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LOSS INSURANCE MODEL OF RISK FOR AGRICULTURAL COMMODITY BASED ON MAXIMUM DAILY RAINFALL INDEX CONSIDERATION

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ABSTRACT

Agricultural commodities in rainfed areas face significant risks of yield loss and crop failure due to uncertain rainfall patterns and intensities. Index-based crop insurance has been introduced as an adaptive strategy to simplify loss assessment using climate indicators. However, most existing schemes cover only a single peril, such as drought. This study aims to develop a loss model of risk for agricultural commodity using maximum daily rainfall index that accounts for both drought and flood risks. The model consists of two components: rainfall modelling and insurance modelling. Rainfall modelling identifies the appropriate probability distribution to define rainfall index parameters—trigger and exit—which represent thresholds for yield reduction and total crop failure, respectively. These parameters are derived through numerical integration and can be approximated using percentiles when crop-specific water requirement data are unavailable. Insurance modelling determines a benefit claim model based on rainfall probability and parameters of rainfall index, with three possible benefit claim conditions: full, partial, and none. A case study using maximum daily rainfall data (September–December, 1984–2014) for paddy in Dramaga, Bogor, indicates that the Burr Type XII distribution fits the data better than the GEV distribution. The estimated premium ranges from IDR 300000 to 300822.9 per hectare. In high-rainfall areas like Dramaga, premiums are primarily influenced by the probability of excess rainfall, while drought risk is negligible. Analysis over a 10-year actual maximum daily rainfall data (September–December, 2015–2024) shows that lower insured percentiles result in lower premiums. To improve accuracy, trigger and exit should ideally be determined based on the specific crop's water requirements. Despite data limitations, this model provides a conceptual model for developing more representative and actuarially fair loss model for agricultural commodity risk.

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1. INTRODUCTION

In recent decades, the impact of weather-related events has increased significantly on a global scale [1]. Climate change adversely affects crop yield through various factors, such as changes in rainfall pattern and intensity that disrupt growing seasons across major cropping systems [2], [3]. Additional impacts include drought, excessive water accumulation, and extreme precipitation events. Drought can interfere with plant metabolism, potentially slowing growth or even causing total crop failure. Meanwhile, floods have become more frequent in many lowland and agricultural areas, causing significant damage to people, including reductions in crop yields and food supplies [4].

Adaptation strategies, such as crop insurance, have been developed to mitigate the risk of losses due to events such as drought. Since 2015, Indonesia has implemented Asuransi Usaha Tani Padi (AUTP) program [5]. The policy covers damage when the intensity reaches ≥75% or when the affected area is ≥75% of each natural plot. However, the AUTP claim process requires an on-site damage inspection, which can lead to inefficiencies and potential moral hazard. Several recent studies have developed yield-based crop insurance and weather index insurance schemes. Both types have been widely implemented as forms of parametric insurance [6]-[10]. Parametric insurance is a type of insurance that involves a predefined agreement between the insurer and the policyholder concerning triggering events, established at the outset of the contract [11]. Yield-based crop insurance typically requires crop yield data to determine the threshold and the premium that policyholders must pay to obtain coverage. But, the data is occasionally unavailable and incomplete. However, such data are often unavailable or incomplete. Therefore, weather index insurance has emerged as a promising alternative to insure agricultural commodities, especially crops in rainfed areas where water requirements rely solely on rainfall.

Weather index insurance uses parameter indices to represent crop failure in specific areas. Rainfall is one of the key climate parameters significantly affected by climate anomalies. Many studies have utilized rainfall data to develop weather index insurance [7]-[11]. The Historical Burn Analysis method can be applied to determine rainfall index [12]. This method estimates potential losses based on past data by analyzing historical events and their impacts to model future risk exposure. Moreover, information about the probability distribution of rainfall realization is essential. To address this issue, the Historical Burn Analysis method should be modified by incorporating a rainfall modeling step. The probability of rainfall realization is then assumed to follow the historical distribution and will be used as the rainfall index. The resulting rainfall index is used to determine the parameters of rainfall index, specifically exit and trigger [7]. In weather index insurance models that cover farmers against drought losses, the exit is defined as the rainfall threshold below which total crop failure occurs. The trigger is defined as the rainfall threshold below which crop yields decrease. Both exit and trigger can be obtained using numerical integration methods that evaluate fixed values against rainfall probability distributions [7]. Then, the benefit claim model is a key component of insurance modelling. A benefit claim model is a framework that defines how, when, and to what extent benefit payment amount is paid to insurance policyholder (i.e. farmer), based on predetermined criteria or parameters. It is integrated with rainfall probability, the benefit payment amount, and the parameters of the rainfall index. The amount of benefit payment defines as compensation of loss that is insured. Then, the implication of insurance modelling is premium model [7]. Premium principal could be used to evaluate the value of premium based on the developed benefit claim model on [7].

