Bartlett Lewis Rectangular Pulse (BLRP) Approach with Proportional Adjusting Procedure in Rainfall Disaggregation Method in Hydrology Laboratory of Brawijaya University Rain Station

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Abstract. Rainfall data is one of the information that can be used in flood prevention, especially low-scale rainfall data (hourly). However, the availability of hourly rainfall data is very limited. It is because not all rain stations have hourly rain gauges which are quite expensive. This research aims to obtain hourly rainfall data based on daily rainfall data with the Bartlett Lewis Rectangular Pulse (BLRP) stochastic disaggregation method. This method was applied to rainfall data at the Hydrology Laboratory of Brawijaya University Malang in 2016. There are six BLRP parameters, namely λ, ν, κ, μₓ, α, φ which are used to produce hourly rainfall data. To maintain the consistency of hourly rainfall data based on daily rainfall data, a proportional adjusting procedure is used. The results showed that the disaggregation method of the BLRP approach can produce good enough hourly rainfall data that is consistent with daily rainfall data, seen from the in-sample MAE value of 0.5348 and 0.3113 for out-sample MAE.

Keywords: rainfall, disaggregation, BLRP, adjusting.

1. Introduction

Geographical locations and topographic conditions are climate determinants of a place on earth. According to [1], Indonesia is an archipelagic country with a very diverse topographic form so that the influence on climate diversity in Indonesia is considered. Indonesia has a wet tropical climate that is influenced by monsoon winds, so it has two seasons, namely dry season and rainy season. The rainy season in Indonesia is often accompanied by strong winds, so heavy rains often occur. Floods and landslides are a feared threat if heavy rains occur.

Information about weather forecasts is needed to deal with the above problems. Weather information generated by each rainfall station, which each watershed is measured based on the tools owned, such as weather radar, automatic rain gauge (ARG), and remote sensors. The limitations of measuring instruments on a low time scale (hourly) that are owned are one of the factors disturbing the accuracy of rainfall information in detecting the arrival of floods. This condition is very common in...
Indonesia, because the availability of high resolution rainfall data obtained from automatic rain gauges (ARG) is difficult to obtain. Not all stations have a low time scale rainfall measurement tool (hourly) because the equipment cost is expensive.

Seeing the importance of low time scale rainfall data (hourly), disaggregation can be obtained to obtain these data. Disaggregation method is a method or process of generating rainfall data which involves two scales of rainfall time, which are high and low with low time scale data conditions indicating consistency of high time scale data.

The first stage is modelling rainfall data can be done one of them with a stochastic model. In the previous research, ARIMA modelling approach was carried out by [2], regression modelling approach was conducted by [3]. Neyman Scott’s Rectangular Pulse Model (NSRP) stochastic model with adjusting procedures has been done by [4], while [5] have modelled rainfall data with the PAR(1) time series approach which adjusting procedures for maintaining consistency. Bartlett Lewis Rectangular Pulse (BLRP) stochastic approach has been carried out by [6] which are applied to two locations in Malaysia. The second stage in this disaggregation method is data generation. Data generation is based on the distribution of each parameter. Then to maintain the consistency of generated data on actual data, an adjusting procedure is applied. Therefore, in this study the rainfall disaggregation using the Bartlett Lewis Rectangular Pulse (BLRP) model approach with an adjusting procedure applied on Hydrology Laboratory of Brawijaya University Rain Station.

2. Methodology and Tools

This study uses rainfall data from The Hydrology Laboratory of Brawijaya University Rain Station, Malang, Indonesia. The stages of analysis consist of modelling and generation carried out on in-sample and out-samples data as follows.

2.1. Bartlett Lewis Rectangular Pulse (BLRP) Modelling

Rainfall modelling is carried out on a low time scale (hourly) to study stochastic BLRP. There are six BLRP parameters, namely \( \lambda, \kappa, \varphi, \alpha, \nu, \mu_x \) [7]. The estimation parameters performed are approached with 4 statistical characteristics of the actual data. These statistical characteristics consist of means, variance, autocovarian lag-1, and proportion of dry days at the aggregation level \((h)\) 1 hour and 24 hours. [8] performed parameter estimates using statistical statistics on (1) means, (2) variance, (3) autocovarian lag-1, and (4) proportion of dry days.

