Reviewer 1

Topic and key findings of manuscript

Thank you for the opportunity to review this manuscript, which analyzes 18 municipal archetypes for the Italian territory, incorporating geographic, demographic, and socio-economic characteristics. Deriving archetypes for risk, exposure and vulnerability analysis is a highly relevant topic for scientific investigation. The paper is therefore an interesting contribution to the interdisciplinary debate on how to construct such archetypes. However, the arguments and the way they are presented need to be revised before publication.

(a) Title: consider revising the title. First of all, you speak of "urban" archetypes but your analysis includes several rural archetypes as well. Maybe "municipal" would be more fitting. I suggest you revise this throughout the manuscript. Secondly, you speak of multi-risk, but do not really elaborate on that. I would suggest you rather revise the title so that it is clear that your main goal is to construct the archetypes.

Response: Thanks for this comment. The term "*urban*" has been replaced with "*urban and rural*", as also rural archetypes are included in this study. It has been reviewed throughout the manuscript. Moreover, the term "multi-risk" has been removed, and the title has been changed from: "*Identifying urban settlement archetypes: clustering for enhanced multi-risk exposure and vulnerability analysis*" to "*Identifying urban and rural settlement archetypes: clustering for enhanced risk-oriented exposure and vulnerability analysis*". In addition, to underline the fact that both urban and rural archetypes are addressed in this study, the following text highlighted in bold has been added in the introduction:

*"The level to which urban settings are prone to the negative impacts of one or multiple hazards is also known as urban vulnerability (Thywissen, 2006), and its assessment is particularly challenging, as cities are intricate systems composed of interdependent networks of built environments, infrastructure, and social systems (Koren et al., 2017). The concentration of assets and people may increase potential losses, while dynamic interactions between individual components that enable efficient system performance can lead to cascading failures. In addition, urban areas are often exposed to multiple hazards, such as earthquakes, floods, heatwaves, each interacting with the built environment and human activities in different ways. **Rural settlements, on the other hand, may experience different forms of vulnerability, often related to geographic isolation, limited access to emergency services and infrastructure, lower institutional capacity, and demographic challenges such as aging population, which can significantly hinder preparedness and recovery**. This complex interplay explains also why often non-extreme hazards can lead to severe consequences, while extreme events in other contexts may not result in disasters (Lavell et al., 2012)"*

(b) Abstract: The abstract should be revised to incorporate the changes detailed below.

Response: The abstract has been modified according to changes made. The new version of the abstract is reported below:

*"Identification of risks and vulnerabilities in **urban and rural areas** is crucial for supporting local authorities in disaster risk reduction and climate change adaptation. Moreover, comparison of risk assessments across **different areas** may help effective allocation of adaptation funding towards more resilient and sustainable **communities**. The distinct physical, social, economic, and environmental characteristics of a **settlement**, along with the relevance of impending hazards, determine the level of risk and vulnerability faced by its residents. While the results of risk assessments will vary from one **settlement** to another, using general **settlement typologies** (e.g. coastal cities, dryland cities, and inland or high-altitude cities) can effectively support the understanding of risk in relation to its key drivers, helping to segmentate the complexity in otherwise too broad problem (Dickson et al., 2012).*

*This study aims to reduce complexity in risk assessment of **urban/rural settlements** at regional and national scale, ensure a baseline for comparison and identify potential hotspots in **risk assessment frameworks**. We* *propose a clustering methodology that groups **human settlements** based on open-source data, used as proxies of urban vulnerability and exposure. Applying two widely used clustering techniques, we define 18 **urban and rural archetypes** for the Italian territory, incorporating geographic, demographic, and socio-economic characteristics. These archetypes satisfy multiple validity dimensions of archetype analysis (Piemontese et al., 2022) and can serve as a valuable tool for policymakers. By providing a structured understanding of **human settlements** vulnerability profiles, they support the design of targeted interventions and resilience strategies tailored to specific risk conditions."*

(b) Structure of the manuscript: I recommend revising the structure to improve conciseness (see detailed comments below). The introduction, discussion, and conclusion are relatively brief, whereas the materials and methods section is quite extensive and could be streamlined. Additionally, clearer section headings, especially in sections 2 and 3, would help distinguish between the introduction and the materials section.

Response: Thanks for this comment. The introduction has been revised, including also concepts presented in section 2 – which has been removed to have a better distinction between the different part of the paper, i.e., introduction, material and methods. See also response to following comment for details about introduction's revisions. In addition, section 3 title has been changed from "*Key indicators of urban vulnerability*" to "*Selection of key indicators of vulnerability dimensions*".

(c) Introduction: The introduction would benefit from further elaboration. Specifically, I suggest clarifying how archetypes enhance the understanding of exposure and vulnerability in this context. Additionally, since archetype analysis can take various forms, it is important to highlight how previous studies have approached archetypes and to clearly define your own understanding of the concept. Providing a brief explanation of how you apply the concept and implement it with your data—before presenting the archetypes in Chapter 5—would improve clarity. A figure of the framework could help with clarity. Further, I suggest to include the research question more prominently in this section.

Response: The introduction has been revised to address the reviewer's comment by: (i) clearly stating the research question early on; (ii) elaborating on how archetypes enhance the understanding of exposure and vulnerability; (iii) clarifying different interpretations of archetypes and explicitly stating the one used in this study; (iv) briefly explaining how the concept is operationalized in this work. To further improve the clarity and readability of the paper, the section where each step of the proposed procedure is described has been referenced. The revised version of the introduction is provided below, with the added or modified sentences highlighted in bold:

"*Over the last few decades, natural disasters have caused devastation to many communities throughout the world, killing about 1.5 million of people and incurring losses exceeding 4.5 billion USD (Centre for Research on the Epidemiology of Disasters - CRED, 2024). Such disasters are the results of the interaction of hazards (natural or man-made) with vulnerable socio-ecological and socio-economical systems. Evidence shows that the level of disaster proneness of communities may vary greatly with their physical, demographic, socioeconomic and institutional characteristics (Cutter et al., 2003a; Wang et al., 2022). For example, low-income and minority communities in New Orleans were disproportionately affected during Hurricane Katrina due to residing in flood-prone, lower-lying areas, and lacking personal transportation, which hindered evacuation (Flanagan et al., 2011). Similarly, aging communities with limited mobility face challenges in evacuating quickly during hazardous events, leading to higher mortality rates, as seen during the 2011 Tohoku Tsunami, Hurricane Katrina, and the 2017 and 2018 California wildfires (Brunkard et al., 2008; Hamideh et al., 2022; Miyazaki, 2022).*

Climate change brings additional challenges to urban management and decision making for city governments and is associated with a growing variety of impacts on cities, the surrounding ecosystems, and livelihood of resident and temporary population (e.g., Dickson et al., 2012). As highlighted in the IPCC's 6th assessment report, in urban areas the risk to people and assets due to climate-related hazard has already increased, and climate impacts are felt disproportionately in urban communities, with the most economically and socially marginalized being most affected (Dodman et al., 2023). Such risks depend on the increase of intensity and frequency of extreme weather *events* (La Sorte et al., 2021; Mulholland & Feyen, 2021) *as well as on the interplay with several non-climatic risk drivers including extent and features of the exposed systems and assets (e.g., European Environment Agency, 2024 and their vulnerability (e.g.,* Cutter & Finch, 2008; Dickson et al., 2012*).*

Exposure is intended as the presence of people; livelihoods; species or ecosystems; environmental functions, services, and resources; infrastructure; or economic, social, or cultural assets in places and settings that could be adversely affected, while vulnerability refers to the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt (Intergovernmental Panel on Climate Change (IPCC), 2022; Koren et al., 2017). It encompasses both the lack of coping capacity and adaptive capacity—factors that influence a community's ability to manage disasters effectively (Cardona et al., 2012; Marin Ferrer, 2017). The level to which urban settings are prone to the negative impacts of one or multiple hazards is also known as urban vulnerability (Thywissen, 2006), and its assessment is particularly challenging, as cities are intricate systems composed of interdependent networks of built environments, infrastructure, and social systems (Koren et al., 2017). The concentration of assets and people may increase potential losses, while dynamic interactions between individual components that enable efficient system performance can lead to cascading failures. In addition, urban areas are often exposed to multiple hazards, such as earthquakes, floods, heatwaves, each interacting with the built environment and human activities in different ways. Rural settlements, on the other hand, may experience different forms of vulnerability, often related to geographic isolation, limited access to emergency services and infrastructure, lower institutional capacity, and demographic challenges such as aging populations, which can significantly hinder preparedness and recovery. This complex interplay explains also why often non-extreme hazards can lead to severe consequences, while extreme events in other contexts may not result in disasters (Lavell et al., 2012).

In this complex context, archetypes can be powerful tools for simplifying and interpreting systemic risks. They provide structured representations of recurrent patterns across diverse cases, helping policymakers understand key drivers of vulnerability and exposure and supporting more effective risk communication and decision-making *(Oberlack et al., 2023; Piemontese et al., 2022; Wicki et al., 2024). Archetypes have been extensively employed to classify cities based on socio-economic and socio-demographic parameters, to support policy decisions on fiscal interventions (Bruce, 1971; Dalton, 2015; Harris, 1943). An increasing amount of climate studies are dedicated to identifying recurring patterns and archetypes, in order to understand local climate vulnerabilities and to formulate specific adaptation strategies (Rocha et al., 2020; Vidal Merino et al., 2019; Wicki et al., 2024). For instance, in Riach et al. (2023) recurring climate risk patterns at the municipal level in Baden-Wuerttemberg, Germany, are identified by analysing indicators for climatic hazards (e.g., annual mean temperature, hot/ice days, heavy precipitation) and exposure/vulnerability (e.g., proportion of elderly, energy production, population density). The nine urban archetypes derived represent municipalities with varying climate risk characteristics that require tailored adaptation measures. Although several examples of city-scale archetypes analysis are available, they often focus on the analysis of single-hazard risk (e.g.,* Awah et al., 2024; Carroll & Paveglio, 2016; Joshi et al., 2022; Riach et al., 2023) ***and may be not applicable in a multi-risk context.***

This study addresses the following research question: can urban and rural settlements be clustered into meaningful archetypes based on shared characteristics of vulnerability and exposure, to improve multi-risk assessment and support more targeted resilience planning at regional and national scale? Indeed, *despite the high specificity of exposure and vulnerability of each urban and rural environment, we assume that a relatively low number of representative archetypes could be found to decrease the level of complexity at regional and national scale, ensure a baseline for comparison and highlight potential hotspots in multi-hazard and multi-risk assessment frameworks.*

The term "archetype" can be interpreted in different ways. In statistics, archetypes refer to extremal profiles used to describe all data points as convex combinations of a few "pure" types (Cutler & Breiman, 1994)***. In contrast, in sustainability science and climate risk research, archetypes are understood as representative specimens or clusters of similar entities that are "crucial for describing the system dynamics or causal effect of interest" and that exhibit recurring patterns of risk-relevant characteristics"*** *(Oberlack et al., 2019)****. We adopt this latter interpretation. In our work, urban and rural settlement archetypes are defined as representative instances (real or ideal) of a group of municipalities sharing similar vulnerability and exposure characteristics.***

*Following the approach suggested in Piemontese et al. (2022), we perform the archetype analysis in Italy according to three phases of Design, Analysis and Application. In the Design phase, the problem framing and attributes selection is performed. In particular, this study seeks to address the challenge of assessing urban/rural exposure and vulnerability by proposing a national-scale clustering of Italian settlements using open-source data. Municipality is selected as the primary geographical boundary for settlements since available authoritative open-source data is often referring to such administrative units. Municipalities are small, well-defined units, making them ideal for detailed spatial analysis and accurate identification of human settlements. These boundaries often reflect historical settlements, preserving the cultural context that is essential for understanding contemporary urban dynamics. Additionally, municipalities are responsible for local governance and urban planning, making them relevant units for studying urban/rural settlements, as local policies directly affect development and quality of life (actionability also for risk mitigation and climate change adaptation). The goal of this study is to group settings (municipalities) to define risk-oriented urban and rural settlements archetype. To this end, we select a set of geographic, demographic, and socio-economic attributes available from open-source data, known to be relevant to vulnerability/resilience (**see section 2**). Thanks to a proper selection of a range of geographic, demographic, and socio-economic parameters, the study provides a robust assessment of the vulnerability of Italian urban and rural settlements, identifying archetypes with varying levels of susceptibility to natural hazards. Moreover, the use of open-source data ensures the approach is both replicable and scalable, making it generalizable and applicable to other regions. For the Analysis phase, **described in section 3**, methods of analysis should be defined, towards generalizability of results. **Archetypes are derived through a two-step clustering process: first, broad urban and rural archetypes are defined using only demographic and geographic data, then they are refined using socio-economic attributes. This initial classification reduces complexity and establishes a baseline for comparison, providing a clear, interpretable framework to capture essential structural differences among urban/rural settlements (e.g., size, density, location). Refining these archetypes with socio-economic parameters allows for a more articulated understanding of vulnerability differences within similar structural contexts, supporting more targeted risk assessment and policy intervention. This two-step approach balances clarity with detail, enhancing both usability and precision.** The proposed methodology utilizes two widely-used clustering techniques—agglomerative hierarchical clustering and partitioning clustering—to analyse vulnerability-related data. Using two clustering techniques allows for cross-validation of results and helps capture different patterns in the data, enhancing the robustness and reliability of the identified archetypes. **Results of the cluster analysis are presented in sections 4 and 5**. Finally, the Application phase entails a real-world check of the archetypes identified towards their empirical validity, meaning they should correspond to variable levels of susceptibility to risk (according to the problem framing), and assessment of the impact, intended as the usefulness of results for application by final knowledge users. **To this aim, a simplified Impact Susceptibility Index is proposed, highlighting the likelihood of experiencing negative consequences based on the combined levels of vulnerability and exposure associated with each identified archetype. Additionally, Section 7 provides a comprehensive discussion on how each dimension of archetype analysis validity - as outlined by Piemontese et al. (2022) - is addressed, emphasizing both the strengths and limitations of the study.***

***By developing a national-scale clustering of Italian municipalities, 10 broad and 18 nested archetypes are identified in this study**. The identified archetypes offer a simplified framework for managing the complexity of diverse areas and their exposure to hazards. This risk-oriented classification offers valuable insights for resilience and disaster management professionals, enabling policymakers and urban planners to design targeted risk-reduction strategies tailored to the specific vulnerability profiles of each archetype, resulting in more efficient resource allocation.”*

(d) Materials and Methods: I appreciate the thorough justification and explanation of the datasets. However, this section could be more concise. For instance, Tables 1 and 2 might be combined. Additionally, it would be helpful to clarify why you differentiate between main and sub-clusters, as this reflects your understanding of archetypes. The methods section is quite extensive and could be streamlined. I also recommend making it clearer why you use different clustering approaches and what distinguishes their outcomes. Since testing these differences appears to be a key finding, it should be addressed not only here but also in the introduction, results, and discussion sections.

