Inconsistency in Household and Community Resilience with Perceived Climate Change Threat across Rural-Urban Contexts: Evidence from 142 Countries

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Abstract

As climate change intensifies globally, effectively managing public perceptions of climate-related threats becomes increasingly vital for climate adaptation strategies. Resilience is a key factor shaping individuals' climate threat perception; however, limited attention has been paid to how the inconsistency between resilience at the household and community levels may influence this perception. This study employs multilevel response surface analysis to examine how consistency and inconsistency between household resilience and community resilience are associated with individual climate change threat perception. Utilizing data from 112,339 individuals spanning rural, town, and urban contexts across 142 countries, our findings indicate that higher consistency between household resilience and community resilience significantly reduces perceived climate change threats. When household resilience exceeds community resilience, it is associated with increased threat perception. These relationships differ notably by urbanization context, with rural residents demonstrating stronger sensitivity to resilience consistency, while urban and town residents are particularly responsive to resilience divergence.

Keywords: Household resilience; Community resilience; Perceived Climate Change Threat; Multilevel Response Surface Analysis; Risk Perception

Introduction

Climate change is one of the major challenges facing the world today, with a series of issues such as extreme weather events and rising sea levels posing severe threats to human survival and development (Barrett et al., 2015; Suter, 2022). The perception of climate change threats by individuals is fundamental for taking adaptive and responsive actions, as it influences whether people are willing to pay attention to climate information, engage in environmental activities, and prepare for future changes (Arıkan & Günay, 2021; Van Valkengoed et al., 2024; Wong-Parodi et al., 2024). An excessively high perception of threat can increase climate anxiety and climate inaction (Aguilar-Luzón et al., 2023; Reese et al., 2023). Resilience is considered a key factor in assessing the adaptive capacity of societies and individuals (Ong & Cammarata, 2020). Community resilience and household resilience, as two important forms of resilience, are often used to describe a group's ability to cope with and recover from disasters or crises (Tan et al., 2024), and may affect the perception of climate change threats (Aven, 2022; Ferreira et al., 2024).

Current research has discussed the impact of community and household resilience on individuals' psychology and behavior, there has been limited exploration of how the inconsistency between the two affects perceptions of climate change threats. In regions with varying urbanization levels (rural, town, and city), significant differences exist in the patterns of interaction between community and household resilience, the pathways for resource access, and the social support systems (Bekteshi & Schootman, 2024; Moskalewicz et al., 2019). Groups in different urbanization contexts exhibit diverse responses and adaptation strategies when facing climate change (Oleson, 2012; Zhou et al., 2022). This study aims to fill this research gap by using globally representative data to deeply analyze the impact of inconsistency between community and household resilience on the perception of climate change threats, and how this effect differs across urbanization levels.

Literature Review

Household and Community Resilience

Resilience encompasses the ability to directly respond to disasters and the planning and adaptation strategies for long-term environmental changes. In the context of climate change, resilience needs to include more forward-looking and transformative elements, requiring the ability to return to normal functioning after a crisis and the capacity to develop under continuous environmental stress (Bahadur et al., 2013; Folke, 2006).

Household resilience emphasizes the degree of integration, interaction patterns, and psychological support systems within the family as a fundamental social unit (Walsh, 1996, 2021). When a household faces environmental or socio-economic shocks, its ability to effectively mobilize internal resources, communicate, and cooperate enables it to better withstand external pressures and maintain household functions (McKinley & Lilly, 2022; Walsh, 2011). However, if household resilience is weak and there is a lack of trust and support among members, even when external resources are abundant, the household may struggle to cope with risks (Keating et al., 2020; Patterson, 2002).

Community resilience focuses on broader interpersonal networks, social capital, and public resources (Norris et al., 2008). As an intermediate level connecting individuals to the larger society, community resilience is often manifested in the quality of infrastructure, the extent of public services, and the mobilization capacity of social organizations(Gillespie-Marthaler et al., 2019). When a community can quickly and effectively integrate resources, organize residents to act together, coordinate mutual assistance, and provide necessary rescue or assistance plans in the face of climate risks, it significantly reduces overall vulnerability (Cano-Calhoun et al., 2024; Choko et al., 2019; Hung et al., 2016).

Household and community resilience are not entirely separate but complement each other. Households often rely on external resources and social support provided by communities to enhance their coping abilities, while communities rely on a large number of resilient households to maintain social networks and order (Landau, 2010). However, they differ significantly in their functional focus, resource mobilization methods, and social support levels. Household resilience is more focused on internal interactions and emotional support, such as division of labor, the stability of parent-child relationships, and reasonable allocation and management of resources. Community resilience involves external public services and social connections, with complementary support provided at the community level through organizational mobilization capacity, public infrastructure, disaster preparedness, and financial support (Ferreira et al., 2024).

Resilience Inconsistency and Perceived Climate Change Threat

Perceived climate change threat refers to the subjective assessment of the risks, damages, or uncertainties brought by climate change by individuals or groups (Hart et al., 2023; Slovic, 1987). Risk perception theory suggests that people's perception of risk is often not entirely based on objective probabilities but is influenced by psychological, social, and cultural factors (Knuth et al., 2015; Nie et al., 2020). In the case of climate change, a complex risk with delayed effects, people's perception of threat is more easily shaped by the combined influence of social environments, group cognition, and personal experiences (van der Linden, 2015; Xie et al., 2019).

Individuals with higher resilience tend to cope better with external shocks, and therefore, their risk assessments are generally lower (Kaim et al., 2024). For example, individuals experiencing financial difficulties perceive climate change threats to be higher, especially in low-income countries (Hornsey & Pearson, 2024). The relationship between resilience and perceived climate change threat is not always a simple negative correlation; it may be influenced by the interaction between different levels of resilience. Household resilience focuses on micro elements such as the psychological atmosphere, communication strategies, and resource allocation within the household (Rao et al., 2020); social resilience emphasizes public resources, social capital, and organizational mobilization provided by the community or broader social systems (Ferreira et al., 2024). In the context of climate change, when both household and social resilience are high, individuals can obtain multiple layers of support, receiving both emotional and material assistance from within the family and public services and mutual assistance networks from the community, effectively reducing their concerns about climate change risks. When both household and social resilience are weak, it leads to overall inadequate coping capacity, resulting in an increased perception of risk (Fan et al., 2022; Oriangi et al., 2020; Sen et al., 2020). Based on this, we propose the following hypothesis:

H1: High household and community resilience is associated with lower perceived climate change threat.

