Humanitarian Aid and Emergency Response Analysis on Pakistan Floods 2022

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Abstract. Pakistan witnessed catastrophic flooding from the month of May to August 2022 as a result of heavy rainfall in different parts of the country [1]. The history of Pakistan dictates a series of similar events almost every year in the country [2]. Yet, the country remains unprepared for such a humanitarian crisis. On a national level, different non-governmental organizations and individuals play a crucial role in serving as the backbone of the country in times of crisis. This case study serves as an ideal platform to employ social network analysis to understand the coordination and collaboration patterns between different Non-Governmental Organizations (NGOs) and individuals in times of humanitarian crisis. Through social network analysis, we were able to identify donations/charity patterns existing in the country and we located the organizations that played an integral role in the floods of 2022 serving as the focal points that the government and NGOs can exploit for future humanitarian crises if any.

1 Introduction

Our topic entails two key terms that are also the crux of our work: humanitarian crisis and emergency response analysis. This project aims to understand the communication and collaboration patterns of different governmental and non-governmental actors in the recent humanitarian crisis i.e. 2022 floods in Pakistan. The 2022 floods caused catastrophic damage to the country and its people, and in the midst of all chaos, the country witnessed several flood relief campaigns and drives. These campaigns were conducted in order to help the affected citizens and restore their homes and livelihoods wherever possible. Hence, in this project, through social network analysis, we are aiming to present a methodology that can point out essential aspects of the flow of the charities/donations targeted to this year's flood crisis. The goal is to understand key organizations within the network that were central to the flood relief campaigns. Furthermore, there is an attempt made to create a network of individuals who have donated to different provinces of Pakistan.

This project can serve as a basis for learning about the future humanitarian crisis if any. As it will allow us to interpret the charity/donation patterns existing in the country.

2 Backgound and Related Work

This project is focused on the 2022 floods in Pakistan. Torrential monsoon rains triggered the most severe flooding in Pakistan's recent history, washing away villages, from June to October 2022. Hundreds of thousands of homes, public health facilities, water systems, and schools were destroyed or damaged [1]. According to National Disaster Management Authority (NDMA), more than 33 million persons were affected by the humanitarian emergency caused by the floods, about 1,739 died and almost 8 million people were displaced [3]

Amidst the humanitarian crises, when the condition of the flood went out of control, the government of Pakistan called for national and international help. Soon after the relevant announcements were made and flood relief news was broadcasted on almost all media channels, the country witnessed many organizations, institutions, and individuals coming forward and collaborating with each other to help the country and its people. Living in Karachi, we saw flood relief camps on every other street in the city. People donated money and many other necessary items such as menstrual kits, chips/biscuits, clothes, etc to different organizations, institutions, or individuals. Hence, this project aims to conduct a social network analysis of different organizations and individuals who collaborated or worked isolatedly to solve a humanitarian crisis in the country.

Social network analysis refers to how agents within a social network interact with the main focus on the patterns within the network [4–6]. The agents in a social network are represented as a node and their link/relationship with another agent (node) is represented as an edge. Despite the existence of social networks since the beginning of societies [4], we have seen limited use of social networks while studying humanitarian crises. However, different fields such as supply chain management have already recognized the importance of employing social network analysis while advancing theory on supply chain complexity and archetypes [6].

The importance of social network analysis in a humanitarian crisis is huge. Humanitarian aid operations are complex in nature, connecting several different sectors, actors, and spheres of activity. Logistics is a crucial area in preparing for and responding to, unwanted events and encompasses purchasing, transport, distribution, and storing of food, water, shelter, energy, etc. A multitude of different organizations participates within a framework of heterogeneous interests and priorities from donors, aid agencies, local and national authorities, and the international society [5–7]. In other words, any humanitarian crisis demands urgent services in the face of dynamic demand and includes complex collaborations between multiple entities [5,6]. In such a scenario, social network analysis becomes very helpful as it allows us to identify the strategies that might or might not work in a particular context [5]. Hence, potentially speeding up the process of providing quality solutions in resolving the crisis. Moreover, through social network analysis, we can also look for intangible connections in any large-scale humanitarian network which will help us better interpret communication and coordination during an incident [6]. Lastly, social networks are an easy-to-understand method to give diverse and dense information regarding the significant characteristics of a large-scale humanitarian crisis to the audience.

