Chapagain, D., S. Hochrainer-Stigler, S. Velev, A. Keating, J. H. Hyun, N. Rubenstein, and R. Mechler. 2024. A taxonomy-based understanding of community flood resilience. Ecology and Society 29(4):36. https://doi.org/10.5751/ES-15654-290436

Research

A taxonomy-based understanding of community flood resilience

Dipesh Chapagain [1,2], *Stefan Hochrainer-Stigler* [1], *Stefan Velev* [1], *Adriana Keating* [1,3], *Jung Hee Hyun* [1], *Naomi Rubenstein* [1] and *Reinhard Mechler* [1]

ABSTRACT. Reducing disaster risk and enhancing resilience are major global societal challenges. To inform this challenge, understanding resilience at the community level is especially important because the impact of disasters and the potential for resilient development are particularly acute at this scale. The last decade has seen a surge in efforts in measuring resilience to a variety of hazards, yet measurement frameworks lack empirical validation and widespread application. To bridge this information gap, we provide analysis into an unprecedented dataset: a standardized, empirically validated approach to community flood resilience measurement, applied in over 290 communities across 20 developing countries. The analysis is based on the Flood Resilience Measurement for Communities (FRMC) framework and tool designed to provide a holistic approach to measuring community flood resilience and to support implementation of resilience-strengthening interventions. Our analysis starts with an assessment of the validity and reliability of the data and leads into querying whether and how to organize the wealth of information of community contexts into a discrete set of clusters. Although we appreciate that fostering resilience has to be strongly context-aware, we also present a taxonomy related to flood risk and socioeconomic community characteristics, which, using multinomial and random forest methods, leads us to identifying five distinct community clusters based on their resilience profiles and capital scores. This clustering taxonomy provides a way to group communities by similarities and differences between absolute and distributional resilience levels and socioeconomic community characteristics. These clusters may serve as a resource for further examining efforts for building resilience, analyzing resilience dynamics over time, and informing policy options across the world.

Key Words: *capital approach; community characteristics; community resilience measurement; flooding; global; local; taxonomy*

INTRODUCTION

In the context of increasing frequency and severity of disasters, reducing risk and enhancing resilience are major societal challenges that have been prioritized at the highest levels through global policy compacts including the Sendai Framework, Paris Agreement, and Sustainable Development Goals (UN 2015, UNDRR 2015, UNFCCC 2015). With increasingly unprecedented frequency and severity of extreme weather events, driven by climate change and the inequitable distribution of social and ecological vulnerabilities both within and between communities, it is imperative to continue to expand the understanding of community resilience at local to global scales (World Bank 2021, IPCC 2023). Although resilience operates across multiple scales, understanding resilience at the community level is particularly important because many of the direct and indirect impacts of disasters are experienced at this level, and it is there that much effective action to build resilience can be taken (Keating 2020). Ecological systems cannot anticipate disturbances or disasters, yet communities can conceptualize such events and take action to manage them (Gunderson 2010). Understanding how to enhance resilience is far from trivial and the social-ecological systems (SES) literature, for example, suggests that resilience has to be understood as an emergent property of both human and environment interrelationships (see Faulkner et al. 2018 for a detailed discussion). Although there is now great attention to resilience by development and humanitarian organizations and policy across scales (Clement et al. 2024), a major information gap relates to empirical evidence on what builds community resilience over time (Florin and Linkov 2016, Linkov and Trump 2019).

Measuring community disaster resilience comes with its share of challenges (Schipper and Langston 2015, Asadzadeh et al. 2017, Cai et al. 2018, Jones et al. 2021). The last decade has seen a surge in efforts aimed at measuring resilience to a variety of hazards, efforts that have resulted in the development of many resilience measurement frameworks, tools, scorecards, indices, etc.; many of these, however, lack a theoretical framework and empirical validation, application, and up-take has been patchy (Cutter 2021, Tan 2021). The lack of definitional or methodological consensus (see, for example, Hahn and Nykvist 2017 in the context of SES) and absence of standardized, empirically validated approaches to resilience measurement undermine confidence by policy and decision makers who seek to translate outcomes into policy advice and implementation (Bakkensen et al. 2017, Cutter 2021, Jones et al. 2021). We suggest resilience thinking must be an integrative approach with regard to sustainability challenges and, as a consequence, this needs to be thought through across scales and dependencies, including corresponding complex mechanisms that can eventually cascade through different sub-systems (see Folke 2016 in the context of SES, Hochrainer-Stigler et al. 2020 in the context of systemic risks).

To bridge these information and practice gaps, the Zurich Flood Resilience Alliance (the Alliance), formed in 2013, developed the Flood Resilience Measurement for Communities (FRMC) approach (Keating et al. 2017). The first phase of the Alliance (2013–2018) saw the application, analysis, and validation of the first version of the FRMC framework in 118 communities between 2015 and 2017 (see Laurien et al. 2020 for a summary, Hochrainer-Stigler et al. 2021 for analytical insights). In the second phase of the Alliance (2018–2024), the framework was

[1]International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria, [2]United Nations University Institute for Environment and Human Security (UNU-EHS), Bonn, Germany, [3]Monash University, Melbourne, Australia

refined into the FRMC Next Gen tool and is currently in use in more than 292 communities (see Appendix 1 for more details). In the current and third phase, the FRMC has been further evolved into the CRMC (C for Climate), an approach that can measure community resilience to multiple hazards including flood, heatwave, and wildfire.

We present the first large-scale analysis of the data generated using the FRMC Next Gen version, collected in 292 communities from 20 developing countries between 2018 and 2022. Our focus is on quantitative findings of this global empirical analysis, building on the rich set of on-the-ground resilience indicators. Our analysis includes an assessment of the validity and reliability of the FRMC Next Gen framework. In addition, we query whether and how to organize the wealth of information of community contexts into a discrete set of clusters, for which we further develop the taxonomy developed in the first phase in Laurien et al. (2020). The theoretical underpinnings of the framework will be briefly discussed as well as advantages and limitations compared to other approaches identified. Special emphasis is put on different types of communities that can be empirically determined. This is especially important as analysis in phase 1 found that the dynamics of resilience are essentially different for different community types (Hochrainer-Stigler et al. 2021). With the larger FRMC Next Gen dataset (compared to phase 1) we are able to provide more nuanced, and empirically tested, perspective with regard to this question.

CHALLENGES AND METHODOLOGICAL APPROACH

A significant challenge of resilience measurement lies in taking a complex, multi-dimensional concept (Folke 2016) and operationalizing it in a measurable way (Alexander 2013). Measuring community resilience involves trying to anticipate, in the absence of a disaster event, which set of community characteristics, and ultimately indicators, will best predict resilient post-disaster outcomes. Holistic frameworks that presume dynamic interactive processes seek to determine which of the multitude of community dimensions, across many attributes and sub-systems, provide the most important resilience proxies (Cutter 2021). Achieving a balance between objective indicators and subjective assessments is essential to provide a comprehensive understanding of community resilience, however, integrating these dimensions into a unified resilience measurement framework is a complex endeavor (Keating et al. 2017).

The literature identifies three further challenges or limitations in relation to disaster resilience measurement. First, little effort has been made to integrate ecological components into community resilience measurement, and spatial scale and cross-scale dynamics have mostly not been considered in community resilience analysis (Chuang et al. 2018). Second, some of the most widely used measures of community resilience, such as the Social Vulnerability Index (SoVI) and Baseline Resilience Indicators for Communities (BRIC) model, rely on census or national-scale survey variables, whose availability differs from country to country, making global analysis difficult (Camacho et al. 2023, Cutter 2024). Finally, the factors identified solely based on multivariate analysis and their aggregation to estimate a single composite index may not be conceptually robust or consistent with the understanding of hazard-specific resilience and its drivers (Camacho et al. 2023).

The literature discusses many definitions of resilience (see for example Béné et al. 2014, Folke 2016, Faulkner et al. 2018) while the concept of resilience in general, and disaster resilience specifically, has evolved from a focus on ecological systems to a holistic perspective with multiple framings according to different disciplines including economics, risk science, ecological system theory, psychology, as well as engineering (Keating et al. 2014). As with resilience in general, the literature on disaster resilience, our focus, and its many definitions and conceptualizations have some key characteristics in common but, as indicated, have challenges with regard to operationalization and practical application.

