



Assessment of Drought Hazard: A Case Study in Sampean Baru Watershed, Bondowoso Regency

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Abstract. The Sampean Baru watershed is categorized as an area with a very high level of vulnerability to drought. The purpose of this study was to assess the hydrological drought in the Sampean Baru watershed. NCEP / NCAR Reanalysis climate change data is used to obtain synthetic rainfall models of the past. This climate change data has crude resolution and is global in scale. The NCEP / NCAR Reanalysis data was processed through a downscaling process to obtain local scale climate data in the form of past synthetic rains. Artificial Neural Network (ANN) is one of the downscaling models used in this study. The ANN downscaling output was processed through discharge modeling using SWAT. Hydrological drought assessment used the Standardized Precipitation Index (SRI) method. The SRI calculation was based on the accumulated discharge over a period of time. The results indicated that the ANN downscaling process can bridge global scale climate data to local scale climate data. SWAT modeling gave excellent results. SRI-6 can describe past droughts. It can be seen from the compatibility between the results of the drought assessment and the drought data belonging to the relevant authorities.

Keywords: Drought assessment, NCEP / NCAR Reanalysis, ANN, SWAT model, SRI.

INTRODUCTION

In the last few decades, climate change has become a common problem. CO₂ emissions from fossil fuel combustion and industrial processes contributed approximately 78% to the total increase in GHG emissions between 1970 and 2010, with the same percentage contribution over the 2000-2010 period [1]. This results in the composition of the atmosphere changing constituent elements, resulting in global warming and climate change [2]. Climate change causes the frequency, duration, and intensity of natural events, such as drought, to increase [3]. Many countries are working to bring climate change under control together.

The Sampean Baru Watershed area has a very high level of drought threat [4]. The impact of this drought is the increasing demand for clean water in several areas. As the authority for providing clean water services, the Regional Drinking Water Company (PDAM) is working with the Regional Disaster Management Agency (BPBD) to distribute clean water to areas affected by drought. 11 villages in 6 sub-districts have submitted requests for clean water to PDAM [5]. The drought also has an impact on the agricultural sector, such as crop failure.

Drought occurs slowly without people being aware of it [6]. However, its impact is damaging. Monitoring of drought by conducting hazard assessment is a necessity and a solution to minimize its impact. However, a limitation in this process is the lack of updated rainfall data available in the Sampean Baru watershed. This study employed NCEP/NCAR Reanalysis dataset to overcome this problem. It is a real-time global reanalysis of atmospheric data from 1979 to the present [7]. This dataset was the result of the reanalysis assimilation data system that continuously used with current data in real-time [8]. This dataset has been widely used in various climate-related researches such as drought assessment [9], precipitation downscaling[10][11], runoff simulation[12], cyclones analysis[13], and so on. The NCEP/NCAR Reanalysis dataset has a global gridded data scale and has a coarse resolution, so it must be processed through a downscaling. Downscaling can determine the relationship between global gridded data and local gridded data, in this case, rainfall data in the Sampean Baru watershed. Downscaling technique consists of Dynamical Downscaling (DD) and Statistical Downscaling (SD) [14]. In this study, the statistical downscaling type is used because of several advantages, namely: it is cheap and does not require large memory hardware[15]. Artificial Neural Network (ANN) is a statistical downscaling method that will be used to obtain a model of rainfall.

This study aims to assess the hydrological drought in the Sampean Baru watershed. The hydrological drought index used for the assessment was the Standardized Runoff Index (SRI) method. SRI is suitable for hydrological drought assessment due to climate change [16]. SRI uses accumulated discharge data over a specific duration as input [17]. Another problem that arises is that discharge data is not always available for a long duration. Thus, rainfall-runoff modeling is necessary. The Soil and Water Assessment Tools (SWAT) is software that can be used for modeling runoff using rainfall input data.

METHODOLOGY

Descriptions of the study area

As seen in **Fig. 1.**, the research was located at the Sampean Baru watershed in Bondowoso Regency, East Java. The Sampean Baru watershed area is 1206 km². The Sampean Baru watershed has a main water control building, namely the Sampean Baru dam.

