The Effect of Community Resilience and Disaster Risk Management Cycle Stages on Morbi-Mortality Following Floods: An Empirical Assessment

Raquel Guimaraes[1], Reinhard Mechler[1], Stefan Velev[1], Dipesh Chapagain[1,2]

[1]International Institute for Applied Systems Analysis, Laxenburg, 2361, Austria.
[2]United Nations University Institute for Environment and Human Security (UNU-EHS), Bonn, 53113, Germany.

Correspondence to: Raquel Guimaraes (guimaraes@iiasa.ac.at)

Abstract. Practice and policy have emphasised the need for building resilience to climate-related events in a further warming world. Scholarship has studied resilience largely in terms of process, latent capacity informing vulnerability, or outcome of risk management interventions, with little work integrating these perspectives. Implementation science work by the Climate Resilience Alliance has developed the Flood Resilience Measurement for Communities (FRMC) process and tool to measure resilience as outcome (post-flood mortality and morbidity reduction) and as capacity (pre- and post-intervention levels). This article builds on FRMC analytics to investigate the effect of resilience capacity, represented by five capitals (5Cs), and five stages of the Disaster Risk Management (DRM) Cycle, on injury and mortality outcomes across 66 flood-affected communities in seven Global South countries. Data was collected using household surveys, community focus groups, key informant interviews, and secondary sources. We applied a quasi-experimental regression design, controlling for demographic and flood hazard/exposure variables, to estimate the effect of 5Cs and DRM stages on health outcomes. Results show that social and human capital help reduce injuries after floods, and preparedness lowers both deaths and injuries. Some results were unexpected, such as the positive association between natural capital and delayed deaths, where limited gains in natural capital may not yield meaningful protection in communities with degraded ecosystems. This study finds that preparedness is the most consistent predictor of positive health outcomes, while forms of 5Cs may not translate into reduced mortality. By combining 5Cs, DRM stages and health indicators, this paper contributes to bridge a gap in the literature and offers policy-relevant insights for improving community-level disaster response.

1 Introduction

Floods are the most frequent disaster triggered by environmental extremes and account for the highest disaster-related death rate (Yari et al., 2020). Also, floods cause severe health impacts worldwide, particularly affecting lower-income, densely populated regions (Escobar Carías et al., 2022; Lynch et al., 2025). Research highlights that mortality and morbidity during and after floods are shaped by a variety of individual and community risk factors, including hazard event type, intensity and duration (Birkmann et al., 2022) and factors associated with exposure and vulnerability including age (Petrucci, 2022; Yang et al., 2023), gender (Jerin et al., 2024; Mucherera and Mavhura, 2020), urban-rural location (Petrucci, 2022), and various other drivers, all of which significantly determine risk and actual impacts of affected populations in disaster events as well as inform interventions to build resilience (Chapagain et al., 2025).

Although the impact of demographic factors – such as age, gender, and rural or urban residence – on flood-related mortality and morbidity is well-documented, the role of 5Cs and stages of DRM cycle, when accounting for demographic factors and flood exposure/hazard, is less clear. One study has explored the role of five capitals (social, human, financial, physical, natural) as drivers of vulnerability on total injuries and fatalities, controlling for flood exposure, but with no control for demographics (Chapagain et al., 2025). Another study examined the challenges faced at stages of the DRM cycle in the context of rural flooding in Pakistan. Employing a qualitative approach with focus groups and key informant interviews in the Khyber Pakhtunkhwa province, the study identified challenges in risk reduction, preparedness, rescue and relief, and rehabilitation and recovery phases (Shah et al., 2023).

Understanding resilience has proceeded. Drawing on Alexander (2013), resilience has evolved from an outcome-oriented concept – "bouncing back" after disturbance – to one that also includes latent features such as inherent capacity and adaptive potential. Initially defined by its etymology and early scientific use in mechanics (resisting and absorbing force), resilience concepts have been advanced to reflect deeper systemic traits in ecology (absorbing shocks while maintaining function), psychology (individual adaptation to adversity), and the social sciences (community robustness and flexibility for transformation). In disaster risk reduction (and climate adaptation) research and implementation, dimensions have seen attention and resilience has been analyzed as observable outcomes after events and latent qualities before events – like adaptability, resistance, and transformative capacity – that enable systems to withstand and evolve through disruption (Alexander, 2013). Yet, there has been limited work combining outcomes and capacity.

Furthermore, understanding resilience and DRM stages effects and their interactions with demographic profiles and exposure are essential for developing effective policy interventions. Available evidence suggests that investing in building community resilience to floods reduces the negative impacts of these events on human health and well-being along a DRM cycle aims to avoid, lessen, or transfer the adverse effects of floods, contributing to better flood outcomes by guiding integrated and proactive management strategies (Hochrainer-Stigler et al., 2020, 2021; Keating et al., 2017a; Laurien et al., 2020).

This article uses the FRMC tool to examine the role of capacities in reducing fatalities (immediate and delayed) and injury outcomes for 66 flood-affected communities across seven countries. Recent global analysis of the FRMC's large-scale application across nearly 400 communities further validates its use, highlighting consistent patterns in how different resilience dimensions relate to recovery outcomes (Keating et al., 2025).

The analysis controls for demographic factors and flood exposure/hazard. Communities are grouped into four resilience clusters and two DRM cycle groups to reflect the tendency of similar capital levels and DRM coping capacities (Hochrainer-Stigler et al., 2021; Keating et al., 2025). A quasi-experimental research design with regression adjustment is applied to evaluate the distinct influence of resilience and DRM cycle stages on morbidity and mortality outcomes after controlling for confounders.

Our findings emphasize the critical role of resilience and DRM cycle stages in shaping health and mortality outcomes after a flood event. Social and Natural capital were assessed to be effective in reducing injuries. DRM models demonstrated stronger predictive power, with Preparedness significantly decreasing both fatalities and injuries. Meanwhile, Corrective Risk Reduction lowered injury rates. Nevertheless, we found some unexpected results. For instance, the positive association between natural capital and delayed mortality may reflect the vulnerability of communities with degraded ecosystems, where limited improvements fail to yield meaningful health benefits. Similarly, unexpected patterns in the DRM stages, such as higher mortality associated with Corrective Risk Reduction, may be explained by lagged effects or measurement timing relative to implementation efforts.

2 Conceptual Foundations and Prior Research on the Independent Variables

This section presents the independent variables, emphasizing their theoretical components and relevant literature. The sections are organized around the key explanatory variables (five capitals – 5Cs – and the DRM cycle stages) and the control variables (demographics and hazard/exposure to floods). We hypothesize that these variables can play a crucial role in influencing mortality and morbidity outcomes after a flood event.

2.1 The FRMC capitals framework (5Cs)

A central component of the framework is the 5Cs which are broadly derived from the Sustainable Livelihoods Framework (Keating et al., 2014). They represent different types of assets and resources that contribute to a community's overall well-being and its capacity to cope with and recover from shocks, including floods. A summary of each capital is provided next (Campbell et al., 2019; Keating et al., 2017a):

- *Human Capital* refers to the education, skills, health, and well-being of household members in a community that enhance their ability to prepare for and recover from a flood. Examples include flood preparedness knowledge, personal safety skills, and education levels.
- *Social Capital* encompasses the social relationships, networks, and shared norms that enable communities to support each other, such as formal community emergency services and community-led flood management efforts.
- *Financial Capital* includes the financial resources available to households and communities, such as savings, income, access to credit, and government funding for infrastructure.
- *Physical Capital* consists of the built infrastructure essential for both daily life and disaster response, including roads, communication systems, and flood defences.
- Finally, *Natural Capital* embodies the natural resources and ecosystems that provide flood protection and sustain livelihoods, such as wetlands, forests, and managed biodiversity.

The 5Cs can play a crucial role in influencing mortality and morbidity outcomes after a flood event. For example, it is expected that communities with strong five capitals will tend to experience fewer injuries and fatalities. A previous study using FRMC data examined these effects; however, the analysis did not control for the demographic profile of the community (Chapagain et al., 2025). Physical capital was linked to fewer fatalities at the 5% confidence level, Social capital was associated with lower fatalities and injuries, with statistical significance at the 6% level, Natural capital showed a significant negative relationship with injuries. In contrast, financial and human capital did not demonstrate statistically significant associations with flood-related fatalities or injuries in the models.

2.2 The DRM cycle stages

FRMC analysis can zoom into key phases of the DRM cycle, which is broken down into five stages (Keating et al., 2017a, b):

- *Prospective Risk Reduction* involves taking proactive steps to prevent new risks from arising.
- *Corrective Risk Reduction* focuses on lowering risks for people and assets already at risk. Preparedness is about getting people and resources ready for possible events.
- *Response* encompasses the immediate measures implemented during and right after a disaster to reduce its effects.
- *Recovery,* on the other hand, includes both short- and long-term efforts aimed at supporting individuals and communities in managing the aftermath.

The DRM cycle has well-documented limitations. Scholars have criticized its continuous cyclic nature and broad phase definitions, which can hinder application across diverse urban settings and complicate its integration into climate change and resilience discourse (Rana et al., 2021). However, while acknowledging its imperfections, the DRM cycle continues to be used due to its convenience and robustness (Alexander, 2018). While debates continue on how to adapt it for more effective management – taking into account time, resources, preferences, capacities, needs, and institutional changes – its practical benefits continue to support its broad use. (Baas et al., 2008). We found no study linking DRM cycle stages with mortality/morbidity outcomes.2.2 Control variables

The following section examines the control variables used in the analysis. Prior literature identifies these factors as important in explaining variations in flood-related mortality and morbidity.

2.2.1 Gender and age composition

Research suggests that the relationship between flood-related morbidity and mortality and age and gender is relevant. For example, evidence on the gender-specific effects of floods on mortality is well-documented:

- Globally, men generally experience higher mortality rates during flood events (Jerin et al., 2024; Petrucci, 2022). An analysis of research conducted in Europe, the United States, and Australia found that 65% of the studies reported consistently higher fatality rates among men. The study highlights that in the United States (1996–2014), male flood fatalities consistently outnumbered female ones across all scenarios. A similar pattern was observed in parts of Europe (1980–2018), where male fatalities were generally higher, except among the elderly. The review attributes this increased male vulnerability to greater exposure to flood hazards and the higher proportion of men who operate vehicles during such events (Petrucci, 2022).
- Morbidity effects, on the other hand, tend to stress the vulnerability of women and of specific population age-groups. For instance, a study emphasizes the heightened health vulnerabilities of women during floods due to factors like polluted water and challenges in menstrual management (Jerin et al., 2024).

