Project 2

Analyzing the inter-agency communication and coordination structure during a multi-agency disaster response.

Code available in GitHub here.

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***Abstract*—This study analyzes inter-agency communication and coordination structures during the response to the tropical cyclone Idai. Idai being one of the deadliest and expensive tropical cyclones in the South-West Indian Ocean region. We used data from 192 situation reports published on ReliefWeb between Friday 1st March, 2019 and Tuesday 30th April, 2019. We investigate the collaboration between over 100 organizations. The data was collected via the ReliefWeb API and analyzed with SNA techniques. We made graphs using different tools and functions from Matplotlib and NetworkX.**

***Index Terms*—social network analysis, sna, disaster management, python, scraping, analysis, inter-agency communication, humanitarian aid**

I. Introduction

One of the most intense tropical cyclones was Cyclone Idai, with winds as intense as 195 km/h and gusts reaching up to 280 km/h. The cyclone did a lot of damage in Africa and in the Southern Hemisphere. The storm was very long lasting, it formed on Monday 4th March, 2019 and ended on Thursday 21st March, 2019. With more than 1500 deaths and more than 2000 missing people, Cyclone Idai is the deadliest recorded Tropical Cyclone in the South-West Indian Ocean basin. Idai is also the second most expensive cyclone in the South-West Indian Ocean basin with damages greater than 3,3 billion USD. Severe flooding was caused throughout Malawi, Madagascar, Zimbabwe and Mozamique. Direct effects of the storm caused harm to over 3 million people [1].

ReliefWeb is an online service maintained by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), providing reports, maps, and infographics to aid with decision-making and planning of humanitarian aid. ReliefWeb has an editorial team that collects data and publications from over 4000 sources and publishes them on the site. As well as delivering situation information to humanitarian workers, the site acts as an information hub for civilians. ReliefWeb also hosts training notices and job listings. ReliefWeb publishes information through multiple sources like ReliefWeb response, API and RSS-feed [2].

ReliefWeb published almost 200 situation reports, about Cyclone Idai, featuring over 100 different agencies during two months between the dates of Friday 1st March, 2019 and Tuesday 30th April, 2019. This period forms the basis for the dataset analyzed in this report. In this report, we will observe the co-occurrence of different agencies and analyze the inter-agency co-operation during a major disaster.

The number of agencies and the type of interactions among them change as disaster management progresses. Quality of the collaboration is subject to change as the collaboration network evolves. Different agencies have largely differing pre-requisites for collaboration, and pre-disaster communication and preparation affect the quality of operations and communication during disaster management vastly [3].

Agency networks can be analyzed for after-the-fact feedback on efficiency, quality, and type of collaboration among agencies. This report applies social network analysis (SNA) to identify frequencies, strength, type, and progression of inter-agency communication during the disaster as a whole and in different stages of disaster management. Agencies are networked using co-occurrence logic. Thus, if two agencies co-occur in a situation report published on ReliefWeb, they are interpreted to collaborate. This logic may introduce some flaws, and we will also discuss the limitations of the methods used for analysis.

II. Problem description

Aim in this report is to study the inter-agency communication and coordination structure during a multi-agency disaster response. ReliefWeb API is used to gather a dataset which will be analyzed using NetworkX, Pandas, Gephi and matplotlib. Aim is to identify key organizations, collaboration structures, types of collaboration, investigate tolerance for failure in key organizations, and observe how these things evolve as the disaster management progresses in time.

III. Dataset description

A. Gathering

Dataset was gathered using ReliefWeb API (RWAPI). Similar data could be scraped using tools such as BeautifulSoup4 (BS4) or Selenium. This allows gathering datasets from virtually any source, as long as the data is published in a semi-consistent way. Scraping methods are usually slower to execute and require more logic for parsing when compared to structured data. RWAPI allowed efficient gathering of articles and made sure that non-related articles did not sneak into the dataset.

