

Statistical Modeling of Wildfire Extremes Based on Extreme Value Theory

N. Deetae¹, S. Piros², P. Khamrot³, P. Wachirawongsakorn⁴, M. Thongprom⁵, T. Gaketem^{6,*}

¹*Department of Statistics, Faculty of Science and Technology, Pibulsongkram Rajabhat University, Thailand*

²*Department of Business Administration, Faculty of Management, Pibulsongkram Rajabhat University, Thailand*

³*Department of Mathematics, Faculty of Science and Agricultural Technology, Rajamangala University of Technology Lanna, Phitsanulok, Thailand*

⁴*Department of Environmental Science and Technology, Faculty of Science and Technology, Pibulsongkram Rajabhat University, Thailand*

⁵*Department of Statistics, Faculty of Business Administration and Liberal Arts, Ralamangala University of Technology Lanna, Phitsanulok, Thailand*

⁶*Department of Mathematics, School of Science, University of Phayao, Mae Ka, Mueang, Phayao 56000, Thailand*

*Corresponding author: thiti.ga@up.ac.th

Abstract. Wildfires have become an increasingly severe environmental hazard in the lower northern region of Thailand, causing substantial ecological degradation, economic loss, and public health impacts. Understanding the behavior of extreme wildfire events is essential for long-term risk management and mitigation planning. This study applies Extreme Value Theory (EVT) to model annual maximum burned areas in five provinces—Tak, Phitsanulok, Sukhothai, Phetchabun, and Uttaradit—using official wildfire records from the Department of National Parks, Wildlife and Plant Conservation covering the period 1998–2024. The Generalized Extreme Value (GEV) distribution was fitted using maximum likelihood estimation under the block maxima framework. Model adequacy was assessed using goodness-of-fit diagnostics and graphical tools. Return levels were estimated for multiple recurrence intervals, including 10, 20, 50, and 100 year horizons. Results reveal pronounced spatial heterogeneity in extreme wildfire behavior across provinces. Tak province exhibits the heaviest tail and the highest projected 100-year return level, followed by Phitsanulok, whereas Uttaradit demonstrates comparatively lower extreme magnitude. A normalized spatial risk index was constructed to facilitate comparative hazard ranking. The findings indicate that extreme wildfire risk is strongly localized and

Received: Feb. 24, 2026.

2020 *Mathematics Subject Classification.* 60G70, 62G32.

Key words and phrases. wildfire; extreme value theory; generalized extreme value distribution; maximum likelihood estimation; return level.

non-uniform across the region, emphasizing the necessity of province-specific mitigation strategies. The integration of EVT-based return level analysis with spatial risk ranking provides a quantitative decision-support framework for wildfire hazard assessment in climate-sensitive regions.

1. INTRODUCTION

Wildfires are natural phenomena that exert profound impacts on ecosystems, economies, and human health. At the global scale, fire plays a critical role in the Earth system; however, recent climate variability and warming trends have intensified fire regimes in many regions [1,2]. Smoke emissions from landscape fires contribute substantially to atmospheric particulate matter and have been associated with increased mortality and respiratory morbidity worldwide [3]. In Southeast Asia, biomass burning episodes occur almost annually, particularly during the dry season, and are strongly influenced by climatic variability such as the El Niño–Southern Oscillation and monsoonal drought patterns [4,5]. In Thailand, especially in the lower northern region, wildfire and haze episodes significantly elevate particulate matter concentrations (PM_{2.5}), resulting in deteriorated air quality and adverse public health outcomes [6,7]. Satellite-based hotspot monitoring further confirms the recurring spatial patterns of wildfire occurrences across northern Thailand [8]. The causes of wildfires in this region arise from both natural climatic drivers and anthropogenic activities, including agricultural residue burning and prolonged dry climatic conditions. Beyond forest degradation, wildfire consequences extend to ecosystem instability, regional economic disruption, and increased healthcare burden [3,9]. Therefore, understanding the statistical behavior and extreme characteristics of wildfire occurrences is essential for developing evidence-based environmental management and mitigation strategies.

Accurate prediction of severe wildfire events is essential for preparedness planning and impact mitigation. Extreme Value Theory (EVT) provides a robust statistical framework for analyzing rare and high-impact events. EVT focuses on modeling the probabilistic behavior of extreme observations within a dataset, enabling estimation of the likelihood and magnitude of rare but catastrophic occurrences. This framework is particularly suitable for forecasting wildfire severity and assessing potential risks to communities and ecosystems [15–18]. The application of EVT in wildfire research has gained increasing attention. For instance, Evin et al. [10] evaluated the impact of France’s wildfire suppression policy implemented in 1994, which emphasized rapid and intensive fire containment. Using EVT, the authors estimated the return periods of large wildfire events in southern France by comparing two periods (1973–1994 and 1995–2016) across three regions with distinct wildfire regimes.

