Determining the premium of paddy insurance using the extreme value theory method and the operational value at risk approach

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Abstract. Paddy farming is a source of livelihood for most rural communities in Indonesia. Indonesia as an agrarian country with a tropical climate, where the sun shines all the time and farmers can grow crops throughout the season. However, changes in air temperature, weather, and annual rainfall which sometimes change uncertainly cause changes in cropping patterns, which are caused by minimal water supplies in the dry season and flooding in the rainy season. This uncertainty will certainly increase the risk of crop failure. In addition to the risk of weather, other disturbances from plant pests and plant diseases also cause the risk of crop failure, which results in greater losses to farmers. One way to transfer this risk is through a rice agricultural insurance program. This study aims to calculate the premium price using the Extreme Value Theory (EVT) method with the Operational Value at Risk (OpVaR) approach based on weather, pests and plant diseases disturbance in West Java in 2009-2019. The stages in this research, the first step is to determine the estimated threshold value to obtain extreme data, then estimate the parameters using the likelihood method. Data suitability test with Generalized Pareto Distribution (GPD) was performed using the QQplot test. Risk is determined by the Operational Value at Risk (OpVaR) approach, the results of which are used to calculate the appropriate premium for paddy agricultural insurance.

1. Introduction

Agricultural sector business, especially rice farming is faced with various risks which are uncertain. These risks include the risk of crop failure caused by climate change, such as: temperature, flooding, drought. [46]. One way to manage these risks is through the Rice Farmer Business Insurance (RFBI) program. RFBI is expected to provide protection to farmers from the risk of loss, with a guarantee that farmers will get working capital when farmers experience crop failure. From this guarantee of protection, if there is a crop failure, the farmer has the capital for production costs in the next planting season. The holding of the RFBI aims to protect farmers from losses through insurance companies. The objective of
the RFBI implementation is that farmers can be protected by obtaining compensation, if they experience crop failure, literature [1]. Risks covered in RFBI include floods, drought, pest attacks, and pests. This paper will discuss weather-based risk determination which includes rainfall, air temperature, and its effect on the amount of rice yields.

Based on the results of the research above, this paper discusses the determination of the risk of crop failure caused by weather, rainfall and temperature factors, farmers in Bandung Regency, West Java. The method used is the Block Maxima method and the Peak Over Threshold method as the threshold. Extreme value theory using the basic concept of generalized extreme value distributions (GEV) [2,8].

The aim of this paper is to provide an in-depth analysis of a class of insurance known as index indemnity insurance, or simply index insurance. In contrast to indemnity loss insurance where the compensation payment is a function of the actual loss incurred by the policyholder, the index insurance payment depends exclusively on a predetermined index or a few well-chosen indicators. In its application, the index that can be used is the average yield of crops, the amount of rainfall received by an area during the growing season, high and low heating levels based on factors of air temperature, wind speed, or based on plant pests, and plant pests. The plant object that is studied more specifically in this case is the agricultural sector, namely rice fields [4,12].

Risk is the prospect of an unwelcome outcome. Risk is also the amount of deviation between the expected rate of return and the actual rate of return. Several definitions of risk, namely; Risk is the chance of loss, Risk is the possibility of loss but this definition is not suitable for quantitative analysis, Risk is uncertain, this risk is subjective and objective, Risk is the probability of any outcome different from the one expected (risk is the probability of an outcome different from the expected outcome). It can be concluded that risk is associated with the possibility of an unwanted or unexpected bad result (loss). In other words, that possibility already indicates uncertainty.

Operational risk comes from processes, structures, systems and externals. In this study, it focuses on operational risks that come from externals, namely the potential of insurance users due to unexpected accidents. And the risk used in this research is a potential form that can lead to a flood of home insurance. This flood of houses will form the basis for the EVT method [2,6,7].

2. Method
In this section, we are asked to describe method, model, design, subject and location of the research. Operational risk comes from processes, structures, systems, and externals. This research focuses on operational risks that come from externals, namely the potential of insurance users due to unexpected calamities. The risk used in this research is a form of potential that can lead to paddy agricultural insurance. Pests of plant diseases, plant pests, and weather are the basis for the EVT method [6,7,9].

