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Perspective

Integrating broad and deep multiple-stressor research: A framework for translating across scales and disciplines

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https://doi.org/10.1016/j.oneear.2024.09.006

SUMMARY

Despite the intense hazard interactions in the Anthropocene, risk research is often limited by disciplinary approaches and single-sector or scale analyses, skewing policy advice toward biased, misguided, and unfair outcomes. Research has been locked in a trade-off between reductionism, ignoring the often-conflictive local contexts, and the holistic imperative, which has been a complex and intractable problem. Here, we provide a framework that embraces the complexities of integrating mixed methods, societal sectors, and analytical scales by using a translator agent-based model. This approach innovates by treating the informational transfers explicitly and dialoguing with different disciplines. We implement it to analyze COVID-19 in Brazil, and our mixed top-down and bottom-up evidence markedly differentiates exposure and vulnerability across social classes. This framework overcomes disciplinary siloing, accounts for cross-sectoral losses, and tracks feedback between environmental and social factors. These innovations are key for promoting evidence-based and context-sensitive policies essential for fairer and more effective adaptation.

INTRODUCTION

The Anthropocene inaugurated an age of increasing complexity that challenged traditional risk assessments and research practices.[1] On the one hand, globalization and urbanization shortened topological and temporal distances, making feedback frequent between local and global phenomena.[2] On the other hand, the global risk profile became more diverse, with climate change, the biodiversity crisis, and global pandemics, among other hazards.[3,4] Researchers have struggled to tackle this complexity (i.e., the amount of information necessary to represent the studied systems[5]), ultimately falling into a trade-off between breadth and depth.[6] To cope with complexity, research has so far been able to either include multiple disciplines, social sectors, and hazards (breadth) or articulate information and resolve conflicting value and knowledge systems (depth) but not both. Academic disciplinary boundaries in the past signified efficient analysis and economical communication of concepts, methods, and results for those initiated in each discipline.[7] Today, these boundaries hinder the understanding of the multifaceted impacts of the Anthropocene, especially when impacts spill over predicted limits, interact, amplify their effects, and lead to chain reactions across the environment, economy, and health.[8] In sum, the challenges of the Anthropocene drive us to overcome analytical boundaries and integrate methods.

From these conditions, we learned that risk research should, on the one hand, increase the breadth of its analysis: risk analysis should account for multiple hazards impacting different societal sectors.[9] On the other hand, local and global feedback means that effective adaptation at one scale cannot take shape to the detriment of another. Put differently, society-wide risk prevention cannot mean shifting losses to the local scale[10] or to socially excluded groups.[11] Nor can local resilience be achieved independent of global resilience.[12] The challenge for science is, thus, to integrate breadth while avoiding losing analytical depth. Global risk models, for example, assume away local risk response capacities or greatly simplify them as constants, ignoring the often conflictive local context.[11,13] We argue that, despite being efficient, information simplification and disciplinary-bounded analysis are ineffective when facing the intertwined multiple stressors of the Anthropocene. Therefore, this paper's research question is: how can we achieve depth and breadth in multidimensional risk assessments by integrating disciplines, social sectors, and multiple risks?

To answer this demand, we present a novel framework for multidimensional risk assessment that advances integrative research on multiple stressors. We structure this framework in four stages: first, we define risk and vulnerability in a transdisciplinary co-design process. Second, we establish an overarching risk context with the support of quantitative and spatially explicit risk assessment. Third, we engage in bottom-up qualitative research at the local scale that reveals rich and potentially divergent evidence based on experience and behavior. Finally, we integrate the preceding stages' findings through a translator model. The novelty is thus the structuring of a four-stage mixed and transdisciplinary approach to risk assessment that stitches the bottom-up and top-down evidence across scales, sectors, and disciplines. The key to achieving this integration is explicitly modeling information transfer across scales, triangulating evidence, treating uncertainty, and reconciling the environmental, social, and behavioral factors influencing vulnerability.

The following sections present the context of risk research in the Anthropocene, reviewing the previous efforts to integrate multiple, compound, and systemic hazards that narrow down our approach toward the core of the challenge. We then present the framework and test its application, considering vulnerability to health and climate impacts based on our previous research. While the main purpose of the framework is to improve multiple-stressor integrative research by bridging scales, sectors, and hazards, we believe it makes contributions to risk assessments and may foster better adaptation and risk mitigation policies, which are the objects of a brief outlook for future risk research and policy development at the end of this perspective.

THE COMPLEXITY OF RISKS IN THE ANTHROPOCENE

The challenge of integrating breadth and depth in research amounts to the diversity of elements at play,[6] the difficulty in defining analytical boundaries,[14] and the unpredictable nature of social systems.[9] In this context, diversity stems from the hazards' multiple effects on the environment and society. These effects also compound over space or during specific periods, generating secondary effects that need tracking.[15] Hazards interact with society, and social behavior connects hazard drivers and impacts across scales. Greenhouse gas emissions lead to more variable weather patterns, driving extreme weather events. Complementarily, certain cities or regions might invest and prepare more than others so that similar hazards impact them differently. These differences often take shape across social classes (e.g., the urban poor are generally more vulnerable to extreme weather events[16,17]). Hazard impacts also diffuse from one social sector to another. For example, failing infrastructure might lead to economic loss or forced migration. Given the numerous interactions between environmental and social risk-influencing factors, the research is thus filled with uncertainty, as it often fails to find enough analytical elements to account for all system parts and their interactions.

To reduce this uncertainty, researchers frequently fall into a conflict between the holistic imperative and reductionism when defining analytical boundaries. The holistic imperative considers all factors significant and seeks to cross the sectoral boundaries and scales to link multiple hazards and geographies.[18,19] However, this increases the number of variables and interrelations that need explaining (i.e., the degrees of freedom), complicating interpretation and requiring more comprehensive data. In addition, as analyses become more sophisticated, they demand more comprehensive global and local data, which are often lacking. A prime example of this limitation is the work from the MCC Collaborative Research Network (e.g., Stafoggia and colleagues[19]), which developed an ambitious global approach that nonetheless presents very little data on the African continent to this date. This approach also requires vast research networks and resources such as fieldwork at a global scale, computing power, and cross-cultural management. While this example might seem ideal, it is not likely all crises in the Anthropocene will receive similar resources.

