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QUANTIFYING THE ROLE OF ASSET MAINTENANCE FOR RESILIENT INFRASTRUCTURE

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Abstract

Asset maintenance and infrastructure resilience are directly related. However, most resilience assessments overlook pre-disaster asset condition. This study develops a probabilistic lifecycle framework integrating stochastic condition-index (CI) evolution, performance degradation, recovery modeling, and explicit maintenance strategies within a multi-hazard simulation environment. The framework quantifies how pre-event maintenance shapes resilience trajectories. Application to a representative bridge portfolio demonstrates that preventive maintenance consistently improves lifecycle performance and the Composite Resilience Performance Index (CRPI), while rehabilitation provides substantial but time-dependent recovery gains. The proposed framework offers a quantitative decision-support tool linking maintenance actions to resilience outcomes, supporting resilience-informed infrastructure planning and management.

Introduction

Critical infrastructure and lifelines such as bridges are fundamental to economic activity, emergency response, and community well-being (Bruneau et al. 2003, Francis and Bekera 2014). The capacity of these assets to resist, absorb and recover from disruptive events determines not only direct repair needs but also continuity of services, the integrity of value chains, and public safety (Bruneau et al. 2003, Cimellaro 2016). Modern resilience thinking therefore extends conventional engineering objectives into life-cycle goals that prioritise robustness, rapidity, redundancy and resourcefulness. Despite this conceptual progress, routine asset management rarely incorporates explicit traceable resilience objectives in maintenance decision processes (Pant et al. 2019).

During normal operating conditions (pre-event or pre-disaster), the infrastructure components often degrade through multiple mechanisms such as chloride ingress, corrosion, fatigue accumulation, scour and freeze–thaw cycles that often produce nonlinear transitions to accelerated capacity loss and discrete damage states (Li 2003, Ghodoosi et al. 2018). Thus, the performance of an asset also decreases during pre-event/pre-disaster phase. Resilience and fragility assessments that assume "as-new" properties therefore risk overestimating robustness and understating recovery needs (Yang and Frangopol 2019). The pre-event condition of an asset is not a peripheral descriptor but a primary determinant of resilience trajectories within the performance–time framework (Poulin and Kane 2021).

As far as pre-event condition is concerned, Practitioners commonly summarise structural health using composite condition indices (CIs) that aggregate inspection observations, monitoring signals and surrogate indicators into a single, interpretable metric (Li 2003, Li and Gao 2022). Treating CI as an explicit, time-evolving state variable creates a direct modelling bridge between maintenance actions, state-dependent vulnerability, and post-event recovery dynamics. Empirical and modelling studies indicate that poorer pre-event condition is associated with larger immediate performance losses and slower recovery for comparable hazard intensities, implying that maintenance which improves CI yields resilience benefits beyond mere reductions in repair effort (Salem et al. 2020, Poulin and Kane 2021). Accordingly, CI provides a practical means to connect inspection data and maintenance choices to probabilistic performance outcomes.

Further, how CI changes over time due to wear and tear dictates maintenance strategies. Maintenance strategies vary in timing, triggering mechanism, cost structure and mobilization lag. Broadly, strategies can be classified as corrective (reactive), preventive (periodic), predictive (condition-based) and rehabilitative (capacity-restoring or upgrading) (Durán and Vergara 2022, Applegate and Tien 2019). These approaches interact with resilience in different ways: preventive and predictive actions tend to preserve pre-event resilience by slowing deterioration, whereas corrective and rehabilitative interventions accelerate recovery and can modify fragility characteristics (Li and Gao 2022, Salem et al. 2020). Because mobilization lag and implementation constraints differ across strategies, resilience-aware decision support must weigh time-dependent benefits (for example, avoided downtime and reduced recovery time) alongside operational feasibility and budgetary limits.

Thus, under normal operation conditions, the maintenance decisions are driven by asset deterioration, maintenance strategies, and budget availability. Additionally, assets' health is impacted by extreme weather events. Fragility curves are used to represent this information.(Otárola et al. 2022) Fragility curves translate hazard intensity into damage probability. Classical fragility formulations commonly assume fixed vulnerability parameters, but recent advances emphasise state-dependent fragility in which median and dispersion parameters vary with CI, cumulative damage or material degradation (Izadi et al. 2020, Otárola et al. 2022). Physically, section loss or foundation scour lowers the intensity required to reach a given damage state; conversely, CI improvements through maintenance shift fragility curves toward lower damage probabilities for the same hazard level. Including CI explicitly in fragility models thus provides a mechanistic pathway to quantify how maintenance investments alter risk exposure and expected performance under stochastic hazards (Liu et al. 2020). State-aware fragility operationalises the causal linkage between maintenance and risk.

