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The Reliability of W-flow Run-off-Rainfall Model in Predicting Rainfall to the Discharge

D. Riyadi Tama [1], Lily M. Limantara [2*], E. Suhartanto [2], Y. Padma Devia [1]

[1] *Department of Civil Engineering, Faculty of Engineering, University of Brawijaya, Malang, Indonesia.*

[2] *Department of Water Resources Engineering, Faculty of Engineering, University of Brawijaya, Malang, Indonesia.*

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Abstract

This research intends to predict the discharge (run-off) from rainfall for which the model is built using W-flow. The research location is in the Gajah Mungkur reservoir (Wonogiri) in Indonesia. The estimation of reservoir inflow has an important role, mainly in the scheme of reservoir operation and management. However, the heterogeneity of complex spatial and temporal patterns of rainfall and also the physiographic context of a watershed cause the development of a model of real-time run-off and rainfall that can accurately predict the reservoir inflow to become a challenge in the development of water resources. In relation to the analysis and prediction of rainfall, the constraint and problem that is still often faced is the minimal availability of observed rainfall data spatially as well as temporally; the time series of rainfall data is not long and complete enough; and the number of rainfall stations is less evenly distributed. The methodology consists of carrying out the literature study, collecting as much rainfall data as possible to build a W flow model, then carrying out the model calibration and analyzing the prediction of real-time reservoir inflow for operation. The result shows that the dependable discharge of the Wonogiri watershed shows that there are two peak discharges, which happened on February II (the second half of February) and December II (the second half of December). However, the discharge is decreasing in July and reaching its lowest level in October II (the second half of October).

Keywords: Rainfall; Run-Off; Model; W-Flow.

1. Introduction

Gajah Mungkur, or Wonogiri reservoir, was built in 1976 and finished in 1981. This reservoir has a catchment area of about 1,350 km^2, and the inundation area is about 90 km^2. The Gajah Mungkur reservoir has the main function of flood control for the Bengawan Solo River. Besides having the main function, this reservoir also has other functions, such as the water supply of the Colo weir for irrigation water supply for more than 24,000 ha of irrigated rice area in the areas of Klaten, Sukoharjo, Karanganyar, and Sragen regencies. Then, it is the hydro-electric power supply for the Wonogiri area, with a maximum capacity of about 12.4 MW, and it also functions as a tourism object.

Water plays an important role in a country's economy and society, in terms of agriculture, irrigation, hydroelectric power generation, industrial use, and drinking water [1]. However, this highlights the importance of proper water management for both economic and social benefits for a country. For proper management of water, accurate predictions from hydrological modeling are required. Hence, the role of spatially distributed precipitation data is crucial in this context [2]. In design, the series data of reservoir inflow is needed as the input in optimization modeling of reservoir operation and sedimentation, so the accuracy of the data is very important. The model result will bias if there is an error

* Corresponding author: lilymont2001@gmail.com

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in the data input. According to Loucks & van Beek [3], in reservoir operation modeling, the error of data input can cause the model to consistently be deficit or surplus in predicting the reservoir release. However, according to Salas and Shin [4], the error in inflow data can cause uncertainty in predicting reservoir sedimentation.

The estimation of reservoir inflow has an important role to play in reservoir operation and management [5]. However, the complex spatial and temporal heterogeneity of rainfall and also the physiographic context of the watershed cause the model development of real-time run-off and rainfall, which can accurately predict the reservoir inflow sometimes before, to become a challenge. In relation to the analysis and prediction of rainfall, the constraint and problem that is still often faced is the minimal availability of observed rainfall data spatially as well as temporally; the time series of rainfall data is not long and complete enough; the number of rainfall stations is less evenly distributed [6], there is less observer power; the system of observation and data inflow is still manual; the data collection from certain areas to the center level is still hampered and slow; and the data format has not been standard. The constraint and problem are that the rainfall observed on the surface is still difficult to obtain quickly and needs evaluation of data quality before it can be used directly. Related to the constraint and problem, it is needed an alternative method for predicting rainfall to fulfill the limitations of the observed rainfall data [7]. One of the alternatives that can be used is the utilization of satellite rainfall data for producing more accurate rainfall information, mainly in areas where the observation of surface rainfall is still very rare.

The utilization of satellite data can be used as the change of ground rainfall, with the requirement to carry out the data correction in the first place. The correction result shows that the characteristic of GPM satellite rainfall has approached the ground rainfall value, as shown by the decreasing error value and the shifting of the probability curve about satellite rainfall to the probability curve of ground rainfall [8]. The advantage of satellite in measuring the rainfall intensity compared to the observed rainfall station on the surface is that it has a high spatial and temporal resolution, covers an area of about ± 770 km [9, 10], has near-real-time data [11], is fast to access, and is economical because the data can be downloaded for free. It can fulfill the problem of rainfall observed data. However, the availability of satellite data started to increase between 1996 until 1998 [12]. In addition, the use of satellite data is necessary to be carried out, as is the correction by surface observed data, so it can be evaluated how accurate the output of satellite data is compared to the observed data on the surface [13, 14]. Therefore, in the next analysis step, the error in the satellite data can be decreased [2, 15, 16], and the data can be dependable. This research intends to investigate the reliability of the W-flow run-off-rainfall model in predicting rainfall at the discharge.

2. Material and Method

2.1. W-Flow Modelling

W-flow is a model that was developed by Deltares and is able to model the hydrology processes so that the user can analyze rainfall, interception, accumulation, snow melt, evapotranspiration, groundwater, surface water, and groundwater recharge in an environment that is fully distributed. W-flow is a platform for complete distributed modeling that maximizes the use of open-earth observed data and makes it the selected hydrology model for the environment with rare data. Based on the topography, soil, land use, and climate data, W-flow analyzes all of the hydrology flux at a certain point in the model at a certain time step. The movement of surface water across the natural span is determined by the reservoir and kinematic wave module, which gives an accurate representation of river discharge. Figure 1 presents the complete distributed modeling approach.

