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Comparing hierarchical and inductive methods reveals fundamental differences in social vulnerability rankings

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Social vulnerability assessments play a crucial role in guiding the allocation of budgets and resources for effective disaster preparedness and humanitarian response. Climate change, escalating conflicts, and the climate finance and humanitarian funding gap make social vulnerability assessments essential. Despite advances in data collection, availability, and analysis, there remains a lack of consensus regarding the most suitable method to assess social vulnerability. This study sheds light on the consequences of methodological choices on social vulnerability assessments by comparing two commonly used methods in space and over time: the inductive principal component approach and the hierarchical INFORM approach. Our analysis focuses on a case study of the 351 communes in Burkina Faso from 2015 to 2022, a period marked by conflicts and extreme weather events. By comparing the two methods, we find important differences in the rankings of the communes' social vulnerability. By investigating the spatial and temporal results, we offer insights into the potential consequences of using different methodological choices. Our findings underscore the need for contextualized approaches.

Keywords Social vulnerability, Principal component analysis, INFORM risk index, Comparative case study, Humanitarian response, Disaster risk reduction

Climate change has led to a rise in extreme weather events, such as floods and droughts. In combination with conflict and violence, this led to a record number of 117 million refugees and internally displaced people in 2023[1] Disasters occur when hazards intersect with exposure and *vulnerabilities*: the susceptibility of the population to impacts and their (in)ability to cope[2]. Low-income countries are particularly vulnerable due to inadequate preparedness, adaptation, and mitigation strategies, making vulnerability assessments and reduction a crucial aspect of disaster risk reduction[3,4]. Because of this prominent role of vulnerability in the allocation of funding and resources, key global agreements such as the Paris Agreement and the Sendai Framework for Disaster Risk Reduction 2015–2030 emphasise the urgent need to better understand and analyse vulnerability[5].

Social vulnerability focuses on the human dimension of hazards and disasters and the coping capacity of people[6,7], as opposed to biophysical or infrastructural aspects[8]. Even though many studies assess social vulnerability, there is no consensus on the underlying conceptualization and assessment methodology[2,9–12].

Various quantitative methodologies have been used to assess social vulnerability, of which the development of a vulnerability index remains the most popular approach[5,7,9,13–16]. These indices serve as summaries of complex and multidimensional issues to support decision-makers in prioritising highly vulnerable communities and assessing spatial needs[16]. In a humanitarian context, these assessments face particular challenges: limited data coverage in regions of the Global South[17]; the need to capture spatial and temporal dynamics in rapidly changing situations[18]; and requirements for methodological transparency and reproducibility.

Traditionally, social vulnerability indicator models fall into three categories: inductive, hierarchical, or deductive[19,20]. As deductive models became outdated when more data-driven methods were introduced that allowed studying more dimensions of vulnerability, and avoided an a priori selection of indicators[21,22], the two dominant methodological paradigms today are: hierarchical models, which organize indicators into theory-

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driven categories with explicit weighting schemes such as the INFORM index; and inductive approaches such as the SoVI method, which use statistical methods such as Principal Component Analysis (PCA) to identify underlying patterns in the data.

The INFORM index[23,24], developed by the European Commission's Joint Research Centre and promoted by UNDP, is widely used by international organizations and government agencies to guide resource allocation. It employs a transparent structure of categories and subcategories, aggregating approximately 10–20 indicators based on a theoretical understanding of vulnerability. In practice, however, the use of a limited number of data inevitably leads to subjectivity[19,25] and has been shown that INFORM has trouble identifying spatially explicit patterns at the commune level[26]. The SoVI method by Cutter et al.[16,27] uses statistical techniques to reduce a larger set of indicators (often 20+) to uncorrelated components that capture maximum variance in the data. However, SoVI neglects existing social vulnerability frameworks and theories that address the importance of indicators, and is demanding in terms of data quality and granularity. A deeper discussion on each approach is provided in the Methods Section.

Each approach embodies different philosophical and practical trade-offs in how vulnerability is conceptualised and measured, with potentially important implications for how resources are allocated to vulnerable populations. Nguyen et al.[28] demonstrated the absence of a consensus among various methodologies for mapping social vulnerability, particularly concerning the analysis scale, variable selection, and their prioritization. The inherent variations in assessment methods pose a challenge in conducting comparative analyses of vulnerability, potentially compromising the acceptance and reliability of the obtained outcomes. Orru et al.[29] stress that vulnerability is addressed in different ways and via different structures in and across countries and sectors. However, outcome disparities resulting from these methods are rarely investigated and hence remain largely unknown. Birkmann et al.[2] compare the INFORM and the WorldRiskIndex (WRI) indices but focus on the internal and external validity of the two hierarchical models, excluding inductive approaches. Further, validation with e.g., mortality, may compound vulnerability with the occurrence of hazardous events. Other studies remained at a relatively abstract level, comparing different applications and methodologies[20], without studying how the results of applying different methods vary, or focused on comparing the inductive approach, to the expert knowledge approach[30], but they lack the temporal granularity required and focus on specific natural hazards (floods). The lack of a systematic comparison of the impact of different methods to assess social vulnerability over space and time and agnostic to the specific hazard leads to insufficient standardisation and comparability of social vulnerability assessments in research, while in practice, misallocations of scarce resources may be the result of inadequate assessments.

This research is intended for both the academic community seeking methodological rigour in vulnerability assessment and for practitioners—including humanitarian organisations, government agencies, and development institutions—who routinely rely on vulnerability assessments for resource allocation and investment decisions. By highlighting how methodological choices influence vulnerability rankings, we aim to stimulate a critical reexamination of established practices, challenge implicit assumptions, and bridge the gap between vulnerability frameworks and practical applications. Our findings thus create an opportunity to rethink how vulnerability assessments are conducted and used in contexts where the identification of vulnerable populations can have life-saving implications.

In this paper, we aim to make headway in addressing this gap by assessing the variability in the output of a social vulnerability index when employing inductive and hierarchical methods. We identify differences in social vulnerability index scores and rankings between the two methods in space and over time in a volatile, disaster-ridden context. To achieve this objective, we compare two widely recognized social vulnerability assessment methods: the INFORM method[31] and the SoVI method[16]. We conduct the comparison for Burkina Faso, a country that experiences a wide range of frequent disasters, including droughts, floods, epidemics, heat waves, wind storms, and insect infestations (an overview of recent shocks is provided in Supplementary Figure S1, d), all of which contribute to pressing issues such as desertification, land degradation, malnutrition (Supplementary Figure S1, e) increased poverty, and migration away from the central areas. The situation was exacerbated due to terrorist attacks leading to population displacements, which led to an increase of internally displaced people (IDPs) from 50,000 in January 2019 to 1.8 million in December 2022[32]. The combined effects of flooding, droughts, and conflicts create complex problems. As such, Burkina Faso presents a case study that allows us to analyse social vulnerability at the intersection of disasters and conflict.

