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Summary

Natural hazards are an increasing concern, placing disaster preparedness and mitigation at the forefront of policy agendas. In this context, Italy's Recovery and Resilience Plan (NRRP) has allocated €3 billion for explicit disaster prevention, with a primary focus on hydrogeological risks such as floods and landslides. This study evaluates the geographical and thematic distribution of resilience-related funding, examining whether financial resources have been effectively targeted toward municipalities with the highest exposure to environmental hazards. Using a clustering classification, we identify substantial disparities in the allocation of resilience funds, revealing that municipalities with relatively low risk levels often receive disproportionately high funding, while high-risk areas remain underfunded. To explore the underlying drivers of this misalignment, we apply a multinomial logit model to assess the socio-economic and geographic determinants of these funding disparities. Our findings indicate that GDP, macro-regional location, and past disaster occurrences significantly influence whether a municipality falls into a misallocated funding cluster. The misalignment between risk exposure and funding allocation raises questions about the criteria used for distributing adaptation investments and highlights the necessity for a more risk-sensitive and equitable approach.

Keywords: Decentralisation; environmental protection; natural disasters; political announcements; voters preferences

JEL Classification: H70, H72, H77, Q54, Q58

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Abstract

Natural hazards are an increasing concern, placing disaster preparedness and mitigation at the forefront of policy agendas. In this context, Italy's Recovery and Resilience Plan (NRRP) has allocated €3 billion for explicit disaster prevention, with a primary focus on hydrogeological risks such as floods and landslides. This study evaluates the geographical and thematic distribution of resilience-related funding, examining whether financial resources have been effectively targeted toward municipalities with the highest exposure to environmental hazards. Using a clustering classification, we identify substantial disparities in the allocation of resilience funds, revealing that municipalities with relatively low risk levels often receive disproportionately high funding, while high-risk areas remain underfunded. To explore the underlying drivers of this misalignment, we apply a multinomial logit model to assess the socio-economic and geographic determinants of these funding disparities. Our findings indicate that GDP, macro-regional location, and past disaster occurrences significantly influence whether a municipality falls into a misallocated funding cluster. The misalignment between risk exposure and funding allocation raises questions about the criteria used for distributing adaptation investments and highlights the necessity for a more risk-sensitive and equitable approach.

Keywords: Resilience and Recovery Facility, Risk, Floods, Disaster management

JEL classification: Q54; H76; C38

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1. Introduction

Natural hazards, exacerbated by climate change, pose significant socio-economic threats globally, necessitating efficient and equitable policy responses to mitigate impacts and foster resilience (IPCC, 2022). Disasters such as floods, landslides, and storms impose severe and often long-term economic and social consequences, particularly in vulnerable territories (Marin & Modica, 2017). The socio-economic repercussions of these disasters are inherently complex due to intricate interrelations between natural and human systems, requiring systemic and multi-dimensional analytical frameworks (Marin et al., 2021; Fantechi & Modica, 2023). Consequently, scholars increasingly emphasize a holistic approach integrating environmental risk assessment with socio-economic vulnerability and institutional capacity to devise targeted and effective mitigation strategies (Alexander, 2018). Italy exemplifies significant vulnerability to hydrogeological hazards, including floods and landslides, largely due to its complex topography, extensive coastline, and intense urbanization processes (Trigila & Iadanza, 2018). These factors render large portions of the Italian territory prone to significant disaster risks, exacerbated by inadequate urban planning, high population densities, and economic disparities among regions (Guzzetti et al., 2020). Given the country's repeated exposure to extreme events, Italy provides a critical case for investigating the effectiveness of public mitigation and adaptation investments, especially within the context of European recovery funds. The European Union has increasingly committed substantial financial resources through initiatives like the Recovery and Resilience Facility (RRF), aimed explicitly at supporting Member States' transitions towards sustainability and resilience (European Commission, 2024). Italy, as one of the main beneficiaries of these investments, has received considerable funds directed specifically at fostering the ecological transitions under the "Mission 2" of its national plan (National Recovery and Resilience Plan, NRRP). Despite the significant resources allocated, preliminary research suggests limited geographical convergence between historical disaster occurrences and current RRF funding distribution (D'Angeli & Gazzellone, 2024). This discrepancy highlights the necessity to critically assess the criteria guiding public financial allocation and investigate whether funds are effectively targeting the most vulnerable territories.

Previous studies underscore the importance of institutional frameworks and governance capacity in mitigating economic impacts of climate-related disasters (Marin & Modica, 2017; Di Marcoberardino & Cucculelli, 2024). The efficiency and effectiveness of disaster-risk management and adaptation policies heavily depend on the institutional capability to allocate resources appropriately and implement resilience strategies tailored to territorial specificities (Driessen et al., 2016). Misallocation of funding, driven by either inadequate risk assessment or political considerations, risks exacerbating territorial disparities and leaving the most vulnerable regions underserved (Cutter et al., 2012; Marin & Modica, 2017). Moreover, territorial analyses employing spatial methodologies are crucial for effectively evaluating disaster resilience funding, where effectiveness is defined as the capability of funding those areas that are more vulnerable or more in need of disaster preparedness financing. Regional variations in hazard exposure, socio-economic vulnerability, and institutional capacity necessitate spatially nuanced evaluations to ensure that resources align adequately with territorial needs (Fuchs & Thaler, 2018). Cluster analyses and regression models emerge as valuable tools in identifying spatial disparities in resource allocation, enabling policymakers to recalibrate funding distributions in line with empirical vulnerability assessments (Birkmann, 2013).

In response to these identified gaps, our study aims to critically assess whether the RRF allocations within Italy's NRRP effectively target municipalities characterized by high hydrogeological risk. The context of these allocations is complex, as EU recovery plans were drafted in 2021 under significant time pressure to meet strict approval deadlines. Consequently, many policies within these plans were adapted from pre-existing frameworks, often without a rigorous assessment of the alignment between resources and actual needs. This evaluation provides a novel contribution, as existing literature has yet to systematically analyze RRF effectiveness in disaster-risk reduction at the municipal level. Specifically, our analysis addresses two critical research questions. First, we examine whether the geographical distribution of RRF funding aligns with the spatial distribution of climate risk across Italian municipalities. Second, we investigate the underlying drivers of allocation patterns, accounting for historical policy legacies, socio-political dynamics, and specific territorial characteristics.

Our empirical approach employs an extensive dataset encompassing all 7,903 Italian municipalities, integrating detailed hydrogeological risk data provided by the Italian Institute for Environmental Protection and Research (Istituto Superiore per la Protezione e la Ricerca Ambientale, ISPRA), which includes comprehensive indicators of flood- and landslide-related risks across the Italian territory. This risk data is combined with precise records of financial allocations from the Italia Domani database under Mission 2 of the NRRP, dedicated explicitly to ecological transition and climate resilience. Specifically, we use data on investments explicitly dedicated to hydrogeological risk mitigation.

Methodologically, our study utilizes cluster analysis combined with multinomial regression models to identify municipalities grouped according to their respective funding levels and risk exposure profiles. Given the skewness and variability of our data we apply a log transformation to financing variables to normalize extreme values, ensuring that our cluster analyses remain balanced and representative. The clusters enable us to pinpoint areas of congruence and divergence between allocated funding and actual risk levels, critically highlighting potential inefficiencies in public investment distribution. We offer the first municipal-level quantitative evaluation of RRF climate-risk alignment in Italy, using a combined cluster analysis and econometric approach.

Our preliminary results indicate significant mismatches, revealing that a notable portion of municipalities with moderate to highrisk exposure receive disproportionately low levels of funding, whereas several municipalities with relatively lower risk profiles receive unexpectedly high per capita allocations. These discrepancies suggest that current funding mechanisms may overlook critical territorial vulnerabilities, necessitating a reassessment of funding criteria and allocation processes. Additionally, our identification of extreme funding outliers raises questions regarding potential political influences on resource distribution, warranting further investigation into governance and institutional factors affecting public policy implementation.