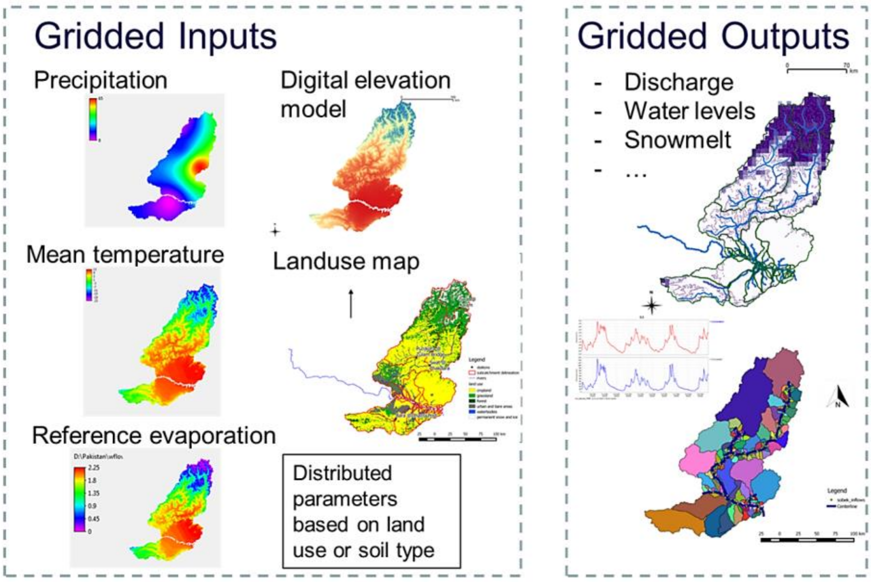


Figure 1. Complete Distributed Modeling Approach

The framework of water flow has an open source and flexible characteristic, and it is more and more used together with the other models for preparing the river flow data for evaluation of water quality, the hydro-dynamic simulation for analysis of flood risk, and the water allocation model for evaluating the water management strategy. W-flow uses the Python language as its base, so it has a transparent structure that can be adapted by the model user for their specific needs. This flexibility gives the integration facility with the other model. At this time, the framework has been adapted to make it possible for users to select and adapt some conceptual hydrology models, such as the HBV classic, the W3RA, and the SBM model concept. The W-flow model processes the hydrology cycle. The hydrology cycle that is modeled is created by combining several sub-models. The sub-models are as follows:

1. *Rainfall drop (schematized by the GASH model);*
2. *River and surface flow are modelled by the kinematic wave model;*
3. *Land preparation (schematized TOPOG_SBM model);*

The data inputs that are needed are rainfall, potential evapotranspiration, factors of crop consumptive use, topography, soil type, land use, and type of land cover.

Rainfall is a main input for determining the total amount of water that is accepted from the atmosphere. Evapotranspiration determines the water volume that will be returned to the atmosphere, which will be different in every location because of the factors of wind velocity, radiation from the sun, and air temperature [17]. The factor of crop consumptive use determines the water volume that is used by crops and vegetation in growing. However, the morphology of the water catchment determines the direction and velocity of flow based on the slope pattern. Soil type determines the infiltration and soil moisture degree, so it directly determines the formation and accumulation of surface flow [18]. Land use and land cover determine the crop consumptive use and also the speed of the rainfall transformation process into surface flow [19]. Figures 2 to 4 each present the hydrology model in W-flow, the scheme of W-flow_sbm, and a grid in the W-flow model [20].

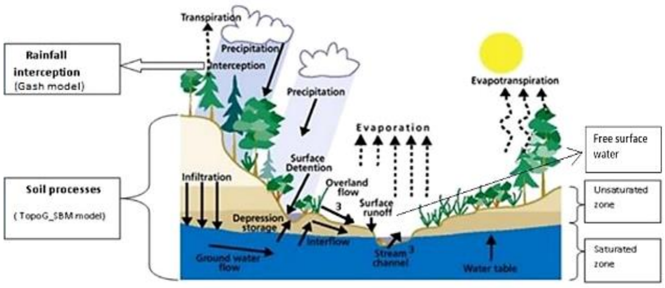


Figure 2. Hydrology Model in W-flow (Deltares)

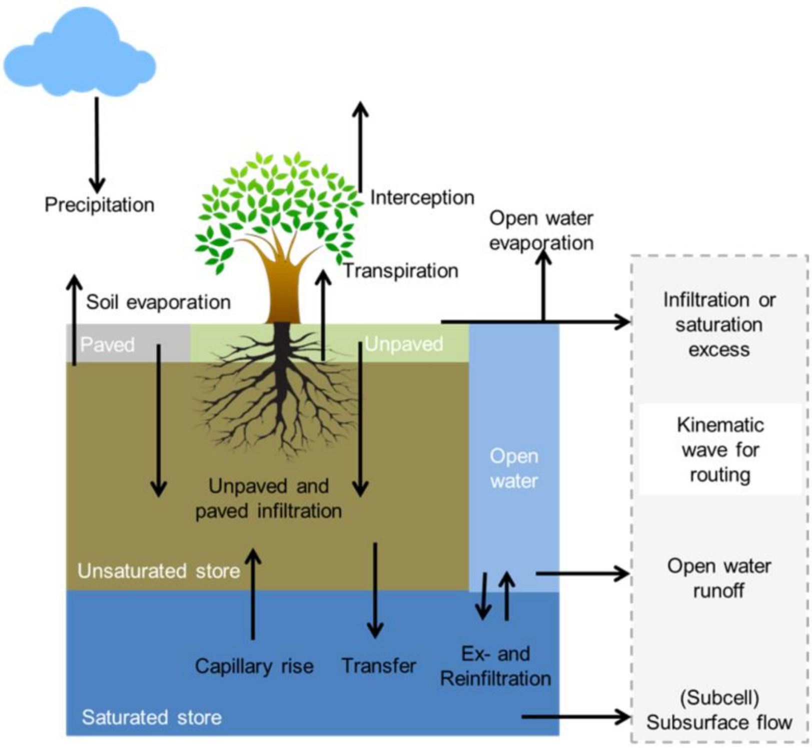


Figure 3. Scheme of W-flow_ sbm (Deltares)

