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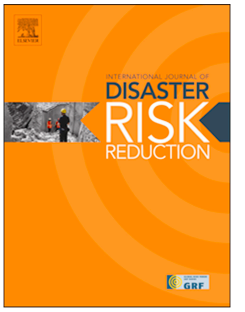

First insights from the Flood Resilience Measurement Tool: A large-scale community flood resilience analysis

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Title

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Abstract:
A major gap in understanding community flood resilience is a lack of an empirically validated measure of it. To fill this gap, the Zurich Flood Resilience Alliance developed an approach to test and validate a measure of community flood resilience. The approach holistically measures a set of sources of community flood resilience and, when floods occur, it also measures resilient outcomes (level of loss and recovery time). The data is collected and assessed via a web and mobile based measurement tool. Here we report results from data collected in 118 communities across 9 countries using mixed method data collection approaches. This study represents the first large scale analysis of systemic and replicable flood resilience baseline data. The learnings from the analysis provide insights into sources of community flood resilience as a first step to building an evidence based approach to building effective flood resilience capacity.

Keywords: Flood Resilience, Community, Flood Resilience Baselines, Measuring and Evaluation

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1 Introduction

Risks arising from floods natural events are increasing worldwide driven by growing populations, increasing development, which puts higher values of property at risk (Meyer et al., 2013; UNISDR, 2011), and changing climate patterns (IPCC, 2012). Thus, there is a growing need to better understand the effectiveness of investments in resilience building (e.g. risk reduction measures) that can help to minimize losses and assure a quick recovery during and after a natural hazard event (such as flooding) (UNISDR, 2015). However, the concept of resilience is inherently complicated for at least two key reasons: (1) it is latent in the sense that it only manifests itself in the case of a risk event (Cutter et al., 2008; Frankenberger et al., 2014; Keating et al., 2016; Schipper and Langston, 2015) and (2) the variables that influence resilience are often a complex set of holistic and interdependent dimensions that are difficult to quantify (Hochrainer-Stigler et al., 2017; Keating et al., 2017). Subsequently, to date, while many theories and frameworks about resilience exist, most of them are difficult to operationalize and/or only apply to specific cases. Furthermore, measuring at the scale of the community level, where latent resilience is often most needed, poses its own difficulties (Twigg, 2009). Thus, there is yet to be an empirically validated measurement framework of resilience (Winderl, 2014). Consequently, policy advice on how to increase resilience on that scale is nearly absent, yet may be the most important for reducing risk in the future (IPCC, 2012).

1.1 Brief Overview of Flood Resilience Measurement Tool

To fill this gap, the Zurich Flood Resilience Alliance (ZFRA) (established in 2013) has developed a holistic framework implemented in a web and mobile based tool for measuring community flood resilience in developing and developed countries[1] (the Flood Resilience Measurement Tool, FRMT). The tool's underlying framework was designed by members of the ZFRA comprising of representatives from the NGO sector, academia, and insurance risk engineering expertise. The approach bridges the resilience measurement gap by developing a comprehensive set of pre-event characteristics across five overarching capitals which are based on the Sustainable Livelihood Framework (DfID, 1999) and comparing them to post-event outcomes. In brief, our approach for measuring community flood resilience is to measure the pre-event characteristics called baseline 'sources of resilience', such as household savings, level of flood risk awareness and whether the community has a flood recovery plan, that contribute to a community's capacity to avoid risk creation, reduce existing risk, prepare for and recover better from a flood event. The FRMT also measures actual or revealed flood resilience in the event of a flood. That is, should a flood event occur, the level of losses and recovery is measured across a holistic set of variables. This measurement process will provide the missing empirical data to allow for large scale, systematic testing over time of the sources of community flood resilience for ultimately achieving resilient outcomes. In this paper we present the tool's baseline results from a large-scale application of the framework and tool across 118 communities (as of January 2018) around the world. To the authors best knowledge, it is the first study which presents results on such a scale across the globe.

The remainder of the paper is organized as follows: we start with a discussion of the resilience literature related to operationalizing and measuring resilience. We then provide the background of the measurement tool, followed by an analysis of the community contexts in which the tool has been tested and how these communities have been affected by floods in the past. Next, we provide further detail on how the baseline tool data has been generated, quantifying the data collection methodologies employed in the 118 communities, as well as the reported confidence in the data generation. We then turn to exploring the graded baseline data that measures the sources of flood resilience and present aggregate level results. Lastly, we provide a preliminary exploration of the drivers of the graded sources of resilience. Importantly we also provide initial insight on how the tool has and can be used within a community resilience decision making process. We conclude with implications and setting out the larger research agenda including the feedback from our partners testing the tool.

[1] For details of the framework and development of the tool see Keating et al., 2017b.

2 Measuring resilience – putting the FRMT in context

The concept of resilience and with it the concept of disaster resilience has evolved from a focus in modelling socio-ecological systems (Holling 1973) to an integrated concept, holistic concept with multiple adoptions in different disciplines including economics (see Berkes and Folke, 1998, Rose 2007, Stockholm Resilience Centre 2007, Folke et. al., 2010), psychology (Welsh, 2013; Berks and Ross, 2013) as well as engineering (Davoudi, 2012). Many resilience definitions have been put forth. We will focus on those that relate most closely with the resilience definition used here. For a more detailed discussion of the evolution of the definitions of disaster resilience we refer to Keating et al. 2014 and Lunavo et al. 2018 as well as the references therein.

The missing link between theory and practice has been highlighted by several other authors in the literature (Mitchell, 2013; Schipper and Langston, 2015; Winderl, 2014). For example, Winderl's (2014) review pointed out that so far "no general measurement framework for disaster resilience has been empirically verified yet" (p. 19). Heinzlef et.al (2019) outline some of the difficulties with operationalizing disaster resilience. Similar to our approach, these authors take the view that resilience is a latent characteristic.

While there is not yet a generalized and validated measure of disaster resilience, there is a growing body of literature that measures disaster resilience in numerous contexts. Measuring resilience is a challenging yet important endeavor. A number of scholars have reviewed the issues and the measurement frameworks and tools available (Cutter et al., 2010; Oddsdóttir et al., 2013; Ostadtaghizadeh et al., 2015; Schipper and Langston, 2015; Winderl, 2014; Wardekker, et.al., 2010).

Our concept of disaster resilience builds on the work of Keating et al (Keating et al., 2016), which outlined a conceptional framework of disaster resilience building on the system interactions between disaster risk, disaster risk management (DRM) and sustainable development (SD). This holistic framework, which will also be used here, has a development-centered disaster resilience approach which shows the positive relations of DRM and SD to promote well-being. More recent work such as Serre and Heinzlef, 2018 and Heinzlef et.al., 2019 also note the importance of the interdependence of systems and network effect and propose a holistic approach to operationalizing resilience.

Furthermore, Keating et al (2017) suggest a definition of disaster resilience which is also applied for this study, resilience is 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, p.80).

For further review of measuring resilience as it relates to this measurement tool, see Keating et al., (Keating et al., 2017).

3 Community Flood Resilience Measurement Background

As we are focused on assessing the actual measurement of the sources of flood resilience, we begin by providing the necessary context concerning the structure and implementation of the flood resilience measurement framework (FRMF).

The FRMF consists of 88 sources of community flood resilience which are based around the holistic Sustainable Livelihoods Framework (DfID, 1999), i.e., the 88 sources are split across human , social, physical, natural, and financial capitals. Sources were identified within each of the 5 capitals (5C) based on literature and expert input. A necessary criteria for a source of resilience was that it needed to provide one (or more) of the 4 properties of a resilient system (4R): Robustness, Redundancy, Resourcefulness, and Rapidity (Bruneau, 2006; Cimellaro et al., 2010). This 5C-4R framework and the 88 sources identified for the beta version of the tool underwent a peer review in a 3-day workshop conducted in July 2015.

This 5C-4R conceptual framework is operationalized via the FRMT - an integrated, web-based and mobile device platform that collects data on the 88 sources of resilience through one or more of five data collection methods selected by the users. The users are trained practitioners working within communities. These trained practitioners are largely international development NGO staff working in developing countries. The five methods of data collection are: household survey, community focus group discussion, key informant interviews, interest group discussion, and third-party data. Usually, it is recommended to choose two or more data collection methods to provide more robust information. Given the selected data collection method the relevant pre-developed questions are then generated by the FRMT for field teams to answer. The FRMT is typically implemented by field teams in a collaborative fashion involving both community stakeholders and NGO partners. The data collected is then used by appointed community and NGO expert assessors to assign a grade from A to D (A being the best and D being the worst) for each of the 88 sources of resilience. Grade results are displayed according to the 5Cs framework as well as other categories (dimensions) to inform a discussion how to identify potential measures for building resilience (4Rs, DRM cycle, themes, context level). For our analysis we focus on the 5 capitals framework as this was the most influential one in designing the tool. In summary, for each of the 88 sources of resilience, the FRMT platform enables: (1) selection of data collection method for each source of resilience (2) assignment of the data collection work to individual field team members, (3) collection of the data stored in a secure and password protected database, (4) expert grading (ranging from A to D) based on the data collected and (5) generation of tables and graphs to help analyze and visualize the grades (see Figure 1 below).

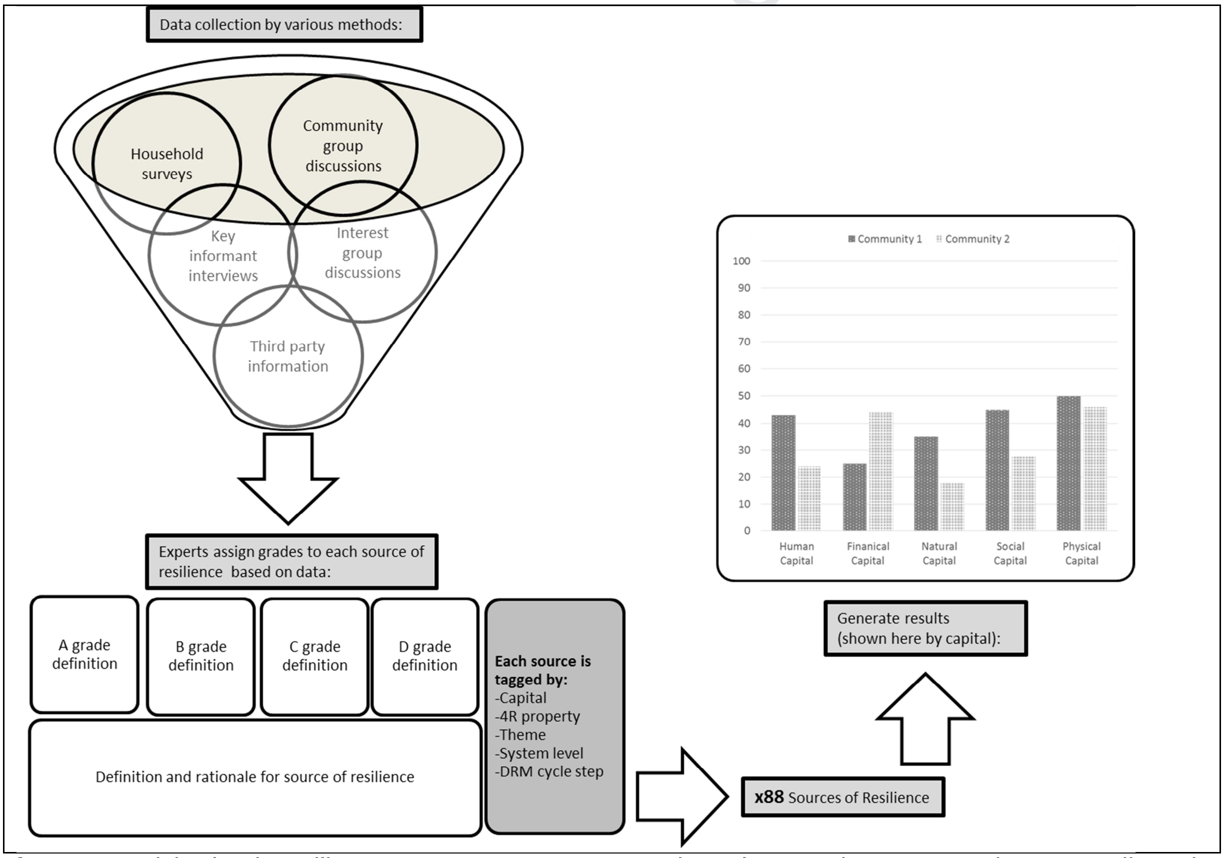


Figure 1: Zurich Flood Resilience Measurement Framework Implementation Process. (Source: Adjusted from Keating et al., 2017b, p. 84 reprinting with permission).

