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Rainfall-Streamflow Relationship using Stepwise Method as a Basis for Rationalization of Rain Gauge Network Density

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Abstract: ***The design of rain gauge network density must be adjusted to meet the information needs of specific water uses, particularly in regard to availability of good quality and quantity of rainfall data. The study has an aim to conduct a rationalization to obtain an optimal number of rain gauge network density based on the WMO standard and the stepwise regression method. The rationalization of rain gauge network density using the stepwise method was carried out by examining the multiple correlation (r) and determination coefficient (R^2) between rainfall and streamflow data and subsequently, to find out the rain gauges that contribute the most to the multiple regression model as a basis to determine the optimal number of rain gauge. The results found that the study area experienced a high density of rain gauge network refer to the WMO standard. The rationalization using the stepwise method showed that five rain gauges recommended as the optimal number of rain gauge. The percentage root mean square (rms) of basin rainfall showed values of 3.58% (less than 10%) which indicated that the recommended rain gauges have no significant problem regarding rainfall variation to determine basin rainfall. The study confirmed that the WMO standard and stepwise method approaches could be used as a sufficient tool to evaluate and rationalize a rain gauge network density in a river basin.***

Keywords: Network density, optimal number of rain gauge, rationalization, stepwise method, WMO standard.

I. INTRODUCTION

Better understanding concerning rainfall runoff relationship on a hydrologic cycle remains important for a hydrologist, particularly in predicting runoff at an ungauged river basin. Most of water allocation and management practices need streamflow data to support well design and planning in water resource projects [1]. Many hydrological models are developed based on rainfall runoff relationship concept to overcome lack of streamflow data availability in a river basin [2]. Hence, it is well understood that necessity to obtain the streamflow data with feasible accuracy strongly depend on how well quality and quantity of rainfall data [3].

Nevertheless, most of water resource managers remain dealing with classical problems concerning availability of rainfall data spatially and temporally. Accordingly, the rain gauge densities and distributions must be well considered in a planning of rain gauge placement in order to allow valid information reflecting spatial and temporal variations of rainfall characteristic in a river basin [4]. A common approach of rationalization of a meteorological network involved decreasing number of locations of measurement station, which was simply a matter of optimization procedure using some statistical measures [5]. Necessity of rationalization of existing rain gauge network was carried out to ensure that adequate information about the occurrence and distribution of rainfall is obtained at an economic cost [6].

The design of rain gauge network density must be adjusted to meet the information needs of specific water uses. The influence of rain gauge density on lumped hydrological runoff modelling was conducted by Zeng et al [7], where modelling uncertainty was reduced by increasing the rain gauge density. The World Meteorological Organization (WMO) has been released a general guide for the minimum required network density of precipitation stations based on basin characteristics. The implementation of stepwise regression method as a tool to overcome water resource problems has been conducted by some researchers. The utilization of the stepwise regression method in climate fields concerns with identification of the relationship between climate data and climate indices [8]. Research conducted by Thomassen et al [9] focused on the implementation of the stepwise regression to simplify the linier models for each of the rainfall variables, while Latt and Wittenberg [10] introduced the stepwise multiple linear regression model as a method for identifying optimal inputs in multistep forecasting floods.

Based on the aforementioned studies, it is acknowledged that most of the studies discussed concerning the implementation of the stepwise regression method as a tool for selecting significant variables, predicting dependent variable, and investigating relationships between variables. Yet, studies regarding feasibility of using the stepwise regression method in examining rationalization of rain gauge network density which associated with streamflow are limited.

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Most of several studies on rainfall-streamflow relationship confirmed that there was a close relationship between rainfall and streamflow [11]. It is well acknowledged that the accuracy of streamflow predictions from a hydrologic model strongly influenced by

