University of Southampton

Faculty of Environmental and Life Sciences

Geography and Environmental Science

Social Connectivity and Disaster Resilience: An Opportunity for Improved Mapping and Measurement using Call Detail Records

Volume 1 of 1

by

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Thesis for the degree of Doctor of Philosophy

March 2020

University of Southampton

Abstract

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Reducing the risk of populations to disaster is a key priority for those working within sustainable development, as highlighted by global policies including the Sustainable Development Goals and the Sendai Framework for Disaster Risk Reduction. Consequently, there is a need to understand where disaster risk is at its greatest, yet its quantification has proven difficult. Disaster risk is a function of the likely occurrence and exposure of a hazard, the vulnerability of the population to the hazard, and their (in)ability to prepare for, absorb and build back from the adverse impacts of the hazard, often understood as their resilience. The quantification of the latter two aspects, vulnerability and resilience, is not straightforward, with both having multiple definitions as well as approaches to their measurement. Within the wider resilience field, an alternative approach to its measurement is evolving, which specifically focuses on social networks as the unit of analysis. The premise is that greater social connectivity will directly enhance resilience, can be evaluated through a singular approach, and can be quantified using social network analysis. This approach has however been limited by the availability of data at substantive spatial and temporal scales.

This PhD proposes that there is a significant opportunity to utilise Call Detail Records (CDRs), the metadata generated from the use of a mobile phone, to address these data limitations. The overall aim of this thesis is to assess the feasibility of using

CDRs to create a social connectivity dataset that can be used specifically within disaster resilience estimation for disaster risk reduction. To substantiate the creation of this dataset from CDRs, the theoretical framework behind using social connectivity for disaster resilience estimation is first established, including a systematic review that evaluates the importance of social networks for disaster risk reduction in Nepal. The thesis then accounts for the representativeness of the CDR dataset through analysing the changing geo-demographics of mobile phone ownership in Nepal. In the last decade, household ownership has grown substantially Nepal across different socio-economic groups, whilst individual ownership stood at 82% in 2016. As a result, the CDR dataset is likely to be representative of a substantial cross-section of Nepal's population. The feasibility of using CDRs to represent real-world social networks is then addressed by mapping the spatial distribution of the social communities detected within the CDR network. The study finds that the social communities are spatially concentrated; within these distributions, geographic communities, such as towns and cities, can be identified.

The thesis then evaluates whether CDRs can be used for improved mapping and measurement of social connectivity for disaster resilience and risk estimation, creating a social connectivity index using novel CDR data and social network analysis. The index and its variables show that there are clear geographical patterns to social connectivity, with the peri-urban middle Hill regions expected to demonstrate the greatest resilience due to their sizeable and strong bonding and bridging networks. The thesis then addresses the limitations of each of the analyses presented and identifies future opportunities for further research. The thesis concludes that CDRs and the emerging body of literature on social connectivity and social network analysis present a significant opportunity to rethink the current methods of measurement of disaster resilience for disaster risk reduction.

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Research Thesis: Declaration of Authorship

Print name:	Joanna Louise Wilkin
Title of thesis:	Social Connectivity and Disaster Resilience: An Opportunity for Improved Mapping and Measurement using Call Detail Records

I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published as:-

Wilkin J, Biggs E, Tatem A.J. Measurement of Social Networks for Innovation within Community Disaster Resilience. Sustainability. 2019. doi:10.3390/su11071943

Within this publication, presented as Chapter 3 in this thesis, Joanna Wilkin was responsible for the conception and design of the study, all analysis, including sourcing and reviewing all literature, and the drafting of manuscripts and revisions. Dr Biggs and Professor Tatem contributed ideas and feedback to each manuscript draft in a supervisory capacity.

In addition to this published work, the three analysis chapters will be submitted as individual papers for publication. Each paper will be submitted under the following authorships and attribution statements; for all three papers, Joanna Wilkin was the lead author and was responsible for conceiving the study, devising methodological approaches, sourcing appropriate data, carrying out the analysis and writing the manuscript. One issue faced during the course of the PhD was the introduction of the General Data Protection Regulation in 2016, which limited the direct access Joanna had to raw Call Detail Records (CDRs) used in Chapters 6 (Paper 3) and 7 (Paper 4). In these cases, Joanna devised and provided extensive code-based scripts to Dr Christopher Brooks (a Senior Data Analyst within the Flowminder Foundation), who then modified and implemented these scripts to process the CDRs to provide aggregated datasets that were then further processed by Joanna before analysis.

Chapter 3, Paper 1

Wilkin J, Biggs E, Tatem A.J. Measurement of Social Networks for Innovation within Community Disaster Resilience. *Sustainability*. 2019. doi:10.3390/su11071943

J.W., E.B. and A.J.T. contributed to the design and implementation of the review; J.W. wrote the manuscript with input and critical revisions from all authors.

Chapter 5, Paper 2

Wilkin J, Biggs E, Pezzulo C, and Tatem A.J. Changing demographics of mobile phone ownership in Nepal, 2006 – 2016. *(To be submitted).*

J.W., C.P., E.B. and A.J.T. contributed to the design and implementation of the study. J.W. liaised with C.P. to access the Worldpop's account to the Demographic and Health Surveys Program data. J.W. processed and analysed all data, with methodological and technical advice from C.P. J.W. wrote the manuscript with input and critical revisions from all authors and formatted the manuscript for publication.

Chapter 6, Paper 3

Wilkin J, Biggs E, Brooks C, Ruktanonchai N, and Tatem A. J. Detecting geographic communities in Nepal using Call Detail Records. *(Submitted for publication).*

J.W. and N.R. conceived the study. J.W. devised the resulting research and methodology. J.W. prepared code-based scripts for C.B. to run, who implemented the scripts with modifications on the external Flowminder-Ncell server to produce aggregate level datasets. J.W. then conducted further data processing and all analysis. J.W. wrote the manuscript with input and critical revisions from all authors and formatted the manuscript for publication.

Chapter 7, Paper 4

Wilkin J, Biggs E, Brooks C, and Tatem A. J. Measurement of social connectivity using Call Detail Records in Nepal for disaster risk reduction. *(To be submitted).*

J.W. conceived the study with guidance from E.B. and A.J.T. in their supervisory capacity. J.W. devised the resulting methodology and prepared code-based scripts for C.B. to run, who implemented the scripts with modifications on the external Flowminder-Ncell server to produce aggregate level datasets. J.W. then conducted further data processing and all analysis. J.W. wrote the manuscript with input and critical revisions from all authors and formatted the manuscript for publication.

Signature: Date:

As a supervisor for this postgraduate student I certify that the authorship attribution statements above are true and accurate.

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Acknowledgements

It feels almost incongruous to submit a PhD that advocates for the importance of social networks at a time where we are in isolation. But as chimed by the Twitterati, we are not social distancing and instead physically distancing ourselves whilst our social networks find a more remote space. The latter, in a fortuitous turn of events, somewhat adds support to this thesis' use of innovative datasets to represent our social networks. This is not to make light of the current situation we find ourselves in, but rather to add to the consistent message of this thesis: our social networks are important and play a driving role in our resilience to respond to shocks and stresses. Whilst in this thesis the focus is on disaster resilience, here in this space, I want to make a small acknowledgement to the importance of my own social networks in my own resilience in the completion of this work. They were undoubtedly vital to my own ability to absorb, adapt and transform in the face of the shocks and stresses that a PhD ultimately entails.

Bonding Networks

The academic success of this PhD, including its legibility, are in part a result of the unrelenting and formidable efforts of Dr Eloise Biggs. Ellie provided exceptional academic guidance and support across the four years, keeping the theoretical development, and then the write-up of the thesis, on track, despite my several missed deadlines.

The confidence to pursue my own ideas and the overarching hypothesis presented within this PhD would not have happened without the freedom and backing offered by Professor Andrew J Tatem. Andy's feedback and support have been instructive within my development over the last four years into a more mature, confident and refined academic, capable now of providing the same standard of supervision to my own future students.

I wish to sincerely thank you both for persisting with me (and terrible first drafts with erratic uses of brackets; and semi-colons) throughout the last four and a half years. Undoubtedly there have been challenges, but from both, I have learnt a significant amount about, and witnessed first-hand, how a team work can work together across time zones and locations constructively and cohesively. I do however apologise for the excessive word counts.

This thesis and the last four years would not have been possible without the direct and unyielding support of my family. Foremost is Mikael, who has been a tremendous partner throughout this process, taking on many roles as soundboard, proof-reader, presentation-watcher and, in these latter stages, coffee-maker, without question or hesitation. More importantly, during the times of my most earnest doubts, his words of confidence, belief and assurance have been the encouragement I have relied upon most. Thank you. For my parents, who fostered my love for education, I also thank wholeheartedly; without their practical support, the last few years would simply not have been feasible. They truly are the people you would want most by your side in a crisis and I am incredibly grateful that they have been mine. I also thank Mikael's parents, whose continued sincere interest and pride in my work has provided invaluable moments of buoyed optimism that have helped immensely during the more frustrating times.

In addition, through a chance reply to an email, I am forever thankful for my friendship with Dr Dianna Smith at the University of Southampton, who, without the need for reciprocity, has invested an incredible amount of time and support in my professional development. Her pragmatic advice has been indispensable and helped me obtain my recent academic appointment at UCL. Between Dianna and Ellie, I could not have had more astute or motivating female mentors during my PhD, who have encouraged me to pursue a career in academia, where hopefully I can also provide the same inspiration to future women interested in quantitative geography/GIS.

To all my wonderful friends (Katie, Heather,…), who have helped in many ways that they are unaware of over the last few years, a thank you – I now look forward to resurfacing and re-strengthening our connections.

Bridging Networks

The completion of this PhD would not have happened without the work and efforts of Dr Christopher Brooks at Flowminder. The implementation of my ideas and code have relied on him investing significant time and belief in my work. I would like to thank him for making this work possible and hope we can continue to work together to trial the many unexplored ideas presented in this thesis over the coming years.

I have also been fortunate to be part of various academic communities over the last four years. First, the WorldPop research group, led by Andy, has been an invaluable resource to help engage with other researchers and find assistance. Within this group, I'd especially like to thank Dr Nick Ruktanonchai and Dr Carla Pezzulo, who have made important contributions to the overall development of my thesis. The PhD researcher community at the School of Geography is also a hub of positivity and support; I'd like to thank my fellow PhD students who helped support, and directly contributed to, the success of the Geography Programming Bootcamp I ran last year. In particular, Kate Rawlings, who is now very much a bond, not a bridge - we achieved something pretty cool together and I look forward to seeing what we can do with it next.

Facilitating my part of these communities, I would like to extend gratitude to the School of Geography and Environment at the University of Southampton and the ESRC Doctoral Training Partnership team who have been instrumental in making the return to University a welcoming environment. Through the various events and free workshops and courses they run, they continually work to create and sustain the connections between a diverse of group of students to ensure that the ensuing PhD life feels a little less isolating, whilst also encouraging our own personal and professional development.

Linking Networks (i.e. Funding and data access)

This work was supported by the Economic and Social Research Council (ESRC) [Award Reference: 1647038] and the University of Southampton School of Geography and Environmental Science. The author also received institutional visit funding support from the University of Southampton via the World University Network (WUN) researcher mobility programme.

Extensive appreciation is given to the Flowminder Foundation and its team of analysts in the facilitation of this thesis. Permission was granted by Ncell, the Mobile Network Operator, to use the data within the context of this thesis. I would like to extend a sincere and unreserved thank you to Ncell for making this data available.

Definitions and Abbreviations

All definitions and abbreviations are re-defined within each chapter in which they feature due to their extensive use within this thesis.

BRIC Baseline Resilience Index for Communities

CDA Community Detection Algorithm

CDR Call Detail Record

CI Confidence Interval

CPA Comprehensive Peace Agreement

CRED Centre for Research on the Epidemiology of Disasters

DHS Demographic and Health Surveys

DMA Disaster Management Act

DPO Disabled People's Association

DROP Disaster Resilience of Place

DRR Disaster Risk Reduction

EWC Eastern, Western and Central

FBSCI Facebook Social Connectedness Index

GDP Gross Domestic Product

GIS Geographic Information Science

GSMA Global System for Mobile Communications Association

HDX Humanitarian Development Exchange

ICT Information and Communication Technologies

IFRC International Federation of the Red Cross and Red Crescent Societies

IWI International Wealth Index

KDE Kernel Density Estimation

KMC Kathmandu Metropolitan City

KIS Key Indicator Surveys

MIS Malaria Indicator Surveys

MNO Mobile Network Operator

MoHA Ministry of Home Affairs

MPO Mobile Phone Ownership

MWFW Mid-Western and Far-Western

NBM Network Based Measure

NCA Natural Calamity Relief Act

NDRF National Disaster Response Framework

NGO Non-Governmental Organisation

NSET National Strategy for Disaster Risk Management

OCHA Office for the Coordination of Humanitarian Affairs

OPA Older People's Association

OSM OpenStreetMap

PAR Participatory Action Research

PDNA Post-Disaster Needs Assessment

QBCI Quantitative Based Composite Indicators

SAR Search and Rescue

SCI Social Connectivity Index

SDG Sustainable Development Goal

SFDRR Sendai Framework for Disaster Risk Reduction

SIM Subscriber Identity Module

SPA Service Provision Assessment

SNA Social Network Analysis

SNM Social Network Mapping

SNMM Social Network Mapping and Measurement

SOCAT Social Capital Assessment Tool

SoVI Social Vulnerability Index

TAM Technology Adoption Model

UAV Unmanned Aerial Vehicles

UN United Nations

UNDP United Nations Development Programme

UNISDR United Nations International Strategy for Disaster Reduction (Office for Disaster Risk Reduction)

US United States

VCA Vulnerability and Capacity Assessment

VDC Village Development Committee

WHO World Health Organisation

Chapter 1 Introduction

1.1 Disaster risk reduction for sustainable development

A disaster is understood as the serious disruption of the functioning of a community or a society at any scale due to hazardous events that leads to one or more of the following: human, material, economic and environmental losses and impacts (UN General Assembly, 2016). In the previous decade (2008-2017), there were on average each year 348 disasters from hazards, resulting in approximately 67,572 deaths, affecting 198.8 million people and causing US$166.7 billion in damages (CRED, 2018)(Figure 1-1). Whilst these statistics capture some of the immediate and short-term impacts of this disruption, research continues to show that disasters have long-term adverse consequences for economic growth; this can lead to a downturn in the trajectory of socio-economic development as well as exacerbate poverty, particularly in less developed countries (Lee and Tang, 2019; Report of the Secretary-General, 2019; Tselios and Tompkins, 2019). These impacts impede the UN's 2030 Agenda for Sustainable Development, where eradicating poverty in all its forms and dimensions, including extreme poverty, is seen as the greatest global challenge and an indispensable requirement for sustainable development (UN General Assembly, 2015a).

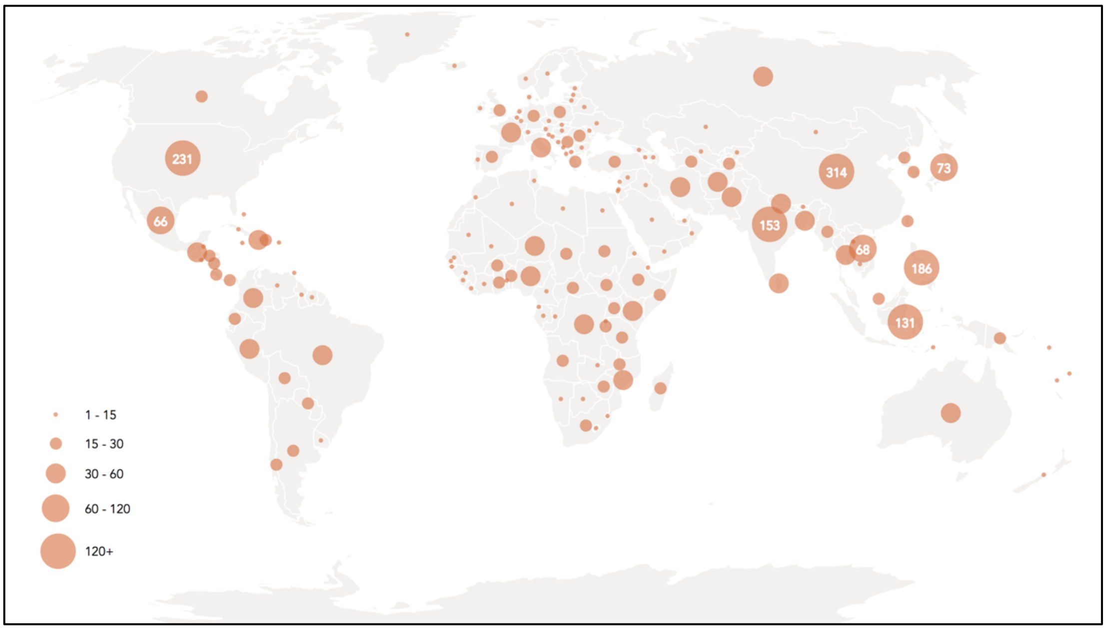

Figure 4-1. Number of natural hazards by country between 2008 – 2017 registered by the EM-DAT database (Data: EM-DAT, CRED/ UCLouvain).

Reducing the risk of populations to disaster is therefore a key priority for those working within sustainable development, reflected in its inclusion within the 2015 Sustainable Development Goals (SDGs) (e.g., SDG Targets 1.5, 11.5 and 13.1) (United Nations, 2015). Target 1.5. of the SDGs, for example, aims to "build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters"(United Nations, 2015, pg.19). This call for action has been further formalised within the 2015-2030 Sendai Framework for Disaster Risk Reduction (SFDRR) (UNISDR, 2015), which is tasked with the reduction of the short-term impacts of disasters, whilst also enhancing the preparedness of populations through the development of national and local Disaster Risk Reduction (DRR) strategies (UNISDR, 2015).

To achieve its various targets and contribute towards the progress of the SDGs, the SFDRR is led by four key priorities. The first priority is to obtain an understanding of what disaster risk is and where it is most prevalent or who is most at risk and why (UNISDR, 2015). This knowledge is required in order to take any practical actions that aim to prevent or mitigate risk, including the development and implementation of DRR strategies. These practical actions are central to the objectives of the three remaining priorities, which are: to strengthen disaster risk governance to manage disaster risk; to invest in DRR for resilience; and enhance disaster preparedness for effective response and to "Build Back Better" in recovery, rehabilitation and reconstruction (UNISDR, 2015). Without this initial step of understanding disaster risk and its distribution, the remaining parts of the SFDRR are likely to fail, which will have adverse consequences for the wider sustainable development agenda. Despite this critical need to know where disaster risks are the greatest, researchers and practitioners alike within DRR are facing several challenges in turning the theoretical understanding of disaster risk into an operational concept.

1.2 The current limitations of understanding and measuring disaster risk

Disaster risk is defined as "the potential loss of life, injury, or destroyed or damaged assets which could occur to a system, society or a community in a specific time period, determined probabilistically as a function of hazard, exposure, vulnerability and capacity" (UN General Assembly, 2016, pg.14). The separation of disaster risk into these four components builds on the fundamental understanding that there is no such thing as a natural disaster (UNISDR, 2016). Instead it is the hazard itself – the process, phenomenon or activity that may cause the loss of life, injury or other impacts and damage (UN General Assembly, 2016) – that can be natural in its origin, for example, geophysical hazards such as earthquakes and volcanoes, hydrological hazards, including floods and landslides, and meteorological hazards, including storms and cyclones. A disaster is created only when a population is exposed to a hazard, but is unable to cope with or respond and adapt to its impacts. The risk of disaster is therefore created by the outcome of continuously present conditions, including the likely exposure of a population to a hazard, the vulnerability of the population to the hazard, and their (in)ability to prepare for, absorb and build back from the adverse impacts of the hazard, often understood as their resilience (UNISDR, 2009).

To reduce the risk of a population to disaster from natural hazards (from here, known as hazards for the focus of this thesis), the factors that create these conditions and thus put the population at risk need to be identified, assessed and, if possible, managed. This involves quantifying what hazards are likely to occur as well as when and why to understand the likely exposure of a population, what makes the population vulnerable to these hazards, and whether the population possesses a level of resilience that will enable them to respond and recover from the impacts. By understanding these factors, efforts can then be made to target and reduce the risk of these populations. This can be achieved by: minimizing their exposure to the hazards; lessening their vulnerability to their likely impacts; and/or improving their resilience to the adverse effects (UNISDR, 2009).

The issue faced by those trying to understand and manage disaster risk is that its quantification is yet to find a common approach, specifically in the measurement of vulnerability and resilience of populations (Beccari, 2016). Whilst calculating the exposure of a population to hazards can primarily rely on well-tested scientific theory and methods to help predict and quantify their occurrence and impact (e.g., earthquakes and volcanoes will occur in tectonically active areas whilst hurricanes and typhoons in specific climate belts in coastal regions), the operationalisation of vulnerability and resilience has not been as straightforward. Due to the ongoing ambiguity over their precise epistemological meanings, a singular approach to their measurement has yet to be found. This heterogeneity is further exacerbated by the shortage of data available to measure the two concepts accurately.

1.2.1 The issue of defining vulnerability and resilience for DRR

The vulnerability of a population is understood as the "conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards" (UN General Assembly, 2016. pg.24). This can also include the infrastructural, institutional, and political environment they occupy, which create and maintain the propensity for the population to be harmed (Cutter *et al.,* 2008; Kelman *et al.,* 2016). One factor, for example, could be a community having a significantly elderly population, who may find it too difficult to evacuate in time during a hazard event; another factor could be inadequate building designs, which are susceptible to collapse in the case of an earthquake or weather hazard.