Response: Thanks for this comment. The following key points raised have been addressed: (i) reorganization of paper's tables; (ii) a clearer justification for the distinction between main and sub-clusters; (iii) an explanation regarding the use of different clustering approaches.

(i) Table 2 and Table 3 have been removed. The indicators selected for urban settlement clustering have been described throughout the text and reported in a new summary Table - provided in Section 4.1. (now, Section 3.1; see response to comment *e*). Specifically, the attributes adopted in the study have been directly linked to the indicators and the vulnerability dimensions presented in Table:

"Table 1 presents a list of key indicators commonly used in literature to assess each dimension of vulnerability mentioned.

In our work we focused on a selection of indicators, expectedly linked with different vulnerability dimensions, and namely: altimetric zone, centeredness degree, urban degree, residential population and social vulnerability indicators. The altimetric zone of a settlement, which refers to their elevation and topographical features, can be considered a proxy of access to the main services – or equally distance to service centres ***(institutional vulnerability, see Table 1)****. Accessibility of services of general interest can be particularly challenging in certain contexts (e.g. mountain regions, islands) due to their geomorphological and settlement structure conditions (Bertram et al., 2023). These accessibility issues can also complicate evacuation efforts and the delivery of emergency services during a disaster. Likewise, urban centeredness degree, which reflects the spatial characteristics and distribution of urban areas, is associated with the availability of public services and the level of spatial connectedness, as it measures the distance and travel time to major service centres* ***(institutional vulnerability, see Table 1)****. The degree of urban centeredness significantly influences the response and resilience of urban systems by affecting resource availability, infrastructure robustness, community networks, and emergency preparedness* (Giuliano & Narayan, 2003; Schwanen et al., 2004). *Ensuring effective access to essential public services, such as healthcare and education, is challenging even under normal circumstances. However, it becomes even more crucial during crises like natural disasters, when the demands on these services and their operating conditions become significantly more complex (Fan et al., 2022; Loreti et al., 2022; Tariverdi et al., 2023). The level of peripherality of the areas with respect to the network of urban centres influence may determine not only difficulties of access to basic services but also lower quality of life of citizens and their level of social inclusion (Oppido et al., 2023).*

Residential population and urban degree are linked to exposure and physical vulnerability dimensions, and specifically to population density ***(physical vulnerability, see Table 1)****. While acknowledging that population density cannot capture the full range of structural vulnerability factors of built environment, it reflects both the intensity of exposure and the systemic vulnerabilities inherent to high-density urban environments (e.g., emergency response complexity and evacuation challenges, increased likelihood of cascading infrastructure failures during hazard events, overburdened urban services that exacerbate systems' physical fragility - healthcare, water systems, mobility - under stress), consistent with its interpretation in urban risk literature (e.g., Balk et al., 2018; Marzi et al., 2019; Opach et al., 2020; Zhao et al., 2017).Residential population significantly influences the exposure to natural hazards, determined not only by the higher presence of people and housing, but also of infrastructure, production capacities, species or ecosystems, and other tangible human assets in places and settings that could be adversely affected by one or multiple hazards. Higher population not only increases the potential for human and property losses, but also complicate evacuation efforts, and strain emergency response resources (Zhao et al., 2017). The degree of urbanization is often used to classify areas into cities, urban areas, and rural areas based on criteria such as population density, concentration of human activities, and built environment (Balk et al., 2018; United Nations, 2018). Indeed, highly urbanized densely populated areas are more likely to experience greater damage, congestion, and strain on resources during emergencies. It affects the capacity for evacuation and accessibility to essential services, due to dense infrastructure, complex urban layouts and the potential for cascading failures in infrastructure* (Kendra et al., 2008; Lall & Deichmann, 2012).

Finally, social vulnerability indicators include those parameters that influence both ***social and economic vulnerability****. Past events highlight that elderly may be more vulnerable due to reduced mobility, poor health, and communication challenges* (ARDALAN et al., 2010; Carnelli & Frigerio, 2017; Cutter et al., 2003a), *while* *education levels can heighten vulnerability to natural hazards influencing risk perception and awareness, knowledge, and skills related to disaster preparedness (Alexander, 2012a; Wachinger et al., 2013). Still, minority groups, including migrants, and ethnic communities, often face heightened social vulnerability, especially in high-risk areas, due to language barriers and communication challenges that can hinder access to critical emergency information* (Carnelli & Frigerio, 2017; Walter Gillis et al., 2012). ***The complete list of socio-economic indicators considered includes age, dependency ratio, level of education, family structures, commuting rate, quality of buildings, race/ethnicity, employment rate, percentage of women in the alterworkforce (Table 2)***.

It is worth mentioning that we only consider indicators for which publicly available and authoritative data exist at the municipal level. For example, since GDP per capita is only available at national, regional, or provincial scales, it is not included in this study. Similarly, many building characteristics affecting physical vulnerability are either difficult to detect or unavailable at the municipal scale (e.g., structural system and earthquake-resistant design level; Tocchi et al., 2022). Moreover, building vulnerability indicators often vary depending on the type of hazard (Kappes et al., 2012), making it challenging to collect all relevant information for multiple hazards across Italy. For these reasons, only population density and general building quality are considered in this study. Indicators suggested for the environmental vulnerability dimension are not included due to data limitations as well. For instance, municipal-level air pollution data in Italy is limited, as such data is only available for major cities with monitoring stations.

Data on urban degree, urban centeredness degree, altimetric zone, social vulnerability factors used herein are primarily sourced from ISTAT (Italian National Institute of Statistics). All data are collected at the municipal level, aligning with the administrative boundaries adopted for the analysis. The dataset includes 7960 objects, representing the 7960 Italian municipalities, and 19 attributes (both numerical and categorical) related to the vulnerability factors outlined in sections 3.1 through 3.5."

The Table listing all variable considered for the clustering is reported at the end of Section 4.1. "Data pre-processing" (now, Section 3.1; see response to comment *e*). It is reported below:

Table 2 – Variable used in cluster analysis.

Variable	Type	Vulnerability dimension
Urban degree	Categorical	Physical
Urban centeredness degree	Categorical	Institutional
Population class	Categorical	Physical
Altimetric zone	Categorical	Institutional
Aging index	Numerical	Social
Low educational index	Numerical	Social
Unemployed	Numerical	Economic
Commuting rate	Numerical	Social
Female employed	Numerical	Economic
Quality of buildings	Numerical	Social
Crowding index	Numerical	Social
Foreign resident	Numerical	Social

(ii) The use of a two-step clustering approach—differentiating between main and sub-clusters—is motivated by the need to balance simplicity with depth. The initial "broad" classification reduces complexity and provides a baseline for comparison, offering a clear and interpretable framework to capture key structural differences among urban and rural settlements (e.g., population size, density, location). This step helps organize the diversity of settlements into coherent categories based on fundamental geographic and demographic characteristics. In the second step, refining these broad archetypes using socio-economic variables allows for a deeper analysis of vulnerability within structurally similar contexts. This nested approach enhances the understanding of intra-group variability and supports more targeted risk assessments and tailored policy interventions. This rationale has also been added to the revised version of the introduction for greater clarity (see response to comment *c*).

(iii) The use of different clustering techniques was already justified in the introduction: "*Using two clustering techniques allows for cross-validation of results and helps capture different patterns in the data, enhancing the robustness and reliability of the identified archetypes*" and in the discussion section: "*Internal Validity is maintained through the rigorous application of hierarchical and partitioning clustering methods. We employed WCD and ICD to select the most suitable clustering approach, ensuring the reliability and robustness of the clustering process*" while specific sub-section is dedicated to the comparison of the outcomes of the two clustering algorithms, i.e., section 4.4.3 (now section 4.2., see response to comment *e*). An additional description of benefit deriving from the adoption of two different clustering techniques has been added in the methodological section (section 3 "*Cluster analysis*"):

"The adoption of two different clustering techniques serves to enhance the robustness, reliability, and interpretability of the archetypes identified in this study. Each method has distinct strengths and analytical advantages, which, when combined, allow for a more comprehensive exploration of patterns in the data. For instance, hierarchical clustering is particularly useful for exploring data structures without the need to predefine the number of clusters. It produces a dendrogram that visually represents nested groupings and their relationships, offering insights into how clusters evolve as dissimilarity thresholds change. This is especially valuable for understanding the hierarchical nature of urban/rural systems and guiding the selection of an appropriate number of clusters. On the other hand, partitioning clustering requires the number of clusters to be predefined, but it typically performs better with larger datasets, producing compact, well-separated clusters when appropriately parameterized. It is computationally efficient and more suitable for refining clusters, especially when working with both categorical and numerical data types. Using both techniques enables cross-validation of clustering outputs, ensuring consistency and increasing confidence in the identified archetypes. Discrepancies between methods can highlight ambiguous or transitional settlement types, while convergences confirm stable, well-defined clusters."

(e) Results: The distinction between the materials, methods, and results sections could be clearer. Since you refer to Italian regions, I suggest adding their borders to the results map to aid readability. Additionally, consider adjusting the colors in Figure 9, as some archetypes are difficult to differentiate.

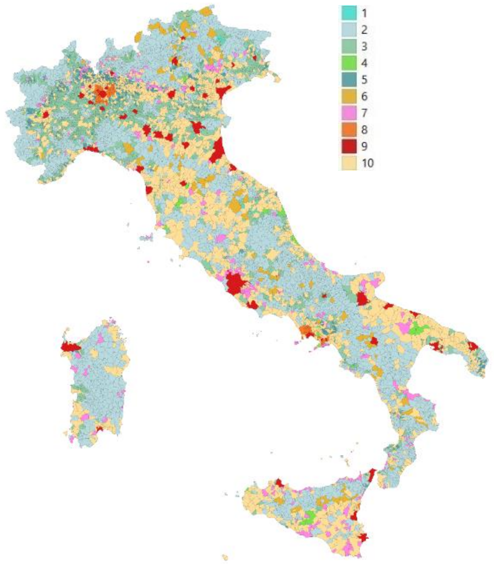
Response: Thanks for this comment. The following key points raised have been addressed: (i) the reorganization of the materials, methods, and results sections; (ii) the modifications of colors in Figure 9.

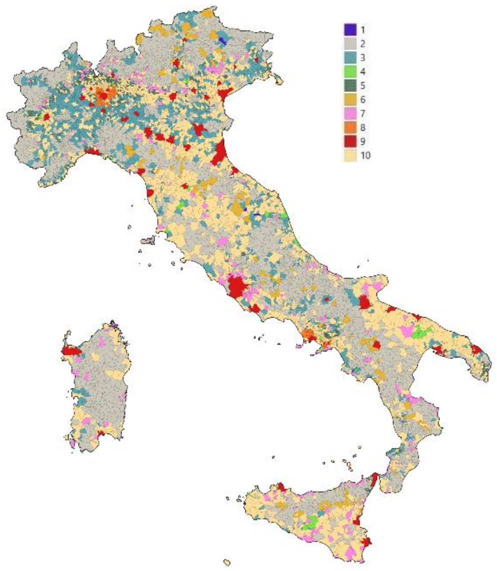
(i) The Methods and Results sections have been clearly distinguished in the revised manuscript. Specifically, the former subsection titled "*Clustering based on demographic and geographic features*" has been updated as section and renamed to "*First-level analysis: clustering based on physical and institutional vulnerability parameters*", while the subsection "*Nested clustering" has been updated as section named "Second-level analysis: nested clustering based on socio-economic parameters*". As a result, the revised paper now includes three distinct sections:

- Section 3: "*Cluster analysis*" – dedicated to the description of the methodology
- Section 4: "*First-level analysis: clustering based on physical and institutional vulnerability parameters*" – presenting the results of the first step of the archetype analysis
- Section 5: "*Second-level analysis: nested clustering based on socio-economic parameters*" – presenting the results of the second step.

The final definition and discussion of the urban and rural settlement archetypes for Italy are provided in Section 6: "*Urban and rural settlement archetypes in Italy*".

