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Identifying disaster risk factors and hotspots in Africa from spatiotemporal decadal analyses using INFORM data for risk reduction and sustainable development

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Abstract

The incidence and magnitude of hazards in Africa are escalating. Extant knowledge base of disaster risk (DR) trends, factors, and hotspots is lacking for the continent. Here we applied random forest machine learning regressions, spatial stratified heterogeneity, and hotspot analyses on INFORM data to identify DR patterns, factors and interactions, and notable risk hotspots. We show that although DR is generally decreasing in Africa, the Eastern, Southern, and Western regions record increasing DR. Physical exposure to floods, epidemics, and violent conflicts are hazard drivers of DR in Africa. Other significant DR drivers are mostly clustered under vulnerable groups and poor infrastructural coping capacities. Human hazards interact with other factors, exhibiting the highest influences on DR. Precisely, 19 out of 53 African countries in this study are DR hotspots. Eritrea is identified as a new hotspot. Targeted policies, resilience building, vulnerability reduction measures and comprehensive sustainability-infused solutions are required for DR reduction and sustainable development in Africa.

KEYWORDS

Africa, disaster risk assessment, disaster risk reduction, resilience, sustainable development, vulnerability

1 | INTRODUCTION

The prevalence of both natural and human-induced hazards in Africa has shown a notable increase (Aliyu, 2015). Hazards, when compounded by vulnerability or insufficient coping capabilities, often culminate in disasters characterized by substantial loss of lives and livelihoods (Raju et al., 2022). An overlooked yet crucial aspect in understanding disasters revolves around the evolution of disaster terminology. The distinction between 'unnatural' disasters in earlier literature (O'Keefe et al., 1976; Wisner et al., 2004) prompts a clear differentiation between hazards and disasters throughout this study. Hazards encompass specific phenomena, whether natural or human-induced, capable of instigating adverse socioeconomic and environmental impacts, including fatalities or injuries. On the other hand, disasters manifest as significant disturbances within a community or society, brought about by the convergence and interactions of hazardous events, exposure, vulnerability, and coping capacity (United Nations General Assembly [UNGA], 2016). Thus, efforts to mitigate disasters, must, according to Rahman and Fang (2019), be based on a comprehensive understanding of all these facets.

A comprehensive report by Mizutori and Guha-Sapir (2020) reveals a stark rise in both the frequency and severity of global disaster events. They captured disaster events as surging by 74.48% from 4212 events in the period between 1980 and 1999 to 7348 events from 2000 to 2019, with attendant losses of human lives, livelihoods, and ecosystems, amounting to trillions of dollars. These disaster-induced losses are inimical to the achievement of global sustainability frameworks such as the Agenda 2030 and the Sendai Framework for Disaster Risk Reduction [SFDRR] (United Nations International Strategy for Disaster Reduction [UNISDR], 2015). The fundamental goal of disaster risk reduction (DRR), as outlined by UNGA (2016), is to prevent the emergence of new disaster risks (DR), mitigate existing ones, and manage any residual risks to improve societal resilience and the achievement of sustainable development. It is noteworthy that Wen et al. (2023) describe the evolution of the concept of DRR through three phases in the 1990s, 2000s, and 2010s, featuring key paradigms of disaster management, risk management, and resilience management and development. Thus, the current paradigm underscores the critical link between enhancing resilience and sustainable development.

The concepts of resilience and development remain subjects of contention, necessitating clarification for collective actions (Park, 2024). In this study, resilience is employed as a rallying call, following Park (2024), to denote the outcomes of disaster risk management (DRM) and DRR initiatives. It emphasizes the fortification of a community or society's structures and functional capacities, enabling them to withstand, assimilate, adjust to, adapt, transform, and swiftly recover from hazard impacts (UNGA, 2016). Such framing of resilience by UNGA (2016) is likely to be understood as the absence of vulnerability or susceptibility of a community to damages from hazards. In fact, prior studies, such as Cardona et al. (2012) and Ismail-Zadeh (2022), highlight vulnerability and exposure as primary drivers of disasters, with natural hazards acting as triggers, and climate change intensifying them. Conversely, other studies like Imperiale and Vanclay (2016, 2021), elucidate that the absence of resilience is not solely characterized by vulnerability, as even highly vulnerable communities possess substantial resources contributing to their resilience during crises and disasters. Similarly, Lavell et al. (2012) assert that the inadequacy of capacity is but one dimension within the context of overall vulnerability. This warrants a focus on not just the vulnerability levels of communities but also their resilience levels while considering the multidimensionality of these concepts.

Multiple dimensions of disasters numbering six have been synthesized by Imperiale and Vanclay (2021) to include the: (i) nature and attributes of the hazard itself; (ii) social aspects of risks and impacts (including distribution, perception, and experiences); (iii) underlying societal conditions and factors preceding disasters; (iv) capacity of local individuals to learn from past failures and disasters to facilitate sustainability; (v) underlying principles, objectives, and approaches embedded within DRM; and (vi) efficacy of social processes, services, and support systems available to a community prior to and post-disasters. The complexities inherent in disasters stem from a complex interplay of social, environmental, and governance factors, significantly amplifying their impact. Such amplification often leads to disparities in both the distribution and potential impacts of disasters. Previous research, as highlighted by Imperiale and Vanclay (2021), and findings from Machlis et al. (2022), attribute these disparities to the profound social dimensions of vulnerability and varying levels of coping abilities prevalent across diverse regions.

Africa, in particular, stands exceptionally vulnerable to the ramifications of natural hazards. Bari and Dessus (2022) identify a total of 13 African countries out of the 15 most vulnerable countries globally. Hazardous events like droughts and floods have further exacerbated poverty in the continent, causing a decline in GDP by 0.7% and 0.4% respectively (Bari & Dessus, 2022). The escalation of poverty suggests a likely simultaneous increase in vulnerabilities across the region. Moreover, a report from The Africa Center for Strategic Studies (2022) reveals a consistent rise in the population affected by disasters, with projections indicating a potential doubling by 2050, reaching nearly 2.5 billion disaster-affected individuals. This concerning trajectory is closely linked to urbanization in hazard-prone regions and increased hazard frequencies driven by climate change (Yaghmaei, 2019). Therefore, tailored DRR strategies are imperative, with a focus on reducing vulnerability dimensions and intentionally improving resilience across different regions within Africa.

Given disparities in disaster distribution across regions, it's imperative to evaluate these variations across countries within Africa, the continent most vulnerable to such challenges. Surprisingly, no prior study, to our knowledge, has delved into this crucial area. Hence, our study pioneers the application of multiple spatial statistical analyses, examining a decade's worth of data encompassing 53 African countries. This comprehensive investigation offers fresh perspectives on national-level DR patterns, trends, and focal points, employing spatio-temporal approaches such as spatial stratified heterogeneity (SSH), optimized hotspot and emerging hotspot analyses. Utilizing a meticulously curated INFORM dataset, we consider three fundamental dimensions: hazard & exposure, vulnerability, and coping capacity, consisting of six categories and 18 components—largely aligned with dimensions outlined by Imperiale and Vanclay (2021) barring one aspect (i.e., social aspects of risks and impacts). Our method hinges on empirical analysis but bears practical implications. By presenting nuanced insights into historical DR trends, we aim to furnish data-driven recommendations conducive to directing DRR efforts across the region. Moreover, our exploration of emerging hotspots serves as robust evidence to identify areas necessitating intervention priorities for mitigating DR.

2 | CONCEPTUAL FRAMEWORK OF THE STUDY

2.1 | Disaster risks, DRR and sustainable development

Natural phenomena, including volcanic eruptions, precipitation patterns resulting in floods and droughts, epidemics, and climatic trends, often transform into so-called natural disasters. While these events, termed hazards, according to (Kelman et al., 2016) are frequently essential for the environment and society, their catastrophic outcomes arise from human-induced vulnerabilities, eroding the natural essence of disasters. Hence, vulnerabilities created by social processes render these events disastrous, necessitating a deeper enquiry. Bailey (2022) simplifies the disaster concept, highlighting hazards and the social system as its fundamental variables.

Disasters, stemming from natural hazards, exert profound impacts on development. They exacerbate vulnerabilities, weaken resilience, and strain coping mechanisms (Pal et al., 2021). Furthermore, Bendimerad (2003) enumerates extensive damages to the environment, economy, and human capital, leading to disruptions in developmental programs. Disaster risks (i.e., different kinds of potential losses), emerge from the convergence of hazards, exposure, vulnerabilities, and coping capacities (Imperiale & Vanclay, 2021; Raju et al., 2022; Trogrlić et al., 2022), necessitating comprehensive consideration in DRR strategies. As natural hazards are uncontrollable, focusing on vulnerabilities and coping capacities becomes imperative (Ginige, 2011). Sometimes, vulnerability concepts are insufficiently covered in DR literature (Zhou et al., 2015).

Vulnerability, according to Birkmann et al. (2006), comprises susceptibility and coping capacity, which embodies weaknesses affecting community well-being, often intensified by social risks (Imperiale & Vanclay, 2021; Samaraweera, 2024). Coping capacities, vital for recovery, entail mechanisms that shape or challenge recovery in the aftermath of disasters (Birkmann & Wisner, 2006). Thus, lack of coping capacity is also vulnerability. However, rectifying vulnerabilities doesn't guarantee increased coping capacity, as existing strengths within vulnerable communities are often overlooked (Samaraweera, 2024). Recent literature emphasizes vulnerability as the underlying cause of disasters. Kelman (2015) advocates for acknowledging vulnerability as the principal cause of disasters and highlights its significance in global policy frameworks. Moreover, Ginige (2011) views vulnerability as a controllable element within disasters, suggesting that managing vulnerabilities is crucial in disaster mitigation.

However, Samaraweera (2024) criticizes the framing of vulnerability, which often equates it with weakness, incapability, and poverty, arguing that such a portrayal overlooks its multifaceted nature, encompassing socio-economic, political, and cultural dimensions. Therefore, addressing vulnerability comprehensively requires a holistic approach considering these diverse factors. Drakes and Tate (2022) delineate social aspects determining vulnerability, including demographics, land tenure, living conditions, and socio-economic status. Hence, specific aspects of vulnerability to be tackled in any community, region or state are known. Also, measures to address vulnerability primarily involve social interventions, albeit supplemented occasionally by technical measures (Kelman et al., 2016). Holistically addressing factors contributing to vulnerability becomes crucial, particularly in policies and actions (Bendimerad, 2003).

