

Article

Typhoon Disaster Chain Evolution Modelling in the Guangdong–Hong Kong–Macao Greater Bay Area Based on GERT Stochastic Networks: A Case Study of Typhoon Mangkhut

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Abstract

Typhoon disaster chains—cascading sequences of hazards triggered by tropical cyclones—pose significant risks to highly urbanized coastal regions. However, quantitative modelling of their stochastic evolution, including both propagation probabilities and temporal dynamics, remains limited. This study develops a typhoon disaster chain evolution model by integrating the FBIREC (Factor-Bearing body- Incident-Response-Environment-Consequence) scenario representation framework with a Graphical Evaluation and Review Technique (GERT) stochastic network. The model is applied to the Guangdong–Hong Kong–Macao Greater Bay Area using Typhoon Mangkhut (2018) as a case study. Ten cascading event sequences are identified, and their transmission probabilities and expected durations are calculated. The model reproduces the observed event probabilities for Typhoon Mangkhut with high fidelity, with a mean absolute error of 4.31% and a coefficient of determination $R^2 = 0.816$. Power facility damage was identified as one of the most influential infrastructure nodes, exhibiting high propagation potential to multiple downstream service systems. The disaster chain unfolds across two temporal scales: short-term risks (0–48 h) and long-term risks (>48 h), providing quantifiable targets for phased emergency response planning. The proposed framework provides a methodological reference that can be adapted to other typhoon-prone regions following case-specific re-parameterization.

Keywords: typhoon disaster chain; GERT network; cascading hazards; Greater Bay Area; emergency management; probabilistic modelling; stochastic network



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1. Introduction

In recent decades, climate change has contributed to an increase in both the frequency and intensity of extreme weather events, resulting in substantial social and economic impacts worldwide. According to the Global Disaster Data Platform of China's Ministry of Emergency Management [1], natural disasters caused approximately USD 1.636 trillion in direct economic losses globally between 2014 and 2023, affecting more than 225 countries and regions. Among these events, storms accounted for nearly USD 961.39 billion, or about 58.76% of total meteorological disaster losses. Within this category, tropical cyclones—commonly referred to as typhoons in the western North Pacific—are widely regarded as one of the most destructive hazards affecting coastal areas. Their impacts extend beyond strong

winds to include a range of interacting hazards such as heavy rainfall, storm surges, urban flooding, landslides, and infrastructure failures. These processes are often interconnected and can evolve into so-called disaster chains, where an initial hazard triggers a sequence of secondary and tertiary events that amplify overall impacts. For instance, Typhoon Haikui (2023) affected southern China by triggering extreme rainfall and widespread urban flooding across the Guangdong–Hong Kong–Macao Greater Bay Area (GBA), which subsequently led to transportation disruptions, infrastructure damage, and prolonged service interruptions [2,3].

The Greater Bay Area is one of the most economically active and highly urbanized coastal regions in Asia. Situated along the northern coast of the South China Sea, it spans more than 1500 km of coastline and contains a major cluster of global ports and densely populated urban centers. However, its location within the primary track of western North Pacific typhoons makes it particularly exposed to typhoon-related hazards. When typhoons make landfall, strong winds, storm surges, and intense rainfall interact with highly interconnected urban systems, often resulting in cascading failures across infrastructure networks. Understanding these cascading dynamics is therefore essential for improving disaster risk management and enhancing regional resilience.

Despite growing attention to typhoon-induced disaster chains, quantitative modelling of their stochastic evolution remains limited, especially in rapidly urbanizing coastal megaregions such as the Greater Bay Area. To address this gap, this study develops a typhoon disaster chain evolution model based on the Graphical Evaluation and Review Technique (GERT) network framework and applies it to the Greater Bay Area. This study makes three contributions to the literature on typhoon disaster chain modelling. First, it proposes a hybrid FBIREC–GERT framework that systematically maps typhoon disaster scenarios into a stochastic network capable of representing both probabilistic branching and temporal dynamics—a combination not previously applied to typhoon disaster chains. Second, the model provides quantitative estimates of transmission probabilities and expected durations for representative propagation pathways, enabling the identification of time-critical intervention windows that static network models cannot offer. Third, through a case-study calibration using Typhoon Mangkhut (2018)—one of the most severe typhoons to affect the region in recent years—the study illustrates the applicability of the proposed framework in reproducing observed cascade patterns and identifying influential infrastructure nodes within typhoon disaster chains. The results provide quantitative insights into disaster propagation probabilities and temporal characteristics that can support emergency response planning and resilience enhancement in coastal megaregions.

Accordingly, this study addresses the following research questions:

- RQ1: How can the FBIREC framework and GERT stochastic network modelling be integrated to represent the probabilistic propagation of typhoon disaster chains in the Guangdong–Hong Kong–Macao Greater Bay Area?
- RQ2: What are the dominant hazard pathways, critical infrastructure dependencies, and temporal characteristics associated with typhoon disaster-chain evolution under super-typhoon conditions?
- RQ3: How can the FBIREC–GERT framework support disaster-risk reduction, emergency-management planning, and sustainable urban resilience in coastal megaregions?

The remainder of the paper is organized as follows. Section 2 reviews relevant literature on disaster chain modelling and applications of GERT. Section 3 presents the methodology, including the FBIREC framework and the GERT network model, and also describes the research design, data sources, and parameter settings. Section 4 presents the simulation results based on Typhoon Mangkhut (2018). Section 5 discusses interruption

risks, implications for emergency management, and study limitations. Section 6 concludes the paper.

2. Literature Review

2.1. Comparative Review of Disaster Chain Modelling Methods

Disaster chain theory provides an important framework for understanding how an initial natural hazard can trigger a sequence of secondary and tertiary disasters, thereby amplifying overall impacts [4]. Similar concepts have been discussed in the international literature under the frameworks of multi-hazard interactions and cascading disasters. Multi-hazard environments are characterized by complex interactions among different hazard processes, creating compound and cascading impacts that are difficult to assess using single-hazard approaches [5]. Recent studies on compound weather and climate events further emphasize that multiple hazard drivers may occur simultaneously or sequentially, leading to amplified impacts beyond those associated with individual hazards alone [6]. Cascading disasters further emphasize the propagation of disruptions across interconnected physical and social systems, where an initial hazard may trigger a sequence of secondary and tertiary consequences [7]. These perspectives provide important theoretical foundations for understanding the evolution of typhoon disaster chains.

In the context of typhoon-prone coastal regions, disaster chains typically involve cascading processes such as wind damage, storm surges, extreme precipitation, urban waterlogging, and geological hazards, which may further disrupt critical infrastructure systems including electricity, transportation, and water supply networks [8–10]. Such processes can also be interpreted from a compound-event perspective, in which multiple hazard drivers interact either simultaneously or sequentially to generate impacts that exceed those associated with individual hazards considered separately [11]. Previous studies have characterized typhoon disaster chains as exhibiting multifactorial, dynamic, and uncertain properties, meaning that a single typhoon event can simultaneously induce multiple hazard factors, all elements of the disaster chain system are in flux, and the timing, location, and intensity of disaster propagation remain difficult to predict accurately.

Several quantitative approaches have been developed to model disaster chain evolution. These can be broadly categorized into four types: Bayesian network models, complex network analysis, knowledge graph methods, and stochastic network models (including GERT). Each offers distinct capabilities and limitations for disaster chain analysis.

- Bayesian network models have been widely used for probabilistic inference in disaster evolution. A Bayesian-network-based reasoning model was developed for rainstorm–geological and rainstorm–flood disaster chains [12]. A Bayesian-based interruption model for the rainstorm–landslide–flash flood disaster chain in the Greater Bay Area was constructed to identify critical thresholds under different rainfall scenarios [13]. Bayesian inference has also been integrated with GERT networks to enable real-time updates of disaster evolution parameters [14]. Recent studies have further extended Dynamic Bayesian Networks (DBNs) for infrastructure resilience assessment and multi-hazard risk analysis. For example, Caetano et al. [15] developed a DBN-based framework for resilience assessment of critical infrastructures through evidence propagation, while Bakhtiari et al. [16] applied DBNs to characterize multi-hazard risks and resilience in interconnected infrastructure systems. The principal advantage of Bayesian networks lies in their capacity for dynamic parameter updating through observed evidence. However, they typically do not incorporate explicit temporal dynamics—that is, they model the probability of event occurrence but not the expected duration or variance of transitions between events. Complex network analysis has been applied to identify critical nodes and topological vulnerabilities within disaster

chains. Previous studies on interdependent infrastructure systems have highlighted the importance of network connectivity and cascading failures in determining systemic resilience [17]. Risk analysis of Shenzhen’s typhoon disaster chains using complex disaster networks identified power infrastructure as a key vulnerability node [18]. Complex network modelling has also been applied to typhoon disaster chains in critical infrastructure systems [19]. In addition, an earthquake disaster chain model for urban engineering systems was developed based on complex network theory [20]. While effective for structural analysis and node criticality identification, complex network approaches are typically static and do not represent the probabilistic propagation of cascading events overtime.

- Knowledge graph methods offer semantic representation of disaster chain relationships. Knowledge graphs have also been applied to urban flood disaster chain deduction and spatio-temporal characteristics analysis [21]. Recent studies have further incorporated knowledge-graph reasoning techniques into emergency-management systems. For example, Chen et al. [22] developed a knowledge-graph and large-language-model framework to support emergency decision-making by improving hazard knowledge extraction, reasoning, and information retrieval. These methods excel at capturing qualitative relationships between disaster events but have limited capacity for quantitative probability estimation or temporal modelling.
- Stochastic network models, particularly the Graphical Evaluation and Review Technique (GERT), have attracted considerable interest due to their ability to represent stochastic processes, probabilistic branching, and feedback loops in complex systems [23]. Unlike Bayesian networks, GERT explicitly represents sequential dependencies and parallel pathways, and its moment-generating function (MGF) framework enables the calculation of expected durations and variances—not just probabilities. Table 1 summarizes the comparative capabilities of these four approaches.

Although recent DBN-based approaches have improved dynamic uncertainty modelling, they generally focus on probabilistic state transitions and infrastructure resilience assessment. In contrast, GERT networks simultaneously represent probabilistic branching structures and temporal characteristics, enabling the direct estimation of both pathway occurrence probabilities and expected propagation durations.

Table 1. Comparative capabilities of disaster chain modelling methods.

Method	Probabilistic Inference	Temporal Modelling	Parallel Pathways	Feedback Loops	Dynamic Updating
Bayesian Network	✓	×	✓	Limited	✓
Complex Network	Partial	×	✓	×	×
Knowledge Graph	×	×	✓	×	×
GERT (this study)	✓	✓	✓	✓	× *

* The proposed GERT framework does not inherently support dynamic parameter updating. Dynamic updating can be achieved through integration with Bayesian inference or other data-assimilation techniques.

2.2. GERT Applications in Disaster Research

The theoretical foundation of GERT networks was established in early work on stochastic network analysis. Feedback mechanisms and path convergence in GERT networks were analyzed to support subsequent model development [24]. Computational efficiency for large-scale network analysis was further improved through matrix representations of GERT networks [25].

Subsequent studies expanded the application of GERT networks to disaster evolution modeling across several domains. In earthquake disaster analysis, Dynamic scenario up-

dating mechanisms have been introduced to enable GERT networks to adapt to evolving disaster conditions during seismic events [26]. Stochastic network modelling has also been applied to simulate the evolution of oil storage fire accidents, demonstrating the potential of scenario-based simulation approaches for analyzing complex disaster processes [27]. In emergency response optimization, FAHP-based approaches have been used to identify critical risk factors in emergency supply chains [28]. GERT-based models incorporating fuzzy comprehensive evaluation and dynamic optimization approaches have also been developed for emergency rescue route selection and disaster resource allocation analysis [29,30]. In addition, infrastructure network optimization models have provided important support for disaster chain interruption strategies from the perspective of emergency resource allocation [31]. Dynamic Bayesian Networks (DBN) have also been integrated with GERT models to achieve multi-objective optimization of risk, time, and cost, highlighting the potential for coordinated optimization of dynamic risk quantification and emergency resource scheduling in disaster response systems [32].