In contrast to gender influences, the effects of age on flood fatalities and injuries vary significantly across studies. Some research, for instance, emphasizes that older individuals are particularly prone to fatalities during and in the aftermath of floods (Ban et al., 2023; Yang et al., 2023), while there is evidence indicating that younger individuals can face a higher risk of mortality, specifically non-accidental deaths, during flood events compared to older adults (Ban et al., 2023).

In sum, the literature indicates that the relationship between flood impacts and risk, age, and gender is multifaceted and requires further attention as some studies have suggested that women's access to human, social, and financial resources can strengthen their ability to adapt to floods (Azad and Pritchard, 2023). This evidence is particularly relevant to our study, as we focus on the net effect of community 5Cs and DRM cycle stages on flood-related mortality and morbidity.

2.2.2 Urban-Rural residence

Urban-rural linkages play a critical role in shaping flood-related mortality.

- Research shows that rural areas face higher flood-related risks due to slower emergency response capabilities, lower population densities – which limit immediate assistance from bystanders – a lack of protective infrastructure such as elevated bridges, and their frequent location in headwater basins where floods develop rapidly, leaving little time for warning or evacuation. In contrast, urban areas tend to demonstrate greater resilience and a lower concentration of risk, largely due to the presence of more valuable assets, higher average incomes, and more robust housing structures. (Petrucci, 2022).
- The interdependencies between rural and urban areas are rarely considered in disaster risk frameworks. Rural areas, particularly in developing countries, depend heavily on cities for jobs, services, and information, while cities rely on rural areas for labor, food, and ecosystem services. Floods alter the flows of people, goods, finances, and information between rural and urban areas (Jamshed et al., 2019, 2020a, b, 2021).
- In some cases, floods increase rural dependence on cities – for example, through heightened migration, financial support from urban relatives, or greater reliance on urban markets and information. In other cases, dependence may shift toward nearby rural areas when access to cities is constrained due to damaged roads or inflated prices (Jamshed et al., 2019, 2020a, b, 2021).

In summary, research suggests that while both urban and rural areas face flood risks, specific setting factors may lead to significantly differential impacts on mortality and morbidity. Further research is needed to understand the complex interplay of factors shaping flood vulnerability across different geographical contexts and population groups.

2.2.3 Flood Hazard and Exposure

Research indicates a strong relationship between the severity of a flood event – often measured by a flood's return period – and its health and mortality impacts. The flood return period refers to the number of years between two flood events of the same or greater magnitude (Paul and Mahmood, 2016). Studies using FRMC data show that communities hit by rare, catastrophic floods affecting large areas tend to report higher rates of injuries. There is a connection between a flood's return period and a community's preparedness; communities frequently exposed to milder recurrent floods (e.g., 1–2-year return periods) may develop adaptive behaviours and a higher preparedness level, which can reduce injuries. In contrast, infrequent but severe floods (e.g., 50 and 100+ year return periods) often overwhelm even resilient communities, leading to more serious health and mortality consequences (Campbell et al., 2019; Chapagain et al., 2025).

Also, the exposure to the flood has found to have consequences on mortality/morbidity outcomes:

- In Bangladesh, studies of flood-related deaths from 1972 to 2013 found that both the extent of the flooded area and the number (or proportion) of people affected had a significant impact on the death toll. (Paul and Mahmood, 2016).

- Also, population density was found to be positively correlated with the number of flood-related victims (including deaths) per unit area. This implies that in more densely populated areas, when floods occur, a higher number of people are likely to be affected and consequently face increased mortality risk (Hu et al., 2018).

In addition to flood intensity and return period, climatic variables may also act as effect modifiers that shape health outcomes following flood events. Certain environmental factors can significantly influence the relationship between floods and diarrheal morbidity. In an empirical study conducted in Sichuan Province, China, three effect modifiers were identified that amplify the impact of flooding on diarrheal outcomes: elevated air pressure, reduced diurnal temperature range, and higher ambient temperatures (Lan et al., 2022). Unfortunately, those variables are not available in our dataset.

3 Data

The FRMC dataset offers a multifaceted view of community-level flood resilience, collected through a standardized, mixed-methods approach. Trained practitioners, often NGO staff, gather data using household surveys, community focus group discussions, key informant interviews, and secondary sources such as census data and government reports (Campbell et al., 2019; Hochrainer-Stigler et al., 2020, 2021; Keating et al., 2014, 2017a, 2025; Laurien et al., 2020).

The FRMC data captures two main phases: Baseline (BL) and Post-Event (PE). While the framework includes an Endline (EL) phase, it is not used in this study and is therefore excluded from the analysis.

- Baseline data (BL) provides a pre-flood snapshot of a community's resilience across 5Cs (human, social, physical, financial, and natural) and its capacity across Disaster Risk Management (DRM) cycle stages – corrective and prospective risk reduction, preparedness, response, and recovery. Variables are scored on a scale from A (best practice) to D (significantly below standard), with numerical equivalents (A=100, B=67, C=33, D=0) used for analysis.
- Post-Event data (PE) is collected after a flood and measures actual outcomes, including death counts, illness-related mortality within three months post-flood, and injuries. It also captures flood exposure (proportion of the community affected) and flood return period.

This study focuses on 66 riverine flood-prone communities across seven developing countries, each of which experienced a flood event following baseline data collection. Table 1 present these communities by country. Post-event data collection occurred between 2019 and 2023. While precise flood dates are unavailable, the PE data was gathered exclusively following confirmed flood events.

Table 1: Distribution of the communities affected by floods by country. FRMC data

Country	Frequency
Bangladesh	32
El Salvador	2
Malawi	8
Mexico	3
Nepal	5

Senegal	4
Vietnam	12
Total	66

Source: FRMC.

We now provide a detailed list of FRMC variables included in the analysis. Indicators for each of the 5Cs is presented in Table 2, while those related to the DRM stages are shown in Table 3. Table 4 provides the outcome variables (mortality and morbidity) and Table 5 provides the control variables (demographics and flood hazard/exposure). In this analysis, variables gathered from different respondents (key informants, focus groups, and secondary sources) were averaged to produce a single response for each community. Household-level variables were also aggregated to the community level by averaging. One limitation is that demographic variables (age, gender, and urban-rural composition) reflect only the respondent's information rather than all household members. Consequently, our approach provides an approximate demographic profile of each community.

Table 2: Variables according to FRMC five capitals

Financial	Human	Natural	Physical	Social capital
Household asset recovery	Evacuation and safety knowledge	Natural capital condition	Flood healthcare access	Community participation in flood-related activities
Community disaster fund	First aid knowledge	Priority natural units	Early Warning Systems (EWS)	External flood response and recovery services
Business continuity	Education commitment during floods	Priority managed units	Flood emergency infrastructure	Community safety
Household income continuity strategy	Flood exposure awareness	Natural resource conservation	Provision of education	Community disaster risk management planning
Risk reduction investments	Asset protection knowledge	Natural habitat restoration	Household flood protection	Community structures for mutual assistance
Disaster response budget	Future flood risk awareness		Large scale flood protection	Community representative bodies
Conservation budget	Water and sanitation awareness		Transportation interruption	Social inclusiveness
	Environmental management awareness		Communication interruption	Local leadership
	Governance awareness		Flood emergency food supply	Inter-community flood coordination
			Flood safe water	Integrated flood management planning
			Flood waste contamination	National forecasting policy & plan
			Flood energy supply	

Source: FRMC.

Table 3: Variables according to DRM Cycle stages

Corrective Risk Reduction	Preparedness	Prospective Risk Reduction	Recovery	Response
Risk reduction	Business continuity	Conservation budget	Household	Disaster response

investments			asset recovery	budget
Asset protection knowledge	Evacuation and safety knowledge	Future flood risk awareness	Community disaster fund	Water and sanitation awareness
Governance awareness	First aid knowledge	Environmental management awareness	Provision of education	Flood healthcare access
Natural habitat restoration	Early Warning Systems (EWS)	Natural capital condition	Flood energy supply	Transportation interruption
Household flood protection	Flood emergency infrastructure	Priority natural units	Community safety	Communication interruption
Large scale flood protection	Community participation in flood-related activities	Natural resource conservation		Flood emergency food supply
Community representative bodies	External flood response and recovery services	Community disaster risk management planning		Flood safe water
Social inclusiveness	Inter-community flood coordination	Local leadership		Flood waste contamination
Integrated flood management planning	National forecasting policy & plan			Community structures for mutual assistance

Source: FRMC.

Table 4: Outcome variables

Outcome variable	Description	Dataset	Respondents
Injuries	How many men in the community suffered serious injuries in the flood? How many women in the community suffered serious injuries in the flood? How many children in the community suffered serious injuries in the flood? How many men in the community suffered serious injuries in the flood?	PE	Key informant, focus group, secondary source
Deaths	How many men in the community lost their lives in the flood? How many women in the community lost their lives in the flood? How many children in the community lost their lives in the flood?	PE	Key informant, focus group, secondary source
Deaths after 3 months	Compared to the number of people who lose their lives from these illnesses in non-flood times, how many additional people lost their lives due to these illnesses in the 3 months following the flood?	PE	Key informant, focus group, secondary source

Source: FRMC. Note: PE: Post-event survey

Table 5: Control variables

Control variable	Description	Dataset	Respondents
Average Percentage of Population Affected by Flood	What percentage of the community was directly impacted by the flood?	PE	Key informant, focus group, secondary source
Average Flood Return Period	What is the return period or re-occurrence interval of this flood, in number of years? In other words, how often is a flood of this size or bigger expected/experienced in the community?	PE	Key informant, focus group, secondary source
Age Group Distribution	Which of the following age groups do you fall into:	BL	Household

(%)	15-25, 26-50, or over 50?		
Gender Distribution (%)	What is your gender: Male, Female, Other?	BL	Household
Average Rural Composition (%)	Is this a rural, urban, or peri-urban community?	BL	Household

Source: FRMC. Note: PE: Post-event survey; BL: Baseline survey

4 Methods

This section outlines the methods used in this study. First, we describe how the indicators for the 5Cs and the DRM cycle stages were constructed. Next, we outline the procedures used to cluster communities into distinct profiles, following approaches adopted in previous FRMC studies. Finally, we present the steps taken for the regression adjustment. A flowchart of the methodology is provided in Figure 1.