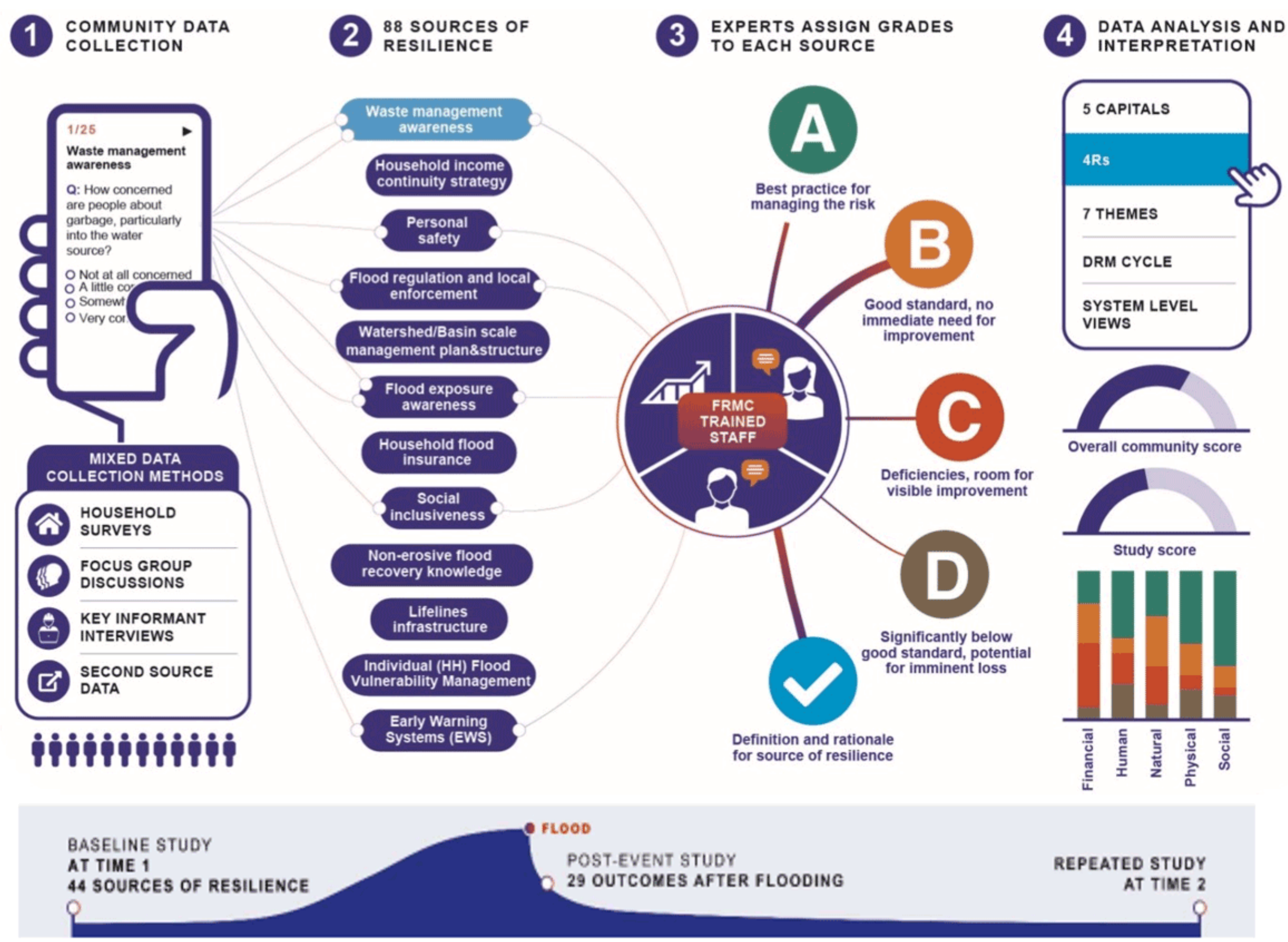
As a step forward, Keating et al. (2017) outlined a conceptional framework of disaster resilience building on the system interactions between disaster risk, disaster risk management (DRM), and sustainable development (SD). It builds on a development-centric disaster resilience perspective. This approach as well as the corresponding definition of resilience is also used here: resilience as the “ability of a system, community, or society to pursue its social, ecological, and economic development and growth objectives, while managing its disaster risk over time, in a mutually reinforcing way” (Keating et al 2017:80). Based on this development-centric definition of disaster resilience, partners of the Zurich Flood Resilience Alliance translated the theoretical framework of disaster resilience into a practical framework for measuring disaster resilience. In the following, we proceed to discussing empirical aspects of the framework and the measurement tool, including key operationalization aspects (for further detailed discussions, we refer to Keating et al. 2017 as well as Laurien et al. 2020.)

The FRMC Next Gen Framework and Tool

The Next Generation FRMC approach, like the first iteration of the framework, is based on the so-called 5C framework: it includes 44 indicators called “sources of resilience” (or “sources” for short) that are distributed across and represent critical aspects of five complementary “capitals” (5C; see Appendix 2). It is built on the five capitals framing of the Sustainable Livelihoods Framework (DFID 1999). This framing emphasizes that community flood resilience is a multi-dimensional concept comprising elements across physical, social, human, financial, and natural aspects that interact over time to inform community well-being and disaster outcomes. The sources are selected for the roles they play in supporting community well-being, helping people on their development path and/or providing capacity to prepare for, withstand, respond to, and recover from floods.

Users collect and analyze data using the FRMC tool, a practical hybrid software application comprising an online web-based platform for setting up and analyzing the process, and a smartphone- or tablet-based app that can be used offline in the field for data collection. After data is collected on the app, it is uploaded to the web application. A grading team composed of the FRMC implementing team, community members, and sometimes other stakeholders such as local government representatives compare collected data to pre-determined grading rubrics to grade each of the 44 sources of resilience on an A–D scale (A being best practice, D being poor). For aggregation, A–D grades correspond to number scores as follows: D = 0, C = 33, B = 66, A = 100. The number scores of corresponding sources of

Fig. 1. Flood Resilience Measurement for Communities (FRMC) data implementation process. Based on Laurien et al. (2020).



resilience for each capital are then averaged to get an aggregate score for each capital; for example, if all sources of resilience in a capital group were graded "A," the community would score 100 for that capital group. Graded results can be explored according to different "lenses" including the 5Cs (Fig. 1).

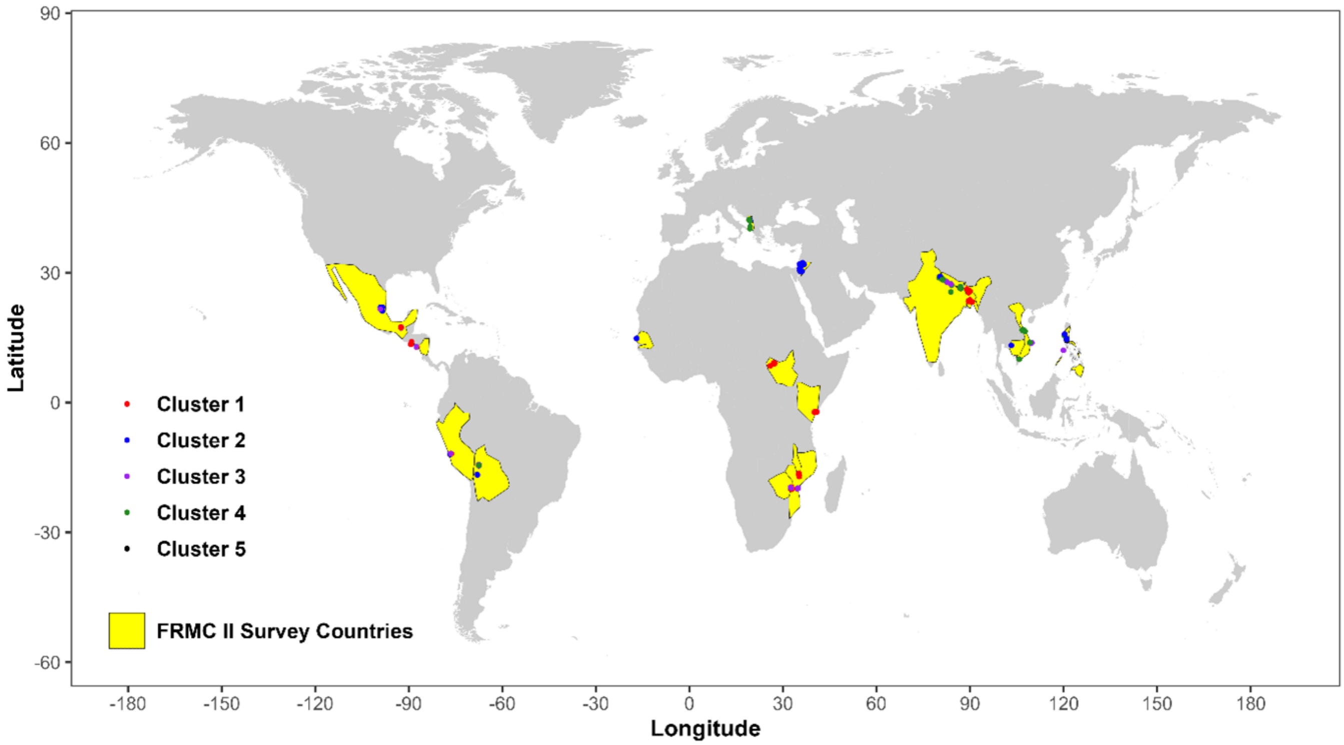
Importantly, the FRMC is a standardized approach to resilience measurement (e.g., not dependent on the location it is applied to) that can therefore be used across the globe (Fig. 2), a feature that is still often lacking in the resilience space. Consequently, it makes it possible to explore differences in resilience profiles across communities, track progress over time, and to learn and improve practices. The FRMC therefore provides a consistent benchmark against which to quantify flood resilience at the community level. Furthermore, it employs several data collection methods (household surveys, focus groups, key informant interviews, and secondary source data) and allows for the collection of data on community perceptions, knowledge, and capacities (Fig. 1, lower left). Use of data collection and software technologies are supported by online or in-person user-training and guidance resources, which help ensure systematic and consistent data collection and framework use. The online platform includes data analysis features that facilitate exploration of interconnections between results and preparation of reports that can be shared with community stakeholders (Fig. 1, right hand side; detailed information of the data acquisition process and approach used can be found in Appendix 3.)