This paper is structured as follows: Section 2 assesses the literature on disaster risk adaptation and public funding allocation; Section 3 and 4 present the data and methodology used to assess the distribution of public funding in accordance with municipalities' risk profiles; Section 5 presents the results, while Section 6 discusses and concludes.

2. Disaster risk adaptation and spatial inequalities

The increasing frequency and severity of climate-related disasters worldwide, driven largely by climate change, have profound socio-economic impacts that challenge policymakers, institutions, and affected communities alike. Research consistently shows that disasters cause significant economic disruptions, particularly in vulnerable sub-national regions with limited adaptive capacity (Deryugina et al., 2018; Felbermayr & Gröschl, 2014). These impacts extend beyond immediate physical damages to affect long-term growth trajectories, deepen regional inequalities, and strain public resources (Hsiang & Jina, 2014; Lodi et al. 2023). Consequently, the efficient and equitable allocation of public funds to mitigate risks and foster resilience has become a critical policy challenge.

Effective disaster risk preparedness and management rely on strong institutional capacity and governance (Marin & Modica, 2017; Fuchs & Thaler, 2018). Regions with robust administrative and technical resources are better equipped to assess local vulnerabilities, plan adaptation measures, and implement recovery efforts that reduce long-term economic and social harm (Birkmann, 2013). However, significant territorial heterogeneity exists in hazard exposure, social vulnerability, and institutional quality, demanding spatially differentiated and evidence-based funding approaches (Cutter et al., 2010; Peruccacci et al., 2023). Ignoring this heterogeneity risks maladaptation, leaving some municipalities underfunded despite high disaster risk, while others receive disproportionate support relative to their needs.

Political economy factors often complicate the efficient distribution of disaster funds. Public investments can be swayed by electoral incentives, lobbying, or historical legacies that do not align with current risk profiles (Garrett & Sobel, 2003; Fuchs & Thaler, 2018). This misallocation undermines overall resilience, potentially amplifying inequalities by privileging wealthier or more politically connected regions at the expense of highly vulnerable communities. Outdated or incomplete risk information further hampers targeting accuracy, as changes in climate dynamics and urban development continuously reshape hazard landscapes (Forzieri et al., 2016). Thus, a dynamic and granular understanding of risk is essential for adaptive governance and resource allocation.

The literature on public spending highlights the importance of both efficiency and equity in disaster risk reduction investments. Hallegatte and Przyluski (2010) emphasize that well-targeted expenditures not only save lives and reduce damages but also stimulate economic resilience and sustainable development. However, many countries struggle to translate this ideal into practice, often due to fragmented institutional frameworks, lack of coordination, or capacity constraints (Kousky et al., 2024). This issue is especially pronounced in multi-level governance systems like Italy's, where municipal, regional, and national authorities share responsibilities but may lack coherent funding criteria (Peruccacci et al., 2023).

Climate mitigation efforts have dominated the policy discourse in recent years, given the urgent need to reduce greenhouse gas emissions (IPCC, 2022). Yet climate adaptation (meant as strengthening resilience against the inevitable effects of climate change) is equally crucial to safeguard communities, infrastructure, and economies (Marin & Modica, 2017). Effective adaptation requires investments in risk-informed infrastructure, early warning systems, and social protection, all necessitating tailored funding aligned with local vulnerabilities (Birkmann, 2013). The integration of mitigation and adaptation strategies presents both a technical and governance challenge but is essential for holistic climate resilience.

Italy exemplifies many of these challenges. Its complex topography, extensive coastline, and patterns of urbanization expose it to a wide array of hydrogeological risks, including floods and landslides (Peruccacci et al., 2023). Italian municipalities show marked heterogeneity in exposure and capacity to cope, compounded by socio-economic disparities between northern and southern regions (Marin & Modica, 2017). Public spending on risk prevention, traditionally characterized by reactive and fragmented approaches, is gradually shifting towards more proactive and integrated resilience investments under frameworks like the National Recovery and Resilience Plan (NRRP) Yet empirical analyses indicate that funding often fails to correspond precisely with actual risk profiles, raising concerns about territorial equity and the efficiency of public expenditures (D'Angeli & Gazzellone, 2024).

Recent Italian studies underline persistent mismatches between hazard exposure and funding allocations. For instance, Moulds et al. (2021) theorised regional disparities in flood prevention investments. Similarly, D'Angeli and Gazzellone (2024) observe that historical disaster exposure is not always positively correlated with the capacity to secure public funding. These findings echo broader European trends where political and socio-economic factors often mediate disaster risk governance outcomes (Forzieri et al., 2016).

Spatial econometric and regional science methodologies have proven valuable in unpacking these complexities. Cluster analyses, spatial regressions, and multi-criteria risk mapping provide nuanced insights into the distribution of hazards, vulnerabilities, and public investments (Forzieri et al., 2016; Fuchs & Thaler, 2018). These tools can facilitate the identification of underserved municipalities and inform more equitable and evidence-based policy adjustments. Nevertheless, the municipal-level impact of large-scale recovery programs like the EU's Recovery and Resilience Facility has yet to be systematically analyzed. This study addresses these gaps by focusing on the Italian case, integrating detailed hydrogeological risk data with granular public funding records to assess alignment and identify drivers of misallocation. Italy's diversity in risk exposure and institutional capacity, combined with the unprecedented scale of the NRRP investments, make it an ideal context to explore how well current funding mechanisms address disaster resilience and territorial equity.

3. Data

This study aims at analysing the relationship between RRF funding distribution and municipal disaster risk to understand which factors (i.e., socio-economic, demographic, geographical and administrative) influenced such distribution. To undertake this analysis, we use information on the Italian allocation of RRF funding, the flood risk assessment for Italian municipalities. The following paragraphs describe in detail the data used in this study.

3.1 Recovery and Resilience Facility in Italy

The Recovery and Resilience Facility (RRF) finances the implementation of the Next Generation EU (NGEU) program, which is implemented in every Member State through a National Recovery and Resilience Plan (NRRP). Italy is the largest recipients of RRF funding in the European Union. The Italian NRRP is structured around seven distinct Missions, each one of them then sub-classified in Components and then in Reforms or Investments, targeting a broad range of policy areas, as seen in Table 1.

Table 1 – Italian NRRP funding amount and share by Mission

Mission	**Description**	**Amount €**	**Percent**
M1	Digitalisation, innovation, competitiveness, culture and tourism	€41,34bln	21,26%
M2	Green revolution and ecological transition	€55,52bln	28,56%
M3	Infrastructure for a sustainable mobility	€23,47bln	12,21%
M4	Education and research	€30,09bln	15,48%
M5	Inclusion and cohesion	€16,92bln	8,70%
M6	Health	€15,62bln	8,03%
M7	RePower EU	€11,18bln	5,75%

Source: own elaboration on data from italiadomani.gov.it

The NGEU is the largest investment package in the history of the EU, providing around €650 billion to Member States. Italy received a total funding amount of €194.4 billion of which €71.8 billion are grants and €122.6 billion are loans. Such investments cover a wide range of sectoral implementation, in particular 150 investment streams and 66 reforms (European Commission, 2024). Given its significance, the plan is subject to rigorous oversight by both public institutions and independent researchers. This is facilitated by the availability of open data on public policy implementation, enabling comprehensive analysis and evaluation.

Official records on RRF funding allocations are collected on the *Italia Domani* database, provided by MEF, dedicated to publishing data on the Italian NRRP. This paper focuses specifically on Mission 2, "*Green revolution and ecological transition*", with a specific focus on those measures directly involving disaster risk reduction projects.