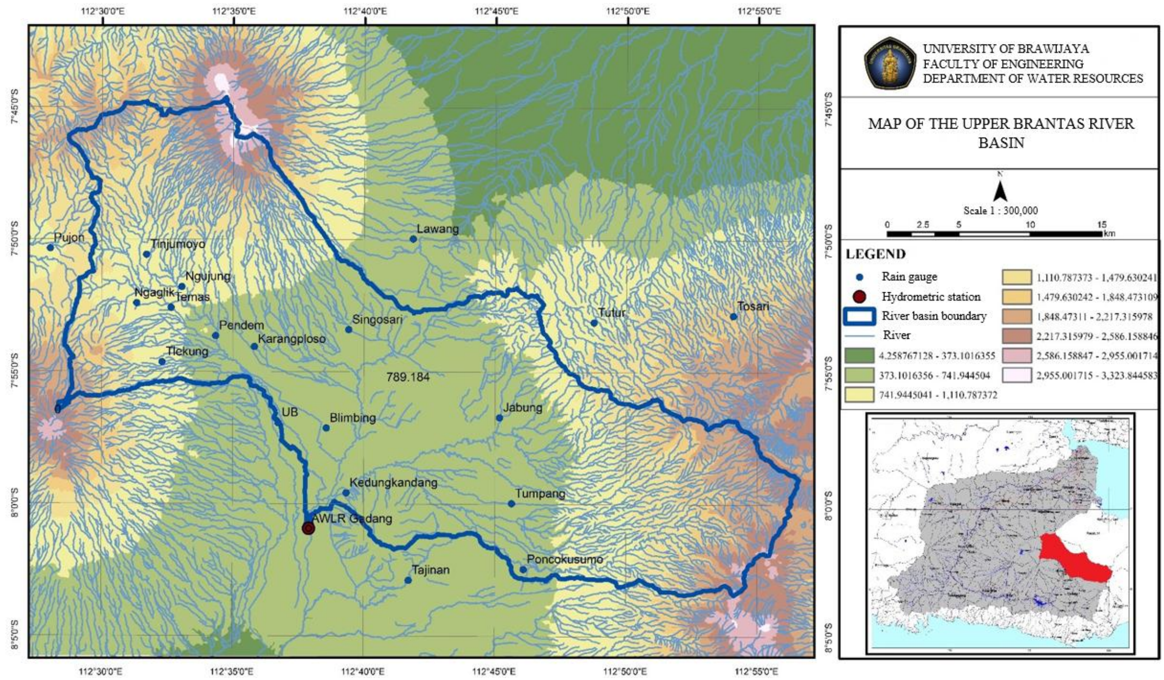

Fig. 1. ap of the Upper Brantas River Basin

the quality of the precipitation inputs [12]. The density of the rain gauge network can affect the results of the calibration and the validation of distributed rainfall-runoff modeling [13]. Due to effect of rainfall event on streamflow characteristic, it is well understood that the reliability of hydrological modelling results strongly depends on the degree of relationship between rainfall and streamflow data. Thus, the present study has an aim to conduct a rationalization of rain gauge network density based on the WMO standard and stepwise method to determine an optimal number of rain gauge in the study area. The multiple linear regression using the stepwise method used to examine the statistical relationship between the rainfall and streamflow data which subsequently used to find out the rain gauges that contribute the most to the multiple regression model as a basis to determine the optimal number of rain gauge.

II. MATERIALS AND METHODS

A. Study Area

The study area was located in the Malang regency, East Java Province, Indonesia. The Upper Brantas river basin has an area of 789.18 km^2 and lies between latitude 7° 45' to 8° 03' S and longitude 112° 34' to 112° 25' E. Topographically, the study area included in highland which is characterized by mountainous area with highest elevation of 3,338 m above sea level. The land slope is dominated by land surface with slope more than 15%. Meteorologically, the area is categorized in tropical zone area with two seasons in annual, dry season (April to September) and rainy season (October to March). Magnitude of mean annual rainfall is around 2000 mm, while mean monthly temperature shows magnitude 20.3^{o}C-25.4^{o}C. Relative humidity in dry season displays value of 67%, while 86% for rainy season, respectively. The rainfall data was collected during 2004 to 2018 from nineteen rain gauges i.e. Tinjumoyo, Ngaglik, Ngujung, Temas, Pendem, Karangploso, Singosari, Blimbing, Kedungkandang, Jabung, Tumpang, Poncokusumo, Lawang, Pujon, Tajinan, Tutur, Tlekung, University of Brawijaya (UB), and Tosari. The source of rainfall data was obtained from Hydrology Laboratory, Department of Water Resources Engineering, University of Brawijaya. Fig. 1 presents the study area along with location of the rain gauge and hydrometric station. The streamflow data were collected from Gadang hydrometric station from 2004 to 2018. A contour map and coordinate of hydrometric station location were used to delineate the basin boundary, while coordinate of rain gauge was used to draw Thiessen polygon in ArcGIS 10.2.2. The estimation of rain gauge coverage area (which indicate an influential of rain gauge) was carried out by the Thiessen polygon method [14]. In order to maintain data quality, some statistical tests were employed for rainfall and streamflow data before proceeding to subsequent analyses, namely homogeneity and normality tests. The normality data was assessed by using Shapiro-Wilk test [15], while the Levene's test was employed to examine homogeneity of rainfall and streamflow data in the study area [16].

