Prioritizing Multidimensional Interdependent Factors Influencing COVID-19 Risk

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COVID-19 has significantly affected various industries and domains worldwide. Since such pandemics are considered as rare events, risks associated with pandemics are generally managed through reactive approaches, which involve seeking more information about the severity of the pandemic over time and adopting suitable strategies accordingly. However, policymakers at a national level must devise proactive strategies to minimize the harmful impacts of such pandemics. In this article, we use a country-level data-set related to humanitarian crises and disasters to explore critical factors influencing COVID-19 related hazard and exposure, vulnerability, lack of coping capacity, and the overall risk for individual countries. The main contribution is to establish the relative importance of multidimensional factors associated with COVID-19 risk in a probabilistic network setting. This study provides unique insights to policy-makers regarding the identification of critical factors influencing COVID-19 risk and their relative importance in a network setting.

KEY WORDS: Bayesian Belief Network; COVID-19 risk; hazard and exposure; pandemics; vulnerability

1. INTRODUCTION

There is a growing concern about the novel coronavirus disease, COVID-19, since it sparked in Wuhan, China, in December 2019. As of September 23, 2021, COVID-19 has infected over 230 million people and killed over 4.7 million patients worldwide (CSSE, 2021). COVID-19 has also significantly affected manufacturing and service industries, including health care systems, worldwide (Emmanouil et al., 2020; Haghani, Bliemer, Goerlandt, & Li, 2020; Tran et al., 2020). Several industry reports, magazine articles, and blogs highlight the increasing vulnerability associated with COVID-19, describing almost every-day real cases (McKinsey, 2020). One main reason for this devastating impact of the pandemic is the highly interconnected nature of businesses, communities, mobility, and operations across the world (Bruinen de Bruin et al., 2020). This cascading nature of the propagation of pandemics such as COVID-19 necessitates a systematic approach to assess the associated risk (Pescaroli, Wicks, Giacomello, & Alexander, 2018). Further, the concurrence of multiple disasters besides a global pandemic presents unique challenges for disaster management (Collier, Lambert, & Linkov, 2020).

The INFORM (Index for Risk Management) is a composite risk indicator developed by an international research consortium evaluating humanitarian crises and disasters (Marin-Ferrer, Vernaccini and Poljansek, 2017). In response to the COVID-19
pandemic, the INFORM has introduced the COVID-19 risk index, which identifies “countries at risk from health and humanitarian impacts of COVID-19 that could overwhelm current national response capacity, and therefore lead to a need for additional international assistance” (INFORM, 2020). We adopt the same interpretation of COVID-19 risk in this article. Multiple factors related to health, safety, socioeconomic and environmental conditions, infrastructure, demographics, technology, and governance must be holistically considered while assessing COVID-19 risk (Cardil & de-Miguel, 2020; Haghani et al., 2020; Thompson, Kalkowska, & Badizadegan, 2020).

COVID-19 is a low-probability, high-impact risk event that requires developing contingency plans and adopting strategies as more information is gained about the nature and ramifications of this rare event. Few studies relevant to the COVID-19 risk assessment have considered multiple factors influencing COVID-19 risk in their modeling frameworks (INFORM, 2020; Pluchino et al., 2021; Sangiorgio & Parisi, 2020); however, their utility is limited due to two main assumptions. First, factors influencing COVID-19 risk are treated as independent variables. Second, point estimates are used to operationalize the risk measure, thereby failing to capture the uncertainty associated with the pandemic. Both these assumptions can lead to undermining the importance of systemic risk factors, which can cascade across multiple factors, thereby aggravating the overall risk (Ackermann, Eden, Williams, & Howick, 2007). Further, any prioritization scheme of factors influencing COVID-19 risk based on the assumptions mentioned above can lead to making suboptimal decisions regarding the allocation of resources to critical factors.

Pandemics can be linked to different factors and sources of vulnerabilities, which can generate severe disruptions among networks (Ivanov & Sokolov, 2018; Ivanov & Dolgui, 2020), with the propagation of negative effects (Fiksel, Polivy, Croxton, & Pettit, 2015; Hearmshaw & Wilson, 2013). As highlighted in recent papers, more investigations are needed to analyze the sources of these disruptions (Ivanov & Dolgui, 2020), and understand how they might propagate, depending on the network complexity (Choi, Dooley, & Rungtusanatham, 2001; Kim, Chen, & Linderman, 2015). Researchers also advocate the need to explore dependencies among risk sources (Garvey, Carnovale, & Yeniyurt, 2015), particularly in the assessment of environmental threats linked to the PESTLE (Political, Economic, Social, Technological, Legal, and Environmental) framework (Gaudenzi, Zsidisin, Hartley, & Kaufmann, 2018).

Several studies have explored the relative importance of risk factors in a network setting to understand how individual risk factors can both increase and reduce the overall impact on a target node representing the corresponding vulnerability and resilience potential, respectively (Hossain et al., 2020; Hosseini & Ivanov, 2019). Subsequently, assessing the vulnerability and resilience potential of individual (risk) factors can help prioritize risk mitigation strategies to enhance resilience and mitigate vulnerability for a given system (Aven, 2011, 2019). To the best of the authors’ knowledge, a network-wide assessment of multidimensional factors associated with COVID-19 has not been explored in the literature.

The main objective of this study is, therefore, to address these challenges in the literature, and to support decision-makers in capturing and assessing multidimensional factors influencing COVID-19 risk in a probabilistic network setting. The scope of this study is limited to risk assessment, which is a “systematic process to comprehend the nature of risk, express and evaluate risk, with the available knowledge” (SRA, 2015). Further, this study aims to help decision-makers prioritize individual factors relative to their network-wide vulnerability and resilience potential such that critical risk factors can be managed using activities, including prevention, mitigation, adaptation, or sharing (SRA, 2015). For instance, at a country-level, this study can help policy-makers identify critical risk dimensions associated with COVID-19 risk and prioritize factors influencing those risk dimensions. Subsequently, optimal risk mitigation strategies can be developed, such as those related to improving governance and the health conditions of vulnerable groups. Similarly, international assistance programs can be designed while considering critical factors influencing COVID-19 risk across different regions.

