Rice Harvest Failure Risk Analysis using Extreme Value Theory Based on Weather Index as Information Supply Chain for Agricultural Business

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***Abstract*— This paper discusses the formulation of a risk model for paddy agricultural insurance in Indonesia. Indonesia as an agricultural country with a tropical climate, where the sun shines throughout its time, farmers can plant crops throughout the season. In particular, rice farming is currently an inseparable part of most agrarian societies in Indonesia, especially in West Java. However, changes in air temperature, weather and annual rainfall, which sometimes changes uncertainly, cause changes in cropping patterns. This weather uncertainty will certainly increase the risk of crop failure. This paper will analyze the effect of climate variables on the risk of crop failure. The climate variables in this analysis consist of temperature, wind speed, maximum temperature, minimum temperature, and rainfall. The method to be developed here is to use the parametric method which will be used as a reference to determine the magnitude of risk, namely generalized pareto distribution and peak over threshold as a threshold. The results obtained that the greatest risk of losses to farmers occurred in November, December, January, February and March with a value of 0.17485. This research is useful as a information supply chain for decision making in agricultural insurance in order to maintain rice availability.**

***Keywords*—** *Rice farming risk, climate, Extreme value theory, Generalized Pareto Distribution, CVaR.*

1. Introduction

Agriculture 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 [1]. One way to manage these risks is through the Agricultural Insurance program, especially Rice Farmer Business Insurance. Agricultural Insurance program, 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 Agricultural Insurance program, aims to protect farmers from losses through insurance companies. The objective of the Agricultural Insurance program, implementation is that farmers can be protected by obtaining compensation, if they experience crop failure [2]. Risks covered in Agricultural Insurance program, 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,

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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) literature [3].

2. Literature Review

Issues of risk and agricultural insurance with various methods have been discussed in several previous studies. Among other things, research on determining the amount of premiums based on climate indices has been carried out by Sonia (2016) with the climate parameters used as rainfall in the period 1966-2008 and data on the incidence of drought in the period 2001-2011 in Sliyeg District, Indramayu Regency [4]. Calculation of the climate index is done by the Historical Burn method. In ref [5], climate index insurance prices using the Black-Scholes framework with a case study in Ghana literature. Also, the option approach price in determining farm land insurance premiums was presented in [6]. Furthermore, the CVaR model to determine agricultural insurance premiums, the results show that farmers' net income is significantly influenced by the agricultural insurance policies purchased and the level of risk aversion chosen [6].

The influence of gender and product design on farmers' preferences for weather-indexed crop insurance was discussed in ref [7]. How to determine the maximum limit of agricultural premiums, with the theory of uncertainty (uncertainty theory) mentioned that events (events) using the utility function of investment capital and view the amount of losses faced by farmers as a random variable, this can be an alternative calculation of the maximum premium limit. In ref [8], the pricing of weather insurance contracts based on the temperature index, the results show that there are significant differences between the burn and index pricing approach and the temperature modeling method. Research on [9], discusses the importance of agricultural insurance in the Asia and Pacific region and exposure to climate hazards. Risk calculation is based on the climate index, using the Historical Burn method. Martin (2001) conducted a research with a developing and pricing Precipitation Insurance to determining the price of agricultural land insurance premiums [10].

The problem of insurance premiums that mimic the option Payoff with a modification of the Black-Scholes option pricing formula was discussed in ref [11]. Also, in ref [12], to development of weather derivatives: evidence from the Brazilian soybean market, determine agricultural insurance premiums. An Innovative Damage Model for Crop Insurance, Combining Two Hazards into a Single Climatic Index, The calculation of the price of agricultural insurance premiums based on rainfall indexes using the Black Scholes scheme is discussed on [13], but this study yields high enough premiums, making it less attractive for farmers to pay such a premium.

In ref [14], discussed about "Does Crop Insurance Influence Commercial Crop Farm Decisions to Expand? An Analysis Using Panel Data from the Census of Agriculture" and determining the maximum limit of agricultural premiums using the theory of uncertainty (uncertainty theory). In ref [15], discusses the Option pricing of weather derivatives based on a stochastic daily rainfall model with Analogue Year component and determination of the price of rice insurance premiums based on rainfall indexes using the mixed exponential distribution generating method. In [16], discusses insurance risk management using the Catrostophe model.