Two main endpoints of RWAPI were used to form the dataset. Publications were listed by https://api.reliefweb.int/v1/reports and filtered with post request params to include only situation reports (situation reports are also referenced as articles in this report) about Cyclone Idai and only between the dates of Friday 1st March, 2019 and Tuesday 30th April, 2019. This allows analysis of early response, mid-term, and long-term collaboration. The early response data consists of articles published between the dates of Saturday 9th March, 2019 and Saturday 16th March, 2019. Interestingly, there were no publications available for the first few days of the disaster. The mid-range dataset consists of articles published between the dates of Sunday 17th March, 2019 and Saturday 30th March, 2019. This time frame falls largely within the time when the storm is still active, but where inter-agency collaboration might have formed into a more mature collaboration stage. The last time frame consists of articles published between the dates of Sunday 31st March, 2019 and Tuesday 30th April, 2019. This includes the final responses to the immediate threat and continues into the recovery phases.

Agencies were listed from https://api.reliefweb.int/v1/sources. Initially, it was intended to use Named Entity Recognition (NER) to construct the agency dataset from the report text. This proved to be a greatly inaccurate method with poor results. In the end, it was easier to list all agencies available in RWAPI and look for the occurrence of either the agency name or acronym in the text. If the agency name appeared anywhere in the article (including body text, author, title, headline title, and headline text) or if any of the words in the article exactly matched the acronym, it was marked as occurring in the article.

Additionally, useful metadata was gathered from RWAPI. This includes, for example, organization type, acronyms, article publication date, mentioned countries, and all the information available about each report.

The dataset was limited to two months to avoid long-term recovery operations affecting the dynamics between agencies. Thus, this report analyzes only the immediate response to the disaster.

As the data was already in a structured format, an edge list was simple to gather. As each situation report had a list of organizations attached to it, all that was required was to iterate through the reports and assign an edge to each of the organizations. This forms the basis for the bipartite graph and further refinement of networks from that.

B. Characteristics and metrics

1) Situation reports: In total, 418 situation reports were published about Cyclone Idai. This came down to 192 with the limitation to the two months analyzed. The most prominent source of publication was OCHA with around 16% contribution to the reports (assuming even distribution of input if multiple sources). Other top publishers include United Nations World Food Programme (WFP) (around 14%), United Nations Children's Fund (UNICEF) (around 7%), and United Nations High Commissioner for Refugees (UNHCR) (around 6%). See Fig.1 for source credits by agency.

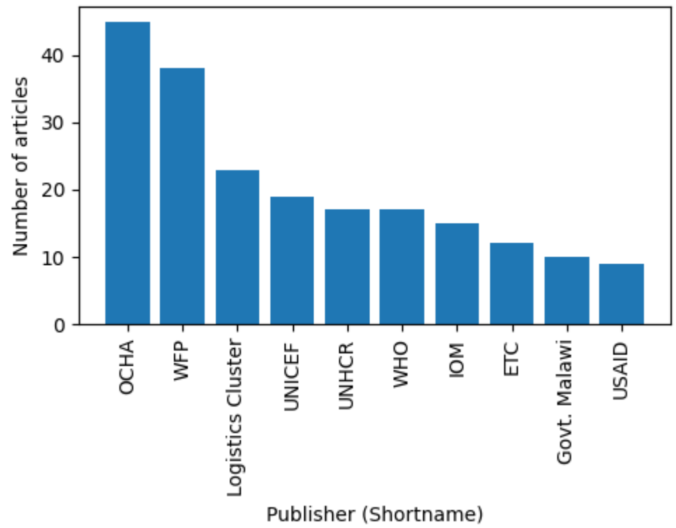

Fig. 1. Source credits by agency

For more information about agencies, please note section III-B2.

On average, there were around four articles published daily. Distribution for the publications is quite even, with only a couple of peaks on Wednesday 3rd April, 2019 and Friday 12th April, 2019. No specific events are evident from the report titles for those dates. On Wednesday 3rd April, 2019, the World Health Organization (WHO) announced the beginning of a cholera vaccination campaign [4]. Below in Fig.2 are plotted published report counts by date.

