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TRANSMISSION LINE ICE ACCRETION PROBABILITY PREDICTION AND DE-ICING THRESHOLD OPTIMIZATION BASED ON BAYESIAN EXTREME VALUE THEORY AND MONTE CARLO SIMULATION

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Abstract: Transmission line icing is a rare and severe hazard; therefore, a fixed de-icing threshold cannot account for forecast uncertainty, accumulated long-term risk, and the economic trade-off between de-icing costs and tower collapse losses. Based on 30 years of annual maximum ice-thickness data, real-time weather forecasts and operating cost parameters, this paper builds a probabilistic prediction and de-icing decision model. A generalised extreme value distribution is used to obtain the prior via maximum likelihood estimation, Bayesian updating and Markov chain Monte Carlo sampling generate the posterior distribution, a homogeneous Poisson process determines the long-term event frequency, and finally, Bayesian expected loss yields a dynamic de-icing threshold. The fitted GEV parameters are μ=11.95, σ=3.08, ξ=-0.19, and the 50-year and 100-year return levels are 21.5 and 23.9 mm, respectively. Under the given severe-weather condition, the posterior mean is 15.6 mm, and the probability of exceeding 15 mm is 0.84. The probabilities of at least one event within 10, 20, 30 and 50 years are 0.9030, 0.9906, 0.9991 and 0.9999, respectively. The optimal de-icing threshold ranges from 14.2 to 18.6 mm, reducing the expected total cost by about 18.7% compared with a fixed-threshold policy. This report provides verifiable statistical decision support for the construction of a high-probability warning system and proactive de-icing measures for transmission lines.
Keywords: Transmission-line icing; Bayesian extreme value theory; Generalized extreme value distribution; Monte Carlo simulation; Poisson process; Dynamic de-icing threshold

1 INTRODUCTION

Transmission-line icing is a serious natural disaster for power systems. Design values are often linked to long return periods; however, severe freezing rain, low temperatures and wind can cause ice accumulation that exceeds the nominal design range. The 2008 freezing-rain event in southern China caused extensive damage to towers and lines, showing that rare icing is simultaneously a structural, operational and planning risk. Recently, monitoring and forecasting studies have continued to use meteorological observations, data assimilation and learning-based prediction to extend warning lead times [1-2].

In the matter of ice thickness, the challenge extends beyond merely making an assessment of a single probable value for how thick the ice might be. Maxima that occur on a yearly basis are uncommon events; usual mean values fail to give a proper picture of the higher end of the range, and measured data can be absent because of land that is hard to access and uneven. A set with few points is, to a greater degree, influenced by shifts in the distribution that is fitted and by the way uncertainty is dealt with when one estimates the period after which a rare event returns. Work done not long ago on pulling out useful features, breaking a sequence of measurements into parts, and maps of danger built from data has made clear that having many kinds of input is of worth, and moreover a single forecast value by itself does not show in a strong way how much the weather that was seen alters the chance of going past a limit that is safe for operations, as noted in sources [3-5].

As a sound way of modeling rare yearly peaks, the theory of extreme values offers a statistical approach, and the method of Bayesian inference makes it possible to bring together records from the past with observations of weather made at present. Through the use of random sampling of the Monte Carlo type, one can acquire the distribution after the fact of the parameters and work out the intervals within which the result can be believed. Inquiries linked to extreme values, as reported in [6-8], have placed attention on the unsure nature of return levels, the lack of steadiness over time, and how short records act upon the danger to built structures. Because of the points raised above, thus the operator of the line is required to take into account the question of whether to initiate a measure that is costly and meant to prevent trouble before it happens.

The first is that there is a problem of temporal accumulation. The probability of a single event does not equal the probability that at least one such event will occur over a 10- or 50-year planning horizon. Modelling exceedance arrivals with a Poisson process provides an open frequency layer, but the resulting risk still needs to be linked to the cost of

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de-icing and the loss from collapse. Bayesian decision theory offers a link by comparing posterior expected losses for different courses of action. Recent Bayesian GEV studies have also supported simulation-based estimation when prior information and small samples need to be combined [9-10].

