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Analysis of Water Availability Based on Satellite Rainfall in the Upper Brantas River Basin

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Abstract**—** *Analysis of water availability for irrigation is a basic analysis in determining the extent of irrigation and cropping patterns. Discharge and rainfall data is most important in the analysis of water availability. By developing an empirical model, rainfall data can be use to estimate discharge. F.J. Mock model can be use for estimating discharge data when there are no or less availability of discharge data. This research was conducted to utilize rainfall satellite based which has an even distribution for the estimation of water availability in the Upper Brantas River Basin. Rainfall satellite PERSIANN and PERSIANN CCS is calibrated and validated against rainfall gauge station observation in the Upper Brantas River Basin and to be used as input in the analysis of water availability. The calibration of satellite rainfall show a strong correlation with correlation coefficient above 0.8 with BIAS values below 27 %, whereas in the validation process the BIAS value is below 20 %. Estimated discharge (water availability) from F.J.Mock models based on satellite rainfall PERSIANN and PERSIANN CCS with AWLR Gadang show good NSE value of above 0.5, model discharge F.J. Mock based calibrated rainfall satellite PERSIANN-CCS data has lower relative error than PERSIANN based.*

Keywords**—** *Satelite Rainfall, PERSIANN, PERSIANN CCS, Rainfall runoff, Water Availability.*

I. Preliminary

The most basic need in analyzing water availability is the availability of adequate hydrological data. In the process of calculating the availability of water requires a long series of discharge data. In observing the discharge data, there were several technical and non-technical constraints. Observation of discharge data requires a crossbar to find out the water level in the river which is then converted to discharge with the rating curve equation. In observing the water level, it is constrained by erosion and sedimentation and the mowing flow which causes poor quality and quantity of discharge data produced.

Beside from observations, discharge data can be generate by approaching the rainfall runoff model that requires rainfall data that is evenly distributed in a watershed. However, in the process of recording rainfall data it is constrained by the difficulty of finding qualified and disciplined person in recording activities, the location of rain gauge station locations is constrained by location conditions especially in locations that are dense building and densely vegetated. The distribution of rain gauges in the upstream area is less evenly distributed due to the difficulty of the terrain because the upstream area is identical to the dense forest.

The development of technology also affects weather observations, some research institutions use weather satellite observation data to estimate rainfall data. Estimates of rainfall data with satellite data offer important advantages in terms of accuracy, spatial coverage, timeliness and cost efficiency (Vernimmen, R.R.E., Hooijer, A., Mamenun, Aldrian, E., van Dijk, A.I.J.M, 2012). While based on the pattern, the corrected monthly rain satellite data statistically has a close relationship with rain observation rain gauge data so that it can be used to complete the incomplete rainfall observation data (Dasanto, B., D., Boer, R., Pramudya, B., Suharnoto, Y, 2014). In addition, monthly rainfall data from satellite has a close value to the observation rain gauge station data, except for high rainfall (Levina, 2016) and in wet months, the estimation of satellite rainfall increases or is higher than observation rain gauge data (Darand, M., Amanollahi , J., Zandkarimi, S., 2017). In monitoring drought conditions in Indonesia, the use of corrected rainfall satellite data can be considered as input data in the drought analysis (Vernimmen, R.R.E., Hooijer, A., Mamenun, Aldrian, E., van Dijk, A.I.J.M, 2012). The use of TRMM (Tropical Rainfall Measuring Mission) satellite daily information is proposed in estimates of extreme rainfall in areas where there is no recorded rainfall gauge data (Cabrera, J., Yupanqui, R., T., Rau, P, 2016). During the wet season, rainfall satellite tends to overestimate (Zheng Duan, Z., Liu, J., Tuo, Y., Chiogna, G., Disse, M., 2016). A good correlation between rainfall satellite data (CHIRPS) and rainfall gauge data, although estimates of rainfall data are too high (Katsanos, D., Retalis, A., Michaelides, S. 2016). In the tropics, rainfall satellite data has a high correlation (Liu, Z. 2015). The location of the rain gauge station elevation and distance from the body of water do not affect the error of the estimated uncorrected satellite rainfall (CMORPH) (Gumindoga, W., Tom HM Rientjes, THM, Haile, A., T., Makurira, H., Reggiani, P. 2017). The results of the discharge simulation using rainfall satellite data without calibration with rain gauge resulted in a poor value compared to the observation discharge (Jiang, S., Ren. L., Hong, Y., Yang, X., Ma, M., Zhang , Y., Yuan, F., 2014). Products from rainfall satellite are very helpful in the application of water resources and hydrological monitoring (Jiang, S., Zhou, M., Ren, L., Cheng, X., Zhang, P., 2016).

