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., 2003; 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)****. 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, 2012; 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.

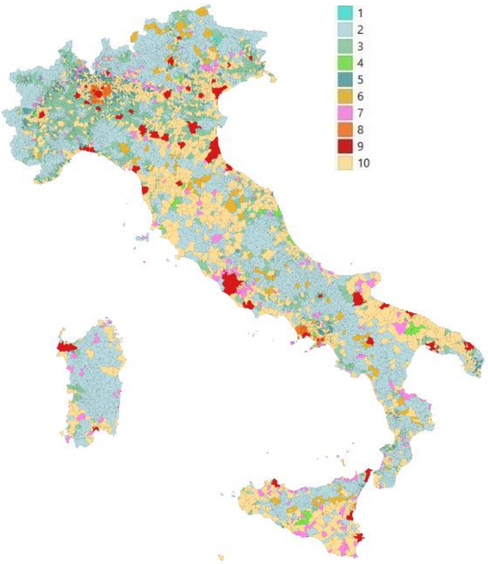
Response: Thanks for this comment. The following key points raised have been addressed: (i) the reorganization of the materials, methods, and results sections; (ii) the modifications of colors in Figure 9.

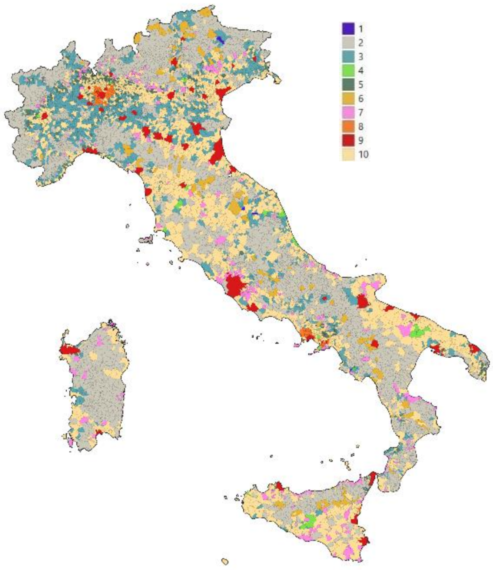
(i) The Methods and Results sections have been clearly distinguished in the revised manuscript. Specifically, the former subsection titled "*Clustering based on demographic and geographic features*" has been updated as section and renamed to "*First-level analysis: clustering based on physical and institutional 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, validation of archetypes' vulnerability profiles with observed impacts or risk analysis outcomes is often hard since (i) many historical impact datasets (such as those from EM-DAT) are only available at national or regional scales, limiting their usefulness for local-level archetype validation; (ii) expected impact results from risk assessments often rely on models that focus on physical exposure and hazard intensity, while frequently neglecting other vulnerability dimensions *(Cardona et al., 2012)***. For instance, social and institutional vulnerabilities - such as aging populations, poverty, and limited access to services - are often overlooked in standard risk models, despite their significant role in influencing disaster outcomes. These factors can delay emergency responses, worsen health impacts, and hinder recovery, ultimately amplifying both direct and indirect losses (Cutter et al., 2003; Cardona et al., 2012; Marin-Ferrer et al., 2017). 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.*

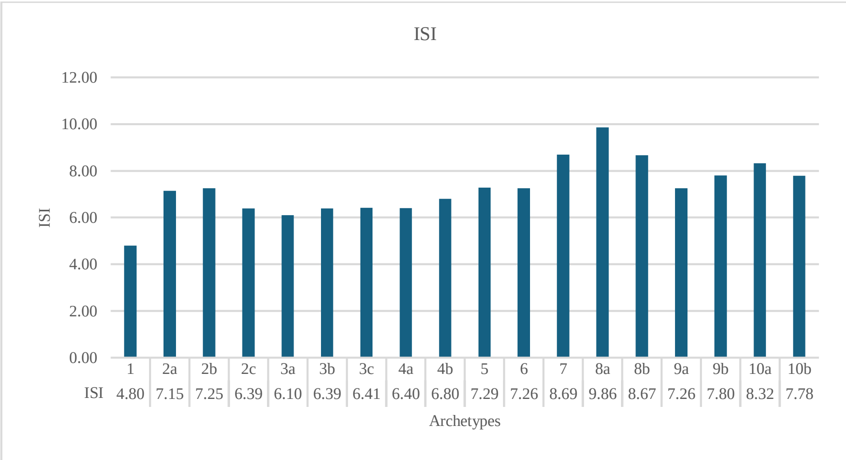


Figure 10 – Average ISI value for each archetype.