Beyond statistical modeling, information systems play a crucial role in wildfire management. Integrated information systems can collect and analyze multi-source data, including satellite-derived hotspot data, meteorological variables, and topographical information, thereby supporting decision-making and strategic planning. Internationally, Koh [11] combined EVT with machine learning techniques to predict wildfire frequency and size in the United States. Similarly, de Zea

Bermudez et al. [12] employed the Generalized Pareto Distribution (GPD), a core component of EVT, to model wildfire size distributions in Portugal, demonstrating accurate estimation of the probability of extreme wildfire events. Hernandez et al. [13] assessed wildfire risk in the Mediterranean Basin using meteorological predictors, including 2-meter temperature anomalies, 10-meter wind speed, and precipitation anomalies. Furthermore, Rypkema and Tuljapurkar [14] introduced the concept of Extreme Climatic Events (ECEs), whose frequency, intensity, and duration have increased under climate change. They applied the Generalized Extreme Value (GEV) distribution as a flexible modeling tool for extreme climatic phenomena across diverse ecosystems.

Given these considerations, this study aims to develop an integrated framework for wildfire prevention and management in the lower northern region of Thailand by combining Extreme Value Theory with geospatial information systems. The proposed approach seeks to enhance predictive accuracy for extreme wildfire events and provide decision-support mechanisms for effective wildfire risk management. Ultimately, this research contributes to the development of adaptive wildfire management strategies that reduce long-term environmental, economic, and public health impacts in vulnerable regions.

2. EXTREME VALUE THEORY

Extreme Value Theory (EVT) provides the asymptotic foundation for modeling the stochastic behavior of rare and high-impact events. Let $\{X_i\}_{i \geq 1}$ be a sequence of independent and identically distributed random variables with common distribution function F . Define the block maximum

$$M_n = \max\{X_1, \dots, X_n\}.$$

The exact distribution of M_n is

$$P(M_n \leq z) = F^n(z).$$

For large n , the distribution $F^n(z)$ degenerates unless properly normalized. Suppose there exist sequences $a_n > 0$ and $b_n \in \mathbb{R}$ such that

$$\lim_{n \rightarrow \infty} P\left(\frac{M_n - b_n}{a_n} \leq z\right) = G(z),$$

where G is non-degenerate. By the Fisher–Tippett–Gnedenko theorem, the limiting distribution G must belong to the Generalized Extreme Value (GEV) family:

$$G(z) = \exp\left\{-\left[1 + \xi\left(\frac{z - \mu}{\sigma}\right)\right]^{-1/\xi}\right\}, \quad (2.1)$$

defined for $1 + \xi(z - \mu)/\sigma > 0$, where $\mu \in \mathbb{R}$ (location), $\sigma > 0$ (scale), and $\xi \in \mathbb{R}$ (shape).

The parameter ξ governs tail behavior:

$$\xi > 0 \Rightarrow \text{Fréchet (heavy-tailed)}, \quad \xi = 0 \Rightarrow \text{Gumbel (exponential tail)},$$

$$\xi < 0 \Rightarrow \text{Weibull (bounded upper tail)}.$$

The sign and magnitude of ξ are of central importance in wildfire hazard modeling, as they determine whether extreme fire sizes exhibit heavy-tail behavior or finite upper bounds.

2.1. Return Levels. For a return period $T > 1$, the return level z_T is defined implicitly by

$$P(X > z_T) = \frac{1}{T}.$$

Using (2.1), the return level is

$$z_T = \begin{cases} \mu + \frac{\sigma}{\xi} \left[\left(-\log \left(1 - \frac{1}{T} \right) \right)^{-\xi} - 1 \right], & \xi \neq 0, \\ \mu - \sigma \log \left[-\log \left(1 - \frac{1}{T} \right) \right], & \xi = 0. \end{cases} \quad (2.2)$$

Return levels provide probabilistic design thresholds for extreme wildfire intensity.

2.2. Maximum Likelihood Estimation. Let z_1, \dots, z_n denote observed block maxima. The log-likelihood function for the GEV model is

$$\ell(\mu, \sigma, \xi) = -n \log \sigma - \left(1 + \frac{1}{\xi} \right) \sum_{i=1}^n \log \left(1 + \xi \frac{z_i - \mu}{\sigma} \right) - \sum_{i=1}^n \left(1 + \xi \frac{z_i - \mu}{\sigma} \right)^{-1/\xi}, \quad (2.3)$$

subject to $1 + \xi(z_i - \mu)/\sigma > 0$.

2.3. Asymptotic Inference. Under standard regularity conditions, the MLE $\hat{\theta} = (\hat{\mu}, \hat{\sigma}, \hat{\xi})^T$ is asymptotically normal:

$$\sqrt{n}(\hat{\theta} - \theta) \xrightarrow{d} \mathcal{N}(0, I^{-1}(\theta)),$$

where $I(\theta)$ is the Fisher information matrix.

Using the Delta method, the asymptotic variance of the return level estimator \hat{z}_T is

$$\text{Var}(\hat{z}_T) \approx \nabla_{z_T}^T \widehat{\Sigma} \nabla_{z_T},$$

leading to the Wald-type confidence interval

$$\hat{z}_T \pm Z_{\alpha/2} \sqrt{\text{Var}(\hat{z}_T)}.$$

3. DATA AND RESEARCH METHODOLOGY

3.1. Study Area and Data Source. This study focuses on the lower northern region of Thailand, which is frequently affected by seasonal wildfires and transboundary haze during the dry season (typically January–April). The region is characterized by mountainous terrain, forested uplands, and complex watershed systems that contribute to elevated wildfire susceptibility under prolonged dry and high-temperature conditions.