Based on the description above, no studies have been found that produce reasonable premium prices. In this paper, a risk model formulation for multi-index based, rice agriculture insurance is carried out. The formulation will start from determining risk with CVaR, extreme value theory threshold limit, and yields with GDP, and finally determining the risk size that will be used to determine the paddy farm insurance premium. The aim is to estimate the period in which the level of rice production has decreased due to climate. The purpose of this research is as a information supply chain for rice agricultural insurance so that rice availability is maintained.

3. Methodology

Risk is a combination of the likelihood of certain events occurring and the possibility of damage resulting in losses [17]. In this definition there are two elements, namely uncertainty and loss. The intended loss is a financial risk that can be measured or valued in money, caused by the danger or failure of a function. Risk assessment is a product of the frequency value and the severity value of the risk. Risk is divided into several criteria, namely low, medium, high, and extreme. Risk assessment is a product of the frequency value and the severity value of the risk. To determine the risk category whether it is low, medium, high or extreme can be determined based on frequency and severity.

The risks faced in rice farming are extreme risks, which mean that the determination of risks in insurance for rice farming cannot be separated from determining thresholds or thresholds to determine the amount of risk. There are two approaches that are often used in models for extreme events, namely the Block Maxima and Peak Over Threshold (POT) methods. Threshold and magnitude of risk, determined based on extreme deviations or Value at Risk (VaR) and plot data in accordance with Generalized Pareto Distribution (GPD).

3.1 Block Maxima Method

Block Maxima method is a method that identifies extreme values through maximum values from observational data grouped in a particular block or period. This approach only produces one extreme value in each block. The Block Maxima method refers to the distribution of GEV [18]. In the Block Maxima method, observational data that has been divided into the same periods is observed for maximum data in each period.

For example, the number of yields per block is a sequence of random variables that have independent identically distributed (iid) symbolized by a random variable: $X_1, X_2, \ldots, X_n$. The cumulative distribution function of the random variable X is defined as

$$F_X(x) = P(X \le x), x \ge 0.$$

If defined $M_n = \max(X_1, X_2, \ldots X_n)$, there are constants $c_n > 0$ and $d_n \in R$, so

$$P\left\{\frac{M_n - d_n}{c_n} \le x\right\} \to G(x),\ n \to \infty, \tag{1}$$

then $G(x) \sim \exp\left[-(1+\xi x)^{-\frac{1}{\xi}}\right]$ where ξ depends on the tail shape of the distribution. Another way, form $P\left\{\frac{M_n - d_n}{c_n} \le x\right\} \to G(x),\ n \to \infty$ can be written as a limit distribution as follows

$$\lim_{n\to\infty} P\left\{\frac{M_n - d_n}{c_n} \le x\right\} = G(x) \sim \exp\left[-(1+\xi x)^{-\frac{1}{\xi}}\right]. \tag{2}$$

In this case, the value $1 + \xi\left(\frac{x-\mu}{\sigma}\right) > 0$, x_i is the realization of the independent random variable, which is distributed Pareto with unknown parameters ξ and σ [16].

This distribution has three parameters, namely:

1. Location parameter μ, which shifts distribution left/right.
2. The scale parameter σ, which determines the distribution of data.
3. The shape parameter ξ, which determines the shape of the distribution.

When formed into a standard model, $G(x)$ is one of the non-degenerate distributions [19].

1. Gumbel distribution

$$G(x) = \exp\left\{-\exp\left[-\left(\frac{x-d}{c}\right)\right]\right\}, \quad x \in R$$

2. Frechet distribution

$$G(x) = \begin{cases} 0 & ,x \le d \\ \exp\left\{-\left(\frac{x-d}{c}\right)^{-\alpha}\right\} & ,x > d \end{cases}$$

3. Weilbull distribution

$$G(x) = \begin{cases} \exp\left\{-\left(\frac{x-d}{c}\right)^{-\alpha}\right\} & ,x < d \\ 0 & ,x \ge d \end{cases}$$