This paper develops a general statistical decision framework for transmission-line icing. Analysis aligns with 30 years of annual maximum ice thickness using meteorological data, fits a GEV prior via maximum likelihood, updates the prior with a Gaussian weather-error likelihood through Metropolis-Hastings sampling, estimates the exceedance rate based on a homogeneous Poisson process, and derives a monitoring-window-dependent de-icing threshold from an explicit loss ratio. The results are return periods, posterior exceedance probabilities, long-term event probabilities, threshold sensitivities, warning grades and model limitations. The aim is to turn the predicted occurrence of a rare event into a practical operating rule without adding new physical or statistical assumptions.

2 DATA AND PREPROCESSING

2.1 Observation System and Annual Extremes

Thirty years of annual maximum ice-thickness observations from 1995 to 2024 and the corresponding meteorological data for transmission-line icing are used in this study. The 18 typical icing sites in central and eastern China are the observation network. Lushan and northern Guangdong had the highest reported values of 71.1 mm and 64.4 mm, respectively, and the inland station of Yinchuan was lower. Therefore, a probabilistic way should be used instead of a single national standard. Figure 1 shows the location of the representative icing observation sites and the marked regional differences in reported ice thickness.

Linear interpolation is used to fill in missing values of the individual observations, and any anomalies are excluded according to the 3σ criterion and operational logic. Extract the maximum value each year from this period as an extreme-value sample. Correlation analysis shows that ice thickness is positively correlated with relative humidity at about 0.70, negatively correlated with air temperature at around -0.60, and has a weak positive relationship with precipitation and wind speed of approximately 0.50 and 0.30, respectively. The above signs are consistent with the physical conditions of freezing rain and wet conductors.

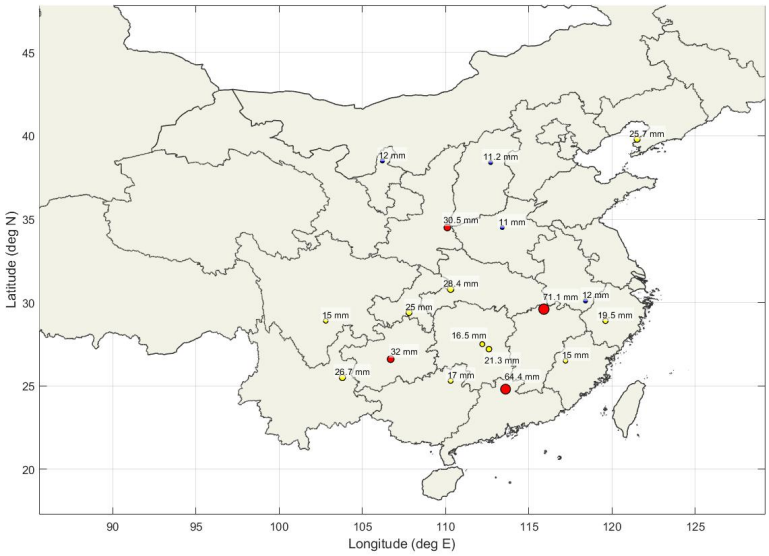


Figure 1 Spatial Distribution of Representative Transmission-Line Icing Observation Sites
Source: http://bzdt.ch.mnr.gov.cn/

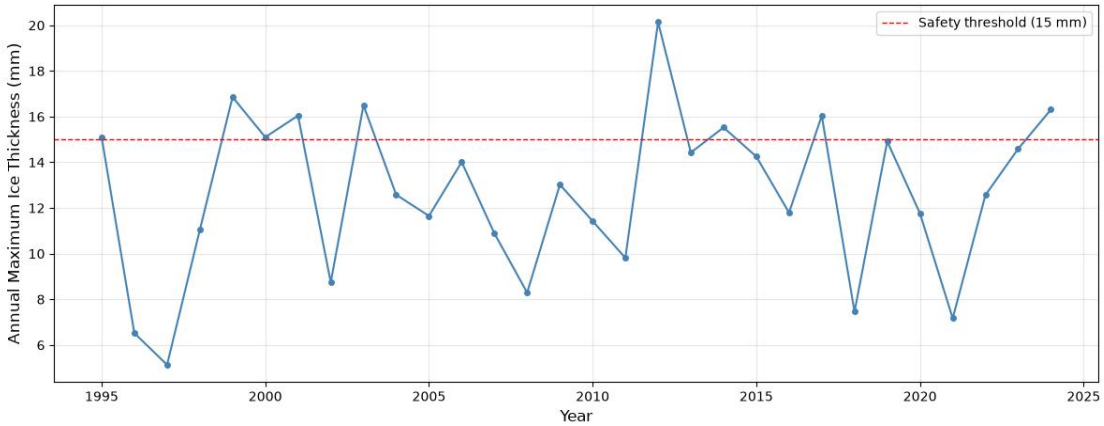


Figure 2 Annual Maximum Ice Thickness from 1995 to 2024

Figure 2 shows significant interannual changes in the time series and repeated exceedances of the 15 mm safety threshold. Therefore, an extreme-value model is suitable for this sample; however, due to the short length of the record, uncertainty reporting must be provided for a long return period.