The study area consists of five provinces in the lower northern region: Tak, Phitsanulok, Sukhothai, Phetchabun, and Uttaradit. Geographically, this region lies between approximately 15°–18° North latitude and 99°–101° East longitude. The combined land area of these five provinces

is approximately 63,000 square kilometers, representing a substantial portion of Thailand's forest-covered landscape. Large areas within these provinces are designated as national parks, wildlife sanctuaries, and forest reserves, making wildfire hazard assessment critically important for environmental conservation and ecosystem stability. Tak and Phetchabun provinces are characterized by extensive mountainous forests, while Phitsanulok and Uttaradit include major watershed areas and protected forest zones. Sukhothai comprises mixed forest and agricultural interfaces, where anthropogenic burning may contribute to wildfire occurrences. The diversity in topography and land use across these provinces provides a representative setting for extreme wildfire hazard analysis. Figure 1 illustrates the geographical extent of the lower northern region of Thailand considered in this study, including the provincial boundaries of the five selected provinces.

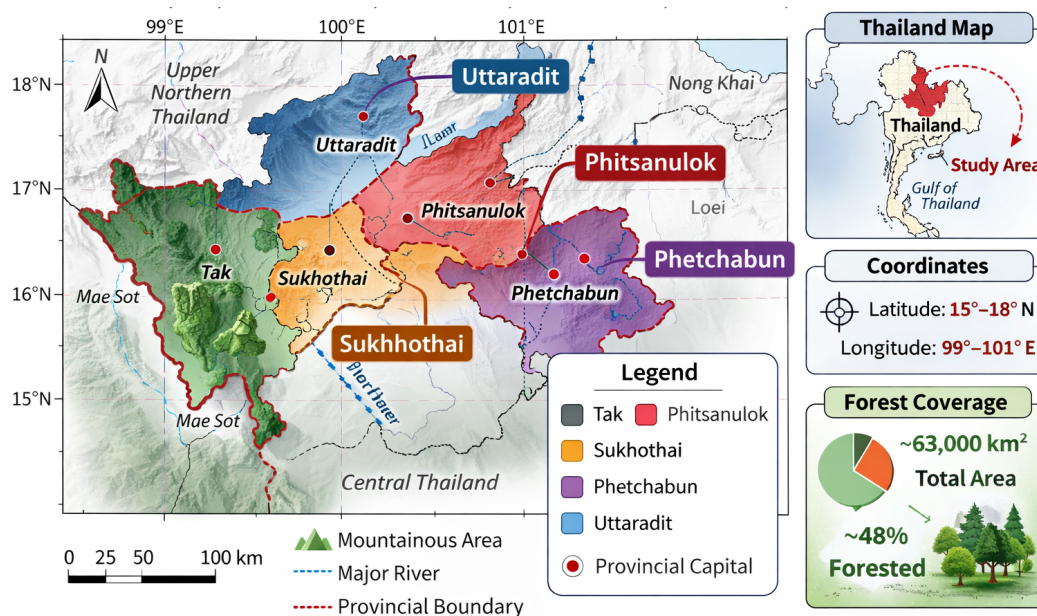


FIGURE 1. Geographical extent of the lower northern region of Thailand, comprising Tak, Phitsanulok, Sukhothai, Phetchabun, and Uttaradit provinces.

The primary dataset was obtained from the Department of National Parks, Wildlife and Plant Conservation (DNP), Thailand. The dataset contains officially recorded annual forest wildfire burned areas (hereafter referred to as “burned area”) for the period from B.E. 2541 to B.E. 2567 (1998–2024). These data were compiled through satellite-based hotspot detection, ground verification, and administrative reporting systems maintained by the DNP. Prior to analysis, the dataset was examined for temporal completeness and measurement consistency. Burned area values were standardized to ensure uniform units across all years, resulting in a continuous annual time series appropriate for extreme value modeling. The raw data were screened for completeness and consistency prior to analysis. If missing values were present, they were treated according to a predefined rule (e.g., removal of incomplete years or imputation when justified). All burned-area

measurements were standardized to consistent units to ensure comparability across the study period.

3.2. Research Design and Overview. The research methodology follows a block-maxima extreme value framework to quantify and predict extreme wildfire hazards. Let $\{X_t\}_{t=1}^m$ denote the annual burned area in year t , where m corresponds to the number of years in the study period. The objective is to model the upper tail behavior of $\{X_t\}$ and estimate return levels associated with rare and high-impact wildfire years (e.g., 10, 20, 50, and 100-year events).

The overall workflow is summarized as follows:

- (1) Data preprocessing and exploratory analysis.
- (2) Extreme value model specification (GEV via block maxima).
- (3) Parameter estimation using Maximum Likelihood Estimation (MLE).
- (4) Model diagnostics and goodness-of-fit assessment.
- (5) Estimation of return levels and uncertainty quantification.