The limitations imposed by reductionism are better known (e.g., incapacity to explain emergence[5,6]). In the Anthropocene, new consequences of reductionism come forth: hiding vulnerabilities behind overtly general conclusions,[20] obfuscating significant yet secondary effects,[18] or delimiting the analyzed hazards short of their impacts' extent.[9] As risks cascade across society and the environment, their effects may become more prominent in certain social groups,[12] as seen during COVID-19, when low-income communities suffered more from the disease and social isolation policies.[4,21,22] These "social outliers" challenge reductions to mean values, where they are frequently underrepresented.[16] Competing value systems result in ethnic, social, or political conflicts[23] that play a significant role in defining vulnerability[11,12] and often configure a blind spot for research for lacking data, interest, and resources.[24] In addition, low-likelihood, high-severity hazards (i.e., black swans[25]) are hardly predicted due to the "unknown unknowns,"[26] which in turn stem from limiting the problem definition (i.e., epistemic uncertainty).[25] Ultimately, reductionism has failed to provide fair and adequate policy advice for hazard mitigation[27] because it creates systemic gaps in research and data,[9] fails to address second-order effects of hazards,[20,28] and erroneously defines independent units of analysis that are conversely empirically entwined.[6,18]

The shortcomings of the holistic imperative and reductionism, thus, highlight the significance of integrative approaches. First, integrating social and environmental empirical evidence shows that climate, health, and social crises increasingly interact and amplify their adverse impacts.[4,29] Social unrest and the rise in political demagoguery display how crises multiply when the conditions are right.[29,30] Secondary effects may also hinder effective adaptation implementation,[12] leading to self-reinforcing adverse impacts for sustainable development (e.g., hazard losses limiting investment). Second, if research cannot fully integrate multiple stressors, it will most likely obtain insights that are limited in scope or gravity. The attention that maladaptation (i.e., when an implemented adaptation measure leads to new problems[27,31]) has recently gathered attests to the harmful consequences of limited or biased insights.[27] Third, overcoming fragmentation in research may lead to yet unrealized synergies. Integrative and context-sensitive research is better positioned to meet the synergies required for the success of global development[32] and climate mitigation and adaptation agendas[11] (i.e., the Sustainable Development Goals and the Paris Agreement).

To integrate depth and breadth, we suggest embracing the complexity of hazards in the Anthropocene and adopting methods that mix qualitative and quantitative evidence.[33] The key to embracing complexity is explicitly treating the information transfers between scales and between qualitative and quantitative evidence sources, allowing researchers to trace any losses in the process. To implement such an approach, we must first identify the requirements for the translating elements, which we turn to next.

MULTIPLE STRESSORS, COMPOUND HAZARDS, AND SYSTEMIC RISKS

Research has devoted significant attention to deep and broad research on multiple stressors. We find that the literature coalesces into three topics: coupled hazards, multiple stressors, and systemic risks. Each topic tackles different aspects of the hazards-society integration, and a structured review provides an outlook beyond the current limitations (see the experimental procedures section for methods and main insights). In addition, we acknowledge that risk may be defined in many perspectives.[25] Throughout this text, we adhere to the definition adopted by the Intergovernmental Panel on Climate Change (IPCC) as being the product of hazards, vulnerabilities, and exposure,[3] as it best fits the disaster risk management and climate adaptation research where this work is situated. Below, we address each of the three research topics, starting with multiple stressors.

The multiple stressors concept appears most frequently in the environmental,[10] ecological,[34] and marine sciences,[35] from which its usage expands into health and climate research.[36] "Stressor," in this sense, is a potentially harmful change in a system's state, either from internal variability or driven by external forces.[20] Stressors may be climatic (e.g., global warming), technological (e.g., an industry plant failing to filter toxins), or social (e.g., political tension). It is thus more general than "hazard," as this tends to describe physical processes. The approach seeks to analyze the interactions between multiple sources of potential or effective adverse impacts.[20] The significant contribution here is that ecosystems do not have well-defined boundaries, and effects from stressors may interact. Neglecting or ignoring the interactions between stressors significantly underestimates risk,[37] even if interaction types vary (e.g., they may be additive, synergistic, or antagonistic[34]). This concept also includes human systems in setting vulnerability,[20,38] showing the significant influence of non-climatic stressors (e.g., from social or technological origin).[10] Spatial overlap is a substantial factor in accumulating stressors,[35] and cities are unique in that they combine multiple exposures, connect systems, and concentrate infrastructure, population, and goods, thus being especially vulnerable to multiple stressors.[2,39] The focus on non-climatic stressors seeks to reconcile conflicting value systems.[6,40] For example, watershed-scale resilience might be unjust and decrease resilience for those displaced by dam construction projects.[10] Finally, adaptation to multiple stressors challenges decision-making by presenting risk-risk trade-offs and conflicting priorities.[10,17,41]

Environmental scientists coined the coupled hazards concept[42] to explore the combination of impacts from similar drivers[43] and later refined it in specific typologies.[44] The core innovation is to track spatial and temporal dependence.[15] This approach statistically associates multiple variables representing drivers and hazards into outcomes that compound their impacts and lead to more significant damage.[45] Most contributions focus on the shared physical drivers (e.g., a single weather event leading to multiple hazards)[43] or combining risks. Examples include storm surges and heavy rainfall resulting in flooding[45,46] or heat waves leading to droughts and wildfires.[47] Recent contributions seek to integrate social processes. For instance, droughts may lead to water scarcity due to poor management.[48] Despite the recent advances, an effective combination of social risks and hazards is still challenging.[6]

The systemic risk perspective looks beyond hazards toward their impact on socioenvironmental systems.[9,28] The conceptual framing comes from complexity, notably dynamic relationships in complex, tightly connected,[9] and open systems,[49] aligned with complex adaptive systems[50] and coupled human-environment systems.[39,51] What distinguishes systemic risks are their non-linear cause-effect patterns, often associated with tipping points and cascading effects across boundaries or societal sectors (e.g., economy and social security).[9,52] Studies often center on social, technological, and environmental hazards, but various other applications exist. The system-wide perspective and interconnectedness of elements make this approach especially susceptible to the holistic imperative.[6] In analytical efforts, complexity challenges the system boundary definition and the selection of meaningful variables, leading to ambiguity and uncertainty.[9,25]

These approaches converge on an integrative perspective on risk research. The first lesson from the review above is the need to break away from siloed risk analysis and crisply delimited research designs. Instead, the approaches argue for widening research scopes to include multiple risks, social sectors, and scales of analysis. Despite efforts to the contrary, the examples above fail to provide a general integrative approach, achieving depth or breadth interchangeably but not simultaneously. They also outline the potential for transdisciplinary research to achieve depth by combining local perspectives in global analysis, for example. The challenge remains, though, to achieve deep integration. Finally, reviewing these approaches allows us to identify specific challenges: managing complex information flows, articulating different epistemological approaches, and outlining system boundaries across sectors and scales. The following section considers these persistent challenges and the added cost of the necessary integration.

THE CHALLENGE

We have established that integrative risk research is topical and that there are recent contributions to achieving it. We seek to forward integration first by outlining a new perspective on this gap and then presenting a framework that fills it. To this goal, Figure 1 illustrates typical approaches in risk assessment located along two axes: breadth and depth. These axes represent the yet disconnected qualities of multiple-stressor research: breadth, to include multiple disciplines, social sectors, and hazards, versus depth, to connect these, articulate information robustly, and resolve conflicting value and knowledge systems. This formulation is inspired by the work of Berrang-Ford and colleagues[53] and Johnson and colleagues,[33] who developed structured approaches to integration through system science and mixed methods, respectively.

