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A framework to study the lifespan resilience of critical infrastructure in the face of the evolution of disaster risks

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The DRUID (Disaster Risk-gUided scenarIo Definition) method is a prospective approach to study the resilience of critical infrastructure against evolving threats such as natural and climate risks. It is structured around four phases. The Problem Definition phase formalizes the research question and collects data across four dimensions - hazards and exposure, absorptive capacity, infrastructure characteristics, and territorial context. The Scenario Building phase uses General Morphological Analysis to develop representative scenarios integrating general context, territorial aspects, disaster risks, and infrastructure considerations. The Resilience Study phase evaluates how risks affect infrastructure throughout its lifespan based on the DROP (Disaster Resilience of Place) and the resilience triangle models. It analyzes interactions between hazards, absorptive capacity, and the performance thresholds. The Problem Resolution phase translates scenarios into practical recommendations for infrastructure planning and management. The method is illustrated through a case study of a photovoltaic power plant in a Mediterranean mountainous region exposed to strong wind risks over 30 years. The study models different decision profiles (repair vs. replacement) and their impacts on system performance. A specific focus of the third phase is proposed, incorporating Monte Carlo simulations to provide statistical insights about system behavior under various conditions while considering both immediate hazard impacts and long-term adaptation needs. Through this comprehensive approach, DRUID helps infrastructure managers better understand vulnerability patterns and develop more effective resilience strategies.
Keywords: critical infrastructure, resilience study, disaster risk evolution, life cycle analysis, methodological framework

1. Introduction

Critical infrastructures form the foundation upon which modern societies function. From electrical grids to telecommunication systems, water treatment facilities, and transportation infrastructures, these critical systems ensure the continuity of vital services for populations and the maintenance of economic activities (Herder et al., 2003). However, their increasing complexity and interconnectedness make them particularly vulnerable to multiple risks (Rinaldi et al., 2001; Ouyang, 2014). Whether they are natural disasters, technical failures, sophisticated cyberattacks, or malicious acts, these threats can generate cascading effects with devastating consequences (Pescaroli & Alexander, 2016). The disruption of a single critical infrastructure can thus trigger a chain reaction affecting other vital sectors, as demonstrated by several significant incidents in recent years (Buldyrev et al., 2010).

Among these threats, the increasing frequency and severity of natural hazards, exacerbated by climate change, are becoming particularly concerning for infrastructure operators (IPCC, 2022; Koks et al., 2019). When these hazards materialize into disasters, they generate immediate human casualties and technical failures and cause substantial environmental damage, requiring significant financial investments for recovery and reconstruction (Hallegatte et al., 2019). However, these post-disaster periods, while challenging, create opportunities for infrastructure modernization and resilience enhancement (Chester & Allenby, 2019).

Critical infrastructure operators face the complex challenge of anticipating how both current and future climate change impacts will affect their system's performance. This raises the fundamental question of how to develop a methodological framework that enables infrastructure stakeholders to project and evaluate the combined effects of gradual climate evolution and extreme weather events on their infrastructure's resilience and operational capabilities over time. To address these challenges, we propose the Disaster Risk-gUided scenarIo Definition (DRUID) method, a comprehensive four-step approach for critical infrastructure performance prospective study.

This paper introduces the DRUID method, focusing on its third step dedicated to critical infrastructure resilience assessment. The first section presents a comprehensive overview of the DRUID methodology. The second section presents the third phase, which studies infrastructure lifespan resilience. To illustrate the description of the method, we use a pedagogical case study examining the establishment of a photovoltaic (PV) power plant in a mountainous region of southeastern France. This case study spans a 30-year time horizon and explicitly addresses the evolving risks associated with intense wind events in a Mediterranean climate context.

2. The DRUID method

Critical infrastructure systems face mounting challenges from climate-driven natural hazards, requiring innovative approaches to assess and enhance their resilience across their lifecycle (IPCC, 2022; Chester and Allenby, 2019). The DRUID method enriches infrastructure planning by providing an integrated three-step framework that combines climate change projections, infrastructure behavior modeling, and post-disaster decision-making analysis to support robust adaptation strategies (Hallegatte et al., 2019).

