Estimated value of insurance premium due to Citarum River flood by using Bayesian method

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Abstract. Citarum river flood in South Bandung, West Java Indonesia, often happens every year. It causes property damage, producing economic loss. The risk of loss can be mitigated by following the flood insurance program. In this paper, we discussed about the estimated value of insurance premiums due to Citarum river flood by Bayesian method. It is assumed that the risk data for flood losses follows the Pareto distribution with the right fat-tail. The estimation of distribution model parameters is done by using Bayesian method. First, parameter estimation is done with assumption that prior comes from Gamma distribution family, while observation data follow Pareto distribution. Second, flood loss data is simulated based on the probability of damage in each flood affected area. The result of the analysis shows that the estimated premium value of insurance based on pure premium principle is as follows: for the loss value of IDR 629.65 million of premium IDR 338.63 million; for a loss of IDR 584.30 million of its premium IDR 314.24 million; and the loss value of IDR 574.53 million of its premium IDR 308.95 million. The premium value estimator can be used as neither a reference in the decision of reasonable premium determination, so as not to incriminate the insured, nor it result in loss of the insurer.

Keyword: flood insurance, right fat tail; Pareto distribution, Gamma distribution, Bayesian method.

1. Introduction

According to Bandung regency government Prevention and Preparedness, flood disaster often rush the regency of Bandung, especially Baleendah District. The intensity of flooding in Baleendah sub-district, which includes the Citarum River Basin, has resulted enormous losses in agriculture, fisheries, economic, health, and education sectors. These losses affect directly the human life, i.e. their homes, vehicles, and property flooded [12]. In anticipation of future losses, one of the most helpful solutions would be insurance protection on property, vehicles and other things vulnerable to flood damage [1]. The circumstances under which people having property insurance are environmental histories...
frequently affected by natural disasters, such as floods, fires, tornadoes, landslides, and so on [3]. Property insurance provides cash when customers lose insured property [4; 5; 15].

When the claim occurs, the insurer gives a sum of money to the client [7]. Insurance companies need to calculate the appropriate premium value for each claim. In this case, it is necessary to estimate the premium value [14]. Referring to Paudel et al. [9], Bayesian Inference can be applied in the estimated value of insurance premiums due to floods. The method is used to estimate the flood loss parameter that will affect the calculation of the premium. This method is suitable to be applied to studies having limited data [9]. The Bayesian approach is also used to analyse the uncertainty in the flood frequency model [2; 13].

Based on the above description, the authors conduct research on Bayesian Inference application on the estimated value of insurance premiums due to Citarum river flood (Case study: Baleendah Village). In general, the purpose of this study is to apply the author’s knowledge of insurance and opportunities as well as reference materials for further researchers.

2. Methodology

In this section we will discuss: likelihood data model and function, priority distribution, posterior distribution, simulation of flood loss data and fitting curve of opportunity density, and estimated value of insurance premium.

2.1. Model Data and Likelihood Data Function

In this sub-section, the discussion of the data model and likelihood function is presented. Assuming that data loss due to flood \( X_1, X_2, \ldots, X_8 \) is a random sample of Pareto distributed with two parameters, that is as known parameter, which is the minimum value of \( X \) and \( \theta \) as parameter is not known. As the function of probability density \( X \) can be written as follows [13]:

\[
p(x) = \begin{cases} 
\frac{x\theta}{x^{\theta+1}}; x_i \geq x_m; \theta > 1, \\
0; & \text{for } x \text{ other}
\end{cases} 
\]  

Based on (1), the likelihood function with parameter \( \theta \) is not known, which is as follow:

\[
L(\theta|X_1, \ldots, X_2) = \begin{cases} 
\theta^n x_m \prod_{i=1}^{n} x_i^{-(\theta+1)}; x_i \geq x_m, \\
0; & \text{otherwise}
\end{cases} 
\]  

Following equation (2), parameter \( \theta \) is unknown, that is to be estimated, that is to determine the parameter estimator value \( \hat{\theta} \) which can maximize equation (2) [6]. The estimation of parameter \( \theta \) in equation (2) is done using Bayesian method.