Based on the previous background, rainfall probability plays an important role in insurance modeling. This probability also depends on the selected indicator. One commonly used indicator in the rainfall index is the cumulative rainfall during the insurance period [7]. Based on the previous background, rainfall probability plays an important role in insurance modeling. This probability also depends on the selected indicator. One commonly used indicator in the rainfall index is the cumulative rainfall during the insurance period. Furthermore, to the best of the author's knowledge, most studies on benefit claim models and premium estimation in rainfall and insurance modeling have focused primarily on crop failure due to drought. There has been no research that incorporates both drought and flood risks into a single loss model for agricultural commodities using the maximum daily rainfall indicator during the insurance period.

This research aims to develop a loss model of risk for agricultural commodity using maximum daily rainfall indicator, which accounts for crop failure due to both drought and flood. The development of this model demonstrates that the rainfall index must adopt both dual-trigger and dual-exit, rather than relying on a single trigger and exit as in previous models. In addition, the benefit payment scheme is divided into three conditions: partial payment, full payment, and no payment. The premium can then be determined as a direct implication of the developed model. To illustrate the model, a case study was conducted using paddy crop data and maximum daily rainfall records from September to December in Dramaga, Bogor, spanning the period from 1984 to 2014. The data were obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG). The maximum daily rainfall was analyzed using the Generalized Extreme Value (GEV) and Burr Type XII distribution models. There are several reasons for selecting the Burr distribution [13], [14]. First, it is defined only for positive values, making it well-suited for modeling hydrological and meteorological data. Second, it has two shape parameters, which provide the flexibility to adapt to diverse datasets by accommodating a wide range of skewness and kurtosis. This parameter variability enables the Burr distribution to effectively fit various empirical datasets in fields such as hydrology, meteorology, and finance [15]. Moreover, to extend the comparative analysis, the Generalized Extreme Value (GEV) distribution—recognized as the most widely used model for block maxima data—was also fitted to the dataset [14], [16], [17]. The parameters of both models, GEV and Burr Type XII, were estimated using the Maximum Likelihood Estimation method and numerically solved with R software version i386 4.1.3. Model validation was conducted using maximum daily rainfall data from September to December in Dramaga, Bogor, for the period 2015 to 2024. This research contributes significantly by developing a conceptual model that supports the advancement of crop insurance schemes designed to protect smallholder farmers from the impacts of drought and flood.

2. RESEARCH METHODS

This research is conducted through a literature review utilizing the latest scientific articles relevant to the research topic. A quantitative modeling approach is applied to develop a risk loss model for agricultural commodities, using maximum daily rainfall as an indicator and a percentile-based benefit claim model. This approach is selected due to the limited availability of crop yield data, enabling the estimation of agricultural losses through historical rainfall records, as commonly implemented in weather index insurance models. Such a model is particularly suitable for rainfed areas that rely heavily on rainfall. This study is carried out in two major stages: rainfall modelling and insurance modelling. The following sections present the conceptual framework and relevant literature used to support both the rainfall modelling and insurance modelling processes.

2.1 Conceptual Framework

Illustrating of the conceptual framework is given by Fig. 1.

Input:
Maximum daily rainfall in Dramaga Bogor.

Process:
1. Rainfall Modelling:
   a. Processing data using block maxima method.
   b. Selecting probability distribution for maximum daily rainfall, which serves as the rainfall index.
   c. Define rainfall index parameters (exit and trigger).
2. Insurance modelling:
   a. Modelling benefit claim model: integrate rainfall probability, benefit payment amount, and rainfall index parameters.
   b. Determining the net single premium.

Output :
5. Selected probability distribution of maximum daily rainfall.
6. Exit and trigger thresholds as rainfall index parameters.
7. Benefit claim model.
8. Net single premium formula of loss insurance model of risk for agricultural commodity.