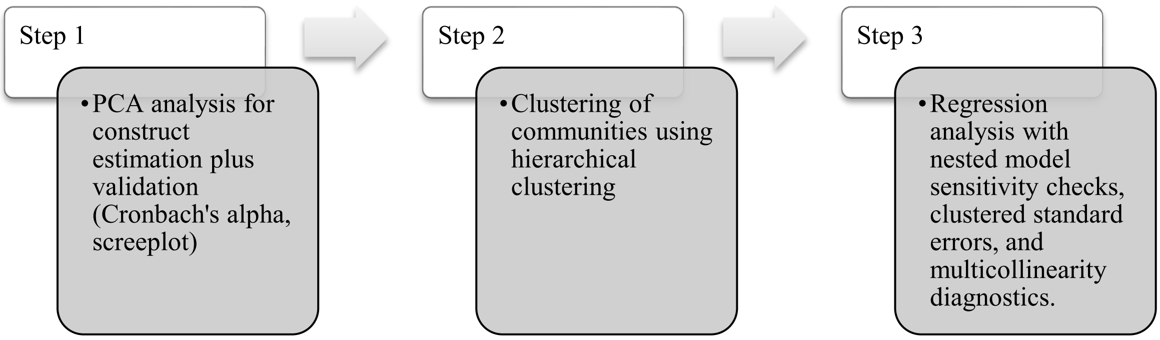


Figure 1: Flowchart of the method

4.1 Principal Component Analysis (PCA) of the 5Cs and DRM cycle stages

To estimate the 5Cs and the DRM cycle stages, we use a latent construct approach. PCA is conducted to derive a single construct for each of the 5Cs: social, physical, natural, human, and financial, as well as along each of the phases of the DRM cycle: Prospective Risk Reduction, Corrective Risk Reduction, Crisis Preparedness, Response, Recovery. Components are weighted by estimated population (households multiplied by average household size) to account for varying community scales. Validation of these constructs starts with decomposing the correlation matrix into eigenvalues and eigenvectors, and a screeplot helped determine the number of factors to retain. We then calculate the Cronbach's alpha coefficients (Table A1 and A2, appendices) to ensure it meets the acceptable threshold of 0.7. All DRM stages except Prospective Risk Reduction and Recovery met this criterion, which were close to 0.6. Histograms of the constructs (5Cs and DRM cycles) are included in the appendices (Figures A1 and A2), as well as their corresponding screeplots (Figures A3 and A4). Most indicators display strong model fit, a key requirement for the validity of the analysis.

4.2 Community clusters

A study using the FRMC framework has emphasized the importance of clustering communities to better understand how resilience changes over time (Chapagain et al., 2024). Using hierarchical clustering methods, the study identifies five distinct community clusters based on the five capitals scores. We now present the characteristics of the clusters calculated according to the key independent variables: 5Cs and DRM cycle stages

4.2.1 5Cs

A summary of the characteristics of the clusters is as follows. Table 6 presents the distribution of the communities across the clusters. We group the 66 communities which experienced a flood event into the five resilience clusters. No community affected by flood was found in Cluster 5. Figure A5 in the appendices present the average score of the 5Cs by cluster in the baseline survey.

Table 6: Distribution of the 66 communities that have experienced flood according to 5Cs

Cluster	Freq.	Perc.	Cum.
1 – low resilience	43	65.1	65.1
2	5	7.6	72.7
3	4	6.0	78.8
4 – high resilience	14	21.2	100.00
Total	66	100	

Source: FRMC

A description of the clusters is as follows:

- Cluster 1: Features the lowest resilience across all 5Cs.
- Cluster 2: Exhibits marginally stronger performance in financial, human, and physical capital compared to natural and social capital.
- Cluster 3: Presents relatively high human, natural, and social capital scores, but lower financial and physical capitals.
- Cluster 4: Demonstrates generally higher average capital scores compared to Clusters 1-3, particularly in human, natural, and social capital.

4.2.2 DRM cycle stages

We applied the same clustering methodology approach to classify the communities based on their DRM cycle performance, maintaining consistency with our earlier analysis approach. The dendogram revealed two distinct clusters according to DRM cycle stages. Figure A6 in the appendices present the average score of the five stages by cluster in the baseline survey. As made for the resilience clusters, we grouped the 66 communities which experienced a flood event into the two DRM cycle clusters. Table 7 presents the distribution of the communities across the clusters.

Table 7: Distribution of the 66 communities that have experienced flood according to DRM cycle clusters

Cluster	Freq.	Perc.	Cum.
1 – high DRM cycle performance	27	40.9	40.9
2 – low DRM cycle performance	39	59.1	100.00
Total	66	100	

Source: FRMC

A description of the clusters is provided:

- Cluster 1: demonstrates strong capabilities across most dimensions of the DRM cycle. These communities exhibit above-average Preparedness. Their Protective Risk Reduction and their Recovery capabilities are notably strong.
- Cluster 2: represent significant weaknesses across all measured DRM stages. These communities show poor Response and Recovery capabilities. Their Preparedness scores are substantially below average.

4.3 Regression adjustment

To estimate the effect of the 5Cs and DRM cycle stages on morbidity and mortality outcomes, we use a quasi-experimental research design based on regression adjustment. This method is a robust approach for identifying causal effects in observational data by addressing the challenge of confounding. While the FRMC dataset includes a longitudinal component, for the post-event (PE) data, we only have one time point available. This necessitates controlling for baseline levels of 5Cs, DRM cycle stages, demographics, and flood exposure/hazard. Regression adjustment allows us to isolate the relationship of interest by accounting for observable characteristics that could otherwise bias the estimated treatment effects. Properly specified regression models reduce systematic differences between units, thereby approximating *ceteris paribus* conditions and enhancing the validity of the causal inference.

To ensure robustness, post-estimation diagnostics were conducted, including tests for overall model significance (R-squared) and comparison of AIC and BIC values to evaluate model fit. Ordinary least squares (OLS) regression was used as the primary method, incorporating nested models to assess how additional predictors contributed to the model's explanatory power. Finally, given the differing scales of predictors – such as the average return period (1 to 35) and the percentage of female household respondents (0 to 1) – all predictors were standardized to enable meaningful comparison and interpretation of their relative importance.

We use clustered standard errors to address the fact that observations within the same cluster might be like each other in terms of both resilience and DRM cycle levels. As we have a small number of clusters – 5 for resilience and 2 for the DRM cycle – we employ the wild bootstrap approach. The wild bootstrap is primarily used to obtain more reliable inference – such as p-values and confidence intervals – by addressing issues like heteroskedasticity or a small number of clusters.

Due to the small sample size, a significance level of 10% was considered relevant. We tested different specifications to analyse the sensitivity of the parameters to the inclusion of control variables, but the preferred model for the analysis is the full model (with all controls). There is a vivid discussion among statisticians and econometricians on the role of control variables and whether they should be excluded if there is not statistical significance. This paper takes the stand that considering the control variables is relevant because they have theoretical meaning and, hence, even a non-significant result is a relevant result. Besides, as they help reduce omitted variable bias and improve causal inference. Another important issue for modelling is that, if the 5Cs or if the five DRM cycle stages are highly correlated, it can cause multicollinearity, making it difficult to determine their individual effects. High variance inflation factors (VIFs) would indicate if this is an issue.

5 Results

Our analysis revealed distinct patterns in the relationships between the 5Cs, DRM cycle stages, and the morbidity and mortality outcomes, controlling for demographic characteristics and flood exposure/hazard. But let's first begin with a description of the data.

The distribution of the dependent variables – average injuries due to floods, average deaths, and average lives lost to illnesses within three months – is shown in histograms in Figures 2 and 3. Notably, all three variables exhibit a high number of zeros, and the death counts are characterized by a low number of cases (maximum of 11 for immediate mortality and 23 for delayed mortality).

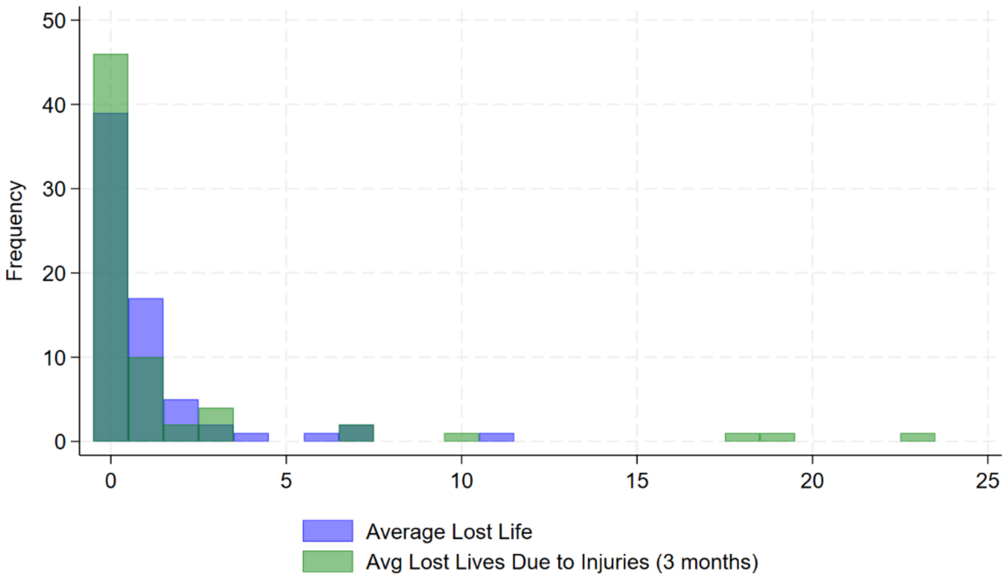


Figure 2: Average Number of Deaths (Immediate and Delayed) Reported in Flood-Affected Communities.

