River Discharge and Reservoir Operation Assessment under a Changing Climate at the Sirikit Reservoir

MANEE Donpapob[a *], TACHIKAWA Yasuto [2,b], ICHIKAWA Yutaka [3,c] and YOROZU Kazuaki[4,d]

Abstract The large scale reservoir plays an important role in modern water resources management by regulating the water to address severe flood and drought problems. Therefore, the proper planning of water resource availability based on uncertainty climate change impact is very necessary. The objective of this study is to evaluate the changes of water storage and outflow based on present and past operation with the different future reservoir inflow data by using Atmospheric General Circulation model (MRI-AGCM3.2S) forcing data which is jointly developed by Meteorological Research Institute of Japan and Japan Meteorological Agency. For each 20-km grid cell, the surface runoff generation of MRI-AGCM3.2S was used to simulated river discharge at the Sirikit reservoir by a distributed flow routing model (1K-FRM) based on the kinematic wave theory. In this study, distribution mapping methods are applied to raw daily river discharge simulated data for remove systematic bias between model and observed data. After bias correction to daily discharge achievement, the future corrected reservoir inflow of different scenarios were given to reservoir operation model algorithms and using the Artificial Neural network (ANN) for calculation the future release flow and reservoir storage based on remain the downstream water requirement and amount of water losses in this reservoir same as present climate condition. The evaluation of future reservoir operation based on present rule curve will show the necessary decision way to revise or improve current operation to adapt to probably water resources availability.

Keywords *Artificial Neural Network, Flow Routing Model, Atmospheric General Circulation Model, Bias Correction*

MANEE Donpapob
Department of Civil and Earth Resources Engineering
Kyoto University
Kyoto, Japan
manee.donpapob.85v@kyoto-u.jp

TACHIKAWA Yasuto
tachikawa@hywr.kuciv.kyoto-u.ac.jp

ICHIKAWA Yutaka
icichikawa@hywr.kuciv.kyoto-u.ac.jp

YOROZU Kazuaki
yorozu@hywr.kuciv.kyoto-u.ac.jp

Introduction

Water is indispensable for all forms of life and is needed, in large quantities, in almost all human activities. According to the 2013 Intergovernmental Panel on Climate Change (IPCC), the global water cycle will change, with increases in disparity between wet and dry regions, as well as wet and dry seasons, with some regional exceptions. Water resources is an increasingly limited and highly essential resource for many countries where agriculture is the main income of the economy corresponding with ensures the well-being of the people. The proper planning of water resource availability based on uncertainty climate change impact is very necessary; because, the projection of hydrologic inflow data can support and help government stakeholder and reservoir operator to adapt their decision making to release the water subjected to the rule or constraint in advance and be consisted of the sustainable development plan in future. The large scale reservoir plays an important role in modern water resources management by regulating the water to address severe flood and drought problems. It is the effective tool to store water when severe flood occurs for mitigation of the huge loss, damage of lives and economics. Not only the excess water resource problem, but the inadequate water supply in Thailand also experienced the extreme drought. Therefore, to investigate the current reservoir operation is an important and interested finding to respond to future climate change for water management effectively and cope with future flood event as well. Therefore, the proper planning of water resource availability based on uncertainty climate change impact is very necessary. The objective of this study is to evaluate the changes of water storage and outflow based on present and past operation with the different future reservoir inflow data by using Atmospheric General Circulation model (MRI-AGCM3.2S).

Study area

The Sirikit reservoir with coverage catchment area of 13,130 km^2 is located of the midstream of Nan River basin in Thailand as shown in **Fig.1**. The upstream of the Sirikit reservoir is a mountainousarea which is not affected by major flow regulations or any other direct human activities impacts.

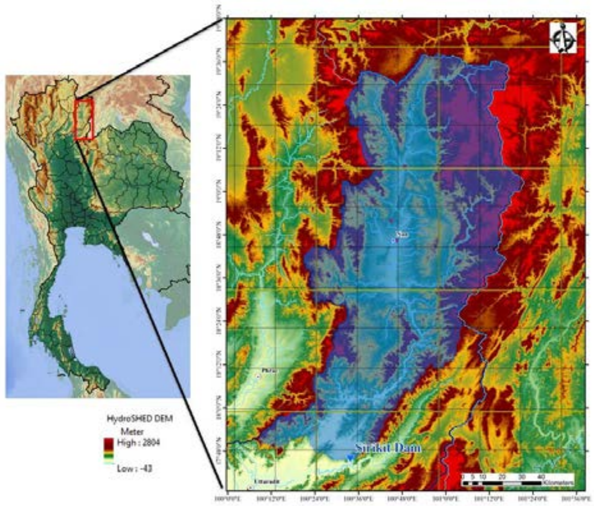

Fig.1 Map showing the study area, reservoir location and spatial 20 km x 20 km square grid of MRI-AGCM3.2S.