Despite this vulnerability, there is a specific capacity within the affected population to cope with these adverse effects (Birkmann, 2006); it is when this capacity is exceeded, there will be a serious disruption to the functioning of the population and as a result a high risk of disaster. To prevent this from occurring, it is essential that the population can resist, absorb, and recover from the effects of a hazard as well as adapt to better manage future events (Walker *et al.,* 2006; Weichselgartner and Kelman, 2014). This capability to respond to a hazard's impact positively is the principal tenet behind the concept of resilience, which has come to be prioritised over vulnerability as a leading concept within DRR research (Weichselgartner and Kelman, 2014). As part of being resilient, a population has the capacity to adapt to the impacts of a hazard through self-organisation (Patel *et al.,* 2017). Theoretically the capacity to adapt differs from the capacity to cope in that adaptation capacity is transformative; the population at risk are able to prepare in advance for stresses and changes as well as respond and adapt to the effects of a hazard (Berman, Quinn and Paavola, 2012). In terms of preparation, a community may put in place strategies that coordinate and prioritise the evacuation of their elderly in the case of a hazard as a resilience building measure. The implementation of this evacuation strategy however then becomes a key coping mechanism for the community, intrinsic to their level of vulnerability.

With these overlapping capacities, providing clear, distinct differences between the concepts of vulnerability and resilience is difficult (Wamsler and Brink, 2014). This is further exacerbated by the changing natures of the two terms; they are not just static properties which the community has, but dynamic processes the community operates within. For example, as a community continues to age (and other factors may come into play, such as outmigration of young families), an elderly population may soon exceed the coping capacity of the community and their (theoretical) resilience-enhancing strategy of evacuation. At this point, a new strategy would need to be found and the community would need to once again adapt to ensure they stay resilient to this changed state of vulnerability. Resilience and vulnerability are thus highly interrelated concepts that rely on many of the same characteristics and factors (e.g., social, economic, political and cultural processes) (Manyena, 2006; Gaillard, 2007). From a practical perspective, this lack of clarity in definition between the two terms has created a substantial challenge in finding a singular approach for their measurement.

1.2.2 Current approaches to measuring vulnerability and resilience for DRR

Trying to identify which characteristics or factors create the vulnerabilities or build resilience of a population has dominated research within DRR over the last fifteen years. Despite these efforts, to date, there is currently no singular method to measure either concept (a more comprehensive review of these efforts is provided in Chapter 2). Instead, the most common approach to measuring either concept is to create a composite index that combines a set of different factors into a single measure (Asadzadeh *et al.*, 2017), for example, the Social Vulnerability Index (SoVI) (Cutter, Boruff and Shirley, 2003) or the Baseline Resilience Index for Communities (BRIC) (Cutter, Burton and Emrich, 2010) for either individual communities or larger spatial scales, such as administrative regions. However, the factors and characteristics utilised often rely on the perspective of the individual researcher. As a result, researchers have struggled to find a single group of factors that can constitute either concept's measurement. A review in 2016 found that there were 106 different methodologies that used 2298 unique variables available to measure the vulnerability, the risk or the resilience of communities to disaster (Beccari, 2016). Alternative qualitative approaches, primarily deployed at the community scale, have been developed (further outlined in Chapter 2), however they simply add further diversity and complexity into the measurements of the two concepts.

These multiple approaches are as a result limited in their application across multiple settings and time scales. This is likely to have substantial consequences for those making practical efforts to reduce a population's risk to disaster as studies cannot be compared and contrasted, which can help to validate the results of an assessment. Without conducting some form of sensitivity or uncertainty analyses, policy makers may believe the results are more accurate than what actually is the case, and therefore unknowingly waste resources in the efforts to reduce risk (Beccari, 2016). Worse still, they may exacerbate current risk levels by misdirecting these resources away from those that need them the most. As Bakkensen *et al.* (2016) summarise, "while all have been motivated by rich theory, few measurement frameworks have been empirically verified… there is little utility unless they can be confidently used to inform decision makers" (Bakkensen *et al.*, 2017, pg.983). These current approaches to resilience and vulnerability assessment may also be a significant barrier to achieving the objectives of the SFDRR and the disaster related targets of the SDGs, to make progress towards a disaster resilient society (Beccari, 2016), as disaster risk is still not yet understood cohesively on a global scale.

To create a singular method to measure either vulnerability or resilience will require creating significant consensus across the entire community involved in DRR, including agreement not only on the factors that constitute either concept but also the methods to combine these factors. Beyond the substantial coordination efforts required to achieve this, there is one major outstanding limiting factor that could prevent a singular approach from being agreed: the availability of data to measure these concepts at suitable spatial and temporal resolutions across a global spatial coverage. This final factor has received limited attention due to a focus on defining and finding measures of the two concepts, despite the fact this measurement intrinsically relies on available and usable data.

1.2.3 Obtaining the necessary data for global disaster risk estimation

The availability of and accessibility to relevant data at the appropriate geographical and temporal scale (i.e., recent subnational data) and for the required spatial coverage (i.e., global) is essential for the implementation of any attempt to measure vulnerability or resilience. For current approaches to vulnerability or resilience measurement, the main source of data for these indices are generally small-scale surveys that have been tailored and conducted for that specific research (these contribute to a significant proportion of the number of indices now available), i.e., for individual community studies, or official large-scale census and programme survey datasets that contain general demographic and socio-economic indicators. The SoVI mentioned previously, for example, was built from US census data (Cutter, Boruff and Shirley, 2003). However, localised surveys and censuses both face significant limitations when considering how to provide a global understanding of disaster risk.

Whilst the expansion of the small-scale surveys to global coverage is unfeasible due to the likely cost in both time and expense to collect the required data, census or larger-scale survey-based indices are limited by the availability of the datasets they use. To expand these indices to other countries, each country will need to have had a (recent) census or survey that also captures the same types of data that can represent the chosen factors of vulnerability or resilience. This will also involve ensuring any country-specific variables can be translated into the new country's context, e.g., the SoVI contains a variable on 'the percentage of residents who are Native American' (Cutter, Boruff and Shirley, 2003). An adjustment approach was employed for a study that sought to apply the SoVI in Nepal; variables such as caste, and populations who cannot understand Nepali were added to reflect the Nepali context (Aksha *et al.,* 2019).

There is however a significant lack of high quality data across many, predominantly low-income, countries over the world (Leidig, Teeuw and Gibson, 2016). Many of these countries have not had a recent census from which data can be extracted (see Wardrop *et al.*, 2018); as a result, creating a globally applicable SoVI-style index may not even be possible for many countries whilst the results for others could be considered to be outdated depending on when the last census took place and what events that have happened since that could invalidate these results. For example, the Nepal study, whilst published in 2018, uses data from the last census, which was in 2011 (Aksha *et al.,* 2019); since then the country has experienced significant disaster events, including the 2015 Gorkha earthquake, which has undoubtedly substantially changed the vulnerability of its population. The possible expansion of many of these index-based approaches is likely to lack the effective and reliable data and information that is needed, particularly for accurate risk assessment and decision-making within DRR and sustainable development (Leidig, Teeuw and Gibson, 2016).

With the majority of research focused on the best approach to operationalise the concepts and build an appropriate indicator, little attention has been paid within DRR to address this lack of data, e.g., Asadzadeh *et al.* (2017) provides a procedure on how to build a composite indicator for resilience but at no point questions the availability of data to generate its various variables. Until this shortage of data is addressed, a singular approach for the measurement of resilience or vulnerability will not be found. Consequently, the current practice of small or independent DRR studies and non-global composite indicators will continue and there will be difficulties in attaining the global understanding of disaster risk required by the SFDRR.

1.3 The use of novel datasets to address data poverty

The lack of comprehensive, globally applicable and up-to-date data is not a problem experienced solely by the DRR community, but also the wider sustainable development field. For example, five years after their launch, only 28% of the global data needed to monitor the SDGs is currently available (UN Women, 2019). This data poverty is primarily caused by the financial and logistical challenges faced with collecting data at large scales that can capture individual level socio-economic demographics. These types of data are usually collected on the ground, through censuses and household surveys, however these methods are often expensive or highly time-consuming to conduct and as a result are either scarce (either non-existent or difficult to obtain) or sparse (limited in their temporal or spatial coverage).

In some cases, the data does exist but are collected or held privately by commercial data collection agencies, governments, businesses or non-governmental organisations (NGOs) (Wardrop *et al.*, 2018). Whilst some of these datasets can be accessed at a price, it can also simply be the case that the data have ended up existing in what is known as a ‘data silo’, i.e., in a location where it is inaccessible to others, such as stored on a single computer hard drive[1]. Finally, in some countries, even the most basic demographic and geographic data can be missing key groups or areas, inaccurate, incomplete or obsolete (outdated) (Wardrop *et al.*, 2018). As highlighted previously, many countries have not had a recent census (Figure 1-1), whilst long delays between their enumeration and data release question their accuracy (Wardrop *et al.*, 2018).

With poor quality data affecting high profile development efforts (Leidig, Teeuw and Gibson, 2016), those working within sustainable development are looking towards the analysis of novel and innovative datasets to address this data scarcity and sparsity (UN Data Revolution Group, 2014; Lokanathan and Gunaratne, 2015; Yu, Yang and Li, 2018). Imagery from satellites and Unmanned Aerial Vehicles (UAVs), as well as the metadata derived from the use of everyday digital technologies (e.g., mobile phones, credit cards, travel passes) and online social network data (e.g., Twitter, Facebook) have been identified as potential sources of data and information on human characteristics and behaviour that could be used to provide a better understanding of global sustainable development and new insights into variations in the vulnerability of societies (Datapop Alliance, 2015; Leidig, Teeuw and Gibson, 2016; UN, 2018; Andries *et al.*, 2019). Their use is part of what the UN identifies as a 'data revolution', which aims to ensure everybody is accounted for, and uses data that reduces the invisibility of those most vulnerable as well as reduce the inequalities that are generated by having unequal data access and coverage (UN Data Revolution Group, 2014).

This optimism in the use of these novel datasets is enabled by the majority having a spatial component to them; the data can be mapped and spatially analysed as well as integrated with other datasets to derive further insights. Many of the datasets are also recent, frequently updated and in some cases openly accessible (e.g., certain types of satellite imagery and Twitter data); they are also available over significant spatial scales, as well as at fine spatial resolutions (e.g., individual level generated data, high resolution aerial imagery). These datasets therefore have significant advantages for use within many

[1] To combat these silos, the Humanitarian Data Exchange (HDX) is one resource that is aiming to open up these datasets by providing an online platform on which data can be freely uploaded, hosted and shared with others. By January 2020, there were over 16,000 datasets from 253 locations (data.humdata.org) that could be searched for in a user-friendly way.

sustainable development relevant applications, including but not limited to: estimating poverty levels (Smith-Clarke and Capra, 2016; Steele *et al.*, 2017); studying the migration patterns resulting from climate stresses (Lu *et al.*, 2016), predicting food insecurity (Decuyper and Rutherford, 2014), and determining the greatest influencers in the spread of disease (Tatem *et al.*, 2014).

For human sensor-based datasets, i.e., those generated from the use of everyday digital technologies, and the data that can be mined from online social networks, there are several fundamental challenges to utilising these novel datasets. Firstly, for both types of data, there needs to be significant consideration in terms of understanding the biases and limitations of representation: who is and is not generating these data types. For example, in the US, surveys by Pew Research show that whilst Facebook has an approximate 69% penetration rate in 2019 amongst adults, Twitter is only used by just over a fifth of the adult population (22%) (Pew Research, 2019). The demographics of these users also need to be considered, with young adults often the earlier adopters of social media: in 2019, 90% of all adults between 18-29 used at least one social media site, in comparison to 40% of adults aged over 65 (Pew Research, 2019). Using social network site datasets to investigate and analyse issues related to the older and elderly is therefore unlikely to provide a representative sample. Any use of these datasets needs to be grounded in an understanding of the likely user base, such as seen in Blumenstock and Eagle (2010) and should include a breakdown of the actual or predicted demographics and geographical coverage of the users behind the datasets.

The second major challenge in using these types of novel datasets is understanding what relevant information can be extracted and what are the best approaches and methods to do so. For example, a study in 2014 tested whether a person's expenditure on a mobile phone could be related to their food security (Decuyper and Rutherford, 2014). When comparing this expenditure to different patterns of food consumption, the study found that the consumption of vitamin rich vegetables, rice, bread, sugar and fresh meat did have a positive correlation with airtime purchases, whilst the consumption of white sweet potato had a significant negative correlation (Decuyper and Rutherford, 2014). However, broadly cultivated items like cassava and beans had no relation with the expenditure on mobile phones (Decuyper and Rutherford, 2014). As a result, the study had to retheorise the relationship between mobile phone expenditure and food security, hypothesising only that mobile phone top-up behaviour could help understand the expenditure on food in markets (Decuyper and Rutherford, 2014). The generalisation of this finding to estimate food security could be argued to be tentative at best, particularly when contextualised within the greater understanding of food security. As food security is based on four pillars of availability, access, utilization and stability (FAO, 2009), in this case, the expenditure on food is just one aspect of a household's access to food.

Other more technical issues also exist, such as the ability to extract reliable and accurate metrics from datasets. An example from mobile phone data is the extraction of meaningful places, such as a home or work location from the user's data. A recent study into current approaches in detecting these locations found that often the algorithms utilise simple and implicit criteria on which no or little assessment of sensitivity exists in the literature (Vanhoof *et al.*, 2018). This lack of sensitivity analysis has meant that there is little consensus regarding which approach is likely to be the most accurate in assigning users to a home location (Vanhoof *et al.*, 2018). The implications of this study and their follow-up work is further discussed in Chapters 6 and 7, however the overall conclusion is that without the ability to ground-truth these datasets, measures of uncertainty should be included with mobile phone dataset analyses (Vanhoof *et al.*, 2018; Vanhoof, Ploetz and Smoreda, 2018). This identification of locations is not just an issue for mobile phone data, with the analysis of online social media datasets relying on either the georeferencing of social media posts or the IP addresses of a user, but these types of location information can also be subject to other socio-technical issues, such as location spoofing (Zhao and Sui, 2017). There are therefore significant complexities to using such novel datasets, and as a result, any analysis of these datasets needs to be grounded in both the context in which the analysis is occurring as well as the more technical aspects of accurate interpretation and processing of the data.

1.3.1 The use of Call Detail Records as a dataset within Sustainable Development

With the representation of the dataset a significant concern in the use of novel datasets, Call Detail Records (CDRs), the metadata generated by the use of a mobile Subscriber Identity Module (SIM) card, have become one of the most popular types of novel datasets investigated for use within sustainable development due to their extensive spatial coverage and population penetration. The use of mobile technology has increased substantially over the last eleven years, from 4 billion SIM connections in 2008 to 8 billion in 2019, representing approximately 5.2 billion individual users or 67% of the global population (GSMA, 2013, 2020). By 2019, Latin America, the Middle East and North Africa, and Asia Pacific had an average 64% penetration rate of unique mobile subscribers[2], whilst Sub-Saharan Africa's penetration rate was 45% (although this is expected to grow to 50% by 2025) (GSMA, 2020). This increase in mobile phone subscriptions is attributed to growing network coverage in rural areas as well as the increasing affordability of both mobile devices and tariffs within these developing markets (GSMA, 2018). As overall user levels increase over time within a country, it is expected that any associated divides in the user base (e.g., differences in ownership due to gender, age, education, wealth or literacy) will also narrow (Zainudeen, Iqbal and Samarajiva, 2010). With these high penetration rates, it is likely that the users generating the CDRs within these various countries represent a substantial cross-section of the population, which supports their use for sustainable development applications.

The scope of detail collected by CDRs also has contributed to their popularity of use within research focusing on human characteristics and behaviours. CDRs detail the usage of every mobile SIM, including who the SIM user contacts, when they make the contact, and the approximate locations of both the user and their contact by using the cell tower through which the call or text was routed. In addition, some CDRs will contain top-up information associated with that SIM as well as the SIM user's data usage. These data are primarily used by the Mobile Network Operator (MNO) to which the SIM is registered for billing purposes. The data is collected in near-real time and stored for extensive periods of time, making current and historical analysis of the data possible (access to and availability of the data permitting). Furthermore, the data is collected for the individual SIM across its entire spatial coverage (i.e., even if the SIM is used on another network, such as when the user travel abroad).

Through these details on user location, contacts, and phone usage, CDRs have been used to infer information on a user's movement (including where they live, where

[2] A unique mobile subscriber is defined by the GSMA as a single individual that has subscribed to a mobile service (Gillet, 2014).

they commute to, and other mobility patterns) (Calabrese *et al.*, 2013; Deville *et al.*, 2014), their social networks (Eagle, Pentland and Lazer, 2009; Deville *et al.*, 2016), as well as their expenditure patterns on their mobile phones (Toole *et al.*, 2015). This information has been used by researchers at universities, UN agencies (such as the UN's Global Pulse) and NGOs (such as the Flowminder Foundation), in partnership with Mobile Network Operators (MNOs), to estimate certain characteristics and behaviour about each user. These characteristics can then be aggregated with other users to identify broader trends, such as large-scale population movements or significant decreases in expenditure in a particular spatial area (Gonzalez, Hidalgo and Barabasi, 2008; Yan *et al.*, 2014; Toole *et al.*, 2015). These patterns can be then connected to ongoing socio-economic processes, for example, deriving insights about employments shocks (Toole *et al.*, 2015) or areas of food insecurity (Decuyper and Rutherford, 2014), a key topic within sustainable development.

The exploration of CDRs for sustainable development began as early as 2009, with a focus on application potential in epidemiology and the prediction of disease spread (Tatem *et al.*, 2009). Since then, multiple papers have been published that propose various uses for the dataset, from population estimates (Kang *et al.*, 2012), poverty modelling (Blumenstock, Cadamuro and On, 2015; Steele *et al.*, 2017), pollution exposure (Picornell *et al.*, 2019) and even food security tracking (Decuyper and Rutherford, 2014) (e.g., a search of the Scopus bibliometric database on the 27th March 2020 for "call detail record" OR "mobile phone data" AND "food security" OR "pollution" OR "poverty" OR "sustainable development" OR "epidemiology" OR "disaster risk reduction" results in 59 articles). This has been aided by several 'Data for Good' challenges, such as Orange's 2012 Data For Development challenge (Blondel *et al.*, 2012) and Türk Telekom's 2017/2018 'Data 4 Refugees' challenge (Salah *et al.*, 2018), where CDR datasets were released to researchers to develop new methods and insights for specific sustainable development purposes, such as identifying ways to integrate refugees into the countries in which they had relocated (Bosetti *et al.*, 2019; Mamei *et al.*, 2019).

Much of these insights have been provided after an event and have struggled to translate these findings from research into a practical use (Maxmen, 2019). As a result, the research on, and ongoing promise of the value of, CDRs within the sustainable development sector has faced substantial criticism: that, in fact, it is not benefitting those it is aiming to help. The use of these individuals' data without their direct consent[3] further questions the integrity behind using the data in the first place (Maxmen, 2019). Data privacy is a key concern with the use of personal sensitive data such as CDRs; in the majority of studies within the SCOPUS search, the results were aggregated to prevent an individual user being identified within the dataset. Despite this, there are still risks associated within the data unless there are proportionate control measures and proper data governance (Jones *et al.*, 2019b). Furthermore, if the analysis of the data does not provide an actual application or real tangible impact, the question still remains whether these really are data 'for good'.

There are examples of the use and application of insights derived from CDRs within real-world disaster events. One recently published study is the analysis of CDRs by the Flowminder foundation in 2015 during the Nepal earthquake; here, analysts calculated the above normal in- and outflows between districts in the country to estimate the likely movement and displacement of people following the earthquake (Wilson *et al.*, 2016). The aim was to help those organisations responding to understand where to send aid: had people moved out of Kathmandu to nearby villages or vice versa, and if so, should aid be redirected. These estimates were used by the U.N. during the response to plan their operations more effectively (Wilson *et al.*, 2016). Another set of studies showed how the spread of cholera after the 2010 Haiti earthquake could have been predicted by studying movements within the CDR data (Bengtsson *et al.*, 2015), as well as how these movements could first have been predicted by studying the users social networks (Lu, Bengtsson and Holme, 2012).

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[3] Consent is given by the individual subscriber through their use of the services provided by the telecom operator. The use of the individual's generated metadata for purposes beyond billing is generally covered in the terms and conditions of service use, however explicit and direct attribution to specific research projects as well as real-world applications is not given. As a result, most individual subscribers do not know that their data is being used for these purposes (e.g., a study in the UK showed only 3% of respondents were aware that their mobile phone data was being used for health research, whilst none had read the terms and conditions of their mobile phone service (Jones *et al.*, 2019a)).

With these datasets providing actionable insights that can inform disaster management operations, the question should be asked whether there is also potential for CDRs to have real impact within DRR as an alternative data source. As yet, the field has had relatively little engagement with these novel datasets. A review in 2018 on the role of big data in disaster management found that CDRs alongside mobile GPS were only mentioned or used in 10% of the articles studied (Yu, Yang and Li, 2018). The inclusion of mobile GPS in their categorisation likely means that this percentage is even lower, whilst the broad encapsulation of 'disaster management' means that DRR was not specifically studied. Furthermore, a search of the SCOPUS database on March 27th 2020 for articles with "Call Detail Records" AND "Disaster Risk Reduction" yielded no results. There is therefore opportunity to investigate if a suitable use or application of the data can be found within current or even novel DRR quantification approaches.

1.4 An alternative approach to measuring disaster resilience

Current approaches to measuring vulnerability or resilience, as described in the previous section, face significant limitations. They suffer from a lack of standardisation as well as a significant lack of data (see Chapter 3). For resilience specifically, these current approaches are also unable to be employed within the wider debate on how resilience changes: a key argument emerging from recent literature on the topic stresses that resilience must be understood as a process, as well as a property or characteristic (Cutter, 2016a) (Chapter 2 provides more detail on this discourse). This need to capture dynamism within its measurement therefore restricts the applicability of these approaches further, particularly if, due to the lack of data, they are unable to repeat the analysis at sufficient time scales to detail this change. Alternative approaches that can understand resilience as a dynamic process as well as a property are therefore needed if there is truly to be an accurate measurement of resilience (Cutter, 2016a). With this dynamism discourse dominating the DRR field at the start of this research, this thesis has focused solely on the measurement of resilience (and not vulnerability), specifically to demonstrate how an emerging alternative approach to resilience measurement could fulfil this gap through the use of innovative datasets such as CDRs.

