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Resilience Analysis in the Wake of COVID-19: Insights from Bayesian Modeling

Aishvarya Kumar Jain
Fraunhofer Institute for High-Speed Dynamics, Ernst-Mach-Institut, EMI, Freiburg-im-Breisgau, Germany.
E-mail: aishvarya.kumar.jain@emi.fraunhofer.de

Caroline Delleske
Fraunhofer Institute for High-Speed Dynamics, Ernst-Mach-Institut, EMI, Freiburg-im-Breisgau, Germany.

Hagen Dreßler
Institute for Sustainable Systems Engineering, Resilience Engineering for Technical Systems, University Freiburg, Freiburg-im-Breisgau, Germany.

Kai Fischer
Fraunhofer Institute for High-Speed Dynamics, Ernst-Mach-Institut, EMI, Freiburg-im-Breisgau, Germany.

Mirjam Fehling-Kaschek
Fraunhofer Institute for High-Speed Dynamics, Ernst-Mach-Institut, EMI, Freiburg-im-Breisgau, Germany.

Alexander Stolz
Institute for Sustainable Systems Engineering, Resilience Engineering for Technical Systems, University Freiburg, Freiburg-im-Breisgau, Germany. E-mail: alexander.stolz@inatech.uni-freiburg.de

The current world has experienced a profound shift from risk analysis to resilience analysis, a transition underscored by the recognition that resilience encompasses more than just a system's response to threats. It also provides critical insights into preparedness for future events and the recovery processes that follow. The recent COVID-19 pandemic has profoundly impacted global societies, illustrating the vulnerabilities within our systems and the need for enhanced resilience. For over three years, communities worldwide faced unprecedented challenges, highlighting the necessity to evaluate the socio-technical resilience of our societies. Understanding how resilient we are against such threats is essential, and ensuring a swift recovery post-event is equally critical.
In this paper, we demonstrate the applicability of Bayesian networks in modeling resilience and its various phases with respect to the pandemic. Unlike deep learning methods, which often rely solely on large datasets, Bayesian networks offer the unique advantage of incorporating expert knowledge alongside empirical data. This dual approach allows for a more nuanced understanding of resilience dynamics. We present a data-driven multilevel hierarchical Bayesian network that not only estimates and compares the different phases of resilience but also identifies and analyzes the underlying factors that influence each phase. To assess socio-technical resilience effectively, we utilized a German dataset (INKAR), which contains vital socio-economic indicators, including population, employment, education, and gender, at a community-level geographical resolution. This research aims to contribute to the growing body of knowledge on resilience, providing valuable insights that can inform policy and practice. The results quantify the resilience of single counties and show the coping capacity concerning the pandemic over the past years.

Keywords: Resilience, Bayesian Networks, Socio-Technical Systems, COVID-19, data-driven

1. Introduction

The recent COVID-19 pandemic posed one of the greatest threats to our world. Immense efforts are ongoing in socio-technical research to understand its impact on our social dynamics and how we can make our communities more resilient towards such dangers. Our local communities are highly interconnected socio-technical systems. It is crucial to understand how societies can withstand and respond to various threats, particularly in the context of global crises such as the COVID-19 pandemic, and recover efficiently to their full performance as quickly as possible. The pandemic has underscored the importance of resilience, as it has exposed vulnerabilities within health systems and social structures. For instance, a comparison of COVID-19 death rates in Fig. 1 reveals stark contrasts between countries with good healthcare systems like Switzerland and Germany ranked 10 and 13 respectively on the Legatum Prosperity Index (Legatum (2023)), and countries with relatively weaker healthcare systems like Croatia ranked 53 on the same index. Switzerland and Germany, although have a higher first peak of daily absolute deaths per million people around May 2020, given their strong health care systems, managed a lower human loss during 2nd and 3rd wave and lower cumulative deaths in total as compared to Croatia. This disparity emphasizes the need for improved preparedness, response, and recovery strategies (indicated by a stronger healthcare system) to enhance resilience against future pandemics.