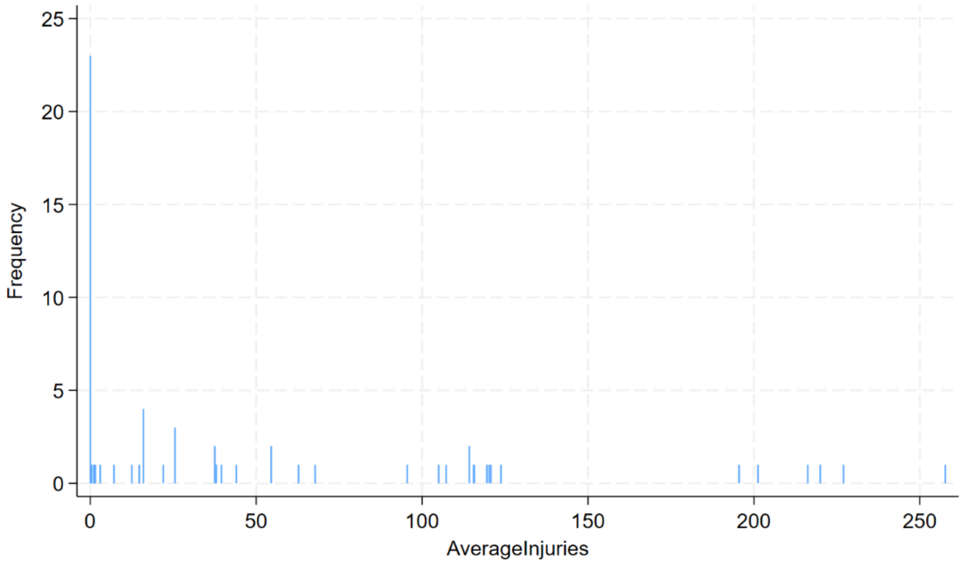


Figure 3: Average Injuries Reported in Flood-Affected Communities.

To facilitate interpretation, we use variable labels for statistics and regression results. We provide in Table 8 a description of the variables and in Table 9 the descriptive statistics.

Table 8: Description of Variable Labels

Variable	Description
AverageAge15to25	The average proportion of the population aged 15 to 25 years in the community.
AverageAge26to50	The average proportion of the population aged 26 to 50 years in the community.
AverageAge50plus	The average proportion of the population aged 50 years and above in the community.
AveragePercFemaleResp	The average percentage of female respondents in the community.
AverageRural	The average proportion of the community classified as rural.
AverageReturnPeriod	The average return period of significant flooding events in years for the community.
AveragePercComAffect	The average percentage of the community affected by the flood.
AvLostLivesDueInjuries3months	The average number of lives lost due to injuries in the three months following the flood.
AverageLostLife	The average number of lives lost directly due to the flood.
AverageInjuries	The average number of injuries reported due to the flood.

Source: FRMC.

Table 9: Descriptive statistics for the control and dependent variables

Variable	Observations	Mean	Std. Dev.	Min	Max
AverageAge15to25	66	0.100	0.079	0.000	0.324
AverageAge26to50	66	0.586	0.185	0.184	0.928
AverageAge50plus	66	0.315	0.203	0.036	0.816
AveragePercFemaleResp	66	0.577	0.143	0.198	0.836
AverageRural	66	0.803	0.401	0.000	1.000
AverageReturnPeriod	66	8.111	8.793	1.000	35.000
AveragePercComAffect	66	0.710	0.225	0.183	1.000
AvLostLivesDueInjuries3months	66	1.695	4.458	0.000	23.000
AverageLostLife	66	1.045	1.978	0.000	11.000
AverageInjuries	66	48.668	68.475	0.000	257.750

Source: FRMC.

The regression results for the 66 communities that experienced a flood while controlling for demographics and flood exposure and hazard, are presented next. The nested models (testing for the inclusion of each control variable) are presented in the appendices (Tables A3-A8) Overall, the full model displayed also better fit in all specifications (R-squared and AIC/BIC). The results for the full model of the VIFs for the independent variables specified in the linear regression model shows that multicollinearity is present but not extreme, with mean VIF of 2.41. A mean VIF below 5 suggests that overall, a model is not suffering from severe multicollinearity.

6.1 The Effect of Community Resilience on Health Outcomes

Table 10 displays the results of the effect of the 5Cs on health outcomes (average deaths, average number of injuries, average number of deaths after three months). For first regression model (column 2), which analysed the effect of the 5Cs on average deaths due to floods, no capital was found to be statistically significant. This lack of significant association is a critical finding. It suggests that certain forms of resilience, as currently measured, may not translate directly into reductions in flood-related mortality – or may only do so above a particular threshold of capital accumulation. Reporting such null results is essential to avoid publication bias and contributes to a more realistic understanding of the limits of resilience-building initiatives in extreme events. Contrary to our study, Chapagain et al. (2025) found that Physical Capital and Social Capital did have a statistically significant negative association with total flood-related fatalities. This difference might be due to how the models are specified: our estimation includes all control variables and accounts for clustered standard errors. The only statistically significant variable in our analysis at the 1% level was the control for the percentage of the community affected by the flood, in which a one-standard deviation increase in this variable was associated with an increase of 0.27 deaths, everything else held constant.

Next, Table 10 (third column) displays the results of the second regression model, which analysed the effect of the 5Cs on average injuries to floods. Social capital was found to be strongly associated with a decline of injuries, with a one-standard deviation increase in this indicator reducing the average number of injuries in 39 units (statistically significant at 1% level). Also, Human capital was found to reduce injuries, with a one standard-deviation increase in this indicator leading to a drop of 5.97 injuries (statistically significant at 1% level). Regarding the controls, the average number of population aged 50 plus was found to be negatively associated with injuries, with a one-standard deviation increase in this variable associated with a decrease in 9.7 injuries, *ceteris paribus* (statistically significant at 1% level). This might indicate that older individuals are more likely to evacuate early or take preventive measures before disasters, reducing their likelihood of flood-related injuries. Finally, the percentage of the community affected by the flood was found to increase the number of injuries, in which a one-standard deviation increase in this variable was associated with an increase of 18 injuries, everything else held constant.

Finally, Table 10 (fourth column) shows the results of the third regression model, which analysed the effect of the 5Cs on average fatalities after three months of the flood event. This model revealed an unexpected result: natural capital scores were positively associated with delayed mortality, everything held constant, with a one standard-deviation increase in this variable associated with an increase in 1.59 delayed deaths (significant at 1% level). To further investigate this unexpected result, we ran a regression model with the same specification by cluster. The large coefficient for std_natural in Cluster 2 (9.387) could be driving the overall significant and positive effect. This makes theoretical sense, as natural capital in this cluster is low due to degraded natural environments and weak ecosystem services, even if some management efforts exist (Chapagain et al., 2024). Because of this, small improvements may not help much, and the positive association with delayed mortality might reflect the overall vulnerability of these communities rather than a real benefit from natural capital. Contrary to the model for injuries, the average number of population aged 50 plus was found to be positively associated with delayed mortality, with a one-standard deviation increase in this variable associated with an increase in 1.07 deaths after three months of a flood, *ceteris paribus* (statistically significant at 1% level). Older individuals may have a higher likelihood of developing complications from flood-related injuries, infections, or chronic disease exacerbation. Conditions such as cardiovascular disease, respiratory illnesses, and weakened immune function could make them more vulnerable to delayed mortality rather than immediate death.

Table 10: Wild Bootstrap Clustered Regression Models with the impact of 5Cs on health and mortality outcomes

Independent variables	Dependent variables		
	Average Fatalities	Average Injuries	Average Fatalities After Three Months
std_social	0.054	-39.976***	-0.179
std_financial	0.203	15.602	-3.341
std_physical	-0.630	8.109	0.047
std_human	-0.256	-5.970***	-0.500
std_natural	0.582	-11.277	1.591***
std_AverageAge15to25	-0.721	1.510	0.285
std_AverageAge50plus	-1.137	-9.735***	1.079***
std_AveragePercFemaleResp	0.459	-1.707	-0.088
std_AverageRural	0.075	0.052	0.124
std_AverageReturnPeriod	0.685	27.150	-0.645
std_AveragePercComAffect	0.271***	18.123***	1.797
Observations	66	66	66
R-squared	0.49	0.61	0.35
AIC	228.12	683.02	381.65
BIC	234.69	689.58	388.22

Observation: *** Significant at 1%; ** Significant at 5%; * Significant at 10%

Source: FRMC.

6.2 The Effect of DRM cycle stages on Health Outcomes

The results for the regressions on the effects of the DRM cycle stages on health/mortality outcomes after a flood event portray a different scenario from the 5Cs estimates presented before. Table 11 summarizes the results. First, both Corrective Risk Reduction and Preparation scores were statistically associated with average number of deaths (second column). Surprisingly, Corrective Risk Reduction was positively associated with average immediate mortality, with a one-standard deviation increase in this score was associated with an increase in 0.65 deaths, everything held constant. To further investigate this counterintuitive finding, we conducted a cluster-specific regression analysis, which revealed substantial heterogeneity across community contexts. In Cluster 1, CRR showed a small negative association (coefficient = -0.03, p = 0.925), while Cluster 2 exhibited a stronger positive relationship (coefficient = 0.84, p = 0.396), suggesting this larger cluster may be driving the overall significant effect. Cluster 2 has significant weaknesses across all measured DRM cycle dimensions. These communities with low CRR scores might have implemented recent improvements that had not yet translated into reduced mortality outcomes during our study period, potentially creating a lagged effect where reported improvements coexist with historically high mortality rates.

Preparation scores were negatively associated with average mortality, with a one standard-deviation increase in this indicator leading to a decrease in 0.53 deaths. Preparedness significantly reduces immediate flood mortality by enhancing early response. Effective warning systems and safety knowledge help individuals take timely protective actions, minimizing exposure to life-threatening conditions. Well-developed emergency infrastructure and coordinated response efforts ensure that communities can react efficiently, preventing avoidable deaths. Additionally, strong community participation and external support improve rescue operations and medical aid delivery, further reducing fatalities.