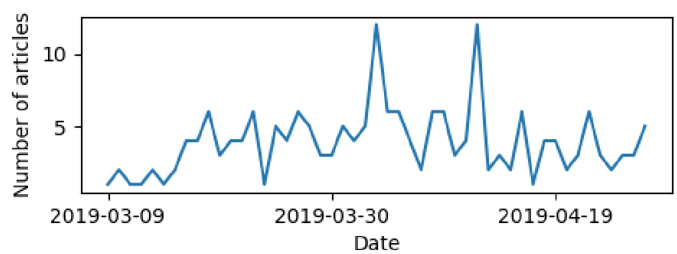

Fig. 2. Published reports by date

2) Agencies: In total, there are 1820 active organizations listed on ReliefWeb (https://reliefweb.int/organizations). From those, 105 were identified from the situation reports. 35 of them were listed as a source to atleast one article. OCHA is represented most as a source for reports with 45 attributions across the 192 reports. OCHA edits and publishes the situation reports for disasters, which explains the high contribution. The source with the second highest attribution is WFP with 38. See Fig.1 for further statistics on article source attribution. On average, around 6 organizations are mentioned per article.

Most of the agencies are listed as either "Non-governmental Organization" (NGO) or "International Organization" (IO) on ReliefWeb. See Fig.V-C for all listed types. Those labels as types are quite broad and could be broken down further. They cover around 64% of the organizations and include organisations like International Search and Rescue Advisory Group (INSARAG), UNICEF, and WFP. With these broad category titles, it might be harder to gain valuable insight into which types of agencies are collaborating.

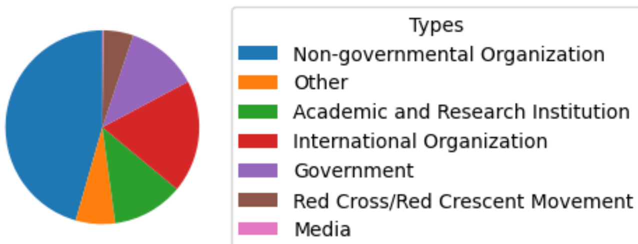

Fig. 3. Organisation type distribution

New types for organizations were roughly assigned by hand within NGO and IO categories. Total of 14 new categories were assigned to the 83 organizations. EU was kept as an IO. See Fig.4 for new types and distribution.

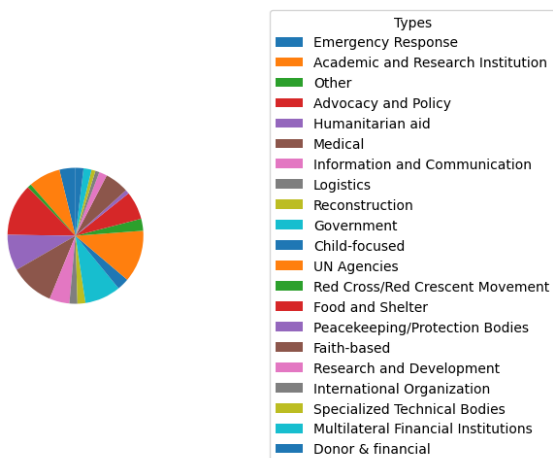

Fig. 4. Organisation type distribution after reassignment

IV. General Methodology

Below is described the steps taken in order to analyze the problem. Please see section V for more in-depth dive to the topics.

A. Scraping

To begin with, a dataset was necessary to be formed. Initially, it was meant to be done by scraping the reports using tools such as BS4 or Selenium. We discovered the RWAPI at the start of the process and decided to use that for more accurate and efficient data gathering. Scraping was done in four parts:

1) Listing articles.
2) Getting article metadata.
3) Listing organizations.
4) Getting organization metadata.

For more detailed information about available data and how the dataset was formed, please see section V-A.

B. Parsing

A lot of information was available about reports and organizations. Few key pieces of information were retained from the data. Following data was collected about situation reports:

- ID.
- Title.
- Body.
- Headline title and summary.
- Sources (agencies used as a source for the report).
- Date information.

Following data was collected about organizations:

- ID.
- Name.
- Short name (acronym).
- Type.

These two object lists were joined so, that each report got "Organizations" data added to them, which included all the agencies appearing in that report. This was then further developed into an edge list. Original data was always preserved to avoid data loss and need for new scraping. For more information about parsing, please see section V-B.

C. Analysis

Operations to the network were performed based on the given instructions. Results from those operations were then analyzed to gain the final product of meaningful insight on the evolution of inter-agency collaboration during Cyclone Idai response. Please note sections V-D1–V-D11 for more information about given steps and how they were performed.