Multi-hazard and cascading risk chains introduce further complexity. Infrastructure commonly experiences sequences of hazards—earthquakes followed by floods or landslides, storms that induce scour and amplify hydraulic vulnerability—where coupled hazards produce non-additive impacts (Ganin et al. 2017, Dong and Frangopol 2016). Prior events can increase susceptibility to subsequent hazards (for example, seismic damage that exacerbates scour), which may reprioritise maintenance when single-hazard assumptions are used Dong and Frangopol (2016). Robust resilience planning therefore requires propagation of uncertainty across multi-hazard sequences and explicit accounting for how maintenance alters residual capacity available to withstand future events. Consequently, life-cycle analyses that simulate hazard sequences and maintenance interactions are essential for realistic prioritisation.

Methodologically, several research streams are mature enough to be integrated into a unified life-cycle framework: stochastic degradation and ageing models (Liu et al. 2020); Bayesian updating of fragility from damage observations (Li and Gao 2022); Monte Carlo simulation of multi-hazard portfolios (Liu et al. 2020); and translation of probabilistic service availability into prioritisation metrics (Poulin and Kane 2021). Nevertheless, three gaps constrain uptake in practice: (1) multi-hazard, state-aware fragility models that directly ingest CI observations are not standard in maintenance portfolios; (2) non-additive coupling of sequential hazard damage within life-cycle analyses remains underexplored; and (3) end-to-end frameworks that convert CI-driven resilience metrics into quantitative decision criteria for maintenance prioritisation under uncertainty are still nascent (Ouyang 2014, Pant et al. 2019).Addressing these gaps would make resilience metrics actionable for asset managers operating under resource constraints.

This paper addresses these gaps by developing a probabilistic lifecycle framework that can be used to estimate the role of asset maintenance in improving resilience of an infrastructure system. The developed framework integrates probabilistic life-cycle methodology linking stochastic CI dynamics with CI-congruent fragility, defines decision policies for preventive, corrective and rehabilitative maintenance strategies , simulates multi-hazard and cascade scenarios via Monte Carlo sampling, and translates probabilistic performance trajectories into resilience-oriented metrics for strategy ranking and portfolio prioritisation. We demonstrate the framework on a synthetic span-bridge portfolio to illustrate how CI-aware fragility modelling combined with hazard sequencing can materially influence resilience outcomes and inform maintenance prioritisation in resource-constrained settings. The proposed approach aims to provide infrastructure operators with a practicable decision-support tool that integrates inspection and maintenance information into investment choices guided by resilience objectives and contemporary asset-management standards (International Organization for Standardization 2014, United Nations Office for Disaster Risk Reduction (UNDRR) 2022, World Bank 2021).

Methodology

This section summarises the probabilistic simulation engine used to compare corrective, preventive and rehabilitation maintenance strategies. The model couples (i) a physics-informed, condition-dependent deterioration law, (ii) log-normal fragility models conditioned on asset condition, (iii) deterministic damage-state (DS) selection via a shared event shock, (iv) loss mapping to condition index (CI), and (v) recovery dynamics. Outputs are life-cycle and event-level resilience metrics (CRPI, Robustness, Recoverability, Rapidity). The approach follows established resilience and fragility practices Bruneau et al. (2003), Cimellaro et al. (2010), Porter (2015), Committee et al. (2013).

Simulation workflow

A Monte-Carlo ensemble of N trials is executed. For each trial: The framework will be implemented using a Monte Carlo loop, where the entire simulation process will be repeated several times in order to capture the variability of hazard occurrence.

1. Pre-sample multi-hazard events (AEPs and intensities) and a uniform shock variable $u \in [0, 1)$ per event; the same u is replayed across all strategies to ensure comparability. All simulations are performed over a fixed lifecycle horizon with identical time discretization, ensuring that all Monte Carlo trials are equal in duration and directly comparable across maintenance strategies.
2. Propagate monthly deterioration (strategy-neutral physics).
3. Schedule/apply maintenance according to the tested strategy (Preventive: periodic jump; Corrective: post-event patch with delay; Rehabilitation: triggered explicit target).
4. If an event occurs at time t, evaluate fragility (CI-conditioned), determine DS via u, map DS to loss fraction, and update CI.
5. Apply recovery dynamics and record time series /