Within resilience measurement outside of the DRR field, there is a growing area of resilience research that focuses on the role of social networks in building the resilience of the individuals, communities and populations (Rockenbauch and Sakdapolrak, 2017). A comprehensive review of this research is provided in Chapter 3, but the essential premise is that greater connectivity between individuals, households and communities, will directly influence resilience (Misra *et al.*, 2017). DRR has long recognised that communities regularly work together to survive and recover from catastrophic impacts (Aldrich, 2015); local social networks, such as family and friends, often act as first responders, whilst weaker ties, including neighbouring communities, help to diversify the types of help available those affected. To capture these contributions to building resilience, social support, social capital, and even social networks all appear frequently as factors within many of the composite indices created to measure resilience. However just like for the indicators for resilience, research determining how to operationalise these social aspects of resilience, particularly under the concept of social capital, has struggled to unite on a singular method or tool for their measurement (Carrillo Álvarez and Riera Romaní, 2017).

Of most interest to DRR resilience measurement therefore is that within this wider resilience literature, connectivity is the main construct studied and solely evaluated through assessing the presence, strength and effectiveness of the social networks present; these properties are assessed through the increasing use of a singular approach, Social Network Analysis (SNA) (as evidenced in Misra *et al.*, 2017 and in Chapter 3). For SNA, a matrix of the relationships between people, or households or communities is constructed and their connectivity can be assessed by certain properties such as the number of relationships relative to their potential network size or how many connections are required to connect to the whole network. This approach even has the potential to evaluate resilience as a process by assessing and evaluating how these social networks change in response to a shock and how this affects the ability of an individual, household, or community to respond. This is evidenced in the review within Chapter 3, indicating how this approach is filtering into DRR resilience measurement, which is likely to offer significant opportunities for research cross-comparability.

Despite the focus on social networks advocated as one of the most promising developments for disaster risk reduction in the last decade (Alexander, 2013), their measurement using social connectivity is still relatively new (Misra *et al.*, 2017). The potential and utility of this approach is currently limited by the cost of collecting social network data at the appropriate temporal and spatial scales. To date, there has been only one SNA-applied study within DRR that has implemented a temporal analysis (Misra *et al.*, 2017), whilst the spatial scale of the majority of studies remains within a single community. There is therefore a need to find an alternative dataset that could explore the full potential of measuring social connectivity for resilience estimation within disaster risk reduction: ideally this would be a dataset that contains the social networks of individuals over substantial temporal and spatial scales.

1.5 Mapping and measuring social connectivity: an opportunity for using CDRs within disaster resilience estimation

Within the context of these three discourses – the need for data for disaster risk quantification, the use of novel datasets within disaster response and sustainable development applications to address data poverty and the emerging focus on social networks to measure disaster resilience – this research proposes that there is a significant opportunity to utilise CDRs as an alternative dataset to measure social connectivity for disaster resilience estimation within DRR. Already CDRs have been shown to be a proxy of an individual's social network (Eagle, Pentland and Lazer, 2009), whilst within disaster-related research, they are shown to be a 'sociometer' to hazards (Bagrow, Wang and Barabasi, 2011; Wang, Lin and Bagrow, 2014). Taking these two findings into account, it suggests that CDRs contain the most important relationships people are likely to use and rely on for support, and thus the ones most critical for resilience-building.

With CDRs collected passively, at an individual subscriber level, across wide geographic coverages, and also in near real-time over many months and years, they have the capacity to provide data to analyse social connectivity over substantial temporal and spatial scales, before, during and after a hazard without the costs and complications of primary data collection. This could lead to a singular approach for resilience measurement as both a property and a process, as well as enable cross-comparability across multiple countries at subnational scales, understanding where connectivity is greatest and, perhaps more importantly, where it is lacking. This measurement could occur at the national, subnational and potentially even further refined spatial scales, such as the community. This would be a substantial step towards a better understanding of disaster risk over larger spatial and greater temporal scales, whilst preserving the detail needed for local-level decision-making on strategies to reduce risk.

Disaster risk however is constituted by both the vulnerability and resilience of a population (as well as the hazard and resulting exposure); as a result, this approach can only offer an understanding of global disaster risk from this perspective. In this context, social connectivity cannot become the sole or single authoritative dataset to understand global disaster risk, but it is one that could be integrated with other measurements to further improve on its current understanding.

Ultimately, the social networks of a community are advocated as one of the primary resources they have for managing risk (Woolcock and Narayan, 2000), and is often the least damaged resource in the event of a disaster (Patel and Gleason, 2018). The review in this thesis (Chapter 3) also finds that without understanding community structures and their social networks through social network mapping, the implementation of top-down preparedness policy and procedures are likely to fail. As a result, whilst this may only provide a single perspective to understanding disaster risk, it is likely to be a significantly important one; this is further reflected in the increased attention social networks have received from both researchers and policy makers in building resilience (Aldrich and Meyer, 2014; Pfefferbaum, Horn and Pfefferbaum, 2015). As a result, there is a significant use case for developing an approach that could map and measure social connectivity from CDRs for resilience measurement within disaster risk reduction.

1.5.1 Nepal: the case study of choice

The potential of CDR-based social connectivity analysis would have no greater application than within countries where social networks are often the primary resource the local population have to respond to the impact of a shock. Already, the last decade has seen numerous disaster events across multiple countries where social networks have been indispensable and instrumental for those affected, from the US (2015 floods) (Meyer *et al.,* 2020) and Japan (2011 tsunami) (Ye and Aldrich, 2019) to the Philippines (2013 Typhoon Glenda and 2014 Typhoon Yolanda) (Han, Howe and Park, 2019) and Nepal (2015 earthquake) (Carrero *et al.,* 2018; Aryal, Wilkinson and Chang-Richards, 2019). For the latter, the 2015 Gorkha earthquake highlighted just how significant social networks are for disaster risk reduction within the country, particularly when other systems of help and support are inadequate and underprepared.

Despite the country being ranked by the World Bank as the 11th most exposed country to multiple hazards (Dilley *et al.*, 2005), disaster risk reduction policy in Nepal has been close to non-existent. Political instability and weak governance within the country has left it open and vulnerable to the mixed agendas and priorities brought in by the funding and aid provided by international governments and NGOs (Regmi, 2016). Furthermore, with no local elections for nearly two decades, there is a disconnect between local government and communities which has resulted in a lack of institutionalisation of DRR training and preparedness strategies. To overcome these failings in the faltering political system, the local communities of Nepal have learnt to be self-reliant, using their relationships with one another to meet their everyday and emergency needs (Ruszczyk, 2014).

The 2015 Gorkha earthquake exemplified this, with the local communities helping each other in the search and rescue efforts in the initial response, the distribution of aid during the aftermath and then the rebuilding of homes as they began to recover (Billingsley, 2016). Nepal, therefore, is a case study of choice when considering developing a dataset that aims to assess social connectivity for use in resilience estimation in DRR (explored in more detail in Chapter 4). With social networks shown to be key to mitigating and rebuilding after a shock in the country, understanding where this connectivity may be lacking is essential to improving the country's overall resilience.

1.5.2 Research Aims and Objectives

This research aims to quantify and evaluate the feasibility of using CDRs for measuring social connectivity to support resilience estimation for disaster risk reduction. The social connectivity of 1.69 million subscribers within 11 districts across Nepal's Western and Central regions is estimated from CDRs generated between January 1st and April 24th 2015. These CDRs were provided by Ncell, a leading MNO in Nepal, and processed in partnership with the Flowminder Foundation.

To develop, enable and substantiate this creation of a social connectivity dataset from raw CDRs, the theoretical framework behind using social connectivity for resilience estimation is established and the representativeness of the CDR data as well as the feasibility of using CDRs to map social connections are quantified and evaluated. The latter addresses the limitations and challenges to use CDRs as a source of social network data, primarily from the geographical assumptions made in the assignment of subscribers to home locations and the resulting categorization of their social networks into bonding and bridging ties.

To critically assess the suitability and validity of CDRs as a source of social network data for resilience estimation, research objectives are extracted from the themes presented in this introduction as well as from research gaps that emerged during the PhD programme. These objectives are divided across a literature review (Chapter 2) and four paper style chapters. An additional case study chapter (Chapter 4) is provided to explore further the suitability of focusing on social networks for disaster risk reduction in Nepal.

The research objectives are to:

1. Establish an understanding of resilience situated within the context of the research, outlining the scope, scale and significance of the proposed work within ongoing debates and discourses in current resilience literature (Chapters 2 and 3).
2. Consolidate emerging disaster resilience literature on the role of social networks through a systematic literature review, utilizing the findings to provide guidance on developing an appropriate methodology for analyzing social connectivity (Chapter 3).
3. Evidence the importance of social networks for disaster risk reduction in Nepal through a review of Nepal’s current DRR policy and a synthesis of recent empirical studies studying the impact of and response to the 2015 Gorkha earthquake (Chapter 4).
4. Quantify the representativeness of the CDR dataset of the population at study through measuring the changing geo-demographics of mobile phone ownership in Nepal between 2006 and 2016 (Chapter 5).
5. Evaluate the validity of using CDRs to map social networks at the community scale through the detection of spatially concentrated social communities (Chapter 6).

6. Develop an operational methodology to measure social connectivity using CDRs for disaster resilience estimation and evaluate the resulting findings for selected districts in Nepal (Chapter 7).

The third objective is increasingly important as the field of computational sustainability, where computer and information scientists join forces with other fields to help solve societal and environmental challenges facing humanity in pursuit of a sustainable future, grows (Gomes *et al.*, 2019). A key challenge in the use of innovative datasets within sustainable development applications is that "there [is] a danger of researchers and others being distracted by the technology and losing track of the key hardships and constraints that are unique to each local context" (Blumenstock, 2018, pg.170). Without thinking through the applicability and the suitability (such as the ethics of using these data) of the proposed analyses and datasets, there is a likelihood that these efforts could result in unanticipated effects (e.g., data used against those analysed) or produce results that do not account for certain biases and are used unvalidated. In this thesis, by focusing on the positive determinants of resilience and giving our CDR generators agency through focusing on their connections and the capacity to build connectivity and thus resilience, we hope to demonstrate how CDRs can be used to ensure that "people are not forgotten when using big data for development" (Blumenstock, 2018. pg.170) and address the concerns on the use of this type of data highlighted in Section 1.3.1.

1.5.3 Thesis Structure

The thesis is structured into three sections, focusing on the conceptual development of the rationale; establishing case study and data suitability; and the exploration and evaluation of Call Detail Records for measuring social connectivity. These three sections are presented across nine chapters, including an introduction, two literature reviews, a case study chapter, the resulting three analysis chapters in the form of research papers, an overall discussion chapter and a final conclusion. Chapter 3 and each of the three paper style chapters are or will be submitted for publication; they have had minor edits to maintain consistency with the thesis format. Figure 1-2 demonstrates how these nine chapters interlink with one another to form a coherent and integrated thesis of novel research.

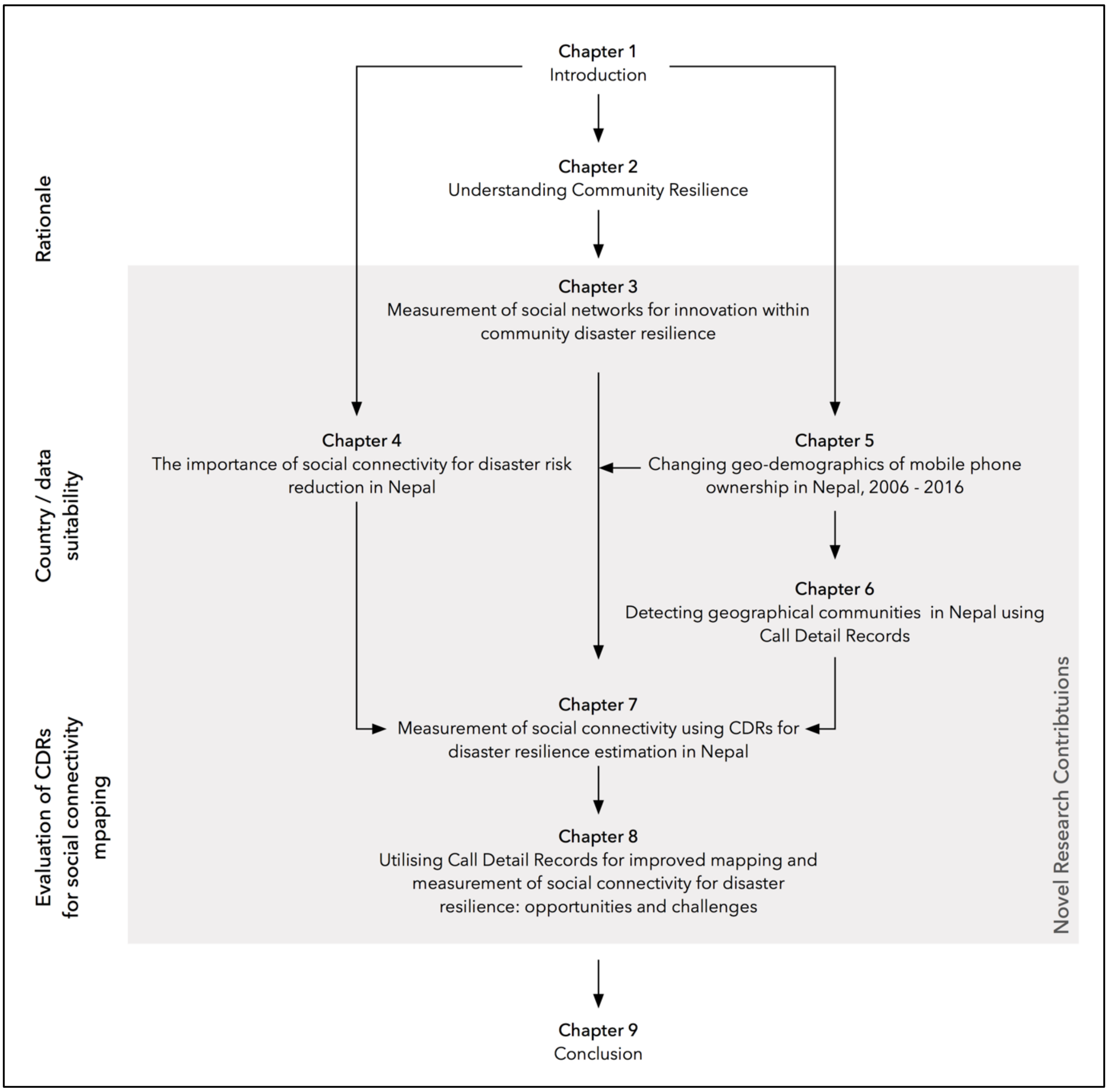


Figure 1-5. Thesis structure.

Following on from this introductory chapter, Chapter 2 introduces and explores the concept of resilience and provides an overview of how resilience is defined within disaster risk reduction. Chapter 3 further explains the efforts to operationalise disaster resilience and the limitations faced, such as using composite indices. It then provides a systematic literature review of recent empirical studies that show how social networks and in particular, those that utilise a social network analysis approach, are being used for the estimation or evaluation of the disaster resilience of communities. The chapter highlights that a common methodology is emerging within these studies; these findings are used to inform the methodological approach used in Chapter 7.

To establish clearly the suitability of studying social networks for disaster resilience in Nepal, Chapter 4 comments on the current state of disaster risk reduction policy and programmes within the country. It highlights recent case studies, such as the 2015 Gorkha earthquake, and how recent empirical research has shown that in these case studies, due to the failed implementation of DRR policy, the primary resource many Nepalese rely on during and after a hazard is their social networks.

Chapter 5 quantifies the ownership of mobile phones at the household and individual level to validate the use of CDRs as a dataset that is likely to be representative of the entire population of Nepal. At the household level, ownership is studied over a ten-year period to assess how mobile phone ownership has changed across different socio-economic groups. The analysis confirms that the CDRs are likely to represent a substantial cross-section of Nepal's population.

To validate the use of CDRs as a dataset that is likely to be representative of social networks at the local geographic level, Chapter 6 shows how the social communities detected within the CDR dataset are spatially concentrated, when mapped using the GIS technique of Kernel Density Estimation (KDE). These spatial concentrations of social communities correspond to geographical and sociological theory on the role of space and homophily on the formation of communities, confirming that the social networks found between mobile phone subscribers within the CDRs are likely to be representative of the subscriber's real-world social networks. The study also finds that these spatial concentrations correspond well with local geographic communities within Nepal, including various cities, towns and villages, highlighting that these subscribers could, in future CDR analyses, be assigned to these geographic communities rather than a cell tower.

Chapter 7 provides the measurement of social connectivity using CDRs for resilience estimation in disaster risk reduction. Utilising the guidance from Chapter 3, the paper develops, devises and deploys a methodology for the analysis of social networks from CDRs through the creation of a social connectivity index.

Chapter 8 critically reflects on the overall body of work, synthesising and evaluating the research contribution, methodological transferability, wider applicability as well as current limitations of the thesis and proposes future research opportunities to address these challenges.

Chapter 9 summarises the key findings of each chapter to answer the overall thesis aim.

Chapter 2 Understanding resilience in disaster risk reduction

2.1 Chapter overview

The chapter introduces and explores the concept of resilience within disaster risk reduction, highlighting the epistemological issues the term faces within the field through an extensive review of current literature. Through this review, it establishes the current direction of research on operationalising resilience, focusing on the major challenges that existing approaches have yet not been able to address.

2.2 Resilience within disaster risk reduction: from bouncing back to bouncing forward

Resilience is a concept that has developed over the last 50 years within various disciplines and fields, including geography, engineering (materials science), psychology, ecology and sustainability science (Thóren, 2014; Weichselgartner and Kelman, 2014). Consequently, our understanding of resilience has expanded from a simplified engineering equilibrium perspective where it is defined as a system's ability to recover or return to its original state after stress has been applied to a complex coupled systems approach which requires multiple post-stress states and adaptive capacities (Alexander, 2013). The development of the concept is widely reviewed and discussed in resilience literature, with Alexander (2013) providing a thorough etymology and history of the term which also reveals the various discrepancies and conflicts embedded within the viewpoints from the various disciplines (Alexander, 2013). These different perspectives are further explored by Birkman *et al.* (2012), who conclude that:

> *"overall it is important to acknowledge that many discourses about resilience developed mainly in parallel and therefore the development of the concept has not just one starting point, but is characterized by different triggers that often evolved in disconnection from each other."*
>
> (pg.10)

Two of the primary triggers for the adoption of resilience into the DRR were the disciplines of ecology and psychology. From the 1970s, both disciplines were engaged in protracted discussions about the subject of resilience (Thóren, 2014), which have contributed to the use and application of resilience as a concept within the field of DRR and management. A key development based on this unification between the ecological and psychological sciences is the argument put forward by Manyena in 2006 and followed up in an editorial article by Manyena *et al.,* in 2011 (Manyena, 2006; Manyena *et al.,* 2011). Manyena proposes that following a disaster individuals, communities and systems have the ability to 'bounce forward' and 'move on', as part of their adaptive capacity to build and learn as well as their ability to self-organise (Manyena *et al.,* 2011). Weichselgartner and Kelman (2014) support Manyena's argument, stating that:

> *"since the early ecology-based 'bounce back' perspective, drawing on psychology as well, geographical interpretations of resilience have been moving towards 'anticipation', encompassing 'capacity' and 'capability' – and now coming the full way to being suggested as doing better than before by 'bouncing forward."*
>
> (pg.252)

This ability to do better than before also draws on the psychological interpretation of resilience, as the need for preparedness, mitigation or protective actions against future shocks requires certain psychological factors, including risk perception and community participation (Birkmann, 2012). Resilience, as a process of bouncing forward, is now a key term for policy makers and researchers alike, forming the basis of many frameworks and models now used within the DRR field.

2.3 Disasters and disaster risk reduction: a field built on rocky foundations

DRR is a relatively new field within disaster management (Twigg, 2009), emerging from the debates and discussions during the International Decade for Natural Disaster Reduction (1990-2000), which was focused on reducing the risk of populations to natural disasters. It is a systematic approach, in both theory and practice, of identifying, quantifying, assessing and reducing the risks of disaster by addressing the socio-economic vulnerabilities of a population, their capacity to respond, also understood as their resilience, as well as their propensity to experience, and exposure to, the hazards that trigger risk (Twigg, 2009; UNISDR, 2015).

As outlined in Chapter 1, the DRR community is plagued by the epistemological development of the terms and models it uses to further quantify disaster risk. At the forefront of this epistemological battlefield are the nebulous terms of vulnerability and resilience, which separately and together have dominated the field with multiple debates, arguments and viewpoints. As Alexander (2013) writes, the amount of literature on resilience is now so copious that it is becoming increasingly difficult to summarise: with multiple comparative tables of definitions of the term and similar compilations for vulnerability and risk, despite this significant amount of research, it seems that no one can agree on the meaning of terms in the disaster risk reduction field.

This lack of academic clarity or consensus has great implications for practitioners and policy developers alike, with no real starting or end point from which to apply the theory in practice. Currently, there is no one model that is agreed upon to help define and assess disaster risk. Despite these fluid foundations, researchers and practitioners alike have pursued the use of these terms, utilising one or a mixture of definitions in order to conduct research and analysis. Consequently, in line with this, the below outlines a broad understanding of the terms when used in the context of this thesis.