2.2. Prior Distribution

Since the data model follows the Pareto distribution with unknown parameters \( \theta \), the conjugate prior \( p(\theta) \) is proportional to the Gamma probability density function [13; 16]. The Gamma function of \( \theta \) undefined with hyper parameter \( a \) and \( b \) as follows:

\[
p(\theta) = \begin{cases} 
\theta^{a-1} \frac{e^{-\frac{\theta}{b}}}{b^a \Gamma(a)}; \theta \geq 0; b > 0, \\
0; & \theta < 0
\end{cases} 
\]  

This posterior distribution is further used in the discussion of posterior distribution, in the next subsections.
2.3. Posterior Distribution

Since the priority distribution has been determined, that is the conjugation for likelihood; the posterior distribution is a combination of likelihood and priority equations. The posterior distribution follows the same distribution as the priority, i.e. [2; 10]:

\[ p(\theta \mid x) = \text{Gamma}(\alpha, \beta) = L(\theta \mid X) p(\theta). \]  

(4)

By substituting equation (2) and (3) to equation (4), therefore the posterior density probability function of the flood loss is as follows:

\[ p(\theta \mid x) = L(\theta \mid X) \, p(\theta) \]

\[ p(\theta \mid x) = \theta^n x_m \prod_{i=1}^{n} x_i^{-(\theta+1)} e^{\frac{\theta}{b}} \left( \theta \beta \right)^\alpha \gamma(\alpha) \]

\[ p(\theta \mid x) = \frac{\theta^{a+n+1} e^{-\frac{1}{b} + \ln \left( \prod_{i=1}^{n} x_i \right) - n \ln x_m}}{\left( \frac{1}{b} + \ln \left( \prod_{i=1}^{n} x_i \right) - n \ln x_m \right)^{a+n}} \, \Gamma(a+n) \]  

(5)

Equation (5) can be rewritten as:

\[ p(\theta \mid x) \propto \frac{\theta^{\alpha-1} e^{-\beta \theta}}{\beta^\alpha \Gamma(\alpha)} \]  

(6)

with \( \alpha = a + n \) and

\[ \beta = \frac{1}{b + n \ln x_m - \ln \left( \prod_{i=1}^{n} x_i \right)}. \]  

(7)

Based on the posterior distribution function, the parameters \( \theta \) can be estimated from the average posterior distribution of flood losses, i.e. [2; 6]:

\[ \hat{\theta} = E[(\theta \mid x)] = \int_{-\infty}^{\infty} \theta \, p(\theta \mid x) \, d\theta. \]  

(8)

This parameter estimator value \( \hat{\theta} \) is then used to simulate the data loss data due to floods that are assumed to be Pareto distributed. This simulation is performed because the data loss caused by flood cannot be determined exactly.

2.4. Data simulation of flood loss and fitting curve of opportunity density

Based on the assumption that data loss caused by floods is Pareto distributed, the chance of damage for each observed area can be simulated with the following model [8]:

\[ \text{Losses} = f^{-1}(\hat{\theta}, x_l, x_u). \]  

(9)

To see the value of estimated loss based on the value of \( \hat{\theta} \) obtained from Bayesian Inference, data grouping is required based on the percentile size. Suppose that the data are grouped into 10 data sets, to find the estimated value of losses per data set, the inverse of the cumulative function of Pareto distribution is as follows [3]:

\[ L = \text{Losses Estimator} = \frac{x_m}{(1 - F(x))^{\frac{1}{\hat{\theta}}}}, \]  

(10)

with \( x_m \) the minimum value of loss derived from information II, and \( F(x) \) in this case is the value of cumulative loss per percentile of data in a single RW.
Due to the data limitations, so for the chance of damage per house, it is used direct simulation data that is using random numbers by Microsoft Excel. The estimated value of losses per house is sought by using the inverse Pareto density probability function as follows [11]:

\[
l = \left( \frac{\hat{\theta} m}{f(x)} \right)^{-\frac{1}{\theta + 1}}.
\]  

(11)

with \( l \) is an estimated loss per household, \( f(x) \) is a chance of flood per home and \( \hat{\theta} \) is a loss estimator obtained from Bayesian inference [16].