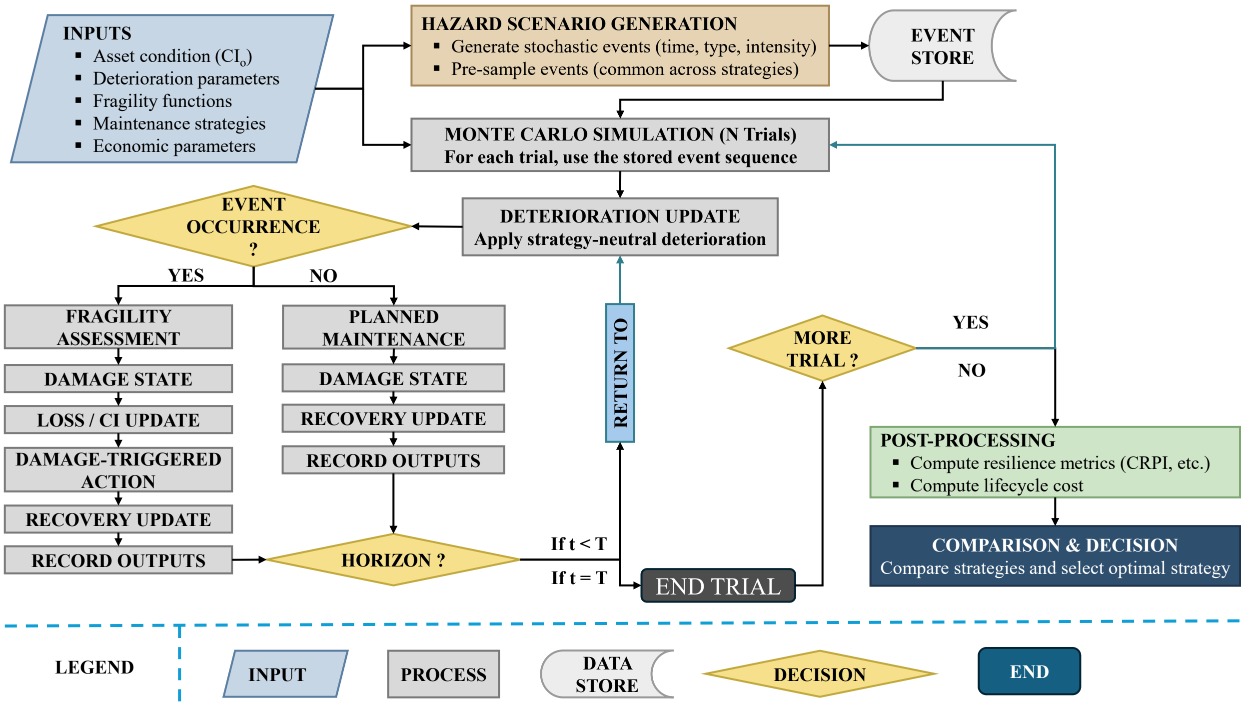

Figure 1: Methodology framework for lifecycle resilience assessment and maintenance strategy comparison, highlighting the integrated simulation process for hazard generation, condition deterioration, damage evaluation, recovery, and maintenance within a fixed time horizon, allowing for fair comparison of maintenance strategies for decision-making purposes.

event outcomes.

Deterioration model

Monthly evolution of asset condition is represented using an age- and condition-dependent deterioration process, with the Condition Index (CI) treated as a bounded state variable in the range $[0, 100]$. The formulation captures stage-wise ageing behaviour, age-related acceleration, and condition-sensitive degradation, while remaining computationally efficient for life-cycle Monte-Carlo simulation.

A smooth transition between early-life and late-life deterioration regimes is modelled using a logistic stage-weight function,

$$w(a) = \frac{1}{1 + \exp\left(-\frac{a-a_0}{s}\right)}, \tag{1}$$

where a denotes asset age (years), a_0 is the transition age, and s controls the smoothness of the transition.

The effective baseline annual deterioration rate is defined as

$$\bar{r}_{\text{base}} = r_{\text{base}} \left[(1 - w(a)) + w(a) \cdot \text{PM} \right], \tag{2}$$

where r_{base} is the nominal baseline rate and PM scales late-stage deterioration intensity. Age- and condition-dependent acceleration is incorporated through

$$r_{\text{ann}}(a, \text{CI}) = \bar{r}_{\text{base}} \, (1 + \gamma a) \big(1 + \eta (1 - \text{CI}/100)\big), \tag{3}$$

with γ governing age-related acceleration and η controlling sensitivity to declining condition.

For numerical implementation, the annual rate is converted to a monthly rate,

$$r_{\text{m}} = \frac{r_{\text{ann}}}{12}. \tag{4}$$

CI evolution over a time step Δ_t is computed using an exponential decay update,

$$\text{CI}_{t+\Delta} = \text{CI}_t \exp(-r_{\text{m}} \Delta_t), \tag{5}$$

which preserves positivity and ensures numerical stability over long simulation horizons.

This expression describes transitions from early to late ageing, rapid degradation at low CI, and continuous degradation dynamics as described in established deterioration modelling practice (McKibbins et al. 2019). The deterioration process is modelled as strategy-neutral, with maintenance activities affecting CI by discrete gains or recovery dynamics, but not affecting the deterioration physics.