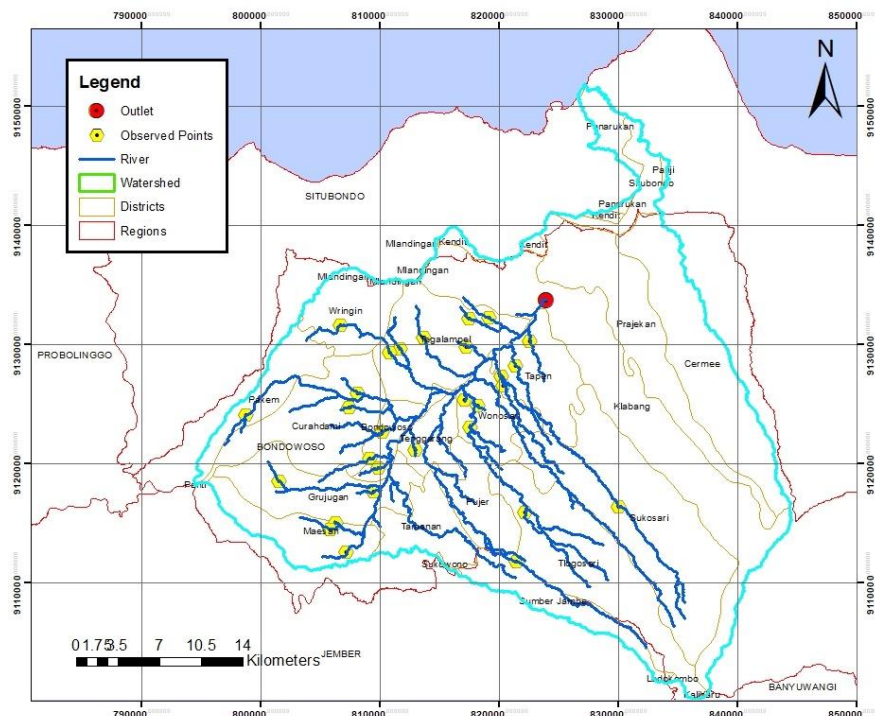


FIGURE 1. Sampean Baru watershed

Updated rainfall data were needed to assess drought. It can be obtained by processing updated global atmospheric datasets taken from the National Center for Atmospheric Research (NCEP / NCAR Reanalysis). The climate data set on the NCEP / NCAR Reanalysis were obtained from the global data assimilation system and various data observation sources, such as satellites, aircraft, ships, and radiosonde

[18]. These data were then quality controlled and assimilated with a data assimilation system kept unchanged over the reanalysis period [8]. NCEP / NCAR Reanalysis data are available from 1979 onwards. **Table 1.** presents several outputs of climate parameters in the NCEP / NCAR Reanalysis data. The NCEP / NCAR Reanalysis data output has a global resolution measuring $2.5^\circ \times 2.5^\circ$; therefore, it cannot be used directly for modeling watershed discharge [19].

TABLE 1. NCEP/NCAR Reanalysis variables

No	Description	Variables
1	Relative humidity at 500 hPa geopotential height	rhum 500
2	Relative humidity at 850 hPa geopotential height	rhum850
3	Specific humidity at 500 hPa geopotential height	shum500
4	Specific humidity at 850 hPa geopotential height	rhum850
5	Precipitation water at the surface	prec_wtr
6	Zonal velocity component at 500 hPa geopotential height	uwd500
7	Zonal velocity component at 850 hPa geopotential height	uwd850
8	Meridional velocity component at 850 hPa geopotential height	vwd850
9	Zonal velocity component at the surface	uwd
10	Meridional velocity component at surface	vwd

A downscaling technique is a method to obtain precipitation by processing coarse resolution data (or large-scale data) into smooth resolution data (or local scale data), in this case, the Sampean Baru watershed. Downscaling techniques consist of a dynamic downscaling model (DD) and statistical downscaling (SD) [14]. DD simulates climatic variables through a higher resolution climate model nested within a GCM grid to define time-varying atmospheric boundary conditions and resolve regional processes [20][21]. The DD approach has a weakness. However, it requires high cost and complicated computational process [14]. In the SD approach, downscaling is carried out by applying empirical equations to obtain a relationship between climate parameters (predictors) on a global scale with local-scale climate parameters (predictants) at a certain period [15]. SD can be done through computation, which is fast and does not require large memory [22]. One of the SD approach models used is the Artificial Neural Network (ANN) model.

