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Article

Valuation model for catastrophe reinsurance contracts covering multiple insurance products: An application to Indonesian earthquake data

Fevi Novkaniza[1,*], Sindy Devila[1], Nadiah Zabri[2]

[1] Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, Depok 16424, Indonesia
[2] Institute of Mathematical Sciences, Faculty of Science, Universiti Malaya, Kuala Lumpur 50603, Malaysia
*** Corresponding author:** Fevi Novkaniza, fevi.novkaniza@sci.ui.ac.id

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Abstract: Catastrophes, like earthquakes, bring sudden and severe damage, causing fatalities, injuries, and property loss. This often triggers a rapid increase in insurance claims. These claims can encompass various types, such as life insurance claims for deaths, health insurance claims for injuries, and general insurance claims for property damage. For insurers offering multiple types of coverage, this surge in claims can pose a risk of financial losses or bankruptcy. One option for insurers is to transfer some of these risks to reinsurance companies. Reinsurance companies will assess the potential losses due to a catastrophe event, then issue catastrophe reinsurance contracts to insurance companies. This study aims to construct a valuation model for catastrophe reinsurance contracts that can cover claim losses arising from two types of insurance products. Valuation in this study is done using the Fundamental Theorem of Asset Pricing, which is the expected present value of the number of claims that occur during the reinsurance coverage period. The number of catastrophe events during the reinsurance coverage period is assumed to follow a Poisson process. Each impact of a catastrophe event, such as the number of fatalities and injuries that cause claims, is represented as random variables, and modeled using Peaks Over Threshold (POT). This study uses Clayton, Gumbel, and Frank copulas to describe various dependence characteristics between random variables. The parameters of the POT model and copula are estimated using Inference Functions for Margins method. After estimating the model parameters, Monte Carlo simulations are performed to obtain numerical solutions for the expected value of catastrophe reinsurance based on the Fundamental Theorem of Asset Pricing. The expected reinsurance value based on Monte Carlo simulations using Indonesian earthquake data from 1979–2021 is Rp 10,296,819,838.

Keywords: fundamental theorem of asset pricing; inference functions for margins; maximum likelihood; Monte Carlo; Poisson process

1. Introduction

Indonesia is an archipelagic country located at the convergence of tectonic plates, namely the Asian Continental Plate, the Australian Continental Plate, the Indian Ocean Plate, and the Pacific Ocean Plate. This condition makes Indonesia highly susceptible to catastrophic events, especially those caused by natural disasters. A catastrophe's occurrence is an abrupt and seriously detrimental calamity. For instance, a devastating earthquake may result in fatalities, injuries, and property destruction. This illness can quickly generate a huge influx of insurance claims (Rejda and McNamara, 2014). Life insurance claims for the insured's demise, health insurance claims for injuries sustained by the injured party, and general insurance claims for property damage are a few instances of claims that might occur. For insurance companies that offer a variety of insurance products, this circumstance could result in losses or bankruptcy. Transferring some of that risk to a reinsurance business is one option available to insurance companies. Because some of the loss risk is shared by the reinsurance business, the presence of a reinsurance firm enables insurance companies to issue contracts with significant coverage amounts. The reinsurance company must assess prospective losses in the event of a catastrophic incident before issuing a reinsurance contract. This valuation aims to determine a net premium that actuarially compensates for the assumed loss risk.