Inconsistencies between household resilience and social resilience often occur. This mismatch can significantly affect an individual's perception of climate change threats.

For instance, in high household resilience – low social resilience scenarios, households may have good internal cohesion and psychological support, but public resources and rescue systems at the community level may be lacking. Without strong support from society and the community, households may face resource constraints in decision-making and response actions, leading to limited overall adaptation to climate change (Kelly & Adger, 2000). Researchers have pointed out that in environments lacking external infrastructure and public services, even households with high resilience may experience greater insecurity due to their inability to effectively use social resources, leading to an increased focus on climate change threats (Chirisa & and Nel, 2022; Peng et al., 2019; Shen et al., 2022; Tan et al., 2024). In low household resilience – high community resilience scenarios, while communities may have good infrastructure, organizational ability, or disaster relief mechanisms, households may lack effective communication and support. Although the community can provide relatively complete disaster prevention plans, information dissemination, and material resources, the internal vulnerabilities of households may still lead to high anxiety or a sense of deprivation, which may increase perceived vulnerability and, consequently, the perception of greater threats (Ma et al., 2023; Pearson et al., 2013).

These two inconsistent resilience states can lead to psychological magnification of perceived climate change threats. Resilience research indicates that the effective integration of multi-level resilience (e.g., the synergy between household and social resilience) can maximize support (Acosta et al., 2017; Brown & Westaway, 2011), while the absence of such synergy may cause individuals or groups to experience contradictions or anxiety when facing climate change. Based on this, we propose the following hypotheses:

H2: In low-resilience communities, high-resilience households may experience a higher perceived climate change threat than low-resilience households.

H3: In high-resilience communities, low-resilience households may experience a higher perceived climate change threat than high-resilience households.

Differences in the Level of Urbanization

The psychological mechanisms underlying climate-change threat perception vary across sociodemographic contexts. The effects of resilience consistency and the psychological burden of resource incongruence are shaped by the structural conditions of respondents' residential environments. Existing evidence shows that threat perception is patterned by sociodemographic characteristics (Lee et al., 2015; Poortinga et al., 2019), while place-based context further conditions how resilience translates into perceived threat. Urbanization captures differences in exposure profiles, infrastructure conditions, institutional reach, and social organization. Climate opinions and risk-related attitudes vary across local geographies, including urban–rural gradients (Howe et al., 2015; Mewes et al., 2024). These differences indicate that the same household–community resilience profile can generate different psychological responses across settlement contexts.

In lower-urbanization settings, weaker formal infrastructure often coexists with stronger local interpersonal ties and collective reciprocity norms (Gao & Fennell, 2017; Yang et al., 2020). Bonding social capital in these settings can buffer household-level deficits through informal support and shared coping capacity (Phuong et al., 2023). In highly urbanized settings, formal infrastructure and service systems are often stronger, while social ties are less cohesive and more individualized (Cornwell & Behler, 2015;

Park & Kang, 2024). Residents in these contexts rely more on linking social capital and institutional channels. Town settings often show transitional features, with partial infrastructure expansion and uneven social integration (Bandile, 2024).

Urbanization also shapes the consequences of resilience mismatch. When household resilience is high, but community resilience is low, private preparedness may not offset weak external systems; under large-scale disruption, perceived threat can remain elevated because household resources do not replace public coordination and service reliability. When community resilience is relatively high, but household resilience is low, institutional support can reduce perceived exposure, although household constraints may sustain vulnerability. This directional pattern is consistent with evidence that coping pathways, resource access channels, and adaptive strategies differ across rural and urban environments (Bekteshi & Schootman, 2024; Moskalewicz et al., 2019; Oleson, 2012; Zhou et al., 2022).

Social-capital structures differ by settlement type: rural settings rely more on localized bonding ties, while urban and town settings rely more on institutional linking ties (Cornwell & Behler, 2015). Second, vulnerability mechanisms differ across settings: urban resilience depends strongly on interdependent infrastructure systems, whereas rural resilience is closely connected to ecosystem services and household self-sufficiency. In rural areas, livelihoods are closely tied to natural resources and local climatic conditions, strengthening the interdependence between household and community capacities. In urban settings, formal institutional safety nets and market-based coping services alter how residents cognitively appraise dependence on neighborhood cohesion.

Therefore, we pose the following research questions:

RQ1: Does the relationship between household/community resilience and perceived climate-change threat differ across urbanization levels?

RQ2: Does the relationship between the inconsistency between household and community resilience and perceived climate-change threat differ across urbanization levels?

The Present Study

Although existing research has highlighted household and community resilience as important resources for individuals in coping with climate change, there are significant gaps in current studies. First, most research focuses on household or community resilience separately, rarely considering the interaction and inconsistency between household and community resilience, especially when there is a significant gap between them and how this affects individuals' threat perception. Second, existing studies often assume a simple negative correlation between resilience and threat perception, neglecting the complex relationships when resilience is misaligned. Furthermore, research on the role of resilience under different urbanization contexts is relatively scarce. Urbanization levels significantly affect community structures, social support systems, and individual family life patterns, which may considerably alter the interaction between household and community resilience and their influence on individuals' perception of threat. Therefore, it remains unclear how inconsistency between household and community resilience affects individual perceptions of climate change threats in areas with different levels of urbanization. To fill these research gaps, this study aims to use globally representative data (from 142 countries and 112,339 individuals) to systematically examine the impact of consistency and inconsistency between household and community resilience on individuals' perceived climate change threat, and further analyze the differences across rural, town, and urban areas.