As the research methodology, we adopted Bayesian Belief Networks (BBNs) that was successfully used in several applications involving risk and uncertainty (Aven, 2016; Hanea, Morales Napoles, & Ababei, 2015; Kabir & Papadopoulos, 2019). BBNs can be particularly useful in analyzing interdependent factors affecting the propagation of network-wide risk (Garvey et al., 2015). Utilizing the INFORM data-set (INFORM, 2020), we propose a probabilistic network model that helps capture interdependencies among multiple factors influencing COVID-19 risk. Further, we illustrate how the
network-wide vulnerability and resilience potential of individual factors can be assessed to identify critical factors. The remainder of the article is organized as follows: A brief overview of the relevant literature is presented in Section 2. The research methodology is described in Section 3. The results are presented in Section 4. We discuss the implications of our study in Section 5 and present conclusions and directions for future research in Section 6.

2. COVID-19 RISK ASSESSMENT

Risk is conceptualized as a three-dimensional construct comprising (i) hazard (an adverse event that could occur) and exposure (potentiality of losses due to the hazard), (ii) vulnerability (the susceptibility of communities to hazards), and (iii) lack of coping capacity (lack of resources that can aggravate the impact of hazards) (Haque, Mimi, Mazumder, & Salman, 2020). For the COVID-19 risk index, the hazard and exposure dimension is assessed in terms of population (population density, urban population growth, the population living in urban areas and slums, and household size), and WaSH (drinking water, sanitation, and hygiene). Vulnerability is a function of movement (both internal and international movement), behavior (awareness and trust) (Bruinen de Bruin et al., 2020), demographic and comorbidities (proportion of the population at increased risk of COVID-19 disease), socioeconomic vulnerability (development and deprivation, inequality, and aid dependency), and vulnerable groups (uprooted people, gender-based violence, health conditions, and food security). Vulnerable groups are found to be more susceptible to the pandemic necessitating swift actions to mitigate their exposure (Emmanouil et al., 2020). Lack of coping capacity is contingent on health capacity specific to COVID-19, governance, and access to health care (Emmanouil et al., 2020). From a network perspective, van Hoek (2020) identified the key challenges in managing COVID-19 risk, related to intertwined sources of the risk, stemming upstream and downstream in the network.

Although the COVID-19 risk index comprehensively captures all relevant dimensions of risk and constituent factors and helps establish the overall risk at a national level (Haque et al., 2020), this index assumes all factors as independent. Besides, it ignores the nonlinear interactions among factors that influence the risk (Marin-Ferrer et al., 2017). Further, the risk is expressed as a point-estimate rather than a probability distribution (Pasman, Rogers, & Mannan, 2017). The same assumptions are made in other risk assessment schemes relevant to the vulnerability assessment of communities to disasters (Marulanda Fraume et al., 2020; Haque et al., 2020). These assumptions can lead to prioritizing factors incorrectly and making suboptimal decisions regarding the allocation of resources to critical factors. Therefore, there is a need to assess statistical dependencies among multidimensional factors and risk dimensions associated with COVID-19 risk in a network setting (Ackermann & Alexander, 2016; Xing & Xing, 2020). As Ivanov and Dolgui (2020) highlighted, there is a need to further investigate how to manage disruptive events, such as Covid-19, in highly competitive networks to achieve the goal of “survivability.”

Techniques such as interpretive structural modeling, analytic hierarchy process and decision-making trial and evaluation laboratory have been explored to establish the resilience and vulnerability of communities to natural disasters (Xu, Zhong, Hong, & Lin, 2020). However, such techniques may fail to generate multiple scenarios in a network setting and prioritize factors in relation to their vulnerability and resilience potential. Similarly, few studies have explored the COVID-19 risk assessment such as Sangiorgio and Parisi (2020) and Boldog et al. (2020). However, multidimensional factors associated with COVID-19 risk have been assumed as independent factors, thereby failing to capture the complex nature of interactions within a network setting (Luo, Zhang, & Wu, 2020).

Although COVID-19 has attracted an abundance of research internationally (Renzaho, 2020; Robinson, Sullivan, & Shogren, 2020), the research reported so far is fragmented across disciplines such as health safety, transport safety, social safety, food security, and domestic safety (Haghani et al., 2020). For instance, Tran et al. (2020) investigated the capacity of local authority and community on epidemic response in Vietnam. They emphasized the importance of building capacity for communities, addressing health and socioeconomic inequalities, and developing collaborative multisectoral mechanisms in controlling COVID-19. According to Renzaho (2020, p. 835): “There needs to be a strong country-level leadership to coordinate and own all aspects of the responses to the COVID-19 pandemic in a collaborative, transparent, and accountable way.”

Therefore, there is a need to undertake a holistic interdisciplinary approach to assess and mitigate risks across multiple dimensions in the case of pandemics (Le Coze, 2018). In this context, risk mitigation is defined as “an interdisciplinary
The research methodology comprised four sequential steps, including the collection and discretization of country-level data specific to COVID-19 risk, development of a data-driven BBN model, validation of the model, and prioritization of factors influencing COVID-19 risk in a network setting.

3.1. Data Collection and Processing

The data-set by INFORM (INFORM, 2020) was used in this study. This data-set is publicly available and INFORM is deemed as a credible international agency for establishing the country-level risk related to natural disasters and pandemics (Haque et al., 2020). The data comprised statistics related to 191 countries. As a widely used approach, the missing values in the data-set were replaced with the average values (Khan & Hoque, 2020). In total, 19 variables, including COVID-19 risk (see bold items in Table I), were selected for the model as these variables comprehensively captured all dimensions of COVID-19 risk (see Appendix Table A.1 for the definition of each variable). The variables were assessed using a continuous scale of 0–10 with 0 representing the most desirable value. The descriptive statistics for the variables are shown in Table II. Using a uniform-width discretization scheme (Ekici & Ekici, 2021; Simsekler & Qazi, 2020), we discretized the INFORM’s ratings for individual variables into three states representing the negative performance of variables: low (0–3.33); medium (3.33–6.67); and high (6.67–10). Several studies have adopted this discretization scheme in decision-making under risk and uncertainty (de Oliveira, Possamai, Dalla Valentina, & Flesch, 2012; Lee, Park, & Shin, 2009; Qazi & Dikmen, 2021).

