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Estimating water runoff from downscaling climate change scenarios using soil and water assessment tool and machine learning: A case study of Lake Tana basin in Ethiopia

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ABSTRACT

Water is a fundamental natural resource necessary for life, and contributes to the development of the nation, including urbanization, shifting agricultural practices, and deforestation. These factors have both direct and indirect impacts on the watershed. This study presented machine learning for statistical downscaling as a means of hydrological modeling. A statistical downscaling model was created using a global circulation model from the community climate system model (version 4.0), and compared to different machine learning techniques, including linear regression, gaussian process, and support vector machine. The soil and water assessment tool (SWAT) was used to model climate-induced runoff and downscaling procedures. The output climate scenarios of the machine learning model were incorporated into SWAT to simulate water runoff in the study area of Lake Tana basin, Ethiopia. The simulation results of SWAT water runoff under deep learning climate conditions demonstrated the highest performance. The results could contribute to the hydrological analysis and improve the quality of statistical downscaling.

Keywords: climate change; machine learning; statistical downscaling method; soil and water assessment tool

1. INTRODUCTION

Rapidly rising temperature of the global surface contributes to the water crisis (Berardy and Chester, 2017). The equilibrium between incoming solar energy and surface reflection determines the Earth's surface temperature. Consequently, solar energy can penetrate the atmosphere and warm the planet's surface (Booij, 2005; Patz et al., 2005). With the rapid increase in greenhouse gases, human-consumed gases, such as chlorofluorocarbons (CFCs) and carbon dioxide, significantly impact climate change (Abbaspour et al., 2009; Akhtar et al., 2008; Haines et al., 2006; Hughes et al., 2017; McMichael et al., 2006).

The rapid increase of greenhouse gases in the 21st

century has significantly impacted the world's water resources (Githui et al., 2009; Piao et al., 2010; Setegn et al., 2011). However, the effect of climate change varies, depending on the topography, atmosphere, and environment (Li and Fang, 2016). Thus, authentic climate information that is fine enough is necessary for an accurate regional-scale analysis. Unfortunately, although regional climate model (RCM) is a regional simulation model that studies climate change, accurate results are hardly received due to coarse information from the general circulation model (GCM) (Nawaz et al., 2010). Therefore, the statistical downscaling model (SDSM) plays a vital role as an information processor to achieve delicate data for regional study (Abatzoglou and Brown, 2012; Anderson et al., 2012; Herrera et al., 2013).

Moreover, temperature and precipitation are essential variables for current climate simulation and risk management research. Many research reports on climate simulation use GCM as big data. However, the data are coarse because the resolution of GCM around 250-600 kilometers. Then, the climate downscaling model has been used to process the information for the regional study. Downscaling is required to increase the resolution of GCM simulations by combining information on local conditions and large-scale climate change (Shrestha et al., 2018; Ullah et al., 2018; Wang et al., 2018). Dynamic and statistical downscaling are two primary strategies for linking the data. Dynamic downscaling is based on a precise depiction of the physical principles (such as thermodynamics and fluid mechanics), which is handled in a model comparable to a GCM. It is a computational luxury and requires a lot of data and expertise to execute and explain the results. The statistical downscaling model (SDSM) is an additional principle that adequately describes the relationship between observation-based surface data and atmospheric circulation (Hadipour et al., 2016; Sachindra et al., 2018).

Regarding hydrology, climate change and its effect on the seasonal timeline are the most crucial water degradation factors (Mankin et al., 2010). Temperature and precipitation variations directly affect evapotranspiration, quantity, and quality. Consequently, water resources have been impacted, causing problems for agricultural sectors, industries, and livelihoods (Bannwarth et al., 2015). Using parameter sensitivity analysis, model calibration, and model validation, Zhu et al. (2019) accurately validated the ability of water basin simulation to predict hydrology. Incorrect input variables such as precipitation and temperature affected sediment and water quality in the hydrological simulation (Birara et al., 2020; Lee et al., 2020; Wang et al., 2020; Zhu et al., 2019).