2.4 The basics of disaster risk reduction: shifting from vulnerability to resilience

The basics of DRR was founded on the understanding that risk is a function of hazard and vulnerability, where:

$$\text{Risk} = f\,(\text{Hazard, Vulnerability})$$

(UNISDR, 2004)

At its most fundamental, disaster risk is perceived as the propensity to which a population can be harmed by the impacts of a hazard (UN General Assembly, 2016), which results from a combination of what the hazard is (including its magnitude) as well as who is exposed to the hazard and their vulnerability to its impacts (Cutter *et al.*, 2008). The harm may be casualties (death or injury) or damage to infrastructure, economy and society in the immediate or future (e.g., damage to grain stores that prevent next year's crops being planted, reducing agricultural output and thus food supplies and economic activity being harmed months after the event) (Kelman *et al.*, 2016; UN General Assembly, 2016). Risk can be reduced by either taking action to prevent a hazard occurring, or reducing the vulnerability of the individual, household, community or society at risk from the hazard.

Within this context, vulnerability becomes a function of the exposure (who or what is at risk) as well as the sensitivity to the hazard (the degree to which people and places can be harmed) (Cutter *et al.*, 2008). This vulnerability will be determined by the pre-event, inherent characteristics or qualities of the population, including the social, economic, political and cultural processes that create and maintain this propensity for the population to be harmed (Cutter *et al.*, 2008; Kelman *et al.*, 2016). This can include, for example, in an earthquake or flood-prone country, poorer households, who have relocated to a city for economic opportunities, living in the most landslide-prone areas, such as a hillside, in unplanned developments, which then have poorly enforced technical regulations and building codes. Thus, any action taken to reduce vulnerability must consider and be deployed within existing societal, economic, political and cultural norms and processes in order to be successful.

Vulnerability is thus deeply embedded within the pre-existing and ongoing conditions at play; furthermore, it is not a static predisposition, but rather a dynamic multi-scalar space-dependent process that is highly concerned with inequity created by human actions, behaviour, decisions, attitudes and values (Vogel and O'Brien, 2004 as cited in Birkmann, 2006). As part of this process, researchers have advocated that there is a specific capacity for an affected population to cope with a hazard (Birkmann, 2006). This coping capacity includes the strategies and actions undertaken by the population within their existing conditions, drawing on available skills, resources, and experiences to manage their immediate response to the hazard's impact (Birkman, Tetzlaff and Zentel, 2009; Berman, Quinn and Paavola, 2012). This inclusion of a capacity to cope has widened the interpretation of what vulnerability comprises: it the propensity to be harmed but one that can be lessened by the strategies of those at risk.

With this focus on harm and coping, vulnerability is often said to have negative connotations (Ruszczyk, 2014), particularly as it focuses on the pre-disaster conditions in which the populations find themselves rather than considers the choices populations make so that they can deal with the hazards ahead. The DRR community have sought to address this passivity and compliance of at-risk populations in accepting their vulnerability by shifting discussions from the agency of the conditions at play to the agency of the populations at risk. As Ruszczyk explains, the emphasis has shifted from reaction to pre-emptive or pro-active action, and thus emerged the concepts of DRR and resilience, led by the incorporation of the concept of building resilience within populations and social systems (Ruszczyk, 2014). Timmerman's (1981) suggestion that resilience should be seen as the building of buffering capacity into society to make it resistant to disaster shocks is just one of many early contributions to contemporary DRR models that include the concept of resilience (Timmerman, 1981). Risk therefore becomes a function of not only the hazard and vulnerability but also of resilience:

$$\text{Risk} = f\,(\text{Hazard, Vulnerability, Resilience})$$

Disaster resilience builds on both the socio-ecological systems concept and psychological science contributions on agency and is formally defined by Manyena *et al.,* as the intrinsic capacity of a system, i.e., a population, predisposed to a shock or stress to bounce forward, adapting in order to survive, changing its non-essential attributes to rebuild itself (Manyena *et al.,* 2011). Unlike the coping capacity of vulnerability, resilience is constituted by an adaptive capacity, where the population at risk are able to prepare in advance for stresses and changes as well as respond, adjust and adapt to the effects of a hazard (Berman, Quinn and Paavola, 2012). This is facilitated through using medium- and long-term strategies that may require substantial changes to the pre-existing conditions the population find themselves in, such as changing the DRR policy followed by local government (Birkmann, 2006). As a result, a population is seen to be resilient if they can:

1) absorb the shock by anticipating and dealing with impacts of natural hazards;

2) have the capacity to adapt to change;

3) transform through self-organisation.

(summarised from Walker *et al.*, 2006; Béné, 2013; Weichselgartner and Kelman, 2014)

Resilience is thus the ability of a population to proactively anticipate, react and absorb a potential shock as well as adapt and bounce forward from the shock, captured within the development policy as build back better. Each of these capabilities requires the population at risk to be proactive and self-determining, rather than reactive and determined by external influences. As a result, it requires these capabilities to already be present within the population prior to the hazard, or at least have the right inherent conditions that enable these capabilities to develop during the initial impact. These capabilities and conditions also need to be in place so that they can drive the post-event adaptive processes that support the reorganisation and transformation of the population in response to a shock (Cutter *et al.,* 2008).

Like vulnerability, resilience therefore is not just is a static property but also a process that changes over time, particularly as it is tested and changed by different shocks and events (Cutter *et al.*, 2008). The resilience of a population can be affected by changes within the wider economic and political system as well as the natural and built environments within the population lives. For example, a spate of political instability within a country may lead to a lack of working local government officials, which could prevent community-based disaster organisations from accessing critical information in the case of a shock; in this case, a more resilient community would be able to find alternative sources of this information to adapt to this change. Resilience therefore incorporates the notion of agency and adaptation within the population to deal with a shock on its own. This adaptive capacity – and its maintenance and enhancement – should be the overall goal of resilience, according to Klein (Klein, Nicholls and Thomalla, 2003).

By promoting this ability for people to adapt for the better after a shock, resilience as a concept is seen to have positive connotations (Levine *et al.*, 2012). This positivity has led to its uptake within the DRR community – and wider afield – and concomitantly led to decreasing attention paid to vulnerability. This shift from vulnerability to resilience however has been criticised for creating a shift of interests and objectives that leave the poor and vulnerable behind (Cannon and Müller-Mahn, 2010). The main argument is that resilience is an unequal term; it has no moral compass and can often prioritise the functioning of the population as a whole, rather than looking at the impact on the individual. Unlike vulnerability which promotes discussions on people, power and politics (Béné *et al.*, 2012), the focus of resilience on the entire population in question fails to make these connections (Gaillard, 2007; Ruszczyk, 2014). As a result, resilience does not consider the power dynamics between winners and losers within communities (Ruszczyk, 2014), particularly marginalized groups within communities or society who are less likely to be included, or be able to invest, in resilience-building measures.

There is also a concern that the focus on resilience building can often occur at the expense of improving poverty or sustainability (key development concepts not covered in this review), and thus in fact increase the vulnerability of at-risk populations; after all, poverty has strongly been linked to vulnerability and disaster causation (Wisner, O'Keefe and Westgate, 1976). As a result, those using resilience within the DRR and the wider development sphere need to consider the agency and inequity of different people, groups and communities, and in particular at risk or marginalized groups (Béné, 2013). For any research concerned with resilience therefore, the pre-existing inequities between and across populations must be acknowledged – it is these inequities that often makes them vulnerable.

There is, as a result, tension between the two terms in DRR research, both in how they are used (at worst, interchangeably) and also how the relationship between them is conceptualised. For example, many have argued that resilience and vulnerability are the opposite sides of the same coin (Folke *et al.*, 2002; Adger *et al.*, 2005), where vulnerability and resilience lie on the same continuum but at opposite ends (Manyena, 2006). This conceptualisation suggests that increasing resilience will reduce vulnerability, whilst reducing vulnerability will increase resilience. Levine *et al.* (2012) argue otherwise, that increased resilience does not lead to decreased vulnerability nor does it reduce risk, and thus they are not opposites of one another (Levine *et al.*, 2012). Others argue instead that the terms are constituted from one another. Pelling (2003), for example, sees resilience as a part of vulnerability, alongside exposure and resistance (Pelling, 2003). Manyena (2006) and Gaillard (2007) conversely see them as discrete but interrelated constructs, relying on the same factors (e.g., social, economic, political and cultural processes) (Manyena, 2006; Gaillard, 2007).

This latter approach has offered a way forward in conceptualising how the two terms can co-exist and how with the two types of capacity, coping and adaptive, interact and link with one another. This approach is illustrated in Figure 2-1, which has been adapted from Dixon *et al*. (2014) and Berman *et al.* (2012) who adapted work from Engle (2011), which was originally based on work from Cutter *et al.* (2008) one of the seminal papers on resilience. In this conceptualisation, resilience and vulnerability can be recognised as separate concepts and processes, that overlap with one another (Kelman *et al.*, 2016). The main overlap, as identified by Berman, is in the two types of capacities, coping and adaptive, which themselves lie on a spectrum: coping capacity may transform into adaptive capacity (Berman, Quinn and Paavola, 2012). How this occurs and the linkages between the two are still unknown (Berman, Quinn and Paavola, 2012), but one approach is to focus on how both types of capacities recognise the importance of assets and institutions in helping to reduce vulnerability but also to foster resilience (Berman, Quinn and Paavola, 2012).

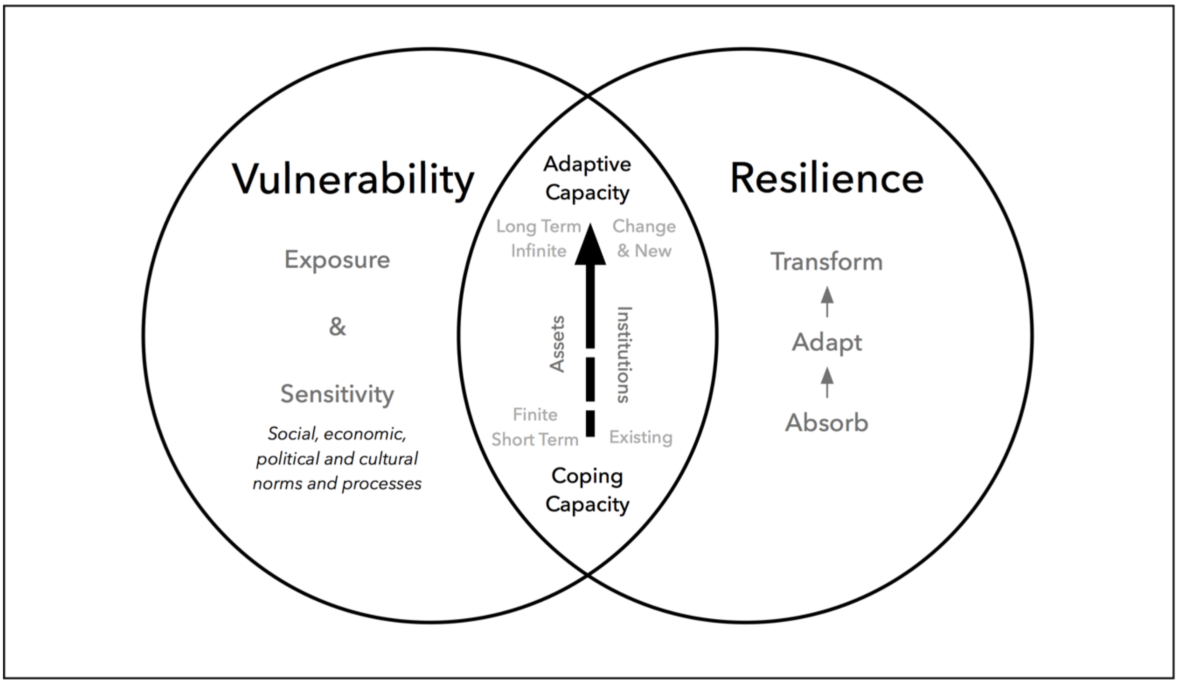


Figure 2-1. Linking vulnerability and resilience concepts through coping and adaptive capacity, adapted from Dixon *et al.* (2014), Berman *et al.* (2012), Engle (2011) and Cutter *et al.* (2008).

For example, a key asset for both types of capacities is a community's social capital, which is commonly perceived as the benefits resulting from the investment and trust in relationships with others, such as reciprocal support, facilitated through people sharing similar social norms and behaviours. Within the vulnerability approach, the reliance on social capital is a prominent strategy for coping with an impact; here, social capital is a finite asset from which to use resources in order to cope in the short-term. For resilience, the level of social capital a community has, alongside its ability to act collectively, is argued to determine its adaptive capacity (Adger, 2010); it is, as a result, an infinite asset which contains what could be described as the latent energy the community has stockpiled from which they can build more and new resources in the case of a hazard and for the longer term.

Overall, as Kelman *et al.* (2016, pg.131) explain, "it is not straightforward to pin down or to develop an unambiguous and universally accepted relationship between the two, notably due to different definitions of vulnerability and resilience". Furthermore, the circular arguments presented across the resilience and vulnerability literature can often be confusing and overwhelming; Guarnacci's (2016) characterisation of the epistemological debate as a 'motley discourse' is apt. Even at the outset of this thesis, there is still no one definition absolute for either term and as a result the relationship between vulnerability and resilience is still not clear. The almost distractive nature of this epistemological debate has appeared to reach its precipice, with some researchers now questioning whether resilience is simply a buzzword rather than a useful concept (Grünewald and Warner, 2012). Recently, however, there has been a drive from many in the DRR field to, as Weichselgartner and Kelman (2014) put it, move past the debates and instead focus on those who should be at the heart of the debate – the populations at risk (Weichselgartner and Kelman, 2014). After all, the purpose of DRR is to develop methods in both theory and practice that will reduce the risk of populations to disasters.

2.5 The vulnerability and resilience of what, to what and for whom?

To be able to understand what this truly means in a practical sense, there is a need to – as Carpenter *et al.* (2001) first proposed – take resilience from 'metaphor to measurement', and ask the question 'the vulnerability and resilience of what to what'. Whilst their paper is written from a socio-ecological systems perspective concerned within landscape management, this question has resonated greatly with the part of the DRR research community searching to develop practical methods to analyse vulnerability and resilience.

The answer has been an increasing focus on the scale of the community: to ask, what is the resilience of a (this) community to the hazards to which they may be exposed. As explained by Pfefferbaum *et al.* (2015):

> *"A focus at the community level is appropriate in disaster management because disasters are local events that have different effects in different communities and that call for and trigger different responses."*
>
> (pg.2)

The community scale lends itself to analysis within DRR research because of the place-based nature of a disaster. A disaster will occur somewhere and primarily affect those within that 'place', and so – to an extent – can be confined to a local area. This thus provides a 'bounding box' that makes the previous question (and overall, our understanding of vulnerability and resilience) theoretically simpler to ask: 'what is the vulnerability and resilience of the community to which hazards and potential disasters?'. The focus on the scale of community within DRR has created a canon of literature that now covers not only the conceptual understanding but also potential methodologies and approaches on which to account for, assess and model resilience and vulnerability.

Leading this work in resilience measurement is a seminal paper by Cutter *et al.* (2008), which proposes a 'place-based model' to understand community disaster resilience, known as the 'Disaster Resilience of Place' (DROP) model. The model is designed to present the relationship between vulnerability and resilience through quantification grounded in theory in order to be used and applied to address real problems in the real-world (Cutter *et al.,* 2008). The model tackles directly the definitions and relationship between resilience and vulnerability, by presenting them as both inherent properties and dynamic processes, which occur at both the local and broader scale.

The DROP model acknowledges that there is a pre-existing requirement for resilience in the form of antecedent conditions. These conditions are seen as the capacities or resources that the community already possesses in the context of its current political, social, economic and cultural situation. In light of this, there is ongoing discussion within the DRR community about what precise capacities or aspects make a community resilient and/or vulnerable, as highlighted in the Introduction.

For some, such as Tobin (1999; Tobin *et al.,* 2014), resilience is about building capacities at a local level i.e., within communities, and thus they fundamentally focus on the social capacities that constitute resilience such as social capital, trust and leadership. Walker *et al.* (2004) on the other hand characterises resilience purely as different forms of capital rather than capacities per se, including social, economic, and political (Walker *et al.,* 2004). They highlight that political knowledge (i.e., being able to understand and harness the role of institutions, political systems and governance) is also important for DRR.

Other viewpoints incorporate more specific types of capacities associated with DRR, including knowledge, risk management and vulnerability, and preparedness and response (Berkes, 2007; Twigg, 2007). Further review of other opinions on capacities can be found in Bahadur *et al. (*, and Ruszczyk (2014). What is recognisable across these viewpoints is that resilience, and some aspects of vulnerability, is constituted by different types of capacities, themselves constituted by different resources. However, whilst this canon of literature has moved the theoretical understanding of resilience and vulnerability forward, it is yet to have a convincing impact on the way they are measured.

2.6 Measuring resilience and vulnerability: relying on capacities

> *"The ability to measure resilience is increasingly being identified as a key step toward disaster risk reduction."*
>
> (Burton, 2015, pg.68)

Over the last fifteen years, researchers have tried to capture and quantify resilience and vulnerability by developing indicators that can be interpreted as a proxy measure (e.g., Cumming *et al.,* 2005; Sherrieb, Norris and Galea, 2010; Burton, 2012). However, as Mayunga (2007) highlights it is hard to create and develop indicators that can adequately measure resilience, due to the multifaceted nature of resilience, including the physical, social, institutional, economic and ecological dimensions (Cutter *et al.,* 2008). In spite of this, the majority of assessment techniques are quantitative, using chosen indicators or variables as proxies to represent resilience and/or vulnerability. These proxies are then used to assess relative levels of resilience and/or vulnerability across different communities and very recently, over different time periods (e.g., Wickes *et al.,* 2015; Abbasi and Kapucu, 2016; Leykin *et al.,* 2016).

The first step for many, following on from the DROP model, is therefore to understand and assess the inherent resilience of a community based on its pre-existing conditions. To do so requires the construction of indicators to measure these pre-existing conditions. The challenge of creating indicators of resilience however lies in its multifaceted nature – once again, asking the question of the 'resilience of what and to what' (Carpenter *et al.,* 2001; Cutter, 2016a) – and ensuring that the indicators selected have validity, sensitivity, robustness, reproducibility, scope, availability, affordability, simplicity, and relevance (Cutter *et al.,* 2008).

With many of the same capacities and characteristics that allow a community to thrive during non-emergency times also helping a community to continue functioning during a disaster, the capacities and characteristics that are part of the everyday geographies of the communities are being used to measure inherent resilience (Ruszczyk, 2014). Since Cutter *et al.*'s 2008 paper, much of the work to date has thus focused on identifying and then assessing these pre-existing capacities within communities that should be able to form indicators of the overall inherent resilience. With no definitive set of indicators for measuring disaster resilience (Burton, 2015), the capacities identified as important were and still continue to be decided by the individual researcher or research team.

This assertion is supported by work conducted by Beccari (2016) who analysed Quantitative-Based Composite Indicators (QBCI) and scorecard methodologies used within the analysis of risk, vulnerability and resilience. In the study, 106 methodologies are reviewed, such as those developed by Sherrieb *et al.* (2010) and Burton (2012, 2015), through a study of academic and grey literature to understand the breadth and depth of composite index development (Beccari, 2016). By collecting data on the index construction including variables used, Beccari found that in total over 2298 unique variables had been covered by the 106 methodologies, with the total number used by each methodology ranging from a minimum of 2 and maximum of 235. The majority of these indices had a low use of direct measures for disaster risk, vulnerability or resilience (which term was used was dependent on the approach taken by the paper), with variables specifically measuring action to mitigate or prepare for disasters comprising only 12% of the total number of variables in each index (Beccari, 2016). This again could weaken the reliability of the index as an actual proxy and thus measure of resilience or vulnerability.

QBCI are thus limited by the types of variables chosen, which themselves are limited by the availability (and scale) of data. As a result, the indices may not cover all aspects of resilience or may be too coarse to extract the factors, processes or capacities that are at play. For example, Burton (2015) states that, in defence of the low explanatory power of his model for the five-year period, contextual factors not measured by the index also contribute to the recovery process (Burton, 2015). QBCI struggle to incorporate or promote these contextual factors that cannot be summed up by a statistic or dataset.

To understand these contextual factors, more local and qualitative approaches to measuring and assessing resilience and vulnerability have been developed. For example, Schwarz *et al.,* 2011. conducted an empirical analysis of resilience for rural communities in the Solomon Islands by drawing on a livelihood assessment method, borrowed from vulnerability measurement. An assessment map was used to systematically scan multiple dimensions of the population and their environment to help develop a household questionnaire that was used to assess individual's perception of the community's resilience (Schwarz *et al.,* 2011).

The assessment focused on four domains: the natural system; people and livelihoods; institutions and governance; and external drivers (factors originating from outside the control of the local community). Explicit attention was paid to external drivers, including focusing on issues impacting fisheries systems that supports the community economically. Questionnaires were distributed among the local community, and included a section on the experience of respondents to events in the past that affected their livelihoods, their perceived capacity of the community to cope with past and future threats, as well as ways to improve livelihoods through individual and collective action (Schwarz *et al.,* 2011). By conducting an assessment at the individual scale, the study was able to identify key drivers of resilience not covered by the composite indices, including good leadership and how the community perceived they coped with past events. The main limitation of this type of resilience assessment conducted by Schwarz *et al.* (2011) is that it lacks repeatability and coverage. It took six months to question three clusters of rural communities, with a total of 67 households interviewed. To provide the same coverage as Burton's (2015) composite index, which covered the entire Mississippi area, using Schwarz *et al.*'s (2011) approach would take years to complete.

As a result, the qualitative analysis, including participatory and mixed method approaches, of resilience is predominantly focused at the local scale and usually with two main applications. As explained by Ross and Berkes (2014), the first is to use a range of mixed methods and participatory action research (PAR) to provide an exploratory analysis of what factors determine a community's resilience (Ross and Berkes, 2014). This allows researchers to understand both the general and contextual factors that influence resilience at the local community level in a certain place. The second is to use PAR approaches to actually build adaptive capacity and community resilience rather than simply explore or measure it. By using techniques such as reflexive learning and building toolkits, researchers aim to engage the local community to identify their strengths and weaknesses and then develop ways to build their capacity (Ross and Berkes, 2014). Due to the range of factors and processes that could be encountered and the variances in methodologies, both approaches are place-specific and researcher-dependent. Comparison between communities and studies, as a result, are limited (unless the research is conducted in precisely the same way). Furthermore, the qualitative nature of the approaches, particularly when exploring what makes a community resilient or vulnerable, presents difficulties when trying to incorporate observations into models for quantification and measurement.

