Part Four

Technical annexes

Description of datasets and scoring system

In our research we used seven main datasets, which came from a variety of sources, such as APIs, or were manually extracted from files such as PDFs and Excel spreadsheets. Each is described below, with a link to download the file itself, any relevant code for compilation of the dataset, and other relevant metadata.

To evaluate the value and quality of each dataset, we applied a five-point scale for each of the following criteria. Our evaluations are reflected in the accompanying charts:

- *Timeliness*: How frequently a dataset is updated, and the last time it was updated, specifically whether there were no big gaps in time and whether records for the last three years were available.
- *Reliability*: The amount of confidence that could be placed in the accuracy of the data.
- *Completeness*: To extent to which data existed for all countries and years covered by our research. Also whether there were no big gaps in geographic coverage or in coverage across indicators.
- *Accessibility*: Ease of accessing the data. Some datasets were accessible through APIs, although some APIs required additional effort to extract data, due to complicated data structures. Scoring also covered inclusion of a data dictionary. Some sources (such as EM-DAT) that contained useful information were excluded, due to insurmountable obstacles to accessing their data.
- *Interoperability*: Ease of merging data into the master dataset. Points were deducted if ISO or similar codes were not included and had to be added. We also considered commonality of crisis typology, population group definitions, and definitions of damage and destruction.

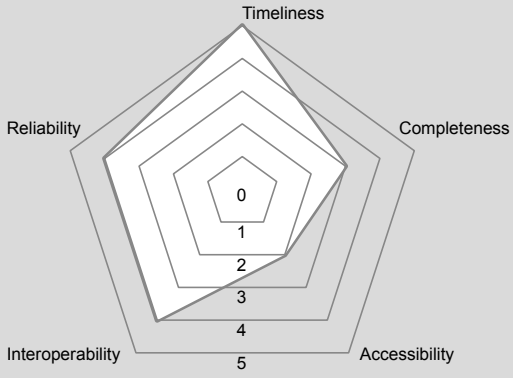
ReliefWeb

Description: A web platform run by UN OCHA, which hosts a wide variety of historical information on humanitarian disasters, accessible through an API. The ReliefWeb API recorded 3021 crises, of which 1701 occurred since 2005. Of these 1701 crises, only 353 occurred in years and countries that matched for shelter crises.
Type of source: API.
Code location: GitHub.
File location: Google Drive.
Number of entries (rows): 1643.
Number of dimensions (columns): 21.
Scoring: Scored highly for timeliness, but accessing data through the API was cumbersome, due to nested data structures and somewhat sparse API documentation.

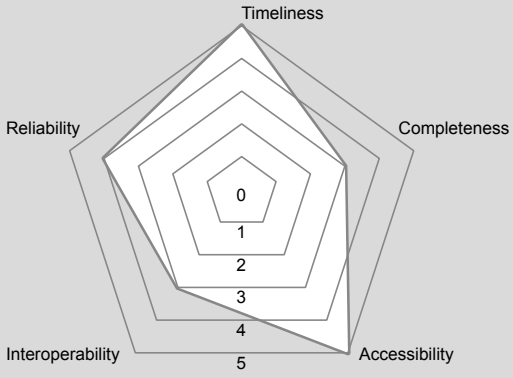
Shelter Cluster Dashboards (GSC dataset)

Description: An historical overview of countries and years in which the SC was activated, including metrics such as funding required and number of beneficiaries assisted. There was some duplication of records, where multiple SC activations occurred in a given country and year; in such cases we merged those records. Although there were two separate datasets from the SC, we merged them into one.
Type of source: Excel download from SC Operations Dashboard and SC homepage.
Code location: GitHub.
File location: Google Drive (Operations, Homepage).
Number of entries when joined (rows): 232.
Number of dimensions when joined (columns): 41.
Scoring: The datasets were easily accessible and timely, but not very interoperable, as they lacked GLIDE numbers and ISO codes.

ReliefWeb



Shelter Cluster Dashboard



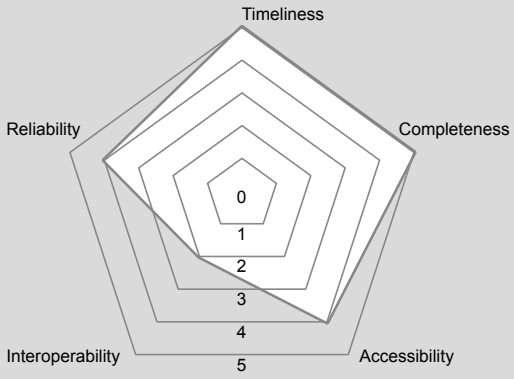
UNCHR displacement data

Description: Yearly statistics on internal and external population movements around the world, collected by UNHCR.
Type of source: Database export provided by UNHCR.
Code location: GitHub.
File location: Google Drive (note: modified data is in the master dataset).
Number of entries when joined (rows): 34,809.
Number of dimensions (columns): 11.
Scoring: The displacement data is updated almost every year for most countries in the world, and is easily accessible in Excel spreadsheet format. It lacks interoperability, in some cases, for country and crisis aggregation and reporting of displacement figures through HNO documents and 4Ws, for example. It has no ISO-compliant identifier or similar for its countries.

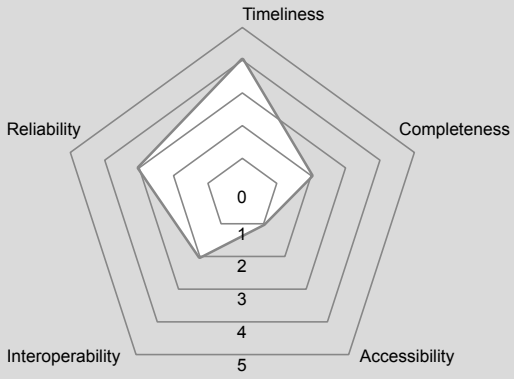
DesInventar

Description: A disaster information system hosted by UNISDR. There was, unfortunately, minimal overlap between countries included and SC activations, due to sparsity of DesInventar data. There were only 54 pairs (20 countries)[1] of year/crisis overlap between the two sets of the total of 253 entries, starting from 2005, in our countries of interest.
Type of source: Online database that was scraped.
Code location: GitHub.
File location: Google Drive.
Number of entries when joined (rows): 254.
Number of dimensions (columns): 13.
Scoring: Although DesInventar is frequently updated and contains relevant information, it was very inaccessible and had to be scraped. It also covered relatively few countries and years.

UNHCR displacement data



DesInventar



Financial Tracking Service (FTS)

Description: A service run by UN OCHA for tracking funding flows by several dimensions including organizations, clusters and locations. There was good overlap between identified SC activations and funding levels per country per year. With this data, we could compare overall funding for the SC with percentage of funding for the sector that went through a plan or outside a plan. We also disaggregated funding by other sectors.

Type of source: API.

Code location: GitHub.

File location: Google Drive.

Number of entries when joined (rows): 226.