Haylock et al. (2006) have studied the statistical and dynamic downscale in the United Kingdom using artificial neural network (ANN), but they have not applied it to a specific problem. Gutmann et al. (2014) has analyzed the statistical decline in the United States but excludes ANN. Mendes and Marengo (2009) used ANN and autocorrelation techniques to downscale daily precipitation in the Amazon Basin, concluding that ANN outperforms statistical models but has no application. Ba et al. (2018) have studied statistical methods that are simple to execute and explain. The SDSM requires lower computing resources. Nonetheless, surface data based on sufficient observation are required. Li and Fang (2021) reported that the SDSM was used in the soil and water assessment tool (SWAT), but did not delve into the distinctions between machine learning methods. Zhou et al. (2015) integrated SWAT and SDSM in the Lake Dianchi watershed, China, using the multi-linear regression method and NCEP/NCAR reanalysis and observed data. Consequently, this research studied the SDSM by four machine learning and then applied the climate scenarios to SWAT for evaluating the water runoff at Lake Tana, Ethiopia. The primary objectives of this study were to find the best machine learning (ML) algorithm applicable to climate change data and use those algorithms to project the climate scenarios that would be used as input for the SWAT analysis.

2. MATERIALS AND METHODS

2.1 General circulation model (GCM)

GCM is the most sophisticated instrument for simulating physical processes in the atmosphere, oceans, freezing temperatures, and land surface. GCM refers to global climate data produced by complex mathematical models that describe climate change due to differential pressures, chemical composition, velocity, and temperature. A typical global three-dimensional grid has a horizontal resolution of 250 and 600 kilometers, 10 to 20 vertical levels in the sky, and as many as 30 layers in the oceans. Consequently, the resolution is relatively coarse, compared to the scale of exposure units in most impact assessments. The GCM has gained attention from researchers who developed a community earth system model called the community climate system model (CCSM) (Gent et al., 2011).

2.2 Soil and water assessment tool (SWAT)

SWAT is a hydrological model that simulates the physical properties of a watershed-based on the physical state of the area as a parametric distribution. SWAT can predict long-term runoff with changing soils, land use, and management conditions (Mankin et al., 2010). The SWAT composed of 6 processes is following.

2.2.1 Determination of sub-watershed boundaries and reservoir location

The determination of sub-watershed boundaries was created by using DEM with following factors: the desired position from the model, the controllable water-flow position such as weir and dam that include the expected future construction as well, and the position of the station that can be calibrated for the model, such as runoff metering station.

2.2.2 Construction of a hydrological management unit (HRUs)

Each sub-watershed generally has a unique land use, soil type, slope, and management strategy. The SWAT model simulates the hydrological cycle based on the water balance Equation (1) (Srinivasan et al., 1998).

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

where SW_t is the final soil water content (mm), SW_0 is the initial soil water content on day i (mm), t is the time (days), R_{day} is the amount of precipitation on day i (mm), Q_{surf} is the amount of surface runoff on day i (mm), E_a is the amount of evapotranspiration on day i (mm), W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm), and Q_{gw} is the amount of return flow on day $\boldsymbol{i}$ (mm).

The SWAT used the spatial data in the GIS program, which calculated three data layers of land use, soil type, and slope of an area (Abbaspour et al., 2018; Zhou et al., 2015), which were then layered on top of one another to create a new layer of information for each area containing these three layers, called HRUs. Each sub-watershed in SWAT is composed of more than one HRUs, which can design different SWAT parameters. Therefore, this type of calculation yields accurate and reliable results.

2.2.3 Climate input

SWAT data includes daily precipitation, temperature, humidity, wind speed, and solar energy. The SWAT automatically selects the climate station for each sub-watershed that best represents the climate of that sub-watershed. In calculating climate conditions, only a single station is used per sub-watershed.

2.2.4 Reservoir input

Location and primary data of the reservoir are entered, including surface area, capacity, and drainage.

2.2.5 Other parameters

Other parameters affect the runoff and groundwater.

