

Article

A BERT-CRF and Case-Crossover Framework for Evaluating Tourism Risk and Warning System Performance in Sichuan, China

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Abstract

Improving the precise perception of disaster risk and evaluating the effectiveness of warning systems are essential for natural-hazard prevention, mitigation, and spatial risk management. Using Sichuan Province, China, as a case study, this study treats government-issued disaster warning texts within 72 h before accident occurrence as formal risk signals and spatiotemporal information sources. Drawing on the protective action decision model and risk communication theory, we propose an integrated framework combining BERT-CRF-based information extraction, spatiotemporal analysis, and a case-crossover design to evaluate a multi-level warning system through the chain of risk identification, risk communication, protective action, and risk outcome. The results show a clear gradient across warning levels. High-level warnings are significantly associated with lower accident risk, whereas lower-level warnings can identify risky contexts but have limited intervention effects. These findings indicate that disaster warning systems have dual functions of risk identification and intervention, while medium-level warnings may reveal a weak link in the transition from risk perception to protective action. The study provides a geospatial analytical framework for linking official warning information with tourism safety outcomes and offers empirical support for optimizing warning systems and strengthening hazard risk governance in high-risk regions.

Keywords: disaster warning; BERT-CRF; case-crossover design; spatiotemporal analysis; tourism safety



Academic Editor: Wolfgang Kainz

Received: 23 July 2026

Revised: 31 August 2026

Accepted: 4 September 2026

Published: 10 September 2026

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1. Introduction

Tourism destinations are often situated in environments exposed to multiple natural hazards, including extreme weather, geological hazards, flash floods, and cascading disaster processes. Because tourism activities depend heavily on environmental conditions and local infrastructure, the impacts of hazards on tourism and tourist activities vary across both space and time and are, therefore, inherently spatiotemporal. Differences in terrain, climate, accessibility, and the distribution of tourism resources create uneven patterns of exposure and vulnerability across destinations [1]. Natural hazards may not only directly threaten tourists' lives and property but also disrupt destination operations, damage destination image, and reduce travel intentions [2,3], with further implications for socioeconomic

recovery and the long-term resilience of tourism destinations [4,5]. Tourists, therefore, rely heavily on timely, credible, and action-oriented risk information. Accordingly, the reliable geospatial identification of hazard signals, accurate linkage of warning information to exposed tourism locations, and quantitative evaluation of warning system performance are important not only for tourism and tourism safety governance but also for extending the application of geographic information science to disaster-risk management.

Research on disasters and tourism has established a substantial foundation in areas such as hazard typology, risk assessment, emergency response, and destination resilience. Kelman [6] summarized the major disaster risks faced by tourists and corresponding coping approaches. At the spatial-assessment level, Xi et al. [7] developed a tourism risk evaluation system for a major travel corridor, while Liu et al. [8] constructed a multifactor risk index for mountainous scenic areas. Based on textual cases of tourism safety accidents, Huang et al. [9] identified human, environmental, equipment-related, and managerial factors associated with such incidents. Other studies have examined climate change-related threats to tourism safety [10], the nonlinear effects of different natural hazards on inbound tourism [11], and the influence of environmental information on tourists' safety behavior [12]. Recent evidence further suggests that tourism emergencies are evolving from isolated events toward spatially and temporally clustered incident patterns [13], while multiple hazard factors may interact synergistically within tourism safety systems [14]. Nevertheless, existing research still focuses largely on static risk indicators, destination-level hazard impacts, or post-event interpretation, whereas the systematic use of official warning information prior to accident occurrences remains limited. In particular, temporal, locational, hazard-type, and warning-level information embedded in warning texts has not yet been sufficiently transformed into structured data suitable for spatial matching and short-term exposure assessment; the short-term spatiotemporal relationships among warning issuance, warning-level differentiation, and accident occurrence remain insufficiently examined.

The rapid growth of web-based textual data has created new opportunities for geospatial information acquisition in disaster monitoring and tourism risk identification. Natural language-processing methods represented by BERT have increasingly been applied to disaster-related geographic information extraction [15], with applications extending to geographic named-entity recognition and correction [16], near real-time disaster-event detection [17], emergency-event knowledge-graph construction [18], and social media-based risk perception and situational analysis [19]. However, social media and general web data often contain substantial noise, ambiguous or incomplete geographic references, and uncertainty regarding source credibility [20,21]. These limitations constrain their direct use in fine-grained spatial exposure matching and warning system performance evaluation. By contrast, government-issued disaster warnings generally contain standardized hazard terminology, explicit administrative locations, release times, and graded warning levels, making them a more stable, traceable, and authoritative source of risk information. Transforming such unstructured texts into structured spatiotemporal records and integrating them with administrative units, tourism safety accidents, and other spatial datasets is consistent with the broader effort to combine social-sensing information with authoritative structured data to enhance situational awareness [22]. It also provides a more reliable data foundation for evaluating warning system performance in tourism safety research.

From a technical perspective, entity recognition in disaster-related texts has evolved from rule- and dictionary-based approaches and conventional statistical learning methods toward deep learning and pretrained language models. Rule- and dictionary-based methods offer relatively high interpretability but have limited adaptability to complex contexts, linguistic variation, and cross-sentence dependencies. Conventional sequence-labeling

approaches can model dependencies among labels but typically rely heavily on manually engineered features. Pretrained language models substantially improve the representation of complex semantic relationships through contextualized representations [23], whereas conditional random fields can further exploit transition constraints among labels to improve sequence-labeling consistency [24]. Combining BERT's contextual semantic representation with the sequence-constrained decoding capability of CRF is, therefore, well suited to identifying key entities—including time, location, hazard type, and warning level—from administratively formulated and standardized Chinese warning texts with complex entity combinations. At the same time, artificial intelligence is becoming an increasingly important technological foundation for tourism management and safety research, with its applications expanding from demand forecasting and operational optimization toward risk perception and safety-related decision support. Recent research has shown that AI-based predictive analytics can support tourism operations and, by forecasting tourist volumes and behavior, provide information for safety preparedness during large-scale events and unexpected situations, including natural disasters [25]. However, existing studies have primarily focused on tourist-flow, demand, and behavioral prediction. Systematic research remains limited on how AI can be used to extract risk information with explicit spatiotemporal attributes from official disaster warning texts and subsequently link such information to observed tourism safety accidents.

The effectiveness of a warning system cannot be assessed solely on the basis of whether a warning has been issued. A warning may accurately identify hazardous locations and periods but may not necessarily trigger sufficient protective action to reduce accident occurrence. To distinguish these two functional dimensions, this study draws on the protective action decision model (PADM) and risk communication theory [26], conceptualizing official warning texts as both geospatial hazard signals and institutional vehicles of risk communication. The risk identification and risk intervention functions of a warning system are related but distinct dimensions. External disaster warning information does not automatically lead to protective action; rather, it must undergo decision-making processes, such as information reception, and is influenced by perceptions of risk information [27,28]. At the same time, the effectiveness of risk communication is also affected by message presentation, source credibility, and action guidance [29,30]. Therefore, in tourism safety contexts, government-issued disaster warnings are not merely descriptions of objective hazards, but also formal external risk signals directed toward tourists, scenic-area managers, and other stakeholders. Different warning levels not only reflect differences in hazard severity but also convey varying degrees of urgency and response requirements, thereby constituting risk-communication signals of different intensities.

Against this background, this study takes Sichuan Province, China, as a case study and develops an integrated analytical framework combining natural language processing, geospatial information extraction, and short-term exposure assessment. First, a BERT-CRF model is used to transform government-issued disaster warning texts into structured records containing time, location, hazard type, and warning level. Second, the extracted information is spatially standardized and subjected to spatiotemporal analysis to identify temporal distributions, spatial patterns, and inter-hazard co-occurrence characteristics. Finally, warning records are spatially matched with tourism safety accidents occurring under natural-hazard conditions at the county level, and a case-crossover design is employed to examine the statistical association between short-term warning exposure and accident occurrence. Specifically, this study addresses three interrelated questions: (1) How can official warning texts be reliably transformed into structured spatiotemporal information suitable for geographic analysis?; (2) What temporal differentiation, spatial patterns, and inter-hazard co-occurrence structures characterize the resulting warning information?; and

(3) Do official warnings identify high-risk spatiotemporal contexts associated with tourism accidents, and do different warning levels exhibit differentiated patterns of association with accident occurrence? The principal contribution of this study to geographic information science lies in integrating textual entity extraction, location standardization, multi-source spatial data linkage, and matched exposure modeling within a unified analytical workflow. By further evaluating multi-level warning systems from the dual perspectives of risk identification and risk intervention, the study provides a testable spatial analytical framework for the geospatial utilization of official warning information and tourism risk governance, thereby supporting more targeted disaster-risk communication and tourism safety decision-making.

2. Theoretical Basis and Analytical Framework

2.1. PADM and Risk Communication Theory

The protective action decision model (PADM) posits that individuals or organizations confronted with external risk information do not automatically take action; instead, they progress through processes of risk cue perception, threat appraisal, coping assessment, and protective-action decision-making [31]. External risk signals are more likely to be translated into avoidance behavior when they are perceived as sufficiently severe, urgent, and credible—and when recipients recognize a feasible response pathway [32]. In tourism safety contexts, disaster warnings are, therefore, not merely neutral information; they function as formal external risk signals that may influence decisions by scenic-area managers and tourists.

Risk communication theory further emphasizes that the effectiveness of risk information depends not only on its availability but also on how severity and urgency are expressed, the clarity of the content, the credibility of the information source, and the explicitness of recommended actions [33]. For the same type of risk, differences in communication intensity and message framing may generate different levels of risk perception and behavioral response. Within tourism warning systems, warning levels represent not only classifications of objective risk severity but also differences in the intensity of risk communication. High-level warnings generally convey stronger risk signals and are accompanied by clearer restrictive measures, whereas medium- and low-level warnings tend to be more advisory in nature and may, therefore, differ in their capacity to prompt protective behavior. The content quality and source credibility of warning information can influence tourists' coping responses, while risk perception and coping efficacy also play important roles in the formation of protective behavior. In the context of natural-hazard warnings, timely, credible, and actionable information can enhance the effectiveness of risk communication and contribute to reducing tourism safety risks [34,35].