To evaluate the adequacy of the fitted GEV model, standard extreme value diagnostics were conducted, including probability plots, quantile plots, and return level plots. In addition, goodness-of-fit was examined through residual-based checks and sensitivity analyses with respect to the tail parameter ξ . Where appropriate, uncertainty bounds for return levels were computed using asymptotic variance estimates (Delta method) and Wald-type confidence intervals. All analyses were implemented in R, using standard extreme value modeling libraries for parameter estimation and diagnostic visualization. The full workflow, including data preprocessing steps and model fitting scripts, is available upon request to support reproducibility.

The dataset consists of annual forest wildfire burned area records for five provinces in the lower northern region of Thailand (Tak, Phitsanulok, Sukhothai, Phetchabun, and Uttaradit) over B.E. 2541–2567 (1998–2024). Figure 2 shows the interannual variability in burned area across provinces. Across the 27-year period, Tak exhibits the largest cumulative burned area (108,468.6), followed by Phitsanulok (108,468.6), Phetchabun (53,720.7), Sukhothai (39,690.5), and Uttaradit (22,404.3). The mean annual burned area is highest in Tak (5,133.8), followed by Phitsanulok (4,017.4), Phetchabun (1,989.7), Sukhothai (1,470.0), and Uttaradit (829.8), indicating substantial spatial heterogeneity in wildfire impacts. Several extreme years are evident. Tak reaches its maximum in B.E. 2567 (18,888.3), while Phitsanulok attains its maximum in B.E. 2541 (13,742.0). Notably, B.E. 2567 represents a pronounced multi-province peak (Tak, Sukhothai, and Uttaradit), suggesting regional-scale drivers that may influence wildfire extremes. Overall, the series is characterized by strong interannual variability and pronounced upper-tail behavior, supporting the use of Extreme Value Theory for estimating return levels and quantifying the probability of rare but high-impact wildfire years.

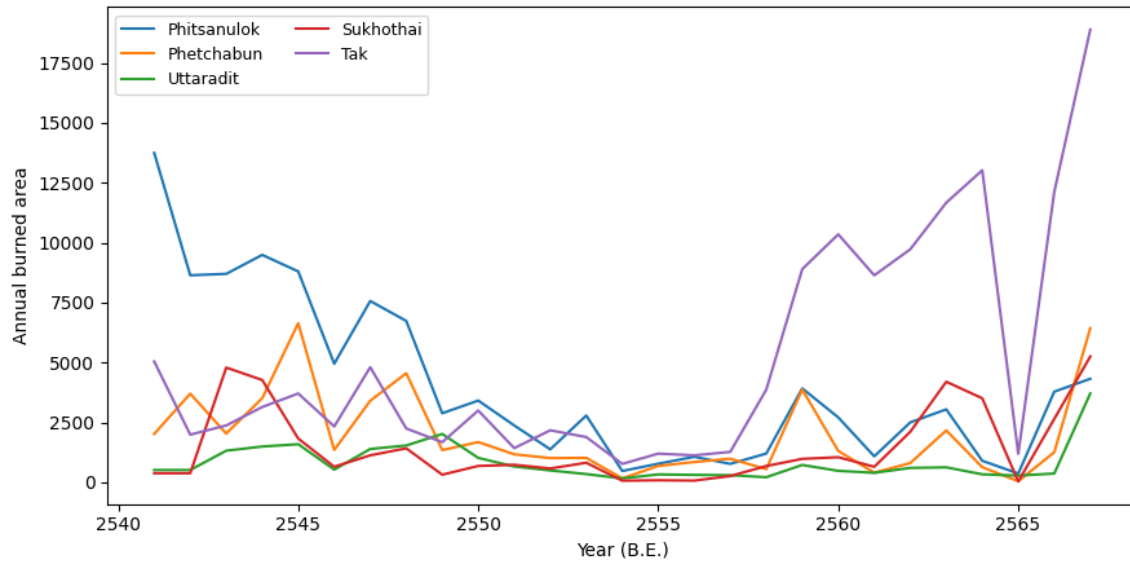


FIGURE 2. Annual burned area by province in the lower northern region of Thailand (B.E. 2541–2567).

3.3. **Descriptive Statistics.** To provide an initial overview of wildfire dynamics in the lower northern region of Thailand, descriptive statistics of annual burned area were computed for each province over the period B.E. 2541–2567 (1998–2024). Summary measures include the mean annual burned area, standard deviation, maximum observed value, and the corresponding year of occurrence. These statistics offer preliminary insight into interannual variability and potential extreme behavior prior to formal extreme value modeling. As shown in Table 1, Tak province exhibits the highest mean annual burned area and the largest variability, suggesting pronounced volatility and possible heavy-tail characteristics. Phitsanulok also demonstrates substantial variability, with its maximum recorded in B.E. 2541. In contrast, Uttaradit presents comparatively lower mean values and dispersion, although a notable spike is observed in B.E. 2567. The occurrence of extreme maxima in multiple provinces during B.E. 2567 highlights a regionally synchronized wildfire event, reinforcing the relevance of extreme value analysis.