3 BAYESIAN EXTREME-VALUE MODEL

3.1 GEV Prior and Maximum Likelihood Estimation

Let $X_1, ..., X_n$ be independent annual maximum ice-thickness values and M_n their maximum. The extreme-value limit is shown below:

$$\frac{M_n - b_n}{a_n} \; d \to H(x) \tag{1}$$

The generalized extreme value distribution used for the annual maxima is

$$F(x) = exp\{ - [1 + \xi(x - \mu)/\sigma]^{-1/\xi} \}, \; 1 + \xi(x - \mu)/\sigma > 0 \tag{2}$$

Here, μ is the location parameter, σ > 0 is the scale parameter, and ξ is the shape parameter. When ξ < 0, it has a Weibull-type tail that reaches a finite upper limit; this is physically reasonable for conductor icing due to constraints on the geometry of conductors and ice density. The return-period level x_T meets

$$x_T = \mu - \frac{\sigma}{\xi}[1 - (-ln(1 - \frac{1}{T}))^{(-\xi)}], \; \xi \neq 0 \tag{3}$$

$$x_T = \mu - \sigma \, ln[-ln(1 - \frac{1}{T})], \; \xi = 0 \tag{4}$$

Maximum Likelihood Estimation must be carried out numerically as there is no closed-form solution for the GEV likelihood, see Table 1 and Table 2. The fitted values are μ=11.95 mm, σ=3.08 mm and ξ=-0.19; their standard errors are 0.52, 0.31 and 0.08, respectively. The 95% intervals are [10.93,12.97], [2.47,3.69] and [-0.35,-0.03]. The K-S p-value is 0.73; therefore, the GEV fit cannot be rejected at the 0.05 level. Figure 3 shows the empirical histogram and Q-Q plot.

Table 1 Maximum Likelihood Estimates of the GEV Parameters

Parameter	Estimate	Standard error	95% confidence interval
μ location (mm)	11.95	0.52	[10.93, 12.97]
σ scale (mm)	3.08	0.31	[2.47, 3.69]
ξ shape	-0.19	0.08	[-0.35, -0.03]

Table 2 Estimated Ice Thickness at Selected Return Periods

Return period (years)	10	30	50	100
Ice thickness (mm)	16.2	19.8	21.5	23.9

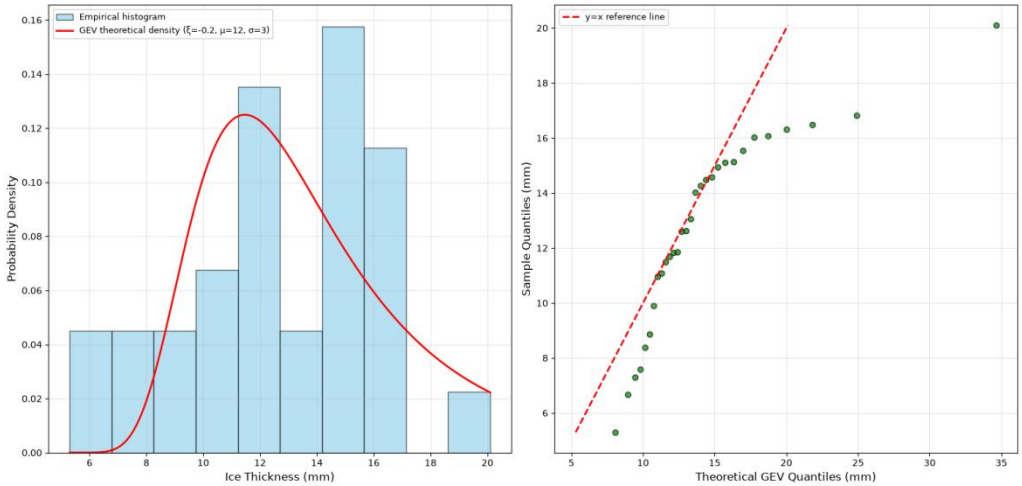


Figure 3 Empirical Histogram, Fitted GEV Density, and Q-Q Diagnostic

The 50-year and 100-year return levels are 21.5 and 23.9 mm, respectively. Their difference is only 2.4 mm, showing the finite upper-bound behaviour indicated by ξ<0. These estimates provide a quantitative reference for safety-threshold selection and are not based on a single observed maximum.