Building on these theoretical considerations, this study conceptualizes government-issued disaster warning texts as formal hazard signals and institutional vehicles of risk communication. Warning levels are treated not only as classifications of potential hazard severity but also as indicators of communication intensity, urgency, and the potential to prompt protective action. Tourism safety accidents occurring under natural-hazard conditions are therefore used as the risk-outcome variable for evaluating warning system performance. Accordingly, the warning system is interpreted through a process chain comprising hazard identification, risk communication, protective action, and risk outcome. The first dimension concerns the hazard-identification function, namely, whether warnings are issued during periods and in areas where natural-hazard-related accident risk has already increased. The second concerns the risk intervention function, namely, whether warnings at different levels exhibit differentiated associations with accident occurrences

that are consistent with differences in risk signals and response requirements. On this basis, the following research propositions are proposed:

Proposition 1. *Warning issuance is expected to occur more frequently in high-risk tourism safety contexts, consistent with a risk identification function;*

Proposition 2. *Higher warning levels are expected to convey stronger risk-communication signals and to be associated with lower odds of accident occurrence;*

Proposition 3. *Medium- and low-level warnings may identify elevated-risk contexts but may show weaker associations with protective outcomes, resulting in a pattern of effective identification but limited intervention.*

2.2. Technical Route

This study develops an analytical workflow linking disaster warning text recognition with warning system performance evaluation. First, tourism risk advisories issued by the Sichuan Provincial Department of Culture and Tourism and disaster warning texts released through the National Emergency Broadcasting Platform are collected, cleaned, and standardized as official hazard-warning information. Second, a BERT-CRF model extracts key disaster-related entities, including time, location, hazard type, and warning level, and the spatiotemporal patterns of the resulting warning records are examined. Third, the extracted warning records are matched with tourism safety accidents occurring under natural-hazard conditions to construct short-term exposure variables for different warning levels. Finally, a case-crossover design is used to assess the association between warning exposure and accident occurrence and thereby evaluate warning system performance in terms of risk identification and risk intervention. The workflow is designed as a continuous analytical process from warning-information construction to performance evaluation. Government-issued warning texts are first transformed from unstructured administrative information into structured records containing time, location, hazard type, and warning level. These records are then standardized and geographically normalized so that warning information from different sources can be assigned to consistent spatial units and linked with tourism safety accident records. Temporal distributions, spatial patterns, and inter-hazard relationships are subsequently analyzed to characterize the spatiotemporal context of warning occurrence.

The subsequent stage links the structured warning records directly to tourism safety outcomes rather than treating warning mapping and effectiveness evaluation as separate analyses. Warning exposure is defined within a fixed temporal window and matched to accident records using the specified spatial units, after which a case-crossover design compares exposure during accident periods with exposure during corresponding control periods. The warning level is retained as a key attribute of each spatiotemporal warning record, enabling the analysis to examine not only whether warnings are concentrated in elevated-risk contexts but also whether different warning levels show distinct patterns of association with accident occurrences. In this way, the workflow integrates text-based information extraction, geographic standardization, spatiotemporal analysis, exposure matching, and statistical evaluation within a single analytical sequence. Figure 1 summarizes these stages and illustrates how official warning information is progressively converted into spatially explicit evidence for identifying risk contexts and evaluating warning system performance.

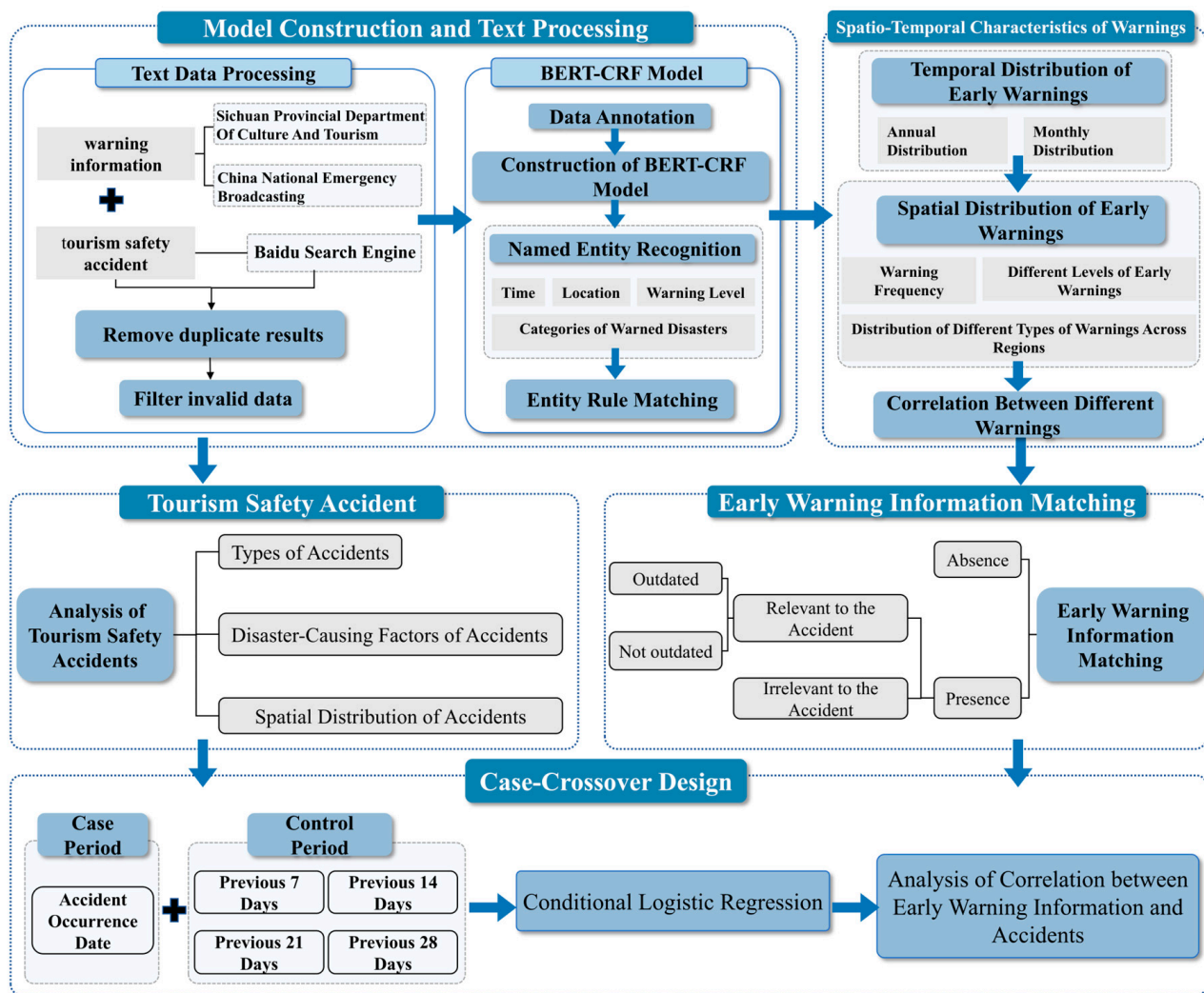


Figure 1. Technical flowchart.

3. Study Area and Methods

3.1. Study Area and Data Sources

Sichuan Province spans an area of 486,000 square kilometers, with elevations ranging from 7556 m at its highest point to 188 m at its lowest. Its terrain slopes steeply from the western plateau to the eastern basin. Sichuan ranks highly among China's western provinces with the richest tourism resources, boasting 987 A-rated scenic areas. From 2020 to 2023, it welcomed 213.40893 million domestic and international visitors. Based on scenic area distribution density, the province can be divided into three major regions: the Western Sichuan Plateau, the Panxi Region, and the Sichuan Basin. The Western Sichuan Plateau frequently experiences extreme weather, such as snowstorms and hails, making it the region most severely affected by landslides and debris flows. Meanwhile, the mountainous and hilly areas surrounding the Sichuan Basin often endure heat waves and rainstorms, with heavy rainfall readily triggering secondary disasters like landslides and debris flows. This combination of diverse disaster types and frequent extreme weather poses the primary threat to tourism safety in Sichuan Province. An overview of the study area is presented in Figure 2.

This study utilizes tourism risk advisories issued by the Sichuan Provincial Department of Culture and Tourism (<https://wlt.sc.gov.cn/>) and meteorological disaster warning information released by the National Emergency Broadcasting Platform (<http://www.cneb.gov.cn/>) from 2021 to 2025 as foundational text data. The Sichuan

Provincial Department of Culture and Tourism is a provincial government department responsible for supervising, managing, and comprehensively coordinating safety within the province's cultural and tourism industry. Its advisories, spanning risk prevention, safety supervision, and post-accident response, represent standardized, authoritative administrative regulatory information. The National Emergency Broadcasting Platform is a core component of the national emergency system, directly linked to information sources, such as the Ministry of Emergency Management, China Meteorological Administration, and China Earthquake Administration, ensuring the standardization and authority of issued warnings. Following the definitions and classifications for disaster types and categories in the National Standard GB/T 28921-2012 [36] Classification and Codes for Natural Disasters, disaster warning information is categorized into meteorological disasters and geological disasters. Additionally, according to the “Regulations on the Issuance and Dissemination of Meteorological Disaster Warning Signals in Sichuan Province” (Provincial Government Decree No. 359), meteorological disaster warnings are classified into: rainstorm, snowstorm, cold-wave, gale, sandstorm, heatwave, drought, lightning, thunder gust, hail, frost, heavy fog, haze, and road icing. Meteorological disaster warning signals are generally divided into four levels based on potential severity, urgency, and development trend: Level IV (General), Level III (Relatively Severe), Level II (Severe), and Level I (Particularly Severe), represented by blue, yellow, orange, and red, respectively.

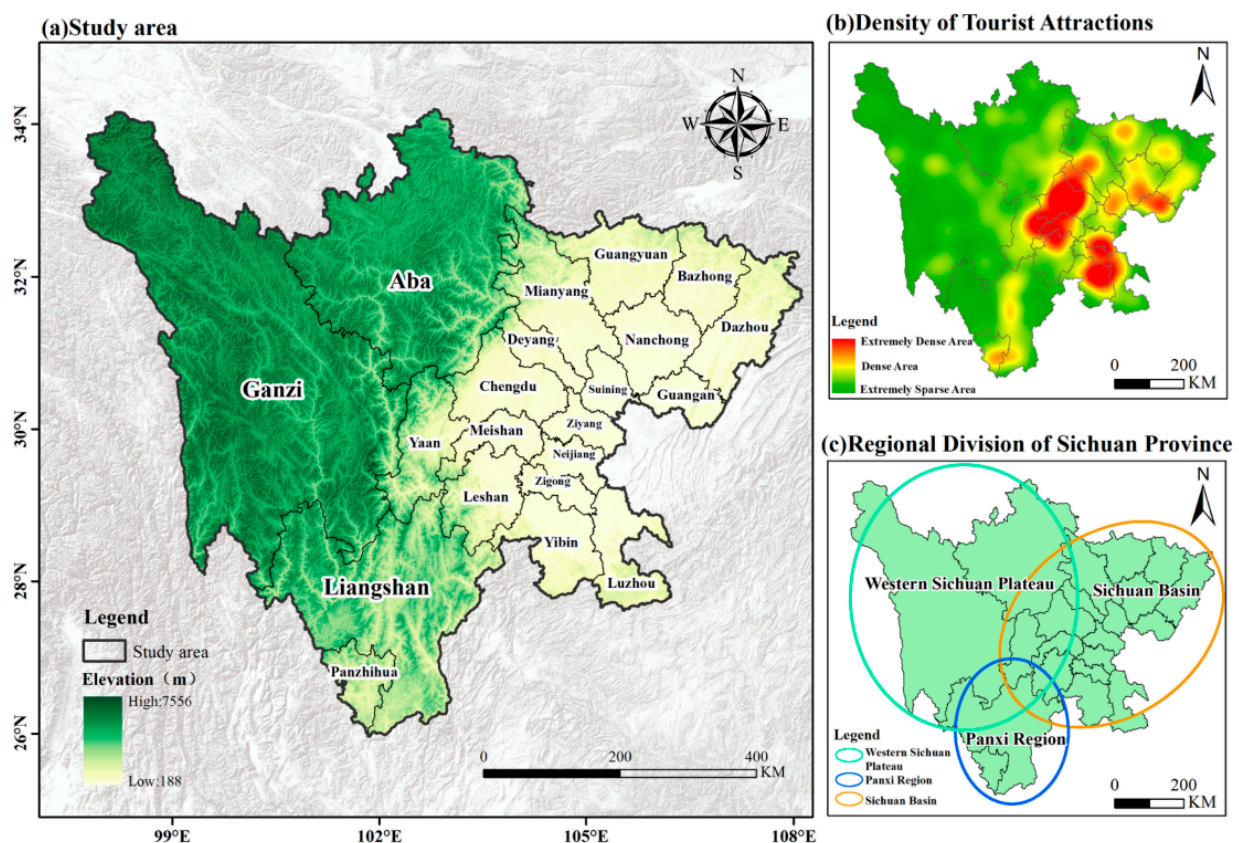


Figure 2. Overview of the study area.