The aim of both QBCI and qualitative analysis is to provide an understanding of what constitutes inherent resilience (or ongoing vulnerability) at the community scale, whether this is through measurement or a set of observations. Beyond the limitations specific to each discussed above, there is one further limitation that faces resilience research in particular; the temporal change of resilience during and post- shock. The creation of QBCI provides a measure of the inherent resilience of a community that should be able to predict how well a community will recover. Qualitative analysis will also use a set of observations to also predict how well a community will recover. Both are however a snapshot in time of the community and thus a static representation of resilience. Unless the analysis is conducted repeatedly (and preferably during and post shock), it only represents inherent resilience as a pre-existing property which we are unable to see change during a hazard event. Repeated analysis is unlikely, primarily due to the unavailability of data at appropriate time scales (composite index) or, in the case of empirical analysis, due to the ethics regarding data collection during times of shock or simply lack of time or money to do so. As a result, there have been few attempts to assess and monitor the resilience of communities over time (Leykin *et al.,* 2016), during disaster events and none at high temporal frequencies.

By using these QBCI and empirical analyses, we are predominantly unable to treat resilience as both a property and process; we cannot see how the capacities change over both time and place and people, and thus understand the potential spatial heterogeneities associated with resilience. New methods are emerging. As Cutter explains, "the broader literature on resilience reflects a tension between static outcomes and dynamic processes, where there are those who wish to treat resilience – and thus community resilience – as a static property or outcome opposing those who see it as a dynamic process" (Cutter, 2016a, pg.110). Whilst those developing the QBCI and qualitative analyses are likely to agree that resilience is dynamic and changes, these current methodological approaches do not treat it as such.

New methodologies – or simply improved (reliant on availability of data) – are required to change the way we measure resilience into a dynamic rather than static property and process. Fortunately, geographers are interested in both: their "fundamental concern [is] with how these static conditions and dynamic processes affect places, especially where inequalities in the physical, social, economic and political contexts constrain the range of opportunities to function, learn and transform" (Cutter, 2016a, pg.111). Resilience, with both its inherent and adaptive resilience, requires researchers to think through both the static property and the dynamic process, a position in which geographers are primed to excel.

Chapter 3 Measurement of social networks for innovation within community disaster resilience

3.1 Chapter overview

With Chapter 2 outlining the key challenges faced in the current operationalisation of resilience for disaster risk reduction, Chapter 3 presents the second half of the theoretical framework of the PhD: a synthesis of a growing area of research that seeks an alternative approach to measuring resilience through the analysis of social networks, primarily at the community scale. Utilising a systematic literature review, the Chapter explores and evaluates numerous empirical studies that have sought to assess a community's resilience through the presence and structure of social networks. The review shows how a singular methodology using a Social Network Analysis (SNA) based approach is developing, and how the majority of the studies advocate for the use of SNA and social network mapping as a key tool for community disaster resilience estimation. The chapter importantly establishes the need for innovation within these SNA-based approaches, with finding alternative sources of data with greater spatial and temporal scales a crucial requirement to develop this area of research further.

3.2 Paper Abstract:

Disaster risk reduction (DRR) research has long recognised that social networks are a vital source of support during and after a shock. However, the quantification of this social support, primarily through its recognition as social capital, has proven problematic as there is no singular method for its measurement, invalidating the credibility of studies that try to correlate its effects with disaster resilience. Within the wider resilience field, research that specifically utilises community social networks as the focus of analysis is evolving. This paper provides a critical synthesis of how this developing discourse is filtering into community disaster resilience, reviewing empirical case studies from the Global South within DRR that use social network analysis and connectivity measurement. Our analysis of these studies indicates that a robust methodology utilising social network analysis is emerging, which offers opportunity for research cross-comparability. Our

review also finds that without this bottom-up mapping, the implementation of top-down preparedness policy and procedures are likely to fail, resulting in the advocation of social network analysis as a critical methodology in future resilience research and policy planning.

3.3 Keywords

Disaster resilience; community; social networks; connectivity; disaster risk reduction; social network analysis; social network mapping; data; innovation

3.4 Introduction

Community resilience is broadly understood as the capacity for a community to be able to recover from a shock (such as a hazard), as well as its capability to undergo transformative changes using self-organisation and collective action to deal with impact (Patel *et al.*, 2017), and adapt as needed in order to move on from the shock. Building and strengthening resilience within vulnerable communities is a key priority for those working with disaster risk reduction, including the International Federation of the Red Cross (IFRC) (International Federation of Red Cross and Red Crescent Societies, 2016), the World Health Organisation (WHO) (World Health Organization Regional Office for Europe, 2017), and the United Nations Office for Disaster Risk Reduction (UNISDR) (United Nations, 2018). Traditionally, these resilience building efforts have focused on the physical and financial aspects of a community, such as improving infrastructure or diversifying livelihood strategies (Aldrich and Meyer, 2014). However, a renewed focus on disaster response and recovery by the Sendai Framework for Disaster Risk Reduction (2015–2030) (UNISDR, 2015) and recent disasters worldwide where social support has been at the forefront of recovery strategies, has put the attention on alternative aspects of community resilience.

Disaster risk reduction (DRR) research fully acknowledges that communities regularly work together to survive and recover from catastrophic impacts (Aldrich and Meyer, 2014). Recent disaster events have highlighted the important role of social support, in which civilians, i.e., persons who are not trained responders or workers from relief agencies, through the provision of aid and supplies, are involved in the immediate response as well as help with longer term recovery (e.g., the 'Cajun Navy' during the 2017 floods in Houston, Texas). This community-based help and support is underpinned by the following tenets of social capital: cooperation and collective action is facilitated by the participation of individuals and communities within different types of social networks, as well as by the trust and belief within and between these networks that this help would be reciprocated if and when needed, creating a sense of goodwill towards one another (Claridge, 2004). This support can come from relationships within the affected communities or through linkages to other communities. However, the quantification of this social support for community DRR, primarily through its recognition as social capital, remains problematic. Despite the first discussions of the concept arising more than thirty years ago (beginning with Bourdieu's 1986 'the forms of capital'), social capital has not found solid singular ground in its definition or its measurement (Carrillo Álvarez and Riera Romaní, 2017). Inconsistencies also lie within community resilience studies, where resilience itself is, similarly, yet to be operationalised under one common method or measure (Asadzadeh *et al.*, 2017).

A growing discourse of research that specifically investigates people's social networks as a core component of community resilience has filtered into DRR research, with the driving interest for DRR researchers working in the Global South being that "the social networks of the poor are one of the primary resources they have for managing risk and vulnerability" (Woolcock and Narayan, 2000, pg.242). Unlike previous approaches to measuring social capital, either as a standalone concept or within resilience, these studies have followed a similar approach to measurement. Such research has attempted to capture the level of help and support within a community by assessing the structure of their social networks, considering different characteristics (e.g., the number and types of relationships) and their overall connectivity. The premise is that the presence, strength, and effectiveness of social networks will directly influence the ability of communities to cope with disaster events (Misra *et al.*, 2017) and this can be quantified through a structural network-based approach.

To encourage engagement with this relatively new discourse, we provide a much-needed synthesis of empirical research to evidence the relationship between social networks and resilience within DRR and advocate for its use within community disaster resilience measurement. The paper builds this evidence through the critical appraisal of eleven case studies from the Global South, assessing their methodologies and their findings, to demonstrate the utility and importance of emerging social network approaches. Our review identifies that a singular methodology is developing around social networks and connectivity within community disaster resilience. Furthermore, the paper's consolidation of the main findings of the case studies indicate that the use of social network-based methodologies is invaluable for practitioners to understand how community resilience is built from the bottom-up. The paper provides substantive evidence that without an understanding of local social structures within a community in the Global South, any top-down implementation of preparedness policy and procedures, such as introducing a community disaster committee, is likely to fail. As a result, this paper proposes that the use of social network mapping and analysis should be promoted and utilised more widely within resilience research and potential policy-influenced programming. To encourage the uptake of these social network approaches as a common resilience measure, this paper provides suggestions on how future studies should develop in order to better understand the role of social networks in disaster response, which can further enhance this bottom-up understanding of community resilience.

3.5 Current Limitations of Operationalising Social Capital Within Community Disaster Resilience

The resilience of communities is a prominent topic within the agendas of development, humanitarian, and DRR policy makers today (Patel *et al.*, 2017). Resilience continues to appear in various programmes for action, from the aforementioned Sendai Framework for DRR as well as the Sustainable Development Goals, where it is explicitly acknowledged in Targets 1.5 (By 2030 build the resilience of the poor and those in vulnerable situations, and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters. Source: UN, 2015.) and 13.1 (Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries. Source: UN, 2015.), as well as implicitly underpinning the achievements of several other targets (Peters *et al.*, 2016). These programmes renew the intention to focus on building resilience within and into communities. However, despite efforts to incorporate resilience into policy making and programme planning, the evidence guiding these developments is limited in its representation of community resilience, particularly as a process a community undertakes and not just a property that a community has (Patel and Gleason, 2018). Primarily, these shortcomings are rooted in a lack of cohesion in the definition and measurement of resilience within and across these different fields. Even the word resilience has a long and fraught modern history, resulting in an amount of literature "so copious that it is becoming increasingly difficult to summarise" (Alexander, 2013).

In this paper we broadly define resilience to be the ability of a system to (i) respond to, or have the capacity to absorb, a disturbance and still retain its basic structure, functions, and processes, (ii) self-organize, and (iii) build capacity for learning and adaptation (Carpenter, Walker, Anderies, *et al.,* 2001; Folke, 2006; Weichselgartner and Kelman, 2014). For DRR, we further this definition to focus on an individual or population being able to absorb and recover from a shock by anticipating and dealing with the impact of a natural hazard, using self-organisation to help as well as having the capacity to adapt to change. Our definition follows core DRR resilience concepts proposed by Manyena *et al. (*2011) stating that following a disaster, individuals, communities, and systems have the intrinsic ability to 'bounce forward' (Manyena *et al.,* 2011), which is the ability of a community to rebuild (preferably better) as part of their capacity to adapt and learn. Scale and geography are also embedded into our considerations and definition of a community. As disasters are local events, they will impact each local geographic community differently as well as require and trigger different responses by these communities (Pfefferbaum, Horn and Pfefferbaum, 2015). Consequently, for community disaster resilience to ensue, the ability for a community to recover from and resume normal activities in the aftermath of a shock is primarily determined by their resilience (Paton and Johnston, 2001; Maguire and Hagan, 2007; Cutter *et al.,* 2008).

The last decade has seen researchers and practitioners attempt to capture and measure community disaster resilience as an absolute characteristic and as a relative asset through both quantitative and qualitative approaches. At the forefront has been the development of composite indicators to assess the proposed capacities of a resilient community, such as economic development, community competence, functioning infrastructure, and organisational capability (e.g., Cutter *et al.,* 2008; Norris *et al.,* 2008;

Cutter, Burton and Emrich, 2010; Sherrieb, Norris and Galea, 2010; Burton, 2015). These indicators use existing empirical variables (such as gross domestic product, percentage of the population over 65, housing types, and insurance coverage) to construct a single indicator of resilience; however, there is no 'one' method to determine individual variables or derive a composite measure. A review by Beccari (2016) analysed over 100 composite indicators that were related to resilience and identified 2298 unique variables covered by 106 different methodologies. Further reviews (e.g., Sharifi, 2016; Asadzadeh *et al.,* 2017; Cai *et al.,* 2018) have developed frameworks on how to build community resilience composite indicators based on consolidating current approaches, but one singular approach is yet to be adopted, preventing measurements from being compared across countries, across time periods, and with other research. There are also continuing limitations with these indicators to take into account cross-scale relationships, as well as dynamics over time and across space (Sharifi, 2016).

Within these different indicators, social support is identified as a key capacity of a resilient community. Recent papers have advocated that social support in the form of social capital is a fundamental capacity that could be used to enhance a community's resilience (Aldrich and Meyer, 2014; Pfefferbaum, Horn and Pfefferbaum, 2015). Focusing on social capital for operationalising community resilience, however, creates its own problems, which are primarily caused by the ambiguity in and variance of social capital as a concept, its definition, and its operationalisation (Carrillo Álvarez and Riera Romaní, 2017).

Social capital was originally conceptualised by Bourdieu (1986) as one of many forms of capital (e.g., financial, cultural etc.) that an individual possesses and utilises to make advancements in their life (Bourdieu, 1986). Social capital is the aggregate of the actual or potential resources that are linked to an individual through their possession of a durable social network i.e., good relationships with family, friends and acquaintances (Bourdieu, 1986). Each member within this social network has the backing of the collectively-owned capital and are entitled to utilize these resources as and when required. For community disaster resilience, social capital drives the social support and collective action of individuals and communities helping one another. The support is provided under the notion of what Lin (1999) identifies as an investment in social relations with expected returns, where one community is motivated to help another in the understanding that help will be returned, whether in smaller, equal, or greater measures, should it be required in the future.

Social capital is therefore created through the presence of social networks, as well as the trust and norms inherent within them, that create a sense of goodwill and facilitate cooperation. The amount of social capital present depends on the size of the network present (i.e., the number of relationships) and whether these relationships can be mobilized, in conjunction with other types of capital possessed by each member of the network. This network can be at the individual or the group scale, including communities and societies which have the tendency to form and benefit from these reciprocal networks (Putnam, 2001). Social capital is thus normally conceptualised by the following two core components or dimensions: the structural aspect, which incorporates the connections, groups, and networks of social relations, and the cognitive aspect, the mobilization and reciprocity underpinned by the norms, values, and trust (Claridge, 2004).

Whilst there is a general agreement on how social capital works, quantifying it is made difficult by the problem of separating its source, form, and consequences for measurement (Adam and Rončević, 2003; Claridge, 2004). For example, whilst social capital is created through the presence of trust, is trust a source, a form, or a consequence? As arguments could be made for each, evaluating these aspects simultaneously has caused ongoing operationalisation issues as researchers try to define what creates social capital, what sustains it, and what it provides.

Consequently, most empirical studies have measured social capital through indirect indicators, such as crime rates, teenage pregnancies, or participation rates, that are believed to be associated with the presence (or lack) of social capital as a whole (Sabatini, 2009). These indicators however do not measure social capital as a source or as a form and as a result, it is argued that these indicators cannot truly represent the intrinsic social capital the population possesses (Adam and Rončević, 2003). There are more holistic approaches to measuring social capital, such as the World Bank Social Capital Assessment Tool (SOCAT) (1999) (Krishna and Shrader, 1999). These surveys attempt to capture individual-based perceptions on social capital, asking questions on group membership, social norms, and support, as well as the more cognitive side, including trust and reciprocity and aggregate responses at the community level (Carrillo Álvarez and Riera Romaní, 2017). However, these surveys again do not attempt to separate the outcomes of social capital from its source or form. Overall, research remains divided on whether such measurement is possible. A recent review by Alvarez and Romani (2017) concluded that no further progress towards a standardised measure has been made since initial research at the start of the millennium. Without a singular way to operationalise social capital, it continues to be a theoretical concept (van Deth, 2003), with its conceptual vagueness partly invalidating the credibility of empirical and theoretical studies that evaluate its possible effects (Sabatini, 2009).

For the DRR community, this doubt in credibility is magnified by the prominent use of these indirect indicators within the aforementioned composite indicators of community resilience. Buoyed by the ease of their extraction from publicly available sources of data, such as national censuses and surveys (Aldrich and Meyer, 2014), it is common to see indirect indicators of social capital, such as participation in volunteer organisations or number of religious organisations within the population, used within community resilience composite indicators (e.g., Cutter *et al.*, 2008; Sherrieb *et al.*, 2010). With both the chosen social capital indicator or indicators and the composite community resilience indicator having weak epistemological foundations, it is questionable that the resulting data actually relates to the phenomena in question—the ability for a community to respond, absorb, and/or recover from a shock and bounce back better. Furthermore, for those in resource-poor settings, such as the Global South, national population and census data are often outdated, inaccurate, or missing key groups or areas (Wardrop *et al.*, 2018), which reduces the likelihood of these datasets being available to use within these indicators. As a result, there are significant epistemological and logistical challenges to operationalising social capital within community disaster resilience under one clear, consistent, and overarching method for its use within and across national policy and global programming.

3.6 Social Networks and the Evolution of a Cohesive and Robust Methodology

To overcome these limitations, it is proposed here that a growing body of literature is focusing solely on the role of social networks, rather than social capital, as a potential measurable approach to assessing and targeting community disaster resilience. The premise is that the presence, strength and effectiveness of social networks will directly influence the ability of communities to cope with disaster events (Misra *et al.*, 2017), which can be quantified through using a structural or network-based approach. This approach is primarily achieved by interviewing individuals or households within the community to collect information about their relationships using interviews or questionnaires. These relationships can be between individuals or households within the community as well as with external connections. Building networks generally follow one of three methods, collecting data on the following: all possible members of the community; a random sample of those within the community; or use a 'snowball' approach by collecting data only on those mentioned by a random 'starter' group within the community (Borgatti, Everett and Johnson, 2013). Once the data are collected, the networks can then be constructed and analysed to assess the overall connectivity of the community.

Social network analysis (SNA) emerged from the confluence of research within three different traditions over a forty year period, including sociometric analysts, who provided many technical breakthroughs on the methods of graph theory, researchers from the 1930s, who were focused on the patterns of interpersonal relations and their role within the formation of cliques, and finally social anthropologists, who built on both of these to study the role of community structure and relations within village societies (Scott, 2012). Contemporary SNA utilises matrices and sociograms (see Figure 3-1), where networks are represented by lines or ties (relationships) and points or nodes (the actors within the network e.g., individuals, households), which are then mathematically analysed using aspects of graph theory. These mathematical quantifications are then connected with a specific sociological or anthropological concept or theory to evaluate the role of the network being considered. This connection was solidified in the seminal work of Mark Granovetter's (1973) sociological article on 'the strength of weak ties', where basic social network analysis (SNA) methods were used to explore not only the importance of close friendships, but also the role of weaker connections to improving personal outcomes (Granovetter, 1973). The work was of central importance for popularising and legitimating SNA as a methodology, contributing to its systematic and analytical development, and showed the power of even the most basic of SNA methods for exploring social structure (Scott, 2012).

Creating social network maps (sociograms)

1. Data is collected on the relationships of each community member.

Community Member: A
Contacts:
Member B
Member C
Member D
Member I
Member K
Member L

Community Member: B
Contacts:
Member A
Member D
Member F

Community Member: C
Contacts:
Member A
Member D
Member G

...

2. Social matrix between community members is constructed.

	A	B	C	D	E	F	G	H	I	J	K	L	⋮
A		X	X	X	-	-	-	-	X	X	-	X	⋮
B	X		-	X	-	X	-	-	-	-	-	-	⋮
C	X	-		X	-	-	X	-	-	-	-	-	⋮
D	X	X	X		X	X	X	X	-	-	-	-	⋮
E	-	-	-	X		-	-	X	-	-	-	-	⋮
F	-	X	-	X	-		-	X	-	-	-	-	⋮
G	-	-	X	X	-	-		-	-	-	-	-	⋮
H	-	-	-	X	X	X	-		-	-	-	-	⋮
I	X	-	-	-	-	-	-	-		X	-	-	⋮
J	X	-	-	-	-	-	-	-	X		X	-	⋮
K	-	-	-	-	-	-	-	-	-	X		X	⋮
L	X	-	-	-	-	-	-	-	-	-	X		⋮
...	...	...	...	...	...	...	...	...	...	...	...	...	

3. The matrix can then be mapped using the sociogram approach.

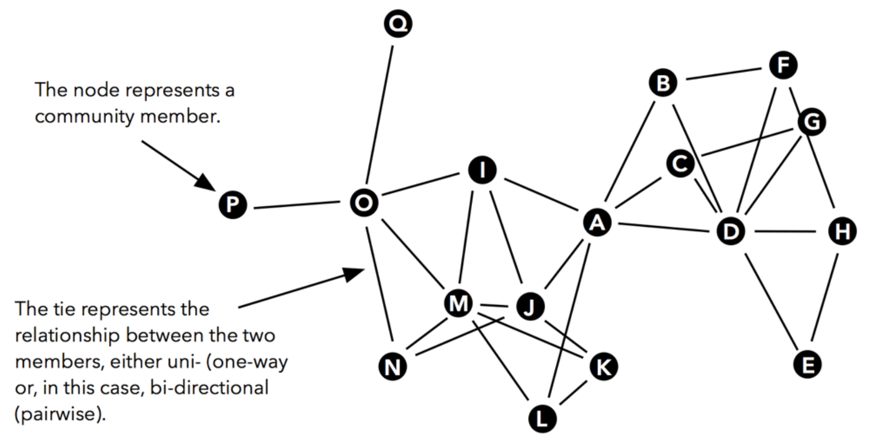


Figure 3-1. Creating social network maps from data collected on hypothetical community member relationships.

SNA has featured within social capital theory. Lin *et al.* (1981) pursued the connection between SNA and social structure with social capital, suggesting that the access to and use of social resources by an individual would be, in part, determined by their position within the network's hierarchical structure and by their ability to use their weaker ties (Lin, Ensel and Vaughn, 1981). Burt continued to develop much of this work, theorising that certain network positions have significant effects on an individual's ability to realize benefits (Burt, 1997). The size or degree, the density, the heterogeneity, and a number of other hierarchical characteristics of an individual's network were, as a result, all considered important measures when evaluating an individual's social capital from a structural viewpoint (Adam and Rončević, 2003). These measures are detailed further in Table 3-1, where their role in enhancing or reducing the amount of structural social capital is linked, and Figure 3-2, where their calculation is explained.