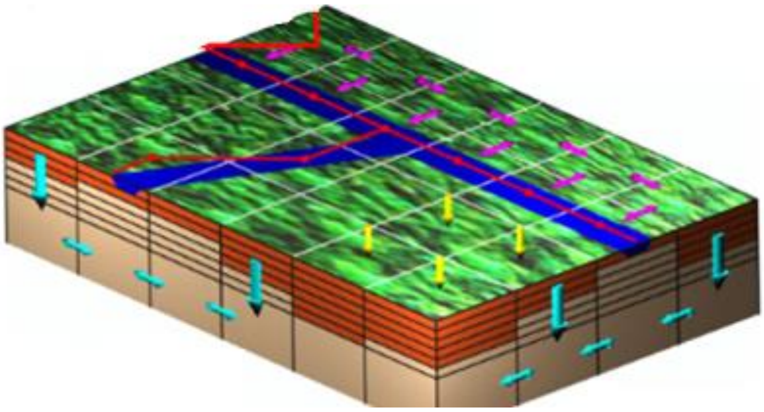


Figure 4. A Grid in the W-flow Model (Deltares)

2.2. Model Evaluation by Using the Statistical Test

Evaluation of data validity that is used in this research consists of 3 methods as follow:

(a) MSE = *Mean Square Error*

In the statistical test, the standard that is used for measuring error is by seeing the mean square error (MSE) which is based on the formula as follow:

$$\text{MSE} = 1/\text{n}\left[\frac{\sum_{n=1}^{n}(St-At)}{At}\right]^2 \quad (1)$$

where MSE is Mean Square Error, St is simulation value at t-time, At is actual value at t-time, and n is number of observation (t = 1, 2, …, n).

The getting smaller of MSE value, it indicates that the error level in the model is also small and vice versa.

(b) RMSPE = Root Mean Square Percent Error

RMSPE is used for measuring the deviation level about estimation result value of endogen variables from each actual value of the endogen variables in the relative measurement (%), or to measure the proximity pf the estimation value with the actual value.

$$RMSPE = 100 \times \sqrt{(1/n) \times \sum\{(Pi - Ai)^2/Ai\}} \quad (2)$$

where *n* is number of observations, *Pi* is value of predicted model, and *Ai* is actual value.

(c) Statistic of U-Theil

Statistic U is used for knowing the model ability to analyze the forecasting simulation analysis. The Theil coefficient value (U) is between 1 and 0. If U = 0, so the model prediction is perfect, however, if U = 1, so the model is naïf. The formulation of U is as follow:

$$U = \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(A_i-P_i)^2\right]^2}{\left[\frac{1}{n}\sum_{i=1}^{n}{A_i}^2\right]^{1/2}+\left[\frac{1}{n}\sum_{i=1}^{n}{P_i}^2\right]^{1/2}} \quad (3)$$

where where n is number of observations, Pi is value of predicted model, and Ai is value of actual model.

2.3. Methodology

The steps of research methodology are as follow:

1. To carry out the literature study: for comparing with the previous research.
2. Data collecting:
   a) Data of satellite observation rainfall
   b) Data of evaporation
   c) Data of discharge
   d) Data of predicted rainfall
   e) Data of pos station rainfall
   f) Map of topography
   g) Map of soil type
   h) Map of land use
   i) Relation between elevation, volume, and reservoir inundation area

j) Data of reservoir operation

k) Data of reservoir service water need

l) Data of information about strategy of reservoir water utilization

3. Development of W-flow model, to build the W-flow model of run-off-rainfall due to the rainfall data
4. To carry out model calibration
5. To carry out the real-time inflow predicted analysis for operation
6. Reporting: conclusion and recommendation

Figure 6 presents the flow chart of study. The input of model generally is static data like map of soil type and map of land use, and others; and dynamic data such as rainfall data and evaporation data that is then producing the information of discharge in every river section as presented in the Figure 5.