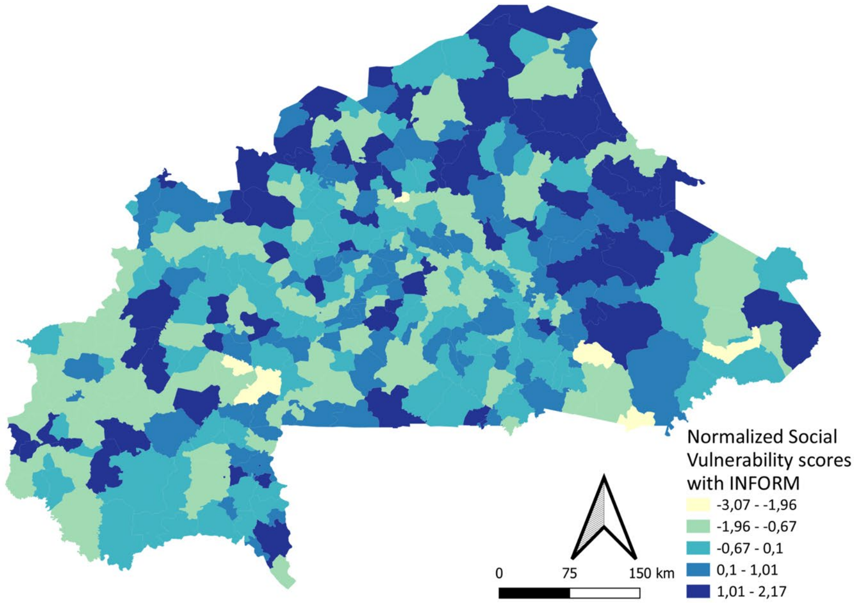
Results

Spatial results

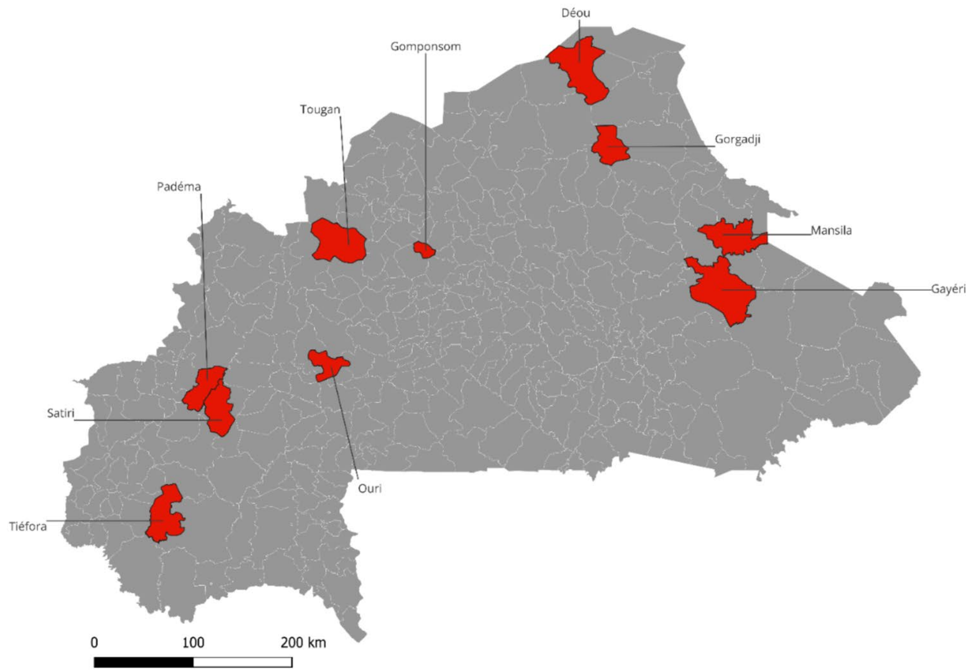
We assessed the spatial social vulnerability in 2020 using two methods: INFORM and SoVI. Figure 1 shows the INFORM results, specifically (a) the spatial pattern of the social vulnerability index across all communes and (b) the location of the ten most vulnerable communes, which are spread across the country. Upon examining the communities associated with high social vulnerability (Fig. 2a) it becomes evident that the vulnerability in these communes is mostly driven by indicators in the group *other vulnerable groups, aid dependency* and *inequality* as depicted in Fig. 2. Coping capacity factors, such as *governance* and *disaster risk reduction,* are present, but not sufficiently to tip the ranking.

For the SoVI method, the principal components' loadings and explained variance values are provided in Supplementary Table S4. Figure 3 shows (a) the social vulnerability index for each commune and (b) the ten most vulnerable communes identified by using the PCA method. These communes are predominantly located in the Sahel, Centre-Nord, and Haute-Bassins regions. Conversely, communes in the center and eastern regions of the country exhibit low social vulnerability indices and consequently have a high ranking.

Upon examining the communities associated with high social vulnerability (Fig. 4a), it becomes evident that the most vulnerable communes have significant populations of internally displaced persons (IDPs) and have