Figure 1. Conceptual Framework

Based on Fig. 1, the proposed loss compensation model is designed to mitigate agricultural risks caused by extreme climate events through parametric insurance. Unlike traditional insurance, this approach relies on objective weather indices [18] — particularly maximum daily rainfall — rather than on-site field verification, thereby improving efficiency and reducing operational costs [19], [20]. Rainfall is chosen as the main index due to its strong correlation with paddy productivity, especially during critical growth stages [21], [22]. Both drought and excessive rainfall are major contributors to crop failure, making rainfall a reliable risk indicator [18]. To capture extreme rainfall events, the block maxima method is applied by dividing daily rainfall data into planting-period blocks and extracting the maximum value from each [23]. These values are modeled using extreme value distributions, such as the Generalized Extreme Value (GEV) and Burr Type XII distributions. From these models, trigger and exit (parameters of rainfall index) are determined—representing different severity levels of loss. These paramaters of rainfall index are the basis for the benefit claim model, which defines the benefit payment amount scheme based on the deviation of actual rainfall from these thresholds [19]. Finally, the net premium is calculated based on the expected of benefit claim derived from the modeled rainfall index.

2.2 Data Type and Source

The rainfall data represent the maximum daily rainfall recorded during the paddy cropping season at the Dramaga Bogor station, covering the period from September to December. The daily rainfall data were collected from January 1984 to December 2024 and obtained from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). The maximum daily rainfall indicator for each cropping period was derived using the block maxima method, which involves dividing the rainfall data into specific time blocks (e.g., planting phases) and selecting the maximum value within each block to represent an extreme rainfall event. This involves dividing daily rainfall data into specific time blocks (e.g., planting phases-September to December), and taking the maximum value within each block to represent an extreme rainfall event. A total of 31 data points (1984–2014) were used to estimate the rainfall probability distribution, while 10 years of data (2015–2024) were used to validate the loss insurance model of risk for agricultural commodities.

2.3 Rainfall Modelling

According to the Meteorology, Climatology, and Geophysics Agency (BMKG), daily rainfall is classified into five categories: very light (less than 5 mm), light (5–20 mm), moderate (21–50 mm), heavy (51–100 mm), and very heavy (more than 100 mm). After selecting appropriate rainfall data, rainfall modeling is conducted to identify the probability distribution that best represents the historical rainfall pattern. The chosen distribution is then used to estimate the probability of loss events. In this study, GEV and the Burr Type XII distribution are selected for analysis. Parameter estimation methods and goodness-of-fit tests are applied to evaluate the suitability of these distributions in capturing the statistical characteristics of maximum daily rainfall.

2.3.1 Generalized Extreme Value Distribution

Suppose $R_1, R_2, \cdots, R_n$ are independent, identical, and GEV-distributed random variable of rainfall, then the extreme value variable converges to the maximum daily rainfall distribution that is given in Eqs. (1) and (2) as follows [15]

$$\text{I} \;:\; F_R(r) = \exp\left\{-\left(1 + \xi\frac{r-\mu}{\sigma}\right)^{-\frac{1}{\xi}}\right\}, \text{for } \xi \neq 0, \text{and} \tag{1}$$

$$\text{II} \;:\; F_R(r) = \exp\left\{-\exp\left(-\frac{r-\mu}{\sigma}\right)\right\}, \text{ for } \xi = 0, \tag{2}$$

where r is defined for $1 + \xi\frac{r-\mu}{\sigma} > 0$, $-\infty < \mu < \infty$, $\sigma > 0$ and $-\infty < \xi < \infty$, μ is the location parameter, σ is the scale parameter, and ξ is the shape parameter.

2.3.2 Burr Type XII Distribution

The Burr type XII distribution model (α, ξ, λ) in probability theory, statistics, and econometrics is a continuous distribution for non-negative random variables. Based on [24], the cumulative distribution function of the Burr type XII distribution is given in Eq. (3) as follows

$$F_R(r) = 1 - \left[1 + \left(\frac{r}{\lambda}\right)^{\xi}\right]^{-\alpha}. \tag{3}$$

2.3.3 Maximum Likelihood Estimator

Suppose $L(r;\theta) = f(r_1, r_2, \dots, r_n ; \theta), \theta \in \Omega$, s the joint probability density function of $R_1, R_2, \cdots, R_n$. This function is called the likelihood function for θ and is denoted by $L(r;\theta)$ [25]. For a given observation point $r_1, r_2, \dots, r_n$, the maximum likelihood estimator (MLE) of θ is denoted as $\hat{\theta}$ and is given in Eq. (4) as follows.

$$L(r;\, \hat{\theta}) = \max_{\theta \in \Omega} L(r;\theta). \tag{4}$$

The estimator can be obtained directly if the first derivative equation with respect to θ forms an algebraically solvable equation. If the resulting equation cannot be solved algebraically, a numerical method is required to obtain the solution [25]. For this research, R software version i386 4.1.3. is used in ismev, mass, and actuar packages to evaluate maximum likelihood estimator.