Let us consider the example of a network constructed to show the population displacement in Afghanistan during the first eight months of 2018 in order to better understand the claims presented above [6].

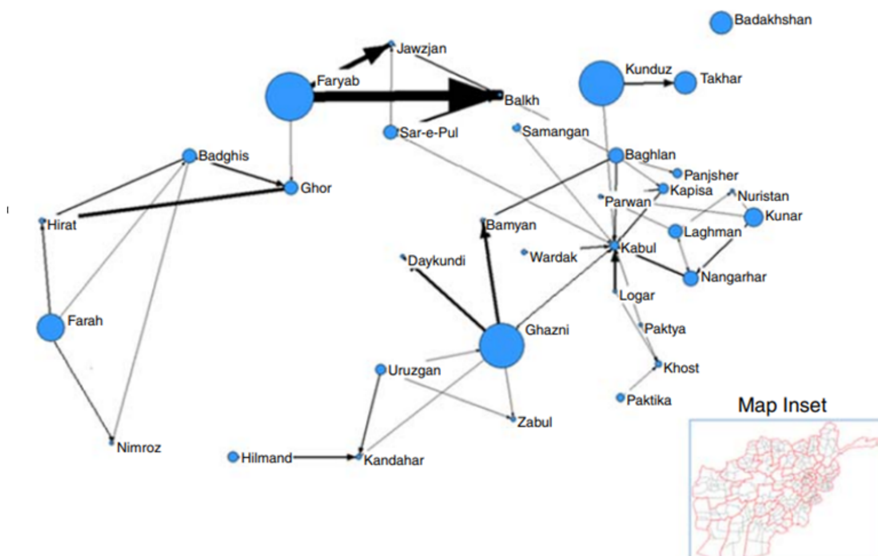

Fig. 1. Map-based graph illustrating movement of the population displaced by conflict in Afghanistan.

It embodies the social network analysis (SNA) framework of systems as networks, consisting of nodes and edges whose meanings change with the application. In Figure 1, the nodes represent Afghan provinces, arranged according to their physical proximity on a map. The edges represent the movement of displaced persons between those provinces. Links are visually weighted by the relative volume of migration, ranging from 50 people in the case of some links to over 9,000 people forced from the province of Faryab into neighboring Balkh. Figure 1 demonstrates how network visualization can render complex interactions in an easy-to-understand way, particularly the representation of multiple characteristics at once. Studies in domains as diverse as sociology, biology, and information science have pointed to the potential of network visualization, provided it conforms to the principle of graphical excellence and contains meaningful information [4, 6, 8]

3 Materials and Methods

The data used in this report was gathered from an online survey and a total of 89 people responded. As the number of responses on the data is less, this study is not representative of the entire population of Pakistan who participated in the donations during this flood crisis. The survey starts off by taking some basic details about the respondents such as income, city, area, age, and profession. It then goes on to ask more donation-related questions such as the amount they donated and to which place, person, or organization. The responses were extracted in the form of a CSV file and the process of data cleaning and analysis was performed in RStudio, after looking at the demographics of the responses in excel. Measures such as degree centrality, transitivity, and others were calculated using RStudio.

3.1 Respondent's demographics

The graphs in figure 2 visualize the age bracket of the respondents and their professions. It is very evident that out of the 89 responses, the majority of the donors fall between the ages of 18-25 years old and most of them are students. We came up with two possible explanations for this vast difference. First and by far the most plausible explanation is, the survey although open for everyone, still reached more students and young adults since it was rotated by people in the same age bracket, on social media. Hence the majority of the audience that participated in the survey fell into the same age bracket. The other very possible explanation is derived from the fact that the youth has been very active in flood relief campaigns in the recent flood crises. Other than numerous social media campaigns to raise funds, students from remote areas, studying in cities, advocated for intervention in their flood-affected areas. One very good example of such an instance is a relief organization that was established at the University of Lahore (UOL) which utilized students' talents and their familiarity with a wide range of communities across the country to take flood recovery and renewal to hard-to-reach areas. [9] According to the sources, the Higher Education Commission (HEC) and the universities committed to mobilizing their resources for immediate, mid-term, and long-term relief of the flood-affected areas of the country [9]. We believe that with more data, we would have seen a rise in the other categories as well, however, the young adult ratio of the donors observed is justified.

