Risk Analysis of Establishing 5G Infrastructure in Tsunami-Prone Areas: Case Study - Honshu Island, Japan

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***Abstract*—This project assesses the risks of deploying 5G infrastructure in tsunami-prone regions, focusing on Honshu Island, Japan. Using real and simulated data, the study applies various risk analysis techniques, including Poisson distribution, fault tree analysis, F-N curves, Bayesian networks, decision trees, and cost-benefit analysis. The results reveal a 99.96%**

***Index Terms*—5G, tsunami, risk analysis, fault tree, Bayesian network, Poisson distribution, survivability, Honshu Island**

I. Introduction

The deployment of 5G technology in disaster-prone areas introduces significant challenges. Honshu Island, being tsunami-prone, presents a case where rigorous risk analysis is essential. This study aims to assess and mitigate the risks using quantitative and qualitative methods, ensuring a resilient 5G rollout.

II. Literature Review

Probabilistic tsunami hazard assessment (PTHA) is critical when planning resilient infrastructure in Japan's coastal regions. A study by Okumura et al. [2] introduced a method for tsunami risk analysis in Kamakura, Japan. Their approach combined scenario-based hazard modeling with consequence and exposure analysis, highlighting how communication infrastructure can be vulnerable in densely populated urban areas. This method provides a strong foundation for understanding the risks facing critical systems like 5G towers in tsunami-prone zones.

Another relevant work by Saito et al. [3] conducted regional tsunami hazard assessments along the eastern margin of the Sea of Japan. Using a Monte Carlo simulation approach, the study evaluated stochastic earthquake scenarios from 60 active faults. The analysis produced hazard curves for 154 coastal locations, showing that the tsunami impact is highly sensitive to geographic fault distribution. This has direct implications for infrastructure planning across Honshu's varied coastal environments.

More recently, Yoshida et al. [4] applied the Gutenberg–Richter law to assess tsunami hazards in the eastern Nankai subduction zone. Their study used 3,480 earthquake simulations to compute tsunami hazard curves and considered tidal interactions and coastal defense structures. The findings emphasize the need for probabilistic design models, especially when deploying high-value communication systems like 5G, which must withstand rare but severe tsunami events.

III. Problem Description

The deployment of 5G infrastructure on Honshu Island, Japan, presents both a technological opportunity and a disaster resilience challenge. The 5G system under consideration includes essential components such as communication towers, underground and undersea fiber optic cables, and backup power systems. These assets, while critical to modern digital infrastructure, are particularly vulnerable in tsunami-prone environments due to their exposure to coastal flooding, limited redundancy, and dependence on conventional power grids that may fail during natural disasters.

Historical tsunami records from 2000 to 2025 show an average occurrence rate of 1.077 tsunamis per year along the coast of Honshu Island [1]. This frequency justifies the use of Poisson distribution modeling to estimate the probability of tsunami events over various time horizons. Given the high likelihood of occurrence, even over short durations, a quantitative approach is essential for effective infrastructure planning and risk mitigation.

Due to the scarcity of real-world failure data for 5G infrastructure affected by tsunamis—especially given the technology's recent deployment—this study employs simulated probabilities for primary risk events (e.g., flooding, wave impact, equipment failure). These simulations are constructed based on historical data from major tsunami events, such as the 2011 Tōhoku disaster, and engineering best practices.

Each risk analysis model used in this project is interconnected: outputs from probabilistic models (e.g., Poisson, fault tree) inform decision-making tools such as Bayesian networks and cost-benefit analysis. This integrated modeling framework ensures that each component of the analysis is grounded in the same hazard profile, yielding a consistent and reliable estimate of overall risk.

The central objective of this study is to evaluate how risky it is to establish 5G infrastructure in a tsunami-prone region like Honshu Island. The focus is not only on identifying vulnerabilities but also on quantifying the potential economic impact. This is done by comparing the expected costs of damage and service disruption against the potential profits from uninterrupted 5G operation. The ultimate goal is to determine whether the infrastructure investment is justifiable under various risk scenarios and what mitigation strategies yield the most cost-effective outcomes.

IV. Risk Assessment

A. Identifying Risks

Threats:

- Tsunamis (varying severity: low, medium, high).
- Physical damage to 5G infrastructure (towers, fiber optics, power supply).
- Service disruption due to flooding or equipment failure.

Vulnerabilities:

- Coastal location of 5G towers.
- Dependence on power grids vulnerable to flooding.
- Lack of redundancy in network connectivity.

Assets at Risk:

- 5G infrastructure (towers, cables, data centers).
- Economic losses from downtime (e.g., \$220M/year estimated from sector-wide disruption).
- Human lives (F-N curve modeling shows fatalities reaching up to 18,428 in worst-case scenarios).

B. Quantitative Risk Analysis

Quantitative models were used to determine the probability and impact of tsunami-related failures. Details of the modeling approaches and their results are elaborated in dedicated subsections under the *Risk Analysis* section. These include:

- Poisson distribution (estimation of tsunami frequency).
- Fault Tree Analysis (Infrastructure Failure Logistic).
- F-N curve (fatality frequency vs. severity).
- Survivability Analysis using K-M Estimate
- Bayesian Network Analysis
- Decision Tree and Payoff Table Analysis
- Decision Making using EV and EVPI Approach
- Decision Making with Conditional Probabilities and Sample Information Efficiency
- Sensitivity Analysis

C. Risk Response Strategies

Avoid:

- Relocating infrastructure inland is not feasible due to signal coverage requirements in coastal zones.