Unfortunately, there is a lack of studies presenting the trends and levels of vulnerability in African countries. The attempt to assess vulnerability in Africa by Ahmadalipour and Moradkhani (2018) was limited to droughts. Drakes and Tate (2022) confirm that current research examining social vulnerabilities in lower-income nations tends to focus on specific localized areas, limiting the identification of vulnerability factors across wider spheres. Furthermore, insights derived from scientific studies conducted in middle- and high-income countries may not be directly applicable or transferable to lower-income nations (Drakes & Tate, 2022). This creates a need for a comprehensive understanding of vulnerability in low-income nations, such as Africa, to provide a research representation necessary for designing sustainable and impactful interventions towards vulnerability reduction. Lower-income economies can cope less with hazards, as they lack resources and infrastructure for preparedness (Abdel Hamid et al., 2020). Moreover, disaster losses extend a vicious cycle of poverty (Hallegatte et al., 2020; Salvucci & Santos, 2020).

Coping capacities are integral prerequisites for reduced vulnerability and resilience. Recommending the improvement of living standards and protection from hazards for increased resilience, Naheed (2021) defines resilience as the stability and persistence of social systems, involving the enhancement of adaptive capacities through the provision of relevant assets and resources for individuals, communities, or states. Thus, initiatives that strengthen societies to withstand the impact of and cope in the face of disasters will reduce their susceptibility. These initiatives should include capacity building and resource provisions (Acharibasam & Datta, 2024). As a crucial factor for disaster recovery and adaptation, Marin et al. (2021) advocate for the inclusion of such resilience components in DR assessments. Notably, acute shortage of skilled practitioners have been identified as a source of delay in translating good policies into actions (Bang, 2014, 2022; Becker & van Niekerk, 2015). Furthermore, Keating et al. (2017) suggest that resilience provides an opportunity to address interconnected social and ecological aspects of DR and development.

Designing effective resilience initiatives should be preceded by a deep understanding of various needs, concerns, contexts, and vulnerability components. Subroto and Datta (2024) present such understanding as a prerequisite for disaster governance and resilience. In addition, McBean and Rodgers (2010) advocate for the establishment of national systems, infrastructure, and social networks to bolster resilience, enabling countries to better absorb the impact of natural hazards and thwart their progression into severe disasters. Therefore, the preparedness of nations to mitigate hazards and prevent their escalation into disasters requires strengthening resilience. Consequently, resilience efforts should not be regarded as singular actions but as ongoing processes. Kapucu et al. (2013) urge for continuous, coordinated local planning for resilience as vital for ensuring sustainability. Local planning plays a crucial role in building resilience, as Chipangura et al. (2017) highlight that communities are the focal point of DR concerns. Consequently, reducing vulnerabilities and exposure levels at the community level stands out as the most effective approach to DRR (Jafari et al., 2018; Zhou et al., 2015). Notably, prior research, such as Bang (2014) and Aka et al. (2017), critiques top-down hierarchical structures for mitigating disasters, advocating instead for community-driven bottom-up approaches. Additionally, Jiménez-Aceituno et al. (2020) suggest that proper DRR governance approaches can simultaneously advance both DRR and sustainable development objectives.

The literature provides evidence that implementing DRR measures, such as reducing hazard exposure and vulnerability levels, can bolster resilience, subsequently advancing the attainment of sustainable development. According to Bello et al. (2021), disasters' consequences are so profound that development cannot occur sustainably without resilience being an inherent component of development policies. The benefits derived from resilience in managing disasters are intrinsically linked to development. For instance, as highlighted by Naheed (2021), resilience leads to a decrease in fatalities during disasters, diminishes property damages, and safeguards socio-ecological systems. These observed advantages align with the economic, social, and environmental aspects of sustainable development. Furthermore, Keating et al. (2017) previously conceptualized resilience as the capability of a system, community, or society to pursue its social, ecological, and economic development objectives while effectively managing DR in a mutually reinforcing manner.

Thus, the widely recognized pillars of sustainable development are captured within the concept of resilience and underscore the synergy between DRR and sustainable development across various domains, encompassing social, economic, and environmental dimensions. Imperiale and Vanclay (2024) establish an explicit connection between DRR, sustainable development, and resilience while emphasizing wellbeing improvement, resources, services, capacities, and skills enhancement as the key to achieving DRR, resilience, and sustainable development. Similarly, Naheed (2021) contends that strategies and investments in DRR are significantly tied to reducing poverty and equitably enhancing social foundations, bearing in mind the needs of future generations. Alike, Akanle et al. (2022) describe poverty as a major concern for development and the success of the SDGs. Moreover, Ginige (2011) asserts that reducing vulnerability stands as the central objective of DRR within the framework of sustainable development.

The intricate relationship between DRR, vulnerability reduction, resilience building, and sustainable development requires a careful policy approach to avoid detrimental outcomes. Previous research like Thomalla et al. (2018) highlights the failure of DRR research to acknowledge and address how developmental processes contribute to the fundamental causes of disasters. Thus, questions arise as to what development would solve, rather than exacerbate, the problem of disasters. For instance, earlier research by Naheed (2021) established a connection between unplanned urbanization and heightened vulnerability levels. Therefore, inappropriate development practices tend to amplify, rather than diminish, vulnerability to DR. Acknowledging this reality, Thomalla et al. (2018) advocate for transformative changes towards equitable, resilient, and sustainable development. They propose a need to challenge prevailing values and objectives in existing development practices, critically evaluate the deficiencies in development and DRR approaches, and advocate for radical policy shifts and systemic changes in social systems to mitigate risks and counteract unsustainable development.

Therefore, policy gaps emerge concerning DRR and sustainable development. According to Kelman (2015), comprehensive DRR frameworks ought to effectively balance the concepts of hazards, vulnerability, and resilience. Similarly, Imperiale and Vanclay (2024) suggest that development policies, plans, programs, and projects should acknowledge, involve, and empower the processes of social learning and sustainability transformation, which are fundamental to fostering proactive resilience. Advancing research, policy, and practice in addressing vulnerability and resilience for sustainable development mandates a clear understanding of the complexities involved. Kelman (2015) argue that comprehending the long-term causes and consequences of vulnerability and resilience requires insights gleaned from various sources and contexts to develop diverse intervention strategies. Moreover, policies driven by information are imperative to progress both DRR efforts and sustainable development (Chen et al., 2021). Further gaps exist in the lack of long-term analyses of DR in African countries, encompassing the various components involved. This dearth of analysis could potentially hinder the continent's ability to enhance resilience for preparedness and DRR, which are crucial elements for advancing towards risk-informed sustainable development.

Previous continental studies in Africa have primarily focused on two major hazards: floods and droughts. Ahmadalipour and Moradkhani (2018) conducted an assessment that evaluated historical drought vulnerability and projected this vulnerability until the end of the century. They identified Egypt, Tunisia, and Algeria as the least vulnerable countries to drought, contrasting Chad, Niger, and Malawi as the most vulnerable in Africa. Similarly, Li et al. (2016) identified Ethiopia, Kenya, Somalia, Tanzania, Nigeria, Libya, and Sudan as countries prone to floods in Africa. They highlighted runoff, per capita GDP, population, and urbanization rate as significant vulnerability factors influencing spatial disparities related to flooding. However, studies encompassing hazards, vulnerability, and coping capacities as interconnected components of disasters are scarce, prompting the necessity for this study. Our research aims to assess historical DR spanning from 2012 to 2022. The objective is to reveal trends, pinpoint significant variables driving these trends, and identify hotspots. Within hotspots, as indicated by Shi et al. (2016), the occurrences of hazards surpass coping capacities, resulting in increased vulnerabilities. Furthermore, Szabo et al. (2016) emphasize that the failure to monitor hotspots could impede progress in both sustainable development initiatives and the achievement of the SDGs.

2.2 | The index for risk management (INFORM) framework

The INFORM is a risk model that encompasses three crucial dimensions of hazards & exposure, vulnerability, and lack of coping capacity, consistent with disaster literature. According to the Joint Research Centre [JRC] (2023), physical exposure and severity of specific natural and human-induced hazards are equally weighted and aggregated to compose the Hazard and Exposure dimension. Under the vulnerability dimension, socio-economic vulnerability and vulnerable groups are the components considered in the determination of the final DR index (Figure 1). Lastly, the lack of coping capacity dimension incorporates

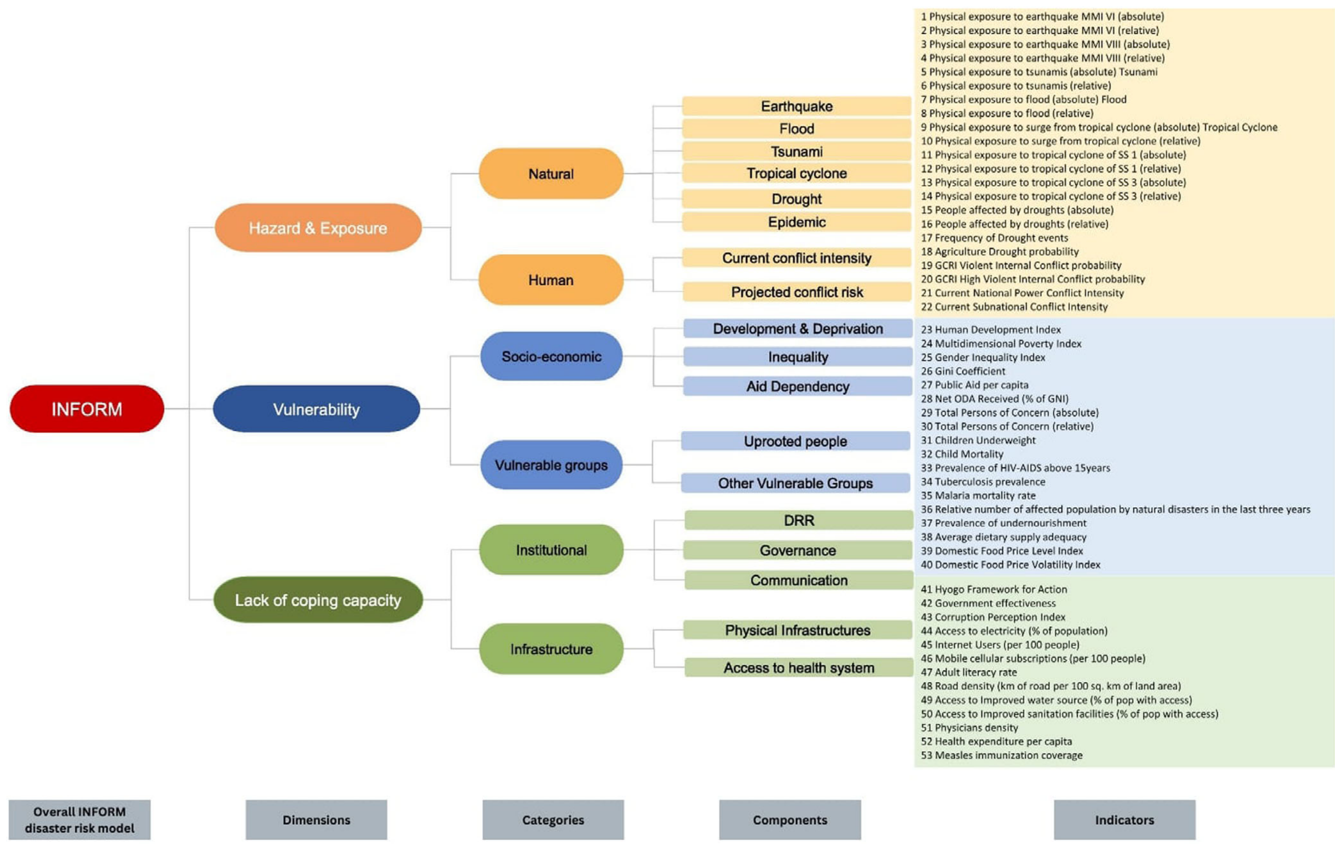

FIGURE 1 Components of the INFORM model. Source: Modified from Marzi et al., (2021); Marin-Ferrer et al. (2017).

