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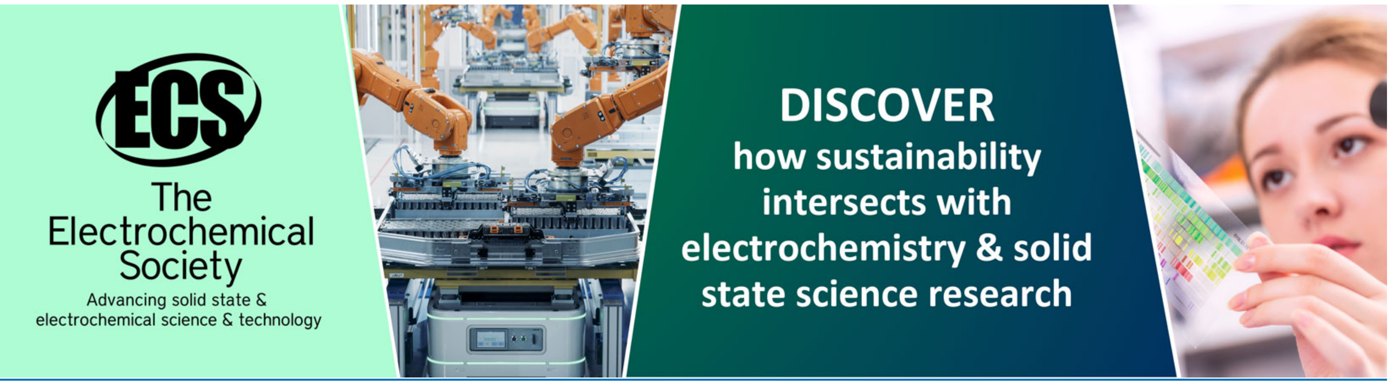

Comparison of rainfall-runoff models for climate change projection – case study of Citarum River Basin, Indonesia

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Abstract. Climate change affects temperature, rainfall and hydrological properties in the river basins. Projected rainfalls for several climate change models are widely available nowadays. However, in water resources planning and management, river discharges data is unfortunately more important. The information on climate change impact on river discharges is very limited. Conversion from the projected rainfall to the runoff in the rivers is needed. This study analyzes the performance of rainfall-runoff models: 1) Empirical Model that defines the discharge as a function of rainfall, evaporation, and temperature, widely applied by climate scientist; and 2) simple lump conceptual model of NRECA. These two rainfall-runoff models are applied during the control period in the year of 2006 to 2015 of the rainfall projections from the seven CMIP5 Global Circulation Models with the worst scenario, RCP 8.5. The ground station river discharge data selected is Nanjung river gauging station at Citarum River, situated just upstream of Saguling Reservoir, the uppermost of the cascade of three reservoirs Saguling-Cirata-Jatiluhur, with the catchment area of 1,675 square kilometers. The results show that the simple conceptual model NRECA significantly gives better fitted to the observation data than the Empirical Model, especially during the dry season.

1. Introduction

Climate change impacts change in temperature, rainfall and consequently affects the hydrological characteristics in the river basins. Climate change impact on rainfall is widely available nowadays, and there are some rainfall projection models. However, water resources planning and management not only depend on rainfall data but more heavily on river discharges data, which is unfortunately not yet widely available.

Modeling the hydrologic impacts of global climate change involves two issues: climate change and the response of hydrologic systems. General Circulation Models (GCMs) are considered to be the most comprehensive models for investigating the physical and dynamic processes of the earth's surface-atmosphere system and they provide plausible patterns of global climate change [1]. However, there are many key challenges in the application of GCMs and hydrological models such as inconsistency of the spatial scales of GCMs and hydrological models also the accuracy of precipitation simulations from GCMs cannot meet the requirements of hydrological simulations [2].