The graph in figure 3 shows the residential area of donors in Karachi. It is good to see that even with very few data points, the responses are distributed i.e they are almost evenly distributed across the districts of Karachi. This shows that the citizens from all over the city actively participated in the flood relief. Karachi, a sprawling urban metropolis, home to more than 20 million people, is said to be very generous in terms of charity even with the absence of a sufficient public welfare system. [10] Hence from the data we collected, flood campaigns observed and the general year round generosity of the citizens, we draw the inference that with more data points we will observe close to mean value for every area. The

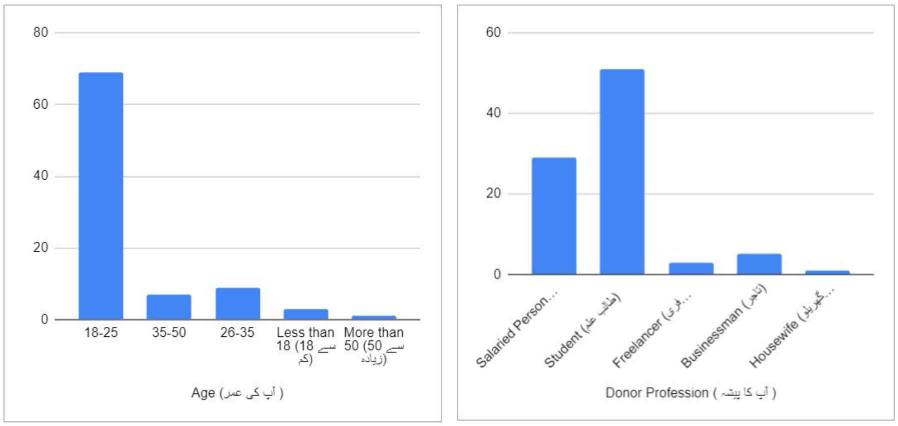

Fig. 2. Donors and their age and Profession

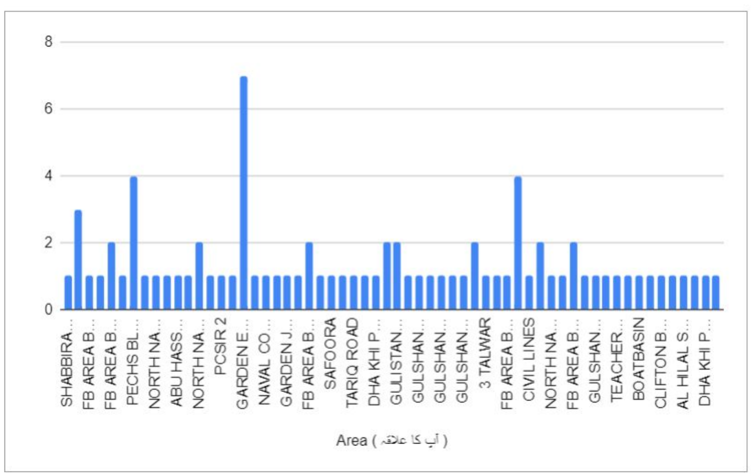

Fig. 3. Donors and their age and the areas in Karachi they belong to

floods in Pakistan started in mid of June 2022 and went on till September. On the 25th of August, The Government of Pakistan officially declared the floods a "national emergency." The Aid started pouring in, locally and internationally. Every Governmental and Non-governmental organization started collecting donations for the flood, there were numerous campaigns raised and Pakistan floods become the top trending hashtag on Twitter. However, after a while, it became old news even though the aftereffects of the flood still remain a huge problem for the victims and it is estimated that it will take about three years for the country to recover from the damages, the aid and campaigns slowed down after a while. It can be observed from the data we received from the respondents (shown in figure 4) that most of the donations were made either during late August or Early September when the hype was created around the floods. As of 8 November, according to World Health Organization (WHO), around 8 million flood-affected people need health assistance. Vector-borne and water-borne diseases remain a major concern in flood-affected areas. Around 1,000 confirmed cholera cases and 64,767 dengue fever cases, with 147 deaths, have been reported. More than 5.1 million women are of reproductive age, including an estimated 410,846 pregnant women. Approximately 136,950 births are expected in the next three months [11]. Hence, it is crucial to study the timeline of the aid received, to better address the long-term problems resulting in the aftermath of the floods, and create awareness about it.