2.2.6 Model calibration and verification

The model was validated using runoff and groundwater indicators after entering SWAT parameters. A statistical relationship was used to validate the model's output by comparing calculated results to observational data.

2.3 Verification of model accuracy

The model's validity was determined by comparing model results to actual measurements and observations. The process of evaluating the model's precision involved considering consistency by examining the graph comparing the two values and calculating the error value using the coefficient of determination (R^2) and Nash-Sutcliffe efficiency (NSE) (Lin et al., 2017), and validating the results of calculations using weather data derived from statistical downscaling by deep learning. The model parameters were optimized to produce an accurate and reliable result.

$$R^2 = \frac{[\sum_{i=1}^{N}(Q_{sim}-\bar{Q}_{obs})(Q_{obs}-\bar{Q}_{obs})]^2}{(\sum_{i=1}^{N}(Q_{sim}-\bar{Q}_{obs})^2)(\sum_{i=1}^{N}(Q_{obs}-\bar{Q}_{obs})^2)} \quad (2)$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Q_{obs}-Q_{sim})^2}{\sum_{i=1}^{N}(Q_{obs}-\bar{Q}_{obs})^2} \quad (3)$$

where Qobs is the amount of observed runoff, Osim is the amount of simulated runoff, and $\bar{Q}$obs is the amount of averaged observed runoff.

2.4 Proposed methodology

This study was divided into two processes. In the first step, the climate model was simulated with statistical downscaling using four machine learning techniques (DL, LR, GP, and SVM) (Campozano et al., 2016; LeCun et al., 2015; Liu et al., 2016). The model producing the best performance was passed through another step. The second step, which is shown in Figure 1, entailed estimating the runoff quantity with SWAT using climate predictions from the previous procedure.

For statistical downscaling, there are two terms of data: predictor and predictand. The predictor utilized GCM data collected by the National Oceanic and Atmospheric Administration (NOAA), as shown in Table 1. The U.S. Department of Commerce provides data, tools, and information to help individuals comprehend climate variability and change, and prepare for it. The predictand used the data from the Global Historical Climatology Network (GHCN), which is climate summaries from weather stations across the globe. GHCN data were archived from more than 20 sources. Statistical downscaling will reduce the ratio from 100-500 km to 10-50 km, based on the station in the research area. In this study, the researchers used data from six stations to downscale. According to Figure 2, four MLs were visible during the downscaling process. We selected each method's covariates from maximum temperature (TMAX), minimum temperature (TMIN), and precipitation. Both predictors and predictands perform quality control on each ML. These two parameters for downscaling were combined to identify all four climate scenario-generating models for SWAT analysis (Figure 1).

Agricultural (AGRL) encircled the research area, as shown in Table 2. Lake Tana consists of nine subbasins and is divided into four categories: pasture (PAST), forest (FRST), corn and teff (*Eragrostis tef*). In addition, various areas are adjacent to the watershed within the subbasin. The largest of the nine subbasins are corn and teff.