Method

Data Resource

The data for this study comes from the 2023 World Risk Poll (Lloyd's Register Foundation, 2024). The World Risk Poll is a biennial global survey designed to map how people experience and worry about everyday safety risks and broader systemic threats. The 2023 wave provides harmonized indicators spanning personal safety, health and injury, food and water security, and environmental and climate-related risks. By capturing both perceived severity and lived exposure across diverse settings, the Poll enables cross-country comparisons of how resilience resources align with perceived climate threats. The dataset constitutes a probability-based, nationally representative sample aged 15 and older across 142 countries and territories. To ensure representativeness, Gallup employed a mixed-mode methodology tailored to local infrastructure. In countries with high telecommunications coverage (e.g., most OECD nations), interviews were conducted via telephone (CATI) using Random Digit Dialing (RDD) or mobile sampling frames. In countries with lower telephone penetration (e.g., much of Africa, Asia, and Latin America), face-to-face interviews (CAPI) were conducted using a stratified, multi-stage cluster sampling design. Specifically, primary sampling units (PSUs) were stratified by population size and geography, and households were selected using a random-route procedure. The average sample size per country is approximately 1,000 respondents. Data weighting was applied to correct for unequal selection probabilities, non-response, and to match national demographic benchmarks (age, gender, and education) derived from the

World Bank and national statistics. The survey included 146,910 samples, and after excluding those with missing main variables, 112,339 participants from 142 countries and regions were included in the final analysis. The average age of the sample was 42.91 years, 52.64% were female, 25.65% were from rural areas, 37.54% were from towns, 36.80% were from cities, and 21.95% had a university degree. Table 1 presents the descriptive statistics for the included variables. A detailed list of the 142 countries, their specific sample sizes is provided in Supplementary Table S1.

Table 1.

Descriptive statistics for the variables

Variable	Level	Mean/N	SD/Percent
Age		42.91	18.04
Perceived Climate Change Threat		2.38	0.73
Community resilience		0.58	0.25
Household resilience		0.55	0.26
Education	Basic	29,724	26.46%
	Secondary	57,961	51.59%
	College	24,654	21.95%
Gender	Male	53,207	47.36%
	Female	59,132	52.64%
Urbanization	Rural	28,817	25.65%
	Town	42,177	37.54%
	City	41,345	36.80%

Measurement

As with the previous study (Hornsey & Pearson, 2024), the perceived individual climate change threat measures the subjective assessment of the risks posed by climate change, using the question "Climate Change a Threat to Country in Next 20 Years" (1 = Very worried, 3 = Not worried). The responses were reverse coded, with higher values indicating greater perception of climate change threat.

Household resilience was measured across various dimensions such as psychological resilience, financial support, and social support within the family. The specific measures included: Financial assets: "Suppose your household suddenly lost all income and had to survive only on savings and things that could be sold. How long would your household be able to cover all basic needs, such as food, housing, and transportation?" Planning: "If a disaster were to occur near you in the future, do you have a plan for what to do that all members of your household who are over 10 years old know about?" Access to communications: "Does your home have access to: 1) the internet, 2) a cellular phone?" The World Risk Poll weighted the responses to these questions equally to create a household resilience index ranging from 0 to 1.

Community resilience was quantified through multiple measures of community adaptation and recovery capabilities, including: Social capital: "How much do you think most of your neighbors care about you and your well-being? Do you feel safe walking alone at night in the city or area where you live? Have you done any of the following in the past month? Helped a stranger or someone you didn’t know who needed help?" Local infrastructure: "In the city or area where you live, are you satisfied or dissatisfied with: The roads and highways? The educational system or the schools? The availability of quality healthcare?" The World Risk Poll weighted the responses to these questions equally to create a community resilience index ranging from 0 to 1.

To reduce confounding in the association between resilience and climate threat perception, four covariates were included at the individual level. Gender was coded as a categorical variable (male and female). Education was coded as an ordinal categorical variable with three levels (basic, secondary, and college). Urbanization was coded as a three-category contextual grouping variable (rural, town, and city). Age was treated as a continuous variable (in years).

At the country level, two macro indicators were added in supplementary analyses to account for structural cross-national context. First, we used the ND-GAIN Vulnerability score, which summarizes a country's climate-related susceptibility by integrating exposure to climate risks, underlying sensitivity, and adaptive capacity across key social and ecological systems (Chen et al., 2015). Higher values indicate greater national vulnerability to climate impacts (ranging from 0 to 1). Second, we included the Human Development Index (HDI) as an indicator of overall development conditions. HDI reflects national attainment in three broad domains (health, education, and material living standards) with higher values representing more advanced human development ranging from 0 to 1 (Sagar & Najam, 1998). These country-level indicators could be matched for a subset of countries in the analytic sample, models including ND-GAIN Vulnerability and HDI are reported as robustness analyses.

The two resilience measures (household resilience and community resilience) were conceptualized jointly as an alignment structure rather than interpreted in isolation. Consistency refers to the extent to which the two resilience levels are similar, including both high–high alignment and low–low alignment. Inconsistency refers to divergence between the two domains, including profiles in which household resilience exceeds community resilience and profiles in which community resilience exceeds household resilience. These framing captures three distinct features: the shared level of resilience across domains, the magnitude of discrepancy between domains, and the direction of that discrepancy. Accordingly, interpretation focuses on whether climate threat perception varies across aligned versus misaligned resilience profiles, whether discrepancies are associated with systematically different outcomes. Detailed statistical implementation is presented in the Data Analysis section.

Data Analysis

The main analysis method for this study is Multilevel Response Surface Analysis (ML-RSA) (Nestler et al., 2019). RSA is a method specifically designed to examine the impact of consistency and inconsistency between two predictor variables on an outcome variable by introducing linear terms (HR and CR), interaction terms (HR*CR), and quadratic terms (HR^2 and CR^2), effectively capturing the complex relationships between variables (Shanock et al., 2010). The formula is as follows:

$$PCCT = b_0 + b_1HR + b_2CR + b_3HR^2 + b_4HRCR + b_5CR^2 + e$$

Specifically, RSA includes the following key coefficient interpretations: the linear terms (HR means household resilience and CR means community resilience) represent the independent linear effects of the variables; the interaction term (HR*CR) represents the additional effect on the outcome variable when both variables change together; and the quadratic terms (HR^2 and CR^2) represent the non-linear relationships between each variable and the outcome. Additionally, RSA incorporates four key parameters (a1–a4) to specifically capture the inconsistency effects between the two variables. Parameters a1 and a2 test the trend of consistency between household resilience and community resilience, while a3 and a4 test the specific effects of inconsistency (when household resilience is greater than community resilience or community resilience is greater than household resilience). Table S1 provides explanations and calculation methods for different coefficients (Kezer et al., 2022).