2.5. Estimated Insurance Premium Value

There are several principles used for the calculation of premiums, namely [12]:

- **Pure premium**

  Principle of pure premium calculate premium based on total loss, total premium, and annuity of premium payment, that is as follows [7; 12]

  \[
P = \frac{Total\ Losses \cdot Total\ Premium \cdot Annuity\ (premium\ payment)}{Annuity},
\]

  \[
  \text{Annuity} = \frac{1-(1+i)^{-t}}{i},
\]

  with \( i \) is the annual interest rate, and \( t \) is the period of payment of premium (annual).

- **Variance principle**

  This method estimates the premium value based on *Modern Actuarial Risk Theory*. The principle of variance can be written as follows [9; 12]:

  \[
c = L + \rho \text{Var}(L),
\]

  with \( c \) is the amount of premium required for property insurance, \( L \) is the loss estimator, \( \text{Var}(L) \) is the variance of the estimated loss, and the \( \rho \) is risk aversion coefficient of the insurer, which is assumed to be 0.005.

- **Standard deviation principle**

  This method is also called the empirical method, which assumes the coefficient of risk aversion by the insurer depends on the standard deviation from the loss. The calculation of premiums by empirical method is as follows [12]:

  \[
c = L + \rho \sqrt{\text{Var}(L)}
\]

  with \( \sqrt{\text{Var}(L)} \) is the standard deviation of loss, and \( \rho \) is coefficient of risk aversion from the insurer, which is assumed to be 0.005.

3. Result and Discussion

In this section, the discussion includes: analysed data, normality testing, estimation of loss data distribution model, and calculation of loss insurance premium due to flood.

3.1. Analysed data

This sub-section discuss about the object data for the research. Objects used in this study are data loss due to flooding, especially submerged houses, experienced by residents Baleendah Village of eight
Citizens Association (RW). The data is obtained from the Office of Baleendah district in the form of secondary data. The value of losses due to floods is obtained based on information from interviews with the Chairman of the Neighbourhood Association (RT) and residents in Baleendah Village. The data used in this study is the homes submerged by the flood of citizens of Baleendah Village. In Information I, the data of submerged housing is processed into data loss due to flood with the assumption of loss per house submerged by IDR 10,000,000. Whereas in Information II, the submerged housing data is processed with the assumption of per house perforated losses of IDR 9,500,000, because each RW is assumed to receive assistance of IDR 500,000 per incident. The loss data is used to estimate the premium value based on the chance of damage per area.

3.2. Result
Flood losses from the submerged housing data are assumed to be Pareto distributed. Since the probability density function of the Pareto distribution is known, the likelihood function can be determined. The value of $\theta$ is estimated by using Bayesian Inference. The prior value of the parameter $\theta$ needs to be determined to obtain its posterior distribution. In this study, it is used prior conjugate which means the distribution of the same prior to the posterior distribution. Posterior distribution is obtained from the multiplication of likelihood function with its priority distribution.

3.2.1. Test of data normality with Shapiro Wilk
In this sub-section, the normality test of data derived from Information II is presented. Normality test is necessary to know whether Information II is normal distribution or not. The test hypothesis is: $H_0$: Information II comes from the normal distribution, against alternative $H_1$: Information II does not come from the normal distribution. The test statistic used is Shapiro Wilk at a significance level of $\alpha = 0.05$. The test criterion is reject $H_0$ if $\text{Sig} < \alpha$. Normality test is done using SPSS software, and the results are given in Table 1.

| VAR00001 | Statistic | df | Sig. |
|----------|-----------|----|------|
| Kolmogorov-Smirnov | .156 | 8 | .200’ |

| Shapiro-Wilk | Statistic | df | Sig. |
|--------------|-----------|----|------|
| .934 | 8 | .557 |

Based on Table 1, in the Shapiro-Wilk test, the significance value $\text{Sig} = 0.557$ is clearly greater than $\alpha = 0.05$. So the decision is to accept the hypothesis $H_0$, which means Information II comes from the normal distribution.