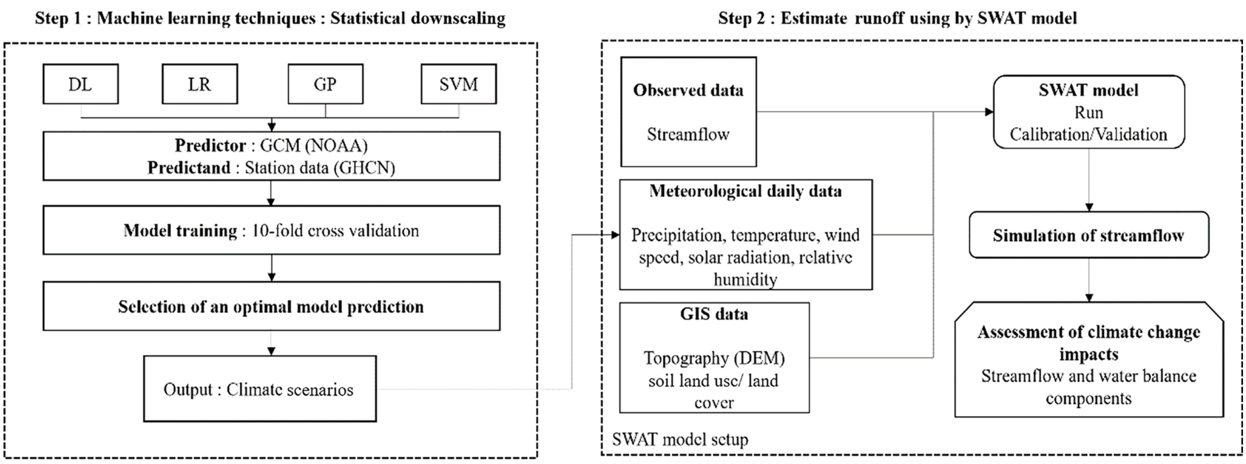

Figure 1. Proposed techniques using machine learning and SWAT analysis

Table 1. Data set of GCM by NOAA

Experiment number	Statistical downscale method	Number of station	GCM models
1	Deep learning	6	CCSM4
2	Gaussian process	6	CCSM4
3	Linear regression	6	CCSM4
4	Support vector machine	6	CCSM4

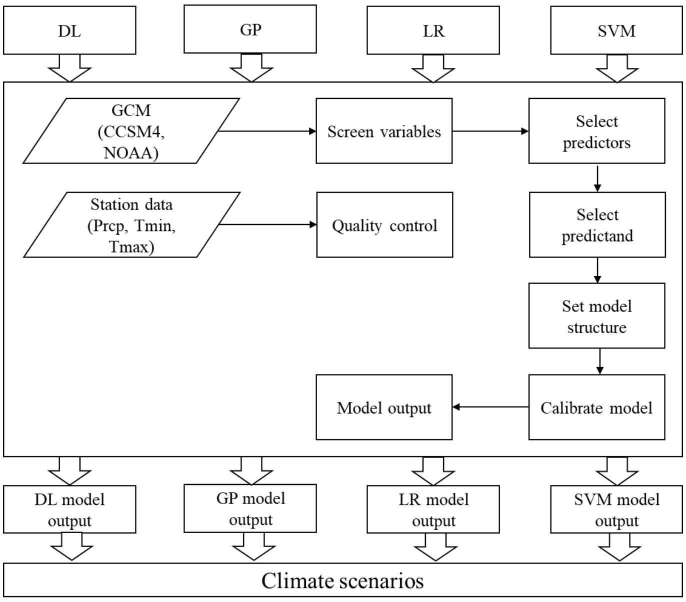

Figure 2. Flow chart of statistical downscale

2.5 Study area

Lake Tana basin has 15,096 km^2 and average annual rainfall of approximately 1,280 mm. The average annual evapotranspiration and amount of water in the catchment area are 773 mm and 392 mm, respectively (Setegn et al., 2008). In addition, it has extensive wetland areas. This basin is of national importance for hydroelectric power, irrigation, livestock production, high-value crops, and ecotourism, among others. Lake Tana is situated in the northwest highlands of the country (latitude 12°00N, longitude 37°150E). This lake has a maximum depth of 15 meters and a surface area of 3,000-3,600 km^2 at an elevation of 1800 meters. The climate of this region is 'tropical highland monsoon' with the primary rainy season between June and September. The average annual temperature is 20°C.

3. RESULTS AND DISCUSSION

The collected data from GCMs and six weather stations were used to calculate correlation and RMSE. The box plot was plotted by being divided into correlation and RMSE, as illustrated in Figure 3. The result showed that the DL performed better than GP, LR, and SVM. Furthermore, RMSE and correlation show that DL performs better than GL, LR, and SVM in Table 3 and Table 4. In this study, we examined many scenarios. The DL method created the scenario with 2, 5, 10, and 15 hidden layers, each consisting of 10, 20, 30, 50, and 100 neurons. The result showed that the best number of nodes and layers was 2 and 50 nodes for each layer. However, an appreciable performance improvement was not observed due to the multiple processor kernels present in GP and SVM. The SDSM study revealed that the best kernel for SVM was polynomial, and the best kernel for GP is cauchy (Chattrairat et al., 2021).