2.3.4 Kolmogorov-Smirnov Test

The goodness-of-fit test is used to assess the validity of the GEVD and Burr Type XII distributions. The most well-known test is the Kolmogorov-Smirnov test (K-S). Let D^+ and D^- are given by Eq. (5) as follows

$$D^+ = \max_{1\le i\le n}\left\{\frac{i}{n} - F\left(r_{(i)}\right)\right\} \text{ dan } D^- = \max_{1\le i\le n}\left\{F\left(r_{(i)}\right) - \frac{i-1}{n}\right\}, \tag{5}$$

where $r_{(i)}$ denotes the i th ordered statistic of the sample and F denotes cumulative distribution of theoritical distribution. Then, the statistic value (D) is given by $\max(D^+, D^-)$. Beside it, critical value for this test is $1.36/\sqrt{n}$ with significant level at five per cent. When D value is smaller than the critical value of statistic, it indicates that the theoretical distribution effectively represent the emperical distribution [26].

2.3.5 Anderson-Darling Test

The Anderson-Darling statistical test was first developed by Anderson and Darling in 1954. The Anderson-Darling test is given by Eq. (6) as follows

$$AD = -n - \sum_{i=1}^{n} \frac{(2i-1)}{n}\left[\ln F_R(r_i) + \ln\left(1 - F_R(r_{n+1-i})\right)\right] \tag{6}$$

where n represents the sample size, $F_R(r_i)$ denotes the specific cumulative distribution function of the data, and i represents the natural numbers of $1, 2, 3, \cdots, n$ which are considered when the data is ordered in ascending order. The distribution that best represents the data among several candidate distributions is the one that yields the largest p-value and the smallest Anderson-Darling (AD) statistic [26].

2.3.6 Previous Insurance Modelling

Based on [7], crop insurance product based on rainfall index, insures rainfall index in specific region. The benefit claim is treated as a random variable, denoted by X, expressed as a percentage of the insured benefit. The assumptions underlying this rainfall index–based agricultural insurance, which influence the benefit claim model, can be broadly summarized as follows: (1) the insured agricultural land is located in rainfed area, (2) the rainfall indicator used is the cumulative rainfall over a specific period, such as one paddy planting season (three months), (3) the extreme daily rainfall events are not considered, the probability of claiming benefits is determined based on historical rainfall distribution, (4) the benefit claim model accounts for losses caused by specific rainfall conditions, including either drought or flood, (5) the rainfall index is established for period estimated to pose a risk of loss, determined through correlation analysis or other appropriate methods, and (6) other loss-causing factors, such as plant diseases or pest infestations, are not considered.

2.3.7 Premium

The premium (P) refers to the cost that must be paid by the policyholder to the insurance company in accordance with the terms agreed upon in the policy. Premium principal method has used to calculate premium [7]. So, the formula of premium is $P = (1+\theta)\mathbb{E}[X] + S$ where θ is premium loading or adding cost which depends on $\mathbb{E}[X]$ and S represents as administration fee . Notation of $\mathbb{E}[X]$ represents average of benefit claim that will be collected by policyholders and means rate premium. The research will be focused for determining $\mathbb{E}[X]$ of the product.

3. RESULTS AND DISCUSSION

The development of the model based on rainfall considerations involves relaxing two assumptions from the previous model: namely, that the model applies only to either drought or flood cases, and that extreme daily rainfall is not considered. Consequently, the insured risks now encompass declines in agricultural production and productivity, as well as total crop failure. The fundamental concepts of the loss insurance model for agricultural commodity risk are as follows:

3.1 Loss Insurance Model of Risk for Agricultural Commodity Based on Maximum Daily Rainfall Index

The loss insurance model for agricultural commodity is a crop insurance model developed based on a rainfall index. This model is applicable to various types of agricultural commodities and can simultaneously cover risks related to both drought and flood. It accounts for extreme variations in rainfall within a given region. However, this model is only suitable for agricultural commodities grown in rainfed areas, meaning that the crops rely solely on rainfall without irrigation. Each agricultural commodity has specific water requirements; for example, paddy grows optimally when water availability meets its needs during the planting period. Paddy crops can suffer total damage if rainfall is either too low or excessively high. This insurance model is designed to mitigate risks associated with uncertain rainfall conditions, including both insufficient and excessive rainfall. Therefore, the loss insurance model requires a rainfall index that is expected to represent the risk of crop failure for the insured agricultural commodity. The assumptions used in this loss insurance model of risk for agricultural commodity are:

1. The insured agricultural land is located in rainfed area;
2. The rainfall indicator used is the maximum daily rainfall over a specific period, such as one paddy planting season (three months);
3. Extreme daily rainfall events are considered;
4. The probability of claiming benefits is determined based on historical rainfall distribution;
5. The benefit claim model covers two cases at once, drought and flood;
6. The rainfall index is established for period estimated to a risk of loss, either through correlation analysis or other methods; and
7. The loss-causing factors, such as plant diseases or pest infestations, are not considered.

