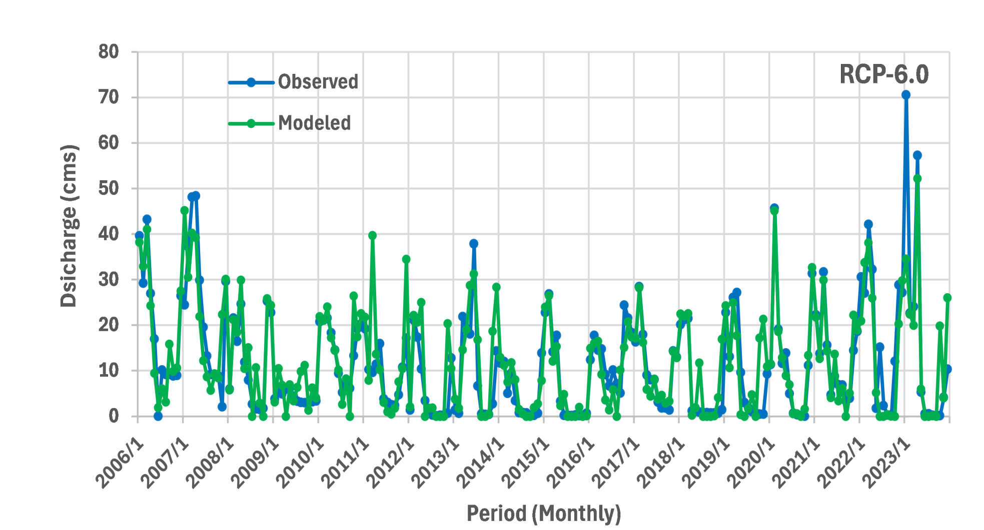

Figure 7. Predicted Discharge under the RCP-6.0.

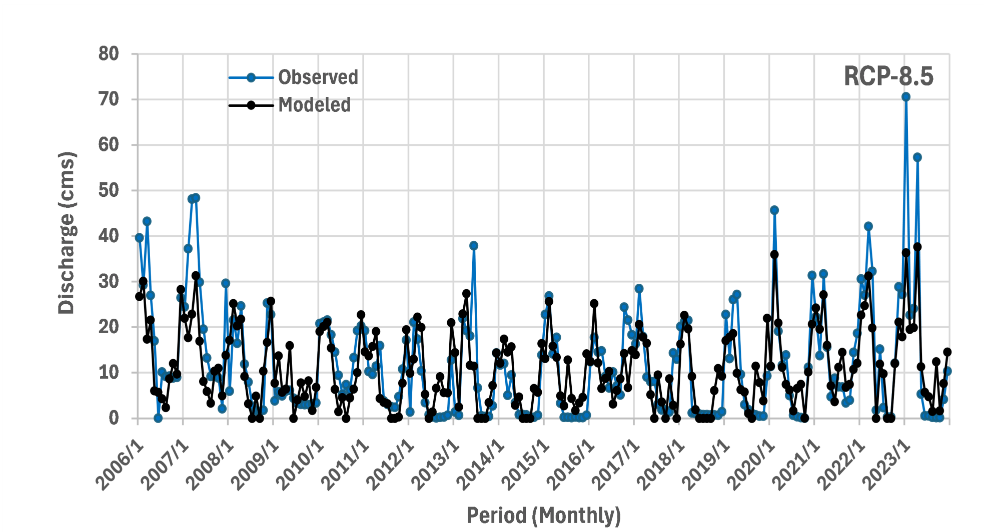

Figure 8. Predicted Discharge under the RCP-8.5.

of the different water scarcity indices are shown in Figure 9 through Figure 10.

Water scarcity based on the SPI index (Figure 9) shows that water scarcity is primarily caused by rainfall deficit, resulting in meteorological drought. This condition occurs when the SST index is positive (El Niño) and the SPI index is negative (indicating severe drought). Water scarcity based on SPI values was observed at the end of the years 2006, 2009, 2015, 2018, 2019, and 2023.