Recent studies on compound hazards have increasingly emphasized the importance of considering interactions among multiple hazard drivers and interconnected infrastructure systems when assessing disaster evolution processes. For example, Ming et al. [33] proposed a quantitative multi-hazard risk assessment framework for compound flooding that explicitly incorporates hazard interdependencies and interactions. These studies demonstrate that cascading consequences may emerge from the combined effects of multiple hazards rather than from individual hazards considered in isolation. However, existing GERT-based applications have predominantly focused on earthquake-triggered, landslide, or industrial disaster chains. The complex cascading processes triggered by typhoons—which simultaneously involve multiple interacting hazard types (wind, storm surge, and rainfall) propagating through highly interconnected urban infrastructure systems—have received comparatively less attention within the GERT framework.

2.3. Research Gaps and Positioning

Despite the advances reviewed above, three specific gaps remain in the literature. First, systematic probabilistic network models for typhoon disaster chains have not yet been fully established. Existing GERT-based disaster chain studies mainly focus on earthquakes, landslides, or flash flood events, while the complex cascading processes triggered by typhoons—involving simultaneous wind, surge, and rainfall hazards—have received relatively less attention. Second, the temporal dimension of disaster chain propagation is underrepresented. Although probability estimation has been addressed through various methods, the expected duration and variance of transitions between disaster events—critical information for emergency response planning—are rarely quantified. Third, the integration of structured scenario representation frameworks with stochastic network simulation remains largely unexplored in the context of typhoon disaster chains, despite previous studies highlighting the need for such combined approaches [32].

This study addresses these three gaps by developing a hybrid FBIREC-GERT framework that (1) provides the first systematic GERT-based probabilistic network model for typhoon disaster chains, (2) quantifies both transmission probabilities and expected durations with variances for each pathway, and (3) integrates structured scenario mapping with stochastic network simulation.

3. Materials and Methods

The overall research workflow adopted in this study is illustrated in Figure 1.

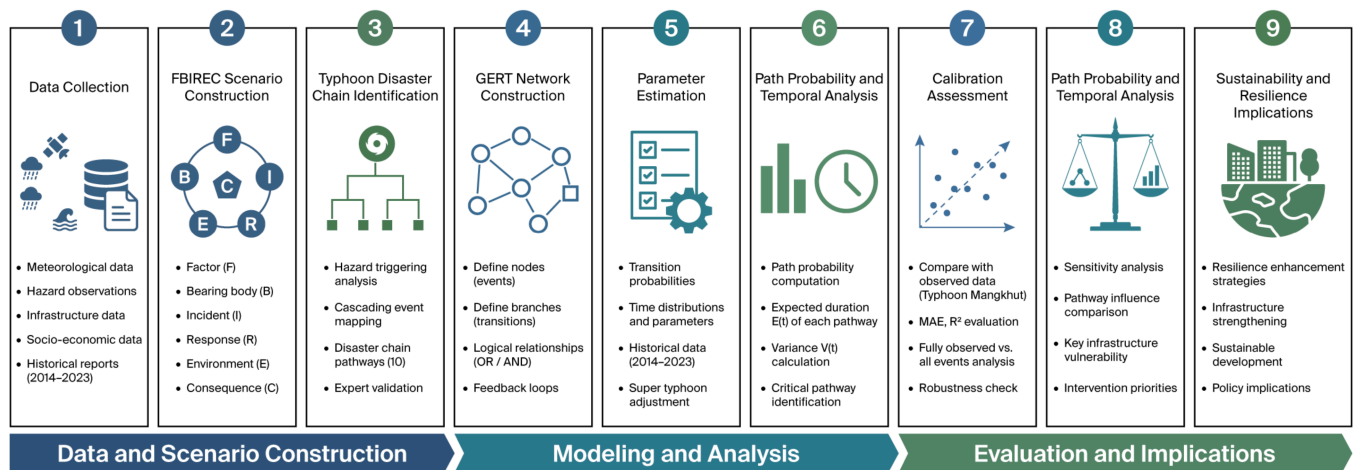


Figure 1. Research Framework of the FBIREC–GERT-Based Typhoon Disaster Chain Assessment.

3.1. The FBIREC Framework for Disaster Chain Representation

To systematically represent typhoon disaster chains and their constituent components, this study adopts the FBIREC framework [34], which consists of six key elements: initial hazard factor (F), disaster-bearing body (B), incident (I), emergency response (R), environment (E), and consequences (C). The framework provides a structured way to capture the contextual characteristics and interaction mechanisms within each branch of a typhoon disaster chain.

The initial hazard factor (F) refers to potentially destructive natural or human-induced triggers, with their impact depending largely on the exposure and vulnerability of affected systems. The disaster-bearing body (B) represents the entities exposed to hazards, whose physical and functional characteristics influence the propagation of disaster effects. Incidents (I) describe the states or events that emerge when disaster-bearing bodies are impacted by hazard factors. For instance, typhoon winds (F) over open seas are typically regarded as meteorological phenomena; however, when they make landfall and interact with coastal urban systems (B), they may trigger a series of hazardous events such as storm surges and structural failures (I), thereby initiating cascading disaster processes.

Emergency response (R) refers to intervention measures aimed at both disaster-bearing bodies and incidents, with the purpose of reducing risk and interrupting the progression of disaster chains. The environment (E) encompasses the broader geographical, meteorological, and socio-economic context in which disasters occur, while consequences (C) represent the resulting losses in terms of infrastructure damage, economic impacts, and casualties.

For example, a typhoon may induce storm surges that damage seawalls, leading to coastal inundation and urban flooding. In response, emergency agencies may implement seawall reinforcement and evacuation measures, while the final consequences include economic losses and service disruptions.

Based on existing literature [19,21] and empirical analysis, typhoon-related hazards can be broadly categorized into three primary types: storm surges, heavy rainfall, and strong winds. These primary hazards further trigger secondary hazards such as floods, building collapses, flash floods, and landslides, which together form a cascading typhoon disaster chain characterized by a sequential process of occurrence, development, and evolution.

Some secondary disasters may be jointly triggered by multiple primary hazards and further develop into cascading chains of subsequent impacts. Taking flooding as an example, storm surges and heavy rainfall can simultaneously affect coastal flood protection infrastructure, such as seawalls and sluice gates, leading to seawater intrusion into low-

lying coastal areas. In addition, short-duration intense precipitation increases pressure on urban drainage systems, further exacerbating surface water accumulation.

Once the drainage capacity is exceeded, urban flooding in roads and residential areas becomes more likely, which in turn increases structural stress and the risk of building damage or collapse. Floodwaters may also transport surface contaminants into groundwater systems, thereby threatening drinking water safety and potentially affecting agricultural productivity and soil conditions.

Based on the theoretical foundation of the FBIREC framework and the disaster chain relationships and emergency response processes described above, this study constructs typhoon disaster scenario evolution pathways. The initial hazard factor is defined as a typhoon event, and the overall evolution process is illustrated in Figure 2. The disaster-forming environment, including spatial and socio-economic conditions, is treated as contextual background and is therefore not explicitly included in the flowchart.

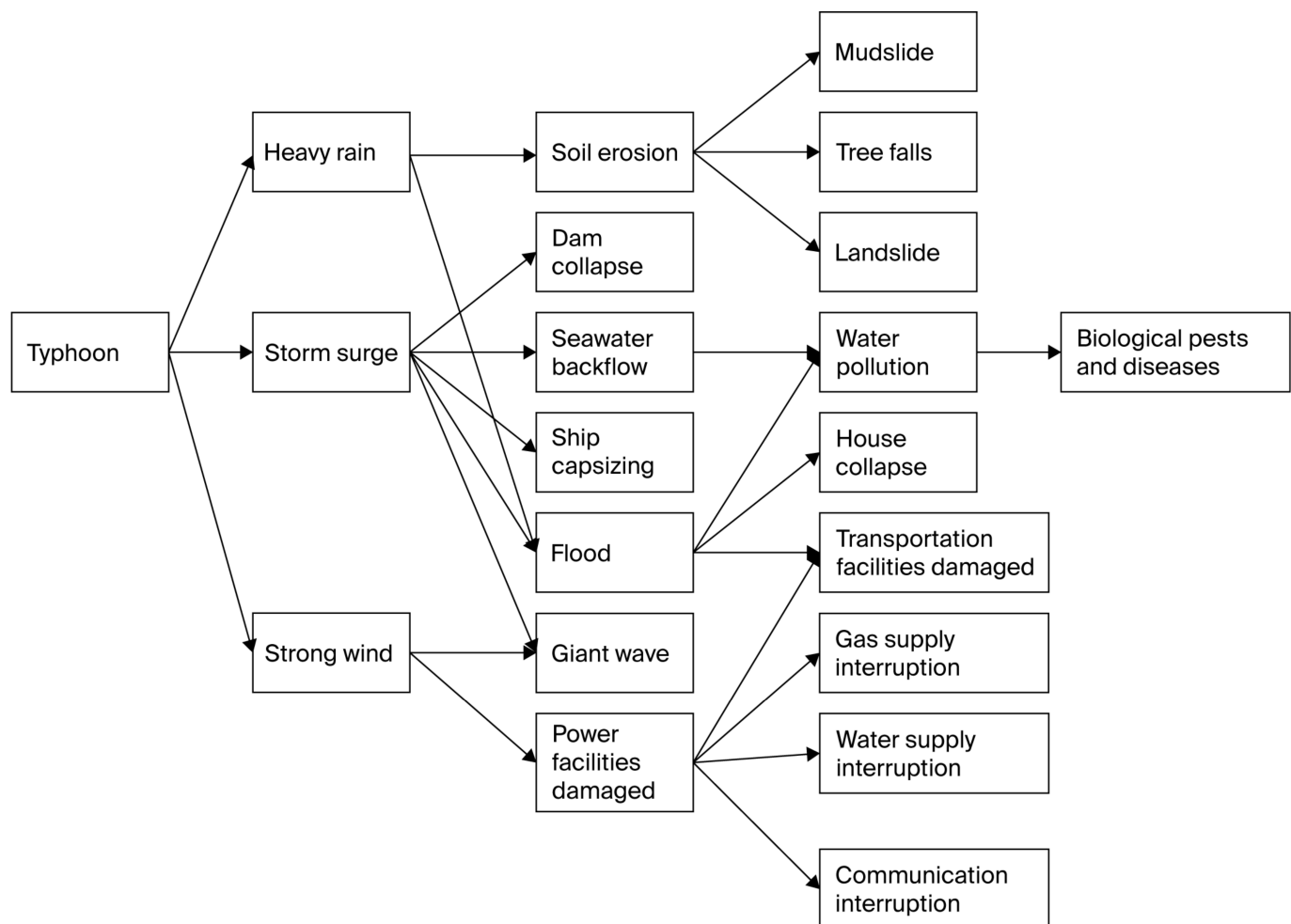


Figure 2. Typhoon occurrence–development–evolution chain.

Some secondary disasters may be jointly triggered by multiple primary hazards and further develop into cascading chains of subsequent impacts. Taking flooding as an example, storm surges and heavy rainfall can simultaneously affect coastal flood protection infrastructure, such as seawalls and sluice gates, leading to seawater intrusion into low-lying coastal areas. In addition, short-duration intense precipitation increases pressure on urban drainage systems, further exacerbating surface water accumulation.

Once the drainage capacity is exceeded, urban flooding in roads and residential areas becomes more likely, which in turn increases structural stress and the risk of building

damage or collapse. In addition, floodwater can transport surface contaminants into groundwater systems. Such water quality contamination not only threatens drinking water safety but may also have longer-term implications for agricultural productivity and soil conditions.