This study employed a Python3.13-based web crawler to harvest data from Baidu (<https://www.baidu.com>). Specific keyword combinations were used to collect tourism safety accident data, which were then verified through government news reports and other sources. Selected keywords included travel, wilderness areas, restricted zones, heavy rain, flash floods, and missing persons. As China's largest Chinese-language search engine with over 600 million daily active users, Baidu serves as a core open-channel portal for

accessing tourism safety accident information. As a comprehensive search engine, it aggregates publicly available information across the web—including news reports, scenic area announcements, local emergency notifications, and user assistance posts—enabling comprehensive coverage of tourism safety accident leads and minimizing information gaps. To further reduce the potential influence of misinformation and unreliable online content, a multi-source comparison and authenticity verification procedure was implemented. In addition to the large-scale retrieval of potential tourism safety accident records from Baidu, accident-related information was independently collected from government websites and government official media. Records obtained from these different channels were compared, screened, and cross-matched according to key attributes, including accident time, location, event type, and other core information.

For accident records identified through Baidu but not directly reported on government websites, an additional authenticity-verification procedure was applied. Original source links were traced to identify the earliest available report, with official announcements and reports from government-affiliated media given priority; information originating solely from unverified self-media sources was not considered sufficient evidence for inclusion. Multiple independent sources were cross-checked to verify the occurrence time, location, accident type, and other key attributes of each candidate case. Supplementary searches were also conducted through official information channels of emergency-management departments, fire and rescue agencies, and other relevant authorities. Photographs and videos associated with candidate cases were examined using reverse-image searches and visual-detail comparisons to identify possible reuse, misattribution, or inconsistencies. Geographic and temporal consistency was further assessed using map information, historical weather records, and other contextual evidence. Before the final dataset was constructed, cases that could not be adequately verified were excluded, and duplicate reports referring to the same accident were removed. Following this screening and verification procedure, 81 tourism safety accidents occurring between 2021 and 2025 were retained in the final dataset.

3.2. Model Overview

3.2.1. BERT-CRF Model for Warning Information Extraction

When performing named entity recognition on texts, the model must deal with issues such as polysemy and complex contexts. BERT, however, can fully integrate information from both the left and right contexts of each token through its bidirectional Transformer encoder architecture and attention mechanism, thereby achieving deep integration of lexical items and their surrounding contexts. The model structure is shown in Figure 3.

The BERT model first tokenizes natural language text and inserts [CLS] at the sequence start to denote the beginning. It inserts [SEP] between sentence boundaries and at the sequence end to mark the conclusion, yielding the token sequence $X = (X_{[CLS]}, X_1, X_2, \dots, X_n, X_{[SEP]})$. These generated tokens then pass through the BERT embedding layer composed of Token Embedding, Segment Embedding, and Position Embedding. Token Embedding captures the fundamental lexical meaning of words; Segment Embedding generates identifying vectors for sentence segments; Position Embedding provides word order information, addressing the inherent limitation of the Transformer's self-attention mechanism to perceive word sequences. The resulting embedding vectors are then fed into its core network architecture, which consists of multiple stacked Transformer encoder layers. Each encoder layer incorporates Multi-Head Attention, a Feed-Forward neural network, and residual connections with Layer Normalization. The attention mechanism calculates the degree of association between characters in the text and adjusts each character's weight based on this association. After passing through the core network architecture, the model outputs a sequence of context-aware word vectors

$T = (T_{[CLS]}, T_1, T_2, \dots, T_n, T_{[SEP]})$. In named entity recognition, each word carries an entity label representing its meaning or category. These output word vectors can then be used to predict the corresponding entity labels.

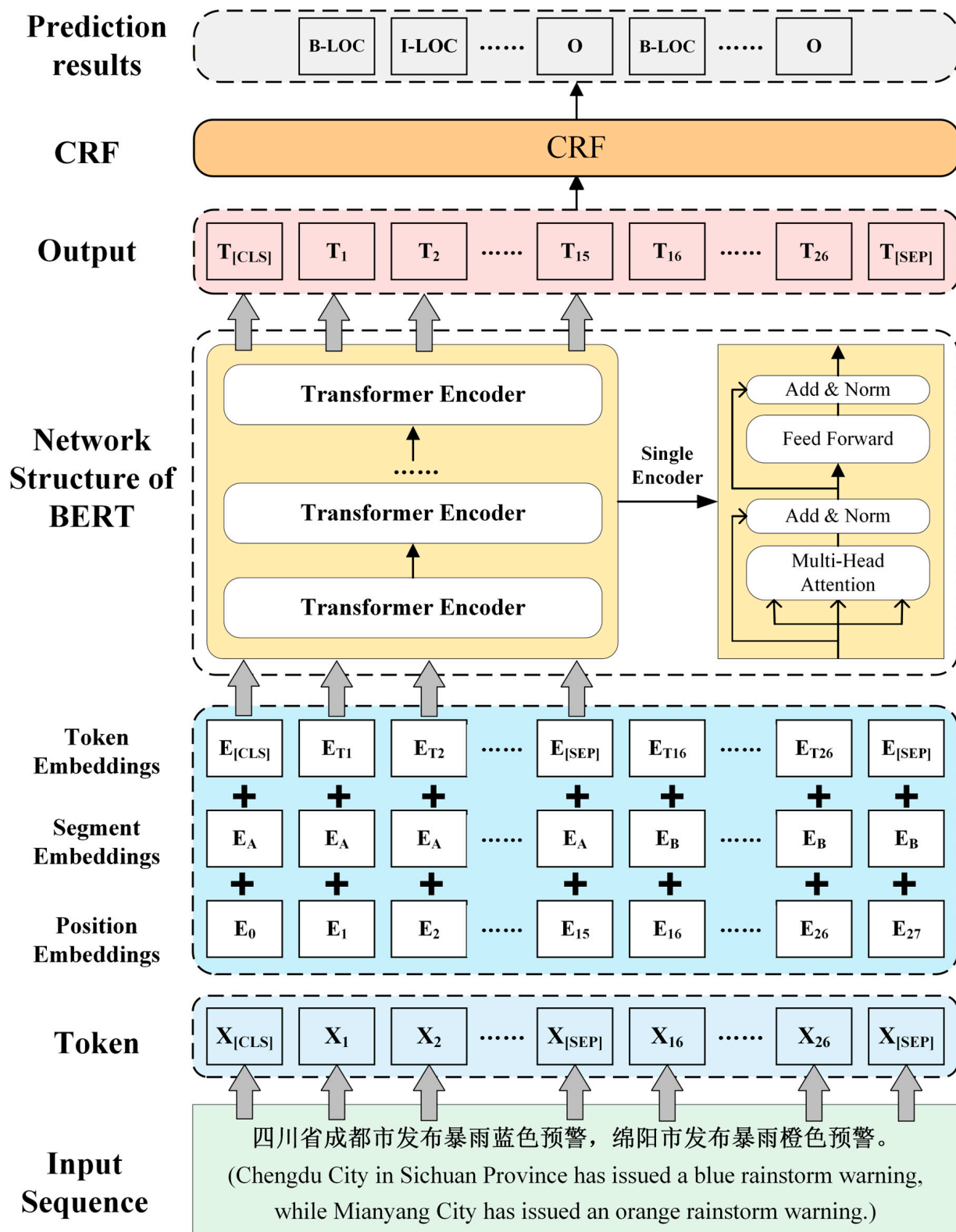


Figure 3. BERT-CRF model architecture diagram.

BERT models token-level contextual relationships but does not explicitly model dependencies among output labels. A CRF layer can capture transition constraints among labels and thereby improve the plausibility and consistency of the predicted label sequence. In sequence-labeling tasks, a common annotation scheme is BIO, in which B (Beginning) marks the start of an entity, I (Inside) denotes a token within an entity, and O (Outside) denotes a token that does not belong to an entity. Under BIO rules, for example, an I-LOC label within a location entity must be preceded by either B-LOC or I-LOC of the same entity type; it should not follow O or the beginning label of another entity type. By modeling these label-transition dependencies, the CRF layer improves sequence-labeling consistency and, consequently, named entity recognition accuracy.

When performing named entity recognition at the CRF layer, the input conversion matrix A is first applied. The conversion matrix A represents the relationships between tags. The input sequence $X = (x_1, x_2, x_3, \dots, x_n)$ corresponds to a tag sequence $Y = (y_1, y_2, y_3, \dots, y_n)$ of equal length, where n denotes the number of input tokens. The evaluation score calculation formula for the output sequence Y from the input sequence X is:

$$s(x, y) = \sum_{i=1}^n P_{i,y_i} + \sum_{i=0}^n A_{y_i, y_{i+1}}. \quad (1)$$

Here, P_{i,y_i} is the score for the i -th token having label y_i , and $A_{y_i, y_{i+1}}$ is the transition score from label y_i to label y_{i+1} . The model outputs the label sequence that maximizes this score, thereby deriving the corresponding entities.

3.2.2. Spatiotemporal Analysis of Warning Information (Spearman)

The Spearman correlation coefficient was used to analyze the spatial co-occurrence relationships among different disaster warnings. As a nonparametric statistic for measuring rank correlation between variables, the Spearman coefficient is suitable for examining the degree of association among different types of disaster warnings at the county scale. By comparing the ranking differences in the frequencies of different disaster warnings across counties, it can be used to determine whether stable co-occurrence relationships exist among hazard types. The formula is as follows:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (2)$$

In Equation (2), d_i^2 represents the rank difference between each pair of variables and n denotes the sample size.

3.2.3. Case-Crossover Design and Conditional Logistic Regression Model

This study employs a case-crossover design to quantify the association between tourism safety warnings and accident occurrence. Before constructing warning-exposure variables, warning records were spatially matched to tourism safety accident locations using the finest identifiable administrative unit. When both the warning and accident location could be identified at the township level, matching was conducted at the township level; when township-level information was unavailable for either record, county-level matching was used. The method is suitable for examining associations between short-term exposures and acute events. Its core advantage lies in eliminating the influence of time-invariant individual confounding factors through self-matching, thereby improving the reliability of the results. The association between warning information and tourism safety accidents is interpreted by the regression coefficient (β), p -value, odds ratio (OR), and its 95% confidence interval (95% CI): the sign of β indicates the direction of the effect, while the absolute magnitude of β reflects effect strength; the p -value is the core indicator used to

determine whether the association between the explanatory variable and the dependent variable is non-random. $OR > 1$ indicates a positive statistical association between warning exposure and accident occurrence, $OR < 1$ indicates that warning exposure is associated with lower accident risk, and $OR = 1$ indicates no association.