3.2 Bayesian Updating with Weather Information

The fitted GEV distribution serves as the prior for current ice thickness θ. A meteorological growth model provides the estimate θ_met, and the uncertainty of this estimate is a Gaussian error with standard deviation σ_ε. Bayes' theorem is employed to obtain

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} \propto p(y|\theta)p(\theta) \quad (5)$$

The posterior is sampled with the Metropolis-Hastings algorithm. A candidate θ* drawn from q(θ*|θ^(t)) is accepted with probability

$$\alpha = min\{1, \frac{p(\theta^*)\, q(\theta^{(t)}|\theta^*)}{p(\theta^{(t)})\, q(\theta^*|\theta^{(t)})}\} \quad (6)$$

Burn-in is performed, and then M=10,000 posterior samples are used to calculate the mean, variance, credible interval and exceedance probability. Given the specified weather conditions of air temperature -2°C, relative humidity 88% and wind speed 4.5 m/s, the posterior distribution shifts to the right of the historical prior and becomes more concentrated, see Table 3. The posterior mean is 15.6 mm, the posterior standard deviation is 1.8 mm, P(θ>15 mm)=0.84, and P(θ>20 mm)=0.12. The 90% credible interval is [12.4,19.2] mm.

Table 3 Posterior Statistics and Sensitivity to Weather Forecast Error

Quantity or σ_ε	Posterior mean (mm)	Probability or interval
Posterior mean	15.6	-
Posterior standard deviation	1.8	-
2.5% / 50% / 97.5% quantiles	12.4 / 15.5 / 19.2	90% interval [12.4,19.2]
P(θ>15 mm)	-	0.84
P(θ>20 mm)	-	0.12
σ_ε=1.0 mm	16.2	P(θ>15)=0.92
σ_ε=2.0 mm	15.6	P(θ>15)=0.84
σ ε=3.0 mm	14.9	P(θ>15)=0.73
σ_ε=4.0 mm	14.3	P(θ>15)=0.61
σ_ε=5.0 mm	13.8	P(θ>15)=0.52

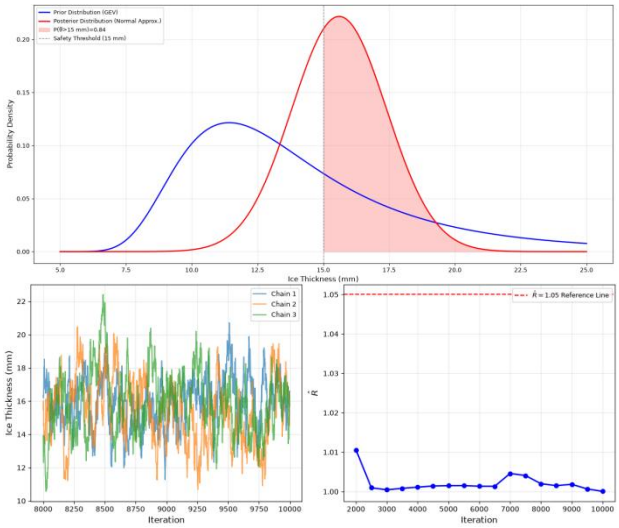


Figure 4 Prior-Posterior Density Shift and MCMC Convergence Diagnostics

As shown in Figure 4, the shift of prior-posterior density and convergence diagnostics can be used to verify the Bayesian update and MCMC sampling. Increasing σ_ε reduces the impact of weather likelihood and brings the posterior closer to the GEV prior. At a forecast-error standard deviation of 1.0 mm, the excess probability is 0.92; at 5.0 mm, it is 0.52, and thus the prediction accuracy directly affects the sensitivity of the alarm. MCMC diagnosis shows that the chains have reached a stable state after the warm-up period, and finally, the Gelman-Rubin statistic is about 1.01 or less than 1.1.