The threshold value is the initial value in the tail of the distribution that satisfies the extreme value distribution [9]. Selecting the threshold value basically seeks the optimal balance in order to get a minimum of model errors and parameter errors. Too low a sink value will result in a relatively high probability of model error, so that the threshold value is too low which results in more data above the threshold value (M). Thus, the parameter error is relatively small, and vice versa. The method for selecting the threshold value which is commonly used because of its practicality is the percentage method. EVT (Extreme Value Theory) is a branch of statistics that discusses the deviation of data from the mean in the distribution of odds. Usually used in extreme modelling such as losses that rarely occur but have a big impact. The losses incurred cannot be modelled by the usual approach, such as the normal distribution [9, 10, 13, 16, 20]. Extreme data is data that has a low incidence rate but has a large impact. The probability of an extreme event is difficult to identify because of the lack of data available in modelling, so modelling cannot be applied [12, 14].

EVT from operational loss data can actually be solved in two ways, namely using block maxima and POT (Peak Over Threshold) [9,15]. The maxima block model is a traditional method for analyzing seasonal data. The POT model is a method of identifying extreme values regardless of the timing of operational risks. The operational disadvantage of the POT method is called GPD (Generalized Pareto Distribution) [18,19]. In this study, the POT method was used to identify extreme values. POT (Peak Over Threshold) is one way to model extreme values. The main concept of this method is to use a
threshold to separate the values that are considered extreme across the data and to create a model for the extreme values by modelling the tails of all values that exceed this threshold. This is done in practice by setting the threshold \( u \) to be some defined value on \( R \) that exceeds most but not all values defined in some time series or some other vector of pooled values. It can further be shown that for some fairly large thresholds the distribution of values that exceeds the threshold approximates the General Pareto Distribution with several parameters \([21, 22]\). The probability density function of GPD (Generalized Pareto Distribution)

\[
f(\xi, \sigma | x) = \begin{cases} \\
\frac{1}{\sigma} \left(1 + \frac{\xi x}{\sigma}\right)^{-\frac{1}{\xi} - 1}, & \xi \neq 0 \\
\frac{1}{\sigma} \exp \left(-\frac{x}{\sigma}\right), & \xi = 0
\end{cases}
\]

where \( 0 \leq x < \infty \) for \( \xi \geq 0 \) and \( 0 \leq x < -\frac{\sigma}{\xi} \) for \( \xi < 0 \).

This GPD has two parameters, namely the shape parameter (\( \xi \)) and the scale parameter (\( \sigma \)). There are three types of distribution in GPD. Type 1 has an exponential distribution if \( \xi = 0 \). Type 2 has a Pareto distribution if \( \xi > 0 \) and type 3 has a Beta distribution if \( \xi < 0 \). The greater the value of \( \xi \), the distribution will have a fatter tail. So that the chances of the occurrence of extreme values are even greater. According to \([24, 25, 26]\), if \( \xi < 0 \) then the incident has a short tail and if \( \xi > 0 \) then the event has a long tail.

**Value at Risk (VaR) and Operational Value at Risk (OpVaR)**

The conditional distribution function \( F_u \) of excess loss above the threshold \( u \) is defined as

\[
F_u(y) = P[X - u \leq y | X > u]
\]

for \( 0 \leq y \leq X_F - u \), \( X_F \) is the southernmost point of \( F \). Where \( X_F = \sup \{x \in R : F(x) < 1\} \leq \infty \) and \( y = x - u \) are the above advantages \( u \) \([23, 26]\). Can be written in the form

\[
F_u(y) = \frac{P[X - u \leq y, X > u]}{P[X > u]} = \frac{P[X - u \leq u + y]}{1 - P[X > u]} = \frac{1 - P[X > u]}{F(u + y) - F(u)} = \frac{1 - F(u)}{1 - F(u)}.
\]

(2)

Parametric model of the excess loss distribution function \( F_u \) of the generalized pareto distribution (GPD) based on the limit theorem, namely the Pickands-Dalkema-de Haan theorem. Based on the Dalkema-de Haan Pickands theorem for \( u \) which is large and close to \( X_F \), where \( \beta(u) \) is a positive real function \([39, 40]\).