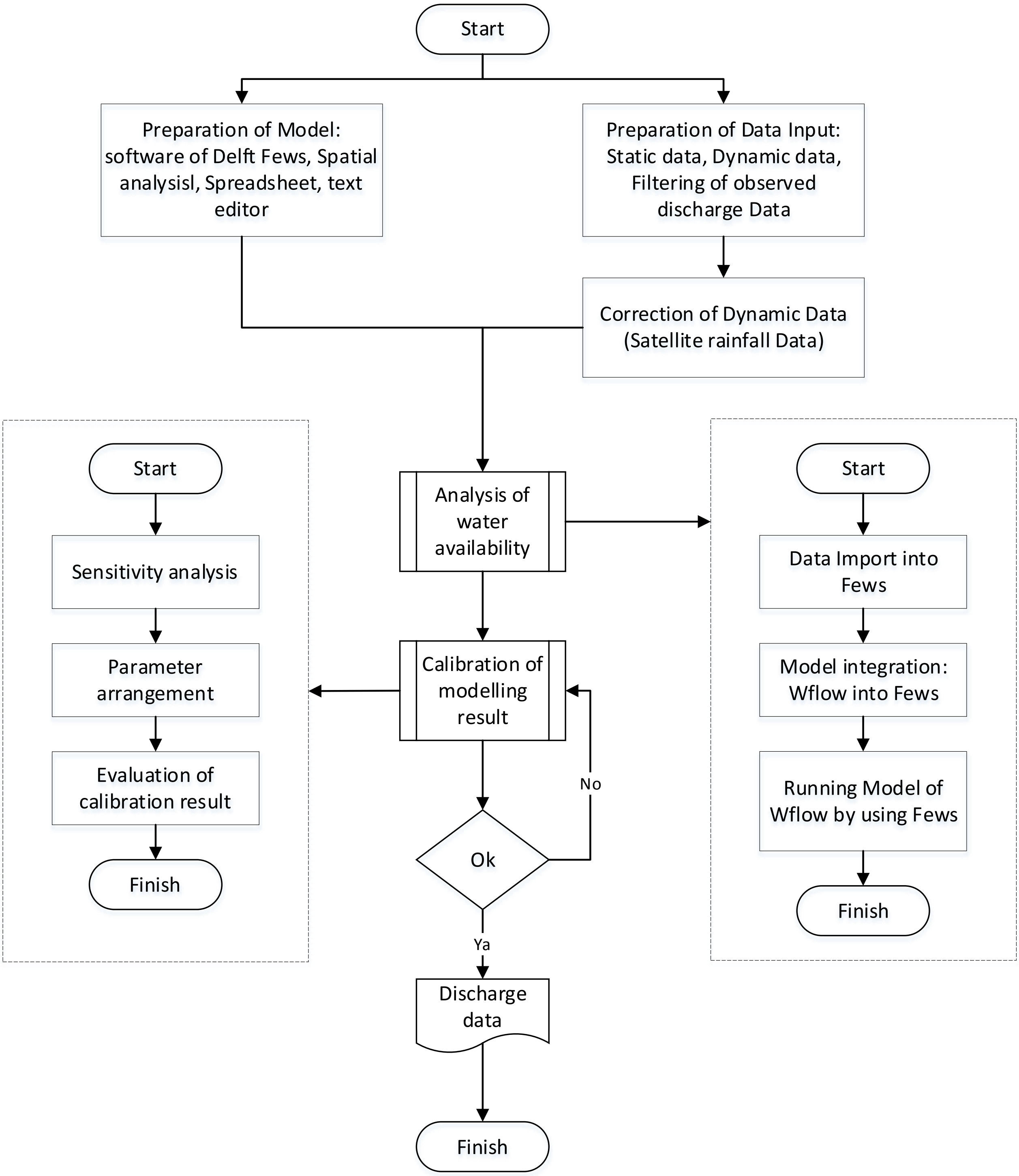


Figure 5. Flow Chart of Study

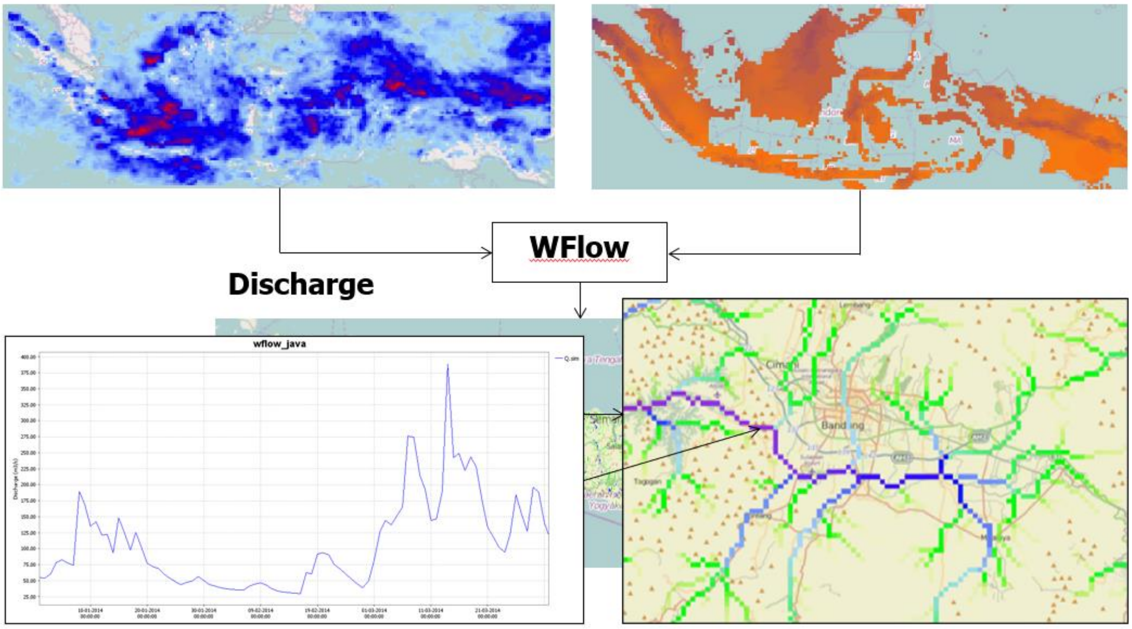


Figure 6. Mechanism of W-flow Modelling

3. Results and Discussion

The W-flow modeling is integrated with the FEWS application so it makes easy in the process of input and presentation of analysis result.

3.1. W-Flow Modeling

The model of W-flow is developed until the middle of Bengawan Solo watershed because it is used for model calibration in one of the water gauges with the good data. Model of W-flow that is built can be seen as in the Figure 7.