Study Locations

The analysis presented here is based on FRMC Next Gen baselines conducted between 2018 and 2022. These assessments were done in 292 communities in 20 developing countries worldwide, covering a population of almost a million (approximately 966,600). From each country, at least four and up to 53 communities are represented. Locations of the communities and countries are presented in Figure 2.

FRMC users include NGOs, humanitarian organizations, and researchers. Users generally consider a variety of criteria when determining precise study locations and which communities to apply the FRMC in. These include history of previous flooding and communities being at high risk, communities' need for external support, their location in a larger river basin (where applicable, this criterion was not considered with communities that suffer from coastal flooding, for example), and a community's representativeness for their region and willingness to take part in the project. One

Fig. 2. World map showing the location of the Flood Resilience Measurement for Communities (FRMC) II baseline survey countries and communities by cluster types.



predominant criterion is the presence and perception of high flood risk by the organization, local authorities, and the community itself. This criterion encompasses terms such as "risk," "exposure," and "vulnerability." Organizations often seek to work in different parts of a watershed in order to advance integrated watershed management, addressing diverse needs, challenges, and opportunities across communities within the same watershed. The interest of local authorities and alignment with government initiatives are also factors in community selection in most locations. Some organizations aimed to collaborate with the government and fill gaps where their efforts fell short, fostering cooperation and complementarity. Several organizations emphasize co-benefits and addressing vulnerabilities, particularly as related to climate change, as an additional criterion for community selection (for further information about the total dataset used we refer to Appendix 4.)

Empirical analysis strategy

Because this is the first time that results from analysis of the FRMC Next Gen dataset are presented, we start with presenting some overall results on capitals and communities, including descriptive and exploratory analysis. We then discuss the internal consistency and reliability tests, possible dimensionality reduction, and sub-group analysis. Based on this we focus in on the main topic of this article, namely the cluster analysis and interpretation of taxonomy characteristics.

The methods employed are discussed in detail in Appendix 5, and here we provide a short summary only. To assess internal consistency and reliability we used the standard tests including Cronbach's alpha, and for dimensionality reduction and sub-group analysis we focused on Principal Components Analysis. To identify possible clusters and taxonomies we used a variety of cluster analysis approaches, especially focusing on schemes that create a strong separation in similarities between clusters and strong similarities within clusters. Clusters are based on community resilience levels across the five capitals. Following the clustering process, clusters were defined by the characteristics of the communities within each cluster, using multinomial regression analysis and random forest models to test the relationship between clusters and with community characteristics. To achieve this, the data was split into 70% model training and 30% test datasets using stratified random sampling to test the model's validity and performance. Confusion matrix and statistics (sensitivity, specificity, and balanced accuracy) were then used to test the accuracy of the cluster prediction by the models. Finally, we used the most significant model and socioeconomic indicators to explain cluster archetypes. In this way, we identified taxonomies and can interpret the taxonomy of community flood resilience as explained in the next section.

As Figure 1 (bottom) indicates, our focus in this paper is on the baseline analysis. There are, however, three additional pieces of data that make up the FRMC measurement approach. These are the post-event study, the intervention data record, and the endline study (a repeat of the baseline). The post-event study evaluates damages of, and community system performance in the event of, any flood disasters that occur in a community following the baseline study. The intervention data record documents the interventions done in the communities following the baseline. Finally, the endline study is a repeat of the baseline study, conducted 2–3 years after the baseline. These four parts are designed to provide a cohesive, empirical global analysis of community flood resilience over time. A further motivation for the present in-depth analysis of the baseline data is the need to establish a strong empirical understanding of the baseline in order to support future analysis of the undoubtedly complex dynamics (Hochrainer-Stigler et al. 2021) between baseline resilience, flood impacts, the effects of interventions, and finally endline resilience.

RESULTS

Community flood risk

We start with some overall insights into the communities in our sample. Most of the communities (73%) are rural, followed by urban (16%), and peri-urban (10%). River flooding is the most common flood type, occurring in 45% of the communities. Flash floods are the next most prevalent, occurring in 36% of the communities. Although surface flooding and coastal flooding are the most common flood type in 4 and 15% of the communities, respectively, for some countries these are a key flood issue, for example, surface flooding in Vietnam, Cambodia, Nicaragua, and Albania. Regarding frequency of flooding, just under half of the communities experience flooding more than once per year on average, with around 65%, on average, of houses affected. One third of communities experience a flood about once a year, and on average 60% of houses are flooded. Regarding the severity of previous floods, 76% of households across the communities reported that in the case of the worst flood they can remember, more than three quarters of the houses/buildings in the community were flooded.

Validity, reliability, and sub-group analysis

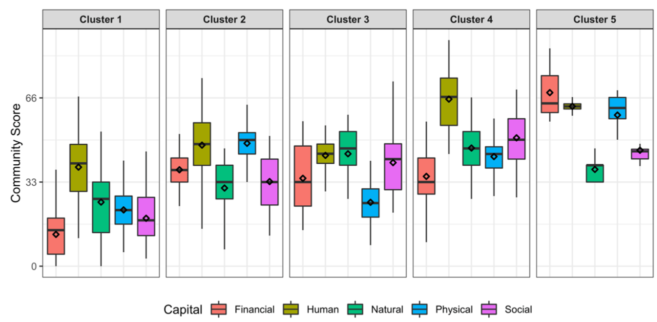
Here we provide a summary of the validity, reliability, and sub-group analysis, with detailed results available in Appendix 6. Face validity looks at whether the FRMC aligns with practitioners' and communities' understanding about the factors that contribute to and build community flood resilience. Practitioners widely agreed that the framework assesses community flood resilience as they perceive it, confirming the importance of all 44 resilience sources and finding no major gaps. For reliability, we evaluated the FRMC's ability to consistently measure resilience across different contexts. The results show high reliability (C-alpha ≥ 0.7) for all capitals except natural capital, which slightly missed the threshold (0.69). Overall, the FRMC reliably measures resilience across all capitals and is valid for aggregation.

The PCA identified two to three sub-groups within each capital. Financial capital were grouped into two components: public and private financial capacity. Human capital had three components: first aid and WASH (water, sanitation, and hygiene) knowledge, flood exposure and evacuation awareness, and environmental management and governance. Natural capital split into physical status and services of resources and management efforts. Physical capital had three components: basic supplies during floods, utilities infrastructure, and early warning and emergency response infrastructure. Last, social capital showed three components: community structure, external flood response services, and DRM policies at national and community levels.

Community cluster analysis

As indicated in section 2, we analyzed the community resilience results using various cluster agglomeration schemes as well as similarity measures; here we report only our main findings. Using the hierarchical clustering method, we identified five distinct community clusters based on their flood resilience capital scores (see Fig. 3 for capital scores by cluster). The first important thing to note is that not only do the absolute levels of scores differ across clusters, but also the distributions of the different capitals are quite distinct. Moreover, the clusters highlight the differences in flood resilience between rural and urban areas. Correlations analysis between the five capitals can be found in Appendix 7. Here we focus on the details between our findings and the underlying resilience sources.

Fig. 3. Community flood resilience capitals (5Cs) scores for the five identified community clusters.



We detect cluster 1, which includes 99 communities and is considered the cluster of communities with the lowest resilience. Ninety-seven percent of communities in this cluster are rural communities primarily from Bangladesh, Kenya, Malawi, South Sudan, and Zimbabwe. Both private and public financial capacity components of these communities are very low. The relatively higher average human capital score is mainly due to a slightly better level of awareness of flood exposure, future risk, WASH, environmental management, and governance. However, other human capital aspects, namely knowledge of evacuation and safety, asset protection, first aid, and education commitment during floods, are very low. The natural capital dimension is also low because of degraded local ecosystems (both wild and managed), and little to no sustainable or regenerative management. Very low physical capital is due to poor utilities infrastructure, early warning systems, emergency response infrastructure, and low levels of basic supplies during an emergency. Social capital is measured to be low in these communities because of missing or inadequate community governance structures and representation, seen in low participation, low inclusiveness, lack of local leadership, and low mutual assistance. These communities also show low levels of external flood response and recovery services, and lack of national and community level DRM and integrated flood management policy and plans.

Cluster 2 contains 56 communities that exhibit slightly higher financial, human, and physical capital scores than natural and social capital. In this cluster, 70% are urban and peri-urban communities primarily from Senegal, the Philippines, Mexico, Jordan, and Bolivia. The public financial capacity of this cluster is moderate, but the private financial capacity is low. Higher awareness of flood exposure, future risk, WASH, environment management, governance, and asset protection improves human capital of this cluster as compared to cluster 1. However, knowledge of evacuation and safety, first aid, and education commitment during floods remain low. Sources of physical capital, mainly basic supplies during an emergency, utilities infrastructure, early warning system, and emergency response infrastructure are slightly higher than in cluster 1. Natural capital is low because of degraded natural environments and ecosystem services, despite some efforts in regard to their management. Social capital is also relatively low because of the status of community governance structures, and lack of DRM and integrated flood management policy and plans. The level of external flood response and recovery services is relatively better in cluster 2 communities, as compared to cluster 1.