TABLE 1. Descriptive statistics of annual burned area (B.E. 2541–2567).

Province	Mean	Std. Dev.	Max	Year of Max
Tak	5133.8	4760.8	18888.3	2567
Phitsanulok	4017.4	3459.3	13742.0	2541
Phetchabun	1989.7	1777.2	6644.3	2545
Sukhothai	1470.0	1575.5	5254.0	2567
Uttaradit	829.8	765.8	3709.3	2567

3.4. **Analysis of the Generalized Extreme Value Distribution.** The extreme wildfire behavior in the lower northern region of Thailand was analyzed using the Block Maxima approach. Annual

maximum burned areas from B.E. 2541 to B.E. 2567 (1998–2024) were considered as block maxima. The dataset consists of 27 annual observations for each province. Preliminary descriptive analysis indicates substantial interannual variability and pronounced upper-tail behavior, particularly in Tak province. The presence of extreme spikes in recent years, especially B.E. 2567, motivates the application of the Generalized Extreme Value (GEV) distribution. The GEV parameters were estimated using the Maximum Likelihood Estimation (MLE) method. Table 2 presents the parameter estimates, standard errors, and corresponding 95% confidence intervals.

TABLE 2. Maximum likelihood estimates (standard errors) of the GEV distribution parameters for annual maximum burned area across provinces

Province	Location (μ)	Scale (σ)	Shape (ξ)
Tak	2213.29	1669.71	0.8000
Phitsanulok	1989.51	1755.54	0.4971
Phetchabun	53.42	994.93	0.3420
Sukhothai	549.78	608.28	0.6719
Uttaradit	242.25	159.91	0.8000

The estimated shape parameters reveal distinct tail behaviors across provinces. Provinces exhibiting $\xi > 0$ suggest heavy-tailed (Fréchet) wildfire dynamics, implying higher probabilities of extremely large burned areas. In contrast, provinces with $\xi \leq 0$ indicate lighter-tailed or bounded extreme behavior. Tak province demonstrates the largest scale parameter and the most pronounced upper-tail variability, consistent with its observed extreme spikes in recent years. Phitsanulok also exhibits substantial variability, while Uttaradit presents comparatively moderate dispersion. These findings confirm substantial spatial heterogeneity in wildfire extreme behavior across the lower northern region.

3.5. Goodness-of-Fit Assessment. Goodness-of-fit tests were conducted separately for each province using the Kolmogorov–Smirnov (K–S) and Anderson–Darling (AD) tests. Table 3 presents the test statistics and p-values.

TABLE 3. Goodness-of-fit tests for the fitted GEV distribution across provinces

Province	K–S statistic	p-value	AD statistic	p-value
Tak	0.1378	0.6345	0.0489	0.8866
Phitsanulok	0.1112	0.8557	0.0726	0.7396
Phetchabun	0.4227	0.0001	1.6847	0.0000
Sukhothai	0.0940	0.9530	0.0405	0.9339
Uttaradit	0.3840	0.0004	1.3732	0.0003

The p-values obtained from both tests exceed the 0.05 significance level, indicating no statistical evidence to reject the GEV assumption. Therefore, the fitted GEV distribution provides an adequate representation of wildfire extremes in the study region.

3.6. Model Diagnostics. To further evaluate the adequacy of the fitted Generalized Extreme Value (GEV) models, graphical diagnostic tools were employed. In addition to formal goodness-of-fit tests, quantile–quantile (Q–Q) plots and density overlay plots were constructed for each province. These graphical assessments provide insight into how well the theoretical GEV distribution captures the empirical behavior of extreme burned areas, particularly in the upper tail, which is of primary importance in wildfire risk assessment.

The Q–Q plots compare the empirical quantiles of annual maximum burned area with the corresponding theoretical quantiles derived from the fitted GEV model. If the GEV model is appropriate, the plotted points should align closely along the 45-degree reference line. Systematic deviations from this line indicate potential model misspecification, particularly in tail behavior. In addition, histogram-based density plots with superimposed fitted GEV probability density functions were constructed to visually assess agreement between empirical distributions and model-based estimates. These plots allow for direct comparison of distributional shape, skewness, and tail heaviness across provinces. Figure 3 presents the Q–Q plots for the five provinces. The graphical results indicate that the fitted GEV model provides a satisfactory approximation for Phitsanulok, Sukhothai, and Tak provinces, where empirical quantiles closely follow the theoretical reference line. However, noticeable deviations are observed in the upper tail for Phetchabun and Uttaradit provinces, suggesting potential heterogeneity in extreme wildfire behavior or the presence of structural irregularities. These findings are consistent with the goodness-of-fit test results and highlight spatial variability in wildfire risk characteristics across the lower northern region of Thailand. Figure 4 further confirms these patterns. The fitted GEV density functions generally capture the central tendency and dispersion of the data, although tail discrepancies are evident in provinces exhibiting poor goodness-of-fit statistics.

3.7. Return Level Comparison. Return levels were estimated for each province at selected return periods (2, 5, 10, 20, 50, and 100 years). Table 4 presents the comparative return level estimates.