To evaluate different NRRPs across the EU, the European Commission has established Common Indicators (Delegated Regulation EU 2021/2106) that facilitate project supervision and track progress towards common objectives and the overall performance of the RRF. This study utilises Common Indicator 4, namely *"Population benefiting from protection measures against floods, wildfires, and other climate related natural disasters"* to objectively identify measures and projects aimed at mitigating the risk of extreme climatic events. The aim is to provide a classification of climate-related risks and related RRF funding across Italian municipalities.

The Italian NRRP employs a structured alphanumeric categorisation system to identify projects, specifying the Mission (M), the Component (C) and the Investment category (I) or Reform (R). We utilize information on projects that refer to Common Indicator 4, which are all related to Mission 2, Component 4. Table 2 presents the projects and related RFF funding in detail.

Table 2 – Common Indicator 4 projects and funding

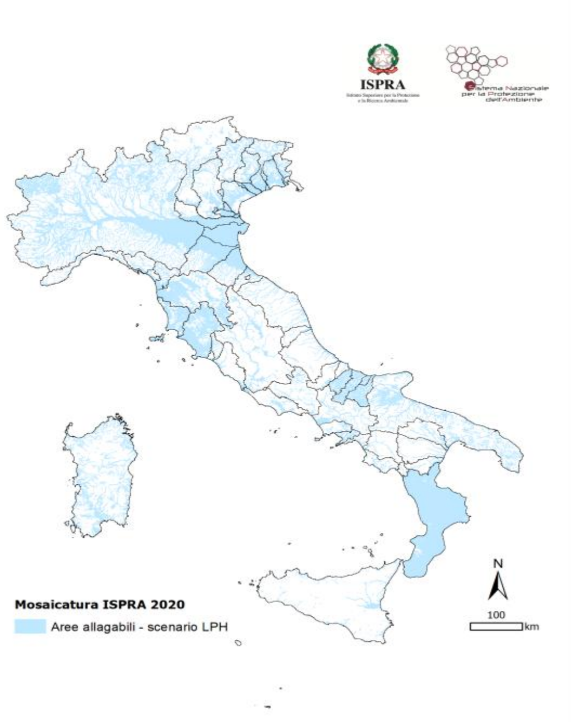
Code	**Description**	**N° of projects**	**RRF funding (mln €)**
M2C4I2.1	Measures for flood risk management and hydrogeological risk reduction	2,117	2.400
M2C4I3.1	Protection and enhancement of urban and extra-urban greenery	203	210
M2C4I3.3	Renaturation of the Po area	12	357
Total		2,332	2.967

Source: own elaboration on data from italiadomani.gov.it, as of NRRP programming of 2025

3.2 Risk assessment

Key data sources in our analysis include comprehensive risk assessments provided by the Italian Institute for Environmental Protection and Research (ISPRA), which offers freely available, detailed profiles of natural hazard exposure across Italian municipalities. This paper concentrates on a specific component of risk, the exposure to potential floods, by considering the data on the area and population at risk in the municipality. In this regard, ISPRA provides the percentage of population considered at flood risk in three categories: low, medium and high. Given the nature of the event considered, the measurement of the population under high risk is the one closer to the possible origin of the event. Therefore, the population with low risk is the one that would be affected by the event if it were to exhibit in its maximum extent, and therefore most devastating nature. This makes it possible to concentrate on the worst-case scenarios. This is fundamental to the aim of this analysis, as the interest lies in how public funding is allocated throughout Italy, and the possibility of "risk averse" policymakers (i.e., the ones that are more likely to use public funding to prevent a disastrous event even if the risk is lower) can be accounted for by using the information provided on the maximum extent of the event, that would involve a greater number of people. Although the probability of such extreme events may be relatively low, a growing body of literature documents a rising frequency and severity of natural hazards (IPCC, 2021). Consequently, focusing on worst-case scenarios is a deliberate and meaningful choice, as it underscores the proactive behaviour of municipalities that invest in risk mitigation even in the face of low-probability but high-impact events. Figure 1 provides a map of the areas that could be subject to the *Low Probability Hazard* (LPH). The data is relative to 2020.

Figure 1. Low Probability Hazard map



Source: ISPRA

3.3 Territorial characteristics

In addition to the data presented above, supplementary sources are used to capture a range of geographical, historical, and socio-economic characteristics, such as demographic context, historical events, and prior policy interventions. Table 3 provides a summary of all variables included in the analysis. While the Recovery Plan spans a multi-year execution period, we treat it as a single-year policy intervention, reflecting its unique context and its specific objective of post-pandemic recovery. Accordingly, all covariates are measured up to the last available year preceding the initial implementation of NRRP projects in 2022.

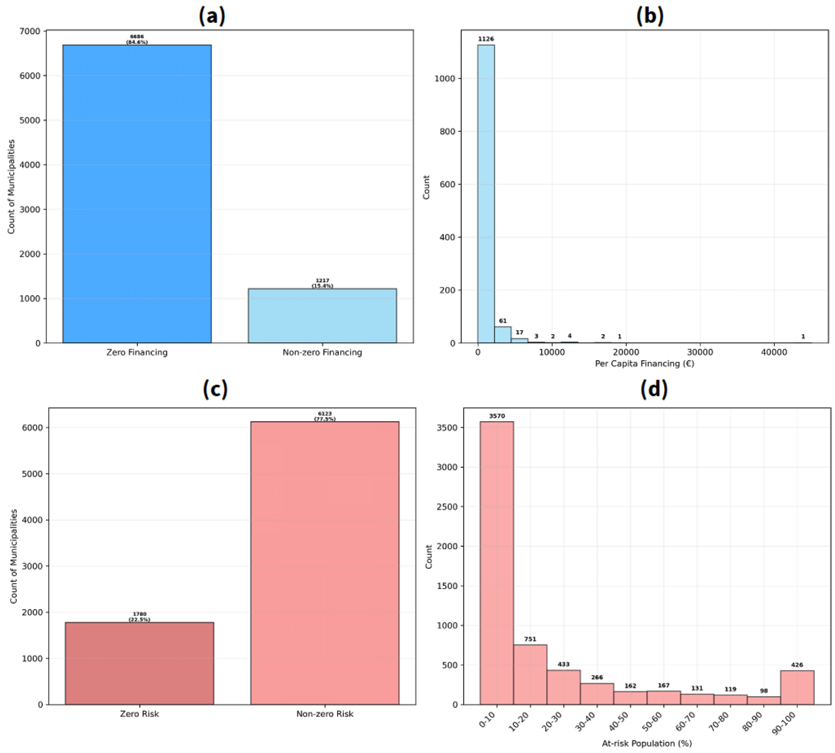
Table 3 – Main variables used in the analysis

Variable	Characteristic	Mean	Median	Year	Source
Income per capita (€)	Economic indicator	14,272.6	14,706.7	2022	Ministry of Economics and Finance
Demographic characteristics	Population	7,495.4	2,411	2021	Italian National Institute for Statistics (ISTAT)
	Foreign population	654.4	127	2021	ISTAT
Municipal dimension	Area (km²)	38.2	22.4	2021	ISTAT
Previous public policy intervention	Number of interventions	26.1	16	2010–2019	Opencup (Department for Economic Policy Planning)
	Amount of funding (€)	11,200,000	3,391,062	2010–2019	Opencup
	Soil defence interventions (n°)	10.9	6	2010–2019	Opencup
	Water resources and wastewater (n°)	7.9	4	2010–2019	Opencup
	Environment protection and enhancement (n°)	7.0	3	2010–2019	Opencup
	Redevelopment and recovery of urban/production sites (n°)	0.2	0	2010–2019	Opencup
Past hydrogeological or seismic events	Past major earthquake (n°)	306	7,599	2009–2012–2016	Breglia & Modica (2025); Russo & Pagliacci, (2019); Fantechi & Modica, (2023)
	Past hydrogeological event (n°)	4,781	3,126	2013-2021	Gatto et al. (2023)