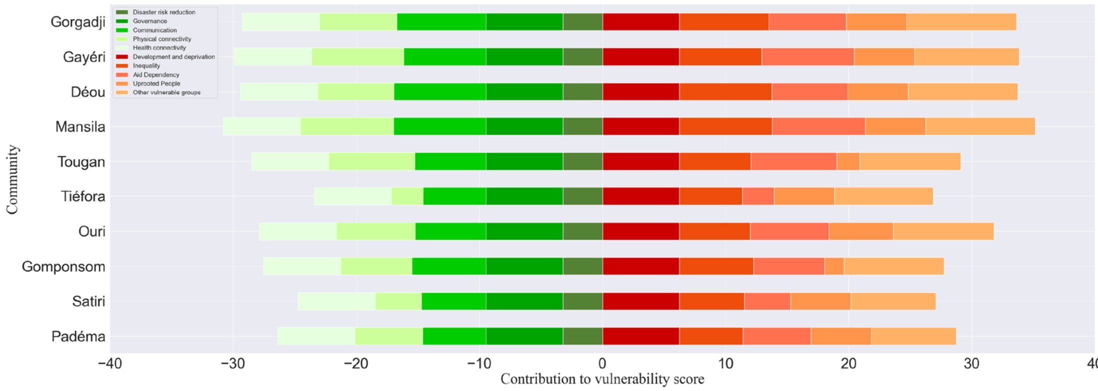
a) Social vulnerability INFORM



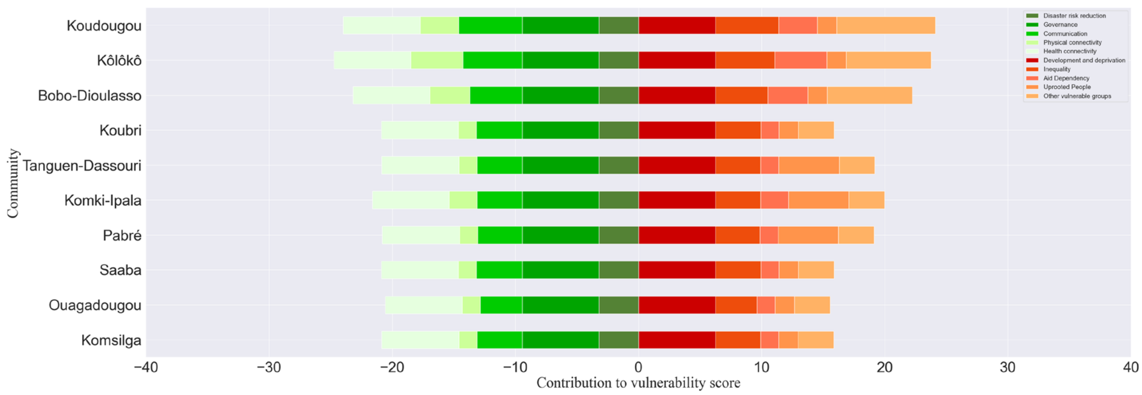
b) 10 most vulnerable communes

Fig. 1. Results for social vulnerability INFORM.

often experienced a combination of climate hazards, conflict, and malnutrition. In contrast to the INFORM index results, we find that the areas with a low vulnerability, exhibit strong coping mechanisms. These include improved access to water sources, shorter travel time to a city (see Fig. 4b), and access to information through television. As such, for the SoVI method, the external components, or the disasters that the communes are confronted with, dominate the social environment, coping capacity or access to infrastructure (travel times; water; sanitation, health; or information). This is also in line with the least vulnerable communes (Fig. 4b), which shows consistently lower values for disaster-related PCs, while especially for the first two communes, the coping capacity is similar to the most vulnerable communes. Especially for Ouagadougou, access to health sites makes a major contribution to the vulnerability profile.



a) 10 most vulnerable communes



b) 10 least vulnerable communes

Fig. 2. Results for social vulnerability INFORM (hierarchical method).

Temporal results

We could not find significant results for the temporal data sets using SoVI because the Kaiser-Mayer-Olkin (KMO) test indicated that our dataset was not suitable for analysis. This result showed that the collected data points contained limited information, and therefore, meaningful findings could not be derived. Consequently, we only assessed temporal social vulnerability using INFORM.

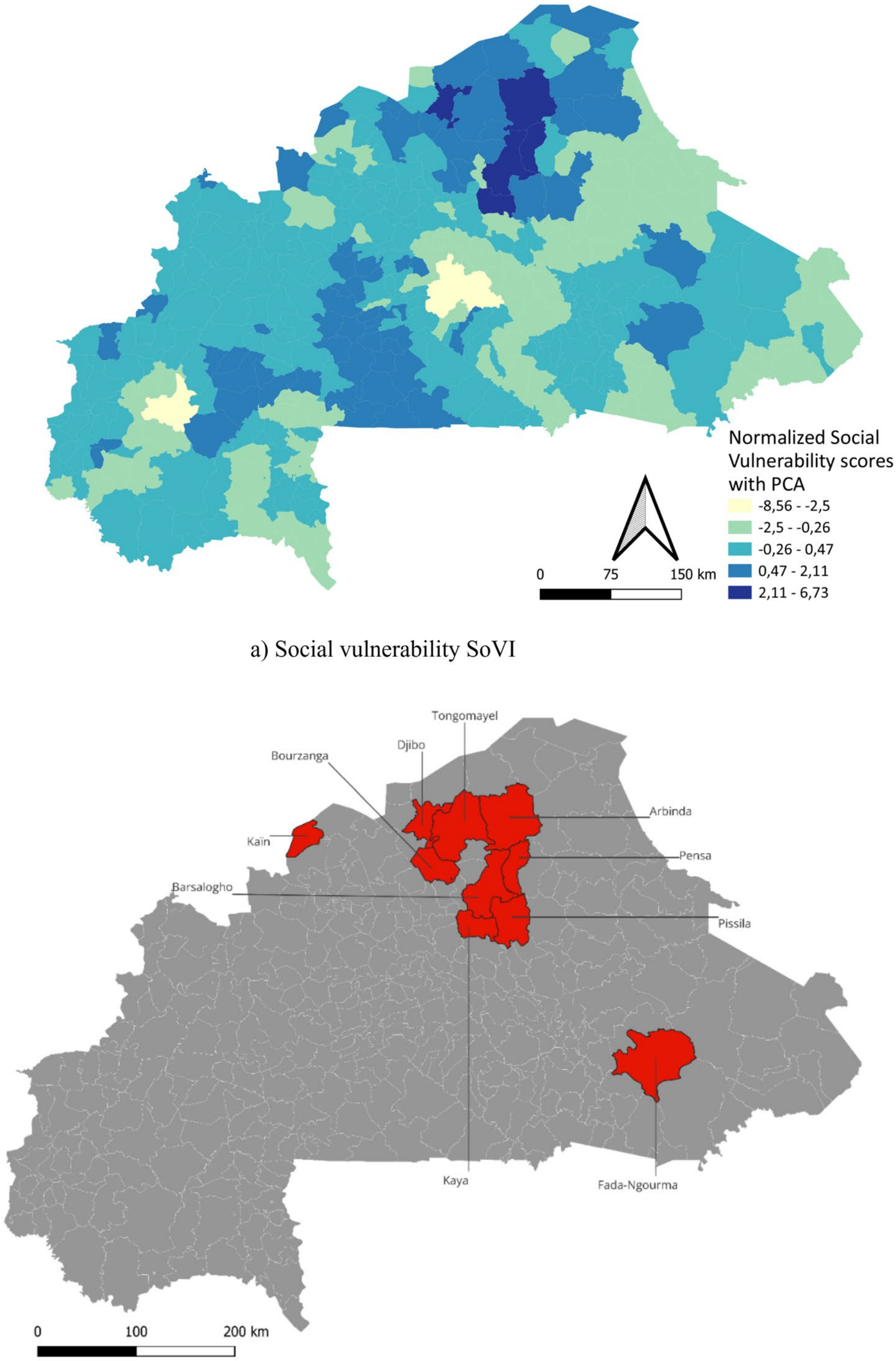
INFORM tracks social vulnerability changes in the regions from 2015 to 2021. Figure 5 shows that social vulnerability mostly increased in the 13 regions. However, in 2017, there was a notable decrease in social vulnerability. The worsening security situation since 2018, with increased presence of non-state armed groups, has caused a surge in forced displacement and food insecurity throughout Burkina Faso[33], resulting in a rise in social vulnerability. This finding emphasizes the impact of conflict on social vulnerability and stresses the need to broaden assessments beyond natural hazards. The only region that maintained low social vulnerability over time was the central region surrounding the capital Ouagadougou. The Sahel region had the highest vulnerability values until 2020, but recently, Centre Nord, Nord, and Est regions surpassed it reflecting the regions with greatest displacement and humanitarian needs in 2023[34].