Mitigate:

- Elevated tower design incurs a +20% cost, and waterproofing equipment adds +15%—both standard civil engineering estimates.
- Redundant power systems (solar + battery) require an upfront cost of \$5M; adding multiple fiber routes is projected at +10% installation cost.
- Integrating tsunami alerts with 5G backbone systems adds an annual operational cost of \$2M.

Transfer:

- Insurance premiums for critical telecom infrastructure were estimated at \$10M/year based on market averages for high-risk coastal assets.

Retain:

- A residual risk of 5% service disruption is deemed acceptable based on benchmarked disaster recovery times.

D. Control Measures Implemented

- **Cost of Controls:**
  The upfront cost of \$50M includes elevation, structural reinforcements, and waterproofing.
  - Annual recurring cost of \$17M covers backup maintenance, early warnings, and insurance.
- **Risk Reduction Achieved:**
  - Physical damage probability reduced from 98.2% to 40%.
  - Power failure risk reduced from 72% to 30%.
  - Overall service disruption lowered from 76% to 25%.

V. Risk Analysis

A. Poisson Distribution

Below is a tabular representation of the data for Total Tsunamis on Honshu Island (Coast) (2000- 2025) and the Poisson Distribution calculations, along with their relevance to risk analysis for building 5G infrastructure in tsunami-prone areas.

TABLE I
Total Tsunamis on Honshu Island (Coast) (2000- 2025)

Year Range	Total Tsunamis	Total Years	Tsunamis per Year (λ)
2000–2025	28	26	1.077

TABLE II
Poisson Distribution Calculations

Time Frame	λ	$P(X \geq 1)$	Relevance to 5G Infrastructure Risk Analysis
1 Year	1.077	65.9%	Infrastructure must withstand at least one tsunami annually.
2 Years	2.154	88.4%	Redundancy and backup systems become essential.
5 Years	5.385	99.54%	Long-term resilience and robust design are needed.
10 Years	10.77	99.998%	Disaster recovery and early warning systems are necessary.

TABLE III
Relevance of Poisson Distribution to 5G Infrastructure Risk Analysis

Poisson Result	Relevance to 5G Infrastructure
High Probability of Tsunamis	Infrastructure must withstand frequent wave impact and flooding.
Need for Redundancy	Redundant systems (e.g., fiber routes, towers) ensure connectivity.
Early Warning Systems	Integrated tsunami alerts reduce damage and save lives.
Resilience Planning	Plans must support rapid recovery and minimal downtime.
Cost-benefit analysis	Investment in mitigation are justified by high risk.
Emergency Response Plans	Rapid restoration protocols post-tsunami are vital.