\[
E(Y^h) = \frac{\lambda h \nu \mu_x}{\alpha - 1}, \quad (1)
\]

\[
Var(Y^h) = 2A_1 \left[ (\alpha - 3) h v^{2-\alpha} - (v + h)^{3-\alpha} \right] - 2A_2 \left[ \varphi(\alpha - 3) h v^{2-\alpha} - (v + \varphi h)^{3-\alpha} \right], \quad (2)
\]

\[
Cov(Y_{j}, Y_{j+1}^h) = A_1 \left[ v + (m + 1) h \right]^{3-\alpha} - 2(v + mh)^{3-\alpha} + \left[ v + (m - 1) h \right]^{3-\alpha} - A_2 \left[ v + (m + 1) \varphi h \right]^{3-\alpha} - 2(v + m \varphi h)^{3-\alpha} + \left[ v + (m - 1) \varphi h \right]^{3-\alpha}, \quad (3)
\]

\[
A_1 = \frac{\lambda \mu_x \nu}{(\alpha - 1)(\alpha - 2)(\alpha - 3)} \left[ E(X^2) + \kappa \nu \mu_x^2 \right],
\]

\[
A_2 = \frac{\lambda \mu_x \nu}{\varphi^2(\varphi^2 - 1)(\alpha - 1)(\alpha - 2)(\alpha - 3)},
\]

\[
P(Y^h = 0) = \exp \left\{ -\lambda h - \lambda \mu_x + \lambda G^* \left( 0, 0 \right) \frac{\varphi + \kappa}{\varphi + \kappa} \right\} \quad (4)
\]
\[ G^*_{\alpha}(0,0) \approx \frac{v}{\phi \left( \alpha - 1 \right)} \left( 1 - \kappa - \rho + \frac{3}{2} \kappa \rho + \rho^2 + \frac{1}{2} \kappa^2 \right) \]

The iteration process is carried out on estimating parameters by minimizing the number of squares of errors between the models formed with the actual data model on the objective function.

\[ Z(X) = \min \left[ \sum_{i=1}^{nk} \left( 1 - \frac{F_i(X)}{F_{\tilde{X}}} \right)^2 \right] \]

Optimization of objective functions was carried out by the evolutionary method of simplex annealing (eas). The aim of minimizing objective functions with constraints includes the upper and lower limits of the model.

2.2. Low Time Scale Data Generation (Hourly)

Disaggregation methods are applied especially in the processing of rainfall data, so rainfall disaggregation is a method of generating data by involving multiple time scales namely high and low [9].

\[ \sum_{i=1}^{nk} Y_i = Z_i \]

Equation 6 explains that the amount of low time scale data \((Y_t)\) must be the same as the high time scale data \((Z_i)\). Adjusting procedure is a method for modifying the results of low-level data generation so that the data remains consistent with the level above and simultaneously does not affect the stochastic structure of the model [10]. One of the adjusting procedures applied in this study is the proportional adjusting method which is a simple method than others with the following equation.

\[ \hat{Y}_t = \frac{Z_i}{\sum_{i=1}^{nk} \hat{Y}_i} \]

Where

- \(Z_i\) \((i = 1, 2... n)\)
- \(\hat{Y}_t\) \((t = 1, 2... k)\)
- \(\hat{Y}_t\) : Low time generation data after adjusting procedure in period i and sub period t
- \(Z_i\) : Actual time scale data high in period i
- \(\hat{Z}_i\) : Low time scale data before adjusting procedure in period i and sub period t
- \(\hat{Z}_i\) : High time scale data before adjusting procedure in period i [8]

3. Results

The rainfall period in this study is from 1 January 2016 to 31 December 2017 with in-sample data starting from 1 January 2016 to 31 December 2016, while the out-sample data starts from 1 January 2017 to 31 December 2017.

| Month | \(E(Y_t)\) | \(\text{Var}(Y_t)\) | \(\text{Var}(\hat{Y}_t)\) | \(\text{Cov}(Y_t, \hat{Y}_{t+1})\) | \(\text{Cov}(Y_{t}^{24}, \hat{Y}_{t+1}^{24})\) | \(P(Y_t=0)\) | \(P(Y_t^{24}=0)\) |
|-------|------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Jan   | 0.303      | 4.195          | 121.82         | 0.626          | 12.35          | 0.954          | 0.484          |
| Feb   | 0.793      | 8.061          | 266.10         | 2.471          | 134.2          | 0.864          | 0.035          |
| Mar   | 0.411      | 5.620          | 389.02         | 3.598          | -10.42         | 0.925          | 0.29           |
| Apr   | 0.164      | 1.375          | 55.38          | 0.552          | 8.43           | 0.971          | 0.667          |
| May   | 0.335      | 4.333          | 164.89         | 0.763          | 44.04          | 0.948          | 0.484          |
| June  | 0.196      | 1.635          | 74.63          | 0.574          | -12.98         | 0.954          | 0.6            |
| July  | 0.035      | 0.260          | 6.25           | 0.009          | -0.64          | 0.985          | 0.74           |
| Aug   | 0.064      | 0.657          | 34.59          | -0.006         | 0.86           | 0.979          | 0.81           |
| Sept  | 0.097      | 1.121          | 26.89          | 0.045          | -5.583         | 0.981          | 0.73           |
| Oct   | 0.270      | 2.788          | 124.58         | 0.880          | 18.57          | 0.93           | 0.48           |
Statistical identification is carried out at the aggregation level of 1 hour and 24 hours from the actual lower time scale data. There are four statistics that predict BLRP parameters, namely mean, variance, auto covariance lag-1, and proportion of dry period are obtained according to the constraints. The modification parameters of BLRP are $\lambda$, $\kappa$, $\varphi$, $\alpha$, $\nu$, $\mu_s$ [7] are presented in Table 2.