Data on previous public policy intervention is gathered from the OpenCup open-source dataset, managed by the Department of Economic Policy Coordination and Programming of the Italian Presidency of the Council of Ministers. To identify projects that are related to risk adaptation, the CUP (Codice Unico di Progetto – Unique Project Code) is exploited. In particular, by selecting only projects in the *Environmental Infrastructure and Water Resources* (Infrastrutture Ambientali e Risorse Idriche) sector and selecting the subsectors related to *"Soil Defence",* "*Water Resources and Wastewater", "Protection, Enhancement and Enjoyment of the Environment",* and *"Redevelopment and Recovery of Urban and Production Sites"* (Difesa del Suolo, Risorse Idriche e Acque Reflue, Protezione, Valorizzazione e Fruizione dell'Ambiente e Riassetto e Recupero di Siti Urbani e Produttivi) it is possible to track the projects undertaken in previous years, to control for path dependency and previous interventions that might make it unnecessary to utilize NRRP funding. This identification returns 404,798 projects that can be localised at the municipal level and are relative to the 2003-2024 period. For the purpose of this analysis, the dataset is the collapsed at the municipal level to obtain the total number of projects localised in that specific municipality in the ten years prior to the Covid-19 pandemic (2010-2019).

Finally, past events may influence policymakers decision-making process, increasing their risk perception, therefore making them more likely to intervene with public funding for disaster prevention. Previous research has shown that mayors getting financial support after a disastrous event are more likely to be re-elected (Fantechi et al., 2025), making the presence of past events a relevant determinant of funding distribution. Hence, to control for this instance we include information on the occurrence of past floods, taken from Gatto et al. (2023), and the three last major seismic events, L'Aquila 2009 (Breglia & Modica, 2025), Emilia-Romagna 2012 (Russo & Pagliacci, 2019), and Central Italy 2016 (Fantechi & Modica, 2022).

Figure 2 - Distribution of NRRP municipal financing and hydrogeological risk exposure



Source: own elaboration on data from italiadomani.gov.it and ISPRA

Figure 2 illustrates the main distributional patterns emerging from the integration of NRRP municipal financing data with hydrogeological risk indicators. Panel (a) highlights the strong concentration at the extensive margin: 84.6% of Italian municipalities received no NRRP hydrogeological financing, while only 15.4% received any amount. Among funded municipalities, the allocation is extremely skewed. As shown in panel (b), 92.5% of beneficiaries fall within the lowest per-capita funding bin (0.35–2251.85€), whereas all upper bins collectively represent fewer than 10% of funded municipalities. A single municipality receives the maximum allocation (45,030€ per capita), and only a handful exceed 10,000€. These patterns confirm a long-tail distribution of transfers, where a small set of localities concentrates disproportionately large resources despite a broad national exposure to hydrogeological hazards.

Panel (c) reports the distribution of municipalities classified with zero or non-zero hydrogeological risk. Approximately 77% of municipalities exhibit some level of risk, indicating that exposure is widespread across the national territory. Panel (d) further shows the distribution of the at-risk population share: while most municipalities fall within the 0–10%

category, the distribution features a persistent tail of municipalities where a substantial proportion of residents lives in at-risk areas, including a notable cluster above 80%.

Taken together, these descriptive patterns point to two consistent features. First, NRRP hydrogeological financing is both geographically sparse and highly unequal at the intensive margin. Second, the prevalence of risk across municipalities does not translate systematically into proportional funding. The combination of widespread exposure, limited coverage, and heavily skewed allocation raises initial concerns regarding alignment between financing decisions, underlying hazards, and population vulnerability, offering a quantitative motivation for the analyses developed in the subsequent sections.

4. Methodology

Our methodological strategy follows a three-step approach designed to progressively deepen our understanding of the relationship between hydrogeological risk and NRRP funding. First, we estimate descriptive OLS models to summarise conditional associations between risk indicators and per-capita financing, without claiming causal inference. Second, we employ K-means clustering to identify latent patterns in municipal profiles that jointly reflect risk exposure and financing patterns, overcoming the limitations of linear specifications in highly skewed data. Finally, we use multinomial logistic regression to examine the determinants of cluster membership, allowing us to analyse which territorial, socio-economic, and geographical factors shape systematic funding misalignments.

The analysis begins with a descriptive examination of the relationship between key variables, focusing on the link between risk exposure and funding while controlling for other relevant factors, as shown in Eq. 1. Although this stage does not establish causality, it provides an essential foundation for understanding how observable characteristics interact. We estimate the following equation:

$$RRF\ funding_i = \alpha + \beta Risk_i + X_i\gamma + \varepsilon_i \quad (1)$$

Where $RRF\ Funding_i$ denotes per capita (or total) RRF funding for disaster prevention and mitigation received by municipality i, $Risk_i$ measures the share of the municipal population classified as at risk of floods, X_i is a vector of control variables (territorial, socio-economic, disaster-related, and policy-related characteristics) and ε_i is an error term capturing unobserved characteristics.

This model is not intended to infer causality but rather to summarise conditional associations between risk exposure and funding. Coefficients are interpreted as partial correlations, holding the other controls constant. Robust standard errors are clustered at the provincial level to account for spatial correlation.

Building on these preliminary findings, the study investigates in greater depth the relationship between the proportion of the population at risk and the allocation of RRF funding for the prevention and mitigation of extreme weather events. This is achieved through a cluster analysis, which groups municipalities according to their risk levels and funding allocations. As an exploratory technique, cluster analysis is particularly effective for identifying latent structures in complex datasets and for revealing municipalities with similar risk and funding profiles. This facilitates a comparative assessment between groups (for example, high-risk but underfunded municipalities versus low risk but well-funded ones) thereby enabling an evaluation of the degree to which funding allocations align with actual needs.

The intersection of risk profiles and funding levels is expected to produce a four-category distribution of municipalities, as outlined in Table 4.

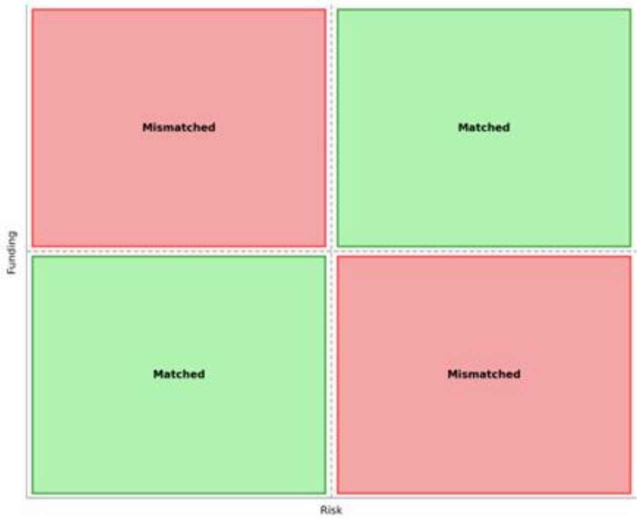
Table 4 – Categories distribution matrix

	Risk	
Funding	Low-risk/high-funding	High-risk/high-funding
	Low-risk/low-funding	High-risk/low-funding

Source: own elaboration

This classification enables a nuanced evaluation of policy alignment in the allocation of RRF resources, as shown in Figure 3. Ideally, municipalities would predominantly fall into either the high-risk/high-funding or low-risk/low-funding categories, indicating a coherent alignment between risk profile and financial support. In contrast, a concentration of municipalities in the mismatched categories (high-risk/low-funding or low-risk/high-funding) would suggest potential inefficiencies or inequities in the distribution of funds. On the other hand, municipalities falling in the low-risk/high-funding category could also indicate an inclination towards preparedness, indicating proactive behaviour within the municipalities' administration. Still, the distribution of municipalities across these clusters is a critical point of analysis, offering insights into whether current funding strategies are effectively targeted according to climate risk profiles. This stage serves as a basis for subsequent inquiry into the fairness and effectiveness of allocation mechanisms. The scheme related to the possible distribution of funding versus risk profiles is shown in Figure 3.

