Unveiling Human-Flood Governance Interlinkages from Forensic Investigations

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Abstract. In order to measure the relationship between governance structure and flood vulnerability, it is important to adopt an approach that can effectively analyze the multi-dimensional aspects of the institution as well as the heterogeneous profiles of the actors.

This paper makes use of Hierarchical Clustering on Principal Components (HCPC), where Multiple Correspondence Analysis (MCA) is combined with hierarchical agglomeration to classify respondents into groups of similar characteristics in a survey-based dataset about flood governance.

Firstly, the respondents are mapped to the principal components explaining most of the inertia, generally the first five, which explain the major sources of variability in flood governance systems. The clustering process continues with calculating Euclidean distances among projected coordinates using the Ward minimum-variance approach for reducing intra-cluster variance in each agglomerative stage. The obtained dendogram determines the optimal partition, whereas the silhouette score and bootstrap sampling are used to evaluate the robustness of the clusters. Symmetric dendrograms and cluster-specific bar plots highlight the main governance features distinguishing each group, enabling the identification of distinct vulnerability profiles.

The approach reveals how governance-related risk misjudgment, delayed decision-making, and preventive omissions systematically co-occur within specific clusters, pointing to structural bottlenecks in multi-level flood risk management.

By linking formal multivariate analysis to policy-relevant patterns, HCPC offers a robust framework to inform targeted disaster risk reduction strategies in flood-prone regions.

Keywords: flood governance · hierarchical clustering · vulnerability profiles

1 Introduction and Literature Background

Flood events are increasingly interpreted as socio-natural processes emerging from the interaction between extreme hydro-meteorological conditions and institutional arrangements [1, 2]. While the physical intensity of precipitation and hydrological dynamics defines the hazard, the severity of impacts often depends on governance structures, decision-making processes, and organizational coordination mechanisms [3–5].

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The literature on flood risk governance has extensively emphasized the importance of institutional capacity, inter-agency coordination, and preventive measures in mitigating disaster impacts [6, 7]. However, less attention has been devoted to the structural role of governance scale. In multi-level governance systems, responsibilities are distributed across local, regional, and national authorities, generating coordination challenges, overlaps, or scale mismatches [8–10]. Whether the administrative scale at which governance operates constitutes a primary determinant of flood severity remains an open empirical question [9, 11].

At the same time, research on disaster governance highlights the relevance of cognitive and organizational failures—such as risk misjudgment, delayed decision-making, and preventive omissions—in amplifying flood impacts [11, 12].

Yet it is unclear whether these failure configurations represent the dominant axis of structural variation across events, or whether governance scale exerts a stronger explanatory influence.

This study addresses this gap by investigating nine Italian flood events through judicial rulings of the Court of Cassation. Rather than treating governance scale and human failures as isolated explanatory factors, the analysis explores their relative structural positioning within a multidimensional categorical space. A Multiple Correspondence Analysis (MCA) is employed to uncover latent oppositions among variables, followed by Hierarchical Clustering on Principal Components (HCPC) to formalize case aggregation patterns.

The core of our study thus revolves around the following key question: "Is flood damage more structurally linked to scale of governance or to the pattern of cognitive and organizational failures?"

The rest of the paper is organized as follows. The second section describes the methodological approach, explaining both MCA and HCPC. The third section describes the data set used for the research, along with its variables. Section four provides the empirical findings, while section five discusses these findings and the shortcomings of this study. Finally, the conclusion is provided in section six.

2 Method

Considering the nature of the variables used in the study, which were categorical, and the sample size (N = 9), the exploratory technique of MCA was applied to investigate the possible latent structure that may be hidden behind the observed multidimensional phenomena of flooding.

In order to facilitate the classification of the cases into clusters based on the factorial structure, HCPC analysis using Ward's method was undertaken. This approach involves clustering cases by MCA axes as opposed to clustering them using categorical variables directly.

2.1 Multiple Correspondence Analysis (MCA)

In order to analyze the relationships among several categorical variables contained in a multidimensional contingency table, MCA was used. The procedure is based on the

principles of Correspondence Analysis (CA), a mathematical procedure developed for the study of mutual dependencies among rows and columns of a contingency table in terms of Cartesian projections [13, 14].