Fragility and damage-state selection

For each hazard intensity I and DS threshold index j the exceedance (upper tail) probability is modeled by a log-normal CDF:

$$P(\text{DS} \geq j \mid I, \text{CI}) = \Phi\left(\frac{\ln I - \ln \mu_j^*(\text{CI})}{\beta_j} \right), \tag{6}$$

where $\Phi(\cdot)$ is the standard normal CDF, β_j is dispersion and $\mu_j^*(\text{CI})$ is the CI-adjusted median:

$$\mu_j^*(\text{CI}) = \mu_j \cdot \left[1 + \phi \frac{\text{CI} - 50}{50} \right] \tag{7}$$

Incremental probabilities for No Damage, DS1, DS2, ... are obtained from successive differences of (6) as customary Porter (2015), Committee et al. (2013). A deterministic DS label is selected by comparing the incremental CDF to the pre-sampled u (same u used across strategies for that event) — this enforces paired comparison across strategies.

Loss mapping and immediate post-event CI

Event-induced damage states (DS) are translated into fractional condition losses L_{DS} using mean loss values (or bounded ranges where uncertainty is characterised). The immediate post-event condition is computed as

$$\mathrm{CI}_{\mathrm{post}} = \mathrm{CI}_{\mathrm{pre}}\big(1 - L_{\mathrm{DS}}\big). \quad (8)$$

By ensuring that the logic of intervention actions determines the differences in condition states after events for various strategies, this deterministic transformation eliminates the impact of maintenance and recovery actions.

Recovery and maintenance models

Recovery toward a target CI is modelled by an exponential approach:

$$\mathrm{CI}(t) = \mathrm{CI}_{\mathrm{post}} + \big(\mathrm{CI}_{\mathrm{target}} - \mathrm{CI}_{\mathrm{post}}\big)\big(1 - e^{-kt}\big), \quad (9)$$

where k is a recovery rate parameter calibrated by resourcefulness and strategy ($k = k_0 \cdot \alpha_{\mathrm{strat}} \cdot \alpha_{\mathrm{res}}$). In the implementation:

- **Preventive**: scheduled periodic jumps (no change to physics): $\mathrm{CI} \leftarrow \min(100, \mathrm{CI} + G)$ at interval.
- **Corrective**: post-event patch scheduled after a resource dependent delay; gain is fraction of event loss subject to a patch cap.
- **Rehabilitation**: triggered when CI falls below a threshold; scheduled to reach an explicit $\mathrm{CI}_{\mathrm{target}}$.

Resilience metrics (CRPI and event metrics)

Normalized performance is $p(t) = \mathrm{CI}(t)/100$. Life-cycle CRPI ($\mathrm{CRPI}_{\mathrm{life}}$) is the time-average normalized area under the performance curve:

$$\mathrm{CRPI}_{\mathrm{life}} = \frac{1}{T}\int_0^T p(t)\,dt. \quad (10)$$

Event-window metrics are computed on the recovery curve following an event Poulin and Kane (2021):

- **Robustness** = $p_{\mathrm{post}}/p_{\mathrm{pre}}$.
- **Recoverability** = $p_\infty/p_{\mathrm{pre}}$ (final steady value relative to pre-event).
- **Rapidity** = $1/\tau_{95}$, where τ_{95} is the time to reach 95% of pre-event performance.
- **$\mathrm{CRPI}_{\mathrm{event}}$** = normalized AUC of the recovery curve over the event window.

Monte-Carlo design and reproducibility

The Monte-Carlo simulations are performed using either fixed or random seeds. For each simulation run, the hazard events are pre-sampled, and a uniform random variable $u \in [0, 1)$ is generated for each event. The same realization of the hazard process and the corresponding sequence of u values are used for all maintenance strategies, such that the differences between all pairs of outcomes are only due to the maintenance strategies.

The cascading effects are modeled in two ways: (i) ordered scheduling of follow-on hazards within a specified vulnerability window, and (ii) probabilistic hazard intensity amplification if the asset is still in the vulnerable post-event state. The simulation outputs for each simulation run include time series of CI, event sequences, maintenance schedules, cost data, and aggregated resilience values, which are exported in structured CSV format.

Implementation details

The simulation engine is implemented with a monthly time step, deterministic damage state (DS) choice, and explicit scheduling of maintenance events. Repair and rehabilitation events are applied when the month of their scheduled execution is reached, allowing for mobilization delays and event timing to be handled consistently across simulations.

Results from the simulation engine include pre- and post-event fragility plots (S-curves with DS indicators), resilience phase plots, resilience dividend summaries, and event-level CSV files summarizing CI trajectories, event histories, maintenance events, and costs. These results enable traceability, diagnostic analysis, and post-simulation processing of lifecycle and event-level metrics.

The simulation methodology is consistent with existing frameworks for resilience quantification and fragility modeling as reported in the literature (Bruneau et al. 2003, Cimellaro et al. 2010, Porter 2015, Committee et al. 2013). Degradation modeling is based on principles recommended in industry guidelines (Owen 2023), and Monte-Carlo simulation and metric estimation follow standard stochastic simulation procedures(Otárola et al. 2022). To ensure transparency and reproducibility, the complete implementation of the simulation framework is provided in a publicly accessible repository (Yadav 2026).