3.2. BBN Modeling

BBNs can effectively capture dependencies among uncertain variables and help decision-makers identify critical factors in a network setting (Hanea, Nane, Wielicki, & Cooke, 2018). The graphical interface of BBNs also helps visualize the propagation impact of uncertainties (Badurdeen et al., 2014; Kabir & Papadopoulos, 2019; Lockamy & McCormack, 2009). Both expert judgment and data can be used to develop a BBN model. Experts can be involved in mapping the qualitative structure of a BBN model and establishing the strength of dependency between interconnected variables (Qazi, Dickson, Quigley, & Gaudenzi, 2018). Arcs connecting variables may represent cause–effect relations or statistical dependencies and the strength of dependency is represented by (conditional) probability distributions (Christophersen et al., 2018; Jäger, Christie, Hanea, den Heijer, & Spencer, 2018).

Discrete BBN models can be developed using a data-set without relying on expert judgment. Initially, the data-set is discretized and mutually exclusive states are established for individual variables. Subsequently, a network structure is developed and probability distributions are extracted from the data-set using an algorithm, such as Naïve Bayes, Greedy Thick Thinning (GTT), PC, and Bayesian Search (Ekici & Ekici, 2021). These algorithms generally utilize a scoring function or seek to explore independent relations among variables. Several software packages can be used to develop a data-driven BBN model, such as Hugin, Netica, and GeNIe (Cox, Popken, & Sun, 2018). For a comprehensive overview of BBNs, interested readers may consult Kelangath, Das, Quigley, and Hirdaris (2012) and Kjaerulff and Anders (2008).

Using the discretized data for the variables (see Table II), we developed a BBN model in GeNIe 2.0 (see Fig. 1(a)) that comprised 19 variables and 33 arcs. We used the GTT algorithm due to its effective utilization in other application areas (Ekici & Ekici, 2021; Qazi & Khan, 2021). The model (see Fig. 1(a)) does not reflect the cause–effect relations between interconnected variables. Rather, it represents statistical dependencies among variables in line with the objective of this study. The use of data-driven BBN models in exploring statistical dependencies...
## Table I. Analytical framework for COVID-19 risk (source: INFORM, 2020)

| Dimension          | Category                        | Component       | Subcomponent                                                                 |
|--------------------|---------------------------------|-----------------|-------------------------------------------------------------------------------|
| **Hazard and exposure** | Person to person                | Population      | Population density, Urban population growth, Population living in urban areas, Population living in slums, Household size |
|                    |                                 | WaSH            | Sanitation, Drinking water, Hygiene                                           |
| **Vulnerability**  | COVID-19 vulnerability           | Movement        | International movement                                                        |
|                    |                                 | Internal movement | Access to cities, Road density                                                 |
|                    |                                 | Behavior        | Awareness, Adult literacy rate, Mobile cellular subscriptions, Internet users |
|                    |                                 | Demographic and comorbidities | Proportion of the population at increased risk of severe COVID-19 disease |
|                    | INFORM vulnerability            | Development and deprivation | Human development index, Multidimensional poverty index |
|                    |                                 | Inequality      | Gender inequality index, Gini index                                           |
|                    |                                 | Economic dependency index | Public aid per capita (USD), Net ODA received (% of GNI) |
|                    |                                 | Vulnerable groups | Uprooted people, Gender-based violence, Health conditions |
| **Lack of coping capacity** | COVID-19 lack of coping capacity | Health capacity | Health capacity specific to COVID-19                                           |
|                    |                                 | INFORM lack of coping capacity | Institutional, Infrastructure                                                  |
|                    |                                 | Governance      | Corruption perception index, Government effectiveness, Health system capacity, Immunization coverage |
|                    |                                 | Access to health care | Per capita public and private expenditure on health care, Maternal mortality ratio |

**Note:** All variables considered in the modeling process of this study appear in bold.
Table II. Descriptive statistics for the variables influencing COVID-19 risk

| Variable                                      | Mean  | Standard deviation | Minimum value | Maximum value |
|-----------------------------------------------|-------|--------------------|---------------|---------------|
| Access to health care                         | 4.24  | 2.29               | 0.2           | 10            |
| Aid dependency                                | 2.19  | 2.51               | 0             | 10            |
| Behavior                                      | 5.28  | 1.59               | 0.8           | 9.3           |
| COVID-19 risk                                 | 4.28  | 1.27               | 1.9           | 7.6           |
| Demographic and comorbidities                | 4.05  | 3.09               | 0             | 10            |
| Development and deprivation                  | 4.16  | 3.17               | 0             | 10            |
| Food security                                 | 3.26  | 2.45               | 0             | 9.6           |
| Gender-based violence                         | 3.40  | 2.55               | 0.2           | 10            |
| Governance                                    | 5.45  | 1.88               | 1.0           | 9.4           |
| Hazard and exposure                           | 4.24  | 1.59               | 1.8           | 7.9           |
| Health capacity specific to COVID-19         | 4.33  | 2.19               | 0             | 9.4           |
| Health conditions                             | 2.00  | 2.27               | 0             | 9.3           |
| Inequality                                    | 4.01  | 1.94               | 0.5           | 8.5           |
| Lack of coping capacity                       | 4.66  | 1.98               | 0.6           | 9.1           |
| Movement                                      | 5.02  | 1.70               | 1.1           | 8.9           |
| Population                                    | 5.05  | 1.27               | 2.6           | 9.6           |
| Uprooted people                               | 3.93  | 3.21               | 0             | 10            |
| Vulnerability                                 | 4.37  | 0.89               | 2.2           | 7.3           |
| WaSH                                          | 2.60  | 2.97               | 0             | 9.9           |

Table III. Confusion matrix (overall accuracy = 0.9005 [172/191])

| Predicted state of COVID-19 risk | Low | Medium | High |
|----------------------------------|-----|--------|------|
| Actual state of COVID-19 risk    |     |        |      |
| Low                              | 43  | 3      | 0    |
| Medium                           | 11  | 128    | 0    |
| High                             | 0   | 5      | 1    |

among variables can provide valuable insights in decision-making under risk and uncertainty (Ekici & Ekici, 2021; Kelangath et al., 2012; Lee et al., 2009; Qazi & Simsekler, 2021).

Exploring causality among multidimensional factors influencing country-level risk, such as COVID-19 risk, can prove beneficial in identifying and mitigating critical risk factors, but it is quite challenging to establish cause–effect relations in this particular setting (Qazi & Khan, 2021). This study aims to prioritize multidimensional factors affecting COVID-19 risk based on their impact across a correlation-based network.