According to research conducted to determine water flow from SWAT analysis using R^2 and NSE in calibration and validation, R^2 must be greater than 0.70 and NSE must be greater than 0.50 for the model to proceed to the next step. The results are shown in the model (Figure 1) calculated within the SWAT+ program.

Figure 4 illustrates the outcomes of the ML data imported in Step 1 of Figure 1, including DL, GP, LR, and SVM. SWAT analysis required DL, GP, LR, and SVM as inputs for calculating water flow. Using meteorological data to calculate the water flow results, the green SWAT in the graph represented the baseline of this study.

Using RMSE and correlation as indicators, the SWAT model results for channel one at latitude 11.66 and longitude 37.42 indicated that statistical downscaling by deep learning outperformed meteorological data. For instance, the RMSE calculation of water runoff using climate scenarios and data from deep learning was 0.1591, which was less than when using meteorological data, which is 0.3596. Moreover, the correlation value derived from deep learning is greater than the value derived from meteorological data, which was 0.9852 and 0.6974, respectively.

The comparison of the water runoff prediction that computed from the SWAT model with the different climate data inputs (DL, GP, LR, SVM) and meteorological data is shown in Figure 5. Again, the result shows that DL was the best performance. Figure 6 shows the comparison of performance of SWAT models, between RMSE and correlation. The DL showed best performance with RMSE of 0.159, and the correlation is 0.98. The climate data from machine learning showed a good correlation, but the RMSE and the DL showed the best performance. Figure 7 shows the monthly result of the flow rate for four climate scenarios, meteorological data, and observed flow. It can be seen from Figure 7 that the flow rate was highest in August and lowest in April. The GP offered the highest value for every month.

Table 2. Landuse of Lake Tana (Ethiopia) consisting of 9 subbasins

Subbasin	AGRL	Area (ha)	% Watershed	% Subbasin
1	PAST	25.83	1.54	11.17
	FRST	12.09	0.72	5.23
	CORN	96.64	5.77	41.8
	TEFF	96.64	5.77	41.8
2	PAST	55.35	3.3	14.94
	FRST	2.71	0.16	0.73
	CORN	156.19	9.32	42.16
	TEFF	159.19	9.32	42.16
3	PAST	19.71	1.18	5.73
	FRST	2.29	0.14	0.67
	CORN	161.04	9.61	46.8
	TEFF	161.04	9.61	46.8
4	PAST	0	0	0
	FRST	8.37	0.5	3.46
	CORN	116.91	6.98	48.27
	TEFF	116.91	6.98	48.27
5	PAST	3.42	0.2	6.16
	FRST	0.27	0.02	0.49
	CORN	25.92	1.55	46.68
	TEFF	25.92	1.55	46.68
6	PAST	0	0	0
	FRST	0	0	0
	CORN	61.11	3.65	50
	TEFF	61.11	3.65	50
7	PAST	0	0	0
	FRST	0.18	0.01	2
	CORN	4.41	0.26	49
	TEFF	4.41	0.26	49
8	PAST	17.01	1.02	8.61
	FRST	2.52	0.15	1.28
	CORN	89.01	5.31	45.06
	TEFF	89.01	5.31	45.06
9	PAST	5.40	0.32	5.24
	FRST	2.03	0.12	1.97
	CORN	47.81	2.85	46.4
	TEFF	47.81	2.85	46.4

Due to the abundance of information, DL was the most widely used ML technique among researchers worldwide for learning new concepts. Wang et al. (2020) have used the ANN and recurrent neural network to downscale extreme precipitation. However, in this study, we calculated TMAX, TMIN, and PRCP; the results showed that the DL calculated the current streamflow in the catchment area and could predict future streamflow. The trained DL model could be applied to future climate data and used as input for the SWAT model to determine what occurs in the watershed and catchment area.