All entities in the dataset that have been processed have their location in a multidimensional Euclidean space, wherein the entity is situated based on its own weight, which determines its significance. The χ^2 distance between two sets of observations is one of the key metrics used in the method, calculated using the value of the χ^2 statistic and indicating the extent to which observed and expected frequencies diverge when assuming independence between variables [14–16].

The visualization of proximity and dissimilarity between categories is easy to understand because close profiles within the factorial space suggest high similarities, while far profiles imply high dissimilarities.

The formula for the chi-square distance is:

$$d^2_{\chi^2}(\mathbf{x}_i, \mathbf{y}_i) = \sum_{j=1}^{n} \frac{\left(x_j - y_j\right)^2}{c_j} \tag{1}$$

where:

- $\mathbf{x}_i = [x_1, x_2, \ldots, x_n]$: factorial coordinates of a profile in the multidimensional cloud;
- $\mathbf{y}_i = [y_1, y_2, \ldots, y_n]$: coordinates of a second profile;
- $\mathbf{c}_i = [c_1, c_2, \ldots, c_n]$: column mass weights (column total/table sum).

Total inertia, expressed by the ratio between $\chi^2_{\text{Pearson}}/n$, measures the proportion of explained variance and the degree of dispersion of the data, which means that higher total inertias correspond to more articulated structures and stronger connections among categories [17].

In situations where data is gathered through purposeful surveys containing sector-specific features and characteristics (such as levels of preparedness within flood-prone areas), factor maps generated through these profiles become differentiated into distinct groups of homogenous elements [14–16].

While symmetric visualizations focus on inter-categorical relationships on a global scale, asymmetric visualizations concentrate on intravariable particularities.

2.2 Hierarchical Clustering on Principal Components (HCPC)

In order to reveal homogeneous sets in the multidimensional space created by MCA or PCA, HCPC was utilized. HCPC is an amalgamation of PCA and hierarchical agglomerative clustering, which allows for the identification of partitions in multivariate datasets by aggregating the data points iteratively [18, 19].

In the processed dataset, individuals are first mapped into the principal components, keeping those that have high inertia (usually five principal components). The cluster formation process is done based on computing the Euclidean distances between the mapped data points using Ward's criteria of minimizing within-cluster variation [18, 20, 21].

Cluster hierarchy graphs are easily interpreted as follows: clusters with dense branches suggest compact groups with common traits, while far-off branches represent structural differences. Cluster partition stability is assessed using the silhouette score and bootstrap analysis methods [19, 20, 22].

The clustering process is formally defined as follows:

$$d\left(\mathbf{F}_i, \mathbf{F}_j\right) = \sqrt{\sum_{p=1}^{P} \left(F_{ip} - F_{jp}\right)^2} \tag{2}$$

where:

- $\mathbf{F}_i$: factorial coordinates of observation i on retained principal components;
- $d(\mathbf{F}_i, \mathbf{F}_j)$: Euclidean distance between observations i and j;

$\mathcal{L}(k)$: linkage criterion (Ward's minimum variance) for k clusters.

The objective at each step is to minimize the total inertia within clusters, computed as:

$$I_{total} = \sum_{c=1}^{k} \frac{1}{n_c} \sum_{i \in c} \|\mathbf{F}_i - \bar{\mathbf{F}}_c\|^2 \tag{3}$$

The total inertia is an indicator of partition quality; the lower the value of the total inertia, the greater cohesion among groups and the more distinct boundaries between groups will be.

Based on factorial coordinates obtained by MCA of surveys reflecting variables concerning flood management systems, HCPC gives well-calibrated dendrograms and clustered maps of the vulnerability profiles [18, 19]. he symmetrical dendrogram stresses hierarchical relations, while the bar charts related to each cluster reveal which variables contribute the most.

3 Data

The data set includes nine cases of floods, all collected from rulings made by the Italian Court of Cassation from 1998 to 2013 (as shown in Fig. 1 below). Cassation decisions were selected to ensure consistency in case reconstruction and responsibility attribution, as they represent the final level of judicial review within the Italian legal system. This guarantees a standardized and definitive account of events, suitable for systematic coding and comparative analysis.