The specific logic was as follows: the date of each tourism safety accident was defined as the case period and the 7th, 14th, 21st, and 28th days before the accident were selected as control periods within the same county, thereby forming matched sets. Matching was based on county-level consistency to ensure that, apart from warning exposure status, other inherent characteristics remained relatively stable between the case and control periods. In the primary analysis, warning exposure was assessed using symmetric 72 h windows for both case and control periods. Specifically, case-period exposure was defined as warning information issued during the 72 h preceding the accident, while each control-period exposure was assessed over the 72 h preceding the corresponding reference time point at 7, 14, 21, or 28 days before the accident. To assess the robustness of the results, sensitivity analyses were further conducted using alternative exposure windows of 48 h and 24 h while retaining the original referent-period structure. In addition, alternative referent periods at 5, 10, 15, and 20 days before the accident were examined while retaining the 72 h exposure window.

Conditional logistic regression models were employed for hypothesis testing. Based on PADM and risk communication theory, this study distinguished two dimensions of warning system performance: the risk identification function and the risk intervention function. Accordingly, four progressive models were constructed on the basis of the case-crossover design to test warning system performance from different perspectives:

$$\log it[P(case = 1|stratum_i)] = \alpha_i + \beta_1 \times I(Warning_{ij}) \quad (3)$$

$$\log it[P(case = 1|stratum_i)] = \alpha_i + \beta_2 \times I(Level_{ij}) \quad (4)$$

$$\log it[P(case = 1|stratum_i)] = \alpha_i + \beta_{3a} \times I(Blue_{ij}) + \beta_{3b} \times I(Yellow_{ij}) + \beta_{3c} \times I(Orange_{ij}) + \beta_{3d} \times I(Red_{ij}) \quad (5)$$

$$\log it[P(case = 1|stratum_i)] = \alpha_i + \beta_4 \times I(HighLevel_{ij}) \quad (6)$$

In Equations (3)–(6), $\log it[P(case = 1|stratum_i)]$ denotes the conditional probability of accident occurrence i , α_i represents the layer intercept term for the i -th paired group; β represents the regression coefficient for the corresponding model, reflecting the direction and strength of the impact of early warnings on the accident probability. $I(Warning_{ij})$ is the regression coefficient for the variable indicating the presence or absence of early warning information, representing the availability of such information. $I(Level_{ij})$ is the regression coefficient for the variable in the highest-level early warning model, representing the highest-level warning among multiple early warnings in an event. $I(Blue_{ij})$, $I(Yellow_{ij})$, $I(Orange_{ij})$ and $I(Red_{ij})$ represent the respective regression coefficients within different warning level models, while $I(HighLevel_{ij})$ is the combined regression coefficient for orange and red warnings in the high-level warning model.

4. Risk Analysis

4.1. Model Training

For the named-entity recognition task, BERT-Base-Chinese served as the pretrained backbone. Released by Google, the model comprises 12 Transformer layers, 768 hidden units per layer, and a maximum sequence length of 512 tokens. It was pretrained on large Chinese corpora using masked language modeling (MLM) and next sentence prediction (NSP), providing general-purpose contextual representations of Chinese text.

The BERT-CRF model was constructed by adding a conditional random field (CRF) layer to the pretrained BERT encoder, which served as the contextual feature extractor. The BERT component was initialized with pretrained parameters, whereas the CRF state-transition matrix was randomly initialized. All parameters were then jointly fine-tuned on the annotated NER dataset. This procedure enabled the model to learn task-specific label distributions and transition constraints while retaining the general linguistic knowledge acquired during pretraining.

The BIO (Beginning, Inside, Outside) annotation scheme was adopted. Four entity categories were defined: TIME, LOCATION, DISASTER_TYPE, WARNING_LEVEL. Annotation followed predefined entity-specific rules. TIME entities included explicit expressions of warning issuance, validity, or duration; LOCATION entities included administrative units and geographic place names mentioned in the warning texts; DISASTER_TYPE entities referred to explicitly stated hazard types; and WARNING_LEVEL entities represented the graded warning categories, including blue, yellow, orange, and red warnings. Entity boundaries were determined according to the complete semantic expression of each entity in the original warning text. Model performance was evaluated using standard metrics: Precision (P), Recall (R), and the F1-score (F1). Precision is the ratio of correctly predicted entities to all predicted entities; Recall is the ratio of correctly predicted entities to all actual entities; and the F1-score is their harmonic mean:

$$P = \frac{T_P}{T_P + F_P} \quad (7)$$

$$R = \frac{T_P}{T_P + F_N} \quad (8)$$

$$F_1 = \frac{2PR}{P + R}. \quad (9)$$

In Equations (7)–(9), T_P denotes the number of entities correctly identified by the model, F_P denotes the number of entities incorrectly identified by the model, and F_N denotes the number of entities not identified by the model.

Text inputs were encoded using BertTokenizerFast corresponding to BERT-Base-Chinese, with the maximum sequence length set to 128. During training, the batch size was set to 16, the initial learning rate was 3×10^{-5} , and the AdamW optimizer was used. The maximum number of training epochs was set to 30, and an early stopping strategy (patience = 8) was applied to select the best-performing model based on validation-set performance. The random seed was set to 42. The model was implemented using PyTorch 2.7.0 and the Transformers library and trained in a computing environment equipped with an NVIDIA GeForce RTX 3050 Ti GPU. During model training, stratified sampling was employed to partition the dataset into training (70%), validation (10%), and test (20%) sets, maintaining consistent category distribution across all partitions. No overlap existed between different corpora within the dataset. The training set was used for model training, the validation set for evaluating the trained model and adjusting hyperparameters to optimize performance on it, and the test set for final model evaluation. The model training data are shown in Table 1 below.

Table 1. Model training performance.

Label	<i>p</i>	R	F1
LOCATION	0.8937	0.8872	0.8904
TIME	0.6889	0.7523	0.7195
DISASTER	0.9127	0.9064	0.9095
WARNING	0.8986	0.9217	0.9099

The relatively lower F1-score for TIME entities is attributable to the diversity of temporal expressions in Chinese. The same temporal information may be conveyed in multiple linguistic forms, including abbreviated expressions and referential terms, which increases the difficulty of accurately identifying temporal entities. To ensure consistency in subsequent temporal matching, the extracted TIME entities were standardized into a unified time format. For temporal expressions that were ambiguous or uncertain, the original warning texts were further reviewed to verify the corresponding time information.

4.2. Spatiotemporal Characteristics

Analysis of the annual and monthly heat maps of disaster warnings from 2021 to 2025 (Figure 4) reveals substantial interannual variation and clear seasonal differentiation. At the annual scale, warnings for heatwaves, rainstorms, and geological hazards remained frequent or showed an upward trend, reflecting persistent or increasing risks associated with extreme weather and secondary hazards. Lightning and gale warnings represented recurrent responses to severe convective weather, whereas road-icing and heavy fog warnings remained relatively infrequent. At the monthly scale, heatwave warnings peaked from June to August, with the highest frequency in August. Road-icing and heavy fog warnings occurred predominantly in winter and were associated with low-temperature conditions. Lightning, gale, and rainstorm-related secondary-hazard warnings were concentrated from April to September, broadly corresponding to the severe convection and flood seasons. Frost and hail warnings were less frequent and more scattered. Overall, these temporal patterns reflect the seasonality of extreme weather, recurrent severe convective events, and interactions within secondary-hazard chains.

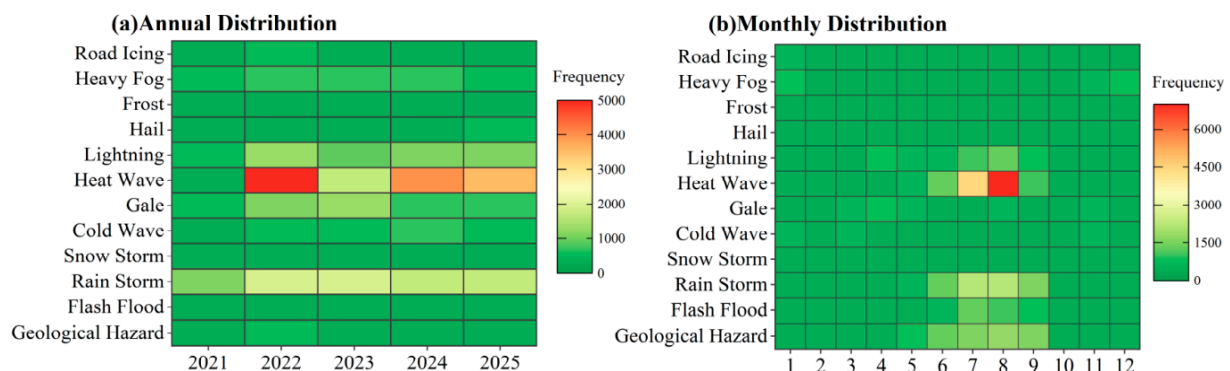


Figure 4. Temporal distribution characteristics of disaster warning information 2021–2025.

Figure 5 presents the proportions of warning levels across hazard types. Based on warning frequency, the hazard types were grouped into four categories: high frequency, medium-high frequency, medium frequency, and low frequency. The composition of warning levels differed across hazard types and also varied interannually within the same hazard type, reflecting year-to-year changes in hazard frequency and intensity.

For example, frost warnings were predominantly blue throughout the study period, indicating that most frost events were classified at a lower warning level. Red heatwave warnings fluctuated across years, reflecting interannual variation in the intensity of extreme heat events. The proportions of yellow and orange cold-wave warnings increased gradually from 2021 to 2025, suggesting an increasing occurrence of higher-level cold-wave warnings over the study period.

Figure 6 shows the spatial distribution of the total number of disaster warnings across counties in Sichuan Province from 2021 to 2025. Using the natural breaks method, warning frequency was classified into five categories: low, low-to-medium, medium, medium-to-high, and high. Marked spatial differentiation was evident in each year. In 2021, high-

frequency areas were concentrated mainly in central and eastern Sichuan, while medium-to-high-frequency areas occurred in scattered patches across southern Sichuan; the Western Sichuan Plateau and northwestern Sichuan were dominated by low-frequency areas. In 2022, high-frequency areas expanded into southern and central Sichuan, and medium-to-high-frequency areas formed contiguous clusters in eastern and southern Sichuan. In 2023, the spatial pattern shifted again, with localized increases in eastern and southern Sichuan. By 2024, high-frequency areas formed two principal clusters in southern and central Sichuan, while medium-to-high-frequency areas covered much of these regions. In 2025, high-frequency areas became more concentrated in eastern and central Sichuan, while southern Sichuan continued to contain a large proportion of medium- to high-frequency counties. These spatial differences are associated with Sichuan's contrasting basin and mountain topography, climatic zonation, and heterogeneous hazard-prone environments. The interannual evolution can be summarized in three phases. From 2021 to 2022, high-frequency areas expanded from localized clusters in central and eastern Sichuan to more contiguous areas in southern and central Sichuan. In 2023, the distribution entered a transition phase, with high-frequency areas shifting toward eastern Sichuan and localized parts of southern Sichuan. From 2024 to 2025, a multicenter pattern emerged across southern, central, and eastern Sichuan.