Figure 3 – Risk and funding allocation category



Source: own elaboration

To identify groups of municipalities with similar profiles in terms of hydrogeological risk and per capita NRRP financing, we rely on the K-means clustering algorithm. This method is well suited to large-N datasets because it partitions observations into k non-overlapping clusters by minimizing within-group heterogeneity. Formally, K-means solves:

$$\min_{C_1,\ldots,C_k} \sum_{j=1}^{k} \sum_{i \in C_j} \| x_i - \mu_j \|^2,$$

where C_j denotes the set of observations assigned to cluster j, x_i represents the feature vector of municipality i, and μ_j is the mean of cluster j (Jain, 2010). This optimization yields compact and internally homogeneous clusters while keeping them maximally distinct from one another. Given our goal of deriving a transparent and data-driven typology of municipal exposure and financing patterns, K-means provides a natural and computationally efficient choice.

The selection of the appropriate number of clusters is of crucial importance in the context of K-means clustering. The identification of the optimal number of clusters is facilitated by several methodologies. Following the implementation of a K-means clustering procedure on a range of clusters between two and eleven, three diagnostic tests are then performed to identify the optimal number of clusters. These are the elbow method, the silhouette score and the gap statistic. We begin with the elbow method, which evaluates the within-cluster sum of squares (WCSS) for each candidate solution. The optimal k is suggested at the point where additional clusters produce only marginal reductions in WCSS, creating a visible "elbow" in the curve. In our case, this criterion points to four clusters. Because the elbow method can be subjective, especially when no single elbow dominates the plot, we complement it with two additional diagnostics, i.e. the silhouette score and the gap statistic. The silhouette score measures how similar each observation is to its assigned cluster relative to other clusters (Rousseeuw, 1987). Scores range from –1 to 1, with higher values indicating better-defined partitions. In our case, the silhouette analysis again identifies four clusters as the best compromise between cohesion and separation. We also compute the gap statistic, which compares the observed clustering structure to that expected under a null reference distribution (Tibshirani et al., 2001). The optimal number of clusters is then computed as the majority agreement among these three methods, which in our case is a four-cluster solution.

To further investigate the determinants of cluster membership, the study employs multinomial logistic regression models, where the dependent variable is represented by the cluster each municipality is assigned to. To examine the determinants of municipal cluster membership, we estimate a multinomial logistic regression of the form:

$$\Pr(C_i = k) = \frac{\exp(\beta_{0k} + X_i\beta_k)}{\sum_{j=1}^{K} \exp\left(\beta_{0j} + X_i\beta_j\right)},\ k = 1,\ \ldots,\ K$$

where C_i denotes the cluster classification of municipality *i* (with *k* = categories: high-risk/high-funding, high-risk/low-funding, low-risk/high-funding, low-risk/low-funding) and is a vector of explanatory variables. One category is selected as the reference group (in our case, *low-risk/low-funding*), against which the relative log-odds of membership in other categories are compared.

The estimating equation for the log-odds ratio of being in category *k* relative to the reference category *r* is:

$$\log\left(\frac{\Pr(C_i = k)}{\Pr(C_i = r)}\right) = \beta_{0k} + X_i\beta_k$$

The vector X_i includes the variables described in section 3.3, incorporating a range of territorial, economic, disaster-related, and policy-related controls to assess the relationship between funding allocation patterns and municipal characteristics. The results provide relative risk ratios (RRRs), which allow interpretation in terms of the multiplicative change in the probability of belonging to a given cluster relative to the reference category for a one-unit change in the predictor. This empirical approach offers insights into the effectiveness of RRF funding distribution across Italian municipalities and provides a platform for future research into the role of institutional capacity in securing resources for disaster preparedness.
The results from a robust ordinary least square regression are presented in Table 5. By using the amount of funding received as the dependent variable, our main driver, the percentage of population at risk, seems to have a positive impact on the amount of funding received. That is, if the percentage of population at risk is higher, the funding is higher. On the other hand, if the percentage of territory at risk is higher, the funding seems to decrease. These preliminary descriptive results may hint at the fact that it is the effects on the population that may drive policymakers in implementing prevention measures more than the percentage of territory that may be at risk, suggesting a conscious decision-making process.

5. Results and Discussion

The OLS model (Table 5) offers an initial descriptive exploration of the determinants of NRRP per-capita financing. Empirical findings highlight a dual impact of hydrogeological exposure on funding: while the extent of high-risk municipal area is negatively correlated with resource allocation, the share of the exposed population acts as a positive and significant driver of funding. Importantly, when the model is re-estimated dropping one of the two exposure variables (area or population) at a time, the remaining risk indicator maintains a negative and highly significant coefficient, suggesting that municipalities with larger at-risk territories generally receive less per-capita financing. Past flood events are strongly and positively associated with funding allocation, while previous policy interventions also display a mild positive effect, indicating some degree of institutional path-dependence.

Table 5 – OLS regression for NRRP financing

Dependent variable: NRRP financing per capita (€, municipality level) **Observations:** 7,838 **R²:** 0.009

Variable	Coefficient
Hydro-risk area (%)	-3.965**
	(1.622)
Population exposed (%)	2.978*
	(1.593)
Flooded (past events)	101.8***
	(29.32)
Earthquake-affected	-26.73
	(38.42)
Previous risk-reduction policies	0.732*
	(0.380)
Foreign residents (%)	0.00686
	(0.00519)
Income per capita (€)	-0.00332
	(0.00436)
Surface area (km²)	-0.0216
	(0.188)
Employed (addetti)	-0.00371*
	(0.00223)
Constant	103.7
	(65.93)

Notes: Robust standard errors in parentheses. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

However, despite the clarity of these patterns, the explanatory power of the model remains extremely limited ($R^2 = 0.009$). This reflects the structural heterogeneity of Italian municipalities and the complexity of NRRP allocation mechanisms. Linear models cannot capture non-linear interactions, latent risk profiles, or multilevel combinations of risk, socio-demographic conditions, and prior interventions. For these reasons, we complement the OLS with a cluster analysis, which allows us to identify internally homogeneous groups of municipalities according to hydrogeological risk and funding allocation and explore whether differentiated patterns of NRRP financing emerge across distinct territorial and risk configurations.

5.1 Cluster Analysis Results

The clustering process can be influenced by the presence of outliers within the dataset, particularly given the sensitivity of the K-means algorithm to extreme observations (Jain, 2010). Outliers may distort the position of cluster centroids and lead to the formation of clusters with disproportionately small memberships (e.g., single-municipality clusters), thereby reducing the interpretability and robustness of the results. To mitigate this issue, a preliminary exploratory analysis of the distribution of all municipalities is conducted to identify anomalous observations. These outliers are subsequently excluded from the clustering sample prior to model estimation. This procedure helps ensure that the resulting clusters more accurately reflect the underlying structure of the data and that methodological biases arising from atypical cases are minimized. Nevertheless, these observations warrant attention, as they may represent specific cases arising from the structural characteristics or implementation mechanisms of the policy itself.