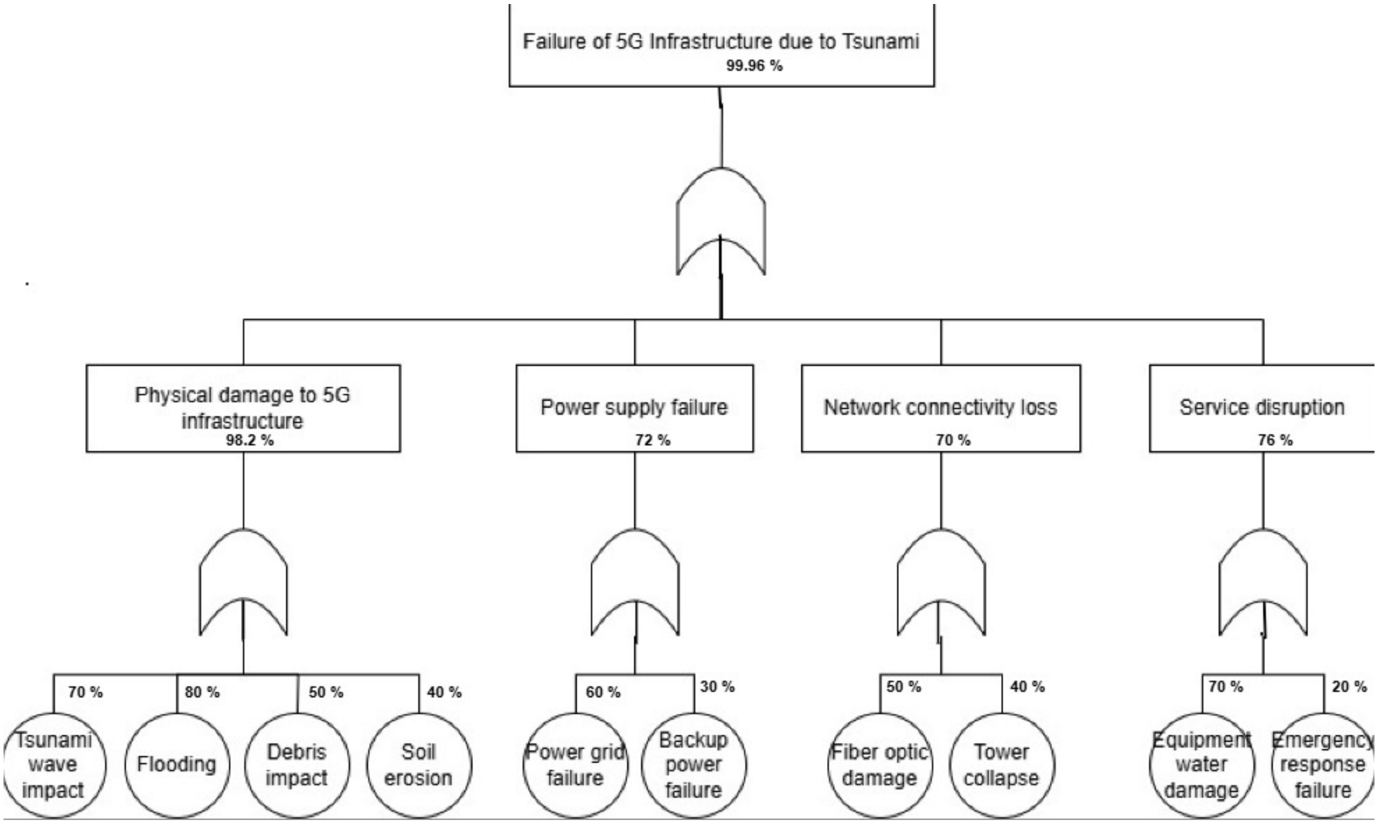

Fig. 1. Fault Tree Diagram of 5G Infrastructure Failure

The above data underscores the need for proactive planning and engineering resilience in deploying 5G networks in tsunami-prone regions like Honshu Island. The Poisson analysis shows a nearly certain probability (99.998%) of at least one tsunami within a 10-year span, which directly informs the infrastructure's design requirements.

The tables highlight both the statistical foundation (Tables 1 and 2) and the strategic relevance (Table 3) of applying the Poisson theory. This not only justifies the integration of mitigation strategies—such as backup power, elevated hardware, and early warnings—but also makes a strong case for investment in long-term sustainability measures.

Hence, understanding tsunami frequency through probabilistic modeling becomes critical in quantifying risk and optimizing infrastructure resilience for Japan's coastal 5G deployment.

B. Fault Tree Analysis

A fault tree identifies how component failures combine to cause system failure. Key simulated probabilities:

Top Event Calculation:

The OR gate formula is applied to the intermediate events:

$$\begin{aligned} P(\text{Top Event}) &= 1 - \prod_{j=1}^{4}(1 - P_j) \\ &= 1 - (1 - 0.982)(1 - 0.72)(1 - 0.70)(1 - 0.76) \\ &= 1 - (0.018 \cdot 0.28 \cdot 0.30 \cdot 0.24) \\ &= 1 - 0.00036 \\ &= \mathbf{0.99964\ (99.96\%)} \end{aligned}$$

The calculated top event probability of 99.96% signifies that, under simulated conditions, 5G infrastructure on Honshu Island is almost certain to fail in the event of a tsunami. This elevated risk is primarily driven by a 98.2% probability of physical damage from wave impact, flooding, and debris, along with a 76% chance of service disruption due to equipment vulnerability and potential failures in emergency response mechanisms.

To mitigate this high risk, infrastructure planning must prioritize structural resilience, such as elevated towers and reinforced foundations, alongside waterproof and reliable backup power systems. Protecting fiber optic cables from water and impact damage and implementing efficient disaster response protocols are also critical. This analysis highlights the necessity of integrating risk-informed design and proactive mitigation strategies into 5G infrastructure development in tsunami-prone

TABLE IV
JUSTIFICATION FOR SIMULATED PROBABILITIES ASSIGNED TO FAULT TREE PRIMARY EVENTS

Primary Event	Simulated Probability	Reasoning	Evidence
Tsunami Wave Impact	70%	Tsunamis generate massive waves that directly impact coastal infrastructure.	2011 Tōhoku tsunami saw wave heights of up to 39 meters, causing widespread damage.
Flooding	80%	Tsunamis inundate coastal regions with large water volumes.	2004 Indian Ocean tsunami caused flooding up to 5 km inland.
Debris Impact	50%	Waves carry debris, which may strike and damage infrastructure.	Debris damage was widely reported in the 2011 Tōhoku tsunami.
Soil Erosion	40%	Tsunami forces can erode soil, destabilizing infrastructure foundations.	Coastal soil erosion and structural collapse observed in the 2011 Tōhoku tsunami.
Power Grid Failure	60%	Flooding and physical damage disrupt the grid and cause shorts.	Fukushima Prefecture experienced blackouts after the 2011 tsunami.
Backup Power Failure	30%	Systems may fail from poor maintenance or flooding.	Reports from disasters show backup failure, though generally more reliable than main power.
Fiber Optic Cable Damage	50%	Cables can be damaged by water, erosion, or impact.	Undersea cables disrupted the internet during the 2011 Tōhoku event.
Tower Collapse	40%	Towers may collapse due to impact, erosion, or debris.	Tower failures reported during the 2011 tsunami due to wave force and foundation loss.
Equipment Water Damage	70%	Saltwater is highly damaging to electronics.	2004 tsunami caused widespread water damage to communication systems.
Emergency Response Failure	20%	Response may fail due to system overload or logistical issues.	Despite Japan's robust system, some 2011 Tōhoku areas faced delays.