The first to design the catastrophe reinsurance value model was developed by Strickler (1960). The model, however, had limits because the rate of catastrophic events was believed to be constant, and there was no way to update the model (Ekheden and Hössjer, 2014). The Peaks Over Threshold (POT) model created by Ekheden and Hössjer (2014) was used to address these limitations. Leppisaari (2014), Liu and Han (2012), and Nowak and Romaniuk (2013) extended the prior POT model by valuing catastrophic reinsurance contracts using the microsimulation method. The previously researched models have a restriction in that they only value one sort of claim coming from a disaster event. A disaster incident frequently leads to multiple types of claims (Chan et al., 2003). As a result, a new approach to valuing catastrophic reinsurance contracts is required to meet the needs of organizations that want to transfer risks from two types of products at the same time. To avoid bankruptcy, reinsurance companies must calculate the extreme values of the impact of catastrophe events while performing appraisals. This is because such large losses have the potential to bankrupt a company. Peaks Over Threshold is a good model for modelling extreme values (Chao, 2021). As a result, each impact of the disaster event is represented in this study using POT model. Inter-impact dependence must be expressed in the computation when valuing two catastrophe event impacts. One method is to use copulas to construct a joint distribution function of the random variables of the catastrophe event impacts. This joint distribution function is utilized in obtaining the numerical solution of the catastrophic reinsurance expectation value using Monte Carlo simulations. In this research, we focused on developing a Peaks-Over-Threshold (POT) model and copula for valuing two-risk catastrophic reinsurance. The main objective was to create and apply these models specifically for calculating and implementing two-risk catastrophic reinsurance using data from Indonesian earthquakes. This approach has never been applied in this way in Indonesia before.

2. Materials and methods

Reinsurance businesses must appropriately forecast extreme loss scenarios when valuing catastrophe reinsurance contracts. Extreme Value Theory (EVT) is a strategy for analyzing numerous extreme events because it may create a model that accurately describes extreme events (Gilli and Këllezi, 2006; Paldynski, 2015). There are two methods for recognizing extreme values in EVT: Block Maxima (BM) and Peaks Over Threshold (POT). The BM method divides the data sample into blocks and then chooses the maximum value of each block as the extreme value. Unlike the BM approach, the POT approach will establish a value known as a threshold and then choose values greater than the threshold as extreme values. The BM strategy has a disadvantage when compared to the POT approach because it is seen to waste available observations. Even if the total value is rather large, the BM method will not accept a value as an extreme value if it is not the greatest value in the observed block. As a result, the POT technique is used in this work since it allows for more observations to be used in inference. POT is an EVT technique for identifying extreme values. POT establishes a threshold value m as a guideline for determining extreme values. Extreme values are those that are greater than the threshold value m. According to Balkema and De Haan's theorem (1974), the distribution function of the extreme values can be approximated using the Generalized Pareto Distribution (GPD) for sufficiently large threshold values. The cumulative distribution function for GPD is as follows:

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

The probability density function for the GPD can be calculated from the cumulative distribution function, which is defined as follows:

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

with $0 \leq x < \infty$ if $\xi \geq 0$ and $0 \leq x \leq -\frac{\delta}{\xi}$ if $\xi < 0$ (Gilli and Këllezi, 2006).

For observations that are below the threshold value m, it could be modeled with an empirical distribution which has the following cumulative distribution function:

$$\hat{F}(x) = \frac{\text{number of observations} \leq x}{n}$$

where n is the total number of observations.

The percentage approach is one approach for figuring out the threshold. According to Chaves-Dermoulin and Embrechts (2002), 10% of the data is considered severe. The percentage technique sets the threshold so that 10% of the data are considered extreme values. The processes for determining the threshold using the percentage technique are as follows:

1) Sort the data from the largest to the smallest.
2) Determine the number of data that is considered as extreme values, which is $0.1n$ observations.

The value at the $(0.1n + 1)$-th position from the largest value will be considered as the threshold value. This study examines the impact of losses on reinsurance contract valuation using two random variables. As a result, the calculation must account for the dependence between the random variables. One method is to use copulas to construct a joint distribution function of the random variables' catastrophic event impact. Copula is a way of modelling the dependency between random variables by generating a combined distribution of numerous marginal distributions (Czado et al., 2011; Wu et al., 2007). Copulas have the advantage of not requiring identical and normally distributed marginal distributions. Assume X and Y are random variables with cumulative distribution functions $F_X(x)$ and $F_Y(y)$. According to Sklar's theorem, $\forall x, y \in R$ there exists a copula C such that the joint cumulative distribution function of X and Y can be written as:

$$H(x,y) = C[F(x), G(y)] = C(u,v)$$

where $u = F_X(x)$ and $v = F_Y(Y)$ are marginal cumulative distribution functions for each variable X and Y respectively. As in (Nelsen, 2005), suppose that C is a copula for 2 random variables X and Y, then C maps $I^2 \to I$ whereas $I = [0,1]$. C has these characteristics:

1) $C(u,0) = C(0,v) = 0$
2) $C(u,1) = u$ and $C(1,v) = v$
3) $\forall u_1, v_1, u_2, v_2 \in I$, with $u_1 \leq v_1$ and $u_2 \leq v_2$, then $C(v_1, v_2) - C(v_1, u_2) - C(u_1, v_2) + C(u_1, u_2) \geq 0$

If X and Y each have probability density functions $f_X(x)$ and $f_Y(y)$ respectively, then the joint probability density function for X and Y can be represented as follows:

$$f(x,y) = f_X(x) \cdot f_Y(y) \cdot c(F_X(x), F_Y(y))$$

whereas

$$c(u,v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$$

would be called a copula density function. The copula density function is used in estimating the copula's parameter (Tse, 2009). The conditional distribution function from a copula can be represented as follows:

$$C(v|u) = Pr(V \leq v | U = u)$$

whereas

$$C(v|u) = \lim_{\Delta u \to 0^+} \frac{C(u + \Delta u, v) - C(u,v)}{\Delta u} = \frac{\partial C(u,v)}{\partial u}$$

The conditional distribution function from a copula is used in generating data for a copula (McNeil et al., 2005). To discover the best acceptable dependence structure for the data, each copula utilized must reflect a different dependency structure. To account for this, the copulas employed in this work are Clayton copulas, Gumbel copulas, and Frank copulas, which represent lower tail, upper tail, and symmetrical dependence structures, respectively (Yu et al., 2020). One of the best copulas from these three categories will be chosen to compute the expected value of disaster reinsurance. Clayton Copulas are the copulate that illustrates the existence of lower tail dependence, which is a stronger dependency on smaller values.

As in McNeil et al. (2005), the cumulative distribution function for Clayton copulas for two random variables are listed below:

$$C^{Cl}(u,v) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-\frac{1}{\theta}}, 0 < \theta < \infty$$

The probability density function for Clayton copulas with two random variables is listed below (Shiau, 2006):

$$c^{Cl}(u,v) = (\theta + 1)\left(u^{-\theta} + v^{-\theta} - 1\right)^{-\frac{1}{\theta}-2}(uv)^{-\theta-1}$$

As in Reddy & Ganguli (2012), conditional copula for Clayton copulas with two random variables are listed below:

$$C^{Cl}(v|u) = \left[1 + u^{\theta}\left(v^{-\theta} - 1\right)\right]^{-1-(1/\theta)}$$

and the inverse:

$$C^{Cl^{[-1]}}(v|u) = \left[\left(v^{-\frac{\theta}{1+\theta}} - 1\right)u^{-\theta} + 1\right]^{-\frac{1}{\theta}}$$

Gumbel copulas is a copula that illustrates the existence of upper tail dependence, which is a strong dependency on larger values.

The cumulative distribution function for Gumbel copulas with two random variables is listed below:

$$C^{Gu}(u,v) = \exp\left\{-\left((-\ln u)^{\theta} + (-\ln v)^{\theta}\right)^{\frac{1}{\theta}}\right\}, 1 \le \theta < \infty$$

probability density function for Gumbel copulas with two random variables as follows:

$$c^{Gu}(u,v) = C^{Gu}(u,v)\frac{[(-\ln u)(-\ln v)]^{\theta-1}}{uv}\left[(-\ln u)^{\theta} + (-\ln v)^{\theta}\right]^{\frac{2}{\theta}-2}$$

$$\{(\theta-1)\left[(-\ln u)^{\theta} + (-\,ln v)^{\theta}\right]^{-\frac{1}{\theta}} + 1\}$$

