

Will Places Survive Disasters? Learning from Recovery Policies through AI-Based Tools for Regional Planning

Giulio Breglia (Gran Sasso Science Institute) and Federico Fantechi (University of Palermo)

Natural hazards are increasing in frequency and magnitude, and while prevention and risk reduction phases are increasingly supported by global policy frameworks, the post-disaster phase still presents several challenges for coherent and transferable policy design. Recovery processes are often fragmented, strongly context-dependent, and influenced by institutional capacity, socio-economic conditions, and local reconstruction cultures, making comparison and learning difficult across territories.

This project aims to develop a data-driven tool for national and local policymakers that learns from previous recovery plans, explicitly taking into account different reconstruction cultures and territorial contexts. Rather than proposing a universal recovery model, the approach builds on observed recovery trajectories and policy choices, with particular attention to the timing, composition, and sequencing of public expenditure after disasters. The broader question underlying the project is simple but demanding: if a given territory experiences a specific type of shock and allocates resources in a certain way over time, what economic and social effects can reasonably be expected?

The empirical strategy unfolds in three interconnected stages. The first stage consists of constructing a structured database of disasters. We start from Europe, primarily for reasons of data availability and institutional comparability, but we rely on global disaster repositories to identify events and characterize them along multiple dimensions. Data sources include EM-DAT and related georeferenced datasets such as Hanze, which allow us to measure intensity, duration, geographic extension, and estimated damages. Disasters will be selected across different typologies (e.g. floods, earthquakes, wildfires, pandemics) and limited to events whose emergency phase has concluded and for which sufficient post-event data are available. As a working criterion, we focus on disasters occurring up to approximately 2015, ensuring a sufficient time span to observe medium-term recovery outcomes. Each event will be characterized not only by physical intensity and damage but also by territorial features (pre-shock economic structure, demographic profile, institutional capacity, resilience markers), drawing on previous work on multi-layer resilience and locked-in regions (Breglia & Modica, 2025; Fantechi & Modica, 2023).

This first stage goes beyond a simple cataloguing exercise. Disasters are not homogeneous even within the same category: a flood in a densely urbanized area differs significantly from a flood in a peripheral rural region. We therefore apply unsupervised machine learning techniques to cluster disasters jointly with territorial characteristics, identifying empirically grounded “shock-territory configurations.” This approach acknowledges that the effect of a disaster depends on both the shock and the place. The resulting classification provides the backbone for the subsequent analysis and for the tool’s scenario-building capacity.

The second stage focuses on post-disaster recovery plans. For each selected disaster, we identify whether formal recovery or reconstruction plans were adopted within a defined time window (for instance, within three to five years from the event). These plans may originate from national governments, regional authorities, supranational institutions, or multi-level governance arrangements. We will construct a database of recovery plans including information on total allocated budget, funding sources, sectoral composition of expenditure, governance mechanisms, and, crucially, the timing of disbursement. Web scraping and text-mining techniques will be used to collect and process policy documents, extracting structured information from heterogeneous textual sources.

Text analysis will allow us to classify recovery plans according to their priorities (infrastructure rebuilding, housing, productive sector support, labour market measures, environmental restoration, social cohesion, etc.), as well as according to their temporal structure (front-loaded expenditure, gradual multi-year programs, delayed investment strategies). The COVID-19 recovery phase provides an additional, though atypical, case of large-scale public intervention following a systemic shock, and may be included to test the generalizability of the framework to non-physical disasters. Again, unsupervised classification methods will be applied to group recovery plans into empirically derived clusters based on expenditure composition and timing patterns.

The third stage integrates disaster-territory clusters and recovery-plan clusters into an empirical evaluation framework. For each disaster-region pair, we construct regional time series covering a range of economic and social outcomes: employment, sectoral value added, firm dynamics (including firm-level data from sources such as Orbis where available), demographic changes, and selected social indicators. Depending on data availability, the spatial scale may vary between NUTS3, NUTS2, or functional labour market areas. The core empirical strategy relies on difference-in-differences designs that compare affected regions with suitable control areas, before and after the shock, and across different recovery plan typologies. This allows us to assess whether distinct recovery strategies, particularly in terms of timing and allocation, are associated with systematically different recovery trajectories.