Furthermore, estimation of distribution data model of loss caused by Citarum River flooding, as follows.

3.2.2. Estimation of data loss distribution model
In this case, it is assumed that the data loss model $x_1, ..., x_n$ derived from information II is a Pareto-distributed random sample. Random variable loss per return period of flood event with two main parameters, namely the scale parameter $x_m$ as the minimum value of $x$, and the shape parameter $\theta > 1$. The first parameter value is assumed to be known, while the second is unknown. The value of the shape parameter is determined by Bayesian inference. Here is a graph of the opportunity density function of information II.
Figure 1. Graph of the density function of information opportunity II is Pareto distributed.

Whereas from Information I, that is, submerged home data which is processed with the assumption of loss per house submerged by IDR 10,000,000, used to find the prior distribution of unknown parameter. Here is a graph of the probability density function of data derived from information I.

Figure 2. Graph of the density function of information opportunity I is Gamma distributed.

3.2.3. Bayesian Inference data loss model

In this sub-section, Bayesian inference analysis is performed on the data model of loss due to Citarum river flood disaster. If we substitute the parameter values $x_m$ by 2024, which is the minimum value of $x$, then equation (1) can be written to:

$$ p(x) = \frac{\theta^{2024} x^{\theta-1}}{\theta^{\theta+1}} ; \theta > 1. $$

The likelihood function of the equation (14) is:

$$ L(\theta \mid x_1, ..., x_n) = \theta^{\text{8}(2024)} \prod_{i=1}^{n} x_i^{\theta+1} $$

In this study we assume the prior distribution for parameters $\theta$ is Gamma with hyper parameter $a$ and $b$. Based on calculations with EasyFit 5.5 software assistance, the likelihood values obtained from $a$ and $b$ parameters are as follows:

$\theta \sim \text{Gamma}(7.075, 607.19)$

Since the value $a$ and $b$ are known, then the posterior distribution parameters, that is $\alpha$ and $\beta$ can be calculated. Based on equation (7), we obtained parameters estimator values $\alpha = 15.0757$ and $\beta = 0.1970494917$. The $x_i$ value is the value of loss based on information II, which is loss due to flood with the assumption of loss per house submerged by IDR 9,500,000.00.

After the parameters of the posterior distribution are estimated, the equation (4) can be written to

$$ p(\hat{\theta} \mid x) = \text{Gamma}(15.0757, 0.1970494917) $$

with the expectation of the parameter $E(\hat{\theta} \mid x) = \ldots$
2.970659022, and the variance of the parameter $\hat{\theta}$ is $\text{Var}(\hat{\theta} | x) = 20.5853668503$. So the standard deviation value is equal to $\sigma_{\hat{\theta}} = 0.765092707$.

A statistical summary of the mean, variance, and standard deviation of the estimated parameters $\hat{\theta}$ from the Citarum River flood loss data for one year is given in Table 2.

**Table 2.** The statistical summary of average, variance, and standard deviation of the parameters $\hat{\theta}$

| Parameter | Posterior $\alpha$ | Posterior $\beta$ | Average  | Variance  | Standard Deviation |
|-----------|-------------------|-------------------|----------|-----------|--------------------|
| $\hat{\theta}$ | 15.075           | 0.1970494        | 2.970659 | 0.5853668 | 0.7650927          |

Based on the posterior distribution function, Gamma, from equation (4) we can determine the estimated value of loss is equal to $\hat{\theta} = 2.970659022$. In this study the loss is estimated based on the value obtained from the Bayesian inference. Parameter $\hat{\theta}$ is Pareto parameter estimator. The value of the variance and standard deviation of the loss model per RW can be determined as in Table 3.