ML-RSA accounts for data dependencies, as participants are nested within different countries, and the effects of perceived climate change threats and household and community resilience vary significantly across countries. In ML-RSA, the RSA formula is split into individual-level (Level 1) and country-level (Level 2) models:

For the Level 1 Model:

$$PCCT_{ij} = b_{0j} + b_1 HR_{ij} + b_2 CR_{ij} + b_3 HR_{ij}^2 + b_4 HR_{ij} \times CR_{ij} + b_5 CR_{ij}^2 + e_{ij}$$

where $PCCT_{ij}$ means represents the perceived climate change threat for the i-th individual in the j-th country; HR_{ij} and CR_{ij} represent the centered predictors (household resilience and community resilience); e_{ij} is the individual-level residual.

For the Level 2 Model:

$$b_{0j} = \gamma_{00} + u_{0j}$$

where γ_{00} represents the fixed effect for the overall intercept (average intercept for all countries); and u_{0j} means represents the random effect for the country, assumed to be normally distributed $u_{0j} \sim N(0,7\sigma^2)$.

To control for potential confounding effects, gender, age, and education level were included as control variables in the model. The analysis was conducted using the RSA package in R (Schönbrodt & Humberg, 2021) and the ML-RSA script from Nestler et al. (2019), using robust standard errors to correct for potential heteroscedasticity.

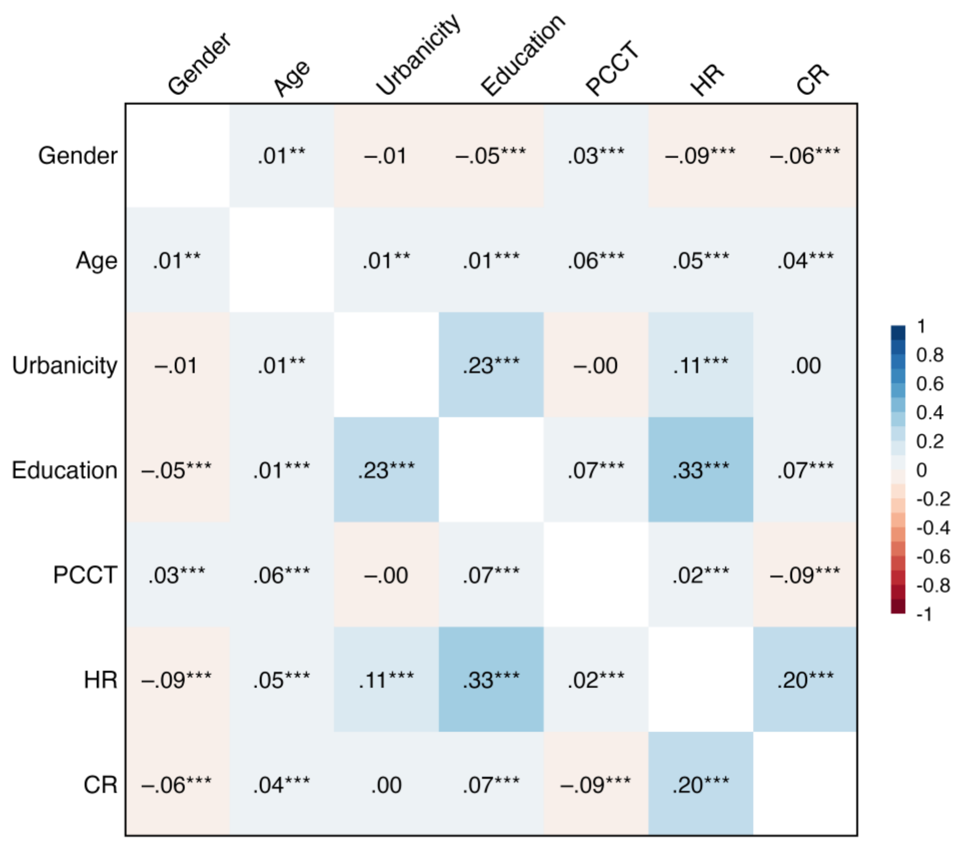
Result

Fig. 1 reports the correlation structure among the key variables. Table 2 and Fig.2 presents the multilevel polynomial regression and response-surface parameters for the overall sample and for rural, town, and city subsamples. In the pooled model, HR is positively associated with perceived climate change threat (b1 = 0.05, p < .001), while

CR is negatively associated with perceived threat ($b2 = -0.17$, $p < .001$). The HR quadratic term is negative ($b3 = -0.15$, $p < .001$); the CR quadratic term is close to zero and statistically indistinguishable from zero; and the interaction of HR and CR is positive ($b4 = 0.11$, $p<.001$). This coefficient pattern indicates that the expected threat level depends on the joint HR–CR profile. Sensitivity models that add country-level controls (HDI and ND-GAIN vulnerability) yield the same substantive conclusions. The key response-surface findings remain unchanged in direction and inference (Table S3). To clarify effect sizes from the fitted surface, predicted contrasts can be illustrated at representative centered values while holding covariates at reference levels. At aligned low resilience (HR = −0.5, CR = −0.5), predicted threat is approximately 2.26; at aligned high resilience (HR = 0.5, CR = 0.5), it is approximately 2.14. Thus, moving from low–low to high–high alignment corresponds to an estimated decline of about 0.12 points on the outcome scale. For misaligned profiles, predicted threat is approximately 2.25 when HR exceeds CR (HR = 0.5, CR = −0.5), versus approximately 2.03 when CR exceeds HR (HR = −0.5, CR = 0.5); the directional gap is therefore about 0.22 points.

Fig. 1

Correlation Matrix of main variables.



Note: PCCT means Perceived Climate Change Threat, HR means household resilience, and CR means community resilience. *** p < .001; ** p < .01; * p < .05.