In addition to collecting data to measure the 88 sources of resilience, for each community a set of community context information – or ‘essentials’ data - was collected through household surveys and from community expert consultation. The information collected focuses on past flood experience as well as socio-economic and demographic characteristics. These characteristics can influence a community's flood resilience and hence are important controls to include when assessing the measured sources of resilience. At the time of writing, there are 118 communities in 9 countries (developed and developing) that have applied this tool, and thus provided *baseline studies* comprised of the 88 sources of community flood resilience measurement and community context information data. The analysis presented here is based on the graded data – 118 x 88 sources[2]. A follow-on paper will present the findings from the analysis of the raw data. While the analysis of the baseline data itself cannot validate whether the sources of community flood resilience are effective for achieving actual resilience (i.e., less loss and quicker/better recovery) in the event of a flood, the learnings from the analysis provide new insights into the sources of community flood resilience.

4 Community Context, Flood Experience and Impact

During calendar year 2016, country teams from five NGOs across 12 country programs in 9 countries conducted their initial baseline studies in 118 communities using the FRMT (Table 1 and Appendix A Figure 1). The selection of communities was based on criteria including: need for NGOs to provide support, history of past flood events (high flood risk), location of communities in the broader river basin (and representativeness for their region). In total more than 350,000 households or approximately 1 million people are located in communities reached by the FRMT (Table 1).

Country	***# of communities***	***Estimation of total population***
Afghanistan	12	13 k
Bangladesh	9	39 k
Haiti	4	36 k
Indonesia	40	258 k
Mexico	19	7 k
Nepal	21	19 k
Peru	5	40 k
Timor-Leste	6	4 k
USA	2	640 k
Total	**118**	**1 M**

Table 1: Summary of countries and communities which applied the FRMT

While the criteria (listed above) for selecting communities was similar, the selected 118 communities vary on several key community characteristics that likely impact community flood resilience. For example, the communities ranged in terms of urban (20%), peri-urban (30%) and rural (50%) settings. Looking at Table 1, the most rural community are from Afghanistan, Mexico, Nepal and Timor-Leste on the other side urban communities have been selected in countries such as Indonesia, Peru, USA.

[2] The graded data are based on these baseline studies and includes more than 1.25 million data points

As we show below, the context has implications for the 5Cs. For example, in rural communities there may be greater social capital among community members but they may lack the linking social capital to larger government bodies. Urban settings may have more physical capital than rural settings but may lack the natural capital protections. Income levels likely play an important role in determining community flood resilience and the 118 communities are at different stages of development ranging from middle income to low income as well as two communities in a high-income country. GDP per person in 2016, as one rough measure of development, ranged from 702 USD in Haiti to 6,145 USD in Peru to 57,500 USD in the United States. Mexico and Peru tend to have similar size economies in terms of both GDP per person and square kilometers of land, whereas Afghanistan, Nepal, Haiti and East Timor are less than half the size of Peru in both square kilometers and GDP per person (calculations based on World Bank data[3]). Similarly, not only do overall income levels likely affect community flood resilience but so too would does living in poverty. Poverty rates used for this analysis is linked to the income distribution and is based on available information in the communities. People are poor when they live in the 4th deciles of average national income. According to this definition more than 50 % of people living in the communities are poor (of these 21% live below the national defined poverty line). The percentage of community members who receive remittances from outside the community (both national and international remittances) is 19 %. Despite the large percentages of poor people and those receiving remittances in the country program communities, there is not a clear relationship between poverty and remittances. In theory, remittances can be an important source of income diversification in case of a flood event. Of course, education is often a key driver of income/poverty levels. The percentage of people with a completed high school education in the 118 communities is on average 33%. Communities range from 0 % in Afghanistan to 95 % in USA.

In terms of flood history, over the past 10 years more than 80% of study communities were affected by at least one significant flood event, and catastrophic flood events occurred in more than one third of the communities (34%).[4] However, while all of the 118 communities are exposed to flood risk, the severity and timing of these events varies widely, as would be expected. For example, over the past 10 years, more than 90% of flood events in the five Peruvian communities reported they experienced either no or just ‘normal’ flooding, but the normal flooding tended to be very frequent – i.e., Peruvian communities experience frequent but not often severe flooding. Nepalese communities (across three country programs), experienced less severe flooding compared to the average for the sample, however Nepal was also the only country where some communities reported experiencing catastrophic floods in the last 10 years (see Figure 2 in the Appendix A).

Finally, we importantly found that the floods described above have had significant impacts on the communities’ livelihoods. On average, households in our 118 baseline communities reported that family members have been injured or their property damaged by a flood 2.1 times, or once every 4.7 years. Additionally, when asked about recovering from the worst flood experienced in the community in the last ten years, 54 percent of households took at least a week to recover financially, and 39 % a month or longer. More than 10 % of households in the sample indicate more than a year of financial recovery time[5] (see **Figure 1** in Appendix A).

5 Baseline Data Collection Methodology: A Quantitative Overview

Of the 88 sources of resilience, financial capital includes 17 individual sources of resilience, human and physical capital each have 16 individual sources, natural capital has 6, and social capital has 33 individual

[3] https://data.worldbank.org/ for the indicators GDP per person by country, square kilometers of land by country for the year 2016.

[4] Teams using the FRMC designated each past flood according to the following definitions, based on the flood return period: normal: 1-2-year event; significant: 2-10-year event; exceptional: 10-100-year event; catastrophic: 100+-year event.

[5] Financial recovery refers to returning to pre-event income levels, and paying off damage and repair costs.

sources of resilience[6] (see Appendix B for full list of 88 sources). Again, in each community baseline study, information about each source was collected through at least one, and up to five separate data collection methods - household survey, community focus group discussion, key informant interview, interest group discussion, and third-party data. Measurement tool users were free to choose which and how many of the available data collection methods would be used to collect the data about each community flood resilience source, but questions were fixed across communities depending on which data method was chosen. Based on the feedback from those that implemented the tool, the main considerations for choosing a particular data collection method were available resources (particularly to do household surveys as well as conduct meetings with stakeholder groups or key informants), data availability and perceived data quality. We are interested in understanding how many of the data collection methods were employed, which type were the most utilized, and how this varied by capital.

Firstly, we find that on average, each community applied 1.7 data collection methods per any one source but this varies by sources and capital. For example, Figure 2 shows that the flood resilience sources assigned to financial and natural capital were most likely to utilize only 1 data collection method as 57 and 81 % of the total financial and natural capital sources respectively utilized only 1 data collection method in each of the 118 communities. In contrast, more than 50 % of the total flood resilience sources assigned to human, physical, and social capital utilized more than one data collection method across the 118 communities. However, across all 5Cs at least 89 % of all the sources of resilience implemented 2 or less data collection methods. See Appendix A Table 3 for list of individual sources with the most often utilized data collection methods. For any source using all 5 data collection methods, sources assigned to human and physical capital were the most likely to do so.

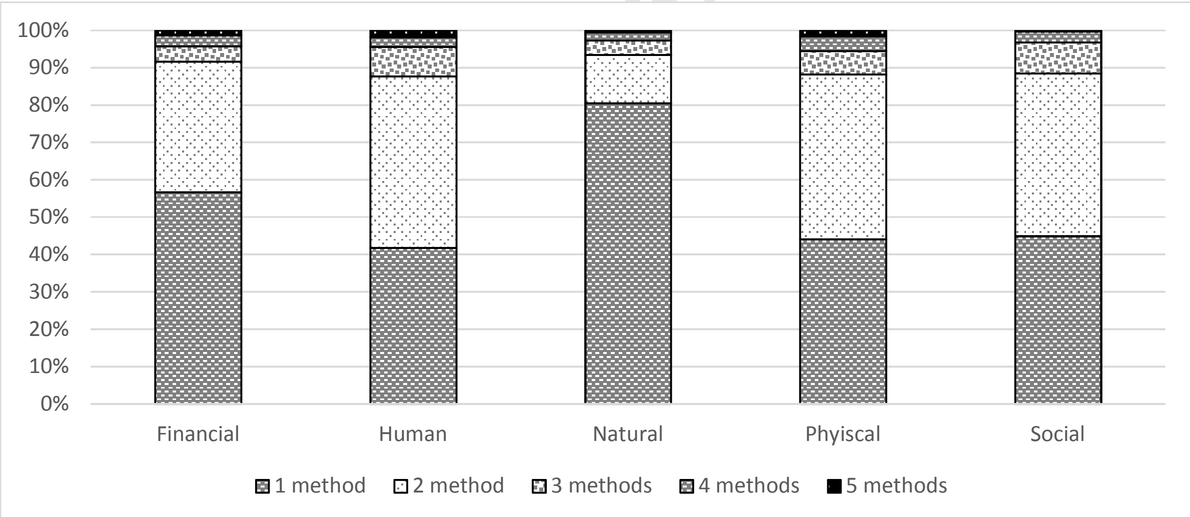


Figure 2: Percentage of data collection methods used for total capital sources of resilience collected

We also find that the most utilized data collection method was key informant interviews, which account of 26%, followed by household surveys and community focus groups with 23%. But Figure 2 further illustrates that key informant interviews were the most utilized of the five data collection methods across all 5 capitals on average (26%), but that data collection methods vary widely by capital. For example, natural capital sources relied heavily on using third party data (67%), and human capital sources used household survey most frequently (31%). Additionally, Table 3 in the Appendix A shows the sources that used the most data collection methods. For example, for the source P02 (Early Warning Systems) 92% of all communities conducted key informant interviews to collect data. 67 % of the sources in natural capital always used third party data collection (i.e., all 118 communities used third party data for those sources of

[6] Note the relatively high number of social capital sources is due to the fact that social capital tends to be less tangible and therefore more indicators are needed to help proxy the measurement and also because social capital also includes aspects of governance or what might be termed ‘political capital’.

resilience). Also, 2 human and 1 financial and 1 social capital source always used household surveys (i.e., all 118 communities chose the same data collection method for those sources).

Household	25%	31%	5%	24%	21%	23%
Community	18%	25%	6%	24%	26%	23%
Key Informant	26%	23%	14%	29%	27%	26%
Interest Group	9%	8%	7%	11%	18%	13%
Third Party Source	21%	14%	67%	12%	8%	15%
Grand Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Table 2: Percentages of each of the five data collection methods that comprise the data input for the sources of flood resilience by type of capital (Note percentages may not sum to 100 due to rounding.)

Again, once the data has been collected using at least one of the five data collection methods, the 88 sources of flood resilience are assigned a grade of A, B, C, or D by appointed experts for each community. Guidance is given for each of the 88 sources as to what might constitute an A through D grade for each source, however in general: A means “Best practice”; B is “Good standard, no immediate need for improvement”; C means “Deficiencies, room for visible improvement” and D stands for “Significantly below good standard, potential for significant loss”. An A through D grade is assigned to each source, based on all the data collected for that source (e.g., if more than one data collection method is used, the assessor with utilize the data from both methods). However, the assessor (or assessment team as was often the case) is also able to bring in their own (expert) judgement based on their knowledge of the community.