B. World Meteorological Organization (WMO)

The WMO presents standard for determining the minimum requirement of coverage area of rain gauge based on topographical and climate characteristics of a basin. Considering that the study area include in mountainous area with tropical climate, thus the minimum coverage area of one rain gauge is 100-250 km^2.

In this study, the rationalization of rain gauge network density was performed by investigating the density of existing rain gauge compared with the minimum standard of rain gauge recommended by the WMO. Further analysis of rationalization of rain gauge network was carried out by applying the stepwise regression method to evaluate the optimal number of rain gauge in the study area, as well.

C. Stepwise Regression Method

Stepwise regression method is a method that is widely used in applied regression analysis to handle a large number of predictor variables to obtain the best model from a regression analysis. The method involves several stages of selecting predictor variables as input to the regression model, of selecting predictor variables of selecting predictor variables as input to the regression model, then selecting one or several predictor variables that are really significant in explaining response variables. In this study, the stepwise method was performed by considering rainfall data at each rain gauge as the predictor variables and streamflow data as the response variable. The stepwise multiple regression equation can be defined as follows:

$$Q_i = \alpha + \beta_1 \times P_{RG\_1} + \beta_2 \times P_{RG\_2} + \ldots + \beta_k \times P_{RG\_k} + \xi \text{ for } i = 1, \ldots, n \text{ samples} \quad (1)$$

$$Q_i = \alpha + \sum_{j=1}^{k} \beta_j P_{RG\_j} + \xi \quad (2)$$

where Q_i is observed streamflow at period i, P_{RGj} is rainfall at rain gauge j in period i, α and β are unknown constant to be estimated from data, and ε denotes random errors. The term of random errors are assumed to be independent and identically distributed as normal distribution with mean zero and variance σ^2 [17]. Predicted values of Q_i expressed as $\hat{Q}_i$ can be obtained by calculating coefficients $\hat{\alpha}$ and $\hat{\beta}$ via a least square method, thus:

$$\hat{Q}_i = \hat{\alpha} + \hat{\beta}_1 . P_{RG\_1} + \hat{\beta}_2 . P_{RG\_2} + \ldots + \hat{\beta}_k . P_{RG}\_k + \xi \text{ for } i = 1, \ldots\ldots, n \text{ samples} \quad (3)$$

In a stepwise regression method, rainfall data at rain gauges as predictor variables are entered into the regression equation one at a time based upon statistical criteria. The selection of each predictor variable (rainfall at rain gauge) is done by assessing the partial correlation value of each predictor variable (rainfall at rain gauges) to the response variable (streamflow at hydrometric station). The predictor variable that contributes the most to the prediction equation in terms of increasing the multiple correlation is entered first at each step in the analysis. This process is continued only if additional the predictor variables add anything statistically to the regression equation. The process stops when no additional predictor variables add anything statistically meaningful to the regression equation. The rain gauges with the highest partial correlation is sequenced for subsequent simultaneous correlation to obtain the highest multiple correlation which addresses to the best model regression. The rain gauges which simultaneously produce highest multiple correlation (r) and determination coefficient (R^2) in the stepwise regression were selected as recommended rain gauges. The best regression model which composed of the recommended rain gauges (selected rain gauges) is considered to have an optimal number of influential rain gauges and used as a basis of rationalization of rain gauge network in the study area. The performance of the regression model resulted was assessed and evaluated through a magnitude of R^2, r, F_{-test} from ANOVA test, and t_{-test} [18]. In order to assure that the recommended rain gauge network shows a good performance, the percentage of root mean square error (*rms*) of basin rainfall was calculated and compared with maximum tolerance of root mean square (*rms*) [19]. Huang et al [20] used 10% as the maximum tolerance of root mean square, whereas 7% of the tolerance of root mean square was applied in New Zealand [19]. The percentage of root mean square error (*rms*) was computed using following equation [19] :