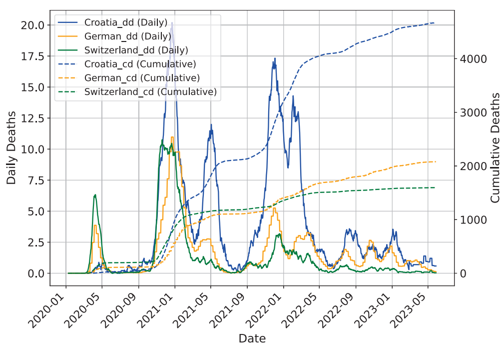


Fig. 1.: Daily absolute and Cumulative COVID-19 related deaths per million people in Switzerland, Germany, and Croatia Mathieu et al. (2020).

Resilience refers to the ability of a system to absorb disturbances, adapt to changing conditions, and recover from adversity (Häring et al. (2016); Stolz et al. (2024)). It is characterized by resilience pillars namely, *prepare*, *prevent*, *protect*, *respond* and *recover* Thoma et al. (2016). In this research, we focus on modeling resilience within the social domain, utilizing socio-economic data to analyze resilience pillars across various communities in Germany. The data source, INKAR (2024) (Indicators and maps for spatial and urban development) provides essential indicators such as population, employment, education, and gender, per district in Germany, enabling us to evaluate socio-technical resilience comprehensively. We employ a multilevel hierarchical Bayesian network approach, integrating both expert knowledge and empirical data to better understand the resilience dynamics. Our findings reveal significant variations in resilience levels among different communities, highlighting the best and worst performers in terms of resilience pillars. We also examine communities with notable differences in pillar values and conduct local and global sensitivity studies to assess the robustness of our results. This research aims to enhance our understanding of resilience and inform policy decisions to bolster community preparedness and recovery processes in future crises.

2. Related Work

Resilience analysis is widely utilized to understand vulnerabilities within the socio-economic domain. Kammouh et al. (2019) developed an indicator-based hierarchical framework known as PEOPLES (Population, Environmental and Ecosystem, Organized Governmental Services, Physical Infrastructures, Lifestyle, Economic Development, and Social Capital) to analyze the resilience of communities against both human-made and natural disasters. Mottahedi et al. (2021) introduced a practical framework that combines expert judgment and fuzzy logic to quantify the resilience of critical infrastructure. This approach addresses the challenge of sparse data, as much of the information collected in the domain of critical infrastructure does not directly pertain to resilience.

Sen et al. (2022) quantified the resilience of housing infrastructure against flood hazards using a dynamic Bayesian network, applying it to assess vulnerabilities in Barak Valley, located in Northeastern India. Hossain et al. (2019) Franco-Gaviria et al. (2022) and Tang et al. (2020) employed Bayesian modeling approaches to assess the resilience of port infrastructure, socio-ecological systems in the high Andes of Colombia, and urban transport infrastructure across four cities in China, respectively. Kammouh et al. (2020) presented a framework to model both static and dynamic socio-economic resilience, which was used to analyze the resilience of Brazil.

In contrast to existing studies, the current work primarily focuses on the quantification of resilience phases, extending the Bayesian framework provided by Tang et al. (2020) and Kammouh et al. (2020).

3. Methodology

3.1. *Data Processing*

This section outlines the data processing steps undertaken to prepare the INKAR dataset for input into the Bayesian model. The INKAR dataset comprises community-level socio-economic indicators for Germany. As illustrated in Fig. 2, the

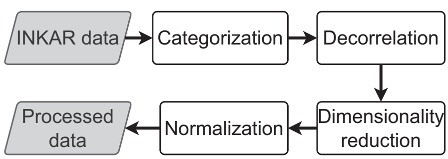


Fig. 2.: Data processing steps.

first step involves categorizing the data, where each feature is assigned to one of twelve socio-economic categories (refer to Tab. 1 for the complete list of categories).

Following categorization, we perform decorrelation on each category, eliminating features exhibiting more than 90% correlation to reduce redundancy. Subsequently, we apply Principal Component Analysis (PCA) to diminish data dimensionality while retaining a maximum variance of 80% (see Fig. 3). The normalized data is then scaled to a range between 0 and 1 to ensure uniformity across features. Tab. 1 details the number of features in each category at various stages of the data processing pipeline. Additionally, to estimate the resilience phases, we employ the Baseline Resilience Indicators for Communities (BRIC) framework (Xu (2024); Cutter et al. (2010)). This systematic approach enhances our capacity to analyze the socio-economic resilience of communities effectively and in a data-driven way.