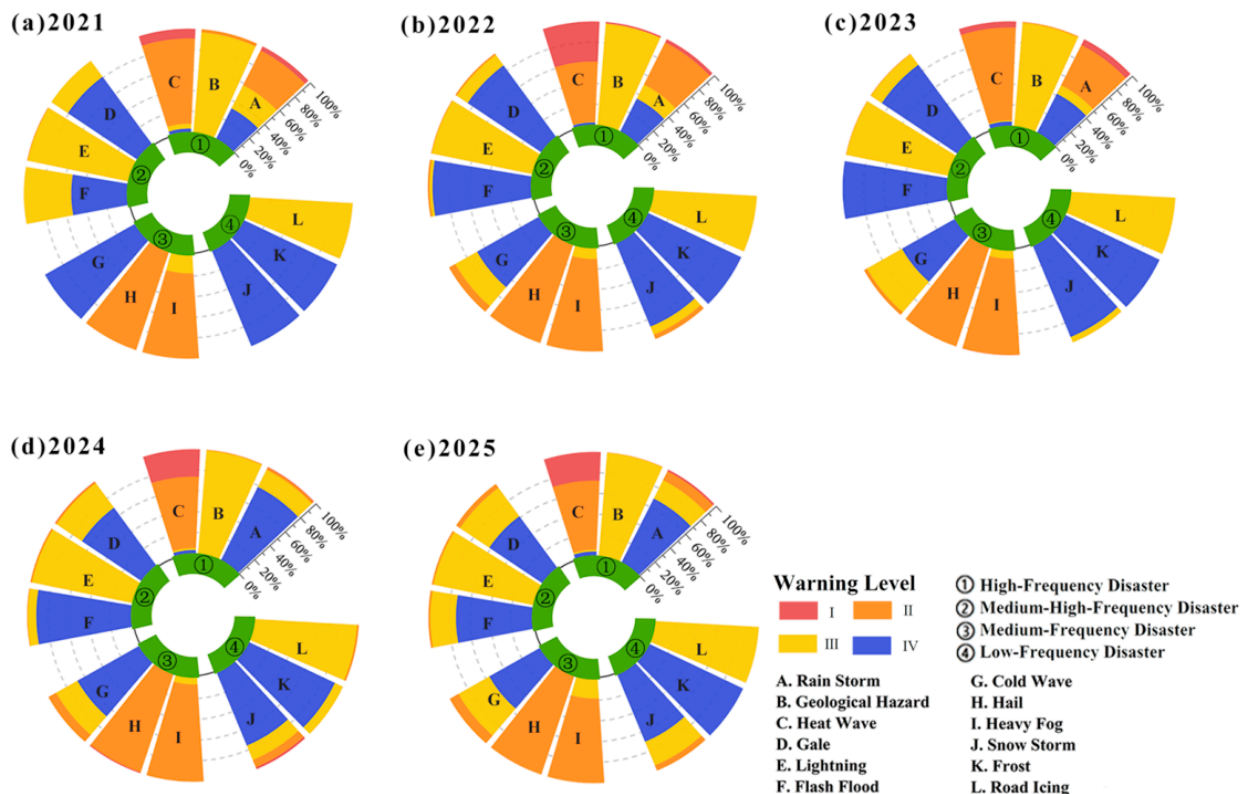


Figure 5. Proportion of disaster warning levels by category 2021–2025.

Analysis of the total number of disaster warnings issued for each county in Sichuan Province from 2021 to 2025 is shown in Figure 7. Among high-frequency disasters, heatwave warnings were most prominent in the high-frequency group, with most counties issuing around 100 warnings, while only a few counties in the basin exceeded 150 warnings. Rain-storm warnings showed a relatively concentrated distribution, overall. Geological disaster warnings exhibited an extremely scattered distribution, ranging from 20 to 150 warnings, clearly reflecting the topographical difference where counties in the mountainous central regions of Sichuan issued more warnings than those in the plains. Within the medium- to

high-frequency disaster group, lightning and gale warnings approached the levels of rainstorms and geological hazards in the high-frequency group. Lightning warnings peaked at 150 times, while gale warnings exceeded 100 times. Flash floods, however, were the least frequent in this group, concentrated in the lower range. The medium-frequency disaster group includes heavy fog, cold-waves, and hail. Heavy fog had the highest number of warnings in this group, with a box plot median of approximately 15 times and outliers exceeding 50 times, concentrated in foggy counties within the basin. The median for cold-waves was about 10 times, with outliers reaching 30 times. Hail showed a median of only about 5 times, with most counties concentrated between 10 and 20 times, making it a low-frequency type within the medium-frequency group. The box plots for the three disaster types in the low-frequency group all showed a median close to 0, indicating that only a few counties in the high-altitude areas of the Western Sichuan Plateau had some warnings, while most counties in the Sichuan Basin had almost no warnings for these disasters.

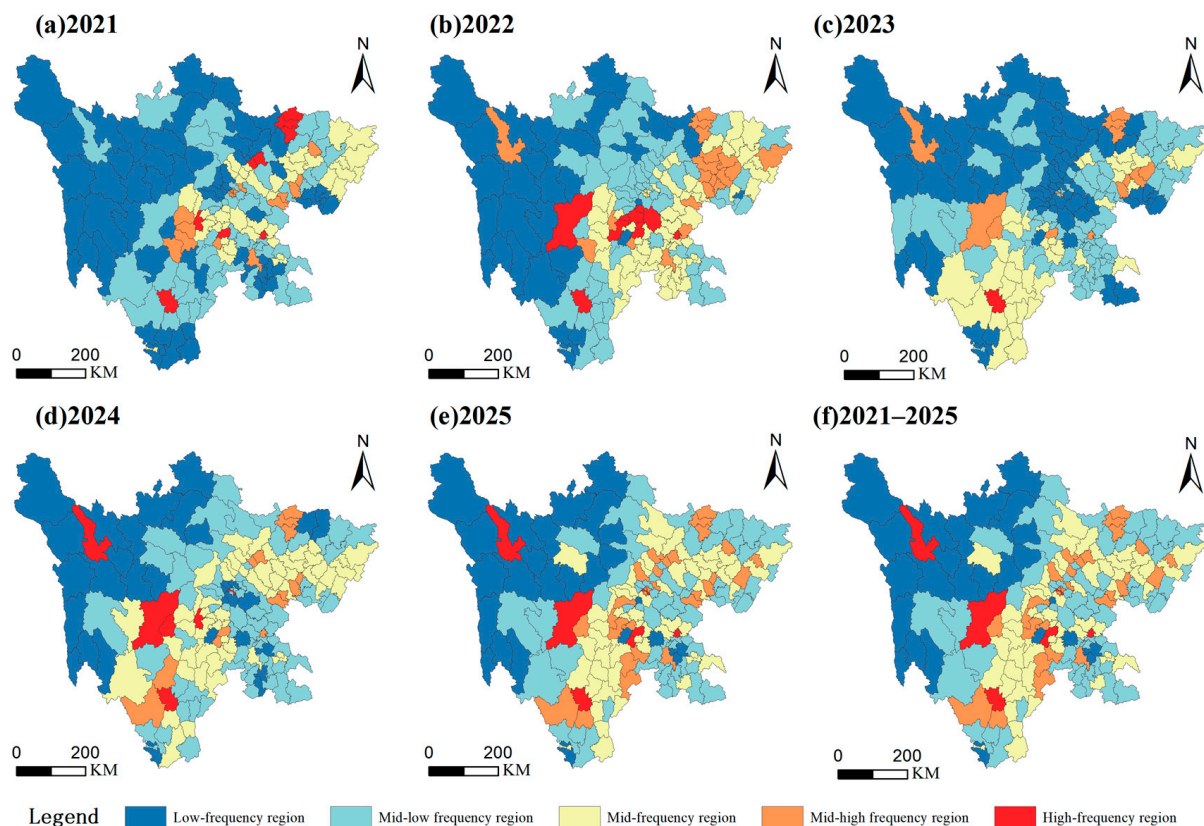


Figure 6. Distribution of total disaster warning counts by county in Sichuan Province, 2021–2025.

Simultaneously, Spearman correlation analysis based on the frequency of various disaster warnings across Sichuan counties from 2021 to 2025 is shown in Figure 7. Different disasters exhibit significant spatial non-independence and structural characteristics. Meteorological disasters, such as rainstorms, heatwaves, gales, lightning, heavy fog, and road icing, generally exhibit moderate to strong positive correlations, indicating their pronounced co-occurrence within the same county. Rainstorms, flash floods, and geological disasters show high correlations, suggesting their spatial distribution is jointly constrained by topographic conditions and short-duration intense precipitation triggering processes. Overall, this correlation structure reveals a composite occurrence pattern among disaster types, jointly shaped by climatic background and topographic environment.