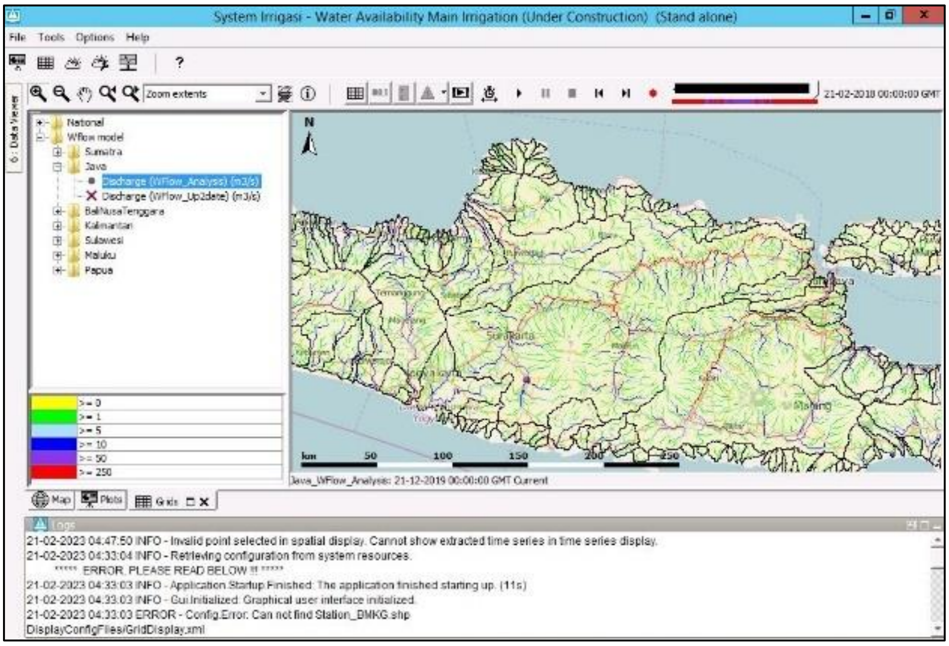


Figure 7. WFLOW Model in the Bengawan Solo Watershed

3.2. Calibration of Model

The reliability of model is necessary to be attended so the result of model simulation produces the discharge data that is close to the condition of discharge data in the field. Due to the data limitation in the research location, the calibration is carried out in the water gauge pos in Bengawan Solo-Jurug that is located in the downstream of Wonogiri dam. By seeing the water level pattern and discharge of water gauge pos, it is assumed that the discharge data in the Bengawan Solo-Jurug water gauge pos is very affected by the rainfall fluctuation from the effect of reservoir operation in the downstream. Therefore, due to the quality and length of data, it can be used for model calibration. The curve of calibration discharge data between Field discharge and simulation result discharge of W-flow model can be seen as in the Figure 8.

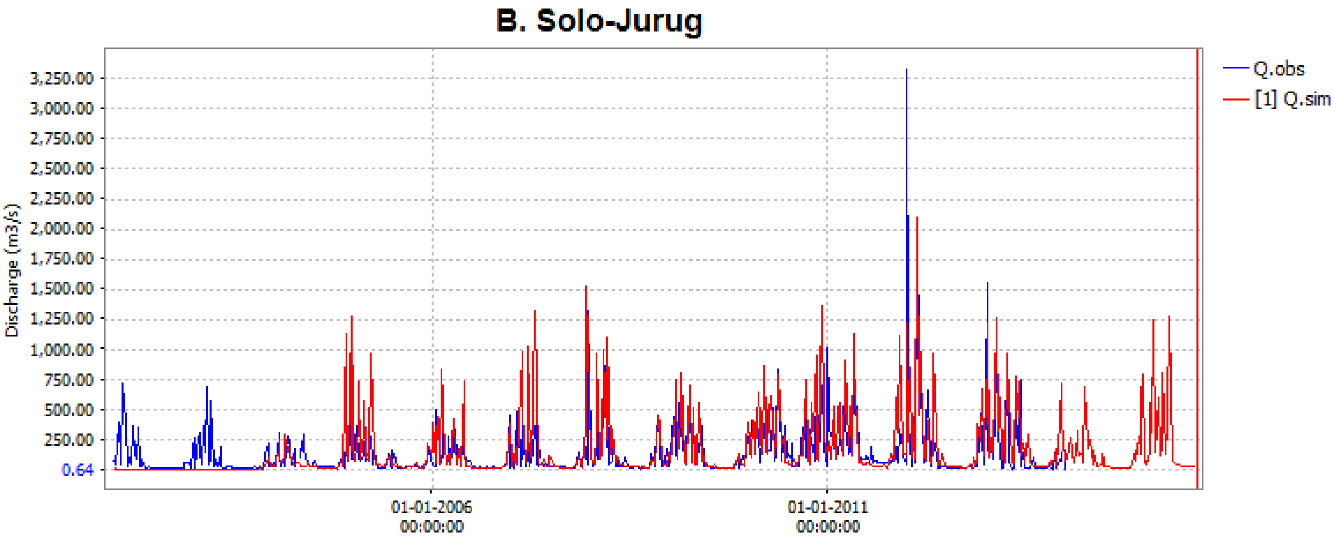


Figure 8. Comparison between WFLOW Model and Observation Data

Statistic measuring of calibration is measured by the 3 conditions that are for all of the data, for the dry season, and for the rainy season. It is carried out for closely seeing the superiority of this model.

The result of statistic measuring shows that the model overall is good enough to predict the discharge from rainfall, and the best is to predict discharge in the dry season. The correlation for the dry season is 83.11% with the smallest RMSE is 99.45. The result of statistic measuring (as presented in the Tables 1 to 3) for the three conditions are presented in the Figures 9 and 10.

