Chapter 9
Managing Complex Systems: The need to Structure Qualitative Data

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9.1 Introduction

Traditional practitioner-led and academic studies of physical or societal resilience often implicitly assume one dominant narrative about natural hazard: often this is a top-down 'objective', or scientific, narrative for physical resilience. The study of community resilience on the other hand might be assumed to adopt a more bottom-up or subjective narrative. Disaster Risk Management (DRM) debates are thus often dominated by hydrologists, geologists, volcanologists, or other technical experts. Chapter 5 noted that this is not helpful in either understanding or addressing the sort of problem we are dealing within the emBRACE program, which is to make the community (more) resilient to the natural. Rather, we need approaches which recognize the complicated and complex nature of both the social and the natural/ecological issues: further, "effective engagement depends upon overcoming basic assumptions that have structured past interactions" (Lowe, Phillipson and Wilkinson 2013: 207) and one of these assumptions is that qualitative data must be descriptive, 'soft', or unquantifiable. However, as this chapter shows, 'messiness' can be resolved adequately and structured so that qualitative data can be looked at more objectively. We believe that "evidence should not be ignored without a very, very good reason — including both quantitative and qualitative evidence" (Edmonds 2015: 1), and that qualitative data, along with tools and methods for its collection and (structured) analysis, are essential to any manager or practitioner.

Figure 9.1 (below) shows one structurally realistic model abstraction (in this case a social network map), which represents part of the workings of a local flood action group. But this structured production is not just an output of itself: it can be used as a heuristic tool to iteratively compare and re-compare with 'reality' in order to improved our understanding of the latter – as well improving as the model itself. It can also be used as a communication device to explain the messy complexity of reality across levels of governance: it is often important to be able to overcome knowledge gaps by describing parts of the system above that of the spatially located issues, which are only capturable at that local level. This can be addressed by using rigorously structured models and maps.

By 'model' we simply mean a formalized description, but this description can be operationalized, for example, into a dynamic agent-based model. As Étienne puts it, we should use "a graphical representation of how stakeholders perceive the system to function" (2011: 11). Co-construction provides an insight into stakeholders' understandings of both natural and human interventions. Put together, process and output can give us a clearer picture of the range of perspectives (‘stratagems’) available to stakeholders and how those perspectives are linked to practical planning at scheme-level. Frameworks are also useful for agreeing a common heuristic, but dynamic modeling may further be used to show how those perspectives are linked to understanding at a more strategic level, and allow “stakeholders to ‘play’ with the idea of community resilience and what it would mean to them and their communities” (Taylor *et al.* 2014: 255).

Thus, this chapter looks at the development of suitable methodologies to elicit such insight, culminating in the authors’ own use of such methods to understand and map qualitative knowledge data regarding communities’ responses to natural disasters. It shows how such data can be represented using structured methods – and thus be sometimes amenable to quantification – while still retaining its veracity as qualitative data. The chapter also has a practical focus on how such positions can find some common language with best available scientific data, through the similar use of such structured methodologies (*cf.* also the preceding chapter on Q^2 indicators).

Having set the scene – along with Chapter 5 – that a wide range of data is important for managing complex systems such as community resilience to natural hazards, the chapter also rests on the axiom that we can and do have access to large qualitative data sets, which are highly relevant to understanding community resilience. In particular we have a set of results from questionnaire studies and more in-depth interviews carried out in Cumbria, South Tyrol, Germany and Turkey. These qualitative data sets are described and explored more fully in relevant chapters of this book (dealing with case studies 1, 2, 3 and 5). This chapter will rather deal with our attempts to rigorously structure that data to both capture the complexity within that data (retaining its grounded veracity) but also allow that qualitative data to be used in a more quick-and-quantitative manner, which is primarily without the need to wade through lengthy reports but instead to use visualizations or quantitative outputs. The discussion within this chapter will then reiterate the utility of this approach.

9.2 Mapping of Social Networks as a Measure of Community Resilience

Social networks play a critical role in resilience to disasters. If argument is needed to support this contention the readers can consult the emBRACE project Deliverable 4.2 (Matin *et al.* 2015) which is available to download from the project website. Social network maps are a useful tool to help assess how the network structure – or pattern – is connected and how those individuals (as ‘nodes’ in the network) interact. Many types of human relationships can be coded as social network maps: across many empirical studies it has been found that such networks follow identifiable and recognizable patterns. Comparing any assessed network with an ideal network may also help researchers identify barriers or gaps among and between significant individuals.