Comparison of methods

For the temporal analysis, we highlighted that the data environment made it impossible to conduct a SoVI in Burkina Faso. As such, the INFORM method was better suited than SoVI to analyse patterns of the evolution of social vulnerability over time in data-sparse environments.

For the spatial analysis, we compared the results of the year 2020 from SoVI and INFORM. We calculated the distributions of the normalised social vulnerability scores (see Supplementary Figure S5). The 50 % quantile for the SoVI method is higher, with 0.023 versus -0.13 for INFORM. Despite these slightly higher results, the spread of results with INFORM is larger compared to SoVI, especially for the higher social vulnerability values. The 25%-quantile is at -0.74 for INFORM and at -0.34 for SoVI. The 75% quantile is at 0.81 for INFORM, vs 0.36 for SoVI. The ranges of social vulnerability values obtained by the two methods indicate that INFORM is more sensitive to variations, especially with respect to higher vulnerability values. This observation aligns with the lack of a 'dampening' effect for higher coping capacity discussed earlier.

Figure 6 displays the spatial distribution of the ranking differences of communes. Notably, 75% of the communes change more than 100 ranking positions between the two methods. High and low ranking



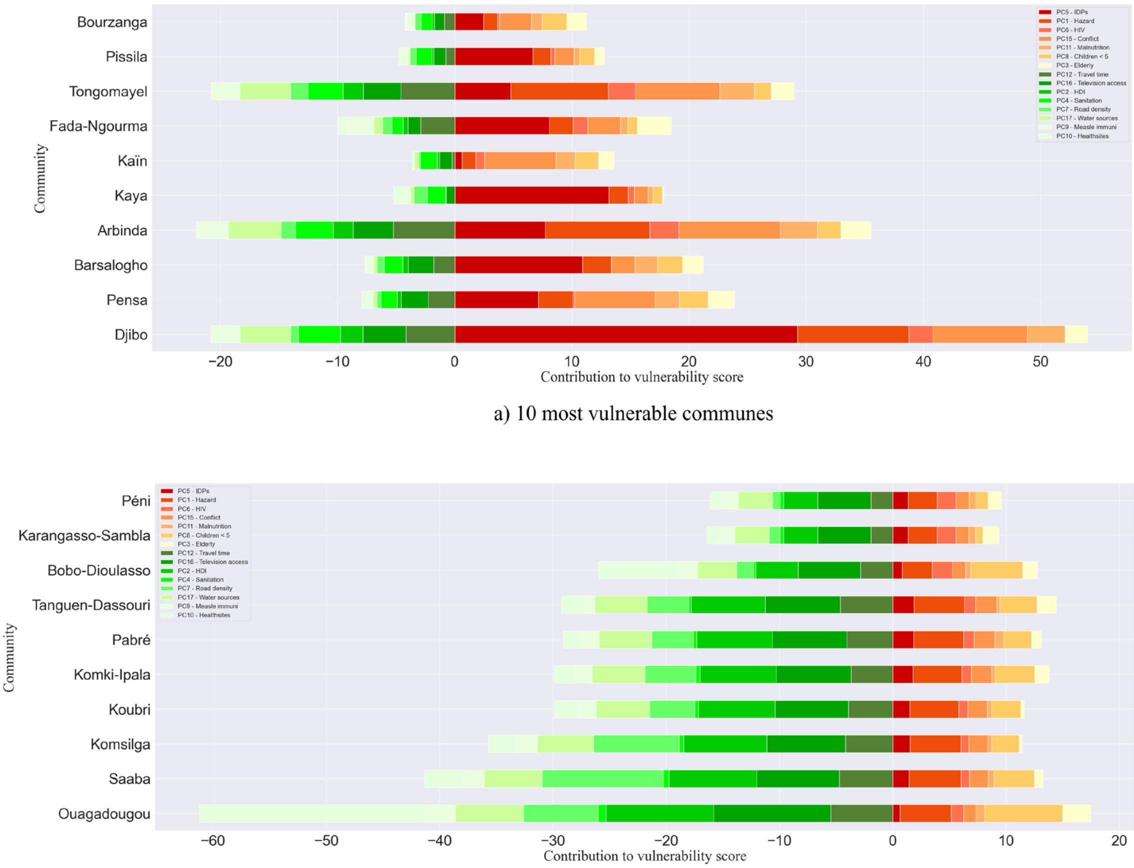
a) Social vulnerability SoVI

b) 10 most vulnerable communes

Fig. 3. Results for social vulnerability SoVI.

distributions were scattered, with communes that hardly change in rank neighbouring some of the communes with the highest changes. Therefore, we could not detect any geographic pattern in the distribution of ranking differences.

Figure 7 provides a visual representation of the different rankings of communes by using SoVI and INFORM. Results show that there is no discernible pattern in the change of rankings. However, those rankings can differ by up to 200 positions. For instance, if a commune is initially ranked within the first-ranking group (1–20) by SoVI, it can be ranked in the second (21–125), third (125–225), or fourth-ranking group (225–330) by the INFORM approach. We found even a direct correspondence of communes ranked in the second, third, and



a) 10 most vulnerable communes

b) 10 least vulnerable communes

Fig. 4. Results for social vulnerability, SoVI (inductive method).

fourth, ranking groups of SoVI and INFORM. This means that a commune ranked in groups 225-330 following the SoVI method can be one of the 20 most vulnerable communes with INFORM.

Discussion

This research demonstrated that the application of different methods to measure social vulnerability can lead to different social vulnerability rankings, even when using identical underlying data. By comparing the INFORM and SoVI methods in Burkina Faso, a country facing multiple natural and man-made disasters, we revealed significant inconsistencies in vulnerability assessments that have direct implications for humanitarian assistance allocation.

This finding raises concerns about the reliability and validity of current assessment methods. The INFORM index is promoted by UNDP and the EU's Joint Research Center as a tool to "*help make decisions at different stages of the disaster management cycle, specifically climate adaptation and disaster prevention, preparedness and response*"[35]. Similarly, the SoVI approach has become influential in academic research and increasingly in policy applications.

When these popular methods produce different rankings of vulnerable communities, the underlying methodological choices or potential biases may influence decisions, and therefore the provision of assistance to the most vulnerable communities. Given the increasing reliance on data-driven or even automated decision-making in humanitarian contexts[36], the stark differences make it crucial to increase transparency regarding the underlying methodological choices, and to analyse how it comes that different methods result in different outcomes (such as different rankings) even when using the same input data.