This study analyzes the performance of two rainfall-runoff models: 1) empirical methods that define the discharge as a function of rainfall, evaporation, and temperature, widely applied by climate scientist; and 2) NRECA, a simple lump conceptual model. This study aims to investigate and evaluate two hydrological simulations and provide an inter-comparison study using a sub-basin of Nanjung Watershed in Upper Citarum as an experimental site. The time period is divided into two groups, the baseline period (1981-2005) and the projection period (2006-2045) while the year 2006-2015 is used

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as the control period. The performances of rainfall-runoff models for climate change projection are compared and analyzed during the control period.

2. Study location and method

2.1. Study location

The study location is the river gauging station Nanjung at Citarum River, West Java, Indonesia (figure 1). Situated just upstream of Saguling Reservoir, the uppermost of the cascade of the three reservoirs Saguling-Cirata-Jatiluhur, irrigate 240 thousand hectares of rice field, water supply for 80% of the domestic, municipal and industrial use for the capital city of Jakarta, and generate hydropower energy of 1,400 megawatts. The catchment area of Nanjung river gauging station is 1,675 square kilometers. The river discharge data of Citarum river at Nanjung gauging station is a consistent and homogeneous, covering monthly discharge from the year of 1974 till present. This gauging station data which is located in the main river to Saguling Reservoir indicate the amount of inflow to the reservoir.

Figure 1 Location of Citarum-Nanjung river gauging station

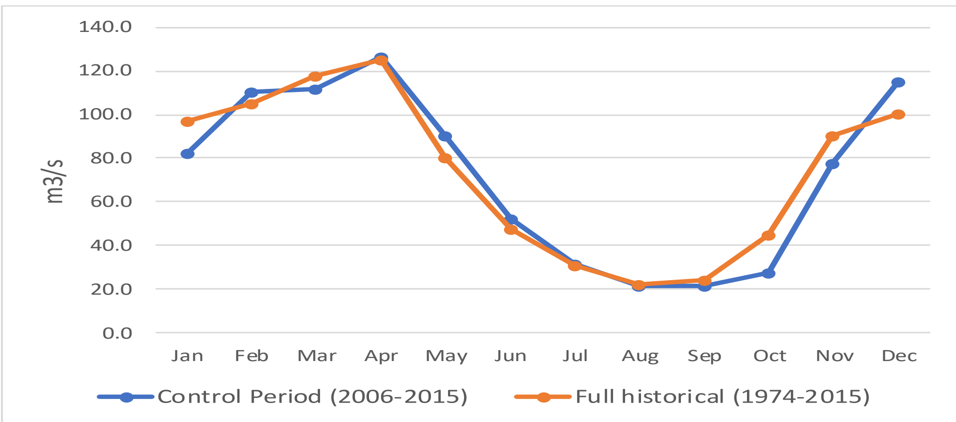

Figure 2 Seasonal discharge of full historical and control period data

Although the available river discharge data at Citarum-Nanjung gauging station is from the year of 1974 until the present time, due to the availability of the climate change rainfall projection which is only from the year of 2006 to 2015, then the analysis will be carried out during the period of 2006-2015. Figure 2 shows that the seasonal average discharge from the two periods of 1974-2015 and 2006-1015 is relatively identical.

2.2. Rainfall projection

The available climate change rainfall projection is the Global Climate Model (GCM) rain projection. Global circulation models (GCMs) are numerical models that provide a quantitative assessment of such warming effects, with all-important climate processes and their internal feedback mechanisms and couplings explicitly modeled within the GCM, completed with appropriate parameterizations [3]. Projections are made using the baseline climate period 1981 -2005, and the climate scenario period 2006-2015, using the worst climate change scenario scheme, namely Representative Concentration Pathway (RCP) 8.5 with the highest greenhouse gas concentration, 1370 ppm. The available seven GCM models are CNRM-CM5, CNRM-RCA, CNRM-v2-RegCM, CSIRO-MK3,6, EC-EARTH, GFDL-ESM, and IPSL. The differences between the models are parameterization of the coupled models, climate model simulations, individual physics tests, and idealized simulations from models including additional processes such as the global carbon cycle [4]. The projected results from the climate scenario are then biased correction using quantile mapping using a quarterly correction factor from the baseline period.