All rulings were retrieved through the OneLegale platform (Wolters Kluwer), which provides access to Italian case law and legal documentation.

A set of descriptive variables was gathered for each case in order to help in its initial classification inside the dataset. The variables consist of the case number (CS), OneLegale reference (Ref. OL), location (city and region), year of the event, nature of the hydro-meteorological disaster, and scale of governance implicated.

These elements, summarized in Table 1, provide the contextual framework for subsequent multidimensional analysis.

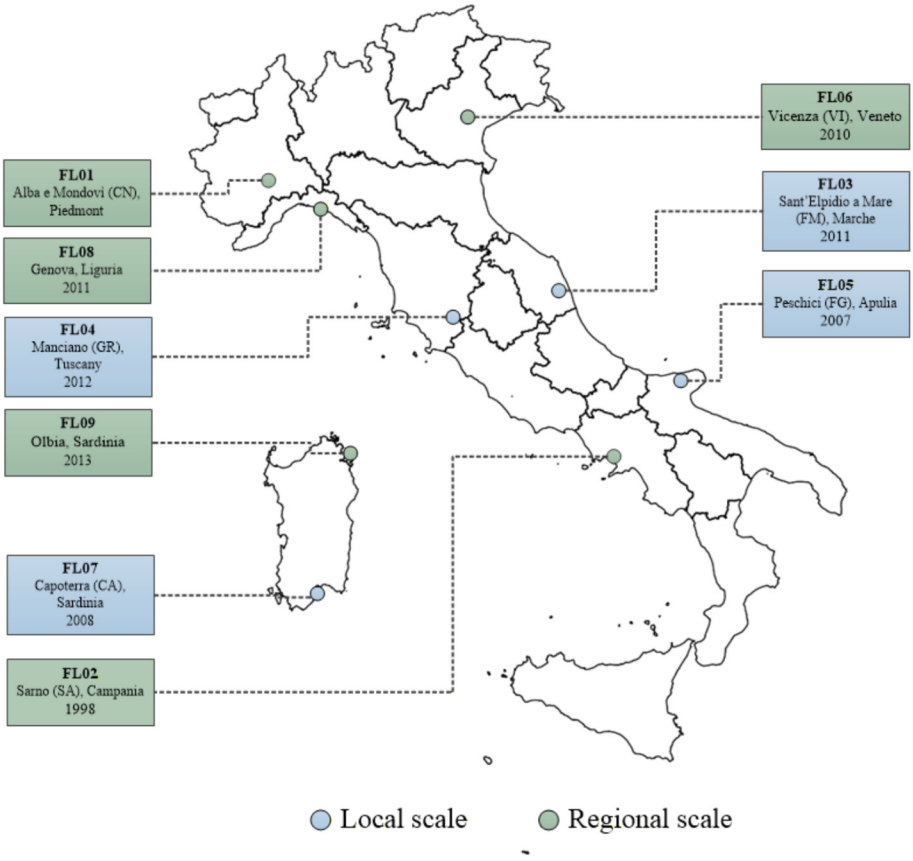

Fig. 1. Geographic distribution of the case studies by governance scale

Following this, the coding process involved identifying the variables needed to answer the following research question: "Does the level of governance matter as a primary determinant of the intensity of floods, or is the failure configuration a primary determinant of variation?" For this purpose, three main categories of variables have been identified: causative variables, effect variables, and the level of governance.

In the first category (causative variables), there are variables related to determinants that cause and escalate the hazard. They include psychological failures (PSY) and behavioral failures (ATT) of the persons involved in risk prevention and territory management, and residual causative factors (RES), which are natural elements and weather conditions that contributed to the occurrence and intensity of the disaster.

The second domain (effects) focuses on the gravest effect of flood occurrences, namely, human deaths (HUM_L), defined as a binary variable. Human casualties were selected as the primary outcome measure because they represent the most critical consequence of hydro-meteorological hazards and are consistently documented within judicial rulings. Other potential effects, such as economic or material damages, were not systematically included due to inconsistent reporting across cases.