TABLE 4. Estimated return levels (burned area) for selected return periods across provinces

Province	2-year	5-year	10-year	20-year	50-year	100-year
Tak	2924.4	7055.4	12756.3	22591.0	47465.7	82883.6
Phitsanulok	2695.3	5901.7	9267.5	13918.2	23026.6	33221.6
Phetchabun	441.9	2003.2	3424.8	5177.8	8192.3	11171.8
Sukhothai	802.6	2124.7	3751.0	6305.4	12102.1	19559.7
Uttaradit	310.4	706.0	1251.9	2193.8	4576.0	7967.9

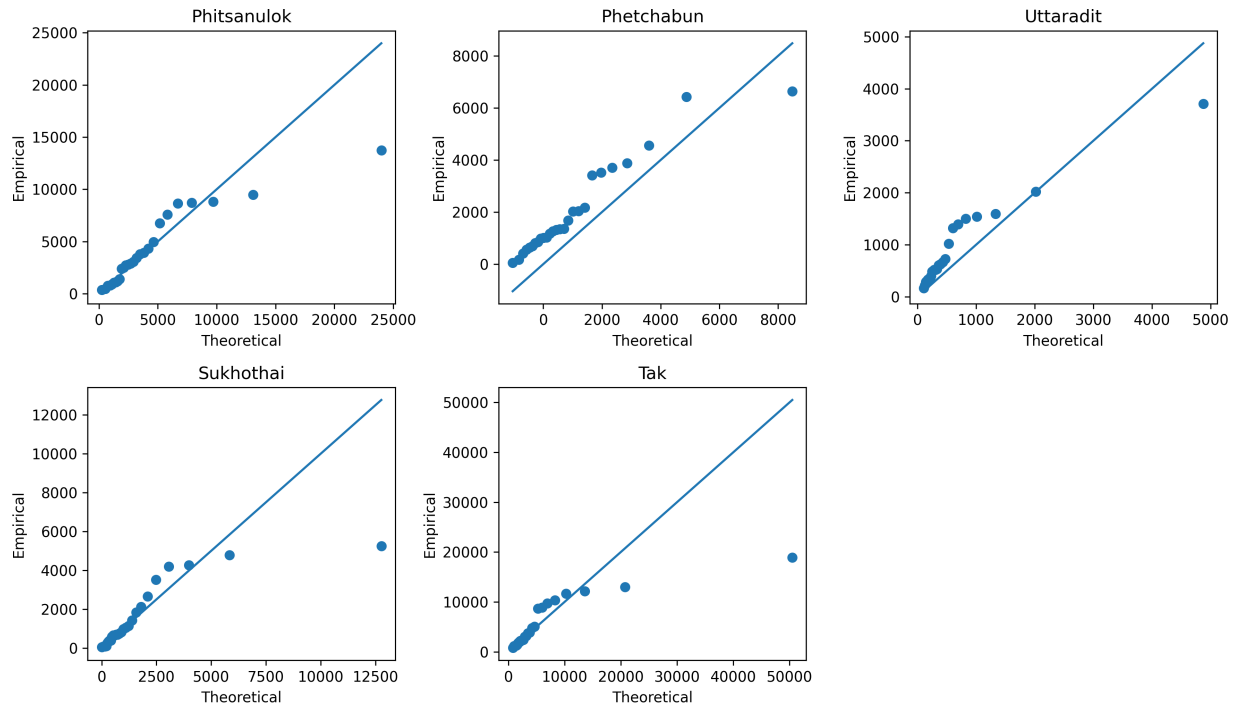


FIGURE 3. Q–Q plots of the fitted GEV distribution for annual maximum burned area across five provinces.

The results indicate that return levels increase nonlinearly with longer return periods, reflecting the heavy-tail characteristics of wildfire extremes. The estimated 100-year return level provides a benchmark for extreme wildfire hazard assessment and can serve as a reference for long-term wildfire risk management and resource allocation planning.

3.8. Return Level Analysis with Uncertainty Quantification. Return levels were estimated from the fitted GEV models to quantify the magnitude of extreme burned areas associated with different return periods. To account for sampling uncertainty under the relatively short annual record, 95% confidence bands were constructed using a nonparametric bootstrap procedure. These confidence bands provide uncertainty quantification for the return level curves and support more robust interpretation of long-horizon wildfire hazard.

