

<https://doi.org/10.1038/s42949-025-00233-9>

# Disparities of urban morphology effects on compound natural risks: a multiscale study across the USA

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Multiple natural hazards stem from interactions within social-ecological systems. Understanding the associations between hazard risks and urban environments is crucial for developing climate mitigation and adaptation strategies. Here, we adopt multilevel regression models to investigate the effects of urban morphologies on the compound risk of natural hazards, leveraging extensive datasets across 3031 counties and 68,623 census tracts in the USA. Results demonstrate that concentrated development does not inherently increase disaster risk while partially validating the efficacy of open space management. The interaction analysis further reveals that disaster risks are significantly intensified in densely populated areas proximate to city centers. Connecting dense buildings with transportation routes can enhance the effectiveness of hazard mitigation. Our findings highlight the societal needs for integrating urban design at various spatial scales for enhancing urban resilience to disasters. The spatial variations observed in the urban morphology effects on compound natural risks have significant implications for formulating context-specific risk mitigation and adaptation strategies.

Climate change and global warming have considerably increased the risks of multiple natural hazards, leading to an uncertain future with rising concerns about the substantial economic losses and irreversible social consequences<sup>1,2</sup>. In particular, rapid urban sprawl in developing regions has brought larger populations and more civil infrastructure to hazard-prone areas and unplanned settlements (such as coastal regions and earthquake-prone areas)<sup>1,3</sup>. The realization of sustainable development goals is therefore challenging due to the unequal frequency, intensity, and consequences of multiple natural hazards in the changing climate<sup>1,2,4</sup>. According to the United Nations Framework Convention on Climate Change (UNFCCC), climate extremes are intensifying global inequalities and threatening sustainable development, with rising costs without intervention<sup>5</sup>. Thus, it is vital to investigate the compound risks of multiple natural hazards for developing mitigation and adaptation strategies and reducing economic losses from these hazards<sup>1,4</sup>.

The paradigm of hazard modeling has transformed from natural determinism to a complex socio-ecological system (SES) framework, emphasizing interactions between human and environmental drivers of disaster losses<sup>6–8</sup>. The world is vulnerable to multiple natural hazards, for instance, floodings, landslides, tsunamis, hurricanes, heat waves, and so on. However, compound natural risks are growing faster than our efforts to build resilience<sup>4,9</sup>. Nature-based solutions (NBS), as an ecosystem

intervention approach to reducing risks and fostering human-nature interaction, signify a shift from reactive infrastructure-centric disaster risk reduction (DRR) to the proactive ecosystem-based framework in which morphological indicators play a critical role in moderating hazard exposure<sup>10–12</sup>. Compound risk assessment examines interconnected hazard systems where disasters interact with socio-ecological vulnerabilities<sup>13</sup>. This framework employs complex systems methodologies to quantify emergent losses that exceed projections based on the business-as-usual (BAU) pathway<sup>1</sup>. Compound natural risk assessment considers the presence of multiple hazards, which mainly focuses on evaluating hazard-induced losses (from economic, ecological, social, and so on)<sup>1,14</sup>. Urban morphology refers to the form and structure of urban environments, considering both physical forms and social conditions<sup>8</sup>. Urban morphology plays a critical role in shaping spatial disparities in disaster risks, affecting urban heat islands<sup>15–17</sup>, air pollution<sup>18,19</sup>, and extreme climate events<sup>20,21</sup>. Thus, it is crucial to explore what urban morphological constituents (for example, compact buildings, open arrangement, and mixed land uses) are associated with higher hazard risks and how urban morphological configurations can mitigate hazard-induced loss<sup>7</sup>.

Growing attention focuses on urban morphology and climate disasters, particularly examining the driving factors<sup>6,22</sup> and physical consequences for specific hazards<sup>23</sup>. Previous studies have suggested that compact buildings

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with dense populations will intensify heat wave risks and inconvenient earthquake evacuation<sup>24–26</sup>. Studies also reported the notable impact of natural lands on mitigating urban heat island effects and flooding events<sup>11,15,27</sup>. However, previous studies mainly focus on specific observed records in limited cases due to data availability and may not be generalizable to other types of hazards and regions<sup>21,28</sup>. Urban morphological interventions present an inherent trade-off, whereby structural adaptations that enhance resistance to certain hazards may inadvertently increase exposure to different hazards<sup>29</sup>. The prevalence of multiple hazards in urban environments renders isolated hazard analysis inadequate for building a resilient future<sup>8,30</sup>. On the one hand, there remains a lack of consensus about the nexus between urban morphologies and risk patterns within multi-hazard environments<sup>9,30–32</sup>. Of particular importance is comprehending the interplays of urban morphology-hazard within the context of compound hazard rather than a specific hazard. On the other hand, previous studies emphasize localized physical forms while neglecting regional contexts<sup>20,21</sup>. Recent findings have highlighted a significant gap between climate disasters and adaptations across varying social groups<sup>9,30</sup>. Their works link disaster risks to social variations, demonstrating that disparities in hazard-induced losses stem from socio-ecological interactions beyond physical factors<sup>9,30</sup>. Thus, it is crucial to consider both localized forms and regional contexts in compound risk assessment frameworks.

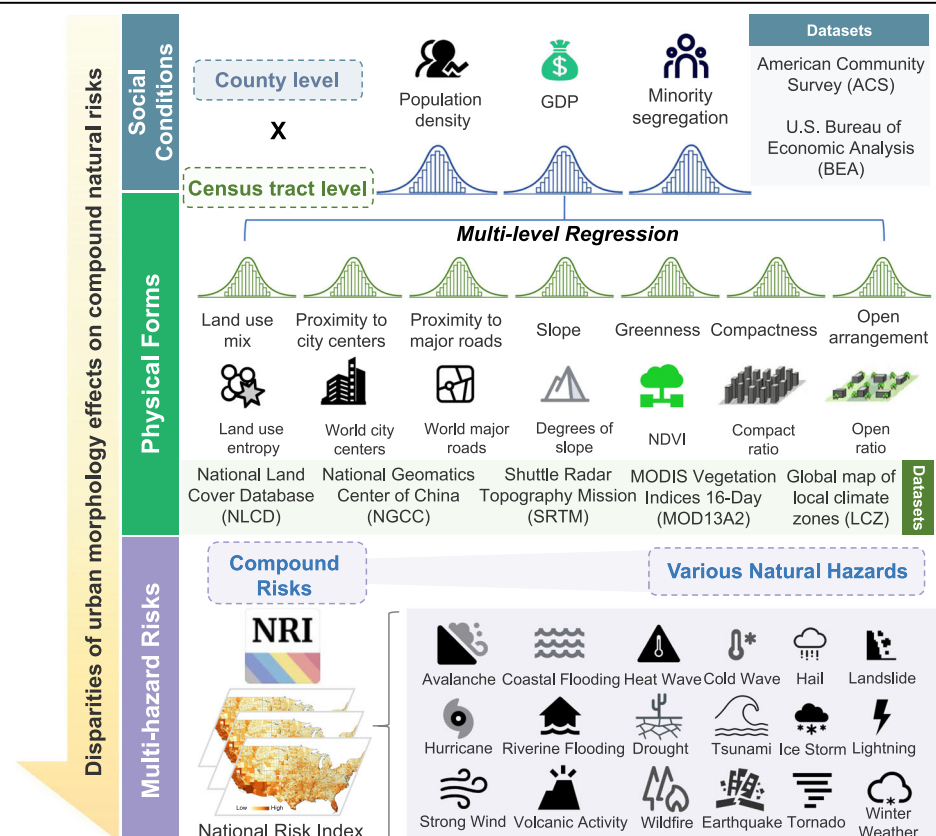
The United States experiences a wide range of natural disasters, including hurricanes<sup>33</sup>, floodings<sup>21,33,34</sup>, drought<sup>35,36</sup>, wildfires<sup>37–39</sup>, and tornadoes<sup>40</sup>, with different regions exposed to distinct hazards due to the geographic and environmental diversity. The increasing frequency and severity of these events, driven by urbanization and the escalating impacts of climate change, pose significant challenges to community resilience and the sustainability of critical infrastructure<sup>7,9</sup>. The comprehensive and openly accessible US databases, such as National Oceanic and Atmospheric Administration (NOAA) Storm Events Database, the Disaster Declarations and National Risk Index from Federal Emergency Management Agency