2.3. Empirical rainfall-runoff model

The empirical relationship between the effect of climate factor changes on discharge changes has been initiated by Langbein (1949) who estimated changes in the annual mean of discharge from 18 regions using five different climate scenarios. The Langbein method was then used by Revelle and Wagoner (1983), Mirza (1997), Leavesley (1994), and Risbey and Entekhabi (1996) [6].

Empirical methods are quite often used in the analysis of discharge projections by inputting climate change scenario models. This method assumes the change in discharge is caused only by certain variables, such as rain. This makes it easier for users who do not have data on the characteristics of catchment, because in climate change analysis it is still difficult to obtain projections of hydrological cycle variables other than rain projections and temperature projections. The lack of data projections such as catchment characteristics such as soil type, land use, etc. makes the factor considered unchanged and assumes the change in discharge is only caused by one or two factors.

The empirical method used previously is usually done in the high and middle latitude regions so that in the baseline period the precipitation and temperature variables are used as the main factors affecting the discharge value. As for Indonesia, the variables rain and evapotranspiration are used as factors influencing the discharge.

In the baseline period, two predictor variables are used because a comprehensive understanding of climate change requires an analysis of the relationships between single indicators [7]. As an important parameter in the hydrological cycle, potential evaporation plays an important role in regulating plant evapotranspiration so it is important to include it in the planning and management of water resources [8]. Therefore, it is very important to investigate spatial planning and temporal changes in potential evaporation patterns especially in dry and semi-arid agricultural areas for better allocation of local water resources and management of irrigation [9]. The relationship between these three variables is illustrated in three-dimensional interpolation using Matlab by determining Qubical Interpolation as the maximum interpolation.

To project the discharge, linear relationship between rainfall-discharge is taken from this interpolation assuming the change in evapotranspiration is 0. This is because the effect of evapotranspiration on discharge insignificant and no data on the evapotranspiration projection. Mathematically written as:

$$Q = R(P) \,.\, P \tag{1}$$

$$Q+\Delta Q = R(P+\Delta P) \,.\, (P+\Delta P) \tag{2}$$

$$\%Q\text{-}\%P = R(P+\Delta P)/(R(P)) \,.\, \%P + R(P+\Delta P)/(R(P)) \tag{3}$$

where

$\% P = \Delta P / P$ as the change in rainfall in percent (as well as the discharge) (4)

If the coefficient R is independent of the value of rain, then the discharge response will be linear to the fluctuations of rain. The linear relationship, $R\ (P + \Delta P) = R\ (P)$ indicates that the term % Q-% P is independent of % P (zero slope).

2.4. NRECA rainfall-runoff model

NRECA is a lumped conceptual rainfall-runoff model developed by National Rural Electric Cooperative Association to estimate hydrological conditions for small hydroelectric projects [10] and [11]. This model is also been applied to compare the performance of satellite based rainfall data TRMM and APRODHITE [12] and [13]. The model basically is a tank model consisting of two tanks representing the storage for moisture storage and groundwater storage as presented in figure 3.

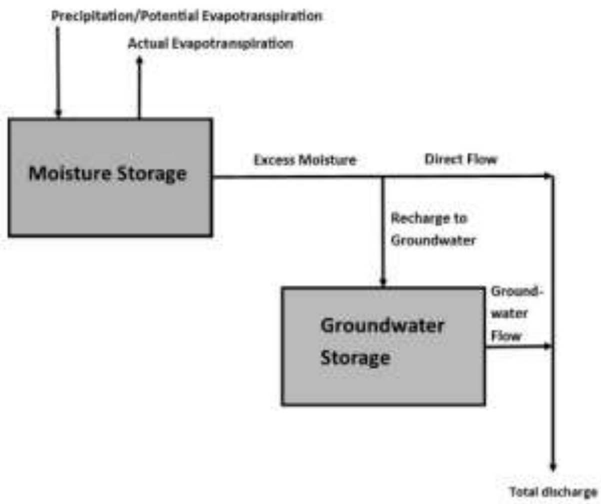

Figure 3. Model structure of the NRECA Model [11]

2.5. Comparison criteria

To compare how close the flow from NRECA and empirical model to the observation ground station data, three criteria are applied: 1) Coefficient of determination R Square, 2) Root mean square error (RMSE); and 3) Nash- Sutcliffe efficiency (NSE).