As mentioned earlier, it can be summarized in Table 5 that four research papers Haylock et al. (2006), Mendes and Marengo (2009), Abatzoglou and Brown (2012) and Gutmann et al. (2014) have presented only statistical downscale while two research papers have exploited the use of only SWAT Bannwarth et al. (2015), Tufa and Sime (2021). The last research paper used statistical downscale and SWAT (Zhou et al., 2015) but did not focus on ML and DL to estimate water runoff. However, no research paper has been proposed on combining the three technique methods (ML, statistical downscale and SWAT). This research presented ML and DL to solve climate statistical downscale and SWAT to estimate water runoff in Lake Tana basin, Ethiopia.).

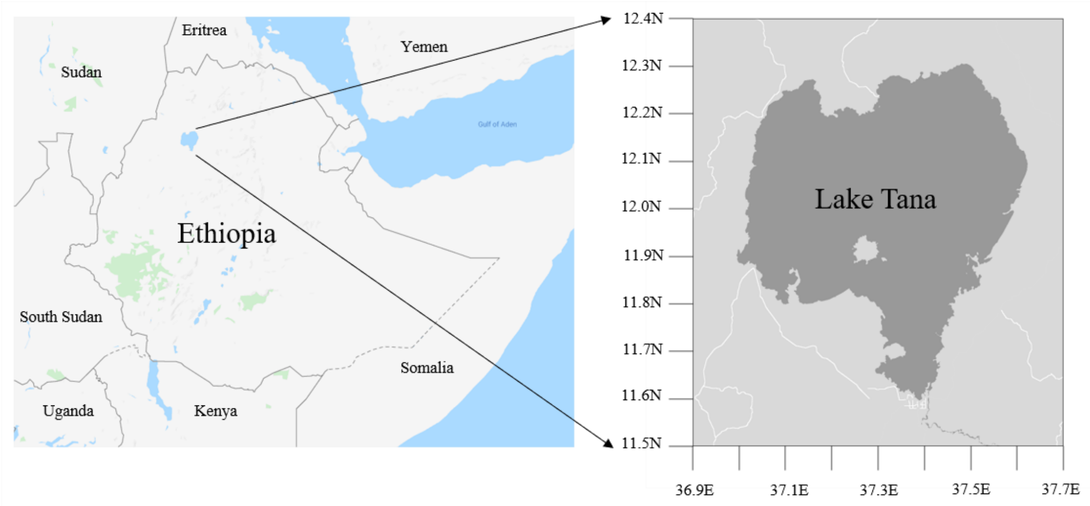

Figure 3. Study area – Lake Tana, Ethiopia

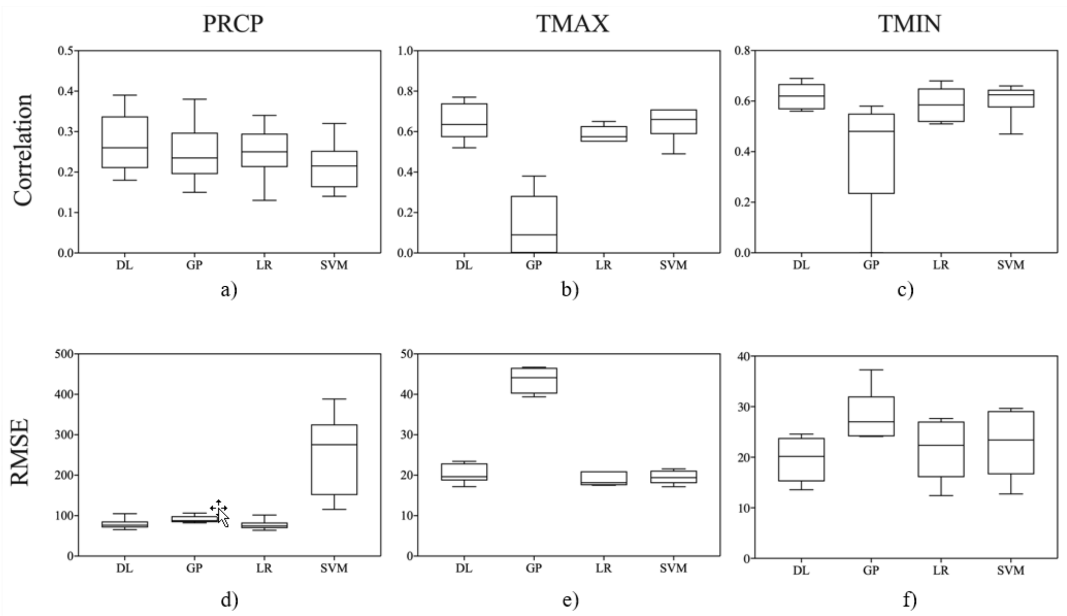

Figure 4. Box plot of correlation and RMSE comparing between four SDSM for PRCP (left), TMAX (middle) and TMIN (right)

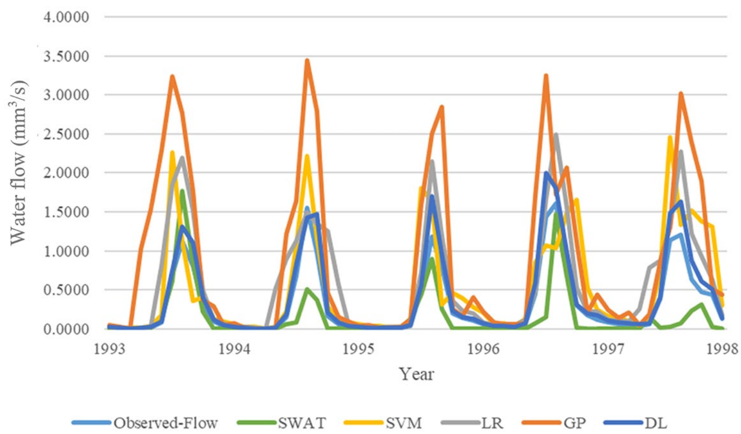

Figure 5. Comparison of water runoff prediction between L and SWAT model

Table 3. The results of RMSE by four machine learning in six stations of data

Station	Latitude (degree)	Longitude (degree)	Precipitation				Maximum temperature				Minimum temperature			