$$\sigma_e = 100.Cv.\left(\frac{1}{3}(1-\rho_n).N^{0.5}\right)^{0.5} \quad (4)$$

where, σ_e is percentage of root mean square error of basin rainfall, Cv is average coefficient of variation of the recommended rain gauges, ρ_n is average of correlation coefficient of the recommended rain gauges, and N is number of the recommended rain gauges. In addition, the interstation of correlation analyses between rain gauges were used as a basis for selecting the rain gauge as well, since Hendrick and Comer [21] recommended that neighboring gauges have a 0.9 correlation or higher could be used as a consideration to select the rain gauge in the rationalization. Moreover, consideration was also taken in regard to dispersion of rain gauge location where the recommended rain gauge should be uniformly distributed over the basin study area [6]. Subsequent analysis concerning the weighted area of the recommended rain gauge was checked its suitability with the WMO standard in order to ensure the result of rationalization of rain gauge.

III. RESULTS AND DISCUSSION

Table-I summarizes annual rainfall characteristics for each rain gauge during 2004 to 2018. From Table-I, it could be known that the mean annual rainfall is in ranging 1470 mm – 2444 mm while the coefficient of variation (Cv) shows a value of 0.12 – 0.40 which indicates homogeneity of rainfall data. The skewness coefficient of rainfall data displays magnitude of 0.08 – 1.26 which denotes that the characteristic of rainfall data tend to fulfill normal distribution assumption. Table-II presents results of statistical testing of rainfall data for each rain gauge and streamflow data, including homogeneity and normality tests. The homogeneity test for rainfall and streamflow data was done by using Levene's test at 0.05 *sig.* level while the normality test was performed by using Shapiro-Wilk test. The statistical tests were performed by using Minitab ver. 17. The decision to accept or reject null hypothesis was decided by assessing p-value and the *sig*. level, where p-value > 0.05 indicate acceptance of null hypothesis.

According to Table-II, it could be known that both rainfall and streamflow owned *p*-value > 0.05 for the Levene's test and Shapiro-Wilk test which means that homogeneity and normality test were accepted for rainfall and streamflow data.

The WMO standard had been used as a tool for evaluating and rationalizing the rain gauge network [22]. Geographically, study area includes in a tropical mountain Mediterranean and moderate region, thus one rain gauge encompasses a minimum coverage area of 100-250 km^2.

Table-I: Summary of annual rainfall characteristics for each rain gauge

Sta. No	Rain gauge	Elev. (m)	Latitude (S)	Longitude (E)	Mean Annual (mm)	Coeff. of Variation (*Cv*)	Coeff. of Skewness
1	Tinjumoyo	1002	7° 50' 35.05"	112° 31' 41.82"	1850	0.26	1.13
2	Ngaglik	929	7° 52′ 24.66″	112° 31′ 19.87″	1470	0.17	0.50
3	Ngujung	825	7° 51′ 52.01″	112° 32′ 58.67″	1599	0.12	1.17
4	Temas	907	7° 53' 3.06"	112° 31' 49.76"	1637	0.25	1.24
5	Pendem	386	7° 42' 19.06"	111° 19' 21.20"	1575	0.22	0.13
6	Karangploso	550	7° 54' 3.6"	112° 35' 49.2"	1793	0.40	1.32
7	Singosari	507	7° 53' 24.72"	112° 39' 24.48'	2093	0.23	0.08
8	Blimbing	470	7° 57' 7.92"	112° 38' 34.08"	1940	0.14	0.41
9	Kedungkandang	434	7° 59' 32.73"	112° 39' 10.63'	1820	0.17	0.33
10	Jabung	543	7° 59' 58.56"	112° 45' 38.16"	2159	0.31	0.82
11	Tumpang	618	7° 59' 58.56"	112° 45' 38.16"	2246	0.17	1.19
12	Poncokusumo	624	8° 2' 26.88"	112° 46' 5.16"	1982	0.23	1.26
13	Lawang	511	8° 2' 26.88"	112° 46' 5.16"	1912	0.25	0.12
14	Pujon	1090	7° 50' 20.76"	112° 28' 1.92"	2317	0.20	1.11
15	Tajinan	489	8° 2' 53.52"	112° 41' 42.72"	2009	0.29	1.24
16	Tutur	1050	7° 53' 7.08"	112° 48' 45.12"	2444	0.23	0.54
17	Tlekung	942	7° 54' 53.19'	112° 31' 47.11"	1606	0.31	0.77
18	Tosari	1714	7° 52' 51.96"	112° 54' 2.88"	2293	0.20	0.90
19	UB	497	7° 57' 6.12"	112° 36' 50.04"	1946	0.32	0.87