DRR programs, emphasis on mitigation and preparedness, emergency response, and recovery capabilities of countries' governments.

Therefore, the Joint Research Centre (JRC) of the European Commission developed the composite INFORM model comprising 53 indicators to gauge factors of global humanitarian crises and DR, in support of initiatives like the SFDRR, 17 SDGs and the global resilience agenda (Marin-Ferrer et al., 2017). The components that make up the three dimensions of the INFORM model have been carefully selected and curated based on scientific literature justification, robustness, transparency, reliability, global consistency, and scalability (JRC, 2023). The multiplicative equation (Equation 1) emphasizes the equal treatment of the three dimensions—hazards & exposure, vulnerability, and lack of coping capacity—within the INFORM model to generate the resulting DR index, usually overall risk scores out of 10 per country (JRC, 2023).

$$Risk = Hazard\&Exposure^{\frac{1}{3}} \times Vulnerability^{\frac{1}{3}} \times Lack\ of\ coping\ capacity^{\frac{1}{3}} \quad (1)$$

As the first global, open-source, and regularly updated tool providing an evidence-based approach to risk analysis, the INFORM model creates an opportunity for developing a comprehensive understanding of DR across 191 countries (Marin-Ferrer et al., 2017). The utility of the INFORM model as a long-term data pool lies in its potential to stimulate national-, regional-, or global-level proactive DRR initiatives, the priority allocation of resources and improving disaster preparedness based on historical trends. However, the absence of regional or national-scale studies employing the INFORM model within Africa at the time of writing this paper (in 2023) is a significant gap, warranting immediate attention to harness its potential benefits in the continent's DRR strategies.

Previous comparative studies, such as those by Beccari (2016), and Visser et al. (2020), have examined the INFORM model alongside other indicator-based assessments. Analyses by Visser et al. (2020) evaluated various criteria including definition precision, handling of uncertainty, data completeness, temporal alignment, and aggregation methods. The findings consistently suggest that the INFORM model demonstrates robustness, validity, reliability, and higher performance in comparison to other models in similar domains. Therefore, the robustness and superior performance of the INFORM model, as indicated by comparative studies across various reliability criteria, endorse its suitability and credibility as an effective tool for comprehensive risk assessment and informed decision-making for DRR, hence its use in this study.

The components, categories, and dimensions of the INFORM model (Figure 1) depict the comprehensive coverage of the dataset used in its development. The six categories (i.e., natural hazards, human hazards, socioeconomic vulnerability, vulnerable groups, institutional capacity, and infrastructure capacity) that make up the three dimensions (i.e., hazard and exposure, vulnerability, and lack of coping capacity) perfectly align with concepts incorporated in DR assessments. It has been widely acknowledged that hazards function as triggers for risks, and their damaging impact can vary significantly based on the level of exposure and vulnerability present in the affected regions (Marin et al., 2021). In the African context, the incidence of both natural and human-induced hazards has escalated (Aliyu, 2015). Natural hazards in Africa, while less frequent, possess the potential to yield higher fatalities and trigger greater population displacement compared to human hazards, as highlighted by Bang (2022). Within the INFORM model, physical exposure to the specified hazards is used for the computation of the natural hazard category. The INFORM model, focusing on the human hazard aspect, incorporates present and anticipated risks associated with societal threats such as violent conflicts encompassing civil wars, unrest, high-intensity crime, and terrorism (Marin-Ferrer et al., 2017).

The inclusion of violent conflicts as human hazards is warranted, especially in light of projections by the World Bank (Corral et al., 2020) indicating that by 2030, around two-thirds of the world's extremely impoverished population will inhabit regions characterized by fragility and conflict. This projection poses a significant challenge to the global sustainability agenda encapsulated in the Sustainable Development Goals (SDGs) and threatens to impede the progress already achieved. A recent decadal analysis by Anderson et al. (2021), spanning from 2009 to 2019, reveals that violent conflicts in sub-Saharan Africa, notably in regions like South Sudan and Nigeria, exacerbated food insecurity to a greater extent than droughts or locust swarms. Similarly, Adaawen et al. (2019) found widespread drought-related farmer–herder conflicts and water tensions to precede violent conflicts in the Sahel, Eastern, and Southern Africa. Consequently, it becomes evident that violent conflicts intensify vulnerability levels as well. Furthermore, as indicated by Caso et al. (2023), the co-occurrence of violent conflicts with disasters leads to severe consequences. They present a consistent increase in the occurrence of countries facing both armed conflict and concurrent disasters, underscoring the compounded challenges posed by these dual crises.

The INFORM model considers two primary vulnerability categories: socioeconomic vulnerability and vulnerable groups. These categories encompass aspects such as income, inequality, overall well-being, and specific groups of individuals more prone to disasters due to inherent or external circumstances. Social factors play a pivotal role in the realm of disasters and risk intensification, as asserted by Bailey (2022) and supported by studies from Samaraweera (2024) and Imperiale and Vanclay (2021). Moreover, the multiplier effect of climate change, poverty, and social insecurity, according to Scheffran et al. (2019), worsens humanitarian crises. Thus, this study's incorporation of these social factors is validated by their potential to exacerbate risks associated with disasters. Notably, the indicators under both vulnerability categories closely correspond to the social aspects, excluding land tenure, outlined as critical determinants of vulnerability by Drakes and Tate (2022). The institutional and infrastructural components constitute the lack of coping capacity dimension within the INFORM model. Marin-Ferrer et al. (2017) integrated governmental initiatives aimed at enhancing resilience, disaster management, and mitigation through organized activities and existing infrastructure. Studies, including the work of McBean and Rodgers (2010), advocate for the establishment of institutional systems and robust infrastructure as crucial elements in fostering resilience and preventing the escalation of hazards into disasters.

Incorporating all variables from the INFORM model offers crucial insights that significantly contribute to disaster education and knowledge in Africa. As highlighted by Zhang and Wang (2022), there's currently a limited presence of disaster education publications or research from African countries, signaling a need for enhancement in this area. Recognizing the potential of disaster education, as suggested by AlQahtany and Abubakar (2020), holds promise in elevating disaster awareness and preparedness. This, in turn, can foster essential positive behaviors conducive to DRR and subsequently advance sustainable development.

3 | METHODS

3.1 | Data source

We obtained the INFORM risk model output for the year 2023 from https://drmkc.jrc.ec.europa.eu/inform-index/. Relying on data spanning from 2012 to 2022, this study extracted component- and category-level data for analysis, consisting of 29 variables per annum (Table 1). Meanwhile, the overall risk index of the INFORM model served as the dependent variable for relevant analyses conducted in this study. The INFORM model is esteemed among the top three indexes in climate risk research, known for its adherence to standardized methodologies and scientific conceptual frameworks (Bornhofen et al., 2019; Garschagen et al., 2021). Additionally, prior research has extensively evaluated the reliability and validity of the INFORM index in DR assessment. For instance, Egawa et al. (2018) underscored the credibility of the INFORM data as a representative DR index. Similarly, Birkmann et al. (2022) affirmed the dataset's reliability, highlighting a remarkable internal consistency and indicator reliability exceeding 90%, hence our adoption of this data for this study.

3.2 | Data preparation

Data was obtained in clean XLS format. We then prepared two separate sets of data for the intended long-term analyses. Firstly, the mean value was calculated across the entire dataset for each variable per country within the timeframe of 2012–2022. This was used for the decadal mean analyses in the study. Subsequently, the complete dataset was compiled for each country for the decadal analyses, maintaining the original structure per variable.

3.3 | Data analyses

3.3.1 | Trend analyses

To examine the trends in DR, our study employed a combination of descriptive chart plots and the Mann-Kendall monotonic trend analysis method (MK). The descriptive chart plots, generated using the

TABLE 1 Variables used in the study.

Variable role	Variable name	Variable type	Purposes
Dependent variable	INFORM risk	Overall risk level	MKTA, VIDA, VIDMA, HSA, SSHq
Independent variables	Physical exposure to earthquakes	Natural hazard	VIDA, VIDMA
	Physical exposure to floods	Natural hazard	VIDA, VIDMA
	Physical exposure to tsunamis	Natural hazard	VIDA, VIDMA
	Physical exposure to tropical cyclones	Natural hazard	VIDA, VIDMA
	Physical exposure to droughts	Natural hazard	VIDA, VIDMA
	Physical exposure to epidemics	Natural hazard	VIDA, VIDMA
	Projected conflict risk	Human hazard	VIDA, VIDMA
	Current highly violent conflict intensity	Human hazard	VIDA, VIDMA
	Development & deprivation	Socioeconomic vulnerability	VIDA, VIDMA
	Inequality	Socioeconomic vulnerability	VIDA, VIDMA
	Economic dependency	Socioeconomic vulnerability	VIDA, VIDMA
	Uprooted people	Vulnerable groups	VIDA, VIDMA
	Health conditions	Vulnerable groups	VIDA, VIDMA
	Children U5	Vulnerable groups	VIDA, VIDMA
	Recent shocks	Vulnerable groups	VIDA, VIDMA
	Food security	Vulnerable groups	VIDA, VIDMA
	Other vulnerable groups	Vulnerable groups	VIDA, VIDMA
	DRR	Institutional coping capacity	VIDA, VIDMA
	Governance	Institutional coping capacity	VIDA, VIDMA
	Communication	Institutional coping capacity	VIDA, VIDMA
	Physical infrastructure	Infrastructural coping capacity	VIDA, VIDMA
	Access to healthcare	Infrastructural coping capacity	VIDA, VIDMA
Category variables	Natural hazards	Hazard	MKTA, SSHq
	Human hazards	Hazard	MKTA, SSHq
	Vulnerable groups	Vulnerability	MKTA, SSHq
	Socio-economic vulnerability	Vulnerability	MKTA, SSHq
	Infrastructure	Coping capacity	MKTA, SSHq
	Institutional	Coping capacity	MKTA, SSHq

Abbreviations: HSA, hotspot analyses; MKTA, Mann-Kendall trend analyses; VIDA, variable importance decadal analyses; SSHq, spatial stratified heterogeneity q-statistics; VIDMA, variable importance decadal mean analyses.

ggplot2 package in R version 4.2.1, were designed as scatter plots with a smoothed line to visually represent the pattern in the data. These visualizations allowed us to illustrate the observed trends effectively.