The continuous time series data of observed inflow into the reservoir is available for the period of 1974-2013 (40 years). Its climate is tropical with distinctly clear dry and wet seasons. The seasons are defined as follows: the dry season starts from November until April and the wet season starts from May until October.

Methodology

The overall of this research can be divided into river discharge prediction part and reservoir operation assessment part for present and future climate scenarios. To estimate river flow for water resource assessment, the hydrological model is widely represented the interaction between hydrologic cycle element such as precipitation, soil Moisture, river flow and evapotranspiration. Several impacts of climate change studies with distributed hydrological model were conducted at the Chao Phraya River Basin in Thailand (Wichakul et al., 2015; Hunukumbura and Tachikawa, 2012). In this study, the 1K-FRM distributed flow routing model was chosen to handle input spatial data such as gridded rainfall; therefore, this model can applicable to access reservoir inflow under a changing climate as well. 1K-FRM is originated development in Hydrology and Water Resources Research Laboratory at Department of Civil and Earth Resources Engineering, Kyoto University.1K-FRM is a distributed flow routing model based on kinematic wave flow approximation. The kinematic wave model is conduct to all rectangular elements gridded to link the water to downstream associate with the derived catchment model. Basically, the selecting of Digital Elevation Model (DEM) data used in catchment model is HydroSHEDS (Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales) provides hydrographic information in a comprehensive and consistent format for both local and global-scale applications (Lehner, 2006).1K-FRM used 30 arc-second resolutions (approximately 1 kilometer at near equator area) as a catchment model. The flow direction is defined into 8 directions which assigns flow depends on the different elevation with in a direction of steepest downward slope as illustrated in **Fig. 2**.The basic kinematic wave equation for each rectangular slope elements is

$$\frac{\partial A}{\partial t}+\frac{\partial Q}{\partial x}=q_L(x,t) \qquad (1)$$

where t denotetime; A is the cross-sectional area;Q is discharge; and q_L (x,t) is the lateral inflow per unit length of each slope element. Another equation used to solve above equation is the relationship of Manning type of the discharge and a rectangular cross-section area of each cell as follows:

$$Q=\alpha A^m, \alpha=\frac{\sqrt{i_o}}{n}\left(\frac{1}{B}\right)^{m-1}, m=\frac{5}{3} \qquad (2)$$

where i_o is slope gradient; n is the Manning's roughness coefficient; and B is the width of the flow. There are two main parameters inside 1K-FRM model which consist of the Manning's roughness coefficient for the slope unit ns and Manning's roughness coefficient for the river channel unit cell n_r. In this study, the parameter of n_s = 0.03 $m^{-1/3}$s and n_r = 0.1 $m^{-1/3}$s were used for the suitable values.

General circulation models (GCMs) have been commonly used in climate change impact studies. The several studies of application to use GCMs in Chao Phraya River Basin and surrounding River Basin were conducted. For instance, Hunukumbura and Tachikawa (2012) utilized the runoff projected by MRIAGCM3.1S, which showed the increasing of extreme discharge at the upper part of Chao Phraya River Basin and the decreasing of monthly discharge in October at the Pasak River basin. Kure and Tebakari (2012) showed the increased tendency of the mean annual river discharge and annual maximum daily flow at the NakhonSawan station located at the downstream of the four major rivers in the in upper Chao Phraya River Basin using the precipitation and temperature projected by MRI-AGCM3.1S and MRI-AGCM3.2S. Champathong et al. (2013) assessed the uncertainty of river flow projections using the outputs of MRIAGCM3.1S and MRI-AGCM3.1H.Kitpaisalsakuiet al. (2016) also used MRI GCM data to assesses the impact of climate change on reservoir operation in Central Plain Basin of Thailand.

The GCM outputs used for this research were gridded runoff generation data from MRI-AGCM 3.2S (Mizuta et al., 2012), where 'S' refers to super-high resolution developed by Japan Meteorological Agency (JMA) and the Meteorological Research Institute (MRI). The AGCMs grids covering the Sirikit reservoir study area were total of 88 grids (8 columns and 11 rows) with the spatial resolution 0.1875 degree (approximately 20 km), located between the latitude of 17 degrees 42 minutes and 19 degrees 35 minutes north and the longitude of 100 degrees 7 minutes and 101 degrees 26 minutes east.To obtain the high resolution of climatic forcing data is to used downscaling technic by an atmospheric general circulation model (Kitoh et al., 2015).The high-resolution that is obtain the observed or projected sea surface temperature (SST) as boundary condition. This type of mechanism simulations, which uses the observed present day inter-annually varying SST plus ensemble mean future SST changes obtained by CMIP-class models, can minimize the effects of climate model bias. Based on the SST data of 28 CMIP5 model, the different SST spatial patterns are analyzed by a cluster analysis of these 28 CMIP5 model. After that, the 28 CMIP5 modelclassified into 3 clusters from 8, 14 and 6 models of cluster 1, cluster 2 and cluster 3, respectively.