(FEMA), offer large and credible disaster records, establishing the United States as an exceptionally data-rich environment for studying the inter-connections between urban form and disaster vulnerability. The United States Geological Survey (USGS) provides critical geospatial data for terrain and urban morphology analysis, including slope derived from high-resolution Digital Elevation Models (DEM), land use and land cover (LULC) information from the National Land Cover Database (NLCD), and Normalized Difference Vegetation Index (NDVI) data obtained through satellite imagery such as Landsat and MODIS. On the contrary, developing countries often lack systematic disaster databases or high-resolution geospatial data, as indicated by the United Nations Office for Disaster Risk Reduction (UNDRR)<sup>41</sup>. While hazard-related studies in the US have leveraged a comprehensive database on risk management, localized urban morphology, and socioeconomic context, gaps remain in understanding long-term compound disaster impacts and localized climate mitigation strategies<sup>13,42–44</sup>.

Given the above, this research empirically verifies the relationship between hazard impacts and urban environments, integrating detailed information across multiple scales. Three research questions guide this investigation: (1) What spatial patterns can be observed in compound natural risks across the conterminous United States (CONUS)? (2) What are the associations existing between compound natural risks and urban morphologies across local and regional scales? And (3) How to understand the disparities of urban morphology effects on compound natural risks?

To address these questions, we adopt multiscale analysis to investigate the effects of local and regional urban morphologies on compound natural risks, examining the interaction effects and the spatial heterogeneity of urban morphologies (Fig. 1). We first examine the spatial inequality of compound risks using spatial Gini index (SGI) at the county level, identifying notable variations across different social conditions. What socio-ecological interactions have generated and reinforced these inequalities? Subsequently, we analyze the associations between urban morphologies and compound risks, by considering seven census tract-level physical forms (i.e.,

**Fig. 1 | The overall research framework.** Research framework examining how urban morphological features are related to multiple natural hazards across 3031 counties and 68,623 census tracts in the USA.



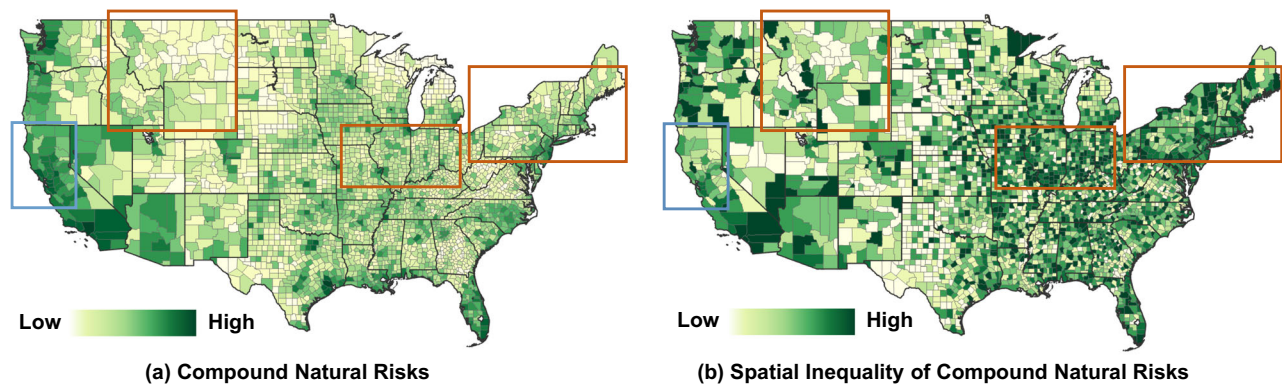
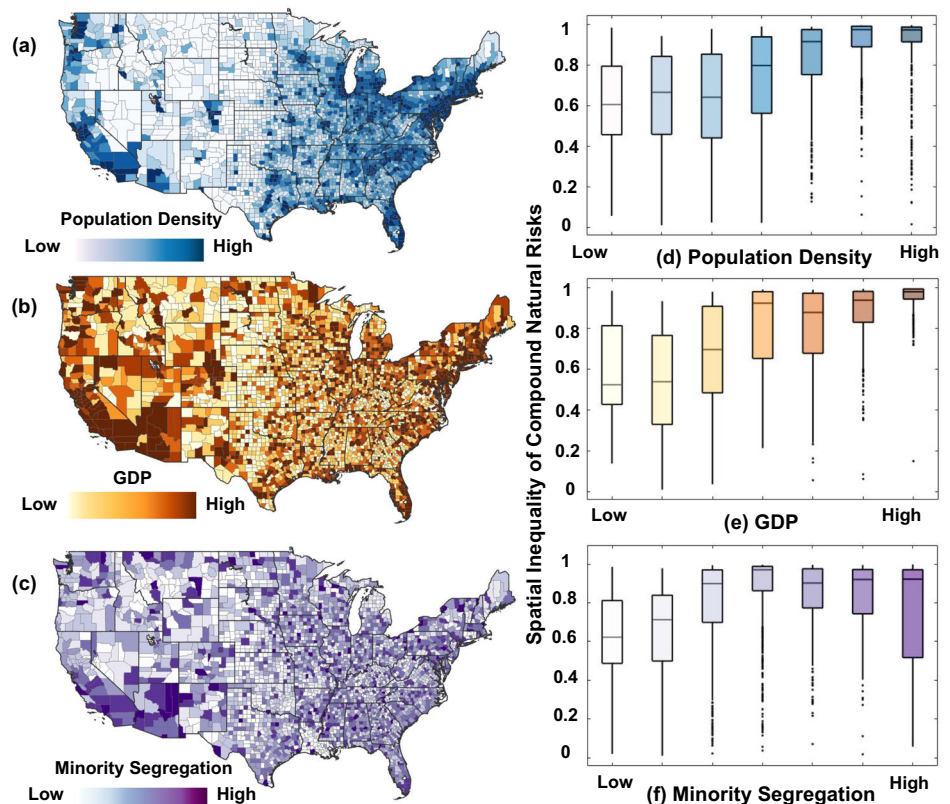