Number of dimensions (columns): 35.

Scoring: FTS is frequently updated and accessible through a user-friendly API. But it is only as accurate as the data submitted by humanitarian agencies; for this reason it should not necessarily be treated as an ultimate source of information on funding levels. Discrepancies became apparent when comparing this data with funding data reported through the Global Shelter Cluster captured in the SC Operations Dashboard.

HNOs, HRPS and RRPs

Description: HNOs and HRPs are produced annually for humanitarian crises, and contain valuable information on humanitarian needs, such as counts of people in need, and funding requirements. We collected 134 HNO/HRP documents from sources such as ReliefWeb and humanitariaresponse.info. For the 231 recorded SC deployments, we found only 134 documents that matched a crisis's given country and year. Relevant information and counts from these documents were then extracted using DEEP, the humanitarian secondary data review platform.

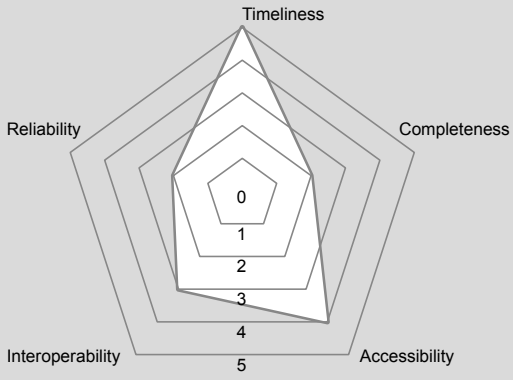
Type of source: Manually collected from disparate PDFs and Word documents.

Code location: GitHub.

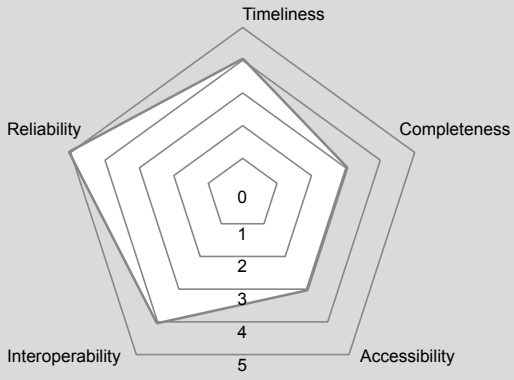
File location: Raw DEEP export, overview of discovered files.

Number of entries when joined (rows): 168 and 132.

Financial Tracking Service



HNOs, HRPS and RRPs

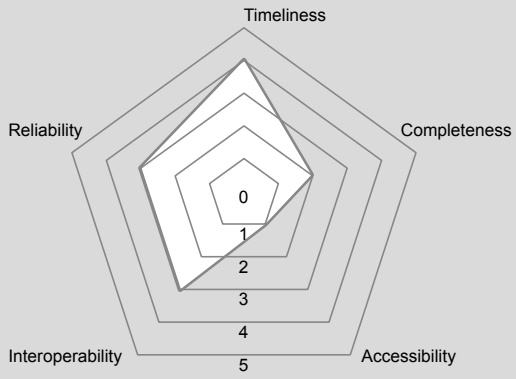


Number of dimensions (columns): 61 and 4.
Scoring: HNOs and HRPs are reliably sourced and edited, and released frequently, but they are not stored in a centralized location, nor are they in tabular formats. Interoperability problems arise from lack of alignment between methodologies for estimating humanitarian population figures between countries and crises.

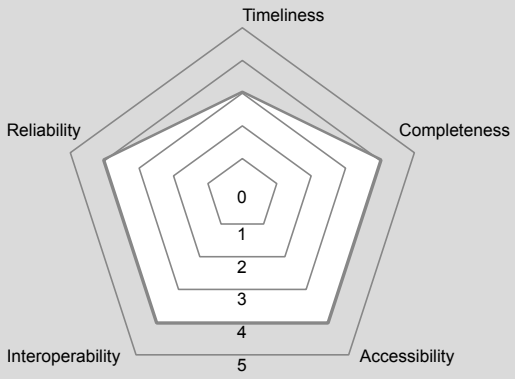
Who, What, Where, When (3/4W) collection

Description: A more thorough description of the 3/4W data collection process and subsequent finds is detailed in the *3/4W Collection* section of this report (see Technical Annex III). In general, we found a surprisingly low number of 4W documents (Who does What, Where?); primarily 3W documents (Who does What, Where?) were uncovered. Due to time constraints, contents of the merged 4Ws were not summarized or included in the master dataset.
Type of source: Collected from HR.info, HDX, SC website and SC DropBox.
Code location: GitHub.
File location: All W files, Merged Ws.
Number of entries before processing: 103,857.
Number of dimensions (columns): 18.
Scoring: The 4Ws scored very low in accessibility, not just because of the difficulty in finding them, but also because of their generally spread and hidden state throughout the web. This is sometimes done deliberately, to protect data in sensitive operations. We recommend testing ways to anonymize those 4Ws, so that they can be shared at the global level. Although reliability of distribution data is dependent on the individuals reporting it, this is the most accurate source for such information.

4W collection



Master dataset



Master dataset

Our master dataset contains 153 dimensions across the varying datasets, and 305 rows. Each row represents a given year/crisis, although there are some duplications due to multiple HNO files.

The number of dimensions in the master dataset does not equal the sum of all of the other datasets in this work. This is intentional, because not all columns from all datasets were merged, partly because they were not relevant to our research or because it was not possible to summarize them into country or year.

The data for the master itself can be found here and metadata for column mapping is here. Code for creating the master file is hosted on GitHub here.

We would be irresponsible data workers if we did not submit our own work to the scoring criteria that we developed. Our master flat file scores high in accessibility (because it is in tabular format and publicly available), and also in interoperability (because ISO codes are provided for each year). It lacks timeliness, because it is at the mercy of the data sources it aggregates (although, given the automated nature of its creation, this could improve over time).

Technical notes on data work

Data for this research was collected – wherever possible – by automated scripting, allowing for easy reproducibility of our work in the future.

Code was written in Python and is hosted in a GitHub repository. Contained in the repository are both Jupyter notebooks and regular Python files. The Jupyter notebooks were used for sandboxing and initial data exploration, but the Python files are the final versions that were used.

A number of open-source libraries were used. An overview of libraries used includes:

- country_converter: For deriving ISOs from country names, as several data sources did not have these codes
- openpyxl: A flexible and fully featured package for managing, reading and writing Excel files
- pandas, numpy: The golden standards for data manipulation in Python
- requests: A library for making HTTP requests for pulling data from web sources
- grequests: Similar to *requests*, but facilitates a quicker version of making multiple requests at once for larger APIs
- beautifulsoup: A fully featured library for scraping data and interacting with websites
- dateparser: An open-source library for extracting date values from pieces of text, in particular when the date formatting is not known.

Recommendations for distribution data (4Ws)

Having completed the process of manual and semi-automated data gathering and merging of 4W data, we offer here a number of recommendations for improving various steps in the life cycle of 4W data collection.