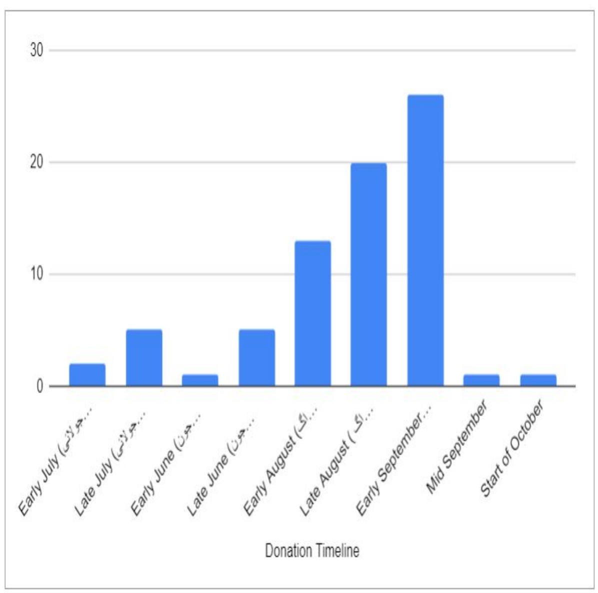

Fig. 4. Timeline of the donations

3.2 Networks from the data

As mentioned in the introduction section, the aim of this research is to analyze two types of networks: people donating to other people, organizations, individuals, and people donating to places directly. The resultant networks are bipartite and directed which were then converted to uni-partite by creating an edge between nodes donating to the same node. The edge were supposed to be weighted with the amount donated as the weight, however, the respondents stated cumulative donation amounts that can not be separated for multiple targeted donation places/organizations. In the following sections, the networks will be further described.

People's donation to NGOs
In the online survey, respondents were explicitly asked to state the organizations, individuals, or NGOs to which they donated the money. Out of the 89 respondents, 40 people donated to the NGOs. Figure 6 is a directed bipartite graph where orange nodes represent the respondents (individuals) and blue nodes represent the NGOs to which they donated. The edge represents the amount donated. On this graph, we will perform in-degree centrality to identify the top three significant NGOs.

People donating to organizations
Figure 8 shows the directed bipartite network for individuals and organizations. In this network, the red nodes represent individuals and the steel blue nodes represent organizations. The edges represent the amount donated.

People donating to other individuals
Figure 5 is a directed and unipartite graph. The nodes represent people and the edges represent the donation. Out of the 89 responses, 24 people donated to other individuals.

Collective network of all donations
To perform further analysis, the above bipartite graphs are converted into a collective unipartite graph. The process of this conversion is mentioned in the introduction paragraph of this section. In Figure 10, all nodes represent the donors and the edges between them represent the donation amount.

People who donated to provinces - bipartite
Figure 11 below shows a directed and bipartite network of people who donated to places in different provinces of Pakistan. The red-colored node represents the donors and the steel-blue-colored nodes represent the affected provinces to which people donated. The edges represent the donation amount. The original responses of some respondents contained cities which were then converted to provinces. Some responses were discarded which contained the places they directly donated to rather than the affected areas to which they donated.

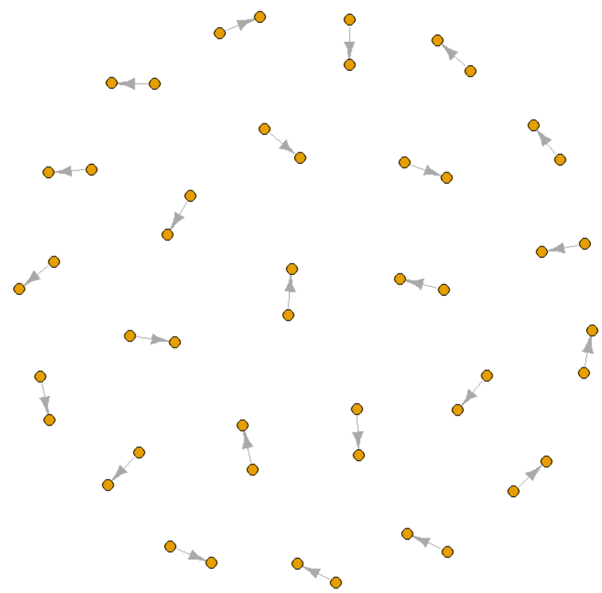

Fig. 5. A unipartite network of people donating to other people

People who donated to provinces - unipartite
The network in figure 11 is converted to an undirected unipartite network in figure 12. The nodes represent donors and the edges represent the donation amount.