On the one hand, research needs to broaden its thematic and disciplinary range. Approaches that did otherwise provided only partial evidence of the second-order impact of hazards and often missed key social elements of vulnerability,[10,36] underestimated the systemic effects,[37] and ignored social tipping points where resilience might suddenly be overcome.[8,28] Uncertainty at the

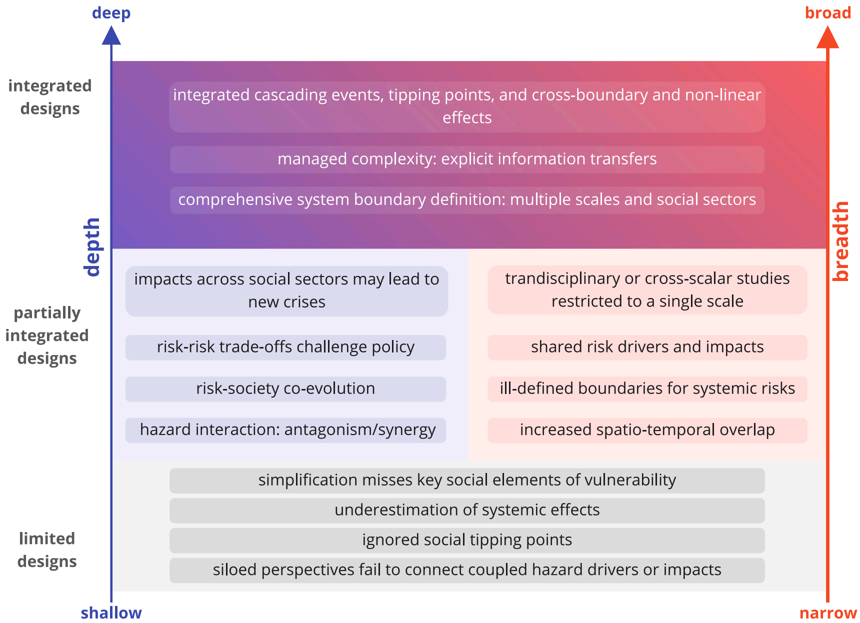

Figure 1. Framing of the gap according to the literature review

Limited research designs present the most significant gaps, as they do not relate scales, sectors, hazards, or disciplines. Partially integrated designs offer some integration but fail to embrace complexity. Integrated designs must embrace complexity, mainly through boundary definition and explicit information transfers.

local level frequently troubles research and couples with conflicts to integrating information across scales.[25] This issue is visible when analysis does not reconcile top-down perspectives with the diverse value systems between the actors who perceive, value, and respond to climate events at the local scale.[6] For example, issues of gender, ethnicity, or social class are often ignored at the city, regional, or national level[10,54] but are highly relevant to actors at the local scale.[52] Limited approaches are also more likely to produce maladaptation.[27,55] Finally, thematically or disciplinarily limited responses often hide adverse unintended consequences[25] that penalize the socially vulnerable.[11,12]

On the other hand, research must be sufficiently deep to represent the analyzed phenomena across their scales, sectors, hazards, or disciplines. This argument means embracing the system's complexity (i.e., the richness of information across its elements) and integrating information flows. For example, this means bringing together the context-specific vulnerability factors at the local scale (i.e., cultural practices, values, or resistive capacity at the local scale)[54,56] and their broader context. Analyses lacking depth enclose insights into separate boundaries, which can be independent analytical scales or geographic regions. In these cases, mean values of neatly defined spatial units such as municipalities or regions hide complex and differentiated environments and societies (i.e., the modifiable areal unit problem[57]). When these averaged notions guide policies, they produce one-size-fits-all measures constituting maladaptation.[3,27,55] Conversely, integration may combat environmental and climate injustice by allowing critical differences to come to the foreground.[58,59] Furthermore, by including local response capacity and community social networks at broader scales, research may reveal drivers to preparedness against multiple hazards,[60,61] such as self-organization. Finally, the richness of the local scale may say little to multiple-stressor research if it is not integrated into context. Managing multiple stressors systemically means understanding the aggregate influence of heterogeneous behavior and change. Depth, therefore, speaks to integrating bottom-up and top-down system representations. To achieve such integration, managing complexity[5] is key and, hence, information, which we turn to next.

To integrate a system representation, it is imperative to translate its information across several socioeconomic sectors, research disciplines, scales, and levels of complexity, as seen in Figure 2. The translator element must account for disciplinary diversity, especially between epistemes (e.g., natural and social sciences). This element must allow risk process representation in multiple sectors, such as the biophysical environment and social support systems. To qualify for deeper research, this translation should negotiate between scales, managing the information transferred between them through down- or upscaling methods or scale-specific modeling techniques. It is critical to preserve the richness of value systems and cultural perspectives from bottom-up approaches. The translation must also transfer such values into their broader context through geographical or demographic categories that allow comparison and societal insight into the phenomena (as opposed to context-bound evidence).

Considering these aspects, we summarize by outlining the challenge to this translator element, which includes different knowledge systems, such as highly structured quantitative data and unstructured personal experiences reporting value systems at different scales. This paper proposes a framework to tackle this challenge by including a translator element.

MULTIPLE-STRESSOR INTEGRATIVE FRAMEWORK

Research and policy must tackle the complexity[6] of multiple stressors by developing deep and broad assessments. The literature review above provides the essential requirements for this translator model, and we outline its main aspects in Figure 3. Therefore, such a framework must first explicitly treat the informational transfers between scales and complexity levels, allowing for the critique and improvement of these. Second, the framework should be flexible and enable its extension into different societal sectors by representing phenomena such as social behavior, the biophysical environment, and economic relations.[62] Finally, this translator should take inputs and provide insights into different disciplines, such as diversifying vulnerability profiles, extending system boundary definitions, and tracking impacts from the environmental to the social domain.

Using the structure above, we propose an integrative research framework that connects emergent phenomena (in the