4W data could be better managed through automated tooling. Although there are standard templates on the SC website for collecting 4W data, we observed minimal adherence to these standards in the 4W sheets that we analyzed. Based on these findings and previous trends, it is naïve to believe that continued attempts to enforce data collection standards through Excel templates is a viable solution, or that all shelter-related 4Ws will be uploaded to the SC website. For these reasons we propose a multi-faceted tool that would:

1. crawl sites of interest – such as ReliefWeb, HDX and the SC website – to retrieve documents that resemble SC 4Ws
2. identify (using pattern matching learned from the existing corpus of 4W documents) whether a document contains a sheet with shelter distributions, and determine which sheet it is
3. identify pertinent columns using techniques such as Levenshtein distance and text clustering to match differently labelled columns (for instance 'Activity' and 'Activity Type')
4. extract information from columns of interest and standardize reporting terms across different documents (for instance 'CGI' and 'Corrugated Iron')
5. merge 4W documents into a unified dataset, to be hosted in centralized data repository.

This technique would initially require some manual intervention to 'teach' the algorithms how to match columns and values between 4W documents. However, as more feedback was provided, the process would become more accurate and would move closer to full automation.

Our other recommendations for distribution data are:

- *Better date handling*. The actual values of dates were not incorporated in this analysis, due to the complexity in handling them, and their inaccuracies. To use dates in further analysis, we identified an open-source library *dateparser* (discussed in *Technical Notes on Data Work* in Technical Annex I) that can

automatically extract dates from pieces of text. Nevertheless, we recommend considering the locales of 4W reports and how their date values may be structured.

- *Separate-column date formatting*. A general best practice for dates in Excel is to have separate columns for day, month and year, to avoid the complexities that come with attempting to store dates as single-text instances. These columns can then be merged when reporting data.
- *Data requests from information management officers*. To increase the number of 4W reports available for future research, we recommend directly contacting individuals who are working, or who have worked, in particular crises. As demonstrated by the fact that we could find reports for only 21 of the 230 crises/year on common data-sharing portals, 4W documents are not always properly uploaded to the internet.
- *Longitudinal studies*. Due to the limited number of 4W documents that we found, we could generally not analyze distribution data longitudinally. Such analysis could reveal trends over time, such as peaks in size and scope of interventions and population covered, which could then be correlated to funding levels, crisis events, and changes in humanitarian access conditions.
- *4W translation*. Analysis of 4W documents would benefit from translation into English, of both content and column headers. Translated columns would permit easier merging of 4W documents. Translated contents (such as activity distribution) would allow these values to be properly added to, and combined with, the general corpus of reporting data. Most 4W documents found were in English, although a few were in French, Arabic or Spanish.
- *Data extraction from PDFs*. We did not extract information contained in PDFs, thus leaving out valuable data. Tabular extraction from PDFs is a messy and time-consuming process, but could benefit the SC. And if PDF extraction is automated, once the structure of a PDF document is known it can be re-used for other PDFs with the same format (assuming it is not changed in the future).
- *Removal of duplicates*. We believe that there are duplicated entries in the collected 4Ws. Further investigation of 4W data should aim to remove duplicate entries, to ensure more accurate counts.
- *Addition of administrative area codes*. Approximately 48 per cent of 4W entries contained codes for administrative areas, leaving more than half of the values without administrative codes. This lack of codes makes it difficult to map and compare data at the sub-national level. Deriving administrative codes from names only is a complicated task, but can be expedited through automated and semi-automated processes. There are many possible sets of codes; we recommend pcodes.
- *Comparison of 4W data with other figures*. Our report only outlined the contents of 4W data; it did not compare it to data contained in the other sources gathered for this research.

The state of 3/4W documents

Our additional observations on the state of 3/4W documents include:

- *Data contained in files rather than databases*. We could not find any environments for hosting SC-related reporting data in a database format. Reporting information is stored mostly in Excel spreadsheets. To complete any kind of analysis on reporting data, individual files had to be found and then merged.

  Moreover, reporting information was also found in PDFs and maps, making it tremendously more complicated, if not impossible, to extract needed information. For our research, we ignored PDF files, but they could be used in future work.

- *Inconsistent name formatting*. Although some organizations label distribution documents consistently (for instance, UN OCHA in Afghanistan uses the labelling format 'afghanistan-3w-january-to-march-2016.xlsx' and 'afghanistan-3w-july-to-september-2015.xlsx'), there is minimal consistency in naming between organizations. This makes it difficult to find documents based on date and location, and leaves a data-forager at the mercy of the accuracy of document metadata in web portals, manually extracting information by opening individual documents, or developing automated processes to extract this information.

- *Inconsistent labelling and structuring in reported data*, including:

  – *Column names*. Although SC reporting templates exist, they are infrequently used. Organizations reporting SC data often use their own templates.

  – *Inconsistent labelling of activities*. Even in reports from the SC, the same activity is referred to in different ways in different documents, although there is generally good consistency within documents.

  – *Varying dimensions for reporting activities*. Some reports list up to four dimensions or columns for categorizing activity, whereas others have as few as one. This makes it difficult to reliably compare reported activities between data sources.

- *Lack of coded administrative areas*. Many distribution documents do not code administrative areas, making it difficult and very time-consuming to merge collection data at lower administrative levels, even when using automated processes. Approximately half of all entries did not have level 2 coding.

Data sourcing overview

Keeping the reporting data landscape in mind, the intrepid data-forager packs his lunch and heads out to the wide world of the web to collect reporting data. For our research, we collected all reporting data manually, although joins were done automatically. Recommendations for a fully automated approach are set out in *Recommendations* below.

Reporting documents were found by iterating through each country and year listed since 2013 in the GSC dataset (the baseline dataset for SC activations) and searching repositories that are known to contain distribution data. We used the sites HR.info, HDX, the SC Dropbox and the SC website.

There are two ways to search for data in these portals: either by free text (entering '3W' or '4W' into the portal's search function) or by using the filtering criteria in the relevant site's search page. These two complementary methods are helpful for locating documents that may not be properly classified as 3/4W, or for finding documents whose names may not indicate that they contain distribution information.

Overview of documents sourced

Operational presence data (3Ws): Who does What, Where?

We found a total of 40 tabular documents and 230 PDFs. The PDF data was not categorized by country and year for this report, but the collection of PDF files can be found here. Of the 40 tabular documents found, an overview of what country and year they covered is in Table 4. In some instances, we found multiple 3W documents for a given year and country.

Table 4 **Count of 3W reports by country, 2014–2017.**

Country	Year	Count	Country	Year	Count
South Sudan	2014	1	Ethiopia	2016	1
Afghanistan	2015	4	Kenya	2016	1
Somalia	2015	1	South Sudan	2016	1
Colombia	2015	1	Sudan	2016	1
Myanmar	2015	1	Philippines	2016	1
Philippines	2015	1	Ecuador	2016	1
Nepal	2015	7	Afghanistan	2017	3
Dem. Rep. Congo	2015	1	Chad	2017	1
Afghanistan	2016	5	Ethiopia	2017	4
Chad	2016	1	Kenya	2017	1

Afghanistan had the highest total number of 3W documents (four), suggesting greater data maturity in terms of publicizing reports in common data portals. Nepal had the highest for a given year (seven, in 2015).