**Fig. 2 | Compound natural risks and spatial inequality across US counties, highlighting regions with contrasting risk and inequality levels.** The extent of compound natural risks among US counties. Compound natural risk is characterized by the annual expected loss in each county, considering building, population, and agriculture consequences for all 18 natural hazard types. **a** Measures the national rank of the total risk of a region, compounding 18 natural hazards. **a** Employs a light-to-

dark (lower-to-higher) green gradient indicating the range of compound natural risk across CONUS; **b** uses a light-to-dark (lower-to-higher) green gradient indicating the range of the SGI across CONUS. Regions delineated with orange borders highlight areas characterized by low risk but high spatial inequality, while blue-bordered regions indicate areas of high risk but relatively low spatial inequality.

**Fig. 3 | Regional social conditions and associated SGI disparities across US counties.** The extent of regional population density, **b** GDP, and **c** minority segregation among US counties, and disparities of corresponding SGI **d–f** across social condition categories in US counties. Visualization employs monotonic color gradients for each variable pair: light to dark blue for population density (**a**, **d**); light to dark orange for GDP (**b**, **e**); light to dark purple for minority segregation (**c**, **f**).



land use mix, proximity to city centers, proximity to major roads, slope, greenness, compactness, and open arrangement) and three county-level social indicators (i.e., population density, gross domestic product, and minority segregation, the separation of racial minority groups from the majority population). Details about the variables can be found in Supplementary Table 1. Using multilevel regression models (MRMs) for hierarchically clustered data, we further examine the interactions and the spatial heterogeneity of the morphology effects. The multiscale analysis shows the disparities of urban morphologies, especially densities and proximities, on the compound risks of natural hazards. Our findings provide some insights into the role of local conditions in hazard assessment and prompt further exploration of resilient planning in the context of compound risk.

Disparities in urban morphology effects are found to have significant implications on compound natural risks, contributing to developing context-specific risk reduction initiatives.

## Results

### Spatial inequality of compound natural risks

To investigate the spatial inequality of compound natural risks, the SGI was calculated based on the NRI (see “Methods” for details). Figure 2a suggests that some counties on the west coast, Arizona and Florida, seem to be exposed to higher compound natural risk, compared to other counties in the nation. Figure 2b suggests that a high spatial inequality pattern can be found across the US counties, indicating that the compound risks of climate

**Table 1 | The multilevel regression results**

| Variables                                      | Model 1                | Model 2                | Model 3                | Model 4                |
|------------------------------------------------|------------------------|------------------------|------------------------|------------------------|
| <i>Census tract level variables</i>            |                        |                        |                        |                        |
| Land use entropy                               | 0.0286***<br>(0.0010)  | 0.0139***<br>(0.0007)  | 0.0137***<br>(0.0007)  | 0.0134***<br>(0.0006)  |
| Proximity to city centers                      | 0.0398***<br>(0.0018)  | 0.0474***<br>(0.0040)  | 0.0423***<br>(0.0041)  | 0.0176***<br>(0.0039)  |
| Proximity to major roads                       | 0.0909***<br>(0.0029)  | 0.0516***<br>(0.0044)  | 0.0524***<br>(0.0044)  | 0.0489***<br>(0.0043)  |
| Slope                                          | 0.0718***<br>(0.0037)  | 0.0224***<br>(0.0030)  | -0.0216<br>(0.0030)    | 0.0226***<br>(0.0030)  |
| Greenness                                      | -0.0056***<br>(0.0014) | 0.0212***<br>(0.0014)  | -0.0181***<br>(0.0014) | 0.0225***<br>(0.0015)  |
| Compactness                                    | 0.0056***<br>(0.0020)  | -0.0126***<br>(0.0013) | -0.0081**<br>(0.0013)  | -0.0093***<br>(0.0015) |
| Openness                                       | -0.0006<br>(0.0008)    | -0.0145***<br>(0.0006) | -0.0151***<br>(0.0006) | -0.0156***<br>(0.0006) |
| <i>County-level variables</i>                  |                        |                        |                        |                        |
| Minority segregation                           |                        | -0.0427***<br>(0.0072) | -0.0438***<br>(0.0072) | -0.0227***<br>(0.0057) |
| Population density                             |                        | -0.1783***<br>(0.0483) | -0.1922***<br>(0.0484) | -0.0400<br>(0.0366)    |
| GDP                                            |                        | 0.0544*<br>(0.0328)    | 0.0538<br>(0.0328)     | 0.0252<br>(0.0248)     |
| <i>Cross-level interactions</i>                |                        |                        |                        |                        |
| Population density × Proximity to city centers |                        |                        | 1.0998***<br>(0.1940)  | 1.2297***<br>(0.1930)  |
| Compactness × Proximity to major roads         |                        |                        | -0.1784***<br>(0.0249) | -0.1729***<br>(0.0250) |
| Intercept                                      | 0.1913***<br>(0.0027)  | 0.1876***<br>(0.0026)  | 0.1913***<br>(0.0027)  | 0.1722***<br>(0.0061)  |
| Log likelihood ↑                               | 83383.74               | 117340.9               | 117386.1               | 118185.54              |
| AIC ↓                                          | -166749.5              | -234655.8              | -234742.3              | -236245.1              |
| BIC ↓                                          | -166667.3              | -234537                | -234605.2              | -235669.5              |
| Degree of freedom                              | 9                      | 12                     | 15                     | 63                     |

Notes: (1) Standard errors in parentheses.

(2) \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

disasters are not uniformly distributed. Specifically, the high compound natural risks shown in Fig. 2b, such as counties in California, are not consistently linked to spatial inequality (highlighted areas with blue borders). In contrast, some counties in the northwestern region, the midwestern region, and the northeastern region have a relatively high SGI. Yet, they have lower compound risks (highlighted areas with orange borders).