Table 3-1. Network-based measures and their relation to structural social capital.
(Adapted from Borgatti, Jones and Everett, 1998; Misra *et al.*, 2017).

Network property	Description	Relation to wider social capital concept
Number of ties	Total number of ties in a network.	Individual: The more ties you have, the greater chance that one of them will help or have the resource you need. Community: The number of ties among the community members indicates level of cohesiveness and their ability to work together through collective action.
Network Density	Number of ties, expressed as proportion of the number of ordered/unordered pairs. When density is close to 1.0, the network is said to be dense, otherwise it is sparse.	Individual: If all your ties are connected, they become redundant – the 'need to put eggs in more than one basket' mantra. Community: Cohesiveness in the community and their ability to undertake collective action.
Overall Centrality	An overall measure of the number of ties that a node* has relative to the total number of ties existing in the network as a whole, considering distance. Centrality incorporates degree, closeness, and betweenness measures.	Individual: High centrality reveals an individual(s) as a key leader or connector within their community. The presence of leaders is indicative of collective action and agency within a community. Community: High centrality reveals a community as highly connected within the overall network; the community is likely to be a key coordinator for dissemination of information and resources in local region.
Degree	Total number of ties a node has to other nodes. A node is central when it has a higher number of ties adjacent to it.	Individual/Community: A high degree means a well-connected individual or community; a low degree could lead to exclusion and marginalization from the wider network.
Closeness	Reciprocal measure of the geodesic distance (the shortest path connecting two nodes) of a node to all other nodes in the network. A node is "close" if it is located a short distance away from many other nodes (i.e., physically proximate).	Individual/Community: The greater the distance to other nodes, the less chance of receiving information and/or resources in a timely way.
Betweenness	Number of times a node occurs along the shortest path between two other	Individual: A node can play the part of a liaison, broker or gatekeeper with a potential for control over others.

	nodes. A node is central the more times it occurs.	Community: Communities with high betweenness levels have few redundant ties with outsiders, resulting in a greater diversity of resources and information.
Bridge	An edge is identified as a bridge if its deletion would cause the full separation of two subgroups.	Important link between subgroups, such as communities separated by constraints; helps maintain information flow.
Clique	Every individual is directly tied to every other individual in a subgroup.	Creates strong internal ties which result in exclusion to those outside. Prevents efficient spread of information and resources with those outside unless connected via multiple bridges.
Structural hole	A structural hole occurs whenever a person (i) has a relationship with someone who is connected to a separate subgroup of people and (ii) has no other direct or indirect connection with the people in that subgroup.	More structural holes in a network is likely to result in exposure to more diverse information and opportunities than a network having relatively few structural holes.

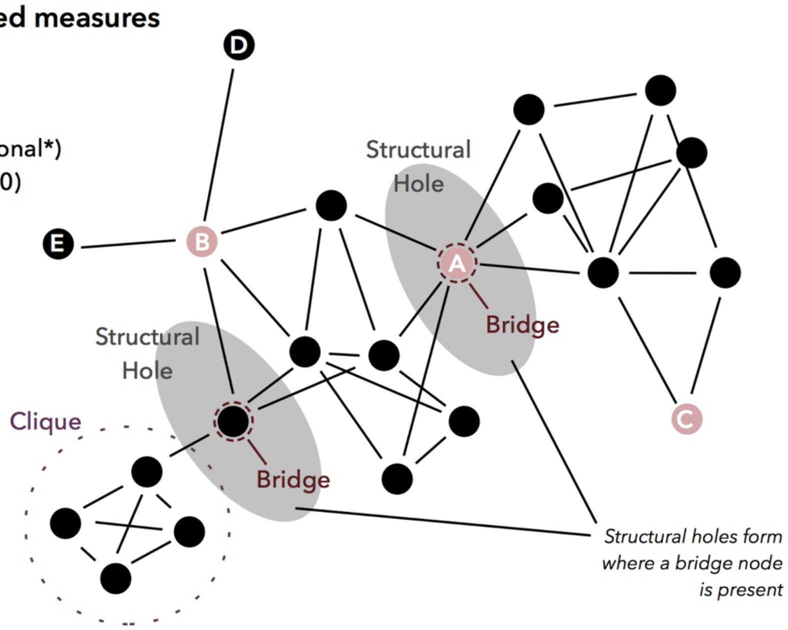
**A node can be an individual or group/community in the network.*

Visualising network-based measures

Network Measures

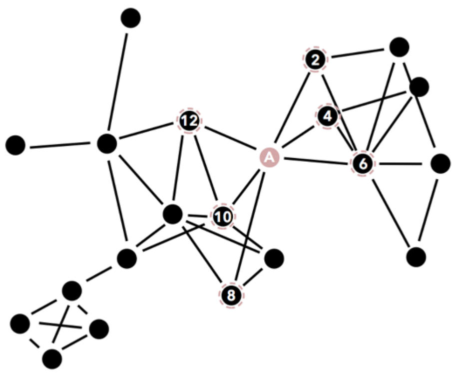
Number of ties: 60 (bi-directional*)
Network density: 0.14 (60/420)

**Each tie represents two connections, e.g. the connection A has with Node X, and the connection Node X has with Node A*

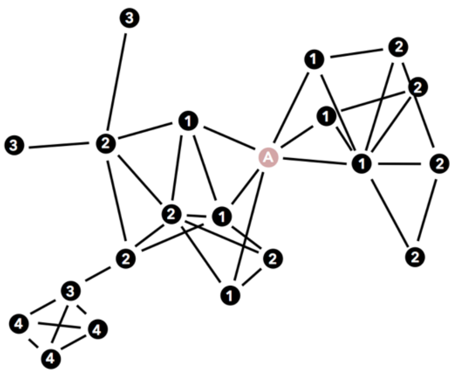


Node Measures

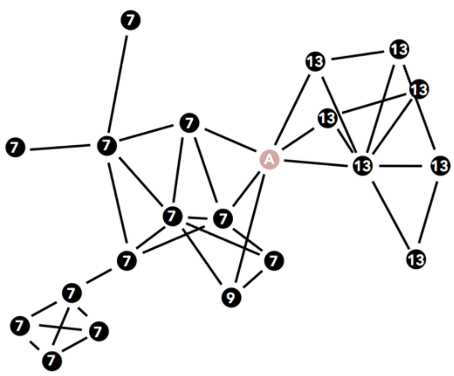
Calculating Degree Centrality:
The number of connections* Node A has to other nodes



Calculating Closeness Centrality:
Reciprocal of the number of ties Node A crosses to reach each node



Calculating Betweenness Centrality:
Number of times Node A connects two nodes



Calculations for Nodes A, B, and C
Overall centrality can be determined, either through subjective interpretation or using a quantitative approach e.g. an index.

	Degree	Closeness	Betweenness
Node A	12	0.23 [1/43]	275
Node B	10	0.2 [1/50]	74
Node C	4	0.012 [1/82]	0

Figure 3-2. Visualising and calculating network-based measures for the overall network and for individual nodes.

The use of these network-based measures (NBM) however was not sufficient to measure social capital as a concept. NBM are merely a mathematical evaluation of a network structure; they do not provide information on the quality of the relationships or the more cognitive aspects of social capital, such as the trusts and norms within a community and, as a result, introduce ambiguity regarding what is actually being measured when it comes to social capital (Adam and Rončević, 2003). NBM therefore do not solve the ongoing dilemma of whether the social networks are a source, form, or consequence of social capital. As a result, NBM can only reveal how relatively well an individual or group is connected and placed within a network and then estimate or assume the implications of this for social capital outcomes, such as agency and collective action. For example, do certain types of network structure have the tendency to facilitate collective action through their very structure? Ultimately, NBM must be linked with other measures of norms, trust, and reciprocity to provide 'local and contextual measurement' (Krishna and Shrader, 1999), in order to assess social capital. As a result, these limitations of this structural approach prevented NBM from becoming an overriding methodology to evaluate social capital.

Despite these shortcomings in measuring social capital as a concept, the influence of social networks, network structure, and connectivity on the ability of a community to deal with stresses and shocks has not been discounted. A review of 80 papers on community resilience by Patel *et al. (*2017), for example, found that community networks/relationships was one of nine core elements of a resilient community most commonly cited within research. It is apparent, therefore, that literature on social networks has developed outside of the main body of literature on social capital. In fact, a recent review, by Rockenbauch and Sakdapolrak (2017), of 60 empirical case studies that focus on the role of social networks within the general resilience of rural communities in the Global South, found that less than half (40%) of these conceptualised the role of social networks as social capital (Rockenbauch and Sakdapolrak, 2017). Instead, social networks were seen either as a form of coordination, connecting people, or as pipe, connecting flows of resources, information, and knowledge. This focus on social networks and connectivity as a means for communities to deal with external stresses, shocks, and risks is also reflected in a high prevalence of structurally-explicit analyses within the review. A total of 26 out of the 60 papers used some form of NBM methodology to evaluate the community's resilience. Furthermore, three-quarters of these papers (20/26) also used the same NBMs within their methodologies. The number or degree of ties, the density of the network, and the overall centrality were all used to evaluate the connectivity of the social networks. The review also showed that there was consistency in the units of analysis used, including which type of actors were studied (individuals, households) and at what scale (community, regional). The findings indicated an increased focus on the role of network connections and structure, rather than social capital. The studies also revealed methodological consolidation around specific NBMs, which together formed a consistent and overarching approach to assessing social networks as a key determinant of a community's resilience.

The implications of Rockenbauch and Sakdapolrak's (2017) research for DRR are important. The review shows that, in the wider resilience literature, a common, robust, and replicable methodology is developing that looks to measure social networks, network structure, and connectivity for resilience estimation. Furthermore, with their focus on the Global South sparked by the frustration that "the role of social networks for resilience of rural communities remained an under researched and under conceptualised issue, with research scattered between different strands and rarely integrated from a resilience perspective" (Rockenbauch and Sakdapolrak, 2017, pg. 1), their review provides a significant step towards consolidating this current disparate research under a singular canon of work. This prioritisation of social networks, rather than social capital, encourages researchers to move away from capturing an immeasurable concept and its associated debates (particularly concerning whether networks are a source, form, or consequence of social capital) to highlighting instead the importance of social connectivity and how different types of social networks and structures can contribute towards or even determine a community's resilience within the Global South.

3.7 Mapping Social Networks for Community Disaster Resilience

This move towards social networks, rather than social capital, as a core component and focus of analysis has started to filter into research on community disaster resilience. As Misra *et al.* (2017) suggested in their own case study, whilst the application of NBM and the use of SNA as a methodology is relatively new for community disaster resilience, it can be anticipated through a reflection on the emerging literature (Misra *et al.*, 2017).

Here we provide a review of several case studies that have used NBM and SNA to assess community disaster resilience to evidence this growing field of research. To enable comparison with and to build on the findings of the Rockenbauch and Sakdapolrak (2017) review, our analysis used the same methodology to assess how each selected case study conceptualised and operationalized social networks specifically within disaster resilience (Table 3-2), a 'strand' not covered by their review.

Table 3-2. Categories used to assess recent research which has analysed social networks; based on Rockenbauch and Sakdapolrak's methodology

	Category Applied	Questions Addressed
Conceptualisation	Conceptual Framing	Is resilience addressed implicitly or explicitly?
		How are social networks and resilience framed?
	Network variable	Are social networks treated as dependent or independent variables?
	Network narrative	What is the underlying conception of social networks?
Operationalisation	Network approach	What operational approach does the study follow?
	Network definition	What are the social relations of interest?
		Who are the actors and what are the relevant scales of interaction?
	Network analysis	On what network level does the analysis focus?
		What network characteristics are addressed?
Key findings		What key findings can be summarized regarding the question of how social networks relate to aspects relevant to the resilience of rural communities?

Our initial literature base was found through searching the Web of Science database (Clarivate Analytics, 2018), using a combination of the terms "social network" or "social capital" and then "community resilience" and "disaster risk reduction". The literature retrieved was filtered to only retain papers that focused on topics such as disaster preparedness, disaster response, disaster impact, and adaptive capacity. This was to ensure our review provided complimentary findings to the three resilience 'strands' covered by Rockenbauch and Sakdapolrak's review (natural resource governance, agricultural innovation, and general social support) and focused on the specifics of community disaster resilience. From the resulting DRR literature, case studies were then selected as per the criteria of Rockenbauch and Sakdapolrak's review, as follows: peerreviewed articles published in English from January 2000 (and in this case, the time period extended to May 2018), which only include empirical articles containing the analysis of data and only select those with case studies from the Global South, based on the categories "low-income" and "middle-income" countries from the World Bank (World Bank, 2016). The latter parameter removed five case studies, of which the majority of research had occurred in the United States, specifically in response to Hurricane Katrina. The Nakagawa and Shaw (2004) article was retained for analysis, despite the inclusion of Japan as a case study. The premise of the paper was that a model was developed for Kobe, Japan and then applied to Gujarat, India (Nakagawa and Shaw, 2004). As a result, the methodological approach was the same and the findings recorded primarily relate to the Gujarat case study. In total, 11 case studies were selected for analysis, the comprehensive results of which are found in Table 3-4 (in the Supplementary Materials section of this Chapter).

The analysis of the literature found that community disaster resilience research involving NBM and SNA in the Global South has primarily focused on the assessment of the strength of relationships within and between communities. The studies also evaluated the role of key actors, respective social positions of community members, and, in some scenarios, the assets and resources exchanged within the network. Five of the studies sought to explicitly compare the influence of these networks and positions directly with their impact on resilience. In terms of framing, only four case studies saw the role of social networks as solely creating, forming, or resulting in social capital, or in the case of Minamoto (2010), structural social capital. Instead, the majority of studies focused on social networks as connections or pipes, with studies aiming to 'connect the dots' (Guarnacci, 2016) and focus on 'the ties that bind' (Chaudhury *et al.,* 2017). Within these studies social networks were seen as a means of accessing and exchanging resources, information, support, and knowledge. Furthermore, there were also two studies that framed social networks by connecting these functions directly with social capital, e.g., social networks mobilise social capital by providing a form of coordination and by acting as pipes they help realise the benefits of social capital (Yandong, 2010; Misra *et al.,* 2017).

Overall social networks were primarily treated as an independent variable, where they are seen as the basic social units to respond to disaster (Sanyal and Routray, 2016).

Two of the studies however considered how social networks themselves are actually dependent on, and often the product of, various underlying social structures and processes (such as large scale migration) (Minamoto, 2010), as well as continually affected by ongoing exposure to hazards and disasters (Tobin *et al.*, 2014). Several of the papers also sought to make a distinction between the different types of networks present, categorising them into the three following types: bonding, bridging, and linking networks. These different types of networks, as outlined in Table 3-3, were primarily distinguished by the way in which an individual, group, or community is connected to another (Hawkins and Maurer, 2010). For several of the studies the importance of these different network types was how and when they would be used in which situations and for what purposes (Byg and Herslund, 2016), with each having a specific role within the disaster management cycle (Tobin *et al.*, 2014; Sanyal and Routray, 2016). For example, Misra *et al.* (2017) found that, in the early phase of a disaster, most of the response comes from social network ties within the community, but in the aftermath, the networks assumed different forms and took on different roles (Misra *et al.*, 2017). One paper also sought to classify the different larger-scale networks that these types of social networks usually form with one another, using their own terminology, including closed networks (dense bonding and bridging networks), extended networks (dense bridging networks), sparse networks (dispersed bridging networks), and subgroup networks (strong bonding networks with adequate bridging networks) (Tobin *et al.*, 2014).

Table 3-3. The different types of social networks. (Adapted from Marin *et al.*, 2012; Matin *et al.*, 2015; Pfefferbaum, Horn and Pfefferbaum, 2015)**.**

Type of social network	Bonding Social Networks	Bridging Social Networks	Linking Social Networks
Structural form	Strong ties, usually between family, close friends and local community.	Weak ties, usually between members of different communities and groups.	Weak ties but across different types of 'formal' agents, i.e., government agencies or organisations.
Network structure and power relations	Horizontal and collaborative – relationships are across the community with individuals at the same power level.	Horizontal and collaborative – relationships are across communities with individuals at the same power level.	Vertical and hierarchical – relationships are between the community and official governmental actors who have access to different levels of power.
Network composition	Homogenous – background, experience and motivation to help one another are similar.	Heterogeneous – background, experience and motivation to help one another are different.	Heterogeneous – background, experience and motivation to help one another are different.
Resources (e.g., initial medical aid, shelter and sustenance, or long-term financial assistance and mental support)	Similar (access to initial response supplies likely determined by geography).	Diverse.	Diverse and potentially unlimited.

To classify these networks, the majority of papers sought to capture an understanding of the social networks present and used by the community in everyday and emergency situations. The majority of papers (6) used a descriptive approach, using interviews and household surveys to gather information on the role of social relations and their outcomes in previous emergency situations (Sanyal and Routray, 2016). Different types of social ties were recorded that could then be classified into one of the three network types, (e.g., Nakagawa and Shaw, 2004; Byg and Herslund, 2016; Sanyal and Routray, 2016), although precise ties between members of the community were not covered. A structurally-explicit approach, where these ties were recorded, was employed by just under half of the studies (5). Of these five, four were published in the last three years. The more recent use of NBM and SNA substantiates Misra *et al.'s* (2017) assertion that the use of the methodology in community disaster resilience is relatively new (Misra *et al.*, 2017). Whilst undertaking a descriptive approach, Zhao (2013) also captured individual ties of the network studied; however, this only included the size and composition of the network and did not have the required detail (who knew who) to create the social matrix and, thus, use SNA or NBMs to assess them (Yandong, 2010). The majority (4) of these studies focused on capturing ties within a community or within several communities, i.e., focused on bonding social networks. Only one study was able to provide cross-community analyses of bridging networks (Tobin *et al.*, 2014). As a result, the majority of these structural-based approaches focused on looking at the importance of key actors and a member's relative positions to these central nodes within a bonding network (e.g., Guarnacci, 2016; Chaudhury *et al.*, 2017; Misra *et al.*, 2017).

Across the case studies, the connections within and between communities and community groups and how they form support networks to facilitate the response, recovery, and adaptation to disaster were the main social relations of interest. In addition, several papers also looked at the relationships the communities had with formal organisations (linking networks), such as non-governmental organisations and governmental departments (e.g., Minamoto, 2010; Sanyal and Routray, 2016). The primary actors were either individuals or households within the community, although three of the papers also looked at community groups (Nakagawa and Shaw, 2004; Minamoto, 2010; Sanyal and Routray, 2016). All of the analyses were conducted at the community scale, with the five structural approach studies capturing social ties from either individuals or household actors, within their village or community. Of these five studies, four used the same NBMs discussed above in Rockenbauch and Sakdapolrak's (2017) review, number of ties, density, and centrality, as measures to assess the social networks. The fifth paper, as outlined earlier, utilised their own method of classifying networks, although this would have been reliant on using the same NBMs to achieve this classification. In addition to the information on social ties, several of the descriptive and structural studies recorded other attributes of each actor, including gender, age, location (urban versus rural), religion, ethnicity, and socioeconomic status, to evaluate whether these attributes had any type of influence on the social networks (Nakagawa and Shaw, 2004; Yandong, 2010; Tobin *et al.*, 2014; Guarnacci, 2016; Sanyal and Routray, 2016; Patel and Gleason, 2018).

The majority of the studies found that, for communities in the Global South, an individual's, household's or a community's social networks are increasingly seen as the basic unit to respond to disaster (Sanyal and Routray, 2016) and that their strength and effectiveness influences the ability of the individual/household/community to respond to disaster (Misra *et al.,* 2017). The consensus across the studies was that social networks positively affected community recovery and resilience by mobilising and providing support, resources, and information to those at need and could even compensate for weaknesses in a wide variety of factors that led to reduced resilience and increased risk (Patel and Gleason, 2018), e.g., failing governmental DRR policy. In fact, the studies overwhelming concluded that failing to consider the local community, their network structure, and their power relations could seriously hamper and even damage how these networks act as a resource for the community during a disaster, putting the communities in greater danger if hit by a disaster (Minamoto, 2010; Sanyal and Routray, 2016; Misra *et al.,* 2017). A further finding of many of the studies was that leadership within the community was particularly important to foster collective action. Without leadership or central players, there could be a lack of trust and coordination among members (Nakagawa and Shaw, 2004; Guarnacci, 2016; Misra *et al.,* 2017), even if their social networks, from a structural perspective, would be considered to be 'good' (e.g., a high density of social relations with few structural holes or bridges).

The evaluation of these case studies by this paper provides several new findings to build on Rockenbauch and Sakdapolrak's review. Firstly, our review indicates that a common methodology is developing around SNA within DRR that corresponds with the approaches documented by the 2017 review. The structurally-explicit studies reviewed here utilised the same NBMs and assessment of social networks as those found within the 2017 review. The synergy between these different strands of research, all within the resilience canon, suggest that SNA and NBM are providing a first step towards a repeatable and robust methodology for community resilience estimation. By moving away from social capital, focusing on a methodology that prioritises social networks, network structure and connectivity "holds promise for theorising and analysing resilience" (MacGillivray, 2018, pg.116), not least because it can bring together and integrate different strands under the resilience perspective.

Secondly, and specifically to this review and DRR, the case studies showed that it is not only important to understand what different types of networks exist (bonding, bridging, and linking), but also how they operate at different points of the disaster management cycle, and how these can either help or hinder a response. For example, a community with a strong bonding network can result in a substantial internal response to a shock; however, if they have weak bridging or linking networks, they will be unlikely be able to access any help or resources beyond their initial community. The presence of these three network types, therefore, can be advantageous or harmful in routine and emergency situations (Byg and Herslund, 2016). As a result, across future DRR and community disaster resilience research, it is imperative that these three network types are assessed across the different timepoints during the response to and recovery from a disaster (Sanyal and Routray, 2016). Furthermore, two of the case studies provide critical reflections on how independent a social network truly is and highlight that any network should be viewed and analysed in light of its ongoing social, economic, geographic, and political context (Minamoto, 2010; Tobin *et al.*, 2014).