Table 1.: Number of dimensions in original and reduced data per category. *column A*: Number of dimensions in unprocessed dataset; *column B*: Number of dimensions after de-correlation; *column C*: Number of dimensions after dimensionality reduction.

Category	A	B	C
Land use	19	16	5
Unemployment	17	15	4
Economy	21	18	8
Building and housing	21	15	4
Employment	43	35	6
Population	45	33	7
Education	14	13	6
Personal income	13	12	4
Medical and social care	22	18	7
Public finances	16	11	4
Social benefits	23	16	4
Transport and accessibility	38	32	10
Total	**292**	**234**	**69**

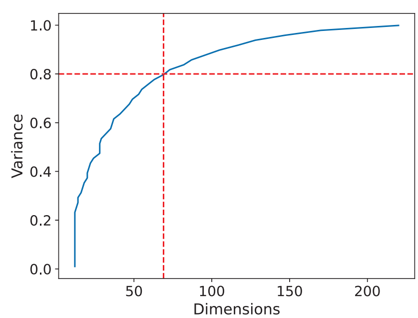


Fig. 3.: Data dimensionality vs. variance plot. The elbow at 80% variance leads to 69 dimensions that total across all the categories.

3.2. *Bayesian Network*

Bayesian networks are directed acyclic graphs (DAGs) that effectively model the interdependencies among system variables. As illustrated in Fig.

4, a Bayesian network consists of nodes representing random variables, with directed edges indicating the conditional dependencies between them. In this figure, the arrows signify how each child node's probability is conditionally dependent on its parent nodes. The joint probability distribution

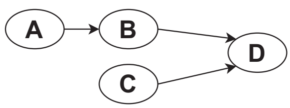


Fig. 4.: A simple Bayesian network with 4 nodes.

of the system, taking into account the local dependencies is,

$$P(A,B,C,D) = P(D \mid BC) \times P(B \mid A) \times P(A) \times P(C) \quad (1)$$

In this equation, $P(A,B,C,D)$ denotes the joint probability distribution of the Bayesian network. The term $P(D \mid B,C)$ represents the conditional probability of node D given its parent nodes B and C, while $P(A)$ and $P(C)$ indicate the prior probabilities of nodes A and C, respectively—nodes that do not have any parents. This framework enables a comprehensive understanding of the probabilistic relationships within the system, facilitating nuanced analyses of resilience dynamics.

Fig. 5 illustrates the Bayesian network developed and employed for this study. The network is structured into three distinct layers: the Macro-layer, Meso-layer, and Micro-layer. The Micro-layer comprises data points extracted from the INKAR dataset, with the figure depicting the categories to which these data indicators belong. The Meso-layer encompasses functions that translate the data indicators into resilience functions, and its ontology is primarily informed by the work of Tang et al. (2020). Finally, the Macro-layer consists of resilience functions (or resilience phases) that directly link the system's performance to its resilience. The ontology for this layer is developed by synthesizing definitions from both Tang et al. (2020) and Kammouh et al. (2020). This layered approach enables a comprehensive analysis of resilience dynamics, facilitating a clearer understanding of the relationships among various factors.

3.3. *Model Initialization and Phase Estimation*

The initial step following the definition of the Bayesian network structure involves quantifying the conditional probability distributions (CPDs) for each node in the Macro and Meso layers, as well as establishing the prior distributions for all indicators in the Micro layer. In the proposed model, each node is represented by one of three discrete states: low (L), medium (M), and high (H), which are encoded as 0, 1, and 2, respectively.

All nodes within the Macro and Meso layers are directly correlated with resilience; specifically, a high state of a node corresponds to high resilience. To accurately map the discrete states of the Micro-level indicators, we utilize a correlation factor with resilience. If the correlation factor of an indicator is zero or positive, a high state of the node inherently implies high resilience. Conversely, for indicators with a negative correlation, a high state of the node results in low resilience. This approach ensures a nuanced understanding of how various indicators influence resilience within the system.