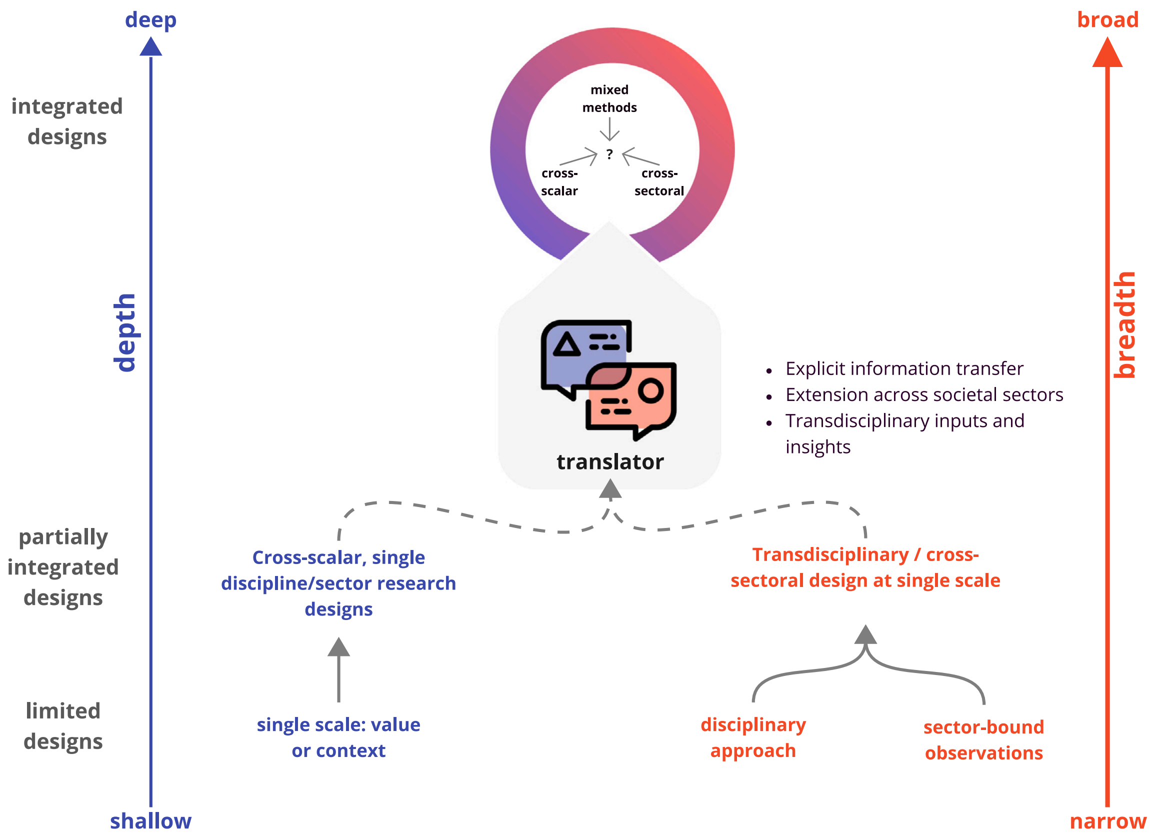

Figure 2. The multiple-stressor research gap filled by a translator model
The translator allows the negotiation across scales, sectors, and disciplines by explicitly managing information transfers and promoting transdisciplinary insight.

implementation below, the health and climate crises) by combining three well-known climate and social research methods to treat the informational ambiguity of this integration. This framework presents four stages that combine top-down and bottom-up perspectives to negotiate complexity across scales iteratively. It also combines qualitative and quantitative evidence to understand multiple stressors across research disciplines and societal sectors.

The framework's first stage involves jointly developing research objectives and analytical framing through co-design practices. Co-design provides empirical grounding to the research questions based on local needs presented by stakeholders such as researchers, practitioners, and community leaders.[63] They also offer an opportunity for second-order learning[6] at the onset of the research design by confronting the researchers' expectations and assumptions with the local knowledge and experiences. This stage also sets a flexible analytical framing (e.g., multidimensional vulnerability to hazards[13,59]), facilitating the later integration.

The framework's second stage involves developing a broad risk assessment through well-known, spatially explicit methods (e.g., geographic information system [GIS]-based vulnerability indicators).[64] This assessment should provide a spatiotemporal appraisal of the distribution of risk factors (i.e., those social or environmental variables increasing the likelihood or magnitude of hazard impacts) well connected to the system's context. It should describe the demographic and environmental setting where the system analysis occurs, carefully considering local variation. Researchers and stakeholders should also evaluate it critically to highlight the known gaps in the assessment, e.g., local hazard experiences or value systems inadequately represented in the analysis.

The third stage is qualitative research at the local scale (e.g., community or individual) exploring the risk experiences of divergent social groups. In this stage, achieving a contrasting perspective sheds light on the gaps identified in the second stage.[33,65] The qualitative evidence thus provides rich detail to the factors, conditions, and processes at play locally.[65] Unstructured or semistructured interviews preserve detail and thus reveal emergent factors with minimal intervention. This perspective provides context-dependent evidence of the impact of the hazard, relief, and response initiatives and the locals' behavior. Flexible techniques such as thematic analysis are well suited to this research.[66,67] This bottom-up evidence gathering should also support further critique of the quantitative evidence by highlighting new gaps or widening previous ones that need discussing or reconciling in further stages or iterations.

Finally, the fourth stage of the framework involves a translation between risk assessment and qualitative research. Agent-based modeling (ABM) presents several advantages when socioenvironmental interaction is significant (e.g., climate risk assessments). First, it preserves complexity by focusing on process simulation rather than on the system states or equilibria.[68,69] To achieve this simulation, social processes need to be

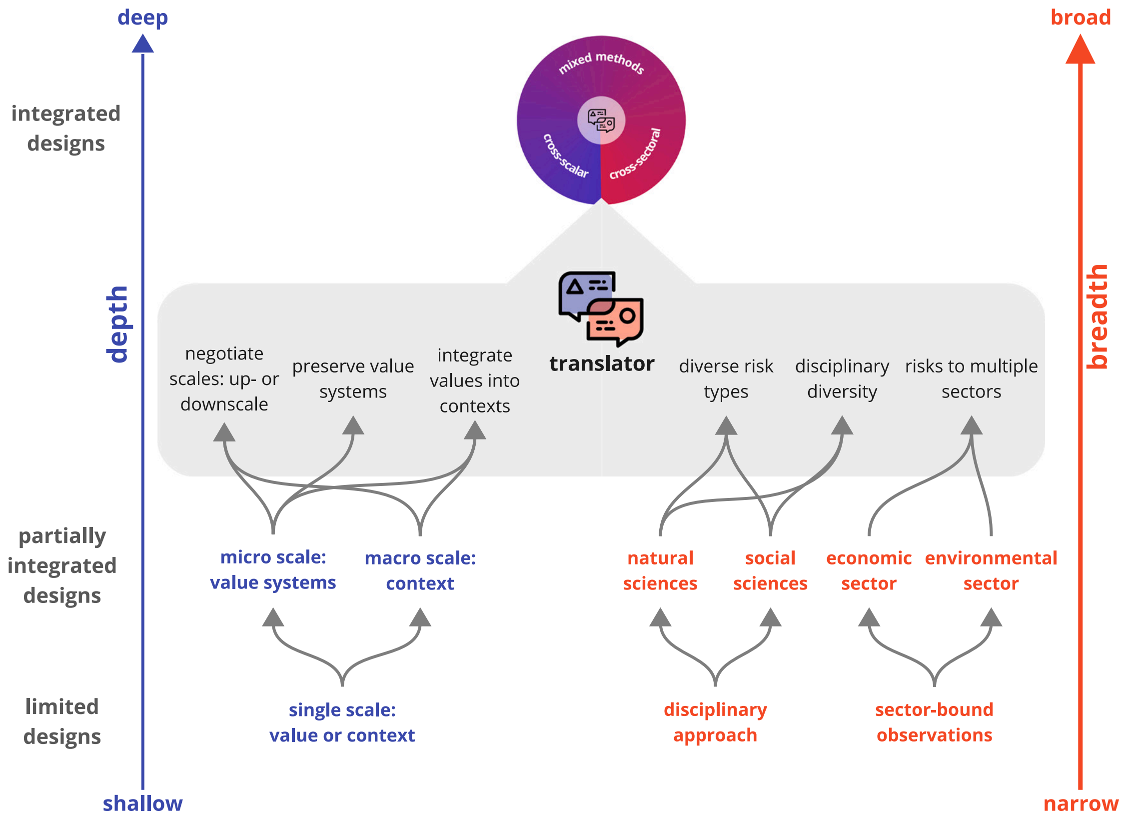

Figure 3. Primary features of the multiple-stressor framework
Following the structure of Figure 2, we provide the key features for transitioning from limited designs (single-scale, disciplinary, and sector-bound approaches) to partially integrated designs (cross scalar, transdisciplinary, or cross sectoral), and finally to integrated designs.