3.3. BBN Model Validation

The BBN model developed was validated using the k-fold cross-validation scheme (Marcot & Hanea, 2021). The model was able to predict the actual state of COVID-19 risk with an accuracy of 90%. The confusion matrix (see Table III) indicates the relationship between the number of actual and predicted states. The numbers shown in bold across the diagonal represent all those instances where the predicted state accurately matched the actual state. For example, out of 191 entries used in the testing phase, 139 were related to the medium-risk state that was correctly diagnosed in the case of 128 entries. The prioritization of multidimensional factors affecting COVID-19 risk is discussed in the next section.

4. RESULTS AND INTERPRETATIONS

4.1. Probability Distributions and Identification of Critical Factors

The probability distribution associated with individual variables is indicated in Fig. 1(a). It shows that 4.6% of the countries were associated with
the “high” state of COVID-19 risk, 70.2% were associated with the “medium” state of COVID-19 risk, and 25.2% were associated with the “low” state of COVID-19 risk. The underlying distribution was highly skewed for some variables, such as WaSH, health conditions, and others. Lack of coping capacity was associated with a significantly higher percentage (15.6%) of risk than hazard and exposure, vulnerability, and COVID-19 risk (nodes with a red border).

The model (see Fig. 1(a)) was analyzed relative to the “low,” “medium,” and “high” states of COVID-19 risk for understanding the change across multidimensional factors in the network (see Figs. 1(b), (c), and (d)). The expected value of each factor/risk dimension was calculated for each
instance while assigning a value of 1, 2, and 3 to the “low,” “medium,” and “high” state, respectively (see Table IV). The maximum and minimum values associated with individual factors/risk dimensions are highlighted in bold. Overall, health conditions was the least critical factor with an expected value of 1.33, whereas governance was the most critical factor with an expected value of 2.11. For “low” risk countries, movement was assessed as the highest-ranking factor, whereas health conditions were evaluated as the least critical factor. This seems logical as most developed countries are highly connected internationally and maintain a high standard of health care and living. For “medium” risk countries, governance appears to be the most critical factor and health conditions still seem to be a low-priority factor. However, for “high” risk countries, lack of coping capacity becomes the most critical factor as such countries lack the capacity and resources to deal with pandemics such as COVID-19.
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Table IV. Expected values of multidimensional factors and risk dimensions influencing COVID-19 risk (“Low” risk: 1; “Medium” risk: 2; “High” risk: 3)

| Factor/Risk dimension | All countries | “Low” risk countries | “Medium” risk countries | “High” risk countries |
|-----------------------|---------------|-----------------------|-------------------------|----------------------|
| Access to health care | 1.79          | 1.21                  | 1.96                    | 2.42                 |
| Aid dependency        | 1.35          | 1.17                  | 1.41                    | 1.53                 |
| Behavior              | 2.06          | 1.78                  | 2.13                    | 2.21                 |
| Demographic and comorbidities | 1.85 | 2.34                  | 1.71                    | **1.52**             |
| Development and deprivation | 1.83 | 1.26                  | 2.01                    | 2.40                 |
| Food security         | 1.53          | 1.17                  | 1.61                    | 1.90                 |
| Gender-based violence | 1.66          | 1.31                  | 1.76                    | 1.97                 |
| Governance            | **2.11**      | 1.52                  | **2.29**                | 2.46                 |
| Hazard and exposure   | 1.76          | 1.50                  | 1.82                    | 2.10                 |
| Health capacity specific to COVID-19 | 1.86 | 1.24                  | 2.04                    | 2.43                 |
| Health conditions     | **1.33**      | **1.11**              | **1.38**                | 1.69                 |
| Inequality            | 1.73          | 1.36                  | 1.83                    | 2.02                 |
| Lack of coping capacity | 1.89       | 1.18                  | 2.09                    | 2.65                 |
| Movement              | 2.02          | **2.36**              | 1.92                    | 1.72                 |
| Population            | 2.00          | 1.98                  | 1.99                    | 2.14                 |
| Uprooted people       | 1.77          | 1.79                  | 1.75                    | 1.99                 |
| Vulnerability         | 1.89          | 1.77                  | 1.93                    | 2.01                 |
| WaSH                  | 1.49          | 1.15                  | 1.58                    | 2.06                 |

Note: The maximum and minimum values appear in bold.

Table V. Entropy (uncertainty) associated with multidimensional factors and risk dimensions influencing COVID-19 risk (a value of 0 and 1 represents the minimum and maximum level of uncertainty, respectively)

| Factor/Risk dimension | All countries | “Low” risk countries | “Medium” risk countries | “High” risk countries |
|-----------------------|---------------|-----------------------|-------------------------|----------------------|
| Access to health care | 0.92          | 0.50                  | 0.86                    | 0.86                 |
| Aid dependency        | 0.67          | 0.41                  | 0.73                    | 0.84                 |
| Behavior              | 0.96          | 0.73                  | 0.73                    | 0.91                 |
| Demographic and comorbidities | 0.68 | 0.90                  | 0.94                    | 0.83                 |
| Development and deprivation | 0.97 | 0.52                  | **1.00**                | 0.87                 |
| Food security         | 0.84          | 0.42                  | 0.89                    | 0.99                 |
| Gender-based violence | **0.98**      | 0.63                  | 0.91                    | 0.95                 |
| Governance            | **0.44**      | 0.80                  | 0.65                    | 0.82                 |
| Hazard and exposure   | 0.88          | 0.78                  | 0.90                    | 0.94                 |
| Health capacity specific to COVID-19 | 0.79 | 0.54                  | 0.82                    | 0.86                 |
| Health conditions     | 0.66          | **0.30**              | 0.71                    | 0.92                 |
| Inequality            | 0.83          | 0.67                  | 0.80                    | 0.82                 |
| Lack of coping capacity | 0.88       | 0.45                  | 0.62                    | **0.67**             |
| Movement              | 0.82          | 0.77                  | 0.76                    | 0.81                 |
| Population            | 0.91          | 0.68                  | 0.52                    | 0.74                 |
| Uprooted people       | 0.58          | **0.95**              | 0.95                    | **1.00**             |
| Vulnerability         | 0.89          | 0.60                  | **0.30**                | 0.85                 |
| WaSH                  | 0.77          | 0.36                  | 0.84                    | 0.97                 |

Note: The maximum and minimum values appear in bold.