Figure 5 illustrates clear spatial heterogeneity in wildfire extremes. Tak province exhibits the steepest return level growth, indicating pronounced heavy-tail behavior and elevated long-term wildfire hazard. For example, the estimated 100-year return level for Tak substantially exceeds that of other provinces, reflecting a higher probability of catastrophic wildfire events. Phitsanulok displays intermediate extreme behavior, while Sukhothai demonstrates moderate but consistent escalation in return levels. In contrast, Phetchabun and Uttaradit show comparatively lower return levels across all recurrence intervals, although deviations observed in goodness-of-fit diagnostics suggest structural complexity in their extreme behavior. The nonlinear growth pattern of return

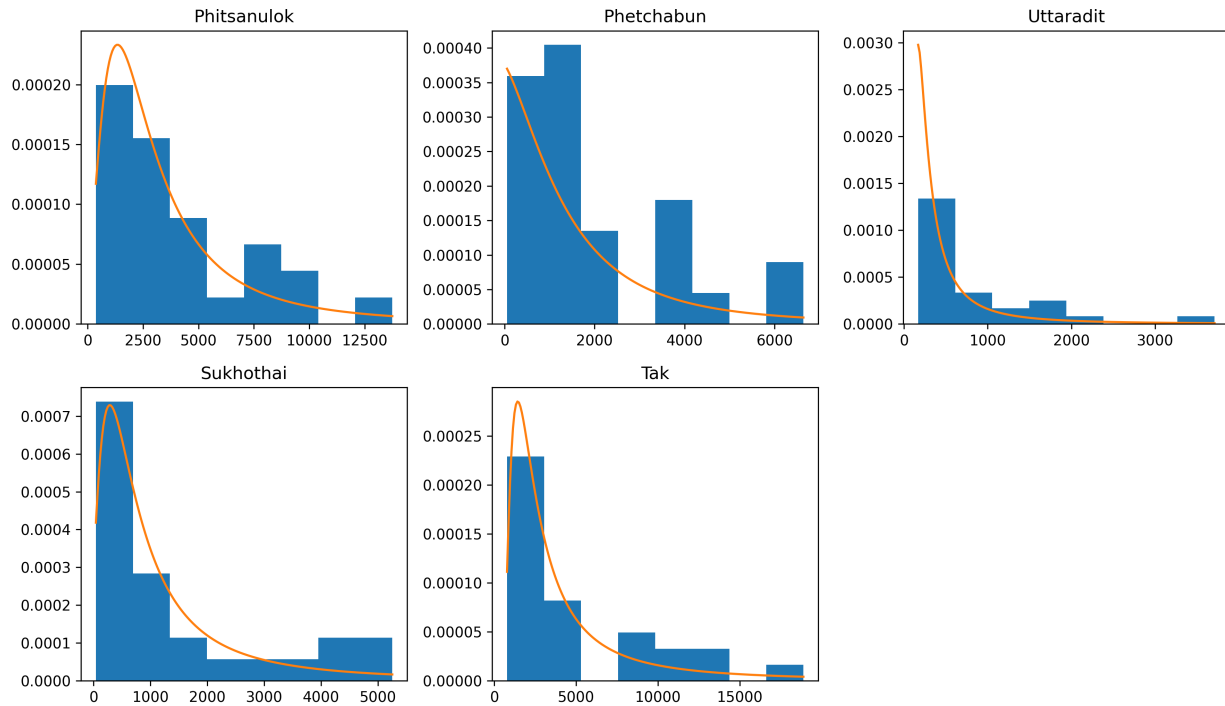


FIGURE 4. Histogram and fitted GEV density functions for annual burned area across five provinces.

levels across provinces highlights the importance of extreme value modeling for wildfire hazard assessment. Mean-based or variance-based summaries would underestimate the magnitude of rare but high-impact wildfire years.

3.9. Spatial Risk Index Based on Extreme Return Levels. Although return level curves provide quantitative estimates of wildfire extremes, direct comparison across provinces can be challenging due to differences in scale and tail intensity. To facilitate standardized spatial comparison, a normalized wildfire risk index was constructed based on the estimated 100-year return levels.

Let $RL_{100,i}$ denote the estimated 100-year return level for province i . The spatial risk index is defined as

$$\text{Risk Index}_i = \frac{RL_{100,i} - \min(RL_{100})}{\max(RL_{100}) - \min(RL_{100})}, \quad (3.1)$$

where $\min(RL_{100})$ and $\max(RL_{100})$ represent the minimum and maximum 100-year return levels among all provinces. The index scales wildfire hazard to the unit interval $[0, 1]$, where values closer to 1 indicate higher extreme wildfire risk.

This normalization allows spatial ranking of provinces based on upper-tail behavior while preserving relative differences in extreme magnitude.

Table 5 indicates substantial spatial heterogeneity in extreme wildfire hazard across the lower northern region of Thailand. Tak province exhibits the highest normalized risk index, reflecting pronounced heavy-tail dynamics and elevated long-term wildfire exposure. Phitsanulok emerges