Both indexes are compensatory in nature, assuming that poor performance in one indicator can be offset by good performance in another. As Figs. 2 and 4 show, however, the underlying assumptions are questionable. For instance, does access to television and more information enable a commune to cope with an influx of IDPs? Does access to more water points help cope with conflict? Especially additive vulnerability frameworks that have their root in multi-attribute utility functions have been shown to generate composite indicators with higher compensability of attribute components. Multiplicative forms can be used to ensure that a low score in one component reduces the composite indicator drastically[37]. These methodological choices have significant implications that are rarely made explicit to end-users. Yet, our findings show that it is advisable to reflect on the underlying aggregation mechanism, and explore alternative aggregation methods, or develop methods to

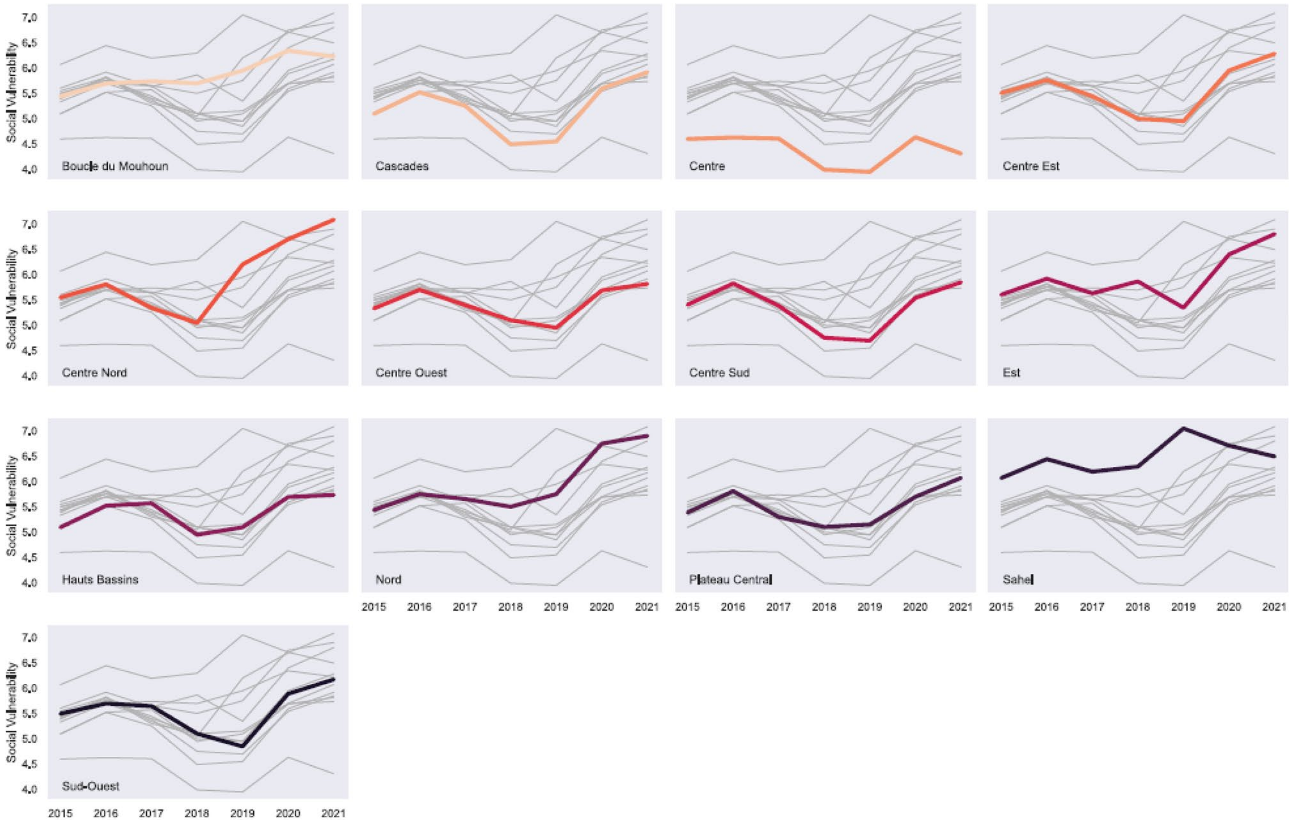


Fig. 5. Temporal dynamics of social vulnerability in Burkina Faso as analyzed using the INFORM method.

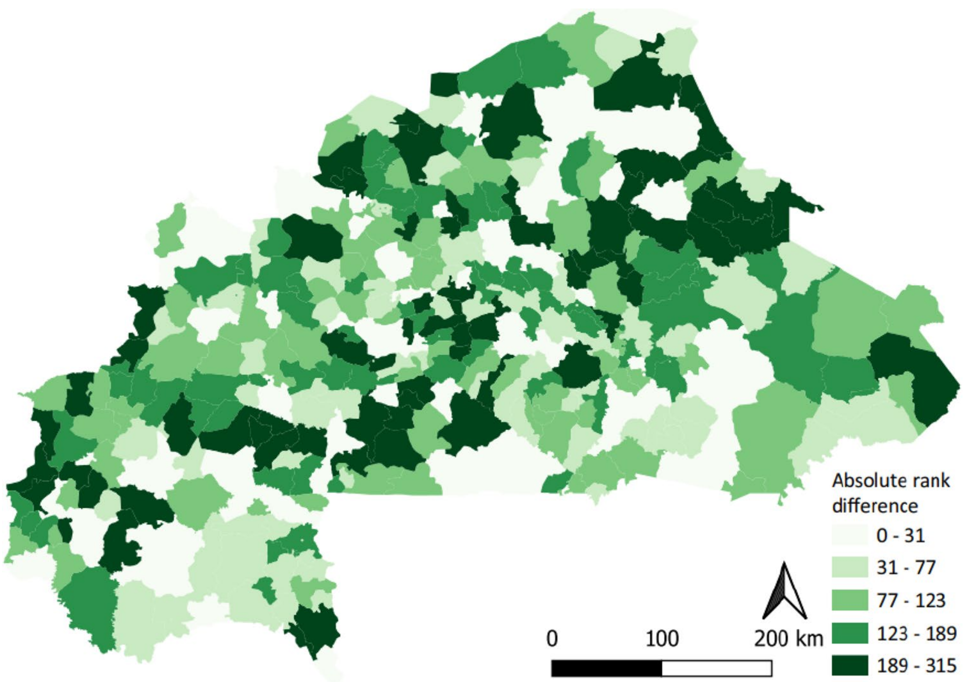


Fig. 6. Spatial distribution of absolute difference in ranking for 2020.