\[
\lim_{u \to X_F, y \leq X_F - u} |F_u(y) - G_{\xi, \beta(u)}(x - u)| = 0
\]

(3)

so that the excess loss function from \( F_u \) converges to \( G_{\xi, \beta} \) and can be written as \( F_u(\xi) = G_{\xi, \beta}(x - u) \). Then, the results of the previous equation are substituted into the equation which underlies the distribution function (\( x \)) so that it can be written as

\[
F(x) = \left(1 - F(u)\right)G_{\xi, \beta}(x - u) + F(u), \text{ for } x > u.
\]

(4)

Estimation of value (\( u \)) is performed to find the quantile corresponding to \( u \), this can be solved from the empirical distribution function

\[
\hat{F}(u) = \frac{n - N_u}{n}
\]
where \( n \) is the sample size of the data and \( N_u \) is the amount of losses above the threshold \( u \). Tail estimator from \( F(x) \) for \( x > u \) becomes

\[
\hat{F}(x) = \frac{N_u}{n} \left( 1 - \frac{\xi(x-u)}{\beta} \right)^{-\frac{1}{\xi}} + \left( 1 - \frac{N_u}{n} \right)
\]

\[
= 1 - \frac{N_u}{n} \left( 1 + \frac{\xi(x-u)}{\beta} \right)^{-\frac{1}{\xi}}.
\]

(5)

Value at Risk or VaR is defined as the maximum expected loss value of the value of assets or shares in a certain period and at a certain level of confidence [25, 34, 35, 36, 38]. If \( p \) is the highest probability above \( (u) \), then if it is substituted into the previous equation, it will be

\[
1 - p = \frac{N_u}{n} \left( 1 + \frac{\xi(x-u)}{\beta} \right)^{-\frac{1}{\xi}}
\]

where \( \alpha = 1 - p \), then the above equation will be

\[
\left( 1 + \frac{\xi(x-u)}{\beta} \right)^{-\frac{1}{\xi}} = \frac{n}{N_u} \alpha
\]

\[
\frac{\xi(x-u)}{\beta} = \left( \frac{n}{N_u} \alpha \right)^{-\xi} - 1
\]

Therefore, for the probability \( p > (u) \), the quantile function estimation can calculate the amount of potential loss with the GPD distribution using the formula [27].

\[
F^{-1}(1 - \alpha) = \text{VaR}_p = u + \frac{\beta}{\xi} \left( \frac{n}{N_u} (1 - p) \right)^{-\xi} - 1
\]

(6)

\( u \) : Threshold  
\( \beta \) : Parameter Scale  
\( \xi \) : Parameter Shape  
\( n \) : Total jumlah data observasi  
\( N_u \) : Jumlah data di atas threshold.

OpVaR is a method for measuring losses arising from operational risk with a certain level of confidence [28, 35, 40]. The OpVaR used in this study illustrates the operational risks of possible claims. The amount of operational risk sought is the VaR with \( p\% \) quantile of the distribution of the total loss value. OpVaR in this study used a confidence level of 95%, 99% and 99.99% as a comparison. OpVaR EVT can be found by reducing the threshold value limit on extreme data so that the OpVaR-EVT value can be found by using a formula.

\[
\text{OpVaR} = u + \frac{\beta}{\xi} \left( \frac{n}{m} (1 - p) \right)^{-\xi} - 1
\]

(7)

where:

\( \text{OpVaR} \) : Operational Value at Risk (p\% quantile)  
\( u \) : Threshold  
\( \beta \) : Scale parameters  
\( \xi \) : Shape parameters  
\( n \) : The total amount of observation data  
\( m \) : Amount of data above the threshold  
\( p \) : Level of confidence

3. Result and Discussion

This section will discuss the calculation of micro insurance premiums using the Extreme Value Theory (EVT) approach starting from descriptive statistical analysis, resampling data, determining parameters, determining the limit value, determining the Operational Value at Risk (OpVaR) EVT, then doing a
portfolio approach, then calculating insurance premium. The data used in this study is data on losses due to crop failure in the weather index, Pests and plant diseases, and Plant pests in Bandung District, West Java, whose area of irrigated rice fields is 31,874 ha (based on BPS data) for a period of 11 years, namely the years 2009-2019. Loss data can be seen in Table 1.