Based on the following explanation, the range of rainfall is divided into five intervals defined by four parameters: exit 1, exit 2, trigger 1, and trigger 2. Definitions of those parameters are as follows.

3.1.1 Exit

The exit is defined as the rainfall threshold which total crop failure occurs. Before that, full benefit (b) is maximum amount of indemnity and proportional with total production cost in specific agricultural region. The exit is divided into two types, those are exit 1 (E_1) and exit 2 (E_2). Rainfall realisation that is lower than exit 1 is categorized as drought. Also, rainfall realisation that is higher than exit 2 is categorized as flood. Exit 1 (E_1) and exit 2 (E_2) can be determined by rainfall distribution and characteristics of water requirement of particular agricultural commodity for extreme conditions.

The probability of rainfall realization that it is less than exit 1 is denoted by K_1 and probability of rainfall realisation that it exceeds exit 2 is denoted by K_2. Formula of K_1 and K_2 are given by Eqs. (7) and (8), respectively.

$$K_1 = F_R(E_1), \tag{7}$$

$$K_2 = 1 - F_R(E_2), \tag{8}$$

where $F_R(r)$ is a cumulative distribution function of the selected distribution in rainfall modelling, and K_1 & K_2 are constant in percent.

3.1.2 Trigger

The trigger is defined as the rainfall threshold which crop yields decrease. Triggers are divided into two types, those are trigger 1 (T_1) and trigger 2 (T_2). Rainfall realisation is less than trigger 1 or it exceeds trigger 2 fulfills partial risk. While the rainfall realisation is higher than trigger 1 and it is lower than trigger 2, the rainfall is in ideal condition for agricultural commodity and it gives optimal production. Trigger 1 and trigger 2 can be determined by rainfall distribution and characteristics of water requirement of particular agricultural commodity that can cause decreasing the yield of productivity.

The probability of rainfall realization that it is less than trigger 1 is denoted by L_1. The probability of rainfall realisation that it exceeds trigger 2 is denoted by L_2. Formula of L_1 and L_2 are given by Eqs. (9) and (10), respectively.

$$L_1 = F_R(T_1), \tag{9}$$

$$L_2 = 1 - F_R(T_2), \tag{10}$$

where $F_R(r)$ is cumulative distribution function of the selected distribution in rainfall modelling, and L_1 & L_2 are constant in percent.

3.2 Developing Benefit Claim Model

The benefit claim model is an indemnity model based on the realization of rainfall identified in the rainfall index. The claim is a random variable, denoted by$X$, and is expressed as a percentage of the benefit. Based on the benefit payment amount, the claim is illustrated by Fig. 2.

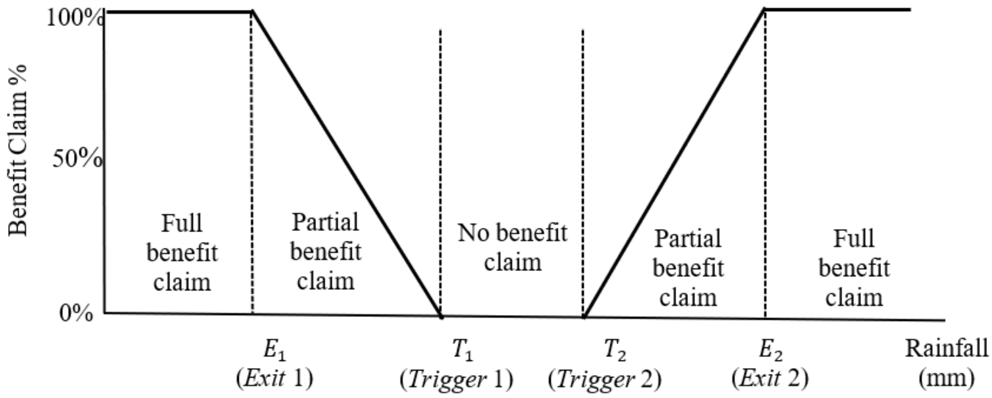

Figure 2. Benefit Claim Model Developed

Based on Fig. 2, the benefit claim model is developed. Previously, the crop insurance model could only cover a single event, either drought or flood [7], [27]. In [7], The high rainfall values that pose a risk to agricultural commodities are not covered under previous models. Therefore, the benefit claim model is developed to address risks from two extreme rainfall events: drought and flood. The X-axis represents the measured realization of rainfall. On the right side of the axis, the risk to agricultural commodities is caused by extremely high rainfall (flood). On the left side, the risk is due to extremely low rainfall (drought). Both extremes can lead to total crop failure. Meanwhile, the Y-axis represents the amount of the benefit claim when certain conditions are met. The benefit claim model is categorized into three conditions, as follows.