The purpose in mapping the network using a structured methodology is to make overt the embodied characteristics and qualities that can contribute towards making any given community resilient. Without the structuring ability of a network mapping tool, it is difficult to rigorously assess or measure connectivity. The embodied property of the community which is made evident in the structure of the map can be considered as analogous to a measure of ‘social capital’ (Bourdieu and Wacquant 1992, Aldrich 2011 and 2012). In this short chapter it is not possible to go into depth on the importance of this concept, but the emBRACE deliverable cited above gives a brief history of the idea and its application as a resource embedded within the community, which individuals may draw upon through, and because of, their social relationships in order to facilitate community resilience.

Traditional social science data-gathering methodologies such as surveys, interviews, and focus groups, while good for getting in-depth understanding of reasons for the resilience of individuals and different communities, do not allow us to easily compare across communities. Social statistical methods do facilitate comparisons (e.g. Paton et al. 2010, Paton et al. 2013,) but also generally trade-off detail against improved rigor. Only a structured approach to collecting and *mapping* social network data allows us to model social relationships in such a way that they are – at some level – comparable. This is much more useful for policymaking: the maps themselves are also useful as a heuristic device to communicate the qualitative data on the social relationships they depict. Finally, as with other forms of mapping and modeling (as will be seen in subsequent sections of this chapter), the actual process of co-creating the map, involving researchers and members of the community, usefully ‘holds up a mirror’ to allow the members of the community themselves to gain new perspectives upon familiar relationships and their role and status within the social network.

Of course there are costs for these benefits. Compared to other forms of qualitative data gathering social network mapping (SNM) – as with agent-based modeling (ABM) – is relatively data intensive, particularly in the early stages. Also it is less easy to apply a grounded approach and allow the data to direct the course of the research as it unfolds. With SNM it is usually best to clearly identify the research issue – what it is you want the network map to show – before any data collection is started (Beilin *et al*. 2013, Tobin *et al*. 2014). Within the emBRACE project fieldwork we employed this ‘traditional’ SNM approach as part of a larger questionnaire study in South Tyrol, but we also extracted network data post-hoc from qualitative interviews in Cumbria. For our purposes, both of these approaches had benefits which we will discuss briefly.

9.2.1 Assessing resilience using network maps: the emBRACE experience

In our case study we refer to two types of communities: geographic or spatial communities and communities of support or practice. Social networks are usually presented in a visual format (map), but characteristics of the network can also be assessed quantitatively through numerous measures of ‘centrality’ and ‘connectivity’ (Freeman 1978, Arceneaux 2012), with these measures useful in describing either type of community.

Geographical communities are those with identifiable geographical or administrative boundaries arising from some form of spatial proximity (a.k.a. a neighborhood). In the context of DRM the neighborhood is obviously key. However, communities of supporters also provide a key function: these are, in the context of DRM, the individuals and institutions that provide disaster-related services and support.

Individuals may, of course, be members of both groups (in which case they may also operate as boundary actors). The relationship between the two communities is, accordingly, crucial. In the case of Südtirol this community of support can be clearly distinguished into the local members of national organizations (e.g. the Carabinieri or national military police of Italy); local officers representing municipal and provincial government; and locally-based volunteer organizations on the one hand, and provincially-responsible officers and experts from different departments within the Province of Bolzano involved in DRM on the other. In this case study – in which we applied SNM deliberatively – we wanted to understand the existing network structure within the communities and also the horizontal and vertical ties between members of social networks operating at different levels of governance and which help transmit information and provide access to resources at critical times.

In order to do this we asked the question “which institutional actors would you connect to in case of an event?”. EURAC researchers, on behalf of the provincial Government, carried out a questionnaire survey of 934 households (see Chapter 13[?]). SEI then produced a map of the bipartite network showing all (conditional) connections between respondents and institutional actors. This map can also be seen in Chapter 13 (Figure13.xx[?]). Subsequently, and using a Net-Map approach (Schiffer 2007), EURAC researchers carried out individual semi-structured interviews with people working for the institutions that were identified in the survey as the most important for disaster resilience. This allows investigating how different kinds of actors and institutions have to work together to reach a common goal. Some of the actors involved held a significant double role as members of the geographic community and the community of support. During the interviews, we applied network mapping tools to visualize the participants’ knowledge and experiences. The use of maps proved very useful at structuring the knowledge of a range of significant actors and re-presenting that knowledge in a way that is quickly and relatively easily usable and understandable by other actors (Taylor *et al.* 2014). The participatory mapping method allowed actors to clearly see and discuss potential weaknesses within their network, and their links with actors from different scales, backgrounds and spheres of influence and responsibilities.