4 Results

In this section, the results are shared corresponding to the analysis measure being used.

4.1 People's donation to NGOs

During the Floods of 2022, many Non-governmental Organizations shifted their focus to assist those in need in the affected areas of several parts of Pakistan. Figure 6 is representing the network as a result of this shift. Some NGOs became prominent centers of donation collection.

In-degree Centrality
Figure 6 is a bipartite graph where individuals are donating to different NGOs. In-degree centrality is calculated by counting the number of incoming edges to a node. In this case, the NGOs having a high in-degree centrality would mean that these organizations played the most significant role during the flood crisis.

Using the degree function in R for the network in Figure 6, the highest in-degree centrality is of Al-Khidmat Foundation. Then, the second highest in-degree centrality is of JDC, and then Akhuwat Foundation. Figure 7 visually represents this information.

This network also identifies potential new NGOs which became active during this crisis. However, due to insufficient data, this identification can not be performed here.

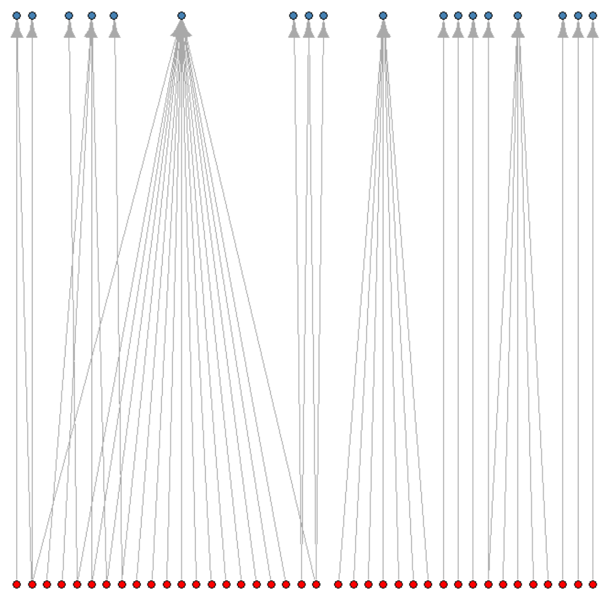

Fig. 6. A bipartite network of individuals donating to NGOs.

4.2 People's donation to Organizations

During the flood crisis, many organizations planned to exploit their contacts and started flood campaigns to assist. These flood campaigns provided accessibility to a lot of individuals planning to help out for this cause. Instead of looking for an NGO, donors were able to contribute to the campaign most reachable to them. Figure 8 is the network representing these flood campaigns. As a result, a few of these campaigns became central to the whole donation drive.

In-degree Centrality

The in-degree centrality, in this case, determines the significance of certain organizations in the flood crisis. Using the degree function in R, only Jamat-e-Islami received donations from more than one person in our network. The figure 9 shows the visual representation of in-degree centrality.

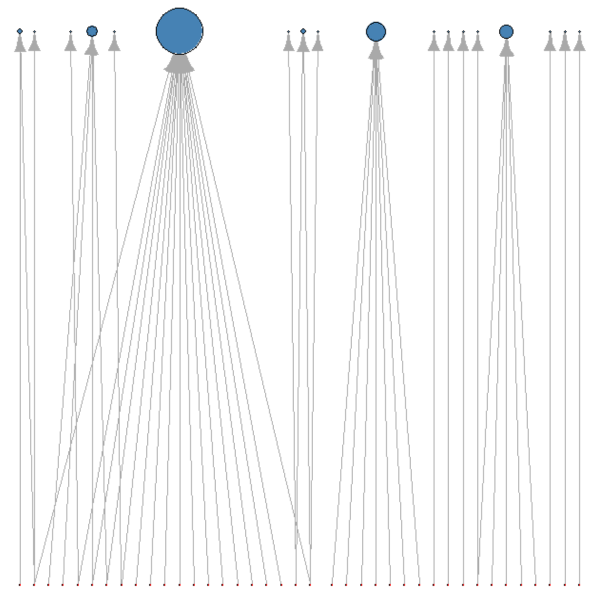

Fig. 7. A bipartite network of individuals donating to NGOs where the size of the nodes represents the in-degree of the nodes.

4.3 Collective network of all donations

Figure 5 shows a unipartite network of people involved in the donations and their connectivity through NGOs and other organizations.