Despite the source-specific guidance and standardized data, grading is largely a judgment-based process and therefore the FRMT also includes a box asking how confident accessors are in the grades they assign to each community flood resilience source. Since the trained assessors are personnel who have been working in each of their respective communities for some time, they have local understanding of their communities and the grades they give for flood resilience are thus influenced by their field experience. We found a relatively high level of confidence across all capitals (93.5 % of the total sources were indicated as being confident); natural capital sources had the least percent of its sources across all communities graded with less than 90 % confidence. 95% of users were confident in the grades they assigned sources, with one exception which was Source Habitat connectivity (N02) where less than 80% of the assessors were confident in their grade assignment. Notably, we found that confidence increased the more data collection methods were used to assess the grade (see Figure 1).

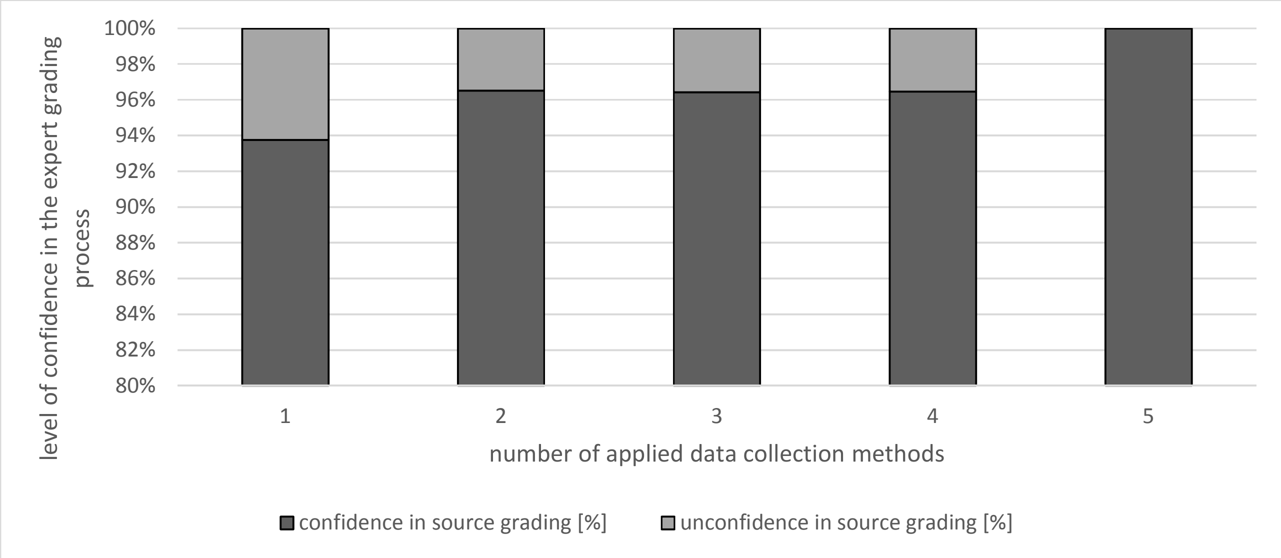


Figure 3: Confidence in grading and number of data collection methods used

6 Baseline Measurement Results

6.1 Sources of Resilience and the Five Capitals

In the following each source letter grade corresponds to a numerical score consistent across all community graded sources where a D = 0, C = 33, B = 66 and an A = 100. Given that there is a total of 118 communities grading 88 sources each, a total of 10,384 numerical graded observations have been generated.

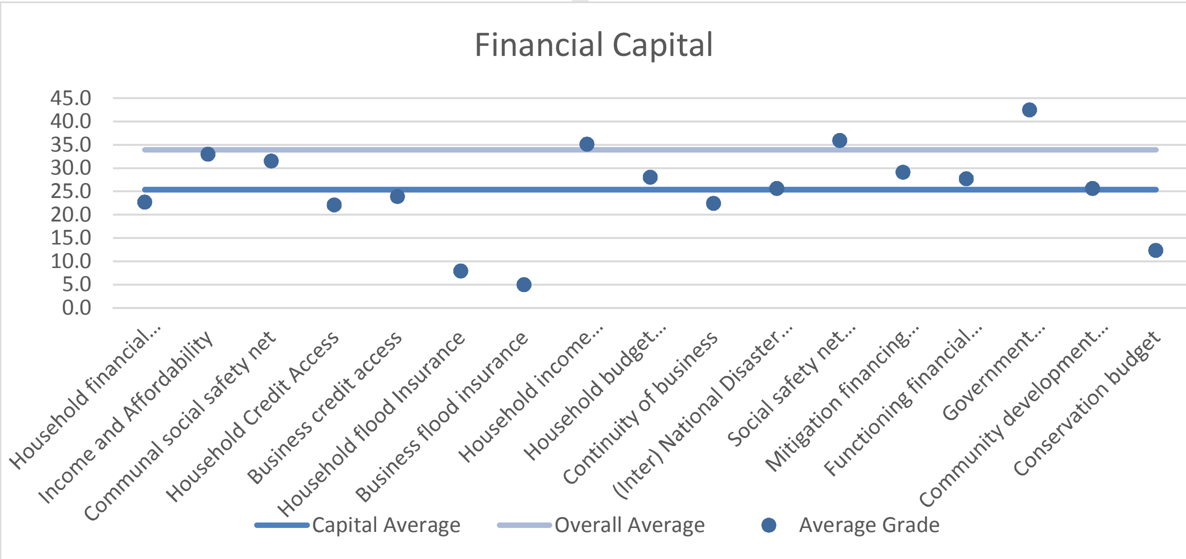
Across all 118 communities we find that as a percentage of the total sources graded, human capital and physical capital have the most sources being assigned a B or an A grade. Of the graded source observations from all 118 communities for human and physical capital (3776 grades in total), at least 35 % of these assigned grades were a B or higher (Figure 4). This compares to financial and social capital where 40 to 50 % of the total grades were assigned a D. Sources assigned to natural capital have been, in general, graded with a C.

***Figure 4:** Overview of frequency of grades for the sources of resilience by capital. Note: Number in bracket of capitals indicates the number sources in that capital.*

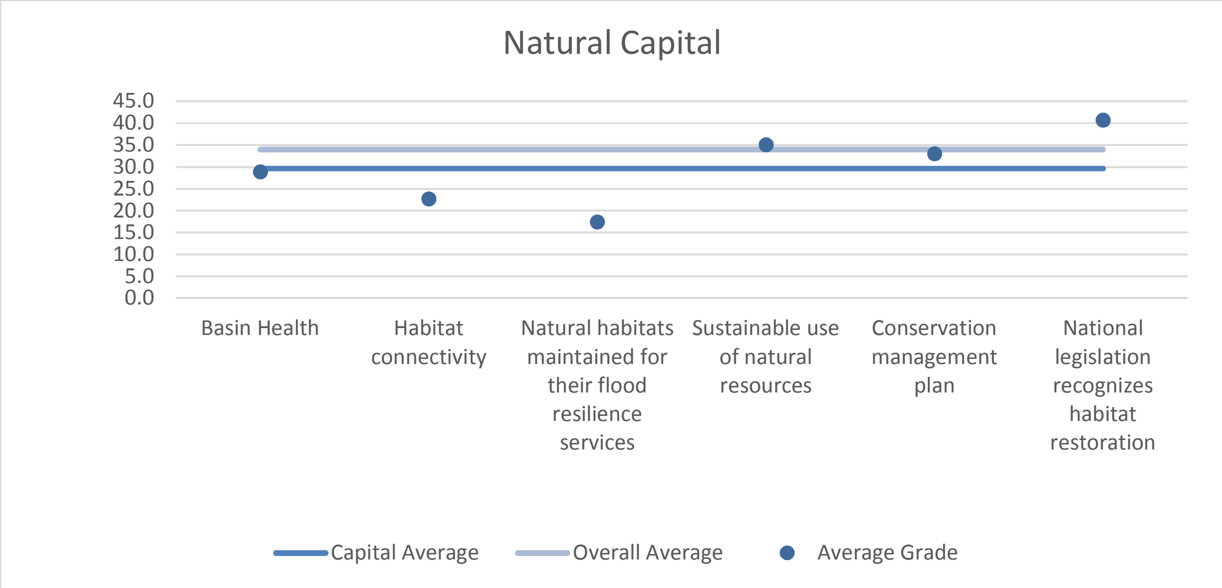
Figure 5 shows the average grade of each source compared to average grade overall. The x-axis lists the sources for each capital. The solid dark line shows the average capital grade, the solid light line the overall average of all capitals. The figure helps illustrate which sources of resilience tended to be relatively strong and which are relatively weak. For example, in Human Capital, communities in general place a high value on education (H4) and very low levels of business flood insurance.[7]

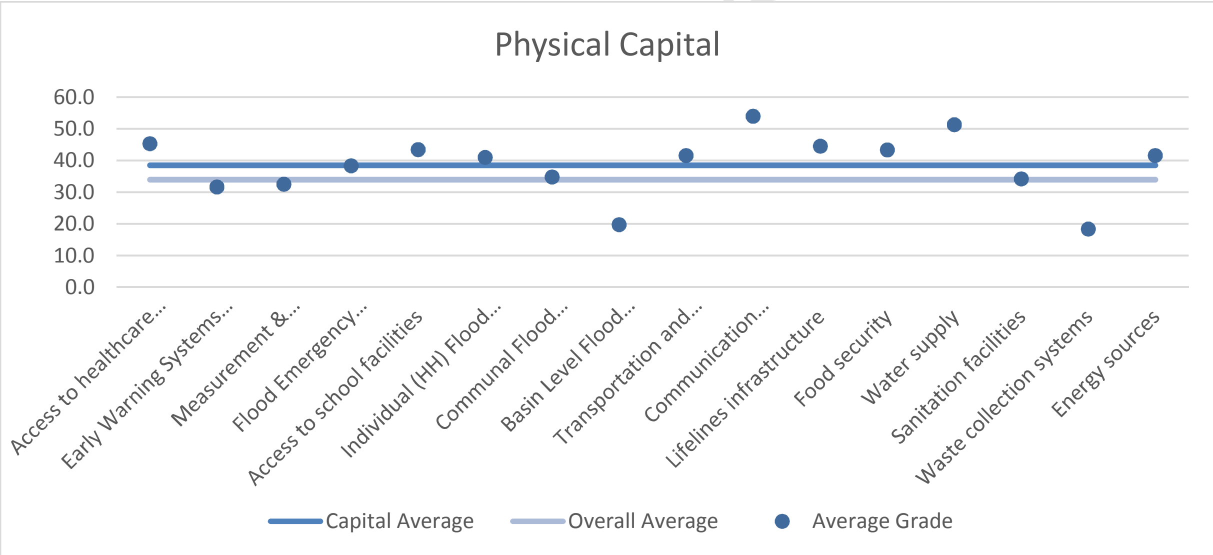
The overall mean (average) score across all 88 sources for all 118 communities was 34, which just crosses the threshold for a C grade[8]. Across all 118 communities the mean scores by capital were financial 25 (D), human 46 (C), natural 28 (D), physical 39 (C) and social 30 (D). Figure 5 illustrates that on average across all 118 communities 4 of the 17 Financial capital, 15 of the 16 human capital, 2 of the 6 natural capital, 12 of the 16 physical capital, and 13 of the 33 social capital sources of resilience scored higher than the overall flood resilience source mean (horizontal red line in each capital figure = 34). Thus again, we see that on average human, and physical capital sources tend to achieve higher grades in our communities. However, there are sources in the other three capitals where relatively higher grades (i.e., in comparison to the overall source mean) are also achieved – for example Household income continuity strategy and Government appropriations for infrastructure maintenance in financial capital.