Table-II: Statistical testing for annual rainfall and streamflow data

Sta. No	Rain gauge	Levene's test *p*-value	Shapiro-Wilk test *p*-value
1	Tinjumoyo	0.078	0.949
2	Ngaglik	0.130	0.936
3	Ngujung	0.082	0.927
4	Temas	0.178	0.976
5	Pendem	0.338	0.968
6	Karangploso	0.606	0.984
7	Singosari	0.919	0.970
8	Blimbing	0.192	0.855
9	Kedungkandang	0.279	0.949
10	Jabung	0.358	0.981
11	Tumpang	0.773	0.989
12	Poncokusumo	0.927	0.980
13	Lawang	0.813	0.915
14	Pujon	0.881	0.980
15	Tajinan	0.462	0.938
16	Tutur	0.872	0.973
17	Tlekung	0.929	0.933
18	Tosari	0.932	0.988
19	UB	0.496	0.962
20	Gadang[a)]	0.595	0.258

[a)] Hydrometric station

A. Rationalization of Rain Gauge Density with WMO Standard

Fig. 2 presents map of existing rain gauge network along with their coverage area created using polygon Thiessen method. The number listed inside the polygon in the Fig. 2 indicated the coverage area (area of polygon) which represents the magnitude of influential area of rain gauge. The higher an area of polygon, the higher an influential area of a rain gauge in a basin. From Fig. 2, it could be revealed that all of coverage area of nineteen rain gauges were less than the minimum standard of coverage area recommended by the WMO. The coverage area of nineteen rain gauges was found less than 100 km^2, which means that high density of the rain gauge network was experienced in the study area. Therefore, the rain gauge network needs to be rationalized. The results were consistent with [23, 24] who found that the rain network density in the most part of Brantas river basin need to be rationalized considering their coverage area that still below the WMO standard.

B. Rationalization Rain Gauge Network Density Using Stepwise Method

The rationalization of the rain gauge network using stepwise regression was performed by using IBM SPSS Statistics 21. The input variables consist of annual rainfall data from nineteen rain gauges as the predictor variables and streamflow data from Gadang hydrometric station as the response variable. The stepwise regression analysis was started by entering the rainfall data at rain gauges (as the predictor variables) into the regression equation one at a time, then the predictor variable that owing highest partial correlation was entered first at each step in the analysis [25]. Table-III shows the summary of the stepwise regression model output. The result of stepwise analysis showed that there were five rain gauges selected as predictor variables that contribute the most to build the regression model, namely Tutur (Sta. No 16), Tlekung (Sta. No 17), Pendem (Sta. No 5), Lawang (Sta. No 13), and Tajinan (Sta. No 15), respectively.

Table-III demonstrated that there were five regression models that likely created from the selected predictor variables as previously explained. The values of correlation coefficient (*r*) displayed ranging between 0.834 – 0.982, while the determination coefficient (R^2) were in range from 0.635 – 0.906. The determination coefficient (R^2) indicates how much degree of influence of the selected predictor variables (rain gauges) simultaneously on the response variable (streamflow data). Thus, it could be confirmed that for each of the five regression