understood as they develop (i.e., dynamically), which often takes place by an iterative process of reflection (called "generative" by Epstein and Axtell[70]) that advances theoretical insights with model development[71] and provides critical contributions to understanding processes in integrative research. This iterative method helps eliminate ambiguities, highlights data and process knowledge gaps, and avoids overtly simplistic descriptions. Insecurities, conflicts, and inconsistencies in mixing different data types may arise and need to be explicitly addressed, which is an added cost to this approach. The analytical framework established in the first stage minimizes such costs, though, by bringing qualitative and quantitative efforts toward convergence.[72]

Second, ABMs explicitly represent agents (e.g., persons or institutions) at the individual scale, aggregating their behavior through clear rules. This allows tracing information across scales, analyzing losses in process descriptions, and avoiding the omission of emergent or non-linear phenomena.[70,71] Third, ABMs are well suited to modular development, enabling research to start simply and grow in complexity as evidence and new data are collected for different sectors or hazards.

Last, the criticism against ABMs concerns their complexity (which may turn the causal links in their insights opaque) and challenges to validation and verification (especially with qualitative and context-bound data). ABMs mixing qualitative and quantitative evidence face additional challenges of balancing and weighting different data types; managing the diversity of behavior, imprecision, bias, and restricted generalization in qualitative data; and the limited coverage and limited complexity in quantitative data.[72,73] The framework seeks to mitigate most of these problems by implementing the ABM in a modular design between the top-down and the bottom-up scales, thus adapting the model complexity to the respective problem. In this way, the model receives the necessary theoretical framing[73] from co-design and top-down assessment and can be "specialized" (i.e., adjusted to fit the local context) from the bottom-up evidence. Nonetheless, the complexity of working with local richness and the degrees of freedom it entails demands balancing the ABM representation of the system. To avoid the depth-breadth trade-off, the framework proposes that these decisions be made explicitly and allows for adding future building blocks, for example, when new evidence becomes available.

THE FRAMEWORK VERSUS THE GAP

The framework proposes explicit information transfers from the top-down and bottom-up perspectives into an intermediary scale. This transfer negotiates information ambiguity and provides a novel yet reproducible method for multiple-stressor investigation. This approach seeks to achieve simultaneous breadth (i.e., integrating sectors and disciplines) and depth (i.e., integrating scales and complexity). We have outlined three requirements for such a framework. In short, it must: (1) treat information transfer between modeling scales explicitly, (2) represent different societal sectors and spatiotemporal scales, and (3) take inputs and provide insights to different disciplines. This framework advances in all these qualities, even if we recognize these are grand scientific problems that can hardly be ultimately solved here.

We need to consider information transfer between modeling scales first. As argued above, ABMs simulate socioenvironmental processes that demand explicit representation of the system's environment, its agents, actions, and interactions. By representing these elements, we need to declare which information each relationship takes in and what are the resulting system changes from it. ABMs articulate depth and breadth by linking the discrete agents and aggregating the impact of individual behaviors to the larger spatial scale,[71,74] often following Coleman's framework.[75] In addition, participatory ABMs (e.g., the companion model by Barreteau and colleagues[76,77]) demonstrate how model development following an iterative process may integrate stakeholders and qualitative fieldwork to provide artificial testing grounds for decision-making.

Concerning the representation of different societal sectors, the framework analyzes risks originating in different drivers (e.g., extreme weather events or COVID-19) and their socioeconomic consequences (e.g., loss of livelihoods). In ABMs, for example, knowledge is transferred between disciplines through agents' negotiation or collaboration.[62] In collaborative dynamics, individuals establish coalitions that span multiple sectors and avoid conflicts.[78,79] Environment-agent interaction may also represent second-order impacts, for example, as changes in the risk assessment influence the agents' decision-making.[80] In addition, discrete agents' collective behaviors, such as mobility or pro-environmental behavior, influence the larger-scale spatial risk and environmental resilience.[81] In the framework, the intermediary translator stage integrates different spatiotemporal scales by downscaling the risk assessment data and upscaling the risk experience.

Third, the most challenging aspect is embracing pluralism and implementing the mixing of transdisciplinary evidence to reduce information ambiguity.[6] This idea is not new,[82] but persisting epistemological differences demonstrate the absence of a general solution.[71–73,83] The framework addresses this issue by developing theoretical insight into a single empirical problem with quantitative risk analysis and qualitative risk experience.[33,82] We build theory through model specification, calibration, and validation,[69] taking in partial insights from the quantitative and qualitative perspectives. Previous ABMs achieved similar integration by bringing stakeholders into the modeling process,[76,84] triangulating qualitative and quantitative evidence to validate the model,[72,85] and integrating the ABMs with cognitive maps.[86]

In this context, it is critical to stress that there is no universal translation solution between qualitative and quantitative methods.[33,82] However, an ABM is the linchpin in this approach, as it explicitly models information transfer decisions, allowing for their tracking and critique. ABMs are also flexible, allowing extensions across multiple model implementations that include new sectors, downscale samples, and accept new empirical data.[74] Finally, they may take information from natural sciences (e.g., in their environment parameters) and social sciences (e.g., in designing agent behavior decision rules), thus articulating often-opposed scientific traditions. The next step is to present an empirical implementation of this framework to test its design and identify possible limitations.

MULTIPLE-STRESSOR FRAMEWORK IMPLEMENTATION

We now turn to an empirical application to verify the plausibility of this multiple-stressor framework. As an initial version of the framework, it supports the theoretical efforts in its conceptualization as much as it provides grounds for extension and improvement. In the following, we present the empirical problem of the health-climate nexus, our approach using the framework, and the new (we hope better) questions arising from it.