Finally, more control variables now display a significant relationship with the average number of deaths, being the average percentage of young population (15 to 25 years) and the average percentage of elderly (50 or more) negatively associated with the number of deaths (significant at 1% level). The explanations are quite straightforward: older individuals tend to take disasters more seriously, acting cautiously in response to early warnings and evacuation orders. Life experience and risk awareness help them recognize the severity of floods and take protective measures earlier, reducing their chances of fatal exposure. Younger individuals, in turn, tend to have better physical strength, endurance, and mobility, which increases their chances of escaping hazardous flood conditions. They typically face fewer mobility challenges or health problems that could complicate evacuation or reduce their chances of survival. Next, the average percentage of rural population was positively associated with the number of deaths, with a one standard-deviation increase in this percentage related to 0.09 deaths. Health complications and mortality can be influenced by factors like socio-economic conditions, access to water and sanitation, and the state of public health infrastructure in rural areas (Jerin et al., 2024). Finally, flood hazard (return period) and exposure (percentage of community affected) are positively associated with mortality at the 1% of confidence level.

The model results for average injuries and its relationship with DRM cycle stages are also presented in Table 11 (third column). For this outcome variable, the results for Corrective Risk Reduction (CRR) and Preparedness are in line with the expectations: a one standard-deviation increase in CRR reduces the average number of injuries in 31 units; also, a one standard-deviation increase in Preparedness reduces the indicator in 23 units. Surprisingly, a one standard-deviation increase in the Prospective Risk Reduction (PRR) increases the number of injuries in 6 units. To further investigate our counterintuitive finding regarding PRR, we again conducted a cluster-specific regression analysis, which revealed that in Cluster 1, which is characterized by high levels of overall preparedness, PRR maintained a significant positive relationship with injuries (coefficient = 4.88, p = 0.021), while in Cluster 2, the relationship was weaker and non-significant (coefficient = 2.93, p = 0.781). This pattern suggests that in communities with stronger overall disaster management systems (Cluster 1), there may be more effective injury reporting and documentation mechanisms in place, leading to higher recorded injury rates despite better prevention measures. The results for control variables show that the average number of elderly is negatively associated with the number of injuries (significant at 1%), whereas flood hazard and exposure are positively associated with the number of injuries.

Finally, Table 11 (forth column) presents the results for the impact along DRM cycle stages on delayed mortality from floods (after 3 months). Results are in line and expected as per the literature regarding two DRM cycle stages: Prospective Risk Reduction (PRR) and Recovery. A one standard-deviation increase in the PRR score is associated with a decrease in 1.75 delayed deaths, everything held constant. Also, a one standard-deviation increase in the Recovery indicator is associated with a decline in 3.57 deaths, *ceteris paribus*. Surprisingly, the only significant control variables for delayed mortality are flood exposure (percentage of the community affected) and hazard (return period), with a one-standard deviation increase in these indicators associated with a decrease in delayed deaths. These results appear counterintuitive, as one would expect communities with more frequent disasters (shorter return periods) and greater affected populations to experience higher delayed mortality. Cluster-specific analysis revealed distinct patterns: in Cluster 1, neither variable showed significant relationships with delayed mortality (return period: coefficient = 1.98, p = 0.523; community affected: coefficient = 0.27, p = 0.877). However, in Cluster 2, both variables showed negative associations, with the community affected percentage approaching significance (coefficient = -1.98, p = 0.089) and return period showing a similar trend (coefficient = -1.42, p = 0.100). This may be associated with a survivorship bias or a "harvesting" effect: the most vulnerable individuals (e.g., the elderly, those with pre-existing health conditions) may succumb quickly after the flood, reducing the number of people who would die in the delayed mortality window. Alternatively, this finding may reflect a reporting phenomenon where communities with more frequent disasters have better systems for attributing later deaths to the original disaster event.

Table 11: Wild Bootstrap Clustered Regression Models with the impact of DRM cycle stages on health and mortality outcomes

Independent variables	Dependent variables		
	Average Fatalities	Average Injuries	Average Fatalities After Three Months
std_CRR	0.656***	-30.906***	1.285
std_PREP	-0.532***	-23.375***	0.637
std_PRR	0.022	5.921***	-1.758***
std_RECOV	-0.019	27.943	-3.577***
std_RESP	-0.419	-3.674	-0.031
std_AverageAge15to25	-0.744***	3.069	-0.045
std_AverageAge50plus	-0.925***	-14.998***	-0.030
std_AveragePercFemaleResp	0.490	-3.284	0.137
std_AverageRural	0.094***	-3.781	0.136
std_AverageReturnPeriod	0.845***	25.841***	-0.458***
std_AveragePercComAffect	0.243***	13.702***	-1.503***
Observations	66	66	66
R-squared	0.45	0.59	0.38
AIC	228.86	681.17	374.33
BIC	231.04	683.36	376.52

Observation: *** Significant at 1%; ** Significant at 5%; * Significant at 10%

Source: FRMC.

Interestingly, several DRM stages – including Corrective Risk Reduction and Preparedness – did not show statistically significant associations with delayed mortality. While these might initially appear as disappointing results, they offer crucial insights: either the health effects of floods evolve differently over time, or current DRM metrics may not fully capture interventions that affect medium-term health outcomes.

7 Discussion

The goal of this paper was to explore the role of 5Cs and DRM cycle stages on health and mortality outcomes after flood events for 66 countries across seven countries participating in the FRMC. Namely, how latent capacities determine outcomes, in terms of reduced mortality and morbidity. We advance current literature not only by incorporating a novel and rich dataset, but also by controlling in our impact analysis by relevant variables such as the demographic profile of the community and flood hazard and exposure. The literature stresses the role of these variables, and they are necessary to avoid confounding in the econometric analysis. Their significance in some models do endorse their relevance for the analysis, and the quality of the adjustment in the full models (with all controls) justify their inclusion.

Our results demonstrate the relevance of selected 5Cs and DRM cycle stages for health and mortality outcomes, with some unexpected results as well.

- The 5Cs models indicate that social and human capital are statistically, strongly, and negatively associated with the average number of injuries. However, none of the 5Cs indicators, except natural capital, showed a statistically significant association with either immediate fatalities or fatalities occurring within three months, when controlling for all other factors. This absence of consistent effects underscores the complexity of translating community capitals into lifesaving outcomes. Surprisingly, natural capital scores were strongly and positively associated with delayed mortality, an unexpected result that warrants further investigation.
- In contrast, the DRM Cycle models demonstrate greater predictive power in terms of significant variables for health and mortality outcomes compared to 5Cs models, although some variables show unexpected effects. Preparedness emerged as the most relevant DRM stage, significantly leading to reductions in both immediate fatalities and injuries. The Corrective Risk Reduction stage was found to decrease injuries but unexpectedly increased fatalities. Recovery and Response were negatively associated with delayed mortality.

Regarding control variables:

- Both elderly and young populations were associated with a reduction in immediate fatalities, while the percentage of elderly individuals specifically contributed to a decrease in injuries. Literature contradicts this claim. Instead, they consistently indicate that both older and younger populations are generally more vulnerable to flood-related mortality and various health impacts (Ban et al., 2023; Bukvic et al., 2018; Doocy et al., 2013; Lowe et al., 2013; Petrucci, 2022; Zagheni et al., 2015). However, older individuals often respond more cautiously to disasters, taking early warnings and evacuation orders seriously. Their life experience and greater risk awareness help them recognize the severity of floods and take protective action sooner, which can lower their risk of fatal exposure. In contrast, younger individuals typically have greater physical strength, stamina, and mobility, which improves their ability to escape hazardous flood conditions. They also tend to face fewer health or mobility issues that might hinder evacuation or reduce their chances of survival. Therefore, we argue that, despite contrasting findings in the literature, this evidence may be theoretically justifiable.
- A higher percentage of the rural population was positively correlated with the number of immediate deaths. Studies generally align with this correlation (Bukvic et al., 2018; Petrucci, 2022).
- For flood exposure and hazard indicators, these variables were strongly and positively associated with average fatalities and injuries, as confirmed by several studies (Ban et al., 2023; Paul and Mahmood, 2016; Penning-Rowsell et al., 2005) but negatively associated with delayed mortality. This last finding contradicts the claim, as multiple studies show that mortality risks can increase and persist for extended periods following a flood event (Yang et al., 2023). This is an unexpected result that warrants further investigation.

The study has limitations that should be considered when interpreting the results. One key limitation is the small sample size, which may pose statistical challenges in estimating more complex models, such as zero-inflated specifications. Additionally, the study includes a small number of clusters, which can impact the reliability of statistical inferences. To mitigate this issue, the analysis incorporates the use of wild bootstrap methods, providing a more robust approach to addressing the potential shortcomings in cluster representation. Another limitation arises from the measurement of certain constructs, as they are not always well defined by a single indicator. This could introduce measurement errors, potentially affecting the accuracy and consistency of the results. Finally, the demographic profile used in the study serves as a proxy variable for population characteristics, but it is representative only of household heads. This limitation may reduce the accuracy of the demographic analysis, as it does not fully capture the diversity and distribution of characteristics across the broader population.

Table 12 provides a summary of the statistically significant findings.

Table 12: Summary of significant findings

Variables	Results

5Cs	• Fatalities:
	    o None of the 5Cs showed a statistically significant association.
	• Injuries:
	    o Social and Human Capital: Negatively associated with injuries
	• Delayed Mortality:
	    o Natural Capital: Positively associated with delayed mortality

DRM cycle stages	• Fatalities:
	    o Preparedness: Negatively associated with injuries and immediate fatalities, consistent with the hypothesis.
	    o Corrective Risk Reduction: Positively associated with fatalities
	• Injuries:
	    o Preparedness and Corrective Risk Reduction are negatively associated, consistent with the hypothesis.
	• Delayed Mortality:
	    o Natural Capital: Positively associated with delayed mortality

Controls	• Elderly population: Negatively associated with injuries, but positively associated with delayed mortality.
	• Younger and elderly populations: Negatively associated with immediate fatalities.
	• Rural population: Positively associated with immediate fatalities.
	• Flood exposure:
	    o Positively associated with immediate fatalities and injuries.
	    o Negatively associated with delayed mortality

Source: Authors

Future research should expand the sample size to improve statistical power and allow for more complex modeling approaches. It should also explore the temporal dynamics of 5Cs and DRM interventions, particularly the lag between implementation and their impact on health outcomes. Additionally, improving demographic data availability would strengthen causal inference and help explain counterintuitive results.