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.

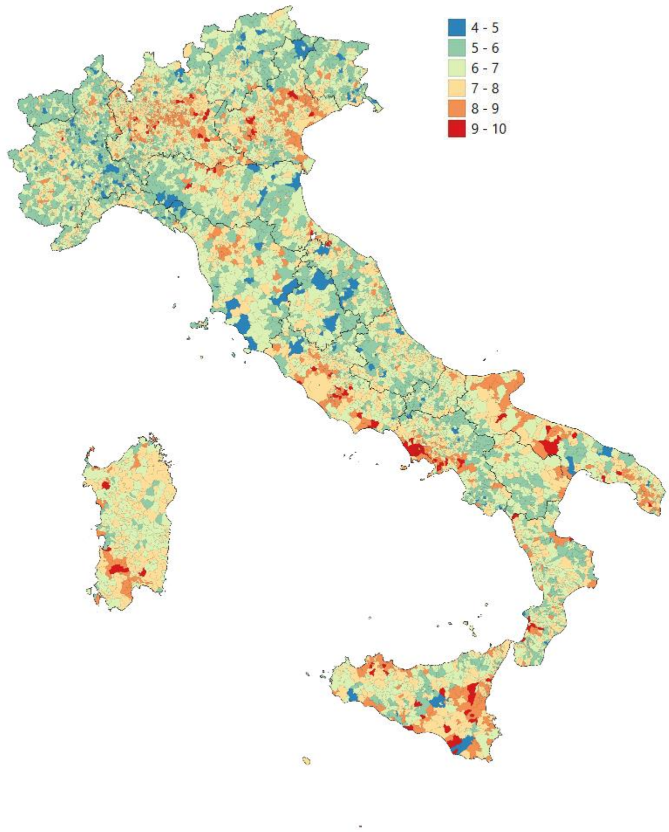


Figure 11 - Map of ISI value at municipal level.

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.

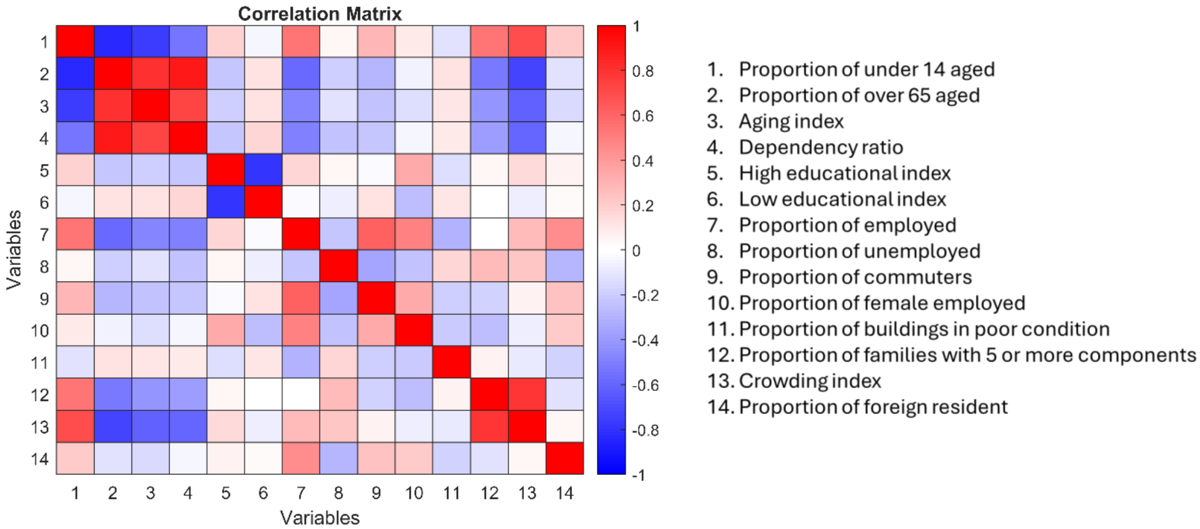
Response: Thanks for this comment. It was a typo. In Line 526 the correct reference is to cluster 2. It has been corrected in the new version of the paper.

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.



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.

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