The Gumbel, Frechet, and Weibull distribution functions can be combined into one generalized extreme value (GEV) distributions family with the following equation.

$$F(x) = \exp\left\{-\left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\}$$

3.2 Peak Over Threshold Method

The POT method is an approach that identifies extreme values through observational data that exceeds a certain threshold value. One or more extreme values in a particular block or period will be generated by the POT Method, which refers to the Generalized Pareto Distribution. The main concept of this method is to use thresholds to separate values that are considered extreme to all data and create a model for extreme values by modeling the tail distribution of all values that exceed this threshold. The Peak Over Threshold (POT) approach provides a good solution, because more data is retrieved, so it can be used to model extreme values even though the amount of data held is very limited. Modeling using the Peak Over Threshold method was adopted from Generalized Pareto Distribution (GPD) [20]. For example: $x_1, x_2, \dots, x_n$ is a sequence of unprocessed observations from an $F(x)$ distribution. For example, given a threshold or a high threshold u, assuming $x_{(1)}, x_{(2)}, \dots x_{(n)}$ is observational data that exceeds the threshold u, define $x_i = x_{(i)} - u$ for $i = 1,2,3, \dots, k$, for the large u threshold. Generalized pareto distribution is defined as a distribution limit that is above the u threshold. The conditional distribution function of the variable $Y = (X - u \mid X > u)$ approaches

$$F(y) = 1 - \left(1 + \frac{\xi(y)}{\sigma}\right)^{-\frac{1}{\xi}}$$

where $\{y: y > 0 \text{ and } 1 + \frac{\xi(y)}{\sigma} > 0\}$

The equation above is a Generalized Pareto Distribution family (*GPD*) [16]. The opportunity density function for GPD is as follows (by returning the variable y to the x variable).

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

where $0 \leq x < \infty$ if $\xi \geq 0$ and $0 \leq x < -\frac{\sigma}{\xi}$, if $\xi < 0$.

GPD has two parameters, namely the form parameter (ξ) and the scale parameter (σ). There are three types of distribution in *GPD*. Type 1 has an exponential distribution if ξ = 0. Type 2 has a Pareto distribution if ξ > 0. Type 3 has a beta distribution if ξ <0. The greater the value ξ, the distribution will have a tail that is getting fatter so that the chances of extreme values are even greater.

The method used to measure risk is Conditional Value-at-Risk (CVaR). CVaR was first introduced in ref [19]. CVaR is the average loss based on the worst case scenario, which is a coherent measure of risk and can work on data that is normally or not normally distributed.

Definition of Value-at-Risk [21]. Let X be a random variable with a cumulative distribution function $F_X(x)$. *Value-at-Risk* (*VaR*) of X with a confidence level α is

$$VaR_\alpha(X) = \min\{x \mid F_x(x) \geq \alpha\}$$

is the lower percentile of the random variable X.

Definition of Conditional Value-at-Risk. For random variables with continuous distribution functions, CVaR of X with a level of confidence α is the average of the generalized α tail distribution:

$$CVaR_\alpha(X) = \int_{-\infty}^{\infty} z dF_X^\alpha(z)$$

where

$$F_X^\alpha(z) = \begin{cases} 0, & \text{where } z < VaR_\alpha(X) \\ \frac{F_X(z) - \alpha}{1 - \alpha} & \text{where } z \geq VaR_\alpha(X) \end{cases} \tag{4}$$

For general distribution, for example, upper CVaR is $CVaR_\alpha^+(X) = E[X \mid X > VaR_\alpha(X)]$ then $CVaR_\alpha(X)$ For general distribution, for example, upper $VaR_\alpha(X)$ and $CVaR_\alpha^+(X)$.

$$CVaR_\alpha(X) = \lambda_\alpha(X) VaR_\alpha(X) + \left(1 - \lambda_\alpha(X)\right) CVaR_\alpha^+(X) \tag{5}$$

where

$$\lambda_\alpha(X) = \frac{F_X\left(VaR_\alpha(X)\right) - \alpha}{1 - \alpha}$$