Cluster 3 has 37 communities with capital score profiles that are somewhat the inverse of cluster 2. Seventy-six percent of these communities are rural communities primarily from Senegal, the Philippines, Mexico, Jordan, and Bolivia. Here, the scores for human, natural, and social capitals are relatively high compared to the rest of the sample, but financial and physical capitals are lower. Public financial capacity is moderate, while private financial capacity is very low. Physical capital is very low because of absent or inadequate utilities infrastructure, early warning systems, emergency response infrastructure, and low levels of basic supplies during an emergency. The average natural capital score in this cluster is higher because of better natural resource management and moderate levels of environmental health and ecosystem services provision. Social capital is higher because of better community governance structures, external flood response, and availability of recovery services. However, DRM and integrated flood management policy and plans remain below good standard. Sources of human capital are similar to cluster 2, with a high to moderate level of awareness of flood exposure, future risk, WASH, environmental management, and governance. However, there is limited knowledge of evacuation and safety, asset protection, first aid, and education commitment during the flood.

Cluster 4 has 92 communities and, along with cluster 5, shows higher scores compared to clusters 1, 2, and 3. Cluster 4 primarily includes communities from Vietnam, Nepal, India, Bolivia, Albania, and Montenegro. Average capital scores are generally higher than the previous three clusters, particularly human, natural, and social capital scores. These communities show high levels of awareness of evacuation and safety, flood exposure, future risk, asset protection, WASH, environmental management, and governance. Similarly, the level of first aid knowledge and education commitment during floods is moderate. Cluster 4 exhibits the highest average natural capital of all the clusters because of the better, or less degraded, state of natural resources and ecosystem services provision, together with stronger conservation and restoration. All aspects of community governance are moderate to high, with the exception of inter-community coordination, which remains low. Similarly, external flood response and recovery services are moderate to high. At both the national and community levels, DRM plans are at a moderate level, but integrated flood management policy is low. Public financial capacity is moderate, while private financial capacity is relatively lower. Physical capital sources are also at a moderate level in these communities.

Finally, cluster 5 is the smallest cluster, with only 8 communities from the Philippines and Vietnam, and exhibits high average capital scores as compared to the other clusters. Financial and physical capitals are the highest of all the clusters. This high financial capital is due to high public and moderate private financial capacity. Physical capital is strongest because of better emergency response infrastructure, utilities infrastructure, early warning systems, and basic supplies during emergencies. Human capital is high because of high awareness and knowledge levels. However, first aid knowledge and education commitment level during floods is relatively low. All aspects of community governance and level of external flood response and recovery services are moderate to high in this cluster, driving higher social capital. DRM policies and planning are at a moderate level, but integrated flood management policy is poor. The natural capital score is the lowest among all capitals for cluster 5 because of the low to moderate level of physical condition of natural resources and absent or limited efforts in their management.

Notably, clusters 1, 3, and 4 predominantly consist of rural communities, while clusters 2 and 5 are mainly composed of urban and peri-urban communities. However, around 24% and 20% of urban communities are also found in clusters 3 and 4, respectively, and around 30% of rural communities appear in cluster 2. This is primarily due to their similar capital score profiles, but it should be noted that there are exceptions within these clusters as communities can differ in other aspects beyond the capital scores. This qualification underlies the point that the clusters are not designed to be predictive or prescriptive about any individual community; they are an analytical tool to help organize and understand the volume of information about community flood resilience contained in this global dataset. Given this detailed information about the communities' resilience sources for each cluster, next we explore the capital score-derived clusters in relation to the characteristics of the communities within them.

Taxonomy of community resilience

The description of the clusters above indicates that there are qualitative differences between the clusters. We now further analyze these by exploring the predominant socioeconomic characteristics in each cluster, to determine whether the resilience profiles have some common patterns with specific community characteristics. To do this, we used the identified clusters to run a multinomial regression model and a random forest model with socioeconomic characteristics as independent variables, separated into training and testing sets. We present the detailed results in Appendix 8.

We want to note that we also analyzed the geo-spatial distribution of the clusters. For this we tested both geographic distances and country locations as explanatory variables, for the clusters themselves and the distance matrix used to make them. Overall, we found no significant pattern, although (when taken as the sole explanatory variable) certain countries are more likely to have communities from specific clusters. Nevertheless, this significance is not present when socioeconomic variables like poverty or urbanization (community type: rural, peri-urban, or urban) are introduced. Further analysis using Voronoi cells showed no

Table 1. The identified five clusters and related most important socioeconomic community characteristics.

Cluster Characteristics	Cluster 1: Rural communities with high risk and vulnerability, and low capacity	Cluster 2: Urban communities with poor natural and social environments	Cluster 3: Rural communities with high capacity but low income and poor physical infrastructure	Cluster 4: Less vulnerable rural communities	Cluster 5: Less vulnerable urban communities
Community Type	97% rural	70% urban and peri-urban	76% rural	80% rural	100% urban and peri-urban
Female education (% of women who have completed secondary education)	Low (below 25% in all the communities)	Relatively moderate (above 25% in most of the communities)	Relatively moderate (between 10 and 50 % in majority of the communities)	Relatively moderate (between 10 and 50 % in majority of the communities)	High (above 50% in majority and above 25% in all of the communities)
Poverty (% of households living below the national poverty line)	High (more than 50% in majority of the communities).	Relatively moderate (10 and 50 % in majority of the communities).	High (more than 60% in majority of the communities).	Relatively moderate (20 and 60 in majority of the communities).	Low (less than 30% in all the communities).
Influence on higher level decisions	Low Never: 63%; Only sometimes: 32% Most of the time: 5%	Relatively moderate Never: 25% Only sometimes: 67% Most of the time: 7%	Relatively higher Never: 27% Only sometimes: 62% Most of the time: 11%	Relatively moderate Never: 16% Only sometimes: 76% Most of the time: 8%	Low Never: 62% Only sometimes: 25% Most of the time: 13%
Flood frequency	High > once per year: 30% ~ once per year: 55%	High > once per year: 53% ~ once per year: 24%	Relatively moderate > once per year: 41% ~ once per year: 24%	Relatively moderate > once per year: 45% ~ once per year: 23%	Very High > once per year: 88% ~ once per year: 12%
Flood impacts (% of households flooded during the floods that occur every year or two)	Very high > 20% in 82% of the communities	High > 20% in 38% of the communities 10–20% in 20% of the communities, and 5–10% in 30% of the communities.	High > 20% in 68% of the communities.	High > 20% in 60% of the communities.	Relatively moderate > 20% in 25% of the communities and 5–10% in 75% of the communities.

significance as well. In some cases, communities that are geographically close do indeed fall in the same cluster, however, we just as often see disparities between geographically close communities. Hence, socioeconomic community characteristics proved to be a much better predictor for clusters compared to geographical positioning. Moving forward, below we summarize the taxonomy of our identified community flood resilience clusters and their key characteristics, which are set out in Table 1.

Cluster 1: Rural communities with high risk and vulnerability, and low capacity

This type of community is mostly rural, with very low financial, natural, physical, and social capital, although with a slightly higher average human capital score due to increased awareness of flood risk and environmental management. Level of poverty is very high and women's education is low. In the majority of communities, more than 50% of the households are living below the national poverty line; the percentage of women who have completed secondary education is below 25% in all the communities. Around 63% of the communities in this cluster report never having influence on decisions that are made at higher levels, while 32% have influence some of the time, and only 5% most of the time. These are also high flood-risk communities: around 30% of these communities typically experience flooding more than once per year, and 55% experience flooding about once per year. In these flooding events, more than 20% of houses are usually flooded in 82% of the communities.

Cluster 2: Urban communities with poor natural and social environments

This community type primarily represents urban communities that possess moderate physical, financial, and human capital, but lack adequate natural and social capital. Compared to cluster 1 communities, this community type is characterized by slightly lower poverty rates and higher women's educational attainment. In most communities, 10–50% of households live below the national poverty line, and more than 25% of women have completed secondary education. Around 67% of the communities report that they sometimes have influence on decisions that are made at higher levels, and 7% report that they do most of the time. Still, 25% of the communities have no influence in higher-level decisions. Flood risk is high for this community type, with around 53% of the communities experiencing flooding more than once per year and 24% experiencing flooding about once per year. In these flooding events, more than 20% of houses are usually flooded in 38% of the communities.

Cluster 3: Rural communities with high capacity but low income and poor physical infrastructure

Similar to cluster 1, this community type primarily consists of rural communities with relatively better human and natural capital, but low physical, financial, and social capital. In the majority of these communities, more than 60% of households are living below the national poverty line. However, women's educational attainment and influence on decisions are slightly higher than in cluster 1. Between 10 and 50% of women have completed secondary education in most communities. In regard to decisions made at higher levels, 62% of the communities have influence sometimes, and 11% have influence most of the time; around 27% have no influence. Flood risk is relatively moderate in these communities, with around 41% of communities experiencing flooding more than once per year, and 24% experiencing flooding about once per year. This flooding results in more than 20% of houses usually being flooded in 68% of the communities.