The DRUID method addresses infrastructure resilience questions through a standardized problem formulation that integrates key analysis dimensions.

Will **<trends>** - driven evolution of the **<type>** risks significantly affect the **<performance type>** performance of **<critical infrastructure>** located in **<location>** within **<time horizon>?**

This formulation considers six essential components: the driving trends (such as climate change or urbanization), the type of risks being analyzed (natural, technological, or hybrid), the specific performance metric under study (technical, economic, environmental, or social), the critical infrastructure system of interest, its geographical location, and the temporal horizon of the analysis. This structured approach enables decision-makers to clearly articulate complex infrastructure resilience challenges while ensuring all relevant factors are considered.

For example, the DRUID formulation of a problem concerning the environmental performance of a photovoltaic power plant can be expressed as follows:

Will **climate change and territorial development** - driven evolution of **strong wind** risks significantly affect the **environmental** performance of a **PV power plant** located in a **mountainous region with Mediterranean climate in south-eastern France** within **the next 30 years**?

The DRUID method addresses problems through four iterative phases (cf. Fig. 1.).

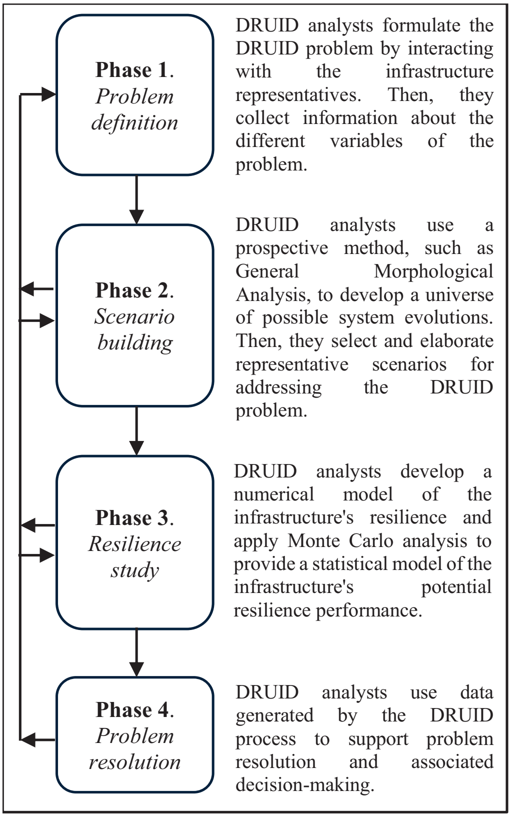

Fig. 1. The Disaster Risk-gUided scenarIo Definition (DRUID) method.

2.1. *Defining the problem*

The first phase of the DRUID method involves problem definition through two complementary activities. First, the problem is formalized using the canonical formulation to identify essential elements. Second, structured data collection is conducted across four key dimensions: hazards and exposure, absorptive capacity, infrastructure characteristics, and territorial context. This process enables identifying and characterizing key parameter classes with their associated conditions.

For example, in the PV power plant case, the analysis considers substantial wind speed ranges and frequency of occurrence as the hazard class while incorporating Mediterranean climate characteristics and topographical features within the territory class. The infrastructure's absorptive capacity is characterized by PV panel wind resistance thresholds, and the infrastructure technology class encompasses PV panel types and mounting systems. Each parameter class is then defined with specific conditions that can evolve based on identified driving trends over the 30-year study period.

2.2. Building scenarios

The second step of the DRUID method focuses on scenario building using the General Morphological Analysis approach (Ritchey, 2011). Based on data collected in step one, a morphological box represents the universe of possible scenarios. Through Cross-Consistency Assessment, this universe is refined to identify a solution space of feasible context scenarios, from which representative scenarios are selected for detailed analysis.