3.3 Estimation of GPD parameters with Maximum Likelihood Estimation

The value of the parameter vector is estimated using the Maximum Likelihood Estimator (MLE) principle which maximizes the likelihood function. The likelihood function is the probability of an observational data which is described as a function of parameters [18]. Thus, the likelihood function is defined by swapping the roles of the data vector and the parameter vector. In GEV, the likelihood functions $L(\mu, \sigma, \xi | x_1, x_2, \ldots, x_n)$ describe the possibilities of parametersμ, σ, and ξ with known data $x_1, x_2, \ldots, x_n$ [22]. The likelihood function is obtained by multiplying the opportunity density function. Following is the equation of the likelihood function of *GEV*, [23].

$$L(\mu, \sigma, \xi | x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} f(\mu, \sigma, \xi; x_i) \quad (8)$$

To simplify the calculation, parameter estimation with MLE can be generated by making the transformation of the function in the form of natural logarithms namely, $\ln L(\mu, \sigma, \xi | x_1, x_2, \ldots, x_n)$. This can be done because the log-likelihood function is monotonically related to the likelihood function so maximizing the log-likelihood function also means maximizing the likelihood function. Assuming a differentiable log-likelihood function, then ξ, σ, and μ exist and satisfy the following partial differential equation.

$$\frac{\partial \ln L(\mu, \sigma, \xi | x_1, x_2, \ldots, x_n)}{\partial \xi} = 0$$
$$\frac{\partial \ln L(\mu, \sigma, \xi | x_1, x_2, \ldots, x_n)}{\partial \sigma} = 0 \quad (9)$$
$$\frac{\partial \ln L(\mu, \sigma, \xi | x_1, x_2, \ldots, x_n)}{\partial \mu} = 0$$

This also satisfies applies to GPD so that the likelihood function of GPD is as follows.

$$L(\sigma, \xi | x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} f(\sigma, \xi; x_i) \quad (10)$$

Assuming equation (10) is differentiable, there are ξ and σ, that satisfy the following differentiable equation [22].

$$\frac{\partial \ln L(\sigma, \xi | x_1, x_2, \ldots, x_n)}{\partial \xi} = 0 \quad 11)$$
$$\frac{\partial \ln L(\sigma, \xi | x_1, x_2, \ldots, x_n)}{\partial \sigma} = 0 \quad (12)$$

Estimated value is obtained, if the first derivative equation forms a *closed form equation*. If the equation formed is not closed form, then an advanced numerical settlement for its completion [3].

3.4 Weather

Weather and climate are symptoms or events that are quite close on earth. Each has similarities and differences. weather is a state of air that occurs in a place with a narrow time. Whereas climate is an average weather pattern that occurs for a relatively longer period and covers a large area. Weather and climate have the same elements, namely sunlight which emits light and energy to the earth's surface, in the form of radiation. As the main source of geothermal energy, the amount of solar radiation reaching the earth reaches 47%. The rest are in air particles, such as dust, water vapour, and clouds. Every place on earth has a different intensity of solar radiation. This is due to the transparency of the atmosphere, the angle of incidence of sunlight, the distance of the earth and the sun, altitude, distance of the sea, and the influence of the wind. The temperature of the air, which is the heat or cold of an object. Air temperature or temperature is the temperature of the hot or cold air in a certain place and time. Air heating is obtained through two processes, namely: direct heating, consisting of reflection, diffusion, and absorption and indirect heating, consisting of conduction, convection, and diffusion [12]. Factors that affect air temperature include atmospheric transparency, angle of sunlight, duration of exposure, distance of the Earth and the Sun, altitude and many others. Air pressure which is the weight of the air mass over a unit area. If air temperature can be measured with a thermometer, air pressure can be measured with a barometer. Weather and climate have fundamental differences, namely: Coverage of regions and observations about weather are narrower and limited, whereas coverage of regions and climate observations are broader. When observing the weather in an area can be done for 24 hours, while for the climate carried out for 11-30 years. Weather has properties that change rapidly and are unstable, whereas climate has properties that are stable and difficult to change. Predictions about the weather are easy to do, whereas climate forecasts are difficult.