Conditional copula for Gumbel copulas with two random variables is listed below:

$$C^{Gu}(v|u) = \frac{1}{u}\exp\left\{-\left((-\ln u)^{\theta} + (-\ln v)^{\theta}\right)^{\frac{1}{\theta}}\right\}\left[1 + \left(\frac{\ln u}{\ln v}\right)^{\theta}\right]^{-1+\frac{1}{\theta}}$$

Note that Gumbel copulas have no closed-form inverse for the conditional copula. Frank copula is a copula that illustrates symmetrical dependence on the lower tail and higher tail which shows that there is weak dependency on both tails but stronger dependency on the middle of the distribution.

The cumulative distribution function for Frank copulas with two random variables is listed below:

$$C^{Fr}(u,v) = -\frac{1}{\theta}ln\left(1 + \frac{\left(e^{-\theta u} - 1\right)\left(e^{-\theta v} - 1\right)}{(e^{-\theta} - 1)}\right), \theta \neq 0$$

The probability density function for Frank copula with two random variables is as follows:

$$c^{Fr}(u,v) = -\frac{\theta e^{-\theta(u+v)}(e^{-\theta} - 1)}{[e^{-\theta(u+v)} - e^{-\theta u} - e^{-\theta v} + e^{-\theta}]^2}$$

Conditional copula for Frank copulas with two random variables is listed below:

$$C^{Fr}(v|u) = e^{-\theta u_1}\left[\left(1 - e^{-\theta}\right)\left(1 - e^{-\theta v}\right)^{-1} - \left(1 - e^{-\theta u}\right)\right]^{-1}$$

with the inverse function:

$$C^{Fr^{[-1]}}(v|u) = -\frac{1}{\theta}\ln\left(1 - \frac{\left(1 - e^{-\theta}\right)}{[(u_2^{-1} - 1)e^{-\theta u_1} + 1]}\right)$$

The Basic Theorem of Asset Pricing is used to do valuation in this study. The following formula can be used to calculate the expected value of catastrophe reinsurance, P, based on the Basic Theorem of Asset Pricing:

$$P = E\left[\sum_{i=1}^{N} f(X_i, Y_i)\exp\left(-\int_0^{t_i} r(s)ds\right)\right]$$

with

$$f(X_i, Y_i) = \max\{c_2X_i + c_2Y_i - D, 0\}$$

whereas $r(s)$ is the single factor spot rate, D is retention, and c_1, c_2 is claim coefficient.

Based on the assumption that interest rate, i, is a constant, then P reformulated as:

$$P = E\left[\sum_{i=1}^{N} f(X_i, Y_i) \cdot (1+i)^{-t_i}\right]$$

3. Results and discussion

The catastrophic event in this study is an earthquake in Indonesia. The information was collected from the National Centers for Environmental Information (NCEI, 2022), and it includes the year of the earthquake from 1979 until 2021, the number of fatalities, and the number of injuries. The summary statistics for Indonesian earthquake data are in **Table 1** as follows:

Table 1. Descriptive statistics for Indonesian earthquakes dataset.

Statistics	Fatalities	Injured
Maximum	5749	38,568
Minimum	3	3
Mean	267.1406	1336.047
Standard Deviation	915.6324	5063.52
Median	17	191
25th Quantile	6	80.75
75th Quantile	70.5	405.75
Skewness	4.995407	6.656709
Kurtosis	26.17931	48.15695

The data is utilized to estimate the rate parameter, $\lambda > 0$, for the Poisson random variable, N, that represents the number of catastrophe events that occurred during the coverage period. In practice, the duration of catastrophe reinsurance coverage is one year, hence the coverage period in this study is one year. The estimator of Maximum Likelihood for λ is $\hat{\lambda} = 1.488372$. This means that the average number of catastrophe events per year is 1.488372.

Let X denote the number of fatalities and Y the number of injuries. Let m_X and m_Y denote the X and Y thresholds, respectively. **Table 2** displays the results of threshold determination and POT parameter estimate.

Table 2. Threshold determination and estimation of POT model parameters.