Each selected scenario is then structured through four interrelated contextual dimensions. First, the general context describes global trends affecting the territory and infrastructure sectors. Second, the territorial context details specific geographical, political, and demographic evolution. Third, the disaster risk context outlines changes in hazard characteristics and infrastructure absorptive capacity. Fourth, the infrastructure context describes sectoral developments, including technological advances and policy changes.

For the PV power plant case, this might explore how climate change affects wind patterns in southeastern France's Mediterranean region, how local development impacts exposure to wind risks, how PV technology evolves to enhance wind resistance, and how energy policies adapt to climate challenges over the 30-year timeframe.

2.3. *Studying infrastructure resilience*

The third step of the DRUID method leverages the context scenarios to assess critical infrastructure resilience through an iterative modeling approach. This assessment examines how disaster risks affect infrastructure resilience throughout its lifespan while considering various maintenance decision alternatives. The analysis produces decision scenarios that reflect different adaptation strategies.

For example, in the case of the PV power plant, the resilience assessment considers three types of maintenance decisions: component repair, component replacement, and complete system repowering. This modeling approach evaluates how different wind event scenarios might affect the infrastructure's performance and how various maintenance strategies could enhance its resilience over 30 years. The resulting decision scenarios provide insights into optimal adaptation strategies that balance performance, cost, and environmental impacts under evolving wind risk conditions.

2.4. *Solving the DRUID problem*

The final step of the DRUID method focuses on translating decision scenarios into actionable insights for infrastructure planning and management. This step integrates the resilience analysis results with performance assessment frameworks to evaluate the implications of different adaptation strategies. For each decision scenario, key performance indicators are calculated to assess their effectiveness, feasibility, and long-term impacts. This comprehensive evaluation supports evidence-based decision-making by providing quantitative and qualitative data on the trade-offs between different adaptation options.

In the PV power plant case, this analysis might compare the long-term performance implications of different maintenance strategies under evolving wind risk scenarios, considering factors such as energy production efficiency, system reliability, and environmental impacts. This integrated assessment helps decision-makers select optimal adaptation strategies that enhance infrastructure resilience while meeting sustainability objectives over the 30-year timeframe.

The next section focuses on the third phase of the DRUID method.

3. Infrastructure lifespan resilience study

The third phase of the DRUID method consists of a set of simulations designed to study the resilience of an infrastructure's lifespan under prospective scenarios elaborated in the preceding phase of the DRUID method. The study of resilience is based on the definition proposed by the UNDRR as *'the ability of a system, community or society exposed to hazards to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management*' (UNDRR, 2007) and more specifically on the Disaster Resilience of Place (DROP) model (Cutter et al., 2008) and the resilience triangle model (Tierney and Bruneau, 2007; Mentges et al., 2023). A simulation algorithm is generated from the DRUID problem formulation. It supports Monte-Carlo simulations that provides insights about the behavior of the system under various conditions. In the following paragraphs the structure of the resilience model is presented, followed by the application to the case study with exploratory results. The practical implementation of the model was done in Python.

3.1. *Theoretical underpinnings*

The DROP model and the resilience triangle model constitute the conceptual foundation of the infrastructure resilience study.

The DROP model (cf. Fig. 2.) presents a relationship between resilience and vulnerability at a local level that aims to improve comparative assessments of communities (Cutter et al., 2008). This model emphasizes the dynamic nature of resilience by incorporating both antecedent conditions and post-event processes. It identifies key pre-existing conditions, including social systems, built environment, and natural systems, which collectively determine a community's inherent resilience and vulnerability. When a hazard event occurs, these antecedent conditions interact with the hazard's characteristics to produce immediate effects. The model then describes how coping responses are activated, drawing upon both inherent resilience and adaptive resilience capacities. A distinctive feature of the DROP model is its recognition of the temporal dimension of resilience, acknowledging that recovery processes can either improve or degrade a community's resilience to future events. This feedback loop, where post-disaster learning can enhance preparedness for subsequent events, underscores the model's dynamic conceptualization of resilience.