Importantly, as the original questionnaire survey data was carried out with the geographic community (and thus shows who the key actors are according to people living in Val Badia), and as the subsequent participatory mapping exercise was carried out with members of the community of support, it allows us to compare the community of support’s idealized and planned version of how the social network should operate with how it actually operates in practice, on the ground, in the case study area. The maps created from the questionnaire surveys were discussed and participants were asked to check and validate if the institutions named by the population were ‘the right ones’ as foreseen by the existing emergency plans.

In Cumbria (see also Chapter 12[?]) the social network data was extracted post-hoc from interview transcripts by the University of Northumbria and mapped by SEI. Data were collected from approximately 60 semi-structured in-depth interviews. Additional data were also obtained from several small workshops with key community members. Social networks emerged strongly from earlier-collected data as a key contributor to community resilience and so it was deemed worth exploring whether the data could be used for SNM in this manner. As a consequence of this approach, data were qualitatively quite rich, yet partial in terms of including all potential nodes and links; in addition, boundaries were less clearly defined than with the South Tyrolean data. The mapping process therefore represented an experimental exercise that sought to identify what could be achieved with structured analysis of the data already collected.

Notwithstanding this post-hoc approach, three clear aims were identified before the mapping process was started. These were to explore whether it was possible to identify: what type of resources or support (e.g. physical, social, emotional, financial) was sought by actors in the case study communities before, during and after the flood; which organizations or individuals are providing this support; and who are the central actors within specific social networks. Color coded links and a descriptive key were used to identify type of resources and support. Individuals and organizations are identified by coded nodes and centrality is depicted using larger sized nodes for higher betweenness centrality (see Figure 9.1, right-hand side).

<insert Fig 9.1 here>

As in South Tyrol, understanding who the central actors are within specific communities can provide insight into how resources are obtained and dispersed into a community. In this Cumbrian study, central nodes constituted well-connected individuals who were seen as having a key role in providing support to their local communities through the mobilization and distribution of resources – including information. The community-based Flood Action Groups were of particular interest due to their ability to access and distribute resources through their well-connected group members. Centrality scores (quantitative) were calculated using both betweenness centrality and degree centrality measurements. Betweeness centrality is a good measure of an actor's wider influence within a network. These findings, definitions, and their implications are further described in Matin *et al.* (2015) as well as in chapters 12 and 13. Cases also identified that the array of resources required for community resilience can be classified into three broad sectors: community, civil protection and social protection. In Cumbria, an overall social network map, constructed from the aggregated interviews responses ($n \approx 60$), depicts the overall network structure in terms of resources and support services, and the organizational sectors that provide these services, across the entire community that took part in the research. This map illustrates the diversity of resources that are being acquired by the community to help build resilience to flooding (see Fig 12.xx). Again as with South Tyrol, resources are clearly being drawn from within the geographic community itself as well as from the wider civil protection and social protection spheres of the community of support and this is highlighted by clustering on the map.

The approaches outlined above involved combinative methodologies of largely qualitative data gathering to capture information on social capital and social networks with the highly structured rigor of the SNM process leading to the quantitative exploration possible using social network analysis techniques. Because of the differences in approach in data gathering, the data from Cumbria is richer offering opportunities for analysis of many facets of disaster networks and their complexity. The concomitant disadvantage is the need to compile a set of maps from a qualitative dataset which did not meet the usual requirements of SNM. In other words the fact that the key questions were not identified at the outset of the research – before data was gathered – led to gaps in the dataset and having an incomplete dataset can be problematic for drawing statistically valid conclusions about specific network maps. Thus, we recommend that comparisons between the South Tyrol maps and the Cumbrian maps are made only at the level of qualitative analysis. Nonetheless, social network maps produced in this way have proved their usefulness as discussion and communication tools within the geographic community, and between the geographic community and the community of support, and by supporting and clarifying some of the more qualitative outputs.