Counties were categorized by social conditions (minority segregation, population density, and GDP, ranging from low to high) to analyze the spatial inequality of compound risks. Notable variations in spatial inequality patterns were found within different social conditions, with some counties in specific conditions demonstrating higher spatial inequality than others. Meanwhile, social condition factors vary substantially from state to state, most prominently in terms of population density. To be specific, densely populated counties suggest higher SGI than counties with relatively low population density (Fig. 3a). Likewise, economically advanced counties show higher SGI than counties with lower economic bases (Fig. 3b). In addition, counties with notable minority segregation appear to display elevated and uneven distribution of compound natural risks (Fig. 3c). It is

noted that some counties with high SGI are located in densely populated, economically robust, minority segregated regions, highlighting the importance of incorporating regional contexts into hazard assessment frameworks.

### Disparities of urban morphological effects on compound natural risks

The multilevel regression results for single-level and cross-level interactions are presented in Table 1. We implemented multiscale analysis based on the hierarchical structure in the dataset. The descriptive statistics of normalized variables in MRMs are shown in Supplementary Table 2. Model 1 at the census tract level is regarded as a baseline model and only includes physical form variables. The coefficients indicate the extent to which considerably increasing this variable alters the level of compound natural risk (risk value was standardized to between 0 and 1). All physical form variables in the single-level regression model, excluding open arrangement, exhibit statistically significant effects ( $p < 0.01$ ) on compound natural risks. The compound risk would exceed or fall behind the percentile of all counties within

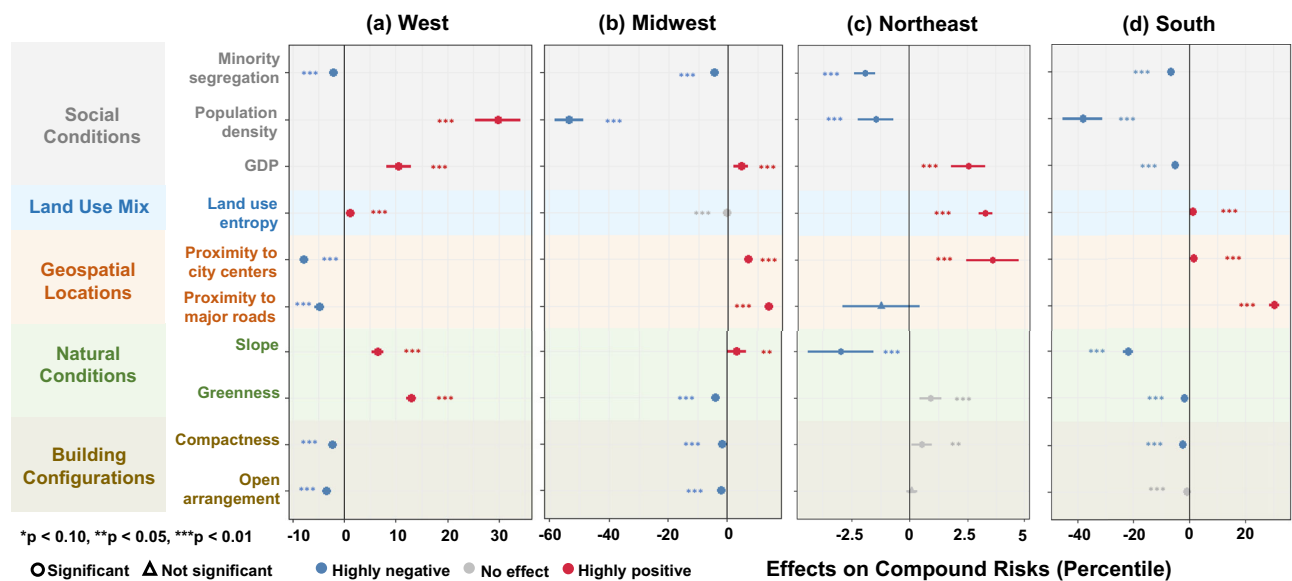


**Fig. 4 | Urban morphological effects on compound natural risks across US Census divisions.** Regional variations of urban morphological effects on compound natural risks across US Census divisions: **a** West, **b** Midwest, **c** Northeast, and **d** South. The Census divisions are from the US Census Bureau; see details in Supplementary Fig. 1.

Percentile-based effects show risk shifts in response to variable increases. Blue/red indicates hazard mitigation/proneness. Circles show significant effects ( $p < 0.1^*$ ,  $p < 0.05^{**}$ ,  $p < 0.01^{***}$ ), triangles show non-significant effects. Error bars represent standard errors.

10 percentiles if a specific morphological feature is considerably increased. The negative effect of greenness is significant in the baseline model, while other physical forms appear to have significantly positive effects on compound risks ( $p < 0.01$ ). The negative association between greenness and compound risks implies that the former serves as a net abator for the latter in the US context, whereas other physical form variables may fuel the increase in compound risks.

Cross-level Model 2 incorporated both physical form variables and social condition variables. The addition of regional contexts significantly improved the model's performance and enhanced the model's explanatory power, as evidenced by a decrease in AIC and BIC values and an increase in log-likelihood. When social condition variables are included, the negative impact of population density becomes significant. As shown in Table 1, density-related variables (i.e., population density and compactness) yield negative associations with compound risks, whereas the proximity variables (i.e., proximity to city centers and proximity to major roads) exhibit positive relations. Specifically, we found evidence that accounting for group-level factors can reduce unexplained variance, making the individual-level effect of open arrangement clearer and potentially significant.

As urban environments embody a confluence of various conditions, exploring the interactions among different morphological characteristics can reveal underlying mechanisms of the uneven distribution of compound risks<sup>43</sup>. Model 3 reveals two distinct interaction patterns of urban morphological features. The first interaction term captures the moderating effect of population density on the relationship between distance to the city center and compound risks. The second interaction term reflects how the spatial configuration of compactness interacts with proximity to major roads to influence compound risks. The significant synergistic interaction ( $\beta = 1.0998$ ,  $p < 0.01$ ) between population density and proximity to city centers indicates that the hazard-mitigating effects of population density are attenuated in areas proximate to city centers. On the other hand, we observed the significant antagonistic interaction ( $\beta = -0.1784$ ,  $p < 0.01$ ) between compactness and proximity to major roads, which suggests that the hazard-mitigating impacts of compactness are intensified in areas proximate to major roads. Interactions between density and proximity variables can substantially intensify or mitigate compound natural risks (even more than 100 percentiles), while individual morphology exhibits a significant yet subtle impact (within 10 percentiles).

Due to the strong spatial heterogeneity across the United States (such as regional policies and climate zone differences), Model 4 is further refined by incorporating state-level fixed effects. State-level fixed effects control systematic state-level heterogeneity, including differences in policies and economic conditions, allowing estimates to capture only within-state variation. The coefficients for county-level variables show marked changes, while census tract-level coefficients remain largely consistent, compared with Model 3. The inclusion of state-fixed effects removes the inter-state variations, leaving only the within-state variation to explain the effect of population density, rendering its coefficient insignificant (Column 4, Table 1). The model exhibited enhanced explanatory power after the state fixed effects were introduced, as indicated by improved log-likelihood and decreased AIC and BIC values.