Distribution data (4Ws): (Who does What, Where, and When?)

4W documents, the main focus of this search section, contained a much higher percentage of accessible tabular data in Excel files than did 3Ws. 4Ws that were not in a tabular format were generally stored in PDF files as maps or, in some cases, as raw reporting data in oddly formatted tables.

From the 4W files that we sourced, we captured the following attributes (along with a description).

Table 5 **Description of columns in 4W data.**

Column	Description
Date Reported	Date that activity was reported
Donor	Donor organization providing funding for activity
Organization	Organization that oversaw distribution (if not done through a partner)
Implementing Partner	Local partner that performed activity distribution
Activity Category	Higher-level category of activity (for instance ‘Shelter’ or ‘NFI’)
Area of Activity	Mid-level category (for instance ‘Reconstruction Supplies’)
Activity Detail	Most granular categorization (for instance ‘Toolkits’ or ‘Tarps’)
Admin Level 1 Name	Name of highest-level administrative unit
Admin Level 1 Code	Code of highest-level administrative unit
Admin Level 2 Name	Name of second-highest level administrative unit
Admin Level 2 Code	Code of second-highest level administrative unit
Status	Distribution status (whether distribution has been completed or not)
# of HH Reached	Count of households reached
# of Beneficiaries Reached	Count of beneficiaries reached
Activity Start Date	Date that an activity began
Activity End Date	Date that an activity ended

A total of 59 Excel files were found and used in the analysis, while another 20 PDF documents were found but excluded from analysis. Table 6 is presented with a similar structure as the 3W data.

Table 6 **Count of 4W documents by year and country.**

Country	Year	Count
Afghanistan	2013	1
Palestine	2014	1
Ethiopia	2015	1
Iraq	2015	1
Pakistan	2015	1
South Sudan	2015	1
Syria	2015	1
Yemen	2015	1
Afghanistan	2016	8
Ecuador	2016	1
Haiti	2016	1
Iraq	2016	7
Nepal	2016	1
Syria	2016	1
Yemen	2016	1
Afghanistan	2017	16
Bangladesh	2017	3
Mali	2017	1
Nigeria	2017	1
Ukraine	2017	5
Bangladesh	2018	1

As can be seen, 4W reports were largely clustered in the same responses, with Afghanistan having the largest cumulative number of available datasets (25), followed by Iraq (8).

Process for merging 4W documents

Once the reporting information was obtained, it then had to be merged into a single file to enable analysis. In this research we did not merge 3W data, as our primary focus was on 4Ws, although our method could be applied to 3W documents.

Merging a large number of reporting files can be done manually, automatically, or using a hybrid method.

Manual merging entails copying and pasting relevant columns into a master Excel spreadsheet. This process allows the researcher to become more familiar with the data, but is very time consuming.

Automated merging requires investment in developing code and in building a library or employing machine learning techniques. This method can correctly relate inconsistently spelled column names and detect content of free text such as activity information. Although we did not employ such a process, if it is used in the future, 4W merging would become easy and straightforward.

A hybrid method combines the best of both worlds, and was chosen for this project due to time constraints. The process went as follows:

1. Columns of interest were identified for extraction.
2. Columns in individual 4W documents were mapped to the desired columns in the master spreadsheet. This was done manually by iterating through each

Excel spreadsheet and mapping the column values. (In the future, a guided user interface could prompt the user with column headers in a 4W document, and the user would do the mapping from there.)

3. After all columns across all 4W documents had been mapped, their contents were merged into one file. We wrote code to merge all files based on the column mapping.

After 4W merging was complete, it was ready for analysis. Most analysis was completed using the Python programming language, and *pandas*, an open-source library similar to R.

Limitations of our findings

Before discussing the content of the merged 4W data, we emphasize again that the figures presented here represent only the data that we found; they do not necessarily accurately reflect the content of all 4W reports in existence. Significant limitations to our work included:

- *Limited scope*. Although we endeavoured to find all available 4Ws, we only found 4W files from our sources above. A more ambitious effort with a broader scope (as discussed in *Recommendations*) should be pursued, in order to get a wider breadth of data.
- *Double counting*. There is no guarantee that reported figures do not count the same beneficiary or sets of beneficiaries multiple times.
- *Overlap*. There may be overlap of entries between 4W files, due either to data being reported to multiple sources or subsequent 4Ws for a given country containing duplicate data. Although we could have made efforts to remove duplicates, this is not a foolproof method and can lead to removal of valid data that happens to overlap with an entry of similar values.
- *Dates*. Summary-level findings are provided for values of date columns, but actual date values were not included in this analysis. Although open-source tools can extract dates, these have limitations, such as deducing whether dates are in a mm/dd or dd/mm format. Further work with dates is outlined in *Recommendations*.
- *Longitudinal findings*. As there were not enough reports gathered for specific countries, it was difficult to extract any longitudinal findings, other than the one shown for report data completeness.

4W content analysis

Before delving into the specifics of how documents were sourced for this research, and what they contain, it is important to consider the context in which 3W and 4W documents exist. Although 3Ws (Who, What, Where) report on operational presence, whereas 4Ws (Who, What, Where, When) present distribution data, we use the term 'reporting data' generically in this section. Our major findings on the state of reporting data include:

- *Multiple repositories.* An information management officer who wishes to publish reporting data in the field, or even at the headquarters level, can upload documents to several different repositories. Some are publicly available, such as HDX or HR.info, while others are private, such as Dropbox (where the SC has a number of reporting data files). This multiplicity of repositories make it difficult to locate data, and creates a problem of duplicate files across different data sources.
- *Predominance of operational presence (3Ws) over distribution data (4Ws)*. The vast majority of documents found were 3Ws rather than 4Ws. We found 270 3W documents, but only 79 4W documents.

Total count of entries

In total, 125,673 entries (or instances of assistance distributions) are contained across the 79 4W files that we found, 114,144 of which are used in the following figures.

When grouping entries by country, the aggregated counts did not correlate with the number of reports gathered. As shown below, Ukraine had the largest number of entries (59,341), although only five 4W files were found. On the other hand, Afghanistan had the largest number of 4W reports (25) and 2685 records.