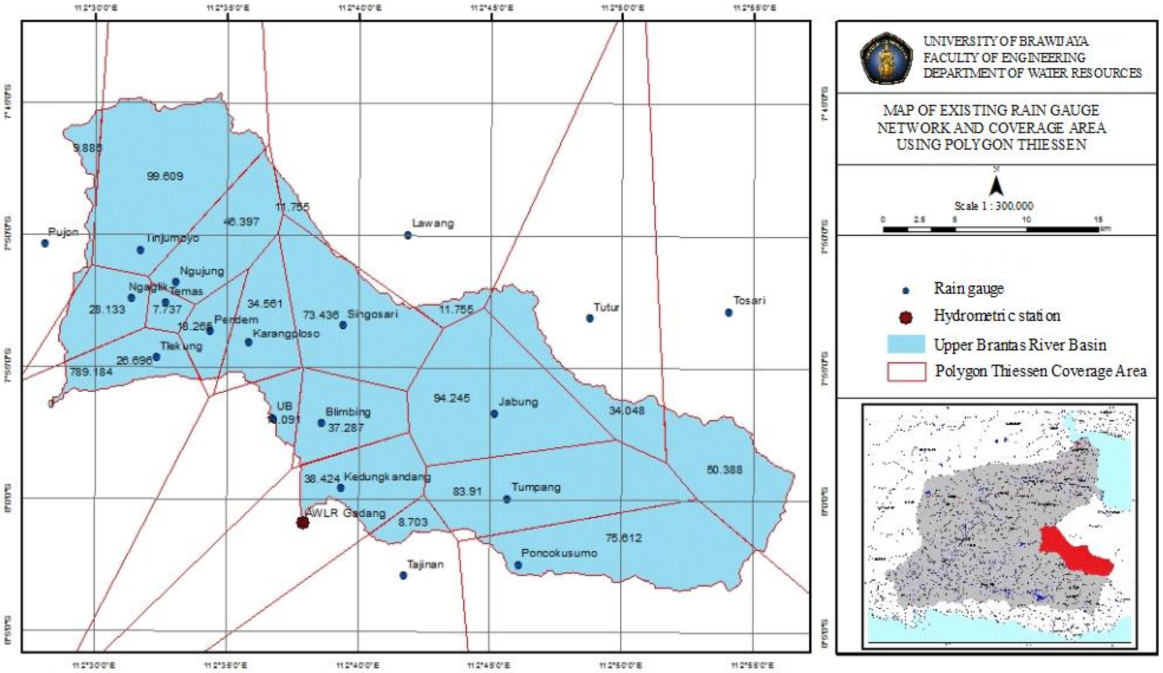

Fig. 2. Map of existing rain gauge network and coverage area

Table-III: Summary of the stepwise regression model output

Model Summary						
Model	**Predictor Variable**	***r***	**Adjusted R^2**	Std. Error of the Estimate	ANOVA F_{test} *Sig.*	t_{test}-*Sig.*
1	Tutur (Sta. No 16)	0.834	0.635	3297.87	0.020	0.155
2	Tutur (Sta. No 16)	0.954	0.865	2005.24	0.008	0.020
	Tlekung (Sta. No 17)					0.014
3	Tutur (Sta. No 16)	0.968	0.884	449.71	0.001	0.006
	Tlekung (Sta. No 17)					0.037
	Pendem (Sta. No 5)					0.000
4	Tutur (Sta. No 16)	0.971	0.887	97.19	0.000	0.002
	Tlekung (Sta. No 17)					0.001
	Pendem (Sta. No 5)					0.003
	Lawang (Sta. No 13)					0.000
5	Tutur (Sta. No 16)	0.982	0.906	4.38	0.001	0.001
	Tlekung (Sta. No 17)					0.000
	Pendem (Sta. No 5)					0.001
	Lawang (Sta. No 13)					0.016
	Tajinan (Sta. No 15)					0.001
Dependent Variable: Streamflow						

models, the predictor variables gave a significant contribution 63.5% - 90.6% to the streamflow characteristic. Table-III exhibits that the result of stepwise regression method with a combination of 5 rain gauges (5^{th} model) have the best correlation coefficient (*r*) and determination (R^2) with the streamflow data.

The 4^{th} model of regression demonstrated high correlation coefficient (*r*) and determination (R^2) as shown in Table-III, as well, however further analysis showed that the 5^{th} model of regression showed the value of 4.38 which was the least value of standard error of estimate compared with the 4^{th} model. In addition, the results of ANOVA F_{test} and t_{test} analysis showed that all the five rain gauges simultaneously have a significant influence on the streamflow at Gadang hydrometric station. The similar results has a good agreement with the researches conducted by Ranesa et al [26]. Accordingly, it could be concluded that the result of rationalization using stepwise regression method showed an optimal rain gauge network which consist of five rain gauges namely Tutur (Sta. No 16), Tlekung (Sta. No 17), Pendem (Sta. No 5), Lawang (Sta. No 13), and Tajinan (Sta. No 15), respectively.