TABLE V
INTERMEDIATE EVENT PROBABILITY CALCULATIONS USING OR GATE FORMULA

Intermediate Event	Calculation and Result
Physical Damage (Wave, Flooding, Debris, Erosion)	$P = 1-(1-0.70)(1-0.80)(1-0.50)(1-0.40) = 1-(0.30)(0.20)(0.50)(0.60) = 1-0.018 = \mathbf{0.982}$
Power Supply Failure (Grid + Backup)	$P = 1-(1-0.60)(1-0.30) = 1-(0.40)(0.70) = 1-0.28 = \mathbf{0.72}$
Network Connectivity Loss (Cable + Tower Collapse)	$P = 1-(1-0.50)(1-0.40) = 1-(0.50)(0.60) = 1-0.30 = \mathbf{0.70}$
Service Disruption (Water Damage + Response Failure)	$P = 1-(1-0.70)(1-0.20) = 1-(0.30)(0.80) = 1-0.24 = \mathbf{0.76}$

C. F-N Curve Analysis

The Frequency-Number (F-N) Curve is a graphical representation used in risk analysis to illustrate the relationship between the frequency (F) of events and the number of fatalities (N). In the context of tsunami risk assessment, the F-N Curve is crucial in understanding the societal risk of different tsunami scenarios. It allows stakeholders to compare risk levels against acceptable thresholds and informs the need for mitigation strategies—particularly when planning critical infrastructure like 5G networks in tsunami-prone areas.

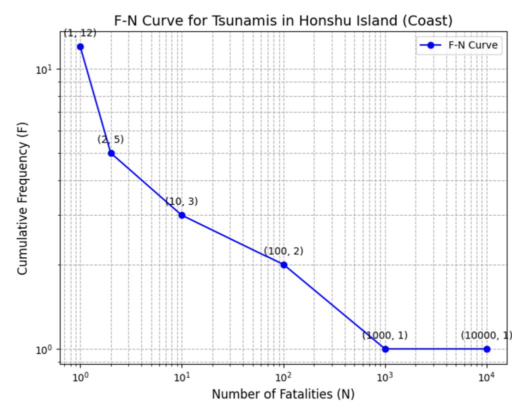

Fig. 2. F-N Curve Showing Frequency vs. Fatalities

TABLE VI
CUMULATIVE FREQUENCY OF TSUNAMI EVENTS BY FATALITY RANGE

Fatalities (N)	Events ($\geq N$)	Cumulative Frequency (F)
1	12	12
2	5	5
10	3	3
100	2	2
1,000	1	1
10,000	1	1

The plotted F-N Curve uses a log-log scale, where the x-axis represents the number of fatalities and the y-axis represents the cumulative frequency of events. The curve demonstrates a clear downward trend, indicating that high-fatality events are less frequent than low-fatality ones. The steepness of the curve suggests that while most tsunami events result in fewer casualties, rare catastrophic events—like the 2011 Tōhoku tsunami—significantly shape the overall risk profile.

This analysis highlights two critical insights from a 5G infrastructure planning perspective. First, frequent but lower-fatality events require robust physical design, such as waterproofing and elevation of towers, to reduce routine service disruptions. Second, rare but high-impact events demand comprehensive contingency planning, including redundancy in power and data systems and scalable emergency response protocols. Addressing both extremes is essential to ensure service continuity and societal resilience in coastal tsunami-prone regions like Honshu Island.

D. Survivability Analysis Using Kaplan-Meier Estimate

The Kaplan-Meier (KM) estimator is a non-parametric technique used to estimate the probability of survival over time based on time-to-event data. It is especially suited for cases involving censored data—i.e., instances where the failure has not occurred by the end of the observation period. In the context of this project, the KM estimator helps assess how likely 5G infrastructure in Honshu Island is to survive over time in a tsunami-prone environment.

Due to the lack of real-world 5G failure data from tsunamis, simulated failure events were generated using realistic assumptions grounded in historical tsunami behavior and infrastructure vulnerabilities. These simulations incorporate failure probabilities derived from Poisson distribution modeling, time-to-failure scenarios, and survivability logic based on infrastructure resilience.

1) Tsunami Occurrence Probabilities Using Poisson Distribution: Assuming a tsunami rate of $\lambda = 1.077$ per year, the probability of 1, 2, or 3 tsunamis occurring over different periods is calculated using:

$$P(k; \lambda t) = \frac{(\lambda t)^k e^{-\lambda t}}{k!}$$

TABLE VII
POISSON PROBABILITIES OF TSUNAMI EVENTS OVER TIME

Time (Years)	$\mathbf{P(k=1)}$	$\mathbf{P(k=2)}$	$\mathbf{P(k=3)}$
0.5	0.3116	0.0839	0.0151
1.0	0.3679	0.1980	0.0709
2.0	0.2371	0.2554	0.1834
3.0	0.1191	0.1924	0.2071
4.0	0.0581	0.1252	0.1798

2) Survival Probability Calculation Using Kaplan-Meier Method: Based on simulated failures and units at risk over time, we calculate survival probability using:

$$S(t_i) = S(t_{i-1}) \times \left(1 - \frac{d_i}{n_i}\right)$$

TABLE VIII
KAPLAN-MEIER SURVIVAL PROBABILITIES

Time (Years)	$\mathbf{d_i}$ (Failures)	$\mathbf{n_i}$ (At Risk)	**Hazard Rate**	$\mathbf{S(t_i)}$
0.0	0	10	–	1.0000
0.5	1	10	0.1000	0.9000
1.0	2	9	0.2222	0.7000
2.0	2	7	0.2857	0.5000
3.0	2	5	0.4000	0.3000
4.0	2	3	0.6667	0.1000