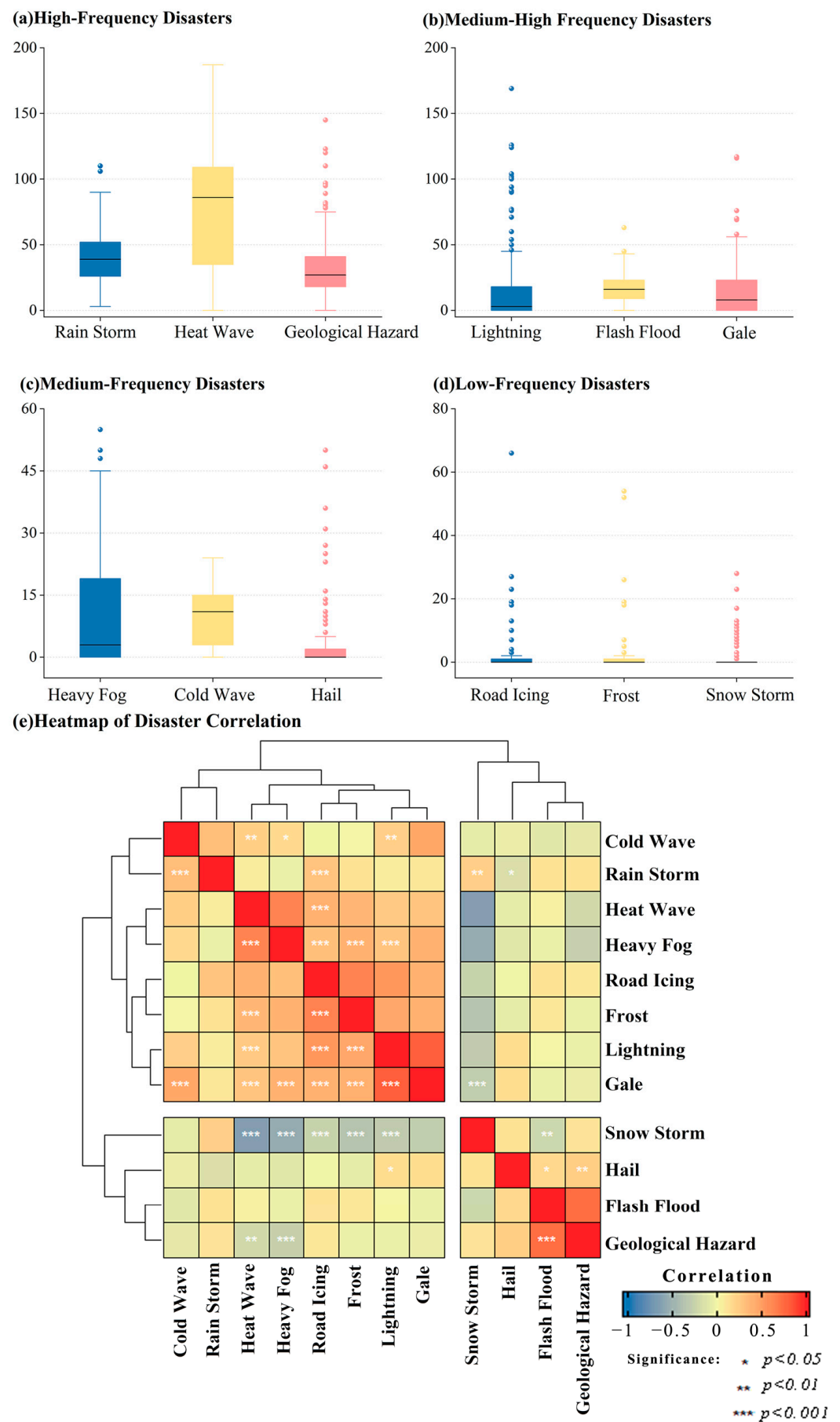


Figure 7. Disaster warning characteristics map for counties in Sichuan Province.

5. Association Analysis

The preceding disaster analysis demonstrates that warning information exhibits pronounced temporal and spatial differentiation, with clear variations in seasonal distribution, geographic concentration, and hazard-type composition. These patterns indicate that official warning signals are closely associated with the occurrence environments of compound natural hazards and can, in general, capture tourism areas characterized by elevated safety risks. However, identifying high-risk contexts through warning information alone does not reveal whether such risk signals are temporally linked to actual tourism safety accidents or whether warnings of different levels exhibit different capacities in risk intervention. Therefore, based on the identified spatiotemporal characteristics of disaster warnings, the present study further applies a case-crossover design to examine the short-term relationship between warning exposure and accident occurrence and to evaluate whether different warning levels demonstrate differentiated risk intervention performance. Specifically, by comparing warning exposure during accident periods with matched control periods, this approach controls for stable individual and regional characteristics and focuses on short-term changes associated with warning conditions. A total of 81 tourism safety accidents occurring in Sichuan Province between 2021 and 2025 were collected from multiple sources, involving 156 injuries and 62 fatalities.

To investigate the association between tourism safety warnings and accident occurrence, a case-crossover design was applied. In the primary analysis, the 7th, 14th, 21st, and 28th days before accident occurrences were selected as referent time points. This specification was primarily based on the principle of time-stratified matching in the case-crossover design. First, using referent intervals in multiples of 7 days ensured that the case and control periods fell on the same day of the week, thereby reducing the potential influence of systematic weekday–weekend differences in tourist activity, travel intensity, and scenic-area operations. Second, restricting the control periods to within four weeks before the accident maintained temporal proximity between case and control periods and, thus, helped to reduce differences arising from seasonal variation and longer-term temporal trends. At the same time, using 7 days as the nearest referent interval also reduced the likelihood that the case and control periods were affected by the same persistent hazard or warning episode. Finally, four control periods were matched to each case period, increasing the amount of within-case exposure information while maintaining temporal comparability. Based on the 7-day interval specification and using a 72 h exposure window in the primary analysis, sensitivity analyses were further conducted by applying alternative exposure windows of 48 h and 24 h while retaining the original referent-period structure in order to evaluate the robustness of the results.

By comparing differences in warning exposure between case and control periods within the same matched set, county-level fixed effects can be stripped away and the short-term influence of warning status on accident occurrence can be isolated. According to the research propositions, four types of models were specified. The risk identification model mainly corresponds to Proposition 1 and is used to examine whether warning issuance significantly co-occurs with high-risk contexts, thereby identifying whether the warning system has a risk identification function. The warning-level gradient model, warning-level difference model, and high-level intervention model jointly correspond to Propositions 2 and 3 and are used to examine whether warnings of different levels exhibit differentiated risk intervention performance owing to differences in the intensity of risk communication and the capacity to trigger behavior, as well as whether medium- and low-level warnings exhibit the mechanism of effective identification but insufficient intervention. The results are reported in Table 2.

Table 2. Results of the case-crossover analysis under different exposure windows.

Exposure Window	Variable	β	OR	95% CI	<i>p</i> -Value	Significance
72 h	Model 1	0.588	1.8	1.01–3.21	0.046	*
	Model 2	−0.382	0.69	0.51–0.93	0.008	**
	Blue	0.673	1.96	0.83–4.65	0.128	n.s.
	Yellow	1.154	3.17	1.27–7.90	0.013	*
	Orange	−1.153	0.32	0.10–1.04	0.057	n.s.
	Red	−1.966	0.14	0.03–0.72	0.019	*
	Model 4	−1.204	0.3	0.14–0.64	0.002	**
48 h	Model 1	0.457	1.58	0.88–2.84	0.127	n.s.
	Model 2	−0.261	0.77	0.58–1.02	0.071	n.s.
	Blue	0.542	1.72	0.74–4.00	0.207	n.s.
	Yellow	0.892	2.44	1.05–5.67	0.038	*
	Orange	−0.734	0.48	0.17–1.38	0.174	n.s.
	Red	−1.514	0.22	0.05–0.92	0.038	*
	Model 4	−0.892	0.41	0.21–0.80	0.009	**
24 h	Model 1	0.507	1.66	0.90–3.05	0.102	n.s.
	Model 2	−0.186	0.83	0.66–1.05	0.118	n.s.
	Blue	0.358	1.43	0.60–3.39	0.416	n.s.
	Yellow	0.963	2.62	1.06–6.45	0.036	*
	Orange	−0.821	0.44	0.15–1.32	0.143	n.s.
	Red	−1.238	0.29	0.08–1.06	0.061	n.s.
	Model 4	−0.693	0.50	0.27–0.93	0.028	*

Note: Model 1 = risk identification model; Model 2 = warning-level gradient model; Model 3 = warning-level difference model; Model 4 = high-level intervention model. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; n.s. = not significant.

From the perspective of risk identification, under the 72 h exposure window, the risk identification model reached statistical significance ($\beta = 0.588$, OR = 1.80, 95% CI = 1.01–3.21, $p = 0.046$), indicating that warning information was more likely to be present during case periods than during control periods. This finding does not imply that warnings themselves increase accident risk; rather, it suggests that warnings tend to be issued in spatiotemporal contexts where tourism safety risk has already increased, thereby reflecting the risk identification function of the warning system. At the level-specific scale, blue warnings showed a positive but non-significant association ($\beta = 0.673$, OR = 1.96, 95% CI = 0.83–4.65, $p = 0.128$), whereas yellow warnings were significantly concentrated in high-risk accident periods ($\beta = 1.154$, OR = 3.17, 95% CI = 1.27–7.90, $p = 0.013$). These findings indicate that low- and medium-level warnings, particularly yellow warnings, can capture elevated-risk spatiotemporal contexts. The warning-level gradient model further showed a significant graded association ($\beta = -0.382$, OR = 0.69, 95% CI = 0.51–0.93, $p = 0.008$), with each one-level increase in warning level associated with approximately 31% lower odds of accident occurrence. Among individual levels, red warnings showed the strongest negative association ($\beta = -1.966$, OR = 0.14, 95% CI = 0.03–0.72, $p = 0.019$), while orange warnings showed a similar direction but did not reach statistical significance ($\beta = -1.153$, OR = 0.32, 95% CI = 0.10–1.04, $p = 0.057$). When orange and red warnings were combined, the high-level intervention model remained highly significant ($\beta = -1.204$, OR = 0.30, 95% CI = 0.14–0.64, $p = 0.002$), indicating approximately 70% lower odds of accident occurrence under high-level warnings. Taken together, the 72 h analysis suggests a clear distinction across warning levels: yellow warnings are more strongly associated with the identification of elevated-risk contexts, whereas high-level warnings show more stable negative associations with accident occurrence.

When the exposure window was shortened to 48 h, the directions of the main associations remained broadly consistent with the 72 h analysis, although the statistical significance of several estimates weakened. The risk identification model remained positive ($\beta = 0.457$, OR = 1.58, 95% CI = 0.88–2.84, $p = 0.127$), indicating that warning information continued to occur more frequently during case periods, although the association was no longer statistically significant. Similarly, the warning-level gradient model retained a negative direction ($\beta = -0.261$, OR = 0.77, 95% CI = 0.58–1.02, $p = 0.071$), with the OR moving closer to 1 compared with the 72 h result. At the level-specific scale, blue warnings remained positively but non-significantly associated with case periods (OR = 1.72, $p = 0.207$), whereas yellow warnings retained a significant positive association (OR = 2.44, 95% CI = 1.05–5.67, $p = 0.038$). Orange warnings continued to show a negative but non-significant association (OR = 0.48, $p = 0.174$), while red warnings remained significantly associated with lower accident odds (OR = 0.22, 95% CI = 0.05–0.92, $p = 0.038$). The high-level intervention model also remained statistically significant (OR = 0.41, 95% CI = 0.21–0.80, $p = 0.009$). Thus, although the overall risk identification and warning-level gradient associations weakened under the 48 h window, the positive association for yellow warnings and the negative associations for red and combined high-level warnings remained evident.

When the exposure window was further shortened to 24 h, the main effect directions again remained broadly consistent. The risk identification model remained positive but non-significant ($\beta = 0.507$, OR = 1.66, 95% CI = 0.90–3.05, $p = 0.102$), while the warning-level gradient model remained negative but was also non-significant ($\beta = -0.186$, OR = 0.83, 95% CI = 0.66–1.05, $p = 0.118$). Compared with the 72 h and 48 h analyses, the gradient estimate moved further toward the null, indicating that the overall association weakened as the exposure window shortened. In the warning-level difference model, blue warnings remained positive but non-significant (OR = 1.43, $p = 0.416$), whereas yellow warnings continued to show a significant positive association ($\beta = 0.963$, OR = 2.62, 95% CI = 1.06–6.45, $p = 0.036$). Orange warnings retained a negative but non-significant association (OR = 0.44, $p = 0.143$), and red warnings showed a strong negative direction that approached statistical significance (OR = 0.29, 95% CI = 0.08–1.06, $p = 0.061$). After orange and red warnings were combined, the high-level intervention model remained statistically significant (OR = 0.50, 95% CI = 0.27–0.93, $p = 0.028$). Overall, shortening the exposure window reduced the statistical significance of some estimates, but did not materially alter the main pattern: yellow warnings remained consistently associated with elevated-risk case periods, whereas high-level warnings maintained relatively stable associations with lower accident odds.