Table 2.

Dyadic polynomial regression coefficients and response surface parameters of household and community resilience with perceived climate change threat.

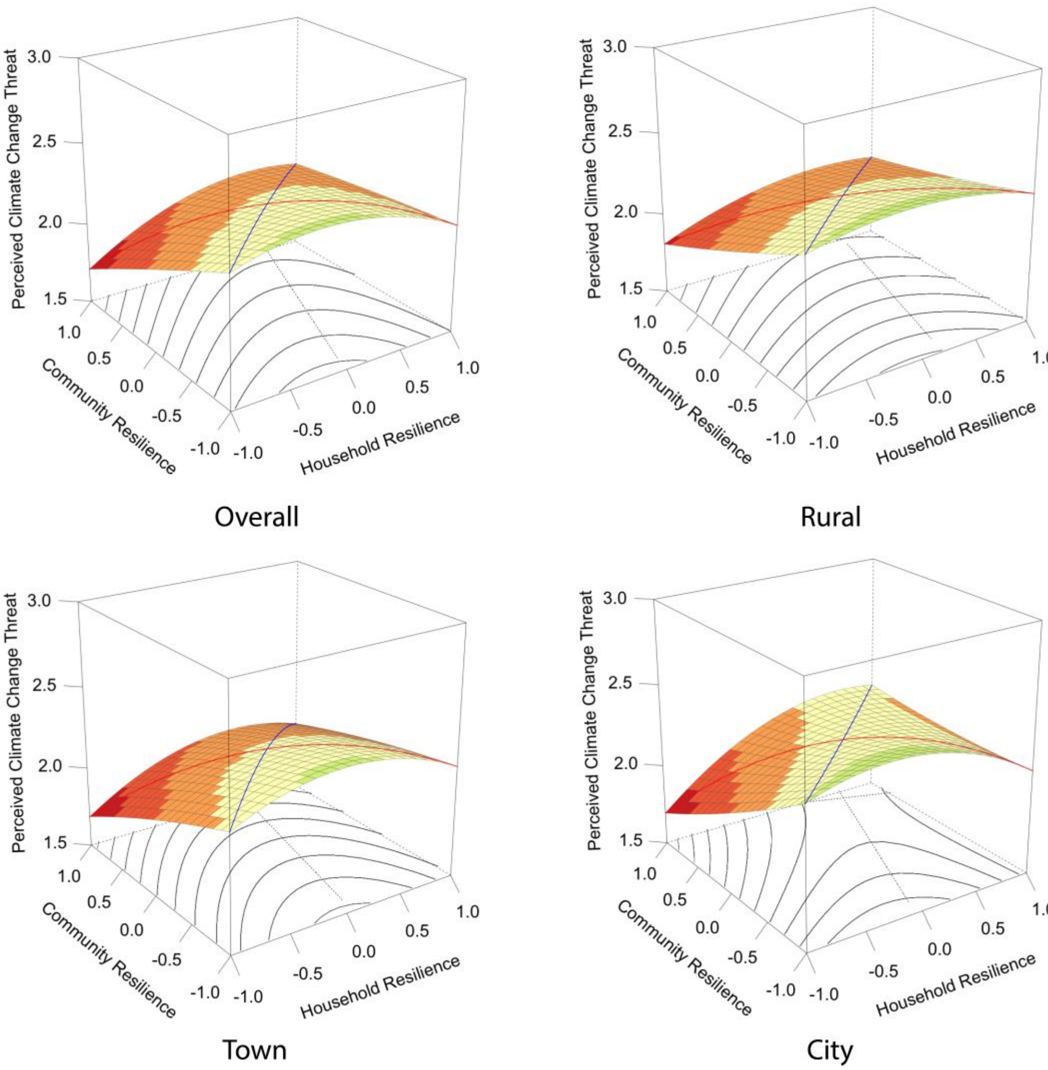
	Overall	Rural	Town	City
(Intercept)	2.21 ***	2.20 ***	2.20 ***	2.24 ***
	(0.02)	(0.03)	(0.02)	(0.02)
HR (b1)	0.05 ***	0.04 *	0.06 ***	0.07 ***
	(0.01)	(0.02)	(0.02)	(0.02)
CR (b2)	-0.17 ***	-0.20 ***	-0.19 ***	-0.15 ***
	(0.01)	(0.02)	(0.02)	(0.02)
HR ^ 2 (b3)	-0.15 ***	-0.10	-0.18 ***	-0.18 ***
	(0.03)	(0.05)	(0.04)	(0.05)
CR ^ 2 (b5)	-0.01	0.01	-0.02	0.03
	(0.03)	(0.06)	(0.05)	(0.05)
HR * CR (b4)	0.11 ***	0.06	0.07	0.17 **
	(0.03)	(0.07)	(0.06)	(0.06)
Age	0.00 ***	0.00 ***	0.00 ***	0.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)
Gender (Ref Male)	0.03 ***	0.00	0.03 ***	0.05 ***
	(0.00)	(0.01)	(0.01)	(0.01)
Secondary Edu (Ref Basic)	0.10 ***	0.11 ***	0.09 ***	0.09 ***
	(0.01)	(0.01)	(0.01)	(0.01)
College (Ref Basic)	0.18 ***	0.20 ***	0.17 ***	0.16 ***
	(0.01)	(0.02)	(0.01)	(0.01)
City (Ref Rural)	0.01			
	(0.01)			
Town (Ref Rural)	0.01			
	(0.01)			
a1	-0.12***	-0.15***	-0.13***	-0.08***
	0.01	0.03	0.02	0.02
a2	-0.04	-0.02	-0.13	0.02
	0.05	0.09	0.08	0.08
a3	0.22***	0.24***	0.24***	0.22***
	0.01	0.03	0.02	0.02
a4	-0.27***	-0.15	-0.27**	-0.33**
	0.06	0.12	0.1	0.11

N	112339	28817	42177	41345
N (Country)	142	140	141	141
AIC	234672.14	61584.08	87751.15	85222.23
BIC	234806.95	61683.31	87854.95	85325.78
R2 (Fixed)	0.01	0.02	0.02	0.01
R2 (Total)	0.10	0.12	0.11	0.12

Note: Standardized regression coefficients with standard errors are displayed. *** p < .001; ** p < .01; * p < .05. HR means household resilience; CR means community resilience.