3.3.1. *Micro-level Indicators*

The data for the micro-level indicators is derived from the INKAR dataset, as detailed in Subsec. 3.1. The correlation factor for each indicator is calculated using the resilience values (BRIC). To determine the prior distribution among the three states—Low, Medium, and High—a binomial distribution is employed (Kammouh et al. (2020)). For illustration, consider an indicator with a value x; the corresponding distribution for a positively correlated indicator is x^2, $2x(1-x)$, and $(1-x)^2$ for the high, medium, and low states, respectively.

3.3.2. *Macro and Meso levels*

The CPTs for all nodes in the Macro and Meso levels are determined as described by Kammouh et al. (2020). To illustrate this, consider the node *Adaptability (adap)* in Fig. 5, which has two parent nodes: *Learning Ability (lear)* and *Anticipa-*

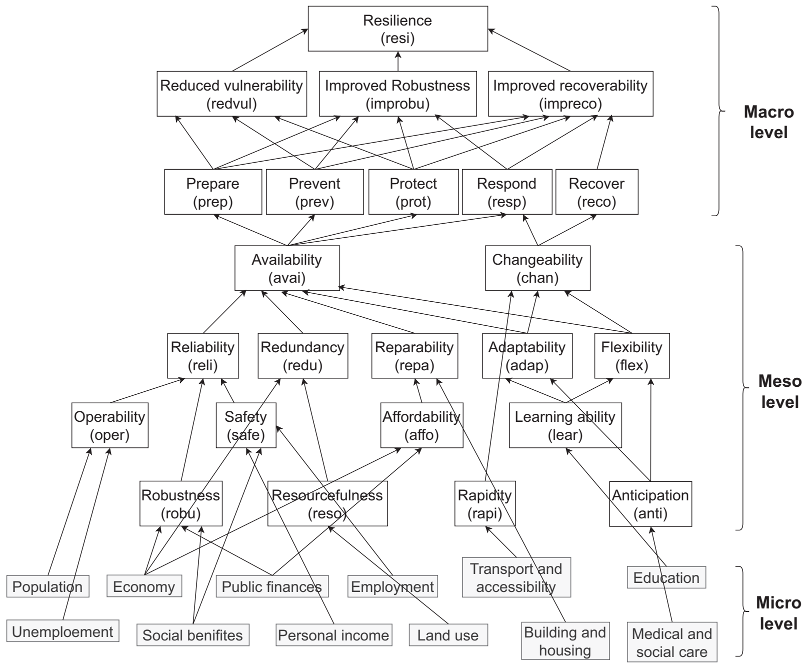


Fig. 5.: Bayes net for socio-resilience quantification using INKAR data.

tion (anti). To calculate the CPT for *adap*, we first calculate a global relative value for the node,

$$x_{adap} = \frac{y_{lear} + y_{anti}}{max_{lear} + max_{anti}}, \quad (2)$$

where x_{adap} is the relative global value of the node *Adaptability*, and y_{lear} and y_{anti} are the values of the two parent nodes. Additionally, max_{lear} and max_{anti} represent the maximum values of the two parent nodes, which are two for the described model. Consequently, the distribution across the three levels (High, Medium, and Low) is calculated using the binomial distribution, as outlined for the micro indicators. Tab. 2 presents the CPT for the node *Adaptability*. Furthermore, to estimate the CPT for the resilience node, first, the resilience is calculated using the BRIC methodology and then binomial distribution, similar to micro-level indicators is calculated.

Given the Bayesian network and the CPTs of all nodes, the joint distribution is calculated using Eq. 1. Consequently, the probabilities of the three resilience phases—*Reduced Vulnerability (redvul)*, *Improved Robustness (improbu)*, and *Improved Recoverability (impreco)*—are quantified using the marginalization of the joint probability distribution. Subsequently, inverse binomial sampling is applied to numerically estimate the phases.

Table 2.: CPT for the node *Adaptibility*.

y_{lear}	y_{anti}	x_{adap}	x^2 (H)	$2x(1-x)$ (M)	$(1-x)^2$ (L)
2	2	1	1	0	0
2	1	0.75	0.5625	0.375	0.0625
2	0	0.5	0.25	0.5	0.25
1	2	0.75	0.5625	0.375	0.0625
1	1	0.5	0.25	0.5	0.25
1	0	0.25	0.0625	0.375	0.5625
0	2	0.5	0.25	0.5	0.25
0	1	0.25	0.0625	0.375	0.5625
0	0	0	0	0	1

4. Results and Discussions

In this section, we show different case analyses and comparisons of quantified resilience phases and factors that affect resilience the most.

