Copula-based Wildfire Bivariate Characteristics Analysis in the United States

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1. INTRODUCTION

Wildfires constitute an integral ecological process in the natural Earth system associated with regional and global biogeochemical cycles, human activities, and vegetation structure (Bowman et al., 2009). Subjectively, it appears that more wildfire activities could lead to more severe wildfires and larger burned areas. However, the reduction in wildfire activities (number of wildfires) driven by policy and wildfire management has resulted in changes in the vegetation structure and an increase in fuel accumulation in the western United States (Hurteau et al., 2014). As a consequence, wildfire suppression and the subsequent increase in fuel loads have coincided with warmer and drier wildfire seasons, causing high-severity wildfire events yielding large burned areas (Dennison et al., 2014). These two seemingly contradictory situations are attributed to the unique structure of the relationship between the wildfire activity and burned area, posing challenges to comprehensively assess the wildfire characteristics.

Accordingly, in this study, we determine the univariate distribution of these two target wildfire characteristics. Second, we calculate the joint probability of the wildfire activity and burned area according to a copula-based joint distribution. Then, the average method is applied to balance the copula-based bivariate and univariate probability distributions to calculate the wildfire priority index. Finally, through this wildfire priority index, the spatiotemporal variability and return period trends of the wildfire risk can be explored.

2. MATERIALS AND METHODS

2.1. Data source

In this study, wildfire statistics data pertaining to the continental United States were obtained from the 5th edition of the Forest Service Fire Program Analysis-Fire Occurrence Database (Short, 2021). This comprehensive dataset includes 2.17 million wildfire records.

2.2. Optimal selection of the univariate distribution

The univariate distribution parameter estimation approach involves L-moment theory, which was developed by Hosking based on order statistics (Hosking, 1990). The L-moment has been widely established in statistics for determining theoretical probability distributions. The main advantage of the L-moment is that the L-moment is less affected by sampling variability, which is more robust to outliers in the data. The three important parameters τ_2 (L-Cv), τ_3 (L- skewness), and τ_4 (L-kurtosis) included in L-moment can be used to calculate a variety of different distribution functions (Hosking, 1990), including one-parameter, two-parameter, three-parameter and four-parameter distribution functions. A total of seven commonly considered marginal distributions were selected in this research.

2.3. Optimal selection of the joint distribution

The joint frequency analysis method used in this study is based on the Multivariate Copula Analysis Toolbox (MvCAT) (Sadegh et al., 2017). This approach to estimate the parameters of the univariate distribution includes Bayesian analysis and the Markov Chain Monte Carlo (MCMC) algorithm.

2.4. Wildfire priority index and return period

As described in the introduction, direct application of bivariate probability distributions in wildfire frequency analysis can result in neglect of single mega-wildfire events and numerous wildfire events with a normal-sized burned area. Accordingly, we adopted the average method to determine the wildfire priority index to balance bivariate joint probability and univariate probability.

2.5. Trend analysis method

The trend analysis method used in this study is the Mann-Kendall (MK) test. The advantage of the MK test is that a particular form of the probability distribution function of the considered time series is not needed, which suggests that the test is less sensitive to potential interference resulting from outliers in the data.

3. RESULTS AND DISCUSSION

Seven marginal distribution functions were employed to fit monthly log-wildfire-activity and log-burned-area values based on the L-moments approach. Analogously, the spatial distribution of the selected univariate probability distributions of the monthly log-burned-area and log-wildfire-activity statistics is shown in **Fig. 1(a-b)**. In regard to the monthly log-burned-area, the WEI distribution is the most applicable to the entire grid of the continental United States, reaching 57.7%, followed by the GEV distribution with 25.6%. Notably, the grid cells under the GEV distribution are mainly concentrated in the central and eastern parts of the continental United States. The optimal marginal distributions for 9.2% and 5.6% of all grid cells are the Pearson type III (P-III) and generalized logistic (GLO) distributions, respectively. The other four distributions (exponential (EVP), Gumbel (extreme-value type I) (GUM), and normal (NOR) only apply to 1.9% of the total grid. For monthly log-wildfire-activity, the WEI distribution occupies a dominant position, accounting for 83.5% of all grid cells. In contrast to log-burned-area, the second-best distribution of log-wildfire-activity is the P-III distribution, accounting for 8.3% of all cells. The GEV, GLO, and EXP distributions accounted for 3.8%, 3.4%, and 1.0%, respectively. These distribution optimization results illustrate that the NOR and GUM distributions are completely unsuitable for monthly log-wildfire-activity.