Degree Centrality
Degree centrality in such a network represents the most connected individuals in this network. These individuals are connected to different organizations or NGOs enabling them to be connected to other individuals. In this network, the individuals n21, n47, and n55 have the highest degree.

Average Path Length The average number of nodes it takes along the shortest path of all possible pairs is known as the average path length. A small average path length signifies that nodes are easily reachable to other nodes. This measure is a good indicator of reachability if the network is large. Although the network in this research does not contain many nodes, we can still find the average path length which turns out to be 1.614173. It is a very small path length, suitable for a small network.

Transitivity Clustering in a network represents the groups that might exist in the network. For this network, a high clustering means that many individuals

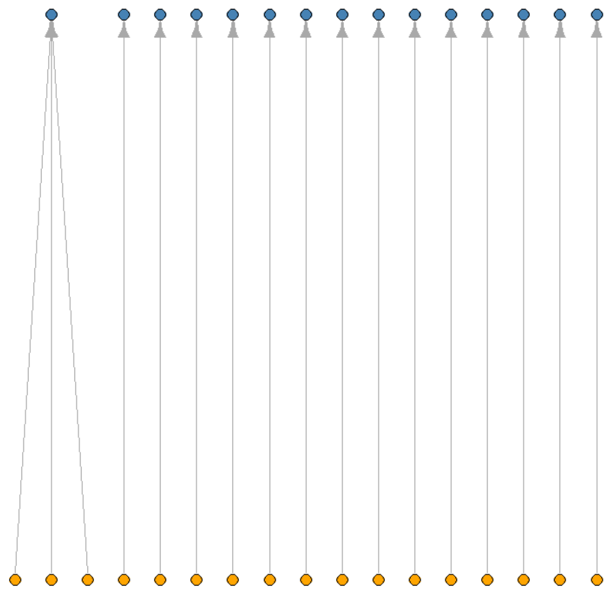

Fig. 8. A bipartite network of individuals donating to organizations.

are highly connected to each other through multiple organizations or NGOs. In the network in Figure 10, the clustering coefficient is 0.93 which is very high.

4.4 People who donated to provinces - bipartite

The Figure 9 presents a graph with two types of nodes - provinces and donors, with edges representing a donation made by a donor to a province.
In Degree Centrality
The in-degree of a node in the graph represents received donations. It is evident from the graph that Sindh has the highest in degree centrality, while it can be observed that Balochistan, Punjab and Gilgit do not have a lot of in coming donations. This conclusion has three driving forces, the first one being the limitation of data points, secondly survey reached more people from Karachi, which is itself in Sindh. However another reason for this distribution, which can be further studied with more data, is that some places are more remote and inaccessible than others. Further studies could also help analyse if some provinces or regions are more neglected when it comes to distribution of resources at time of a crises, however we are far from making such a point with such limited data.

4.5 People who donated to provinces - unipartite

Figure **??** was converted into a unipartite graph to further analyze other attributes **Transitivity**

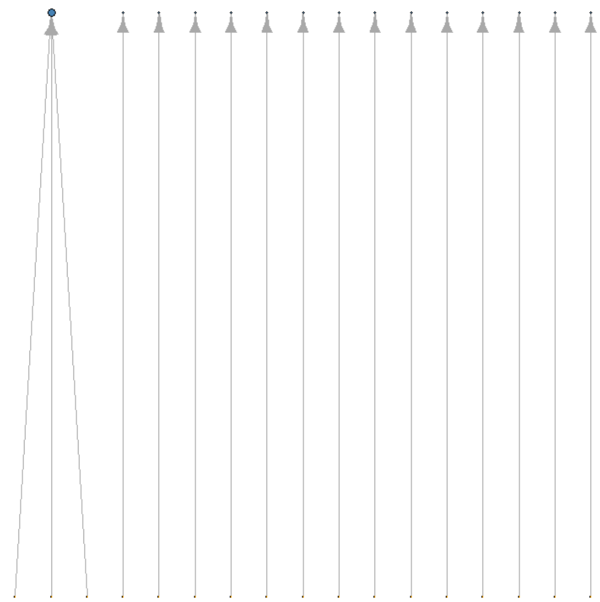

Fig. 9. A bipartite network of individuals donating to organizations where node sizes correspond to in-degree value.