Table 1. Case study's identification

Case study	Ref. OL	City and region	Year	Hydro-meteorological hazard typology	Governance scale
CS01	cass-pen-sez-iv-sent-data-ud-10-07-2001-13-09-2001.pdf	Alba e Mondovì (CN), Piedmont	1994	Riverine Flood	Regional
CS02	cass-pen-sez-iv-sent-data-ud-11-03-2010-03-05-2010.pdf	Sarno (SA), Campania	1998	Debris Flow / Landslide	Regional
CS03	cass-pen-sez-iv-sent-data-ud-13-11-2019-23-10-2020.pdf	Sant'Elpidio a Mare (FM), Marche	2011	Riverine Flood	Local
CS04	cass-pen-sez-iv-sent-data-ud-15-05-2025-03-06-2025.pdf	Manciano (GR), Tuscany	2012	Riverine Flood	Local
CS05	Peschici_cass-civ-sez-unite-sent-data-ud-05-12-2017-21-09-2.pdf	Peschici (FG), Apulia	2007	Multi-hazard / Cascading Disaster	Local
CS06	t-a-r-veneto-venezia-sez-iii-sent-data-ud-05-03-20.pdf	Vicenza (VI) Veneto	2010	Urban Flood	Regional
CS07	corte-d-appello-cagliari-sez-ii-sent-09-04-2020.pdf	Capoterra (CA), Sardinia	2008	Flash Flood	Local
CS08	Cass. pen., Sez. IV, Sent., (data ud. 12/04/2019) 22/05/2019, n. 22214.pdf	Genova, Liguria	2011	Flash Flood	Regional
CS09	Cassazione penale sez. IV - 20/12/2023, n. 15405.pdf	Olbia, Sardegna	2013	Flash Flood	Regional

The third domain concerns governance scale and represents the core variable of the study. It identifies whether the flood event primarily involved local or regional governance arrangements. The identified domains, corresponding variables, and their values are summarized in Table 2.

Table 2. Domain and variables coding

Domain	Code	Variable	Description	Values
Causes	PSY	Psychological causes	Cognitive and decision-making failures	0: Absent;
				1: Risk misjudgment;
				2: Flawed decision-making
	ATT	Attitude and behavioral causes	Managerial omissions and operational behaviors	0: Absent;
				1: Preventive failures;
				2: Implementation errors
	RES	Residual causes	External meteorological conditions and contributing factors	1: Exceptional rainfalls;
				2: Inclement weather
Effect	HUM_L	Human losses	External meteorological conditions and contributing factors	(Binary) 1: Yes
Governance scale	SCALE	Governance scale	Institutional level involved in flood management	1: Local
				2: Regional

4 Results

4.1 Multiple Correspondence Analysis (MCA)

The MCA results are reported in Fig. 2 and Table 3. The factorial map illustrates the relational structure among the modalities of the variables considered and allows the identification of the main axes of variation that organize the analyzed phenomenon.

Dimension 1, which explains 70.3% of the total inertia, clearly represents the dominant structural axis of the dataset, and the analysis of the column standard coordinates highlights a strong polarization along this first dimension.

Modalities with strongly positive coordinates include PSY = absent (1.86), ATT = absent (2.10), HUM_L = No (2.12), and RES = exceptional rainfall (1.38), whereas on

the negative side are PSY = risk misjudgment (–1.25), PSY = flawed decision-making (–0.87), ATT = preventive failures (–0.54), ATT = implementation errors (–0.96), and HUM_L = yes (–0.60). This configuration indicates that the first dimension contrasts coherent sets of modalities associated with different configurations of failure, in which psychological, attitudinal, response-related components, and human factors combine. The main axis is therefore not structured by an institutional variable but by systematic patterns of error and vulnerability.

By contrast, the variable SCALE shows limited coordinates along Dimension 1 (0.42 for SCALE = local and –0.34 for SCALE = regional), significantly lower than those observed for the variables defining the main polarization.