Appendices

Table A1: Cronbach's alpha for the 5Cs

Capital	Number of items on the scale	Cronbach's alpha
Financial	7	0.7710
Social	11	0.8453
Physical	12	0.8275
Human	9	0.7053
Natural	5	0.7022

Source: FRMC.

Table A2: Cronbach's alpha for the DRM cycle stages

DRM Indicator	Number of items on the scale	Cronbach's alpha
Corrective Risk Reduction	9	0.7365
Preparedness	9	0.7404
Prospective Risk Reduction	8	0.5646
Recovery	5	0.5830
Response	9	0.7727

Source: FRMC.

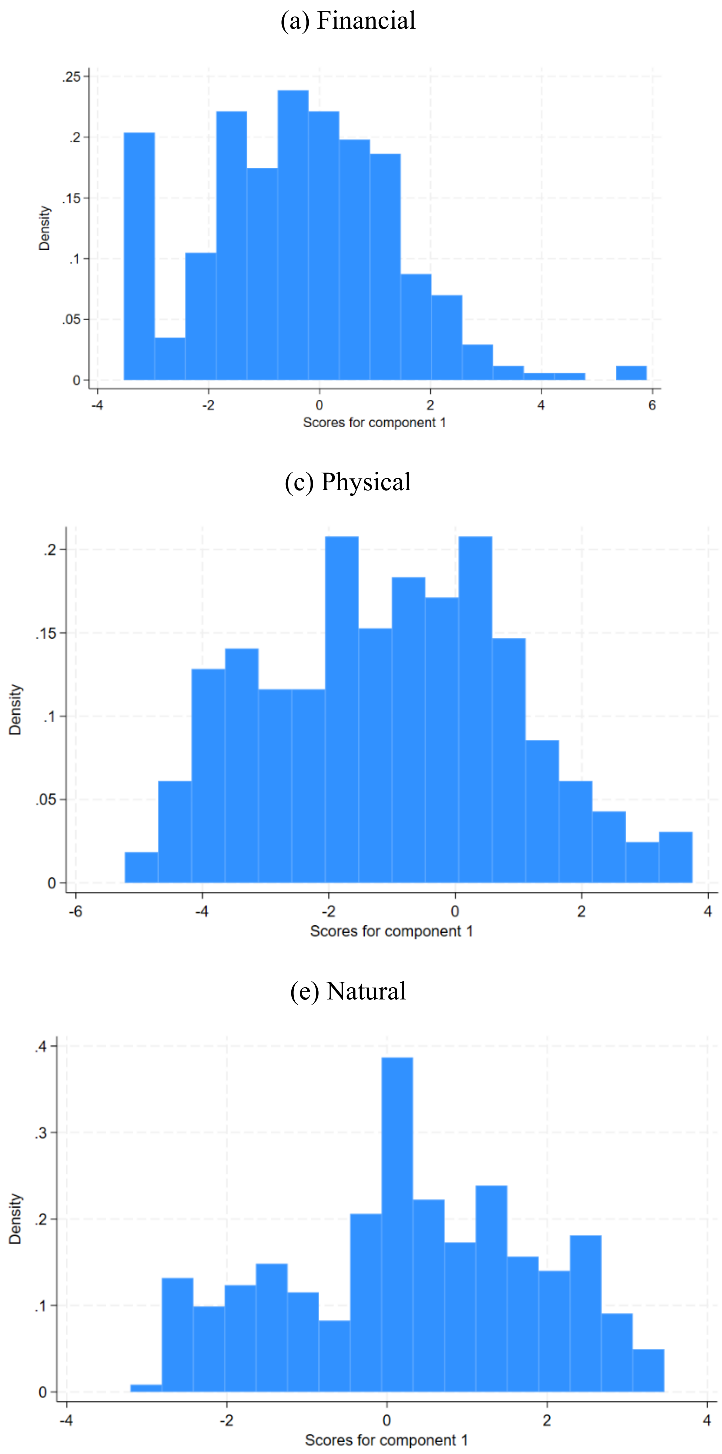


Figure A1: Histograms for the 5Cs

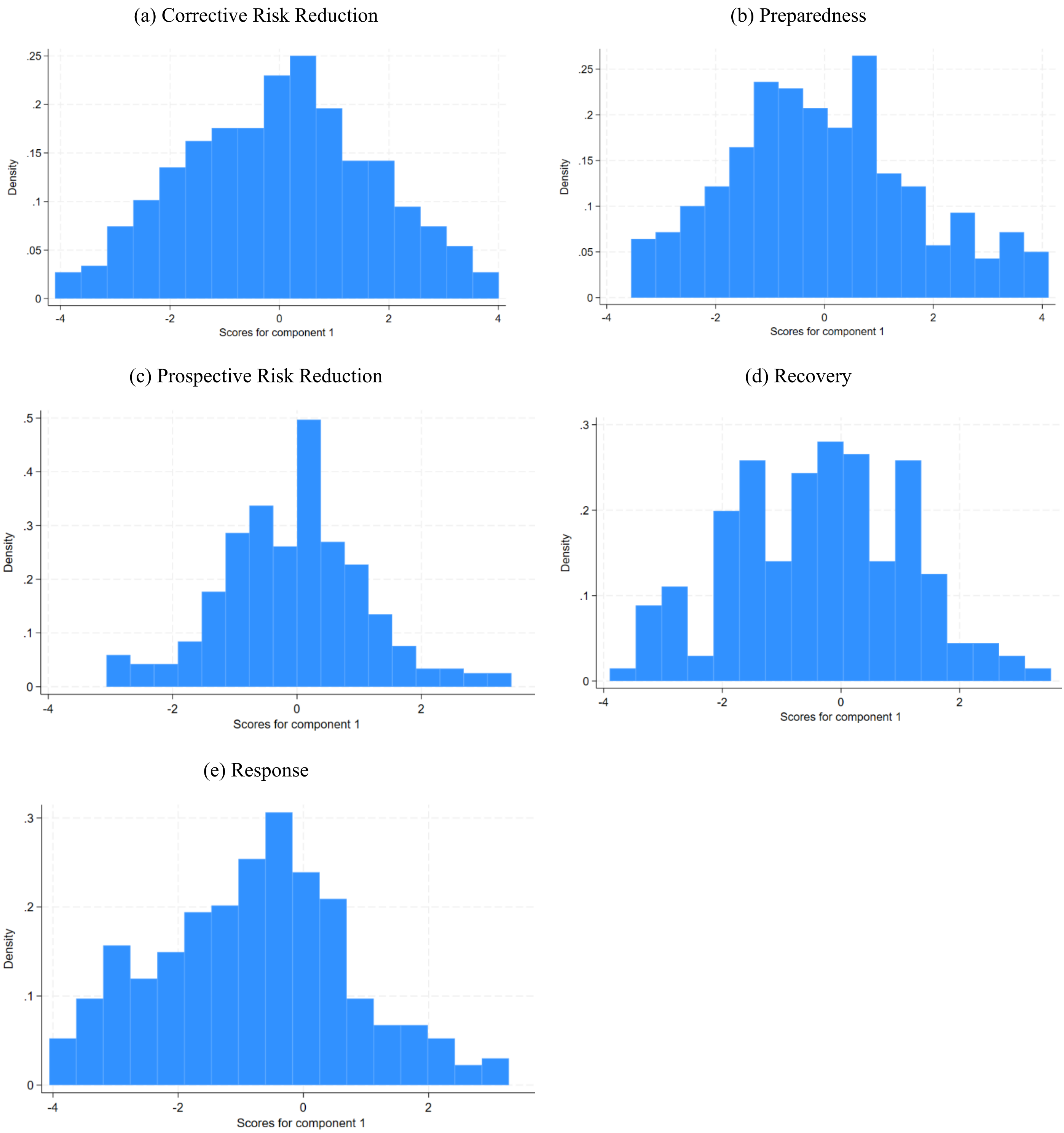
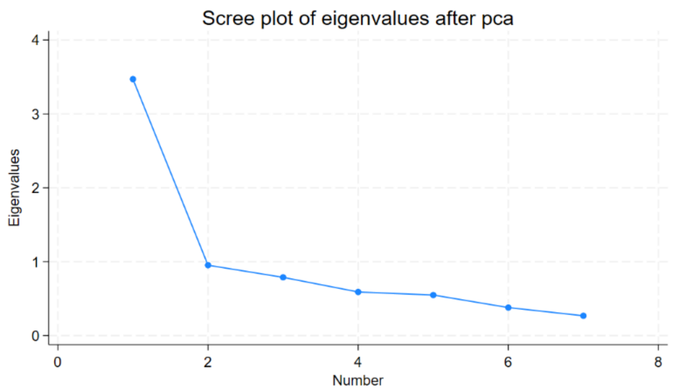
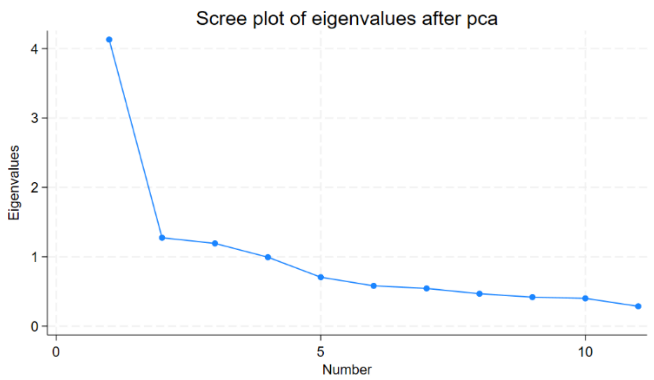