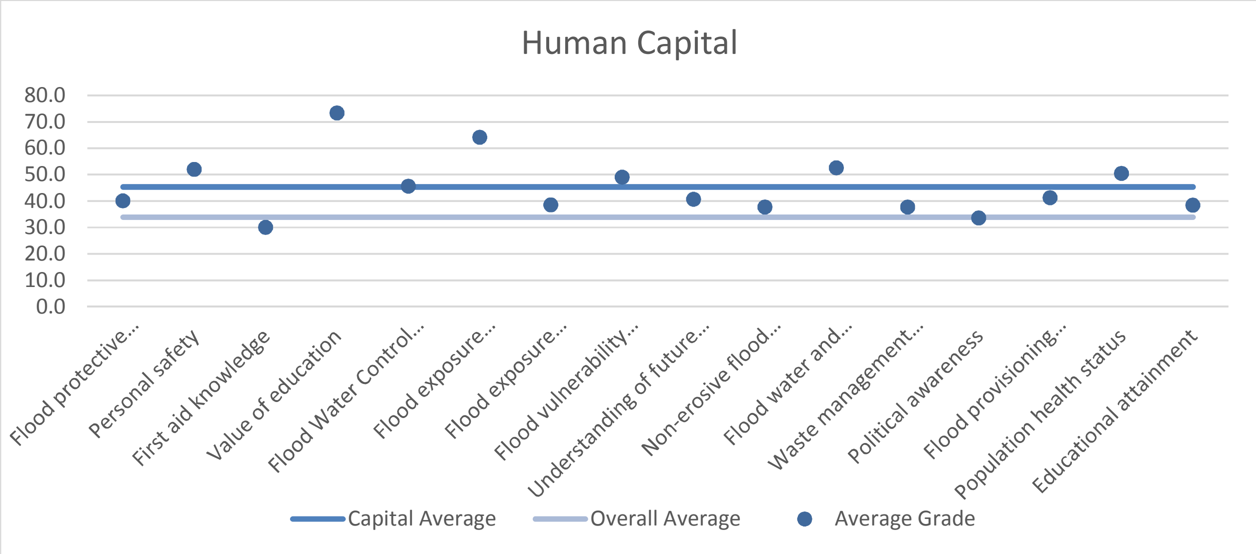
Figure 5: Mean grade of sources compared to average grade overall

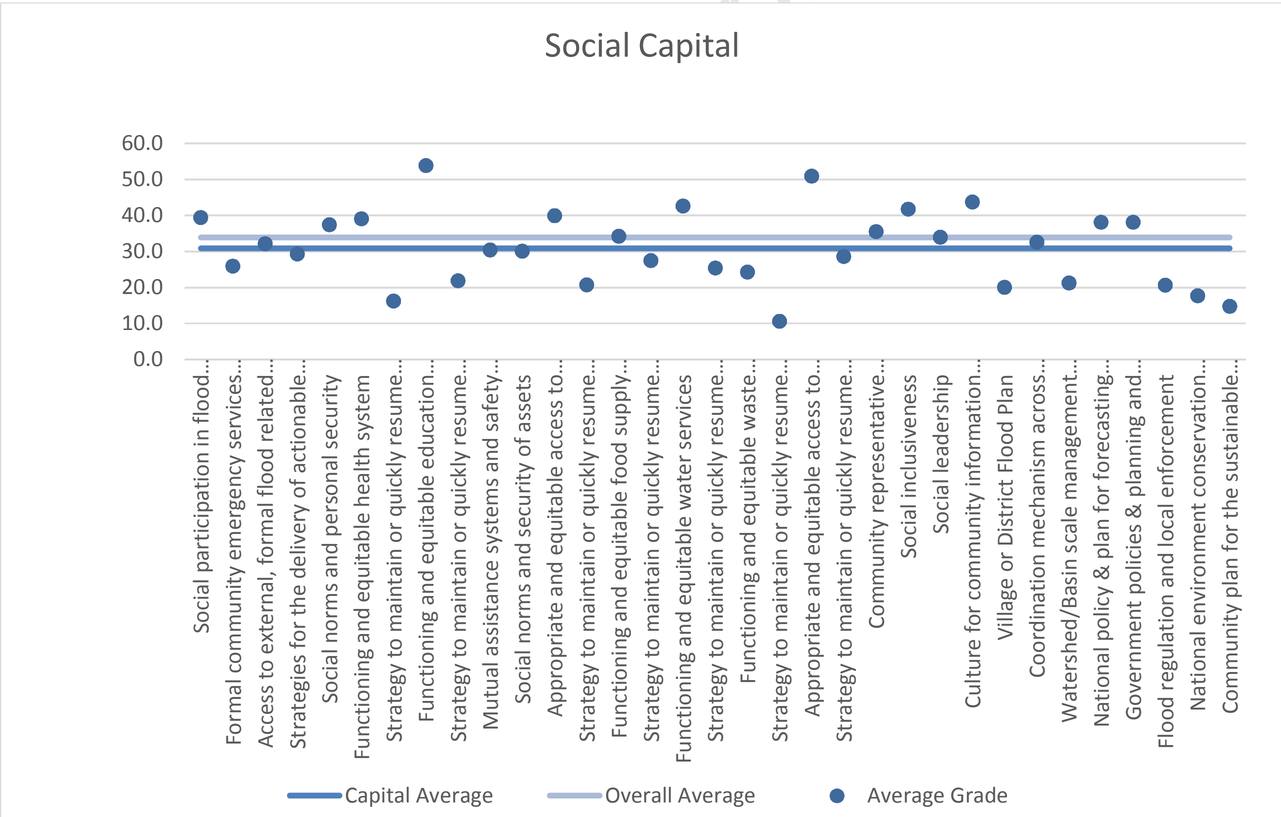


[7] Note this is not surprising given many of the communities in this study are in developing countries.
[8] Note, we assume equal weights between sources for each capital in the aggregation process as we treat each single resilience source as equally important.


Natural Capital
45.0
40.0
35.0
30.0
25.0
20.0
15.0
10.0
5.0
0.0
Basin Health
Habitat connectivity
Natural habitats maintained for their flood resilience services
Sustainable use of natural resources
Conservation management plan
National legislation recognizes habitat restoration
Capital Average
Overall Average
Average Grade


Physical Capital
60.0
50.0
40.0
30.0
20.0
10.0
0.0
Access to healthcare...
Early Warning Systems...
Measurement &...
Flood Emergency...
Access to school facilities
Individual (HH) Flood...
Communal Flood...
Basin Level Flood...
Transportation and...
Communication...
Lifelines infrastructure
Food security
Water supply
Sanitation facilities
Waste collection systems
Energy sources
Capital Average
Overall Average
Average Grade





Of the 88 sources of resilience, sources assigned to human and physical capital are, in general, the highest graded sources. From Table 3 we see that these two capitals represent 80% of the 10 highest graded sources (in terms of average score) and only one source in physical capital is among the bottom performing (in terms of average grade). The highest graded sources are: education (value and equity); flood exposure perception, knowledge and awareness; communication, water, personal safety as well as health and sanitation and health status. *One hypothesis might be that these two categories are traditionally targeted by flood mitigation projects, i.e., interventions tend to focus on building people's skills and knowledge and physical structures.*

Highest graded sources				Bottom performing sources			
Rank	**Source name**	**Source**	**Mean**	**Rank**	**Source name**	**Source**	**Mean**
1	Value of education	H04	74.43	88	Business flood insurance	F07	4.77
2	Flood exposure perception	H06	64.19	87	Household flood Insurance	F06	7.85
3	Functioning and equitable education system	S08	55.65	86	Strategy to maintain or quickly resume local waste collection & disposal services in the event of a flood	S19	10.09
4	Communication infrastructure	P10	54.63	85	Conservation budget	F17	11.47
5	Personal safety	H02	54.10	84	Community plan for the sustainable management of natural resources and preservation of ecosystem services	S33	14.31
6	Flood water and sanitation (WASH) knowledge	H11	53.60	83	Strategy to maintain or quickly resume healthcare services interrupted by flooding	S07	16.25
7	Water supply	P13	53.23	82	Natural habitats maintained for their flood resilience services	N03	16.52
8	Appropriate and equitable access to energy	S20	52.27	81	National environment conservation legislation	S32	18.19
9	Population health status	H15	52.07	80	Basin Level Flood Controls	P08	18.74
10	Flood vulnerability perception and management knowledge	H08	49.02	79	Village or District Flood Plan	S26	19.31

Table 3: Overview of top and bottom performing sources

On the other end of the performance spectrum, sources of resilience assigned to financial or social capital represent 80 % of the bottom performing sources. In only two countries were there communities where at least one source in financial capital was graded in the highest 10 graded sources for that community. Lowest graded sources tended to be insurance; strategies to maintain or quickly resume waste collection, healthcare services and mobility services; the conservation and maintenance of natural resources and habitats; and watershed basin management.

In addition to the baseline data, users (practitioners) were also surveyed in the spring of 2016 after completing their training, setting up the baseline study and beginning field work to collect the data. One of the questions on the survey asked which sources of resilience in each capital they saw as most relevant for actual flood resilience. From this data we can also compare how the most relevant sources as identified in the survey of users fared in terms of their average grade across the communities. Table 4 shows that none of the sources identified as the most relevant sources for each capital ranked in the top 25% in terms of their overall resilience grade. Flood protective behavior and knowledge was graded the highest of the five with a rank of 28. *In other words, those sources seen as most relevant for reducing losses and enabling a faster/better recovery were, on average, assessed as deficient or needing improvement*. If these sources prove, over time, to empirically be the most effective, they are areas that will need to be strengthened to improve overall flood resilience in the community.

Most Relevant Sources (Highest survey response for each capital)	Rank of the graded source (Baseline data) (Mean of 118 grades)
H1. Flood protective behavior and knowledge	30 (39.7)

S1 Social participation in flood management related activities	28 (39.9)
P2 Early Warning Systems (EWS)	54 (30.3)
F1 Household financial savings that protect long term assets	71 (23.2)
N3 natural habitats maintained for their flood resilience services	82 (16.5)

Table 4: Comparison of survey responses and baseline data

6.2 Linking Resilience and Community Characteristics

As already indicated community characteristics were included in the tool because each communities' unique social demographic and economic factors are likely to play a role in the communities' flood resilience and thus it is important to control for these factors. That is, we want to include community characteristics in the equation as these can play a role in the community's flood resilience. In this section we explore the relationship between baseline community characteristics and its sources of resilience grades. Specifically, we look at how the community context relates to the communities' overall community flood resilience grade as well as individual capital scores. The analysis can help practitioners better understand where particular socio-economic characteristics are most related to the sources of resilience within their communities. To perform this analysis, we employ a robust regression model[9]. We look at the effects of: having experienced a severe flood in the last 10 years, experiencing a greater number of floods in the last 10 years, the education rate, the poverty rate, and the level of remittances flowing to the community. In addition to these community characteristics, we also control for fixed (and unobservable) effects that might be due to a particular context. This would normally be a country fixed effect, but due to data limitations we use a rural, urban, peri-urban fixed effect as the second-best solution to control for missing variables (controlling for rural, urban and peri-urban settings controls for characteristics that are stable and common to all the communities in a given setting that may explain some of the resilience grade versus being attributed to a particular 5C capacity). The detailed results can be found in the Appendix C but the summary of results can be found in Table 5.