Health and climate crises are converging in the Anthropocene and provide the test case for a framework integrating cross-sectorial analysis of multiple systemic shocks in a context of high vulnerability.[4,22] Climate change is a global systemic crisis that combines slow-onset events, such as rising sea levels and salinization, with sudden events, such as flooding and forest fires.[28] The COVID-19 pandemic revealed that health crises are also systemic in character. This crisis led to significant fatalities and other long-term health impacts.[87] The secondary effects of health impacts (e.g., missing workdays due to sickness) added to the effects of containment measures (e.g., border closure, curfews, and lockdowns). Significant disruptions in global flows of goods and people resulted in increased poverty and social inequality.[88,89] These two crises coincided in that the most vulnerable groups suffered more intensely from their direct and secondary effects,[90,91] even if local conditions affected the intensity.[11,12]

Ultimately, the multiple social impacts of the climate and health crises present a nexus that converges on the vulnerability to these hazards. While physical exposure to health or climate hazards may be diverse, the drivers of vulnerability are often very similar: poverty, lack of social or governmental support, and socioterritorial segregation.[11,12] Previous research explored vulnerability concerning climate change[90] and the COVID-19 pandemic.[81,91,92] We now adapt this concept as the linchpin of a multiple-stressor integrated approach. This approach connects different sources of evidence that demonstrate the systemic impacts of these crises and allows us to draw the connections between their multiple stressors.[53]

Taking the case of the health-climate nexus, we implemented the multiple-stressor framework, as seen in Figure 4. We realize the first stage of the framework by engaging Brazilian stakeholders in academia and civil society to establish a co-design, realization, and dissemination research scheme, as reported elsewhere.[64] In short, the stakeholders (policymakers, nongovernmental organizations [NGOs], and experts) provided breadth in the form of multidisciplinary insights from geography, economics, urban planning, and environmental science into the COVID-19 pandemic in Brazil, a highly unequal country. Interaction with stakeholders also grounded the research team in the local research and empirical issues. To answer the stakeholders' expectations and information needs, we established a mixed research design with methods from climate sciences, physical

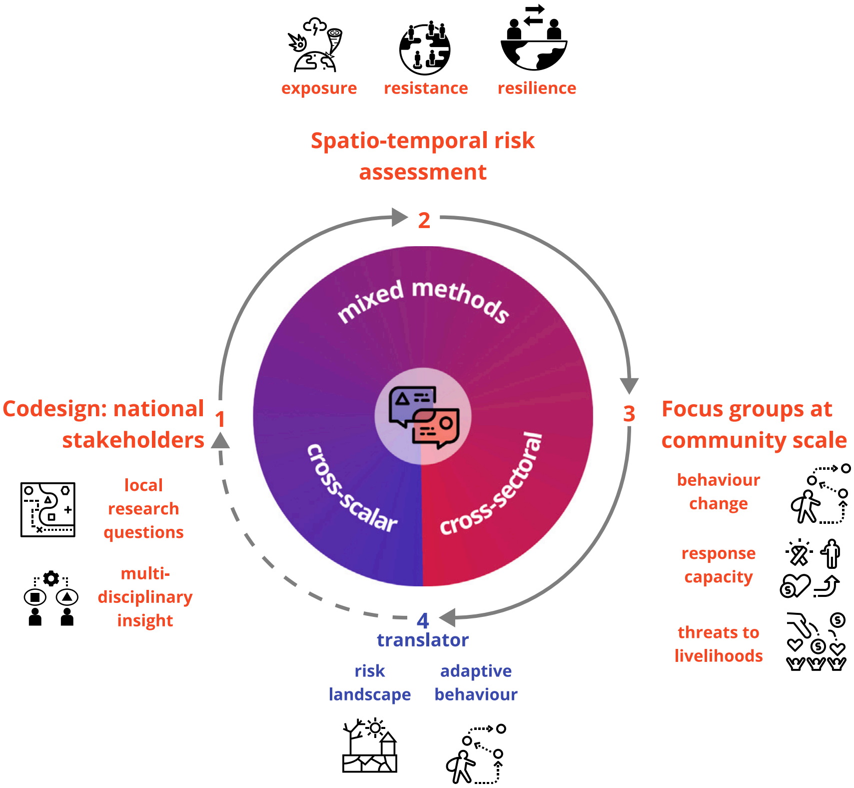

Figure 4. The stages of the multiple-stressor framework

(1) Engaging local stakeholders to co-design the research approach. (2) Spatiotemporal risk assessment of the multiple risks considering exposure, resistance, and resilience factors. (3) Focus groups at the local scale with thematic analysis to obtain the primary codes, themes, and behavior patterns. (4) Translator to integrate scales and mix qualitative and quantitative evidence with ABM.

geography, and social sciences. This mixed-methods design implemented fieldwork and analysis for two regional capitals in the country, Porto Alegre (PA) and São Paulo (SP), as examples of cities from the Global South. In this sense, we achieved a broad representation of the crises by including multidisciplinary viewpoints in socially and geographically diverse cases. This stage also supported depth via its transdisciplinary research framing that included the mixing of qualitative and quantitative methods.

The second framework stage took shape as a spatiotemporal risk assessment. We sought to answer what was the spatiotemporal COVID-19 risk during 2020. From a top-down perspective, we employed a multidimensional risk assessment to represent potential risk using biophysical, demographic, and behavioral data[64] to represent resilience, resistance (i.e., the capacity to adapt to and resist impacts, respectively), and exposure (the degree to which one is subject to potential adverse impacts).[59] We represented these risk dimensions according to Pelling,[59] in a definition fairly aligned with that of the IPCC.[3] In our spatiotemporal assessment, they feature as different risk-influencing factors. The assessment thus included traditional COVID-19 risk factors (e.g., age) and novel factors adjusted to the Global South (i.e., social vulnerability and mobility). The results for SP indicated the importance of social vulnerability in defining the most at-risk sectors in the city.[64] Behavior in both cities significantly influenced the risk assessment, eventually becoming so prominent as to overcome the other vulnerability factors. The significance of these results for the framework was in demonstrating the spatiotemporal distribution of risk and vulnerability. Their limitations also pointed out the restricted descriptive capacity of the assessment at the local scale and the counterintuitive behavior of increased exposure over time. Breadth here came from the multiple data sources that provided the broadest context for the study. The need for depth took shape as we identified the limitations of the top-down assessment in explaining behavior. In short, this turned an unknown unknown into a known one, reducing uncertainty.[25,26]

The focus groups in two locations in SP and PA shaped the third stage of the framework. Facing the limitations from step 2, we wanted to assess the distribution of the burden of COVID-19 in each city from a bottom-up perspective. To this end, we applied semistructured questionnaires in group discussions. Following the multidimensional risk framing,[59] we had groups with contrasting degrees of social vulnerability in each city: the first group had people from the low-vulnerability urban core, while the second group had participants from the outer periphery with very high social vulnerability. Diverging experiences during the pandemic emerged from the thematic analysis[67] we performed on the focus group data. In both cities, the core groups had tangible improvements in their quality of life (e.g., education, employment, and lifestyle) after the pandemic. In contrast, the periphery groups faced reduced work, anxiety, fear, and other mental health issues while struggling to avoid contagion. These results showed how significant the local scale was in portraying the risk experiences, including behavior and reasons for exposure (e.g., trade-offs between securing income and avoiding contagion). This step provided breadth by including diverse experiences from the bottom up and insights that were not possible in our earlier top-down perspective alone. As in the third stage, the limitations of the evidence demonstrated the need for integration that may provide depth.