(ii) Colors of figure 9 have been slightly modified, to better differentiate the broad archetypes. The old and the updated figures are reported below. Moreover, on the right part of Figure 9, a map showing the border and names of the Italian regions is reported





(f) Discussion: The discussion could be expanded, as it is currently quite brief. It should engage more with existing literature and clarify how your choice of data and methods influenced the results. Since you refer to dimensions of validity, I recommend elaborating on this aspect by discussing how these dimensions are addressed in relation to the literature. Currently, the claim that your archetypes meet validity requirements lacks sufficient support.

Response: The discussion section has been expanded. Specifically, discussion about how validity dimensions are addressed in literature has been added. The new version of this section is reported below (with modified or added text highlighted in bold):

"The proposed study of human settlements archetypes leverages the framework and guidelines set forth by Piemontese et al. (2022) to ensure a robust and reliable archetype analysis, focusing on six dimensions of validity: conceptual validity, construct validity, internal validity, empirical validity, external validity, and application validity. The proposed archetypes conform to each of these dimensions as follows.

Conceptual Validity is achieved by ensuring the research problem and questions are scientifically sound and relevant to real-world issues. In this study we addressed the need to categorize urban and rural areas based on geographic, demographic, and socio-economic factors to understand urban/rural vulnerabilities better. By focusing on these pertinent aspects, this study aligns with the conceptual framework and reflects real-world challenges faced by urban and rural settlements in Italy.

Construct Validity involves the careful selection of attributes that define the archetypes, ensuring their connection to the conceptual framework. We meticulously selected attributes **relevant to vulnerability of urban/rural systems and their potential exposure to different hazards**. These attributes are justified based on existing literature, **ensuring indicators are theoretically and empirically linked to several vulnerability dimensions, thereby reinforcing the construct validity** (Diogo et al., 2023; Nagel et al., 2024)**.**

Internal Validity is maintained through the rigorous application of hierarchical and partitioning clustering methods. **In previous studies, such as Bilalova et al.** (2025)**, internal validity has been addressed through a transparent and replicable methodology, incorporating widely used validity metrics which measures how similar an object is to its own cluster compared to other clusters like silhouette scores, and evaluating both within-cluster and between-cluster cohesion. Similarly, Nagel et al. (2024) assessed internal validity by testing cluster robustness using R packages NbClust and clValid. The NbClust package supports the determination of the optimal number of clusters by computing and comparing multiple internal validity indices (e.g., silhouette score, Dunn index), while the clValid package enables the evaluation of clustering stability and comparative performance across different algorithms (e.g., k-means, hierarchical clustering). Building on these approaches, internal validity in this study is ensured through: (i) the determination of the optimal number of clusters using established internal validity indices—specifically, the inconsistency coefficient and the WCD; (ii) the assessment of cluster robustness, by repeating the partitioning clustering procedure multiple times with randomized initial centroids and selecting the best-performing result based on WCD, thus reducing sensitivity to initialization; (iii) the comparison of clustering algorithms, by applying both hierarchical and partitioning methods and evaluating their performance using WCD and ICD to identify the most internally coherent solution. This combination of techniques ensures methodological rigor, reproducibility, and robustness in the clustering process, thereby addressing the internal validity dimension as recommended in the literature (Piemontese et al., 2022).**

Empirical validity in archetype analysis is commonly supported through various means, including stakeholder surveys (Nagel et al., 2024), the integration of diverse data sources at different spatial resolutions, and cross-comparisons of archetyping approaches at multiple scales (Diogo et al., 2023). It may also be demonstrated through consistency with prior empirical observations or theoretical expectations (Bilalova et al., 2025). However, validating archetypes' vulnerability profiles against observed impacts or risk outcomes remains challenging. For example, many historical impact datasets—such as those from EM-DAT—are available only at national or regional levels and include only events meeting specific severity criteria. As a result, they often exclude smaller-scale, yet locally significant, events, introducing both a selection bias and a scale mismatch that limit their utility for validating local-level archetypes. Furthermore, expected impact outputs from risk assessments are typically model-driven, emphasizing hazard intensity and physical exposure, while often overlooking the broader dimensions of vulnerability (Cardona et al., 2012)**. These limitations highlight the need for improved access to fine-grained, georeferenced impact data and the potential value of complementing quantitative validation with qualitative or stakeholder-informed insights at the local level. Empirical validity in our research is partially supported by** stakeholder engagement-based risk storylines, as outlined e.g., in Marciano et al.(2024). Marciano et al. (2024) present an exploratory case study using a participatory approach to develop multi-risk storylines, illustrating the cascading effects of a heatwave followed by intense rainfall in two Italian urban contexts: a peri-urban area and a metropolitan area. Findings reveal that peri-urban settlements face limited emergency resources and higher infrastructure failure risks, while metropolitan hubs have stronger emergency systems but face coordination challenges in managing large-scale events. The study highlights the varying levels of vulnerability across different archetypes. While these elements contribute to the empirical grounding of the archetypes, **we acknowledge that empirical validation remains a limitation of this study**. Further studies should explore the impacts of natural disasters on different archetypes, revealing key differences in vulnerability and response capabilities across the considered urban contexts.

External Validity assesses the generalizability of archetypes beyond the studied cases. It is typically addressed by applying archetypes across multiple regions and evaluating the consistency of resulting patterns across different scales (e.g., Diogo et al., 2023; Nagel et al., 2024) or linking archetypes to theoretical expectations or global typologies (e.g., Bilalova et al., 2025). While this study acknowledges the challenge of fully satisfying this dimension, given that the identified archetypes are specific to the Italian

context and broader applicability requires further investigation, it also provides a foundation for generalization. The identification of archetypes across diverse Italian regions, combined with the careful selection of relevant variables and the use of a replicable methodology, may serve as a valuable reference for archetype-based analyses in other national or regional settings, particularly within Europe. Notably, many of the variables adopted in this study, such as urban degree, population class, and census-based demographic and socio-economic indicators, are also available at comparable spatial resolutions through Eurostat, EUROPOP, or pan-European datasets such as Urban Atlas, CORINE Land Cover, and GHSL (Global Human Settlement Layer). Similarly, the urban centeredness degree, while constructed using national criteria in Italy, relates closely to the concept of accessibility and service availability, which can be captured using EU-wide datasets on transport networks, healthcare access, and educational infrastructure. Therefore, the consistent use of open-source and harmonized data sources enhances the potential for applying the methodology beyond the Italian context, fostering comparative analyses and supporting the construction of cross-country urban and rural archetypes within Europe.

Application Validity evaluates the practical usefulness of the archetypes. ***This dimension can be addressed emphasizing practical applications of archetypes in policy, planning, and governance, for instance, by presenting results to government officials and researchers, guiding inform local policy discussions, with archetypes guiding differentiated policy interventions (Nagel et al., 2024). Section 6.1 illustrates the potential of urban/rural archetypes to enhance risk communication through the assignment of a simplified impact susceptibility index to each identified archetype. Additionally, the exploratory case study presented in Marciano et al. (2024) highlights how these archetypes can support stakeholder engagement by informing the development of multi-risk storylines.*** *By categorizing human settlements into distinct archetypes, it becomes possible to assess how different hazard scenarios may unfold in each context, considering their specific vulnerabilities, exposure levels, and adaptive capacities. This structured approach enables policymakers to design tailored interventions and resilience strategies based on specific vulnerability profiles. However, to further strengthen resilience planning and develop targeted mitigation measures, it is crucial to consider not only exposure and vulnerability but also hazard data for each archetype—particularly the level of exposure of a settlement to various natural hazards. Although in this study we did not yet integrate hazard information, there is a clear need for future research to incorporate this aspect and conduct GIS-based analyses for a more comprehensive assessment of risk (e.g., Tocchi et al., 2024).”*

Moreover, application validity has been further improved and presented in a new section of the paper (6.1), reported below.

“6.1 Archetypes' vulnerability profiles

Composite indices are widely used to measure multidimensional concepts, as they enable the integration of various sub-indicators representing different dimensions that lack a common unit of measurement (Nardo et al., 2008). Social vulnerability and community resilience are often quantified through composite indices (e.g., Cutter et al., 2003;Bruneau et al., 2003; Frigerio et al., 2018; Marin Ferrer et al., 2017). In Sibilia et al. (2024) for instance, a multidimensional composite index is proposed to assess vulnerability across Europe. The vulnerability index proposed, developed within the Risk Data Hub, evaluates vulnerability at three geographic levels—national, regional, and provincial—from 2005 to 2030. It encompasses five key dimensions of vulnerability: physical, social, economic, political and environmental.

To investigate the level of exposure and vulnerability associated with each identified archetype, this study adopts a composite index-based framework. We define an Impact Susceptibility Index (ISI) which describes the potential for experiencing adverse consequences given existing vulnerabilities and exposure levels, without implying the occurrence of a specific hazard. The construction of the composite indicator involves four main stages: selection of sub-indicators, normalization, choice of aggregation method, and assignment of weights to the sub-indicators. The indicators used are those applied in the cluster analysis and described in Sections 2.1 to 2.5. Normalization—required to make the variables comparable and suitable for aggregation—is carried out by assigning categorical scores to each indicator, following approaches used in previous studies (e.g.,Greiving et al., 2006). Scores range from 1 to 3, where 1 indicates low exposure or vulnerability and 3 indicates high exposure or vulnerability, hence contributing more to the susceptibility to impact for the given variable. For example, peripheral areas are considered the most vulnerable due to their greater distance from essential services and are therefore assigned a *score of 3. Peri-urban areas receive a score of 2, and urban hubs are assigned a score of 1. Similarly, since high population density is linked to greater physical vulnerability, cities are scored as 3, towns and suburbs as 2, and rural areas as 1. The highest population class (municipalities with over 250000 inhabitants) is also assigned the highest exposure and vulnerability score, while the lowest class (less than 5000 inhabitants) receives the lowest score. In terms of social vulnerability, three categories—high, medium, and low—are defined based on the Social Vulnerability Index range (0.84–2.01, see Table 4), and scores are assigned accordingly. The final ISI for each municipality is obtained by summing the individual scores for each vulnerability dimension (e.g., Greiving et al., 2006), and therefore ranges between 4 to 10. Figure 10 displays the resulting ISI at the municipal level and the average ISI for each archetype.*

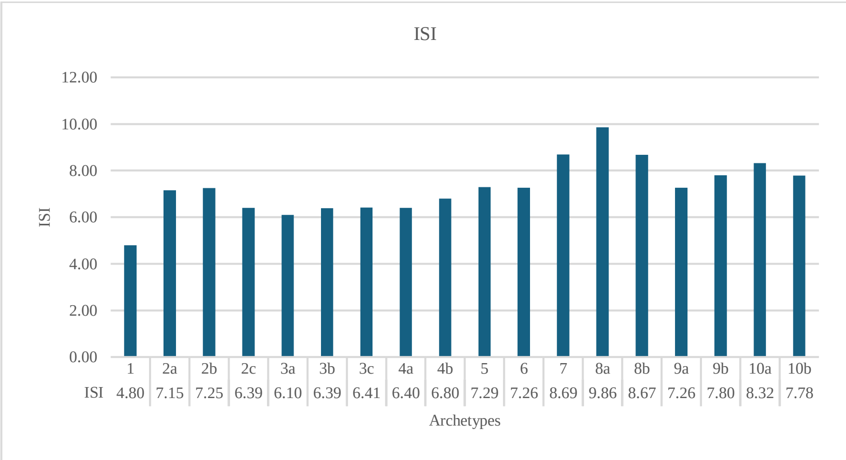


Figure 10 – Average ISI value for each archetype.

The highest average ISI is observed for Archetype 8a (mean ISI = 9.86), which includes densely populated peri-urban municipalities characterized by very high social vulnerability. Other archetypes with notably high average ISI values include Archetype 7 (mean ISI = 8.69), characterized by their relative remoteness (100% peripheral municipalities), medium-high population density (100% classified as towns and suburbs) and high social vulnerability; Archetype 8b (mean ISI = 8.67), marked by high population density (cities), peri-urban location and medium social vulnerability; and Archetype 10a (mean ISI = 8.32), largely driven by poor accessibility to services (only 12% of municipalities are classified as hubs), medium-high population and high social vulnerability.

Figure 11 highlights that many municipalities with high ISI values are concentrated in the regions of Apulia, Sicily and Lombardy, with average regional ISI values of 7.8, 7.7, 7.6, respectively. In details, 37% of Apulia's municipalities fall under Archetype 10a; 25% of Sicily's municipalities are categorized as Archetypes 10a while 14% belong to Archetype 7. In Lombardy, 22% of municipalities belong to Archetype 10b, 19% to Archetype 5 and 14% to Archetype 2a. These archetypes all show medium-high average ISI values: 7.78, 7.29, and 7.15, respectively. Overall, the ISI tends to be higher in southern regions of Italy, with an average value of 7.3, compared to 6.9 for central and northern regions. The lowest average VI values are observed in the Valle d'Aosta (ISI = 6.4) and Piedmont (ISI = 6.7) regions.