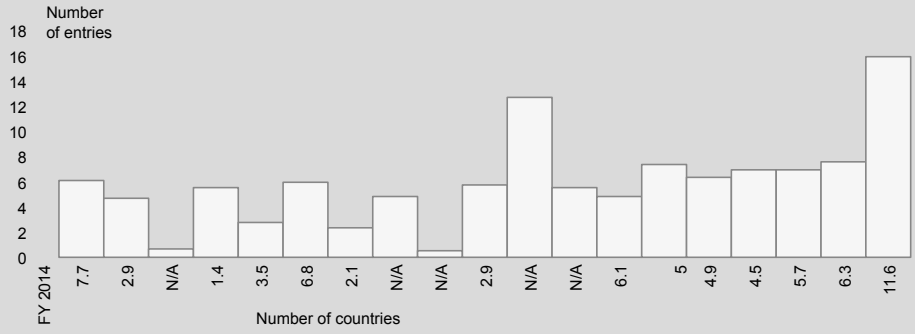


Figure 21 **4W reports: count of entries by country, 2014.**

Data completeness: attributes

We calculated a data completeness score for each attribute by taking the percentage of non-empty cells for a given column. The findings do not take into account data validity, that is, whether a numerical column actually contains a number (rather than text, for example).

In terms of dates reported, Activity Start Date and Activity End Date are much more populated than Date Reported – by about 40 per cent each. Some 4W documents did not have a column for Date Reported – a large contributor to this discrepancy.

A surprisingly high percentage of entries had values for administrative 1 and 2 levels and also for their associated codes. With a semi-automated process, the missing codes for administrative levels could be added, although we did not do this.

The activity categories were all surprisingly incomplete, with Activity Detail being the most complete, at 49 per cent. This is surprising, as Activity Detail is the most granular category for classification, and intuition would suggest that it would be the most populated.

It seems that reporting organizations favour reporting counts of beneficiaries reached, as opposed to households reached, as there was a difference of 17 per cent between the two. This probably indicates that during distributions it is easier to count individuals reached than to apply a formula based on local conditions to calculate how many households have been reached. Many reports had decimal values for number of beneficiaries reached or number of households reached, possibly indicating that these may not have been collected at time of distribution, but rather were calculated using an average household size value.

Table 7 **4W variable completeness scores.**

Variable	% of completed entries
Admin Level 1 Name	99%
Admin Level 2 Name	98%
Organization	80%
Status	75%
Number of Beneficiaries Reached	74%
Activity Start Date	68%
Donor	62%
Activity End Date	62%
Number of Households Reached	57%
Implementing Partner	53%
Activity Detail	49%
Admin Level 1 Code	48%
Admin Level 2 Code	48%
Activity Category	36%
Date Reported	22%
Area of Activity	20%

Data completeness: reports

Taking this same approach, we examined how complete individual reports were. The basic arithmetic is total number of empty cells in a given report, divided by total number of cells in the report. For a given country and year, all reports meeting our criteria were merged to give the following scores:

Table 8 **Completeness of 4W reports, by country and year.**

Country	Year	Total no. of values	No. of missing values	Cells filled
Nigeria	2017	5,168	814	84%
Pakistan	2015	12,160	3,861	68%
Nepal	2016	142,640	48,132	66%
Bangladesh	2018	282,464	104,450	63%
Iraq	2016	31,568	12,270	61%
Haiti	2016	34,048	13,530	60%
Syria	2016	16,944	7,994	53%
Ukraine	2017	1,111,152	525,556	53%
Bangladesh	2017	6,848	3,496	49%
Iraq	2015	5,008	2,820	44%
Ecuador	2016	14,240	8,160	43%
Palestine	2014	784	454	42%
Ethiopia	2015	96	57	41%
Yemen	2015	23,984	14,256	41%
Afghanistan	2017	21,296	13,515	37%
Mali	2017	2,784	1,834	34%
Yemen	2016	46,720	30,920	34%
Afghanistan	2016	19,984	13,823	31%
Afghanistan	2013	12,720	8,981	29%
Syria	2015	4,368	3,550	19%
South Sudan	2015	214,736	175,179	18%

The breakdown of filled data per country per year shows that the values run from Nigeria in 2017 (84 per cent of cells with a value), down to South Sudan (only 18 per cent of cells with values). Across all reports, there is a slightly positive trend of data completeness over time, as indicated in Figure 22.

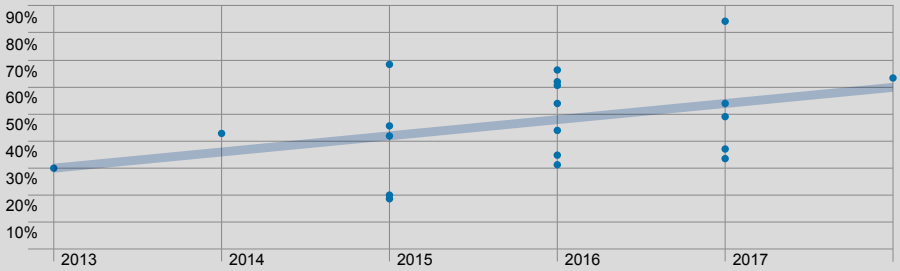


Figure 22 **Percentage of complete entries over time, 2013–2018.**

Beneficiaries and households reached

Across all 4W documents found, 48 per cent of entries contained counts for number of households reached, while a slightly higher proportion (64 per cent) counted the number of beneficiaries reached. A complete overview of both counts is provided in Table 9, although some entries do not show counts for beneficiaries or households, as they were not present in the 4W data.

Table 9 **Counts of beneficiaries reached in 4W reports, by country and year.**

Year	Country	Total no. of beneficiaries reached	Total no. of households reached
2015	South Sudan	168,057,250	3,599,988
2018	Bangladesh	27,502,761	14,195,878
2016	Nepal	13,879,605	–
2017	Afghanistan	6,667,285	111,698
2017	Ukraine	5,563,765	1,646,432
2015	Pakistan	687,939	105,631
2016	Syria	469,286	76,431
2015	Syria	412,551	–
2017	Bangladesh	261,470	51,241
2014	Palestine	244,482	49,801
2016	Yemen	216,247	34,099

Year	Country	Total no. of beneficiaries reached	Total no. of households reached
2015	Yemen	209,776	32,229
2016	Afghanistan	197,422	13,325
2013	Afghanistan	189,608	30,752
2016	Haiti	67,247	644,730
2016	Iraq	6,796	313,320
2016	Ecuador	2,944	872,372
2015	Ethiopia	–	–
2015	Iraq	–	60,137
2017	Mali	–	–
2017	Nigeria	–	49,320

The country and year with the largest reported count of beneficiaries reached is – by far – South Sudan: approximately 168 million in 2015. But given that South Sudan has a population of about 12 million, the validity of this figure in the relevant 4W document is questionable, and highlights the difficulty of using 4W documents for accurate analysis.

Furthermore, we found very large discrepancies between the count of total beneficiaries reached and figures in HNO documents and official SC statistics.

If we were to assume that reports correctly count households reached and beneficiaries reached, we can calculate an implied average household size by dividing the count of households reached by the count of beneficiaries reached. Unfortunately however, as with counts of entries, there is significant discrepancy in these figures. Afghanistan had an average derived household size of six people in 2013, 15 in 2015 and 60 in 2016. Ecuador, on the other hand, had an average derived household size of 0.002 people in 2016. These calculations reveal that the figures reported in 4Ws are incomplete, or do not accurately reflect the number of beneficiaries reached versus households reached. Or it can mean that, in many 4Ws, organizations might report either one figure or the other.