Based on the theoretical foundation of the FBIREC framework and the disaster chain relationships and emergency response processes described above, this study constructs typhoon disaster scenario evolution pathways. The initial hazard factor is defined as a typhoon event, and the overall evolution process is illustrated in Figure 3. The disaster-forming environment, including spatial and socio-economic conditions, is treated as contextual background and is therefore not explicitly included in the flowchart.

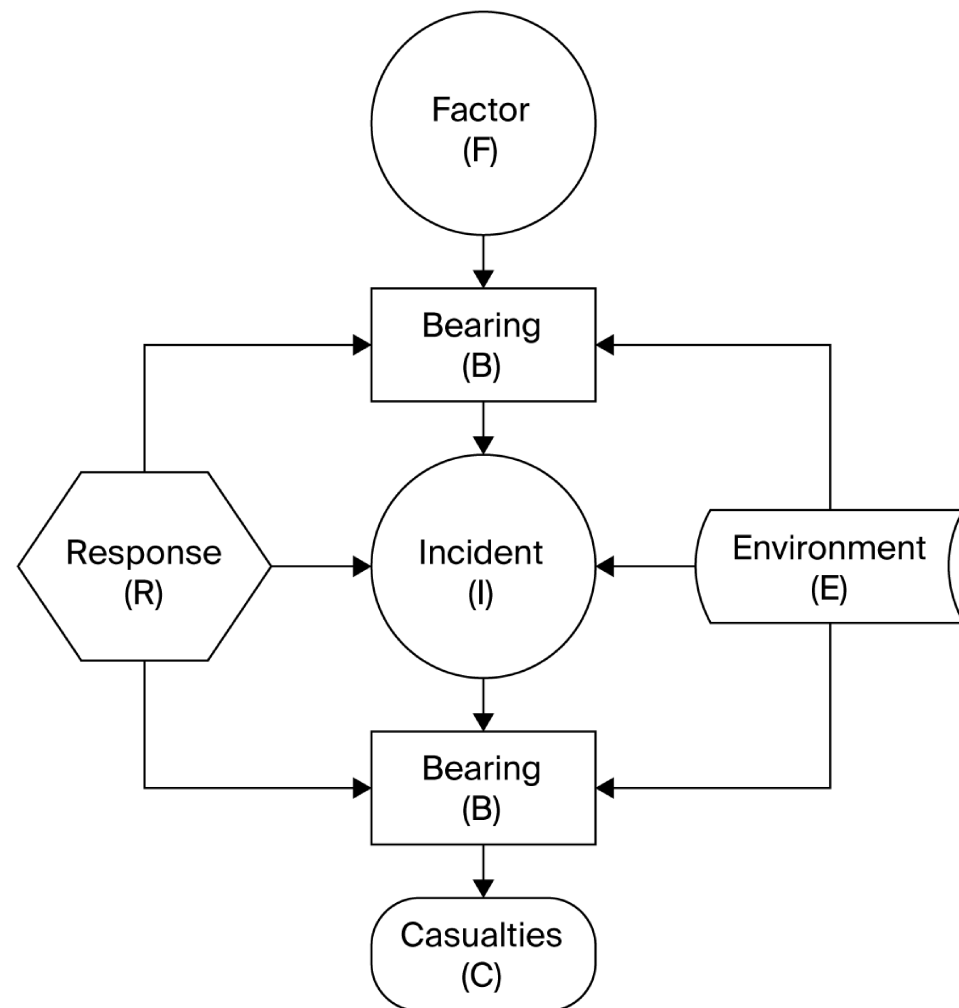


Figure 3. FBIREC Model: Single Scenario Relationships.

By combining the typhoon occurrence–development–evolution chain shown in Figure 2 with the FBIREC single-scenario framework shown in Figure 3, the complete typhoon disaster scenario evolution process was constructed, as illustrated in Figure 4.

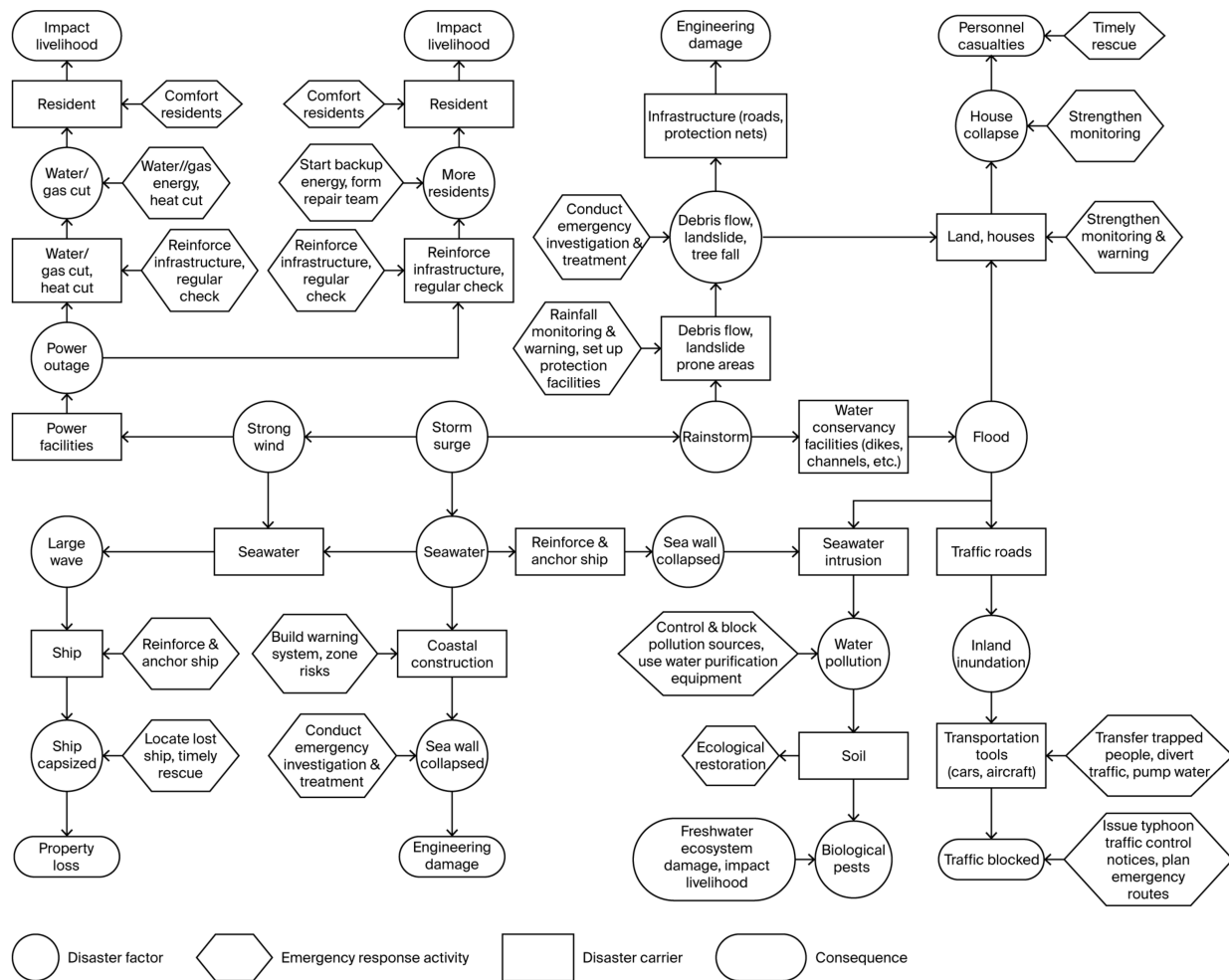


Figure 4. Typhoon disaster scenario evolution process.

3.2. GERT Network Model

GERT integrates network theory, probability analysis, simulation modeling, and signal flow graphs to form a system analysis method with stochastic characteristics. Compared to traditional network techniques, GERT's core value lies in its ability to effectively handle probabilistic associations and stochastic logical relationships between nodes, providing a mathematical foundation for dynamic behavior modeling of complex systems.

The three elements of a GERT network are logical nodes, directed branches, and flows [35]. Nodes are jointly composed of input and output ends. The input end has three logical relationships (exclusive-or, inclusive-or, and-and), while the output end has two logical relationships (deterministic and probabilistic). This configuration yields six node types, as summarized in Table 2.

Table 2. GERT logical node characteristics and symbols.

Node Type		Node Meaning
Input end	Exclusive-or	Any branch leading to the node being realized results in node realization, but only one branch is realized at a given time.
	Inclusive-or	Any branch leading to the node being realized results in node realization.
	And	Node realization occurs only when all branches leading to the node are realized.
Output end	Deterministic	Activities emanating from the node are always realized (probability of realization = 1 for all branches).
	Probabilistic	Only one activity emanating from the node is realized upon node realization.

GERT networks are essentially models of semi-Markov processes. In this process, the transition probability from state i to state j (or itself) is determined by a Markov chain, while the transition time is a random variable associated with states i and j . In GERT networks, transition probabilities correspond to the realization probabilities of activities (i, j), and transition times correspond to the durations of activities (i, j). The basic building block of the GERT network is shown in Figure 5.

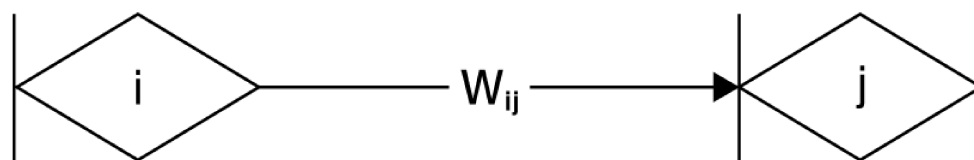


Figure 5. Basic unit structure of the GERT network.

Based on the typhoon disaster chain constructed in Section 3.1 and following logical transformation rules, the typhoon disaster scenario evolution process (Figure 4) is mapped into a GERT network model. The key scenarios in the evolution process are identified in Table 3.

Table 3. Key scenarios in the typhoon evolution process.

Scenario and Description	Scenario and Description
Typhoon generation S_0	Short-duration heavy rainfall S_1
Storm surge formation S_2	Strong winds S_3
Debris flows S_4	Landslides S_5
Tree falls S_6	Dam breaches S_7
Seawater intrusion S_8	Floods S_9
Giant waves S_{10}	Power facility damage S_{11}
Infrastructure damage S_{12}	Water quality pollution S_{13}
Building damage S_{14}	Transportation disruption S_{15}
Gas supply interruption S_{16}	Water supply interruption S_{17}
Communication interruption S_{18}	Increased biological pests/diseases S_{19}
Ship capsizing S_{20}	Reconstruction S_{21}
Emergency repair S_{22}	Ecological restoration S_{23}

In the GERT network, each scenario state is represented by corresponding “or-type” nodes. The network beginning has probabilities all equal to 1, using “deterministic” output nodes. Through appropriate logical transformations, both “inclusive-or” and “and-type” nodes can be converted to “exclusive-or” nodes. Through appropriate logical transformations, inclusive-or and and-type structures can be represented using equivalent exclusive-or computational forms. Accordingly, exclusive-or nodes were adopted for analytical tractability in the transfer-function calculation. It should be noted, however, that the branch probabilities used in this study represent conditional hazard-transition probabilities derived from historical observations rather than mutually exclusive routing probabilities. Therefore, multiple downstream consequences may be associated with the same upstream hazard event.

It should be noted that this simplification may affect model fidelity for nodes that inherently require multiple simultaneous inputs (and-type logic). For instance, in reality, certain infrastructure failures may require the co-occurrence of both flooding and power outage rather than either alone. However, the exclusive-or simplification is standard practice in GERT modelling and enables tractable analytical solutions. The implications of this modelling simplification are further discussed in the Limitations section (Section 5.4).

The resulting GERT network diagram for typhoon disaster chain evolution is presented in Figure 6. This network comprises two basic structural types: series structure and parallel

structure. Series structures represent sequential causal relationships (e.g., typhoon → heavy rainfall → tree falls), while parallel structures represent concurrent multiple pathways leading to the same outcome (e.g., both debris flows and landslides affecting infrastructure).