4. Results and Discussion

The weather variables analysed were wind speed, maximum temperature, minimum temperature, and rainfall in Bandung Regency, West Java, Indonesia from 2008-2019. Productivity data were obtained from the Bandung District Agriculture Office in West Java Province, Indonesia in 2008-2019. Climate variable data presented in Table 1 and Table 2, and plotted in Figure 1, while rainfall data are plotted in Figure 2. Large data on rainfall variability is presented in Figure 2. From the results of the plot, it can be seen that the greatest rainfall is in the range of November, December, January, to April. Figure 2 show the plot of average yields per month per planting period. The lowest yields occur around the month of January and December. This is certainly related to high rainfall in the month.

Table 1 Average Bandung Weather per month from 2008-2019

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
Temperature (°C)	23.3	23.2	23.5	23.7	23.7	22.7	22.5	22.8	23.3	23.7	23.5	23.6
Min Temperature (°C)	19.5	19.2	19.2	19.2	19	17.5	17	17	17.4	18.3	18.8	19.3
Max Temperature (°C)	27.1	27.3	27.9	28.3	28.4	28	28	28.6	29.2	29.2	28.3	27.9
Rainfall (mm)	243	217	257	246	166	77	70	68	83	174	272	291
Paddy Rice Productivity (ton/ha)	9.0	10.6	16.2	15.9	11.4	11.3	11.6	12.6	11.2	10.3	9.7	8.7

Source: Processed from BPS Regency data, West Java, 2020

Table 2 Average Bandung Weather per semester from 2008-2019

	Paddy Rice Productivity (ton/ha)	Wind velocity (km/h)	Max Temperature (◦C)	Min Temperature (◦C)	Rainfall (mm)
Total	71.84	83.48	723.41	521.81	2,164.00
Average	11.97	3.79	32.88	23.72	180.33
Maximum	12.43	5.66	34.68	24.37	291.00
Minimum	11.59	2.13	31.18	23.15	68,00
Variance	0.09	1.10	0.80	0.10	7,390.97
Standard Deviation	0.3	1.05	0.90	0.31	85.97

Source: Processed from BPS Regency data, West Java, 2020

The most dominant climate change is determined by the rainfall parameter. The growth of rice plants whose irrigation system depends on rain water will be influenced by the volume of rainfall each month. In this section, the effects of rainfall on the amount of rice produced will be explained. Data on rainfall, temperature, and rice production are defatting and the results of the meters are estimated using the MLE Maximum Likelihood Estimator with the help of easy fit software, presented in Table 3 and Table 5. While the statistical analysis results are presented in Table 4 and Table 6. Descriptive statistical results of the above yield data are presented in Table 3.

Rice productivity risk analysis is carried out using a Conditional Value at Risk (CVaR) risk measure. Based on the estimated model in equation (2), it was found that the risk of lowland rice productivity with climate variable variability is presented in Figure 3., with a significant level of value of 0.9588, the worst CVaR productivity occurred since the average productivity was 11.078 tons / ha. While the results of the risk analysis of climate variables on the productivity of inland rice are 8.7 tons / ha. This means that climate variability can cause the worst risk of CVaR of 0.17485, where there is no yield of inland rice production in a given variable situation.