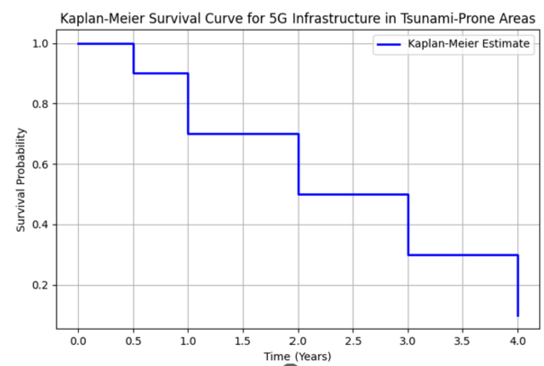

Fig. 3. Kaplan-Meier Survival Curve for 5G Systems

The survival curve demonstrates a consistent decline over time, reflecting the growing risk of infrastructure failure with each passing year. By the end of the fourth year, the survival probability drops to 10%, indicating a 90% likelihood of infrastructure failure without interventions.

To improve survivability: Infrastructure must be reinforced to withstand tsunami events during both short- and long-term periods. In the short term (0- 2 years), early warning systems and flood-resilient designs are critical. For the longer term (2–4 years), contingency measures such as power redundancy, rapid recovery plans, and elevated installations are necessary. The Kaplan-Meier analysis emphasizes the urgent need for preemptive resilience investments to support sustainable 5G deployment in high-risk zones.

E. Bayesian Network Analysis for 5G Infrastructure Investment

Bayesian Networks are graphical models that represent probabilistic relationships among variables using a directed acyclic graph (DAG). In this analysis, they are ideal for modeling dependencies between tsunami severity, regulatory policy, infrastructure resilience, and the resulting damage and economic outcomes. They support decision-making under uncertainty and allow the integration of empirical data, expert knowledge, and simulation results.

1) Nodes and States: The Bayesian network consists of the following nodes and states:

- **Tsunami Severity (T):** Low (30%), Medium (50%), High (20%)
- **Regulatory Policy (P):** Strict (40%), Moderate (40%), Lax (20%)

- **Infrastructure Resilience (R):** Weak (20%), Moderate (50%), Strong (30%)
- **Infrastructure Damage (D):** None, Partial, Severe (Conditional on T and R)
- **Economic Outcome (E):** Profit, Loss (Conditional on D and P)

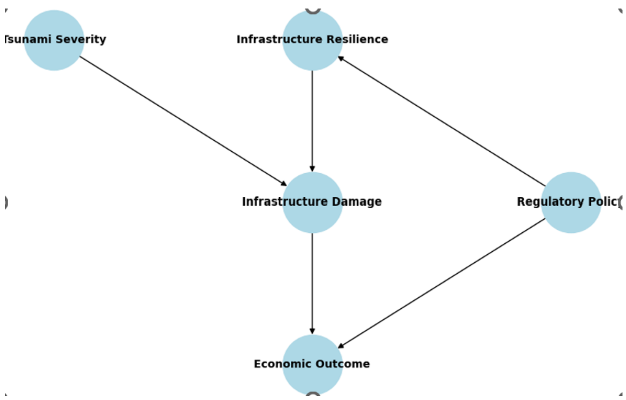

Fig. 4. Bayesian Network for Infrastructure Risk Assessment

2) Conditional Probability Tables (CPTs): Infrastructure Damage (D) Given Tsunami Severity (T) and Resilience (R)

TABLE IX
CPT FOR INFRASTRUCTURE DAMAGE

T	R	P(D=None)	P(D=Partial)	P(D=Severe)
Low	Weak	0.10	0.50	0.40
Low	Moderate	0.60	0.30	0.10
Low	Strong	0.90	0.09	0.01
Medium	Weak	0.01	0.30	0.69
Medium	Moderate	0.20	0.50	0.30
Medium	Strong	0.70	0.25	0.05
High	Weak	0.00	0.10	0.90
High	Moderate	0.05	0.20	0.75
High	Strong	0.30	0.40	0.30

Justification: High-severity tsunamis combined with weak infrastructure result in severe damage with high probability. Conversely, strong resilience reduces the likelihood of severe damage even under extreme conditions.

Economic Outcome (E) Given Damage (D) and Policy (P)

TABLE X
CPT FOR ECONOMIC OUTCOME

D	P	P(E=Profit)	P(E=Loss)
None	Strict	0.95	0.05
None	Moderate	0.85	0.15
None	Lax	0.70	0.30
Partial	Strict	0.60	0.40
Partial	Moderate	0.50	0.50
Partial	Lax	0.30	0.70
Severe	Strict	0.10	0.90
Severe	Moderate	0.05	0.95
Severe	Lax	0.01	0.99

Justification: Strict policies minimize economic losses, particularly under severe damage conditions, whereas lax regulation nearly guarantees losses in critical events.