Fig. 2

Response-surface plots about the multilevel models assessing the association of household and community resilience with perceived climate change threat.



Note. The blue line on the surface represents the line of congruence, where the two predictors share identical values. The red line denotes the line of incongruence, indicating cases where the two predictors exhibit opposing values.

Response-surface parameters provide the same interpretation. The congruence slope (a1) is negative and statistically significant in all models (overall $\beta = -0.12$, rural $\beta = -0.15$, town $\beta = -0.13$, city $\beta = -0.08$; ps <.001), indicating that higher aligned resilience (HR and CR increasing together) is associated with lower perceived threat (supporting H1). The congruence curvature (a2) is not statistically distinguishable from zero in any model (overall $\beta = -0.04$, rural $\beta = -0.02$, town $\beta = -0.13$, city $\beta = 0.02$). Accordingly, the dominant evidence along the congruence line is a monotonic slope pattern; strong curvature is not clearly identified in the current data.

Directional mismatch is captured by (a3), which is positive and statistically significant across all models (overall $\beta = 0.22$, rural $\beta = 0.24$, town $\beta = 0.24$, city $\beta = 0.22$; ps<.001). This indicates consistently higher perceived threat on the side of the incongruence line where household resilience exceeds community resilience, compared with profiles where community resilience exceeds household resilience (supporting H2). The incongruence curvature parameter (a4) is negative in the pooled model ($\beta = -0.27$, $p<.001$) and in town and city samples (town $\beta = -0.27$, $p<.01$; city $\beta = -0.33$, $p<.01$), while the rural estimate is negative but not statistically distinguishable from zero ($\beta = -0.15$, ns). This pattern suggests that nonlinear structure along incongruence is strongest in town and city contexts and weaker (or less precisely estimated) in rural settings.

For RQ1, the subgroup polynomial coefficients are consistent with this surface-level interpretation. In rural areas, HR remains positive ($b1 = 0.04$, $p<.05$) and CR remains negative ($b2 = -0.20$, $p<.001$); HR^2 and HR$\times$CR are directionally similar to the pooled model but are not estimated with high precision. In towns, HR is positive ($b1 = 0.06$, $p<.001$), CR is negative ($b2 = -0.19$, $p<.001$), HR^2 is negative and significant ($b3 =$

−0.18, $p<.001$), and HR×CR is positive but statistically imprecise. In cities, the interaction pattern is most pronounced: HR is positive ($b1 = 0.07$, $p<.001$), CR is negative ($b2 = -0.15$, $p<.001$), HR^2 is negative ($b3 = -0.18$, $p<.001$), and HR×CR is positive and significant ($b4 = 0.17$, $p<.01$). Non-significance for terms such as CR^2 and selected higher-order rural/town terms does not establish true zero effects; it indicates that coefficients are not distinguishable from zero at current precision. Notably, several non-significant estimates preserve the same direction as the corresponding pooled estimates (e.g., positive HR×CR in rural and town models), which is consistent with weaker precision rather than directional contradiction.

Taken together, higher aligned resilience across household and community domains is associated with lower perceived climate threat. Second, resilience mismatch is directional: threat perception is higher when household resilience exceeds community resilience than in the reverse configuration. Third, settlement-context differences are expressed primarily in the strength and precision of higher-order terms rather than in reversals of the core directional pattern.

Diagnostic checks supported the adequacy of the fitted specification. Across the four multilevel models (overall, rural, town, city), estimation returned valid solutions with no recorded convergence warnings and no singular random-effects structures. Model-comparison tests favored the full second-order response-surface model over reduced alternatives (Table S4): adding quadratic terms improved fit versus the linear model ($\chi2=28.70$, $p<.001$), and adding the interaction term further improved fit ($\chi2=14.51$, $p<.001$). Collinearity was low (VIF range: 1.01–1.13; tolerance: 0.88–0.99; Table S5).

Discussion

This study used data from 112,339 respondents across 142 countries to investigate the impact of consistency and inconsistency between household and community resilience on individuals' perception of climate change threats, and how these effects vary across regions with different levels of urbanization. The findings clearly demonstrate that consistency between household and community resilience significantly reduces perceived climate change threats. When household resilience exceeds community resilience, individuals' perception of climate change threats significantly increases, while when household resilience is lower than community resilience, individuals' perception of climate change threats significantly decreases. Slightly differences were observed in the above patterns across urbanization levels.

The results from the polynomial regression showed an unexpected positive relationship between household resilience and perceived climate change threat. This may be because household resilience reflects the internal preparedness of individuals' families to cope with crises. Higher resilience in households may lead to heightened sensitivity to external risks, increasing attention and anxiety about future climate threats (Tung et al., 2022). Household resilience is also correlated with education, connectivity, and media access, which are robust predictors of climate-change awareness and worry in cross-national research (Lee et al., 2015; van der Linden, 2015). Higher household resilience may reflect greater capacity paired with greater perceived salience rather than complacency. Alternatively, it is possible that individuals with higher perceived climate threats might invest more in increasing their household resilience (Azadi et al., 2019; Ricart et al., 2025; Tiet et al., 2022). The negative relationship with community resilience highlights the important role that public resources and support systems in the community play in reducing individual anxiety. Good community infrastructure, effective social mobilization, and public services likely provide strong external security, making residents feel more at ease in the face of climate risks (Haas et al., 2021; Jensen & Ong, 2020).

The Response Surface Analysis further clarified the mechanisms of resilience consistency and inconsistency. When household and community resilience rise simultaneously, the perception of climate change threats significantly decreases, verifying the positive effect of resilience synergy. However, when household resilience is significantly higher than community resilience, individuals' perception of climate change threats significantly increases. This reflects a discrepancy effect, where high internal coping capabilities within households’ contrast with insufficient external support from the community, amplifying individuals' perception of external risks (Peng et al., 2019). Many climate impacts are systemic (e.g., service outages and disrupted supply chains) and therefore cannot be fully neutralized by private resources alone. When community-level institutions are perceived as weak, private preparedness may even accentuate awareness of residual vulnerability and the need for coordination, elevating perceived threat. When community resilience higher than household resilience, collective efficacy and institutional reliability can function as a buffering safety net that lowers perceived exposure and uncertainty (Adger, 2003; Sampson et al., 1997). Interestingly, when community resilience exceeds household resilience, individuals' perception of climate change threats decreases, indicating that community support effectively compensates for household resilience deficiencies.