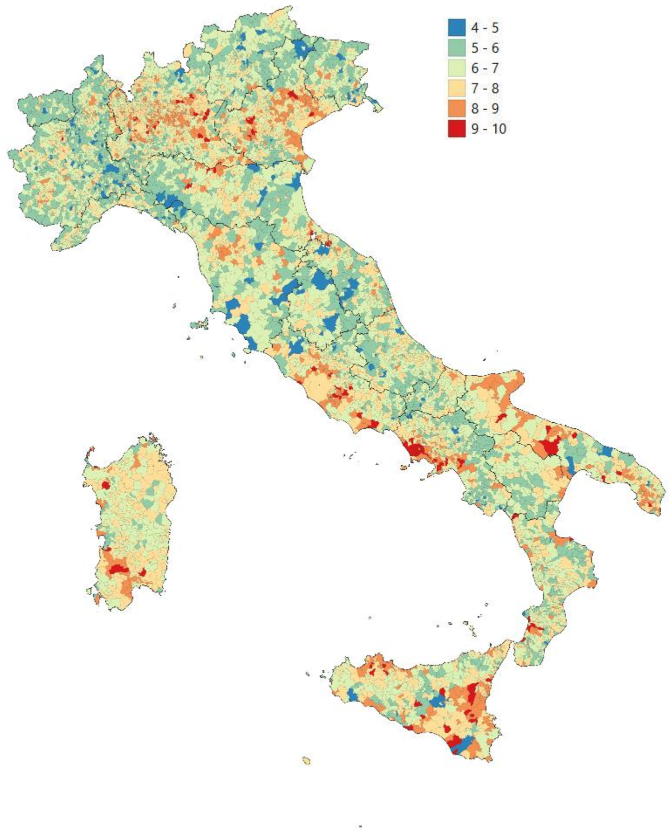


Figure 11 - Map of ISI value at municipal level."

g) Conclusion: Ensure that the conclusion aligns with the preceding sections. Either here or in the discussion, clarify what is needed to refine the archetypes and how they enhance the understanding of exposure and vulnerability.

Response: Thanks for this comment. The revised version of the conclusion, which incorporates the suggested modifications and clearly outlines the strengths and limitations of the proposed study, is provided below:

"This study presents a set of archetypes for urban and rural settlements in Italy, based on geographic, demographic and socio-economic factors that cover different vulnerability dimensions. Using a two-step cluster analysis, ten broad archetypes were first defined according to structural features (e.g., location, size, density), further refined into 18 nested archetypes to account for socio-economic diversity.

The proposed archetypes were developed by applying the six dimensions of validity outlined by Piemontese et al. (2022), offering a robust and replicable methodology for vulnerability-oriented archetype analysis. While several of these validity dimensions was successfully addressed (conceptual, construction, internal and application validity), empirical and external validity was only partially addressed. Conceptual, construct, and internal validity are robustly established through scientifically sound research questions, careful attribute selection, and rigorous clustering methods. Empirical validity of proposed archetypes may be hardly satisfied, as discussed, due to the lack of fully integrated social and institutional vulnerability data. External validity remains an open challenge: while the archetypes are context-specific to Italy, the use of open and harmonized data sources (e.g., Urban Atlas, CORINE Land Cover, Eurostat demographic indicators, GHSL datasets) enhances the potential for replicating the methodology in other European contexts, fostering future comparative studies. Application validity was demonstrated by linking each archetype to an Impact Susceptibility Index, providing a tool for prioritizing areas for risk reduction strategies. The archetypes also offer structured support for developing multi-risk storylines and informing resilience planning efforts.

Despite some limitations, this study provides a valuable framework for simplifying complex urban and rural vulnerability patterns. It lays a strong foundation for both scientific advancements and practical applications in the *field of multi-risk assessment, resilience planning, and targeted policy design. Defining urban and rural archetypes based on vulnerability factors may help identify areas with higher susceptibility to natural hazards and socio-economic challenges, supporting better resource allocation for disaster preparedness and response. It also highlights critical areas for future research. In particular, integrating hazard-specific exposure data and further empirical validation through observed impact data are needed to fully realize the potential of archetype-based approaches in disaster risk management and climate change adaptation."*

Minor issues:

Figures 4 and 6: Both figures currently have the same caption. To avoid confusion, clarify that they represent different methods and specify the distinctions in their captions.

Response: Thanks for this feedback. To avoid confusion, the caption of the figures has been modified as follows:

(i) **Figure 1 - Representativeness of clusters resulting from hierarchical clustering in terms of urban degree (a), urban centeredness degree (b), population class (c) and altimetric zone (d).**

(ii) **Figure 6 - Representativeness of clusters resulting from partitioning clustering in terms of urban degree (a), urban centeredness degree (b), population class (c) and altimetric zone (d).**

Introduction and Abstract: You mention single and multiple hazards but do not elaborate on them in the main sections. Since your focus is primarily on exposure and vulnerability, consider toning down these references for consistency.

Response: Introduction and abstract have been modified accordingly. See also response to comments (b) and (c).

Tables and Formatting: The placement of tables is inconsistent, with some splitting across pages in a way that affects readability. The editorial team should ensure that, where possible, tables fit within a single page to improve clarity.

Response: Position of tables (specifically, table 1) has been modified in order to avoid splitting of the table across pages.

Line 526: Is the reference to cluster 6 correct here? The number does not align with Figure 5. Please verify and ensure consistency between the text and the figure.

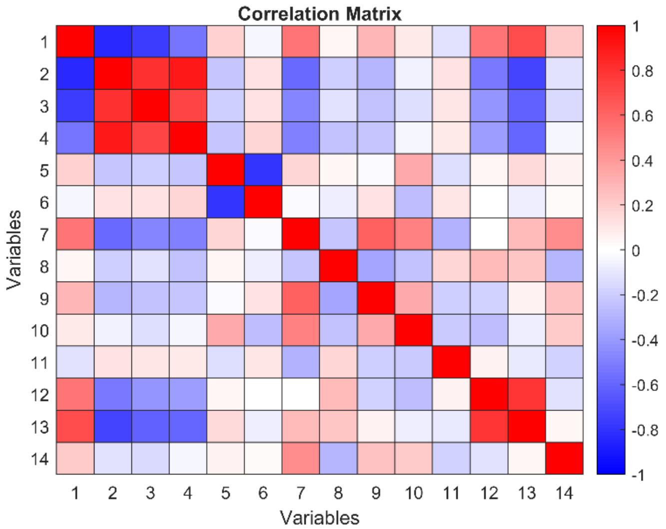
Response: Thanks for this comment. It was a typo. In Line 526 the correct reference is to cluster 2. It has been corrected in the new version of the paper.

Line 287: write remaining instead of remain

Response: The term "remain" has been replaced by "remaining".

Figure 3: The colors used in this figure may be difficult to interpret for readers with color blindness. Consider using a blue-white-red color scheme to improve accessibility.

Response: Colors of the figure have been modified. Please find below Figure 3 revised with new color scheme.



1. Proportion of under 14 aged
2. Proportion of over 65 aged
3. Aging index
4. Dependency ratio
5. High educational index
6. Low educational index
7. Proportion of employed
8. Proportion of unemployed
9. Proportion of commuters
10. Proportion of female employed
11. Proportion of buildings in poor condition
12. Proportion of families with 5 or more components
13. Crowding index
14. Proportion of foreign resident

Figures: Please ensure consistency in your referencing throughout instead of alternating between, for example, "Fig" and "Figure."

Response: The term “Fig.” has been replaced by “Figure” throughout the paper.

Reviewer 2

This manuscript uses clustering algorithms to define settlement archetypes for the Italian territory based on variables known to be relevant metrics for risk/resilience from previous studies. The outcome is a set of 10 first-level archetypes, some of which are sub-divided and lead to a total of 18 categories, as well as a classification of Italian municipalities into each of these categories. As the authors well state, the definition of such archetypes has the potential to be relevant for supporting decision-making processes associated with vulnerability and risk reduction.

However, the manuscript appears as incomplete work in this regard. Clustering algorithms are numerical methods that group individuals (in this case, municipalities) as per their similarity with respect to the variables considered. The algorithms know nothing about the meaning of these variables. The manuscript is lacking: (1) a more in-depth interpretation of what it means or what consequences may stem from the fact that municipalities with some differences in certain attributes end up grouped together, as well as (2) a demonstration of some sort that these 18 archetypes are indeed associated with relevant risk metrics. In other words, do these groups actually make sense when confronted against risk analyses (single or multi-hazard)? Is the "vulnerability profile" (as the authors phrase it) meaningful? The fact that the variables selected as input for the clustering are known to be relevant from previous studies does not guarantee that the grouping is relevant and consequential in the risk domain, or suited for designing risk reduction actions.

I believe this manuscript should address this major shortcoming as well as the following main comments before it is considered for publication.

Main comments

1. Title: The archetypes defined are not just urban. Please erase "urban" from the title and throughout the body of the manuscript.

Response: Thanks for this comment. The term "*urban*" has been replaced with "*urban and rural*", as also rural archetypes are included in this study. It has been reviewed throughout the manuscript.

2. As stated above, the major shortcoming of this manuscript is the lack of in-depth interpretation of the results and confrontation against risk data or models that demonstrate its relevance and meaning for the purpose that the authors state this work has. Here are some thoughts that aim at helping with developing the work further:

    a. The clustering was carried out using a series of parameters known to be relevant to vulnerability/resilience. The outcome is groups of data points that are "similar" to each other with respect to those same parameters. Without a comparison against actual risk metrics, it is not proven that these archetypes mean anything to risk. Moreover, there is no conclusion with respect to how exactly decision makers should use them. Which archetypes should be prioritised for in-depth risk assessments, for example?

    Response: Thanks for this important comment. To ensure consistency, the empirical validation of archetypes ideally requires comparison with actual risk metrics that incorporate all relevant dimensions of vulnerability used in the archetype analysis—such as social and institutional vulnerability. However, such comparisons are often hindered by practical limitations. For instance, observed disaster impact data at fine spatial resolutions (e.g., municipal level) are frequently incomplete, inconsistent, or unavailable, especially in contexts where disaster reporting is not standardized or centralized. Additionally, many historical datasets, like EM-DAT, typically provide information only at national or regional scales, limiting their utility for local-level validation. Furthermore, existing risk assessments often rely on models focused primarily on physical exposure and hazard intensity, while overlooking critical vulnerability dimensions such as social or institutional factors. These aspects—like population aging, poverty, and limited access to services—can significantly influence disaster outcomes by delaying emergency response, worsening health impacts, and hampering recovery efforts (Cardona et al., 2012; Cutter et al., 2003b; Marin Ferrer, 2017). Some studies adopted composite risk indices that integrate multiple dimensions of risk and vulnerability to validate urban archetypes (e.g., Riach et al., 2023). Despite several examples of composite risk index are available in literature, many of these are primarily designed for national or regional-level assessments and are less suitable for high-resolution, multi-hazard risk evaluation (e.g., Greiving et al., 2006; Marin Ferrer, 2017). Other approaches, such as the U.S. national risk index by Zuzak et al.(2022), despite offering integrated multi-hazard assessments using high-resolution data, could be hardly applied in countries like Italy due to the unavailability of similarly detailed and harmonized data, especially for resilience metrics. Also, the study proposed by Tocchi et al. (2025) - which introduces a multi-hazard risk index specifically developed for the Italian context, integrating multiple hazards with physical and social vulnerability dimensions, as well as exposure – is not suitable for assessing empirical validity, since it partly overlaps in the choice of exposure and vulnerability indicators and also includes hazard descriptors.

Given the challenges associated with validating this dimension, we acknowledge that empirical validation remains a limitation of the present study. Further research is necessary to better understand and demonstrate the differences in vulnerability and response capacities across the various urban contexts analyzed. However, this work offers a valuable foundation for both future scientific investigations and practical applications. By systematically identifying and classifying urban settlements into archetypes based on a range of (accurately selected) vulnerability-related factors - using a replicable, data-driven approach grounded in open-source information - this study contributes to simplifying the complexity of urban risk landscapes. It provides a structured framework that can support more targeted and effective risk reduction strategies, inform urban resilience planning, and facilitate stakeholder engagement (as demonstrated also by the study conducted by Marciano et al., 2024). To underline this limitation, the following text has been added in the discussion section:

"Empirical validity in archetype analysis is commonly supported through various means, including stakeholder surveys (Nagel et al., 2024), the integration of diverse data sources at different spatial resolutions, and cross-comparisons of archetyping approaches at multiple scales (Diogo et al., 2023). It may also be demonstrated through consistency with prior empirical observations or theoretical expectations (Bilalova et al., 2025). However, validating archetypes' vulnerability profiles against observed impacts or risk outcomes remains challenging. For example, many historical impact datasets—such as those from EM-DAT—are available only at national or regional levels and include only events meeting specific severity criteria. As a result, they often exclude smaller-scale, yet locally significant, events, introducing both a selection bias and a scale mismatch that limit their utility for validating local-level archetypes. Furthermore, expected impact outputs from risk assessments are typically model-driven, emphasizing hazard intensity and physical exposure, while often overlooking the broader dimensions of vulnerability (Cardona et al., 2012). These limitations highlight the need for improved access to fine-grained, georeferenced impact data and the potential value of complementing quantitative validation with qualitative or stakeholder-informed insights at the local level. Empirical validity in our research is partially supported by stakeholder engagement-based risk storylines, as outlined in Marciano et al. (2024). Marciano et al. (2024) present an exploratory case study using a participatory approach to develop multi-risk storylines, illustrating the cascading effects of a heatwave followed by intense rainfall in two Italian urban contexts: a peri-urban area and a

metropolitan area. Findings reveal that peri-urban settlements face limited emergency resources and higher infrastructure failure risks, while metropolitan hubs have stronger emergency systems but face coordination challenges in managing large-scale events. The study highlights the varying levels of urban vulnerability across different archetypes. While these elements contribute to the empirical grounding of the archetypes, we acknowledge that empirical validation remains a limitation of this study. Further studies should explore the impacts of natural disasters on different archetypes, revealing key differences in vulnerability and response capabilities across the considered urban contexts."