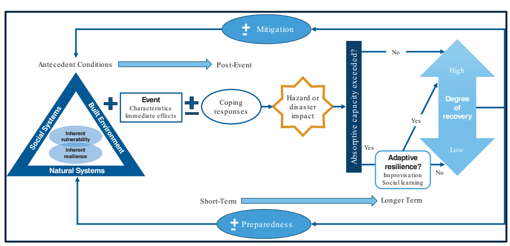

Fig. 2. The Disaster Resilience of Place (DROP) model (Cutter et al., 2008)

The resilience triangle model (cf. Fig.3.), introduced by Tierney and Bruneau (2007), provides a conceptual framework to analyze and quantify the loss and restoration of system functionality following a disruptive event. In this model, resilience is represented through a triangle-shaped graph where the vertical axis represents the system's performance level (ranging from 0% to 100%), and the horizontal axis represents time. The triangle is formed by the sudden drop in performance when a disruption occurs, followed by a gradual recovery period until the system returns to its pre-event performance level. The area of this triangle represents the loss of functionality over time, with a smaller triangle area indicating higher resilience. This graphical representation emphasizes two key aspects of resilience: the magnitude of functionality loss and the time required for recovery.

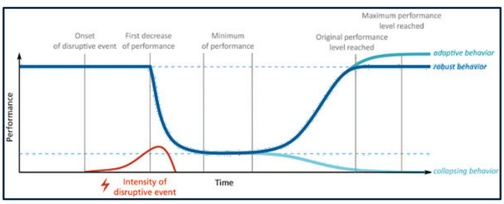

Fig. 3. The Resilience triangle model adapted from (Tierney and Bruneau, 2007; Mentges et al., 2023).

3.2. *Methodology*

The third phase of the DRUID method studies the infrastructure's resilience throughout its lifespan through two interconnected phases (cf. Fig. 4). The first phase consists of elaborating a computational model to study the infrastructure's resilience over its lifespan. Then, the second phase exploits this model to generate a statistical analysis of the variability in the infrastructure's resilience performance.

3.2.1. *Defining the Resilience model*

For each representative scenario, the resilience model uses the described elements and parameters to estimate: i) the hazards that could affect the critical infrastructure during the studied period, ii) the infrastructure's vulnerability to these hazards, iii) the potential magnitude of damage to the infrastructure, and iv) the decision-making consequences for the infrastructure following a shock of a certain magnitude. The key elements of the proposed resilience model are hazards, absorptive capacity, shock levels, event type, performance thresholds, and decision-maker profile.

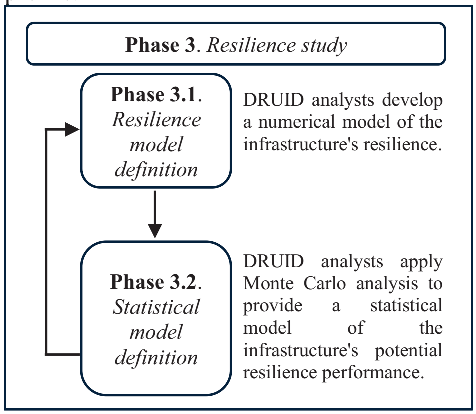

Fig. 4. The third phase of the DRUID method

Hazards are characterized by their intensity and probability of occurrence over a specific period. Case-specific considerations involving causal chains may be necessary when dealing with compound hazards and complex risks. Absorptive capacity is categorized into classes or levels representing different thresholds of likely failure or damage conditions of the infrastructure in relation to varying hazard intensities. Shock levels quantify the intensity of damage sustained by the infrastructure, determined by comparing the hazard's probability of occurrence with the infrastructure's absorptive capacity. Event type categorizes the occurrence with three alternatives: No event**,** when the shock level is zero, resulting in no changes; repair-type event when the infrastructure's production capacity is restored to its original level for the next iteration; and replacement-type event**,** when the infrastructure's production capacity is upgraded for the next iteration. Performance thresholds define limits for the infrastructure's performance, consisting of upper and lower bounds that guide post-shock decisions. Performance above the upper threshold triggers a repair-type event. Performance between thresholds requires decision-makers to choose between repair and replacement. Performance below the lower threshold automatically initiates a replacement-type event. Decision-maker profile characterizes the probability that an actor will choose either repair or replacement when the infrastructure's performance falls between the repair and replacement thresholds.