Parameters	Estimate of Parameters
m_X	$\hat{m}_x = 560$
ξ_X	$\hat{\xi}_X = 0.1259463$
δ_X	$\hat{\delta}_X = 1625.965$
m_Y	$\hat{m}_Y = 2000$
ξ_Y	$\hat{\xi}_Y = 0.1283386$
δ_Y	$\hat{\delta}_Y = 10{,}690.31$

Based on **Table 2** and empirical cumulative distribution function, $\hat{F}(\cdot)$, we derived cumulative distribution function for fatalities, $F_X(x)$, and injured, $F_Y(y)$, as follows:

$$F_X(x) = \begin{cases} \left(1-\hat{F}_X(560)\right) G_{\hat{\xi}_X,\hat{\delta}_X}(x-560) + \hat{F}_X(560), x > 560 \\ \hat{F}(x), x \leq 560 \end{cases}$$

where

$$G_{\hat{\xi}_X,\hat{\delta}_X}(x-560) = 1 - \left(1 + 0.1259463\frac{x-560}{1625.965}\right)^{-\frac{1}{0.1259463}}$$

and

$$F_Y(y) = \begin{cases} \left(1-\hat{F}_Y(2000)\right) G_{\hat{\xi}_Y,\hat{\delta}_Y}(y-2000) + \hat{F}_Y(2000), y > 2000 \\ \hat{F}(y), y \leq 2000 \end{cases}$$

where

$$G_{\hat{\xi}_Y,\hat{\delta}_Y}(y-2000) = 1 - \left(1 + 0.1283386\frac{y-2000}{10690.31}\right)^{-\frac{1}{0.1283386}}$$

The parameter estimation for Clayton copulas, Gumbel copulas, and Frank copulas are in **Table 3**.

Table 3. Copulas parameter estimation.

Copula	$\hat{\theta}$
Clayton	1.664978
Gumbel	1.985682
Frank	5.721489

By substituting the estimation result for each copula, the cumulative distribution function for the copulas can be derived as follows:

$$C^{Cl}(u,v) = (u^{-1.664978} + v^{-1.664978} - 1)^{-\frac{1}{1.664978}}$$

$$C^{Gu}(u,v) = exp\left\{-((-\ln u)^{1.985682} + (-\ln v)^{1.985682})^{\frac{1}{1.985682}}\right\}$$

$$C^{Fr}(u,v) = -\frac{1}{5.721489}\ln\left(1 + \frac{(e^{-5.721489u}-1)(e^{-5.721489v}-1)}{(e^{-5.721489}-1)}\right)$$

Based on all three copulas, the best copula in evaluating catastrophic reinsurance contracts would be the one with the lowest Akaike Information Criterion (AIC) value and it is presented in **Table 4** as follows:

Table 4. Copulas AIC score.

AIC	Copula
−42.15	Clayton
−42.95	Gumbel
−37.76	Frank

Gumbel copulas have the lowest AIC score compared to others. Hence, Gumbel copulas would be used in evaluating catastrophic reinsurance contracts. The joint cumulative distribution function for X and Y will be constructed by these copulas as follows:

$$C^{Gu}(u,v) = \exp\left\{-((-\ln u)^{1.985682} + (-\ln v)^{1.985682})^{\frac{1}{1.985682}}\right\}$$

Then, the expected value for the catastrophic reinsurance would be presented by an illustration below. Let insurance company A offer two types of products: life insurance and health insurance. To minimize losses from claims on both products in the event of a catastrophe, insurance company A has purchased a reinsurance contract for the next year. Insurance company A and reinsurer B have agreed to set a retention limit of Rp1,000,000,000 for the excess of loss reinsurance scheme. This means that insurance company A will only cover losses up to Rp1,000,000,000 for each catastrophic event occurring within one year, with the remainder being covered by the reinsurer. According to company A's data, 5% of the Indonesian population holds life insurance policies, and 10% hold health insurance policies with insurance company A. Additionally, based on company A's historical experience, the average claim per person is Rp500,000,000 for life insurance and Rp5,000,000 for health insurance.