Moreover, to underline the usefulness of this study in decision-making process, a simplified index (named Impact Susceptibility Index) is assigned to each archetype. It is presented in a new section of the paper (6.1), reported below:

"*Composite indices are widely used to measure multidimensional concepts, as they enable the integration of various sub-indicators representing different dimensions that lack a common unit of measurement (Nardo et al., 2008). Social vulnerability and community resilience are often quantified through composite indices (e.g., Cutter et al., 2003;Bruneau et al., 2003; Frigerio et al., 2018; Marin Ferrer et al., 2017). In Sibilia et al.(2024), a multidimensional composite index is proposed to assess vulnerability across Europe. The vulnerability index proposed, developed within the Risk Data Hub, evaluates vulnerability at three geographic levels—national, regional, and provincial—from 2005 to 2030. It encompasses five key dimensions of vulnerability: social, economic, political, environmental, and physical.*

To investigate the level of exposure and vulnerability associated with each identified archetype, this study adopts a composite index-based framework. We define an Impact Susceptibility Index (ISI) which describes the potential for experiencing adverse consequences given existing vulnerabilities and exposure levels, without implying the occurrence of a specific hazard. The construction of the composite indicator involves four main stages: selection of sub-indicators, normalization, choice of aggregation method, and assignment of weights to the sub-indicators. The indicators used are those applied in the cluster analysis and described in Sections 2.1 to 2.5. Normalization—required to make the variables comparable and suitable for aggregation—is carried out by assigning categorical scores to each indicator, following approaches used in previous studies (e.g.,Greiving et al., 2006). Scores range from 1 to 3, where 1 indicates low exposure or vulnerability and 3 indicates high exposure or vulnerability, hence contributing more to the susceptibility to impact for the given variable. For example, peripheral areas are considered the most vulnerable due to their greater distance from essential services and are therefore assigned a score of 3. Peri-urban areas receive a score of 2, and urban hubs are assigned a score of 1. Similarly, since high population density is linked to greater physical vulnerability, cities are scored as 3, towns and suburbs as 2, and rural areas as 1. The highest population class (municipalities with over 250000 inhabitants) is also assigned the highest exposure and vulnerability score, while the lowest class (less than 5000 inhabitants) receives the lowest score. In terms of social vulnerability, three categories—high, medium, and low—are defined based on the Social Vulnerability Index range (0.84–2.01, see Table 4), and scores are assigned accordingly. The final ISI for each municipality is obtained by summing the individual scores for each vulnerability dimension (e.g., Greiving et al., 2006) and therefore ranges between 4 and 10. Figure 10 displays the resulting ISI at the municipal level and the average ISI for each archetype.

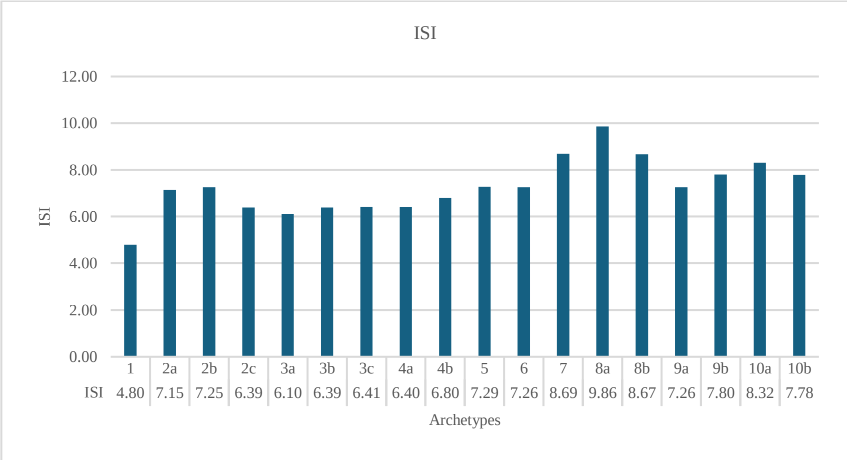


Figure 10 – Average ISI value for each archetype.

The highest average ISI is observed for Archetype 8a (mean ISI = 9.86), which includes densely populated peri-urban municipalities characterized by very high social vulnerability. Other archetypes with notably high average ISI values include Archetype 7 (mean ISI = 8.69), characterized by their relative remoteness (100% peripheral municipalities), medium-high population density (100% classified as towns and suburbs) and high social vulnerability; Archetype 8b (mean ISI = 8.67), marked by high population density (cities), peri-urban location and medium social vulnerability; and Archetype 10a (mean ISI = 8.32), largely driven by poor accessibility to services (only 12% of municipalities are classified as hubs), medium-high population and high social vulnerability.

Figure 10 highlights that many municipalities with high ISI values are concentrated in the regions of Apulia, Sicily and Lombardy, with average regional ISI values of 7.8, 7.7, 7.6, respectively. In details, 37% of Apulia's municipalities fall under Archetype 10a; 25% of Sicily's municipalities are categorized as Archetypes 10a while 14% belong to Archetype 7. In Lombardy, 22% of municipalities belong to Archetype 10b, 19% to Archetype 5 and 14% to Archetype 2a. These archetypes all show medium-high average ISI values: 7.78, 7.29, and 7.15, respectively. Overall, the ISI tends to be higher in southern regions of Italy, with an average value of 7.3, compared to 6.9 for central and northern regions. The lowest average VI values are observed in the Valle d'Aosta (ISI = 6.4) and Piedmont (ISI = 6.7) regions.

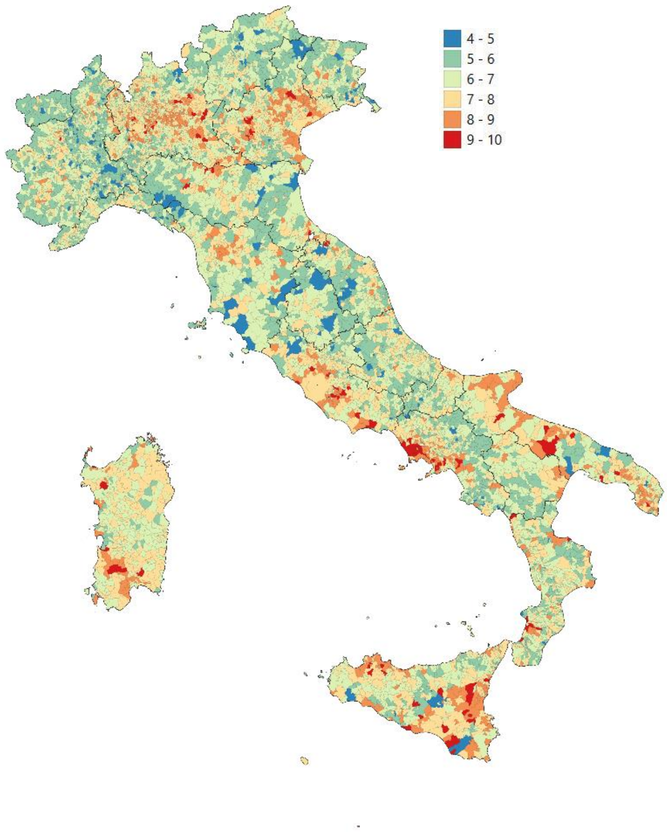


Figure 11 - Map of ISI value at municipal level."

b. What would happen if you just enumerated all possible combinations of your categorical parameters (which could also be used by decision makers to prioritise areas of intervention)? What would the map look like in that case? Does the difference between this "full enumeration" map and the one you obtained say anything about the relevance of the clustering?

   Response: In theory, enumerating all possible combinations of the four categorical parameters used as input in our clustering analysis—urban centeredness degree (3 classes), urban degree (3 classes), population (3 classes), and altimetric zone (3 classes)—would yield a total of 3 × 3 × 3 × 3 = 81 possible combinations. This "full enumeration" approach would result in a highly granular classification, where each municipality is assigned a unique label corresponding to its specific combination of characteristics. Furthermore, these combinations would have a very heterogeneous distribution in size, given to implicit constraints across the parameters (e.g. few highly populated municipalities are located in high altimetric zones, as also highlighted by the comment "C").

   While such a map might be useful for purely descriptive or diagnostic purposes, especially for decision-makers aiming to filter or prioritize interventions based on specific parameter configurations, it would lack the ability to generalize across similar contexts. In contrast, the clustering approach aggregates municipalities into a reduced number of archetypes that share common multi-dimensional characteristics, even when those characteristics are not identical across all variables. This enables the identification of broader, more interpretable settlement typologies that reflect meaningful patterns and shared vulnerability profiles, which is particularly valuable in risk-informed decision-making.

   Moreover, the difference between the "full enumeration" map and the clustering-based archetype map highlights the relevance of clustering in simplifying complexity and enhancing interpretability. Such a comparison can be inferred from Figures 4 and 5 in the paper, which illustrate how the clusters represent the underlying attributes. These figures highlight correlations between variables that would not be discernible through a simple full enumeration map. While the full enumeration map would display a highly fragmented spatial pattern with many singletons or very small groups, the clustering outcome promotes synthesis by grouping municipalities with similar profiles, facilitating communication and operationalization of results. Therefore, the clustering does not simply reproduce the combinations of categorical inputs but instead detects underlying structures and similarities that may not be immediately apparent in the raw categorical space. This supports the added value of our approach for both scientific analysis and practical applications.

c. Some combinations of parameters simply do not exist in Italy. This is one of the reasons that may prevent the exact same archetypes from being applicable to other regions (which is a potential limitation raised in lines 732-736 of the manuscript). A comparison across countries is only relevant in terms of risk metrics, otherwise the comparison is just about knowing how many combinations of parameters exist in each country.

Response: Thanks for this comment. The authors acknowledge the limitations in generalizing the archetypes beyond the studied context. Indeed, the identified archetypes are specific to the Italian case, and their broader applicability would require further investigation. However, the identification of archetypes across diverse Italian regions—along with the careful selection of relevant variables and the use of a replicable methodology—may serve as a valuable reference for archetype-based analyses in other national or regional settings, particularly within Europe. The limitations and potential of applying the proposed archetype analysis to other regions are discussed in the Discussion section:

"External Validity assesses the generalizability of archetypes beyond the studied cases. It is typically addressed by applying archetypes across multiple regions and evaluating the consistency of resulting patterns across different scales (e.g., Diogo et al., 2023; Nagel et al., 2024) or linking archetypes to theoretical expectations or global typologies (e.g., Bilalova et al., 2025). While this study acknowledges the challenge of fully satisfying this dimension, given that the identified archetypes are specific to the Italian context and broader applicability requires further investigation, it also provides a foundation for generalization. The identification of archetypes across diverse Italian regions, combined with the careful selection of relevant variables and the use of a replicable methodology, may serve as a valuable reference for archetype-based analyses in other national or regional settings, particularly within Europe. Notably, many of the variables adopted in this study, such as urban degree, population class, and census-based demographic and socio-economic indicators, are also available at comparable spatial resolutions through Eurostat, EUROPOP, or pan-European datasets such as Urban Atlas, CORINE Land Cover, and GHSL (Global Human Settlement Layer). Similarly, the urban centeredness degree, while constructed using national criteria in Italy, relates closely to the concept of accessibility and service availability, which can be captured using EU-wide datasets on transport networks, healthcare access, and educational infrastructure. Therefore, the consistent use of open-source and harmonized data sources enhances the potential for applying the methodology beyond the Italian context, fostering comparative analyses and supporting the construction of cross-country urban and rural archetypes within Europe."

d. A clustering algorithm is agnostic to the meaning of the input data. The analysis could have included variables that are not relevant to risk at all, and they would have still come up in the clustering. This is not to say that the risk metrics should be included in the clustering. There is value in carrying out the clustering using the variables you used (because these are variables easily obtained from open datasets, because they can be used as proxies, etc), but the output needs to be interpreted in terms of risk metrics in order to be meaningful for vulnerability/risk reduction.

Response: All variables included in the analysis have been deemed relevant to vulnerability/resilience and exposure, since have been identified through a detailed literature review. This accurate selection of variables ensures indicators are theoretically and empirically linked to several vulnerability dimensions, thereby reinforcing the construct validity, as also shown in other archetypes studies (e.g., Diogo et al., 2023; Nagel et al., 2024). This has been also underlined in the discussion session:

"Construct Validity involves the careful selection of attributes that define the archetypes, ensuring their connection to the conceptual framework. We meticulously selected attributes relevant to vulnerability of urban systems and their potential exposure to different hazards. These attributes are justified based on existing literature, ensuring indicators are theoretically and empirically linked to several vulnerability dimensions, thereby reinforcing the construct validity (Diogo et al., 2023; Nagel et al., 2024)."

Moreover, the outputs have been also interpreted in terms of susceptibility to impacts using the Impact Susceptibility Index, and the limitations related to the comparison with real-world impact data or the outcomes of existing risk analyses have been clearly highlighted in the discussion section. Please refer to the response to comment 2a for further details.

3. The selection of variables to include is difficult to follow. During my first read I could not understand why some variables from Table 1 were missing in Table 2. It only became clear as I kept on reading (around line 180, i.e. ~50 lines after Table 2 is mentioned in the text). Moreover, line 189 mentions 19 attributes, but Table 2 contains 15. It is only clear in Table 3 that some of the socio-economic parameters of Table 2 are further subdivided. Moreover, in Table 2 it is not clear how some of the parameters are measured (e.g., "quality of the buildings"). Then there is the issue that the number of numerical variables is further reduced due to their correlation (section 4.1), which is correct. But then the final variables used are only listed within the text (lines 386-388), which gets lost with respect to what the reader can easily identify from the tables. In lines 366-367 it is stated that the population variable is used as classes, which was already implicit in section 3.4 (consider moving the spirit of what is said in lines 361-367 to section 3.4). All these issues result in the manuscript feeling messy. Please consider unifying some of the three tables (Tables 2 and 3 are good candidates), using more columns or bullet points to sub-classify items, perhaps marking the 8 numerical variables used in the end, and indicating which variables are categorical and which numerical. Please make it clear from the beginning that Table 1 is just a discussion of potential parameters to include, but not the parameters used.