V. Detailed Methodology

A. Scraping

To form the basis for the dataset, a four step process was formulated.

First we listed each report available in ReliefWeb about Cyclone Idai. This was also the first touch to the JSON-format RWAPI uses to deliver information. Based on available information, date boundaries were specified for limiting the dataset size and minimizing irrelevant skews, between which the articles must have been published. This step gave us basic information such as how much data there was going to be and IDs for reports to be used in the next step.

After listing each report, more detailed information was retrieved about them on report at a time. This included the body of the report, associated countries, source, language, affected bodies of people, more detailed date information, type of disaster covered in the article and topics of the article. This data was filtered down to include data only relevant to the given analysis constraints.

After that we moved on to forming the organization aspect of the data set. This was originally meant to be done by using NER but we diverted to a different technique to achieve higher accuracy and more easily manageable data. Please see section V-B for more information. We started by listing all the sources available on ReliefWeb. This included 1820 organizations used as a basis for identifying organizations from reports. We listed each organization to gain basic information, most importantly, the ID of the organization on ReliefWeb.

Lastly, we got detailed information about each organization in similar manner to reports. This included organization long name and short name (acronym) which were used in parsing organizations from the reports. In this step we also gained information about organization types (please note V-C on how these were refined), which are used in the analysis of organizations tendency to work with similar organizations.

All of the work was done by creating an API helper class. This class called the RWAPI and returned the filtered objects. All work was done sequentially, since there was not too much data. If needed, the requests can be broken down and executed in parallel. All responses were cached to avoid unnecessary calls due to crashes or similar issues.

B. *Parsing*

With the data being scraped we moved on to parsing the data into an network form. This began with identifying the organizations from the article data. This was originally meant to be done by using NER. This proved highly inefficient, with around 1 out of 4 organization being picked up. The resulting list contained also a lot of false positives, and positive positives were often partial or in need of some form of clean up. We came up with an idea to use the organization names available on ReliefWeb to identify the organizations.

First the input text was formulated in the following manner. All data (organization names, report text) was transformed to lower case. Report body text was appended with report title, headline title and summary if available, and each source name and acronym. Then the resulting text was iterated word-by-word and checked for exact match with the acronym. Then the text was checked against containing the organization name. If either of those cases were true, the organization was added as appearing in the report.

Once each report had associated organizations listed to them, it was possible to form the first dataset. This dataset contained data (edge list) for the full two month period. Edge list contains the organization ID as the source and report ID as the target. These IDs can then be used to retrieve metadata from the stored JSON-files if necessary. The dataset was formed by iterating through the reports, and creating an edge between the report and each organization assosiated with the report. This was transformed into an Pandas dataframe. A third column, containing the report date, was added at this point for further development of datasets.

The full data set acted as a basis for three more datasets. First, the earliest date present (D0) was identified to be Saturday 9$^{\text{th}}$ March, 2019. From there, the dataset was split into three sets. Short range, mid range and long range sets. The short range set included reports from D0 - D0 + 7 (D1). The mid range set contained reports from D1 to D0 + 21. The long range dataset included the rest of the reports. This was done using Pandas functions.

The short range set includes 54 edges, the mid range set includes 341 and the long range set includes 759. From the edge count in each set it is possible to already see the rapid increase in either reporting or participating organizations. From Fig.2 it is possible to see that after the first few dates, the number of published reports stay mostly even by date. This indicates a heavy rise in participating organizations.

Datasets were saved seperately, to seperate the parsing code from analysis. Also, only source-target pairs were saved for the same reason. This makes metadata loading explicit. It is clear when metadata is loaded and used and what for.

C. *Organization types*

Organization types proved insufficient for further analysis. IO and NGO types were too general for sufficient interpretation about organization collaboration structures. IO and NGO types were reassigned to 14 new types. A helper script was created for managing this. Script printed out description of organization fetched from RWAPI and prompted user to assign a new category.

D. *Analysis*

Here we describe how the data was analyzed in the main jupyter notebook. Each step or task given to us in the project description and how we approached those tasks, is explained below. This section does not aim to display analysis results but how we approached the analysis process itself. For analysis results and discussion, please note VII.