Figure A2: Histograms for the DRM cycle stages

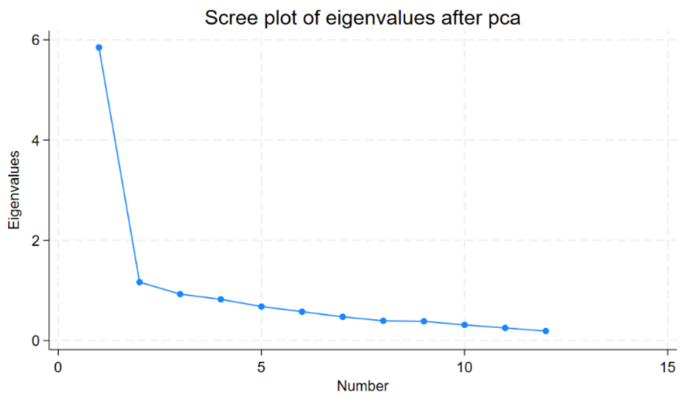
(a) Financial



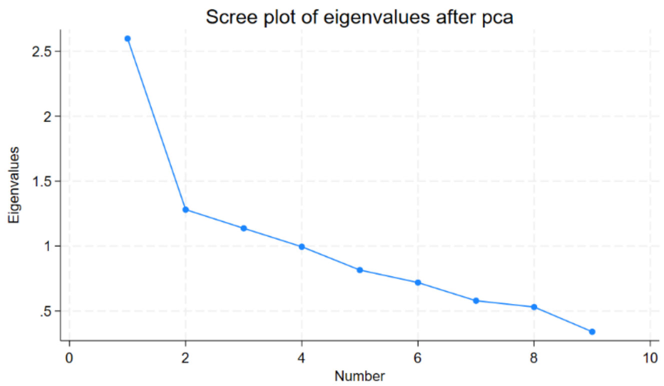
(b) Social



(c) Physical



(d) Human



(e) Natural

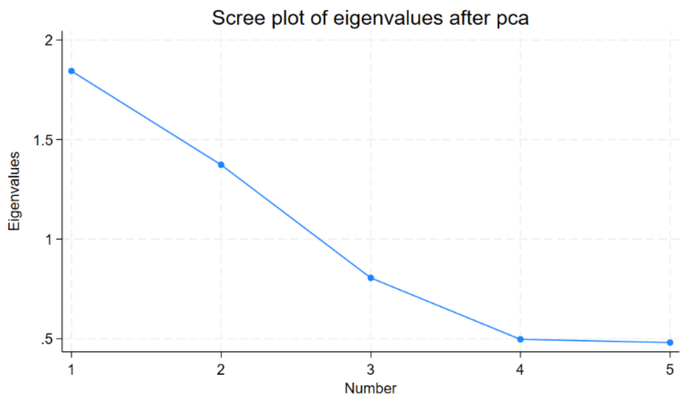


Figure A3: Screeplots for 5Cs

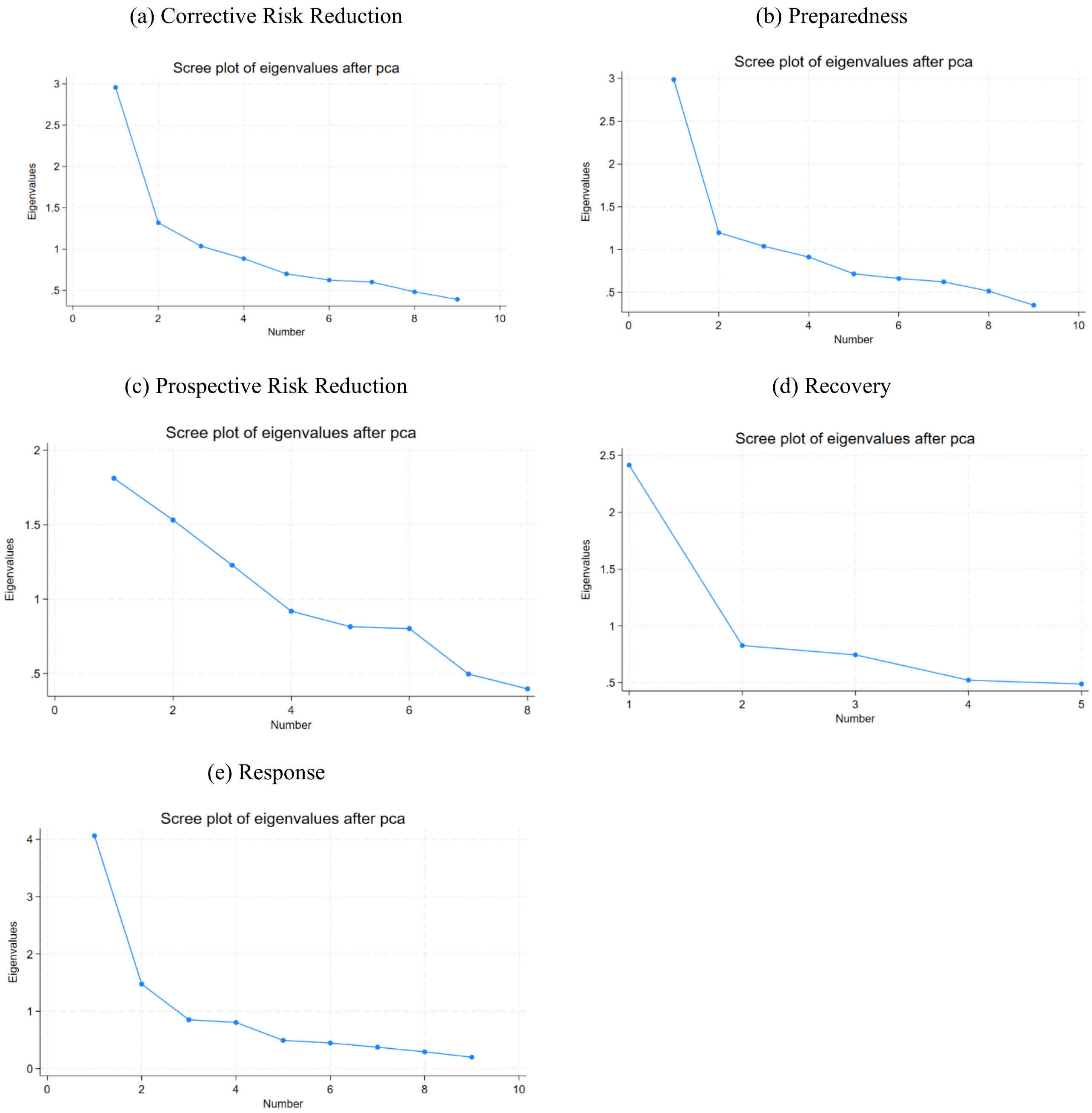


Figure A4: Screeplot for the DRM cycle stages

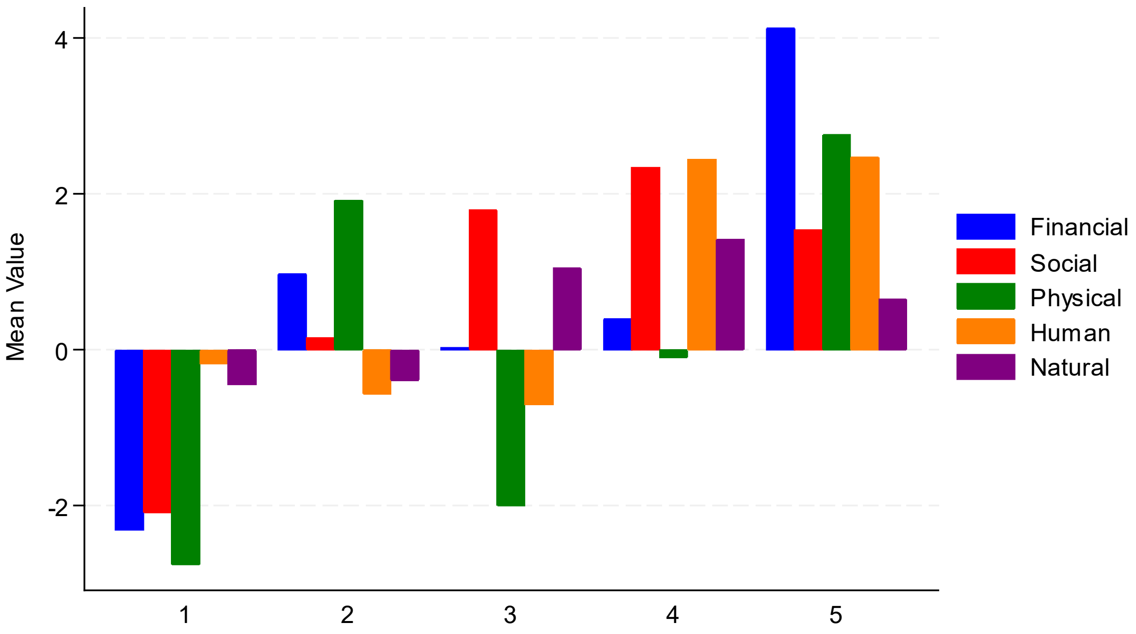


Figure A5: Mean of resilience capitals scores by cluster in the baseline survey

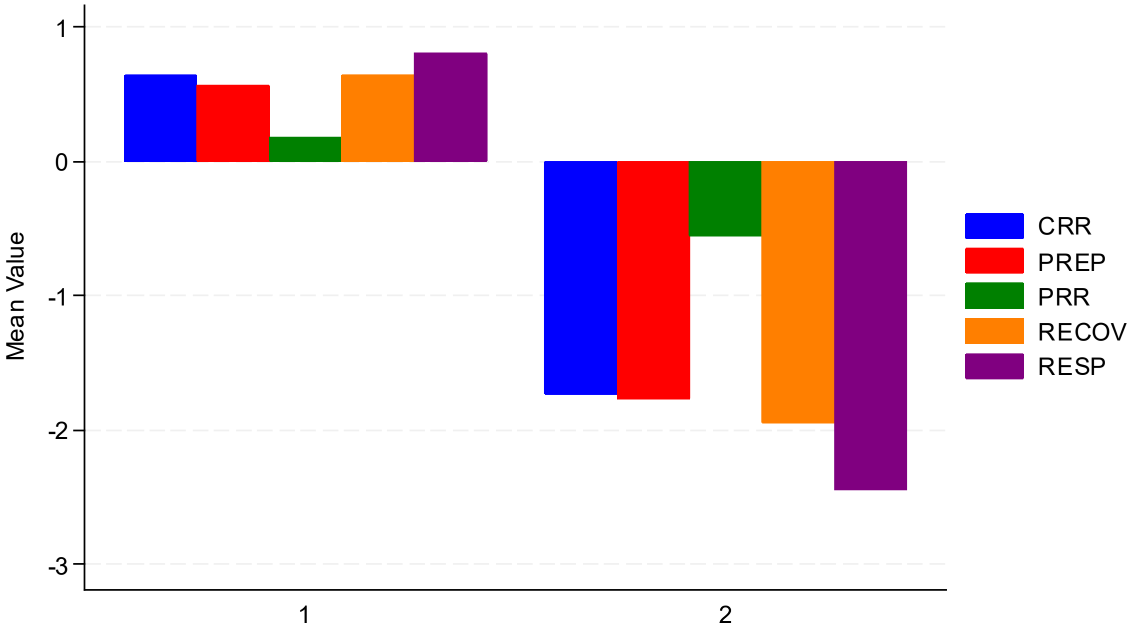


Figure A6: Mean of DRM cycle stages scores by cluster in the baseline survey

Table A3: Comparison of Wild Bootstrap Clustered Regression Models for Assessing Community Resilience and Its Impact on Average Loss of Life