4.2. Uncertainty Assessment

The uncertainty associated with multidimensional factors influencing COVID-19 risk was ascertained using entropy assessment (see Table V) (Durowoju, Chan, & Wang, 2012). A variable with a uniform distribution (the same probability for all states) yields an entropy value of 1, whereas the realization of a variable into one of its states results in an entropy value of 0, reflecting certainty. Governance (gender-based violence) was assessed as the least (most) uncertain factor. Lack of coping capacity...
Table VI. Network-wide impact assessment of risk dimensions

| Risk dimension         | Impact on hazard and exposure | Impact on lack of coping capacity | Impact on vulnerability | Impact on COVID-19 risk |
|------------------------|-------------------------------|----------------------------------|--------------------------|-------------------------|
|                        | “High” state                  | “Low” state                      | “High” state             | “Low” state             | “High” state | “Low” state |
| Hazard and exposure    | -                             | 2.35                             | 1.62                     | 1.97                    | 1.92         | 2.00       | 1.65       |
| Lack of coping capacity| 2.23                          | 1.43                             | -                        | 1.93                    | 1.85         | 2.17       | 1.21       |
| Vulnerability          | 1.97                          | 1.78                             | 2.14                     | 1.80                    | -            | -          | 2.13       | 1.59       |

was observed as the least uncertain risk dimension contributing to “high” risk. Development and deprivation was the least certain factor for “medium” risk, implying that it has the least exploratory power for the medium state of COVID-19 risk.

4.3. Network-wide Impact Assessment of Individual Factors Across Different States of COVID-19 Risk

As hazard and exposure, vulnerability, lack of coping capacity, and COVID-19 risk are modeled as interdependent variables (see Fig. 1), we investigated the impact of the variation of each risk dimension on other dimensions and COVID-19 risk (see Table VI). Lack of coping capacity significantly influenced COVID-19 risk in comparison with other risk dimensions. Similarly, lack of coping capacity and hazard and exposure were found to be relatively highly correlated.

We evaluated the network-wide impact of individual factors across risk dimensions corresponding to the two extreme states of each factor for “high” risk countries (see Table VIII). The maximum and minimum values associated with each risk dimension are highlighted in bold. In comparison with the results specific to “high” risk countries (see Table VII), some significant differences were observed in the case of “low” risk countries. For example, health capacity specific to COVID-19 was the most significant factor in reducing the lack of coping capacity. Further, reduction in population size significantly reduced the hazard and exposure; however, for “high” risk countries, improvement in the access to health care significantly contributed to the reduction in hazard and exposure. Access to health care was assessed as the most critical factor in terms of both reducing and aggravating the overall risk across the network.

4.4. Network-wide Impact Assessment of Individual Factors

We also conducted stress testing of the model to understand the propagation impact of individual factors across the network (see Table IX). The maximum and minimum values associated with each risk dimension are highlighted in bold. Health capacity specific to COVID-19 was the most critical factor influencing the lack of coping capacity with a network-wide spread of 1.37 across the two extreme states. Behavior was evaluated as the most critical factor influencing vulnerability, whereas hazard and risk exposure was significantly influenced by WaSH with a spread value of 1.02. Overall, limited access to health care significantly enhanced COVID-19 risk, whereas the population was the least critical factor in enhancing risk. Similarly, good governance significantly reduced the risk, whereas uprooted people had the least influence on risk. In terms of the spread associated with the impact of individual factors
Table VII. Network-wide impact (expected values) of individual factors influencing lack of coping capacity, vulnerability, and hazard and exposure for “High” risk countries (“Low” risk: 1; “Medium” risk: 2; “High” risk: 3)

| Factor in “High” state | Factor in “Low” state | Factor in “High” state | Factor in “Low” state | Factor in “High” state | Factor in “Low” state | Factor in “High” state | Factor in “Low” state | Network-wide spread |
|------------------------|-----------------------|------------------------|-----------------------|------------------------|-----------------------|------------------------|-----------------------|---------------------|
| Access to health care   | 2.36                  | 1.45                   | 1.69                  | 2.36                   | 1.53                  | 1.72                   | 1.75                  | 0.62                |
| Aid dependency         | 2.79                  | 1.99                   | 1.90                  | 2.77                   | 1.94                   | 1.94                   | 2.23                  | 0.43                |
| Behavior               | 2.87                  | 1.94                   | 1.94                  | 2.87                   | 1.94                   | 1.94                   | 2.23                  | 0.43                |
| Development and deprivation | 2.90   | 1.91                   | 1.91                  | 2.90                   | 1.91                   | 1.91                   | 2.23                  | 0.43                |
| Gender-based violence  | 2.82                  | 1.99                   | 1.99                  | 2.82                   | 1.99                   | 1.99                   | 2.23                  | 0.43                |
| Health capacity specific to COVID-19 | 2.96 | 1.99                   | 1.99                  | 2.96                   | 1.99                   | 1.99                   | 2.23                  | 0.43                |
| Health conditions      | 2.80                  | 1.99                   | 1.99                  | 2.80                   | 1.99                   | 1.99                   | 2.23                  | 0.43                |
| Inequality             | 2.80                  | 1.99                   | 1.99                  | 2.80                   | 1.99                   | 1.99                   | 2.23                  | 0.43                |
| Population             | 2.80                  | 1.99                   | 1.99                  | 2.80                   | 1.99                   | 1.99                   | 2.23                  | 0.43                |
| Uprooted people        | 2.80                  | 1.99                   | 1.99                  | 2.80                   | 1.99                   | 1.99                   | 2.23                  | 0.43                |
| Wash                   | 2.80                  | 1.99                   | 1.99                  | 2.80                   | 1.99                   | 1.99                   | 2.23                  | 0.43                |

Note: The maximum and minimum values appear in bold.

across the network, *governance* (uprooted people) was evaluated as the most (least) critical factor.

The results in Table IX were statistically analyzed using Spearman’s correlation at a significance level of 0.05 (see Table X). A moderate negative correlation was observed between the ranking schemes relative to the extreme states of each factor across *lack of coping capacity, vulnerability, hazard and exposure*, and COVID-19 risk. The negative sign is justified considering the opposite effects of the realization and mitigation of individual risk factors. Since the correlation is not very strong, the positive and negative influence of factors is quite different across the risk dimensions. In the case of rank correlation between different pairs of risk dimensions, only *lack of coping capacity* and COVID-19 risk were found to be strongly correlated. In contrast, all other correlations were classified as nonsignificant, implying that factors influencing risk dimensions had significantly different impacts across different combinations of factors.