Table 1. Statistical Result for the Calibration of Overall Data

Statistical parameter	Value
R2	67.28%
Bias	32.35
MAE	78.51
MSE	23,231.25
MAPE	1.45
RMSE	152.42

Table 2. Statistical Result for Calibration of Dry Season (April-September)

Statistical parameter	Value
R2	83.11%
Bias	21.86
MAE	48.20
MSE	9,890.76
MAPE	1.13
RMSE	99.45

Table 3. Statistical Result for Calibration of Rainy Season (October-March)

Statistical parameter	Value
R2	60.54%
Bias	42.98
MAE	109.22
MSE	36,751.19
MAPE	1.77
RMSE	191.71

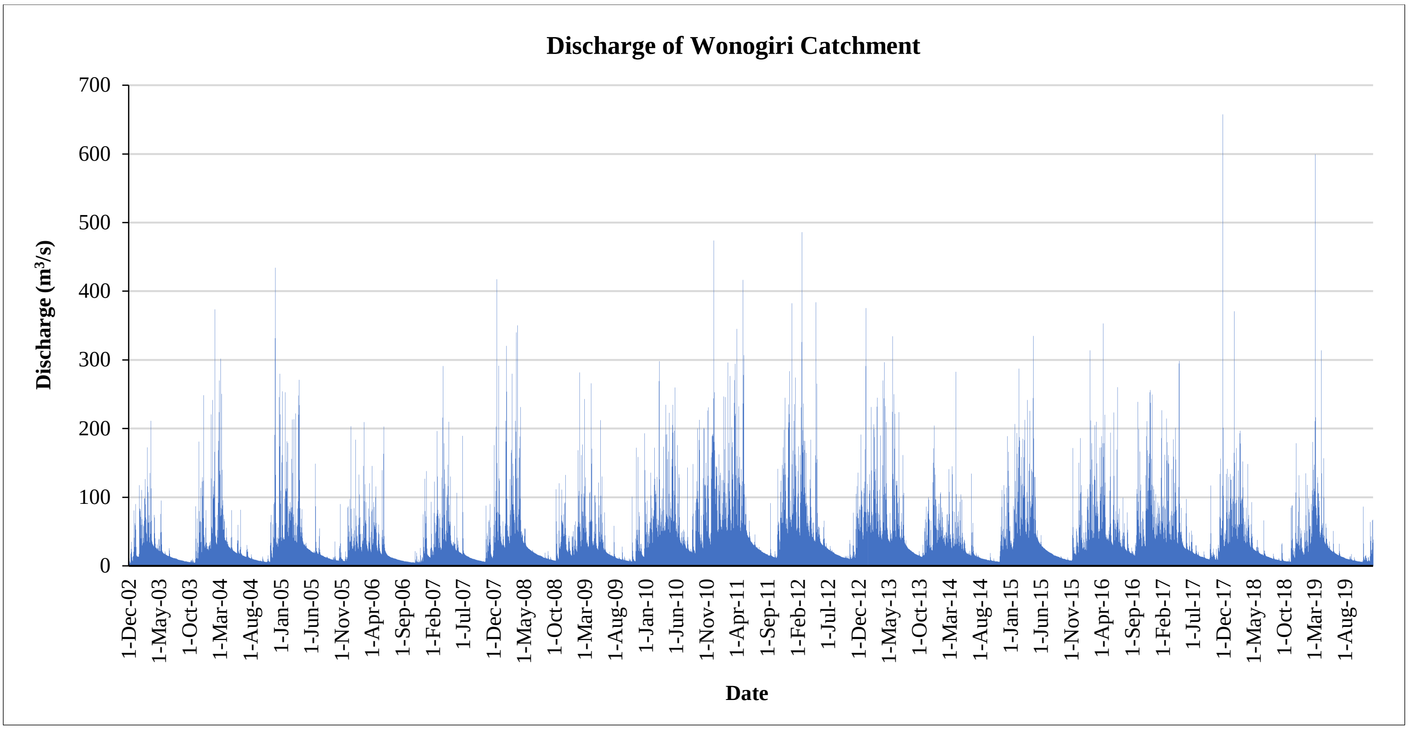
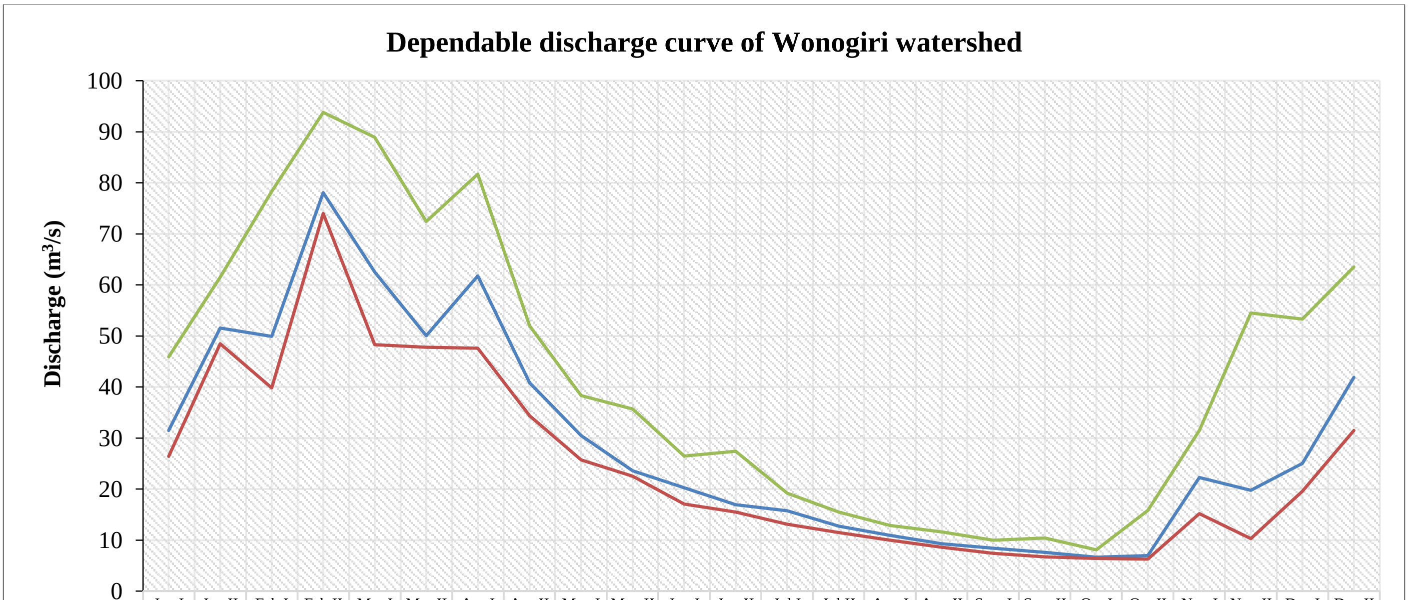