In the analysis of urban-rural differences, while it was initially expected that regions with different levels of urbanization would show marked differences in how resilience affects threat perception, the results indicated a largely consistent pattern across all areas. Rural residents often experience climate impacts through direct livelihood–ecosystem links, making aligned household–community capacities especially diagnostic for future security, whereas urban and town residents are more exposed to interdependent infrastructures and institutional coordination, so mismatch can amplify perceived cascading risk and uncertainty (Cornwell & Behler, 2015; Kasperson et al., 1988). This may be due to the universal nature of climate change issues and the consistency of resilience mechanisms across regions. Regardless of whether the area is rural or urban, the basic logic of household and community resilience remains unchanged. In rural areas, although community infrastructure and public services are relatively weaker, high levels of neighborhood mutual assistance and social networks likely compensate for these deficiencies (Gao & Fennell, 2017). In urban areas, while infrastructure is better, higher levels of individualization mean that inconsistencies between household and community resilience still amplify individuals' anxiety (Wang et al., 2021). The lack of significant differences between urban and rural areas may also be attributed to the heterogeneity of global sample data and the universality of resilience mechanisms across different regions. The urban-rural distinction and the actual conditions in different countries and regions may weaken the sensitivity of the results to urban-rural differences (Çörek Öztaş, 2021; Roca & Arellano, 2017).

Theoretical and Practical Implications

From a theoretical perspective, this study enriches the application of resilience in climate change adaptation. By distinguishing between the functional differences of resilience at the household and community levels, this study further reveals the complex relationship between multi-level resilience and individual risk perception, particularly emphasizing the synergetic and misalignment effects of resilience. While resilience theory generally assumes that higher resilience reduces individual risk perception, this study's results suggest that household resilience alone has a positive effect, while community resilience has a negative effect. This adds a new perspective to existing resilience frameworks, highlighting the heterogeneity of functions between different levels of resilience. The consistent patterns observed in the response surface analysis across urbanization levels suggest that the coordination (or misalignment) effects between multi-level resilience are likely a universal phenomenon, not specific to particular contexts.

From a practical perspective, this study underscores the importance of coordinating the development of household and community resilience to reduce individuals' perceptions of climate change threats. It highlights that climate change adaptation policies should consider both internal resilience at the household level and public resource development at the community level. Many current climate adaptation policies focus on a single aspect of resilience, but the coordinated allocation of resilience resources between household and community levels is key to reducing residents' excessive anxiety about climate risks (Oza et al., 2025). Policymakers should incorporate both household and community support systems when planning climate adaptation programs to achieve effective integration and coordination of resilience resources.

Additionally, this study points out that when household resilience significantly exceeds community resilience, it can significantly heighten residents' perception of threats. Policymakers should avoid imbalanced resource allocation and intervention strategies, such as focusing solely on strengthening household disaster response plans or material reserves while neglecting community-level public facilities (transportation, education, healthcare) or social support systems (neighborhood mutual assistance, community organizations), as this could increase residents' anxiety and cause negative psychological effects. Although response surface analysis showed consistent trends across urbanization levels, polynomial regression indicated that there were differences in residents' psychological sensitivity to resilience misalignment between rural and urban areas. While the overall policy framework may apply universally across different urbanization levels, specific interventions can be tailored to local conditions. For instance, rural areas should focus on improving community infrastructure and resource provision, while urban areas should pay additional attention to cultivating residents' emotional networks and community interactions to prevent psychological isolation caused by the lack of community support.

Limitation

Despite the use of comprehensive cross-national data, this study has some limitations. First, the study uses cross-sectional data, making it difficult to rigorously examine the causal relationship between changes in household and community resilience and risk perception. There may also be reverse causality, where an increase in climate change threat perception may lead to greater household resilience preparation. Future research should consider adopting longitudinal study designs or experimental methods to more clearly reveal the causal pathways of resilience changes. Additionally, perceived climate change threat is a complex psychological and social phenomenon, influenced not only by resilience and urbanization level but also by psychological factors such as individual risk perception, emotional responses, and political attitudes (van der Linden, 2015). Future research could further explore how these psychological and social factors interact with household and community resilience to jointly influence individuals' perception of climate change threats.

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Appendix

Table S1.

Country	N	Country	N	Country	N
China	2836	Peru	932	Tanzania	855
India	2748	Poland	932	El Salvador	854
Russia	1678	Eswatini	930	Malaysia	854
Kuwait	1038	Brazil	929	Philippines	851
Iraq	1021	Costa Rica	929	Sri Lanka	851
Italy	1000	Egypt	929	Ukraine	849
Cyprus	998	Singapore	929	Lithuania	848
South Korea	998	Chad	925	Malta	844
Austria	997	Mexico	924	Tajikistan	840
Spain	996	Australia	923	Niger	834
Germany	995	Bosnia Herzegovina	923	Congo Brazzaville	829
Switzerland	994	Mauritius	923	Honduras	829
Hungary	990	Bulgaria	921	Bahrain	828
Ireland	989	Ivory Coast	921	Liberia	825
Japan	987	New Zealand	917	Zambia	821
Finland	985	Argentina	915	South Africa	817
Luxembourg	982	Ecuador	914	Azerbaijan	813
Portugal	981	Guatemala	914	Montenegro	807
United Kingdom	980	Romania	914	Botswana	804
Greece	979	Kosovo	912	Gambia	799
Taiwan	973	Nicaragua	912	Ethiopia	798
Georgia	972	United States	911	Moldova	797
Estonia	971	Algeria	907	Mozambique	796
North Macedonia	970	Uruguay	907	Iran	790
Sweden	969	Albania	903	Jordan	783
Croatia	967	Benin	903	Nepal	780
Vietnam	962	Mongolia	901	Cambodia	778
Slovenia	961	Colombia	899	Madagascar	778
Latvia	960	Israel	893	Thailand	767
Slovakia	959	Bolivia	890	Congo Kinshasa	765
Norway	958	Pakistan	890	Uganda	763
Chile	957	Turkey	888	Bangladesh	756
Serbia	957	Sierra Leone	887	Yemen	755
Tunisia	955	Senegal	880	Comoros	746
Belgium	954	Guinea	878	Afghanistan	745