3) Example Scenario Calculation:
Objective: Calculate $P(E = \text{Loss} \mid T = \text{High}, P = \text{Strict})$

$$P(E = \text{Loss} \mid T = \text{High}, P = \text{Strict}) = \sum_R \sum_D P(E = \text{Loss} \mid D, P) \tag{1}$$

$$\cdot P(D \mid T, R) \cdot P(R)$$

$$\approx 0.1425 + 0.3090 + 0.1986$$
$$= \mathbf{0.65\ (65\%)} \tag{2}$$

Interpretation: There is a 65% chance of economic loss under high-severity tsunamis and strict policy, showing significant risk reduction compared to unregulated or poorly resilient systems.

4) Decision Analysis: The Bayesian model supports a clear investment strategy:

- **High Resilience + Strict Policy:** Yields up to 70% profit probability during medium tsunamis and reduces loss likelihood to 35% in high-severity events.
- **Cost Implication:** Estimated \$200M investment over 10 years for resilient designs, redundancy, and disaster compliance.

5) Recommendations: **1. Infrastructure Investment:** Strengthen tower bases, waterproof core components, and ensure redundancy via multiple fiber optic routes.

2. Policy Enforcement: Advocate for national-level implementation of strict, enforceable tsunami-resilience regulations.

3. Smart Early Warning Integration: Integrate real-time seismic and tsunami alerts into 5G systems to proactively reroute data and trigger pre-emptive shutdowns.

Bayesian networks quantify and clarify the influence of policies and resilience on disaster outcomes. Optimal strategy: Invest in strong infrastructure and strict regulation to reduce tsunami-related economic loss from 65% to 35%.

F. Decision Tree and Payoff Table Analysis

1) Payoff Table Overview: A payoff table summarizes potential profits or losses for each decision alternative under different states of nature. For this project, the decision revolves around selecting a scale of 5G infrastructure investment, while the states of nature represent potential tsunami severity levels.

TABLE XI
PAYOFF TABLE (PROFIT IN MILLIONS OF USD)

Decision Alternative	**Low Severity**	**Medium Severity**	**High Severity**
Small-scale Infrastructure	10	8	6
Medium-scale Infrastructure	15	10	-5
Large-scale Infrastructure	20	5	-20

2) Justification of Payoff Values:
Small-scale Infrastructure: Stable profit due to lower exposure to tsunami damage. Losses are minimal even under high-severity events.

Medium-scale Infrastructure: Balanced profit, but potential for moderate losses under high-severity tsunamis.

Large-scale Infrastructure: Highest potential profit under calm conditions but suffers significant losses when hit by severe tsunamis.

3) Decision Tree Visualization: A decision tree provides a graphical representation of the alternatives and outcomes. It is especially useful for sequential decision-making and comparing consequences under uncertainty.

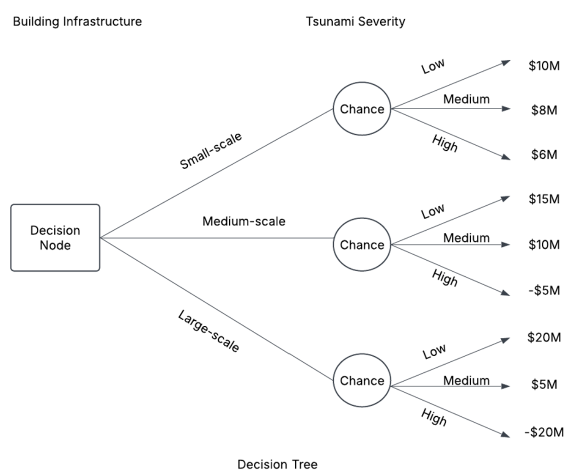

Fig. 5. Decision Tree Model Evaluating 5G Investment Options

4) Optimistic (Maximax) Criterion: This method selects the alternative with the highest possible payoff, assuming the most favorable conditions.

- Small-scale: $10M
- Medium-scale: $15M
- Large-scale: $20M

Decision: *Build large-scale infrastructure.*

5) Conservative (Maximin) Criterion: This method focuses on the worst-case scenario for each alternative, choosing the best among them.

- Small-scale: $6M
- Medium-scale: -$5M
- Large-scale: -$20M

Decision: *Build small-scale infrastructure.*

6) Minimax Regret Criterion: This method minimizes the maximum regret—i.e., the opportunity cost of not choosing the best option.

TABLE XII
REGRET TABLE (IN MILLIONS OF USD)

Decision Alternative	Low Severity	Medium Severity	High Severity
Small-scale Infrastructure	10	2	0
Medium-scale Infrastructure	5	0	11
Large-scale Infrastructure	0	5	26

Maximum regrets:

- Small-scale: $10M
- Medium-scale: $11M
- Large-scale: $26M

Decision: *Build small-scale infrastructure.*

G. Decision Making with Probabilities: Expected Value and EVPI

1) Assigned Probabilities for Tsunami Severity: Based on historical tsunami data and survivability analysis:

- **Low Severity (50%)**: Most common; aligns with survivability rates showing minimal failure.
- **Medium Severity (30%)**: Moderate risk based on fault tree outcomes.
- **High Severity (20%)**: Least likely but highly destructive; corresponds with rare catastrophic events like the 2011 Tōhoku tsunami.