Assumptions and limitations

- Damage-state (DS) to loss mapping is done by using mean fractional losses to facilitate deterministic and repeatable paired comparisons of maintenance strategies. The variability of loss estimates is not sampled in the baseline simulations.
- The degradation process is considered strategy agnostic, where the baseline degradation physics are the same for all strategies, and the impact of maintenance is only felt after repair and recovery activities.
- The analysis is done based on resilience performance metrics or other related metrics. However, other economic valuation metrics such as resilience dividend, net present value, or life cycle cost are not included in the analysis for the current study. The consideration of these metrics, along with other consequence-based

factors such as traffic demand or network importance, is an important area for future research directions.

Results and discussion

This section presents numerical results obtained from the Monte-Carlo simulation framework and discusses their implications for maintenance-strategy selection. The number of simulations (5000 for each strategy) was chosen to ensure that there was convergence of the resilience metrics, as no significant changes were found in the results for a larger number of simulations.

Ensemble summary statistics

Table 1 summarizes ensemble lifecycle resilience metrics obtained from 5000 Monte–Carlo realizations per strategy, including mean and standard deviation of $\mathrm{CRPI}_{\mathrm{life}}$ along with robustness, recoverability, and rapidity. Figure 2 shows the corresponding $\mathrm{CRPI}_{\mathrm{life}}$ distributions. Preventive maintenance exhibits the highest median and the narrowest interquartile range, indicating both superior and stable lifecycle performance. The no-maintenance strategy shows the lowest median and a pronounced lower tail, reflecting frequent excursions into low-performance states. Corrective and rehabilitation strategies provide intermediate performance with larger dispersion than preventive maintenance. These ensemble results demonstrate that scheduled preventive actions improve average resilience while reducing variability across hazard realizations.

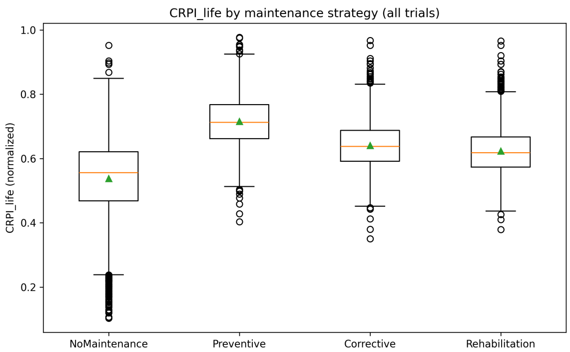

Figure 2: Distribution of lifecycle Composite Resilience Performance Index (CRPI_{life}) across 5000 Monte–Carlo trials for each maintenance strategy. Boxes indicate interquartile ranges, whiskers denote 1.5×IQR, and markers represent ensemble means.

Table 1: Ensemble lifecycle resilience metrics for maintenance strategies (5000 Monte–Carlo trials per strategy).

Strategy	Mean $\mathrm{CRPI}_{\mathrm{life}}$	Robustness	Recoverability	Rapidity
No Maintenance	0.5376	0.9474	0.9974	0.5499
Preventive	0.7158	0.9483	0.9974	0.4755
Corrective	0.6405	0.9474	0.9974	0.5499
Rehabilitation	0.6235	0.9474	0.9974	0.5417

To better understand how infrastructure behaves under each maintenance strategy, a representative trial is examined in detail. This trial run helps explain the ensemble results by showing condition changes, damage response, and recovery at the event level.

Event-level behaviour and fragility mapping

Fig. 3 shows prior vs post S-curves for a representative event. Key points:

- Pre-event condition (CI) shifts fragility medians, increasing probability of severe DS when CI is low.
- A deterministic per-event shock u is reused across strategies to isolate strategy effects.
- Post-event CI uses the mean-loss mapping $\mathrm{CI}_{\mathrm{post}} = \mathrm{CI}_{\mathrm{pre}}(1 - L_{\mathrm{DS}})$
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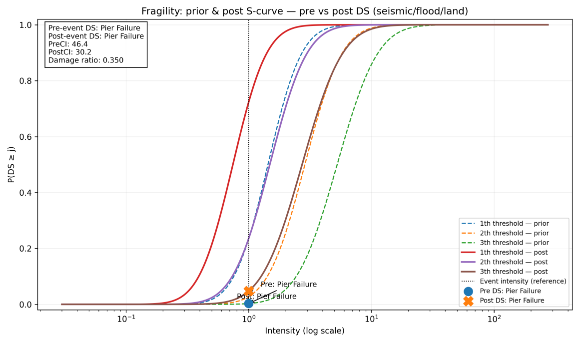

Figure 3: Condition-dependent fragility S-curves (prior and post) with realized damage states for a representative hazard, showing the effect of asset condition on damage exceedance probability.