**Table 1.** Loss data due to weather index, plant pests and diseases, and plant pests

| Year | Weather index | Pests and plant diseases | Plant pests |
|------|---------------|-------------------------|-------------|
|      | Incident | Loss (IDR)      | Incident | Loss (IDR) | Incident | Loss (IDR) |
| 2009 | 8        | 27,736,000       | 15      | 119,884,000 | 17      | 145,229,000 |
| 2010 | 13       | 46,537,000       | 6       | 39,024,000  | 8       | 137,228,000 |
| 2011 | 5        | 13,375,000       | 9       | 79,626,000  | 13      | 124,265,000 |
| 2012 | 9        | 28,641,000       | 17      | 406,357,000 | 16      | 137,080,000 |
| 2013 | 11       | 41,249,000       | 12      | 155,886,000 | 10      | 126,886,000 |
| 2014 | 18       | 67,487,000       | 4       | 96,157,000  | 6       | 73,223,000  |
| 2015 | 8        | 23,299,000       | 7       | 48,826,000  | 12      | 95,990,000  |
| 2016 | 14       | 165,460,000      | 10      | 130,624,000 | 20      | 209,974,000 |
| 2017 | 12       | 94,463,000       | 12      | 80,039,000  | 11      | 102,182,000 |
| 2018 | 4        | 40,011,000       | 8       | 86,927,000  | 13      | 174,789,000 |
| 2019 | 7        | 99,402,000       | 10      | 65,778,000  | 15      | 146,098,000 |

From Table 1, descriptive statistics are obtained which are shown in Table 2.

**Table 2.** Descriptive statistics of risk loss data

| Descriptive Statistics | Weather index | Pests and plant diseases | Plant pests |
|------------------------|---------------|-------------------------|-------------|
| Data                   | 11            | 11                      | 11          |
| Mean                   | 58,878,183.73 | 119,011,636.4           | 133,902,185.4 |
| Standard Deviation     | 45,146,269.71 | 101,411,243.6           | 37,449,562.03 |
| Sample Variance        | 2.03819E+15   | 1.02842E+16             | 1.40247E+15 |
| Kurtosis               | 2.067455325   | 7.791165345             | 0.770406633 |
| Skewness               | 1.476769083   | 2.648905358             | 0.467367174 |
| Minimum                | 13,375,021    | 39,024,000              | 73,223,000  |
| Maximum                | 165,460,000   | 406,357,000             | 209,974,000 |
Table 3. Total loss data

| Year | Incident | Loss (IDR)  |
|------|----------|-------------|
| 2009 | 40       | 292,849,000 |
| 2010 | 27       | 222,789,000 |
| 2011 | 27       | 217,266,000 |
| 2012 | 42       | 572,078,000 |
| 2013 | 33       | 324,021,000 |
| 2014 | 28       | 236,867,000 |
| 2015 | 27       | 167,575,000 |
| 2016 | 44       | 506,058,000 |
| 2017 | 35       | 276,684,000 |
| 2018 | 25       | 301,727,000 |
| 2019 | 32       | 311,278,000 |

From the data in Table 3., the descriptive statistics are obtained which are shown in Table 4.

Table 4. Descriptive statistics of total loss data

| Descriptive Statistics | Data |
|------------------------|------|
| Mean                   | 311,744,727.3 |
| Standard Deviation     | 122,719,020.2 |
| Sample Variance        | 1.506E+16 |
| Kurtosis               | 1.189626048 |
| Skewness               | 1.320523265 |
| Minimum                | 167,575,000 |
| Maximum                | 572,078,000 |