4.1. *Resilience and Resilience Phases*

Fig. 6 compares the resilience phases of two German communities, Passau and Kusel. Passau ranks highest on the BRIC indicator with a value of 0.786544, while Kusel, with a value of 0.24626, ranks the lowest. The plot indicates that Kusel is weak in all phases of resilience, although some factors contribute more significantly than others. Fig. 7 displays the comparison of all resilience factors for the two communities alongside the overall distribution of these factors among all German communities. As can be deduced, Passau is overall a better-performing community in contrast to Kusel; however, there are some factors for Kusel, such as *Rapidity (rapi)*, that are above average when compared to the mean value.

Fig. 8 shows the distribution of the BRIC indicator (static resilience) throughout Germany. Additionally, Fig. 9 illustrates how different resilience phases are distributed across the country.

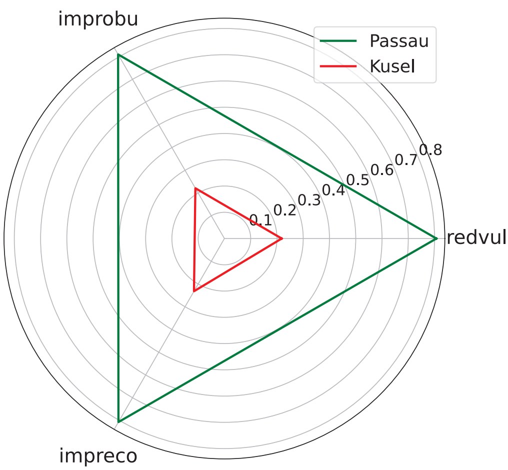


Fig. 6.: Resilience phases distribution of two German communities.

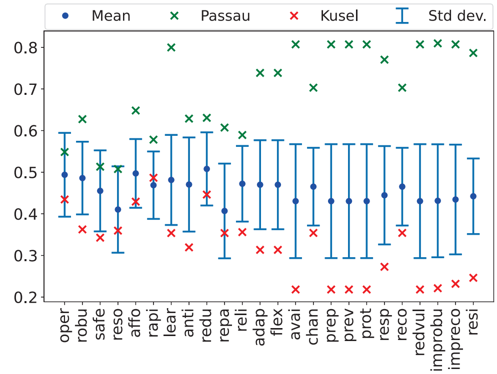


Fig. 7.: Bayes node value distribution of Kusel and Passau in comparison to the overall distribution of all communities of Germany .

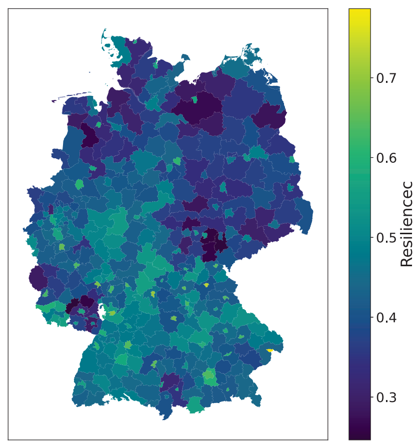
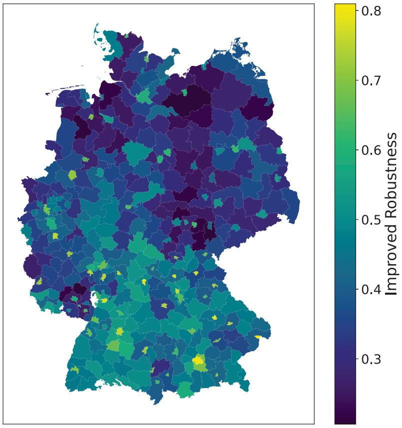


Fig. 8.: Resilience distribution over Germany quantified using the BRIC indicators.