The proposed resilience model is an iterative process which has n iterations in a period of evaluation. It begins by evaluating the exposition to risk of the critical infrastructure by comparing the maximum intensity of the hazard experienced per iteration with the absorptive capacity. If the intensity of the hazard is within the range of a given absorptive capacity level, then a second evaluation takes place that depends on the definition of the failure condition, and the result is the shock level associated to this yearly event. The shock level has a direct impact on the production capacity of the critical infrastructure. Thus, the production capacity of the current iteration is compared to the performance thresholds and the type of event is established with its corresponding effects on the production capacity of the critical infrastructure. Afterwards, a new iteration begins unless it is the last iteration.

At the end of the iterative process, the model stores data on the number and level of shocks, the amount and the type of events that occurred, and when the replacement-type event took place. These represent the decision scenarios for a given representative context scenario.

In the case of the PV power plant example, the performance of the 1 MWp PV installation throughout its 30-year lifespan is the focus of the resilience study. The function of a PV installation is to produce electrical energy, therefore the performance-related parameter is the electricity produced by the PV system ($E_{lifetime}$) throughout its lifespan, represented by the following equation:

$$E_{lifetime} = \sum_{n=1}^{lifetime} E_{PV}(n)$$
$$E_{PV}(n) = P_{OutputAnnual}(1-d)^n \qquad (1)$$

Where: $E_{PV}(t)$ is the overall electricity produced in a certain year, expressed in kWh per year, n is the "nth" year when the PV system is operating, d is the annual degradation rate of the PV modules, an indication of the loss of efficiency which represents a degradation of their output production throughout their lifespan.

Four types of decision-making profile are considered:

1. 0% repowering: Decision-makers that would always choose to repair when they can.
2. *10% repowering:* Decision-makers that would mostly opt to repair of the time so there is only a 10% probability of deciding to repower.
3. *50% repowering:* Decision-makers with a more leveraged perspective who would choose to repair 50% of the time.
4. *100% repowering:* Decision-makers that will always choose to improve the production capacity, therefore will never choose to repair.

The only hazard the PV infrastructure is exposed to is strong wind, represented by the probability of occurrence of wind gust throughout three distinct decades. Per iteration representing a year, the resilience model uses the hazard dataset to choose a wind gust value and compares it to the absorptive capacity of the critical infrastructure. The absorptive capacity and the shock levels are both described by the fragility curve determined for the example, which represents the probability of PV panel failure under given wind gusts. To estimate the potential damage that the PV infrastructure could be subject to per year, the following considerations are made. The following figures illustrates PV infrastructure electricity production performance with no shock (Fig. 5.), with two (Fig 6.) and several shocks (Fig 7.)