Calculate data using the EVT method for the amount of loss data that has been made in Table 3. Calculate the extreme data from resampling to find OpVaR (Operational Value at Risk) then determine the premium by paying attention to OpVaR. Then, what must be done is to calculate the MEBoot based on the annual loss data for paddy harvest based on the three causes of weather, pests, and plant diseases, listed in Table 1. There is a repetition by this MEBoot, according to the results of MEBoot, it shows the tail of the data in the form of an approach line away from normal. The number of repetitions is determined by trial and error and for this data, the same results are obtained for 121 repetitions in the risk data due to high rainfall, and 121 repetitions in the risk data for pests and plant diseases. From the descriptive statistical data in Table 5, there is extreme data on the MEBoot results from each risk that does not spread normally; because the skewness value ≠ 0 and kurtosis ≠ 3. This data estimate assumes the distribution of GPD. Then perform a distribution suitability test and calculate the estimated GPD parameters for each distribution of risk.
Table 5. MEBoot total loss data

| Event Type | Repetition | Number of Data | Extreme Data | Threshold (IDR) |
|------------|------------|----------------|--------------|----------------|
| Total      | 110        | 1,210          | 121          | 474,267,366    |

Table 5., shows the total loss data into 1,210 data. MEBoot produces data, then it is selected because it is the same as the assumption of a large data tail distribution.

Table 6a. Extreme data descriptive statistics
results of MEBoot data for each risk

| Descriptive Statistics | Count | Pests and plant diseases | Plant pests |
|------------------------|-------|--------------------------|-------------|
|                        | Weather index | 121 | 121 | 121 |
| Mean                   | 548,372,779.2 | 560,563,180.3 | 203,762,427.3 |
| Standard Deviation     | 50,455,651.08 | 49,094,884.42 | 15,102,110.79 |
| Sample Variance        | 2.54577E+15   | 2.41031E+15   | 2.28074E+14  |
| Kurtosis               | -0.776962279 | -0.949862108 | -1.0806828   |
| Skewness               | 0.286402024   | 0.250727952   | 0.279970902  |
| Minimum                | 473,553,678   | 483,505,733   | 182,265,898  |
| Maximum                | 669,494,253   | 678,072,076   | 238,277,309  |
| Sum                    | 66,353,106,289| 67,828,144,818| 24,655,253,705|

This is the result of calculating the fit distribution with GPD for extreme data which can be seen in Figure 1. for polygon histograms and Figure 2. for QQPlot.

Figure 1. Polygon histogram for total MEBoot data extreme with GPD
The fit-test was carried out using the Kolmogorov Smirnov test with the help of Easyfit Software, the results are presented in Table 6.

**Table 6b. Goodness of fit extreme data with GPD total**

| Gen. Pareto [#24] | Kolmogorov Smirnov |
|-------------------|--------------------|
| Sample size       | 121                |
| Statistic         | 0.05554            |
| p-value           | 0.82909            |
| Rank              | 2                  |

| A          | 0.2 | 0.1 | 0.05 | 0.02 | 0.01 |
|------------|-----|-----|------|------|------|
| Critical Value | 0.09755 | 0.11118 | 0.12345 | 0.138 | 0.14809 |
| Reject?    | No  | No  | No   | No   | No   |

Because there is no rejection of the tests carried out, it can be continued to estimate the parameters. The results of the three OpVaR calculations with three confidence levels are summarized and presented in Table 7.

**Table 7. Numerical result using OpVaR method**

| Loss          | OpVaR  |
|---------------|--------|
|               | $p = 90\%$ | $p = 95\%$ | $p = 99\%$ |
| Total (IDR)   | 413,998,816 | 474,267,636.9 | 534,533,106 |
| Premium/ha (IDR) | 12,988.61 | 14,879.45 | 16,770.19 |

From the calculations using the OpVaR method in Table 7, illustrates the value of expected total claims at each level of confidence. With a 95% confidence level of IDR474,267,636.9, a 99% confidence level of IDR534,533,106, and IDR413,998,816. That is, we believe 95% of the expected claim from the risk of loss in the next year is IDR 474,267,636.90. This means that for irrigated rice fields, which is 31,874 hectares, the premium price for OpVaR is IDR 14,879.45 per hectare for the 95% confidence interval.

4. Conclusion

Based on the results of the discussion, the following conclusions can be drawn: The use of this risk value can be used to calculate the premium. OpVaR premium calculations vary, depending on the level of
confidence chosen. The results of calculations using the extreme value approach and $OpVaR$ with the selected confidence level and threshold limit provide the results as shown in Table 7. To obtain optimal risk and premium values, other approaches can be used, which will be carried out in subsequent studies.

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