In addition to the chart plots, we conducted the MK using the Kendall package of McLeod and McLeod (2015) to rigorously assess the presence and nature of monotonic trends in the DR data. The MK, introduced by Kendall (1975), is a non-parametric statistical test specifically designed to evaluate whether values in a dataset demonstrate consistent trends of increase, decrease, or stability over time. This method is particularly advantageous as it does not rely on assumptions regarding the distribution of the data, ensuring robustness in trend analysis.

Hence, for the DR trend analyses for Africa for the period 2012–2022, we followed two major steps: first, generating descriptive chart plots through the ggplot2 package in R to visually depict patterns in the data. Secondly, we performed the MK using the Kendall package in R to statistically assess the presence and nature of monotonic trends in the DR dataset. The p-values were computed at a 5% significant level to highlight significant trends, if any. This combined approach allowed for both visual and statistical analyses, providing a comprehensive understanding of DR trends without imposing stringent assumptions on the data's distribution. R scripts used for trend analyses are contained in the Data S1. A positive value from the output means that the trend is increasing, while a negative value means that the trend is decreasing.

3.3.2 | Variable importance analyses

This study extensively explored variables' importance through the application of random forest regression analyses. To achieve this, we employed the randomForestExplainer package, recognized for its robustness in explaining variable importance within random forest models, as developed by Paluszynska et al. (2020). The analyses were conducted using R version 4.2.1, and the R scripts utilized for these analyses are provided in the Data S1 for reference.

Our methodology encompassed a two-fold investigation, using both decadal and decadal mean data of independent and dependent variables in Table 1 for all African countries for the period 2012–2022. To identify the pivotal factors influencing DR, an unsupervised Random Forest (RF) regression consisting of 500 trees was trained. Subsequently, we assessed the distribution of minimal depth derived from the constructed forest through the application of the min_depth_distribution function. Furthermore, various other crucial importance measures, including the number of nodes, accuracy decrease (MSE increase), Gini decrease (node purity increase), number of trees, times_a_root, and *p*-value, were derived. To delve deeper into the statistical aspects of the methodology we employed to determine top important DR variables in this study, Paluszynska (2017) provides extensive analysis worth exploring.

In summary, the methodology used for ascertaining important variables for both decadal and decadal mean DR factors through the randomForestExplainer package encompassed the following steps:

Step 1: Training of the data with a randomForest classifier comprising 500 trees.

Step 2: Utilizing the created forest with the min_depth_distribution function to acquire the distribution of minimal depth. A total of seven measures of importance – mean minimal depth, number of nodes, accuracy decrease (MSE increase), Gini decrease (node purity increase), number of trees, times_a_root, and *p*-values are obtained from our analyses and used in the next step.

Step 3: Plotting the top ten important variables alongside the distribution of minimal depth.

Step 4: Visualizing multi-way importance with mean squared error post-permutation and the increase in the node purity index (y-axis).

3.3.3 | Spatial stratified heterogeneity (SSH) models

Spatial Stratified Heterogeneity (SSH) models serve to unravel associations between geographical attributes by comparing variations in regional and global data (Wang et al., 2010; Wang et al., 2016). We conducted our analysis leveraging the Geographical detector tool, a widely acclaimed method for assessing the power of determinants and attributions for SSH (Song, 2021). We sought to identify and measure the heterogeneity with spatial strata of our DR datasets, assess the coupling between factors Y and X without assuming linearity of their association, and lastly determine the interaction between explanatory factors X1 to X6 (corresponding to the six category-level variables of DR, i.e., natural hazards, human hazards, vulnerable groups, socio-economic vulnerability, Infrastructure, and institutional) and a response factor of Y (DR index).

Three major steps were followed in the SSH model performed in this study:

Step 1: mapping response variable Y in strata according to X using the risk detector function;

Step 2: using the factor detector q-statistic to measure the degree of spatial stratified heterogeneity of a variable Y if Y is stratified by itself; and the determinant power of an explanatory variable X on Y if Y is stratified by X;

Step 3: employing the interaction detector to reveal whether the risk factors X1 to X6 have an interactive influence on a response variable Y.

Using the decadal mean value of the six category-level variables as X1 to X6 and the INFORM DR model as Y, we obtained three crucial results: the risk detector, factor detector (q-statistic), and interaction detector. The risk detector illustrates how the response factor Y varies across strata defined by X; the factor detector assesses the level of spatial stratified heterogeneity within a factor Y when Y is stratified by itself. Furthermore, it quantifies the determinant power of an explanatory factor X on Y when Y is stratified by X. The interaction detector scrutinizes whether risk factors like X1 to X6 exhibit an interactive influence on the response factor Y. Readers seeking in-depth statistical insights into the SSH are directed to Wang et al. (2016) for further details.

3.4 | Hotspot analyses

For our analysis, we employed two fundamental techniques, namely the optimized hotspot analyses and emerging hotspot analyses, using ArcGIS Pro version 3.0.2. The Hot Spot Analysis tool in ArcGIS employs the Getis-Ord Gi* statistic (Getis & Ord, 1992) to compute z-scores and *p*-values for each feature in a dataset, revealing spatial clusters where features with either high or low attribute values tend to cluster together (Esri, 2023a). Additional results from the emerging hotspot analyses incorporate hotspot bin classification based on the MK accounting for temporal dimensions of the data. Consequently, these complementary methods contribute to identifying significant spatial patterns of DR in Africa. They highlight areas with high or low values concerning neighboring features and describe the trends of DR per country based on the DR index spanning from 2012 to 2022. This combined approach provides a comprehensive understanding of the spatial distribution and temporal trends of DR within the dataset.

These methodologies are widely acknowledged for their efficacy in pattern analysis (Khan et al., 2022) and we utilized them to unravel the spatial and temporal variations, patterns, and emerging hotspots of DR across Africa. While the optimized hotspot analysis serves to identify spatial relationships and statistically significant clusters of DR hotspots and cold spots within the African region, the emerging hotspot analysis adds a temporal dimension by scrutinizing the evolving patterns of DR per country during the study period (2012–2022). The temporal aspects of the emerging hotspot analysis enabled us to capture the dynamic nature of DR hotspots and cold spots, providing insights into the changing patterns over time in the period under consideration. Together, both analyses reveal countries that demand focused attention and urgent intervention measures.

We conducted an analysis using decadal data from the INFORM risk index covering the period from 2012 to 2022, examining yearly data points for 53 countries. This involved utilizing 530 valid input features to perform permutations and clustering, identifying significantly high and low clusters, known as hotspots and cold spots, respectively, using the ArcGIS optimized hotspot analyses tool. For the emerging hotspot analyses, we generated 530 space–time bins to incorporate the temporal aspect of trends. The optimized hotspot analysis involved considering neighboring values to yield clustered outputs of low and high DR values, categorizing them as cold spots and hotspots, respectively. Conversely, the emerging hotspot analysis focused on changes within specific bins (representing a country's distinctive DR data) to present a more robust output based on trends or alterations. This latter analysis categorized locations as new, consecutive, intensifying, persistent, or other types of hot- or cold spots, offering a more nuanced understanding of the evolving DR landscape. For a more comprehensive technical analysis of how the optimized and emerging hotspot analyses in ArcGIS works, readers are encouraged to review Esri (2023a), (2023b) respectively.

4 | RESULTS

4.1 | Patterns and trends of DR in Africa (2012–2022)

4.1.1 | Continental, regional and country-level trends

From our analyses of the data, DR in Africa from 2012 to 2022 reveals intriguing trends and regional disparities. Notably, there has been a slight overall increase in DR across the continent during this period (Figure 2a). Regional disaggregation shows variations across the continent (Figure 2b). Among the regions, Northern Africa stands out as the exception, demonstrating a decline in DR since 2020. Conversely, Central, Eastern, Western, and Southern Africa have witnessed a steady rise in DR during the same timeframe. Furthermore, individual country-level analysis exposes a spectrum of trends in DR (Figure 2c).

Burkina Faso, Central African Republic, Uganda, and South Africa notably experienced a steep increase in DR in recent years. Meanwhile, countries like Cameroon, Chad, Ethiopia, Mali, Mozambique, Niger, South Sudan, Sudan, and Tanzania have seen a gradual but persistent rise in their DR. Within the study period, Algeria, Botswana, and Gabon have displayed a consistent reduction in DR trends, reflecting proactive measures or unique circumstances mitigating disaster occurrences. However, the situation in Libya stands in contrast, characterized by a volatile pattern in DR, showcasing intermittent declines in recent years.

4.1.2 | Mann-Kendall analyses results

Surprisingly, the outcomes derived from the MK monotonic trend analyses present a contrast to the trends depicted visually in Figure 2a–c. The MK analysis suggests an overall decrease in DR for the entire African continent, which diverges from the visual representations. Again, the MK results shed light on the disparities within Africa's regions (Table 2). They indicate a decreasing trend in DR for Central and Northern Africa, while showcasing an opposing trend of increasing DR in Eastern, Western, and Southern Africa. It's crucial to note that despite these observed trends, these findings are not statistically significant.

The non-significant trends revealed by the MK analyses across the regions imply caution in interpreting the directionality of the observed changes. While the visual representations in Figure 2a–c might suggest specific patterns, the statistical analysis portrays these trends as not meeting the threshold of significance. This incongruence between visual representations and statistical analyses prompts a deeper exploration into the reasons behind these disparities. It underscores the complexity of assessing trends in DR and emphasizes the need for multifaceted analyses, considering factors beyond mere visual observations. Recognizing the lack of statistical significance in the observed trends is crucial in preventing premature conclusions. Despite the apparent trends in different regions, the absence of significance calls for a cautious interpretation of these findings.

4.1.3 | Trend results of category-level DR factors

The analysis of key components constituting African DR in the last decade exposes intriguing patterns (Figure 3a). Notably, human hazards and vulnerabilities among specific groups have seen an alarming rise, while there's been a slight reduction observed in institutional and infrastructural coping capacities. Regional assessments further illuminate the disparities in these DR factors across Africa (Figure 3b). Central, Eastern, Southern, and Western Africa have experienced a significant and steep increase in human hazards, while a contrasting decline in this factor has been observed in Northern Africa.

Interestingly, all regions have shown a linear reduction in the lack of coping capacity, notably in the infrastructural component. However, three African regions—East, North, and South—have witnessed an increase in vulnerable groups. Moreover, while Central Africa's socio-economic vulnerability component remained stagnant, the other four regions—East, West, North, and South—exhibited a reduction in this factor (Figure 3b). At the country level, specific trends in category-level DR factors are discernible (Figure 3c). Burkina Faso, Mozambique, Niger, South Africa, and Tanzania witnessed a steep increase in human hazards, whereas Algeria and Tunisia experienced a significant reduction in this factor.