While we do not have a large enough sample size to make robust conclusions about the influence of various socio-demographic variables on overall sources of resilience grades, the analysis provides insight into the direction of the influence (positive or negative) and the relative magnitudes of the variables. The results are intuitive: we find that experiencing more severe floods tends to have a negative impact on the sources of resilience (an eroding effect on capital) but having experienced more frequent flooding (where more frequent flooding tends to also be less severe) has a positive influence on the sources of resilience, possibly because the community has adapted somewhat to floods. Furthermore, remittances and education tend to have a positive influence on sources of resilience grades, while higher rates of poverty tend to have a negative influence. Lastly, being in an urban environment is correlated with higher resilience grades, followed by a peri-urban context, and finally a rural context, all else equal. Interestingly however, this relationship is reversed for natural capital: while we must be cautious in our interpretation of natural capital results, this makes intuitive sense since natural capital sources of resilience would increase in a rural versus peri-urban versus urban contexts. Furthermore, the relationship between community context and social capital grades mirrors feedback from users that communities in urban settings, while having less inter-personal social dynamics, are stronger regarding the governance aspects of social capital. As you move to a rural setting the governance aspects of social capital tend to be less formal but there is more of the informal and interpersonal social capital. Lastly, the peri-urban environment loses some of both and thus has the least positive influence on the social capital sources of resilience.

[9] Our dependent variable is pseudo-continuous in that the ordered grades are assigned numerical values and summed over their categories. However, we do not assume a normal distribution or equal variance of the model variables.

		Most Severe Flood	Number of Floods	Education Rate	Poverty Rate	Remittances rate	Peri-Urban	Urban
Dependent Variable	Overall Resilient Capital	-1.260	0.842**	0.185***	-0.134 ***	0.134***	-3.65	0.949
	Financial Capital	-1.315	0.532	0.215***	-0.147***	0.1242**	-2.089	9.814**
	Human Capital	-3.928***	1.114***	0.102***	-0.143***	0.0405	-5.156**	0.311
	Natural Capital	3.062**	-0.186	0.175***	-0.178***	0.294***	16.763***	10.343**
	Physical Capital	-1.947	1.498***	0.0889*	-0.138**	0.004	4.084	10.683**
	Social Capital	-0.483	0.886	0.305***	-0.064	0.14*	-7.315**	1.043

***Significant at the 0.01 level. **Significant at the 0.05 level.
* Significant at the .1 level

Table 5: Relationship between community characteristics on sources of resilience grades

6.3 Decision Making Context

To understand the relationship between baseline flood resilience measurement and interventions in Alliance country programs, researchers within the Alliance reviewed extensive feedback provided by users including program reports, surveys, interviews and discussion within workshops. We were interested in understanding how the baseline data informed resilience intervention decision making. We found that the baseline grades for the sources of resilience helped the users and communities jointly identify areas that needed to be strengthened within the community. Interventions implemented across the communities focused on the following areas: flood preparedness (strengthens human, physical and social capital sources); disaster risk management capacity building (strengthens human and social capital sources); water and sanitation (WASH) (strengthens human and physical capital sources); education (strengthens human , social and physical capital sources); infrastructure works (strengthens physical capital sources); flood provisioning ecosystem services (strengthens social and natural capital sources); livelihoods and food security (strengthen financial capital sources); and, enhancing financial capital (strengthens financial and social capital sources). The breadth of the interventions informed by the FRMT process shows the breadth of the underlying conceptualization of resilience. The purpose of the tool was to help communities recognize and strengthen their sources of resilience in a holistic way and the interventions demonstrate that this was achieved.

However, a more nuanced key question to ask is whether the process of undertaking baseline measurement and sharing results with communities resulted in interventions substantively different from what would have been implemented in the absence of the FRMT? We find evidence that it did, to varying degrees, across the country programs. In some instances, the measurement process confirmed or validated the original intervention planned to be implemented. In other cases, it was successful in identifying gaps to be filled and/or strengths to be built upon, which the NGO could address or support others to address. Regardless of whether the implementation of the FRMT directly resulted in previously unconsidered interventions or not, country teams overwhelmingly reported that the process helped them, their stakeholders, and communities to see flood resilience in a much more interconnected and holistic way. Broadening the perspective of flood resilience beyond physical infrastructure to include social capital was frequently raised. This was seen as a significant benefit, even when directly implementing this systems thinking was not possible within the current project cycle.

For many country programs, general project plans and even log-frames and budgets put in place at the beginning of the project were revised after baseline measurement was completed. In some instances, the measurement process confirmed or validated the original intervention setup. In other cases, it was successful in identifying gaps to be filled and/or strengths to be built upon, which the NGO could address or support others to address. Many country programs followed a similar process for prioritizing sources to design interventions. First, after the tool had generated results, country teams extracted the sources which were graded C or D and grouped them according to their linkages and commonalities. These potential intervention foci were then evaluated according to other criteria such as: relevancy to the country program's overall strategic plan; the original focus of the funding proposal; budget and resource requirements; time frame; and available technical expertise and capacities.

In some cases, a second phase of the selection process evaluated potential intervention areas according to value-add criteria such as: contribution to social inclusion such as the empowerment of women; cost-effectiveness; sustainability of the intervention beyond the life of the program; and complementarity with other initiatives occurring in the community or region. All country programs reported undertaking this prioritization process jointly with communities, although with varying degrees of community input.

A number of implementation teams expressed that the funder's flexibility on project plans in light of measurement results greatly improved their intervention design. They reported that they would like other funders to follow this example and provide for in-depth analysis such as resilience measurement *prior* to intervention design.

7 Discussion and Conclusion

With 118 communities across the world, our analysis presented here is the first large scale analysis of community resilience. We have explored various aspects of the graded data. First, we analyzed how data was gathered in terms of what methods are used most frequently to gather data. We found that choices for data gathering varied by capital as well as the number of data gathering methods chosen. We also found that grading confidence increased if more than one data collection method is used but there are decreasing returns to scale in data gathering with somewhere between 2 and 3 methods per source being often optimal (but this varies by resilience source). We analyzed by source and capital which sources of resilience are most highly graded and which tended to be graded the lowest. Lastly, we presented a preliminary analysis of how socio-demographic factors within a community impact sources of community flood resilience.

Specifically, we find that.

1. *Key informant interviews, household surveys and community discussion groups were the most utilized data collection methods (between 23-26%).*
2. *Those grading the sources were mostly confident in the grades assigned – with the average confidence being 95 %; grade assessors were the least confident when grading natural capital sources of flood resilience.*
3. *Of the 88 sources of resilience, human and physical capital sources, on average, received the highest grades --- 35-43 % of these sources are a B or A.*
4. *40-50 % of financial, natural, and social are a D which is significantly below good standard and has the potential for significant loss.*
5. *The highest graded sources on average are education (value and equity); flood risk perception, knowledge and awareness; communication, water, and healthcare infrastructure; and personal safety as well as health and sanitation.*
6. *Lowest graded sources on average are insurance; strategies to maintain or quickly resume waste collection, healthcare services and mobility services; the conservation and maintenance of natural resources and habitats; watershed basin management and* flood plan
7. *An initial assessment of community characteristics impact on grades finds that the education rate is most significant for the resilience grades of all five capitals.*

Ultimately the purpose of measuring community flood resilience is to aid in helping communities enhance their flood resilience. Therefore, an important question is whether and in what way practitioners and communities utilized the baseline assessment of their flood sources of flood resilience. We found that the baseline information was utilized in community flood resilience intervention decision-making - making a significant difference in addressing the sources of resilience in holistic way. In addition to helping design interventions to strengthen sources of resilience that that were assessed as D or C grades, the practitioners said that the framework and measuring process helped them think and design interventions for enhancing flood resilience in a more holistic way.

Lastly, the testing and data analysis of the FRMT has fed into the revision process for the development of the Next Generation FRMT, which will be scaled to many more communities. The analysis here is based on more than 10,384 data points asked on the household and community level. While other studies have sought to operationalize the measurement of resilience, this level of detail, multi-dimensional attribution of relevant resilience sources and the large scale systematic approach to applying the data collection and measurement tool across many different communities makes this analysis the first of its kind. In addition to insight into the sources of community flood resilience, what we are learning so far from the testing phase is that the tool implementation and grading process itself has tremendous value as a collective community flood risk identification and corresponding gap assessment exercise. Feedback from users finds co-benefits particularly in terms of capacity building. Qualitative feedback from the users of the tool has validated the usefulness of the tool and provided functional improvements that will go into the Next Generation version.

In fact, the next generation version has been implemented in more than 40 communities. In particular, a focus on urban and developed country contexts has been prioritized for this testing stage. Also learning from the pilot stage helped to tie funding more closely to the use of the tool. As the tool and associated measurement gets tested in more environments and used in decision making for flood resilient investments the overarching goal is that the usefulness of the tool will be demonstrable and adopted by many more organizations working building flood resilience into communities. Additionally, as the tool is utilized the database that is created can help further research on pre-flood sources of resilience and their effectiveness for flood resilient outcomes (less losses experienced and quicker, better recoveries). The incremental approach to testing the tool, refining the tool, testing again, refining again, etc. is meant to help strengthen the tools usability and thus make adoption of the tool easier. There are also efforts underway to provide training on the tool, which again will help with adoption. Additionally, as the data requirements become more known, other organizations may find the data useful and thus it is anticipated that the data collected will have many co-benefits and therefore can also be co-funded. The ultimate test of the tool is its usefulness for understanding and prioritizing evidence based flood resilience investments. This validation process will take time and funding, which increases the risks of a fully scaled tool that operationalizes flood resilience measurement.

Due to space restrictions, a full statistical analysis of all the grading as well as dynamics between capitals could not be presented here, but will follow in a separate paper. Early indications show that a simple correlation analysis between the capitals finds strong interdependencies overall, and particularly with financial capital. Natural capital is relatively highly correlated (and of the four, it is most correlated with social capital at 0.7). Societies with stricter environmental regulations often have high social equity (Beder, 2000) and perhaps this is evidenced by the high correlation between natural and social capital. However, it is also interesting that the lowest correlation of the capitals is between physical and natural. This finding may be born from the fact that many physical projects tend to disrupt rather than enhance natural capital. Communities may see that physical capital comes at the expense of natural capital, in cases where traditional physical projects may not have adequately taken into account their impact on natural capital.

A follow-on paper will examine the post event data (actual flood resilience measures) across communities that have experienced a flood. Over time and as more data is collected across communities, we will be able to test and empirically validate a measure of community flood resilience. This measure can then be used to aid in the decision-making process for strengthening community flood resilience as well as benchmarking and tracking over time. The unique dataset being created through the use of the tool will also allow for a large research agenda studying the intersections of development, resilience and risk. Lastly, the FRMT underwent a revision and is now entering a second phase of testing. During this phase, the tool will be implemented in more communities thus providing more baseline studies of the sources of resilience.