Based on this background, this research aims to calibrate and validate rainfall satellite data so that it can be used to analyze water availability (discharge) and can also be used to fill empty rain data due to equipment damage so that it can describe hydrological conditions in a river basin / watershed.

II. RESEARCH METHODOLOGY

The research location is in the Upper Brantas River Basin which is geographically located on 7^0 44' 55,36" S – 8^0 03' 40,56" S dan 112^0 28' 25,63" E – 112^0 56' 37,51" E. The Upper Brantas River Basin is administratively located in the Batu City, Malang District and Malang City with an area of ± 778,849 km^2. The Upper Brantas River Basin is one of the Basin that has an important influence on the quality and quantity of water availability in parts of East Java Province, Indonesia.

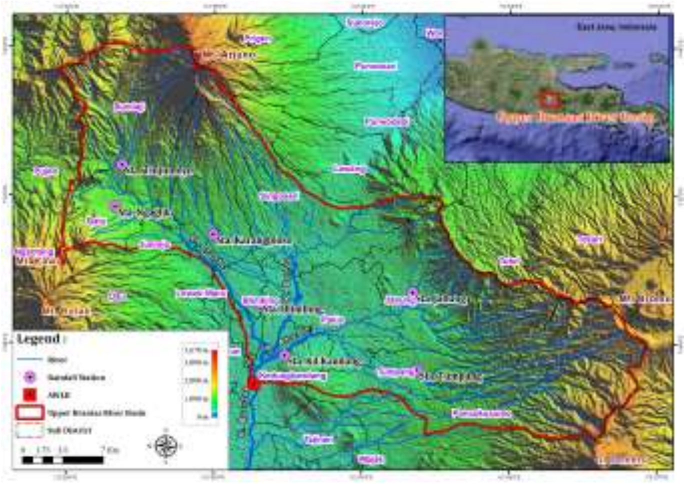

Fig. 1. Location of the Upper Brantas River Basin

Data

The data in this study are:

1. Rainfall of rain gauge stations data for 13 Years (2005-2017). The rain gauge station used in this study can be seen in table 1.

TABLE 1. Rain Gauge Station

No	Rainfall Station	Long	Lat
1	Tinjumoyo	112° 31' 37"	07° 50' 35"
2	Ngaglik	112° 52' 58"	07° 87' 78"
3	Karangploso	112° 35' 53"	07° 53' 28"
4	Blimbing	112° 38' 33"	07° 57' 08"
5	Kedungkandang	112° 39' 20"	07° 59' 35"
6	Jabung	112° 45' 16"	07° 57' 16"
7	Tumpang	112° 45' 38"	07° 59' 57"

2. PERSIANN and PERSIAN CCS rainfall satellite data for 13 years (2005-2017) obtained from the website http://chrsdata.eng.uci.edu/
3. Coordinate of rain gauge station
4. Climatology data
5. Discharge data

In this study using two types of rainfall satellite data, namely PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) and PERSIANN-CCS (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Cloud Classification System). Rainfall satellite data of PERSIANN and PERSIANN CCS were obtained from the website http://chrsdata.eng.uci.edu/.

PERSIANN was developed by the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California, Irvine (UCI) using artificial neural networks. PERSIANN is estimated rain data from infrared brightness provided by geostationer satellites. PERSIANN has a spatial resolution of 0.25° x 0.25° or about 27.8 km x 27.8 km. Examples of PERSIANN rainfall can be seen in Figure 2.