1) Entity co-occurence detection: To analyze collaboration, we first detected co-occurrences of agencies within each situation report. A co-occurrence was defined as the presence of two or more agency names or acronyms in the same report. For each report, all unique agency pairs were identified and an undirected edge was created between them. This step resulted in a basic undirected network structure where the presence of an edge signifies collaboration (or at least simultaneous mention) in one or more reports.

The frequency of co-occurrence (i.e., the number of shared reports) was used as the weight of the edge between the agencies. This weighting enabled us to distinguish between occasional and frequent collaborations.

2) Bipartite network construction: Next, we created a bipartite network where one node set represented agencies and the other set represented reports. Each edge linked an agency to the reports in which it was mentioned. This structure preserved full information about which agencies appeared in which reports and allowed further analysis from both the agency and report perspectives.

We used NetworkX's from_pandas_edgelist() function to efficiently build this bipartite graph from the previously created source–target pairs.

3) Projection of agency-only graph: To focus on inter-agency relationships, the bipartite graph was projected into a unipartite graph consisting only of agency nodes. An edge between two agencies indicated that they co-occurred in at least one report. Edge weights were preserved to indicate how often the pair collaborated across all reports.

This projection was performed using NetworkX's bipartite.weighted_projected_graph() method. The resulting graph served as the primary data structure for centrality, community, and assortativity analyses.

4) Time-segmented graph construction: To observe how the collaboration network evolved during different phases of the disaster response, the dataset was divided into three time segments:

Short-term (Early Response): 9–16 March 2019
Mid-term (Ongoing Crisis): 17–30 March 2019
Long-term (Recovery Phase): 31 March–30 April 2019

For each period, an independent co-occurrence network was generated using the same logic described above. This enabled us to study temporal changes in collaboration intensity, network density, and agency centrality.

5) Organization type assignment: Initial organization type labels from ReliefWeb (e.g., "NGO", "IO") were too broad to support detailed analysis. To address this, we manually reclassified organizations into more specific categories such as:

UN Agencies
Medical organizations
Humanitarian aid
Advocating agencies
Child-focused
RND, etc.

This classification was done using a helper script that prompted the user to assign a new category based on ReliefWeb metadata and short descriptions. These refined types were later used to evaluate homophily in agency interactions.

6) Centrality analysis: To identify key players in the collaboration network, we calculated three centrality measures using NetworkX:

Degree Centrality: Measures the number of direct collaborations an agency had.

Betweenness Centrality: Captures agencies that frequently occur on the shortest paths between other pairs of agencies, indicating brokers or coordinators.

Eigenvector Centrality: Evaluates not only how many collaborators an agency has, but how important those collaborators are.

These metrics were calculated for the overall network as well as for each time-segmented graph, allowing comparison of agency influence over time.

7) Community detection: We applied the Louvain method for community detection to identify clusters of agencies that collaborated closely. Communities were detected both in the full network and in each time-segmented subgraph to understand how the modular structure of the network changed during the disaster response.

This analysis helped reveal whether certain agency clusters formed around thematic roles (e.g., health, logistics) or regional operations.

8) Assortativity analysis: Finally, we measured assortativity to assess whether agencies tend to collaborate with similar types. Using NetworkX's attribute_assortativity_coefficient() function, we calculated the assortativity coefficient based on the refined organization type labels.

A high positive value would suggest that agencies tend to work with similar types (e.g., NGOs collaborating mostly with other NGOs), while a negative value would indicate cross-type collaboration (e.g., UN agencies working with local NGOs).

9) Visualization: Network visualizations were produced primarily using Python's NetworkX and Matplotlib libraries. For each agency only graph whether derived from the full dataset or from time-segmented intervals we generated static visualizations using a force-directed layout algorithm (spring_layout). This facilitated a clearer depiction of the relational structure among agencies.

Node size was scaled according to degree centrality to visually emphasize the most connected organizations. Node color was mapped to organization type, allowing for immediate differentiation between actors such as UN agencies, NGOs, and governmental bodies. Edge width reflected the weight of the connection—that is, the number of reports in which two agencies co-occurred.

To enhance readability, label visibility and font size were adjusted based on node prominence. Visualization functions including draw_networkx_nodes, draw_networkx_edges, and draw_networkx_labels were customized to control layout aesthetics. The resulting plots were exported as high-resolution image files for inclusion in reports and presentations.