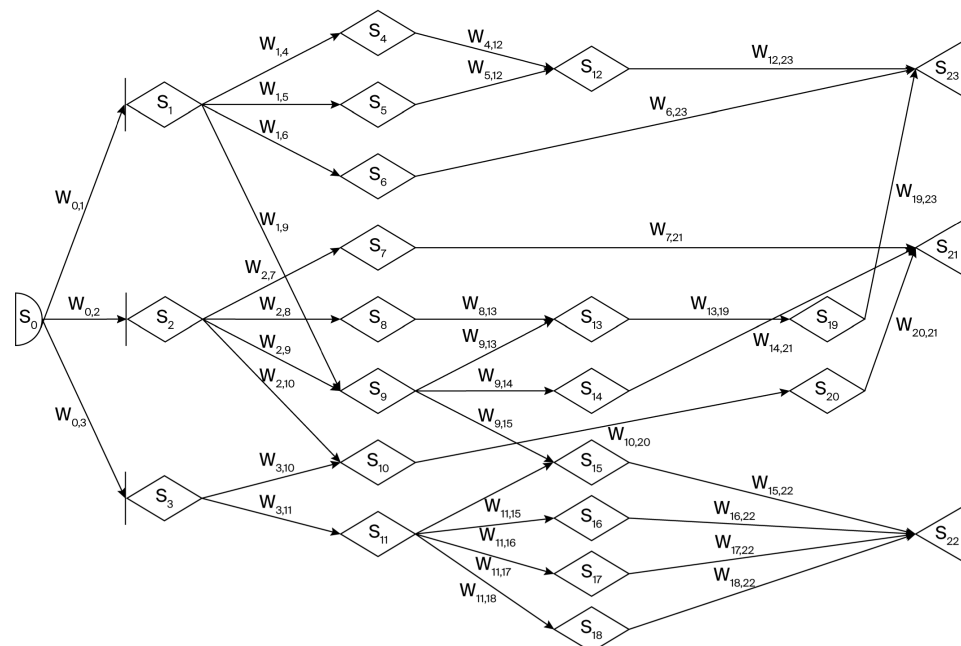


Figure 6. GERT network diagram for typhoon disaster chain evolution.

The complete GERT network shown in Figure 6 represents the full typhoon disaster-chain structure derived from the FBIREC framework. However, not all pathways were incorporated into the quantitative simulation. In particular, the environmental-impact pathway involving S_{13} (water quality pollution), its downstream consequence S_{19} (increased biological pests and diseases), and the reconstruction stage S_{21} were excluded from the quantitative GERT calculation because sufficient duration parameters and downstream transition information were not available for reliable parameterization. To ensure consistency between the simulation network and the available data, a reduced quantitative GERT simulation network was constructed, as shown in Figure 7.

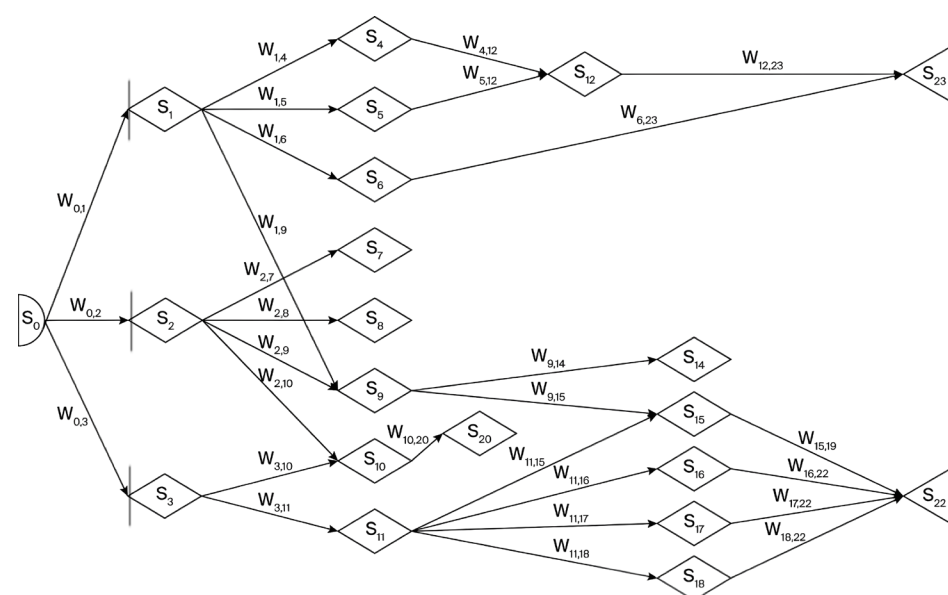


Figure 7. Quantitative GERT Simulation Network used in this study.

3.3. Model Logic and Transmission Mechanisms

The GERT network for typhoon disaster chains operates through directed branches that represent evolutionary relationships between disaster events. Two basic types of network structures govern the propagation of hazards: series structure and parallel structure. Understanding these structures is essential for calculating the overall transfer function of the disaster chain.

- **Series structure.** In a series structure, hazards propagate sequentially from one node to the next. This structure captures causal chains where one event must occur before the next can happen. For example, in the typhoon disaster chain, the sequence “typhoon → heavy rainfall → flood → building damage” follows a series structure because each event is a prerequisite for the subsequent one. In this case, the overall transfer function from the start node i to the end node j through intermediate nodes $a, b, \dots, d$ is the product of the individual transfer functions:

$$W_E(s) = W_{ia}(s) * W_{ab}(s) * \dots * W_{dj}(s) \quad (1)$$

- **Parallel structure.** In a parallel structure, multiple independent pathways can lead to the same outcome. This structure captures situations where different hazard processes can trigger the same disaster event. For example, infrastructure damage (S_{12}) may result from multiple independent hazard pathways, such as debris flows (S_4) or landslides (S_5). In a parallel structure, the overall transfer function from the start node i to the end node j is the sum of the individual transfer functions:

$$W_E(s) = W_{i1}(s) + W_{i2}(s) + \dots + W_{in}(s) \quad (2)$$

The overall probability of the outcome cannot be obtained by directly summing the probabilities of individual pathways, as parallel pathways may partially overlap. Therefore, the calculation must account for the logical relationship at the merging node, particularly the exclusive-or condition between alternative branches.

- **Combination of series and parallel structures.** The Quantitative GERT Simulation Network used in this study (Figure 7) consists of multiple series and parallel substructures arranged hierarchically. For series structures, the transfer functions of consecutive branches are multiplied sequentially. For parallel structures, the transfer functions of alternative branches are combined according to the exclusive-or relationship at the corresponding node. This recursive decomposition allows the systematic calculation of both transmission probabilities and expected durations throughout the disaster chain. In addition, the moment-generating function (MGF) associated with each branch describes the probability distribution of activity completion times, enabling the estimation of both expected values and variances. These measures are important for characterizing uncertainty in disaster propagation processes.
- **Example application.** Consider the pathway corresponding to Event 1: typhoon → heavy rainfall → (debris flow OR landslide) → infrastructure damage → ecological restoration. This pathway contains both series and parallel structures. The parallel substructure consisting of debris flow and landslide branches is first combined using the parallel reduction rule. The equivalent transfer function obtained from this step is then multiplied by the transfer functions of the remaining series branches, including typhoon → heavy rainfall and infrastructure damage → ecological restoration. Through this stepwise reduction process, the overall transfer function incorporates all feasible propagation pathways within the network.

By systematically applying these combination rules, the GERT network model quantifies both the occurrence probability and expected timing of disaster chain propagation

pathways, thereby providing a basis for identifying critical nodes and evaluating emergency response strategies.

3.4. Research Design and Data Sources

The GERT network model developed in Section 3.2 requires empirical parameterization to simulate typhoon disaster chain evolution. This section describes the data sources, parameter estimation methods, and the overall research design employed in this study.

The empirical data used in this study were obtained from multiple authoritative sources. Historical typhoon disaster records and conditional probability information were collected from the Ministry of Emergency Management of China, the Guangdong Meteorological Bureau, and the Shenzhen Meteorological Bureau, covering the period from 2014 to 2023. Additional information on event-level impacts and damage assessments was extracted from post-disaster reports and statistical yearbooks at both provincial and municipal levels in Guangdong Province. For the case study of Typhoon Mangkhut (2018), supplementary data were obtained from official government reports, meteorological bulletins, and verified media archives, including the 2018 Shenzhen Climate Bulletin. All datasets used in this study are publicly accessible through official institutional sources or available upon reasonable request.

3.5. Conditional Probability Estimation

For a given node S_j being realized, the conditional probability of a subsequent event S_i is defined as:

$$P_{ij} = P(S_j|S_i) = \frac{P(S_i \cap S_j)}{P(S_i)} \quad (3)$$

In this study, (p_{ij}) represents the conditional occurrence probability of event (S_j) given the realization of event (S_i) . Therefore, multiple downstream events may be triggered by the same upstream event, and the probabilities associated with outgoing branches from a node are not required to sum to one. The branch probabilities should thus be interpreted as conditional hazard-transition probabilities rather than mutually exclusive routing probabilities.

Based on existing studies compiling historical typhoon loss data and probabilistic estimates for Guangdong Province [34,35], the conditional probabilities for all event transitions were calculated and are summarized in Table 4.

Table 4. Conditional probabilities of activities in the typhoon emergency process.

Conditional Probability Code	Probability (%)	Conditional Probability Code	Probability (%)
P _{0,1}	85.4	P _{9,14}	40.0
P _{0,2}	67.0	P _{9,15}	65.0
P _{0,3}	67.1	P _{10,20}	5.0
P _{1,4}	19.6	P _{3,11}	48.6
P _{1,5}	19.6	P _{3,10}	70.7
P _{1,6}	20.5	P _{11,15}	65.2
P _{4,12}	46.0	P _{11,16}	20.0
P _{5,12}	32.0	P _{11,17}	66.0
P _{2,7}	10.6	P _{11,18}	66.0
P _{2,8}	33.5	P _{15,22}	85.0
P _{1,9}	35.6	P _{16,22}	98.0
P _{2,9}	37.8	P _{17,22}	95.0
P _{2,10}	12.8	P _{18,22}	98.0
P _{8,13}	15.0	P _{12,23}	90.0
P _{9,13}	30.0	P _{6,23}	90.0

Table 4 presents the historical conditional probabilities for the complete typhoon disaster-chain framework. Not all conditional probabilities reported in Table 4 were subsequently incorporated into the quantitative GERT simulation. In particular, environmental-impact processes associated with S_{13} and its downstream consequence S_{19} , as well as the reconstruction stage S_{21} , were retained in the conceptual framework but excluded from the quantitative simulation because reliable duration parameters and complete downstream transition information were unavailable. Therefore, these pathways do not appear in the activity parameter tables used for simulation (Tables 5 and 6).

3.6. Activity Parameters for Super Typhoon Scenarios

In the GERT network simulation, each directed branch is characterized by two core parameters: occurrence probability P_{ij} and time parameter t_{ij} . The time parameter represents the expected duration of transition from S_i to S_j .

It should be noted that the probability values assigned to activities in the super typhoon scenario (Table 5) differ from the historical conditional probabilities in Table 4. Table 4 reports average conditional probabilities derived from all typhoon events affecting Guangdong Province during 2014–2023, whereas Table 5 presents adjusted parameters specifically calibrated for super typhoon conditions (sustained winds category 14). The adjustment is based on empirical evidence from the literature [5,36,37] indicating that super typhoons exhibit systematically higher hazard transition probabilities due to their greater energy input and wider impact area. For example, the probability of typhoon-to-heavy-rainfall transition increases from 85.4% (historical average, Table 3) to 90.0% (super typhoon scenario, Table 5) based on observed data from category 14+ events. The parameter adjustment was intended to reflect the increased hazard intensity associated with super typhoon conditions and should therefore be interpreted as scenario-specific calibration rather than direct empirical estimation. These calibrated values were used to represent a plausible super-typhoon scenario based on historical observations and published literature, rather than to establish universally applicable transition probabilities.