Armenia	952	Gabon	875	Kazakhstan	742
Netherlands	952	Ghana	874	Nigeria	742
France	947	Kyrgyzstan	871	Saudi Arabia	738
Lebanon	947	United Arab Emirates	871	Dominican Republic	733
Czech Republic	945	Cameroon	868	Namibia	709
Hong Kong	945	Somalia	868	Indonesia	637
Malawi	943	Uzbekistan	868	Morocco	598
Zimbabwe	941	Palestine	867	Myanmar	573
Denmark	939	Togo	865	Laos	564
Canada	937	Paraguay	864	Libya	523
Mali	937	Venezuela	861	Iceland	460
Burkina Faso	935	Kenya	860		
Panama	932	Mauritania	859		

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Table S2.

The meaning of the coefficients of the polynomial regression and the response surface.

Coefficient	Calculation	Meaning
Polynomial Regression		
b_1		Linear effect of predictor X.
b_2		Linear effect of predictor Y.
b_3		Curvilinear effect of predictor X.
b_4		Interaction of predictor X and predictor Y.
b_5		Curvilinear effect of predictor Y.
Response Surface		
a_1	$b_1 + b_2$	The outcome is higher when the values of the predictors are on higher levels.
a_2	$b_3 + b_4 + b_5$	The outcome value is highest for a specific X-Y pair but is lower for other combinations of the predictors.
a_3	$b_1 - b_2$	The outcome is higher when predictor X is on a higher level than predictor Y.
a_4	$b_3 - b_4 + b_5$	The outcome is higher when predictors are at similar values.

Note: This table summarizes the coefficient, calculation, and meaning of polynomial regression and response surface analysis, as detailed by Kezer et al.(2022).

823 Table S3.

824 Sensitivity analysis with country-level controls.

	Overall	Rural	Town	City
(Intercept)	2.53 ***	2.09 ***	2.57 ***	2.33 ***
	(0.42)	(0.48)	(0.43)	(0.47)
HR (b1)	0.05 ***	0.05 **	0.06 ***	0.07 ***
	(0.01)	(0.02)	(0.02)	(0.02)
CR (b2)	-0.18 ***	-0.20 ***	-0.19 ***	-0.15 ***
	(0.01)	(0.02)	(0.02)	(0.02)
HR ^ 2 (b3)	-0.15 ***	-0.11 *	-0.18 ***	-0.19 ***
	(0.03)	(0.05)	(0.05)	(0.05)
CR ^ 2 (b5)	-0.02	0.01	-0.04	0.00
	(0.03)	(0.06)	(0.05)	(0.05)
HR * CR (b4)	0.13 ***	0.07	0.08	0.20 ***
	(0.03)	(0.07)	(0.06)	(0.06)
Age	0.00 ***	0.00 ***	0.00 ***	0.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)
Gender (Ref Male)	0.03 ***	0.00	0.04 ***	0.05 ***
	(0.00)	(0.01)	(0.01)	(0.01)
Secondary Edu (Ref Basic)	0.10 ***	0.11 ***	0.09 ***	0.09 ***
	(0.01)	(0.01)	(0.01)	(0.01)
College (Ref Basic)	0.18 ***	0.20 ***	0.17 ***	0.16 ***
	(0.01)	(0.02)	(0.01)	(0.01)
City (Ref Rural)	0.01			
	(0.01)			
Town (Ref Rural)	0.01			
	(0.01)			
HDI	-0.24	-0.03	-0.29	-0.03
	(0.29)	(0.34)	(0.30)	(0.32)
Vulnerability	-0.31	0.32	-0.37	-0.15
	(0.51)	(0.58)	(0.52)	(0.57)
a1	-0.12***	-0.15***	-0.14***	-0.08***
	0.01	0.03	0.02	0.02
a2	-0.05	-0.02	-0.14	0.01
	0.05	0.09	0.08	0.08
a3	0.23***	0.25***	0.25***	0.23***

	0.01	0.03	0.02	0.02
a4	-0.31***	-0.17	-0.30**	-0.39***
	0.06	0.12	0.1	0.11
N	108532	28355	40856	39321
N (Country)	137	135	136	136
AIC	226652.75	60454.93	84955.95	81139.66
BIC	226806.27	60570.46	85076.60	81259.78
R2 (Fixed)	0.01	0.01	0.02	0.01
R2 (Total)	0.11	0.11	0.11	0.12

Note: Standardized regression coefficients with standard errors are displayed. *** p < .001; ** p < .01; * p < .05. HR means household resilience; CR means community resilience; HDI means Human Development Index.

Table S4. Model specification comparison.

Model	npar	AIC	BIC	logLik	Chisq	Df	p
m_linear	9	269041.28	269129.18	-134511.64			
m_quad	11	269016.58	269124.02	-134497.29	28.70	2	<.001
m_full	12	269004.07	269121.27	-134490.03	14.51	1	<.001

Table S5. Collinearity diagnostics.

Variable	VIF	VIF_CI_low	VIF_CI_high	SE_factor	Tolerance
HR	1.08	1.07	1.09	1.04	0.93
CR	1.06	1.06	1.07	1.03	0.94
HR ^ 2	1.07	1.06	1.07	1.03	0.94
CR ^ 2	1.09	1.08	1.10	1.04	0.92
HR * CR	1.12	1.11	1.13	1.06	0.89
Age	1.05	1.05	1.06	1.03	0.95
Gender	1.01	1.01	1.02	1.01	0.99
Education	1.13	1.12	1.14	1.06	0.88
Urbanization	1.03	1.02	1.04	1.01	0.97