Analysis and Projections of Rainfall using representative concentration pathways (RCPs) Scenarios in Sleman Yogyakarta

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Abstract. Climate change has affected many agricultural areas, and further problem in food security. One of indicator in climate change is the pattern of rainfall, then it is necessary to predict that. This research was conducted in Sleman due to this area has a lot of agricultural activities which greatly influence human life in Yogyakarta. Monthly rainfall data were obtained from Balai Besar Wilayah Sungai Serayu Opak (BBWSSO) from 1988 to 2019. Statistical Downscaling Model (SDSM) was used to downscale 21st century rainfall for 30 years in Sleman, Yogyakarta. Downscaling was performed on the basis of established relationships between historical data observed rainfall records from 7 stations and National Center for Environmental Prediction re-analysis large scale atmospheric predictors. General Circulation Models (GCMs) under Representative Concentration Pathways (RCPs) climate change with scenarios of RCP 2.6, RCP 4.5, and RCP 8.5. Rainfall prediction with RCP scenarios is needed to be used as a guide for adaptation of crops in agriculture because it relates to water availability.

1. Introduction
Water is a fundamental need for living things. In term of climate, its affects various aspects of human life and other organisms, therefore climate analysis is needed especially for the agricultural sector. The response to climate change is adaptation and mitigation [1]. Rainfall is one of result of climate change phenomenon which affect water resource. The main tools to predict the variability and changes in climate variable such as rainfall global and continental levels is Global Climate Models that are called General Circulation Models (GCMs) [2].

There is a model which is similar to GCMs, which is used for dynamic scaling. This model is more accurate because the time and place used in determining the network step is very small. After determining the optimal function, a statistical scaling is performed, and a large-scale climate variable is simulated by the future general circulation model, and is applied as input in the function, then the desired surface variable is obtained. The statistical relationship between the actual station behavior and the output of the general circulation model gives better results in this method. By using a published scenario, this verified equation can be used to scale down future predictions. In term of build a suitable relationship, this method gives better results than the previous method, although it requires more
observational data and expert consideration. SDSM is a model that can be used for main downscaling to statistical methods and was also used to downscale the regional climate information. This model has been applied in various parts such as rainfall climate variable for downscale. The statistical downscaling model (SDSM) is one of the downscaling models that have been widely used in the assessment of climate change (both mean and extreme) [3, 4, 5, 6].

The relationship between predictors with large-scale climate variables and weather on a local scale as predictions was built with statistical downscaling. Its based on the conditions of regional climate which determined using two factors, namely climatic conditions on a large scale and physiographic features on a regional scale [7]. To produce downscaled local predictions, derived relationships were used then applied to future climatic conditions. The minus of statistical scaling is that the relationship is derived based on predictions of historical observations and large-scale predictions assume that it applies to future climate change. Statistical scaling is as strong as dynamic scaling, which makes it widely used in the hydrological area, because it is independent of GCM, computationally inexpensive, and easy to implemented [4, 8, 9]. The success of predictions, depends on calibrated data for observation, the predictor of historical lengths, data records, selected predictors and statistical techniques of downscaling. In the aim to decrease the statistical scale, there are techniques namely stochastic weather generator techniques and multiple regression, which are frequently used [10]. The Downscaling Statistical Model (SDSM) was used in this study [3], basically the hybrid model of stochastic weather generator techniques combined with multiple regression. This model has been widely applied, and give good results for rainfall scaling down, and able to provide the characteristics of observed data [11].

The objective of this study was to investigate that adaptability of SDSM in downscaling rainfall for stations to produce monthly mean rainfall for the period 2020 – 2050 reflective of climate change signals obtained by downscaling from GCM predictors, to determine the climate change that occurred in 2020 – 2050 with 3 scenarios (namely RCP 2.6, RCP 4.5, and RCP 8.5) regarding rainfall, and to determine the distribution of rainfall in Sleman area.