Based on the moment-generating function (MGF) framework and empirical evidence from the literature, as well as datasets from the Ministry of Emergency Management of China, the parameters for each activity were estimated. Short-term parameters for super typhoon scenarios are presented in Table 5 while long-term ecological recovery parameters are provided in Table 6.

Additionally, the environmental-impact pathway (S_{13} – S_{19}) and the reconstruction stage (S_{21}), previously introduced in Figure 6, were not included in the quantitative parameterization presented in Tables 5 and 6 because corresponding duration parameters and complete downstream transition information were unavailable.

Table 5. Short-term activity parameters for super typhoon disasters.

Activity	Node Pair	Probability	Distribution	Parameter/h	MGF $M_{ij}(s)$
A ₁	$S_0 \rightarrow S_1$	0.90	Constant	$t = 0.2$	$\exp(0.2s)$
A ₂	$S_1 \rightarrow S_4$	0.20	Constant	$t = 0.2$	$\exp(0.2s)$
A ₃	$S_1 \rightarrow S_5$	0.20	Constant	$t = 0.2$	$\exp(0.2s)$
A ₄	$S_4 \rightarrow S_{12}$	0.50	Exponential	$t = 0.5$	$\exp(\frac{0.5}{0.5-s})$
A ₅	$S_5 \rightarrow S_{12}$	0.40	Exponential	$t = 0.5$	$\exp(\frac{0.5}{0.5-s})$
A ₆	$S_1 \rightarrow S_6$	0.28	Normal	$t = 1 \ \sigma = 0.2$	$\exp(1s + 0.02s^2)$
A ₇	$S_1 \rightarrow S_9$	0.40	Constant	$t = 0.5$	$\exp(0.5s)$
A ₈	$S_9 \rightarrow S_{14}$	0.42	Normal	$t = 1 \ \sigma = 0.2$	$\exp(s + 0.02s^2)$
A ₉	$S_9 \rightarrow S_{15}$	0.66	Constant	$t = 0.2$	$\exp(0.2s)$

Table 5. Cont.

Activity	Node Pair	Probability	Distribution	Parameter/h	MGF $M_{ij}(s)$
A ₁₀	S ₀ → S ₂	0.70	Constant	t = 0.1	exp(0.1s)
A ₁₁	S ₂ → S ₇	0.15	Constant	t = 0.1	exp(0.1s)
A ₁₂	S ₂ → S ₈	0.35	Exponential	t = 0.3	$\exp(\frac{0.3}{0.3-s})$
A ₁₃	S ₂ → S ₉	0.35	Constant	t = 0.5	exp(0.5s)
A ₁₄	S ₂ → S ₁₀	0.15	Constant	t = 0.05	exp(0.05s)
A ₁₅	S ₀ → S ₃	0.70	Constant	t = 0.2	exp(0.2s)
A ₁₆	S ₃ → S ₁₀	0.72	Constant	t = 0.05	exp(0.05s)
A ₁₇	S ₁₀ → S ₂₀	0.06	Constant	t = 0.02	exp(0.02s)
A ₁₈	S ₃ → S ₁₁	0.50	Constant	t = 0.2	exp(0.2s)
A ₁₉	S ₁₁ → S ₁₅	0.66	Constant	t = 0.5	exp(0.5s)
A ₂₀	S ₁₁ → S ₁₆	0.30	Constant	t = 0.4	exp(0.4s)
A ₂₁	S ₁₁ → S ₁₇	0.66	Constant	t = 0.5	exp(0.5s)
A ₂₂	S ₁₁ → S ₁₈	0.67	Constant	t = 0.2	exp(0.2s)
A ₂₃	S ₁₅ → S ₂₂	0.80	Normal	t = 12 σ = 3	exp(12s + 4.5s ²)
A ₂₄	S ₁₆ → S ₂₂	0.92	Normal	t = 10 σ = 3	exp(10s + 4.5s ²)
A ₂₅	S ₁₇ → S ₂₂	0.91	Normal	t = 10 σ = 3	exp(10s + 4.5s ²)
A ₂₆	S ₁₈ → S ₂₂	0.90	Normal	t = 12 σ = 3	exp(12s + 4.5s ²)

Duration parameters and distribution types were determined from published studies, official emergency-management reports, and engineering judgment according to the characteristics of different disaster processes under limited empirical data availability.

Table 6. Long-term activity parameters for super typhoon disasters.

Activity	Node Pair	Probability	Distribution	Parameter/h	MGF $M_{ij}(s)$
A ₂₇	S ₁₂ → S ₂₃	0.90	Normal	t = 25 σ = 10	exp(25s + 50s ²)
A ₂₈	S ₆ → S ₂₃	0.90	Normal	t = 5 σ = 5	exp(5s + 12.5s ²)

Duration parameters and distribution types were determined from published studies, official emergency-management reports, and engineering judgment according to the characteristics of different disaster processes under limited empirical data availability.

The selection of probability distributions for activity durations was guided by the operational characteristics of different disaster processes and common practices in GERT-based stochastic network modelling. Three distribution types were adopted in this study: constant, exponential, and normal distributions.

Constant distributions were assigned to rapid triggering processes and direct hazard transitions (e.g., typhoon occurrence, heavy-rainfall generation, storm-surge formation, and immediate infrastructure impacts). These activities typically occur within a relatively short time window and exhibit limited temporal variability compared with the overall disaster-chain evolution. Therefore, they were approximated as deterministic transitions for modelling simplicity.

Exponential distributions were assigned to hazard-development processes characterized by stochastic waiting times, including debris-flow generation, landslide-induced infrastructure impacts, and seawater intrusion. Such processes are influenced by multiple environmental conditions and may occur randomly after threshold exceedance, making the exponential distribution suitable for representing their temporal uncertainty.

Normal distributions were assigned to recovery-related activities and processes with relatively stable average durations, including emergency repair, utility restoration, ecological restoration, and tree-fall clearance. These activities are typically influenced by multiple independent factors, such as resource availability, workforce deployment, weather conditions, and logistical constraints. According to the central limit theorem, the combined effects of multiple independent factors can often be reasonably approximated using normal distributions.

The mean duration parameters were estimated from official disaster reports, emergency-management documents, and published studies concerning typhoon impacts in Guangdong Province. Standard-deviation parameters were introduced to represent operational uncertainty associated with disaster response and recovery activities. Specifically, $\sigma = 3$ h was assigned to emergency-repair processes (A23–A26), reflecting moderate variability in resource deployment, repair efficiency, and weather conditions during post-disaster operations. Larger uncertainty was assumed for long-term ecological restoration activities (A27), for which $\sigma = 10$ h was adopted because recovery durations are influenced by multiple environmental and management factors and generally exhibit substantially greater variability than short-term emergency repairs. These values should therefore be interpreted as representative scenario parameters rather than precise empirical measurements. Future studies may improve parameter accuracy through detailed empirical observations and larger post-disaster datasets.

For the stochastic network $G = (N, A)$, where node set N contains only “exclusive-or” type nodes, the probability parameter p_{ij} and moment-generating function were combined into a single parameter represented by the transfer function $W_{ij}(s)$:

$$W_{ij}(s) = p_{ij}M_{ij}(s) \quad (4)$$

where p_{ij} represents the occurrence probability of node (S_i, S_j) and $M_{ij}(s)$ represents the moment-generating function of that node. For transfer functions in parallel structures, Mason’s formula can be applied for solution:

$$W_E(s) = \frac{\sum_i P_i \Delta_i}{\Delta} = \frac{\sum_i P_i [1 + \sum_m (-1)^m (\text{m-order loop that does not touch path } i)]}{1 + \sum_m (-1)^m (\text{m-order loop})} \quad (5)$$

For transfer functions in series structures, the transfer function can be expressed as:

$$W_E(s) = W_{ia}(s) * W_{ab}(s) * \dots * W_{dj}(s) \quad (6)$$

From these, the transfer probability P_E , expected time $E(t)$, and variance $V(t)$ can be obtained by setting $s = 0$:

$$P_e = W_E(s) = W_E(0) \quad (7)$$

$$E(t) = \left. \frac{dM_E(s)}{ds} \right|_{s=0} \quad (8)$$

$$E(t^2) = \left. \frac{d^2 M_E(s)}{ds^2} \right|_{s=0} \quad (9)$$

These equations form the computational basis for quantifying the probabilistic propagation of typhoon disaster chains, enabling the calculation of transmission probabilities, expected durations, and their variances for each pathway in the network.

4. Results

4.1. Case Study Background: Typhoon Mangkhut (2018)

Typhoon Mangkhut, the 22nd named storm of the 2018 Northwest Pacific typhoon season, formed on 7 September and intensified gradually as it moved westward. On 15 September, it made landfall over Luzon Island in the Philippines as a super typhoon. It subsequently affected the coastal areas of Taishan, Guangdong Province on 16 September as a severe typhoon (category 14, central pressure 955 hPa), and was widely regarded as one of the most intense tropical cyclones to impact China in 2018. With a maximum sustained wind speed of approximately 65 m s^{-1} and a large-scale circulation system

exceeding 1000 km in diameter, Mangkhut generated widespread cascading impacts across the Guangdong–Hong Kong–Macao Greater Bay Area.

Following landfall, significant storm surge events were observed in the Pearl River Estuary region. In Humen Town, Dongguan, seawall overtopping and breaching led to seawater intrusion and inundation over an area of approximately 3.8 km². In Shenzhen, 493 power line failures were recorded, while waterlogging depths exceeded 1.2 m in parts of Bao'an and Pingshan districts. At Yantian Port, container damage rates exceeded 12% [38]. Transport infrastructure was also severely affected; operations at Guangzhou South Railway Station were suspended, and regional passenger flows decreased by approximately 70%.

Strong winds resulted in extensive urban treefall (approximately 17,000 cases in Shenzhen), contributing to traffic disruptions, with 97 road sections reported as impassable. Power outages affected approximately 150,000 households, which in turn constrained medical service capacity, with 12 hospitals experiencing temporary power loss and emergency response delays of up to 8.2 h. In Dongguan, industrial production was significantly disrupted, with an estimated 83% of manufacturing activities temporarily suspended, particularly within the electronics supply chain, resulting in direct economic losses of approximately CNY 120 million. In addition, more than 30,000 communication base stations were temporarily offline, and disruptions to public services were associated with a marked increase in emergency service demand.

Overall, the typhoon caused approximately 5800 building damage incidents and 320 km of road damage across the Greater Bay Area, with total direct economic losses estimated at CNY 4.06 billion. These impacts illustrate a typical cascading disaster chain, progressing from extreme wind hazards to flooding, infrastructure disruption, and subsequent socio-economic system disturbances.

4.2. GERT Network Simulation for Typhoon Mangkhut

Based on the quantitative GERT simulation network shown in Figure 7 and the calibrated activity parameters presented in Tables 5 and 6, the disaster-chain evolution of Typhoon Mangkhut (2018) was simulated.

Given that Typhoon Mangkhut made landfall with maximum sustained winds of category 14, exhibiting destructive power exceeding that of ordinary typhoons and falling within the super typhoon category, the activity parameters presented in Tables 5 and 6 are applicable. Based on Figure 7 and the data between nodes in Tables 5 and 6 for relevant routes in the typhoon disaster chain evolution GERT network (Figure 6), the complete activity links were identified, and probabilities for each complete event were calculated, as summarized in Table 7.

Table 7. Typhoon event sequences and corresponding links.

Event No.	Complete Link
Event 1	Typhoon → Heavy rainfall → Debris flow/Landslide → Infrastructure damage → Ecological restoration
Event 2	Typhoon → Heavy rainfall → Tree fall damage → Ecological restoration
Event 3	Typhoon → Heavy rainfall/Storm surge → Flood → Building damage
Event 4	Typhoon → Heavy rainfall → Flood → Transportation disruption → Traffic interruption./Typhoon → Storm surge → Flood → Transportation disruption → Traffic interruption./Typhoon → Strong wind → Power facility damage → Transportation disruption → Traffic interruption
Event 5	Typhoon → Storm surge → Dam breach
Event 6	Typhoon → Storm surge → Seawater intrusion
Event 7	Typhoon → Storm surge/Strong wind → Giant wave → Ship capsizing
Event 8	Typhoon → Strong wind → Power facility damage → Gas supply interruption → Emergency repair

Table 7. Cont.