Condition 1 ($r \leq E_1$) or ($r \geq E_2$):

Condition I refers to situations where the rainfall realization is less than or equal to Exit 1, or greater than or equal to Exit 2. This condition is associated with total crop failure, which is typically caused by extreme weather events such as drought or flood. If Condition 1 is met, the policyholder is eligible to claim the full insurance benefit ($x = b$).

Condition 2 ($E_1 < r < T_1$) or ($T_2 < r < E_2$):

Condition II refers to situations where the rainfall realization falls between Exit and Trigger thresholds. This condition indicates the beginning of a decline in agricultural production. Economically, it is characterized by yields that fall below production costs. If Condition 2 is met, where the rainfall realization satisfies $E_1 < r <$

T_1, the policyholder is entitled to receive a partial benefit claim, depending on the severity of the loss. The amount of the claim can be calculated as shown in Eq. (11) as follows.

$$x = \frac{b(T_1 - r)}{T_1 - E_1}, \tag{11}$$

with b is full benefit, $r \geq 0$ and $E_1 \neq T_1$. If the conditio $T_2 < r < E_2$ n is fulfilled, the policyholder can ask partially insurance claim as given at Eq. (12) as follows.

$$x = \frac{b(r - T_2)}{E_2 - T_2}. \tag{12}$$

Condition 3 ($T_1 \leq r \leq T_2$) :

In Fig. 2, Condition 3 refers to situations where the rainfall realization during a specific period falls between Trigger 1 and Trigger 2. This range represents the ideal rainfall level for a particular agricultural commodity in a given region. If the rainfall meets this condition, it implies that no significant loss has occurred. Therefore, if Condition 3 is fulfilled, the policyholder is not eligible to receive any insurance claim ($x = 0$).

3.3 Developing Premium

In actuarial science, premium can be calculated based on the expected value of the benefit claim. The premium is paid once at the beginning of the insurance contract and represents the implication of developing crop insurance model. Unlike conventional insurance premiums, this premium accounts for the minimum and maximum water requirements of agricultural commodities, which are represented by the exit and trigger. After calculating exit and trigger, the value of premium (in IDR per hectare) in loss insurance model of the risk for agricultural commodity can be formulated as shown in Eq. (13).

$$P = \mathbb{E}[X] = b\left[F_R(E_1) + \left(1 - F_R(E_2)\right)\right] + \int_{E_1}^{T_1} \left(\frac{b(T_1 - r)}{T_1 - E_1}\right) f_R(r)dr + \int_{T_2}^{E_2} \left(\frac{b(r - T_2)}{E_2 - T_2}\right) f_R(r)dr. \tag{13}$$

with r is the rainfall, b declares full benefit, F_R denotes cumulative distribution function of rainfall, f_R is defined probability density function of rainfall (the derivative of F_R), E_1 and E_2 are rainfall threshold which total crop failure occurs, and T_1 and T_2 are the rainfall threshold which crop yields decrease. Based on Eq. (13), The numerical value of the premium can be calculated once all relevant parameters are known. Therefore, a case study was conducted to simulate and determine the numerical values of these parameters.

3.4 Case Study

A case study was conducted to simulate the premium calculation for loss insurance of agricultural commodity risk. The stages of rainfall modeling and insurance modeling are outlined below.

3.4.1 The Distribution of Maximum Daily Rainfall and Parameter Estimation

The rainfall modelling is required for selecting the best-fit probability distribution for a certain location. In this section, Generalized Extreme Value distribution (GEVD) and Burr type XII distribution which are suspected suitable to model a maximum daily rainfall data are presented. The method of parameter estimation of Burr type XII used maximum likelihood estimator to calibrate parameter of Burr type XII distribution Furthermore, Kolmogorov-Smirnov (K-S) test and Anderson Darling (A-D) test are used for checking the validity of assumed probability distribution model. Parameter estimators and statistic values that were obtained using R software could be seen in Table 1.