To assess the robustness of the results, sensitivity analyses were conducted using alternative referent periods (5, 10, 15, and 20 days before the accident) while retaining the 72 h exposure window. The results are shown in Table 3.

Table 3. Results under alternative referent periods.

Variable		β	OR	95% CI	p -Value	Significance
Risk Identification Model		0.512	1.67	1.01–2.77	0.047	*
Warning-Level Gradient Model		−0.301	0.74	0.56–0.98	0.034	*
Warning-Level Difference Model	Blue	0.718	2.05	0.87–4.84	0.101	n.s.
	Yellow	1.058	2.88	1.20–6.93	0.018	*
	Orange	−0.994	0.37	0.12–1.10	0.074	n.s.
	Red	−1.715	0.18	0.04–0.80	0.024	*
High-Level Intervention Model		−1.050	0.35	0.17–0.71	0.004	**

Note: Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; n.s. = not significant.

When alternative referent periods 5, 10, 15, and 20 days before the accident were used, the risk identification model remained statistically significant, with a regression

coefficient of 0.512 and an OR of 1.67 (95% CI = 1.01–2.77, $p = 0.047$). This indicates that, even after changing the referent-period specification, warning information remained significantly more likely to occur during case periods than during control periods. The correspondence between warning exposure and high-risk accident contexts, therefore, did not depend on the original 7-, 14-, 21-, and 28-day referent periods, further supporting the risk identification function of the warning system. The warning-level gradient model also remained statistically significant, with a regression coefficient of -0.301 and an OR of 0.74 (95% CI = 0.56–0.98, $p = 0.034$), indicating that accident odds continued to decline overall as warning levels increased under the alternative referent-period specification. Compared with the OR of 0.69 in the 72 h primary analysis, the effect magnitude was slightly attenuated, but both the direction and statistical significance were preserved, suggesting that the warning-level gradient was not driven by the choice of a particular referent-period specification. In the warning-level difference model, blue warnings had an OR of 2.05 (95% CI = 0.87–4.84, $p = 0.101$); although not statistically significant, the association remained positive. Yellow warnings had an OR of 2.88 (95% CI = 1.20–6.93, $p = 0.018$), retaining a significant positive association and indicating that yellow warnings remained clearly concentrated in high-risk accident periods. This finding was consistent with the primary analysis and further supports the relative stability of the risk identification pattern associated with yellow warnings. High-level warnings continued to show an overall protective association. Orange warnings had an OR of 0.37 (95% CI = 0.12–1.10, $p = 0.074$); although not statistically significant, the estimate still indicated a pronounced tendency toward lower accident odds. Red warnings retained a significant protective association, with an OR of 0.18 (95% CI = 0.04–0.80, $p = 0.024$). When orange and red warnings were combined, the high-level intervention model also remained significantly protective, with an OR of 0.35 (95% CI = 0.17–0.71, $p = 0.004$). Overall, after changing the referent-period specification, the effect directions and principal significance patterns of the risk identification model, warning-level gradient model, yellow warnings, red warnings, and the high-level intervention model remained broadly consistent with those of the primary analysis.

Although the directions of the main effects were generally consistent across alternative exposure windows and referent-period specifications, the statistical significance of some level-specific estimates varied. Given that this study included only 81 tourism safety accidents and that stratification by warning level further reduced the information available for estimating individual level-specific effects, it was necessary to assess whether the limited sample size might constrain the models' ability to detect true effects. Accordingly, a simulation-based power analysis was conducted to evaluate the statistical power of each model under the observed sample size and matched design. Unlike conventional power calculations based on simple independent sample assumptions, simulation-based power analysis can preserve the matched structure of the case-crossover design, in which each case period is paired with multiple control periods, while incorporating the observed exposure distribution and model effect sizes. By repeatedly generating simulated datasets and refitting the corresponding conditional logistic regression models, this approach estimates the probability of obtaining a statistically significant result under the current study conditions. Specifically, 5000 simulations were performed for each model while retaining the original matched case-crossover structure, with a two-sided α level of 0.05 used as the significance criterion. Statistical power was defined as the proportion of the 5000 simulations in which the regression coefficient of interest reached statistical significance. The purpose of this analysis was not to re-estimate the direction of the effects, but rather to evaluate the statistical stability and detection capacity of each model under the current sample size, particularly for level-specific warning effects.

The simulation-based power analysis showed clear differences in statistical power across models under the current sample size. The risk identification model and the warning-level gradient model achieved powers of 51% and 70%, respectively, indicating some ability to detect the overall risk identification and warning-level gradient effects, but not at a high level of power. This helps to explain why the statistical significance of some estimates varied across alternative exposure windows or referent-period specifications. More pronounced differences were observed within the warning-level difference model, for which the estimated powers were 32% for blue warnings, 61% for yellow warnings, 49% for orange warnings, and 65% for red warnings. Blue warnings had the lowest statistical power, at 32%, indicating a relatively limited ability to detect this level-specific effect under the current sample size. The power for orange warnings was also low, at 49%, which is consistent with the pattern of a comparatively clear protective direction accompanied by wide confidence intervals and non-significant estimates in some analyses. By contrast, the powers for yellow and red warnings were higher, at 61% and 65%, respectively, indicating relatively better detection capacity, although some statistical uncertainty remained. Notably, when orange and red warnings were combined, the high-level intervention model achieved a power of 83%, the highest among all models. This suggests that treating high-level warnings as a combined category increased the effective information available for estimation, resulting in greater statistical power and more stable estimation of the high-level intervention effect. Consistent with the sensitivity analyses described above, the high-level intervention model retained a significant protective association across alternative exposure windows and referent-period specifications, indicating greater robustness than the effects estimated for individual warning levels. Overall, the simulation-based power analysis indicates that the current sample size still limits the precision and significance-testing capacity of some level-specific estimates, particularly those for blue and orange warnings, whereas the combined high-level intervention effect shows comparatively greater statistical reliability.

After assessing the influence of limited sample size on the stability of the model estimates, we further considered whether different warning levels corresponded to systematically different underlying risk contexts. Because high-level warnings may be more likely to occur under particular hazard types, seasons, or terrain conditions, differences in ORs across warning levels may reflect not only differences in the intensity of warning intervention but also differences in the underlying risk context. To assess the potential for confounding by indication, we therefore compared the seasonal, hazard-type, and county-level terrain distributions associated with the highest warning level observed during the 72 h case-period exposure window. The results showed that the seasonal distributions of case periods were broadly similar across warning levels. Summer accounted for 44.4%, 47.6%, 50.0%, and 66.7% of case periods associated with blue, yellow, orange, and red warnings, respectively, with no pronounced differentiation across warning levels. By contrast, some differences were observed in terrain context. Case periods associated with blue and yellow warnings were mainly located in plateau or high mountain-valley areas, accounting for 66.7% and 71.4%, respectively. Orange-warning case periods were evenly distributed between mountainous and plateau areas, whereas all red-warning case periods occurred in mountainous counties. Differences in hazard-type composition were more pronounced. Blue-warning case periods were mainly associated with heavy rainfall; yellow-warning case periods more often involved thunderstorms, geological hazards, road icing, and compound-warning contexts; orange-warning case periods were mainly associated with heavy rainfall and heatwave conditions; and red-warning case periods were concentrated primarily in heatwave conditions. These patterns indicate that warning levels do not occur within entirely homogeneous risk contexts but are associated, to some extent, with different hazard processes and spatial environments. Accordingly, differences in level-specific

effects may partly reflect differences in underlying risk contexts, particularly in hazard type and terrain. Although seasonal distributions did not show pronounced differentiation across warning levels, confounding by indication in the OR estimates for individual warning levels cannot be fully excluded. The level-specific effects should, therefore, be interpreted in relation to the risk contexts in which the warnings occurred. By contrast, the overall warning-level gradient and high-level intervention effects showed more consistent directions and comparatively greater statistical stability across analytical specifications.

Taken together, the main effect patterns identified in the primary analysis remained generally stable across the different analytical specifications. After applying alternative 48 h and 24 h exposure windows and alternative referent periods 5, 10, 15, and 20 days before the accident, the directions of the estimated effects remained broadly consistent with those of the 72 h primary analysis. Yellow warnings consistently exhibited a pronounced risk identification pattern, whereas high-level warnings generally retained protective associations. At the same time, the simulation-based power analysis indicated that the statistical detection capacity for some individual warning levels remained constrained by the limited sample size, particularly for blue and orange warnings, whereas the high-level intervention model showed comparatively higher statistical power and greater estimation stability. Further comparison of underlying risk contexts revealed some differences in hazard type and terrain across warning levels, which helps to explain the variation in the magnitude and statistical significance of level-specific effects. By comparison, the overall warning-level gradient and the protective association of high-level warnings showed more consistent directions and comparatively greater statistical stability across analytical specifications. Overall, the case-crossover results indicate that the tourism safety warning system in Sichuan Province simultaneously possesses risk identification and risk intervention functions. The risk identification model shows that warning issuance can, in general, point relatively accurately to high-risk tourism safety contexts, indicating that the system has a basic capacity for risk identification. The risk identification model, warning-level difference model, and high-level intervention model further show that warnings of different levels differ significantly in their risk intervention performance. High-level warnings are more likely to reduce accident risk through stronger risk communication signals and clearer action requirements, whereas medium- and low-level warnings, especially yellow warnings, exhibit clear shortcomings in the transformation from risk identification to risk avoidance. Thus, the optimization of the tourism safety warning system should focus not only on improving the accuracy of warning issuance, but also on enhancing the behavioral triggering capacity and supporting the governance effectiveness of warnings at different levels, especially those at medium levels.

6. Discussion

6.1. Dual Functions and Level-Specific Differences in Warning Effectiveness

This study integrated a BERT-CRF model with a case-crossover design to transform government-issued disaster warning texts into structured spatiotemporal records containing information on time, location, hazard type, and warning level, and subsequently matched these records with tourism safety accidents associated with natural hazards in Sichuan Province, China. Disaster warning texts often contain complex place names, hazard terminology, warning levels, temporal expressions, and administrative formulations. Therefore, accurately extracting key spatiotemporal information from unstructured texts remains an important challenge in disaster-text processing [37]. By identifying time, location, hazard type, and warning level, this study converted dispersed administrative warning texts into a structured warning-information layer that can support spatial matching, temporal analysis, and statistical testing. The resulting warning data exhibit clear seasonal

variation, spatial differentiation, and inter-hazard co-occurrence, thereby providing a basis for further examining short-term statistical associations between warning information and tourism safety accidents. The case-crossover analysis further indicates that the warning system performs both risk identification and risk intervention functions. First, the positive association between warning exposure and accident case periods in the risk identification model does not imply that warnings cause accidents; rather, it indicates that warnings are more likely to be issued in temporal and spatial contexts where disaster risk has already increased. Second, clear differences are observed in the associations between warning levels and accident occurrence. Overall, the odds of an accident occurrence decline as the warning level increases.