### Spatial heterogeneity of the effects on compound natural risks

Spatial variations in socioeconomic and environmental conditions influence how urban morphologies relate to compound natural risks<sup>1</sup>. We further analyzed how the effects of urban morphology on disaster risks vary across geographic locations. Model 3 was selected as it retains the state-level variation within shared geographic regions, representing substantial differences in cultural, economic, and geographical characteristics. The morphology effects shown in Fig. 4 measure the shifts in risk percentiles across census tracts in response to significant variable increases. Population density is essential in either intensifying or mitigating compound natural risks with regional variance. In the western US, population density is regarded as the principal risk determinant, elevating risk levels by around 30 percentiles and accompanied by positive GDP correlations with risks—patterns that are opposite in trend across other regions (Fig. 4a). The western region is also characterized by high and significant spatial variations in compound natural risks according to Fig. 2. Thus, the positive impacts of population density and GDP can be explained by the concentrated assets and increased development in hazard-prone areas<sup>37,45</sup>. Proximity to major roads increases risk levels in the midwestern and southern US, potentially by more than 20 percentiles in southern regions; however, the effect is opposite in regions such as the northeastern US or West Coast (Fig. 4). This aligns with historical transportation routes and river corridors in flood-prone regions<sup>46–49</sup>. Increased greenness may relate to elevated compound natural risks in western areas while mitigating risks in other regions. Seasonal drought stress

on plants and strong winds in California may fuel wildfires and increase landslides, exacerbating disaster risks in the western US<sup>50</sup>. In most regions, the individual effects of minority segregation, land use mix, compactness, and open arrangement demonstrate a marginal influence, indicating slight shifts in risk levels. In the northeastern US, urban morphology factors appear to have subtler impacts on risk levels, ranging within 5 percentiles compared to other regions.

## Discussion

Urban environments are characterized by inherent disparities in both physical morphologies and social conditions, and spatial inequality is not inevitable<sup>51</sup>. Developing effective mitigation strategies requires a multi-hazard framework, as the influences of human activities on natural processes continue to intensify, creating complex relationships between various risk factors<sup>13,52</sup>. This study provides empirical evidence for integrating urban design at multiple spatial scales to enhance urban resilience to compound natural risks, utilizing abundant datasets across the United States. The variables examined in this study are verified to have no multicollinearity. It is generally accepted that VIF values exceeding 10 conventionally indicate substantial multicollinearity. As shown in Supplementary Table 3, all VIF values were found to be less than 3, indicating that the developed multilevel regression model is statistically robust and reliable. In addition, the observed ICC of 67% indicates that substantial variations of compound natural risks among counties can be attributed to regional effects. We therefore developed multilevel regression models based on hierarchically structured data. The flexibility of multiscale analysis enables broader applications to hierarchical hazard datasets. Our findings indicate that integrating regional contexts and the state-level fixed effects improves the statistical robustness of the MRMs, as evidenced by decreases in AIC and BIC values and an increase in log-likelihood shown in Table 1. The model is further enhanced by isolating and decomposing state-level confounding factors, thereby enabling a more comprehensive investigation of how urban morphological effects interact across spatial scales. Since there are substantial spatial variations in the estimated morphology-risk relationship, the following discussion focuses on how planning strategies for resilience enhancement should be tailored to specific local geographical settings.

As cities confront escalating challenges from multiple natural hazards, there is a mounting imperative to examine what configurations of urban environments predispose areas to disasters. Specifically, multilevel regression results indicate the hazard-mitigating effects of density-related variables (i.e., population density and compactness) and openness. Previous studies show that compact spaces have a dual effect on disaster risks<sup>53–55</sup>. Our findings align with the view that concentrated development can be a resilient urban pattern for climate change in specific contexts, and does not inherently increase disaster risk, given robust prevention systems and locational advantages relative to hazard-prone zones<sup>43</sup>. Additionally, the hazard-mitigating effect of open-space arrangement aligns with previous research, suggesting that open spaces act as natural buffers and provide areas for mitigation and recovery, thus enhancing resilience to risks across scales<sup>43,56</sup>. The effect of population density derives substantial explanatory power from interstate variation when the state-level fixed effects are omitted. As the analysis narrows to the localized scale and the relevance of population density declines, disaster risk at the local level is more directly affected by urban morphological variables (e.g., land use, building configuration, topography, and location). Our results reveal the risk-amplifying effect of proximity to major roads, which partly confirms the association between transportation infrastructure and elevated compound risks, supporting the findings drawn from previous studies<sup>21,52,57</sup>. Car-centric urban planning has shaped many communities, resulting in concentrated development along major transportation corridors in the United States. This type of spatial pattern creates disaster vulnerability through increased exposure of populations and infrastructure while simultaneously generating critical dependence on transportation systems that could fail during emergencies. The vulnerability becomes most pronounced in disaster-prone regions, such as tornado corridors throughout the South and Midwest, hurricane-

susceptible coastal areas, and flood-prone inland regions along major roadways (Fig. 4b, d). These areas face heightened risk due to the intersection of natural hazards with vulnerable development patterns and transportation dependencies<sup>52</sup>. Our findings further demonstrate that slope and greenness exacerbate hazard risks under similar broader environmental conditions across the state (Table 1), with particularly pronounced effects observed in the western region (Fig. 4a). Steep slopes and abundant vegetation in the western US exacerbate natural hazards by intensifying landslides, wildfire spread, and runoff, while vegetation loss further destabilizes slopes and increases erosion risks<sup>37–39</sup>. High-risk areas, such as California and the Pacific Northwest (Fig. 2), are consistently characterized by dense populations and concentrated economic activities (Fig. 3). Figure 4a further reveals that regions with high population density in the western United States are exposed to significantly greater risks compared to sparsely populated areas, providing strong evidence for the assertion that urbanization in hazard-prone zones intensifies disaster-related losses<sup>58</sup>.

The interaction analysis highlights the critical importance of analyzing morphological features as an integrated system rather than as discrete features<sup>43</sup>. The density-proximity interactions suggest significant synergistic and antagonistic effects on compound natural risks. Disaster risks are significantly intensified in densely populated areas proximate to city centers, although population density as an independent factor does not necessarily signify increased risk (Table 1). Major roads often connect densely populated cities or suburbs and are key hubs for transportation and logistics in the United States. However, the proximity of these regions to primary transportation arteries potentially amplifies hazard exposure due to the tendency toward concentrated development patterns along transportation corridors, encompassing residential, commercial, and industrial land use typologies. When acute hazard events, including but not limited to hurricanes, flooding, and tornados occur in these transportation-adjacent zones, populated concentrations frequently experience disproportionate economic impacts and more substantial losses to both human life and material assets<sup>52,57</sup>. The spatial interplay between transportation networks, built-up density, and disaster susceptibility emerges as a pivotal concern within modern hazard mitigation protocols and urban resilience conceptualizations<sup>44,57,59</sup>. Empirical evidence indicated by Table 1 also suggests several policy implications for implementing optimal demographic arrangements and urban planning initiatives that mitigate population concentration in hazard-prone city centers. The compact configuration of urban centers enhances resilience by promoting efficient resource utilization and facilitating effective emergency response, thereby partially mitigating the elevated risks associated with proximity to the city center<sup>55</sup>. The interaction analysis partly confirms the effectiveness of concentrated development in building a resilient city<sup>55,60</sup> and further demonstrates that complementing it with proximity to major roads can reinforce their impacts. The interaction effect of cross-level urban morphologies can be further extended to comprehend the integrated urban systems in future studies.