The outcomes derived from the MK monotonic trend analyses present a unique narrative, diverging from the visual representations of trends (Figure 3). Overall, these analyses highlight a declining trend in the lack of infrastructural coping capacity against an increasing deficit in institutional coping capacity. Notably, Central Africa's escalating lack of institutional coping capacity holds statistical significance, alongside the declining socio-economic vulnerability factor (Table 2).

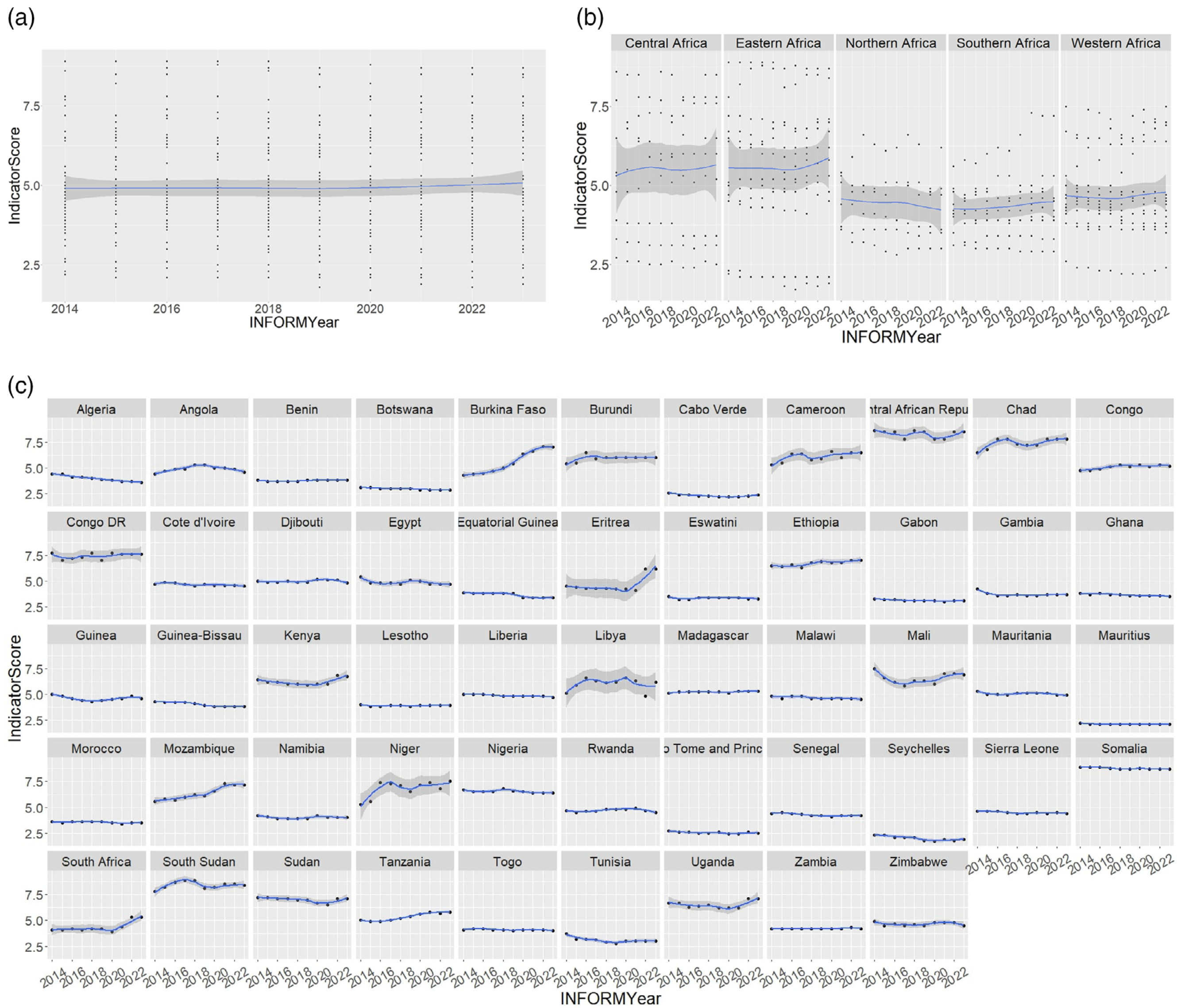

FIGURE 2 Smoothened trend plots of INFORM risk index (2012–2022) (a) continental DR trend for Africa (b) regional–level trends (c) country–level trends.

TABLE 2 Mann-Kendall monotonic trend analyses results.

Region	Risk index	Natural hazards	Human hazards	Vulnerable groups	Socio-economic vulnerability	Infrastructure	Institutional
Central Africa	−ve	−ve	−ve	−ve	−ve*	−ve	+ve*
Eastern Africa	+ve	−ve	+ve	+ve	+ve	−ve	+ve
Northern Africa	−ve	−ve	−ve	−ve	+ve	−ve	+ve
Southern Africa	+ve	+ve	+ve	+ve	+ve	−ve	+ve
Western Africa	+ve	+ve	+ve	+ve	+ve	−ve	+ve
ALL continent	−ve	−ve	−ve	+ve	+ve	−ve	+ve

Note: +ve* = Positive trend (significant at $p < .05$); +ve = Positive trend (non-significant). −ve* = Negative trend (significant at $p < .05$); −ve = Negative trend (non-significant).

4.2 | Results of variable importance for DR factors in Africa

In this section, we provide the findings of our decadal and decadal mean assessments of significant factors impacting DR in Africa. Our Random Forest (RF) models constructed 500 trees for each assessment, with seven factors explored at each split. Remarkably, the RF regression algorithm effectively explained the dependent variables, accounting for 62.42% and 91.59% of variables in the decadal and decadal mean analyses, respectively. Seven key measures of importance, as listed in the methods section, were obtained from our analyses. Table 3 displays the frequency of occurrence among the top ten factors identified by each measure.

From our comprehensive decadal and decadal mean assessments involving 22 factors as independent variables, only ten are identified by the variable importance measures for up to a 50% frequency as significant DR factors. These factors include economic dependency, inequality, physical exposure to tropical cyclones and tsunamis, recent shocks, current conflicts, DRR, physical exposure to earthquakes, epidemics, and uprooted people (Table 3). Additionally, health conditions, other vulnerable groups, people affected by droughts, and violent conflict probability, while slightly below 50%, warrant attention due to their significance (Table 3).

Furthermore, the multi-way importance plots, another product of RF regression analyses, offer substantial insights into the factors of Africa's DR (Figure 4a,c). These plots provide a machine-combined perspective, highlighting essential aspects such as the mean depth of initial splits on variables, the number of trees with root splits, and the total nodes splitting on specific variables, with notable factors highlighted in blue.

Machine-combined importance measures from the decadal analyses pinpoint significant drivers influencing Africa's DR. Notable among these drivers are epidemics, governance, physical infrastructure, poverty and development, physical exposure to floods, health of children under five, food security, communication, and access to healthcare (Figure 4b) (Table 4). Similarly, the decadal mean analyses highlight impactful drivers like violent conflict probability, uprooted people, poverty and development, physical exposure to floods, physical infrastructure, communication, governance, health of children under five, and access to healthcare (Figure 4d) (Table 4).

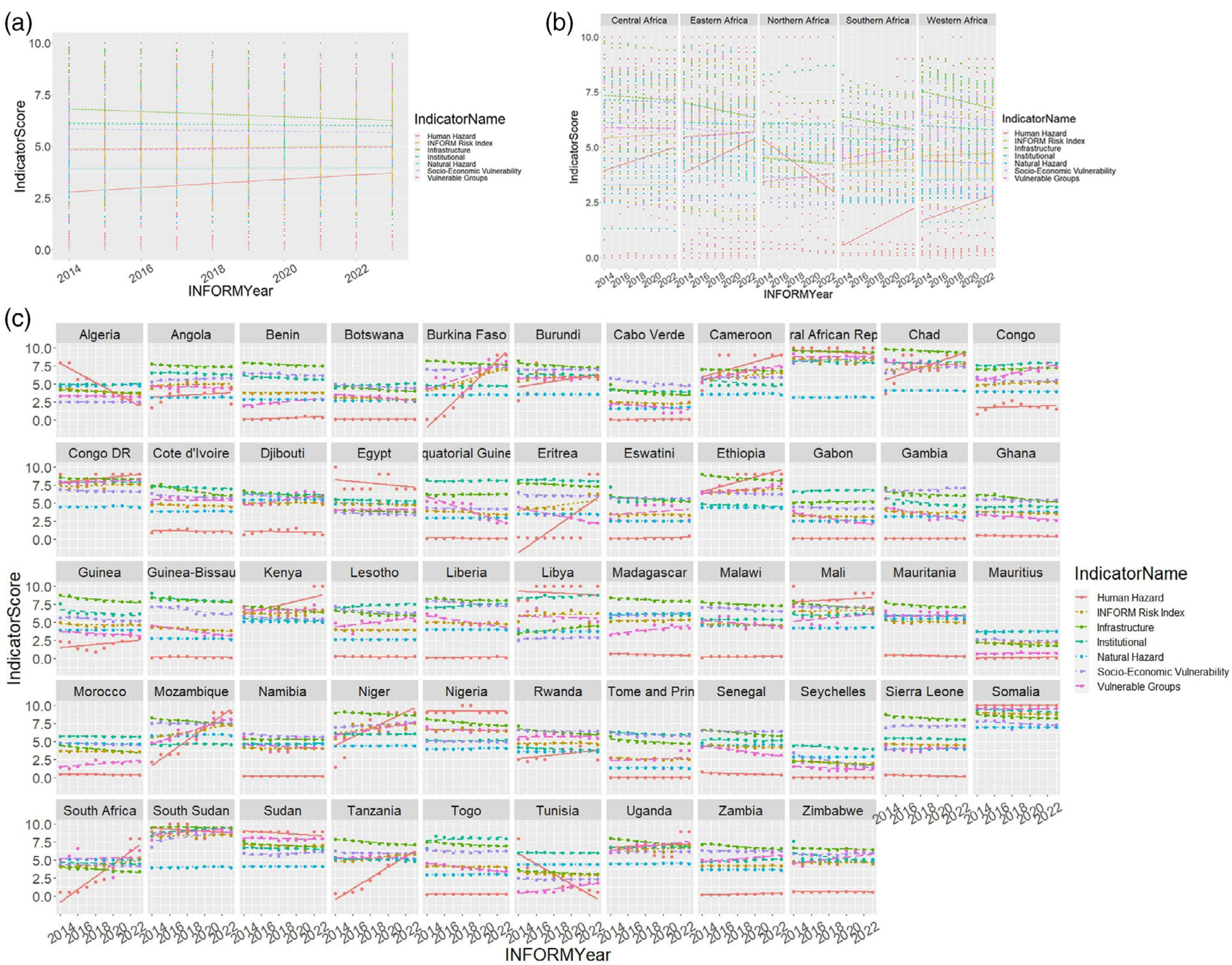

FIGURE 3 Multi trend plots of category-level risk factors (a) continental–level (b) regional–levels (c) country–levels.