Separate from the Rockenbauch and Sakdapolrak's (2017) review, this evaluation provides a practical understanding of why social networks and social network mapping should be used within community disaster resilience research in the Global South. Mapping the community's networks, including their external relations, provides a clearer picture of the community structure and the role of local actors and local networks (Chaudhury *et al.*, 2017), which can then be directly linked with particular resilience features (Rockenbauch and Sakdapolrak, 2017). For researchers and practitioners alike, these case studies showed that social network mapping is an imperative step to understanding how community disaster resilience is built from the bottom-up. Without taking into account local social structures within a community, any top-down implementation of preparedness policy and procedures, such as introducing a community disaster committee, are likely to fail and could even harm the community and its networks it uses to protect, help and rebuild itself (Sanyal and Routray, 2016).

The significance of bringing together the case studies reviewed, and the consensus of their findings, is that this paper can offer tangible actions that can be used directly by DRR practitioners. The collective case study evidence reviewed suggests that social network mapping could be an invaluable tool for practitioners to understand how community resilience is built from the bottom-up. To date, social network mapping is not a common tool found within DRR practice, programming, and policy, remaining primarily in the hands of researchers who are only just making the connections between high-level development concepts, such as resilience, and community-level processes such as social support, response, and recovery. This is despite these types of bottom-up approaches being at the heart of the recent resilience-focused frameworks, such as the roadmap to resilience by the International Federation of the Red Cross (IFRC) (International Federation of Red Cross and Red Crescent Societies, 2016). The IFRC roadmap, for example, advocates that resilience-building processes must be people-centred and inclusive and that a key priority is to encourage communities to engage and connect with other stakeholders, such as nearby communities and government agencies (International Federation of Red Cross and Red Crescent Societies, 2016). The IFRC roadmap, in fact, recognises SNA as a tool within their roadmap, however it is not explicitly linked with the mapping of community networks to assess resilience nor are there suggestions of how to deploy SNA. However "the capacity of social network maps as a multi-purpose heuristic device is very useful—indeed necessary – if we want to explore ideas of community resilience and planning in the face of natural disasters" (Matin *et al.*, 2015, pg.0), suggesting that SNA and NBM are a critical tool for those working in the Global South to fully understand community disaster resilience.

3.8 Innovation Within Social Network Mapping for Community Disaster Resilience

Despite the initial positive start of connecting research to practice and even policy, many researchers, agencies, and disaster practitioners are yet to fully embrace social networks as a priority for preparedness. One potential reason for this lack of engagement is that much of the literature supporting these theories is nascent and relatively disparate and does not end up in the hands of those who need it most. Here, our review provides a first attempt to consolidate this emerging field of research and address it within the challenges of current community resilience and social capital research, with case studies drawn from the Global South. The studies we reviewed show that the creation of these social network maps is possible and these maps provide invaluable information that can be utilised by practitioners to make tangible improvements to a community. However, there are still limitations to using social network mapping for this type of DRR policy.

The major challenge of moving current SNA research forward is that social networks need to be viewed through what Rockenbauch and Sakdapolrak (2017) call a 'translocal' lens, one that not only assesses networks with regards to how they change over time but also over space as they become coupled with mobility (Rockenbauch and Sakdapolrak, 2017). Unlike the strands of research studied by Rockenbauch and Sakdapolrak (2017), DRR has the ability to explicitly account for the temporal dynamics of social networks by pinpointing a time when a disaster or event has occurred and comparing the changes in pre- and post-disaster networks. By having an event (real or hypothetical) to account for, it is proposed here that DRR research can lead the study of how social networks evolve and how this impacts a community's resilience (Minamoto, 2010; Tobin *et al.,* 2014; Sanyal and Routray, 2016; Misra *et al.,* 2017). The issue of spatio-temporality in the current literature (Misra *et al.*,2017) is pertinent when considering the importance in community disaster resilience of asking not only the question of resilience of whom, but also the resilience to what (Cutter, 2016a).

The mapping of social networks pre-, during and, post-disaster may provide insight about how a community's disaster resilience changes in response to a shock, underlining resilience not just as a property but also as a process. For example, Misra *et al. (*2017) used the case study of a cyclone-affected community in coastal West Bengal (India) to identify how network structure and different key actors changed within the different phases of response, resulting in "a changing pattern of evolving networks during and after the disaster"(Misra *et al.,* 2017, pg.281). However, the scale of their study was limited; a sample size of 33 actors in a specific area, covering a timespan of thirteen months and one week post-event, was "not large enough for reaching a generalized inference in the area of disaster management" (Misra *et al.,* 2017, pg.295). Extending network analysis beyond the immediate community and over longer timespans is essential to capture the temporal and spatial change, not only of the community's networks but also their disaster resilience.

The ability to extend analyses across communities and timespans is currently a significant obstacle that SNA in community resilience measurement will need to overcome and, primarily, data collection is the cause of this obstacle facing most studies. Firstly, social network mapping is limited in geographical scope due to the traditional collection of the data using individual or household interviews and questionnaires. Whether it is the cost or logistics, extending SNA studies over greater geographical scales is likely to be difficult with traditional data collection, i.e., surveys and questionnaires. This method of data collection also limits the temporal analysis, where logistical and ethical reasons challenge the collection of data directly after a disaster hits (such as travelling to areas immediately after a disaster and potentially diverting resources away from the communities that need them more, e.g., shelter, food). Capturing the changes in the social networks during the different phases of the disaster management cycle, however, constitutes an important scope for future studies (Misra *et al.,* 2017) and, as a result, innovation within social network measurement needs to occur to facilitate Rockenbauch and Sakdapolrak's (2017) translocal lens.

A potential answer to this problem is through the use of dynamic datasets, currently underutilised, within community resilience research. Here we propose that the growing intersection between big data and development, as promoted by the UN's data revolution (UN Data Revolution Group, 2014), could be used within community resilience research. Dynamic network datasets, such as mobile phone metadata (known as call detail records) and social network datasets, could be used to map community connectivity through the reconstruction of community social networks. Already, research has shown that these datasets are able to reconstruct key human behaviours, including mobility, social contact, and expenditure, at fine spatial and temporal resolutions, at national spatial coverages, and over extensive time periods (Blondel, Decuyper and Krings, 2015).

These outputs have been used to provide estimates on the total population of an area (useful for when a census is unavailable) (Douglass *et al.,* 2015), explore daily and seasonal travel patterns (national and internationally) (Deville *et al.,* 2014; zu Erbach-Schoenberg *et al.,* 2016), and characterise these behaviours, along with different expenditure-top up routines, to predict socio-economic characteristics (Fernando *et al.,* 2018). These insights have found multiple uses within sustainable development applications, including poverty estimation (Blumenstock, Cadamuro and On, 2015; Steele *et al.,* 2017), epidemiology (Bengtsson *et al.,* 2015), and disaster response (Bengtsson *et al.,* 2011). The need for investigating such an approach is timely considering the call within the Sendai Framework to promote and enhance the use of big data to support national measures for successful disaster risk communication (UNISDR, 2015). Here we suggest that understanding the feasibility of using these types of data is a key step towards viewing community disaster resilience through the proposed 'translocal' lens and should be of significant interest and focus to those working to bring innovative insight into research within DRR and community resilience.

3.9 Summary

Social networks are seen as crucial to helping individuals and communities recover from and rebuild after a disaster. Whilst social networks have been traditionally evaluated in the wider concept of social capital, difficulties in the definition and operationalisation of social capital has led to the development of a subsection of literature specifically on mapping and measuring social networks for community resilience. Moving beyond social capital to focus on the structure, content, and geography of social networks is argued to hold great promise for the theorising and analysis of community resilience (MacGillivray, 2018). As a result, social networks, and their measurement, have become "one of the most promising developments for disaster risk reduction" (Alexander, 2013, pg.2713). This paper provides a review of recent case studies in the Global South to provide evidence to further substantiate this argument, showing that not only is a cohesive and robust methodology is developing around SNA and NBMs within community disaster resilience research, but that social network mapping is an imperative and essential step to truly understand how a community's resilience is built from the bottom-up. Without a thorough understanding of local structures and relationships, policies are likely to fail in the countries that need them most.

Current studies are, however, limited by space (extending analysis beyond the community), time (showing dynamic changes in networks), and, when considered together, 'translocality' (understanding how changes occur over time and space). To move research forward, using Rockenbauch and Sakdalporak's (2017) translocal lens, we suggest here that dynamic datasets could provide proxies of people's social networks communities. Whilst these data have provided some new insights into social response during a disaster, their capacity has yet to be truly intersected with DRR policy and practice. Here it is proposed that mapping community social networks provides the ideal opportunity to explore the use of innovative data for community disaster resilience estimation. Overall, this paper advocates that the use of social network mapping and analysis should be utilised more widely, within resilience research and potential policy-influenced programming, to contribute towards fulfilling the current priorities outlined by international DRR frameworks.

3.10 Supplementary Materials

Table 3-4: Results of Literature Review Analysis

Author	Research interest	Conceptualization			Operationalization				Key findings
		Conceptual framing	Network variable	Network narrative	Network approach	Network definition	Network analysis		
							Network level	Network characteristics	
Nakagawa and Shaw, 2004	Examine the role of social capital in post-earthquake rehabilitation and reconstruction programs in Kobe, Japan and Gujarat, India.	Implicit reference to resilience: Social capital, leadership and a tradition of community activities encourage participation in reconstruction programs and are the most effective elements in enhancing collective action and disaster recovery.	Independent: Influence of community networks to encourage participation within rehabilitation events post-disaster. Networks categorised into the three types of social capital (Bonding, Bridging, Linking) for modelling.	Social capital: Social networks as source of social capital. Different networks confer different types of social capital on their members.	Descriptive: Interviews with key stakeholders, including government officials, NGOs and academics. Social capital questionnaire for communities, based on Integrated Questionnaires for the Measurement of Social capital. Secondary analysis of related studies, articles and documents.	Social relation: connections within and between community groups, collective decision making, and links to formal organisations Actors: Community groups Scale: Local / Community	Individual: Community members Subgroup: Community groups	Actor: Group affiliation (age, employment, gender, religion, caste) Tie: Tie type (bonding/bridging/linking)	At every stage of the disaster cycle, the communities played the most important role among other concerned stakeholders. Communities with social capital are found to be efficient in rescue and relief. Social capital is not the sole factor determining speedy and satisfying recovery – strong leadership inside the community is also essential for any collective action. Leadership is an important issue in any community-based activity and in development projects.

Minamato, 2010	Examine the relationship between livelihood recovery and social capital to help improve disaster response at the community level in Sri Lanka.	Implicit reference to resilience: Micro-social capital (linkages within communities, relationship of trust and norms during recovery) may help the process of disaster recovery.	Dependent: Networks are the product of various social structures.	Social capital: Social networks provide the structural component of social capital.	Descriptive: Household surveys, using World Bank Social capital Tool. Regression analysis.	Social relation: Mutual support networks. Actors: Households / Community-based organisations Scale: Local / Community	Individual: Community members Subgroup: Community-based organisation	Actor: Group affiliation (Community-based organisation) Tie: Reciprocity, trust Context: During reconstruction programmes	Formal community networks, and the leadership and trusteeship of community-based organizations improve people's perceptions of livelihood recovery. Establishment of new organisations after an event which involve semi-forced participation can create negative social capital. Disaster aid needs to consider seriously the social factors and power structure of the community during the reconstruction stage.
Yandong, 2010	Role of social networks during and after a disaster as a conduit of social capital in China.	Implicit reference to resilience: Social networks play an important role in reducing risk during and after a disaster by facilitating the flow of information, as well as providing various types of support and help maintain the mental health of victims. These all contribute to improving and increasing the speed of recovery.	Independent: Influence of social networks on recovery from a disaster.	Social capital / Pipes: Social networks providing support, information and knowledge after an earthquake, which realises the benefits of social capital.	Descriptive: Post-Wenchuan Earthquake Rapid Needs Assessment (Household). Social network basic attributes: Chinese version of position generation – 'spring festival network', no. of people contacted (baseline); change since earthquake. Ordinary Least	Social relation: recovery, support (mental and physical) and information Actors: Individual Scale: Individual; Regional	Individual: Respondents	Actor: Age, health, network change, income Tie: Support, information Structural characteristics: Size of network, composition of network (number of relatives in network), deterioration of networks, new members.	Majority of disaster victims are rescued by their social network members. Social networks played an indispensable role in facilitating information flows in disaster affected areas. A more heterogeneous network is better for getting new information. Social networks played a supplementary role (to governmental assistance) in providing support to victims. Social networks are very important in maintaining the mental health of disaster victims. The bigger the network, the better the psychological outcomes. Dense and homogeneous

					Squares regression.				networks are good for providing emotional support.
Tobin *et al.*, 2014	Modeling the impact of personal networks on community resilience in Ecuador and Mexico.	Explicit reference to resilience: Social networks may enhance individual and group recovery from hazard exposure and ultimately enhance community resilience.	Dependent: Chronic exposure to ongoing disaster may influence social network structures, which in turn may shape individuals' abilities to adapt to the hazardous conditions.	Form of coordination: How people are connected, how they support each other and how individuals play different roles within a network can significantly impact decision-making and eventual outcomes.	Structurally explicit: Questionnaires, in depth interviews and focus groups in 6 communities (4 in Ecuador, 2 in Mexico). Socio-demographic survey for basic community characteristics. Wellbeing survey for one participant per household. Social Network Analysis (SNA): Wellbeing participants, 45 contacts, 25 of which selected for attribute and relation analysis.	Social relation: Emotional closeness, support (social, personal, financial or material), interaction with others within their network Actors: Community members Scale: Local / Community	Individual: Personal networks	Actor: Individual attributes (sex, age, socioeconomic status, ethnicity) Tie: Bonding and bridging ties Structural characteristics: Classification of networks into four types: tight/closed; extended; subgroups; sparse.	Disaster recovery is impacted by social network type and these networks play different roles depending on the prevailing conditions in the community. Medium density, sub-group networks with good bridging or connectivity to different sub-groups were better adapted to the demands of disasters and evacuations than those with denser networks and limited bridging. Sparse or open/weak networks may not have sufficient social influence to act in emergency situations and are often more vulnerable and show lower levels of wellbeing. Networks with close ties provide greater support mechanisms fostering reciprocal relationships amongst their contacts, reporting more sharing of resources. Conflicting results regarding the role of density. Geographic distance was negatively correlated with frequency and strength of contact. Structure of relations is indeed important for disaster recovery but mechanisms depend on context.

									Must consider to a degree to which network structure is a product of the hazards themselves.
Byg & Herslund, 2016	Investigate the use of social capital in the form of social ties to increase livelihood diversity and decrease vulnerability in Nepal.	Implicit reference to resilience: Adaptation – the ability to adjust to a disturbance, take advantage of opportunities and to cope with the consequences of transformations, usually for climate change but can be applied to other kinds of changes. The adaptive capacity of a system is influenced by factors including social capital.	Independent: Social ties can be used to access resources which can help people make use of opportunities and deal with change. Not only the number and kind of ties, but also the situations in which different ties can be used and for what purposes.	Pipes: Benefits of social networks include the ability to provide individual or groups with access to resources (material as well as information) and enable group action.	Descriptive: Household questionnaire, interviews and focus groups in three areas (lowland, mid-hills and the Himalaya).	Social relation: Information sharing, labour sharing, Actors: Households in the communities / Individuals Scale: Local / Community	Individual: Households / Personal	Actor: Location type Tie: Different types of ties for different purposes. Context: Information on climate changes, agriculture, jobs and business opportunities i.e., livelihood changes.	People made use of a mix of ties that could be classified as strong and weak – but it is difficult to maintain clear distinctions between the two. Distinguish between the existence of ties and the resources which become available through them. Some ties were used in some situations but not in others. Personal ties were used to obtain information, references and sometimes loans. Within the villages, people were very reluctant to cooperate and share resources or information with each other. Sharing only took place among the closest relations or with people situated elsewhere. Location influenced access to markets, jobs and enterprises despite social contacts. Diversification reduces levels of vulnerability at the household level.
Guarnacci, 2016	Social networks and community resilience in post-disaster and -conflict Indonesia.	Explicit reference to resilience: The ability of a community to absorb the negative impacts	Independent: Social networks give rise to social capital which becomes an	Social capital: Value arises from social networks, which is a crucial resource for	Structurally explicit: Semi-structured interviews. SNA: Whole	Social relation: Social support (close ties); Information / materials (weak ties)	Individual: Community members Network: Community network	Actor: Impact of disaster, ethnicity, religion, gender, urban vs rural Tie: Betweenness centrality (gatekeeper role), modularity	Affected communities are not uniform entities since survivors' personal characteristics such as ethnicity, religion and gender contribute to create different social circles. Need to give consideration to the smaller

		of a disaster, The capability to adapt and transform depends on the structure of social networks which varies according to the strength of ties, the social position of key actors and the nature of information and resources exchanged among them.	asset for communities to use in disaster response.	engaging in rescue activities, facilitating evacuation, acquiring information about policies, enhancing household-level disaster preparedness and improving community-based disaster risk management.	network, with attributes, using name generator approach.	Actors: Individuals Scale: Local/ Community + linkages to external actors		Context: Impact of Indian Ocean tsunami in 2004	closely knitted subgroups. SNA used to identify central players who have fundamental role to help victims in dealing with crises and without whom the buffering capacity of the community is deeply altered. Community resilience is also fostered through the help and resources channelled by regional and global players, including religious and ethical organisations located outside the local area.
Sanyal and Routray, 2016	Examining social capital as a resource to help reduce disaster risk for communities, applying findings from empirical studies to the Sundarbans.	Implicit reference to resilience: Social capital plays an important role in the disaster management cycle, reducing risk within communities and helping them to survive by providing support and insurance when infrastructure and disaster management institutions fail.	Independent: Social networks and social associations are considered as the basic social units to respond to disasters. Networks categorised into the three types of social capital.	Social capital: Social networks as source of social capital. Different networks confer different types of social capital on their members. Each type of social capital has a specific role within the disaster management cycle.	Descriptive: Field survey, key informant interviews, focused group discussions in one community. Secondary data collected on role of social resources in past emergency situations.	Social relation: connections within and between community groups, collective decision making, and links to formal organisations. Actors: Community Groups Scale: Local / Community	Individual: Community members Subgroup: Community groups	Actor: Group affiliation (age, employment, gender, religion, caste) Tie: Tie type (bonding/bridging/linking) Context: Participation within community activities leading to recovery. Exclusion due to environmental and political issues.	Social capital plays an important role throughout the disaster management cycle. The network at the community level is crucial for the survival of the overall community. Huge role to play in strengthening capacities at the community level for better risk reduction. Similar culture and religious institutions act as de-facto community centres. Might be different drivers of social capital across countries, but there is a lot of similarity in the way social capital works in the event of a disaster. Social capital and the experience of dealing with adversities is vital for remote

									communities. The efficiency and effectiveness of activities can be influenced positively by the use of the traditional structure of the community rather than creating new ones. Just the top-down approach can seriously hamper and damage how social capital acts as a resource for reducing the risk of and responding to disasters.
Schramski, 2017	Using SNA at the household level to assess the role of social networks within adaptive capacity in rural South Africa.	Explicit reference to one component of community resilience: Social networks can help households improve their adaptive capacity, one of the main features of community resilience.	Independent: Network capital improve a household's capacity to conduct and engage with resource exchange that helps with adaptive capacity.	Pipes: Social networks as a means of accessing and exchanging information, financial and material resources.	Structurally explicit: Adaptive capacity index, Livelihood survey, Ethnographic interviews. SNA: Personal, whole network.	Social relation: resource exchange Actors: Households Scale: Local / Community	Individual: Households Network: Community	Tie: Exchange of food, water, wood, labour, information about diseases, money Structural characteristics: Betweenness centrality, degree centrality	Exchanges of labour, money, and disease information are all related to adaptive capacity. Households that exhibit greater degree centrality in labour exchanges appear to have greater adaptive capacity, although the same cannot be said for their betweenness centrality. Natural resource exchanges are not necessarily associated with measures of adaptive capacity in a rural poor region of South Africa.
Chaudhury *et al.*, 2017	Examine how bridging relations of rural communities with local actors impact their own bonding structures as well as their	Implicit reference to resilience: The capacity of any individual or household to cope and adapt to threats largely depends on their personal networks,	Independent: Strong networks are essential for improving everyone's adaptive typical.	Pipes: Relationships, network structures and networks positions are crucial to understanding the adaptive capacity of both	Structurally explicit: Workshops, surveys, network mapping and semi-structured interviews. SNA: External relations of a	Social relation: Links to outside actors Actors: Individuals and local 'actors' Scale: Local / Community	Individual: Household / Member Network: Community	Actor: Local actors by type of group Tie: Number of links to overlapping local actors Structure: Network size, network position (indegree centrality), density, degree centrality, betweenness centrality	Social connections provide important resources and knowledge to build adaptive capacity. A household's capacity to adapt and its network position is linked, but it is difficult to be certain which way around this relationship works. Close relations with local actors improve responses to

	capacity to adapt in Ghana.	attributes, livelihoods and capital bases.		households and the community, providing resources and knowledge.	community (bridging ties) – used to infer internal relations (two-mode data). Adaptive capacity measures.	and links with local 'actors'			environmental change and associated problems, which can enhance household capability, influencing adaptive capacity. Drawing community networks based on external relations helps gain a clearer picture of the community structure, centrality and stratification of households and the role and changing position of local actors and redundancy of networks.
Misra *et al.*, 2017	Community networks before, during and after a disaster in West Bengal, how they changed and their role in community resilience.	Explicit reference to resilience: Social capital and agency lead to collective action in the community at different phases of the disaster which enhances the resilience of households and the community itself.	Independent: The strength and effectiveness of social networks influence the ability of a community to cope with disaster events.	Social capital / Form of coordination: Agency is realized through the existence of agents in the network who mobilize social capital to produce a sustained flow of resources i.e., social networks work together by encouraging agency as well as providing the resources used by that agency.	Structurally explicit: Focus group discussions. SNA: Whole network – measure cohesiveness to determine social capital; identify key players based on structural position in community social network. Resilience measured by index adapted from FAO, using income, food security and other variables.	Social relation: Aid and support, contact Actors: Individuals and households in the community Scale: Local / Community	Individual: Household Network: Community	Actor: Background variables, institutional affiliation Tie: Number of ties, network density, average degree and network centralization (including degree centrality, closeness centrality, betweenness centrality) Context: Changing over different phases	Importance of network structure and different central node/s in the networks that evolved over time. In the early phase of the disaster, most of the searching and rescuing endeavours came from endogenous social network ties of the community. In the aftermath, networks assumed different forms and featured different key actors. Networks facilitated the flow of information and external support, to maintain the daily life of the victims. The underlying perspective in disaster research, which claims that communities are important collective units, is clearly evident in the findings presented here. Networks played an important role in reducing the risk during and after disaster. The change in these networks in different phases of the disaster

									constitutes an important scope of further studies. Social networks, along with community leaders and local administration, can be used during and after the occurrence of disasters to make effective interventions. Failing to understand this network and local culture may endanger the disaster-hit communities badly. The analysis of social networks in the context of a disaster may illustrate the interactions within and between community networks, which itself can improve situational awareness, as well as enhance planning and optimise resource allocation. All of these are essential for improving disaster preparedness, response and recovery efforts, and community resilience.
Patel and Gleason, 2018	Association between social cohesion and community resilience in urban slums in Haiti.	Explicit reference to resilience: Social cohesion (rather than networks) may enable a wider array of resources drawn for greater cooperation, sharing and help in times of stress, conferring greater	Independent: Social cohesion is a positive factor in community resilience, playing an important compensatory role, particularly when all other	Form of coordination: The presence of social cohesion features (e.g., organization, trust, norms and networks) can improve the efficiency of society by facilitating	Descriptive: Population survey, developed from focus group discussions, to gain information for four main indicators. Social cohesion index developed	Social relation: Trust, wellbeing, collective action Actors: Individual, community Scale: Local / Community	Individual: Community members Network: Community	Actor: Socio-economic / demographic data, time in community, time in house	Social cohesion helps drive resilience, highlighting the importance of considering social cohesion in all programs and policies aimed at improving resilience and disaster risk reduction. Decision makers should not make assumptions about individual, demographic or other factors that may be assumed to enhance resilience or focus resources solely those, including

		resilience on communities to disasters.	systems of support fail.	coordinated actions.	from neighbourhood cohesion index. Community resilience, using Communities Advancing Resilience Toolkit.				social resilience. Social cohesion may compensate for weaknesses in a wide variety of factors that lead to reduced resilience and increased risk.