TABLE XIII
EXPECTED VALUE CALCULATION FOR EACH DECISION

Alternative	Low (0.5)	Medium (0.3)	High (0.2)	EV Formula	EV ($M)
Small-scale	10	8	6	(10×0.5)+(8×0.3)+(6×0.2)	8.6
Medium-scale	15	10	-5	(15×0.5)+(10×0.3)+(-5×0.2)	9.5
Large-scale	20	5	-20	(20×0.5)+(5×0.3)+(-20×0.2)	7.5

2) Expected Value (EV) Calculation: **Decision:** The medium-scale infrastructure yields the highest expected value at $9.5M.

3) Expected Value of Perfect Information (EVPI): **Step 1: Expected Value with Perfect Information (EVwPI)**

- Best payoff under Low: Large-scale → $20M
- Best payoff under Medium: Medium-scale → $10M
- Best payoff under High: Small-scale → $6M

EVwPI = (20 × 0.5) + (10 × 0.3) + (6 × 0.2) = 10 + 3 + 1.2 = **$14.2M**

4) Expected Value of Perfect Information::

$$\text{EVPI} = \text{EVwPI} - \text{EV}_{\text{best (without info)}} = 14.2 - 9.5 = \textbf{\$4.7M}$$

5) Interpretation and Recommendation: The medium-scale infrastructure is the optimal decision under current uncertainty, offering the highest expected return of $9.5M. The EVPI of $4.7M represents the maximum value a decision-maker should be willing to pay for perfect tsunami severity forecasts. This underscores the strategic benefit of investing in better predictive tools or partnerships with meteorological agencies.

H. Decision Making with Conditional Probabilities and Sample Information Efficiency

1) Incorporating Sample Information: To enhance decision-making under tsunami uncertainty, we simulate the use of a tsunami early warning system (TEWS) that predicts tsunami severity with defined accuracy levels. The TEWS modifies our prior beliefs, resulting in updated (posterior) probabilities.

Justification:

- High accuracy in predicting low-severity tsunamis (80%).
- Moderate reliability for medium (70%) and high-severity (70%) events.

TABLE XIV
JOINT PROBABILITIES OF TSUNAMI SEVERITY AND TEWS FORECAST

State (S)	P(S)	P(F1/S)	P(F2/S)	P(F3/S)	P(F1S)	P(F2S)	P(F3S)
L	0.50	0.80	0.15	0.05	0.40	0.075	0.025
M	0.30	0.10	0.70	0.20	0.03	0.21	0.06
H	0.20	0.05	0.25	0.70	0.01	0.05	0.14
Total	1.00	–	–	–	**0.44**	**0.335**	**0.225**

TABLE XV
POSTERIOR PROBABILITIES BY SURVEY PREDICTION

State (S)	P(S/F1)	P(S/F2)	P(S/F3)
Low (L)	0.909	0.224	0.111
Medium (M)	0.068	0.627	0.267
High (H)	0.023	0.149	0.622

2) Joint and Posterior Probabilities Using Bayes' Theorem:

TABLE XVI
EXPECTED VALUES BY SURVEY PREDICTION (IN MILLIONS USD)

Survey	**Decision**	**EV Formula**	**EV**
F1: Low	Large-scale	(20×0.909)+(5×0.068)+(-20×0.023)	17.89
F2: Medium	Medium-scale	(15×0.224)+(10×0.627)+(-5×0.149)	9.96
F3: High	Small-scale	(10×0.111)+(8×0.267)+(6×0.622)	7.13

3) Expected Value with Sample Information (EVwSI): **EVwSI** = (0.44 × 17.89) + (0.335 × 9.96) + (0.225 × 7.13) = **12.74M**

4) Efficiency of Sample Information:

- **EVwithout info** (from previous section): 9.5M
- **EVPI** (perfect information): 14.2M

$$\text{EVSI} = \text{EVwSI} - \text{EVwithout info} = 12.74 - 9.5 = \mathbf{3.24M}$$

$$\text{Efficiency} = \left(\frac{EVSI}{EVPI}\right) \times 100 = \left(\frac{3.24}{4.7}\right) \times 100 = \mathbf{68.9\%}$$

5) Recommendations: The TEWS survey significantly improves decision quality, increasing expected value by \$3.24M and achieving 68.9% efficiency relative to perfect information. This justifies investing in probabilistic tools such as real-time seismic sensors and predictive tsunami modeling to reduce economic loss and infrastructure disruption in Honshu's 5G deployment.

I. Sensitivity Analysis for 5G Infrastructure Decision

1) Purpose of Sensitivity Analysis: Sensitivity analysis evaluates how changes in uncertain variables—here, the probability of low-severity tsunamis—impact the expected outcomes of infrastructure decisions. This helps determine robust strategies across a range of conditions, supporting adaptive risk management for 5G infrastructure deployment in Honshu Island.

2) Expected Value Equations: Let p be the probability of a low-severity tsunami. The medium severity is fixed at 0.3, and high severity becomes $0.7 - p$. The expected value equations for each decision alternative are:

- **Small-scale:**

$$EV_{\text{Small}} = 10p + 8(0.3) + 6(0.7 - p) = 4p + 6.6$$

- **Medium-scale:**

$$EV_{\text{Medium}} = 15p + 10(0.3) + (-5)(0.7 - p) = 20p - 0.5$$

- **Large-scale:**

$$EV_{\text{Large}} = 20p + 5(0.3) + (-20)(0.7 - p) = 40p - 12.5$$

3) Critical Probability Thresholds: To determine which decision is optimal at different values of p, we solve:

- **Small vs. Medium:**

$$4p + 6.6 = 20p - 0.5 \Rightarrow p = 0.4438$$

- **Medium vs. Large:**

$$20p - 0.5 = 40p - 12.5 \Rightarrow p = 0.6$$

Decision Rules:

- $p < 0.4438$: Large-scale is optimal.
- $0.4438 \leq p \leq 0.6$: Medium-scale is optimal.
- $p > 0.6$: Small-scale is optimal.