ANN is developing an SD empirical method to obtain the relationship between predictors and predictors of non-linear regression models [10]. In this case, the prediction used was the rainfall data (1988-2018) at 28 rain observation stations obtained from the Public Works and Water Resources Office of Bondowoso Regency. The ability of ANN to overcome non-linear relationship problems makes ANN often used for downscaling rain [19]. Several previous studies have shown that ANN gives better results than other SD models [23]–[25]. ANN’s work concept resembles that of the human brain. It results in ANN having the ability to adapt to new things [26]. In the process, predictors as input data were processed through the transfer function to obtain the output data. The output data were then tested for the reliability of the predictions. If the output data provided results with a good reliability test, then the output data in the form of a synthetic rain model can be used in the next process. If the output data gave unsatisfactory results with the reliability test, then the downscaling process was carried out again [27]. The process in ANN was indicated by a simple mathematical equation below:

$$y(k) = F \left(\sum_{i=0}^m w_i(k)x_i(k) + b \right) \quad (1)$$

where x_i is input data; w_i is the weight value; b is biased; F is the transfer function, and $y(k)$ is the output

The SRI hydrological drought assessment used discharge data as input data. This study used SWAT software to get the discharge model in the Sampean Baru watershed. Some of the data entered in the discharge modeling process are 1) Synthetic rain data from ANN, 2) Land use data obtained from the Geospatial Information Agency (BIG), and 3) Earth surface data using ASTER 30M DEM obtained from the United States Geological Survey (USGS). The SWAT process results were re-tested for reliability against the Sampean Baru river discharge data (1988-2018) of Sampean Baru dam obtained from the Public Works and Water Resources Office of Bondowoso Regency. The reliability test of a model is expressed in two indicators, namely the Deterministic Coefficient (R^2) and the Nash Sutcliffe Error (NSE)[28]. The classification of reliability test results using these two indicators can be seen in **Table 2.** If the reliability test gives satisfactory results, the discharge model can be used at the drought modeling stage.

SRI applies a similar work concept to SPI, where the accumulated discharge over a certain period is used as input data [17]. The result of drought modeling in the Sampean Baru watershed is the SRI value. The period for determining the value of SRI is based on a time scale of 1, 3, 6, 9, 12, 24, and 48 months. The SRI value indicates the severity of drought. The SRI drought severity classification is shown in **Table 3.**

TABLE 2. Reliability test using R^2 and NSE classification

No	Classification	NSE	R^2
1	Very Good	$0.75 < NSE \leq 1.00$	$0.75 < R^2 \leq 1.00$
2	Good	$0.60 < NSE \leq 0.75$	$0.60 < R^2 \leq 0.75$
3	Satisfactory	$0.36 < NSE \leq 0.60$	$0.50 < R^2 \leq 0.60$
4	Bad	$0.00 < NSE \leq 0.36$	$0.25 < R^2 \leq 0.50$
5	Inappropriate	$NSE \leq 0.00$	$R^2 \leq 0.25$

Source: [28]

TABLE 3. SRI drought classification

No	Classification	SRI Index
1	Extreme Wet	$SRI \geq 2.00$
2	Severe Wet	$1.50 < SRI \leq 1.99$
3	Moderate Wet	$1.00 < SRI \leq 1.49$ $-0.99 < SRI \leq$
4	Normal	0.99 $-1.00 > SRI \geq -$
5	Moderate Dry	1.49 $-1.50 > SRI \geq -$
6	Severe Dry	1.99
7	Extreme Dry	$-2.00 \geq SRI$

Source: [29]

RESULT AND DISCUSSION

ANN's downscaling process aims to obtain a synthetic rain model for the past 30 years. The architecture of ANN used a multilayer perceptron network and backpropagation learning methods. This study employed the sigmoid function as an activation function of 30 neurons and a linear function of the output neurons. The Levenberg-Marquardt method was used to improve the weight of backpropagation learning. The division of the training period by validation is 90:10. The results of the ANN downscaling process can be seen in **Table 4**. The coefficient of determination (R^2) in the downscaling process of the NCEP / NCAR Reanalysis of the data has shown good results with a value close to 1. The monthly average plotting of synthetic rain provided results resembling the average plotting observation rain. It is shown in **Fig. 2**. Overall, the downscaling process can describe past climatic conditions.