Figure 9. Simulation of Discharge in the Wonogiri Watershed by Using W-flow



	Jan I	Jan II	Feb I	Feb II	Mar I	Mar II	Apr I	Apr II	May I	May II	Jun I	Jun II	Jul I	Jul II	Aug I	Aug II	Sept I	Sept II	Oct I	Oct II	Nov I	Nov II	Dec I	Dec II
Q80	31.5	51.5	49.9	78.1	62.5	50.1	61.7	40.8	30.5	23.6	20.2	17.0	15.8	12.7	10.9	9.3	8.4	7.6	6.6	7.0	22.3	19.8	25.1	41.9
Q90	26.4	48.5	39.8	74.0	48.3	47.8	47.6	34.4	25.7	22.5	17.1	15.5	13.1	11.5	10.0	8.6	7.4	6.7	6.4	6.3	15.2	10.3	19.6	31.5
Q50	45.9	61.5	78.3	93.8	88.9	72.4	81.7	52.0	38.3	35.7	26.5	27.4	19.2	15.5	12.9	11.6	10.0	10.4	8.1	15.8	31.5	54.5	53.3	63.6

Figure 10. Two Weekly Dependable Discharge in the Wonogiri Watershed

The correlation in the dry season is about 83.11% with the smallest RMSE is 99.45. The statistical results for the three conditions are presented in the figures below.

Based on the result of the statistical test that has been carried out in the condition of the whole data, the conditions of dry and rainy seasons, it can be known that the W-flow model that is built has met the requirement of a valid model, so it can be used for carrying out the generation of discharge data for every other year, including to predict the discharge data by using the projection rainfall data. By using the W-flow model with the calibrated parameter, it is possible to know the discharge potential in the Wonogiri watershed, as presented in Figure 8.

Due to the simulation result that has been carried out, it can be known the two weekly dependable discharges: $Q_{80\%}$, $Q_{90\%}$, and $Q_{50\%}$, as presented in Figure 9 and Table 4.

Table 4. Two Weekly Water Availability of Discharge in the Wonogiri Watershed
(Explanation: I = first half month, II = second half month)

Year	Jan I	Jan II	Feb I	Feb II	Mar I	Mar II	Apr I	Apr II	May I	May II	Jun I	Jun II	Jul I	Jul II	Aug I	Aug II	Sept I	Sept II	Oct I	Oct II	Nov I	Nov II	Dec I	Dec II
2002	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	13.2	24.8
2003	30.9	45.4	48.8	71.1	73.8	64.1	38.0	24.4	38.3	18.9	15.8	15.4	11.9	10.7	8.9	7.8	6.7	5.9	6.2	10.0	26.7	64.7	82.7	34.4
2004	27.0	94.3	86.4	116.4	123.9	48.9	33.7	32.4	22.3	25.3	26.5	15.5	16.2	14.0	11.0	9.0	7.7	7.0	7.2	7.3	22.9	47.3	116.7	110.9
2005	75.3	99.1	70.5	93.8	78.7	91.9	91.1	35.7	27.7	23.0	19.8	40.6	24.9	15.5	13.0	11.6	9.7	12.8	8.1	24.0	8.0	11.4	50.5	55.5
2006	53.7	51.4	32.2	78.3	44.8	42.2	61.2	48.4	32.4	59.8	23.3	14.5	12.2	10.6	9.1	8.0	6.9	6.2	5.5	5.0	9.9	8.0	16.4	52.7
2007	15.5	29.3	40.8	83.3	37.2	113.0	63.9	93.1	31.9	37.7	25.6	33.5	19.7	13.9	11.5	10.0	8.5	7.5	6.6	20.8	41.7	18.2	77.8	112.5
2008	45.8	50.5	106.7	78.0	100.8	130.8	107.8	41.2	37.6	25.4	22.0	18.8	16.3	14.5	12.9	12.1	10.0	8.3	25.7	29.2	55.9	58.5	27.1	22.0
2009	33.7	58.0	77.4	96.0	61.3	50.0	79.9	52.6	46.5	61.9	31.0	18.4	16.1	18.9	11.5	10.3	11.3	8.5	7.6	19.9	27.7	54.5	23.7	50.9
2010	45.9	60.0	81.6	84.8	94.1	72.4	85.3	104.5	92.7	119.4	67.9	49.4	39.1	39.2	22.6	40.4	57.3	106.8	42.3	105.8	100.9	93.2	181.7	91.4
2011	88.6	108.5	101.9	123.7	107.0	147.4	132.3	91.3	158.0	51.4	40.9	31.7	29.0	23.9	20.1	17.6	15.4	22.2	13.5	45.4	68.0	125.2	77.3	122.1
2012	140.3	108.6	97.8	205.6	118.3	57.4	81.7	50.8	115.4	39.1	40.0	27.4	23.7	20.6	17.2	15.2	13.0	12.1	11.5	15.8	23.7	67.7	76.6	72.5
2013	124.9	74.9	96.1	115.3	97.5	65.9	138.4	76.8	41.1	137.9	82.2	79.8	69.6	34.8	25.0	21.3	18.1	15.6	14.5	30.0	47.9	45.9	86.0	70.7
2014	63.4	58.5	38.2	68.9	50.7	50.3	73.8	48.8	35.4	21.7	17.1	41.1	15.7	13.2	10.9	9.8	8.6	9.1	7.5	6.5	18.8	60.4	45.8	90.7
2015	34.6	70.7	141.2	75.9	125.1	74.8	105.3	133.0	71.2	34.9	30.2	24.3	20.9	18.3	15.4	13.7	12.0	10.4	9.4	8.0	40.6	26.1	56.1	64.6
2016	34.8	61.5	129.8	97.2	88.9	92.2	122.9	62.7	65.3	58.1	63.0	82.2	32.8	42.6	32.1	20.0	17.3	69.2	83.8	47.0	83.9	139.6	120.2	62.5
2017	64.1	85.3	70.4	100.4	67.5	78.4	84.3	95.5	42.3	35.7	29.3	28.8	19.2	18.6	13.9	13.4	10.6	28.3	16.9	12.9	31.5	129.9	42.3	71.6
2018	76.4	105.9	78.3	103.5	77.9	46.3	54.1	40.7	22.7	23.5	17.1	21.8	13.7	12.0	11.2	9.2	8.4	12.3	6.8	6.9	40.0	38.1	46.3	40.2
2019	25.6	52.1	54.4	93.0	138.0	79.1	73.9	52.0	30.1	23.8	23.0	16.6	16.7	12.6	10.7	10.3	9.4	8.0	6.5	6.1	22.1	8.8	20.9	44.5
Average	57.7	71.4	79.6	99.1	87.4	76.8	84	63.8	53.6	46.9	33.8	32.9	23.4	19.6	15.1	14.1	13.6	20.6	16.5	23.6	39.4	58.7	64.5	66.4
Q80	31.5	51.5	49.9	78.1	62.5	50.1	61.7	40.8	30.5	23.6	20.2	17.0	15.8	12.7	10.9	9.3	8.4	7.6	6.6	7.0	22.3	19.8	25.1	41.9
Q90	26.4	48.5	39.8	74.0	48.3	47.8	47.6	34.4	25.7	22.5	17.1	15.5	13.1	11.5	10.0	8.6	7.4	6.7	6.4	6.3	15.2	10.3	19.6	31.5
Q50	45.9	61.5	78.3	93.8	88.9	72.4	81.7	52.0	38.3	35.7	26.5	27.4	19.2	15.5	12.9	11.6	10.0	10.4	8.1	15.8	31.5	54.5	53.3	63.6

