Climate change impact to dam Operation, case study of Darma Dam, West Java

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Abstract. Darma Dam is located in the upstream of Cisanggarung River, Kuningan Regency, West Java Province. Darma Dam construction dated from about 1922. Indonesian government continued the construction and began operating in 1962. With effective storage of about 40 million m³, Darma Dam provides water for about 22 thousand irrigation areas and bulk water for several cities and regencies. Several problems encountered in Darma Dam operation and water management are 1) increasing water demand from domestic and industrial sectors, and 2) high inflow variation during the dry and wet season, resulting in a large amount of water spill from the dam spillway. This paper addressed the impact of climate change on the inflow variation of Darma Dam in the dry and wet seasons. Further analysis shows average water spills from the spillway during the wet season may increase from about 12 million m³/year in the present condition to about 20 million m³/year in 2020-2050, while the average water volume during the dry season may reduce from 22.5 million m³ in the present condition to about 20.7 million m³ in 2020-2050. This study suggests that dam operation need adjustment in the future as part of adaptation to climate change.

1. Introduction
West Java Province is one of the primary rice producers in Indonesia. In 2018, this province produced 9.5 million unhusked rice, nearly 17% of Indonesia's total rice production. However, rice production facing challenges from rapid urban development, high population growth, increasing domestic and industrial water demand, which compensated by more water extraction from surface water and groundwater [1], [2], [3]. Climate change may also increase the complexity of water resources problems. As intense extreme rainfall and prolonged drought tend to appear more frequent, the conflict between water users such as agriculture, domestic, and industry may intensify in the future [4]. Darma Dam is one of the dams in West Java with the primary purpose of irrigation water supply. Besides agriculture, this dam is also used for fish farming (using floating net cages), a raw water source of Kuningan Regency Water Supply Company, and a tourist destination. The decline in the service functionality of Darma Dam will give the highest economic losses to the agriculture and fisheries sectors [5]. Dam inflow may be profoundly affected by climate change as the rainy season tend to be
wetter and dry season tends to be dryer. With the decreasing effective volume due to sedimentation, the probability of water spills from the dam's spillway during the rainy season and water level drop during the dry season may increase in the future. Therefore, it is necessary to update the dam operation to adapt to climate change, including the Darma Dam operation.

2. Materials and Method

2.1. Location
The maximum water surface of Darma Dam is about 0.425 km$^2$, with effective storage in the about 40 million m$^3$. Darma Dam is the primary water source for about 22,000 hectares of the irrigation area in the downstream of the dam. The location of the Darma Dam is shown in Figure 1.

![Figure 1. Location of Darma Dam](image)

The average annual rainfall in Darma Dam Rainfall station from 2009-2018 is about 2680mm/year. The average monthly rainfall in the rainy season is about 364mm/month, while the average monthly rainfall in the dry season is about 83mm/month. Based on data from Dam Operation and Improvement Safety Project (DOISP), in 2013, about 54% of the catchment area of Darma Dam was rice fields. Other land-use types, such as production forest, settlement, dry farmland, and mixed plantation, covered about 38% of the catchment area, with nearly a similar proportion. Waterbody covered about 8% of the total Darma Dam catchment area.

2.2. Climate Projection
The World Climate Research Programme’s (WCRP) Working Group on Coupled Modelling (WGCM) started to promote the fifth phase of the Coupled Model Intercomparison Project (CMIP5) in 2008. CMIP5 provides a multi-model context for assessing climate change feedbacks, predictability, and range of responses among the climate models [6]. This study compares 15 CMIP5 model outputs with the average rainfall of 21 stations in West Java Province for the 1980-2009 rainfall data series. CMIP5 datasets are available on the KNMI Climate Explorer website [7] (https://climexp.knmi.nl). This study uses only RCP8.5 for rainfall future prediction scenario.