TABLE 4. ANN downscaling result

Model Performances	NCEP/NCAR Reanalysis
Coefficient of Determination (R^2)	0.91
Root Mean Square Error (RMSE)	60.57

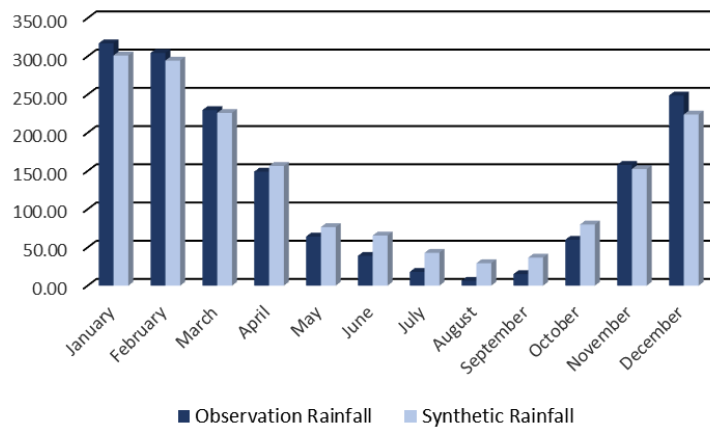


FIGURE 2. The result of plotting synthetic rainfall against observation rainfall

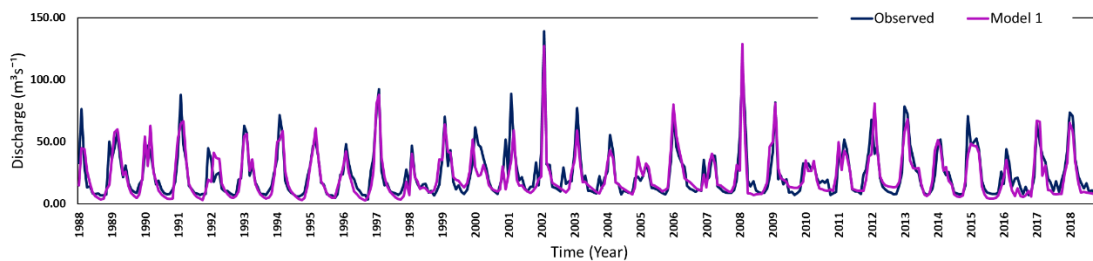
Discharge modeling in the Sampean Baru watershed used SWAT software. In the discharge modeling, the Sampean Baru watershed was divided into 21 sub-watersheds. Synthetic rain resulting from ANN downscaling was used as one of the input data in addition to observation rain data, land use data, earth surface relief data, and soil data. The Sampean Baru river discharge data was the model reference data. In the first step, observational rainfall data is used as input data in modeling discharge. The result is called model 1. It can be seen in **Table 5** and **Fig. 3**. The calibration result of discharge model 1 showed R^2 and NSE of 0.7528 and 0.7422. The validation result of discharge model 1 showed R^2 and NSE of 0.7933 and 0.7782. In the second step, NCEP/NCAR Reanalysis rainfall data from ANN downscaling was used as input data in modeling discharge. The result was called model 2. Discharge model 2 showed good results on the observation discharge of the Sampean Baru river, which can be seen in **Table 6** and **Fig. 3**. It is indicated by the calibration result of discharge model 2 showed R^2 and NSE of 0.7858 and 0.7620. The validation result of discharge model 1 showed R^2 and NSE of 0.7741 and 0.7333. These results are categorized as very good.