The Gajah Mungkur or Wonogiri reservoir has a catchment area of about 1,350 km^2 and an inundation area of 90 km^2 with its main function being flood control in the Bengawan Solo River. Besides the main function, this reservoir has other functions, such as being the supplier of Colo weir for supplying irrigation water to more than 24,000 ha of irrigated rice area, which is spread in Klaten, Sukoharjo, Karanganyar, and Sragen regencies. Then, as the hydro-electric power supply for Wonogiri area with the maximum capacity of 12.4 MW, it also functioned as tourism.

The prediction of reservoir inflow has an important role in reservoir operation and management [21]. However, the heterogeneity of complex spatial and temporal information from rainfall plus the physiographic context of the watershed causes the model development of real-time run-off and rainfall, which can accurately predict the reservoir inflow some times before, to become a challenge. In relation to the analysis and prediction of rainfall, the constraint and problem that is still often faced is the minimal availability of observed rainfall data spatially as well as temporally; the time series of rainfall data is not long and complete enough; and the number of rainfall stations is less evenly distributed.

Water balance is an important part of water resource utilization. The existence can give an illustration of the water balance condition between water availability and water need in the specific period. The water balance can show the status of water availability as a deficit or surplus. Irrigation as part of water resources management [22], which is a system in society, has a dynamic characteristic that is dependent on the environment's condition, mainly due to some involved actors, the variety of usage, and some types of culture. This condition is getting worse due to the decreasing water resources that can be utilized as irrigation mains, which is caused by climate change, land use change, and other utilizations like domestic needs. Therefore, the complexity and limitations of water resources become challenges to irrigation development today and in the future. By analyzing the relationship between cause and effect that influences water availability and water need and making the formulation an effort of intervention with high leverage.

4. Conclusions

The prediction of reservoir inflow has an important role in reservoir operation and management. However, the heterogeneity of complex spatial and temporal information from rainfall plus the physiographic context of the watershed makes the model development of real-time run-off-rainfall, which can accurately predict the reservoir inflow sometimes before, becomes as a challenge. In design, the series data of reservoir inflow is needed as the input in optimization modeling of reservoir operation and sedimentation, so the accuracy of the data is very important. The model result will bias if there is an error in the data input.

There are 12 ground rainfall stations in the Wonogiri watershed. This data is needed to make easy the correction of satellite rainfall data through comparison with ground station data. The W-flow model is a distributed model that is built for generating discharge data in a region by using rainfall data and the characteristics of the watershed. By using the W-flow model, it can be known the discharge in a river that has not had recorded data, making it easy for the manager to carry out the analysis for the demand of water resources management.

The result of statistical measurement shows that the model overall is good enough to predict discharge from rainfall, and the best is to predict discharge in the dry season. The correlation for the dry season is 83.11% with the smallest RMSE is 99.45. The correlation in the dry season is about 83.11% with the smallest RMSE is 99.45. The analysis result of dependable discharge in the Wonogiri watershed shows that there are two discharge peaks that happened in February-II (the second half of February) and December-II (the second half of December). However, the discharge is decreasing in July, and the lowest point happened in October-II (the second half of October).

5. Declarations

5.1. Author Contributions

Conceptualization, D.R.T. and L.M.L.; methodology, E.S. and Y.P.D.; validation, R.R.T. and E.S.; formal analysis, D.R.T.; investigation, D.R.T. and Y.P.D.; resources, D.R.T. and L.M.L.; data curation, D.R.T. and E.S.; writing—original draft preparation, D.R.T. and L.M.L.; writing—review and editing, Y.P.D. and L.M.L.; visualization, D.R.T., E.S., and Y.P.D. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

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5.4. Conflicts of Interest

The authors declare no conflict of interest.

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