From the perspectives of PADM and risk communication theory, higher-level warnings generally convey stronger risk signals, greater urgency, and clearer requirements for action, and are, therefore, theoretically more likely to facilitate threat appraisal and protective decision-making. Warning systems are an indispensable component of risk communication; the effectiveness of disaster warnings depends on how warning information is communicated and how it is interpreted by recipients [38]. Previous studies have also shown that whether warning information is translated into behavioral responses depends not only on whether the risk is identified, but also on how the warning is communicated and whether it provides adequate support for practical action [39,40]. Therefore, the association observed in this study between higher-level warnings and lower odds of accident occurrence may be interpreted as suggesting that stronger risk communication signals are more conducive to translating risk information into protective responses. Yellow warnings consistently show a positive association with accident case periods in both the primary analysis and the sensitivity analyses, indicating that they occur relatively frequently in spatiotemporal contexts where risk has already increased and, thus, exhibit a relatively clear risk identification function. However, this positive association cannot be attributed solely to insufficient risk communication intensity. Comparisons of seasonal, hazard-type, and terrain contexts across warning levels show that seasonal distributions are broadly similar among the different levels, whereas some differences exist in hazard type and terrain background. In particular, the risk contexts associated with yellow, orange, and red warnings are not entirely homogeneous. Accordingly, differences in ORs across warning levels may reflect both differences in warning-communication intensity and heterogeneity in the underlying risk contexts; confounding by indication cannot be completely excluded when interpreting the effects of individual warning levels.

6.2. Structured Warning Information and the Case-Crossover Design in Tourism Risk Research

This study further demonstrates the applicability of structured official warning information in tourism safety and disaster-risk research [41]. Following entity recognition and spatial standardization, government-issued warning texts are no longer treated merely as static administrative information; instead, they can be transformed into structured geographic information containing temporal, spatial, hazard-type, and warning-level attributes, which can then be matched with administrative boundaries, tourism safety accidents, and different hazard categories. Compared with social-sensing data, such as social media, which may be affected by user-group bias, differences in participation, and uneven information credibility [42], official warning information generally provides clearer administrative locations, issuance times, hazard terminology, and warning levels, while also originating from relatively stable and authoritative sources [43]. Structuring official warning texts for short-term risk-exposure matching, therefore, provides a comparatively stable spatiotemporal information source for tourism safety research.

The case-crossover design further extends the geospatial analytical value of these records. Existing tourism risk studies have often relied on static risk assessments or post-event explanatory frameworks [44], whereas the case-crossover design is more suitable for examining statistical associations between short-term exposures and acute events [45–47]. In this study, differences in warning exposure between accident case periods and corresponding control periods are compared within the same county. This approach controls for relatively stable spatial characteristics, such as topographic background, the general level of tourism development, and infrastructure, while focusing the analysis on the relationship between temporal changes in warning exposure and accident occurrences within the same spatial unit. Previous methodological research has also indicated that the case-crossover design provides an important basis for analyzing associations between short-term exposures and acute outcomes, although causal interpretation still depends on the adequate control of conditions such as time-varying confounding [48].

Within the Chinese context, the significance of this study also lies in its differentiated evaluation of a multi-level warning system. Disaster warnings in China generally have a clear administrative basis and a defined hierarchical structure, with different warning levels reflecting not only different degrees of hazard severity but also different intensities of risk communication and emergency-management requirements. Sichuan is characterized by complex terrain and diverse hazard types, while tourism activities depend heavily on mountainous transportation networks, outdoor spaces, and natural environments. Under such conditions, evaluating only whether a warning has been issued is insufficient to fully characterize the performance of the warning system. The findings of this study suggest that the evaluation of multi-level warning systems can move beyond the simple presence or absence of warnings to examine whether different warning levels correspond to different risk contexts and distinct patterns of association with accident occurrence. This approach can help to identify potential weaknesses in the transition from risk identification to risk response within the warning system. At the international level, the analytical framework developed in this study does not depend on the specific characteristics of China's warning system, but rather on whether warning information contains clearly identifiable temporal, spatial, risk category, or severity attributes. The approach may, therefore, be transferable to other countries or regions where graded warning systems are in place and accident-outcome data are available. Nevertheless, countries differ in the meanings assigned to warning levels, issuing authorities, dissemination channels, administrative spatial units, and requirements for protective action. Future cross-regional or cross-national comparisons should, therefore, redefine exposure indicators and matching rules according to local warning semantics, spatial scales, and governance systems.

6.3. Theoretical and Practical Contributions

From theoretical and geoinformation-science perspectives, the contribution of this study extends beyond improving the accuracy of warning-text recognition. By transforming government-issued warning texts into structured spatiotemporal records and linking them with observed tourism safety outcomes, the study establishes an analytical connection between geographic information construction and warning system performance evaluation. The workflow integrates text-based geographic entity extraction, location normalization, multi-source spatial data linkage, spatiotemporal visualization, and temporally matched exposure modeling, thereby incorporating warning mapping and effectiveness assessment into a unified analytical process. Drawing on PADM and risk communication theory, the findings further indicate that a multi-level warning system is not merely an instrument for classifying and reporting hazard severity but may also function as a governance mechanism involving both risk identification and behavioral intervention. In this framework, the

warning level represents both a hazard-severity category and a semantic attribute associated with each time–location record, reflecting differences in communication intensity, action requirements, and the potential to trigger protective responses. The stronger protective associations observed for high-level warnings are consistent with the interpretation that stronger expressions of risk, clearer action instructions, and more explicit restrictive measures may facilitate the transition from risk information to threat appraisal and protective action. By contrast, the pattern observed for yellow warnings suggests a potential level-specific weakness in the transition from risk communication to behavioral response.

From a practical perspective, warning system optimization should not be limited to improving the accuracy and timeliness of warning issuance but should also consider how information is expressed at different warning levels and how effectively it supports protective responses. Medium-level warnings, in particular, should provide clearer expressions of urgency, action-oriented guidance, and management requirements, and should be more closely coordinated with measures such as visitor-flow restriction, intensified patrols, temporary closure, route adjustment, and evacuation. A more consistent translation of warning information into concrete protective action is, therefore, important for strengthening the transition from risk signaling to risk reduction. Overall, the proposed framework provides a spatially explicit empirical basis for evaluating the performance of multi-level disaster warnings and may inform the refinement of warning communication and preventive management in tourism destinations exposed to natural hazards.

6.4. Limitations and Future Directions

Several limitations of this study should be acknowledged. First, sample size remains an important factor affecting the precision of the results. The number of tourism safety accidents included in this study is relatively limited; further stratification by warning level reduces the amount of information available for estimating some level-specific effects. Second, although the case-crossover design can control for relatively stable time-invariant factors within counties, it cannot fully eliminate time-varying confounding. Short-term environmental and contextual factors, such as holidays and large-scale events, may simultaneously influence both the probability of accident occurrence and warning exposure. Although sensitivity analyses using different exposure windows and alternative referent periods yielded generally consistent effect directions, these analyses can reduce but cannot completely eliminate the potential influence of time-varying confounding. Third, warnings and accidents were standardized to county-level spatial units for the analysis, which improves the consistency of spatial matching across different data sources but also introduces sensitivity to spatial aggregation. The modifiable areal unit problem (MAUP) indicates that the results of spatial analysis may change with the scale and boundary configuration of the analytical units, while aggregation into larger spatial units may smooth or obscure local spatial heterogeneity [49]. This issue is particularly relevant in western Sichuan, where some counties cover very large areas and exhibit substantial within-county variation in terrain, elevation, hazard-affected areas, and the spatial distribution of tourism activities. During warning-information extraction, township-level locations were retained whenever they could be identified from the warning texts; county-level locations were used only when township-level information was unavailable. However, in practice, government disaster warnings are predominantly issued at the county administrative level. County-level information, therefore, constitutes the most common and relatively consistent spatial level in the warning dataset. Under the assumption of uniform county-level exposure, a warning issued for only part of a county may be assigned to the entire county, whereas the actual accident location may not fall within the same hazard-affected area, thereby potentially introducing a certain degree of exposure misclassification.

Future research can proceed in three directions. First, the accident sample and spatial coverage should be expanded by incorporating warning and tourism safety accident data from multiple provinces or even multiple countries, thereby improving the statistical power and external validity of effect estimates for different warning levels. Second, the mechanism analysis could be further developed by examining the moderating roles of warning dissemination, implementation by scenic-area management, and tourist behavior in the relationship between warnings and accidents, as well as the association between warning information and accident occurrences. Third, multi-scale spatial matching and sensitivity analyses should be conducted by comparing warning exposure and accident outcomes across counties, townships, scenic areas, or finer spatial units. Such analyses would allow for the sensitivity of the current findings to spatial aggregation and the MAUP to be evaluated and would further improve the spatial precision of warning-effectiveness assessments.

7. Conclusions

This study develops an integrated framework combining natural language processing, geospatial information extraction, and spatiotemporal analysis to evaluate the performance of the tourism warning system in Sichuan Province, China. First, a BERT-CRF model was employed to transform official warning texts into structured records containing information on time, location, hazard type, and warning level. These records were then standardized and linked with tourism safety accident records at the county level within a 72 h exposure window preceding each accident. The resulting dataset supported analyses of the temporal distribution, spatial differentiation, and inter-hazard co-occurrence of warning information, and was further used in a case-crossover design to estimate the short-term association between warning exposure and accident occurrence. By linking authoritative textual information with administrative spatial units and observed safety outcomes, the proposed framework provides a systematic pathway for converting unstructured warning information into spatially explicit evidence for risk evaluation.

The results show that warning issuance is concentrated in periods and locations where tourism safety risk has already increased, supporting the interpretation that the warning system performs a risk-identification function. However, the association between warning information and accident risk varies substantially across warning levels. The warning-level gradient model indicates an overall decline in accident risk as warning levels increase, while red warnings and the combined category of orange and red warnings exhibit the strongest protective associations. Yellow warnings are significantly concentrated in high-risk contexts but do not show a stable risk reduction association comparable to that observed for high-level warnings. This pattern suggests that yellow warnings can function effectively as spatiotemporal risk markers but remain relatively limited in facilitating the transition from risk identification to protective action.

Optimization of the warning system should, therefore, not be limited to improving the accuracy and timeliness of warning issuance but should also consider how information is communicated at different warning levels and how effectively such information supports protective action. A more consistent translation of warning information into concrete protective measures is important for strengthening the transition from risk signaling to risk reduction. Overall, the framework proposed in this study provides a spatially explicit empirical basis for evaluating the performance of multi-level disaster warning systems and may inform improvements in warning communication and preventive management in tourism destinations exposed to natural hazards.

Author Contributions: Aike Kan: Conceptualization, Methodology, Supervision, Project administration, Writing—Original Draft, Writing—Review and Editing, Validation. Nengsheng Li: Formal analysis, Software, Data Curation, Writing—Original Draft, Visualization. Xiao Yang: Writing—Original Draft, Writing—Review and Editing, Project administration. Yichen Li: Investigation, Resources, Data Curation, Software. Hongzhou Deng: Visualization, Resources, Software, Formal analysis. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Key Laboratory of Plateau Mountain Tourism Equipment and Intelligent Technology (Sichuan Tourism University), Sichuan Provincial Department of Culture and Tourism (Grant No. 24MTE101) and the Key Project of Sichuan Provincial Cultural and Tourism Scientific Research Program (Grant No. 2024ZD16).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflict of interest.

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