In the fourth research stage, we developed an ABM that presented translating qualities.[81] This model integrated top-down quantitative spatial risk in its environment and bottom-up agent behavior from the focus groups. The model built on our previous experience with the VIABLE modeling framework[62] and aimed at understanding the aggregate mobility behavior of individual agents at the neighborhood scale. To this end, the agents first decided if the benefit of leaving their house was worth the risk. Then, they chose a transportation mode and a destination based on their needs and capacities (e.g., budget). The results showed that agents with similar vulnerability and economic backgrounds tended to select the same mobility patterns and activities, thus

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Table 1. Summary of evidence acquired by each framework stage

Stage	Main contribution to the framework	Evidence type	Evidence without integration	Evidence with integration
(1) Co-design with stakeholders	breadth (stakeholder diversity) and depth (analytical framing)	qualitative (co-design)	• multidisciplinary problem outline • limited sectoral, disciplinary, or scalar integration	• transdisciplinary analytical framing • mixed-method integrative approach research design
(2) Spatiotemporal risk assessment	breadth (risk context)	quantitative (risk index)	• quantitative estimation of risk • spatial distribution of risk factors	• evidence gaps or blind spots (e.g., behavior) • risk experience overarching context
(3) Focus groups and thematic analysis	breadth (divergent experiences)	qualitative (content analysis)	• in-depth case studies (focus groups) • divergent risk experiences • limited generalization potential	• behavioral drivers of risk experiences • novel research gaps from divergent experiences
(4) Translator ABM	depth (evidence integration)	qualitative-quantitative	• process representation based on complexity • challenging calibration and validation	• convergence between qualitative and quantitative parameters and evidence • explicit information transfer from down- and upscaling

Source: the authors.

leading to clustering and agent segregation at the neighbor scale. This stage was key in bringing the preceding evidence, methods, and observations together, thus providing depth to the framework application. Only through the integrated perspective of the risk assessment and the focus groups could we understand the complementarities between these methods and build a more robust perspective on the crises. Finally, while this was the last step in this implementation, the framework should be understood as a cycle. In this way, the insights from one stage feed new iterations with increasing knowledge of the hazards.

The above examples demonstrate how it is possible to integrate disciplines and sectors and include different spatiotemporal scales and complexity. They are part of a concerted effort to cross disciplinary boundaries and provide mixed evidence on the same problem: vulnerability to systemic crises with multiple stressors. Table 1 presents a summary of the evidence acquired at each stage and, critically, the benefits from the integrative effort in the framework.

This summary shows the added evidence at each stage and the integration between them that the framework fosters. The approach's transdisciplinarity was the major contribution from the first stage. It was achieved by co-designing the integrative approach with the stakeholders, and it broadened the thematic range to address multidimensional vulnerability. While the second stage provided context by assessing exposure and vulnerability, it also demonstrated the uncertainty at the local level that demanded bottom-up exploration. For example, this stage's results indicated that the COVID-19 risk varied somewhat linearly over the territory, following the different demographics and behavior patterns. This method could not report local outliers such as very-high-vulnerability informal settlements. The third stage reduced the epistemic uncertainty[25] by incorporating divergent risk experiences and allowing critical differences to emerge. It included previously unaddressed factors (e.g., gender or health facilities accessibility) that critically influenced vulnerability. Finally, the fourth stage translated information across several socioeconomic sectors, research disciplines, scales, and levels of complexity, reconciling the top-down perspective with the diverse value systems found locally. In our implementation, the ABM allowed us to verify that there was reason to generalize the relationship between very high social and COVID-19 vulnerabilities across sectors (for example, health, economy, and society).

Our contribution does not extinguish this discussion. It adds a novel perspective to the grand challenge of transdisciplinary integration in multiple-stressor research. First, we must recognize that the integration presented here was mainly exploratory (i.e., it seeks knowledge through a process rather than validating or testing initial assumptions). By building on a comprehensive review of the field, we aimed to extend missing links between well-known methods and theories. Second, the empirical research we developed would benefit from more breadth and depth. Increasing the number of case-study cities and considering other hazards (e.g., extreme weather events or heat waves) would widen the framework's application and test its robustness. Developing more in-depth fieldwork with groups in intermediary positions of the sociovulnerability gradient would provide nuance and precision. Validating the risk analysis and the ABM results is also crucial in establishing robustness. We sought to build a methodological typology that advances research on complex contemporary phenomena. New framework implementations can overcome current limitations and test it for explanatory and predictive designs. Finally, these limitations demonstrate the necessity for further research, especially multidisciplinary projects structured in mixed-methods research designs.

OUTLOOK

Scientific research agendas on multiple stressors, compound hazards, and systemic risks present many missed opportunities for integration. The lack of capacity of different scientific fields to gain experience from other areas and the challenges of

Table 2. Main insights from the literature review

Main insights	Sources
Multiple stressors	
Ecosystems do not have well-defined boundaries, and stressors and sectors interact	Elmqvist et al.[2]; Lele et al.[10]; O'Brien et al.[20]; O'Brien and Leichenko[38]; Ramírez et al.[35]; Räsänen et al.[36]; Watts et al.[4]
Climate change increases the temporal and spatial overlap of stressors, which multiplies their impacts	
Stressors have environmental, technological, and social origins	
Stressors may add, reach synergies, or have antagonistic effects on one another	
The Anthropocene presents multiple stressing factors to human society	
Cities are frequently exposed to multiple hazards	
Adapting to multiple stressors challenges decision-making by presenting risk-risk trade-offs and conflicting priorities	
Compound hazards	
Severe weather or climate impacts from risks sharing drivers or hazards	Bevacqua et al.[45,48]; Leonard et al.[43]; Raymond et al.[14]; Sutanto et al.[47]; Wahl et al.[46]; Westra & Zscheischler[6]; Zscheischler et al.[15,44]
Compounding hazards may generate more frequent "black swan" events: highly unlikely and damaging	
Non-extreme events may combine their effects, leading to extreme impacts	
Hazards may compound depending on their preconditions (same driver to multiple hazards) or outcome (spatial or temporal co-occurrence)	
Systemic risks	
Systemic risks present cascading and cross-boundary effects, tipping points, and non-linear developments	Juhola et al.[28]; Schweizer[9]; Schweizer et al.[52]; Sillman et al.[8]; United Nations University and UNDRR[22]
Systemic risks are unique; their outcomes cross system scales and affect multiple locations or sectors of society	
Systemic risks are more likely to interact with other hazards and conflicts, tipping social systems beyond their resistive thresholds	
Systemic risks challenge rational boundary definitions, and they lack a clear definition of the problem, its causes, and solution options	

terminology, language, and formal aspects of research contribute to this problem. However, the rapidly evolving crises in the Anthropocene urge us to stop missing potential synergies in the name of (intra)disciplinary progress. In contrast, the perspective presented here shows the similarities between these three scientific agendas. Specifically, it demonstrates the overlapping goal of preventing and managing the increasing natural, technological, and social risks emerging as the Earth moves beyond its planetary boundaries. Information ambiguity has hindered joint research, notably when it avoided transdisciplinarity to contain it. Similarly, most analyses have not incorporated the complexity of cross-sectoral and transscalar analyses. Ultimately, these shortcomings have biased research and policy measures toward the physical aspects of hazards, underestimated hazard damages, and spurred adaptation measures away from the values of specific communities.