2. Materials and methods

2.1. Study area description

This study was conducted in Sleman Yogyakarta. Sleman Regency is located at 110°13'00" - 110°33'00" E and 7°34'51" - 7°47'03"S with altitude ranging from less than 100 to more than 1000 meters above sea level. The total area of Sleman Regency is 57,482 ha or about 18% of the Special Region of Yogyakarta. The average annual rainfall for Sleman is 4 mm for the lowest average and the highest average rainfall is 8 mm. Study suggest that changes in rainfall predictions as a result of climate change are impacting the regional agricultural activities in Sleman as wide issue from crops adaptation [12]. Rainfall projected at the regional scale is the main input for impact assessment. To help to study the impact of climate change on a regional to local scale to develop early adaptation strategies, we choose Sleman for the application of statistical scaling down approach to produce a series of rainfall projections that enhance the projections given by GCM.

Figure 1. Stations in Sleman
2.2. Data description

Historical daily data of rainfall was obtained from Balai Besar Wilayah Sungai Serayu Opak (BBWSSO) at time span 1988-2019 from 7 rainfall stations namely Angin-angin, Beran, Bronggang, Kemput, Prumpung, Santan, and Tanjung Tirto. Among that data, there were missing parts that were completed with US National Weather Service. To obtain the two types of daily rainfall predictor data which required in this study, it is obtained from the Canadian website (http://www.cics.uvic.ca/scenarios/sdsm/select.cgi), namely: (1) 26 predictors National Center for Environmental Prediction (NCEP) (Table 1) for the period 1988-2019; and (2) using the CanESM2 climate model from the CMIP5 model collection and scenarios (RCP 2.6, RCP 4.5, and RCP 8.5), which can be used to predict future rainfall.

Table 1. List of 26 NCEP predictor variables and selected predictors for calibration within each station

| Predictors         | Angin-angin | Beran | Bronggang | Kemput | Prumpung | Santan | Tanjung Tirto | Description                      |
|--------------------|-------------|-------|-----------|--------|----------|--------|---------------|----------------------------------|
| ncepmslpgl        |             |       |           |        |          |        |               | Mean sea level pressure          |
| ncepp1_fgl        |             | x     |           |        |          |        |               | 1000 hPa Wind speed              |
| ncepp1_ugl        | x           | x     | x         | x      | x        | x      |               | 1000 hPa Meridional velocity    |
| ncepp1_vgl        |             |       |           |        |          |        |               | 1000 hPa Vorticity               |
| ncepp1thgl        | x           | x     | x         | x      | x        | x      |               | 1000 hPa Wind direction          |
| ncepp1zhgl        |             |       |           |        |          |        |               | 1000 hPa Divergence              |
| ncepp5_fgl        |             |       |           |        |          |        |               | 500 hPa Wind speed               |
| ncepp5_ugl        |             |       |           |        |          |        |               | 500 hPa Zonal velocity           |
| ncepp5_vgl        |             |       |           |        |          |        |               | 500 hPa Meridional velocity      |
| ncepp5_zgl        |             |       |           |        |          |        |               | 500 hPa Vorticity                |
| ncepp500gl        |             |       |           |        |          |        |               | 500 hPa Geopotential height      |
| ncepp5thgl        |             |       |           |        |          |        |               | 500 hPa Wind direction           |
| ncepp5zhgl        |             |       |           |        |          |        |               | 500 hPa Divergence               |
| ncepp8_fgl        |             |       |           |        |          |        |               | 850 hPa Wind speed               |
| ncepp8_ugl        |             |       |           |        |          |        |               | 850 hPa Zonal velocity           |
| ncepp8_vgl        |             |       |           |        |          |        |               | 850 hPa Meridional velocity      |
| ncepp8_zgl        |             |       |           |        |          |        |               | 850 hPa Vorticity                |
| ncepp850gl        |             | x     |           |        |          |        |               | 850 hPa Geopotential height      |
| ncepp8thgl        |             |       |           |        |          |        | x             | 850 hPa Wind direction           |
| ncepp8zhgl        |             |       |           |        |          |        | x             | 850 hPa Divergence               |
| ncepprcpgl        | x           |       |           |        |          | x      | x             | Precipitation                    |
| nceps500gl        |             |       |           |        |          |        |               | 500 hPa Specific humidity        |
| nceps850gl        | x           | x     | x         |        |          |        |               | 850 hPa Specific humidity        |
| ncepsshumgl        |             |       |           |        |          |        |               | 1000 hPa Specific humidity       |
| nceptempgl        |             | x     | x         | x      | x        | x      | x             | Screen (2 m) air temperature     |
2.3. Predictors
The GCM data and NCEP predictors, based on scenarios intended to predict the atmospheric situation from 2020 to 2050, were obtained from Canadian climate change site. In this section by looking at the intended RCP scenario and selecting the CanESM2 prediction model, it determines the studied area to prepare and download the first data box of the prediction model [13]. To prepare an SDSM model other than predictive data, an observation station is needed which is obtained every day. By considering the selected area, the nearest rainfall station, and daily observation temperature the rainfall data were obtained. The closest rainfall stations to the target area, where the daily data are available, can be obtained from BBWSSO namely Angin-angin, Beran, Bronggang, Kemput, Prumpung, Santan, and Tanjung Tirto stations. Therefore, daily rainfall data for 31 years (1988 to 2019) at these stations were obtained to be included in the SDSM model. To develop SDSM, NCEP predictor daily time series and the observed daily time series were required [5].