TABLE 3 Top occurring significant factors of disaster risks in Africa from seven variable importance measures.

Rank	Factor	Frequency (decadal analyses)[a]	Frequency (decadal mean analyses)[b]	Total frequency[a,b]	% of all occurrences[c]
1	Economic dependency	5	5	10	71.43
2	Inequality	5	5	10	71.43
3	Physical exposure to tropical cyclones	4	5	9	64.29
4	Physical exposure to tsunamis	4	5	9	64.29
5	Recent shocks	5	4	9	64.29
6	Current conflicts	5	3	8	57.14
7	Disaster risk reduction	5	3	8	57.14
8	Physical exposure to earthquakes	3	5	8	57.14
9	Epidemic	2	5	7	50.00
10	Uprooted people	5	2	7	50.00
11	Health conditions	2	4	6	42.86
12	Other vulnerable groups	4	2	6	42.86
13	People affected by droughts	2	4	6	42.86
14	Violent conflict probability	4	2	6	42.86
15	Food security	2	3	5	35.71
16	Access to health care	2	2	4	28.57
17	Communication	2	2	4	28.57
18	Governance	2	2	4	28.57
19	Physical infrastructure	2	2	4	28.57
20	Poverty and development	2	2	4	28.57
21	Health of children under five	2	1	3	21.43
22	Physical exposure to floods	1	2	3	21.43

[a]Frequency of the factor's occurrence among the top ten importance measures in the random forest regression of decadal analyses of disaster risk.
[b]Frequency of the factor's occurrence among the top ten importance measures in the random forest regression of decadal mean analyses of disaster risk.
[c]The percentage of the factor's occurrence of the total possible occurrences of both the decadal and decadal mean analyses of disaster risk.

4.3 | Results of DR and factors' SSH

4.3.1 | Detected risks

Our analysis, delineated in Table 5, meticulously maps the distribution of DR across different strata based on specific factors. Notably, higher DR are clustered within strata exhibiting higher values of specific category-level factors. Specifically, higher strata memberships were recorded in higher levels of human hazard, lack of infrastructural coping capacity, institutional coping capacity, natural hazards, socio-economic vulnerability, and vulnerable groups. Overall strata membership of DR levels based on these category-level data are designated in percentages as 12.4% (very low), 17.8% (low), 26.4% (medium), 25.6% (high), and 17.8% (very high).

4.3.2 | Risk factors

Our exploration further delves into the significance of DR factors, elucidating their contribution to spatial stratified heterogeneity. As detailed in Table 6, three pivotal factors stand out significantly – vulnerable groups, human hazard, and lack of infrastructural coping capacity, respectively explaining 75%, 70%, and 42%, of DR in Africa. Distinct influential factors are spotlighted across various African regions. For instance, vulnerable groups emerge as a compelling explanatory factor, significantly driving DR in Central, Eastern, and Northern Africa, explaining between 88% and 100% of DR in the region. Conversely, human hazard significantly explains DR in Eastern and Western Africa, accounting for 83% and 92%, respectively. Notably, natural hazard factors predominantly explain DR in Central Africa over the last decade (90%).

4.3.3 | Risk factor interactions

The examination of category-level factors interactions reveals compelling dynamics shaping DR. Our results, depicted in Table 7, primarily showcase a bi-enhanced interaction among these factors. This signifies that their combined effect on DR surpasses the mere sum of their individual influences. However, a noteworthy exception emerges in the interaction between lack of institutional coping capacity and socio-economic vulnerability, indicating a non-linear enhancement

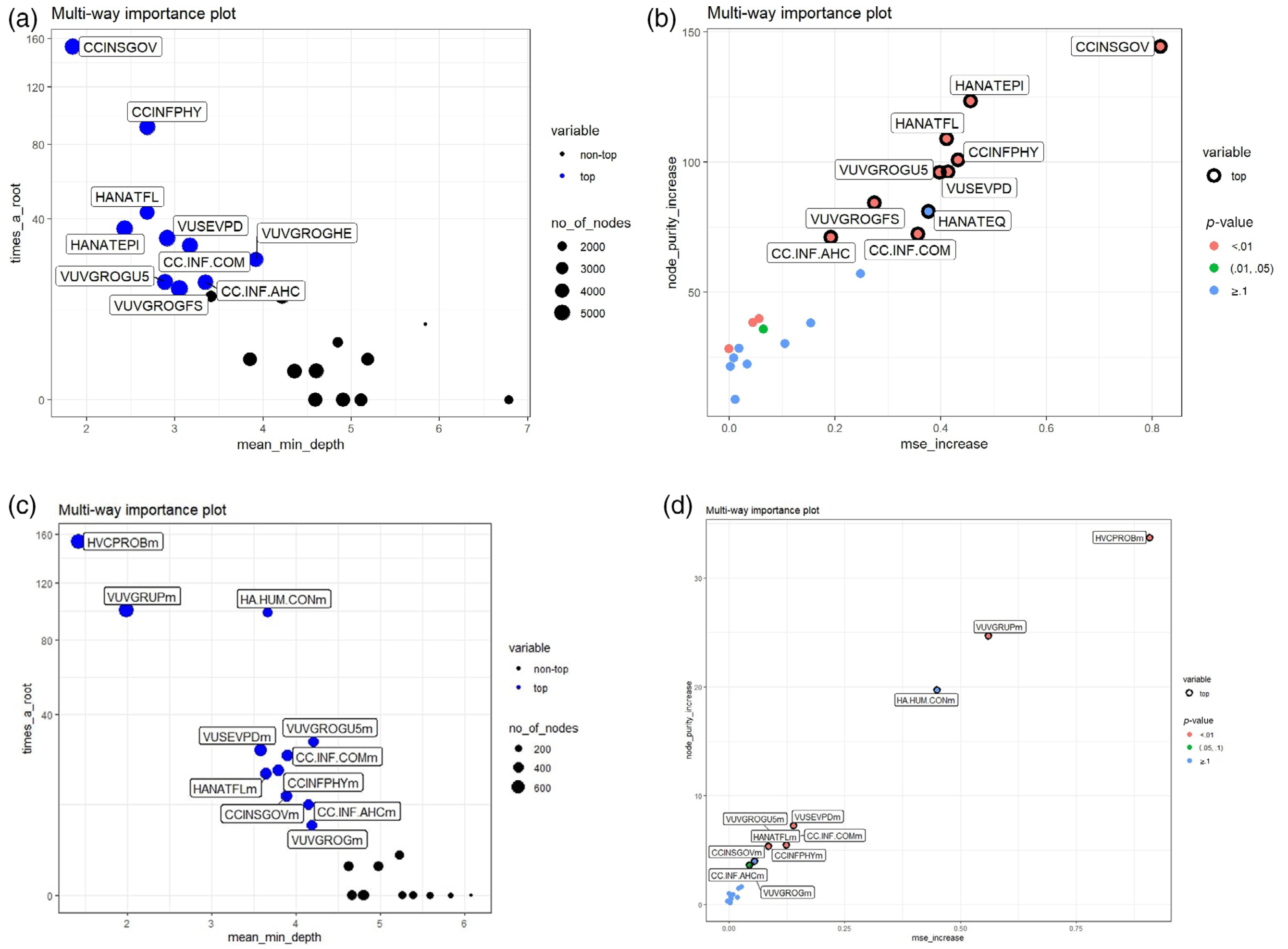

FIGURE 4 Multi-way importance plots: (a, c) – classification of the top and non-top factors based on the minimum average depth, times to root and the number of nodes (b, d) – top factors based on MSE increase, node purity increase and *p*-value (pink circle = $p < .01$). *Note*: Codes with 'm' are for results from the decadal mean values. Abbreviations: CC.INF.AHC, Access to Health Care; CC.INF.COM, Communication; CCINFPHY, Physical infrastructure; CCINSGOV, Governance; HANATEPI, Epidemics; HANATEQ, Physical exposure to earthquake; HANATFL, Physical exposure to floods; VUSEVPD, Poverty and Development; VUVGROGFS, Food security; VUVGROGU5, Health of children under five; HVCPROB, Highly Violent Conflict Probability; VUVGRUP, Uprooted Persons.

(Table 7). This suggests a complex relationship between these factors, implying that despite their individual influence on DR, their interaction operates beyond a linear trajectory.

The interaction dynamics among DR factors shed light on factors shaping the continent's DR profile. Notably, the interplay between human hazard and lack of infrastructural coping capacity emerges as the most potent, influencing DR significantly at 86%. Conversely, the combined effects of lack of institutional capacity and natural hazards exhibit a comparatively weaker influence, accounting for 35% of DR (Table 7). Apparently human hazards and other factors' combinations wield more substantial impacts on DR, necessitating focused attention in risk mitigation strategies.

The region-based results uncover intriguing regional differences in factor interactions, particularly in Central, Eastern, and Western Africa. These regions notably exhibit very high to perfect interaction effects ranging from 91% to 100% among category-level DR factors. Specifically, the interactions involving human hazard and lack of infrastructural coping capacity, institutional coping capacity, natural hazards, socioeconomic vulnerability, and vulnerable groups are notably robust (Table 7). These interactions in Central Africa portray exceptionally high influences, ranging from 75% to 100%. However, it's important to note that the model couldn't be computed for Northern Africa, potentially signifying distinctive complexities or limitations in data availability for this region.

4.4 | Disaster risk hotspot results

4.4.1 | Disaster risk index of African countries

From the comprehensive decadal mean analyses, we observed a distinct categorization of African countries based on their DR indexes (Figure 5a). Strikingly, 11 countries demonstrated very high DR, while an additional 10 countries showcased high-risk profiles. The middle

TABLE 4 Top significant factors of Africa's disaster risk based on machine-coupled importance measures of decrease in accuracy, node purity increase, and *p*-value.

Core factor	Top significant component
Hazard	
Natural hazard	Epidemics[d] Physical exposure to floods[d]
Human hazard	Projected conflict risk[m]
Vulnerability	
Socioeconomic vulnerability	Developmennt and deprivation[d,m]
Vulnerable groups	Uprooted people[m] Health of children under five[d,m] Food security[d]
Lack of coping capacity	
Institutional	Governance[d,m]
Infrastructure	Physical infrastructure[d,m] Access to health care[d,m] Communication[d,m]

Note: d = Significant factors unique to decadal analyses; m = Significant factors unique to decadal mean analyses; d,m = Significant factors recurring in both decadal and decadal mean analyses.

ground was occupied by 24 countries exhibiting medium DR indexes. Surprisingly, only eight countries, predominantly island states such as Botswana, Cabo Verde, Eswatini, Gabon, Mauritius, Sao Tome and Principe, Seychelles, and Tunisia, displayed very low DR.