Cluster 4: Less vulnerable rural communities

This community type primarily consists of rural communities that exhibit better capital scores compared to cluster 1 and 3 rural community types. Poverty is less than for cluster 3 but still prevalent, with 20–60% of households living below the national poverty line in most communities. Between 10 and 50% of women in the majority of the communities have completed secondary education. Seventy-six percent of the communities have influence over decisions made at higher levels sometimes, 8% influence decisions most of the time, and only 16% have no influence. Flood risk is moderate in these communities, with 45% of communities experiencing flooding more than once per year and 23% experiencing it about once per year. During floods, more than 20% of houses are usually flooded in 60% of the communities.

Cluster 5: Less vulnerable urban communities

This cluster consists of urban communities with lower poverty rates and higher women's educational attainment. People living below the national poverty line are below 30% in all communities. Similarly, in the majority of communities more than 50% of women have completed secondary education. Around 25% of the communities have influence over decisions made at higher levels sometimes and 13% have influence most of the time. However, 62% of the communities report never having influence on these decisions. Flood risk is quite high in these communities: around 88% of the communities experience flooding more than once per year and the remaining 12% experience it once yearly. During those flood events, only 5–10% of the houses are flooded in around 75% of the communities, and in only 25% of the communities, more than 20% of the houses are usually flooded.

DISCUSSION

The literature has shown that disaster resilience is strongly case and context specific. While accepting these findings, our analysis also empirically shows that various clusters of community resilience can be distinguished using statistical analysis. We identify five types of community clusters with different resilience profiles. This taxonomy supports a nuanced understanding of different community types classified according to settlement type/density, poverty, education, socio-political influence, and flood risk exposure. This result supports the conceptualization of resilience as a "multifunctional" concept, with inherent complexity and dynamics (Wilson 2008).

The clusters defined here are similar to the four community types identified by Laurien et al. (2020) based on the FRMC phase I data. Compared to Laurien et al. (2020), in this study we were able to further disaggregate communities that have similar aggregated levels of resilience but differ in their resilience scores across capitals (their resilience profiles). Specifically, we found that clusters 2 and 3 exhibit similar resilience scores but cluster 2 is characterized by higher physical capital and lower natural and social capitals, while cluster 3 shows lower physical capital and higher natural and social capitals. Our taxonomy indicates the existence of some overall "resilience structures" across diverse sets of dimensions and supports the argument that resilience thinking has to be understood as an integrative approach for dealing with sustainability challenges (Folke 2016). This includes integration between system dynamics and scale (see the work on panarchy by Gunderson and Holling 2002) as well as methodological integration across scientific disciplines, two targets for integration with regard to resilience that are in need of attention.

In this regard, the identified taxonomy of community resilience and its foundation in indicators of community characteristics can provide insights into the multiple functionalities of communities and their development trajectories. Because different clusters have different resilience profiles, or distributions of capitals, we suggest that resilience-enhancing efforts ought to be diverse when enhancing across community types (Hochrainer-Stigler et al. 2021). This insight supports targeting of interventions that meet increasingly urgent needs for bolstering capitals depending on the community type. Caution needs to be exerted as goals and targets, for example with regard to adaptive capacity, have normative connotations, associated ontologies and value systems, which do not always overlap with perspectives held by stakeholders, risk bearers, or policy makers.

Our analysis shows that although resilience measurement is a time-consuming and resource intensive task, socioeconomic characteristics can be more easily gathered, therefore making it possible to provide indications of which cluster a community is likely to belong to. As a consequence, our analysis has the potential to cultivate a foundation for shared understanding of flood resilience, thus providing an analytical platform for relationship building with and between community members, local and national governments, development practice, and international policy. Bringing this insight together with FRMC user interviews, we argue that the FRMC approach thus can foster systems thinking, which is fundamental to resilience and which supports informed decision making (albeit with important caveats). Such a systems-thinking approach could also assist in developing a deeper understanding of what it means to engage in flood resilience-enhancing processes and programming by exploring gaps and strengths across the range of sources of resilience and recognizing the wide range of sectors involved in resilience. Such systems-based analysis can further assist in the identification of both co-benefits and maladaptive consequences of various activities on the individual as well as at system level.

CONCLUSION

We presented validation and a resilience taxonomy analysis using the FRMC Next Gen baseline data set, which includes 292 communities from 20 countries across the world and provided insights into the measurement and characterization of community flood resilience. Using a PCA and Cronbach Alpha analysis for validation, we concluded that the FRMC Next Gen approach of measuring 44 sources of community flood resilience and aggregating those to financial, human, natural, physical, and social capitals leads to valid and reliable results. Each capital can be disaggregated into two to three components representing different aspects of the capitals. We presented an empirically based taxonomy related to flood risk and community socioeconomic characteristics, where, using multinomial and random forest methods, we identified five distinct community clusters based on their capital score profiles. This taxonomy provides a way to group communities by similarities and differences between absolute and distributional resilience levels and socioeconomic community characteristics. For programs lacking a foundational quantitative resilience baseline analysis our results may be a useful additional metric for informing and monitoring resilience programming.

Finally, we emphasize that our approach focuses on broad-based characteristics and does not circumvent the need for determining appropriate resilience-enhancing decisions at the community level with deep community and stakeholder engagement, which will always be case specific. In addition, communities are always embedded within larger systems, and there are different advantages as well as limitations at each scale for enhancing resilience. Yet, as we suggest, integrating generic insights associated with different community types with case-specific contextualization may help to support community-level engagement, programming, and intervention implementation.

Acknowledgments:

This work was funded by the Z Zurich Foundation, Zurich, Switzerland. We want to thank Karen MacClune, Michael Szoenyi, as well as Seona McLoughlin for helpful comments and suggestions in making the manuscript.

Data Availability:

The data and code that support the findings of this study are available on request from the corresponding author, S.H-S. None of the data and code are publicly available because they are proprietary. No ethical approval for this research study was conducted as questions and grading are based on stakeholder input.

LITERATURE CITED

Alexander, D. E. 2013. Resilience and disaster risk reduction: an etymological journey. Natural Hazards and Earth System Sciences 13:2707-2716. https://doi.org/10.5194/nhess-13-2707-2013

Asadzadeh, A., T. Kötter, P. Salehi, and J. Birkmann. 2017. Operationalizing a concept: the systematic review of composite indicator building for measuring community disaster resilience. International Journal of Disaster Risk Reduction 25:147-162. https://doi.org/10.1016/j.ijdrr.2017.09.015

Bakkensen, L. A., C. Fox-Lent, L. K. Read, and I. Linkov. 2017. Validating resilience and vulnerability indices in the context of natural disasters. Risk Analysis 37:982-1004. https://doi.org/10.1111/risa.12677

Béné, C., A. Newsham, M. Davies, M. Ulrichs, and R. Godfrey-Wood. 2014. Resilience, poverty and development. Journal of International Development 26(5):598-623. https://doi.org/10.1002/jid.2992

Cai, H., N. S. Lam, Y. Qiang, L. Zou, R. M. Correll, and V. Mihunov. 2018. A synthesis of disaster resilience measurement methods and indices. International Journal of Disaster Risk Reduction 31:844-855. https://doi.org/10.1016/j.ijdrr.2018.07.015

Camacho, C., P. Bower, R. T. Webb, and L. Munford. 2023. Measurement of community resilience using the Baseline Resilience Indicator for Communities (BRIC) framework: a systematic review. International Journal of Disaster Risk Reduction 95:103870. https://doi.org/10.1016/j.ijdrr.2023.103870

Chuang, W. C., A. Garmestani, T. N. Eason, T. L. Spanbauer, H. B. Fried-Petersen, C. P. Roberts, S. M. Sundstrom, J. L. Burnett, D. G. Angeler, B. C. Chaffin, L. Gunderson, D. Twidwell, and C. R. Allen. 2018. Enhancing quantitative approaches for assessing community resilience. Journal of Environmental Management 213:353-362. https://doi.org/10.1016/j.jenvman.2018.01.083

Clement, S., J. Jozaei, M. Mitchell, C. R. Allen, and A. S. Garmestani. 2024. How resilience is framed matters for governance of coastal social-ecological systems. Environmental Policy and Governance 34(1):65-76. https://doi.org/10.1002/eet.2056

Cutter, S. L. 2021. Urban risks and resilience. Pages 197-211 in W. Shi, M. F. Goodchild, M. Batty, M.-P. Kwan, and A. Zhang, editors. Urban informatics. Springer Singapore, Singapore. https://doi.org/10.1007/978-981-15-8983-6_13

Cutter, S. L. 2024. The origin and diffusion of the social vulnerability index (SoVI). International Journal of Disaster Risk Reduction 109:104576. https://doi.org/10.1016/j.ijdrr.2024.104576

Department for International Development (DFID). 1999. Sustainable livelihoods guidance sheets. DFID, London, UK.

Faulkner, L., K. Brown, and T. Quinn. 2018. Analyzing community resilience as an emergent property of dynamic social-ecological systems. Ecology and Society 23(1):24. https://doi.org/10.5751/ES-09784-230124

Florin, M. V., and I. Linkov, editors. 2016. IRGC resource guide on resilience. EPFL International Risk Governance Center (IRGC), Lausanne, Switzerland.

Folke, C. 2016. Resilience (republished). Ecology and Society 21 (4):44. https://doi.org/10.5751/ES-09088-210444

Gunderson, L. 2010. Ecological and human community resilience in response to natural disasters. Ecology and Society 15(2):18. https://doi.org/10.5751/ES-03381-150218

Gunderson, L. H., and C. S. Holling. 2002. Panarchy: understanding transformations in human and natural systems. Island, Washington, D.C., USA.