Table 3. Column Standard Coordinates of Categories (MCA Results)

Categories	Values	Dim1	Dim2
PSY	Absent	1.863	0.007
	Risk misjudgment	−1.252	−2.808
	Flawed decision-making	−0.868	0.557
ATT	Absent	2.101	−0.149
	Preventive failures	−0.540	−0.606
	Implementation errors	−0.961	3.934
RES	Exceptional rainfalls	1.383	−0.201
	Inclement weather	−0.395	0.058
HUM_L	No	2.117	−0.494
	Yes	−0.605	0.141
SCALE	Local	0.424	1.542
	Regional	−0.340	−1.233

This suggests that governance scale does not constitute the structuring factor of the dominant axis. Instead, SCALE shows greater differentiation along Dimension 2 (10.6% of the inertia), with values of 1.54 for SCALE = 1 and –1.23 for SCALE = 2.

However, since this dimension explains only a residual share of the variance, its role remains secondary in the overall structure of the factorial space. Dimension 2 appears rather to capture a differentiation among specific types of error, as also indicated by the high coordinates of ATT = 2 (3.93) and PSY = 1 (–2.81), rather than a genuine divide related to institutional scale.

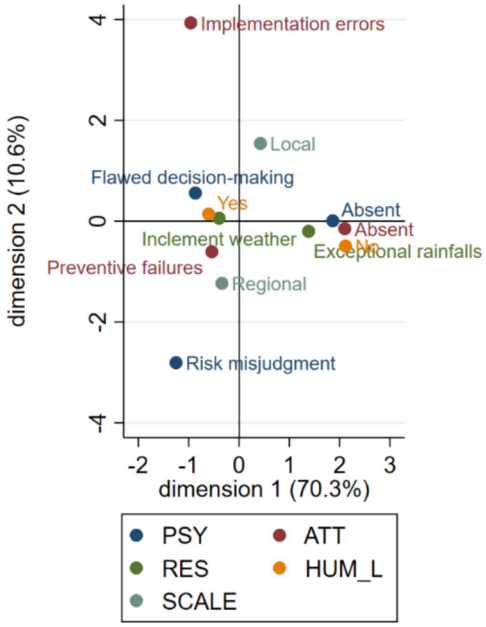

Fig. 2. MCA Factorial Map of Failure Configuration and Governance Scale

Overall, the MCA suggests that the configuration of failures constitutes the dominant axis of variation in the dataset, whereas governance scale does not emerge as a primary structural determinant of flood severity. Instead, event severity appears to be associated with systematic combinations of cognitive, decision-making, and operational errors, which occur across different levels of governance.

4.2 Hierarchical Clustering on Principal Components (HCPC)

To further examine the structural grouping of cases in the factorial space, a HCPC was performed using Ward's linkage method and the L2 squared dissimilarity measure on the first two MCA dimensions.

As shown in Fig. 3, the dendrogram reveals a marked increase in L2 squared dissimilarity in the final aggregation step, when the two main branches are merged into a single cluster. The substantial jump in fusion distance suggests that the two-cluster solution represents the most parsimonious and structurally coherent partition of the dataset.

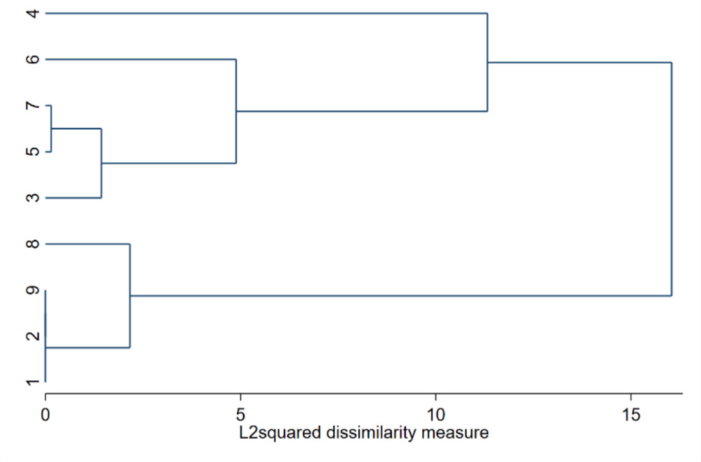

Fig. 3. Dendrogram for cluster analysis

The spatial distribution of the two clusters in the factorial plane is illustrated in Fig. 4. Cluster 1 groups four cases located predominantly on the negative side of Dimension 1, whereas Cluster 2 includes five cases mainly positioned on the positive side of the first dimension.