That model has a horizontal resolution of triangular truncation 959 (TL959) and a vertical resolution of 64 levels (top at 0.01 hPa) to transform grid uses 1920* 960 grid cells with corresponding to approximately a 20 km grid interval. The 20-km mesh MRI-AGCM3.2 was employed in each 25-year time-slice experiment for the present-day climate (1979-2003) and late 21stcentury climate (2075-2099) scenarios with the Representative Concentration Pathway (RCP) 8.5 that refers to the final radiative forcing achieved by the year 2100 around 8.5 watts per square meter (W/m^2).Moreover, the cluster analysis also analyzed the ensemble SST to classify the characteristic pattern of SST into three groups as following 1) cluster 1: Uniform warming in the tropics zone pattern or in the both hemispheres, 2) Cluster 2: Larger warming over the central equatorial Pacific (so-called EI Nino-like pattern) and 3) Cluster 3: Larger warming in the north Indian Ocean and north-west Pacific pattern. Therefore, the future climate projection was combined of different SST (4 future SSTs) to assess the uncertainty of future water availability.However, for 20 km grid output data provide a new cumulus convection scheme (Yoshimura et al, 2015), called the "Yoshimura scheme" only. For each 20-km grid cell, the various hydrological components of MRI-AGCM 3.2S such as precipitation, evaporation, transpiration and surface runoff generation were calculated through the land surface scheme as shown in **Fig 2**.The runoff generation of MRI-AGCM3.2S was used to simulated river discharge at the Sirikit reservoir by a distributed flow routing model (1K-FRM) based on the kinematic wave theory(Tachikawa and Tanaka, 2013).All period of simulation has been performed at a spatial resolution of 1 km and temporal resolution of one day. For the verification data, the observed time series of daily inflow was obtained from the Electricity Generating Authority of Thailand (EGAT).

A recent bias correction method based on a relationship of cumulative distributions (CDFs) of the GCMs and observation data has been commonly used for hydrologic simulations and climate change studies.The distribution mapping technique adjusts all particles of the cumulative distribution function (CDF) of projected data with GCM outputs by using the CDF of observation and construct a transfer function to convert the projected data using GCMs to corrected data.

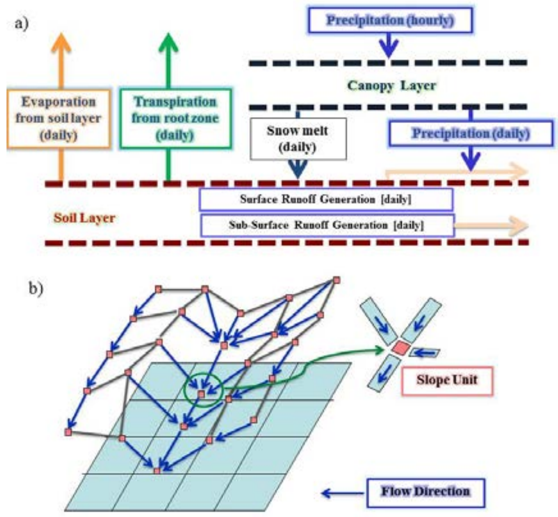

Fig.2 The framework diagram river discharge simulation.

a) Land surface generation data of MRI-AGCM3.2S fed into river discharge simulation in a grid. b) Schematic drawing of a catchment and flow routing model using HydroSHEDS DEM.

All bias correction methods of quantile mapping have to initiate by 1) sorting long-term observation and simulation river discharge data to create CDFs for each calendar month (Jan-Dec); 2) correcting bias in the frequency and intensity distribution on each different method; and 3) rearranging corrected data back to the original time series.

The classical distribution quantile mapping (eQM) is expressed by setting the pair with the same non-exceedance probability as follow

$$Q^{*}_{c} = F^{1}_{obs,C}(F_{raw,C}(Q_{raw,C})) \quad (3)$$

where Q* is the corrected river discharge value, Qraw,C is the raw original river discharge value and stands for the inverse function of CDFs of the observed daily discharge, and accordingly Fraw,C as the CDFs of the projected river discharge using MRI-AGCM3.2S.However, for the application of eQM method to the future climate condition, if we assume that the transfer function is stable and follows the same current climate condition. Li et al. (2010) proposed the eQM with the difference of CDFs or referred to as equidistant CDF matching ($EDCDF_m$) to calculate by adding the difference between CDFs of GCM and observation river discharge during future climate condition as following equation:

$$Q^{*} = Q_{raw,P} + [F^{-1}_{obs,C}(F_{raw,P}(Q_{raw,P})) - F^{-1}_{raw,C}(F_{raw,P}(Q_{raw,P}))] \quad (4)$$

where, $Q_{raw,P}$is the original river discharge value for the future projection period. The $F^{-1}_{obs,C}$ and $F^{-1}_{raw,C}$ stand for the inverse function of CDFs of the observations and raw GCMs during present climate period, respectively.