Hahn, T., and B. Nykvist. 2017. Are adaptations self-organized, autonomous, and harmonious? Assessing the social-ecological resilience literature. Ecology and Society 22(1):12. https://doi.org/10.5751/ES-09026-220112

Hochrainer-Stigler, S., C. Colon, G. Boza, S. Poledna, E. Rovenskaya, and U. Dieckmann. 2020. Enhancing resilience of systems to individual and systemic risk: steps toward an integrative framework. International Journal of Disaster Risk Reduction 51:101868. https://doi.org/10.1016/j.ijdrr.2020.101868

Hochrainer-Stigler, S., S. Velev, F. Laurien, K. Campbell, J. Czajkowski, A. Keating, and R. Mechler. 2021. Differences in the dynamics of community disaster resilience across the globe. Scientific Reports 11:17625. https://doi.org/10.1038/s41598-021-96763-0

Intergovernmental Panel on Climate Change (IPCC). 2023. Climate change 2023: synthesis report. Summary for policymakers. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Core Writing Team, H. Lee and J. Romero, editors. IPCC, Geneva, Switzerland. https://www.ipcc.ch/report/ar6/syr/

Jones, L., A., M. A. Constas, N. Matthews, and S. Verkaart. 2021. Advancing resilience measurement. Nature Sustainability 4:288-289. https://doi.org/10.1038/s41893-020-00642-x

Keating, A. 2020. Measuring and building community disaster resilience: essential for achieving Sendai. Pages 169-190 in M. Yokomatsu and S. Hochrainer-Stigler, editors. Disaster risk reduction and resilience. Springer Singapore, Singapore. https://doi.org/10.1007/978-981-15-4320-3_9

Keating, A., K. Campbell, M. Szoenyi, C. McQuistan, D. Nash, and M. Burer. 2017. Development and testing of a community flood resilience measurement tool. Natural Hazards and Earth System Sciences 17:77-101. https://doi.org/10.5194/nhess-17-77-2017

Keating, A., R. Mechler, J. Mochizuki, H. Kunreuther, J. Bayer, S. Hanger, I. McCallum, L. See, K. Williges, S. Hochrainer-Stigler, and C. Egan. 2014. Operationalizing resilience against natural disaster risk: opportunities, barriers, and a way forward. Zurich Flood Resilience Alliance, Zurich, Switzerland.

Laurien, F., S. Hochrainer-Stigler, A. Keating, K. Campbell, R. Mechler, and J. Czajkowski. 2020. A typology of community flood resilience. Regional Environmental Change 20:24. https://doi.org/10.1007/s10113-020-01593-x

Linkov, I., and B. D. Trump. 2019. The science and practice of resilience. Springer International, Cham, Switzerland. https://doi.org/10.1007/978-3-030-04565-4

Schipper, E. L. F., and L. Langston. 2015. A comparative overview of resilience measurement frameworks: analyzing indicators and approaches. Overseas Development Institute, London, UK.

Tan, S. B. 2021. Measuring community resilience: a critical analysis of a policy-oriented indicator tool. Environmental and Sustainability Indicators 12:100142. https://doi.org/10.1016/j.indic.2021.100142

United Nations (UN). 2015. The Sustainable Development Goals. UN, New York, New York, USA. https://sdgs.un.org/

United Nations Framework Convention on Climate Change (UNFCCC). 2015. Adoption of the Paris Agreement. Report No. FCCC/CP/2015/L.9/Rev.1. UNFCCC, New York, New York, USA. https://unfccc.int/documents/9064

United Nations Office for Disaster Risk Reduction (UNDRR). 2015. Sendai Framework for Disaster Risk Reduction 2015-2030. UNDRR, Geneva, Switzerland. https://www.undrr.org/publication/sendai-framework-disaster-risk-reduction-2015-2030

Wilson, G. A. 2008. From 'weak' to 'strong' multifunctionality: conceptualising farm-level multifunctional transitional pathways. Journal of Rural Studies 24:67-383. https://doi.org/10.1016/j.jrurstud.2007.12.010

World Bank. 2021. Financial risk and opportunities to build resilience in Europe. World Bank, Washington, D.C., USA. https://hdl.handle.net/10986/35685

Appendix 1: Phase 1 and 2 of the FRMC Resilience Approach

The Zurich Flood Resilience Alliance (the Alliance), formed in 2013, developed the Flood Resilience Measurement for Communities (FRMC) approach. The Alliance was formed as a multi-sectoral partnership led by the Z Zurich Foundation – the philanthropic foundation of Zurich Insurance - with research institutions and international non-government and humanitarian organisations to "advance knowledge, develop robust expertise and design strategies that can be implemented to help communities in developed and developing countries strengthen their resilience to flood risk" (Keating et al. 2014). One of the key initiatives of the Alliance has been the FRMC, which aims to address the challenge of resilience measurement through a conceptual framework, measurement tool, and process designed to support the holistic measurement of flood resilience at the community-scale by local practitioners across different locations and contexts. Notably, the FRMC is not intended to be used for measurement's sake, but to support the selection and implementation of resilience-building actions in close collaboration with communities themselves.

With its focus on working within the most flood vulnerable communities across the globe, the Alliance seeks to connect disaster resilience with community development by defining community flood resilience as "the ability of a community to pursue its development and growth objectives while managing flood risk over time in a mutually reinforcing way". This definition emphasizes that the goal of disaster resilience is long-term well-being, transforming systems where needed to prevent or adapt to the increase in disaster risk. Our analysis in this paper builds on the phase 1 analysis, which included the validation of the first version of the FRMC as well as the analysis of resilience dynamics over time (Keating 2020; Laurien et al. 2020; Hochrainer-Stigler et al. 2021). During phase 1, we found that one of the key advantages of the FRMC is the standardized approach which enables an analysis across communities and their resilience profiles (Hochrainer-Stigler et al. 2021). Another advantage is how the FRMC collects, structures, and semi-quantifies empirical data gathered on the ground, resulting in millions of data points from across different communities around the globe (Laurien et al. 2020). The FRMC was further developed in 2017, including a significant revision of the sources of resilience based on learning from phase 1. It is now being utilised in a new set of communities, including in additional countries.

References:

Keating, A., Mechler, R., Mochizuki, J., Kunreuther, H., Bayer, J., Hanger, S., McCallum, I., See, L., Williges, K., Hochrainer-Stigler, S. and Egan, C., 2014. Operationalizing resilience against natural disaster risk: opportunities, barriers, and a way forward. Zurich Flood Resilience Alliance

Keating, A., 2020. Measuring and Building Community Disaster Resilience: Essential for Achieving Sendai, in: Yokomatsu, M., Hochrainer-Stigler, S. (Eds.), Disaster Risk Reduction and Resilience, Disaster and Risk Research: GADRI Book Series. Springer Singapore, Singapore, pp. 169–190. https://doi. org/10. 1007/978-981-15-4320-3_9

Laurien, F., Hochrainer-Stigler, S., Keating, A., Campbell, K., Mechler, R., Czajkowski, J., 2020. A typology of community flood resilience. Reg Environ Change 20, 24. https://doi. org/10. 1007/s10113-020-01593-x

Hochrainer-Stigler, S., Velev, S., Laurien, F., Campbell, K., Czajkowski, J., Keating, A., Mechler, R., 2021. Differences in the dynamics of community disaster resilience across the globe. Scientific reports 11, 17625.

Appendix 2: Resilience Indicators

Source Code	Source of Resilience Name	Theme	Capital	4Rs	DRM Cycle
F01	Household asset recovery	Assets	Financial	Redundancy	Recovery
F02	Community disaster fund	Governance	Financial	Resourcefulness	Recovery
F03	Business continuity	Livelihoods	Financial	Rapidity	Preparedness
F04	Household income continuity strategy	Livelihoods	Financial	Redundancy	Preparedness
F05	Risk reduction investments	Assets	Financial	Robustness	Corrective Risk Reduction
F06	Disaster response budget	Governance	Financial	Rapidity	Response
F07	Conservation budget	Natural Environment	Financial	Robustness	Prospective Risk Reduction
H01	Evacuation and safety knowledge	Life and Health	Human	Robustness	Preparedness
H02	First aid knowledge	Life and Health	Human	Robustness	Preparedness
H03	Education commitment during floods	Livelihoods	Human	Resourcefulness	Prospective Risk Reduction
H04	Flood exposure awareness	Assets	Human	Resourcefulness	Corrective Risk Reduction
H05	Asset protection knowledge	Assets	Human	Robustness	Corrective Risk Reduction
H06	Future flood risk awareness	Assets	Human	Robustness	Prospective Risk Reduction
H07	Water and sanitation awareness	Life and Health	Human	Robustness	Response
H08	Environmental management awareness	Natural Environment	Human	Resourcefulness	Prospective Risk Reduction
H09	Governance awareness	Social Norms	Human	Resourcefulness	Corrective Risk Reduction
N01	Natural capital condition	Natural Environment	Natural	Redundancy	Prospective Risk Reduction
N02	Priority natural units	Natural Environment	Natural	Robustness	Prospective Risk Reduction
N03	Priority managed units	Natural Environment	Natural	Robustness	Corrective Risk Reduction
N04	Natural resource conservation	Governance	Natural	Resourcefulness	Prospective Risk Reduction
N05	Natural habitat restoration	Governance	Natural	Resourcefulness	Corrective Risk Reduction
P01	Flood healthcare access	Life and Health	Physical	Robustness	Response
P02	Early Warning Systems (EWS)	Life and Health	Physical	Robustness	Preparedness
P03	Flood emergency infrastructure	Life and Health	Physical	Resourcefulness	Preparedness
P04	Provision of education	Livelihoods	Physical	Robustness	Recovery