Event No.	Complete Link
Event 9	Typhoon → Strong wind → Power facility damage → Water supply interruption → Emergency repair
Event 10	Typhoon → Strong wind → Power facility damage → Communication interruption → Emergency repair

Using the GERT network calculation formulas described in Section 3.6, all evolution route values were converted into specific data. Two representative paths were selected for detailed analysis.

Path 1: $S_0 \rightarrow S_1 \rightarrow S_9 \rightarrow S_{14}/S_0 \rightarrow S_2 \rightarrow S_9 \rightarrow S_{14}$ (event 3). For flood-related events, both heavy-rainfall-induced flooding ($S_0 \rightarrow S_1 \rightarrow S_9$) and storm-surge-induced flooding ($S_0 \rightarrow S_2 \rightarrow S_9$) may contribute to the occurrence of the same downstream flood node. Because direct observations of their joint occurrence probability were unavailable, the two pathways were assumed to be statistically independent. The two upstream flood-generating pathways were therefore combined using the parallel transfer-function addition rule in the GERT framework. The transfer function is:

$$W(s) = [W_1(s) * W_7(s) + W_{10}(s) * W_{13}(s)]W_8(s) = 0.1512e^{1.7s+0.02s^2} + 0.1029e^{1.6s+0.02s^2} \quad (10)$$

Setting $s = 0$ gives:

$$P_e = W_E(0) = 0.2541 \quad (11)$$

$$E(t) = \left. \frac{dM_E(s)}{ds} \right|_{s=0} = 1.66 \text{ (hours)} \quad (12)$$

$$V(t) = E(t^2) - E(t)^2 = 0.0424 \quad (13)$$

Path 2: $S_0 \rightarrow S_3 \rightarrow S_{11} \rightarrow S_{18} \rightarrow S_{22}$, which represent event 10, and the transfer function is:

$$W(s) = W_{14}(s) * W_{17}(s) * W_{21}(s) * W_{25}(s) = 0.2111e^{12.6s+4.5s^2} \quad (14)$$

Setting $s = 0$ gives:

$$P_e = W_E(s) = W_E(0) = 0.2111 \quad (15)$$

$$E(t) = \left. \frac{dM_E(s)}{ds} \right|_{s=0} = 12.6 \text{ (hours)} \quad (16)$$

$$V(t) = E(t^2) - E(t)^2 = 9 \quad (17)$$

To avoid repetitive derivations, detailed calculations are illustrated for two representative pathways (Path 1 and Path 2), while the probability, expected duration, and variance results for all ten representative disaster-chain pathways are summarized in Table 8.

Table 8. Summary of probability and temporal characteristics for representative disaster-chain pathways.

Event	Representative Pathway	Calculated (%)	E(t) (h)	V(t)
1	$S_0 \rightarrow S_1 \rightarrow S_4 \rightarrow S_{12} \rightarrow S_{23}/S_0 \rightarrow S_1 \rightarrow S_5 \rightarrow S_{12} \rightarrow S_{23}$	14.58	25.90	100.25
2	$S_0 \rightarrow S_1 \rightarrow S_6 \rightarrow S_{23}$	22.68	6.20	25.04
3	$S_0 \rightarrow S_1 \rightarrow S_9 \rightarrow S_{14}/S_0 \rightarrow S_2 \rightarrow S_9 \rightarrow S_{14}$	25.41	1.66	0.0424
4	$S_0 \rightarrow S_1 \rightarrow S_9 \rightarrow S_{15} \rightarrow S_{22}/S_0 \rightarrow S_2 \rightarrow S_9 \rightarrow S_{15} \rightarrow S_{22}/S_0 \rightarrow S_3 \rightarrow S_{11} \rightarrow S_{15} \rightarrow S_{22}$	50.42	12.87	9.0019
5	$S_0 \rightarrow S_2 \rightarrow S_7$	10.50	0.20	0

Table 8. Cont.

Event	Representative Pathway	Calculated (%)	E(t) (h)	V(t)
6	$S_0 \rightarrow S_2 \rightarrow S_8$	24.50	0.40	0.09
7	$S_0 \rightarrow S_2 \rightarrow S_{10} \rightarrow S_{20}/S_0 \rightarrow S_3 \rightarrow S_{10} \rightarrow S_{20}$	3.65	0.25	0.0014
8	$S_0 \rightarrow S_3 \rightarrow S_{11} \rightarrow S_{16} \rightarrow S_{22}$	9.66	10.80	9.00
9	$S_0 \rightarrow S_3 \rightarrow S_{11} \rightarrow S_{17} \rightarrow S_{22}$	21.02	10.90	9.00
10	$S_0 \rightarrow S_3 \rightarrow S_{11} \rightarrow S_{18} \rightarrow S_{22}$	21.11	12.60	9.00

E(t) and V(t) represent the expected duration and temporal variance of each disaster-chain pathway conditional on pathway occurrence. Constant-duration activities contribute zero variance; therefore, pathways dominated by constant transitions may show small V(t) values.

4.3. Model Calibration Fidelity Assessment

To assess the calibration fidelity of the GERT model for the Typhoon Mangkhut case, observed probabilities for each event sequence were derived from post-disaster reports and statistical yearbooks. For area-based hazards (e.g., flooding, building damage), probabilities were calculated as the ratio of affected area to the total assessment area. For count-based hazards (e.g., tree falls), probabilities were calculated as the proportion of damaged units relative to the total inventory. For example, based on the 2018 Shenzhen Climate Bulletin [38], approximately 17,000 trees fell during Typhoon Mangkhut, yielding an observed probability of 23.4% for Event 2 (typhoon $\rightarrow$ heavy rainfall $\rightarrow$ tree fall damage). These observed probabilities were used for consistency assessment of the calibrated model rather than for independent predictive validation. The objective was to evaluate whether the proposed framework could reasonably reproduce the observed disaster-chain evolution process associated with Typhoon Mangkhut. Event-specific probabilities derived using this approach are presented in Table 9.

Table 9. Calculated values of each event and the true values.

Event	Calculated (%)	Observed (%)
1	14.58	14.34
2	22.68	23.40
3	25.41	17.20
4	50.42	40.00 *
5	10.50	8.50
6	24.50	21.00 *
7	3.65	1.90
8	9.66	15.00
9	21.02	25.00
10	21.11	28.00 *

* Estimates based on incomplete information.

The comparison indicates a reasonable level of consistency between simulated and observed probabilities for the Typhoon Mangkhut case (Figure 8). The mean absolute error (MAE) across all events is 4.31%, and the coefficient of determination is $R^2 = 0.816$. These results suggest that the calibrated FBIREC–GERT framework is able to reproduce the general structure and dominant propagation patterns of the observed disaster-chain evolution process associated with Typhoon Mangkhut. However, because the model was calibrated and assessed using the same event dataset, the results should be interpreted as calibration fidelity rather than independent predictive validation.

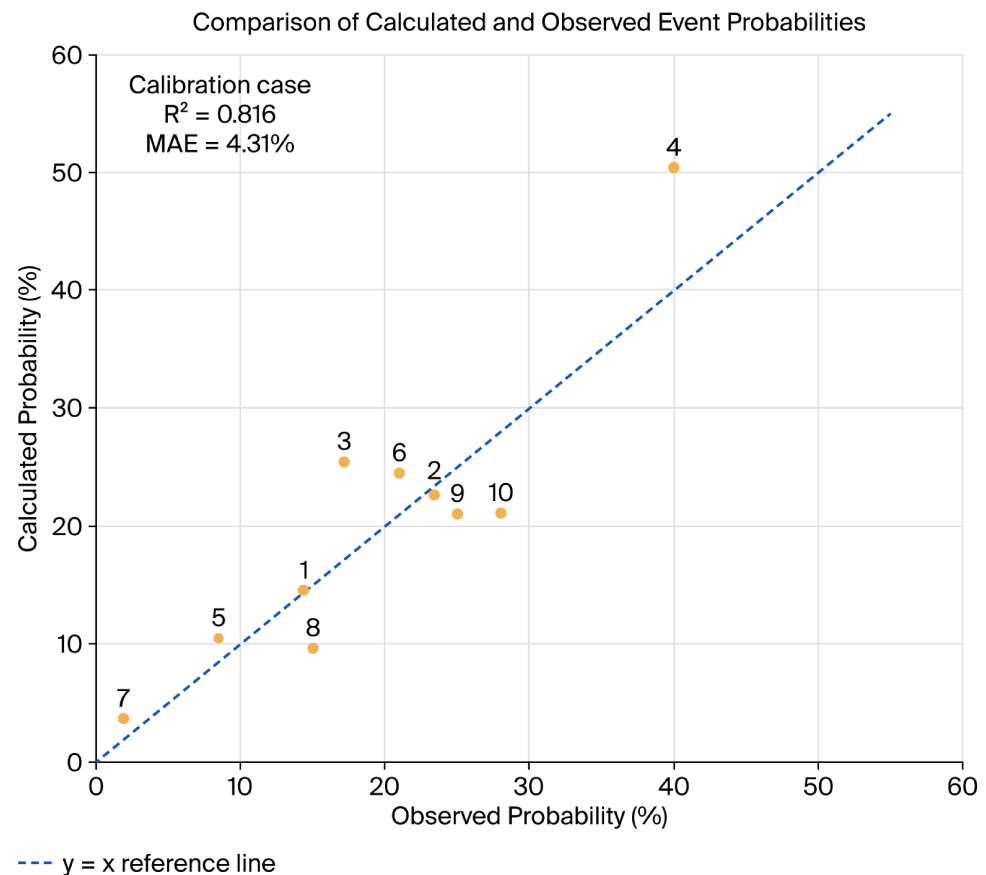


Figure 8. Comparison between calculated and observed event probabilities for the Typhoon Mangkhut (2018) calibration case.

To examine the influence of data completeness on calibration performance, an additional assessment was conducted using only events with fully observed probability records (Events 1, 2, 3, 5, 7, 8, and 9). The results are summarized in Table 10.

Table 10. Comparison of All events and Fully observed events only.

Dataset	MAE (%)	R^2
All events	4.31	0.816
Fully observed events only	3.18	0.716

The exclusion of partially observed events reduced the MAE from 4.31% to 3.18%, indicating that uncertainty associated with incompletely documented events contributed to a portion of the calibration error. The R^2 value decreased from 0.816 to 0.716, which is likely attributable to the smaller sample size (seven events instead of ten) and the narrower range of observed probabilities within the fully observed subset. Overall, the results suggest that the calibrated model remains reasonably consistent with observed event probabilities, while also highlighting the influence of data completeness on model-performance assessment. Therefore, uncertainty in partially observed events should be considered when interpreting the calibration results.

4.4. Hazard Pathway Comparison

To compare the relative contribution of different hazard mechanisms to disaster-chain evolution, the ten representative events were grouped into rainfall-driven, storm-surge-driven, and wind-driven pathways according to their dominant triggering hazards (Table 11).

Table 11. Comparison of occurrence probabilities across different hazard pathways.

Hazard Pathway	Events	Mean Probability (%)
Rainfall-driven	1–4	27.89
Storm-surge-driven	5–6	17.50
Wind-driven	7–10	13.86

The results indicate that rainfall-driven pathways exhibit the highest overall occurrence probabilities, with an average probability of 27.89%. In particular, Event 3 (flood-induced building damage) and Event 4 (transportation disruption) represent the most prominent cascading consequences within the network. This suggests that heavy rainfall and flood generation constitute the dominant propagation mechanisms during severe typhoon events in the Greater Bay Area.

Storm-surge-related pathways show intermediate occurrence levels, with an average probability of 17.50%. These pathways mainly affect coastal infrastructure through seawater intrusion and dam-breach processes.