Size of distributions

Looking more closely at the instances of distributions, we can find the median number of households or beneficiaries reached per distribution. For this analysis, we calculated the median, due to the great variability in the counts reported.

As with average household size, there are very large differences in the median sizes of distributions, for both households and individual beneficiaries. The median number of households reached by distribution for all entries was 22, while the median number of beneficiaries reached was 39.

Table 10 **Median counts of beneficiaries and households reached in 4W reports, by country and year.**

Year	Country	Median no. of households reached by entry	Median no. of beneficiaries reached by entry
2013	Afghanistan	13.0	43.0
2014	Palestine	700.0	2709.0
2015	Ethiopia	–	0
2015	Iraq	104.0	–
2015	Pakistan	16.0	96.5
2015	South Sudan	1093.5	1472.0
2015	Syria	–	0
2015	Yemen	34.0	209.0
2016	Afghanistan	22.0	80.0
2016	Ecuador	240.0	79.5
2016	Haiti	200.0	263.0
2016	Iraq	75.5	6796.0
2016	Nepal	–	570.0
2016	Syria	40.0	157.0
2016	Yemen	61.5	0
2017	Afghanistan	43.0	222.0
2017	Bangladesh	200.0	1000.0
2017	Mali	–	–
2017	Nigeria	100.0	–
2017	Ukraine	8.0	13.0
2018	Bangladesh	306.0	805.0

The median counts for both households and beneficiaries reached in Afghanistan increased over the same three-year period as it did for calculated average household size.

Organizations

Table 11 lists the 10 organizations reporting the highest total numbers of distributions. As stated earlier, these figures are not necessarily indicative of the counts of shelter distribution across all crises, but rather of what is represented by the data that we found and analyzed. Also, although some basic text matching was done to match mis-spelled or abbreviated organization names, a more thorough automated approach or manual classification would provide more accurate counts.

Table 11 **Top organizations by distribution counts in 4Ws.**

Organization	Total no. of distributions	Total no. of households reached	Total no. of beneficiaries reached	Average households reached per distribution	Average beneficiaries reached per distribution
People in Need (Czech NGO)	21,694	384,989	1,038,136	18	48
UNHCR	20,144	3,596,187	7,207,700	179	358
International Organization for Migration (IOM)	15,231	4,805,128	9,898,057	315	650
Adventist Development and Relief Agency	3,907	79,480	194,929	20	50
Mercy Corps	3,633	116,159	335,608	32	92
UNICEF	2,285	1,515,687	2,341,217	663	1,025
Norwegian Refugee Council	2,262	106,721	272,866	47	121
Save Ukraine Help Center	2,198	74,474	214,937	34	98
Danish Refugee Council	1,995	60,143	182,758	30	92
BRAC (formerly Building Resources Across Communities, Bangladesh)	1,446	848,072	2,973,027	586	2,056

Based on these figures on the top 10 distributors, the Czech-based organization People in Need made the largest number of distributions, but reached the smallest average number of households and beneficiaries per distribution (18 and 48 respectively). UNICEF, on the other hand, reached the largest number of households and beneficiaries per distribution: 663 and 1025 respectively.

People in Need's distribution counts draw almost exclusively from Ukraine 2017, where they represent 21,694 of the instance's 69,447 entries.

Exploration of available damage data

Disaster impact on shelter needs

The occurrence of disasters has been increasingly documented and accounted for in international disaster databases, and the scope and validity of those databases is being periodically discussed. A broader comparative review of these databases and their limitations and advantages goes beyond the scope of our research.[2] EM-DAT and DesInventar are central to our analysis, as they are two of the most popular international databases and are widely cited in policy documents and research analyses. Both attempt to aggregate and classify data to support analysis of the types and effects of the disasters recorded. They are based on a common standardized classification and definition of types of perils and hazards. However, the comparison of the two main global disaster databases, EM-DAT and DesInventar, undertaken by Osuteye and colleagues in 2017,[3] rightly concludes that their quantity of data and coverage of disasters is insufficient to support robust conclusions with greater detail, for instance on lower administrative levels. Data on losses to health from everyday hazards are provided by demographic and health surveys, but their sample sizes are too small to provide accurate or detailed data on lower administrative levels or even lower municipal areas (such as urban centres). The findings highlight the need for more robust data collection, which would help national and local decision makers make more informed and location-specific choices about disaster risk management. Systematic collection and cataloguing are needed if information is to be robust enough to support good planning and policy making.

When recording disaster losses, the major databases focus on loss of life, injury, and displacement. Detailed information on economic (or monetized) losses are poorly documented in EM-DAT. Non-economic losses are poorly documented as well. For example, the categories for ‘death’ and ‘injury’ do not include morbidity as a secondary effect, even though disasters often create the conditions for disease transmission and the spread of epidemics. The data further suggest that the number of people injured may be under-reported considering the total number of people affected by a disaster. Financial losses were computed for floods only, despite the relative importance of other types of disasters from country to country. DesInventar data for the same period provides a more detailed account of loss by itemizing the number of ‘houses destroyed’ and ‘houses damaged’, and the numbers of deaths, injuries, and missing persons by disaster. DesInventar currently has very limited information on the monetized losses

from disasters. However, unlike EM-DAT, which computes financial losses for floods only, DesInventar includes in its limited dataset some detail on financial losses from droughts, coastal erosion, and fires.

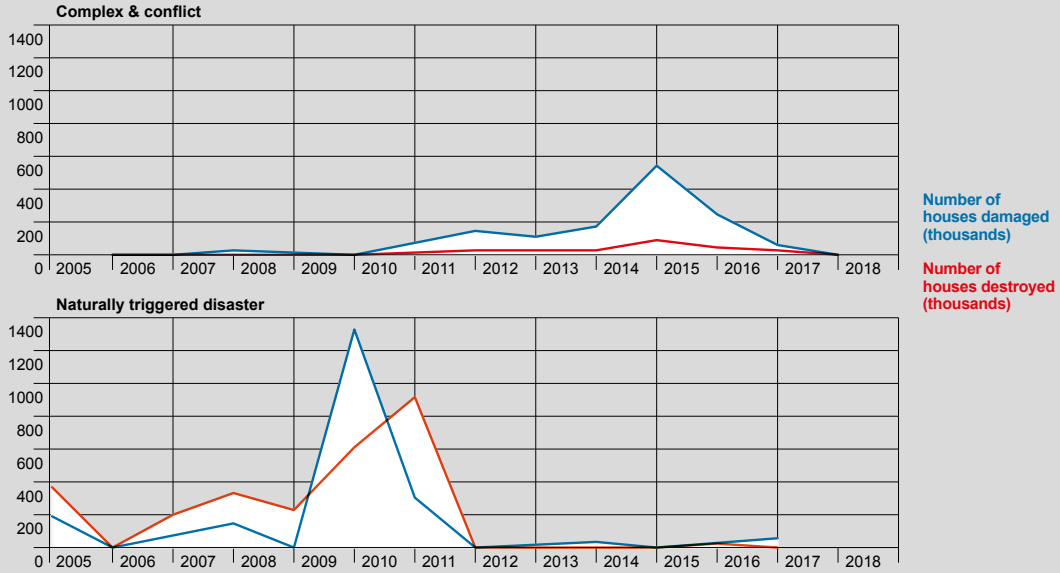


Figure 23 **Housing damaged and destroyed, per DesInventar for applicable regions, 2004–2018.**