P05	Household flood protection	Assets	Physical	Robustness	Corrective Risk Reduction
P06	Large scale flood protection	Assets	Physical	Robustness	Corrective Risk Reduction
P07	Transportation interruption	Lifelines	Physical	Redundancy	Response
P08	Communication interruption	Lifelines	Physical	Rapidity	Response
P09	Flood emergency food supply	Lifelines	Physical	Robustness	Response
P10	Flood safe water	Lifelines	Physical	Robustness	Response
P11	Flood waste contamination	Lifelines	Physical	Robustness	Response
P12	Flood energy supply	Lifelines	Physical	Redundancy	Recovery
S01	Community participation in flood related activities	Life and Health	Social	Resourcefulness	Preparedness
S02	External flood response and recovery services	Life and Health	Social	Resourcefulness	Preparedness
S03	Community safety	Life and Health	Social	Robustness	Recovery
S04	Community disaster risk management planning	Governance	Social	Rapidity	Prospective Risk Reduction
S05	Community structures for mutual assistance	Social Norms	Social	Resourcefulness	Response
S06	Community representative bodies	Governance	Social	Resourcefulness	Corrective Risk Reduction
S07	Social inclusiveness	Social Norms	Social	Resourcefulness	Corrective Risk Reduction
S08	Local leadership	Governance	Social	Resourcefulness	Prospective Risk Reduction
S09	Inter-community flood coordination	Social Norms	Social	Resourcefulness	Preparedness
S10	Integrated flood management planning	Governance	Social	Resourcefulness	Corrective Risk Reduction
S11	National forecasting policy & plan	Governance	Social	Resourcefulness	Preparedness

Appendix 3: Data Gathering Process and Timesteps Involved

As resilience is influenced by a diverse range of community and other-level assets and capacities, collecting the data to capture them holistically them can be challenging. The approach taken in the FRMC was co-developed by community development experts, researchers, and experienced local practioners to address these challenges with a practical yet theoretically robust framework and tool. In application, incorporating community perspectives is vital to understanding community resilience, but it requires considerable time and resources to collect community data and engage in participatory methods that capture the varying perceptions and experiences of different community members and key stakeholders, including vulnerable and marginalized groups. As a consequence, practitioners using the FRMC spend considerable time socializing the project within the community and with local authorities to identify key community and stakeholder groups, data sources, and to build acceptability and relevance even before the data collection begins. Further, they involve local community members in validating results and prioritizing interventions. The process of asking community questions and closely engaging the community during data collection not only helps ensure results reflect community perceptions but also leads to learning by the community about flood resilience and actions they can take to strengthen their resilience.

The FRMC is applied at the beginning of a community resilience project in what is termed the T0 or 'baseline' study (Figure 1, bottom, main document). It then informs the selection and design of resilience-strenthening initiatives. 1-3 years later, the FRMC is applied again in a T1 or 'endline' study; results from the endline can then be compared to baseline results to track changes over time in the community. Either T0 alone or the package of T0-initiatives-T1 as well as post-event data can be shared with decision-makers to advocate for scaling of activities, and policy and/or investment changes. At the time of writing, Alliance teams are finalising their endline studies. Thus the focus of this paper is on the baseline analysis, which is essential for determining community similarities as well as differences in regards to baseline resilience levels.

Appendix 4: Data Summary

In total, for this analysis we utilized more than 13,000 grades for the sources of resilience, the grading of which was based on more than 24,000 household surveys, focus group discussions, and key informant interviews in 292 communities: a total of 7.6 million data points. This data is stored in a relational database that adheres to Google's standards of data management. This relational structure allows for efficient organization and retrieval of information, enabling faster and more effective data processing. By following Google's guidelines, we also ensure that our data storage system meets the current industry standards for reliability, scalability, and performance as well as ease of sharing between different users. Furthermore, it allows easy conversion between different formats, which may be required in the future, from analysis, spatial mapping, and encryption to using it for cloud computing or embedding it in an online application including dashboards (see also Laurien et al. 2020 and Hochrainer-Stigler et al. 2021).

References:

Laurien, F., Hochrainer-Stigler, S., Keating, A., Campbell, K., Mechler, R., Czajkowski, J., 2020. A typology of community flood resilience. Reg Environ Change 20, 24. https://doi. org/10. 1007/s10113-020-01593-x

Hochrainer-Stigler, S., Velev, S., Laurien, F., Campbell, K., Czajkowski, J., Keating, A., Mechler, R., 2021. Differences in the dynamics of community disaster resilience across the globe. Scientific reports 11, 17625.

Appendix 5: Validity and Reliability tests, Cluster Analysis and Random Forest

Internal consistency and reliability test: We tested the internal consistency and reliability via the aggregation of the 44 sources of resilience according to the five capitals (5Cs) in the FRMC framework. Cronbach's alpha (C-alpha) is the most commonly used statistical measure in surveys to assess how closely related a set of indicators are as a group and how well they measure a single latent construct (Nardo et al. 2005). We also used the C-alpha coefficients to test the validity of using respective sources of resilience to measure 5Cs in the FRMC framework.

Dimensionality reduction and sub-group analysis: After the internal consistency and reliability test, we conducted a Principal Component Analysis (PCA). PCA is a statistical method to summarize a large set of variables into a smaller number of representative variables or components that collectively explain as much of the original variance as possible (Nardo et al. 2005; James et al. 2013). Here we used PCA to i) check if the 44 sources of resilience in the FRMC Next Gen framework could be represented by a smaller number of representative components, and ii) test the consistency of the FRMC Next Gen measures of 5Cs with the identified components. We applied one-component PCA as well as PCA using the Kaiser criterion (Eigenvalue > 1) to identify the number of components needed and applied a varimax rotation to enhance the interpretation of the component themes. The PCA was conducted at the capital scale as well as for all 44 sources of resilience.

Cluster analysis: We applied a cluster analysis technique to classify the communities with similar resilience profiles. Cluster analysis is a method to classify objects, in this case communities, into homogenous subgroups based on the similarity and dissimilarities between the observations (Nardo et al. 2005; James et al. 2023). Here, we used the community flood resilience five capitals (5Cs) scores to identify the underlying clusters in the communities in the dataset. Among various clustering approaches, we applied hierarchical clustering in this study. This is a bottom-up or agglomerative clustering approach suitable for the exploratory analysis where the number of underlying clusters is unknown (James et al. 2023). Each observation (community) is, at the beginning, treated as its own cluster in this method. The clustering algorithm then fuses the two clusters that are least dissimilar (or most similar) to each other to form a larger cluster and continues this fusion process until all of the observations come under a single cluster forming a dendrogram (James et al. 2023). Various distance measures are used to identify the most similar pair of clusters. Among several cluster agglomeration methods, such as single linkage, complete linkage, and Ward's methods, we tested and selected the complete linkage method in this analysis. The complete linkage method maximizes the inter-cluster dissimilarity and is better suited when the observations form natural clusters (Nardo et al. 2005; James et al. 2013, 2023). Finally, we also used dendrograms for determining a suitable and interpretable number of clusters.

Cluster validation and interpretation of their characteristics: Following the cluster analysis, we applied a multinomial regression analysis and random forest model to test the relationship between the clusters (based on 5C resilience profiles) with a set of community characteristics. Here, we used data collected on community flood risk and socioeconomic characteristics as possible predictors of the cluster type that a given community might fall into. Following the regression model building process (using the AIC for comparison) and expert judgment, we identified ten indicators as the appropriate set of community cluster predictors:

i. Community type (rural, peri-urban, or urban).
ii. Female education (% of women completing secondary education).

iii. Female headed households (% of households headed by a woman).
iv. Community influence on decisions that are made at higher levels.
v. Poverty (% of households living below the national poverty line).
vi. Outside labor (% of community members who regularly leave the community for a month or more to work).
vii. Outside income (% of households receive income from family members who live and work outside the community for part or all of the year).
viii. Minority population (% of the minority groups in the community).
ix. Flood frequency experienced by the community.
x. Flood impacts (% of households flooded during the floods that occur every year or two).

As indicated in the paper, the data was split into 70% model training and 30% test datasets using stratified random sampling to test the model's validity and performance. Confusion matrix and statistics (sensitivity, specificity, and balanced accuracy) were used to test the accuracy of the cluster prediction by the models. Afterwards, we used the most significant model and socioeconomic indicators to explain the cluster characteristics.

References:

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., Giovannini, E. 2005. Handbook on constructing composite indicators: methodology and user guide.

James, G., Witten D., Hastie T., Tibshirani R. 2013. An introduction to statistical learning: with applications in R. Spinger.