9.3 Agent-based Models

Modeling helps explore the complexity of the situation where social and natural systems are coupled (i.e. intertwined, with feedbacks) and where sub-systems need to be considered: the modeling process and model outputs can also help to clarify and to communicate that complexity. Issues such as unpredictability, uncertainty, sensitivity to initial conditions, and interconnectedness can be included, as can possible future evolutions of the situation by using simulations. We will show this from two case study applications within emBRACE. Further, the dynamics of social complexity which are particularly relevant for us in emBRACE – as well as the interplay between social and natural sciences and engineering involved in DRM – can be represented in models, as can the convolution of our responses to these complex situations.

Using simulations as an aid, and in combination with other methods, helps both researchers and practitioners, as well as community members themselves, understand dynamic correlations among different factors, as well as identifying possible causal mechanisms. Furthermore, modeling itself offers an opportunity for integration of different types of knowledge (technical, traditional, local) and, with the participation of different stakeholders, reality-checking and elicitation of preferences. Moreover, it allows different actors to play with (i.e. examine in an unconstrained manner) some representations of community resilience, on the basis of including different knowledge frames, to generate shared understandings and co-learning.

As with SNM above, the use of ABM within the emBRACE project is documented in a report available from the project website (see Taylor *et al.* 2015). Within emBRACE, the case study team working on floods in Central Europe used ABM themselves, while the case study team working on earthquakes in Turkey commented on another model prepared by SEI which was found relevant. Therefore, again, we report on two distinct approaches.

ABM concentrates on describing the social system at the level of the actors within it: this is usually done using a computer model (program) within which an autonomous piece of program code represents each actor. ABM can be used to model multiple types of agency at different levels of action. This is a highly flexible method, which does not depend on an *a priori* set of given techniques or assumptions, and it is without particular attachment to any theoretical approach. In this respect, ABM may lend itself to being more directly informed from observation and evidence although the cost and difficulty to collect sufficient data continually presents a practical barrier. Usually the rules of behavior of agents are informed empirically from a combination of field studies; participant methods (e.g. games, co-construction workshops, etc.); and case studies; or sometimes from stylized facts (*cf.* also the emBRACE deliverable on SNM (Matin *et al*. 2015: 8) which also discusses data gathering issues and the use of stylized facts: see particularly the section on complex dynamic social networks). Much more literature on ABM, including an updated review, can be found in Taylor *et al.* (2015).

One of the ongoing and active areas in modeling research and related fields is the development of methods for incorporating qualitative field data into model specifications in a more rigorous way (*cf.* Edmonds 2015). New methods and tools are needed to address data scarcity and to make better use of existing data sets. This is particularly relevant for DRM. Within emBRACE, we have thus both generated ABM from existing datasets and also generated a model to compare with an existing dataset.

9.3.1. Two Case studies of ABM in emBRACE

The modeling case studies are different to the emBRACE case studies, but with an overlap as the former focused on smaller more “partial” areas, or particular aspects of interest to the case studies (i.e. describing *part* of the system well, but also from a *particular standpoint*: see Zeitlyn 2009). Data collected in the Turkish case study using mix of qualitative and quantitative methods, as discussed in Chapter 15[?], is extensive on individual psychological resilience, and on response, recovery and reconstruction processes as perceived by different stakeholders. Focus groups were also carried out with actors from various organizations and institutions. Data also include semi-structured interviews plus in-depth interviews with 20 disaster survivors, as well as quantitative survey data, which were used in statistical analysis. Modeling was carried out using NetLogo software (Wilensky 1999). R statistical programming (R Core Team, 2015) was used for the analysis. 'Rnetlogo' makes it possible to use the two applications jointly by exchanging commands and data and simulations were run from Rnetlogo.

The Multivariate Risk Factor (MRF) model of Freedy, Resnick and Kilpatrick (1993), which includes many pre-disaster factors, was used. A second model, focusing on individual and household-level resilience, is the Disaster Preparedness (DP) model of Paton and colleagues, which is discussed at length in emBRACE deliverable 4.1 (Karanci *et al*., 2015). The main focus is on the individual, although the research also connects with community factors and analyses how community resilience is perceived. The main outcome of interest for testing the model is the individual actors’ intention to prepare, which was identified as an important variable. The ABM was developed to show the interaction of several of the variables in the precursor stage that are thought to affect intentions. In particular, we wanted to extend the static picture of preparedness to include a more time-dependent analysis. The importance of time as a moderating factor is demonstrated by Paton *et al.* (2005). The time analysis of intention to prepare shows which actors are ready to accept which kind of preparedness measures, and therefore its signature – the output of the simulation – could indicate resilience or lack of resilience.