The transitivity of the network here depends upon donors that donated to multiple provinces. We can see here that even with a few data points, there are donors that have donated to multiple provinces. These donors form a bridge between regions, and depict that there are donations from a single entity made to multiple effected areas. This kind of graph open grounds to study the relation between donors and provinces, it can be expanded to study the network between orgnizations and effected areas, to study nd understand any biases and preferences in donations to different regions.

4.6 Summary

The results obtained were successful in laying the foundation to understand the social networks created with Humanitarian aid distribution. They give an insight as to what kind of analysis can be done with the donation data modeled as a network. Even though the study is still in its initial stages to deduce any conclusions, the analysis of the obtained social networks provide theoretical and methodological understanding of the dynamics of exchange that occur between the different actors involved in humanitarian protection. With further data these networks can be improved and some sub networks and communities can be identified and their influence can be analyzed in the network. For future crises, it might be insightful to understand which organizations and communities are cen-

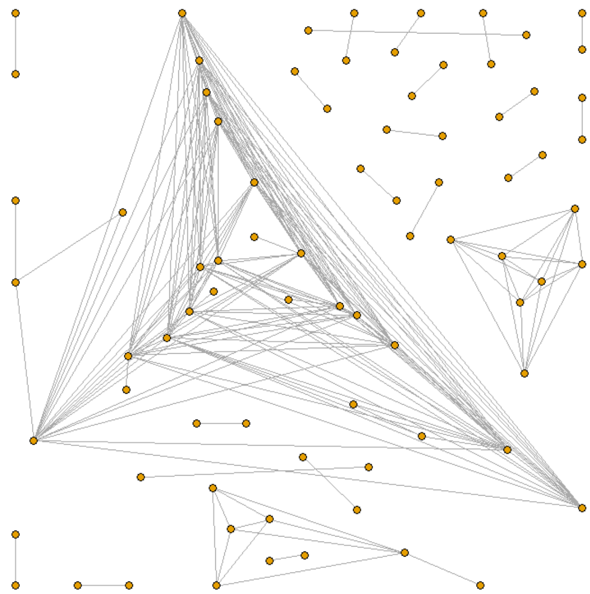

Fig. 10. A unipartite network of the donors.

tral, who has the most influence or who will be able to help out in times of disasters, based on indicators of centrality and other assessment of key nodes.

Measure	Unipartite Individual Donations Network	Unipartite To Place Donation Network
Average Path Length	1.614173	1.470588
Diameter	4	4
Average Degree	5.0886	10.88889
Global Clustering Coefficient	0.9311224	0.8891753
Density	0.06523856	0.6405229
Average Edge Betweenness	0.9565217	2.295918
Average Total Closeness	0.5417135	0.04233739