TABLE 5. Reliability test of model 1

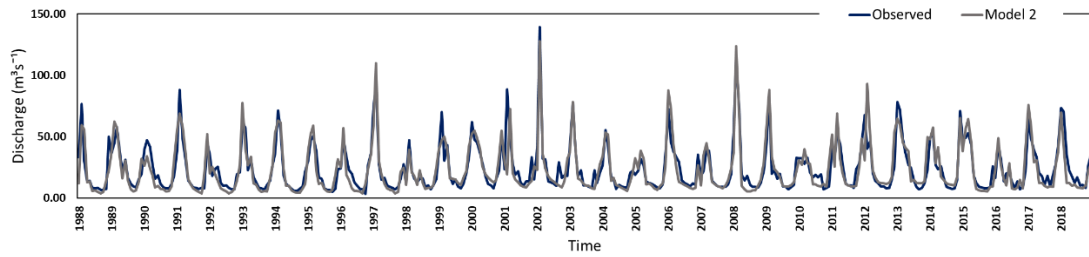
Model Performances	Calibration	Validation
Coefficient of Performance (R^2)	0.7528	0.7933
Nash-Sutcliffe Efficiency (NSE)	0.7422	0.7782

TABLE 6. Reliability test of model 2

Model Performances	Calibration	Validation
Coefficient of Performance (R^2)	0.7858	0.7741
Nash-Sutcliffe Efficiency (NSE)	0.7620	0.7333



(a)



(b)

FIGURE 3. Discharge simulation using: (a) Observation rainfall; (b) NCEP/NCAR Reanalysis rainfall.

Hydrological drought assessment of the Sampean Baru watershed using SRI with a time scale of 6 months (SRI-6). The SRI index chart with a time scale of 6 months is shown in **Fig. 4**. The calculation of SRI-6 was based on the results of watershed discharge modeling with synthetic rainfall input data. The SRI-6 assessment was carried out at 21 discharge observation points in the Sampean Baru watershed. The results show that 1992, 1994, 1996, 2015, and 2018 had SRI-6 values smaller than minus two, so that those few years experienced extreme drought. The assessment results were evaluated against data on rice plant areas affected by the 2003-2010 drought belonging to the Directorate of Food Crops, the Ministry of Agriculture, and data on clean water distribution for 2018 belonging to BPBD-PDAM Bondowoso. Based on data from the Directorate of Food Crops, the highest area affected by drought occurred in 2007, followed by 2008 and 2005. It is shown in **Fig. 5**. It follows the results of drought assessment in 2007, 2008 and 2005, where SRI-6 shows a value of -1,9555; -1,8565; and -1.5105. Based on the results of the evaluation of BPBD-PDAM data, the drought assessment results show the suitability of the 2018 clean water distribution data. As seen in **Fig. 6**, the data shows that Wringin, Jatisari, Pameton, Karangsengon, Botolinggo, and Gayam have received clean water distribution due to drought. It is in line with the SRI-6 drought assessment results, where the villages experienced extreme drought (SRI < -2.00).