The actuary at reinsurance company B will simulate the value of the catastrophe reinsurance contract to determine the premium. Based on the information previously provided by insurance company A, it is known that $D = 1{,}000{,}000{,}000$, $c_1 = 5\% \times 500{,}000{,}000 = 25{,}000{,}000$, and $c_2 = 10\% \times 5{,}000{,}000 = 500{,}000$. Additionally, the interest rate is assumed to be constant at $i = 6\%$. By substituting the values of D, c_1, c_2, and i into equation (3.20), the formula to be used in the simulation is:

$$\pi = \sum_{i=1}^{N} f(X_i, Y_i) \cdot (1 + 6\%)^{-t_i}$$

where

$$f(X_i, Y_i) = \max\{0, (25 \times 10^6\, X_i + 5 \times 10^5\, Y_i - 10^9)\}$$

Based on the information obtained, the actuary at reinsurance company B will simulate the value of insurance company A's catastrophe reinsurance contract. The steps required to perform the simulation are as follows:

1) The first step is to simulate the number of catastrophic events during the one-year coverage period, denoted by N, and the set of times when these events occur, denoted by $T = \{t_i, i = 1,2, \ldots, N\}$. Based on estimated Poisson parameter $\hat{\lambda} = 1.488372$, we generated number of catastrophe event from Poisson distribution ($\hat{\lambda} = 1.488372$) and time between catastrophe events from Exponential distribution with mean $\frac{1}{\hat{\lambda}}$. The simulation will be performed 10,000 times, resulting in $N_1, N_2, \ldots, N_{10{,}000}$ and $T_1, T_2, \ldots, T_{10{,}000}$.
2) Simulate the number of fatalities and the number of injuries, denoted by X and Y respectively. The data will be generated using the copula. This simulation will produce $\{(x_i, y_i), i = 1,2, \ldots, N_1\}, \{(x_i, y_i), i = 1,2, \ldots, N_2\}, \ldots, \{(x_i, y_i), i = 1,2, \ldots, N_{10{,}000}\}$.
3) Substitute the data generated in steps 1 and 2 into π, resulting in $\pi_1, \pi_2, \ldots, \pi_{10{,}000}$ and we would get $\hat{P} = \frac{\sum_{i=1}^{10{,}000} \pi_i}{10{,}000} = 10{,}296{,}819{,}838$.

The kurtosis of the data on the number of fatalities and injuries is more than three, according to **Table 2**. This suggests that the number of fatalities and injuries each has long tails. As a result, the POT model is appropriate for simulating the impact of catastrophic events. According to **Table 4**, the Gumbel copula is appropriate for building the joint distribution function of the number of fatalities and injuries. Upper-tail dependence is the dependency character described by the Gumbel copula. This suggests that there is a substantial dependence on large numbers of fatalities and injuries, as opposed to small numbers.

4. Conclusion

The Peaks Over Threshold and Copula models can be used to calculate the estimated value of catastrophic reinsurance for two risks. We use a Poisson process to calculate the number of disaster occurrences over the coverage period. We modelled the impact of the disaster occurrences, the number of fatalities and injuries, as two random variables, each using Peaks Over the Threshold, and calculated the expected value of catastrophic reinsurance based on the Basic Theorem of Asset Pricing. In this analysis, the expected value of disaster reinsurance is Rp10,296,819,838. Other insurance firms' values for catastrophe reinsurance may fluctuate based on the agreement on the desired reinsurance contract. An empirical distribution function is used in this work to model the values of the impact of catastrophic occurrences that are less than the threshold value. It is proposed that further study be conducted to examine many additional heavy-tailed distributions to discover which distribution is best suited for simulating these values. This study's copula is from the Archimedean family of copulas. Additional studies can be conducted to investigate several different families of copulas to identify the copula that is best suited for modelling catastrophic event data.