10) Failure simulation: To estimate the tolerance of the network to loss of key nodes, we performed robustness tests. Central nodes were iteratively removed, and changes in graph connectivity and component sizes were observed. This tested the reliance of the network on central hubs.

11) Temporal evolution analysis: We compared the three time-segmented graphs in terms of density, centralization, and collaboration diversity. This helped track how collaboration patterns matured or changed throughout the response period.

VI. Limitations of the Methodology

The co-occurrence logic disregards completely the type of interaction between the agencies. The report could be about the discrepancies of two agencies, or the agencies might not be working together at all. This bias could be minimized by handpicking articles talking solely about collaboration between agencies. This method however is neither efficient nor expandable to scale. For longer disasters such as global pandemics, it would be time consuming to pick articles from all stages of the disaster management.

Organization types were for more than half of the organizations assigned by hand and the assignment was done quite roughly. This might create biases or inaccuracies in the type data.

VII. Results and discussions

The analysis of inter-agency coordination through network visualization revealed several key insights into the structural dynamics of humanitarian collaboration. By mapping co-occurring organizations in situation reports, we observed distinct patterns in the ways agencies interact across time. The results show varying degrees of centralization, shifts in core-periphery structures, and different levels of connectivity among organizations. These findings are critical to understanding how coordination evolves during a humanitarian crisis, both in terms of agency involvement and how information is exchanged and shared. In our dataset we got 192 reports and from there we have scraped 105 agencies. See Fig.5 for the whole network including reports and organizations.

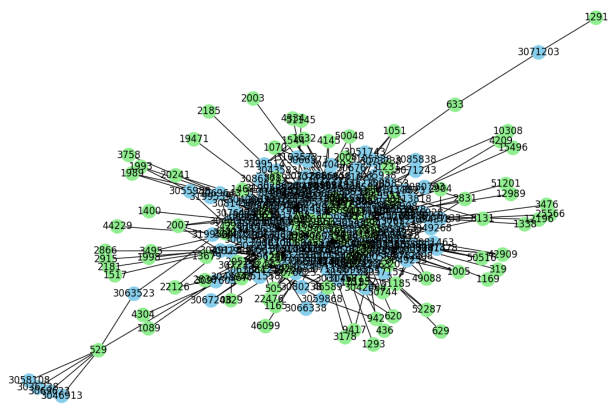

Fig. 5. Organizations and reports visualized in a bipartite graph. Reports are colored blue, organizations green.

The agency-report network was projected into an agency-agency network, where an edge represents co-occurence in an report. This network is the basis of the analysis in this report. Please note Fig.6 which displays the resulting graph.

The centrality measures, such as degree and betweenness centrality, highlighted the significant role of a few dominant actors in the humanitarian ecosystem. Agencies like UN OCHA, WHO, and UNICEF consistently held central positions in the network, confirming their leadership and coordination roles within the crisis response framework. These organizations were not only connected to a broad array of agencies but also acted as bridges between clusters of organizations with specialized roles, showcasing the importance of these agencies in ensuring information flow and cross-agency collaboration. See tables VII and VII for specific values for top fice agencies.

Temporal changes in the network structure revealed shifts in agency engagement. Early in the crisis, a relatively small set

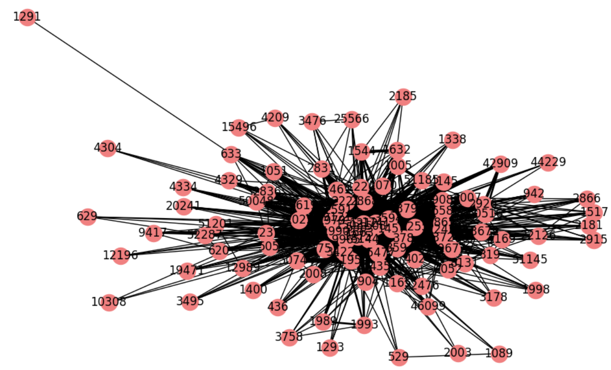

Fig. 6. Agencies projected from the bipartite graph. Edge is drawn based on the co-occurence logic.