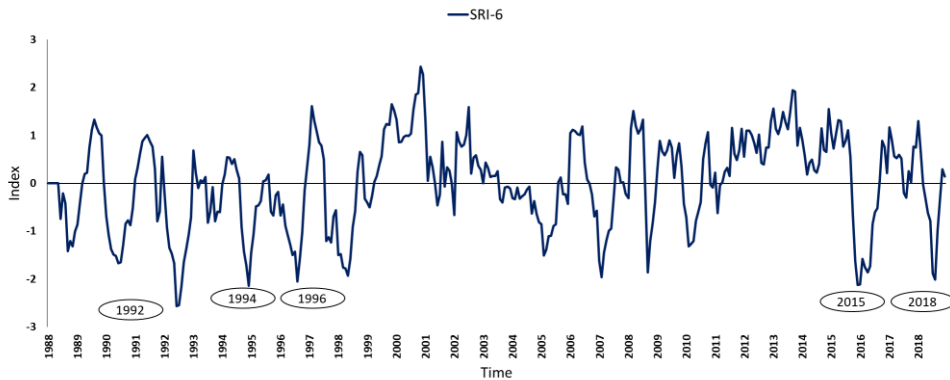


FIGURE 4. Drought assessment using SRI-6

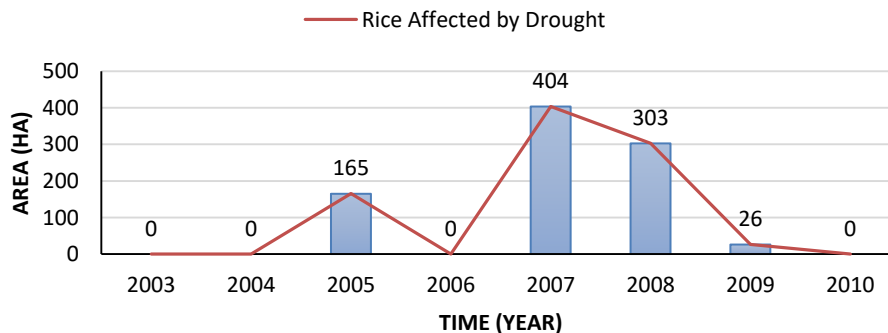


FIGURE 5. Rice field area affected by drought

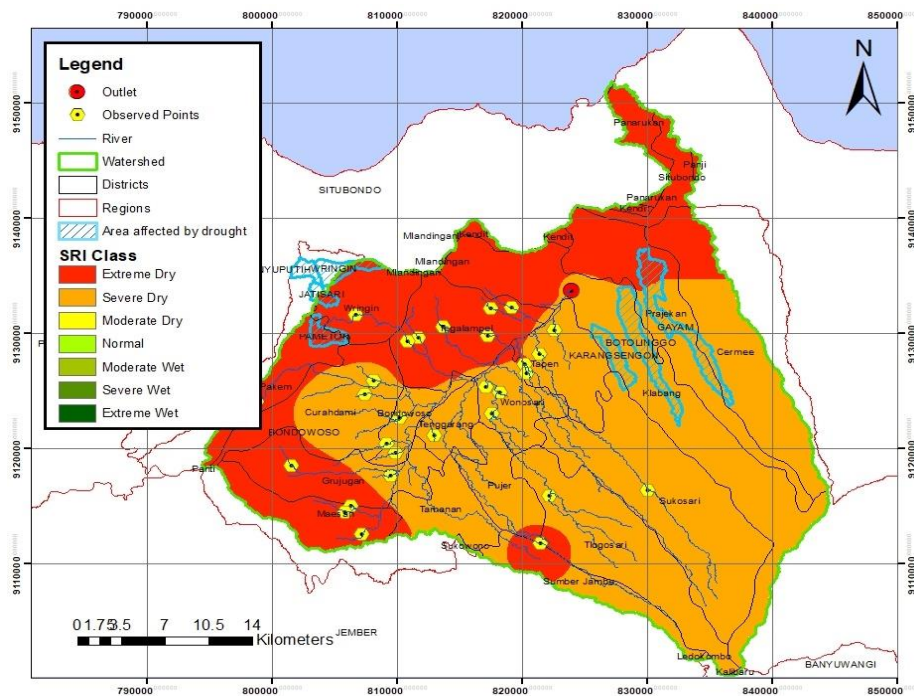


FIGURE 6. Drought assessment SRI-6 in 2018

CONCLUSION

Downscaling using ANN successfully bridged climate variable data from the global scale NCEP/NCAR Reanalysis to local climate data in the form of observed rainfall. The results at this downscaling stage can be seen from the coefficient of determination, close to one. With this, the output data in the form of historical downscaling rainfall can be used at the discharge modeling stage.

Discharge modeling using SWAT has yielded good results. Through the calibration process of the discharge model with observational rain input data, the R^2 and NSE values increased until they reached the very good category. It caused the model to be used with synthetic rainfall input data. The reliability test results of the discharge model with synthetic rain input data were categorized as very good.

The hydrological drought assessment SRI-6 can describe the drought that occurred in the past 30 years. The evaluation of the drought assessment on the clean water distribution data belonging to the BPBD-PDAM Bondowoso and the data on the area of rice plants affected by drought belonging to the Directorate of Food Crops show suitability. The hydrological drought assessment SRI-6 can be used as a good reference for future drought assessments.

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