**Table 3.** Summary statistics Pareto distributed loss estimates.

| Parameter | Average (million IDR) | Variance (million IDR) | Standard Deviation (million IDR) |
|-----------|-----------------------|------------------------|---------------------------------|
| $\hat{\theta}$ | 3051.06            | 3,228,376.33            | 1,796.76                         |

So that the loss value can be seen more clearly, then we draw the grouping of data into 10 groups of data based on the percentile size of the data. The estimated value of accumulated losses per RW is derived from Eq. (8) as given in Table 4.

**Table 4.** Estimated losses per RW with percentile size of data.

| Percentile | Estimated Losses (million IDR) | Information (million IDR) |
|------------|--------------------------------|---------------------------|
| 0.0        | 0.1 2024.00 From percentile 0-10, Losses 2024 |
| 0.1        | 0.2 2097.09 From percentile 10-20, Losses 2097.09 |
| 0.2        | 0.3 2181.92 From percentile 20-30, Losses 2181.92 |
| 0.3        | 0.4 2282.26 From percentile 30-40, Losses 2282.26 |
| 0.4        | 0.5 2403.84 From percentile 40-50, Losses 2403.84 |
| 0.5        | 0.6 2556.03 From percentile 50-60, Losses 2556.03 |
| 0.6        | 0.7 2755.47 From percentile 60-70, Losses 2755.47 |
| 0.7        | 0.8 3035.73 From percentile 70-80, Losses 3035.73 |
| 0.8        | 0.9 3479.79 From percentile 80-90, Losses 3479.79 |
| 0.9        | 1.0 4394.51 From percentile 90-100, Losses 4394.51 |

Based on equation (9), the estimated value of losses per house is as given in Table 5.
Table 5. Estimated losses per house based on chance of damage caused by flood.

| No | Possibility of Flood Damage | Infrastructure losses (million IDR) | No | Possibility of Flood Damage | Infrastructure losses (million IDR) |
|----|-----------------------------|-----------------------------------|----|-----------------------------|-----------------------------------|
| 1  | 0.151278                    | 629.65                            | 31 | 0.359383                    | 506.34                            |
| 2  | 0.203541                    | 584.30                            | 32 | 0.682983                    | 430.72                            |
| 3  | 0.217636                    | 574.52                            | 33 | 0.282827                    | 537.83                            |
| 4  | 0.245526                    | 557.34                            | 34 | 0.378848                    | 499.65                            |
| 5  | 0.252445                    | 553.45                            | 35 | 0.106752                    | 687.44                            |
| 6  | 0.335881                    | 515.04                            | 36 | 0.896009                    | 402.25                            |
| 7  | 0.418629                    | 487.24                            | 37 | 0.819895                    | 411.35                            |
| 8  | 0.423930                    | 485.70                            | 38 | 0.259707                    | 549.51                            |
| 9  | 0.500231                    | 465.87                            | 39 | 0.261163                    | 548.74                            |
| 10 | 0.553040                    | 454.24                            | 40 | 0.513234                    | 462.87                            |
| 11 | 0.609898                    | 443.18                            | 41 | 0.056486                    | 806.98                            |
| 12 | 0.628365                    | 439.86                            | 42 | 0.798198                    | 414.14                            |
| 13 | 0.734245                    | 422.94                            | 43 | 0.586077                    | 447.65                            |
| 14 | 0.751399                    | 420.49                            | 44 | 0.835044                    | 409.46                            |
| 15 | 0.837337                    | 409.18                            | 45 | 0.395094                    | 494.40                            |
| 16 | 0.843138                    | 408.46                            | 46 | 0.136767                    | 645.84                            |
| 17 | 0.865072                    | 405.83                            | 47 | 0.581367                    | 448.56                            |
| 18 | 0.908786                    | 400.82                            | 48 | 0.081245                    | 736.38                            |
| 19 | 0.971257                    | 394.17                            | 49 | 0.189281                    | 595.09                            |
| 20 | 0.998131                    | 391.47                            | 50 | 0.200963                    | 586.18                            |
| 21 | 0.784533                    | 415.94                            | 51 | 0.475310                    | 471.91                            |
| 22 | 0.663157                    | 433.93                            | 52 | 0.624854                    | 440.48                            |
| 23 | 0.957423                    | 395.59                            | 53 | 0.297789                    | 530.89                            |
| 24 | 0.952795                    | 396.08                            | 54 | 0.101663                    | 695.95                            |
| 25 | 0.462114                    | 475.26                            | 55 | 0.842171                    | 408.58                            |
| 26 | 0.892646                    | 402.64                            | 56 | 0.421062                    | 486.53                            |
| 27 | 0.094485                    | 708.90                            | 57 | 0.476273                    | 471.67                            |
| 28 | 0.101737                    | 695.82                            | 58 | 0.840137                    | 408.83                            |
| 29 | 0.085835                    | 726.26                            | 59 | 0.967047                    | 394.60                            |
| 30 | 0.683979                    | 430.57                            | 60 | 0.381981                    | 498.62                            |