The observed differences in magnitude, direction, or statistical significance between Model 3 and Model 4 in Table 1 emphasize that the scale of analysis matters when exploring the relationship between urban environments and disaster risks. To disentangle this, we further decompose county-level social conditions into their within-state and between-state components, as shown in Supplementary Fig. 2. The retained county-level random intercepts further account for residual spatial heterogeneity within states, ensuring robustness in multi-level inference. Supplementary Fig. 2b indicates that states characterized by heightened population density and elevated GDP demonstrate pronounced associations with high compound risks, which is attributed to the confluence of geographic vulnerability, economic development, and social complexities. Based on our findings, this association is particularly evident in such states as California, Florida, and Texas, where high risks coincide with concentrated demographic distributions and substantial accumulations of financial and infrastructural assets. Besides, states with advanced economic development may possess higher-risk territories (including coastal zones or flood-susceptible areas) as a consequence of accelerated urbanization and industrial expansion<sup>33,54</sup>.

Within states, localities characterized by elevated GDP and population density (exemplified by prosperous urban centers) are expected to develop more sophisticated infrastructure (including drainage systems and flood mitigation structures) and enhanced disaster-resilient resources, thus mitigating disaster losses (Supplementary Fig. 2). Economically advanced regions within states generally demonstrate superior disaster response capabilities and may circumvent development in high-risk zones through more comprehensive land use planning strategies<sup>7</sup>. The decomposition mitigates bias from unobserved state-level confounders and clarifies whether the effects of variables operate predominantly through macro-scale (state) or micro-scale (county) pathways.

The mechanisms and pathways of the historically severe and costliest hazards were further examined to empirically verify whether the selected variables are universally applicable across different disaster types or if certain variables exhibit greater explanatory power for specific disaster categories. As evidenced by Supplementary Fig. 3a, proximity to major roads and higher levels of greenness are significantly associated with increased hurricane risk. Proximity to major roads likely reflects higher exposure due to the concentration of infrastructure and economic activities in these areas, which are often hubs of human settlement and development<sup>52</sup>. Similarly, areas with higher greenness may coincide with regions closer to coastal zones or low-lying areas prone to hurricane impacts<sup>61</sup>. In contrast, steeper slopes that are associated with reduced hurricane and tornado risk, possibly due to their higher elevation, tend to be further from flood-prone coastal areas and less susceptible to storm surges<sup>62</sup>. However, steeper terrains also amplify the speed and intensity of fire spread, making them particularly dangerous in fire-prone areas<sup>38</sup> (over 20 percentiles in Supplementary Fig. 3). The localized destruction caused by tornadoes makes areas with high land-use diversity, dense building concentrations, and open spaces more prone to tornado risks (Supplementary Fig. 3). These morphological factors increase both the physical exposure to tornado paths and the potential for substantial damage in affected areas. For instance, urban cores in states like Oklahoma and Texas, characterized by dense buildings and high levels of economic activity, are more susceptible to severe impacts from tornadoes. The central and southern plains, designated as “Tornado Alley”, exhibit multiple land-use configurations alongside extensive topographical continuity, facilitating tornadic formation and intensification. High population density and concentrated residential development are associated with increased earthquake risk (Supplementary Fig. 3), as these factors amplify the potential for damage and casualties in densely built environments<sup>43,56</sup>. Economically robust regions may benefit from better infrastructure and advanced earthquake-resistant construction, reducing earthquake vulnerability (Supplementary Fig. 3). As a seismically active state, California has implemented strict construction standards and innovative practices that have played a significant role in mitigating the destructive impacts of earthquakes, demonstrating the efficacy of proactive risk management strategies in minimizing seismic-related losses. Significant state fixed effects of individual hazards suggest that policies or conditions in specific states are important for understanding these effects. This study yields a solid foundation for disaster risk management by simultaneously addressing the inherent complexities of disasters while facilitating targeted policy interventions tailored to specific disaster requirements.

Developing urban resilience to natural disasters requires attention to multiple dimensions of risk mitigation and adaptation initiatives operating across various interconnected urban domains and scales<sup>43,44,63</sup>. By incorporating environmental, social, and economic dimensions of sustainability, we can better understand how urban morphology relates to disaster risks and develop targeted climate adaptation strategies<sup>42,44</sup>. Although climate change presents a long-term and global challenge, strategic urban design could help transform these challenges into opportunities for risk reduction and sustainable urban development. Our findings suggest that strategically optimizing population distribution and promoting polycentric urban development can enhance regional resilience and sustainability. Strategic and context-specific urban morphology design may yield more climate resiliency than previously observed. At the macro level, resource allocation

across states should be optimized by ensuring equitable distribution of resources in resource-limited areas, while addressing concentration risks through balanced regional development and promoting growth in less disaster-prone areas<sup>9</sup>. At the micro level, local disaster resilience should be enhanced by developing robust infrastructure<sup>64</sup> and reducing exposure in high-density areas. As discussed, the physical urban forms and socioeconomic contexts that are vulnerable to specific types of hazards require targeted and sustainable management strategies, supported by policies designed specifically for high-risk regions.

As an initial attempt to employ an integrated perspective for understanding compound risks and urban environments, this study is constrained by several limitations. Although the variables adopted in this study are statistically robust based on multicollinearity criteria, incorporating additional variables may further enhance the model’s explanatory power. While the county-level random effect and the state-level fixed effect were introduced to control different types of variation or unobserved heterogeneity across scales, the proposed model may not fully account for all potential confounders that could impact the results. Our results highlight the importance of understanding the differences across states and suggest that further exploration of state-level factors (such as state-specific policies or socioeconomic conditions) could provide a broader insight into the mechanisms. However, the effectiveness of state-specific policies may also be influenced by such factors as the degree of implementation and public acceptance, which are challenging to fully capture. Besides, the multi-hazard data from FEMA was aggregated by hazard impacts over several years, precluding analysis of temporal trends and annual variations. This study focuses mainly on understanding the disparities of urban morphological effects on compound natural risks, and the responses of hazards to urban environments are therefore out of the scope of this study.