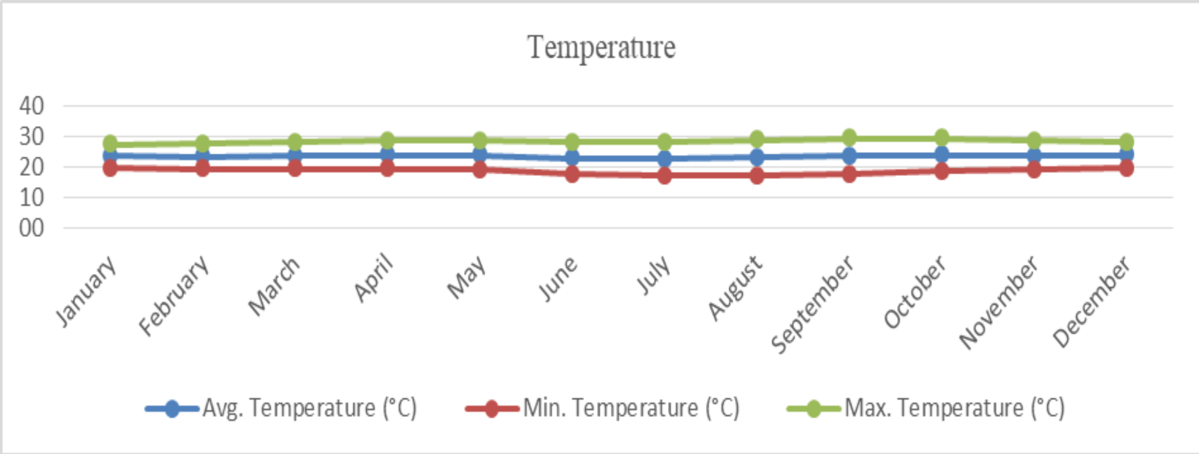

Figure 1 Temperature Variable Data, Average per Month Bandung Regency 2008-2019

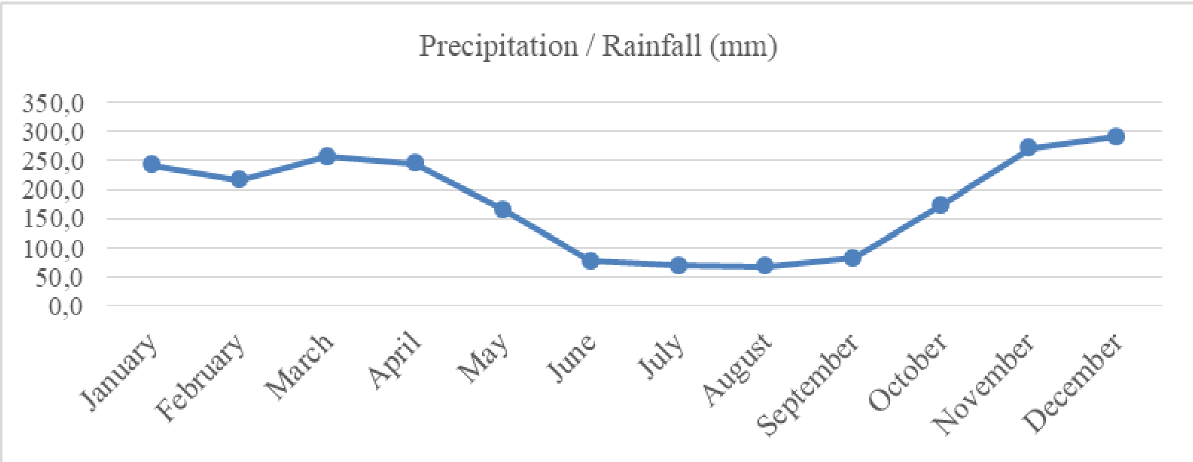

Figure 2 Variable Data Average rainfall per month in Bandung regency 2008-2019

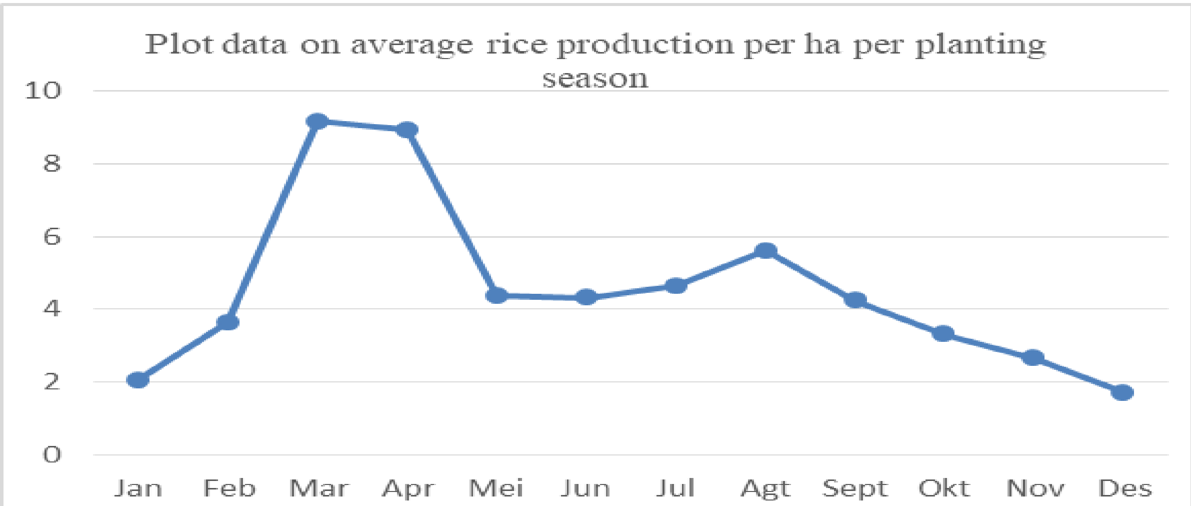

Figure 3 Average rice production per planting season in Bandung Regency 2008-2019

Table 3 Descriptive statistics of rice yield data

Statistic	Value		
Sample Size	12	Min	8.7
Range	7.5	5%	8.7
Range	7.5	10%	8.7
Mean	11.078	25% (Q1)	9.7
Variance	3.7522	50% (Median)	11.2
Std. Deviation	1.9371	75% (Q3)	11.6
CVaR	0.17485	90%	12.6
Std. Error	0.55918	95%	15.9
Skewness	1.1938	Max	16.2
Excess Kurtosis	1.2945	Min	8.7
		5%	8.7

Table 4 Results of statistical analysis of yield data

Gumbel Max					
Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	12 0.13566 0.95887 2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.29577	0.33815	0.37543	0.41918	0.44905
Reject?	No	No	No	No	No
Anderson-Darling					
Sample Size Statistic Rank	12 0.52578 5				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No

Table 5 Results of statistical analysis of rainfall

Statistic	Value	Percentile	Value
Sample Size	12	Min	68
Range	223	5%	68
Mean	181.36	10%	70
Variance	6725.5	25% (Q1)	83
Std. Deviation	82.009	50% (Median)	217
Coef. of Variation	0.45218	75% (Q3)	257
Std. Error	23.674	90%	272
Skewness	-0.26392	95%	291
Excess Kurtosis	-1.5245	Max	291

Table 6 Results of statistical analysis of rainfall data

Gen. Extreme Value					
Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	12 0.19431 0.68702 7				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.29577	0.33815	0.37543	0.41918	0.44905
Reject?	No	No	No	No	No
Anderson-Darling					
Sample Size Statistic Rank	12 0.49818 4				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No