The spatial distribution of the selected bivariate copulas of the monthly log-burned-area and log-wildfire-activity is shown in **Fig. 1(c)**. The applicability of the Gaussian (GAU) function is the highest among the six alternative copulas, reaching 43.1%. The second most applicable copula is the Clayton (CLA) function, reaching 22.5%,

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followed by the Frank (FRA) function with 17.0%. Additionally, the Gumbel (GUM) and Ali-Mikhail-Haq (AMH) functions account for 16.4% and 1.0%, respectively. As expected, the independent function is unsuitable in all grid cells, reflecting the correlation between log-wildfire-activity and log-burned-area. Bivariate distribution functions show more evident regionality than univariate distribution functions.

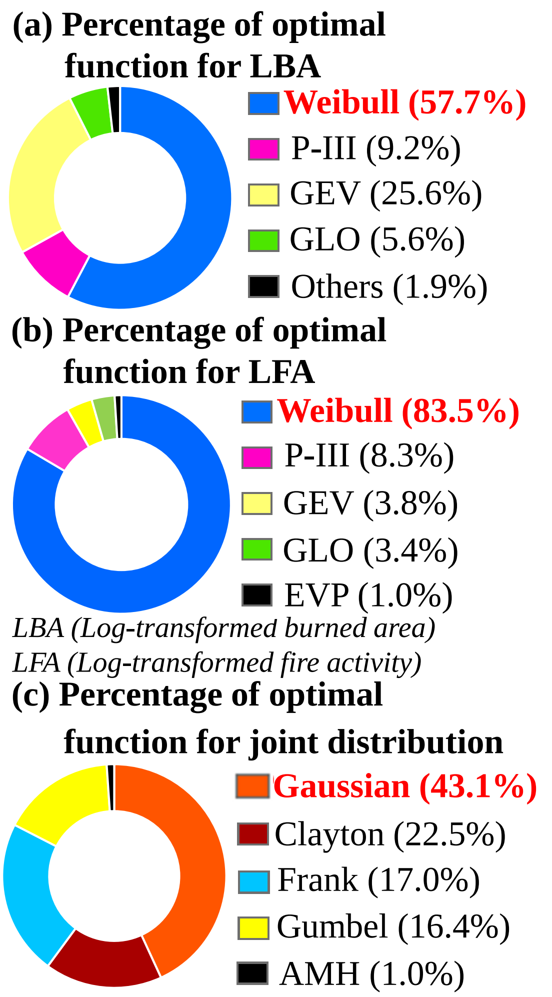

Fig. 1. Proportion of optimal univariate and bivariate distribution functions.

From the univariate probability and the joint bivariate probability of wildfire, we calculated the wildfire priority index. The wildfire priority index is the average of the three probability values of the wildfire univariate probability and the bivariate joint probability. Then, according to the return period trends of wildfire priority index, future wildfire risk changes can also be determined. In particular, the return period trends of wildfire priority index are shown in **Fig. 2**. The results indicated that the return period of log-burned-area exhibits a significant increasing trend in California, Texas, and Arkansas. Moreover, most of the southeastern continental United States exhibits significant decreasing trends.

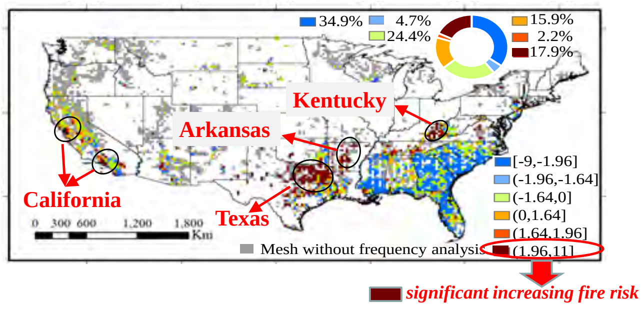

Fig. 2. The trends of wildfire bivariate characteristic.

4. CONCLUSIONS

The main conclusions obtained from this paper are summarised as follows: (1) the statistical structure of the burned area is more variable than that of the wildfire activity, and different probability distributions are suitable for various regions; (2) through trend analysis of the return period of wildfire priority index, an increasing trend occurs in California, Texas, and Arkansas. Moreover, most of the southeastern continental United States exhibits significant decreasing trends in terms of wildfire risk.

Overall, the framework of wildfire frequency analysis proposed in this study can provide a reference to better understand the spatiotemporal characteristics of wildfire statistics. This new approach of wildfire risk assessment will also facilitate the consideration of postfire effects.

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The authors declare no conflict of interest. All datasets utilized to perform this study are freely available on the internet.

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