Moreover,The gamma distribution with shape parameter β and scale parameter α is defined as:

$$f(x) = x^{\alpha-1} \cdot \frac{1}{\beta^{\alpha} \cdot \Gamma(\alpha)} \cdot e^{\frac{-x}{\beta}}; x, \alpha, \beta > 0 \qquad (5)$$

where Γ is the gamma function. In this study, the shape and scale parameter were fitted with observation and GCMs projection on each calendar month. The gQM method is a parametric correction method which can be expressed as:

$$Q_c^* = F_Y^{-1}(F_Y(Q_{raw,C} | \alpha_{raw,C}, \beta_{raw,C}) | \alpha_{obs,C}, \beta_{obs,C}) \qquad (6)$$

$$Q_p^* = F_Y^{-1}(F_Y(Q_{raw,P} | \alpha_{raw,C}, \beta_{raw,C}) | \alpha_{obs,C}, \beta_{obs,C}) \qquad (7)$$

Maneeet al. (2016) found the equidistant CDF matching (EDCDFm) and the empirical with gamma distribution quantile mapping (gQM) methods showed the good overall performance and applicable to potentially changed climate condition in term of less bias of water balance and proper for adjusted peak river discharge.

For reservoir operation assessment part aims to estimate the future water storage and to evaluate the tendency of excess water use (flood risk) and insufficient water use (drought risk) by given the bias-corrected river discharge based on the methodology of previous section. The Flowchart of reservoir simulation procedure for calculated future reservoir outflow and storage is shown as **Fig. 3**. Kim et.al (2009) investigated the adaptability of current dam operation rules under climate change condition to a dam in the upper part of Tokyo, Japan based on AGCM20 input data. The Artificial Neural Network (ANN) is selected to learn the past reservoir operation and transferred to the machine learning. The relationship of storage and reservoirs inflow is important to give through covariates (also known as input variables) and response variables (also known as output variables) is represented as release flow of reservoir.The ANN consists of the neurons are organized in layers, which are usually fully connected by synapses. A synapse can only connect to subsequent layers.The input layer consists of all covariates in separate neurons and the output layer consists of the response variables.

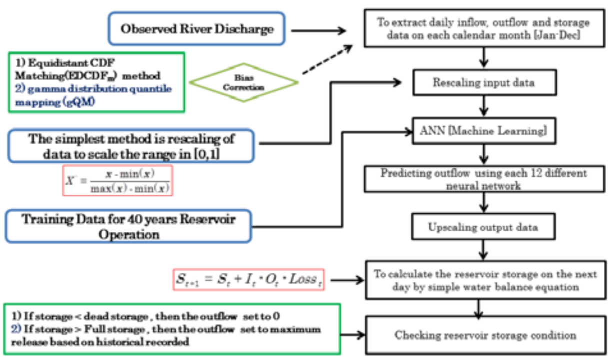

Fig.3 Flowchart of reservoir simulation for future reservoir outflow and storage.

The layers in between input and output layers are referred to as hidden layers, as they are not directly observable. Input layer and hidden layers include a constant neuron relating to intercept synapses. The number of hidden layers and numbers of nodes in each hidden layer are usually determined by a trial-and-error procedure (Govindaraju, R. S., 2000); therefore, the output of a node in a layer is only a dependent on the inputs it receives from previous layers and the corresponding weight.

This neural network models the relationship between the two covariates (inflow and water storage) and the response variable outflow.There are twelve neural networks which are constructed by separating reservoir operation data (reservoir inflow, outflow and water storage) into on different each calendar month. For the future outflow estimation, the analysis was calculated by bias-corrected inflow as an input to reservoir and setting the daily loess in the reservoir based on 40 years historical reservoir operation. Lastly, the general water balance equation was used to calculate the future reservoir storage as

$$S_{t+1} = S_t + I_t - O_t - Loss_t \qquad (8)$$

where t stands for the month, S_{t+1} stands for next day reservoir storage, S_t is current reservoir storage, I_t is daily inflow to reservoir, O_t is the daily outflow that is acquired from different model structure of ANN and $Loss_t$ is total daily losses from reservoir. In this study, the losses from reservoir were calculated by the different water storage from general water balance equation and the observed water storage. According to the various the future river discharge projection was conducted before given to reservoir operation model, the initial reservoir storage setting is also important to control reservoir storage at the initial condition, So the initial reservoir storage condition is defined into three different level as follow, normal condition (at 8,250 MCM), upper rule curve condition on January, 1st (at 9,494 MCM) and lower rule curve condition on January, 1st (at 6,405 MCM).