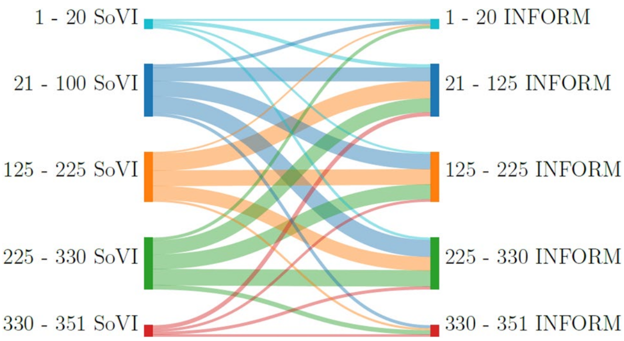


Fig. 7. Flow of rankings of the communes.

		Inductive: SoVI	**Hierarchical: INFORM**
Selection of indicators	Choices	Automated	Theory-driven
	Contextualisation	Automated	No, global standard
	Accounting for double counting	Yes (+)	No (–)
	Large numbers of data sets	Possible	Max 10–20
	Data requirements	Very high	High
Dynamic behavior represented	Spatial consistency	Yes (+)	Yes (+)
	Temporal assessment	Not possible for Burkina Faso (–)	Possible (+)
	Interpretability	Complex (–)	Based on literature (+)
Suitable for decision making	Computing time	Time consuming (–)	Quick (+)
	Black box	Yes (–)	No (+)
	Humanitarian principles	No (–)	No (–)
	Intrinsic functioning	Medium (–)	Good (+)
	Post-hoc evaluation	Good (+)	Good (+)

Table 1. Comparison of the methodologies with benefits (+) and drawbacks (–) for decision making.

capture the non-compensurability of certain indicators, e.g., via taboo trade-offs, (situations where comparing sacred values like human life with secular values like economic costs is considered morally problematic, see e.g.,[38].

For humanitarian and development actors guided by principles of neutrality and impartiality, it is essential that vulnerability assessment methods identify those most in need without introducing biases. Contextualised transparency[39] in decision-making (whether automated or not) is important for accountability both towards donours and populations affected. As a starting point towards accountability and methodological transparency, we discuss the methodological benefits and drawbacks encountered during the analysis of our case study and in the literature. We will discuss the 1. indicator selection 2. dynamic behaviour both spatially and 3. temporally suitability for humanitarian decision-making of the two methods. We summarise and synthesise our findings on all categories in Table 1.

The statement "garbage in, garbage out" often used in modeling, also holds true in the development of social vulnerability indices. It emphasises the importance of including accurate and relevant indicators that truly reflect the factors shaping social vulnerability. In the case of the inductive approach, a larger pool of indicators is typically used by an automated method (PCA) to select the indicators that explain the most variance. While this approach accounts for the double counting of correlated indicators, it provides limited opportunity to reflect upon the meaning of indicators or PCs within their context. Normative choices are hidden and are therefore more difficult, especially for the less data and model-literate users, to be challenged or adjusted. For instance, in Cutter's initial work on SoVI, migrants were considered as negative for resilience[16]. However, there is increasing evidence to suggest that migrants may possess significant resilience due to the challenging journeys they have undertaken[40]. Moreover, it is crucial to consider broader perspectives and incorporate distributional impacts and inequality within social vulnerability assessments[41].

Localisation and the need to be sensitive to different contexts are at the heart of the humanitarian agenda since the 2016 World Humanitarian Summit[42]. The SoVI approach automatically accounts for the different situations in different countries (or different years): depending on the data (and the explained variance) different sets of PCs and underlying indicators may be chosen to calculate social vulnerability. However, this purely data-driven approach does not integrate the view of local decision-makers or communities and does not allow them to raise their views on how to interpret or weigh the indicators. The globally standardised INFORM-index claims to support a 'global comparison' of different countries as the same indicators are used for each country. However, the underlying mechanisms that drive vulnerability may be very different; or different indicators may have different meanings and interpretations. To address these limitations, it is important to involve local authorities, communities, and stakeholders in the design, and interpretation of social vulnerability analyses, and to discuss potential trade-offs and choices.

There is a broadly recognised need to understand the dynamics of social vulnerability, both in terms of spatial differentiation and temporal dynamics[43]. Our spatial analysis reveals that the hierarchical INFORM approach provides greater differentiation among highly vulnerable communes as compared to the SoVI approach (Supplementary Figure S5). This enhanced differentiation is particularly important for communities with higher vulnerability scores, allowing for more nuanced prioritization among the most vulnerable populations.

Our temporal analysis clearly show that social vulnerability changes over time, driven by the dynamic situation on the ground, see Fig. 5. However, the methods differ markedly in their ability to capture these temporal changes. While the INFORM method successfully tracked temporal variations, the SoVI approach could not produce meaningful temporal results in our case study due to data limitations. This highlights a fundamental challenge: despite advances in data collection through satellite imagery and other technologies, data gaps remain prevalent in many vulnerable countries. The SoVI method, being more data-intensive, requires substantial information to achieve statistically significant results-a requirement often difficult to meet in rapidly evolving crises, as in our case study on Burkina Faso.

Although increased investment in data collection and technology may eventually address some of these limitations, for both types of social vulnerability assessment, it will remain difficult in very dynamically evolving situations to rapidly recalculate social vulnerability, as these situations require data with high spatial and temporal resolution. This could include scenarios involving fast-onset natural hazards, the outbreak of violent conflict, or mass migration, where timely and accurate assessment of social vulnerability is crucial.

Throughout the paper, we investigated different ways of assessing social vulnerability. Social vulnerability assessments form an important input for decision-making. We can distinguish different decision-making processes along the disaster risk management cycle. Usually, social vulnerability assessments are used to plan and budget for prevention or preparedness (DRR) type of interventions. This can be both at the global, national or local level (across or within administrative units). In some cases, social vulnerability assessments might be used in anticipatory action and humanitarian response, especially if, for example, damage and needs assessments are not yet available. All these applications require that social vulnerability assessments are contextualised and situation-specific[43], which depend heavily on the spatial and temporal resolution of available indicator data.

Drawing from concepts in explainable AI[44,45], we can evaluate both methods based on their intrinsic functioning (model transparency) and post-hoc behavior (outcome analysis). In terms of intrinsic functioning, the inductive SoVI approach requires more computational time than the hierarchical INFORM approach. This might be acceptable for preparedness and mitigation when social vulnerability assessments are not used in real-time. For anticipatory action or humanitarian response, computational effort might be more important; however, the most important bottleneck at this stage is data availability. In terms of transparency, the inductive SoVI approach, though potentially more statistically robust, creates a "black box" effect where composite principal components may increase mathematical explanatory power but reduce human interpretability. This has been shown to be particularly problematic for decision-makers operating under crisis conditions with cognitive constraints[46]. Humanitarian organisations are, by their very mandate, committed to the principles of humanity, neutrality, impartiality, and independence. However, neither method explicitly incorporates these principles into their methodological frameworks. The statistical automation of weights and indicators in SoVI potentially obscures normative choices, while INFORM's standardised approach may overlook crucial contextual factors. This is particularly important in situations where vulnerable populations are relying on humanitarian assistance and support. Given the differences between both approaches that we found, we suggest undertaking broad sensitivity analyses and methodological comparisons before sparse resources are allocated to ensure the robustness of the chosen approach.