Water scarcity based on the WSI index (Figure 10) shows that water scarcity is driven by deficits in meeting water demand. This condition occurs when the SST index is positive (El Niño) and the WSI index is above 0.7 (high water scarcity). Water scarcity based on the WSI values occurred at the end of the years 2006, 2012, 2014, 2015, and 2023.

The SPI and WSI indices are effective tools for assessing water scarcity in the Semajid watershed of Pamekasan Regency.

4 DISCUSSION

Rainfall prediction is influenced by global atmospheric circulation dynamics and local climate phenomena such as ENSO. Several researchers have carried out research on the use of the General Circulation Model (GCM) data and the development of downscaling models for rainfall prediction. Manfouo et al. (2023) applied a deep learning downscaling model (LSTM) to predict rainfall in an arid climate basin in Nigeria (Lake Chad Basin). Although the domain of this study is an ENSO-affected area, in rainfall modeling with the LSTM model, the ENSO such as SST factor was not considered as an input variable in the modeling. The results of LSTM modeling demonstrated very good reliability.

Nourani et al. (2023) compared rainfall downscaling model between Artificial Neural Networks (ANN) model and LSTM model in a subtropical climate area (Tabriz and Rasht watershed) in Iran. Input variables were obtained from a climate model developed by Canadian Center for Climate Modeling and Analysis (CCCMA). The SST variables were not considered in the selection of model inputs. Rainfall prediction results with the LSTM model showed better performance than those of the ANN model. In contrast, the results of this study show that the LSTM model with GCM-MIROC5 and SST input variables can adequately predict monthly rainfall in the Semajid watershed.

Based on the aforementioned studies, it can be concluded that developing deep learning-based downscaling models can effectively overcome the limitations of the spatial resolution of climate model or GCM. Rainfall prediction with LSTM model provides adequate model reliability in both tropical and subtropical climates. Rainfall prediction is strongly influenced by global atmospheric circulation dynamics. In addition, climate phenomena such as ENSO also play a significant role in rainfall prediction in tropical regions, including Indonesia.

Meanwhile, Clark et al. (2024) compared water availability or rainfall-runoff models between deep learning models using LSTM and conceptual hydrological models (WAPABA). Model tests were conducted in several catchments in Australia. Neither LSTM nor WAPABA considered ENSO variable when developing their models. The results showed that the rainfall-flow model with LSTM produced results comparable to those conceptual hydrological models (WAPABA). Both models provide satisfactory reliability for modeling rainfall-runoff under moderate-flow conditions rather than low-flow or high-flow conditions. In contrast, the results of rainfall-runoff modeling in the Semajid watershed using the integration of LSTM and the SWAT hydrological model provide more accurate results, both for low flow and moderate flow conditions.

Wang, Wang and Zhao (2024) found that the integration of global climate models with Deep Belief Networks (DBN) models and SWAT hydrological models can be used to model rainfall-runoff or water availability. The results of their research show that water availability is predicted to decrease in the future with climate change. This condition is consistent with the results of the present study conducted in the Semajid watershed of Pamekasan Regency with the integration of the LSTM model and the SWAT hydrological model.

Water scarcity in a watershed is also influenced by population pressure. Increase in population growth has a positive correlation with water scarcity over time (Yan et al., 2023). This relationship is observed in the Semajid watershed, where population growth has led to increasing domestic water demand has increased from year to year.

Meanwhile, rising global temperatures have influenced the hydrological cycle, including changes in evapotranspiration, precipitation, and streamflow, thereby impacting water availability (Wubneh et al., 2023). A temperature increase of 2.2°C by 2,100 under RCP-6.0 climate change scenario provides water availability predictions in the Semajid watershed that are closer to observed water availability patterns compared to other climate change scenarios (RCP-4.5 and RCP-8.5).