Our findings can be further extended in future studies on several fronts. First, future research could consider adopting more comprehensive urban morphology measures, such as the polycentric patterns, infrastructure quality, proximity to healthcare, and so on. Additionally, explicitly including confounders (such as policies, governance, and past hazard frequency) reduces the reliance on random effects or fixed effects to absorb unobserved variation, making the model more robust and interpretable. However, the differences in statewide policies and regulations are not explicitly considered in this study, leaving an important avenue for future exploration. For instance, variations in building standards, land-use planning, and disaster preparedness across states may explain the observed heterogeneity in compound natural risks. Future studies could introduce interaction terms to assess whether the effectiveness of statewide policies varies by factors such as population density or geographic conditions. Our findings could further be extended to a precise analysis of time-varying factors if more detailed temporal data on disaster losses or the historical disaster frequency become available. Future research could leverage advanced analytical approaches and include more confounding variables, enhancing the robustness and validity of the model.

## Methods

### Urban morphology measures

Urban morphologies in this study include census tract-level physical forms and county-level social conditions. Detailed data sources are presented in Supplementary Table 1. Previous studies have defined exposure and vulnerability as core drivers of disaster risk, highlighting the importance of social conditions (e.g., population density and social inequality) and the physical environment (e.g., topography, geospatial locations, land use, and building configurations)<sup>65</sup>. Physical forms at the local scale include building configuration, land use patterns, geographical locations, and landscape metrics, all of which are closely related to disaster risks reported in previous studies<sup>9,21,29,43</sup>. Building density and configuration represent significant determinants of disaster risks, where compact development patterns may reduce overall exposure while simultaneously exacerbating urban heat island effects<sup>29,43</sup>. Open space captures the spatial and environmental characteristics of cities and exerts substantial influence on disaster exposure,

mitigation, and the livability of constructed environments<sup>56</sup>. Proximity to city centers and major roads captures key aspects of physical accessibility, infrastructure connectivity, and socio-economic conditions, which are essential for understanding disaster risks<sup>44,52,57,59</sup>. Vegetation mitigates risk by reducing heat and buffering against wind and flooding; however, excessive vegetation can increase wildfire risks<sup>37,39</sup>. Slope and topographical metrics directly influence exposure levels to landslides, constituting critical variables in geomorphological risk assessment frameworks<sup>20</sup>. The diverse land use patterns can also moderate urban resilience to climate extremes<sup>7,34,43</sup>. These variables are representative of physical urban forms since they comprehensively capture the drivers of vulnerability, exposure, and resilience in urban environments.

To capture building configuration, we identified two typical building patterns (i.e., compact and open arrangement) based on the classification system of local climate zones<sup>66</sup>. Evidence suggests that diverse open space configurations enhance multi-hazard response capacity through shelter and evacuation functions, while compact forms with high population density exacerbate climate-related hazard impacts<sup>67,68</sup>. The proportion of compact urban cores (compact high-rise, compact mid-rise, and compact low-rise) and open arrangement buildings (open high-rise, open mid-rise, and open low-rise) was calculated for each census tract. Higher compactness or openness means more compact urban cores or open configuration in a tract.

We measured land use mix based on the US land use data derived from the latest epoch of the NLCD<sup>69</sup>. This dataset provides conterminous LULC extents at a 30-meter spatial resolution with 16 original classes, which were regrouped into 8 primary categories (i.e., developed, forest, shrubland, herbaceous, cultivated, wetland, bare land, and water). We measured the diversity of land use types within each census tract using the entropy index, shown as Eq. (1). The entropy value ranges from 0 to 1, with higher entropy value being higher land use mix level<sup>25,70–72</sup>.

$$\text{Entropy} = - \left( \left[ \sum_{j=1}^k p^j \ln p^j \right] \right) / \ln k \quad (1)$$

Where  $p^j$ , is the percentage of land use type  $j$  in the area and  $k$  is the total amount of land use types.

Geographical locations and traffic characteristics were further included to capture the influence of accessibility. The distributions of transportation networks and city centers were extracted from Open Street Map. We calculated the distances to major roads and the distances to city centers in the Euclidean distance. Slope was calculated based on the DEM data for terrain characteristics. We adopted the NDVI from Terra MODIS (MOD13A2) to indicate the proportion of greenness at the local scale.

Regional social conditions in this study at the regional level reflect the demographic, social, and economic developments. High-density and economic robust regions may have greater access to infrastructure and services, but they also face specific disaster risks<sup>6,33,58,64,73</sup>. Minority segregation reflects the spatial distribution of marginalized groups, indicating potential disparities in access to needed resources<sup>9,51</sup>. Regional contexts play crucial roles in influencing and shaping urban morphologies<sup>8</sup>. These factors are representative of social conditions since they capture key aspects of demographic distribution, economic capacity, and social inequality, which are critical determinants of community vulnerability and resilience to disasters<sup>43,51,65</sup>.

Population data and land area were obtained from the US Census Bureau (Details in Supplementary Table 1). County-level population density was calculated by dividing the total population by land area. County-level GDP data were obtained from the US Bureau of Economic Analysis.

Demographic data for minority segregation analysis were obtained from the 2020 US Census Bureau. This study examines three primary racial groups: non-Hispanic White, non-Hispanic Black, and non-Hispanic Asian residents. The selection of non-Hispanic populations aligns with previous studies, ensuring that the racial categories being analyzed (e.g., White, Black, Asian) remain mutually exclusive and minimizing overlap with ethnic categories<sup>9,19,21,74</sup>. The non-Hispanic Black and non-Hispanic Asian were classified as the minority population, and the non-Hispanic White was

classified as the reference population. The Dissimilarity Index (DI) was calculated to show the extent of minority segregation in each county. The DI is the commonly used measure of spatial segregation between two groups, indicating their relative distributions across neighborhoods within the same region<sup>75</sup>. DI (0 = evenness, 1 = separation) was calculated using tract-to-county minority population ratios<sup>76,77</sup>:

$$DI = \frac{1}{2} \sum_{i=1}^n \left| \frac{m_i}{M} - \frac{n_i}{N} \right| \quad (2)$$

Where  $m_i$  is the minority population in the smaller geographical unit;  $M$  is the minority population in the larger geographical unit.  $n_i$  is the reference population in the smaller geographical unit;  $N$  is the reference population in the larger geographical unit. In this study, the smaller geographical unit refers to the census tract, while the larger geographical unit refers to the county.