4 LONG-TERM RISK AND BAYESIAN DE-ICING DECISION

4.1 Poisson Accumulation of Icing Events

An icing disaster is defined as an annual maximum exceeding the safety threshold of θ_th = 15 mm. Let N(t) be the number of such events in a time window of t years. The maximum-likelihood intensity of a homogeneous Poisson process is

$$\hat{\lambda} = \frac{N_T}{T} = 7/30 \approx 0.2333 \quad (7)$$

$$P(N(t) = k) = \frac{\lambda t^k e^{-\lambda t}}{k!}, \quad k = 0,1,2,\ldots \quad (8)$$

$$P(N(t) \geq 1) = 1 - e^{-\lambda t} \quad (9)$$

Seven threshold exceedances have been observed over the past 30 years, so λ=0.2333 events per year. The probability of at least one event occurring within ten years is about 0.9030, and after twenty years it increases to approximately

0.9906; by thirty years, it has risen to nearly 0.9991, and finally reaches about 0.9999 after fifty years, see Table 4. Modify the safety threshold and thus change the estimated rate; for 10, 12, 15, 18 and 20 mm, the reported intensities are 0.74, 0.54, 0.27, 0.11 and 0.05 per year, respectively, and their corresponding probabilities of a 10-year event are 0.9994, 0.9955, 0.9328, 0.6671 and 0.3935.

Table 4 Long-Term Event Probability and Threshold Sensitivity

Time or threshold	10	20	30	50
P(N(t)≥1)	0.9030	0.9906	0.9991	0.9999
θ_th (mm)	10	12	15	18 / 20
λ (events/year)	0.74	0.54	0.27	0.11 / 0.05

4.2 Loss-Based Dynamic De-Icing Threshold

The Decision Set is to open de-icing or not to open de-icing. The assumed de-icing cost is C_ice = 100,000 CNY per action, and the collapse loss is C_collapse = 10,000,000 CNY per tower; thus, the cost ratio is r=0.01. Given the posterior probability P(θ>θ_th|weather), the expected losses are C_ice for opening and C_collapse multiplied by the exceedance probability for not opening. After a monitoring period of t years, the optimal opening condition will be

$$P(\theta > \theta_{th} \mid weather) > \frac{-ln(1-r)}{\lambda t} \tag{10}$$

The threshold θ* is obtained from the posterior quantile satisfying

$$P(\theta > \theta^* \mid weather) = Pcrit,\ \theta^* = F_{post}{}^{-1}(1 - Pcrit) \tag{11}$$

The rule can accommodate both the posterior risk and the monitoring period. When weather information shifts the posterior to the right, a fixed thickness has a higher exceedance probability; therefore, given the same cost and arrival-rate relationship, the decision threshold also changes. Simulated threshold values range from 14.2 to 18.6 mm under different weather conditions and risk preferences, and the expected total cost is about 18.7% lower than that of a traditional fixed-threshold policy. Figure 5 shows the positive correlation between the posterior mean and the optimised threshold.

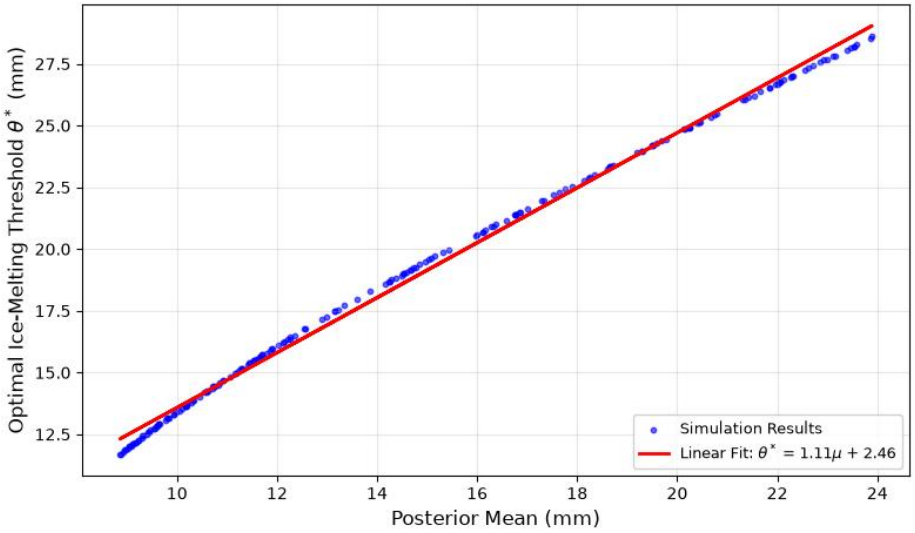


Figure 5 Relationship between Posterior Mean Ice Thickness and the Optimal De-Icing Threshold

The dynamic critical probability has three warning levels for operating communications. Green is a low-risk area, less than half of the critical probability; no countermeasures are needed at present. Yellow shows that there is some danger and preparation should be started; red means there is an extremely high risk, so emergency action must be taken to remove ice immediately. A continuous posterior can be converted into a graded action without changing the underlying probability calculation.