The ABM was developed and explored through simulation experiments. The scope of this model is limited: the outcome of interest is only the intention to prepare (i.e. the first two stages of the conceptual model of Paton, 2003). The simulation model also includes a simple social network in which messages related to hazards are transmitted. The time step for the model is the week – an approximate correspondence with a real time frame. Each week time step in the model is broken down into 4 sub-steps in which agents: i) update network connections; ii) send, receive and process messages; iii) calculate risk, and expectations (beliefs); and iv) formulate intentions. A set of 5 simulation experiments were carried out to better understand the effect of different model parameters on results. These investigated four parameters in the category of motivating factors – critical awareness, hazard anxiety, risk perception, underlying risk – and one parameter in the category of moderator variables, self-efficacy – which affect indirectly intentions to prepare.

One of the most interesting areas of study for emBRACE work in Turkey was researching the changes observed in DRM between the 1999 Marmara earthquake event and the 2011 Van event. Considering state interventions, emBRACE Del. 5.3 (Karanci *et al*. 2014) concluded that participants perceived improvements in disaster response capacity (search and rescue, mobile health services and psychological support) but also interventions in risk minimization (improved construction and land use regulation). The report also highlights the Turkish Catastrophe Insurance Plan (TCIP) that was launched in September 2000. TCIP differs to the other interventions described because, rather than aiming at improving disaster response services, TCIP is a risk transfer strategy and assures repayment in case of damage. Thus, it can speed recovery. TCIP is an intervention which targets individual households by requiring them to make regular payments which afford security against potential catastrophic damage. At the household level, all of these state-level interventions seem to raise the prospect that risks can be better managed, and in fact all are cited as important measures for supporting resilience (Karanci *et al* 2014: 26-27).

TCIP in particular is an intervention that seems to have a lot in common with preparedness measures: therefore, as a 'what-if' experiment, the following intervention scenario was considered where, after two years, the insurance intervention was introduced at a rate of one agent per month up to 50% of agents. Sub-scenarios include: a) after adopting, insured agents have a higher risk tolerance level – meaning that risk is a less intrusive factor (based on risk compensation logic); b) after adopting, insured agents have a hazard anxiety threshold set at the maximum level – meaning that hazard denial does not occur; and c) a combination of the two above sub-scenarios. In this exploration to assess the impact of insurance on the population of agents it was found that insurance could be particularly important in terms of its potential effect on hazard anxiety (sub-scenario b) whereas a risk compensation effect did not seem to be important. In other words, insurance could be important but only if it acts towards preventing denial. However, this is a tentative and exploratory finding but one which can be explored with the communities involved – both geographic and support.

The Germany case study is in some ways simpler as it is to do with modeling several conditions: the availability of resources; the number of helpers that are deployable; and the effectiveness of communication and coordination. Another crucial aspect is time: if lead times are too short or the time needed to put all necessary measures into place – the coping (i.e. *effective* response) time – is too long, then disaster management might be unable to ensure the required protection.

Several modeling studies exist that address natural hazards and their influence on community functioning (these are described in Taylor *et al* 2015). Like the Turkish case though, the aim of the model developed in this case study is not to serve as a prediction tool but rather as a 'what-if'-toolbox. Using an ABM approach allowed researchers to incorporate the micro-level decision-making of actors explicitly, thus it is legitimately within the field of qualitative as well as quantitative. Accordingly, this offers a capacity to observe these actors' joint emergent behavior on a macro or system level (Holland 1992). In the German case the UFZ researchers were successfully able to model the behavior of individual actors such as disaster management units that act independently to solve the common goal of protecting the geographic community (Taylor *et al* 2015: 48-63). In this way the German use of ABM again provided a useful discussion and exploration tool that included some qualitative data.

9.4 Other Structuring Qualitative Data Methodologies

Obviously a short chapter cannot deal with *all* relevant methodologies extensively, and we have used only the two above within the emBRACE project. However, within the context of DRM there are other methodologies which are particularly appropriate and they will be discussed briefly.