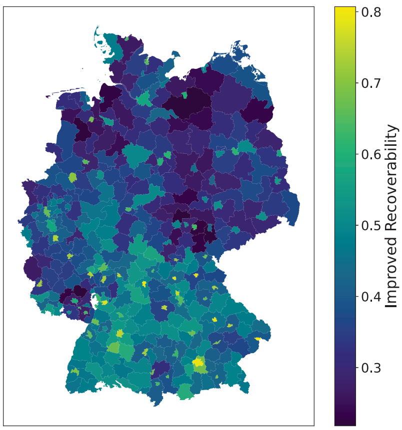
4.2. *Sensitivity Analysis*

To identify the factors that can contribute the most to improving resilience, the study concludes with a sensitivity analysis. Fig. 10 presents the local sensitivity analysis for the community of Kusel, illustrating how resilience changes with respect to individual data categories.

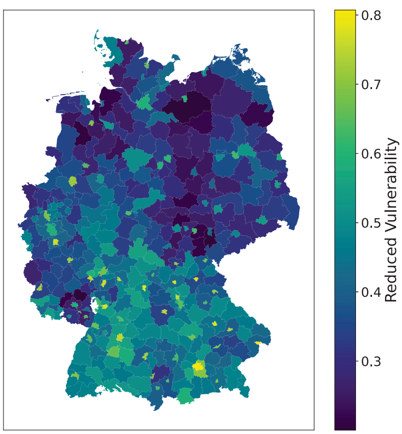
As observed, certain categories significantly affect resilience. For instance, *medi-social*, *education*, and *economy* are the top three categories that have the greatest impact on resilience.



(a)



(b)



(c)

Fig. 9.: Distribution of a. Improved robustness; b. Improved recoverability; c. Reduced vulnerability, across all communities in Germany.

Fig. 11 presents the second-order sensitivity analysis (Sobol (2001)) of the Bayesian model. The heat map displays pairs of collaborating categories that have the most impact on resilience.

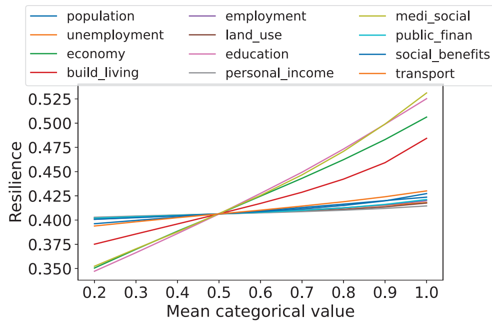


Fig. 10.: Local sensitivity analysis for the community of Kusel.

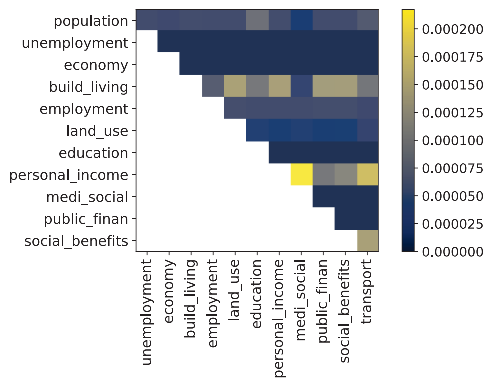


Fig. 11.: Second-order Sobol sensitivity indices, showing the impact of pair-wise collaborating categories on the overall resilience of Kusel.

5. Conclusion and Outlook

The study demonstrates a data-driven methodology to quantify the static resilience phases. Additionally, it highlights the applicability of a community-driven Bayesian approach to enhance regional resilience. To illustrate this applicability, a comparative analysis of two German communities, Passau, which is the most resilient, and

Kusel, the least resilient, is provided. It is concluded that Passau's overall performance during the COVID-19 pandemic, was notably effective, resulting in lower human losses. Additionally, the study summarizes the overall distribution of resilience phases across all German communities.

The article also presents the methodology for quantifying the impact of indicator categories on overall resilience. The applicability is demonstrated for the community of Kusel, identifying the factors that most significantly impact resilience. The results indicate that regional indicators related to medical-social support, education, and the economy have the greatest impact on community resilience when acting independently. Factors within the categories of medical-social support and personal income exert the highest impact on resilience when considered collaboratively in the context of threats similar to a pandemic.

Looking ahead, this framework can be extended to evaluate temporal performance during pandemic scenarios and can also be applied to other cases, such as extreme weather events.

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