5. DISCUSSION AND IMPLICATIONS

5.1. Salient Findings

5.1.1. Interdependent Nature of Multidimensional Factors Influencing COVID-19 Risk

The model presented in this article (see Fig. 1) depicts the interdependent nature of various socioeconomic, health, and safety factors influencing all three dimensions of COVID-19 risk, namely *hazard and exposure, vulnerability, and lack of coping capacity* (Marin-Ferrer et al., 2017). There is a wide variation in the probability distribution of individual factors across the extreme states of COVID-19 risk (see Figs. 1(b), (d)). However, some factors across both low- and high-risk countries are highly uncertain; therefore, such factors do not significantly contribute to the assessment of the overall risk such as *uprooted people* (see Table V). On the other hand, *health conditions* and *lack of coping capacity* are associated with low uncertainty for low-risk and high-risk countries, respectively.

5.1.2. Critical Factors Across Different States of COVID-19 Risk

In general, *governance* is considered as a high-risk factor across the world (Cardil & de-Miguel, 2020), whereas *health capacity specific to COVID-19*...
Table VIII. Network-wide impact (expected values) of individual factors influencing lack of coping capacity, vulnerability, and hazard and exposure for “Low” risk countries (“Low” risk: 1; “Medium” risk: 2; “High” risk: 3)

| Factor                                      | Lack of coping capacity | | | Vulnerability | Factor in “High” state | Factor in “Low” state | | | Hazard and exposure | Factor in “High” state | Factor in “Low” state | | | Net impact | Factor in “High” state | Factor in “Low” state | Network-wide spread |
|---------------------------------------------|-------------------------|---|---|-----------------|----------------------|----------------------|---|-------------------|----------------------|----------------------|---|-----------------|----------------------|----------------------|
| Access to health care                       | 2.42                    | 1.03 | 1.69 | 1.82 | 2.23 | 1.41 | 2.11 | 1.42 | 0.69 |
| Aid dependency                              | 1.47                    | 1.14 | 1.74 | 1.79 | 1.68 | 1.47 | 1.63 | 1.47 | 0.16 |
| Behavior                                    | 1.37                    | **1.19** | 2.00 | **1.67** | 1.63 | **1.52** | 1.67 | 1.46 | 0.21 |
| Development and deprivation                | 1.88                    | 1.07 | 1.76 | 1.80 | 2.07 | 1.41 | 1.90 | 1.43 | 0.47 |
| Food security                               | 1.72                    | 1.10 | 1.78 | 1.80 | 1.94 | 1.44 | 1.81 | 1.45 | 0.36 |
| Gender-based violence                       | 1.81                    | 1.09 | 1.88 | 1.79 | 1.95 | 1.44 | 1.88 | 1.44 | 0.44 |
| Governance                                  | 1.77                    | 1.08 | 1.64 | 1.82 | 1.82 | 1.44 | 1.74 | 1.45 | 0.29 |
| Health capacity specific to COVID-19        | 2.06                    | **1.02** | 1.63 | 1.83 | 1.74 | 1.43 | 1.81 | 1.43 | 0.38 |
| Health conditions                           | 1.80                    | 1.14 | **2.23** | 1.76 | 2.00 | 1.44 | 2.01 | 1.45 | 0.56 |
| Inequality                                  | 1.74                    | 1.05 | 1.97 | 1.80 | 1.93 | 1.43 | 1.88 | 1.43 | 0.45 |
| Population                                  | 1.34                    | 1.14 | **1.51** | **1.92** | 2.03 | **1.22** | 1.63 | 1.43 | 0.20 |
| Uprooted people                             | **1.23** | **1.19** | 1.77 | 1.78 | **1.52** | 1.49 | **1.51** | **1.49** | **0.02** |
| WaSH                                        | 1.92                    | 1.11 | 1.91 | 1.79 | **2.29** | 1.43 | 2.04 | 1.44 | 0.60 |

Note: The maximum and minimum values appear in bold.
### Table IX. Network-wide impact (expected values) of individual factors influencing risk dimensions and COVID-19 risk ("Low" risk: 1; "Medium" risk: 2; "High" risk: 3)

| Factor                          | Lack of coping capacity | Vulnerability | Hazard and exposure | COVID-19 risk |
|---------------------------------|-------------------------|---------------|--------------------|---------------|
|                                 | Factor in “High” state  | Factor in “Low” state | Spread | Factor in “High” state  | Factor in “Low” state | Spread | Factor in “High” state  | Factor in “Low” state | Spread | Factor in “High” state  | Factor in “Low” state | Spread |
| Access to health care           | 2.65                    | 1.30          | 1.35               | 1.97          | 1.85          | 0.12               | 2.37          | 1.40          | 0.97               | 2.11          | 1.45          | 0.66               |
| Aid dependency                  | 2.14                    | 1.79          | 0.35               | 1.92          | 1.87          | 0.05               | 1.92          | 1.66          | 0.26               | 1.95          | 1.74          | 0.21               |
| Behavior                        | 2.20                    | 1.62          | 0.58               | 2.02          | **1.69**       | **0.33**           | 1.99          | 1.64          | 0.35               | 2.00          | 1.54          | 0.46               |
| Development and deprivation    | 2.35                    | 1.49          | 0.86               | 1.96          | 1.85          | 0.11               | 2.26          | 1.43          | 0.83               | 2.02          | 1.56          | 0.46               |
| Food security                   | 2.36                    | 1.67          | 0.69               | 1.95          | 1.88          | 0.07               | 2.22          | 1.56          | 0.66               | 2.01          | 1.67          | 0.34               |
| Gender-based violence           | 2.34                    | 1.62          | 0.72               | 1.99          | 1.87          | 0.12               | 2.16          | 1.54          | 0.62               | 2.02          | 1.64          | 0.38               |
| Governance                      | 2.35                    | 1.24          | 1.11               | 1.93          | 1.84          | 0.09               | 2.09          | 1.50          | 0.59               | 2.03          | **1.20**       | **0.83**           |
| Health capacity specific to COVID-19 | 2.60                  | **1.23**       | **1.37**           | 1.93          | 1.87          | 0.06               | 2.03          | 1.52          | 0.51               | 2.07          | 1.39          | 0.68               |
| Health conditions               | 2.26                    | 1.74          | 0.52               | **2.12**      | 1.85          | 0.27               | 2.19          | 1.57          | 0.62               | 2.01          | 1.71          | 0.30               |
| Inequality                      | 2.27                    | 1.49          | 0.78               | 2.01          | 1.86          | 0.15               | 2.13          | 1.49          | 0.64               | 2.01          | 1.56          | 0.45               |
| Population                      | 2.10                    | 1.68          | 0.42               | **1.72**      | **1.95**       | **-0.23**          | 2.21          | **1.39**       | 0.82               | **1.79**       | 1.70          | 0.09               |
| Uprooted people                 | 2.03                    | **1.88**       | **0.15**           | 1.91          | 1.89          | 0.02               | **1.88**      | **1.72**       | **0.16**           | 1.86          | **1.82**       | **0.04**           |
| WaSH                            | 2.43                    | 1.68          | 0.75               | 2.00          | 1.86          | 0.14               | **2.51**      | 1.49          | **1.02**           | 2.04          | 1.68          | 0.36               |