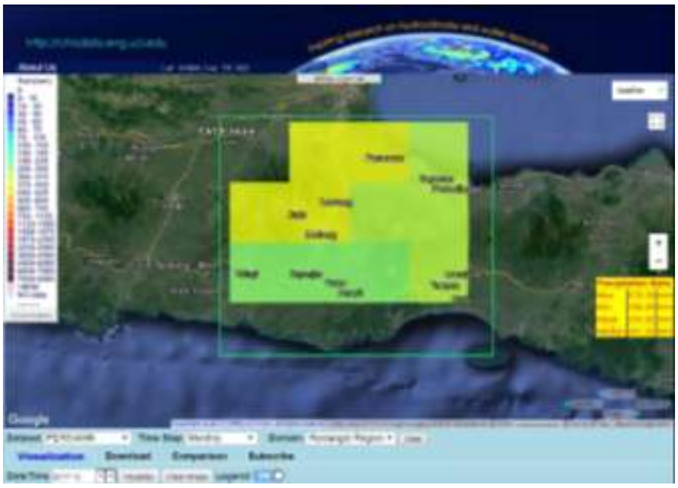

Fig. 2. PERSIANN CCS satellite rainfall in December 2017 around the Upper Brantas River Basin

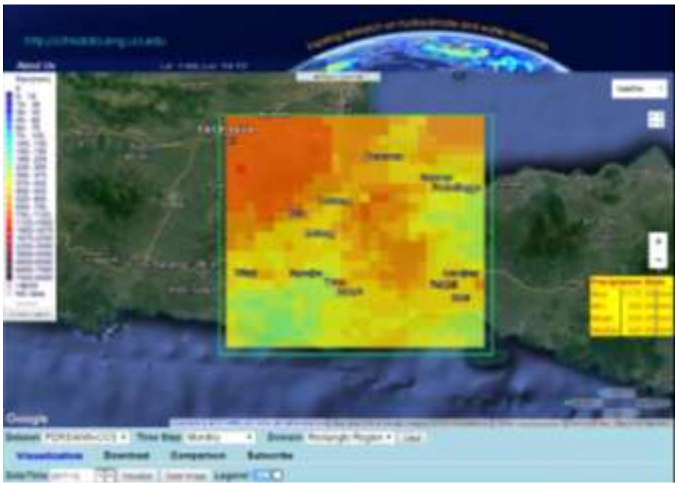

Fig. 3. PERSIANN CCS satellite rainfall in December 2017 around the Upper Brantas River Basin

Figure 3 is rainfall satellite PERSIANN-CCS data which is estimated by the separation of several layers of clouds. PERSIANN CCS rainfall data has a spatial resolution of 0.04° x 0.04° or about 4.4 km x 4.4 km available from January 2003 to the present.

Regional Average Rain

This method takes into account the weight of each station which represents the area around it. In an area within a watershed / basin it is assumed that rain is the same as what happened to the nearest station, so that the rain recorded at a station represents that area.

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$$P = \frac{A_1P_1+A_2P_2+\ldots+A_nP_n}{A_1+A_2+\ldots+A_n} \quad (1)$$

With P_1, P_2,…,P_n is rainfall recorded in the rain gauge station, A1, A2,....An is the area of influence of the rain station and 1,2,3,…, n is the number of rainfall gauge station.

Satellite Rainfall Calibration

Rainfall calibration analysis uses the regression equation y = f (x) which is built from the relationship of satellite rainfall as variable x and measuring rainfall as the variable y which produces the satellite rainfall correction equation. The selection of the regression type based on the highest R^2 value approaches the value 1 because it describes the closeness of the relationship between the two variables. The regression equation is then used to correct the satellite rainfall data by entering satellite rainfall data into the regression equation that is built so that a corrected satellite rainfall.

Linier	$y = a + bx$	(2)
Exponetial	$y = ab^x$	(3)
Polynimial	$y = ax^2 + bx + c$	(4)

With :
y = Rainfall Observation
x = Satellite Rainfall
a,b,c = Coefficient

Calibration accuracy was assessed by correlation coefficient (R) statistics, Bias, Nash sutcliffe efficiency coefficient (NSE). Nash Sutcliffe efficiency coefficient (NSE) is a statistical value that determines the relative magnitude of the residual variance (noise) compared to the measured data variance (information).

Nash-Sutcliffe efficiency can range from −∞ to 1. NSE = 1 indicates that a perfect model, NSE values are recommended between 0.36 <NSE <0.75 (Motovilov, 1999).