2.5.1. *Coefficient of Determination.* The coefficient of determination is the square of the Pearson's product-moment correlation coefficient and describes the proportion of the total variance in the observed data that can be explained by the model [14]. However, this coefficient of determination is limited in a term that it standardizes for differences between the observed and predicted means and variances since it only evaluates linear relationships between the variable [14].

$$r^2 = \left(\frac{\sum_{i=1}^{n} (Obs_i - \overline{Obs})\ (Sim_i - \overline{Sim})}{\sqrt{\sum_{i=1}^{n} (Obs_i - \overline{Obs})^2}\ \sqrt{\sum_{i=1}^{n} (Sim_i - \overline{Sim})^2}} \right)^2 \tag{5}$$

2.5.2. *Root mean square error (RMSE).* The root mean square error [15] has been used as a standard statistical metric to measure model performance in meteorology, air quality, and climate research studies. RMSE penalizes variance as it gives errors with larger absolute values more weight than errors with smaller absolute values. The underlying assumption when presenting the RMSE is that the errors are unbiased and follow a normal distribution. For other kinds of distributions, more statistical moments of model errors, such as mean, variance, skewness, and flatness, are needed to provide a complete picture of the model error variation. Some approaches that emphasize resistance to outliers or insensitivity to non-normal distributions have been explored by other researchers [16].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Obs_i - Sim_i)^2}{n}} \tag{6}$$

2.5.3. *Nash- Sutcliffe Efficiency (NSE).* This model shows how well the plot of observed versus simulated data fits the 1:1 line. NSE ranges between −∞ and 1.0 (1 inclusive), with NSE = 1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates unacceptable performance [17]. NSE can be interpreted as a classic skill score where skill is interpreted as the comparative ability of a model with regards to a baseline model, which in the case of NSE is taken to be the 'mean of the observations' [18].

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Obs_i - Sim_i)^2}{\sum_{i=1}^{n}(Obs_i - \overline{Obs})^2} \tag{7}$$

3. Results and discussions

The results of comparison between the two models of NRECA and Empirical Model to the observation data at Citarum-Nanjung river gauging station in the year of 2006 to 2015 for the seven climate change projection models is presented in Table 1. Most of the projection model using the NRECA Model get a higher coefficient of determination than the Empirical Model except for GFDL_ESM with almost the same low value of R square. The Root Mean Square Error (RMSE) of all seven projection models under the NRECA Rainfall-runoff Model gives significantly better results than under Empirical Rainfall-runoff Model. The same case also applied to the Nash- Sutcliffe Error, all of the NSE values of the Empirical Model are negative, while the NRECA Model gives positive results for the three CNRM models. These three CNRM model are also having a distinctive higher correlation as well as better RMSE compared with the other projection model.

Figures 4, 5, and 6 show seasonal, time-series and flow duration curve of the best projection model from NRECA Model, CNRMv2RegCM in the left part; and the best projection model from Empirical Model, CNRM_RCA in the right part. Seasonal plot in figure 4 shows that the average seasonal flow from NRECA Model is plotted very close to the observed data, especially for the low flow during the dry season, while Empirical Model can also follow the general pattern of average seasonal observed flow, not as close as NRECA Model but having the advantage of reproducing better high flow. The time series plot in figure 6 presents the NRECA Model fitted very good during the dry season but consistently cannot follow the high flow. On the other hand, Empirical Model failed to follow the observation ground station data during the dry season but can reach high flow close to the observed data. Flow duration curve in figure 6 displays the NRECA Model fitted perfectly with the observation data from the probability of exceedance from 50% to 100%, while Empirical Model fitted perfectly for the probability of exceedance from 70% to 100% only. However, the Empirical Model roughly follows the observed curve better for high flow.