The estimated value of the loss is affected by the possibility value of each house damages. The less possibility of damage to a house due to flooding, the greater the estimation of losses in case of damage. For example, the value of loss B on the possibility of damage A indicates that if a house has a possibility of damage A, then the house has a chance of losing B.

3.3. Calculation of premiums

The amount of the premium depends on the value of the loss, the risk aversion parameters derived from the insurance company, as well as other factors. In this research, it is assumed that risk aversion parameter of insurance company $\rho$ is equal to 0.005. Based on equations (12), (13), and (14), the value of premiums for each house with the principle of pure premiums, variance, and standard deviation, a portion of the proceeds from the calculation of premiums is presented in Table 6.
Table 6. Estimated premiums per house within 1 year based on three principles

| No. | Loss per house (million IDR) | Variance principal (million IDR) | Standard deviation principal (million IDR) | Pure premiums (million IDR) |
|-----|-----------------------------|---------------------------------|------------------------------------------|-----------------------------|
| 1   | 629.65                      | 16,771.53                       | 638.63                                   | 338.62                      |
| 2   | 584.30                      | 16,726.18                       | 593.29                                   | 314.24                      |
| 3   | 574.53                      | 16,716.41                       | 583.51                                   | 308.98                      |

Based on Table 6, it can be seen that insurance premium based on the principle of variance is very much different from the principle of standard deviation and pure premium. This is due to the large value of loss variance. In determining the value of premiums, the insurance company will choose the greatest value so that the risk for the loss of the company is getting smaller. However, in many cases, there are still many factors that influence premium value besides loss, possibility of damage, and risk aversion value. If the premium is set the largest, then it will not be affordable by the community. Conversely, if the premium set too small, it will cause bankruptcy in the insurance company. Therefore, the determination of the magnitude of the insurance premium needs to consider many other factors which may affect.

4. Conclusion
In this paper, the estimated value of insurance premiums due to Citarum River flood by Bayesian method has been discussed. It is assumed that the risk data for flood losses follows the Pareto distribution with the right fat-tail. Based on the result, it can be obtained that the probability of damage to the building is Pareto distributed, with estimator parameters $\theta$ estimated using Bayesian inference method value is $\hat{\theta} = 2.970659022$. Furthermore, the insurance premium is estimated based on the probability of damage and the estimated value of the loss. The estimation results obtained based on the principle of pure premium are as follows: for the loss value of IDR 629.65 million of premium IDR 338.63 million; for a loss of IDR 584.30 million of its premium IDR 314.24 million; and the loss value of IDR 574.53 million of its premium IDR 308.95 million. Large insurance premiums based on the principle of variance are very much different high, with the principle of standard deviation and pure premium. This is due to the large value of the variance of loss. In determining the value of premiums, the insurance company will choose the greatest value so that the risk for the loss of the company is getting smaller. However, in fact, there are still many factors to consider in the determination of the premium. In addition to loss factors, building damage possibility, risk aversion values, and fairness levels also need to be considered. So this paper recommends the insurer to determine the premium value based on the principle of pure premium.

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