Node	Degree Centrality	Betweenness Centrality
1212	0.8365	0.1292
538	0.8077	0.1112
508	0.7885	0.1020
1663	0.7115	0.0836
1275	0.6442	0.0618

TABLE I
Top 5 agencies by Degree and Betweenness Centrality

Node	Closeness Centrality	Eigenvector Centrality
1212	0.8595	0.2272
538	0.8387	0.2261
508	0.8254	0.2249
1663	0.7761	0.2031
1275	0.7376	
1741		0.2013

TABLE II
Top 5 agencies by Closeness and Eigenvector Centrality

of agencies dominated the coordination efforts, with a more centralized structure evident in the network graphs. However, as the crisis evolved, there was a gradual decentralization in network centrality, with additional actors, including regional NGOs and local bodies becoming more prominent. This reflects a possible shift toward localized coordination efforts, driven by evolving operational needs and the emergence of new crisis stages. The force-directed layout visualizations further underscored this dynamic, with organizations clustering in new formations over time. See figures 7–9 for progression of the network through different phases.

Additionally, the edge weights, representing the frequency of co-reporting between agencies, provided insights into the intensity of collaboration. Stronger, more frequent interactions were observed between key actors, particularly in the initial stages of the crisis, whereas later periods showed a more dispersed pattern of collaboration. This suggests that as the crisis matured, coordination became more distributed, with an increasing number of specialized agencies taking active roles.

Despite these findings, some notable limitations emerged. Governmental bodies, particularly national governments, were underrepresented in the co-reporting networks, which may indicate a lack of publicly available data or informal coordina-

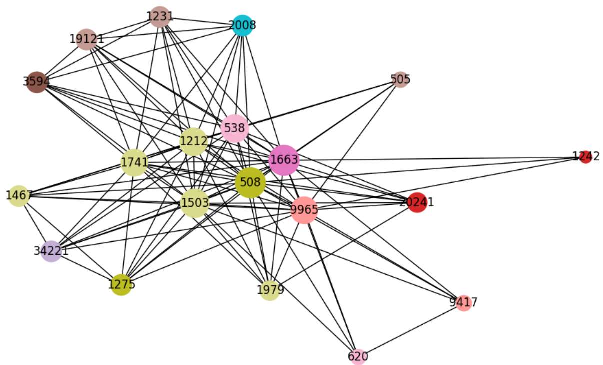

Fig. 7. Agencies with roles for the first 7 days.

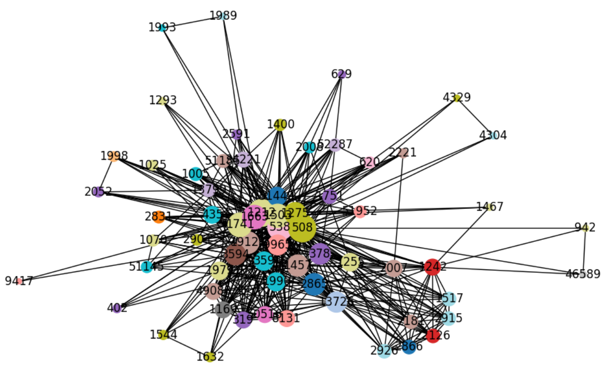

Fig. 8. Agencies with roles from days 8 to 21

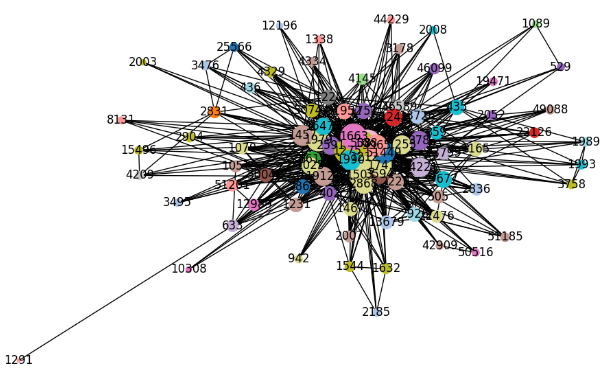

Fig. 9. Agencies with roles from day 22 onwards

tion that was not captured in the reports. Furthermore, while the core-periphery structure in the earlier crisis stages made sense in terms of operational focus, it also revealed possible gaps in the exchange of information between specialized actors and the broader humanitarian response network. These gaps may point to inefficiencies in coordination that could be addressed to ensure a more holistic approach to crisis management.