Statistical data confirms that the NRECA Rainfall-runoff model is superior to the Empirical Model. However, seasonal plot, time-series graph, and flow duration curve suggest the NRECA to be suitable for low flow and water availability study, while Empirical Model covers low flow as well as high flow although in lower accuracy compared with NRECA for the low flow.

Table 1. Comparison Statistics between Empirical and NRECA Model

Rainfall-runoff Model	Projection Model	R Square	RMSE	NSE
Empirical	CNRM_CM5	0.07	77	-1.01
Empirical	CNRM_RCA	0.10	73	-0.83
Empirical	CNRMv2RegCM	0.11	75	-0.89
Empirical	CSIRO_MK3.6	0.03	71	-0.72
Empirical	EC_EARTH	0.02	79	-1.11
Empirical	GFDL_ESM	0.00	79	-1.10
Empirical	IPSL	0.05	89	-1.68
NRECA	CNRM_CM5	0.27	50	0.16
NRECA	CNRM_RCA	0.33	47	0.25
NRECA	CNRMv2RegCM	0.37	47	0.24
NRECA	CSIRO_MK3.6	0.15	58	-0.15
NRECA	EC_EARTH	0.19	65	-0.42
NRECA	GFDL_ESM	0.01	68	-0.60
NRECA	IPSL	0.16	57	-0.12

The conceptual structure of the NRECA Model which is consists of two tanks enables the soil moisture accounting from the antecedent months, and better flow computation during the dry season, compared with the Empirical Model which takes into account the variation of rainfall in the same month only. This fact explains why the NRECA model makes significantly superior to the Empirical Model for the low flow during the dry season.

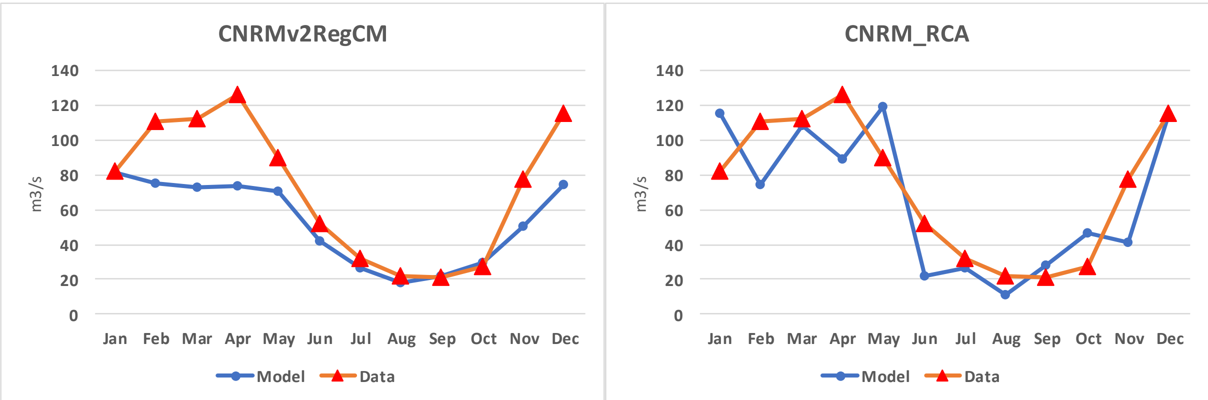

Figure 4. Comparison of seasonal average flow from the best of NRECA (left) and empirical (right)