The most important is Q-methodology. A fuller review of the methodology can be found in Forrester *et al*. (2015) but essentially, Q fills a gap between qualitative and quantitative methodologies: it is particularly suited to purposeful sampling of individually-held perspectives within stakeholder groups (Raadgever *et al.* 2008), and imposes a useful structure upon those 'subjectivities' (Eden *et al.* 2005). This makes Q-methodology ideal for use where it is necessary to recognize social complexity (Donner 2001) and, consequently it, has been used in a range of wicked and messy issues. Q-methodology involves stakeholders sorting of a range of items, usually written statements or photographs, onto a predetermined 'biased' grid. A regression analysis is then used on each participant's 'Q-sort' to identify whether there are statistically significant 'types' amongst the range of stakeholders interrogated. These ideal types can then be used either as a communication device, or investigated further such as using wider 'intercept' consultation methods to ask people which type they prefer (see Forrester *et al.* 2015). If such wider population surveys also collect locational data (e.g. postcodes), then the qualitative data from the Q-sort can be readily included in a spatial database to present a correlated 'belief versus location' map.

Using methods such as Q in conjunction with other structured subjective methodologies explores the problem of representing the connection between what people say or do and their underlying beliefs. This can offer a pathway to reconciling and integrating social factors with their spatial context if the output is mapped, for example within a GIS. Q methodology, along with participatory spatial mapping, also helps participants and researchers understand and communicate their own perspectives as part of reflexive research process.

9.5 Discussion

Mixed structured methods using qualitative data allow researchers to check whether characteristics of an actor are correlated with their position in the network, and also if the measure of the network as a whole is correlated with some other indicator of the system, such as resilience. Simulation – e.g. using ABM – investigates the results of their interactions through patterns or trends of behaviors. This is relevant because of growing recognition of the importance of cross-scale interactions in DRM. Structuring qualitative methods addresses the question of how localized interactions among social actors give rise to larger scale patterns or structures that may facilitate or constrain behavior of actors.

There are, however, important methodological differences between SNM and ABM. The can briefly be summarized as follows: both are 'data-hungry' but models even more so. This makes models better at being used as exploratory tools and/or heuristic (communicative) devices rather than as metric tools. ABM can be good test beds for thinking about decision-making and management alternatives in many different human domains including those linked with transformative resilience to natural disasters. The modeling case examples presented here demonstrate that a range of phenomena are readily amenable to study, from disaster preparedness measures to disaster response situations. Moreover, other empirical experience by the authors (*cf*. Forrester *et al*. 2014) suggests that, whilst they can initially be difficult to understand, ABMs can also be very appealing to both geographic- and support-stakeholders and, further, "complexity concepts were helpful in capturing factors that were interactive and manifested in multiple outcomes" (Matin and Taylor 2015).

Thus, our recommendation is that simulation modeling may deliver a partial picture of resilient communities, systems and individuals, which appears most promisingly used when ABM is included alongside other methods (and other modeling approaches), which are complementary and may facilitate better use of empirical data to inform and constrain the models. The advantages and disadvantages of quantification approaches to the appraisal of community resilience are discussed in detail in emBRACE Deliverable 3.5 (Becker *et al.* 2015) and also in Chapter 9. The message from this work is that some of emBRACE's key qualitative indicators are directly measurable using either a SNM or SNA approach, or other structured subjective methods such as Q-methodology – and, further, changes to these (in terms of an ordinal or nominal scale – that is direction of change) are directly explorable using ABM. This will provide a useful tool for engaging with decision makers, practitioners, and community members. Structuring qualitative data helps in understanding relationships and thus possible causal mechanisms in complex systems, especially when they are generated 'from the bottom-up'. In other words, their use can help with the explanation of certain complex phenomena.

In conclusion, then, using structured subjective methods allows both a deeper and a wider appreciation of the range of qualitative and subjectively-held stakeholder's positions. Outputs – if they retain their grounded nature in the local community – can allow significant community stakeholder buy-in to both research and governance processes, as well as better planning and policy outputs. Further, they facilitate the bringing together of ‘soft’ assessments of community – and often personal and inter-personal resilience – with ‘harder’ assessments of engineering methods. However, engineering interventions also need to be grounded and contextualized within the social (*cf.* the German ABM outputs), thus a new form of risk assessment is needed to allow practitioners at all levels to take the social into account.