Table 1. Network topology measure comparison

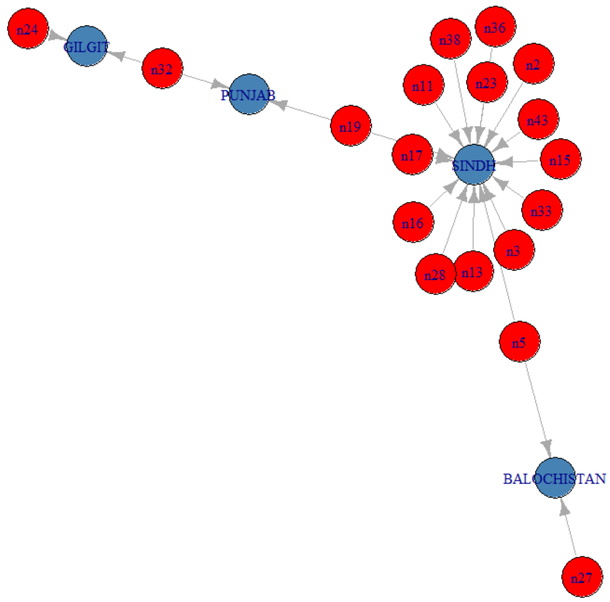

Fig. 11. A bipartite network of people who donated to places

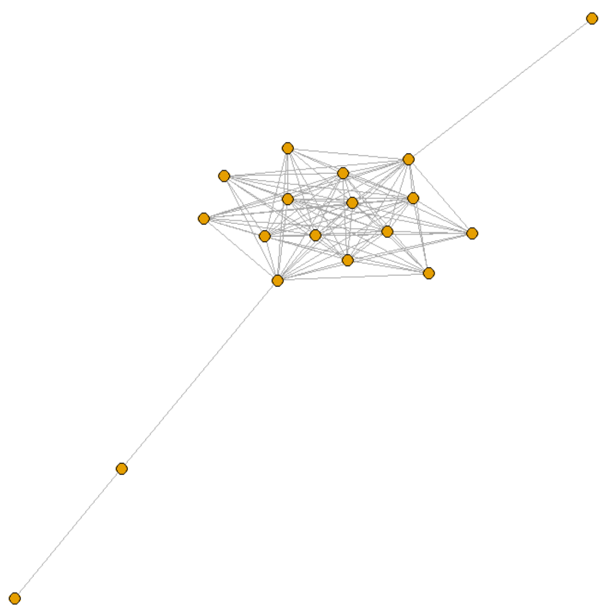

Fig. 12. A unipartite network of people who donated to places.

5 Discussion and Outlook

Social network analysis enables the study of the structure of relationships at different individual, community, and organizational levels and with different entities or subjects [12]. Our work here lays the basis for using Social Network Analysis as a tool to understand the network structures that emerged in response to Pakistan Floods 2022.
Pakistan is a very generous country, that donates over 1% of its GDP to charity, and over 98% of its population is involved in charitable events [13]. However Pakistan still qualifies as a third-world country, and even though it is responsible for less than 1% of global warming gasses emissions, the country is the eighth most vulnerable nation to the climate crisis [14]. With the drastic increase in climate change, natural disasters such as the floods of 2022, are foreseen, and hence it is crucial to identify the communities and networks that can contribute to these calamities.
We have worked with regional data to model the networks that emerged as a result of the donations made by the citizens of Karachi, which even though sets precedence for further work, lacks to capture a complete image. We aim to further work upon the networks gained, by first working to get more local data points to study trends and analyze the network well, then moving on to identify international links and networks, that are central during the relief and recovery period after a natural disaster. Pakistan did receive humanitarian funding for flood response from the United Nations, US, UK, Canada, Malaysia, and other countries, [15] [16] [17] [18] along with the aid to the NGOs by overseas Pakistanis, which can create networks that can be exploited in times of crisis. We also hope to study the ties between local and international NGOs and the persistence of this network after the emergency period ends and the after-effects of the crisis take place.
These social networks have the potential to visualize connections amongst entities and model the chain of transmission of funds received, to address corruption and exploitation of capital received as aids. These social networks collaborated with other technologies such as Blockchain networks, have the potential to model the chain of accountability or the flow of resources, from donor to victims.
In conclusions using Social Networks to Perform emergency Response Analysis and Humanitarian aid distribution, and to come up with a framework to ensure human safety and in times of calamities is crucial in times of increasing climate change and natural disasters.

6 Appendix

Donation Form
This survey is designed to collect data on the donation campaigns for the Flood Crisis 2022. It consists of 13 questions and should take about 5 minutes to complete.

Figure 13: Combined bipartite graph of individuals donating to organizations and NGOs. The red nodes represent individuals and the blue nodes represent organizations and NGOs.

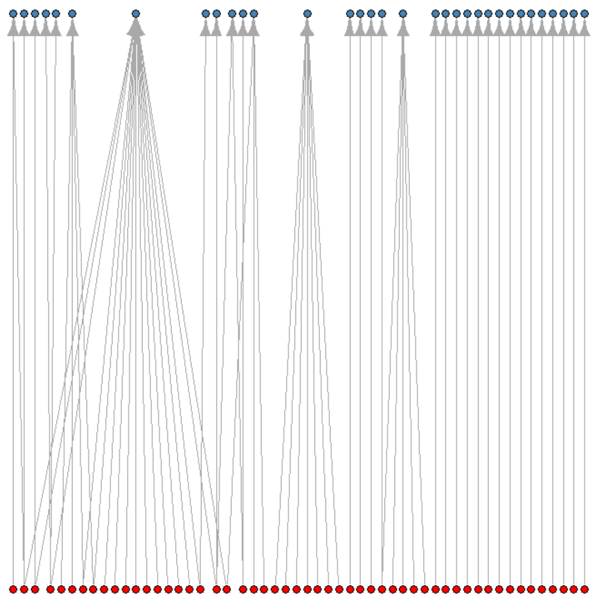

Fig. 13. A bipartite network of individuals donating to organizations and NGOs both.

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