Results and discussion

The results of average daily reservoir inflow of bias-corrected river discharge at Sirikit dam during present climate (1979-2003) were summarizes in the flow duration curve plot for comparison the characteristic of high and low flow between reservoir inflow observation and both bias-correctedriver discharge as shown in**Fig4**.

Table1 Summary of ensemble simulation name for future experiment.

Bias Correction Method / Future SST setting	Empirical distribution quantile mapping	Gamma distribution quantile mapping
Ensemble Mean SST	Mean_EDCDF	Mean_gQM
Cluster1 SST	C1_ EDCDF	C1_gQM
Cluster2 SST	C2_ EDCDF	C2_gQM
Cluster3 SST	C3_ EDCDF	C3_gQM

For the changes in river discharge through Sirikit reservoir under a changing climate. The majority cases of the future annual reservoir inflow are higher than present observed Sirikit reservoir except the c1_gQM and c2_gQM. The amount of water resources availability in the future climate experiment showed that the reservoir inflow with SST of c3 pattern reproduce a highest value. However, after applying bias-corrected reservoir inflow data can cause the contrast of low flow occur in the case of reservoir inflow with SST of c2 pattern as shown in **Fig.5** and **Fig.6**.

Comparison release flow simulation and observation during 1974-2013

The output of reservoir operation based on the Artificial Neural Network (ANN) have been evaluate by compared with the observed outflow from 1974-2013.

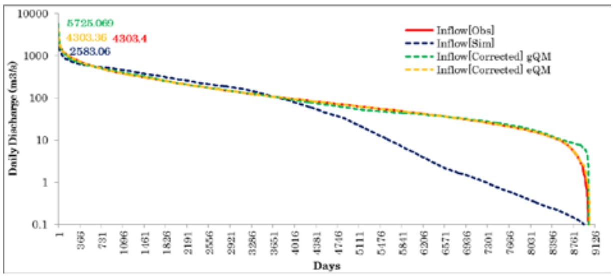

Fig.4 The total-flow duration curve between observation, raw simulation and bias-corrected river discharge at Sirikit dam during present climate (1979-2003).

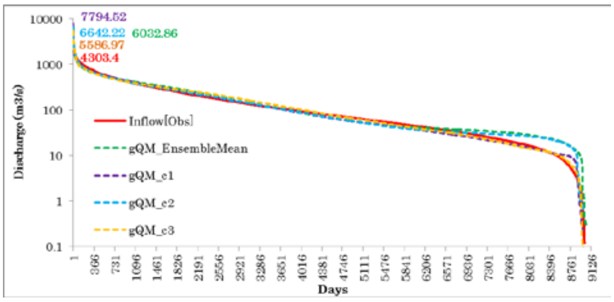

Fig.5 The total-flow duration curve between observation, raw simulation and bias-corrected river discharge (gQM method) at Sirikit dam during future climate (2075-2099).

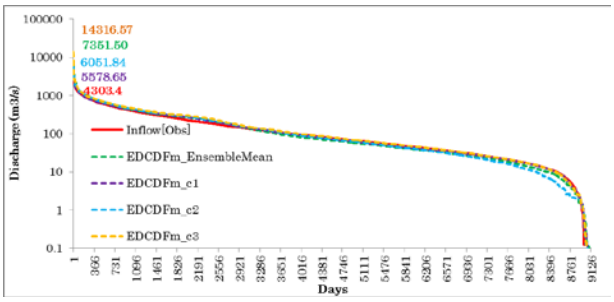

Fig.6 The total-flow duration curve between observation, raw simulation and bias-corrected river discharge (EDCDF$_m$ method) at Sirikit dam during future climate (2075-2099).

The best simulated results of average monthly outflow and water storage showed a good performance and reasonable to utilized for the future release flow assessment under the impacts of climate change. **Fig.7** showed that the average outflow simulation performed well with the small difference between average outflow and water storage. However, the amount of outflow in particular month found some error for monthly outflow analysis as shown in **Fig.8**.

Lastly, the future reservoir storage and outflow simulation under different scenarios showed that in percentage of changes in **Table 2** for water storage and **Table 3** for water release of different reservoir inflow projection data. The limitation of this projection is to assume the same rate of downstream water requirement and reservoir loss during present climate condition. According to the **Table 2**, the tendency of future storage might be decreasing of all scenarios with bias-corrected gQM cases of reservoir inflow projection data.

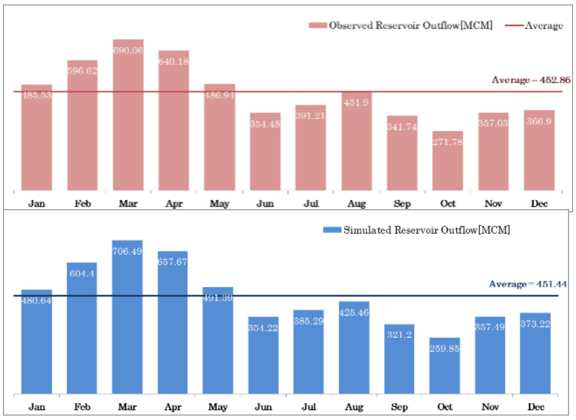

Fig.7 The average monthly observed and simulated outflow during 1974-2013.