We have used methodologies such as co-construction of social network maps to characterize stakeholders’ positions in a clearer way and communicate that information. The utility of rigorously structured and quasi-quantitative interpretative methodologies has the great benefit that the output is apparently simple and interpretable by actors with a wide range of backgrounds. Such structured outputs can have immediate utility in a way that more ‘fuzzy’, ‘thick’ or descriptive qualitative outputs cannot. SNM and ABM can both be used to help explain complexity (and thereby justify clumsy solutions for wicked and messy problems – *cf.* Chapter 5). Other associated benefits are that structured outputs such as maps and models can be used to ‘open up’ and ‘close down’ (both boundaries and discussion) and, as noted above, SNM in particular may be able to identify a form of social capital.

Finally, we believe that you cannot address complex problems with simple solutions. Taken together (and alongside other methodologies) participatory ABM and participatory SNM can help get this message across. It must be remembered that a model is an abstraction for a purpose: their beauty lies in their utility. Used properly, such as to describe and compare data, structured outputs from qualitative data might help understanding, predict what happens next, or stand in for the thing we cannot study any other way.

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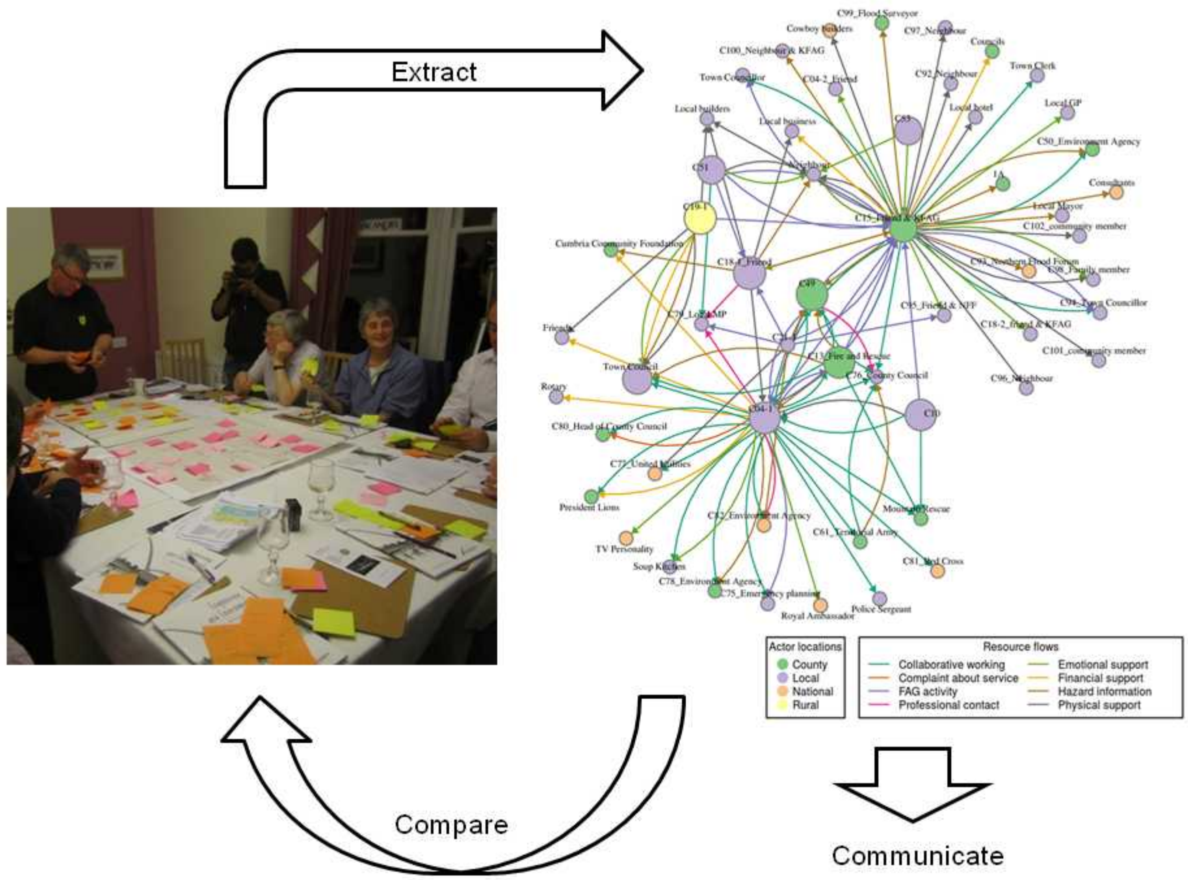

Fig 9.1: Network map (RHS) of all relevant connections in sample of members of a local Flood Action Group (photo) and what the extracted data may be used for