Wind-driven pathways exhibit the lowest average probability (13.86%) but show substantial variability among events. While ship capsizing (Event 7) remains relatively infrequent, wind-induced infrastructure failures generate several important downstream disruptions, including gas-supply interruption, water-supply interruption, and communication interruption.

Overall, the results demonstrate that different hazard mechanisms contribute differently to disaster-chain evolution and highlight the importance of considering multiple propagation pathways when assessing typhoon risk.

5. Discussion

The GERT-based simulation results presented in Section 4 provide quantitative evidence on the probabilistic propagation of typhoon disaster chains. This section interprets these findings, discusses their implications for disaster risk management, compares them with previous studies, and acknowledges the limitations of the current approach.

5.1. Interruption Risks Identified in the Typhoon Disaster Chain

The simulation results identify two categories of interruption risks within the typhoon disaster chain, distinguished by their temporal characteristics: short-term risks (0–48 h) and long-term risks (>48 h).

1. Short-term interruption risks (0–48 h). The simulation results identify that short-term interruption risks are dominated by cascading failures of critical infrastructure systems, particularly power facilities (S_{11}). Under strong wind conditions, power system failure propagates to transportation disruption, water supply interruption, communication failure, and gas supply interruption, indicating strong interdependencies among urban lifeline systems.

Among all downstream impacts, transportation disruption (Event 4, $P = 50.42\%$) emerges as one of the most significant short-term consequences, driven by both rainfall-induced flooding and power-driven infrastructure failure pathways. This dual-path structure highlights the compound nature of transportation vulnerability in coastal megacities.

Communication interruption (Event 10, $P = 21.11\%$) represents a notable downstream consequence of wind-induced power-facility damage. However, the available data are insufficient to determine whether communication systems exhibit threshold effects or saturation behaviour under different typhoon intensities.

2. Long-term interruption risks (>48 h). Long-term risks are primarily associated with infrastructure recovery and ecological restoration processes. Debris flows and landslides trigger infrastructure damage with probabilities of 50.0% and 40.0%, respectively, while ecological restoration requires approximately 25 days to complete. Treefall damage leads to shorter recovery cycles (~5 days), whereas post-disaster environmental recovery exhibits greater uncertainty due to spatial heterogeneity and secondary hazards.

5.2. Implications for Emergency Management

The simulation results provide several practical implications for typhoon emergency management in the Guangdong–Hong Kong–Macao Greater Bay Area.

First, rainfall-driven pathways constitute the dominant source of cascading disaster risk. The hazard pathway comparison indicates that rainfall-related events exhibit the highest average occurrence probability among all pathway categories. In particular, flood-related impacts, including building damage (Event 3) and transportation disruption (Event 4), represent the most significant downstream consequences in the disaster chain. This finding suggests that improving rainfall forecasting, flood-control infrastructure, urban drainage systems, and early-warning dissemination mechanisms could substantially reduce the overall propagation of disaster impacts.

Second, transportation systems function as critical convergence points within the disaster network. Transportation disruption is jointly influenced by multiple upstream hazards, including flood-related pathways and power-facility failures. As a result, transportation infrastructure is exposed to compound risks rather than a single hazard source. This highlights the importance of integrated resilience planning that simultaneously considers hydrological hazards, power-system reliability, and emergency accessibility. Investments targeting only one hazard pathway may therefore provide limited reductions in overall transportation risk.

Third, power infrastructure plays a central role in supporting the continuity of urban lifeline systems. Strong-wind-induced power-facility damage can propagate to gas-supply interruption, water-supply interruption, and communication failure, demonstrating the strong interdependence among critical infrastructure systems. Strengthening power-system resilience through redundancy design, underground transmission systems, backup power capacity, and rapid restoration mechanisms may therefore provide benefits that extend beyond the electricity sector itself.

Although the present study focuses primarily on physical infrastructure disruptions and recovery processes, urban resilience is determined not only by infrastructure robustness but also by the adaptive capacity of affected communities. Vulnerable groups, including elderly residents, low-mobility populations, and socioeconomically disadvantaged communities, may experience disproportionately longer service interruptions and recovery times following typhoon events. Therefore, future emergency-management strategies should integrate both infrastructure resilience and social-vulnerability considerations to enhance the sustainability, equity, and community resilience of disaster-risk reduction efforts.

Overall, the results demonstrate that effective typhoon-risk reduction requires a systems-based approach that addresses both dominant hazard pathways and the critical infrastructure nodes through which cascading failures propagate.

5.3. Comparison with Previous Studies

The findings of this study are broadly consistent with previous research that has identified infrastructure interdependencies as a key driver of cascading disaster impacts during extreme weather events. Similar to earlier studies using complex-network and

disaster-chain approaches, the results indicate that power-facility damage represents a critical intermediary process linking primary meteorological hazards with multiple downstream infrastructure disruptions. This supports previous observations that power systems often function as central transmission hubs in typhoon-induced disaster networks [17,18].

The present study further demonstrates that different hazard pathways contribute unequally to disaster-chain evolution. Rainfall-driven pathways generate the highest overall occurrence probabilities, particularly through flood-related impacts on buildings and transportation systems. This finding is consistent with previous studies highlighting urban flooding as one of the most significant consequences of typhoon events in densely populated coastal regions. This observation is also consistent with recent compound-flooding studies that identify rainfall–flood interactions as dominant drivers of urban disaster impacts [33]. At the same time, storm-surge pathways and wind-driven infrastructure failures contribute additional cascading effects through distinct propagation mechanisms, illustrating the multi-hazard nature of typhoon disasters.

Compared with DBN-based approaches, which emphasize probabilistic updating, and knowledge-graph methods, which focus on semantic reasoning and information extraction, the FBIREC–GERT framework is particularly advantageous for representing sequential disaster propagation processes and quantifying their temporal characteristics. However, unlike DBN models, the present framework does not perform real-time probability updating, and future work could integrate Bayesian inference mechanisms to improve adaptive modelling capabilities. The integration of GERT enables simultaneous modelling of event occurrence probabilities and recovery durations, allowing both short-term interruption risks and long-term restoration processes to be represented within a unified analytical framework.

Furthermore, unlike static network representations, the proposed framework explicitly captures the sequential propagation structure of typhoon disaster chains and enables comparison among different hazard categories. This contributes to a more comprehensive understanding of how meteorological hazards evolve into infrastructure disruptions and ecological consequences through multiple interconnected pathways.

Recent studies have increasingly applied Dynamic Bayesian Networks (DBNs), knowledge-graph reasoning techniques, and compound multi-hazard assessment frameworks to disaster-chain analysis. DBN-based approaches have demonstrated strong capabilities in modelling dynamic uncertainty and infrastructure resilience through probabilistic updating and evidence propagation. Knowledge-graph methods have been used to support emergency decision-making by improving hazard relationship extraction, semantic reasoning, and information retrieval. In addition, compound-hazard assessment frameworks emphasize the importance of explicitly considering interactions among multiple hazard drivers and interconnected infrastructure systems. Compared with these approaches, the FBIREC–GERT framework provides a complementary advantage by simultaneously quantifying disaster occurrence probabilities, expected propagation durations, and temporal variances within a unified stochastic-network structure. These temporal outputs are particularly valuable for emergency-response scheduling, resource allocation, and recovery planning. Future research may further enhance the framework through the integration of Bayesian updating mechanisms, knowledge-graph reasoning techniques, and more sophisticated representations of compound-hazard interactions.

Overall, the results support the applicability of the FBIREC–GERT approach as a useful tool for analysing complex typhoon disaster chains and identifying priority areas for disaster-risk reduction and resilience planning.

5.4. Limitations

Several limitations of this study should be acknowledged.

First, data limitations. The conditional probabilities were derived from historical data across multiple typhoon events in Guangdong Province (2014–2023). While this provides a robust statistical basis, event-specific variations in typhoon intensity, local topography, and infrastructure conditions may still introduce deviations. The model shows the largest discrepancy in wind- and marine-related processes (e.g., Event 7), where calculated probabilities may differ from observed values due to incomplete reporting of maritime incidents and limited availability of offshore damage records. Future work should incorporate real-time observational datasets to improve parameter updating accuracy.

Second, model assumptions. The model assumes uniform emergency response effectiveness across the Greater Bay Area, whereas actual response capacity varies significantly across cities. Highly developed cities such as Shenzhen may exhibit faster recovery rates compared to less developed regions. Incorporating spatial heterogeneity indicators such as fiscal capacity, emergency resource density, infrastructure redundancy, and community resilience characteristics would improve model realism.

Additionally, the representation of compound-hazard interactions in the GERT formulation (Section 3.2) remains simplified. For example, severe urban flooding may result from the simultaneous occurrence of storm surge (S_2) and heavy rainfall (S_1), rather than either event independently. Although the model allows multiple upstream pathways to contribute to selected downstream events, concurrent hazard interactions are represented through simplifying assumptions rather than explicit multi-hazard coupling mechanisms. This simplification may therefore affect the representation of compound-hazard interactions. Future work could explore mixed-logic or AND-enhanced GERT formulations.

Third, static parameterization. The model relies on fixed probability and time parameters derived from historical averages. However, climate change and rapid urbanization may alter hazard intensity, exposure, and vulnerability patterns, limiting long-term transferability.

Fourth, scope limitation. The model focuses primarily on physical infrastructure disruption, emergency repair processes, and ecological restoration pathways, while social vulnerability and socioeconomic resilience factors are not explicitly represented. Variables such as age structure, mobility constraints, income disparities, access to emergency resources, and community adaptive capacity may significantly influence both disaster impacts and recovery outcomes. Consequently, the current framework may underestimate differences in vulnerability and resilience among population groups. This limitation is particularly relevant in the context of sustainable urban resilience planning, where infrastructure robustness and social capacity jointly determine recovery performance.

In addition, several delayed environmental-health and recovery processes included in the conceptual FBIREC framework were not quantitatively parameterized. Specifically, the water-quality impact pathway (S_{13}), its downstream ecological-health consequence (S_{19}), and the reconstruction stage (S_{21}) were excluded from the quantitative GERT simulation because reliable event-level duration parameters and complete downstream transition information were unavailable. Although historical occurrence probabilities were available for certain environmental-impact processes (e.g., S_{13}), the available data were insufficient to support full GERT parameterization. Consequently, the current model may underestimate certain long-term environmental, public-health, and recovery-related consequences associated with major typhoon disasters. Future studies could incorporate these pathways and integrate social-vulnerability indicators to provide a more comprehensive representation of disaster-chain evolution and sustainable disaster resilience.

Fifth, single-case calibration. The model was calibrated and assessed using a single typhoon event—Typhoon Mangkhut (2018). Although the calibration results indicate a reasonable level of consistency between simulated and observed event probabilities

(MAE = 4.31%, $R^2 = 0.816$), these metrics reflect goodness-of-fit for the calibration case rather than independent predictive performance. Consequently, the current findings should not be interpreted as evidence of model generalizability across different typhoon events. Future research should apply the framework to multiple typhoon cases, such as Hato (2017) and Rammasun (2014), to conduct independent validation and evaluate model applicability under different hazard intensities and disaster-chain propagation mechanisms.

6. Conclusions

This study developed a GERT-based stochastic network model integrated with the FBIREC framework to simulate the dynamic evolution of typhoon disaster chains in the Guangdong–Hong Kong–Macao Greater Bay Area. Typhoon Mangkhut (2018) was used as a calibration case. The main conclusions are as follows.

First, the proposed FBIREC–GERT framework is capable of representing the probabilistic propagation of typhoon disaster chains and capturing major cascading relationships among hazard events. For the Typhoon Mangkhut calibration case, the model achieved a mean absolute error (MAE) of 4.31% and a coefficient of determination (R^2) of 0.816, indicating a reasonable level of consistency between simulated and observed event probabilities. These results suggest that the framework can reproduce the main characteristics and dominant pathways of disaster-chain evolution under severe typhoon conditions.