This separation reflects the dominant structural axis identified by the MCA and indicates that cluster allocation is strongly aligned with the principal latent contrast emerging from the data.

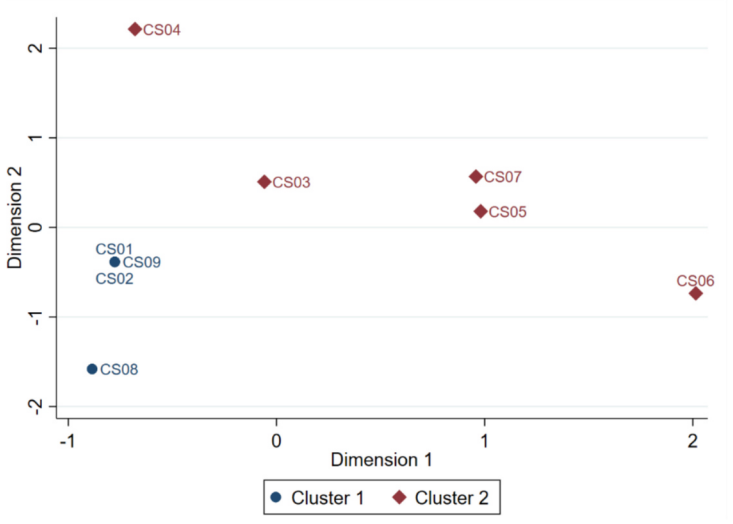

Fig. 4. Spatial distribution of the two clusters in the factorial plane

To evaluate whether cluster membership corresponds to governance scale, a cross-tabulation between clusters and SCALE was conducted (Table 4). The results reveal a marked association: all cases in Cluster 1 belong to scale category 2, while Cluster 2 is primarily composed of scale category 1 cases (4 out of 5). Fisher's exact test confirms that this association is statistically significant ($p = 0.048$).

Table 4. Distribution of case studies by cluster membership and governance scale

Case study	Place	Cluster 1	Cluster 2
CS01	Regional	1	0
CS02	Regional	1	0
CS03	Local	0	1
CS04	Local	0	1
CS05	Local	0	1
CS06	Regional	0	1
CS07	Local	0	1
CS08	Regional	1	0
CS09	Regional	1	0
Fisher's exact		0.048	
1-sided Fisher's exact		0.040	

Note: 1 = case belongs to the cluster; 0 = case does not belong to the cluster.

Although the limited sample size ($N = 9$) warrants cautious interpretation, the HCPC results indicate that governance scale is structurally embedded in the clustering pattern derived from the factorial coordinates. The observed partition suggests that institutional level contributes to the differentiation of case profiles within the multidimensional space identified by the MCA.

5 Discussion and Limitations

Although the analysis was conducted on a relatively small sample ($N = 9$), the results obtained through MCA and HCPC provide meaningful insights that deserve further discussion.

The MCA identifies Dimension 1 as the dominant axis of representation of the dataset, while Dimension 2 plays a secondary and comparatively weaker role. The first dimension clearly separates two opposing poles. The positive pole is characterized by events in which flood severity is primarily attributable to natural and physical causes, particularly exceptional rainfall (RES = 1). This configuration is associated with the absence of psychological and behavioral failures (PSY = 0; ATT = 0) and, notably, with the absence of human losses (HUM_L = 0).

This first structural result suggests that when preventive and decision-making mechanisms function effectively, even severe natural conditions do not necessarily translate

into fatal outcomes. In the cases analyzed, the absence of organizational and behavioral failures appears to mitigate the most critical consequences of the flood events.

The second pole, located on the opposite side of Dimension 1, presents a more complex configuration. Here, natural factors such as inclement weather (RES = 2) are combined with organizational and psychological failures that exacerbate the severity of the event and are associated with the presence of human losses (HUM_L = 1). Flawed decision-making (PSY = 2) and preventive failures (ATT = 1) appear strongly linked to this configuration. Conversely, risk misjudgment (PSY = 1) and implementation errors (ATT = 2) do not show a clear alignment with either pole.