5 CONCLUSIONS

Based on the above results, a single Bayesian extreme-value decision framework can be used to assess transmission-line icing risk and de-icing operation. GEV modelling describes the upper tail of annual maximum ice thickness; weather-informed Bayesian updating modifies the current risk; MCMC sampling quantifies posterior uncertainty; a Poisson process models the accumulation of long-term events; and Bayesian expected-loss minimisation converts the resulting probability into an operating threshold. Given the above severe weather conditions, the posterior mean is 15.6 mm and P(θ > 15 mm) = 0.84; using a loss-based rule, the de-icing threshold is set at 14.2-18.6 mm, and the expected total cost is reduced by approximately 18.7% compared to a fixed-threshold policy.

From an application perspective, the framework is transparent and operationally feasible because each layer uses interpretable inputs and produces quantities that can be checked separately, including return levels, posterior exceedance probabilities, long-horizon event probabilities and the final de-icing trigger. It therefore provides a traceable route from historical extreme-value evidence and real-time weather information to an actionable transmission-line icing decision, rather than relying on a single point forecast or a uniform threshold.

The limitations are a short 30-year extreme-value record and its partial reconstruction from regional measured characteristics, the Gaussian weather-error likelihood that does not describe nonlinear interactions among meteorological variables, the assumption of fixed de-icing and collapse costs, and the use of a homogeneous Poisson process. Future research will enhance the construction of site-specific and time-dependent risk models. Hierarchical Bayesian models can incorporate multi-site observations; nonhomogeneous Poisson models can model changes in the intensity of events; and spatial statistical models can account for regional dependency. The decision layer can also be extended to time-varying or uncertain costs via robust Bayesian rules, and edge-side decision terminals can support a faster operational deployment of the probabilistic warning and de-icing strategy.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Wang G, Shen J, Jin M, et al. Prediction model for transmission line icing based on data assimilation and model integration. Frontiers in Environmental Science, 2024, 12: 1403426.

[2] Zhou R, Zhang Z, Zhang H, et al. Reliable monitoring and prediction method for transmission lines based on FBG and LSTM. Advanced Engineering Informatics, 2024, 62: 102603.

[3] Ke H, Sun H, Zhao H, et al. Ice cover prediction for transmission lines based on feature extraction and an improved transformer scheme. Electronics, 2024, 13(12): 2339.

[4] Li Q, Liao X, Cui W, et al. Online prediction method of transmission line icing based on robust seasonal decomposition of time series and bilinear temporal-spectral fusion and improved beluga whale optimization algorithm-least squares support vector regression. Applied System Innovation, 2024, 7(3): 40.

[5] Snaiki R, Jamali A, Rahem A, et al. A metaheuristic-optimization-based neural network for icing prediction on transmission lines. Cold Regions Science and Technology, 2024, 224: 104249.

[6] Jamali A, Snaiki R, Rahem A. Towards accurate ice accretion and galloping risk maps for Quebec: a data-driven approach. Cold Regions Science and Technology, 2025, 233: 104460.

[7] Davalos D, Chowdhury J, Hangan H. Joint wind and ice hazard for transmission lines in mountainous terrain. Journal of Wind Engineering and Industrial Aerodynamics, 2023, 232: 105276.

[8] Anzolin G, de Oliveira D Y, Vrugt J A, et al. Nonstationary frequency analysis of extreme precipitation: embracing trends in observations. Journal of Hydrology, 2024, 637: 131300.

[9] Habeeb S B, Abdullah F K, Shalan R N, et al. Comparison of some Bayesian estimation methods for type-I generalized extreme value distribution with simulation. Alexandria Engineering Journal, 2024, 98: 356-363.

[10] Elsom H, Pawley M D M. Extreme value statistics for analysing simulated environmental extremes. Extremes, 2025, 28: 47-73.