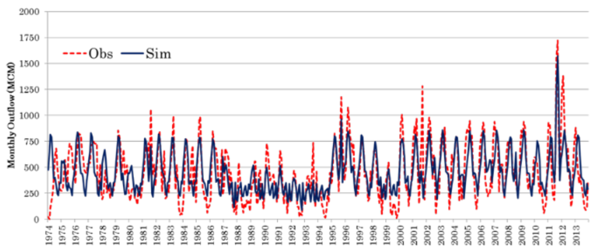

Fig.8 Comparison of monthly outflow observation and simulation by ANN

Furthermore, the future storage water storage of bias-corrected Mean_EQCDFm and c1_ EQCDFm showed the decreasing water storage from January until July and increasing water storage from August until December. For c2_ EQCDFm and c3_ EQCDFm cases showed the increasing water storage trend throughout the year. The overall water release flow results showed the reasonable and matching with the relationship of water storage. For instance, the tendency of future water release might be decreasing of all scenarios with bias-corrected gQM cases.

Table 2 The percentage of water storage changes on each different reservoir inflow projection data.

Scenarios	Initial Storage	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Observed	normal	6,742	6,406	5,900	5,316	4,847	4,675	4,780	5,466	6,406	6,918	6,931	6,776
EDCDFm_EnsembleMean	Upper	2.26	0.36	-0.68	-0.87	-0.28	-0.40	2.14	2.79	4.47	6.57	6.36	5.21
	Normal	0.28	-1.69	-3.02	-3.77	-3.80	-4.16	-1.43	0.15	2.83	5.24	5.10	3.93
	Lower	-1.39	-3.33	-4.64	-5.33	-5.22	-5.43	-2.58	-0.76	2.14	4.68	4.55	3.33
EDCDFm_c1	Upper	-0.15	-2.17	-3.32	-3.88	-4.22	-3.79	0.15	3.29	3.07	2.28	2.63	1.73
	Normal	-0.95	-3.01	-4.42	-5.62	-6.43	-6.11	-1.92	1.99	2.53	2.19	2.58	1.68
	Lower	-2.21	-4.29	-5.75	-7.00	-7.75	-7.32	-3.05	1.15	2.14	1.95	2.38	1.48
EDCDFm_c2	Upper	8.94	7.10	6.28	6.52	7.32	7.48	10.36	9.37	11.13	13.12	13.93	13.22
	Normal	6.25	4.33	3.17	2.91	3.24	3.30	6.52	6.37	8.91	11.21	12.02	11.24
	Lower	4.41	2.52	1.38	1.22	1.73	1.99	5.32	5.41	8.11	10.48	11.29	10.45
EDCDFm_c3	Upper	12.35	10.61	9.70	9.15	8.68	9.11	14.15	16.19	15.11	15.36	15.86	15.35
	Normal	10.47	8.60	7.27	6.14	5.09	5.30	10.69	13.80	13.51	14.21	14.70	14.18
	Lower	8.76	6.84	5.54	4.48	3.73	4.23	9.74	13.05	12.94	13.71	14.19	13.67
gQM_EnsembleMean	Upper	-3.15	-5.05	-6.10	-6.01	-4.79	-3.93	-1.93	-2.06	-1.09	0.39	0.13	-0.82
	Normal	-5.88	-7.91	-9.33	-9.85	-9.22	-8.50	-6.22	-5.33	-3.44	-1.68	-1.91	-2.87
	Lower	-8.00	-10.02	-11.42	-11.82	-11.04	-10.21	-7.76	-6.60	-4.47	-2.62	-2.83	-3.87
gQM_c1	Upper	-2.42	-4.24	-5.16	-5.18	-4.89	-3.53	-2.01	-1.39	-0.56	-0.43	-0.40	-1.05
	Normal	-3.21	-5.05	-6.27	-6.83	-7.02	-5.82	-4.15	-2.84	-1.14	-0.55	-0.46	-1.11
	Lower	-4.62	-6.51	-7.80	-8.39	-8.51	-7.19	-5.39	-3.81	-1.77	-0.95	-0.80	-1.45
gQM_c2	Upper	-3.95	-5.83	-7.29	-7.31	-7.23	-6.51	-4.71	-4.89	-2.21	-0.79	-0.71	-1.22
	Normal	-6.93	-8.88	-10.53	-11.06	-11.21	-10.60	-8.29	-7.77	-4.50	-2.84	-2.75	-3.38
	Lower	-8.39	-10.25	-11.93	-12.40	-12.45	-11.64	-9.26	-8.57	-5.16	-3.46	-3.39	-3.90
gQM_c3	Upper	1.13	-1.08	-2.51	-3.36	-3.77	-3.15	0.55	1.37	1.76	3.54	3.80	3.04
	Normal	-1.33	-3.65	-5.45	-6.85	-7.74	-7.19	-3.16	-1.42	-0.15	1.86	2.12	1.31
	Lower	-2.86	-5.10	-6.91	-8.27	-9.07	-8.40	-4.23	-2.34	-0.90	1.19	1.45	0.71

Table 3 The percentage of water release changes on each reservoir inflow projection data.