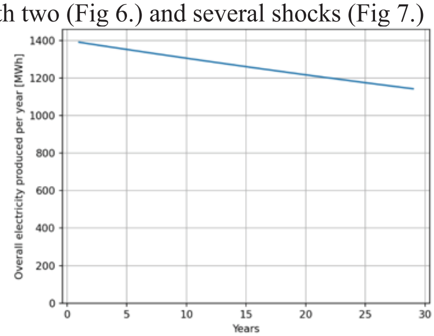

Fig. 5. The PV performance with no shock

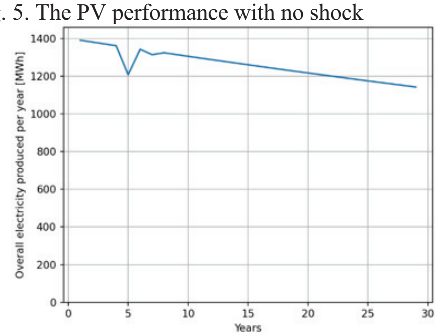

Fig. 6. The PV performance with two shocks

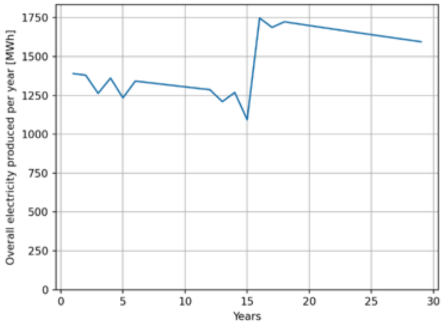

Fig. 7. The PV performance with several shock

3.2.2. *Generating the statistical model*

The following figure (Fig. 8.) depicts distribution of damages modelled throughout the 800,000 Monte Carlo simulations. It is observed that in an overwhelming majority of years the PV infrastructure suffers no damage and thus continues to operate as usual. Most instances of damage occur between 0.028% and 1% of the PV infrastructure, which for the baseline system represents damage to components related to a range of 0.28 kWp to 10 kWp of installed power. For the baseline PV system with a total of approximately 3530 modules, this loss is equivalent to having between 1 and 35 potentially damaged PV modules.

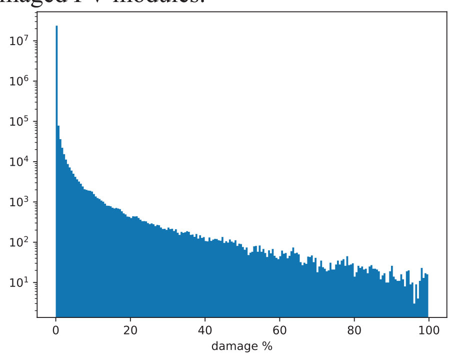

Fig. 8. Distribution of shock intensity on the PV infrastructure.

The average number of shocks that cause damage to the PV infrastructure throughout the studied 30-year period is 1.13, meaning that at least one event could happen during the expected operational lifespan of the PV infrastructure. The following figure (Fig. 9) presents that the infrastructure may suffer a cumulated damage that also tends to the minimum 1% of its total components, with a mean of 1.75% damage. Additionally, in 31.5% of cases the PV infrastructure does not suffer from any damage at all throughout its operational lifespan.

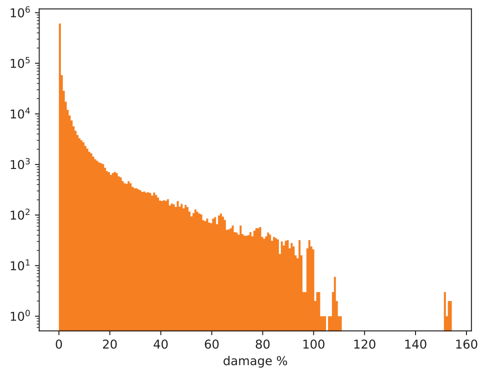

Fig. 9. Distribution of accumulated damage to PV plant throughout the 30 years

4. Conclusion

The DRUID methodology presented in this paper offers a comprehensive framework for assessing and enhancing critical infrastructure resilience in the face of evolving natural and climate-related risks. Through its systematic four-phase approach, it addresses the complex challenges of infrastructure vulnerability assessment and adaptation planning. The method's application to a photovoltaic power plant case study demonstrates its practical utility in evaluating infrastructure resilience under specific hazard conditions, while the integration of Monte Carlo simulations with established resilience models provides quantitative insights for long-term decision-making problems.

This research contributes to developing a structured approach to integrate climate change projections with infrastructure resilience assessment, establishing a quantitative basis for comparing different alternatives and their long-term implications. Future research will be dedicated to applying DRUID to a realistic case study and exploring applications to multiple concurrent hazards, incorporating more sophisticated decision-making models, and extending to different geographical contexts.

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