4.4.2 | Optimized hotspot results

Showcasing the consistency of DR patterns, our optimized hotspot analysis revealed intriguing insights. Figure 5b highlights the clustering effect, where hotspots represent regions with concentrated high DR values, and cold spots indicate areas of comparatively lower DR Our results show 23 countries as cold spots, showcasing statistically significant lower DR values over the period 2012–2022 (i.e., Angola, Benin, Botswana, Burkina Faso, Cape Verde, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Lesotho, Liberia, Madagascar, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Senegal, Seychelles, Sierra Leone, South Africa, and Swaziland).

Conversely, 19 countries manifested as hotspots, signifying statistically significant higher DR values for the period (i.e., Burundi, Cameroon, Central African Republic, Chad, Congo, Democratic Republic of the Congo, Djibouti, Egypt, Equatorial Guinea, Eritrea, Ethiopia, Kenya, Libya, Malawi, Niger, Nigeria, Sudan, Uganda, and United Republic of Tanzania). Interestingly, six countries displayed non-significant results, not fitting into either hotspot or cold spot categories.

4.4.3 | Emerging hotspot results

Unveiling emerging trends in DR during the period 2012–2022, the emerging hotspot analysis shed light on noteworthy changes in the period (Figure 5c). Remarkably, Algeria emerged as a consecutive cold spot, indicating consistent lower DR levels, while Eritrea surfaced as a new hotspot, showcasing a recent significant rise in DR. Additionally, seven countries, including Burundi, Chad, Djibouti, Niger, Rwanda, Somalia, and Uganda, exhibited a consecutive hotspot trend, experiencing a surge in DR over the later period covered by the analyses. Amidst these analyses, specific countries showcased distinctive patterns in DR intensification or persistence. Central African Republic and Kenya emerged as intensifying hotspots, with a consistent increase in DR intensity over time. Conversely, Ethiopia, South Sudan, and Sudan appeared as persistent hotspots, maintaining consistently high DR indexes over the studied period. No discernible pattern was detected in 37 other countries, as they did not align with either the identified hotspots or cold spots derived from the analyses.

5 | DISCUSSION

5.1 | Disaster risk trends and hotspots in Africa

During the study period, Africa experienced a slight overall increase in DR, but the MK analysis revealed statistically non-significant declining trends. Smoothened plots and MK outcomes highlighted escalating DR in Eastern, Western, and Southern Africa. Specific countries—such as Cameroon, Chad, Ethiopia, Mali, Mozambique, Niger, South Sudan, Sudan, and United Republic of Tanzania—consistently observed rising DR trends. While six of these countries (i.e., Cameroon, Chad, Ethiopia, Niger, Sudan, and United Republic of Tanzania) are also identified as DR hotspots in Africa Other hotspot countries such as Burundi, Central African Republic, Congo, Democratic Republic of the Congo, Djibouti, Egypt, Equatorial Guinea, Eritrea, Kenya, Libya, Malawi, Nigeria, and Uganda were not detected by the initial smoothened plots. This reveals a potential limitation in the efficacy of such methods in visualizing trends accurately. Notably, infrastructural deficiencies displayed a consistent decreasing trend across all African regions, in contrast to the escalating lack of institutional coping capacity.

The findings from our study reveal a combination of anticipated and surprising outcomes. The observed slight overall increase in DR across Africa appears consistent with the global trend of escalating disaster occurrences, as reported by Mizutori and Guha-Sapir (2020), who noted a sharp rise in both the frequency and severity of global disaster events. This aligns with prior studies emphasizing the increase of various dimensions of DR, encompassing hazards and vulnerability, as reported by Aliyu (2015). Specifically, research by Bari and Dessus (2022) underscores the detrimental impact of floods and droughts in Africa, causing up to a 0.7% decline in GDP, indicative of increased poverty resulting from hazardous events.

The identification of statistically non-significant declining trends through the MK analysis introduces complexities in drawing definitive conclusions. Also, comparing our trend results with previous works is challenging due to limited available data. Nevertheless, assessments like Ahmadalipour and Moradkhani's (2018) drought vulnerability

TABLE 5 Results of stratified detected risks.

Core disaster risk factors		Very low (0)	Very low (1)	Low (2)	Medium (3)	High (4)	Very high (5)
Human hazard	Continental	1.5	2.86	3.14	3.43	4.55	5
	Central	2	2.5	4	4	4.67	5
	Eastern	1	3	3.33	3	4.75	5
	Northern	*	3.5	2	3	3.5	*
	Southern	*	2.71	*	3.33	*	*
	Western	*	2.89	3	4	5	5
Infrastructure	Continental	*	1.5	2	2.7	3.39	4.05
	Central	*	*	*	2	3.67	4.75
	Eastern	*	1.5	*	*	3.75	4.43
	Northern	*	*	2	3.25	4	*
	Southern	*	*		2.67	2.75	3.33
	Western	*	*	2	3.33	3.63	
Institutional	Continental	*	*	2.91	3.42	3.33	4.09
	Central	*	*		3	3	4.4
	Eastern	*	*	2.75	4	4.25	4.33
	Northern	*	*	*	3.25	2	4
	Southern	*	*	3	2.75	3	*
	Western	*	*	3	3.86	3	3
Natural hazard	Continental	*	2	2.33	3.6	3.64	*
	Central	*	2	2	4.29		*
	Eastern	*	*	*	3.63	4	*
	Northern	*	*	*	3	3.33	*
	Southern	*	*	2.33	3	3.33	*
	Western	*	*	2.5	3.54		*
Socio-economic vulnerability	Continental	*	*	2.5	2.89	3.56	4.5
	Central	*	*		2.5	4	5
	Eastern	*	*	1.5		4	5
	Northern	*	*	3	3	4	*
	Southern	*	*	*	2.5	2.86	4
	Western	*	*	*	3.25	3.33	4
Vulnerable groups	Continental	*	1.67	2.4	2.94	3.44	4.72
	Central	*	*	2	3	4	4.6
	Eastern	*	1.5	*	3.5	3.33	4.83
	Northern	*	2	3	3	4	*
	Southern	*	*	*	2.33	3	4
	Western	*	*	2.5	3	3.75	5

*No strata membership.

assessment highlighted Chad and Niger as highly vulnerable countries in Africa, correlating with our findings of increasing DR in these regions and their designation as hotspots. Similarly, Li et al.'s (2016) Africa-wide flood disaster assessment identified Ethiopia, Sudan, and United Republic of Tanzania as among the most affected countries, consistent with our identification of these nations as experiencing rising DR and as hotspots. The varying levels and trends of DR identified in our study align with the risk distribution dimension expounded by Imperiale and Vanclay (2021). The variability observed in DR levels and hotspots across different regions and the fluctuating trends over time resonate with the concept of risk distribution as an essential component in understanding the spatial and temporal dynamics of risks.

The declining trend in infrastructural coping capacity might signify improvements in infrastructure development, potentially attributed to increased investments or initiatives targeting infrastructure resilience, possibly influenced by global frameworks like the UN's Agenda 2030 and SFDRR. These initiatives could be translating into specific

TABLE 6 Results of SSH q-statistics and factor significance.

Regions	Human hazard	Infrastructure	Institutional	Natural hazard	Socio-economic vulnerability	Vulnerable groups
Central	0.90	0.88**	0.38	0.70*	0.44	0.90*
Eastern	0.83*	0.66**	0.30	0.02	0.68	0.88***
Northern	0.65	0.74	0.74	0.05	0.29	1***
Southern	0.28	0.28	0.05	0.53	0.53	0.77
Western	0.92*	0.21	0.23	0.16	0.07	0.72
Continental	0.70***	0.42***	0.14	0.20	0.28	0.75***

Note: Significance of q: *** above 0.001 level, ** at 0.01 level, * at 0.05 level.

TABLE 7 Interaction results of core factors of disaster risk.

	Regions				
Interacting factors	Central	Eastern	Southern	Western	Continental
Human hazard ∩ Infrastructure	1	0.95	0.46	1	0.86
Human hazard ∩ Institutional	1	1	0.46	0.96	0.80
Human hazard ∩ Natural hazard	0.95	0.98$^{e\text{-}n}$	0.64	0.96	0.84
Human hazard ∩ Socio-economic vulnerability	0.91	0.94	0.74	0.96	0.85
Human hazard ∩ Vulnerable groups	0.95	0.94	0.79	0.96	0.85
Infrastructure ∩ Institutional	0.96	0.74	0.59$^{e\text{-}n}$	0.46	0.52
Infrastructure ∩ Natural hazard	0.89	0.70	0.84	0.30	0.55
Infrastructure ∩ Socio-economic vulnerability	0.95	0.73	0.61	0.36	0.50
Infrastructure ∩ Vulnerable groups	1	0.93	0.84	0.80	0.80
Institutional ∩ Natural hazard	0.75	0.49$^{e\text{-}n}$	0.84$^{e\text{-}n}$	0.41	0.35
Institutional ∩ Socio-economic vulnerability	0.79	0.76	0.61	0.70$^{e\text{-}n}$	0.54$^{e\text{-}n}$
Institutional ∩ Vulnerable groups	0.94	0.98	0.84	1	0.82
Natural hazard ∩ Socio-economic vulnerability	0.91	0.73	0.84	0.31	0.45
Natural hazard ∩ Vulnerable groups	0.91	0.93	1	0.78	0.82
Socio-economic vulnerability ∩ Vulnerable groups	0.92	0.89	0.84	0.84	0.78

Note: The model returned no results for the computation of factors' interaction effects for Northern Africa. e-n = factors have an 'enhance, non-linear' interaction, all others are bi-enhance interaction.

improvements in physical infrastructures and access to healthcare, as captured in the INFORM model. Conversely, the escalating lack of institutional coping capacity could mirror challenges in governance, resource allocation, corruption, or the efficacy of disaster management policies. However, our study lacks additional data to delve deeper into the specific reasons for these trends beyond the indicators within the INFORM model.

Additionally, it's important to note that the data analyzed in this paper pertains to 2012–2022, a period preceding recent disasters occurring between April and September 2023. These disasters, stemming from natural hazards such as the floods in Libya, DR Congo, and Rwanda, the earthquake in Morocco, wildfires in Algeria, and the cyclone in Mozambique, are not accounted for in our analysis. These recent events might have influenced the evolving landscape of DR in Africa, potentially altering the trends and dynamics observed in our study. Their omission underscores a limitation in our analysis, indicating the need for further assessment and updated data to comprehensively capture the contemporary scenario of DR in the region.