Thus, from the total number of existing rain gauge (nineteen rain gauges), it was only five rain gauges were recommended to be used based on the stepwise regression method. It is obviously that if compared with the other rain gauges, the value of rainfall data

Table-IV: Interstation of correlation analyses between each recommended rain gauges

Rain gauge	Correlation coefficient (*r*)					Average of correlation coefficient (*r*)
	Pendem	Lawang	Tajinan	Tutur	Tlekung	
Pendem	1					
Lawang	0.79	1				
Tajinan	0.87	0.89	1			0.81
Tutur	0.75	0.88	0.88	1		
Tlekung	0.59	0.86	0.71	0.81	1	

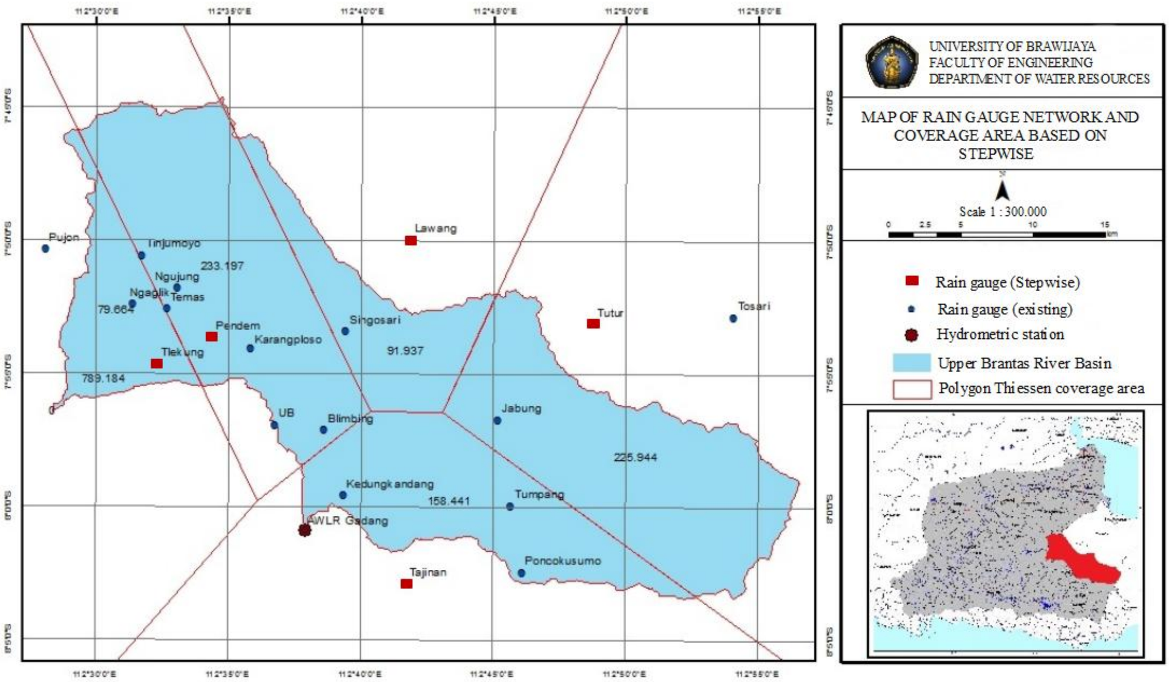

Fig. 3. Map of recommended rain gauge network and coverage area from the stepwise method

at the recommended rain gauges has a good quality to depict the relationship with the streamflow data. Note that the stepwise regression emphasizes on the relationship between the rainfall data with the streamflow data, thus the quality of rainfall data plays an important role in this matter. Regardless the location of rain gauge in the basin area, the rainfall data remain an essential factor in regard to produce the best statistical regression.