Resilience phase diagrams (illustrative trial)

Figures (4–7) depict sample single-trial realizations to demonstrate the behavior of each maintenance strategy, whereas statistical results are based on all Monte Carlo simulation runs. Representative resilience phase diagrams illustrate the joint evolution of asset condition and performance for the illustrative trial. Monthly Condition Index (CI) trajectories are shown in the left subpanels, while the corresponding normalized performance used to compute $\mathrm{CRPI}_{\mathrm{life}}$ is shown in the right subpanels. Preventive maintenance produces frequent moderate CI restorations that stabilize baseline condition and sustain performance. Corrective maintenance results in event-triggered recovery with implementation delays and partial restoration, whereas rehabilitation generates large but infrequent CI resets governed by trigger thresholds. These trial-level dynamics provide mechanistic insight into the ensemble $\mathrm{CRPI}_{\mathrm{life}}$ trends reported in Table 1 and Figure 2.

Lifecycle dynamics and recovery mechanisms

Representative resilience phase diagrams (Figures 4–5) illustrate how ensemble trends arise from trial-level condition and performance trajectories. Under no maintenance, continuous deterioration exposes progressively weakened assets to successive hazards, leading to sustained performance decline. Preventive maintenance introduces frequent moderate CI restorations that stabilize baseline condition, thereby limiting damage severity and shortening recovery periods. Corrective maintenance relies on post-damage interventions with implementation delays, result-

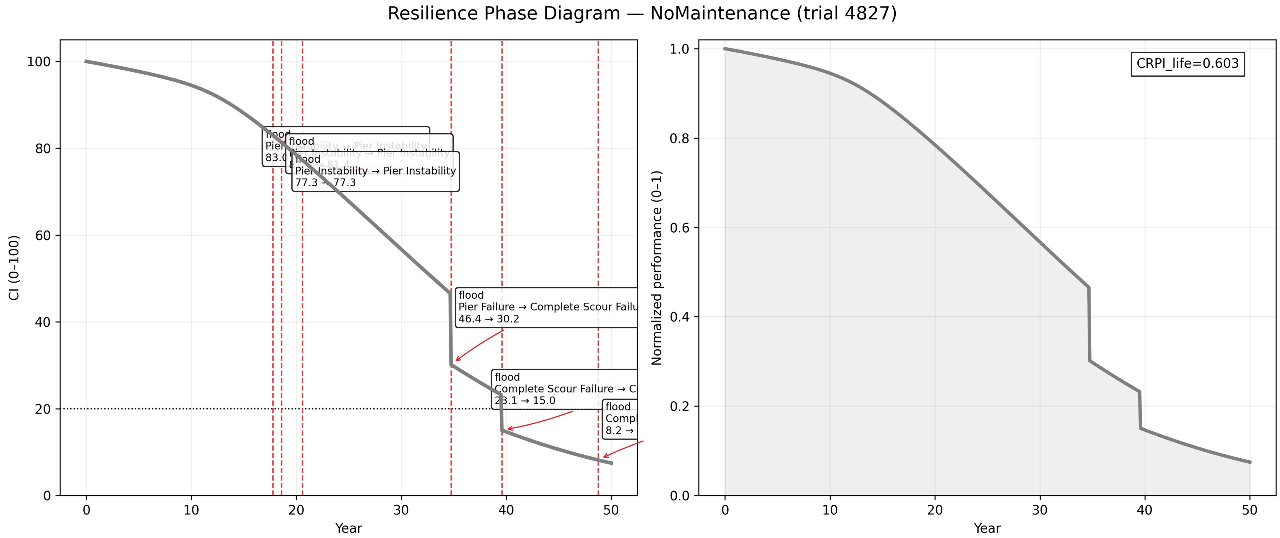

Figure 4: Representative Resilience Phase Diagram for No Maintenance Strategy, with monthly degradation of Condition Index shown in the left panel, and corresponding performance trajectory shown in the right panel.