**Note:** The maximum and minimum values appear in bold.
is relatively a low-risk factor (see Table IV). Health capacity specific to COVID-19 is significantly reduced from low-risk countries to high-risk countries, implying that high-risk countries lack a robust risk management process (SA, 2009) to contain the impact of damage associated with the pandemic (Tran et al., 2020). This is substantiated by the fact that the lack of coping capacity is assessed as the most critical factor in high-risk countries (see Table IV). Development and deprivation, access to health care, and governance are other critical factors relevant to high-risk countries (Emmanouil et al., 2020).

5.1.3. Relative Contribution of Individual Risk Dimensions to COVID-19 Risk

In terms of the relative contribution of hazard and exposure, vulnerability, and lack of coping capacity to the overall risk, contrary to the belief that each dimension is equally important in establishing the risk (Marin-Ferrer et al., 2017), the lack of coping capacity appears to have a significant impact on COVID-19 risk (see Table VI). This is also a critical factor in recent studies (Bruinen de Bruin et al., 2020; Cardil & de-Miguel, 2020). This fact is also substantiated by the wide variation in the expected value of health capacity specific to COVID-19 (see Table IV). It also implies that although few countries in the low-risk category are associated with a high level of hazard and exposure due to their mobility and interconnectedness with the rest of the world (movement), those countries have a strong coping capacity, which significantly reduces their risk.

5.1.4. Network-wide Impact Assessment of Individual Factors Across Different States of COVID-19 Risk

WaSH is assessed as the most critical factor in terms of its propagation impact for high-risk countries, whereas access to health care significantly reduces COVID-19 risk for such countries (see Table VII) (Emmanouil et al., 2020). Uprooted people appear to be the least critical factor. Improvement in the health capacity specific to COVID-19 can reduce the risk for high-risk countries; however, besides such preventive measures, there is a need to adopt reactive strategies such as providing access to health care. For low-risk countries, the extent of propagation impact of adverse events is significantly reduced (see Table VIII), whereas the improvement margin across the network is significantly enhanced. Further, the
variation in the network-wide improvement of risk relative to the mitigation of individual factors is significantly reduced, indicating that the susceptibility of low-risk countries to individual factors is very low.

5.1.5. Network-wide Impact Assessment of Individual Factors

Overall, access to health care is assessed as the most critical factor responsible for enhancing COVID-19 risk, whereas governance can significantly reduce the risk (see Table IX) (Emmanoul et al., 2020). Vulnerability is significantly influenced by the health conditions and behavior relative to the high and low state of the factor, respectively. Similarly, lack of coping capacity is significantly aggravated by the limited access to health care and mitigated by the health capacity specific to COVID-19. For hazard and exposure, WaSH is the most critical risk factor, whereas population can significantly reduce the hazard and exposure (see Table IX).

5.1.6. Correlation Analysis

The positive and negative impacts of individual factors on hazard and exposure, vulnerability, lack of coping capacity, and COVID-19 risk are moderately correlated (Table X), implying that various factors impact the network differently relative to their improvement and deterioration potential (Qazi & Dikmen, 2021). Therefore, the priority of factors is changing concerning their vulnerability and resilience potential. There was a strong correlation observed in the ranking schemes for lack of coping capacity and COVID-19 risk (see Table X), implying that the strategies adopted for improving coping capacity can significantly reduce COVID-19 risk (Cardil & de-Miguel, 2020). However, the rank correlation across all other pairs of variables was nonsignificant, implying that the strategies adopted for individual factors might not prove beneficial for the entire network in terms of reducing COVID-19 risk. Rather, strategies would need to be designed holistically across a network of interacting factors (Bruinen de Bruin et al., 2020).

5.2. Implications

This article makes a theoretical contribution to the literature on risk assessment of pandemics. A data-driven process is operationalized to model and prioritize multiple socioeconomic, health, and safety factors in a network setting that can significantly influence the risk of pandemics such as COVID-19. To the best of the authors’ knowledge, none of the studies have assessed the relative contribution of factors toward COVID-19 risk in a network setting. Given the availability of sufficient data about COVID-19, the proposed methodology can be used to dynamically predict and manage the uncertainty associated with the pandemic (Kabir & Papadopoulos, 2019).

The model presented in this article can be used by international health agencies such as the World Health Organization to prioritize critical factors and design effective strategies to cope with the pandemic (Cardil & de-Miguel, 2020). At a national level, policy-makers can prioritize factors and make optimal decisions regarding developing proactive and contingency plans to manage COVID-19 risk.

The proposed methodology can be applied at a national level to segregate cities and states into different risk zones and prioritize strategies at the state level (Haque et al., 2020). Such granular-level analysis will be more suitable to large countries with a nonhomogeneously distributed demographic, among other factors. In the case of heterogeneous data, factors with a significant range could be identified to help establish their relative network-wide impact. The main merit of the model presented in this article is its visual ability to help policy-makers understand the highly connected nature of the network. They can appreciate how the realization of individual risk factors can cascade across the entire network. Similarly, they would understand the implications of potential strategies as those strategies might have nonlinear interactions, and multiple positive and negative correlations across factors might lead to undesired consequences (Ackermann, Howick, Quigley, Walls, & Houghton, 2014).

The assessment of the risk of individual countries provides valuable information to policy-makers (Marulanda Fraume et al., 2020); however, existing risk assessment techniques cannot help in prioritizing factors holistically in a network setting (Bruinen de Bruin et al., 2020). The proposed methodology helps generate and visualize multiple scenarios such that the vulnerability and resilience potential of individual factors can be ascertained. The proposed methodology and the model presented in this article can help the decision-makers model and manage risks concerning pandemics, disasters, floods, epidemics, and other natural calamities. The sensitivity analysis performed in Section 4 can help in prioritizing multidimensional factors influencing a target...
node (Hossain et al., 2020), such as COVID-19 risk in the context of this study. Subsequently, the relative contribution of critical factors can be established for resource allocation using scenario analysis-based techniques (Qazi, Quigley, Dickson, & Ekici, 2017; Quigley & Walls, 2007).