| Month | $\lambda$  | $\kappa$ | $\varphi$ | $\alpha$ | $\nu$ | $\mu_s$ |
|-------|------------|----------|-----------|----------|-------|---------|
| Jan   | 0.0299     | 1.7744   | 0.9431    | 17.495   | 2.7162| 16.872  |
| Feb   | 0.0954     | 0.6682   | 0.8733    | 6.1150   | 1.5681| 11.474  |
| Mar   | 0.0504     | 8.0494   | 0.8524    | 6.6493   | 0.0744| 47.787  |
| Apr   | 0.0158     | 0.5371   | 0.1093    | 3.441    | 0.4447| 8.3358  |
| May   | 0.0292     | 2.5847   | 0.8805    | 16.132   | 2.6686| 12.505  |
| June  | 0.0220     | 2.27     | 0.7378    | 9.8248   | 2.7591| 5.5257  |
| July  | 0.0118     | 3.8866   | 0.7161    | 19.983   | 0.6866| 13.379  |
| Augst | 0.0084     | 1.0567   | 0.2234    | 9.3595   | 2.7993| 0.00001 |
| Sept  | 0.0150     | 3.4493   | 0.3746    | 18.346   | 0.4358| 22.949  |
| Oct   | 0.0283     | 0.7264   | 0.2871    | 2.9849   | 0.9453| 4.7493  |
| Nop   | 0.0466     | 3.5319   | 0.9441    | 12.827   | 2.7852| 12.1344 |
| Dec   | 0.0396     | 0.00001  | 0.7974    | 19.967   | 6.6617| 9.8021  |

This disaggregation method is applied to in-sample and out-samples data. After the modelling phase, then low time scale data generation (hourly). Data generation with input parameters, actual high time scale data (daily) and actual low time scale data (hourly) generated on each parameter according to its distribution. The plot of comparison of actual and hourly generation data is presented in Figure 1. The low time scale data generation (hourly) was carried out with the Hyetos program [11] that included proportional adjusting procedures for consistencing data generation and it can be seen in Figure 2.

![Figure 1. 2016 Actual Rainfall Plots and Hourly Generated Results (in-sample)](image-url)
The model results of estimating parameters of in-sample data and actual daily out-sample data are used as inputs in the generation of hourly out-sample data. In this case, the out-sample data is the 2017 daily rainfall data. The out-sample data generation is carried out with the Hyetos program, so that it has applied a proportional adjusting procedure. Comparison of actual and hourly generated data on the out-sample data is presented in Figure 3. The defense of consistency with the actual daily data on the out-sample is shown in Figure 4.

**Figure 2.** 2016 Actual Rainfall Plots and Daily Generated Results (in-sample).

**Figure 3.** 2017 Actual Rainfall Plots and Hourly Generated Results (out-sample).

**Figure 4.** 2017 Actual Rainfall Plots and Daily Generated Results (out-sample).
Characteristics identification of generation data are used to find out how far the actual generation difference is. Comparison is done by testing the mean difference between the actual data and generated data. The comparison shows that the entire mean of the two showed no significant differences with p-value of 0.8406 for in-sample. It also showed no significant differences with p-value of 0.7659 for out-sample.

4. Conclusion
The consistency of low time scale generation data (hourly) is shown from the results of daily generation that have the same value as the actual daily data through the BLRP approach with a proportional adjusting procedure resulting in an MAE of 0.5348 for in-sample and 0.3113 for out-sample. Comparison of generated data with actual data through t test. It shows that almost the whole month there is no difference in the average between the two groups with a p-value of 0.8406 for in-sample and 0.7659 for out-sample. This means that there is no difference in the average between the two groups. Therefore, the generated data has represented the actual data.

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