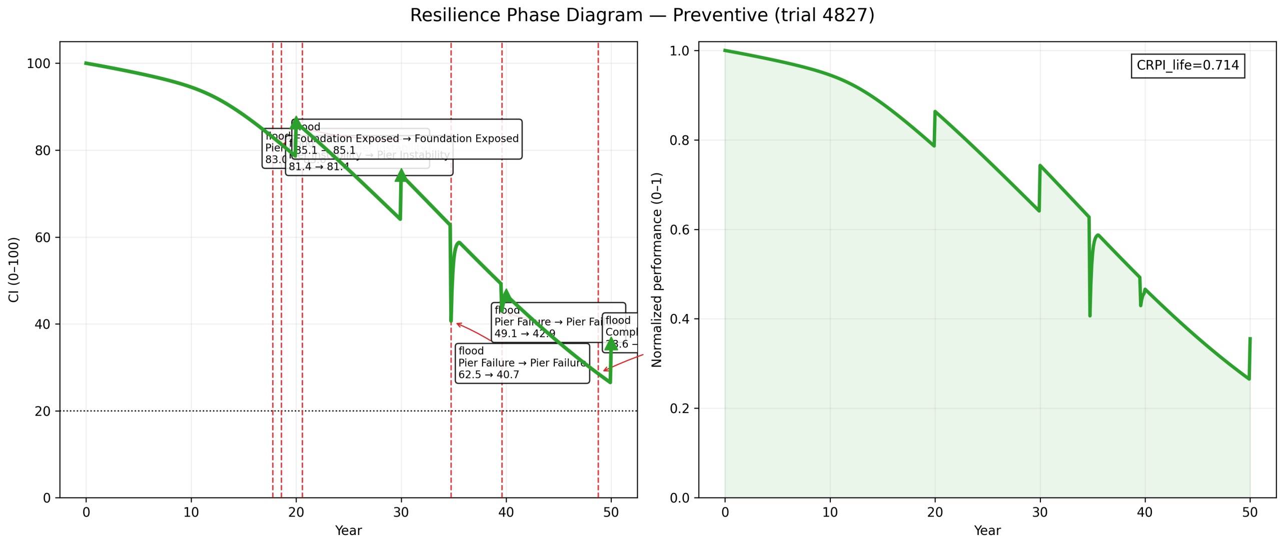

Figure 5: Representative resilience phase diagram for the preventive maintenance strategy (single trial), with the Condition Index on the left and the corresponding normalized performance used in the calculation of the CRPI on the right.

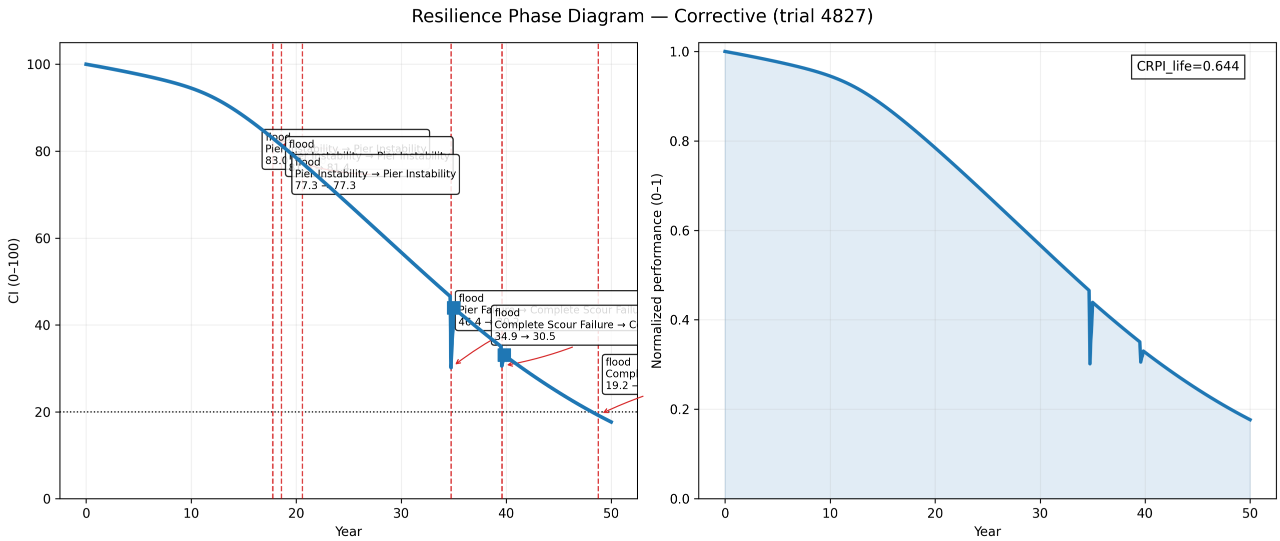

Figure 6: Representative resilience phase diagram for the corrective maintenance strategy (single trial): Condition Index (left) and normalized performance (right) used for the computation of the CRPI.