James, G., Witten, D., Hastie, T., Tibshirani, R.,Taylor, J. 2023. An introduction to statistical learning: With applications in python. Springer Nature.

Appendix 6: Validity and Reliability Analysis, Principal Components Results

Face validity looks at whether the FRMC aligns with practitioners' and communities' understanding about the factors that contribute to and build community flood resilience. We investigated this by conducting semi-structured qualitative interviews with practitioners about the FRMC framework and sources of resilience. This research found that practitioners have a high degree of agreement with the framing and content of the FRMC. Alliance practitioners confirmed that, in their expert opinion, all 44 of the sources of resilience included in the FRMC are indeed important for strengthening community flood resilience. Furthermore, practitioners did not identify any major gaps in the sources of resilience, i.e. sources that they believed were missing. Practitioners stated that the various lenses used in the FRMC framework – in particular the five capitals and disaster risk management cycle – were particularly useful for informing programming. Practitioners using the FRMC reported widespread acceptance and engagement by the communities they are working with, which further supports the finding that the FRMC makes sense to people on the ground.

Reliability considers whether the FRMC Next Gen constitutes a standardized measurement approach, i.e. that the same thing is being measured across communities, grading teams, and time. For raw data reliability we conducted an automatic reliability evaluation of each raw data observation. Overall, we found that the FRMC data is very reliable and consistent. Results show that the internal consistency and reliability of the 5Cs is near or above the commonly used acceptable threshold (C-alpha >= 0.7) for all capitals except natural capital (see Table 1). In the case of natural capital, the C-alpha coefficient is slightly below the threshold at 0.69, however, the reliability increases to an acceptable level if one of the sources (N04: natural resource conservation or N05: natural habitat restoration) is dropped. Based on stakeholder discussions, we concluded that this marginally low C-alpha in natural capital is mainly due to the existence of sub-groups within the sources, which we discuss within the PCA below. Stakeholder discussions also highlighted that these two sources are valuable in capturing natural capital's conservation and management aspects. Overall, we conclude that the FRMC sources of resilience consistently measure their respective capitals, and their aggregation to the five capitals is valid and reliable.

S. No.	**Capital**	**C-alpha coefficient**	**No. of sources**
1.	Financial	0.78	7
2.	Human	0.72	9
3.	Natural	0.69	5
4.	Physical	0.83	12
5.	Social	0.85	11

Table 1: Internal consistency and reliability test results using Cronbach's alpha for 5Cs of FRMC framework.

When conducting the PCA we first explored whether any of the sources are highly correlated with other sources such that measuring both might be considered superfluous. We also analyzed whether the sources are loading on the right capital levels (i.e., are especially relevant in regard to the specific capital it was designed to measure). A one-component PCA shows that a single component could explain between 31% to 45% of the total variance explained by the original set of sources assigned for the FRMC capitals. Furthermore, PCA using Kaiser criterion (Eigenvalue > 1) identified 2 to 3 components in each capital cumulatively, explaining 55% to 67% of the total variance (Table 2). The variance explained by the one-component PCA and PCA using the Kaiser criterion is considered good for a complex construct like community flood resilience capitals.

We furthermore identified component themes in each capital based on the PCA with a varimax rotation, as shown in Table 2. We found that the sources of resilience in financial capital can be grouped into two components representing public and private financial capacity. Public financial capacity reflects the status of community disaster funds, risk reduction investments, disaster response budgets, and conservation budgets in the communities; private financial capacity captures the community's capacity for household asset recovery and business and household income continuity after the flood. Human capital showed three components representing knowledge and awareness of first aid, and water and sanitation (WASH); flood exposure, safety, and evacuation; and environmental management and governance. Similarly, the two components identified in natural capital are physical status and services of natural resources, and management efforts through policy and plans. Physical capital comprises three components covering basic supplies (such as food, safe water, sanitation, and energy) during flooding; utilities infrastructure and facilities (such as health, transportation, communication, and education) functioning during and after the flooding; and early warning and emergency response infrastructure. Finally, social capital also showed three components: community structure which reflects participation, representation, inclusiveness, local leadership, solidarity, and mutual assistance within the community; external flood response and recovery services; and national and community-level DRM and integrated flood management policy and plans.

Capital	Var. 1-component (%)	No. of comp. (eigv. >1)	Cum. var. explained (%)	Component themes after varimax rotation
Financial	43	2	59	Public financial capacity
				Private financial capacity
Human	31	3	56	First aid and WASH knowledge and awareness
				Flood exposure, safety, and evacuation knowledge, and awareness
				Environment management and governance knowledge and awareness
Natural	45	2	67	Physical status and services of natural resources
				Management efforts through policy and plans
Physical	36	3	55	Basic supplies (food, safe water, sanitation, and energy) during flooding
				Utility infrastructure and facilities (health, transportation, communication, and education) function during and after the flooding
				Early warning and emergency response infrastructure (public and private)
Social	40	3	63	Community structure (participation, representation, inclusiveness, local leadership, solidarity, mutual assistance)
				External flood response and recovery service and feeling of safety
				National and community-level DRM and integrated flood management policy and plan
All	24	11	63	Very similar to above

Table 2: Results of Principal Component Analysis (PCA) for five capitals (5Cs) and all 44 sources of resilience in FRMC framework.

PCA using all 44 sources of resilience together also showed results consistent with the capital level PCA. One-component PCA explains 24% of the total variance, and PCA using Kaiser criterion identified 11 components with 63% cumulative variance explained. The themes of the 11 components are very similar to the 13 components identified and discussed by the capital-level PCA (Table 2). Summarizing these results, we conclude that the FRMC capitals are consistent with the components identified from the PCA and the results further validate the FRMC approach of aggregating the 44 sources of resilience into five capitals as well as that the underlying latent construct is measured through the FRMC tool.

Appendix 7: Correlations between Capitals

For cluster 1 it is important to note that relative to the other clusters, the variance between capitals in this cluster is moderate ($\sigma^2 = 95.96$). The correlation between the capitals is mostly positive, with the strongest positive correlation between human and social capitals. Financial and natural capital show the strongest negative correlation (see Table 1 for details).

Between capitals in cluster 2, variance is low ($\sigma^2 = 65.05$). The capitals are mostly negatively correlated, with the strongest negative correlation between financial and human capitals. Physical and social capitals show the strongest positive correlation (Table 1, second row).

Between capitals, variance is low ($\sigma^2 = 63.16$) in cluster 3 as well. In cluster 3 the capitals are both negatively as well as positively correlated with each other in this cluster. The strongest negative correlation is observed between financial and social capital, whereas the strongest positive correlation is between natural and physical capital (Table 1, third row).

	Correlation										σ^2
	F-H	**F-N**	**F-P**	**F-S**	**H-N**	**H-P**	**H-S**	**N-P**	**N-S**	**P-S**	
Cl. 1	0.15	**-0.42*****	0.21**	0.15	0.05	0.28***	**0.50*****	-0.20*	0.13	0.28***	95
Cl. 2	**-0.30****	-0.14	0.03	-0.03	-0.06	-0.19	-0.05	-0.09	-0.03	**0.47****	65
Cl. 3	-0.04	-0.34**	-0.07	**-0.45*****	0.29*	-0.05	0.17	**0.32***	-0.03	0.08	63
Cl. 4	0.33***	0.26**	**0.49*****	0.23**	0.16	0.42***	0.41***	0.17*	0.13	0.14	125
Cl. 5	**0.60**	0.15	0.42	0.02	0.51	0.37	-0.01	**0.60**	-0.31	**-0.53**	157

Table 1: Results of within cluster variance and bivariate correlation analysis. *** *$p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

In cluster 4 the variance between capitals is high ($\sigma^2 = 125.95$), and all capitals are positively correlated with each other in this cluster. Financial and physical capitals are strongest positively correlated (Table 1, fourth row).

Finally, within cluster 5 the variance of capitals is high ($\sigma^2 = 157.30$). The capitals are mostly positively correlated, but the correlation is not statistically significant (Table 1, last row).

Appendix 8: Multinomial Logistic and Random Forest Model Results

The results of this analysis (Table 1) show that there is a strong relationship between community characteristics and flood resilience clusters. The accuracy of the resilience cluster prediction by community flood resilience and socioeconomic characteristics is high in multinomial logistic regression and random forest models. The overall accuracy of the multinomial logistic regression model is 63%, with balanced accuracy between 65% to 89% for all clusters (see Table 1). The overall accuracy is even higher in the random forest model at 72%, and cluster-wise balanced accuracy is between 54% to 89%. This indicates that, for our current global sample of communities, utilizing only a small subset of community flood resilience sources and socioeconomic indicators, it would be possible to identify the community flood resilience cluster it belongs too.

Reference / Prediction	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Cluster 1	28	4	2	3	0
Cluster 2	0	6	0	3	1
Cluster 3	0	0	5	3	0
Cluster 4	2	6	3	15	0
Cluster 5	0	1	1	3	1
Statistics by cluster					
Sensitivity	0.93	0.35	0.45	0.56	0.50
Specificity	0.84	0.94	0.96	0.82	0.94
Balanced Accuracy	0.89	0.65	0.71	0.69	0.72
Overall model accuracy	63 % (95% CI: 52% - 73%)				

Table 1: Confusion matrix showing accuracy of cluster prediction by multinomial logistic regression model (70% training and 30% test data).