Based on the results of the analysis presented in Tables 5 and 6, as well as the previous discussion, this is very useful as a supply chain in insurance company decisions to determine premiums and benefits for farmers. Insurance in agriculture aims to prevent losses on the part of the farmer in the event of undesirable things during the cultivation process. Agriculture is considered to be one type of business that is full of risks. Agricultural businesses can lose money at any time, for example due to drought, pests, landslides and prolonged rains will certainly disrupt farmer productivity. To avoid this situation, the government is currently providing the best solution in the form of the Rice Farmers Business Insurance program, which is expected to provide protection against the risk of uncertainty by ensuring that farmers get working capital to farm from insurance claims. So that farmers can continue to be enthusiastic about increasing their rice production.

Rice production improvement programs have always been a top priority in agricultural development, so that the rice supply chain can be fulfilled properly. The hope is that prosperous farmers and consumers will get a fair price. The rice supply chain is a concept that has a regulatory system related to product flow, information flow, and financial flows in the rice distribution process. In the case of rice, supply chain management includes purchasing raw materials (unhulled) from farmers, transportation to rice mills, processing (drying and milling) in factories, packaging, warehousing, and distribution to various traders (wholesalers and retailers) and finally to consumers.

4 Conclusions

Based on the results of the discussion of the risk of the effects of changes in climate variables consisting of temperature, wind speed, maximum temperature, minimum temperature and rainfall which have Generalized Extreme Value distribution on the yield of rice production with Gumbel Max distribution, it is significant to the amount of yield. The lowest yields occur around January and December. This is certainly related to high rainfall in the month. This research serves as a information supply chain for insurance companies in determining the premium rates and benefits of agricultural insurance, and for the government it is useful for improving the performance of rice supply chain management.

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