A central methodological challenge concerns the counterfactual: what would have happened in the absence of a specific recovery plan or under an alternative expenditure timing? Recent advances in machine learning for policy evaluation provide tools to address this issue by improving the estimation of heterogeneous treatment effects and by enhancing the credibility of counterfactual predictions (Fantechi & Cusimano, 2025). Our framework leverages these developments, combining traditional quasi-experimental designs with predictive models to simulate alternative expenditure paths. In this sense, the project does not merely describe recovery outcomes but attempts to model plausible alternative scenarios.

The final output is an interactive AI-based decision-support tool. The tool is conceived as a scenario generator: given a specific disaster-territory configuration and a hypothetical budget allocation over time (for example, a certain share devoted to infrastructure in the first two years and to business support in subsequent years), it produces predicted trajectories for selected economic and social dimensions. The tool incorporates regional resilience indicators and macro-structural variables, acknowledging that “Italy today is not Italy tomorrow,” and that fiscal space, institutional quality, and economic structure constrain feasible policy options. It is designed to assist policymakers in exploring trade-offs, margins of expenditure, and timing effects rather than prescribing a single optimal solution.

Expected contributions are both methodological and substantive. Methodologically, the project combines unsupervised learning for classification, quasi-experimental impact evaluation, and predictive modelling within a unified framework. Substantively, it contributes to the literature on regional resilience and post-disaster recovery by systematically linking expenditure timing and composition to medium-term territorial outcomes. Previous research has documented short-term labour market reactions to earthquakes across countries (Mendoza, Breglia, & Jara, 2020) and has explored the determinants of regional resilience to shocks (Fantechi & Modica, 2023; Breglia & Modica, 2025). However, less attention has been paid to the structured comparison of recovery policies themselves, especially regarding their temporal dimension. By focusing explicitly on when and how public resources are deployed, the project addresses a gap in both regional studies and policy evaluation literatures.

While the empirical work is at an initial stage, the feasibility of the project rests on the availability of disaster databases, regional socio-economic time series, and increasingly accessible policy documents. The European focus allows for institutional comparability and relatively harmonized statistical systems, providing a controlled environment in which to develop and test the framework before potential

extension to other regions. A preliminary meta-analysis of disaster impact quantification may also be conducted to harmonize effect measures and guide the selection of outcome variables.

Ultimately, the project seeks to transform accumulated but fragmented recovery experiences into structured, comparable knowledge. By learning from past disasters and recovery strategies, and by embedding this learning into an AI-supported planning tool, we aim to contribute to more transparent, evidence-informed, and temporally aware post-disaster policymaking. The guiding question, whether a place will survive and how it will transform, cannot be answered deterministically. Yet, by systematically combining data, policy learning, and counterfactual reasoning, it becomes possible to narrow uncertainty and to support more resilient regional futures.

References

- Breglia, G., & Modica, M. (2025). A world of shocks: mapping multi-shock and multilayer resilience, assessing resilience markers and drivers. *Regional Studies*, 59(1), 2579631.
- Fantechi, F., & Cusimano, A. (2025). The counterfactual challenge: How machine learning can enhance policy evaluation. *Journal of Policy Modeling*.
- Fantechi, F., & Modica, M. (2023). Learning from the past: a machine-learning approach for predicting the resilience of locked-in regions after a natural shock. *Regional Studies*, 57(12), 2537–2550.
- Hochrainer-Stigler, S., Mechler, R., Pflug, G., & Williges, K. (2014). Funding public adaptation to climate-related disasters. *Natural Hazards and Earth System Sciences*, 14(4), 1051–1066.
- Mendoza, C. A., Breglia, G., & Jara, B. (2020). Regional labor markets after an earthquake. Short-term emergency reactions in a cross-country perspective. Cases from Chile, Ecuador, Italy. *Review of Regional Research*, 40(2), 189–221.
- Rose, A. (2004). Defining and measuring economic resilience to disasters. *Disaster Prevention and Management*, 13(4), 307–314.