2.4. SDSM Model
This SDSM relates the statistical relationship between large-scale behavior as a predictor and regional predictors based on multiple linear regression methods. It will be created using station-witnessed data and the output of a general circulation model in the same observation period. The basic assumption in scaling down the statistics is the independence of the timing of this relationship. Before performing the downscaling process with this model, the witnessed data and the general circulation model data were normalized by taking into account the mean and standard deviation in the intended period. In this model there are several micro-scale statistical processes which are described as 7 steps, first quality control of observational data and screening, then model calibration, and followed by data production. Next step is down scaling and scouting data analysis, frequency analysis, and last step is scenario production [13].

2.5. RCP scenarios
The new scenario RCP is a line agent of varying greenhouse gas densities. The newly released scenario has four main passes that are RCP 8.5, RCP 6, RCP 4.5, and RCP 2.6 which are labelled after radiation rates at 2100 production [13]. By using a weather generator based on the selected predictors, rainfall and temperature were modelled. In the SDSM model, a large-scale predictor for meteorological projections then used for re-analysis of NCEP. Its aimed for calibration and validation process of CanESM2 for long term generation. There were 3 RCPs used in this study to provide plausible future rainfall scenarios which covering various low emission scenarios characterized by active mitigation (RCP 2.6), through two medium scenarios (RCP 4.5 and RCP 6), and high emission scenarios (RCP 8.5).

2.6. Model performance
The simulations of monthly during the calibration of the SDSM time series calibration or validation were examined using the root mean square error (RMSE). It was defined as:

\[ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_{\text{obs},i} - X_{\text{model},i})^2}{n}} \]  

An RMSE value that is close to 0 means that the resulted predictions were better. To establish confidence with analysis performance, the average rainfall is were graphically compared with the observed data. This graphical comparison can identify the patterns and variations captured by all models [14].

2.7. GIS – data distribution
One of the important computerized information systems is GIS. GIS has the difference in that geographic spatial references both latitude and longitude, and other spatial coordinates must be associated with all
information in the GIS. According to the Environmental Protection Agency, to map and analyse geographic data, GIS works by combining database functions with computer mapping. It uses layering techniques to combine different types of data. This special GIS software is used to analyse layered data and create new data layers. Geographical is a geographic reference, meaning that it is spatial coordinate data on a map of the earth's surface, with an attribute database information system that is in accordance with spatial location and procedures to provide information for decision making. The need in spatial analysis is that the location of the rainfall station is plotted using its coordinate points, then a decrease or increase in annual rainfall is plotted at each rainfall station [15].