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Vmi - Voi)^2}{\sum_{i=1}^{n}(Pmi - \overline{Voi})^2} \quad (5)$$

Where :
Vm = Model result
Vo = Observation result
$\overline{Vo}$ = Average observation result

$$BIAS = \frac{\sum_{i=1}^{n}(Voi - Vmi)}{\sum_{i=1}^{n} Vmi} \times 100\% \quad (6)$$

Where :
Vm = Model result
Vo = Observation result

Water Availability Analysis

Analysis of water availability using the F.J Mock model. The process of F.J.Mock model can be seen in Figure 4, in this stage there are three scenarios based on the type of rain data used, namely rain based rain gauge station (observation) and two rainfall data satellite based, namely PERSIANN and PERSIANN-CCS. F.J method. Mock has two principles for calculating surface runoff, namely water balance above the land surface and water balance under the land surface which are all based on rain, climate and soil conditions.

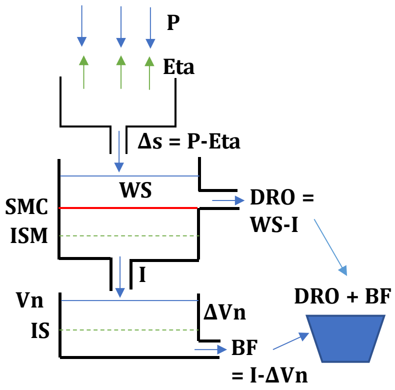

Fig. 4. Model F.J.Mock

Mock (1973) explained the method for estimating river flow discharge with the following stages:

The formula for calculating surface flow consists of:

1. Limited Evapotranspiration
   - $\Delta S = P - ET_p$
   - $E/ET_p = (m/20) . (18 - n)$
   - $E = Et_p . (m/20) . (18\text{-}h) ET_p$
   - $ET_a = ET_p - E$
2. Water Balance
   - $WS = \Delta S - SS$
   - $SS = SMC_n - SMC_{n-1}$
   - $SMC_n = SMC_{n-1} + P_1$
3. Surface water balance
   - $\Delta V_n = V_n - V_{n-1}$
   - $I = i . WS$
   - $V_n = 1/2.(1+k) . IS + k . V_{n-1}$
4. Surface Flow
   - $R_o = BF + DR_o$
   - $BF = 1 - \Delta V_n$
   - $DR_o = WS - I$

Where :
ΔS = Netto rainfall (mm)
P = Rainfall (mm)
ET_p = Potential evapotranspiration (mm)
ET_a = Limited evapotranspiration (mm)
WS = Water surplus (mm)
SS = Soil storage (mm)
SMC = Soil moisture content (mm)
ΔV = Change in groundwater storage (mm)
V = Groundwater content (mm)
IS = Initial storage (mm)
I = Infiltration rate (mm/dt)
i = Infiltration coefficient (<1)
k = Coefficient of groundwater recession (<1)
DR_o = Direct runoff (mm)
BF = Baseflow (mm)
R_o = Runoff (mm)
n = Number of calendar days in 1 month
m = Weight of land not covered by vegetation

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III. Result and Disscussion

Rainfall Area in the Upper Brantas River Basin

Rainfall area calculation of the Upper Brantas River Basin uses the polygon thiessen method with seven influential rain gauge stations in the area. The polygon thieesen map can be seen in Figure 5 while the rain area results of the Upper Brantas river basin can be seen in Figure 6.

Fig. 5. Polygon Thiessen Upper Brantas River Basin

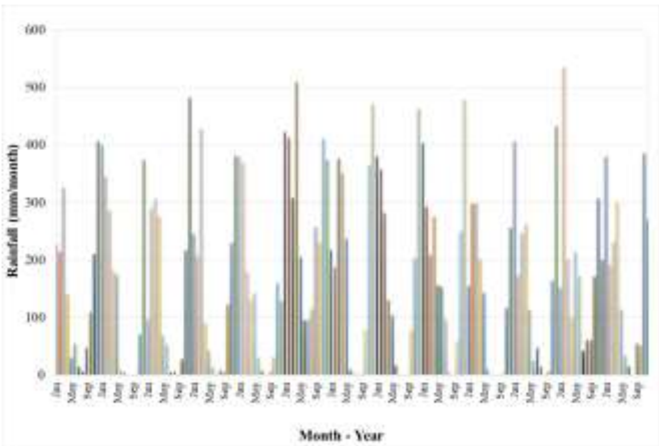

Fig. 6. Rainfall Upper Brantas River Basin

In figure 4 it can be seen that the type of rain on the Upper Brantas river basin is monsoon that in one year there are two seasons namely the rainy season and the dry season. The graph show that the average rainy season starts in October and ends in March while the dry month begins in April to September. the average peak of rain occurs in December and January.