We found minimal overlap between countries included in DesInventar and SC deployments: only 54 pairs (20 countries) of year/crisis overlap between the two sets, although DesInventar has a total of 253 entries (starting from 2005) in our countries of interest.[4] Our analysis of physical (infrastructure), economic and human impact of disasters on shelter needs is limited to those overlapping contexts. And, as described below, the explanatory power allowing for closer analysis of the relationship between destruction of physical infrastructure, economic loss and human impact is limited to just a few case studies for which such data is available.

Physical and infrastructure impact

According to DesInventar, more than 3.3 million houses were damaged and 2.7 million were destroyed between 2005 and 2018 in countries where the SC was deployed. Some 94 per cent of all houses recorded as destroyed between 2005 and 2018 were destroyed due to naturally triggered disasters (and 6 per cent in complex and conflict crises), whereas only 65 per cent of houses recorded as damaged were damaged as a result of naturally triggered disasters. The other 35 per cent were damaged in complex and conflict crises, as shown in Figure 23. Peaks in naturally triggered disaster damage are attributed to several disasters in Pakistan between 2008 and 2011, including floods and earthquakes. The peaks in conflict-related damage are attributed to damage reported in Myanmar between 2014 and 2016. A decrease in naturally triggered disaster damage and

destruction after 2013 reflects the absence of any major large-scale naturally triggered disaster, and a lack of related data for the countries reviewed.

Information fed into the DesInventar database is collected and provided by countries themselves.[5] As the capacity of national statistics offices and other data providers can vary greatly between countries, the quality and quantity of available information also varies. According to DesInventar data, the Asia Pacific region (primarily Pakistan, Myanmar and Indonesia) reported the highest levels of physical (infrastructure) damage, followed closely by the Americas (Chile, Colombia and Paraguay). But all these countries have a high capacity to collect, record and analyze statistical data. Physical and infrastructure damage remains under-reported in countries with less or no such capacity, which include crisis countries where a shelter response is continuing.[6] As a result, the data showed a positive correlation between damage and destruction to housing and the Asia Pacific region. That is, the Asia Pacific showed the highest levels of damage of all regions.

Thus the findings are skewed towards countries in the Asia Pacific region that provided more robust information to this particular dataset. In the Philippines, more than 1.1 million people were assessed to be in need of shelter in the aftermath of Typhoon Haiyan in 2013. Funding of shelter response averaged 46 per cent of total funding received for the country between 2013 and 2018, and almost half of all financial contributions across all sectors. It needs to be noted, however, that DesInventar has no data on destruction and damage to housing for this particular disaster, despite Haiyan being one of the most devastating typhoons in the country's history.

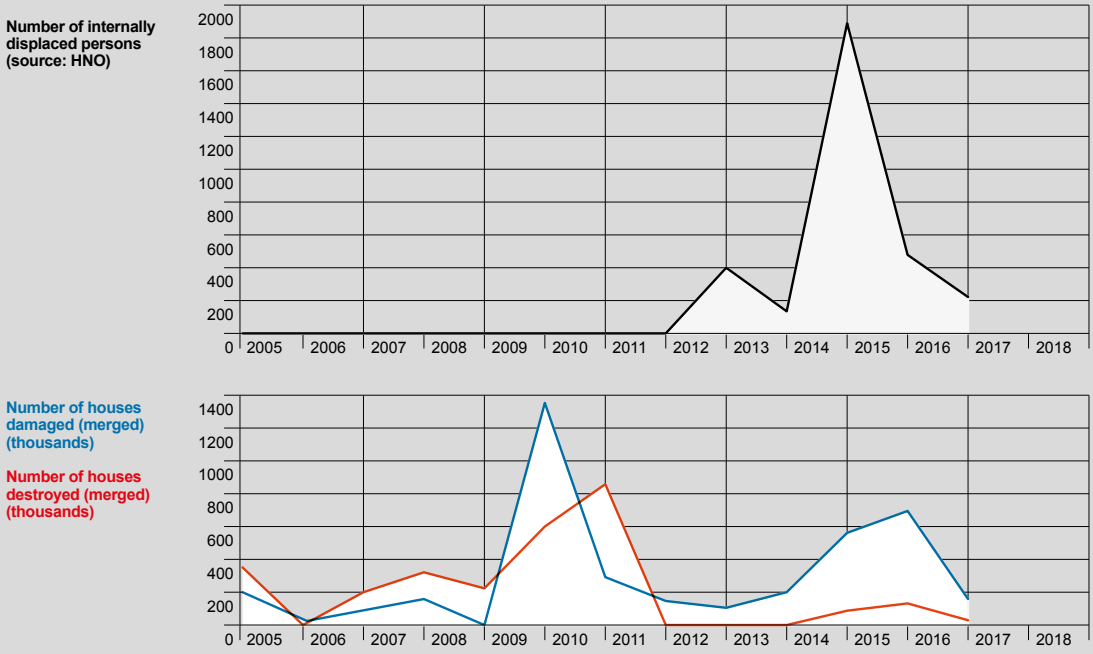


Figure 24 **People displaced (top) and houses destroyed or damaged (bottom) per DesInventar for applicable regions, 2005–2018.**

According to the available data, shelter is worse affected in naturally triggered disasters (positive correlation p = 0.006) than in other types of disasters, although it is also likely that DesInventar data focuses more closely on those areas that suffer naturally triggered disasters. Nevertheless, in conflict areas there is a positive correlation between losses, evacuations and relocations. Conflicts seriously damage infrastructure, reduce the availability and accessibility of basic services and goods in the immediate term, and destroy social fabric and diminish knowledge and skills in the long term.

Figure 24 gives an indication of reported continuing internal displacement levels, based on figures extracted from HNOs for damaged and destroyed housing. The peak between 2015 and 2017 can be attributed mostly to displacement recorded in Colombia and Myanmar. Consistently collected data from HNOs is available only from 2013 onwards; this was extracted for our research. A correlation could not be statistically established between any of the displacement indicators and housing damage.

Housing damage can be serious even in emergencies where populations are not displaced or are displaced only temporarily, but we could establish no correlation between any other available vulnerability indicators through the DesInventar data, such as persons relocated, evacuated, injured, dead or missing. More data is necessary to understand the relationship between those indicators for given years and crises.