This section presents the results of the cluster analysis conducted on the per capita distribution of NRRP financing and the population at risk of floods. As previously outlined, an exploratory analysis of the distribution of the clustering variables was conducted prior to the execution of the cluster analysis. This procedure was implemented with the objective of identifying potential outliers, and, if present, excluding them from the analysis. When plotting per capita financing against the population at risk of floods, one clear outlier emerged. This municipality exhibits exceptionally high levels of both flood risk and per capita financing (97% of at-risk population and 47.000€ per capita, respectively), compared to the average distribution of such variables without the outlier (namely 15.74% of at-risk population and 108.12€ per capita). Further investigation identified the outlier as Ollomont, located in the Valle d'Aosta region[4]. This municipality receives 9.46 million € for a single project related to the safety of a mountain stream system[5], but, having only 170 inhabitants, it becomes an extreme outlier. As a

[4] A scatterplot displaying the distribution of funding against at-risk population including the municipality of Ollomont is available in the Appendix.
[5] Source: https://openpnrr.it/progetti/72036/

consequence, Ollomont was excluded from the cluster analysis. Figure 4 shows a scatterplot of the distribution of the two clustering variables without the removed municipality.

Figure 4 – Scatterplot of at-risk population vs per capita financing

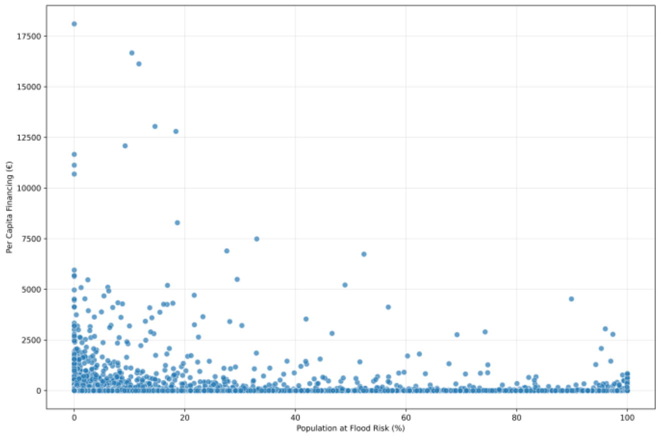
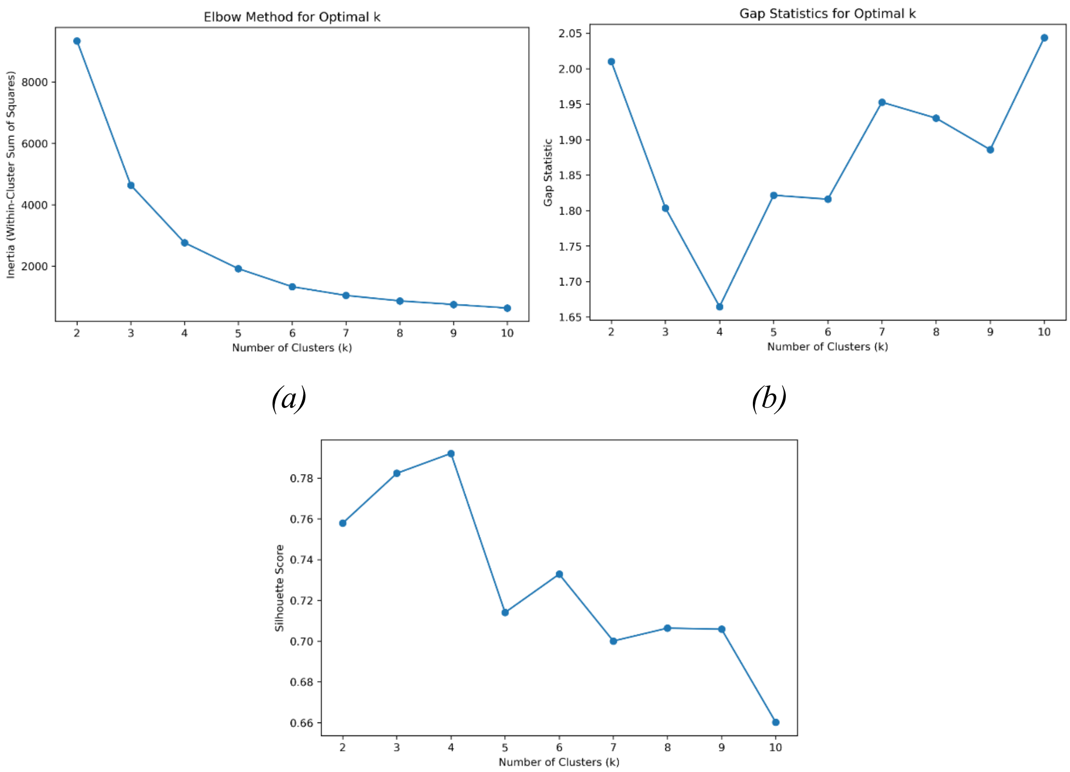


Figure 5 – Diagnostic tests for detecting the optimal K



(a) *(b)*

(c)

(a) Elbow Method; (b) Gap Statistics; (c) Silhouette Score

To detect the optimal number of clusters, K-means algorithm is implemented on a range of k clusters from one to eleven. For each cluster solution, three diagnostic tests are then implemented, i.e. the elbow method, the gap statistics and the silhouette score. Then, the optimal number of clusters is identified as the result of a majority vote among these three diagnostics. As discussed in the previous section, the majority vote yielded a four-cluster solution. This is reflected in the result of the three diagnostic tests provided in Figure 5 (a), (b) and (c). The three indicators used to assess the optimal number of clusters provide broadly consistent guidance. The elbow plot (Figure *a*) shows a sharp decline in within-cluster inertia when moving from $k = 2$ to $k = 4$, after which the marginal improvement becomes increasingly small. This suggests that most of the meaningful variance reduction is achieved within the first four groups. The gap statistic (Figure *b*), although slightly more irregular, identifies local minima at $k = 4$ and then gradual increases for higher values of k. A local minimum in the gap statistic is a common indication that the chosen k adequately captures the structure of the data before overfitting begins. Finally, the silhouette score (Figure *c*) reaches its highest value at $k = 4$, indicating that cluster separation and internal cohesion are jointly maximized at this level. Silhouette values decline consistently beyond four clusters, signalling that additional groups would create partitions that are less statistically meaningful and less interpretable.

Taken together, the three diagnostics converge in supporting a four-group cluster solution as the best compromise between model parsimony and explanatory power. This choice allows the algorithm to capture the key heterogeneities in hydrogeological risk and per capita financing without fragmenting the dataset into clusters that would be either too small or too similar to each other. Moreover, removing the extreme outlier (the municipality of Ollomont) stabilizes the diagnostics and confirms that four clusters provide a robust and substantively interpretable classification of Italian municipalities.