C. Feasibility Analysis of the Recommended Rain Gauges Network from the Stepwise Method

Table-IV describes the interstation of correlation analyses between each recommended rain gauges. From, Table-IV, it could be known that the entire of correlation coefficients (*r*) were less than 0.9. Thus, the present study adopted criteria of correlation coefficient 0.6 or higher to perform the rationalization of rain gauge by considering that the study area is included in highland region which is most likely experiencing in heterogeneity of rainfall data characteristics [23]. Based on Table-IV, it could be seen that the correlation coefficient (*r*) showed higher than 0.6, thus it means that the recommended rain gauges were feasible to be proposed in the study area. Further, the tolerable percentage root mean square (*rms*) error of basin rainfall for the recommended network of rain gauges was computed according to Eq. (4) proposed by Dymond [19] where the equation needed the variable of average of correlation coefficient (*r*) and average of coefficient of variation (*Cv*) in its computation process. Table-IV displays the value of 0.81 of the average of correlation coefficient (*r*), while the average of *Cv* of the recommended rain gauges obtained from Table-I which showed value of 0.26. Then, the computation of the tolerable percentage root mean square (*rms*) of basin rainfall using Eq. (4) displays a result of 3.58%. A good network of rain gauges should have the tolerable percentage root mean square (*rms*) of basin rainfall less than 10% [20] or 7% [19]. Thus, the network of the recommended rain gauges fulfills the requirement as a good network. Since the percentage root mean square (*rms*) of basin rainfall indicates level of variation of rainfall data caused by spatial of rain gauges location, thus it is confirmed that the recommended rain gauges have no significant problem regarding rainfall variation to determine basin rainfall.

Additional feasibility analyses were employed to examine dispersion of location of the recommended rain gauges in the study area. O'Connel et al [6] mentioned that the recommended rain gauge should be uniformly distributed over the basin. The location of the recommended rain gauges was checked with the WMO standard in terms of the coverage area of each recommended rain gauge. The five recommended rain gauges were considered represent spatially rainfall characteristic of the fourteen rain gauges based on the coverage area of each recommended rain gauges. The new coverage area was developed using Thiessen polygon for each five recommended rain gauge resulted from the stepwise method. The new coverage area for each rain gauge was verified with the minimum standard coverage area recommended by the WMO.

Fig. 3 displays the new coverage area for five recommended rain gauges from the stepwise method using the Thiessen polygon. The coverage area of each recommended rain gauge was shown by the number listed inside the polygon boundary.

Table-V: Coverage area of recommended rain gauges based on stepwise regression

No.	Rain gauge	Coverage area (km^2)	Percentage of coverage area (%)
1	Pendem	233,19	29.55
2	Lawang	91,93	11.65
3	Tajinan	158,44	20.08
4	Tutur	225,94	28.63
5	Tlekung	79,66	10.09
Total		789,18	100

As displayed in Fig. 3, there are three recommended rain gauges situated beyond the boundary of basin area (Tutur, Lawang, and Tajinan). This circumstance should not be a problem as long as the three rain gauges situated in neighborhood of basin boundary. Accordingly, it is possible to the rain gauge to have a considerable contribution to the mean areal rainfall on a basin [24]. Table-V summarizes the coverage area for each recommended rain gauge based on stepwise regression analysis. Based on Table-V and Fig. 3, the coverage area of recommended rain gauges from the stepwise method does not exceed the WMO standard where the minimum coverage area of one rain gauge should take value in range 100-250 km^2 for a tropical, mountainous, mediterranean, and moderate region type. Table-V reveals that the coverage area of each recommended rain gauge (Pendem, Lawang, Tajinan, Tutur, and Tlekung) is less than 250 km^2 which meet with the WMO guidelines. Moreover, the value of the percentage of coverage area which is in range of 10.09% - 29.55% as shown in Table-V, shows the dispersion of the location of the recommended rain gauges has been relatively accommodated geographical representation of the rain gauges area from Western, Northern, Southern, and Eastern parts of the study area. The result of the present study have been revealed that the stepwise regression method combined with the WMO guidelines feasible to be implemented as a tool to evaluate and rationalize the rain gauge network in the study area.

IV. CONCLUSION

The rationalization of the existing rain gauge network density was performed based on the WMO standard and stepwise regression method. The results found that the study area experienced a high density of rain gauge network where all the existing rain gauges have a coverage area less than 100 km^2 which was below the minimum standard of coverage area recommended by the WMO. The rationalization of rain gauge network density using the stepwise regression method showed that only five rain gauges recommended in the study area considering their best multiple correlation (r) and determination coefficient (R^2) with the streamflow data. The percentage root mean square (*rms*) of basin rainfall showed values of 3.58% (less than 10%) which indicated that the recommended rain gauges have no significant problem regarding rainfall variation to determine basin rainfall. Further analysis confirmed that the coverage area of recommended rain gauge fulfilled the WMO guidelines where the coverage area of each recommended rain gauges represents value in range 100-250 km^2. The results of the present study confirmed that the WMO guidelines and stepwise regression method approaches could be used as a sufficient tool to evaluate and rationalize a rain gauge network density in a river basin.

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