Two main methods for downscaling climate data are dynamical and statistical. While dynamic downscaling uses a physical-based climate model to get higher resolution output, statistical downscaling uses a statistical relationship between climate variables. Reference [8] use Multivariate Adapted Constructed Analogs downscaling method in a case study of Western US, which gives better results than direct interpolation method due to its ability to capture relative humidity and winds more accurately. The study shows that the statistical downscaling method performs well to capture variations in meteorological parameters. However, data reconstruction based on statistical correlation requires a fairly long time series of observation station data (e.g., > 10 years). In this study, data samples from more than 20 rainfall stations from 1980-2009 (30 years) covering the Upper Citarum Basin in West Java were used as basis for downscaling calibration.
Reference [9] use four statistical downscaling methods to downscale the native-scale output of NCEP/NCAR Reanalysis into a 12km grid. This study uses wet day fraction, extreme events, and weather patterns as comparison criteria for the downscaled data. Reference [10] use three statistical downscaling methods to downscale daily precipitation over the Yellow River Region, comparing spatial dependence, wet and dry spell, and inter-annual variability. This study suggests that more than one downscaling method may give a better interpretation of climate change projection better. Reference [11] uses fifteen different RCP models and is downscaled using different statistical downscaling methods to study the projection of extreme river flows in 11 catchments in Europe. References [9], [10], and [11] use several methods to downscale a global model output, i.e., NCEP/NCAR reanalysis data. Reference [9] and [10] use the downscaled results to evaluate climate change scenarios based on IPCC AR4 (2007). This study takes a different approach, where one downscaling method is used to evaluate several GCM outputs based on IPCC AR5 climate change scenarios (2014).

Reference [12] uses HBV and XAJ rainfall-runoff model to simulate discharge in Upper Hanjiang Basin, China, using statistically downscaled GCM data as input. This study suggests using multiple GCM outputs and downscaling methods to study climate change's impact on runoff. HBV and XAJ models are rarely used in Indonesia. Therefore, this study uses the The National Rural Electric Cooperatives Association (NRECA) model [13] as one of the rainfall-runoff models widely used in Indonesia. Model calibration uses inflow-outflow data of Darma Dam. The bias-corrected data from the selected CMIP5 model for 2030 to 2050 are used as input of the NRECA Rainfall-Runoff Model for future river discharge projection. No further land cover change is assumed from 2015 to 2050.

3. Result and Discussion

3.1. Bias Correction of CMIP5 Rainfall
CMIP5 provides climate change scenario simulations from several models. This study uses average rainfall data from 1980-2009 as a reference for bias correcting CMIP5 rainfall data output. The steps for preparing the bias correction are as follows: 1) Create a frequency duration curve (FDC) of historical data; 2) Create a CMIP5 and FDC graph in the same data period; 3) Create a correction equation to produce CMIP5’s FDC close to historical data’s FDC.

Goodness of fit assessment of CMIP5’s FDC and historical data’s FDC is performed using NSE and Pearson Correlation Coefficient. Comparison between monthly historical rainfall data and GCM output during the period of 1980-2009 is used to select which GCM output is best to be used as input for future discharge projection, which is shown in Table 1.

Table 1 shows that the Multi-Model Mean of 32 CMIP5 models computed in KNMI gives the best statistical fitness in NSE (=0.206) and r (=0.600) compared to other CMIP5 output. Based on this result, Multi-Model Mean CMIP5 data is used to simulate future discharge using NRECA Rainfall-Runoff Model.

Data obtained from CMIP5 is monthly rainfall data. However, the rainfall-runoff simulation is carried out using daily data. In this study, the transformation of monthly data into daily data is carried out through the following steps: 1) split historical rainfall data from 1980-2009 into the criteria of wet and dry months 2) plot the daily data in point 1 into duration curve; 3) approximate the duration curve in point 2 using the gamma two-variable function; 4) approximate the function of the number of wet days in a month; 5) Generate daily rainfall using a Monte-Carlo Simulation using monthly rainfall input, the average number of rainy days and gamma functions at point (3); 6) Adjust sum of daily rainfall in a month to be equal with monthly rainfall data.

3.2. Rainfall-Runoff Model Calibration and Future Discharge Simulation
Daily river discharge data in Darma Dam in 2015 is used for NRECA Rainfall-Runoff Model calibration. A comparison between river discharge data and the calibrated model result is shown in Figure 3. Calibration by using daily data gives NSE=0.70 and r=0.85. Based on the above calibration,
the model then used for simulation of river discharge in 2030-2050. This simulation is conducted by assuming no further land cover change from 2015 data to 2050.