Human impact

To measure human impact, DesInventar includes information on disaster-related deaths, injuries, missing persons, number of persons relocated, and number of persons evacuated. This data is available mostly for specific events, such as the 2008 earthquake in Baluchistan, Pakistan, and where countries have reported their disaster-related impact. For the selected countries of interest, no meaningful further exploration in conjunction with data on displacement and needs was possible.

If we compare the number of disasters attracting an SC reponse by year (extracted from ReliefWeb) with the number of people in need across all sectors, and with people in need of shelter assistance, we see that while the overall number of disasters has been decreasing since 2013, the number of people in need has steadily increased. A positive correlation was found between the number of people in need and the type of crisis (in particular conflict). This could be because no major, large-scale natural diasaster has been recorded since 2013, so most of the available data is from conflict situations. Nevertheless, we cannot safely assume that conflict has generated a higher need than natural diasters over the last five years, as no comprehensively and systematically collected data on damages, losses, and people in need across countries and disasters currently exists. With the accumulation of more rigorous historical data, this assumption will need to be explored.

The figures for people in need were extracted from HNOs. It needs to be noted that the HNO process was modified and methodologically strengthened between 2013 and 2018, including the introduction in 2016 of a much stricter definition of populations affected and in need, with a nuanced exploration of levels of need being introduced. Although such guidance was made available in 2016, it has not been consistantly

applied; people in need calculations are not standardized, so any comparison of those figures between countries should be treated with caution.

None of the human impact indicators showed correlation with damaged or destroyed housing.

We found a positive correlation between naturally triggered disasters and death and injuries. As discussed above, the data tends to show that the effect of a naturally triggered disaster on a population is immediate and severe, while the long-term effects of conflict are devastating and profound, resulting in a high prevalence of humanitarian needs.

We found a positive correlation between death and injuries and the Asia Pacific region, particularly in Indonesia and Pakistan. This can be explained by the large-scale naturally triggered disasters that affected Indonesia and Pakistan between 2005 and 2013.

Economic losses

Little systematically collected information is available on economic losses, because DesInventar quantifies and describes disaster impact and economic loss locally or for each crisis, whereas the value of critical infrastructure, including housing, is defined at the country level.

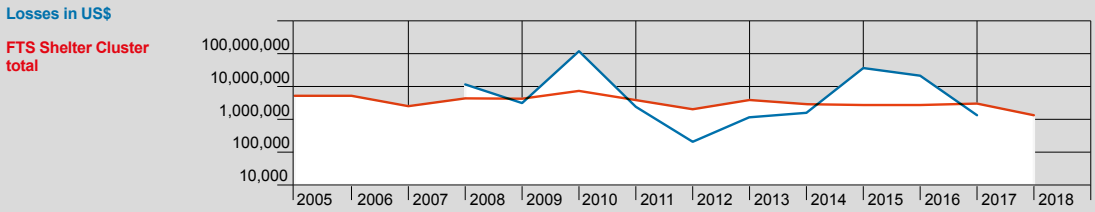


Figure 25 **DesInventar losses versus Shelter Cluster funding, 2005–2018.**

DesInventar data on economic loss that matched the criteria for inclusion in the ReliefWeb list with an activated SC response was available for only 20 countries, and for 54 out of 353 crises. However, even among those matching pairs, for only five countries is information available on economic loss that can be analyzed over time: Myanmar, Chile, Paraguay, Peru and El Salvador. Again, these are countries with the capacity to capture and quantify disaster-related economic loss. When we looked at levels of economic loss and shelter funding received, two outliers become apparent: Chile and Myanmar surpass and overwhelm the available shelter-related funding, but government response and other response outside the SC Plan is not captured in this observation.

Economic losses show a positive correlation with the number of houses damaged and destroyed, and these are unarguably linked. Strictly speaking, economic losses are quantified by type of infrastructure destroyed and its itemized cost. However, aspects such as loss of income, skills, capacities, knowledge and development are not captured. This leaves a big gap in knowledge, information and data. Losses were higher where there were higher numbers of asylum seekers and stateless persons (positive

correlation p = 0.010), which supports the assumption that indirect losses – such as of knowledge and skills – may be even higher but are not captured.

This is particularly important when trying to understand the self-recovery path and capacity of populations who have needed shelter support. The relative ability of the economy to cope and recover will influence the ease or difficulty of reconstruction and the extent of welfare effects.[7] The World Bank Group argues that this ability, which can be referred to as macro-economic resilience to naturally triggered disasters, is an important parameter when estimating the overall vulnerability of a population. Resilience is divided into two components: instantaneous resilience, which is the ability to limit the magnitude of the immediate loss of income for a given amount of capital losses; and dynamic resilience, which is the ability to reconstruct and recover quickly. This definition of resilience outlines that the ability to recover and reconstruct, as well as to absorb immediate losses, is contingent not only on material resources but also on the knowledge and skills to do so. The ability to quantify loss, including the loss of those skills, remains to be academically explored and its measurement operationalized, but will be crucial for the attempt to build measurements of self-recovery.

1 Burkina Faso, Chile, Colombia, Ecuador, El Salvador, Ethiopia, Indonesia, Kenya, Kyrgyzstan, Lebanon, Mali, Mozambique, Myanmar, Nepal, Pakistan, Paraguay, Peru, Sri Lanka, Uganda, Yemen.

2 For a detailed comparison of the two main global disaster databases, EM-DAT and DesInventar, see E Osuteye et al (2017) 'The data gap: An analysis of data availability on disaster losses in sub-Saharan African cities'. *International Journal of Disaster Risk Reduction* (26), pp. 24–33.

3 Ibid.

4 Countries not included: Afghanistan, Bangladesh, Benin, Central African Republic, Chad, Cote d'Ivoire, Democratic Republic of the Congo, Fiji, Georgia, Haiti, Iraq, Lesotho, Liberia, Libya, Madagascar, Malawi, Nigeria, Palestine, Philippines, Solomon Islands, Somalia, South Sudan, Sudan, Syria, Tajikistan, Tonga, Ukraine, Vanuatu.

5 The analysis is based on data of uncertain reliability, due to considerable national variations in collection methods.

6 Countries with an active SC presence or SC-like mechanism are Afghanistan, Bangladesh, Central African Republic, Chad, Colombia, Democratic Republic of the Congo, Ecuador, El Salvador, Ethiopia, Fiji, Iraq, Kenya, Madagascar, Mali, Mozambique, Myanmar, Nepal, Nigeria, Pacific Region, Pakistan, Palestine, Peru, Philippines, Somalia, South Sudan, Sri Lanka, Sudan, Syria, Tonga, Ukraine, Vanuatu, Yemen (SC Operations Dashboard. https://goo.gl/rjLXsW).

7 See Stephane Hallegatte (2015) *The Indirect Cost of Natural Disasters and an Economic Definition of Macroeconomic Resilience*. Policy Research Working Paper 7357. World Bank Group – Finance and Markets Global Practice Group and Global Facility for Disaster Reduction and Recovery. https://openknowledge.worldbank.org/handle/10986/22238.