To overcome these challenges, we propose, not to avoid complexity, but to embrace it via a four-stage framework. The different methods in the research design have broad applications, are robust, and are well known in their respective fields (e.g., climate and social sciences), but are seldom put together. We innovate by employing them concertedly with contributions that produce a broad and deep analysis of a systemic problem. The transdisciplinary methods bring about broad evidence. The robustness of the individual methods allows the framework to achieve much-needed depth. Finally, the sequential mixing of the methods supported by the ABM provides convergence and reconciles the complexity of the evidence.

Multiple-stressor research and policy cannot ignore the interactions of hazards nor assess them in disciplinary silos.[6] Future research should implement qualitative and quantitative investigations that use mixing to challenge each evidence source and avoid epistemological blind spots.[82] A synthesis is possible and necessary. We provide the elements to advance in such direction by demonstrating a research framework that engages stakeholders at the project onset, promotes transdisciplinarity to address the root causes of health and climate crises, and includes local agency and capacity in determining risk. The alternative is research that relies on artificial intelligence methods (e.g., neural networks), which are becoming increasingly popular. While we do not oppose these approaches, we are also weary of their limitations, for example, the bias these models inherit from the data they rely on,[93,94] which might reinforce blind spots instead of countering them. Ultimately, these methods may offer new silos, albeit larger and probably more enticing. As argued here, transdisciplinary research projects on multiple hazards can provide a much-needed synthesis. Their strength should lie in embracing complexity, managing conflict, and learning from differences.

Table 3. Joint display of evidence and meta-inference from the framework's exploratory sequential mixed methods design

Stage	Evidence types and scales	Existing evidence	Meta-inference from mixing
(1) Co-design with stakeholders	qualitative (interviews), national scale	• COVID-19 reporting through dashboards • case studies focusing on special populations (homeless or Indigenous)	• usual COVID-19 reporting is biased • research needs to account for local vulnerability • inequality is central to vulnerability
(2) Spatiotemporal risk assessment	quantitative overview of the urban scale	• vulnerability factors: age and co-morbidities • lacking spatiotemporal disaggregation of risk	• social vulnerability influences COVID-19 risk • behavior is a significant factor • risk assessment does not portray local outliers (e.g., extremely vulnerable slum dwellers)
(3) Focus groups and thematic analysis	qualitative (focus groups), local urban scale	• there are linear differences between high- and low-vulnerability population groups • counterintuitive exposure behavior is puzzling	• differences in COVID-19 vulnerability are non-linear • low-vulnerability group improved during the pandemic • counterintuitive behavior can be explained by trade-offs between income and exposure
(4) Translator ABM	quantitative, neighborhood scale	• divergent evidence from qualitative and quantitative perspectives • behavior process was not explored at the neighborhood scale	• low- and high-vulnerability agents cluster, generating new segregation because of exposure • location choice and transportation mode depend on vulnerability conditions • qualitative evidence (from stage 3) has generalization potential to other population groups

Source: the authors, following templates by Creswell and Cresswell.[65]

EXPERIMENTAL PROCEDURES

Structured literature review

We conducted the review structuring our integrative approach using records from the Web of Science with individual queries for compound hazards, multiple stressors, and systemic risks (i.e., [“compound event*” or “compound hazard*”], [“multiple stressor*” or “multiple hazard*”], and [“systemic risk*”], respectively). We refined the query results by selecting the areas of knowledge of interest for this research (i.e., environmental sciences, environmental engineering, water resources, geosciences multidisciplinary, and ecology). We then scanned titles and abstracts to guarantee adherence to each topic (when we found duplicates, we assigned titles exclusively to the most significant). We identified the most recent and relevant contributions among the classified titles and delved into the full texts. Eventually, we added older references found in these key articles that demonstrated the chronology of each research area. Upon theoretical saturation (i.e., new articles did not add novel insights), we concluded the search and synthesized the notes for each corpus. We present the main insights from this review in Table 2.

Joint display of evidence

To dialogue with the mixed-methods literature, we develop below the joint display of evidence from the framework's exploratory, sequential, and mixed-methods design,[65,82] as presented in Table 3. The column “stage” identifies one of the four stages in the framework, and “evidence types and scales” shows the geographic reference for them. Finally, the columns “existing evidence” and “meta-inference from mixing” work together to present the evidence gathered from each stage alone and what was the novel insight brought by the mixing, respectively. The contrast provided by the last two columns is key in qualifying an integrated mixed-methods design (as opposed to non-integrated designs, such as comparative or simple triangulation).

RESOURCE AVAILABILITY

Lead contact

Any correspondence or requests for further information should be directed to the lead contact for this study, Alexandre Pereira Santos (alexandre.santos@lmu.de).

Materials availability

This study did not generate new unique materials.

Data and code availability

This research produced new queries in the Web of Science, which are described below. We can provide the queries reports, if necessary. Additional information on the modeling, coding, and data generated in our previous work described in this paper may be found in the original publications. Alternatively, the lead author has also made the codes public in the GitHub repository, available at https://github.com/alexandrepereiraarq/.

ACKNOWLEDGMENTS

We thank our local partners in Brazil for their intellectual and physical support to co-design and co-realize this research: Cleiton Fernandes Chiarel from INSPE, Ygor Melo from TETO, Abel Escovedo from Sindicato dos Arquitetos do Distrito Federal, Bibiana Borda Valiente, Prof. Ricardo Dagnino and Prof. Julio Celso Borello Vargas from Universidade Federal do Rio Grande do Sul (UFRGS), Ernesto Galindo from the Instituto de Economia Aplicada (IPEA), Claudia C. Soares and Ana Ribeiro Neves from Terroá, and Marcela dos Santos Ferreira from Associação Fênix Renascendo das Cinzas Cidade Tiradentes. We also thank the co-authors of our previous research, upon which this investigation is based: Dr. Katharina Heider and Sergio Gresse. We thank Lazslo Steinwärder and Ream Moghames for their support as student assistants. We also extend our gratitude to the two anonymous reviewers for their dedication to improving this article. We thank the scholars who discussed previous versions of this article, especially Prof. Jana Sillmann and Prof. Pia-Johanna Schweizer, whose insight we greatly value. We are also grateful to Dr. Silvia de Angeli, Dr. Franziska Hanff, and Charlotta Mirbach for the lively discussions on breaching siloes that chart the future of this research. The icons in the figures were developed by BomSymbols and Nithinan Tatah and distributed via the Noun Project. The lead author has acquired all necessary rights. This research is part of the COVIDGI Project, funded by a Corona Crisis and Beyond grant from the VolkswagenStiftung. It contributes to the Cluster of Excellence Climate, Climatic Change, and Society (CLICCS), funded by the Deutsche Forschungsgemeinschaft (DFG) (grant ID EXC 2037).

AUTHOR CONTRIBUTIONS

Conceptualization, A.P.S., J.M.R.L., Y.P., and J.S.; methodology, A.P.S., J.M.R.L., Y.P., and J.S.; investigation, A.P.S., Y.P., and J.M.R.L.; data curation (review), A.P.S.; writing – original draft, A.P.S., J.M.R.L., and Y.P.; writing – review & editing, A.P.S., J.M.R.L., Y.P., and J.S.; supervision, J.S. and J.M.R.L.; funding acquisition, J.S. and J.M.R.L.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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