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References

Balkema, A. A., & de Haan, L. (1974). Residual Life Time at Great Age. The Annals of Probability, 2(5). https://doi.org/10.1214/aop/1176996548

Chan, W. S., Yang, H., & Zhang, L. (2003). Some results on ruin probabilities in a two-dimensional risk model. Insurance:

Mathematics and Economics, 345–358. https://doi.org/10.1016/S0167-6687(03)00115-X
Chao, W. (2021). Valuing Multirisk Catastrophe Reinsurance Based on the Cox–Ingersoll–Ross (CIR) Model. Discrete Dynamics in Nature and Society, 1–8. https://doi.org/10.1155/2021/8818486
Chaves-Dermoulin, V., & Embrechts, P. (2002). Smooth External Models for Operational Risk. Financial Valuation and Risk Management Working Paper Series, 135.
Czado, C., Kastenmeier, R., Brechmann, E., & Min, A. (2011). A mixed copula model for insurance claims and claim sizes. Scandinavian Actuarial Journal, 123–135.
Ekheden, E., & Hössjer, O. (2012). Pricing catastrophe risk in life (re)insurance. Scandinavian Actuarial Journal, 2014(4), 352–367. https://doi.org/10.1080/03461238.2012.695747
Gilli, M., & Këllezi, E. (2006). An Application of Extreme Value Theory for Measuring Financial Risk. Computational Economics, 27(2–3), 207–228. https://doi.org/10.1007/s10614-006-9025-7
Leppisaari, M. (2014). Modeling catastrophic deaths using EVT with a microsimulation approach to reinsurance pricing. Scandinavian Actuarial Journal, 2016(2), 113–145. https://doi.org/10.1080/03461238.2014.910833
Liu, S., & Han, L. (2012). Pricing Catastrophe Bonds under Safety Constraints. Managing Safety of Heterogeneous Systems. Berlin, Heidelberg. Springer.
McNeil, A., Frey, R., & Embrechts, P. (2005). Quantitative risk management: concepts, techniques and tools. Princeton: Princeton Univ Pr.
NCEI. (2022). National Centers for Environmental Information. Available online: https://www.ngdc.noaa.gov/ (accessed on 1 September 2022).
Nelsen, R. (2005). An introduction to copulas, 2nd ed. New York: Springer Science and Business Media.
Nowak, P., & Romaniuk, M. (2013). Pricing and simulations of catastrophe bonds. Insurance: Mathematics and Economics, 52(1), 18–28. https://doi.org/10.1016/j.insmatheco.2012.10.006
Paldynski, H. (2015). Modelling Large Claims in Property and Home Insurance-Extreme Value Analysis [Master's thesis]. Lund University.
Reddy, M. J., & Ganguli, P. (2012). Bivariate Flood Frequency Analysis of Upper Godavari River Flows Using Archimedean Copulas. Water Resources Management, 26(14), 3995–4018. https://doi.org/10.1007/s11269-012-0124-z
Rejda, G. E., & McNamara, M. J. (2014). Principles of risk management and insurance, 12th ed. England: Pearson Education Limited.
Shiau, J. T. (2006). Fitting Drought Duration and Severity with Two-Dimensional Copulas. Water Resources Management, 20(5), 795–815. https://doi.org/10.1007/s11269-005-9008-9
Strickler, P. (1960). Reinsurance of the accumulation risk in life insurance. XVI International Congress of Actuaries. Brussels.
Tse, Y. K. (2009). Nonlife Actuarial Models, methods and evaluation. New York: Cambridge University Press. https://doi.org/10.1017/cbo9780511812156
Wu, F., Valdez, E., & Sherris, M. (2007). Simulating from Exchangeable Archimedean Copulas. Communications in Statistics—Simulation and Computation, 36(5), 1019–1034. https://doi.org/10.1080/03610910701539781
Yu, Y., Chen, M., Qi, H., et al. (2020). Copula-Based Travel Time Distribution Estimation Considering Channelization Section Spillover. IEEE Access, 8, 32850–32861. https://doi.org/10.1109/access.2020.2970530