VIII. Relevant literature

The delivery of humanitarian aid faces numerous challenges, including logistical, managerial, and structural obstacles that hinder effective resource distribution. One framework that helps conceptualize these barriers is the ”Overcoming Obstacles” framework proposed by De Grasse (2024), which emphasizes recurring issues such as poor coordination, limited resources, and inadequate infrastructure.

Given the presence of over 100 distinct humanitarian agencies in our dataset, De Grasse’s findings underscore the inherent difficulty of achieving seamless collaboration in large-scale disaster responses. The article confirms that coordination problems are not only frequent but expected in such contexts, supporting the premise of this study—that inter-agency cooperation is a critical, yet fragile, component of effective disaster relief. These systemic issues often lead to resource misallocation, duplicated efforts, and communication breakdowns, particularly in natural disasters like Cyclone Idai. [5]

IX. Conclusion and perspectives

In this report, we analyzed the inter-agency communication and coordination structures during the response to Cyclone Idai, one of the deadliest tropical cyclones in the South-West Indian Ocean basin. By utilizing data from ReliefWeb and applying social network analysis techniques using tools like NetworkX and matplotlib, we were able to model and interpret how agencies collaborated throughout different phases of disaster response.

Our results demonstrate that collaboration among agencies evolved significantly over time. Initially, a core group of international organizations like OCHA, WFP, and UNICEF dominated early response activities. As the disaster progressed, the network expanded both in size and complexity, indicating a broader range of participating agencies and more distributed coordination. This evolution highlights the adaptability and responsiveness of the humanitarian network during large-scale emergencies.

The analysis revealed several key insights:

A small set of central actors held significant structural power in the network, acting as hubs for communication and coordination.

Inter-agency collaboration tends to grow denser and more diverse during mid-to-late phases of disaster management.

Organizational type (e.g., NGO vs. IO) and geographic focus influenced the likelihood and pattern of collaboration.

Despite the insights gained, certain limitations were identified. The use of co-occurrence in situation reports as a proxy for collaboration assumes that all mentioned agencies actively cooperated, which may not always be the case. Additionally, while the ReliefWeb API provided structured and consistent data, nuances of informal communication and unreported collaborations are inherently excluded.

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X. APPENDIX

See figures 10 and 11 for edge weight distribution among the main agency-agency-network.

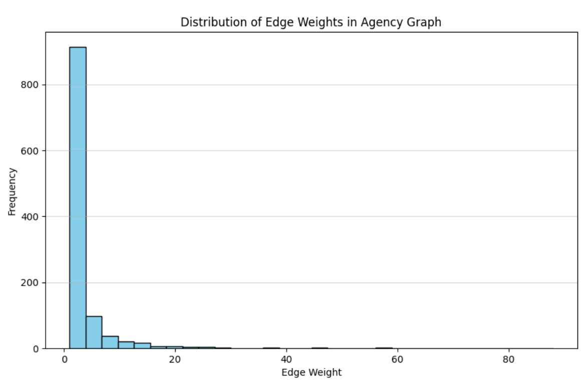

Fig. 10. Graph with edge weight distribution

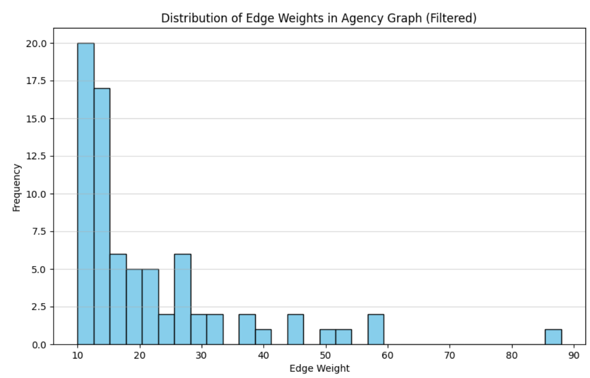

Fig. 11. Graph with edge weight distribution filtered. Includes values that are more or equal to ten. Values are filtered for more clear graph of the minority of values.