   Response: Thanks for this comment. To improve clarity, Table 2 and Table 3 have been removed. It has been specified that Table 1 only reports a list of indicators commonly used in literature to assess the different vulnerability dimensions, while all the variables selected for the clustering are mentioned in the text in the section dedicated to data section ("*Selection of key indicators of vulnerability dimensions*") and connected to vulnerability indicators presented in Table 1. More specifically, the text has been modified as follows:

   "Table 1 presents a list of key indicators commonly used in literature to assess each dimension of vulnerability mentioned.

   In our work we focused on a selection of indicators, expectedly linked with different vulnerability dimensions, and namely: altimetric zone, centeredness degree, urban degree, residential population and social vulnerability indicators. The altimetric zone of urban settlements, which refers to their elevation and *topographical features, can be considered a proxy of access to the main services – or equally distance to service centres (institutional vulnerability, see Table 1). Accessibility of services of general interest can be particularly challenging in certain contexts (e.g. mountain regions, islands) due to their geomorphological and settlement structure conditions (Bertram et al., 2023). These accessibility issues can also complicate evacuation efforts and the delivery of emergency services during a disaster. Likewise, urban centeredness degree, which reflects the spatial characteristics and distribution of urban areas, is associated with the availability of public services and the level of spatial connectedness, as it measures the distance and travel time to major service centres (institutional vulnerability, see Table 1). The degree of urban centeredness significantly influences the response and resilience of urban systems by affecting resource availability, infrastructure robustness, community networks, and emergency preparedness* (Giuliano & Narayan, 2003; Schwanen et al., 2004). *Ensuring effective access to essential public services, such as healthcare and education, is challenging even under normal circumstances. However, it becomes even more crucial during crises like natural disasters, when the demands on these services and their operating conditions become significantly more complex (Fan et al., 2022; Loreti et al., 2022; Tariverdi et al., 2023). The level of peripherality of the areas with respect to the network of urban centres influence may determine not only difficulties of access to basic services but also lower quality of life of citizens and their level of social inclusion (Oppido et al., 2023).*

Residential population and urban degree are linked to exposure and physical vulnerability dimensions, and specifically to population density (physical vulnerability, see Table 1). While acknowledging that population density cannot capture the full range of structural vulnerability factors of built environment, it reflects both the intensity of exposure and the systemic vulnerabilities inherent to high-density urban environments (e.g., emergency response complexity and evacuation challenges, increased likelihood of cascading infrastructure failures during hazard events, overburdened urban services that exacerbate systems' physical fragility - healthcare, water systems, mobility - under stress), consistent with its interpretation in urban risk literature (e.g., Balk et al., 2018; Marzi et al., 2019; Opach et al., 2020; Zhao et al., 2017).Residential population significantly influences the exposure to natural hazards, determined not only by the higher presence of people and housing, but also of infrastructure, production capacities, species or ecosystems, and other tangible human assets in places and settings that could be adversely affected by one or multiple hazards. Higher population not only increases the potential for human and property losses, but also complicate evacuation efforts, and strain emergency response resources (Zhao et al., 2017). The degree of urbanization is often used to classify areas into cities, urban areas, and rural areas based on criteria such as population density, concentration of human activities, and built environment (Balk et al., 2018; United Nations, 2018). Indeed, highly urbanized densely populated areas are more likely to experience greater damage, congestion, and strain on resources during emergencies. It affects the capacity for evacuation and accessibility to essential services, due to dense infrastructure, complex urban layouts and the potential for cascading failures in infrastructure (Kendra et al., 2008; Lall & Deichmann, 2012).

Finally, social vulnerability indicators include those parameters that influence both social and economic vulnerability. Past events highlight that elderly may be more vulnerable due to reduced mobility, poor health, and communication challenges (Ardalan et al., 2010; Carnelli & Frigerio, 2017*;Cutter et al., 2003), while education levels can heighten vulnerability to natural hazards influencing risk perception and awareness, knowledge, and skills related to disaster preparedness (Alexander, 2012b; Wachinger et al., 2013). Still, minority groups, including migrants, and ethnic communities, often face heightened social vulnerability, especially in high-risk areas, due to language barriers and communication challenges that can hinder access to critical emergency information* (Carnelli & Frigerio, 2017; Walter Gillis et al., 2012). *The complete list of socio-economic indicators considered includes age, dependency ratio, level of education, family structures, commuting rate, quality of buildings, race/ethnicity, employment rate, percentage of women in the workforce (Table 2).*"

Since the number of numerical variables is further reduced due to their correlation, to make clearer which variables are finally adopted in the clustering (and their type) the following table (the new Table 2) has been added in the paper. It is reported at the end of Section 4.1. "Data pre-processing" (now, Section 3.1; see response to comment *4*).

Table 2 – Variable used in cluster analysis.

Variable	Type	Vulnerability dimension
Urban degree	Categorical	Physical
Urban centeredness degree	Categorical	Institutional
Population class	Categorical	Physical
Altimetric zone	Categorical	Institutional
Aging index	Numerical	Social
Low educational index	Numerical	Social
Unemployed	Numerical	Economic
Commuting rate	Numerical	Social
Female employed	Numerical	Economic
Quality of buildings	Numerical	Social/Physical
Crowding index	Numerical	Social
Foreign resident	Numerical	Social

4. There is some imbalance in the level of detail provided for the first level of clustering (section 4.4), which is associated with the categorical variables, and that of the second level (section 4.5), which refers to the numerical variables. Please consider expanding section 4.5, perhaps including informative figures/plots.

   Response: Section 4.4 included both a detailed description of the adopted methodology (i.e., the clustering techniques applied) and the corresponding results. This led to a more extensive discussion, whereas Section 4.5, which employed the same methodology already presented in Section 4.4, focused solely on presenting the results and was therefore shorter.

   In the revised manuscript, we have clearly distinguished between the Methods and Results sections to improve structure and balance. Specifically:

   - The subsection previously titled "*Clustering based on demographic and geographic features*" has been renamed "*First-level analysis: clustering based on physical and institutional vulnerability parameters*."
   - The subsection "*Nested clustering*" has been updated to "*Second-level analysis: nested clustering based on socio-economic parameters*."

   As a result, the revised paper now includes three distinct sections:

   - Section 3: "*Cluster analysis*" – dedicated to the description of the methodology
   - Section 4: "*First-level analysis: clustering based on physical and institutional vulnerability parameters*." – presenting the results of the first step of the archetype analysis
   - Section 5: "*Second-level analysis: nested clustering based on socio-economic parameters*" – presenting the results of the second step.

   The authors believe that this restructuring improves the clarity and coherence of the manuscript.

5. Section 5 (results) is merely descriptive. Deeper insights on the meaning of the resulting clusters and their spatial distribution are completely missing. Lines 642-683 mostly repeat what is already said in Tables 4 and 5. Lines 684-705 mostly describe the spatial distribution of the archetypes with respect to Italian regions but (i) the regions are not marked in any map (please do not assume all readers will know where these regions are) and, most importantly, (ii) no insights are provided with respect to what this spatial distribution may mean or imply.

   Response: Thanks for this feedback. Section 5 (now Section 6; see response to comment 4) presents the results of the cluster analysis, and the characterization of the archetypes derived from both categorical and numerical variables used in the study. This section is essential for understanding the rationale behind the archetype names and how they relate to the attributes shown in Tables 4 and 5. Moreover, section 5 (now section 6) includes also a discussion on spatial distribution to reflect on regional differences in terms of vulnerability drivers and settlement patterns, offering meaningful insights into what the spatial distribution of archetypes implies in terms of regional risk governance and planning needs.

To better address your comment and enhance the interpretability of the results:

- A new overview map of Italy has been added next to Figure 9, showing the names and locations of all Italian regions, to assist readers who may be unfamiliar with the country's geography (see below).
- A new section has also been added to discuss the vulnerability profiles of the identified archetypes, providing a deeper interpretation of their characteristics and the implications for disaster risk and resilience (see also response to comment 2a).

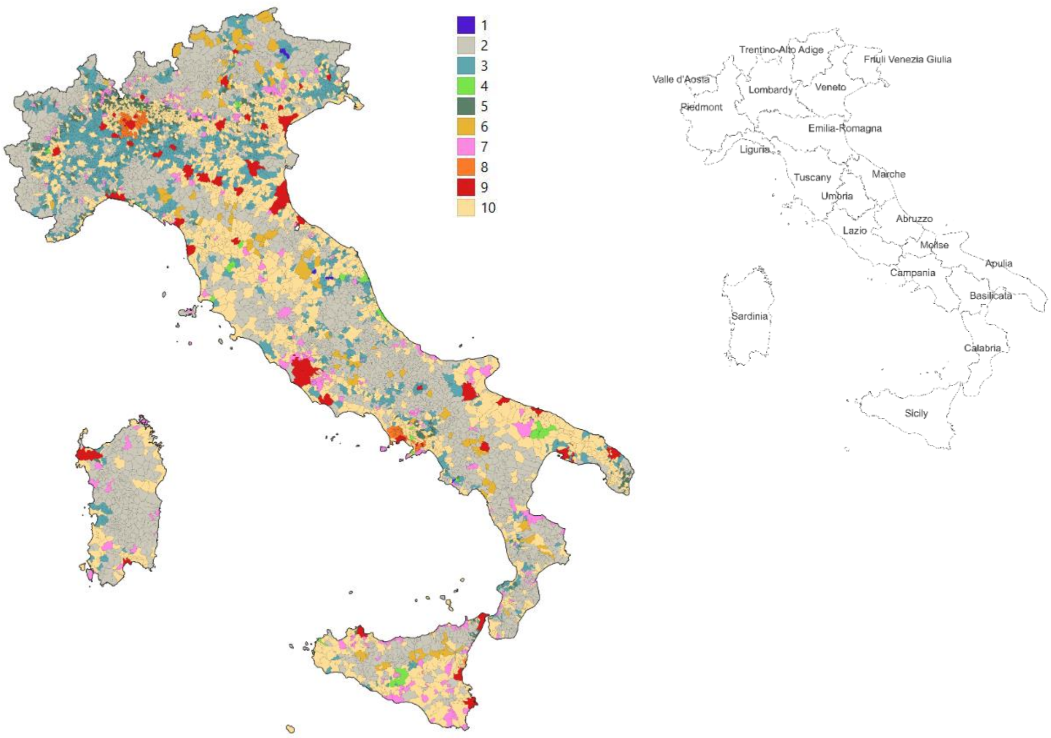


Figure 9 – Broad urban archetypes across Italian territory. On the right the map with the Italian regions is reported.

6. Section 6 (discussion) only refers to how the methodology used complies with the guidelines of Piemontese et al.(2022), in some cases inaccurately or obscurely. In some detail:

   a. L720-722: Employing WCD and ICD does not ensure the reliability or robustness of the clustering process. Again, too much faith is being put on the numerical algorithms. How is the accuracy (with which the dataset is represented, as per the wording in L721-722) measured?

      Response: Thank you for the comment. We acknowledge that relying solely on numerical metrics such as Within-Cluster Distance (WCD) and Inter-Cluster Distance (ICD) may not fully ensure the reliability or robustness of the clustering process. However, these metrics are widely recognized in literature as important tools for assessing internal validity, by quantifying how well data points are grouped within clusters and separated from other clusters (Bilalova et al., 2025; Nagel et al., 2024). In addition to these metrics, we also evaluated the interpretability and coherence of the resulting clusters in relation to known patterns in demographic and geographic data. This qualitative cross-check helps reinforce the internal consistency of the archetypes.

Regarding the term '*accuracy*' in L721–722, we refer to the degree to which the clusters reflect meaningful patterns in the dataset, based on both numerical cohesion/separation and the interpretability of the resulting groups. To clarify this, we have revised the manuscript text accordingly:

"Internal Validity is maintained through the rigorous application of hierarchical and partitioning clustering methods. In previous studies, such as Bilalova et al. (2025), internal validity has been addressed through a transparent and replicable methodology, incorporating widely used validity metrics which measures how similar an object is to its own cluster compared to other clusters like silhouette scores, and evaluating both within-cluster and between-cluster cohesion. Similarly, Nagel et al. (2024) assessed internal validity by testing cluster robustness using R packages NbClust and clValid. The NbClust package supports the determination of the optimal number of clusters by computing and comparing multiple internal validity indices (e.g., silhouette score, Dunn index), while the clValid package enables the evaluation of clustering stability and comparative performance across different algorithms (e.g., k-means, hierarchical clustering). Building on these approaches, internal validity in this study is ensured through: (i) the determination of the optimal number of clusters using established internal validity indices—specifically, the inconsistency coefficient and the WCD; (ii) the assessment of cluster robustness, by repeating the partitioning clustering procedure multiple times with randomized initial centroids and selecting the best-performing result based on WCD, thus reducing sensitivity to initialization; (iii) the comparison of clustering algorithms, by applying both hierarchical and partitioning methods and evaluating their performance using WCD and ICD to identify the most internally coherent solution. This combination of techniques ensures methodological rigor, reproducibility, and robustness in the clustering process, thereby addressing the internal validity dimension as recommended in the literature (Piemontese et al., 2022)."

b. L730-731: While the authors imply that confronting the archetypes against risk data/models is outside of the scope of the paper, the classification work per se does not hold relevant meaning without this confrontation.