Figure 6 – Scatterplot for the four-cluster solution

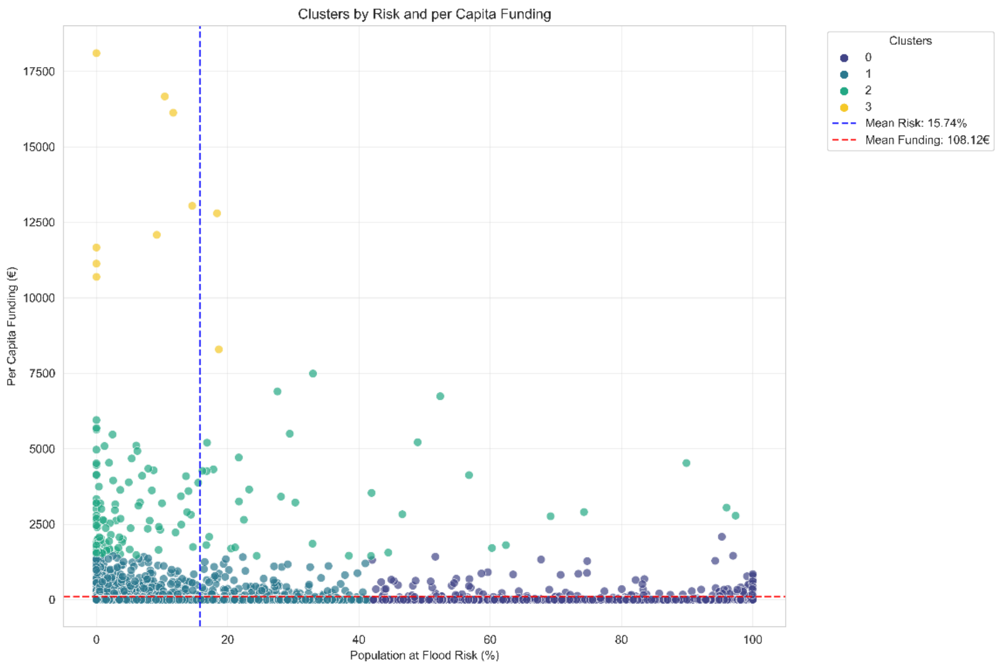


Table 6 – Cluster composition and average values

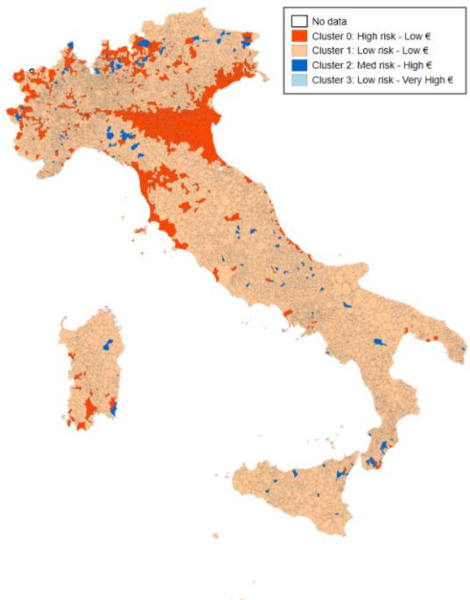
Cluster	Number of municipalities	Mean population at risk (%)	Mean per capita financing (€)
High risk – Low € (Cluster 0)	1,055	77.45	48.63
Low risk – Low € (Cluster 1)	6,699	6.11	40.75
Med risk – High € (Cluster 2)	138	12.32	2,894.21
Low risk – Very high € (Cluster 3)	10	8.29	13,059.88

Table 6 shows the descriptive statistics of the four identified clusters, while Figure 6 shows the scatterplot depicting the identified cluster for each municipality across the two clustering variables. The descriptive table and scatterplot jointly reveal a pronounced disconnect between hydrogeological risk and per capita financing. The largest group of municipalities (Cluster 1) shows both low exposure and low financing, which is expected, also considering the high number of zeros in municipality financing. Cluster 0, however, is particularly problematic: it includes more than 1,000 municipalities with extremely high flood-risk levels (on average above 77%) but receiving very limited per capita financing (around €49). This misalignment appears clearly in the scatterplot, where many high-risk municipalities cluster near the horizontal axis, signalling minimal funding despite substantial exposure.

In contrast, Clusters 2 and 3 receive disproportionately high funding allocations relative to their risk profiles. Municipalities in Cluster 2, although displaying only moderate risk values, receive nearly €2,900 per capita. Cluster 3 municipalities, with similarly low-to-moderate exposure, receive exceptionally high financing (over €13,000 per capita). The scatterplot reflects these patterns: the highest financing values correspond almost entirely to municipalities with modest risk, creating a visually clear vertical cluster of outliers.

Overall, both the table and the plot indicate that financing is not systematically aligned with exposure to hydrogeological risk. Instead, a substantial share of high-risk municipalities remains significantly underfunded, while a small number of low-risk municipalities receive exceptionally large sums.

Figure 7 – Geographic distribution of municipality clusters



Source: own elaboration from clustering results

The spatial distribution of the four clusters reveals a clear geographic pattern, with most Italian municipalities belonging to the Low risk – Low € category, shown in light orange, which dominates the national landscape. The High risk – Low € municipalities (dark orange) form a concentrated belt across parts of Northern and Central Italy, particularly in Emilia-Romagna, Tuscany, and the northern Apennines. These areas exhibit substantial exposure to hydrogeological hazards yet continue to receive limited per capita NRRP financing. The Med risk – High € and Low risk – Very high € municipalities (blue and light blue) are numerically rare and spatially scattered, often located in specific pockets of Northern Italy or isolated coastal and island areas. Their presence highlights targeted episodes of high investment unrelated to current hydrogeological exposure levels.

What is particularly notable is the persistence of Cluster 0 municipalities (High risk – Low €) in regions heavily affected by the 2023 floods in Emilia-Romagna, Marche, and Tuscany. Despite the extensive reprogramming of the Italian NRRP in 2023, which redirected substantial resources toward post-disaster interventions in these areas, many of the municipalities most affected by those events still appear in the High risk – Low € group when considering NRRP project data as of March 2025. This indicates that, even after the reallocation of funds following the floods, NRRP projects have not yet translated into proportionately higher per capita financing for the municipalities with the highest levels of hydrogeological risk. The map therefore underscores a persistent misalignment between risk exposure and NRRP resource allocation, raising concerns about the capacity of emergency-driven reprogramming to correct long-standing territorial imbalances.

5.2 Multinomial regression results

The multinomial logistic regression (Table 5) explores the probability of belonging to each of the four clusters of municipalities, taking Cluster 1 (Low € – Low risk) as the baseline category. Converting coefficients into Relative Risk Ratios (RRR) facilitates interpretation by expressing how a one-unit change in each predictor alters the likelihood of belonging to cluster 0, 2, or 3 instead of the baseline.

Table 5 – Multinomial logistic regression for Risk-financing clustering

Baseline cluster: 1 — Low risk – Low € (most numerous category)

Variable	Cluster 0: High risk – Low €	Cluster 2: Med risk – High €	Cluster 3: Low risk – Very High €
Past hydrogeological event	1.531*** (0.075)	2.175*** (0.205)	5.777*** (0.620)
Past earthquake	4.275*** (0.116)	0.959 (0.524)	5.89×10^{-9}*** (0.486)
Number of past projects	1.006*** (0.0013)	1.018*** (0.0035)	1.060*** (0.0152)
Population	0.99999*** (0.000003)	0.99949** (0.000166)	0.9963** (0.00114)
Foreign population	1.00018*** (0.000048)	0.9972 (0.00201)	1.0105 (0.0079)
Income per capita	1.00015*** (0.000011)	1.00003 (0.000028)	1.00011 (0.000080)
Area (km²)	1.00000 (0.000765)	1.0071** (0.00249)	0.9976 (0.0075)
Employment in vulnerable sectors	0.99996*** (0.000013)	0.99926 (0.000673)	0.9978 (0.0024)
Constant	0.0098*** (0.183)	0.0186*** (0.411)	5.83×10^{-10}*** (1.791)

Observations: 7,837;

Pseudo R^2: 0.0923

Notes: Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. RRR shown; standard errors in parentheses.

Several factors significantly increase the relative risk of belonging to Cluster 0 (Low € – High risk), relative to the baseline cluster. Municipalities with past hydrogeological events show higher probabilities of belonging to this cluster, suggesting that exposure history contributes to their placement despite low financing levels. Earthquake-affected municipalities also exhibit a higher likelihood of being in this group, hinting at overlapping vulnerability profiles. Greater numbers of past projects increase the probability of belonging to this cluster, although the magnitude is small and this cannot explain completely the probability of being in this cluster[6]. Demographic structure matters: larger foreign-resident populations increase the relative risk, while total population size reduces it. Income per capita has a strong positive RRR, implying that relatively wealthier municipalities may still be under-financed relative to their risk. Employment in vulnerable sectors reduces the likelihood of being in this cluster. Overall, Cluster 0 appears to capture municipalities with documented exposure but also signs of demographic pressure and economic vitality.