6. CONCLUSIONS

This study establishes the relative importance of individual factors in terms of their network-wide impact on hazard and exposure, vulnerability, lack of coping capacity, and the overall COVID-19 risk. The main contribution of this study is to evaluate the relative significance of multidimensional factors affecting COVID-19 risk while considering both the vulnerability and resilience potential of individual factors. This study provides unique insights to policymakers regarding identifying critical factors and the allocation of resources according to the relative importance of individual factors.

Among the three risk dimensions, only lack of coping capacity appears to have a significant impact on COVID-19 risk. Similarly, a strong correlation between the ranking schemes for lack of coping capacity and COVID-19 risk reveals that the strategies adopted for improving coping capacity can significantly reduce COVID-19 risk. While considering the network-wide propagation impact of individual factors, access to health care is assessed as the most critical factor relative to its negative impact on COVID-19 risk. In contrast, governance can considerably mitigate the risk. Health conditions and behavior can significantly impact the vulnerability dimension relative to their vulnerability and resilience potential, respectively. Similarly, lack of coping capacity is significantly aggravated by the limited access to health care and mitigated by the health capacity specific to COVID-19. In the case of hazard and exposure, WaSH is the most critical risk factor relative to its vulnerability potential, whereas population can significantly reduce the hazard and exposure.

This study has a few limitations. Individual factors are discretized in the model. Further, the risk treatment stage of the risk management process (SA, 2009) is not covered in the modeling process. The dynamic nature of risk is not captured. Future research can benefit from modeling individual factors as continuous variables given the availability of sufficient data, which can enhance the efficiency of the proposed model in predicting COVID-19 risk. Potential risk mitigation strategies can be added to the model to account for any positive and negative synergies across risks and strategies. Dynamic BBNs can be used to establish the behavior of risk over time. A multifactor sensitivity analysis of the interdependency arcs can show a better picture of how the weightage of each factor might affect the network. This might provide the stakeholders with a chance to revise the weights based on their observation of results and prior knowledge. The sensitivity analysis is not performed while selecting the discretization scheme and the BBN learning algorithm. Such analysis could help establish the sensitivity of results to different discretization schemes and algorithms. Further, additional socioeconomic factors can be added to the model for establishing a holistic account of complex dynamics concerning pandemics such as COVID-19.

Appendix

Table A1. Definitions of multidimensional factors and risk dimensions (source: Marin-Ferrer et al., 2017; INFORM, 2020)

| Factor/Risk dimension     | Definition                                                                                                                                 |
|---------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| Access to health care     | This is based on health system capacity, immunization coverage, per capita public and private expenditure on health care, and maternal mortality ratio.  |
| Aid dependency            | With the “aid dependency” component, the methodology points out the countries that lack sustainability in development growth due to economic instability and humanitarian crisis. It is comprised of two indicators: public aid per capita; and net Official Development Assistance (ODA) received in percentage of Gross National Income (GNI) by the World Bank. |
| Behavior                  | Behavior is a function of awareness and trust. Awareness is measured through adult literacy rate and the number of mobile cellular subscriptions and internet users.  |

(Continued)
### Table A1. (Continued)

| Factor/Risk dimension | Definition |
|-----------------------|------------|
| COVID-19 risk         | The INFORM COVID-19 risk index aims to identify countries at risk from health and humanitarian impacts of COVID-19 that could overwhelm current national response capacity, and therefore lead to a need for additional international assistance. |
| Demographic and comorbidities | Demographic and comorbidities represent the proportion of the population at increased risk of severe COVID-19 risk. |
| Development and deprivation | It describes how a population is doing on average. It comprises two well-recognized composite indices by UNDP: the Human Development Index (HDI); and the Multidimensional Poverty Index (MPI). |
| Food security | This subcomponent is dependent on food access, food availability, and food utilization. This concept serves as a set of proxy measures for the number of people lacking secure access to food. |
| Gender-based violence | Gender-based violence is based on the proportion of ever-partnered women and girls subjected to physical and/or sexual violence by a current or former intimate partner in the previous 12 months and attitudes toward violence. |
| Governance | Governance is a function of both the Government Effectiveness and Corruption Perception Index. The Government Effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political influences, the quality of policy formulation and implementation, and the credibility of the government’s commitment to such policies. The Corruption Perception Index adds another perspective that is the level of misuse of political power for private benefit, which is not directly considered in the construction of the Government Effectiveness even though interrelated. |
| Hazard and exposure | This dimension reflects the probability of physical exposure associated with specific hazards. |
| Health capacity specific to COVID-19 | This is dependent on International Health Regulations Core Capacities average score and Country Preparedness and Response Status for COVID-19. |
| Health conditions | This subcomponent refers to people in a weak health condition. It is calculated as the arithmetic average of the indicators for three deadly infectious diseases, AIDS, tuberculosis and malaria, which are considered as pandemics of low- and middle-income countries. |
| Inequality | The “inequality” component introduces the dispersion of conditions within population presented in the “development and deprivation” component with two proxy measures: the Gini Index by the World Bank; and the Gender Inequality Index by UNDP. |
| Lack of coping capacity | This dimension measures the ability of a country to cope with disasters in terms of formal, organized activities and the effort of the country's government as well as the existing infrastructure, which contribute to the reduction of disaster risk. |
| Movement | Movement comprises international and internal movement. International movement is based on air transport, passengers carried, international tourism, number of arrivals, and points of entry. Internal movement is a function of access to cities and road density. |
| Population | Population is a function of population density, urban population growth, population living in urban areas, population living in slums, and household size. |
| Uprooted people | The total number of uprooted people is the sum of the highest figures from the selected sources for each uprooted group. The “uprooted people” component is the arithmetic average of the absolute and relative value of uprooted people. The absolute value is presented using the log transformation while the uprooted people relative to the total population are transformed into an indicator using the GNA (Global Needs Assessment) criteria and then normalized into a range from 0 to 10. |
| Vulnerability | This dimension represents economic, political, and social characteristics of the community that can be destabilized in case of a hazardous event. |
| WaSH | WaSH represents the availability of drinking water, sanitation, and hygiene. |

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