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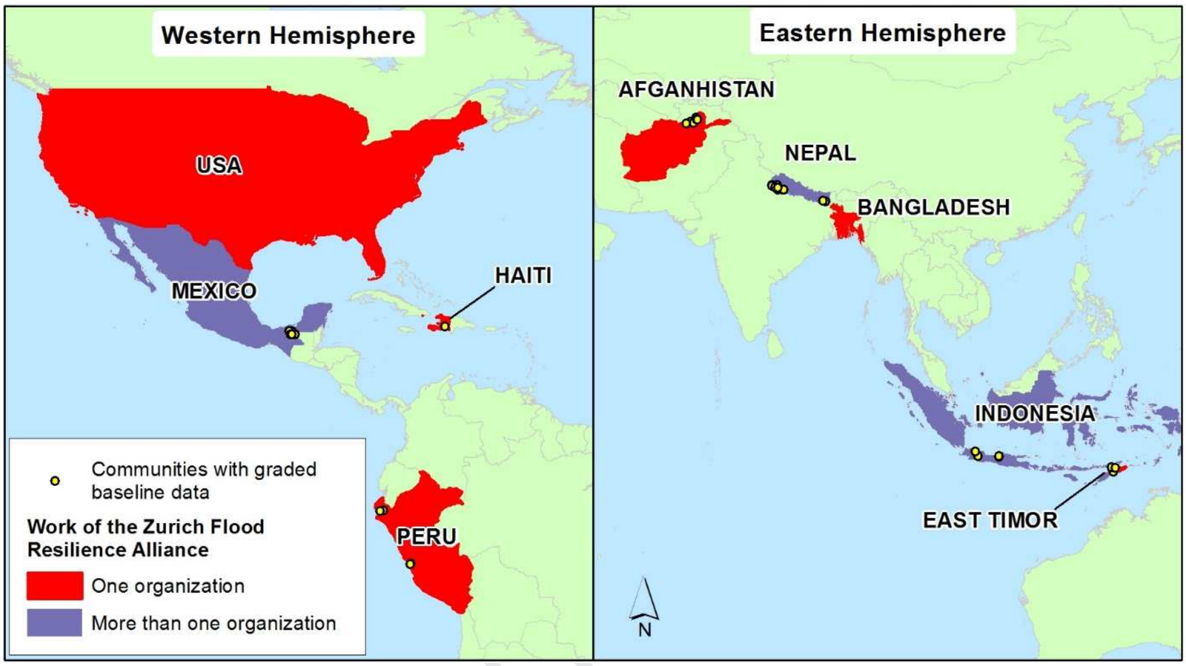
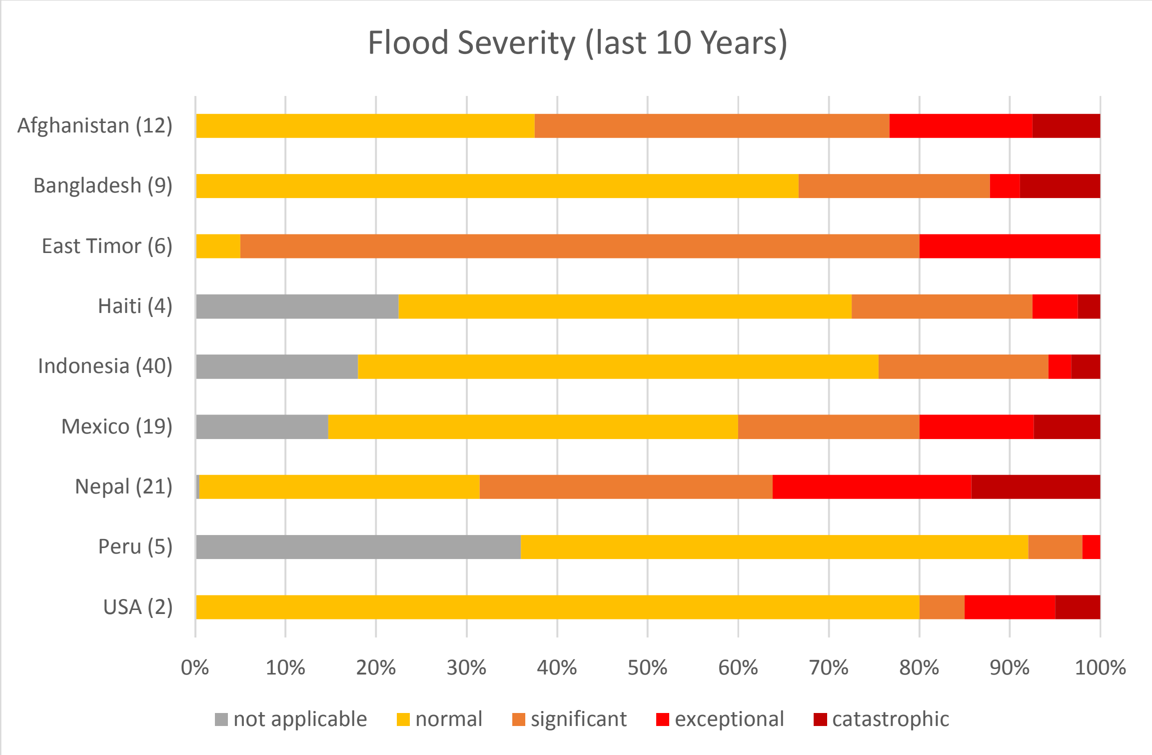
Appendix A: Context and Flood Resilience

Figure 1 Map of the countries where our Partners are working



Note: the points show locations of the communities in each country that completed Baseline grading

Figure 2: Frequency of worst flood events for the last 10 years (basis year 2016).

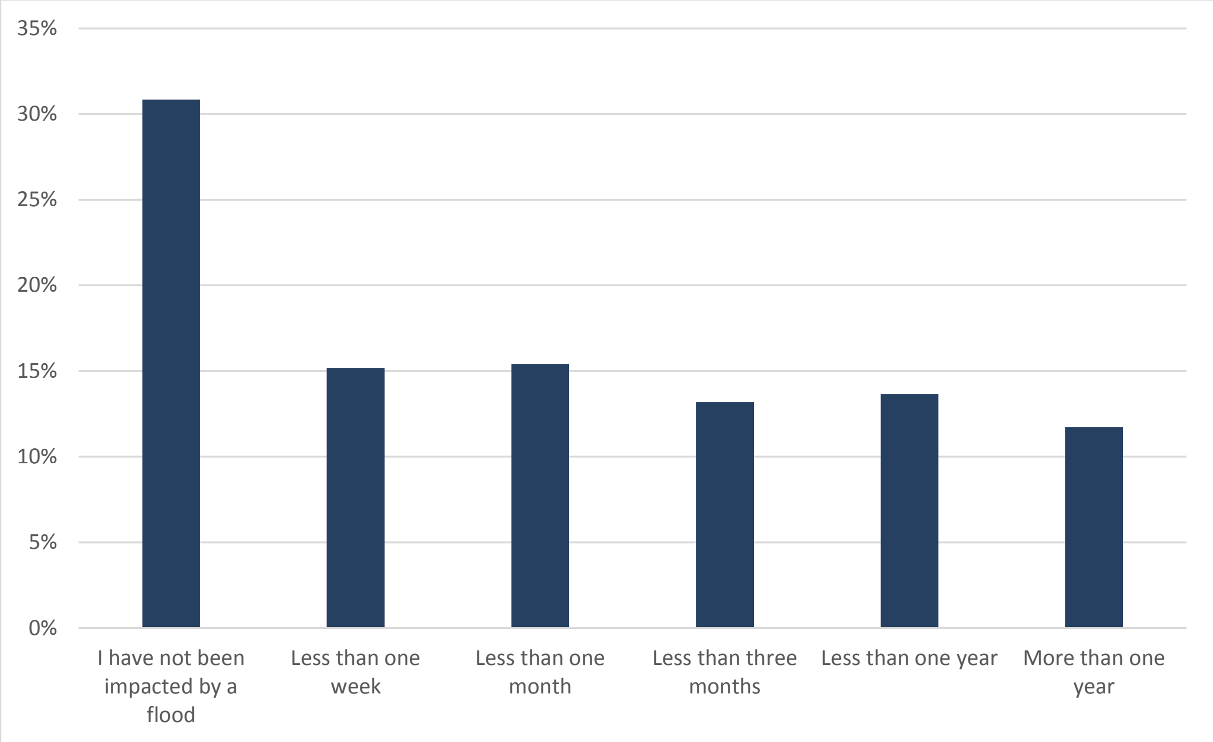


Note: Normal: 1-2-year event; significant: 2-10-year event; exceptional: 10-100-year event; catastrophic: 100+-year event.

We find that the floods described above have had significant impacts on the communities' livelihoods. On average, households in our 118 baseline communities report that family has been injured or their property damaged by a flood 2.1 times, or once every 4.7 years. Additionally, Figure 1 illustrates that in regard to the worst flood experienced in the community in the last ten years, 54 percent of households take at least a week to recover financially, and 39 percent a month or longer. More than 10 percent of households indicate more than a year of financial recovery time[10].

[10] Financial recovery refers to returning to pre-event income levels, and paying off damage and repair costs.

Figure 1: Financial Recovery time from previous flood



In order to take a first look at relating our sources of resilience to actual resilient outcomes, we correlated each of the 88 source grades for each community with the community's average financial recovery time as reported in the household survey data. We found that forty sources were significantly correlated with faster financial recovery (positively or negatively). Twenty-four sources are negatively correlated with financial recovery time (which for recovery time is good since the higher the sources grade the faster the recovery time (less time)) at a 5% confidence level and 16 sources were positively correlated with financial recovery time at a 5% confidence level. The top 5 sources that were most highly (and significantly) associated with a faster financial recovery time in the past were: Waste collection systems (P15), Community development investment vehicles (F16), Household income continuity strategy (F08), Value of education (H04) and Income and Affordability (F02). Only source F16 (Community development investment vehicles) is positively correlated.

Table 1: Top 5 correlated source with financial recovery time

Source	Source name	Correlation Coefficient
P15	Waste collection systems	-0.472**
F16	Community development investment vehicles	0.456**
F08	Household income continuity strategy	-0.438**

H04	Value of education	-0.427**
F02	Income and Affordability	-0.419**
P12	Food security	-0.386**
P01	Access to healthcare facilities	-0.381**
S22	Community representative bodies/structures for flood management coordination	0.380**
S18	Functioning and equitable waste collection & disposal services	-0.375**
N01	Basin Health	0.357**

** Correlation is significant at the 0.01 level (2-tailed)

As Table 2 shows financial recovery is negative with financial, human and physical capital but positive correlated with natural capital and social capital. Also note that human, natural and physical capital are significant correlated at a 5 % confidence level and financial capital is significant at a 15 % confidence level.

Table 2 Spearman's rho correlation coefficient with average financial recovery and 5 capitals

		average financial recovery	*Financial Capital*	*Human Capital*	*Natural Capital*	*Physical Capital*	*Social Capital*
Average financial recovery	Correlation Coefficient	1.000	-0.148	-.234*	.362**	-.268**	0.084
	Sig. (2-tailed)		0.126	0.015	0.000	0.005	0.386
Financial Capital	Correlation Coefficient	-0.148	1.000	.640**	.390**	.724**	.723**
	Sig. (2-tailed)	0.126		0.000	0.000	0.000	0.000
Human Capital	Correlation Coefficient	-.234*	.640**	1.000	.224*	.655**	.590**
	Sig. (2-tailed)	0.015	0.000		0.015	0.000	0.000
Natural Capital	Correlation Coefficient	.362**	.390**	.224*	1.000	0.138	.534**
	Sig. (2-tailed)	0.000	0.000	0.015		0.137	0.000
Physical Capital	Correlation Coefficient	-.268**	.724**	.655**	0.138	1.000	.605**

	Sig. (2-tailed)	0.005	0.000	0.000	0.137		0.000
Social Capital	Correlation Coefficient	0.084	.723**	.590**	.534**	.605**	1.000
	Sig. (2-tailed)	0.386	0.000	0.000	0.000	0.000	