3. Results and discussion

Daily data obtained from the BBWSO for 1988 to 2019 was inputted to SDSM model and relies on general climate prediction information from miniature scale air. After assessing the results of the adjustments, information is generated on 3 situations RCP 2.6, RCP 4.5, and RCP 8.5 day by day of rainfall for the period of 2020-2050.

3.1. Identifying predictors

Table 1. shows the SDSM predictors and selected predictors at p<0.05 and positive P.r value for each station. Result suggest that 8 out of 26 predictors were potentially useful for downscaling rainfall in these 7 rainfall stations, especially mean sea level pressure, 1000hPa zonal velocity, 1000 hPa wind direction, 850 hPa geopotential height, 850 hPa wind direction, precipitation, 850 hPa specific humidity, and screen (2 m) air temperature. The 1000 hPa zonal velocity and screen air temperature were found to be an effective predictor for downscaling rainfall in all stations. Geopotential height and specific humidity along with a few other variables including temperature at 2 m have been found to be potentially useful predictors for downscaling rainfall.

3.2. SDSM calibration and validation

SDSM is widely used in hydrological issues in climate scenarios. It is built the relationship between GCM’s predictors and local predictands period of 30 years or more as the recommended standard for studies of climate change and climate variability. The local climate was projected using the same predictor set and this time provided by CanESM2. Based on Figure 2, all RCP’s agree that the long-term annual rainfall has the potential to produce the intensity of annual rainfall compared to the historical at all stations. This figure shows the projection of monthly mean rainfall for the period 2020 to 2050 under the RCP 2.6, RCP 4.5, and RCP 8.5. Angin-angin station showed different results for each RCP. The prediction rainfall tends to increase than the historical rainfall. It also happened for prediction rainfall in Beran, Bronggang, and Kemput station tend to increase than the historical rainfall While Prumpung, Santan, Tanjung Tirto station showed that prediction rainfall tends to decrease than historical rainfall. RMSE value of all stations were under 1.0.
Figure 2. Comparison between the projected rainfall (2020 - 2050) by all RCPs with historical rainfall trends (1988 - 2019) for stations, (a) Angin-angin, (b) Beran, (c) Bronggang, (d) Kemput, (e) Prumpung, (f) Santan, (g) Tanjung Tirto.
3.3. Climate projection

Fig 3. Showed the spatial distribution of each stations. Distributions map of the projection with 3 RCPs was derived from the topographic maps with the help of ArcGIS. The geographical coordinates of the stations were used in the GIS to capture the grids of monthly mean rainfall. The existing rainfall analysis was the result of SDSM which did not produce identical conclusions among the 7 rainfall stations. Difference in downscaled rainfall maybe due to the SDSM model use several predictor variables on a large scale. In addition, differences in the results of decreasing rainfall scale were caused by the inability of GCM to capture local dynamics related to rainfall patterns. In addition, SDSM used in this study is able to shows better performance than previous studies which conducted in Sleman. In addition, the GCM model output is based on a large grid scale. Due to their crude resolution, they’re the resulting output cannot be fully utilized to investigate the environmental and hydrological impacts of climate change at a regional scale.

![Figure 3](image-url)

**Figure 3.** Increase and decrease spatial distribution of predicted monthly mean rainfall in each station with RCP 2.6, RCP 4.5, and RCP 8.5.

4. Conclusions

In this study, General Circulation Model and Statistical Downscaling Model (SDSM4.2) and were employed to generate future rainfall scenarios at eight locations in Sleman for the period 2020-2050. Climate change in the prediction of rainfall for 30 years (2020 - 2050) which is analyzed using the RCP scenario will increase and decrease. The distribution of changes using the RCP 2.6 and RCP 8.5 scenarios, shows that there is an increase and decrease in rainfall. In the RCP 4.5 scenario, there is a decrease in rainfall at all stations. Statistical downscaling methodologies have several practical advantages over dynamical downscaling approaches. In situations where low–cost, rapid assessments of localized climate change impacts are required, statistical downscaling represents more promising option. In this paper we describe an accompanying statistical downscaling methodology, that enable the construction of climate change scenarios for individual sites at daily time–scales, using grid resolution GCM output.

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