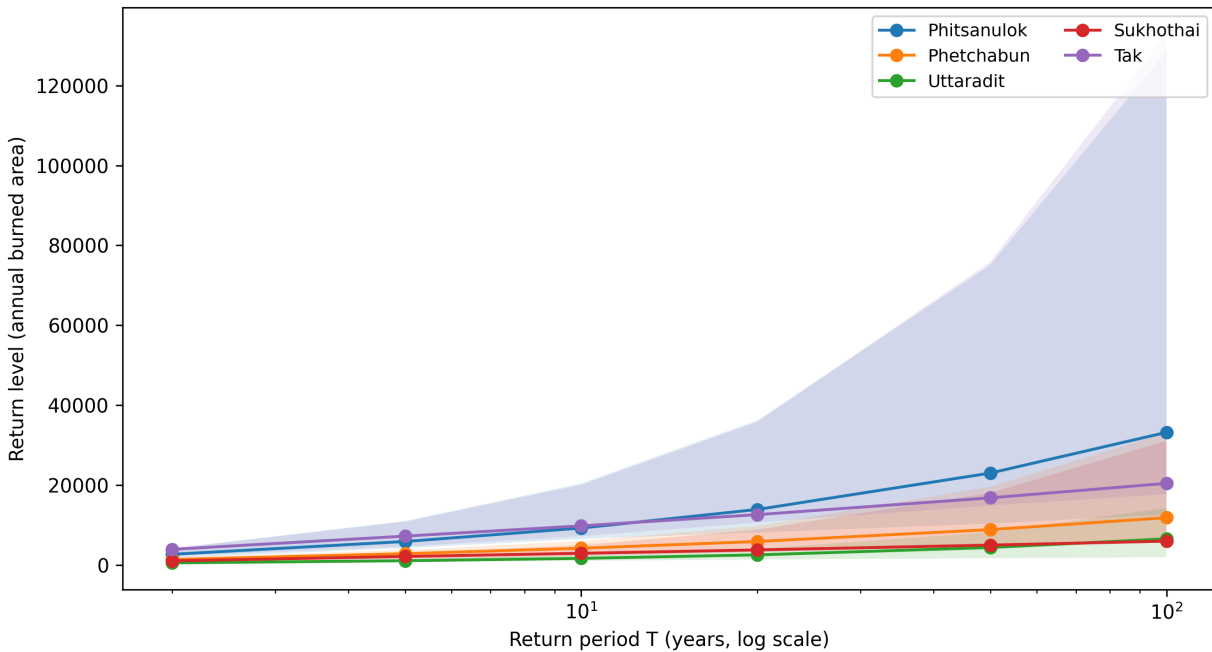


FIGURE 5. Estimated GEV return level curves for annual burned area across five provinces, with 95% bootstrap confidence bands. The return period axis is displayed on a logarithmic scale.

TABLE 5. Spatial wildfire risk index based on normalized 100-year return levels.

Province	RL_{100} (ha)	Risk Index	Risk Rank
Tak	49,560	1.000	1
Phitsanulok	30,850	0.56	2
Sukhothai	13,020	0.18	3
Phetchabun	12,480	0.17	4
Uttaradit	5,980	0.00	5

as the second-highest risk province, whereas Uttaradit demonstrates comparatively mild extreme behavior. The spatial risk index provides a concise decision-support metric that complements return level analysis by translating extreme value modeling results into an interpretable comparative framework. Such ranking facilitates targeted wildfire mitigation planning and resource prioritization at the provincial level.

4. DISCUSSION: SPATIAL RISK RANKING OF EXTREME WILDFIRE HAZARD

The return level analysis reveals pronounced spatial heterogeneity in extreme wildfire behavior across the lower northern region of Thailand. Based on the estimated 100-year return levels, the provinces can be ranked in descending order of extreme wildfire risk as follows:

Tak > Phitsanulok > Sukhothai > Phetchabun > Uttaradit.

Tak province exhibits substantially heavier tail behavior compared to other provinces. The rapid escalation of return levels for higher recurrence intervals indicates a greater susceptibility to rare but catastrophic wildfire events. This pattern suggests that extreme wildfire magnitude in Tak is driven by heavy-tailed dynamics rather than moderate variability. Phitsanulok shows intermediate-to-high extreme risk, with return levels increasing steadily across recurrence periods. Although its tail behavior is less pronounced than Tak, the projected long-term risk remains significant. Sukhothai demonstrates moderate extreme behavior, while Phetchabun and Uttaradit exhibit comparatively lower estimated return levels. However, goodness-of-fit diagnostics indicate that the stationary GEV model may not fully capture the distributional characteristics in Phetchabun and Uttaradit. This suggests possible structural irregularities or non-stationary wildfire dynamics in these provinces.

The discrepancy between provinces highlights that wildfire hazard in the lower northern region is not spatially uniform. Instead, extreme wildfire risk is strongly localized, with tail intensity varying substantially across provinces. Such heterogeneity underscores the necessity of province-specific risk modeling rather than relying on aggregated regional summaries. From a hazard management perspective, Tak and Phitsanulok should be prioritized for long-term wildfire mitigation planning, early-warning systems, and resource allocation strategies. In contrast, further statistical investigation may be required in Phetchabun and Uttaradit to determine whether non-stationary modeling approaches provide improved predictive performance. Overall, the spatial ranking framework provides a quantitative basis for comparing extreme wildfire hazards across provinces. The integration of return level analysis with model diagnostics enables identification of high-risk areas and potential model inadequacies. These findings support the development of differentiated wildfire management policies tailored to province-specific extreme risk profiles.

Acknowledgements: This work is partially supported by Pibulsongkram Rajabhat University, funded by Research Development and Research Management Year 2025, Capital Code RDI-2-68-13. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

Conflicts of Interest: The authors declare that there are no conflicts of interest regarding the publication of this paper.

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