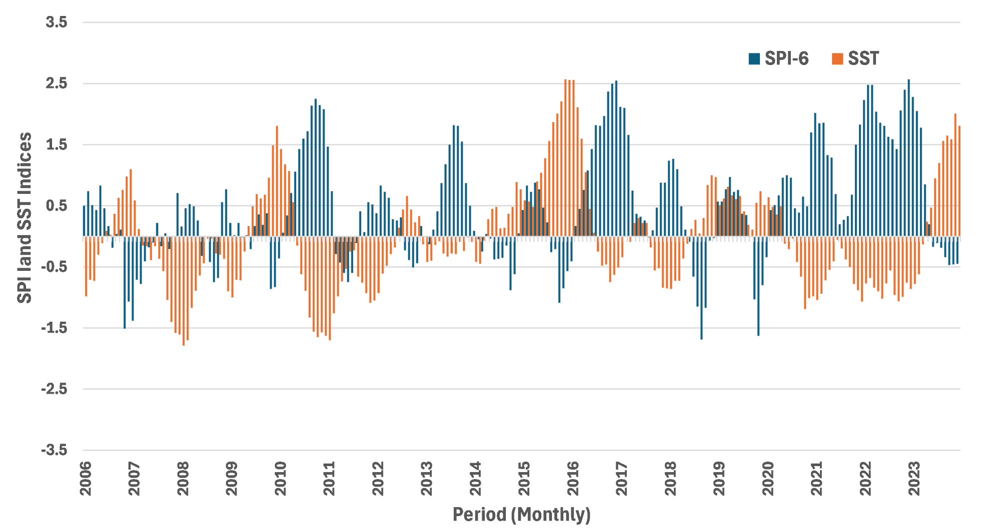

Figure 9. Water Scarcity based on SPI and SST.

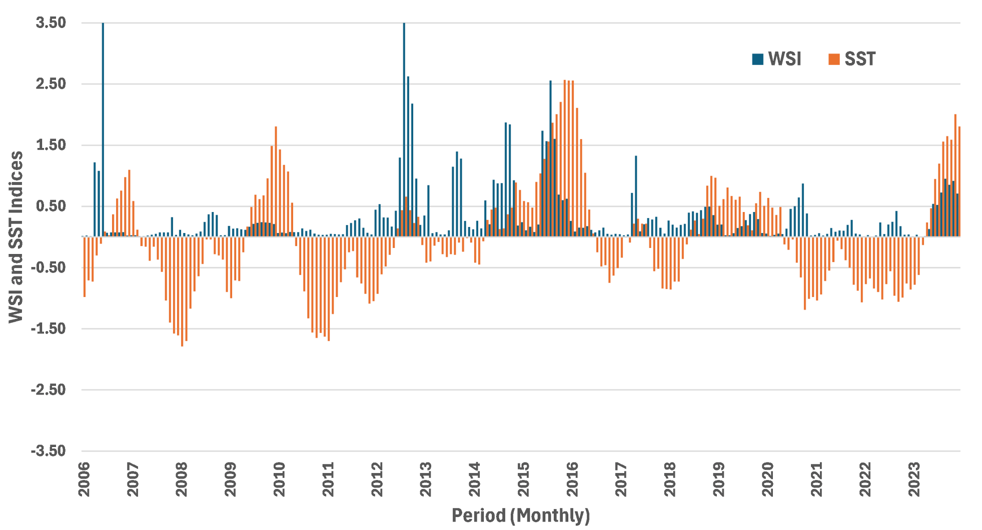

Figure 10. Water Scarcity based on WSI and SST.

5 CONCLUSION

The monthly rainfall predictions based on atmospheric circulation dynamics from GCM-MIROC5 and local climate phenomena such as ENSO using the LSTM downscaling model provide satisfactory prediction results. The rainfall prediction with the RCP-6.0 climate change scenario for representing an average temperature increase 2.2°C by 2,100 is the most realistic scenario for describing future climate change conditions and for anticipating the future impacts of climate change in the Semajid watershed, Pamekasan Regency, East Java. The model integration of a deep learning-based rainfall downscaling model with LSTM and SWAT hydrological models can provide reliable predictions of water availability, thereby enabling their use as tools for planning mitigation strategies for climate change impacts on water scarcity, both structural and non-structural based Nature based Solutions (NbS).

DISCLAIMER

The authors declare no conflict of interest.

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