While MCA provides an exploratory representation of latent structures, it does not formally define case groupings. The hierarchical clustering performed on the MCA coordinates through HCPC allows for the identification of structured aggregations within the same Euclidean space.

The HCPC results reveal that cluster membership is significantly associated with governance scale (Fisher's exact test, $p = 0.048$). One cluster is entirely composed of cases characterized by local governance, while the other is predominantly composed of regional cases. This indicates that even if governance scale is not the dominant factorial dimension, it is inherently structured within the case set up. Governance scale acts as the second-level factor influencing the expression of the failure structure. Decision-making and preventative failures do not occur independently of their institutional setting but could well depend on the structural attributes inherent to each level of governance.

The main limitation of the study lies in the small number of cases analyzed ($N = 9$), which constrains statistical generalization and limits the robustness of inferential claims. The findings should therefore be interpreted as exploratory rather than confirmatory. In addition, the use of MCA provides a structural representation of associations within the dataset but does not allow for causal inference. The coding of psychological and organizational variables, derived from judicial documents, may also involve interpretative margins, as court rulings reconstruct events through a legal lens rather than a purely managerial or governance perspective. Furthermore, cluster stability cannot be fully assessed given the limited sample size, and minor variations in the data could potentially affect case aggregation. Finally, governance scale is operationalized as a simplified binary variable, which may not fully capture the complexity and multi-level nature of institutional arrangements in flood risk governance.

6 Conclusions and Future Developments

The present contribution aimed to investigate whether governance scale plays a structural role in shaping flood events and their consequences within a dataset of nine flood cases that occurred in Italy between 1994 and 2013.

The results obtained through MCA and HCPC reveal a nuanced picture. On the one hand, the factorial structure highlights the dominant role of individual and organizational failures in differentiating flood severity. Behavioral and decision-making dimensions emerge as the primary axis structuring the dataset, suggesting that flawed decision-making and preventive failures represent critical factors in the escalation of flood impacts. On the other hand, the HCPC results indicate that governance scale, although not dominant along the main factorial dimension, is nonetheless significantly associated with case

aggregation patterns. This suggests that institutional level contributes to shaping how failure configurations manifest, even if it does not fully determine the severity outcomes. Overall, these results reveal that scale of governance is not adequate for explaining the magnitude of floods. Even though the institutional environment at the local and regional level affects organizational action, the behavioral aspects of failure continue to be structurally essential in the selected cases. Hence, scale of governance does not directly predict the magnitude of floods, but rather, it acts as a secondary but structurally significant variable that affects the manner in which behavioral and organizational aspects of failure are arranged within the local and regional institutional environment.

In contrast to other methods, including cluster analysis, for instance k-means method, the application of MCA and HCPC offers distinct advantages in this context. The k-means method is effective in terms of computation time but presupposes that the number of clusters be fixed in advance, as well as that there be no consideration of correlations between different variables. At the same time, the HCPC method makes it possible to determine clusters according to the MCA model and make the structure more interpretable.

Regression-based approaches (e.g., logistic models) could quantify predictive power but treat variables linearly, missing the multidimensional, non-linear associations revealed in this research. Therefore, MCA-HCPC offers a more sophisticated depiction of the structure that reflects the association—although not dominance—of the governance scale in the disaster governance context.

Further studies may consider widening the empirical basis through the inclusion of a larger number of cases, as well as cross-country analysis to test the resilience of the structural patterns established. Other innovations may enhance the measurement of governance scale through additional variables, including institutional coordination, resource distribution, and emergency planning capabilities.

Moreover, integrating quantitative structural analysis with qualitative process tracing could provide deeper insight into the mechanisms through which behavioral and institutional failures interact during extreme events. Such an approach would contribute to a more comprehensive understanding of how governance structures and human decision-making jointly shape disaster outcomes.

Disclosure of Interests.. The authors have no competing interests to declare that are relevant to the content of this article.

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