			DL	GP	LR	SVM	DL	GP	LR	SVM	DL	GP	LR	SVM
GONDAR	12.55	37.42	72.64	84.36	70.73	256.87	19.43	45.60	18.15	19.88	15.78	25.39	17.27	17.91
COMBOLCHA	11.12	39.73	79.34	96.34	76.46	388.49	23.43	42.61	18.15	21.58	20.11	28.63	23.51	24.43
JIMMA	7.67	36.83	78.64	88.33	76.98	162.65	19.22	46.69	20.97	18.31	23.55	30.28	26.86	29.66
GORE	8.15	35.53	104.88	106.25	101.53	115.58	17.17	39.38	20.97	17.16	13.57	24.13	12.41	12.74
GORE	9.03	38.75	74.21	86.87	72.53	294.01	19.85	40.45	17.50	18.93	20.19	24.10	21.22	22.38
DIREDAWA	9.60	41.85	65.32	82.16	63.94	304.88	22.77	46.51	17.53	20.98	24.58	37.27	27.66	28.94

Table 4. The results of correlation by four mac-hine learning in six stations of data

Station	Latitude (degree)	Longitude (degree)	Precipitation				Maximum temperature				Minimum temperature			
			DL	GP	LR	SVM	DL	GP	LR	SVM	DL	GP	LR	SVM
GONDAR	12.55	37.42	0.39	0.38	0.34	0.32	0.77	0.06	0.62	0.71	12.21	19.69	13.31	13.73
COMBOLCHA	11.12	39.73	0.22	0.23	0.25	0.20	0.59	0.25	0.57	0.62	0.81	1.13	0.77	0.79
JIMMA	7.67	36.83	0.25	0.24	0.24	0.17	0.64	0.00	0.65	0.66	17.95	22.32	18.25	18.58
GORE	8.15	35.53	0.27	0.21	0.25	0.23	0.73	0.12	0.55	0.71	0.92	0.86	0.71	0.72
GORE	9.03	38.75	0.32	0.27	0.28	0.23	0.52	0.00	0.58	0.49	19.45	23.80	20.64	22.51
DIREDAWA	9.60	41.85	0.18	0.15	0.13	0.14	0.63	0.38	0.55	0.66	0.79	0.86	0.75	0.81