Satellite Rainfall Grid Selection

The selection of PERSIANN and PERSIANN CCS satellite rainfall grids that affect the Upper Brantas river basin by overlaying river basin map with satellite rain grid maps can be seen in Figure 7 and Figure 8. From the map overlay it generates 5 grids for rainfall satellite PERSIANN and 59 grids for PERSIANN-CCS.

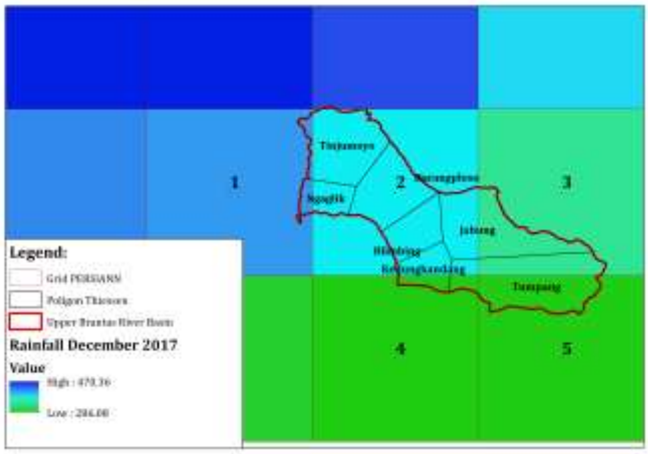

Fig.7. Grid Rainfall PERSIANN Upper Brantas River Basin

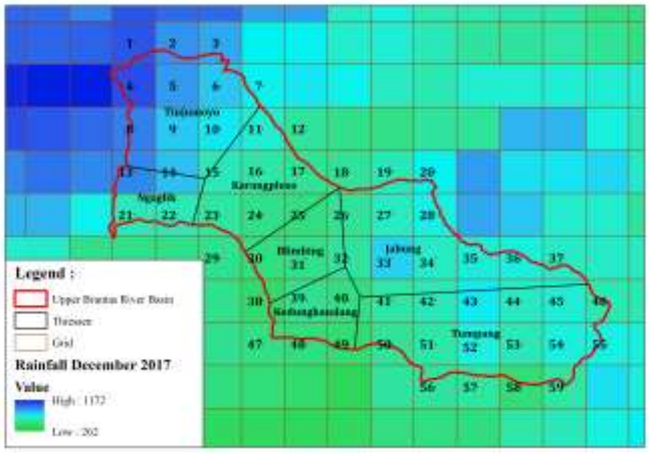

Fig. 8. Grid Rainfall PERSIANN-CCS Upper Brantas River Basin

Comparison of Satellite Rainfall with Gauge Station Rainfall

Monthly patterns of rainfall satellite that occurred in 2005 - 2017 in the Upper Brantas river basin has almost similar with monthly patterns of rainfall rain gauge. Especially PERSIANN-CCS, during wet months has a higher value than rainfall rain gauge while in dry months it close.

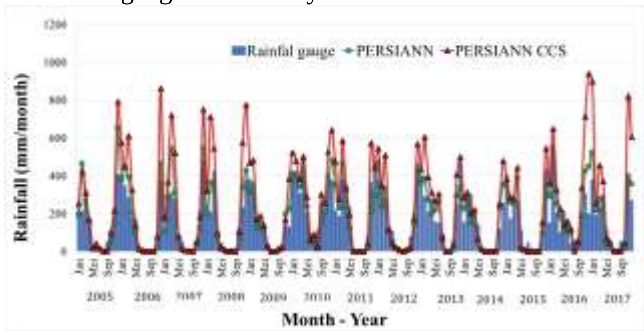

Fig. 9. Monthly Rainfall Upper Brantas River Basin

Calibration of Satellite Rainfall Data

Rainfall calibration is done to minimize the residual value between rainfall satelite with rainfall rain gauge by using a regression equation that is built from satellite rainfall relations as independent variables and rainfall observation as dependent variables using 2005 - 2016 data, while 2017 data to validate the equations model.