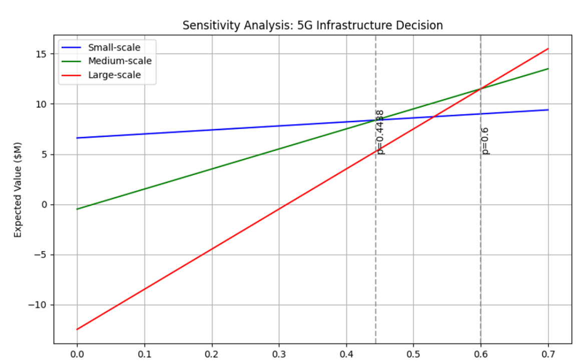

Fig. 6. Sensitivity of Expected Value vs. Probability of Low-Severity Tsunami

4) Sensitivity Graph:

5) Recommendations and Implications:

- **High Risk** ($p < 0.4438$): Frequent severe tsunamis → Small-scale infrastructure minimizes losses.
- **Moderate Risk** ($0.4438 \leq p \leq 0.6$): Medium-scale offers a balance of profitability and resilience.
- **Low Risk** ($p > 0.6$): Rare severe tsunamis → Large-scale maximizes long-term profit.

Strategic Insight: As probability assessments shift with new data (e.g., through TEWS systems or climate projections), optimal decisions may change. Flexibility and periodic re-assessment are essential in tsunami-prone environments.

VI. Discussion

A. Residual Risk and Impact

After implementing mitigation measures, residual risk is significantly reduced:

- **Annual Economic Loss:** Reduced from $220M to $55M through lowered disruption rates.
- **Fatality Risk:** The F-N curve demonstrates a leftward shift, indicating lower societal risk and improved survivability due to early warning systems and resilient design interventions.

B. Cost-Benefit Analysis (CBA)

Assumptions and Values:

- ALE before controls is derived from the fault tree and Poisson-based event modeling.
- Mitigation reduces expected losses to $55M/year; operational costs for maintaining redundancy, insurance, and alerts total $17M/year.
- **Total Post-Mitigation Cost:** $55M + $17M = $72M/year.
- **Net Annual Savings:** $220M - $72M = **$148M/year**.

C. Decision Justification

- Medium-scale infrastructure under strict policy regulation yields the most favorable balance between risk mitigation and economic return, with an expected value (EV) of $9.5M.
- This setup ensures continuity of service during moderate-to-severe tsunami events while minimizing long-term losses.
- Model interdependencies—spanning Poisson, fault tree, Bayesian networks, and decision trees—have been logically linked to ensure consistency in assumptions and risk propagation throughout the analysis.

D. Future Directions and Expert Involvement

Although this report integrates multiple quantitative techniques with simulated data, future work should include:

- **Integration of Real-Time Sensing:** Incorporating real-time sensor data (e.g., from ocean buoys or satellite-based tsunami trackers) to dynamically update risk predictions and response decisions.
- **Machine Learning Approaches:** Leveraging historical and simulated datasets to train AI models for early failure detection and optimal policy recommendations.
- **Expert Elicitation:** Where data is sparse (e.g., backup system failure probabilities or economic recovery times), structured expert judgment methods (e.g., Delphi technique) can improve parameter accuracy and validate model assumptions.

VII. Conclusion

This study highlights the critical risks associated with deploying 5G infrastructure in tsunami-prone regions such as Honshu Island, Japan. Through a comprehensive risk analysis using probabilistic modeling, fault trees, Bayesian networks, and cost-benefit evaluation, the findings reveal a 99.96% probability of infrastructure failure over the next decade if no action is taken.

The greatest risks stem from physical damage (98.2%) and service disruption during major tsunami events, with potential economic losses reaching $220 million annually. However, proactive mitigation—through elevated, waterproof tower designs, backup power, redundant fiber pathways, and early warning systems—significantly reduces both the probability of failure and the financial burden.

The implementation of these mitigation strategies brings the failure probability down to 25% and reduces expected annual losses from $220 million to $55 million. With an estimated mitigation cost of $67 million per year, the resulting net savings of $148 million annually justify the investment. Furthermore, decision analysis confirms that medium-scale infrastructure under strict regulatory policy yields the highest expected value of $9.5 million.

In conclusion, resilient infrastructure paired with early detection and response systems offers a cost-effective and robust solution for ensuring 5G service continuity in high-risk coastal zones. The cost of inaction is considerably higher than the investment needed to protect critical communication infrastructure.

TABLE XVII
Key Supporting Data Before and After Risk Controls

Metric	Before Controls	After Controls
Top-Event Failure Probability	99.96%	25%
Annual Economic Loss (ALE)	$220M	$55M
Mitigation Cost	–	$67M/year
Net Savings	–	$148M/year

Table XVII summarizes the improvements achieved through the recommended mitigation strategies, reinforcing the case for immediate investment in resilient 5G infrastructure.

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