** Correlation is significant at the 0.01 level (2-tailed)

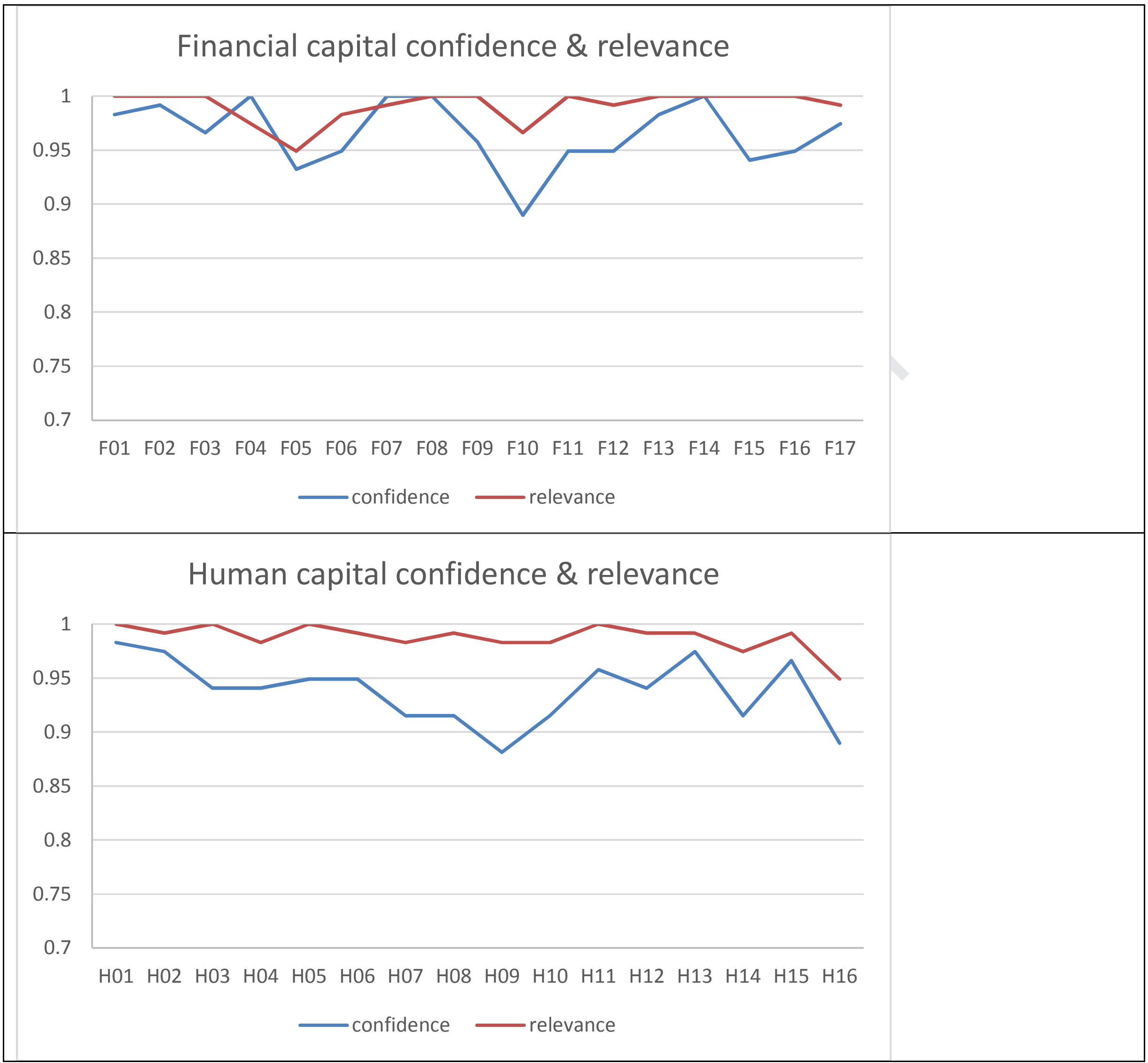
** Correlation is significant at the 0.05 level (2-tailed)

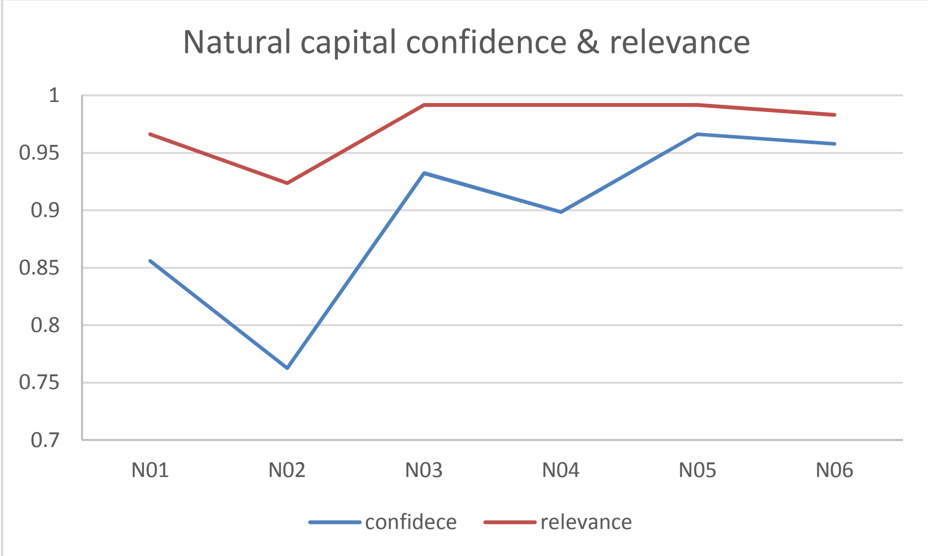
While there are many factors that need to be controlled for in order to establish causation or a source's importance for a resilient outcome, it is useful to see that the correlation for financial recovery includes sources from other capitals, supporting the use of a holistic 5C approach.

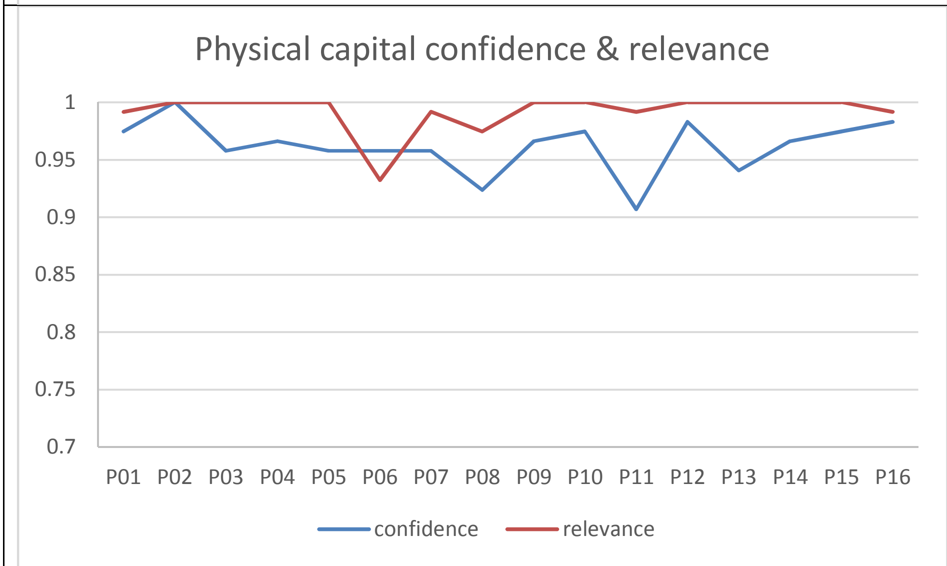
Table 3 Source with most utilized data collection methods

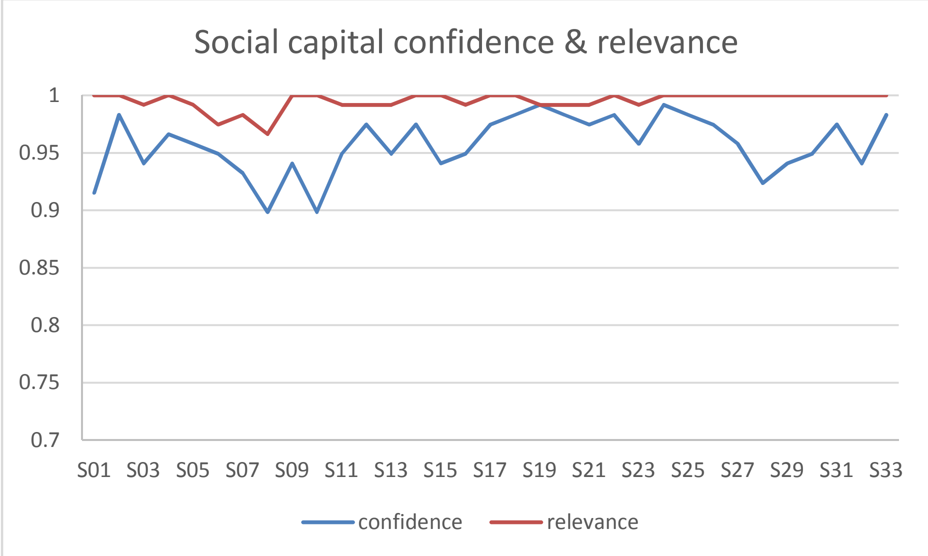
Source	Source Name	Ave. # of input method used
P02	Early Warning Systems (EWS)	2.3
H05	Flood Water Control Knowledge	2.2
H09	Understanding of future flood risk	2.2
H08	Flood vulnerability perception and management knowledge	2.2
S17	Strategy to maintain or quickly resume provision of local safe water in the event of a flood	2.2
S21	Strategy to maintain or quickly resume local energy supply in the event of a flood	2.1
S15	Strategy to maintain or quickly resume provision of local food supplies in the event of a flood	2.1
S19	Strategy to maintain or quickly resume local waste collection & disposal services in the event of a flood	2.1
N04	Sustainable use of natural resources	2.1
H07	Flood exposure management knowledge	2.1
P04	Flood Emergency Infrastructure	2.1

Figure 4: Confidence and relevance scores




Natural capital confidence & relevance
1
0.95
0.9
0.85
0.8
0.75
0.7
N01
N02
N03
N04
N05
N06
confidece
relevance


Physical capital confidence & relevance
1
0.95
0.9
0.85
0.8
0.75
0.7
P01
P02
P03
P04
P05
P06
P07
P08
P09
P10
P11
P12
P13
P14
P15
P16
confidence
relevance



Appendix B: List of the sources of resilience

Source name	**Code**	**5C**	**4R**
Household financial savings that protect long term assets	F1	Financial	Robustness
Income and Affordability	F2	Financial	Resourcefulness
Communal social safety net	F3	Financial	Rapidity
Household Credit Access	F4	Financial	Redundancy
Business credit access	F5	Financial	Redundancy
Household flood Insurance	F6	Financial	Rapidity
Business flood insurance	F7	Financial	Rapidity
Household income continuity strategy	F8	Financial	Resourcefulness
Household budget management	F9	Financial	Resourcefulness
Continuity of business	F10	Financial	Rapidity
(Inter) National Disaster Response budget	F11	Financial	Rapidity
Social safety net (legislative, national schemes)	F12	Financial	Redundancy
Mitigation financing (provided through public	F13	Financial	Robustness

or private)			
Functioning financial market	F14	Financial	Resourcefulness
Government appropriations for infrastructure maintenance	F15	Financial	Robustness
Community development investment vehicles	F16	Financial	Resourcefulness
Conservation budget	F17	Financial	Robustness
Flood protective behavior and knowledge	H1	Human	Robustness
Personal safety	H2	Human	Resourcefulness
First aid knowledge	H3	Human	Robustness
Value of education	H4	Human	Resourcefulness
Flood Water Control Knowledge	H5	Human	Resourcefulness
Flood exposure perception	H6	Human	Robustness
Flood exposure management knowledge	H7	Human	Robustness
Flood vulnerability perception and management knowledge	H8	Human	Robustness
Understanding of future flood risk	H9	Human	Robustness
Non-erosive flood recovery knowledge	H10	Human	Robustness
Flood water and sanitation (WASH) knowledge	H11	Human	Robustness
Waste management awareness	H12	Human	Robustness
Political awareness	H13	Human	Resourcefulness
Flood provisioning ecosystem services awareness	H14	Human	Resourcefulness
Population health status	H15	Human	Robustness
Educational attainment	H16	Human	Resourcefulness
Basin Health	N1	Natural	Resourcefulness
Habitat connectivity	N2	Natural	Resourcefulness
Natural habitats maintained for their flood	N3	Natural	Redundancy

resilience services			
Sustainable use of natural resources	N4	Natural	Resourcefulness
Conservation management plan	N5	Natural	Redundancy
National legislation recognizes habitat restoration	N6	Natural	Robustness
Access to healthcare facilities	P1	Physical	Robustness
Early Warning Systems (EWS)	P2	Physical	Robustness
Measurement & Forecasting	P3	Physical	Resourcefulness
Flood Emergency Infrastructure	P4	Physical	Rapidity
Access to school facilities	P5	Physical	Robustness
Individual (HH) Flood Vulnerability Management	P6	Physical	Robustness
Communal Flood Protection (Flood controls)	P7	Physical	Robustness
Basin Level Flood Controls	P8	Physical	Robustness
Transportation and community access	P9	Physical	Redundancy
Communication infrastructure	P10	Physical	Rapidity
Lifelines infrastructure	P11	Physical	Robustness
Food security	P12	Physical	Robustness
Water supply	P13	Physical	Redundancy
Sanitation facilities	P14	Physical	Robustness
Waste collection systems	P15	Physical	Robustness
Energy sources	P16	Physical	Redundancy
Social participation in flood management related activities	S1	Social	Resourcefulness
Formal community emergency services integrate flood advice and management	S2	Social	Resourcefulness
Access to external, formal flood related services	S3	Social	Resourcefulness
Strategies for the delivery of actionable information for flood management	S4	Social	Resourcefulness