Second, rainfall-driven pathways constitute the dominant disaster-propagation mechanism within the typhoon disaster chain. Flood-related events, particularly building damage and transportation disruption, exhibit the highest occurrence probabilities among all representative events, highlighting the critical role of rainfall accumulation and flood generation in cascading disaster development.

Third, critical infrastructure systems play a central role in transmitting disaster impacts. In particular, disruptions to power facilities may indirectly reduce the accessibility of essential services, including healthcare, water supply, communications, and transportation. Such cascading failures are likely to disproportionately affect vulnerable populations, including elderly residents, low-mobility communities, and socioeconomically disadvantaged groups, whose recovery capacity is generally lower than the regional average.

Fourth, the simulation results support phased emergency-management strategies. Typhoon disaster chains evolve across two main temporal scales: short-term risks (0–48 h), including flooding, transportation disruption, and infrastructure failures, and long-term risks (>48 h), primarily associated with ecological restoration and recovery processes. This temporal differentiation provides quantitative support for allocating emergency resources across different stages of disaster response.

Fifth, comparison among different hazard pathways indicates that rainfall-driven, storm-surge-driven, and wind-driven processes contribute differently to disaster-chain evolution. Rainfall-related pathways exhibit the highest overall occurrence probabilities, while wind-driven pathways are primarily responsible for propagating failures across interconnected infrastructure systems. These results demonstrate the importance of adopting multi-hazard perspectives when designing disaster-risk-reduction strategies. This also provides a basis for prioritizing interventions that protect socially vulnerable communities facing disproportionate disaster risks.

From a sustainability perspective, the findings contribute to improving urban resilience and supporting sustainable and equitable disaster-risk management in rapidly urbanizing coastal regions. By identifying dominant hazard pathways and critical infrastructure dependencies, the proposed framework can assist decision-makers in prioritizing investments in flood mitigation, power-system resilience, emergency preparedness, and long-term recovery planning. Beyond infrastructure resilience, the proposed framework

can support decision-makers in identifying communities that may experience prolonged service interruptions and recovery delays, thereby facilitating more equitable allocation of emergency resources.

Future research should focus on integrating real-time monitoring data for dynamic parameter updating, incorporating spatial heterogeneity and social-vulnerability indicators into resilience assessment, and extending the framework to climate-change-related extreme-weather scenarios. Particular attention should be given to vulnerable population groups, including elderly residents, low-mobility communities, and areas with limited emergency-response resources, whose recovery trajectories may differ substantially from regional averages. Integrating community-resilience metrics and socioeconomic factors into the FBIREC–GERT framework would provide a more comprehensive understanding of disaster impacts and support more equitable and sustainable disaster-risk management. The proposed framework may also be adapted to other cascading hazard systems, provided that the network structure, probability parameters, and activity-time parameters are appropriately recalibrated according to local hazard characteristics and available observations.

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References

1. Global Disaster Data Platform of China's Ministry of Emergency Management. Available online: <https://www.gddat.cn/gd-en/#/previewNewDisaster> (accessed on 29 May 2026).
2. Hong Kong Observatory. Report on Severe Typhoon Haikui (2311). Available online: https://www.hko.gov.hk/en/publica/tc/tc2023/section3_4rpt.html (accessed on 29 May 2026).
3. Reuters. Two Dead after Hong Kong's Heaviest Rain in at Least 140 Years. Available online: <https://www.theguardian.com/world/2023/sep/08/hong-kong-weather-record-rain-flooding-after-typhoon-haikui> (accessed on 29 May 2026).
4. Editorial Committee of Dictionary of Earth Sciences. *Dictionary of Earth Sciences: Applied Sciences Volume*; Geological Publishing House: Beijing, China, 2005.
5. Pescaroli, G.; Alexander, D. A definition of cascading disasters and cascading effects: Going beyond the “toppling dominos” metaphor. *Planet@Risk* **2015**, *3*, 58–67.
6. Zscheischler, J.; Westra, S.; van den Hurk, B.J.J.M.; Seneviratne, S.I.; Ward, P.J.; Pitman, A.; AghaKouchak, A.; Bresch, D.N.; Leonard, M.; Wahl, T.; et al. A typology of compound weather and climate events. *Nat. Rev. Earth Environ.* **2020**, *1*, 333–347. [CrossRef]
7. Kappes, M.S.; Keiler, M.; von Elverfeldt, K.; Glade, T. Challenges of analyzing multi-hazard risk: A review. *Nat. Hazards* **2012**, *64*, 1925–1958. [CrossRef]

8. Lu, X.; Xu, Z.; Shi, Q.; Tang, Q. Evolution Characteristics of Urban Flood Disaster Chains and Approaches for Disaster Mitigation. *Adv. Water Sci.* **2025**, *36*, 97–108.
9. Ye, J. Comprehensive Risk Assessment Model and Information Mapping Expression of Typhoon Disaster Chains Based on Multidimensional Matrices. Ph.D. Thesis, Fujian Normal University, Fuzhou, China, 2015.
10. Shuai, J.; Xu, W.; Shi, P. Characteristics of Typhoon Disaster Chains in the Yangtze River Delta Region. *J. Nat. Disasters* **2012**, *21*, 36–42.
11. Leonard, M.; Westra, S.; Phatak, A.; Lambert, M.; van den Hurk, B.; McInnes, K.; Risbey, J.; Schuster, S.; Jakob, D.; Stafford-Smith, M. A compound event framework for understanding extreme impacts. *WIREs Clim. Change* **2014**, *5*, 113–128. [[CrossRef](#)]
12. Shuai, M.; Guo, H.; Liu, X.; Wang, D.; Chen, W. Bayesian-Network-Based Reasoning Model for Rainstorm-Geological and Rainstorm-Flood Disaster Chains. *Sci. Technol. Manag. Res.* **2021**, *41*, 191–197.
13. Xiao, P.; Wang, T.; Tan, X. Bayesian-Network-Based Interruption Model for Rainstorm-Landslide-Flash Flood Disaster Chains. In Proceedings of the 11th China Water Ecology Conference, Guangzhou, China, 24–26 September 2023; pp. 635–649.
14. Fang, Z.; Yang, B.; Lu, Z.; Li, S.; Chen, Y.; Chen, W.; Yao, G. Disaster Evolution GERT Network Model Based on Bayesian Inference. *Chin. J. Manag. Sci.* **2009**, *17*, 102–107.
15. Caetano, H.O.; Desuó, L.; Fogliatto, M.S.; Maciel, C.D. Resilience Assessment of Critical Infrastructures Using Dynamic Bayesian Networks and Evidence Propagation. *Reliab. Eng. Syst. Saf.* **2024**, *241*, 109691. [[CrossRef](#)]
16. Bakhtiari, S.; Najafi, M.R.; Goda, K.; Peerhossaini, H. A Dynamic Bayesian Network Approach to Characterize Multi-Hazard Risks and Resilience in Interconnected Critical Infrastructures. *Reliab. Eng. Syst. Saf.* **2025**, *257*, 110815. [[CrossRef](#)]
17. Zuccaro, G.; De Gregorio, D.; Leone, M.F. Theoretical Model for Cascading Effects Analyses. *Int. J. Disaster Risk Reduct.* **2018**, *30*, 199–215. [[CrossRef](#)]
18. Liu, H.; Luo, N.; Zhao, Q. Risk Analysis of Shenzhen Typhoon Disaster Chains Based on Complex Disaster Networks. *J. Catastrophol.* **2023**, *38*, 228–234.
19. Chen, M. Complex Network Modelling of Typhoon Disaster Chains in Critical Infrastructure Systems. Ph.D. Thesis, Wuhan University, Wuhan, China, 2020.
20. Lu, Z.; Yan, D.; Jiang, H. Earthquake Disaster Chain Model of Urban Engineering Systems Based on Complex Networks. *J. Southeast Univ. Engl. Ed.* **2024**, *40*, 230–237.
21. Wang, H.; Du, W.; Liu, J.; Wang, J.; Mei, C. Urban Flood Disaster Chain Deduction and Spatio-Temporal Characteristics Analysis Based on Knowledge Graphs. *Adv. Water Sci.* **2024**, *35*, 185–196.
22. Chen, M.; Tao, Z.; Tang, W.; Qin, T.; Yang, R.; Zhu, C. Enhancing Emergency Decision-Making with Knowledge Graphs and Large Language Models. *Int. J. Disaster Risk Reduct.* **2024**, *113*, 104804. [[CrossRef](#)]
23. Zhao, Y. Illustration and Overview of the Graphical Evaluation and Review Technique (GERT). *Syst. Eng.-Theory Pract.* **1983**, *47–51*.
24. Neumann, K. Recent Advances in Temporal Analysis of GERT Networks. *Z. Oper. Res.* **1979**, *23*, 153–177. [[CrossRef](#)]
25. Tao, L.; Liu, S.; Fang, Z.; Chen, X. Matrix Representation and Solution Model of GERT Networks. *Syst. Eng. Electron.* **2017**, *39*, 1292–1297.
26. Zhou, Y.; Ma, Z. Scenario Inference-Based Dynamic GERT Network Model for Evolution of Earthquake Disasters. *J. Nat. Disasters* **2013**, *22*, 68–75.
27. Wang, J. Study on Scenario Deduction of Oil Storage System Fire Accident Based on Graphical Evaluation Review Technique Network. Master's Thesis, Dalian Maritime University, Dalian, China, 2022.
28. Chukwuka, O.J.; Ren, J.; Wang, J.; Paraskevadis, D. A Comprehensive Research on Analyzing Risk Factors in Emergency Supply Chains. *J. Humanit. Logist. Supply Chain Manag.* **2023**, *in press*. [[CrossRef](#)]
29. Li, Y.; Luo, X.; Che, G.; Cao, Y. Identification of Critical Emergency Rescue Road Sections Based on GERT Networks. *J. Transp. Syst. Eng. Inf. Technol.* **2017**, *17*, 166–172.
30. Chen, W.; Pei, L.; Yang, B.; Wang, Z. Dynamic Optimisation Model for Disaster Relief Personnel Allocation Based on GERT Networks. *J. Chongqing Norm. Univ. Nat. Sci. Ed.* **2015**, *32*, 125–130.
31. Pu, G.; Su, Q.; Liu, C. Post-Disaster Rescue Infrastructure Network Design under Interruption Conditions. *Syst. Eng.-Theory Pract.* **2016**, *36*, 1453–1461.
32. Liu, X.; Wang, C.; Yin, Z.; An, X.; Meng, H. Risk-Informed Multi-Objective Decision-Making of Emergency Schemes Optimization. *Reliab. Eng. Syst. Saf.* **2024**, *245*, 109979. [[CrossRef](#)]
33. Ming, X.; Liang, Q.; Dawson, R.; Xia, X.; Hou, J. A Quantitative Multi-Hazard Risk Assessment Framework for Compound Flooding Considering Hazard Interdependencies and Interactions. *J. Hydrol.* **2022**, *607*, 127477. [[CrossRef](#)]
34. Jiang, B.; Zhang, C.; Chen, T.; Yuan, H. Rainstorm Scenario Construction and Evolution Method Based on Bayesian Networks. *J. Tsinghua Univ. Sci. Technol.* **2021**, *61*, 509–517.
35. Shi, P. Reconsideration of Disaster Research Theory and Practice. *J. Nat. Disasters* **1996**, *5*, 6–17.

36. Liu, Z. Case Study on Emergency Management of Typhoon Mangkhut in Guangdong Province. Master's Thesis, Lanzhou University, Lanzhou, China, 2020.
37. Zhang, R. Characteristics Analysis and Prevention Suggestions of Marine Meteorological Disasters in Guangdong Province from 2015 to 2023. In *Proceedings of the Academic Conference on Cultural Heritage and Modern Governance*; Guangdong Ocean University: Zhanjiang, China, 2024; pp. 23–27.
38. Shenzhen Meteorological Bureau. *Shenzhen Climate Bulletin 2018*; Shenzhen Meteorological Bureau: Shenzhen, China, 2018.

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