In Figure 10 and Figure 11, we can see the regression equation that was built in the type of polynimial with the value R^2 = 0.8191 for PERSIANN and R^2 = 0.8306 for PERSIANN-CCS which indicates a very strong relationship between rainfall satellite with rainfall rain gauge.

The monthly rainfall satellite data in 2005 - 2016 are inputed in the regression equation which is constructed as the x variable and y variable is the result of calibrated rainfall satellite. The results of the calibration using the polynimial regression equation indicate good results, the correlation value rises from 0.89 to 0.91 for PERSIANN and 0.87 to 0.91 for PERSIANN-CCS. RMSE value PERSIANN reduce from 75.76 to 62.56 and PERSIANN-CCS reduce from 148.57 to 61.14. The NSE value of the two types of satellite rainfall are increase while the BIAS value reduce 20 %. In the validation process using 2017 data, PERISANN and PERSIANN CCS corrected satellite rainfall have close values with rainfall rain gauge proven NSE values closer 1 and RMSE values lower than the initial value.

From the accuracy test values in table 2 and table 3 indicate the initial value of rainfall satellite PERSIANN is closer to rainfall gauge data, but after calibration of rainfall satellite PERSIANN-CCS gets better.

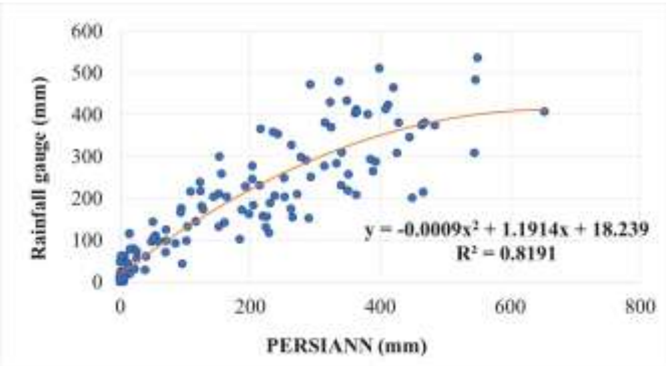

Fig. 10. Equation of Regression of Satellite Rainfall PERSIANN with Monthly Rainfall Observation Upper Brantas River Basin

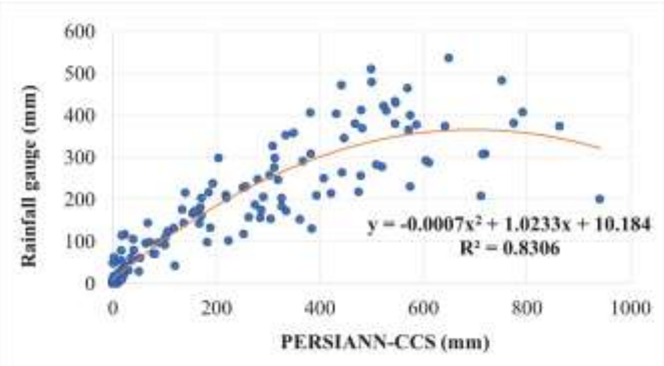

Fig. 11. Equation of Regression of Satellite Rainfall PERSIANN CCS with Monthly Rainfall Observation Upper Brantas River Basin

TABLE 2. Recapitulation of Rainfall PERSIANN Accuracy Test

Parameter	Original	Calibration	Validation
R	0.89	0.91	0.96
RMSE	75.76	62.56	39.01
NSE	0.74	0.82	0.92
MAE	53.28	45.31	34.81
BIAS	31.27	26.59	20.58

TABLE 3. Recapitulation of Rainfall PERSIANN-CCS Accuracy Test

Parameter	Original	Calibration	Validation
R	0.87	0.91	0.96
RMSE	148.57	61.14	46.34
NSE	-0.01	0.83	0.88
MAE	86.06	42.94	32.01
BIAS	50.50	25.19	18.93

Discharge Analysis

Discharge analysis using the F.J Mock method with input of rainfall data, evapotranspiration, river basin area, soil moisture content (SMC), infiltration (I), groundwater recession (K), Initial Storage (IS). Input of rainfall data using rainfall gauge data, calibrated rainfall satellite PERSIANN data and calibrated rainfall satellite PERSIANN-CCS data. The values of SMC, I, K, and IS with trial and error simulations using a solver can be seen in table 4. The results of trial and error result in parameter values that are not much different from F.J.Mock discharge calculation based on rainfal rain gauge with rainfall satellite, this indicates that rainfall data will be the determinant in the calculation of the model.