In terms of post-hoc evaluations of how the model behaves, we have clearly shown the considerable differences between INFORM and SoVI. The difficulty with the post-hoc evaluation of social vulnerability is that we have no means to validate the outcome of the model behavior with actual ground-truth data and to determine whether INFORM is better representing the ground truth than SoVI or the other way around. Medina et al.[47] propose combining hierarchical and PCA approaches, using PCA to screen variables before applying them in a hierarchical framework, a promising direction for more robust assessments that merits further exploration.

This exploratory study on Burkina Faso compares two prominent methods for assessing social vulnerability, Cutter's Social Vulnerability Index as an inductive method and the JRC's INFORM as a hierarchical method. While our findings clearly demonstrate significant variations in vulnerability rankings between these two methods, we acknowledge that the generalisability of these results is constrained by our single-case design and the specific context of Burkina Faso. Burkina Faso represents a particularly dynamic context subject to large fluctuations in vulnerability factors due to overlapping crises of conflict, displacement, and natural hazards. Different countries with varying hazard profiles, data availability, and socioeconomic conditions might exhibit different patterns of methodological divergence, and the ranking differences we observed might not be as extreme in more stable contexts. Further, while we chose Cutter's SoVI and the INFORM index as two prominent assessment methods, we acknowledge that there is a variety of different approaches to assessing and quantifying social vulnerability. We therefore encourage further comparative studies that encompass diverse contexts and include a broader range of assessment methods.

Rather than providing conclusions about the universal superiority of any method, our research thus aims to initiate a critical discussion about the implications of methodological choices in vulnerability assessment. We encourage similar comparative analyses across diverse geographical and socioeconomic contexts to build a more comprehensive understanding of when and how methodological differences manifest. This broader investigation would help determine whether the discrepancies we observed are unique to Burkina Faso or represent a systematic issue in vulnerability assessment. By highlighting methodological sensitivities in Burkina Faso, we hope to stimulate more extensive cross-contextual research and methodological refinement to strengthen vulnerability assessment practices globally.

Further, the duration and scope of the study may also limit our findings, especially in terms of data availability. When we conducted the study, in 2022, the data available for Burkina Faso was still limited. As data collection efforts continue and improve, it is possible that more comprehensive data will become available, enabling broader comparison and temporal analyses using the inductive PCA-based method.

In addition, we acknowledge that while quantitative measures provide valuable insights into social vulnerability, they often lack the nuanced understanding of local contexts and the perspectives of those directly involved in the decision-making processes. We have clearly shown that the different approaches lead to different results and rankings. However, there remains the issue of a lacking 'ground truth' that makes it possible to decide why and how to prioritise certain indicators, or how to avoid that potential critical factors being overlooked. While the study's comparison provides valuable insights into the comparative performance of these methods in Burkina Faso, by engaging decision-makers in interviews, insights can be gained into priorities and considerations involved in addressing social vulnerability assessments, particularly for indicator selection, debiasing, and explainability.

In sum, our findings speak directly to the needs of both researchers and practitioners. For researchers, we contribute to the methodological discourse on social vulnerability. For practitioners who use vulnerability assessments to guide resource allocation and program design, our results stress the importance of critically examining the methodological foundations of the tools they employ. When different methods result in substantially different vulnerability rankings despite relying on identical data – as we have demonstrated in Burkina Faso – decision-makers must carefully consider how their methodological choices might inadvertently influence which communities receive assistance.

This observation calls for a collaborative approach that brings together researchers, practitioners, and – crucially – local communities who have vital contextual knowledge. This collaboration could take different forms such as co-design workshops where vulnerability frameworks are collectively developed, participatory validation processes where communities evaluate and interpret assessment results, and knowledge exchange platforms where methodological innovations are tested against local realities. By integrating local expertise and lived experience, vulnerability assessments can become more scientifically rigorous and more contextually relevant. In addition, this approach may also enhance the legitimacy, acceptability, and access to vulnerability assessments among the populations they aim to serve.

Conclusions

This study highlights the impact of methodological choices on social vulnerability assessment, even when using the same underlying data. By comparing the INFORM and SoVI methods as representatives for hierarchical and inductive methods in a case study of Burkina Faso, a country prone to frequent disasters, we have demonstrated that different approaches can yield divergent outcomes and rankings.

In particular, we found four main findings. First, spatial results showed that the ten most vulnerable communes were located in the Sahel, Centre-Nord, and Haute-Bassins regions by using SoVI, while they were spread across the country by using INFORM. Second, temporal results could be calculated using the INFORM method only, due to data limitations in our case study, and they showed that social vulnerability mostly increased in Burkina Faso. Third, comparison analyses showed that results derived from the INFORM method exhibited greater variation, particularly in the regions with the highest vulnerability. Fourth, ranking differences did not display any spatial pattern, nor did they indicate any consistent pattern between INFORM and SoVI, however, they did show a large deviation in ranking when using SoVI or INFORM.

These findings raise concerns about the reliability of current assessment methods in capturing social vulnerability accurately. In the context of increasing reliance on data-driven and automated decisions in humanitarian contexts, the significant differences underscore the need for transparency regarding the underlying methodologies and choices. It is crucial to understand the prioritisation of specific communities by different approaches and to analyse the reasons behind these choices.

In conclusion, this study highlights the importance of understanding the methodological differences in assessing social vulnerability and the potential implications for decision-making. It emphasizes the need for increased transparency in the consequences of methodological choices, involvement of local authorities and communities, and consideration of trade-offs and normative choices. While the comparison focused on Burkina Faso, further studies in different contexts using various assessment methods are encouraged. Engaging decision-makers can provide valuable insights into indicator selection, debiasing, and explainability, leading to a more comprehensive understanding of social vulnerability and its implications for addressing humanitarian challenges. This enhanced understanding of vulnerability assessments can enable a more effective decision-making process in disaster risk reduction efforts.

Methods

Data selection

To assess social vulnerability using different methods, namely the INFORM method as a hierarchical approach, and the SoVI method as an inductive approach to derive social vulnerability, we developed an identical data set for both methods. We started by collecting data on social indicators in our case study area, Burkina Faso. As the spatial scale, we selected the communes (i.e., 351 areas) and regional levels (i.e. 13 areas) (see Supplementary Figure S2 for their spatial locations). Supplementary Tables S1 and S2 list the collected data, which refers to the vulnerable groups, and socioeconomic, infrastructural, and institutional indicators in Burkina Faso for spatial and temporal assessments respectively. In cases where primary sources were unavailable, we retrieved the data from the Humanitarian Data Exchange platform. Additionally, we used the data used for the sub-national analysis of risk done by INFORM[48]. The suitability of the dataset was tested for spatial and temporal analyses respectively by the decision model shown in Supplementary Figure S3. From the original list of 32 indicators, we retained 22 indicators for the spatial assessment (see Supplementary Table S1), and 16 for the temporal assessment (see Supplementary Table S2).