Table 1. Bias Correction Function of CMIP5 Model for Case Study of West Java

| Model                | Bias correction function | NSE   | r    |
|----------------------|--------------------------|-------|------|
| Multi Model Mean     | R=–2.9835P^3+3.6875P^2-1.9716P+1.1802 | 0.206 | 0.600|
| ACCESS1-0            | R= 1.2703P + 0.9798; P≤0.8; R= -0.1006P + 0.0971; P>0.8 | -0.300| 0.363|
| ACESS1-3             | R=5.0503P^3-7.8013P^2 + 1.7908P + 1.0325 | -0.648| 0.155|
| MIRROC-ESM           | R=0.1173P^2 - 0.9808P + 1.0703 | -1.012| -0.03|
| BCC-ESM1-1           | R= 3.3307P^2+0.3694P + 0.8675; P≤0.6 | -0.168| 0.425|
| BNU-ESM              | R= -5.7172P^2 + 4.18P + 1.852; P>0.6 | -0.012| 0.425|
| CESM-BGC             | R= 1.2703P + 0.319P + 0.6213; P≤0.7 | 0.064 | 0.540|
| CAMCC-CM             | R=0.027; P>0.7 | -0.192| 0.415|
| FGOALS-g2            | R=0.9816P^2 + 0.5058P + 0.9404; P≤0.9 | -0.192| 0.415|
| GFDL-CM3             | R=8.3356P + 8.4038; P<0.95 | -0.018| 0.506|
| GFDL-ESM2g           | R=-2550P^3+7169P^2-6718.7P+2100; P>0.9 | -0.012| 0.446|
| GFDL-ESM2M           | R=0.607P | 0.055 | 0.454|
| GISS-E2-Hp3          | R=4.84P^3-3.111P^2+0.673P + 0.608; P≤0.7 | -0.032| 0.482|
| GISS-E2-RP3          | R=0.000154e^{12.512P} | -0.032| 0.482|
| HadGEM2-A0          | R=0.178P^3-0.4567P^2 + 0.1584P + 0.5118 | -0.535| 0.226|
| HadGEM2-A0          | R=3.961P^3-1.320P^2 + 1.620P + 1.0315 | -0.188| 0.418|
| HadGEM2-CC          | R=2.635P^3-0.688P^2+0.071P+1.11; P≤0.65 | -0.215| 0.405|
| HadGEM2-CC          | R=-10.3P^3+27.88P^2-25.16P+7.58; P>0.65 | -0.127| 0.446|

R = monthly rainfall (mm), P = probability of occurrence

Figure 2. Rainfall-Runoff Model Calibration

Figure 3 shows the trend of low flow decrease within the observation period 2009-2018 and the projection 2030-2050. Compared to data series 2009-2018, Q50% decreases from 1.34m^3/s to 1.11m^3/s. Meanwhile, Q80% decreases from 0.33m^3/s to 0.05m^3/s in 2030-2050. The simulation shows the trend of longer drought and wetter rainy season in the future compared to what had happened in the past.
3.3. Dam Operation
The average water level of Darma Dam, irrigation supply, and spillway discharge is shown in Figure 4. Figure 4 (left) shows that the average water level in Darma Dam is at a high level from April to June. Figure 4 (right) shows the discharge from the tunnel for irrigation supply and from the spillway. The average volume of water spills from the spillway in a year is about 12.2 million m$^3$. During this period the average volume of water flows from the tunnel outlet to supply irrigation demand and volume of water from spillway were nearly equal. The water level started to drop from July to October, which corresponds to high water demand from irrigation during the third planting season. This figure shows that there is room for further water optimization, for example, if the water, which usually spills, can be used for other water users.