Cluster 2 (High € – Low risk) shows a different profile. Past hydrogeological events increase the RRR, which is consistent with financing driven more by historical occurrences than by current exposure. The number of past projects substantially raises the relative risk of belonging to this cluster, indicating path-dependency in financing patterns. Larger municipalities exhibit lower probabilities of being in Cluster 2, whereas municipal area has a positive effect, suggesting that large-surface but sparsely populated municipalities benefit disproportionately. Income per capita and foreign-resident population are not significant in this case. Cluster 2 therefore appears to reflect municipalities that are territorially extensive and historically active in project acquisition rather than objectively at risk.

The most distinctive pattern emerges for Cluster 3 (High € – High risk). Here, past hydrogeological events have an extremely large RRR, confirming that this cluster concentrates municipalities with intense exposure and correspondingly high financing. Earthquake-affected municipalities, however, have dramatically lower probabilities of belonging to this cluster, suggesting a clear differentiation between hydrogeological and seismic risk in funding allocations. Higher numbers of past projects again increase the relative risk, reinforcing the finding that financing tends to follow administrative experience. Larger populations sharply reduce the probability of entry into this cluster, implying that high per capita financing is more common in small municipalities, possibly due to project size relative to resident base. Income and sectoral employment are not significant predictors. Cluster 3 thus identifies areas where high exposure and administrative activity combine to generate substantial per capita allocations.

Altogether, the model highlights the coexistence of path-dependent financing, demographic effects, and partial alignment with risk levels. Financing increases strongly where risk and

[6] A t-test comparing past policy financing shows that Cluster 0 municipalities received, on average, a similar level of prior public investment for risk reduction as the rest of the sample (about €11 million vs. €10 million), and the difference is not statistically significant ($t \approx 0.77$). This suggests that membership in the High risk – Low € cluster is not driven by earlier policy allocations.

institutional capacity overlap, but significant mismatches persist, especially in large or economically dynamic municipalities.

6. Policy implications

The central normative premise of this paper is the equitable distribution of resources based on territorial needs, in this case intended as the risk level of Italian Municipalities. However, the empirical results provide a critical diagnostic of the RRF's actual allocative dynamics in Italy, revealing a significant spatial decoupling between financial disbursements and objective climate risk factors. Our findings indicate that rather than being driven by vulnerability, the distribution of funds is shaped by underlying path-dependencies linked to previous disaster occurrence and past prevention and recovery projects.

The mismatch identified in both the descriptive and econometric analyses suggests that the current funding stream is not following a risk-based criterion, but is rather driven by the occurrence of previous disastrous events. Alarmingly, allocation is not following objective risk measures, but is concentrated in those areas that were already receiving funding and undertaking projects for recovery from previous events.

To prevent a widening "resilience divide", policymakers must transition to a risk-based spatial targeting framework. By indexing funding to high-resolution climate risk data (e.g., geo-referenced hydro-geological and temperature exposure), policymakers can ensure that financial resources are directed toward the territories in need of climate change adaptation policies.

While this study focuses on the Italian case, the implications are highly generalisable to other decentralised governance structures. As extreme weather events increasingly threaten the economic, social, and cultural capital of regions across Europe, the Italian case offers a crucial analytical lens to assess the coherence of RRF allocations for nations implementing similar climate-resilient policies.

7. Conclusions

This paper set out to assess whether Italy's Recovery and Resilience Facility allocations under Mission 2 effectively align with the geography of hydrogeological risk across nearly eight thousand Italian municipalities. By integrating granular data on exposure to floods with detailed information on NRRP-funded projects, we developed a comprehensive assessment of how resilience-oriented investments correspond to territorial vulnerabilities. The combination of descriptive statistics, clustering, and multinomial regression allows us to move beyond simple correlations and uncover stylised patterns of mismatch between climate risk and public spending.

Three main findings emerge. First, the distribution of disaster preparedness funding is both geographically sparse and highly uneven. While hydrogeological risk is widespread (77% of municipalities present some level of exposure) 84.6% receive no NRRP financing for hydrogeological prevention. Among the funded municipalities, allocations follow a starkly skewed distribution, with a very small number absorbing extremely high per capita transfers while the vast majority receive relatively modest support. Second, the cluster analysis reveals that the largest group of Italian municipalities falls into a category characterised by low risk and low financing, a pattern fully consistent with the extensive margin being dominated by zero funding. However, more concerning is the identification of over one thousand municipalities classified as high-risk but systematically underfunded. Conversely, a smaller set of municipalities displaying low or moderate risk receive disproportionately high levels of financing. Taken together, these results point to a structural misalignment between public investment decisions and the spatial distribution of climate risk. Third, the multinomial regression results illuminate the drivers of this misallocation. Past hydrogeological events and indicators of administrative path-dependency (such as prior project activity) are strong predictors of cluster membership. In contrast, current risk exposure, especially in its territorial dimension, does not systematically explain higher levels of financing. Demographic and economic characteristics also play a role, although not substantive. Our results therefore point to the persistence of structural inequalities in Italy's disaster-preparedness landscape, where vulnerable communities may lack both the resources and the administrative capacity to benefit from large-scale national and European investments.

These patterns carry important policy implications. First, disaster-risk financing requires more transparent and risk-sensitive allocation criteria. While the NRRP represents a landmark investment programme, resilience-building objectives are unlikely to be achieved if funding does not align with areas of highest exposure and vulnerability. Second, institutional capacity-building should be considered a core component of climate adaptation strategies. Strengthening the administrative and technical capabilities of municipalities, especially smaller and geographically disadvantaged ones, could help reduce disparities in the ability to apply for, manage, and execute public projects.

Finally, our findings open several avenues for future research. A first extension involves incorporating dynamic risk measures that account for climate projections and evolving exposure patterns. A second avenue involves comparing Italy with other EU Member States to evaluate whether similar misalignments arise in different institutional contexts. A third direction concerns the integration of spatial econometric models to better account for spillovers, interdependencies, and clustering of vulnerabilities. Overall, this study underscores the critical importance of aligning public investment with climate risk, not only to enhance the efficiency of disaster prevention policies but also to promote territorial equity and long-term resilience across regions.

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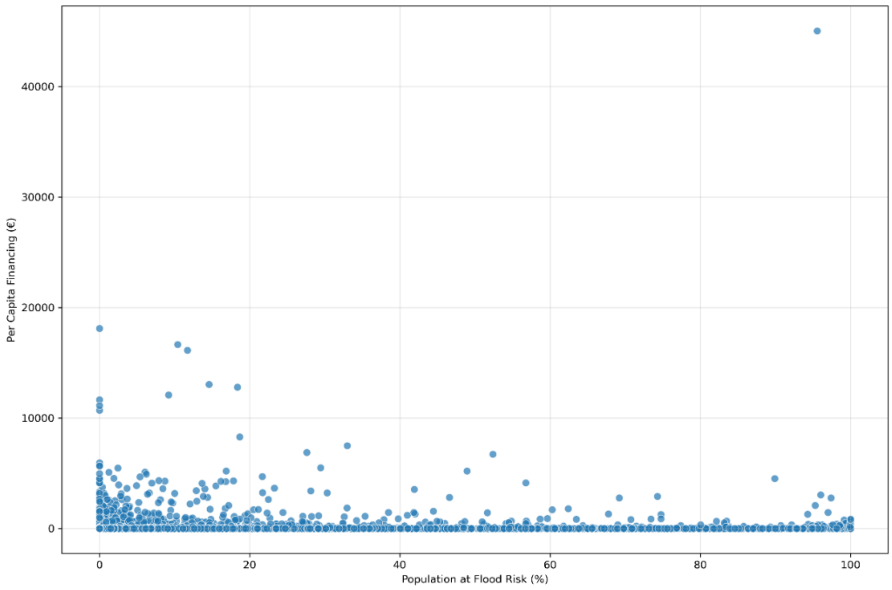
Appendix

Figure A.1 - *Scatterplot of at-risk population vs per capita financing including the municipality of Ollomont*



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