Table 1. Estimated Parameter and Statistic Value of K-S & A-D Test

Number	Type of The Result	GEVD	Burr Type XII
1	Parameter Estimator	$\mu = 90.57$	$\alpha = 0.29$
		$\sigma = 18.31$	$\xi = 15.24$
		$\xi = 0.15$	$\lambda = 0.01$
2	Statistic Value of K-S Test	0.11	0.07
3	Statistic Value of A-D Test	1.9352 (p-value = 0.1001)	0.24799 (p-value = 0.9713)

Based on Table 1, The statistic values of GEVD and Burr type XII distribution by Kolmogorov-Smirnov test were smaller than the critical value (0.24) with significant at the five per cent level, those were 0.11 and 0.07, respectively. According to Anderson Darling test result, statictic value of Burr Type XII as 0.24799 was smaller than statictic value of GEVD as 1.9352. It means data is better to represent by Burr Type XII than GEVD. Then, let see Fig. 3 shows below.

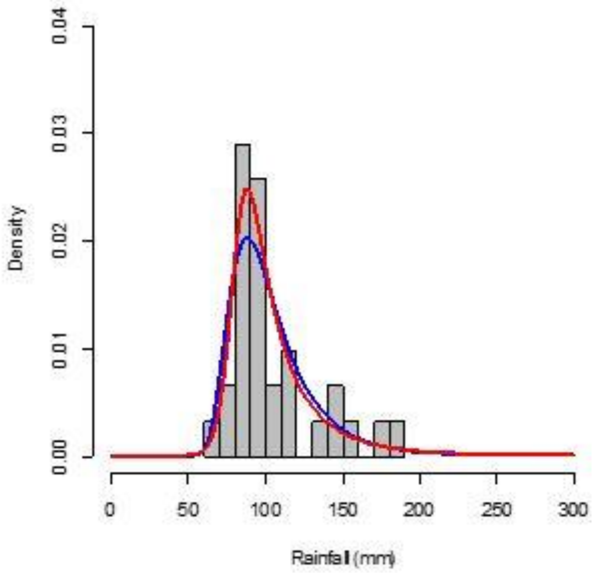

Figure 3. PDF Curve of Burr Distribution (Red Line) and PDF Curve of GEVD (blue line) for Data Set

The information was just presented by Fig. 3 which curve of probability density function of Burr type XII distribution (red line) followed data pattern closer than what curve of probability density function of GEVD (blue line) did. Therefore, the Burr type XII distribution was more suitable than GEVD in modelling maximum daily rainfall in Dramaga Bogor.

3.4.2 Illustration of Developing Premium Determination and Implementing Benefit Payment Scheme

The illustration is only example to show premium value of one scenario as the implication of the loss insurance model of risk for agricultural commodity that is developed. To illustrate the premium determination, some assumptions are stated. The first assumption policyholders or farmer paid premium once at the beginning of the contract insurance and claimed benefit at the end of the period. Then, full benefit was IDR 6 million per hectare which was equivalent with paddy production cost. The characteristics data of water requirement of paddy in rainfed area of Dramaga Bogor is not available, so the characteristics of paddy is determined from this scenario case based on percentile of probability Burr Type XII distribution ($K_1 \in [0\%, 0.00000001181824\%], K_2 = 5\%,\ L_1 = 4\%, L_2 = 7\%$). In other word, trigger and exit can be dealt with by establishing the probabilities of insurer are willing to ensure the risk of loss.

Based on the scenario case, exit 1 is in the range $(0, 50)$ in mm, exit 2 is at 163.54 mm, trigger 1 is at 73 mm and trigger 2 is at 151.5 mm. It means that the policyholder can obtain full benefit if maximum daily rainfall realisation is less than exit 1 or more than exit 2, 163.54 mm. The policyholder can obtain partial benefit if maximum daily rainfall realisation is between exit 1and 73 mm or between 151.5 mm and 163.54 mm. The policyholder has no benefit if maximum daily rainfall realisation is between 73 mm and 151.5.

The value of premium for scenario case was in the range of $[300000, 300822.9]$ in IDR per hectare depending on the value of exit 1. The illustration of changing the premium value curve is given at Fig. 4.