Figure 3. Future rainfall and discharge projection

Figure 4. Future rainfall and discharge projection

Figure 4 (left) also shows a comparison between the average Darma Dam water level from 2009-2018, and simulated water level based on future discharge projection from 2020-2050. With the assumption of constant irrigation and domestic water demand, the probability of water spills and deficit may increase in the future. With the current dam operation rule, the average volume of water spills from the spillway may increase by 20 million m$^3$ in a year. Meanwhile, water elevation in the dry season (Sept-Nov) may decrease, lower than the level in the current condition. Water demand will continue to increase in the future. Based on the above simulation to minimize water spills from the spillway, Darma Dam can supply more water to the domestic sector up to 0.74 m$^3$/s. However, the water level in the dry season may drop 5m below the average level in the current operation rule. This simulation shows the importance of dam operation as one of the adaptation measures to climate change.
4. Conclusion
High economic development and population growth may lead to an increase in water demand. In this study, river discharge projection in the future is simulated by using NRECA Rainfall-Runoff Model, with data input of the bias corrected model output of the multi-model mean of CMIP5 for the RCP8.5 scenario. Simulation period of 2020-2050 shows that the average water spills from the spillway during the wet season may increase from about 12 million m$^3$/year in the present condition to about 20 million m$^3$/year in 2020-2050, while the average water volume during the dry season may reduce from 22.5 million m$^3$ in the present condition to about 20.7 million m$^3$ in 2020-2050. This study suggests that the probability of a long drought period in the Darma Dam may increase in the future. If land cover change is considered, the simulation result might give even lower discharge. There is still an opportunity to mitigate the impact of climate change by optimizing the present dam operation rule, for example, by preventing water spill out from the spillway and by managing water demand in the dry season.

References
[1] Nurcahyo H, Soekarno I, Hadihardaja I K, Rosyidie A, Hydrologic Alteration in Watershed Using Flow Duration Curve, Case Study Upper Citarum Watershed, Indonesia 2016 International Proceedings of Chemical, Biological and Environmental Engineering, V94 24
[2] Julian M M, Nishio M, Poerbandoono P, Ward P J, Simulation of River Discharges in Major Watersheds or Northwestern Japan from 1901 to 2006 2011 International Journal of Technology 1 pp 37-46
[3] Agaton M, Setiawan Y, Effendi H, Land use/land cover change detection in an urban watershed: a case study of upper Citarum Watershed, West Java Province, Indonesia 2015, LISAT-FSEM Procedia Environmental Sciences 33 pp 654 – 660.
[4] Yoshida K, Azechi I, Hariya R, Tanaka K, Noda K, Oki K, Hongo C, Honma K, Maki M, and Shirakawa H, Future Water Availability in the Asian Monsoon Region: A Case Study in Indonesia 2013 Journal of Developments in Sustainable Agriculture 8 pp. 25-31.
[5] Pratama D S, Syaukat, Y, and E kayani M Estimasi Nilai Ekonomi dan Eksternalitas Negatif Pemanfaatan Waduk Darma 2017 Risalah Kebijakan Pertanian dan Lingkungan Vol4 1 pp 13-27
[6] Taylor E T, Stouffer R J, and Meehl, G A, An Overview of CMIP5 and the Experiment Design 2012 American Meteorological Society pp 485-498.
[7] KNMI Climate Explorer https://climexp.knmi.nl.
[8] Abatzoglou J T, and Brown T J, A comparison of statistical downscaling methods suited for wildfire applications 2012 Int. J. Climatol 32 pp 772-780.
[9] Gutmann E, Pruitt T, Clark M P, Brekke L, Arnold J R, Raff D A, and Rasmussen R M, An intercomparison of statistical downscaling methods used for water resource assessments in the United States 2014 Water Resour. Res 50 pp.7167–7186
[10] Hu Y, Shreedhar M, and Uhlenbrook S Downscaling daily precipitation over the Yellow River source region in China: a comparison of three statistical downscaling methods 2013 Theor Appl Climatol 112 pp 447–460.
[11] Hundecha Y, Sunyer M A, Lawrence D, Madsen H, Willems P, Bürger G, Kiraučiūnienė J, Loukas A, Martinkova M, Osuch M, et al., Inter-comparison of statistical downscaling methods for projection of extreme flow indices across Europe 2016 Journal of Hydrology 541 pp 1273–1286
[12] Chen H, Xu, C, and Guo S Comparison and evaluation of multiple GCMs, statistical downscaling and hydrological models in the study of climate change impacts on runoff 2012 Journal of Hydrology 434–435 pp 36-45
[13] Crawford N H and Thurin S M 1981 Hydrologic estimates for small hydroelectric projects Small Decentralized Hydropower Program, National Rural Electric Cooperative Association.
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