Scenarios	Initial Storage	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	DrySeason	WetSeason	Annaul
Observed	normal	486	597	690	640	487	354	391	452	342	272	357	367	3,136	2,298	5,434
EDCDFm_ Ensemble Mean	Upper	-0.77	-3.37	-3.73	-3.94	-5.36	-1.12	2.17	7.42	21.03	35.86	10.91	-0.38	-1.19	7.89	2.65
	Normal	-0.70	-4.14	-1.25	-1.25	-2.30	-2.38	0.10	-2.50	14.93	31.23	10.95	-1.47	-0.35	4.59	1.74
	Lower	-2.17	-5.36	-2.93	-3.33	-5.37	-3.59	-1.05	-3.62	12.42	30.92	11.04	-0.51	-1.48	2.92	0.38
EDCDFm_c1	Upper	-2.21	-4.17	-4.58	-2.96	-2.29	-3.05	-3.21	9.51	6.23	-1.51	-1.66	-2.30	-3.20	1.11	-1.38
	Normal	-2.00	-4.34	-0.70	0.79	-0.87	-4.11	-7.94	1.40	-5.09	-5.07	-1.67	-2.34	-1.59	-3.25	-2.29
	Lower	-3.96	-4.83	-1.42	0.77	-2.24	-5.14	-8.49	-1.51	-9.94	-8.57	-2.17	-2.95	-2.28	-5.50	-3.64
EDCDFm_c2	Upper	-0.40	-7.39	-1.69	-1.21	-2.55	4.92	4.88	15.40	24.99	6.21	2.82	1.81	-1.55	8.53	2.71
	Normal	-1.09	-8.17	0.56	-0.53	-1.19	1.49	2.19	8.65	20.50	5.95	2.86	2.05	-1.14	5.80	1.80
	Lower	-3.27	-9.29	-1.40	-3.41	-4.30	-0.63	1.24	8.01	20.44	5.82	2.89	3.55	-2.53	4.51	0.44
EDCDFm_c3	Upper	5.01	2.38	5.80	9.33	9.77	7.74	16.12	32.71	44.66	19.66	0.32	1.13	4.58	21.41	11.69
	Normal	5.07	2.84	9.41	10.79	13.28	5.44	11.22	22.72	36.42	19.57	0.24	0.28	5.66	17.76	10.78
	Lower	6.46	1.66	7.52	8.13	8.12	3.48	10.59	21.30	35.50	19.89	0.26	0.25	4.69	15.88	9.42
gQM_EnsembleMean	Upper	-3.74	-4.05	-6.53	-8.56	-11.00	-5.80	-1.76	-3.71	-10.73	5.17	-0.37	-2.89	-4.91	-5.24	-5.05
	Normal	-4.04	-4.10	-4.55	-6.39	-9.76	-7.97	-4.59	-13.68	-13.69	4.34	-0.35	-4.36	-4.26	-8.29	-5.97
	Lower	-5.73	-5.34	-6.90	-9.63	-11.94	-9.91	-6.16	-14.29	-14.50	3.96	-0.28	-1.95	-5.65	-9.61	-7.32
gQM_c1	Upper	-6.85	-5.10	-9.90	-11.73	-11.77	-8.51	-4.73	1.71	-3.07	-2.72	-0.18	-11.74	-8.00	-5.05	-6.75
	Normal	-7.15	-5.07	-6.14	-8.77	-9.62	-9.10	-7.12	-6.66	-15.69	-6.85	-0.18	-11.78	-6.61	-9.11	-7.67
	Lower	-7.59	-5.37	-6.94	-10.26	-11.85	-10.52	-8.30	-8.59	-21.03	-9.15	-0.20	-12.05	-7.25	-11.45	-9.02
gQM_c2	Upper	-11.98	-1.64	-7.53	-9.33	-4.99	-10.41	-4.88	-10.47	-20.35	-8.07	-0.90	-15.52	-7.64	-9.53	-8.44
	Normal	-11.50	-4.04	-6.16	-9.24	-6.00	-12.28	-10.79	-13.16	-22.79	-8.41	-0.95	-13.21	-7.44	-11.97	-9.36
	Lower	-14.43	-4.37	-7.63	-11.00	-8.58	-14.52	-11.19	-13.34	-22.98	-7.64	-1.10	-17.03	-9.11	-12.91	-10.71
gQM_c3	Upper	0.36	1.36	-1.53	-1.70	-6.80	-2.24	-11.40	-7.13	-15.55	-12.53	0.26	-7.28	-1.19	-8.92	-4.46
	Normal	0.23	0.89	1.23	-0.20	-6.41	-5.04	-15.15	-15.71	-19.38	-12.62	0.30	-7.37	-0.39	-12.18	-5.38
	Lower	-2.97	0.05	-0.04	-2.25	-8.22	-7.04	-15.72	-16.39	-19.61	-12.91	0.14	-9.48	-2.01	-13.17	-6.73