### Compound natural risks

The compound risks of natural hazards were calculated based on the NRI version 1.19 from FEMA, aggregating hazard impacts from 1996 to 2019<sup>78</sup>. The dataset quantifies census tract-level compound risks of climate extremes of 18 hazard types, including avalanche, coastal flooding, cold wave, drought, earthquake, hail, heat wave, hurricane, ice storm, landslide, lightning, riverine flooding, strong wind, tornado, tsunami, volcanic activity, wildfire, and winter weather (see Supplementary Table 4 for details). FEMA calculates expected annual loss (EAL) by integrating exposure, annualized frequency, and historic loss ratio across three impact categories: buildings, population, and agriculture. The EAL quantifies each census tract's percentile ranking regarding hazard-induced negative impacts across all US census tracts. The EAL in each census tract is a standardized measure comparing hazard-induced economic losses across counties:

$$EAL = \text{Exposure} \times \text{Annualized frequency} \times \text{Historic loss ratio} \quad (3)$$

Where *exposure* is the combined exposure of buildings, agricultural assets, and population to climate disasters. *Annualized frequency* is the expected annual occurrence rate of climate disasters. The *historic loss ratio* is the expected proportion of building, agricultural, and population losses in climate disasters.

Identifying unequal spatial patterns is a foundational step in preventing the conversion of difference into inequality<sup>51</sup>. We measured the spatial inequality of compound natural risks using SGI, which is calculated as the area difference between a perfectly equal distribution and the actual distribution. SGI ranges from 0 (perfect equality) to 1 (maximum inequality). The entropy-based SGI is given by<sup>79</sup>:

$$SGI = \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij} |x_i - x_j| + (1 - w_{ij}) |x_i - x_j|}{2n^2 \langle x \rangle} \quad (4)$$

Where  $N$  is the number of counties, and  $\langle x \rangle = \frac{1}{N} \sum_{i=1}^N x_i$  is the mean value of the variable. The spatial weight  $w_{ij}$  is defined according to the adjacent matrix  $A$  where  $w_{ij} = 1$  for neighboring areas, and 0 otherwise. The diagonal elements  $w_{ii} = 0$  as defined in  $A$  and  $W$  correspond to the sum of all weights.

### Model specification and robustness tests

Multilevel regression was employed to analyze hierarchically structured data (census tracts are nested within county regions)<sup>80–82</sup>. Considering the differences in the values of urban morphological features, we normalized all the variables through Eq. (5). The descriptive statistics of normalized variables used in MRMs are presented in Supplementary Table 2.

$$X_i = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (5)$$

Where  $X_i$  is the value of variable  $i$  after normalization,  $X_{\min}$  and  $X_{\max}$  is the minimum value and the maximum value of variable  $i$ .

Intraclass correlation coefficient (ICC) was used to check the need for using hierarchical linear models, estimating the variance in compound natural risk at the census tract level that can be explained by cross-level effects<sup>80–82</sup>. An ICC larger than 0.1 urges the control of regional effects<sup>80</sup>. ICC is calculated as follows:

$$\rho = \frac{\delta_0^2}{(\sigma^2 + \delta_0^2)} \quad (6)$$

Where  $\delta_0^2$  is the measure of variation of compound natural risks in each census tract between counties, while  $\sigma^2$  is the measure of variation of compound natural risks in each census tract within counties.

The intraclass correlation analysis revealed a significant ICC value of 0.6774 ( $p < 0.001$ ), indicating that substantial variances stem from differences between counties. Therefore, multiscale analysis is an appropriate method to estimate urban morphology effects on compound natural risks. The model is specified as:

$$Y_{ij} = \gamma_{00} + \gamma_{01}Z_j + \gamma_{10}X_{ij} + n_{0j} + \gamma_{ij} \quad (7)$$

Where  $Y_{ij}$  is the risks of multiple disasters in the  $i_{th}$  census tract of the  $j_{th}$  county and  $\gamma_{ij}$  is the census tract-level residual.  $X_{ij}$  denotes local physical form variables.  $Z_j$  are county-level social condition indicators of the  $j_{th}$  county.  $\gamma_{00}$  is the overall mean value of census tract compound natural risks across counties, and  $n_{0j}$  is the county-level residual.

It is crucial to test robustness by calculating multicollinearity with hierarchical variables in MRMs. The variance inflation factor (VIF) was used to evaluate multicollinearity amongst all the variables. Specifically, a VIF value greater than 10 is often considered indicative of significant multicollinearity<sup>83</sup>.

### Interaction effect analysis

We examined how the combined effects of different urban morphologies intensify or mitigate compound natural risks<sup>84</sup>. We hypothesized that regional contexts would have different effects for census tracts located in various economic and demographic conditions<sup>31,80,85</sup>. It is generally believed that high population density and compact buildings near hazard-prone areas may exacerbate risks, while high-density regions provide easy access to essential services and may benefit from comprehensive risk reduction. It remains unclear, however, how the density (population density and building compactness) and proximity (proximity to city centers and proximity to major roads) have interacted to intensify or to mitigate risks.  $Den_{ij} * Prox_{ij}$  was added as an interaction indicator to test the hypothesized interaction between various intensities of concentration and proximity. Here,  $Den_{ij}$  denotes the population density and compactness, reflecting how concentrated people and structures are in an area.  $Prox_{ij}$  includes proximity to major roads and city centers, indicating how close an area is to urban cores and key transportation routes. After the cross-level interaction term was added, the model becomes:

$$Y_{ij} = \gamma_{00} + \gamma_{01}Z_j + \gamma_{10}X_{ij} + \gamma_{02}Den_{ij} * Prox_{ij} + n_{0j} + \gamma_{ij} \quad (8)$$

The state fixed effect captures differences that may arise from state-specific characteristics such as governance, economic conditions, or geographic features, which are not explicitly modeled but could influence the dependent variable. When the state-level fixed effects were further included, the model becomes:

$$Y_{ij} = \gamma_{00} + \gamma_{01}Z_j + \gamma_{10}X_{ij} + \gamma_{02}Den_{ij} * Prox_{ij} + \delta_{state(j)} + n_{0j} + \gamma_{ij} \quad (9)$$

### Data availability

The authors declare that data supporting the findings of this study are available within the paper and its supplementary information files. Multi-hazard data supporting the results of this study are available at <https://hazards.fema.gov/nri/data-resources>. Urban morphology data supporting the results of this study are available in Supplementary Table 1.

### Code availability

Code in this study will be available upon request.

Received: 14 December 2024; Accepted: 4 June 2025;

Published online: 14 June 2025

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## Acknowledgements

This research has received funding from the Global STEM Professorship, Hong Kong SAR Government (P0039329), Hong Kong RGC (grant reference # 15300923), and Hong Kong Polytechnic University (P0046482 and P0038446). The authors are grateful to the editor and two anonymous reviewers for their constructive comments and suggestions, which helped improve the paper.

## Author contributions

Wanru He: Writing—original draft & editing, Conceptualization, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. Prof. Qihao Weng: Writing—review & editing, Supervision, Resources, Project administration, Conceptualization, Formal analysis, Investigation, Funding acquisition.

## Competing interests

The authors declare no competing interests.

## Additional information

**Supplementary information** The online version contains supplementary material available at <https://doi.org/10.1038/s42949-025-00233-9>.

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