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
std_social	-0.537***	-0.371	0.190	0.191	0.097	0.112	0.054
std_financial	0.260	0.053	0.215	0.322	0.391	0.218	0.203
std_physical	-0.583	-0.706	-0.846	-0.917	-0.854	-0.755	-0.630
std_human	-0.472	-0.609	-0.601	-0.466	-0.468	-0.229	-0.256
std_natural	0.434	0.464	0.644	0.618	0.659	0.543	0.582
std_AverageAge15to25		-0.449	-0.529	-0.650	-0.651	-0.744	-0.721
std_AverageAge50plus			-0.887*	-1.011	-0.961	-1.146	-1.137
std_AveragePercFemaleResp				0.409	0.464	0.432	0.459
std_AverageRural					0.236	0.131	0.075
std_AverageReturnPeriod						0.695	0.685
std_AveragePercComAffect							0.271***
Observations	66	66	66	66	66	66	66
R-squared	0.23	0.27	0.35	0.38	0.39	0.48	0.49
AIC	255.23	251.66	243.44	240.39	239.63	229.43	228.12
BIC	261.79	258.23	250.01	246.96	246.20	236.00	234.69

Observation: *** Significant at 1%; ** Significant at 5%; * Significant at 10%

Source: FRMC.

Table A4: Comparison of Wild Bootstrap Clustered Regression Models for Assessing Community Resilience and Its Impact on Average Injuries

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
std_social	-36.145	-37.254	-33.537	-33.547	-36.736	-36.127***	-39.976***
std_financial	19.833	21.218	22.288	21.208	23.513	16.631	15.602
std_physical	-6.930	-6.104	-7.032	-6.320	-4.203	-0.243	8.109
std_human	-13.281	-12.361	-12.310	-13.667	-13.742	-4.156	-5.970***
std_natural	-11.879***	-12.076***	-10.884***	-10.627***	-9.240***	-13.873	-11.277
std_AverageAge15to25		3.013	2.486	3.704	3.672	-0.068	1.510
std_AverageAge50plus			-5.878	-4.633	-2.935	-10.352	-9.735***
std_AveragePercFemaleResp				-4.106***	-2.251	-3.516	-1.707
std_AverageRural					7.992***	3.786	0.052
std_AverageReturnPeriod						27.799	27.150
std_AveragePercComAffect							18.123***
Observations	66	66	66	66	66	66	66
R-squared	0.45	0.45	0.46	0.46	0.46	0.57	0.61
AIC	705.24	705.07	704.72	704.44	703.68	688.74	683.02
BIC	711.81	711.64	711.29	711.01	710.25	695.31	689.58

Observation: *** Significant at 1%; ** Significant at 5%; * Significant at 10%
Source: FRMC.

Table A5: Comparison of Wild Bootstrap Clustered Regression Models for Assessing Community Resilience and Its Impact on Average Fatalities After Three Months

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
std_social	0.096	-0.011	-0.687	-0.687	-0.546	-0.561	-0.179
std_financial	-3.493	-3.359	-3.554	-3.517	-3.619	-3.443	-3.341
std_physical	0.846***	0.925***	1.094***	1.070	0.976	0.875	0.047
std_human	-0.565	-0.476	-0.485	-0.439	-0.436	-0.680	-0.500
std_natural	2.037***	2.017***	1.801	1.792	1.730	1.849	1.591***
std_AverageAge15to25		0.291	0.387	0.345	0.346	0.442	0.285
std_AverageAge50plus			1.069***	1.026***	.951***	1.140***	1.079***
std_AveragePercFemaleResp				0.141	0.059	0.091	-0.088
std_AverageRural					-0.354	-0.246	0.124
std_AverageReturnPeriod						-0.710	-0.645
std_AveragePercComAffect							1.797
Observations	66	66	66	66	66	66	66
R-squared	0.27	0.27	0.28	0.28	0.29	0.30	0.35
AIC	389.93	389.74	388.34	388.30	388.12	387.08	381.65
BIC	396.50	396.31	394.91	394.87	394.69	393.65	388.22

Observation: *** Significant at 1%; ** Significant at 5%; * Significant at 10%
Source: FRMC.

Table A6: Comparison of Wild Bootstrap Clustered Regression Models for Assessing DRM cycle levels and Its Impact on Average Fatalities

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
std_CRR	-.015***	0.100	0.315***	0.335***	0.613***	0.716***	0.656***
std_PREP	-.577***	-0.550***	-0.460***	-0.491***	-0.699***	-0.597***	-0.532***
std_PRR	0.095	0.131	0.022	0.025	0.029	0.068	0.023
std_RECOV	0.482	0.062	0.299***	0.314***	0.874***	0.079***	-0.019
std_RESP	-.774***	-0.640***	-0.743***	-0.734***	-1.063***	-0.563***	-0.420
std_AverageAge15to25		-0.344***	-0.312***	-0.313***	-0.447***	-0.741***	-0.744***
std_AverageAge50plus			-0.528***	-0.516***	-0.733***	-0.901***	-0.925***
std_AveragePercFemaleResp				0.599	0.676	0.491	0.491
std_AverageRural					0.278***	0.172***	0.094***
std_AverageReturnPeriod						0.832***	0.845***
std_AveragePercComAffect							0.243***
Observations	66	66	66	66	66	66	66
R-squared	0.20	0.22	0.25	0.31	0.32	0.44	0.45
AIC	253.52	251.91	249.00	243.61	242.67	229.72	228.86
BIC	255.71	254.10	251.19	245.80	244.86	231.91	231.04

Observation: *** Significant at 1%; ** Significant at 5%; * Significant at 10%
Source: FRMC.

Table A7: Comparison of Wild Bootstrap Clustered Regression Models for Assessing DRM cycle levels and Its Impact on Average Injuries

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
std_CRR	-32.123***	-36.119***	-32.668***	-32.294***	-30.654***	-27.559	-30.906***
std_PREP	-28.290***	-29.227***	-27.792***	-27.963***	-30.126***	-27.041***	-23.375***
std_PRR	10.098***	8.831***	7.077***	7.057***	7.290***	8.478***	5.921***
std_RECOV	36.256***	50.975	54.779	55.717	57.476	33.488	27.944
std_RESP	-19.805***	-24.528***	-26.193***	-26.870***	-26.831***	-11.777	-3.675
std_AverageAge15to25		12.051	12.555	12.306	12.081	3.224	3.070
std_AverageAge50plus			-8.446***	-8.934***	-8.557***	-13.617***	-14.998***
std_AveragePercFemaleResp				1.259	2.309	-3.256***	-3.285
std_AverageRural					3.814***	0.593	-3.782
std_AverageReturnPeriod						25.092***	25.841***
std_AveragePercComAffect							13.702***
Observations	66	66	66	66	66	66	66
R-squared	0.46	0.48	0.49	0.49	0.49	0.58	0.59
AIC	699.54	697.23	696.38	696.35	696.17	684.03	681.17
BIC	701.73	699.42	698.57	698.54	698.36	686.22	683.36

Observation: *** Significant at 1%; ** Significant at 5%; * Significant at 10%
Source: FRMC.

Table A8: Comparison of Wild Bootstrap Clustered Regression Models for Assessing DRM cycle levels and Its Impact on Average Fatalities After Three Months

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
std_CRR	0.956	1.020***	1.085	1.132	0.964	0.917	1.285
std_PREP	0.843	0.858	0.885	0.863	1.085***	1.039***	0.637
std_PRR	-1.983***	-1.962***	-1.995***	-1.997***	-2.021***	-2.039***	-1.758***
std_RECOV	-4.314***	-4.553***	-4.482***	-4.365***	-4.545***	-4.185***	-3.577***
std_RESP	1.127***	1.204***	1.173***	1.088***	1.084***	0.858***	-0.031
std_AverageAge15to25		-0.196	-0.187	-0.218	-0.195	-0.062	-0.045
std_AverageAge50plus			-0.157	-0.219	-0.257	-0.181	-0.030
std_AveragePercFemaleResp				0.158	0.050	0.134	0.137
std_AverageRural					-0.392	-0.344	0.136
std_AverageReturnPeriod						-0.376	-0.458***
std_AveragePercComAffect							-1.503***
Observations	66	66	66	66	66	66	66
R-squared	0.34	0.34	0.34	0.34	0.35	0.35	0.38
AIC	378.63	378.55	378.51	378.46	378.22	377.91	374.33
BIC	380.82	380.74	380.70	380.65	380.41	380.10	376.52

Observation: *** Significant at 1%; ** Significant at 5%; * Significant at 10%

Source: FRMC.

Code availability

Code available upon request.

Data availability

The FRMC data is owned by the organisations that collected it. The authors of this paper were granted access to the data but do not have permission to share it further.

Author contribution

RG designed the study, wrote the manuscript, and prepared and analysed the data. RM contributed to the study design, manuscript writing, and data interpretation. SV participated in data preparation, manuscript writing, and data interpretation. DC contributed to the writing of the manuscript and to data interpretation.

Competing interests

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: RG reports financial support was provided by Z Zurich Foundation.

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