For the *spatial analysis*, we used 2020 as the base year. First, the dataset was completed by adding data from the nearest data source available between 2017 and 2022 if data from the base year was not available. Second, the aggregation level was evaluated. Community-level data was directly included, while data at the regional and national levels were disaggregated if a suitable method was found. Regional data was considered of sufficient quality if disaggregation was not viable. The dataset was excluded if disaggregation was not successful. For the resulting dataset, spatial analysis could then be conducted for 2020 at the *commune* level.

The *temporal analysis* had to be done at a regional level since there was insufficient data available on a community level. To capture temporal variability, time series data were used for each indicator to calculate the social vulnerability for each year across the study period (2015-2022). All indicators were first tested on their temporal availability; indicators available for all years between 2015 and 2022 were (dis-)aggregated to the regional level and thereafter included. Indicators were excluded if they were only available for a single year between 2015 and 2022. The process for data inclusion for both spatial and temporal analyses is shown in Supplementary Figure S3.

INFORM AND SOVI calculations

To compare the INFORM and SoVI methods, we first calculated both indexes as described in this section. Supplementary Table S3 reports the analytical steps for each method, and Supplementary Figure S4 shows the hierarchical structure for INFORM indicators. The INFORM method was applied as the hierarchical approach. To calculate the INFORM scores, we followed the procedure proposed by the Joint Research Center of European Commission (JRC) (see[23]). We first selected the indicators and standardized the values. Standardization was calculated by using the min-max rescaling technique, calculated as (score - min) / (max - min), where the min is the 25^{th} percentile and the max is the 75^{th} percentile. The 25^{th} and 75^{th} percentiles were chosen as the minimum and maximum values, respectively, to avoid outlier errors (see[48]). Second, we aggregated the standardized indicators into a composite score. Weights were assigned according to the standard INFORM methodology, which applies equal weighting to all indicators within each dimension. This approach ensured that all indicators contributed equally to the composite index, as depicted in Supplementary Figure S4. Beginning at the lowest level of the hierarchy, we averaged the indicators within each subgroup and progressively aggregated these means at higher levels, ultimately obtaining scores for the vulnerability and the lack of coping capacity groups. Finally, we averaged the vulnerability score and lack of coping capacity score to calculate the INFORM social vulnerability index.

For the temporal analysis, this process was repeated for the dataset of each year. To assess the direction of change in social vulnerability over time, the scores were normalized using z-score normalization. A simple linear regression was then applied to calculate the line of best fit for each of the 13 regions. The resulting R^2 values were used to assess the strength of the relationship between the fitted line and the yearly changes in social vulnerability. Following[27], significance was evaluated at the 0.05 level. No significant changes were detected.

In this study, we used SoVI as the inductive approach. The SoVI scores are calculated following the procedure proposed by Cutter et al.[16], which used Principal Component Analysis (PCA)[49]. Through orthogonal linear transformations, PCA calculates vectors, also known as principal components (PCs), that capture the maximum total variability possible. By removing lower-order PCs, dimensionality is reduced while minimizing information loss[50]. To calculate the SoVI indices, we first selected the indicators and standardized their values. All indicators were standardised using z-score normalisation. Second, collinearity was assessed to reduce the initial set of indicators to a smaller set of slightly correlated indicators. The indicators with a Pearson's R > 0.7 were removed. Third, we tested the suitability of the dataset for the analysis. In particular, the dataset was tested by the Bartlett Sphericity test (p=0.0001) and the Kaiser-Mayer-Olkin (KMO) test (Spatial analysis: KMO-value = 0.62, temporal analysis: 0.13 < KMO-value < 0.375). This suggests that for the spatial analysis, the indicator set was suitable for conducting PCA, while for the temporal analysis, the dataset was not suitable. Fourth, the varimax rotation of the correlation matrix was used to simplify the underlying structure of the dimensions and to create higher statistical independence between the indicators. Fifth, the eigenvalues and eigenvectors were determined from the rotated matrix to identify the most significant components for the analysis. The eigenvectors were ranked in descending order based on the eigenvalue. In this study, we include 15 principal components, which account for 90% of the original variance, calculated by summing the eigenvalues. Sixth, the score of each PC per administrative unit was calculated by obtaining the dot product of the loading matrix and the normalised indicator values. The cardinality of each PC is determined based on the effect of the vulnerability of the highest contributing indicators within the component. Finally, to assess social vulnerability in each administrative unit, we calculate the weighted sum of the component scores. All the analyses were conducted using Python.

Analyses and comparison

For the spatial analysis, we analyzed the INFORM and SoVI results for the year 2020. We first mapped the spatial distributions of scores to show how social vulnerability is distributed across communes with each method. Second, we calculated the ranking of each commune based on the social vulnerability scores, and mapped communes accordingly. Ranking values ranged from 1, indicating the most vulnerable commune, to 351, indicating the least vulnerable commune. Third, we mapped the ten most vulnerable communes to identify vulnerability hotspots. For the temporal analyses, we encountered a significant decrease in data points from

351 to 13. Due to the lack of sufficient datasets at the commune level, we selected the regional levels. Because of the limited data, we were unable to calculate the social vulnerability using the SoVI for the temporal analysis. Precisely, for spatial analysis, the Kaiser-Mayer-Olkin test was 0.62, and for temporal analysis, it was between 0.13 and 0.375. To assess temporal variation across regions, we therefore could only calculate the scores of INFORM from 2015 to 2021.

To understand the difference between the SoVI and the INFORM methods, we analyzed the difference in rankings of communes in the spatial assessment. First, we compared the probability distributions of the normalised social vulnerability scores obtained from SoVI and INFORM. Second, we calculated the absolute difference in ranking values for each commune. We studied the statistical and spatial distributions of the differences in these rankings. The 20% quantiles of the differences in ranking distributions were used as a criterion to display class values. Third, we designed a Sankey diagram of the ranking values, which depicts the flow of ranking classes when using the SoVI and INFORM methods. Against the backdrop of our quantitative findings, we then discuss the benefits and drawbacks of each method in terms of indicator selection, dynamic behaviour, and suitability for humanitarian decision-making.

Data availability

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

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Author contributions

All authors have contributed to the design and drafting of the manuscript. They also approve the submission of the current manuscript.

Declarations

Competing interests

The authors do not have any competing interests.

Additional information

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