Social norms and personal security	S5	Social	Robustness
Functioning and equitable health system	S6	Social	Robustness
Strategy to maintain or quickly resume healthcare services interrupted by flooding	S7	Social	Rapidity
Functioning and equitable education system	S8	Social	Robustness
Strategy to maintain or quickly resume schooling interrupted by flooding	S9	Social	Rapidity
Mutual assistance systems and safety nets	S10	Social	Resourcefulness
Social norms and security of assets	S11	Social	Robustness
Appropriate and equitable access to mobility	S12	Social	Robustness
Strategy to maintain or quickly resume provision of mobility services in the event of a flood	S13	Social	Rapidity
Functioning and equitable food supply systems	S14	Social	Robustness
Strategy to maintain or quickly resume provision of local food supplies in the event of a flood	S15	Social	Rapidity
Functioning and equitable water services	S16	Social	Robustness
Strategy to maintain or quickly resume provision of local safe water in the event of a flood	S17	Social	Rapidity
Functioning and equitable waste collection & disposal services	S18	Social	Robustness
Strategy to maintain or quickly resume local waste collection & disposal services in the event of a flood	S19	Social	Rapidity
Appropriate and equitable access to energy	S20	Social	Robustness
Strategy to maintain or quickly resume local energy supply in the event of a flood	S21	Social	Rapidity
Community representative bodies/structures for flood management coordination	S22	Social	Resourcefulness
Social inclusiveness	S23	Social	Resourcefulness
Social leadership	S24	Social	Resourcefulness

Culture for community information sharing	S25	Social	Resourcefulness
Village or District Flood Plan	S26	Social	Rapidity
Coordination mechanism across communities	S27	Social	Resourcefulness
Watershed/Basin scale management plan & structure	S28	Social	Resourcefulness
National policy & plan for forecasting ability	S29	Social	Rapidity
Government policies & planning and mainstreaming of flood risk	S30	Social	Robustness
Flood regulation and local enforcement	S31	Social	Robustness
National environment conservation legislation	S32	Social	Resourcefulness
Community plan for the sustainable management of natural resources and preservation of ecosystem services	S33	Social	Resourcefulness

Appendix C: Regression Results

Dependent Variable: CAPITALMEAN
Method: Robust Least Squares
Date: 05/13/18 Time: 11:19
Sample: 1 118
Included observations: 118
Method: M-estimation
M settings: weight=Logistic, tuning=1.205, scale=MAD (median centered)
Huber Type I Standard Errors & Covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MAX_FLOOD_EXP	-1.260375	1.004140	-1.255179	0.2094
NUM_FLOOD_EXP	0.842326	0.387571	2.173346	0.0298
A03_EDU	0.185072	0.037835	4.891501	0.0000
A03_POORPEOPLE	-0.134294	0.043130	-3.113673	0.0018
A03_REMITTANCES	0.134034	0.049142	2.727470	0.0064
SETTLEMENT="rural"	28.93846	5.423996	5.335267	0.0000
SETTLEMENT="peri-urban"	25.28876	4.994031	5.063797	0.0000
SETTLEMENT="urban"	29.88826	3.749595	7.971062	0.0000

Robust Statistics

R-squared	0.261839	Adjusted R-squared	0.214865
Rw-squared	0.407864	Adjust Rw-squared	0.407864
Akaike info criterion	139.2419	Schwarz criterion	164.4728
Deviance	8517.613	Scale	8.211919

Rn-squared statistic	1472.907	Prob(Rn-squared stat.)	0.000000

Non-robust Statistics

Mean dependent var	34.18813	S.D. dependent var	12.17194
S.E. of regression	10.52896	Sum squared resid	12194.49

Dependent Variable: FINCAP_MEAN
Method: Robust Least Squares
Date: 05/13/18 Time: 11:38
Sample: 1 118
Included observations: 118
Method: M-estimation
M settings: weight=Logistic, tuning=1.205, scale=MAD (median centered)
Huber Type I Standard Errors & Covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MAX_FLOOD_EXP	-1.314801	1.197009	-1.098405	0.2720
NUM_FLOOD_EXP	0.532244	0.462013	1.152012	0.2493
A03_EDU	0.214574	0.045103	4.757454	0.0000
A03_POORPEOPLE	-0.146559	0.051415	-2.850539	0.0044
A03_REMITTANCES	0.124184	0.058581	2.119849	0.0340
SETTLEMENT="rural"	20.69308	6.465800	3.200390	0.0014
SETTLEMENT="peri-urban"	18.60452	5.953251	3.125103	0.0018
SETTLEMENT="urban"	30.50721	4.469792	6.825196	0.0000

Robust Statistics

R-squared	0.356879	Adjusted R-squared	0.315953
Rw-squared	0.502975	Adjust Rw-squared	0.502975
Akaike info criterion	116.5074	Schwarz criterion	143.2666
Deviance	11988.28	Scale	10.68009
Rn-squared statistic	628.3892	Prob(Rn-squared stat.)	0.000000

Non-robust Statistics

Mean dependent var	25.55733	S.D. dependent var	14.86092
S.E. of regression	12.07636	Sum squared resid	16042.22

Dependent Variable: HUMCAP_MEAN
Method: Robust Least Squares
Date: 05/13/18 Time: 11:40
Sample: 1 118
Included observations: 118
Method: M-estimation
M settings: weight=Logistic, tuning=1.205, scale=MAD (median centered)
Huber Type I Standard Errors & Covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MAX_FLOOD_EXP	-3.927987	1.071409	-3.666187	0.0002
NUM_FLOOD_EXP	1.113669	0.413535	2.693047	0.0071
A03_EDU	0.102229	0.040370	2.532305	0.0113
A03_POORPEOPLE	-0.143204	0.046020	-3.111787	0.0019

A03_REMITTANCES	0.040533	0.052435	0.773015	0.4395
SETTLEMENT="rural"	51.52970	5.787358	8.903839	0.0000
SETTLEMENT="peri-urban"	46.37385	5.328590	8.702837	0.0000
SETTLEMENT="urban"	51.84105	4.000787	12.95771	0.0000

Robust Statistics			
R-squared	0.311277	Adjusted R-squared	0.267449
Rw-squared	0.431049	Adjust Rw-squared	0.431049
Akaike info criterion	110.4637	Schwarz criterion	137.2404
Deviance	9079.765	Scale	9.573165
Rn-squared statistic	2373.163	Prob(Rn-squared stat.)	0.000000

Non-robust Statistics			
Mean dependent var	46.16896	S.D. dependent var	12.24471
S.E. of regression	10.28766	Sum squared resid	11641.95

Dependent Variable: NATCAP_MEAN
Method: Robust Least Squares
Date: 05/13/18 Time: 11:41
Sample: 1 118
Included observations: 118
Method: M-estimation
M settings: weight=Logistic, tuning=1.205, scale=MAD (median centered)
Huber Type I Standard Errors & Covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MAX_FLOOD_EXP	3.061883	1.358945	2.253133	0.0243
NUM_FLOOD_EXP	-0.185983	0.524516	-0.354581	0.7229
A03_EDU	0.175246	0.051204	3.422491	0.0006
A03_POORPEOPLE	-0.178093	0.058370	-3.051091	0.0023
A03_REMITTANCES	0.294114	0.066506	4.422338	0.0000
SETTLEMENT="rural"	25.26969	7.340518	3.442495	0.0006
SETTLEMENT="peri-urban"	16.76268	6.758630	2.480189	0.0131
SETTLEMENT="urban"	10.34318	5.074483	2.038274	0.0415

Robust Statistics			
R-squared	0.339973	Adjusted R-squared	0.297971
Rw-squared	0.462330	Adjust Rw-squared	0.462330
Akaike info criterion	135.3976	Schwarz criterion	161.1629
Deviance	16069.76	Scale	11.43027
Rn-squared statistic	614.0173	Prob(Rn-squared stat.)	0.000000

Non-robust Statistics			
Mean dependent var	28.67514	S.D. dependent var	17.24587
S.E. of regression	14.44013	Sum squared resid	22936.92

Dependent Variable: PHYCAP_MEAN
Method: Robust Least Squares
Date: 05/13/18 Time: 11:43
Sample: 1 118

Included observations: 118
Method: M-estimation
M settings: weight=Logistic, tuning=1.205, scale=MAD (median centered)
Huber Type I Standard Errors & Covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MAX_FLOOD_EXP	-1.947405	1.326638	-1.467925	0.1421
NUM_FLOOD_EXP	1.498004	0.512046	2.925525	0.0034
A03_EDU	0.088805	0.049987	1.776557	0.0756
A03_POORPEOPLE	-0.138118	0.056983	-2.423868	0.0154
A03_REMITTANCES	0.004256	0.064925	0.065547	0.9477
SETTLEMENT="rural"	32.48104	7.166008	4.532655	0.0000
SETTLEMENT="peri-urban"	36.56478	6.597953	5.541837	0.0000
SETTLEMENT="urban"	43.16409	4.953844	8.713252	0.0000

Robust Statistics

R-squared	0.282026	Adjusted R-squared	0.236337
Rw-squared	0.407117	Adjust Rw-squared	0.407117
Akaike info criterion	122.4434	Schwarz criterion	148.0175
Deviance	13454.15	Scale	11.06685
Rn-squared statistic	1173.563	Prob(Rn-squared stat.)	0.000000

Non-robust Statistics

Mean dependent var	39.58210	S.D. dependent var	14.75787
S.E. of regression	12.63623	Sum squared resid	17564.19

Dependent Variable: SOCCAP_MEAN
Method: Robust Least Squares
Date: 05/13/18 Time: 11:44
Sample: 1 118
Included observations: 118
Method: M-estimation
M settings: weight=Logistic, tuning=1.205, scale=MAD (median centered)
Huber Type I Standard Errors & Covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MAX_FLOOD_EXP	-0.483432	1.510377	-0.320074	0.7489
NUM_FLOOD_EXP	0.886073	0.582965	1.519942	0.1285
A03_EDU	0.304850	0.056910	5.356694	0.0000
A03_POORPEOPLE	-0.064079	0.064875	-0.987736	0.3233
A03_REMITTANCES	0.139662	0.073917	1.889428	0.0588
SETTLEMENT="rural"	16.21584	8.158499	1.987601	0.0469
SETTLEMENT="peri-urban"	8.900701	7.511769	1.184901	0.2361
SETTLEMENT="urban"	17.25918	5.639951	3.060164	0.0022

Robust Statistics

R-squared	0.212598	Adjusted R-squared	0.162490
Rw-squared	0.317941	Adjust Rw-squared	0.317941
Akaike info criterion	115.7734	Schwarz criterion	142.1084
Deviance	17986.66	Scale	13.15461
Rn-squared statistic	539.9271	Prob(Rn-squared stat.)	0.000000

Non-robust Statistics

Mean dependent var	30.95711	S.D. dependent var	16.32989
S.E. of regression	14.63179	Sum squared resid	23549.82