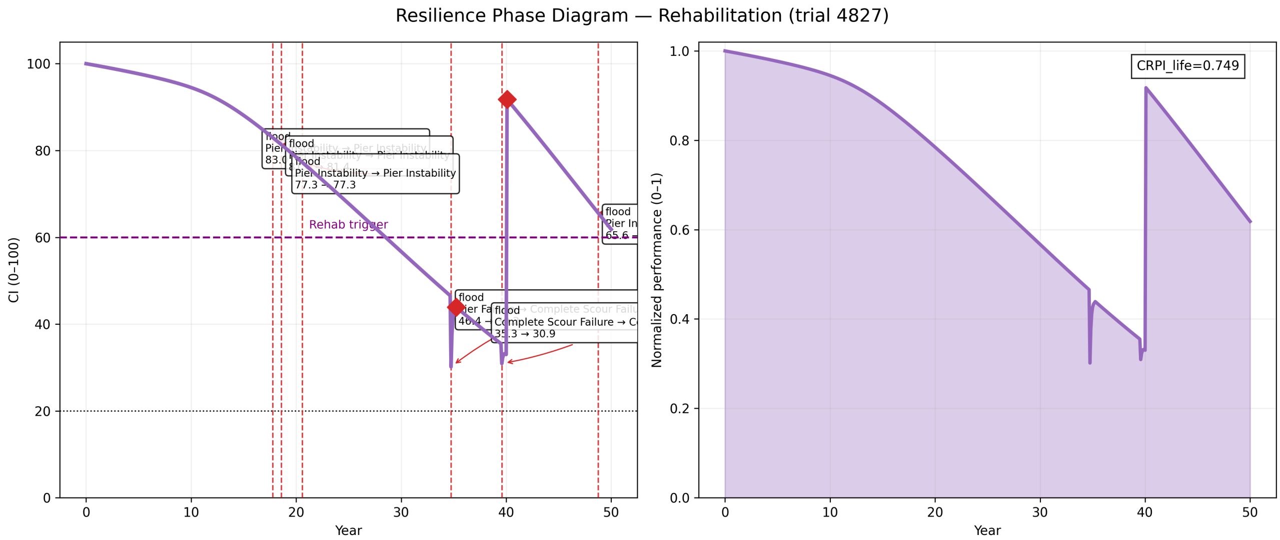

Figure 7: Representative Resilience Phase Diagram for Rehabilitation Strategy (single trial): Condition Index (left), and corresponding normalized performance for CRPI computation (right), highlighting threshold triggering and lifecycle restoration.

ing in partial and delayed recovery, while rehabilitation produces large but infrequent CI resets governed by trigger thresholds, allowing substantial degradation between interventions.

These contrasting recovery behaviors explain the ensemble outcomes summarized in Table 1 and visualized in Figure 2. Preventive maintenance achieves the highest mean $\mathrm{CRPI}_{\mathrm{life}}$ (0.716) with the lowest dispersion, whereas no maintenance exhibits both the lowest mean value (0.538) and the largest variability. Corrective and rehabilitation strategies yield intermediate life-cycle performance.

Implications for resilience-informed maintenance

Combining Table 1, Figure 2, Figure 3 and the phase diagrams shows that life-cycle resilience in this study is driven primarily by pre-event asset condition. Preventive maintenance preserves higher CI prior to hazard exposure, shifts fragility toward lower damage probabilities, reduces immediate losses and time in low-performance states, and therefore yields higher mean $\mathrm{CRPI}_{\mathrm{life}}$ and lower ensemble variability. Corrective and rehabilitation strategies provide post-event recovery but are limited by delay and infrequency, producing lower mean CRPI and greater uncertainty. Although the framework provides quantification of the impact of maintenance strategies on resilience performance, the decision-making process is also dependent on the consequences of failure. Therefore, assets with higher traffic demand or network importance may need higher prioritization even when the resilience performance is similar. The resilience indicator CRPI is a component of the decision-making process and should be used in conjunction with consequence-based measures.

Conclusions

This study shows that asset maintenance during normal operating conditions is critical to improving infrastructure resilience. Resilience thinking must extend to the pre-event stage of the lifecycle: proactive condition preservation strengthens robustness, limits damage at hazard exposure, and accelerates recovery. By embedding maintenance within a probabilistic Monte–Carlo lifecycle framework that couples condition-index (CI) evolution with CI-conditioned fragility, the analysis places pre-event condition at the center of resilience outcomes.

Across strategies, preventive (scheduled) maintenance consistently delivers the highest lifecycle resilience by reducing time spent in high-vulnerability CI ranges. Corrective maintenance provides moderate benefits but is strongly controlled by repair delay and effectiveness, while rehabilitation yields large one-time CI recovery yet is highly sensitive to cost, timing and trigger rules. A key mechanism is the condition-dependent shift in fragility: lower pre-event CI substantially increases the probability of severe damage states and collapse, amplifying the value of proactive, condition-preserving interventions.

The quantitative results should be interpreted in light of the modelling assumptions used here (simplified loss/cost representation, deterministic event impacts, strategy-independent deterioration physics and a single-asset formulation). Extensions such as stochastic loss dispersion, Bayesian fragility updating from observed damage, resource-constrained optimization with discounting, and multi-asset modelling would increase decision relevance.

Overall, the results support prioritising preventive, pre-event maintenance as a core asset-management strategy to enhance resilience under increasing hazard uncertainty.

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