Response: The authors have strengthened the practical relevance of this study for decision-making processes by calculating a simplified index—the Impact Susceptibility Index—for each identified archetype. This index measures the propensity for impacts based on the exposure and vulnerability characteristics of each archetype (see also response to comment 2a). The authors believe that this addition significantly enhances the satisfaction of the application validity dimension and offers a useful ranking to help prioritize archetypes in risk reduction strategies. At the same time, the authors acknowledge that fully satisfying the empirical validity dimension remains a limitation of this study. Nevertheless, the work provides a solid foundation for future scientific research and practical applications, successfully addressing the other validity dimensions (see also responses to comments 6a, 2a, and 2c). This issue has already been discussed in response to comment 2a.

c. L732-736: As stated above, comparing the clustering output of different countries without going into the risk domain is just a comparison of how these sets of variables are combined and spatially distributed in different countries. There would be no further implication.

Response: The authors agree that comparing clustering outputs across different countries without connecting them to the risk domain may appear to be a purely descriptive exercise with limited implications. However, the authors believe such a comparison can still provide meaningful insights, particularly when the clustering is based on vulnerability-related indicators that are theoretically and empirically associated with disaster risk. By identifying whether similar vulnerability profiles (e.g., combinations of socio-economic, demographic, and geographic characteristics) emerge across diverse national contexts, we can begin to assess the universality or context-specificity of certain vulnerability patterns.

While our primary focus in this study is on the Italian context, we acknowledge that extending the methodology to other countries and explicitly linking the resulting archetypes to risk metrics or impact data (e.g., disaster losses, preparedness levels, or recovery times) would be necessary to fully move from a descriptive typology to one with predictive and policy-relevant implications. The authors have clarified this point in the revised manuscript (see response to comment 2a and 2c), and we frame our current analysis as a foundational step that enables such future cross-country, risk-informed comparisons.

d. L737-738: The sentence "This study demonstrates the potential of urban archetypes in developing risk storylines, enhancing risk communication, and supporting stakeholder engagement" is simply not true. Where exactly in the manuscript are these three points demonstrated?

Response: Section 6.1 has been added to underline the usefulness of this study in decision-making process. This section presents a simplified impact susceptibility index assigned to each archetype, based on their demographic, socio-economic and geographic characteristics, that reflect their vulnerability and exposure level. See also response to comment 2a. To underly this point, the paragraph dedicated to application validity dimensions in the Discussion section has been modified as follows:

"*Application Validity evaluates the practical usefulness of the archetypes. This dimension can be addressed emphasizing practical applications of archetypes in policy, planning, and governance, for instance, by presenting results to government officials and researchers, guiding inform local policy discussions, with archetypes guiding differentiated policy interventions (Nagel et al., 2024). Section 6.1 illustrates the potential of urban archetypes to enhance risk communication through the assignment of a simplified impact susceptibility index to each identified archetype. Additionally, the exploratory case study presented in Marciano et al. (2024) highlights how these archetypes can support stakeholder engagement by informing the development of multi-risk storylines. By categorizing urban areas into distinct archetypes, it becomes possible to assess how different hazard scenarios may unfold in each context, considering their specific vulnerabilities, exposure levels, and adaptive capacities. This structured approach enables policymakers to design tailored interventions and resilience strategies based on specific vulnerability profiles. However, to further strengthen urban resilience planning and develop targeted mitigation measures, it is crucial to consider not only exposure and vulnerability but also hazard data for each archetype—particularly the level of exposure of urban settlements to various natural hazards. Although in this study we did not yet integrate hazard information, there is a clear need for future research to incorporate this aspect and conduct GIS-based analyses for a more comprehensive assessment of urban risk (e.g., Tocchi et al., 2024).*"

7. In the last paragraph of the conclusions (L759-761): "its findings offer a valuable tool for policy makers to design targeted interventions based on specific vulnerability profiles": The paper does not demonstrate that the archetypes are indeed associated with specific vulnerability profiles, it just assumes they are. Again, the paper needs to somehow show that the archetypes are indeed associated with vulnerability profiles that make sense for policy making.

Response: The authors fully acknowledge the need to demonstrate, rather than assume, that the identified archetypes correspond to specific and meaningful vulnerability profiles. The carefully selection of indicators based on both theoretical relevance and empirical evidence from the literature linking them to disaster risk and vulnerability (e.g., demographic pressure, social fragility, accessibility to services, and urban density) used for clustering ensure that each archetype is indeed associated with specific and different vulnerability profiles. The carefully selection of indicators also fully satisfy the construction validity dimension of archetype analysis (e.g.,Diogo et al., 2023; Nagel et al., 2024). To further demonstrate that each archetype is associated with a distinct vulnerability profile, we developed a simplified impact susceptibility index (see responses to Comments 2a and 6d). This index aggregates the key vulnerability-related indicators used in the clustering process, allowing us to rank archetypes according to their average vulnerability and exposure levels. The results show that archetypes differ significantly in their composite index scores, supporting the interpretation that they represent distinct profiles of susceptibility to hazard impacts. Still, the limits of this study in fully satisfy empirical evidence of archetypes has also been addressed (see response to comment 2a).

Minor Comments/Edits

1. L13: "complexity in an otherwise too broad problem".

   Response: The text has been modified from "helping to segmentate the complexity in otherwise too broad problem" to "helping to segmentate the complexity in an otherwise too broad problem".

2. L24: "Over the last few decades".

   Response: The text has been modified from "Over last few decades" to "Over the last few decades".

3. L43: Exposure is not "intended". Do you mean understood? Defined?

   Response: The text has been modified as follows: "*Exposure refers to the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected, while vulnerability refers to the propensity or predisposition to be adversely affected*"

4. L43-45: Please replace the semicolons (;) by commas.

   Response: The text has been modified. Please, see the response to the previous comment.

5. L58: It says "we assume", but perhaps you mean "we hypothesize"?

   Response: In this case, "we assume" was deliberately chosen, as it reflects the starting premise or working assumption of the study rather than a formal, testable hypothesis. The use of "assume" emphasizes that this is an underlying premise guiding the methodological approach — that a limited number of archetypes can sufficiently represent the diversity of urban vulnerability and exposure profiles at regional and national scales. Therefore, we prefer to maintain the use of "we assume" in this context.

6. L61: Erase "We note that". It is not necessary.

   Response: The second part of the introduction section has been totally revised as suggested by reviewers, in order to: (i) clearly stating the research question early on; (ii) elaborating on how archetypes enhance the understanding of exposure and vulnerability; (iii) clarifying different interpretations of archetypes and explicitly stating the one used in this study; (iv) briefly explaining how the concept is operationalized in this work. Specifically, lines from 58 to 68 have been modified as follows:

   "*This study addresses the following research question: can urban settlements be clustered into meaningful archetypes based on shared characteristics of vulnerability and exposure, to improve multi-risk assessment and support more targeted resilience planning at regional and national scales? Indeed, despite the high specificity of exposure and vulnerability of each urban and rural environment, we assume that a relatively low number of representative archetypes could be found to decrease the level of complexity at regional and national scale, ensure a baseline for comparison and highlight potential hotspots in multi-hazard and multi-risk assessment frameworks.*

The term "archetype" can be interpreted in different ways. In statistics, archetypes refer to extremal profiles used to describe all data points as convex combinations of a few "pure" types (Cutler & Breiman, 1994) *. In contrast, in sustainability science and climate risk research, archetypes are understood as representative specimens or clusters of similar entities that are "crucial for describing the system dynamics or causal effect of interest" and that exhibit recurring patterns of risk-relevant characteristics " (Oberlack et al., 2019). We adopt this latter interpretation. In our work, urban and rural settlement archetypes are defined as representative instances (real or ideal) of a group of municipalities sharing similar vulnerability and exposure characteristics."*

7. L83-85: Are capitals really needed for "design", "analysis" and "application"?

   Response: As suggested, capital letters have been removed.

8. L95: No comma after "defined".

   Response: As suggested, comma has been removed.

9. Table 1: It says "GPD per capita" instead of "GDP per capita".

   Response: In Table 1 the text "*GPD per capita*" has been corrected to "*GDP per capita*".

10. L161: "complicates evacuation efforts and strains emergency response resources".

    Response: Text has been modified from "*complicates evacuation efforts and strain emergency response resources*" to "*complicates evacuation efforts and strains emergency response resources*".

11. L167: Consider breaking the paragraph here and starting a new one to talk about the socio-economic factors.

    Response: As suggested, a break has been introduced between the paragraph describing the demographic parameters and the one describing the socio-economic parameters.

12. L169: "highlight that the elderly".

    Response: The text has been modified from "*highlight that elderly*" to "*highlight that the elderly*".

13. L192: "proposed a grid-based approach".

    Response: The text has been modified from "*proposed grid-based approach*" to "*proposed a grid-based approach*".

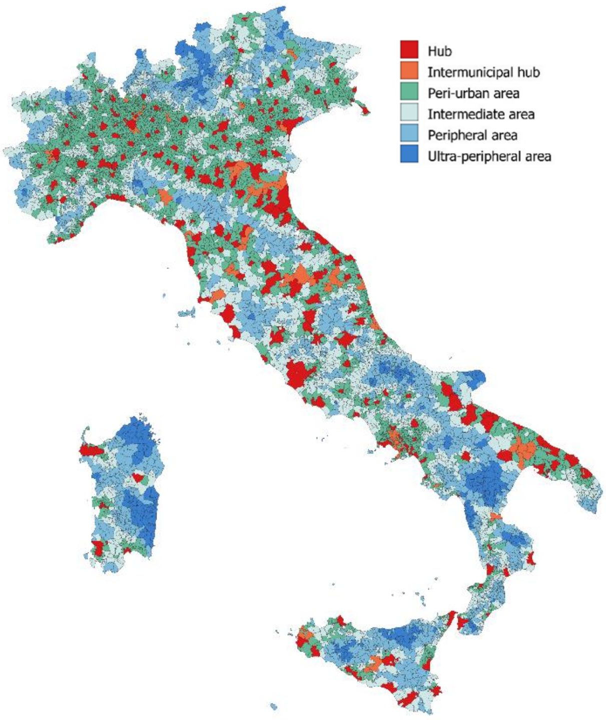
14. L201: "adopting to the abovementioned" (remove "to").

    Response: The text has been modified from: "*classification of municipalities adopting to the above-mentioned Eurostat procedure is provided by ISTAT*" to "*classification of municipalities adopting the above-mentioned Eurostat procedure is provided by ISTAT*".

15. Fig. 1: Please consider changing the colour of peri-urban areas. The map on the right shows six labels, but only three classes of urban centeredness degree are considered in the analysis. "Hub" and "municipal hub" can be seen as different shades of red of the final class "urban hubs", while the intermediate, peripheral and ultra-peripheral inland areas are indifferent shades of blue, so that is clear. However, peri-urban areas are in orange, which makes them very similar to the "urban hubs" class. A different colour for peri-urban areas would make it easier to visualise the final three classes used. Parentheses in the text (lines 243-245) could clarify this. E.g. "namely urban hubs (represented..., shades of red in Fig. 1), peri-urban areas (new colour) and inland areas (shades of blue)".

    Response: Thanks for this comment. As suggested, Figure 1 has been modified changing the colour of peri-urban areas (from light orange to green). Moreover, a clarification about colour used in the map has been added in the text: "*namely urban hubs (represented by both hubs and intermunicipal hubs, **shades of red in Figure 1**), peri-urban areas (**green in Figure 1**) and inland areas (that includes intermediate, peripherical and ultra-peripherical areas, **shades of blue in Figure 1**)*".

The new map is reported below:



16. L258: “lead to the model becoming”.

    Response: The text has been modified from “*lead the model becoming*” to “*lead to the model becoming*”

17. L259: “correlation that may exist”.

    Response: In the sentence “*Furthermore, despite some correlation may exist between urban vulnerability and coastal/inland areas*…" the term "*despite*" should be directly followed by a noun, gerund (-ing form), or pronoun, not a full clause with "*that may exist*". Therefore, the mentioned sentence has been modified as: “*Furthermore, despite some correlation existing between urban vulnerability and coastal/inland areas…*”.

18. Table 2 vs line 377 and Fig. 3: Is it population aged under 15 or 14 (different numbers in different places).

    Response: The correct variable is the population under 15 (not under 14). The text in line 377 and Figure 3 has been modified accordingly.

19. Table 2 vs line 311: Should it be “total population aged over 30” under “high educational index”?

    Response: The high educational index is calculated as people with at least a university degree compared to the total population aged over 30, as mentioned in the text (line 311). There was a type in Table 2 (table that has been removed after the revision process; see response to comment 3).

20. L344: Clustering methods per se do not “ensure” that observations within the same group are highly similar. It is their goal, but it is not guaranteed. They are just numerical methods. They will return some sort of clustering no matter what you provide as input. Please re-phrase.

    Response: To correctly reflect that clustering methods seek to achieve internal similarity and external separation, but do not guarantee it, the sentence: “*This method ensures that observations within the same group are highly similar, while those in different groups are distinctly different*” has been changed to "*This method is designed to group together observations that are highly similar, while separating those that differ into distinct clusters*"

21. L354-355: "More detailed information".

    Response: The text "*Most detailed information*" has been replaced by "*More detailed information*".

22. L359: "is crucial for enhancing the quality of the clustering".

    Response: The text "*Data preprocessing is crucial for enhance quality of clustering*" has been replaced by "*Data preprocessing is crucial for enhancing the quality of clustering*".