Conclusions

The tendency of future reservoir inflow after applying both the empirical distribution quantile mapping with difference between cumulative distribution functions (CDFs) of GCM and observation river discharge (eQM) and the empirical with gamma distribution quantile mapping (gQM) provides higher than present climate condition at Sirikit Reservoir.

Finally, the future reservoir storage and outflow simulation under different scenarios showed the tendency of future storage might be decreasing of all scenarios with bias-corrected gQM cases of reservoir inflow projection data. On the other hand, the scenarios with bias-corrected eQM cases of reservoir inflow projection data presented the increase storage due to high reservoir inflow on wet season as similarly with the water storage trend analysis.(Maneeet.al, 2015). The results indicated that, The SK dam seems to reduce the release flow due to decreasing bias-corrected gQM reservoir inflow. The overall water inflow and storage results showed the reasonable and matching with previous studies (Kitpaisalsakuiet.al, 2016).

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References

Champathong, A., Komori, D., Kiguchi, M., Sukhapunnaphan, T., Oki, T., &Nakaegawa, T. (n.d.). Future projection of mean river discharge climatology for the Chao Phraya River basin. Hydrological Research Letters, 7(2), 36-41.

Govindaraju, R. S. (2000). Artificial neural networks in hydrology. I: Preliminary concepts. Journal of Hydrologic Engineering, 5(2), 115-123.

Hunukumbura, P. B., &Tachikawa, Y. (2012). River discharge projection under climate change in the Chao Phraya River Basin, Thailand, using the MRI-GCM3.1S dataset. Journal of the Meteorological Society of Japan, 90A, 137-150.

IPCC. (2013). Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Kim, S., Tachikawa, Y., Nakakita, E., & Takara, K. (2009). Reconsideration of reservoir operations under climate change: case study with Yagisawa Dam, Japan. Annual Journal of Hydraulic Engineering, JSCE, 53, 597-611.

Kitoh, A., & Endo, H. (2016). Changes in precipitation extremes projected by a 20-km mesh global atmospheric model. Weather and Climate Extremes, 11, 41-52.

Kitpaisalsakui, T., Koontanakulvong, S., &Chaowiwat, W. (2016). Impact of Climate Change on Reservoir Operation in Central Plain Basin of Thailand. Journal of Thai Interdisciplinary Research, 11(2), 13-19.

Kure, S., &Tebakari, T. (2012). Hydrological impact of regional climate change in the Chao Phraya River Basin, Thailand. Hydrological Research Letters, 6(0), 53-58.

Lehner, B., Verdin, K., & Jarvis, A. (2006). HydroSHEDS technical documentation, version 1.0. World Wildlife Fund US, 1-27.

Li, H., Sheffield, J., & Wood, E. F. (2010). Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching. Journal of Geophysical Research: Atmospheres, 115 (D10), 1-20.

Manee, D., Tachikawa, Y., & Yorozu, K. (2015). Analysis of hydrologic variable changes related to large scale reservoir operation in Thailand. Journal of Japan Society of Civil Engineers, Ser. B1 (Hydraulic Engineering), 71(4), 61-66.

Manee, D., Tachikawa, Y., Ichikawa, Y., & Yorozu, K. (2016). Evaluation of Bias Correction Methods for Future River Discharge Projection. Global environment engineering research, 24, 7-12.

Mizuta, R. Y., Matsueda, M., Endo, H., Ose, T.,&Kusunoki, S. (2012). Climate Simulations Using MRI-AGCM3.2 with 20-km Grid. Journal of the Meteorological Society of Japan. Ser. II, 90A, 233-258.

Tachikawa, Y., & Tanaka, T. (n.d.). 1K-FRM. Retrieved June 23, 2016, from Hydrology and Water Resources Research Laboratory Webpage: http://hywr.kuciv.kyoto-u.ac.jp/products/1K-DHM/1K-DHM.html

Wichakul, S., Tachikawa, Y., Shiiba, M., & Yorozu, K. (2015). River discharge assessment under a changing climate in the Chao Phraya River, Thailand by using MRI-AGCM3.2S. Hydrological Research Letters, 9(4), 84-89.