TABLE 4. Parameters of the F.J.Mock

Parameter Mock	**Rain gauge**	**PERSIANN**	**PERSIANN CCS**
Area (km^2)	774.85	774.85	774.85
m	30	30	30
SMC	250	250	250
I	0.75	0.75	0.75
K	0.85	0.86	0.85
IS	250	250	250

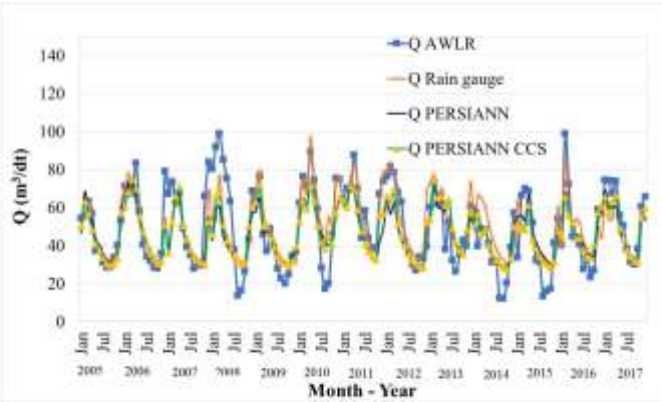

Fig. 12. Discharge Upper Brantas River Basin

From Figure 12 it can be seen that the graph of the discharge value between the AWLR Gadang discharge (observation) and the discharge from F.J.Mock model simulation based on rain gauge and rainfall satellite have a similar pattern, while for the accuracy indicator the model can be seen in table 5.

TABLE 5. Accuracy Test of F.J.Mock Model

Parameter	Based rain gauge	Based PERSIANN	Based PERSIANN-CCS
R	0.80	0.79	0.81
MAE	9.31	10.16	9.50
RMSE	12.35	13.38	12.59
NSE	0.63	0.57	0.62
KR	25.01	24.37	22.97

The discharge model correlation coefficient (R) with three sources of rainfall data types have value above 0.7 which indicates that the model discharges have a strong corellation with AWLR discharge (observation). The RMSE value is also not significantly different from the three results, the model discharge based rain gauge has the smallest RMSE value while based PERSIANN CCS has a smaller RMSE value than the based PERSIANN, this indicates model discharge based rain gauge has smallest the deviation from AWLR discharge, while based PERSIANN-CCS is better than PERSIANN. The NSE value discharge model with three sources of rainfall data types have value above 0.36 which indicates that the model results have quite acceptable results. Of the three discharge models have a value of relative error (KR) below 30 %, this indicates the error value of the discharge model is still within tolerant limits. Model discharge F.J.Mock based rainfall satellite PERSIAAN CCS data has a relative error (KR) value that is smaller than rain gauge based and satellite PERSIANN based, this is interpreted that rainfall satellite PERSIANN-CCS has a smallest error.

IV. Conclusion

Based on the results of data analysis, some conclusions can be taken as follows:

1. Rainfall Satellite PERSIANN and PERSIANN-CCS in the Upper Brantas river basin have a similar pattern and a strong correlation with rainfall rain gauge, this is indicated by the correlation value (R) greater than 0.7. The smaller grids have not provided results that are more closer with rainfall gauge station because the PERSIANN CCS (4.4 km) has a higher residual value for rainfall gauge data than rainfall satellite PERSIANN (27.8 km).
2. Calibration using the regression equation provides significant results for the value of rainfall satellite, especially PERSIANN-CCS. Accuracy of PERSIANN-CCS becomes more closely related to rainfall gauge than rainfall satellite PERSIANN with a smaller BIAS value.
3. Discharge model F.J. Mock of Upper Brantas river basin based on calibrated rainfall satellite PERSIANN CCS produces a lower relative error value against AWLR Gadang discharge (observation) than discharge model based on calibrated rainfall satellite PERSIANN.

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