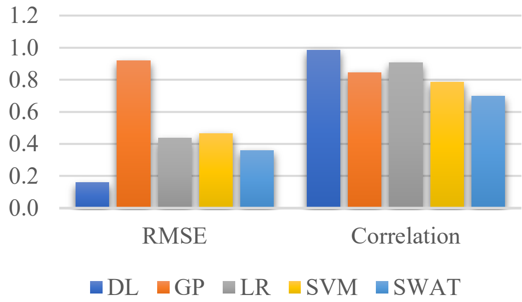

Figure 6. Comparison of performance of SWAT models

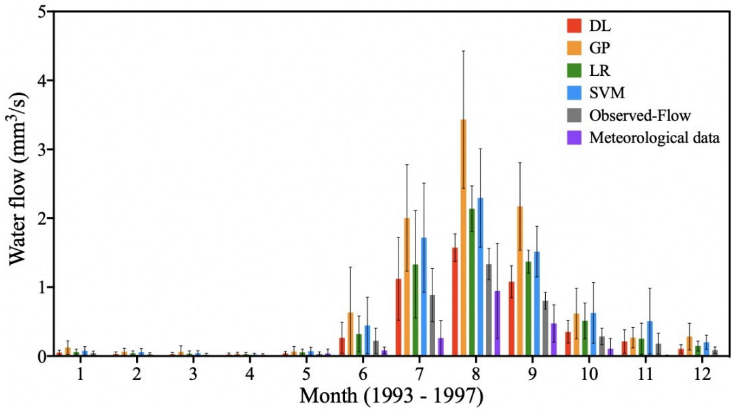

Figure 7. Comparison of monthly water flow of all models

Table 5. Comparisons of downscaling methods and SWAT application

References	**Methodology**					**Study area**	**Application (SWAT)**
	Statistical model		**Theories**	**Training model**	**Validation**		
	One model	Various models					
Haylock et al. (2006)		✓	ANN	✓	Separate Validation period	northwest and southeast England (UK)	
Gutmann et al. (2014)		✓	BCSDd, BCSDm, AR, and BCCA*	✓	Separate Validation period	United States	
Mendes and Marengo (2009)		✓	ANN, Autocorrelation	✓	CV	Amazon Basin Lake Tana (Ethiopia)	
Abatzoglou and Brown (2012)		✓	BCSD, MACA	✓	CV	North American (US)	
Bannwarth et al. (2015)			ANSELM	✓	Separate Validation period	Thailand	✓
Zhou et al. (2015)	✓		SDSM	✓	Separate Validation period	Lake Dianchi watershed, China	✓
Tufa and Sime (2021)			ArcSWAT	✓	SWAT-CUP	Toba sub-watershed, Ethiopia	✓
This research	✓	✓	DL, LR, GP, and SVM	✓	10-Fold CV	Lake Tana, Ethiopia	✓

Note: *bias corrected spatial disaggregation (BCSDd, BCSDm), asynchronous regression (AR), and bias corrected constructed analog (BCCA), cross-validation (CV), artificial neural network (ANN), soil and water assessment tool (SWAT)

4. CONCLUSION

This research is focused on the topic of global warming. Maximum temperature, minimum temperature, and precipitation are among the methods that lead to climate forecasts. The research was conducted on Lake Tana in Ethiopia. The experiments consisted of statistical simulations on a smaller scale utilizing ML techniques such as DL, LR, GP, and SVM. Experiments employing ten-fold cross-validation demonstrated that DL was sufficient. The climate scenario derived from the DL model proved optimal for surface water volume calculations using SWAT analysis. It can be stated that the DL algorithm outperformed other ML techniques used in this study.

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