5.2 | Disaster risk drivers in Africa

Our findings pinpointed key drivers of DR, including epidemics, flood exposure, projected conflict risk, development indicators, displacement, child health, food security, governance, infrastructure, healthcare access, and communication. Approximately 43% of the countries assessed fell within high and very high clusters of DR levels. Our continental-wide findings revealed that vulnerable groups and human-induced hazards collectively accounted for more than 70% of the explanation for the DR index. Evidently, the interaction between human-induced hazards and factors in other categories exerted the most significant influence on DR across the continent. The interaction between human-induced hazards, encompassing current highly violent conflicts and projected conflict risks, emerged as the primary amplifier of DR across the African continent. This concurs with projections made by Corral et al. (2020), highlighting a grim outlook should violent conflicts persist in the region. Notably, violent conflicts not only impede sustainable development but also exacerbate DR by escalating

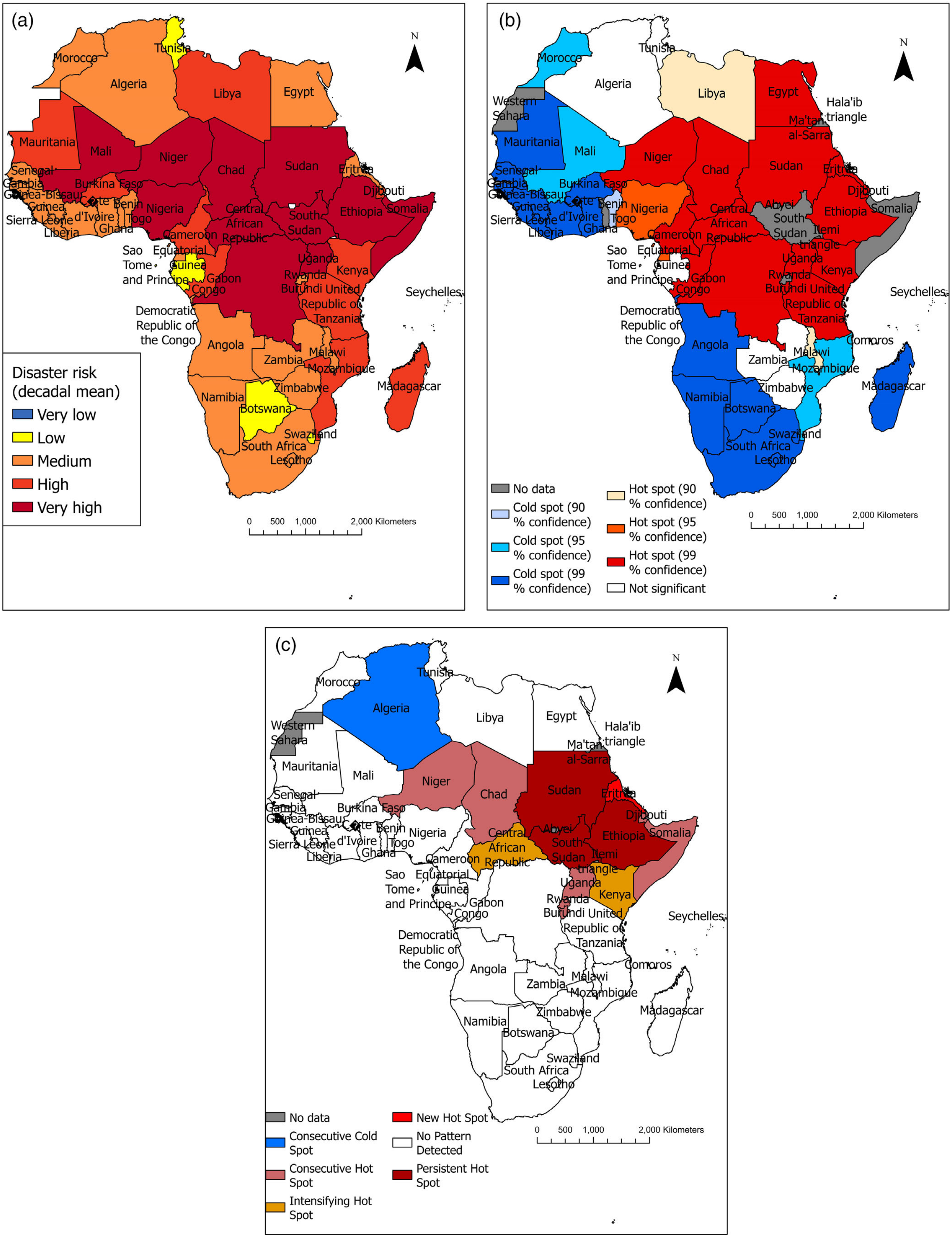

FIGURE 5 Map of African countries showing: (a) DR classes based on decadal mean analyses of INFORM risk index (b) optimized Hotspots analyses results (c) emerging hotspots of DRs.

displacement, adversely impacting vulnerable groups, and intensifying food insecurity, as illuminated by Anderson et al. (2021).

Among the 11 key DR drivers in Africa identified in our study, only two are associated with hazards, while the rest pertain to vulnerability and lack of coping capacity dimensions. This aligns with Bailey's (2022) conceptualization of disasters as comprising hazards and the social system. These dimensions encompass weaknesses capable of exacerbating social risks and affecting the wellbeing of countries, as echoed by Samaraweera (2024) and Imperiale and Vanclay (2021). Encouragingly, the influence of natural hazards on DR in Africa seems lower, providing an opportunity for addressing controllable social drivers emphasized by Ginige (2011).

Our findings bridge a gap highlighted by Drakes and Tate (2022), addressing the scarcity of large-scale research into social vulnerabilities in lower-income nations. The identified social vulnerability drivers could guide interventions aimed at reversing these trends. Failure to mitigate vulnerability may lead to increased future disaster losses, potentially perpetuating the poverty cycle, as suggested by Hallegatte et al. (2020) and Salvucci and Santos (2020). This emphasizes the interconnectedness of poverty reduction, equitable resource distribution, DRR, and sustainable development advocated by Naheed (2021), as well as the impact of poverty on impeding development and the success of SDGs, as emphasized by Akanle et al. (2022).

Furthermore, our findings provide insights into the long-term causes and consequences of vulnerability, aligning with Kelman (2015) assertion that such insights are crucial for developing diverse intervention strategies to build resilience. Information-driven policies, as highlighted by Chen et al. (2021), are imperative for DRR and sustainable development. Governance, identified as a DR driver, underscores the necessity for capacity building to enhance the effectiveness of human resources (Acharibasam & Datta, 2024), addressing concerns raised by Becker and van Niekerk (2015), Bang (2014, 2022), about the deficiency of skilled DRR practitioners in Africa, which leads to delay in the translation of policies into actions.

Lastly, the identified DR drivers emphasize the need, as advocated by Imperiale and Vanclay (2016, 2021), for deliberate efforts to reduce vulnerability while simultaneously increasing resilience. For example, addressing vulnerability drivers such as child health does not inherently provide healthcare access, a coping capacity driver of DR, highlighting the importance of a multifaceted approach. However, it's essential to note that the coarse national-level data used in this study might not capture community-level variations in vulnerabilities and coping capacities. Therefore, community-level studies across African states and regions are crucial to fully optimize the potential of such studies, enabling the most effective DRR approaches, as advocated by Jafari et al. (2018) and Zhou et al. (2015), and the implementation of robust DRR governance, as highlighted by Jiménez-Aceituno et al. (2020).

6 | CONCLUSION

In examining DR trends, drivers and hotspots in Africa, our study unveiled various outcomes. The results from our MK trend tests indicate an overall decrease in DR across the continent over the studied period, albeit with regional variations. Specifically, the patterns of DR in Central and Northern Africa align with the continental trend, showing a decline. In contrast, Eastern, Western, and Southern Africa exhibit increasing trends in DR during the same period. Notably, Eritrea emerged as a new hotspot. While Burundi, Chad, Djibouti, Niger, Rwanda, Somalia, and Uganda, exhibited consecutive hotspot trends; Central African Republic and Kenya intensified in DR, and Ethiopia, South Sudan, and Sudan remained persistent hotspots. These findings indicate the evolving nature of DR and highlight specific countries that require more focus and tailored interventions. Additionally, our identification of vulnerability and lack of coping capacity dimensions as predominant drivers of DR corroborates existing research. However, the intricate interplay between human-induced hazards related to violent conflicts and all other vulnerability and coping capacity factors form part of our primary contribution to understanding DR in Africa and warrants the consideration for multifaceted DRR strategies. Moreover, while recognizing the commendable declining trend in infrastructural deficiencies, persistent vulnerabilities and inadequate institutional coping capacity emphasize the imperative for sustained policy interventions. Targeted strategies should be focused on simultaneously addressing these persisting vulnerabilities and building resilience. Strategies such as poverty reduction approaches, effective community-level bottom-up DRR governance and increased investments in capacity building initiatives are pivotal for mitigating risks and achieving sustainable development. Future community-level studies to complement our national-level analyses are required to enable more tailored and effective DRR strategies. Moreover, findings such as the conflicting outcomes of the smoothened plots and the MK trend tests can be easily avoided. Also, contextual policy actions can be founded on such community-level research. Furthermore, DR assessments ought to be ongoing and updated to ensure evolving and recent risk scenarios are adequately captured. We, therefore, present a compelling call for coordinated efforts with local communities, policies, actions, and further research to address the multifaceted nature of DR in Africa to fortify resilience, and reduce vulnerabilities to achieve sustainable development in the continent.

6.1 | Limitations of the study

The study's design was significantly influenced by the limited availability of long-term data on DR dynamics in Africa. Despite the preference for designing community-level DR assessments, the absence of prior empirical assessments at lower scales constrained the scope of this study. Likewise, the scarcity of local studies on DR limits the validation of findings on lower-level scales. To address this, we strongly advocate for in-depth case studies on specific hazard-induced disasters that provide deeper insights into DR at local scales in Africa. Such studies could supplement our findings by offering context-specific knowledge on social dimensions of risks and resilience, like the insights provided by Imperiale and Vanclay (2016, 2021), Samaraweera (2024), Fransen et al. (2024) and other local research captured in this work.

Furthermore, our study utilized the INFORM index data, acknowledging the providers' identification of methodological and data limitations (Marin-Ferrer et al., 2017). Methodologically, the use of proxies, such as malaria mortality rates for malaria prevalence, might limit the representativeness of the findings. Additionally, incomplete data, reliance on self-measured Hyogo self-assessment reports from countries, and the static nature of natural hazard data necessitate caution in interpreting the results. It's crucial to recognize these limitations and their potential impact on the study's conclusions. Moreover, our study excludes the recent hazardous events in Africa within 2023, which emphasizes the necessity for ongoing and updated DR assessments to capture the ever-evolving landscape of DR in the continent. Also, while our smoothened trend plots offer insights into DR trends, contrasting outcomes yielded by the MK results warrant careful interpretation. The divergence in results signifies the complexity of trend analyses and underscores the need for cautious interpretation of the study's findings. Despite these limitations, our study offers a distinctive panoramic view of DR trends, influential factors, and hotspots across Africa. By uncovering these insights, our research presents actionable opportunities for DRR strategies and sustainable development initiatives.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

The datasets analyzed during this study are freely accessible at https://drmkc.jrc.ec.europa.eu/inform-index/.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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