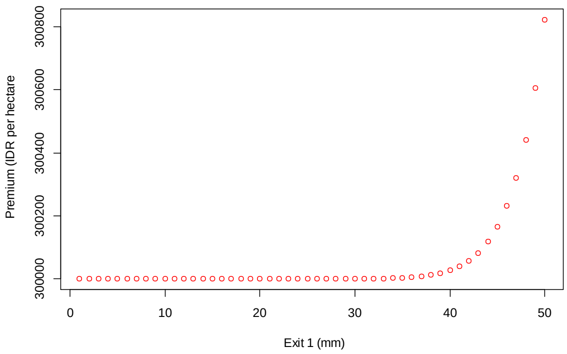

Figure 4. Changing the Premium Value Curve when Exit Moved Incrementally from 0 to 50 mm

Based on Fig. 4, maximum daily rainfall in Dramaga Bogor from September to December approached zero while the rainfall was less than 30 mm. Moreover, the value of premium go up slightly for exit 1 in the range $(30, 40]$. Changing value of premium began to increase exponentially as exit 1 in the range of $(40, 50)$. Implementing benefit payment scheme on loss insurance model of risk for agricultural commodity that is developed is illustrated by Table 2.

Table 2. Implementing Loss Insurance Model of Risk for Paddy Based on Actual Maximum Daily Rainfall

No	Year	Actual Maximum Daily Rainfall (mm)	Parameters of Rainfall Index	Premium (IDR)	Claim Status	Benefit Payment (IDR)
1	2015	155.8	$E_1 = 50$ mm	300822.9	Partial Benefit Payment	2143801
2	2016	96.3	$E_2 = 73$ mm	300822.9	No Payment	0
3	2017	76.9	$T_1 = 151.5$ mm	300822.9	No Payment	0
4	2018	116	$T_2 = 163.5347$ mm	300822.9	No Payment	0
5	2019	141		300822.9	No Payment	0
6	2020	122.9		300822.9	No Payment	0
7	2021	74.6		300822.9	No Payment	0
8	2022	79.9		300822.9	No Payment	0
9	2023	148		300822.9	No Payment	0
10	2024	105.6		300822.9	No Payment	0
		Total		3008229		2143801

Based on Table 2, during the period from September to December, there is consistently at least one instance of daily rainfall classified as heavy or very heavy in Dramaga Bogor, assuming that future maximum daily rainfall follows the same distribution as in the past. The recorded maximum daily rainfall ranges from 63 mm to 188.3 mm, with an average of 104.42 mm, placing it within the very heavy rainfall category. This indicates that, historically, Dramaga faced a significant flood risk between September and December, while the probability of drought during this period is low. Consequently, the risk of drought-induced crop failure—particularly for rice—is estimated to be near zero.

According to Table 2, the premium that must be paid by the policyholder (i.e., the farmer) over a 10-year period exceeds the potential claim value. Increasing the insured percentile will raise the premium, but it also increases the potential claim value. This is affected by the chosen parameter values A key limitation of this model is that the parameters are still based on percentiles from a probability distribution, and there is a lack of reliable data on the actual water requirements for paddy or verified crop yield data in Dramaga. If these parameters are modified, the results will also change. Therefore, parameter selection is crucial to ensure the model accurately reflects real-world conditions. The model remains flexible, as it can incorporate alternative parameters derived from probability distributions, with benefit adjustments determined by the farmer, data sourced from other regions, and can be adapted to the specific water requirements of the insured crop. Moreover, it is recommended to apply the model to rainfed areas that are more prone to drought or flooding, as these conditions pose greater risks to agricultural production.

4. CONCLUSION

The loss insurance risk model for agricultural commodities presented in this research offers an alternative approach to risk management by developing a loss model based on the maximum daily rainfall index, accounting for crop failure due to both drought and flood. The case study demonstrates that the Burr Type XII distribution provides a better fit for modeling maximum daily rainfall in Dramaga, Bogor (from September to December, covering the period 1984–2014) compared to the Generalized Extreme Value (GEV) distributions. When combined with specific threshold values and integrated into the benefit claim model and premium formula, the Burr Type XII distribution indicates that the premium increases exponentially as exit 1 increase by one unit. The premium paid by policyholders aligns with the insured risk level—the higher the insured risk, the higher the premium, and vice versa. Although validation using specific crop's water requirements has not yet been conducted, this model establishes a conceptual model for a dual-risk agricultural commodity loss insurance scheme (covering both drought and flood risks), utilizing the maximum daily rainfall index—a metric that has received limited attention. The model also integrates dual exit and trigger thresholds and employs a three-tier payout system (full, partial, or no payment). Further empirical studies are necessary to assess the effectiveness of the parameters of rainfall index and the fairness of the loss insurance model of risk for agricultural commodity.

Author Contributions

Siti Umamah Naili Muna: Conceptualization, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing-Original Draft. I Gusti Putu Purnaba: Conceptualization, Methodology, Supervision, Validation, Writing – Review and Editing. Berlian Setiawaty: Conceptualization, Methodology, Supervision, Validation, Writing – Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no competing interest.

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