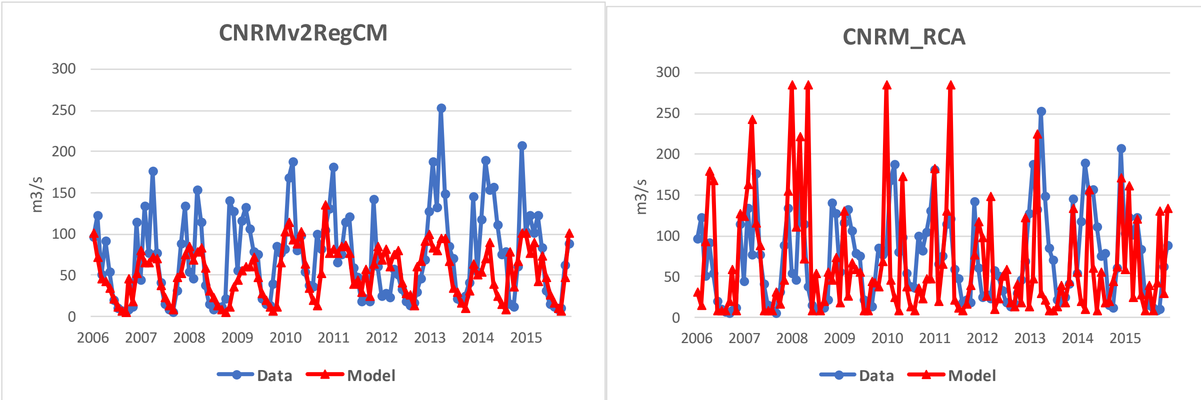

Figure 5. Comparison of time-series flow from the best of NRECA (left) and empirical (right)

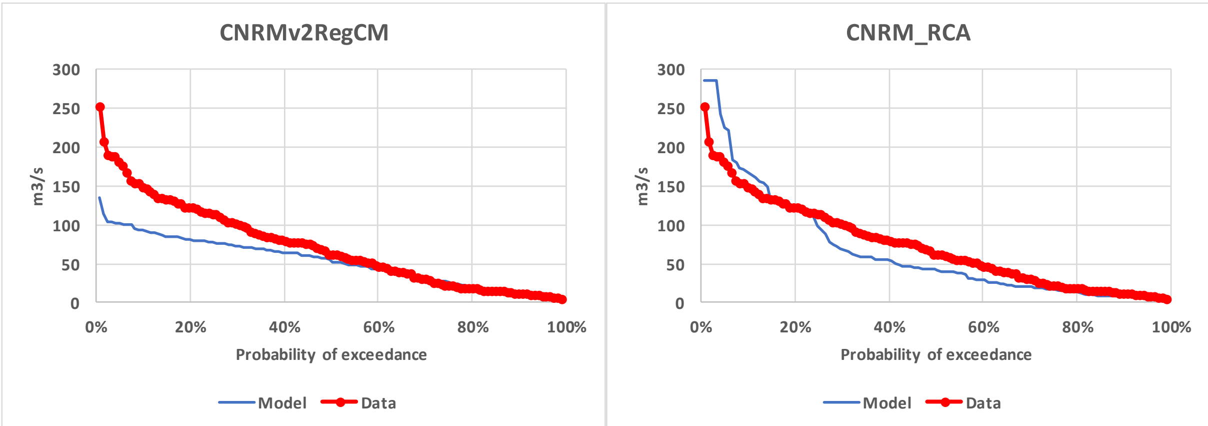

Figure 6. Comparison of flow duration curve from the best of NRECA (left) and empirical (right)

4. Conclusions and recommendations

It is concluded that the conceptual rainfall-runoff model NRECA generally is better than the Empirical rainfall-runoff model, especially for the low flow during the dry season. The Empirical Model performance falls below NRECA in terms of statistical coefficient of determination, RMSE, and NSE. Among seven projection models available in Indonesia, the CNRM-CM5, CNRM-RCA, and CNRM-v2-RegCM gives the best estimates, very close to the observed ground station data for the low to average flow. However, these projection models still lack of accuracy for the high flood. Empirical Model can be applied to obtain a comprehensive picture of the data to overcome the high flow problem of the NRECA Model.

It is recommended to use the NRECA conceptual rainfall-runoff model in Indonesia in converting the rainfall projection model into river discharge for drought and water availability studies. Further study concerning bias correction of the NRECA model on high flow should be investigated to have a full accurate valid indication of climate change impact on streamflow in the rivers.

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