23. L376-383: The strong negative correlation between the proportion of employed and un

    Response: In the previous lines of the same paragraph (lines 374-375) it is already specified that "*The value of r ranges between -1 and 1, with values higher than 0 that indicate a positive correlation and values lower than 0 a negative correlation*." Thus, there is no need to further specify whether the correlation is negative or positive in lines 376-383, the sign of *r* is clearly provided for each pair of variables.

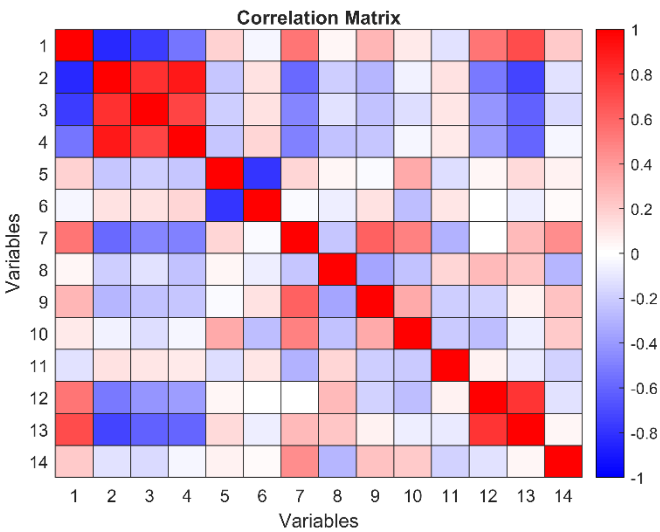
24. Fig. 3, labels (list 1-14):
    a. "Proportion of population under 14" (or another alternative, the current grammar is not right).
    b. "Proportion of population over 65" (or another alternative, the current grammar is not right).
    c. Replace "components" with "members".
    d. "Residents" (plural), not "resident" (singular).

    In general, please aim for consistency between the labels used in this figure and in table 3.

    Response: As suggested, the labels have been modified. Please, see the response to the following comment which provides the new version of figure 3 with corrected labels.

25. Fig. 3: It would be easier to interpret the matrix if the colour scale was based on three colours instead of two (right now, from yellow to blue, passing through green). This would make values around zero more visible.

    Response: Colors of the figure have been modified, in order make it easier to interpret also for readers with color blindness. Specifically, a blue-white-red color scheme has been adopted to improve accessibility. Please, find below the figure with new color scheme.



1. Proportion of population under 14
2. Proportion of population over 65
3. Aging index
4. Dependency ratio
5. High educational index
6. Low educational index
7. Proportion of employed
8. Proportion of unemployed
9. Proportion of commuters
10. Proportion of female employed
11. Proportion of buildings in poor conditions
12. Proportion of families with 5 or more members
13. Crowding index
14. Proportion of foreign residents

26. Fig. 3: Is it correct that the correlation between features 7 and 8 is so low, numerically? These features are the proportion of employed and unemployed among the working-age population. Are they not one minus the other (1 – employed = unemployed) and, if not (because of some other category), are they not at least highly negatively correlated?

    Response: In Italy, according to ISTAT definitions, the number of employed refers to people aged over 15 who are actively working. However, the category of "working-age population" (people aged over 15) also includes individuals who are not in the labor force, such as students, retirees, housewares and others not seeking employment. Therefore, 1 – employed ≠ unemployed. For this reason, the correlation between the proportion of employed and unemployed among the working-age population is not necessarily strongly negative.

    In the revised version of the paper, when presenting social vulnerability variables (section 3.5), it has been specified that working-age populations adopted for the calculation of the employment/unemployment rate is the population aged over 15.

27. L406: Should the subscript of the x variables be "l" instead of "k", to be consistent with Eq. (1) and the text?

    Response: Yes, it is correct. The subscripts of the x variables have been corrected using the right letter ("l" instead of "k").

28. L515: "The attributes' importance for clustering is evaluated adopting the simplified procedure".

    Response: The text "*Attributes importance for clustering is evaluated adopting simplified procedure*" has been replaced by "The attributes' importance for clustering is evaluated adopting the simplified procedure".

29. L516: "to assess their contribution".

    Response: The text "to assess its contribution" has been replaced by "to assess their contribution".

30. L519: "WCD as the performance metric".

    Response: The text "In this study we consider WCD as performance metric" has been replaced by "In this study we consider WCD as the performance metric".

31. L526: Do you mean cluster 2, instead of 6?

    Response: Yes, it was a typo. In the text, "Cluster 6" has been replaced by "Cluster 2".

32. L564: "The lower is the WCDl" (erase "is").

    Response: The text "The lower is the WCDl" has been replaced by "The lower the WCDl".

33. Table 4 is colour-coding the SoVI. Please mention the colours in the text (lines 614-616).

    Response: The description of color code used to rank SoVI value has been added in the text. Specifically, lines 613-617 have been modified as follows (added text is reported in bold):

    "*The criteria used to identify the different socio-economic condition categories is based on SoVI values and specifically: a value lower than 1 corresponds to low social vulnerability **(dark green in Table 4)**, value between 1 and 1.20 to moderate social vulnerability **(light green in Table 4)**, values between 1.20 and 1.40 to intermediate social vulnerability **(yellow in Table 4)**, values between 1.40 and 1.60 to high social vulnerability **(light red in Table 4)**, values higher than 1.60 to very high social vulnerability **(dark orange in Table 4)**. The average values of individual variables for each sub-cluster are provided in Table 4.*"

34. Table 4:
    a. "Building poor state"? You used "poor" before. Please be consistent.
    b. "Foreigners" or "Foreign residents".
    c. Clusters 2a and 4b: "Settlements with high social vulnerability".

Response: The suggested corrections have been applied. Specifically:

a. "*Buildings bad state*" has been replaced by "*Buildings poor state*"
b. "*Foreign*" has been replaced by "*Foreigns*"
c. "*High socially vulnerability settlements*" has been replaced by " *Settlements with high social vulnerability*" for Clusters 2a, 3c, 4b and 10a. Accordingly, Cluster 8a has been renamed as "*Settlements with very high social vulnerability*" and Cluster 9a as "*Settlements with low social vulnerability*".

35. Table 4: As they are phrased, sub-clusters 2a (settlements with high social vulnerability) and 2b (settlements with aged population with high social vulnerability) overlap, with 2b seemingly a sub-category of 2a. If 2a explicitly excludes aged populations, then the label should reflect this

Response: As mentioned in the text, sub-cluster names may also incorporate the specific social vulnerability factors that contribute most significantly to the SoVI value. Therefore, since sub-cluster 2a shows the highest average crowding index, it has been renamed as "*High household density settlements with high social vulnerability*".

36. L696-697: "in the southern regions, with almost all cases located".

Response: The text "*in the southern regions, which almost all cases located in Campania*" has been replaced by "*in the southern regions, with almost all cases located*".

Response to editor

We thank the editor for these thoughtful suggestions.

We appreciate the recommendation to include recent conceptualizations of institutional vulnerability, particularly the work of Papathoma-Köhle et al. (2021). We would like to note that this reference was already included in our original manuscript and was used specifically to support the definition of institutional vulnerability. To address the editor's concern more fully, we have revised the relevant paragraph to better reflect the nuanced understanding of institutional vulnerability as presented in Papathoma-Köhle et al. (2021). We now emphasize in the main text (line 141) that institutional vulnerability not only includes deficiencies in governance and preparedness, but also reflects the capacity of institutions to anticipate, absorb, and adapt to hazard-related shocks, a dimension that is increasingly discussed in literature:

"*Institutional vulnerability arises from limitations in governance structures, risk communication, preparedness, and emergency management systems. Following Papathoma-Köhle et al. (2021), institutional vulnerability also encompasses the capacity of institutions to anticipate, absorb, and adapt to hazards, highlighting the importance of coordination, contingency planning, and learning mechanisms as part of adaptive risk governance.*"

We appreciate the editor's insightful concern regarding the use of population density as a proxy for physical vulnerability. We agree that population density alone does not capture the structural and material characteristics of the built environment, which are essential components of vulnerability, especially in hazard-specific contexts (e.g., building resistance to floods, seismic events, etc.). However, in our study population density is used as proxy for physical vulnerability in line with established literature (Marzi et al., 2019; Opach et al., 2020; see also Table 1). Several works support the dual-role interpretation of population density as proxy for both physical exposure and vulnerability. Population density directly reflects the potential concentration of people and assets at risk, thus serving as a valid proxy for exposure (Balk et al., 2018; Zhao et al., 2017). Densely populated urban areas inherently include higher quantities of built structures and socio-economic activities, increasing the absolute potential for loss. While density does not capture the material quality of buildings, it has been widely used in literature as a structural vulnerability indicator due to its implications for:

- Emergency response complexity and evacuation challenges (Kendra et al., 2008; Zhao et al., 2017)
- Increased likelihood of cascading infrastructure failures during hazard events (Lall & Deichmann, 2012), particularly within the context of urban systems where high density co-occurs with complex spatial configurations and infrastructure interdependencies
- Overburdened urban services that exacerbate physical fragility (e.g., healthcare, water systems, mobility) under stress
- Congested spatial layouts that hinder hazard mitigation and amplify damage, especially in the absence of resilience-oriented planning (Opach et al., 2020)

Therefore, while acknowledging its limitations, we align with works such as Balk et al. (2018), Marzi et al. (2019), Opach et al. (2020) that incorporate population density as a compound proxy for exposure and physical vulnerability, especially when detailed structural data are unavailable or impractical to obtain at the considered scale.

In summary, our use of population density reflects a composite spatial risk indicator that captures (i) the intensity of exposure (people/assets at risk), and (ii) the systemic vulnerabilities inherent to high-density urban environments that increase the likelihood and magnitude of damage during hazardous events. We acknowledge the editor's point and have added a clarification in the revised manuscript to distinguish between intrinsic vulnerability (e.g., structural/material resilience) and systemic or operational vulnerability as reflected by density and urban form. Specifically, we modified the text (line 165) as follows (the added part is reported in bold):

"*Residential population and urban degree are linked to exposure and physical vulnerability dimensions, and specifically to population density (physical vulnerability, see Table 1).* ***While acknowledging that population density cannot capture the full range of structural vulnerability factors of built environment, it reflects both the intensity of exposure and the systemic vulnerabilities inherent to high-density urban environments (e.g., emergency response complexity and evacuation challenges, increased likelihood of cascading infrastructure failures during hazard events, overburdened urban services that exacerbate systems' physical fragility - healthcare, water systems, mobility - under stress), consistent with its interpretation in urban risk literature (e.g., Zhao et al. (2017), Balk et al. (2018), Marzi et al., 2019; Opach et al., 2020).*** *Residential population significantly influences the exposure to natural hazards, determined not only by the higher presence of people and housing, but also of infrastructure, production capacities, species or ecosystems, and other tangible human assets in places and settings that could be adversely affected by one or multiple hazards. Higher population not only increases the potential for human and property losses, but also complicates evacuation efforts, and strains emergency response resources (Zhao et al., 2017). The degree of urbanization is often used to classify areas into cities, urban areas, and rural areas based on criteria such as population density, concentration of human activities, and built environment (Balk et al., 2018; United Nations, 2018). Indeed, highly urbanized densely populated areas are more likely to experience greater damage, congestion, and strain on resources during emergencies. It affects the capacity for evacuation and accessibility to essential services, due to dense infrastructure, complex urban layouts and the potential for cascading failures in infrastructure (Kendra et al., 2008; Lall & Deichmann, 2012).*"

Finally, we agree that the EM-DAT database, while widely used in disaster impact research, includes only events that meet specific thresholds related to fatalities, affected population, or economic losses. As a result, many smaller-scale or localized events—especially those with significant but sub-threshold impacts—are not captured. This introduces a selection bias that limits the representativeness of EM-DAT for validating vulnerability patterns at finer spatial scales.

We also acknowledge the editor's important point regarding scale mismatch: using national- or regional-level impact indicators to validate local-level archetypes risks overlooking local heterogeneity in vulnerability and resilience. While our current approach integrates spatially disaggregated socio-environmental data to define vulnerability profiles, the lack of corresponding fine-scale impact data (e.g., damage, recovery) limits the possibility for direct validation of these profiles against observed disaster outcomes. To address this, we have modified the paragraph in the discussion section highlighting the limitations of using large-scale impact databases like EM-DAT for local archetype validation. We also emphasize the need for improved access to high-resolution, georeferenced impact datasets, and we note that future work could benefit from collaboration with local stakeholders or municipalities to validate archetype-specific vulnerability profiles through qualitative insights or case study-based impact observations. The modified text (line 810) is reported following (added text is reported in bold):

"*Empirical validity in archetype analysis is commonly supported through various means, including stakeholder surveys (Nagel et al., 2024), the integration of diverse data sources at different spatial resolutions, and cross-comparisons of archetyping approaches across spatial and thematic scales (Diogo et al., 2023). It may also be demonstrated through consistency with prior empirical observations or theoretical expectations (Bilalova et al., 2025). However, validating archetypes' vulnerability profiles against observed impacts or risk outcomes* ***remains challenging. For example, many historical impact datasets—such as those from EM-DAT—are available only at national or regional levels and include only events meeting specific severity criteria. As a result, they often exclude smaller-scale, yet locally significant, events, introducing both a selection bias and a scale mismatch that limit their utility for validating local-level archetypes.*** *Furthermore, expected impact outputs from risk assessments are typically model-driven, emphasizing hazard intensity and physical exposure, while* *often overlooking the broader dimensions of vulnerability (Cardona et al., 2012). These limitations highlight the need for improved access to fine-grained, georeferenced impact data and the potential value of complementing quantitative validation with qualitative or stakeholder-informed insights at the local level."*

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