Chapter 4 The role of social networks within disaster risk reduction in Nepal

4.1 Overview

This chapter establishes the suitability of Nepal as a case study for the thesis and its main objective of using Call Detail Records to measure social connectivity for community disaster resilience. Whilst, as shown in the previous chapters, there is substantial evidence that social networks are critical for community disaster resilience, assessing the applicability of the measure specifically for Nepal is important to understand its potential impact for resilience estimation within the country. The Chapter uses the case study of the 2015 Nepal earthquake to illustrate why understanding social connectivity in Nepal is essential for disaster risk reduction.

4.2 Introduction

Nepal is a hotspot for disasters (Dilley *et al.,* 2005). Its climate and geography subject it to frequent climatic and climate-induced hazards such as flooding and landslides, whilst its location in the middle portion of the Hindu Kush Himalayan region, a highly seismic prone region, has resulted in a long history of destructive earthquakes. However, the country's predisposition to turn these natural hazards into a disaster is deeply embedded within the wider inequalities within the social, economic and political systems operating in Nepal (Devkota, 2007). Concomitantly, Nepal's Disaster Risk Reduction (DRR) policy has also suffered from inaction within the government, with many policies drafted but often never implemented (Regmi, 2016). Local-level disaster preparedness and management activities have been minimal (Lam and Kuipers, 2018), despite being identified as a key mitigation strategy in global DRR policy (International Federation of Red Cross and Red Crescent Societies, 2016). With this inequality and inaction, Nepal's communities have learnt to be self-reliant, striving to meet their needs within their extended family, neighbours and ties to other communities (Ruszczyk, 2014). This social system of support, created through the presence of social networks within and between families, households, and communities, is a critical resource for their ability to respond to and recover from a natural hazard (Carrero *et al.,* 2018).

This chapter provides a critical review of the importance of these social networks for community disaster resilience in Nepal and why an understanding of social connectivity is essential to DRR within the country, reflecting on evidence from the 2015 Gorkha earthquake. The risk of Nepal to disaster first is outlined by exploring its natural susceptibility to hazards due to its geography and climate as well as how Nepal's populations are substantially vulnerable to the impact of these hazards, due to the effects of structural inequality and weak DRR policy implementation. The chapter then highlights the importance of local social networks for communities in Nepal, particularly during and in the aftermath of a disasters, as illustrated by the findings of thirty-two articles and reports from the 2015 earthquake (Neupane, 2015; Carrero *et al.,* 2018; Hillig and Connell, 2018).

4.3 Understanding disaster risk in Nepal

4.3.1 Susceptibility of Nepal to hazards: geography and climate

Nepal's geography and climate has rendered it susceptible to natural hazards. Sitting on the converging boundary between the Indo-Australian and Eurasian plates, the country is an active tectonic region and prone to earthquakes. The collision between these two plates has resulted in a varied topography, with three major elevation-based physiographic regions (or 'belts'), the Mountains (Himalayas), the Hills (Mahabharat Range), and the Terai lowlands, which transect the width of the country in a north-south direction. These three regions are divided by three major river systems that flow from the mountains through the hills into the Terai, carrying alluvium and debris downstream. In addition to a wide-ranging topography, the country has a varied climate, from alpine to tropical temperatures, as well as being subject to a monsoon season (Shrestha and Aryal, 2011). The occurrence of the monsoon is a sensitive balance; failure of the rains has historically resulted in drought and famine (Piya, Maharjan and Joshi, 2013), whilst above-normal rains can cause flooding and landslides (Talchabhadel *et al.,* 2018), which can lead to other cascading hazards, such as disease spreading through contaminated water.

The predictability of the monsoon and the preceding rains and/or dry spells is becoming more difficult and problematic. Recent research shows that precipitation extremes in Nepal (including intensity and frequency of both rainy and dry days) are increasing, as well as there being a greater tendency for the country to experience warmer temperature extremes (Shrestha and Aryal, 2011; Piya, Maharjanan and Joshi, 2013; Karki *et al.,* 2017; Talchabhadel *et al.,* 2018). The cause of these extremes is argued to be global climate change, which is the warming of the atmosphere and world's ocean systems, in part influenced by human activity (Shrestha and Aryal, 2011). The rise in global temperatures is having specific consequences for Nepal's own climate and physiography; the country is showing an average warming trend of 0.06°C per year (Shrestha and Aryal, 2011). The warming rates are also higher for high elevation locations and has resulted in the rapid shrinking of the majority of glaciers in the Himalayas (Shrestha and Aryal, 2011). With glaciers providing up to 50% of the average annual flows within Nepal's rivers (in addition to the summer monsoon rains), this increased glacial melt is having serious implications for downstream water availability in both the short and long term (Dahal *et al.,* 2019), including increasingly the likelihood of intense flooding events.

These changes in climate extremes are increasing the susceptibility of Nepal to weather-related hazards, with precipitation extremes and glacial meltwater increasing the likelihood of seasonal and sporadic flooding as well as the resulting fast and substantial river flows causing landslides through erosion (Piya, Maharjan and Joshi, 2013; Talchabhadel *et al.,* 2018). Even when the original hazard may not be climatic by source, e.g., an earthquake, the impact of the hazard may be exacerbated by these extremes and result in cascading hazards, such as liquefaction or landslides triggered by an earthquake. Nepal's natural hazardous conditions are key factors that need to be considered within disaster risk reduction policy, including adaption and mitigation strategies.

4.3.2 Vulnerability of Nepal to hazards: population, economy and social structure changes

The number of people that could be exposed to these hazards in Nepal is growing: in 2015, Nepal's population was estimated to be around 27 million people and is likely to reach over 30 million by 2022 (United Nations, Department of Economic and Social

Affairs and Population Division, 2019). This population is also on the move and becoming more concentrated in the Terai lowlands as well as in cities within the Kathmandu Valley (United Nations Population Fund, 2017), which is creating new population-related pressures and vulnerabilities, such as overcrowding and inadequate infrastructure, in areas that are susceptible to flooding (Karki *et al.,* 2017) and landslides (Petley *et al.,* 2007). This movement of people in Nepal has been driven by economic need, with regional imbalances existing in the distribution of resources, opportunities, and access to services resulting in varying levels of poverty, unemployment and food insecurity (Suwal, 2014).

The rural population has principally been reliant on agriculture as a primary source of income, however with only 17% of Nepal's land being suitable for productive cultivation, earning a livelihood from the land is difficult, particularly in the Mountain regions (Donohue and Biggs, 2015). Furthermore, with much of this agriculture entirely dependent on rain, long-term climatic events such as drought can cause widespread food insecurity as well as put livelihoods at risk (Donohue and Biggs, 2015). With the poverty rate in rural areas more than double that in urban areas (Von Einsiedel, Malone and Pradhan, 2012), many Nepalese have sought employment in the growing service sector within Nepal's growing cities (International Labour Organization, 2014), as well as further afield, or moved towards the Terai where the climate is more favourable but land is scarcer.

The migration into the main urban cities has created new hazard-related vulnerabilities. It is predicted that between the period of 2014-2050, Nepal will remain amongst the top ten fastest urbanising countries in the world with a projected annual urbanisation rate of 1.9% (Bakrania, 2015), with the Kathmandu Valley growing at around 7% per year (The World Bank, 2013). The movement has resulted in extensive and unplanned urban sprawl, resulting in infrastructure that is not suitable for earthquake-prone areas (The World Bank, 2013). Densely packed, uncontrolled and substandard housing on narrow streets increase vulnerabilities, such as building collapse, and present challenges, e.g., emergency service vehicles being able to access trapped residents, in the event of a hazard (Carpenter and Grünewald, 2016). Other pressures, such as inadequate access to potable water and sanitation facilities, can create additional hazards, such as the spread of waterborne diseases (Sekine and Roskosky, 2018), whilst faltering power supplies can create or exacerbate vulnerabilities, such as maintaining communication lines during disaster response (Wendelbo *et al.*, 2016).

The current rate of urbanisation however is unsustainable as the economy in these urban areas is unable to support the number of people searching for jobs. Unemployment in urban areas has grown substantially, with the lack of jobs resulting from declining investment and the faltering export and manufacturing industry as Nepal undergoes 'premature de-industrialisation' (International Labour Organization, 2014). Many turn to work in informal sectors, which creates insecure livelihoods and leaves populations highly exposed to the potential financial impacts of a hazard (Brown, McGranahan and Dodman, 2014). Others have turned to international migration, which has become a prominent phenomenon in the population dynamics of Nepal (International Labour Organization, 2014; United Nations Population Fund, 2017). Many Nepalese workers have sought employment in nearby countries to earn higher monthly incomes, of which a proportion is sent back home as remittances. By 2015/16, remittances were contributing approximately 32% of the country's Gross Domestic Product (GDP) (United Nations Population Fund, 2017) and have had a profound effect on many of the socio-economic, demographic and political issues in Nepal (Lokshin, Bontch-Osmolovski and Glinskaya, 2010).

Whilst remittances have had a positive impact on household income and consumption, and a demonstrable effect in reducing the income inequality and poverty gap of Nepal (Sunam, 2014; Thapa and Acharya, 2017; Bam, Thagurathi and Neupane, 2018), this outward migration is changing traditional social structures within the country. One in every four households has at least one member absent or living out of the country and, in 2011, 77% of the total absentee population (1,921,494 international migrants) in Nepal were aged between 15-34 (United Nations Population Fund, 2017). With the majority of these members being part of the young workforce, rural households in Nepal are becoming increasingly constituted by dependents, resulting in high population dependency ratios (Speck, 2017; United Nations Population Fund, 2017). Whilst these households are financially supported by those members abroad, the departure of youth creates more burdens for older people who stay behind in the villages to look after the family home and land (Speck, 2017).

This outward migration disproportionately affects the poorest areas[4], who rely on remittances as a primary livelihood strategy (Speck, 2017) due to the inequality in accessing education and resulting high-skilled employment across different ethnic groups in Nepal (Gautam, 2017). As Gautam and Andersen (2016) find in their study on rural livelihood diversification, a household's ability to diversify into a high return sector is dependent on the antecedent level of resources and assets, including tangible assets such as school qualifications and intangible assets, such as networks and political favouritism (Gautam and Andersen, 2016). As a result, only certain groups of the population are able to access high-skilled jobs, such as governmental or civil service positions as well as other public and private sectors employment, including working for NGOs (Gautam, 2017). This has a cyclical effect, with resource-poor households likely to lack the ability to invest in new capacities, such as continuing onto higher education, and as a result, are forced to continue their low return diversification strategies, such as labour migration (Gautam and Andersen, 2016).

4.3.3 At risk of disaster: structural inequality and weak DRR policy

These structural inequalities were built into the country's political, economic and social system at its very inception, where during the country's unification not all ethnicities and castes were respected and treated equally, resulting in a caste system (Billingsley, 2016). Whilst the caste system was legally abolished in 1962, discrimination continues to reverberate into modern society, preventing people from certain ethnicities and castes from access and taking advantage of economic and social opportunities (DFID, 2006). This is despite the signing of the Comprehensive Peace Agreement (CPA) in 2006 at the

[4] Bringing together data from the 2011 Census, the Department of Foreign Employment (DOFE), and the 2016 Demographic Health Survey (DHS) Program, Table 4-1 in the Supplementary Materials details the percentage of migrant permits granted between 2008/2009 until 2016/2017 for each Province. Despite accounting for 37% of the population, Province 1 and 2 received 49% of permits; they are also the third and most poor Provinces in the country, respectively. Records from the DOFE show that nearly 75% of these migrant workers are unskilled, which opens up concerns as, according to Nepal's Ministry of Labour and Employment, low level skills are often associated with low paying jobs, such as working in manufacturing factories or as general labour, and result in vulnerable working conditions (Ministry of Labour and Employment, 2018).

end of the last civil war, which was based on espousing the end of systemic and structural inequality within Nepal (National Legislative Bodies / National Authorities, 2006).

The lack of government action has enabled systemic structural inequalities to persist within the country. The Government as a result has been perceived as weak and dominated by corruption in the form of clientelism and rent seeking (Jones *et al.,* 2014). In rural areas, for example, in their research Korzenevica (2016) found that many villages had been operating without elected bodies, and poorly functioning local governance has been concentrated around party patronage networks (Korzenevica, 2016). In the urban scenario, local government exists at the ward and municipality level but, for each, the representatives are chosen by central government rather than locally elected. With no local elections since 1997, there is a sense of detachment between the local population and the Government.

The pervasive structural inequality reinforces and often increases the vulnerability of many of these excluded or marginalized groups in the event of a hazard, for example, preventing the delivery of aid and support to certain populations based on gender, caste and ethnicity discrimination (Watson, 2017; Lam and Kuipers, 2018; Vaidya *et al.,* 2019). To account for this, DRR policy needs to address these inequalities including ensuring that access to support and training is equal across the entire population and tailored according to need. Nepal however has a pitted history of attempting to introduce and apply DRR policy, including The Natural Calamity (Relief) Act (NCA) in 1982 and the 1996 National Action Plan for Disaster Risk Management in accordance with the International Decade of Natural Disaster Reduction. With little guidance or specific funds to implement any of the recommendations, they have had little impact (Jones *et al.,* 2014; Nepal, Khanal and Sharma, 2018).

A further notable attempt was in 2005-2006 when, in response to the Hyogo Framework for Action, there was stimulus for change (Jones *et al.,* 2014). It was then identified Nepal's current approach to disaster management required significant conceptual changes to move the focus from recovery and response towards risk reduction. Two disparate initiatives began; one by Oxfam and the National Centre for Disaster Management (to draft a new National Policy and Act) and a second led by UNDP and National Society for Earthquake Technology – Nepal (NSET) (to develop the National Strategy for Disaster Risk Management in accordance with the Hyogo Framework for

Action) (Jones *et al.*, 2014). The former whilst submitted was never passed or enacted and the latter was only approved in 2009 by Nepal's Ministry of Home Affairs (MoHA) when redrafted as part of the overall National Strategy, with the long-term vision of making Nepal a disaster resilient country (Jones *et al.*, 2014).

Finally in 2013, a National Disaster Response Framework (NDRF) was launched. Whilst this fourteen-page document was prepared for the effective coordination and implementation of disaster preparedness and response activities by developing a national Disaster Response Plan (DRP) (Ministry of Home Affairs, 2013), the Framework solely focused on the roles and responsibilities of government and non-government agencies in the event of a disaster. No specific preparedness activities were recommended e.g., a Vulnerability and Capacity Assessment (VCA), a key preparedness activity used by organisations such as the International Federation of the Red Cross (IFRC) (IFRC, 2006). The prioritisation of DRR within the country is minimal (Jones *et al.*, 2014), with disaster policy based on the imaginings of policy makers and not rooted in reality (Hall *et al.*, 2017); political instability had hindered any efforts to reduce disaster risk and improve disaster response (Hall *et al.*, 2017).

4.3.4 Community social networks in Nepal

With faltering political and economic systems and a substantial lack of DRR implementation, Nepal's population has learnt to be self-reliant, using their relationships with one another to meet their everyday and emergency needs (Ruszczyk, 2014). These relationships primarily form the rural villages and towns, i.e. small place-based communities that have existed in the same location for hundreds of years. However with an increase in internal and external migration, these communities and relationships often stretch across districts, provinces and even countries. Whether local or not, these communities are incredibly important as they form the basis of the networks that can provide resources and assets within and between these different communities, particularly if one of the communities finds itself in times of need, for example, after the impact of a hazard.

The embedded and networked benefits resulting from relationships and ties are usually understood as social capital. In Nepal, this generally translates to the relationships within a household as well as their extended family and friends, which are incredibly important for support: as Ruszczyk (2014) found in her observational research on community resilience in Nepal, "the family bond is strong, this makes the community strong. People are rooted to the land, festivals, and relationships to each other" (Ruszczyk, 2014, pg.151). There is also the expectation in Nepal that once grown up and with their own families, parents expect their children to care and support them – although this expectation is changing as education and international travel influence attitudes of what responsibilities children should bear (Compernolle, 2015). Historical and cultural activities have also played a role in bonding a community together over traditions and heritage, creating a strong bond within the community (Devkota, Doberstein and Nepal, 2016). These strong bonds and networks between families and within the community result in high social capital; the community are there to help one another when in need (Devkota, Doberstein and Nepal, 2016).

The ability for the community to help one another is strengthened by the fact that, for many Nepalese, being self-sufficient in the face of adversity and even disaster is a feature of day to day life. For example, most households will have a stockpile of food and water as part of their ongoing coping strategies to everyday exposure to issues such as intermittent electricity and water shortages (Ruszczyk, 2014). With communities receiving little help from the Government in day to day life, minimal reliance is placed on their intervention.

The formation of these tight-knit communities can however have negative consequences through the exclusion of those not part of the community from these benefits (Adhikari and Goldey, 2010). For example, communities that have formed around the caste system can result in the marginalisation of individuals not part of the same caste (DFID, 2006). These individuals or subgroups are often excluded from accessing the same networks or resources as others who are in a similar spatial location (Adhikari and Goldey, 2010). Furthermore, economic migration has also extended rural communities remotely into city ‘toles’ (or neighbourhoods), requiring them to integrate with other communities that have originated from other areas of Nepal. Within these mixed neighbourhoods, communities and sub-groups may form around preferences in ethnicity and caste, and again result in exclusionary practices. As noted earlier, migration has also spread these communities internationally with small clusters of immigrants settling in specific locations and establishing a secondary location for their group. A community in Nepal may therefore also include family members who may not be located physically nearby, but are socially close through their social networks (Agergaard and Broegger, 2016).

This changing social landscape has had significant implications for this social support within both urban and rural communities. In rural areas, the migration of young families to the cities and further afield is thoroughly changing the social structure, with those relations unable to move, such as the elderly and the disabled, becoming more vulnerable by not having their immediate family as part of their support network (HelpAge International, CBM and NDRC Nepal, 2016; Speck, 2017). In the case of a hazard, such as an earthquake, they lack the physical and practical support that may be needed in an emergency (HelpAge International, CBM and NDRC Nepal, 2016) and may result in them losing one of the main resources they have to maintain their resilience: their familial support and the social networks these family members possess (Woolcock and Narayan, 2000).

Whilst in the rural areas this role may be filled by other community members, in urban areas, the amalgamation of multiple communities into shared spaces has resulted in a lack of community (Shrestha, 2013). Individuals are less willing to understand and invest in their relationships with their neighbours, providing little social cohesion for collective action (Carpenter and Grünewald, 2016). As a result, informal civil organizations are often not in place or do not function well within urban areas (Ruszczyk, 2014). These organizations, such as local help groups, play an important role in providing support for communities in day to day life as well as times of disaster. This lack of self-organization and community support has left those at the edge of the communities (primarily the elderly and disabled) increasingly vulnerable (Ruszczyk, 2014).

To combat this vulnerability, approaches that build resilience from the bottom-up through community engagement and participation have been recommended as a critical DRR strategy for Nepal: for example, USAID in 2011 stated, as part of its 'US DRR Strategic Framework Nepal 2012 – 2016' report, that future DRR activities and plans should prioritise community level engagement (USAID, 2011). To enable these community level resilience building initiatives, as identified in Chapter 3, social network mapping would be an essential step to understand how to build the community's resilience from the bottom-up. It would provide a thorough understanding of these local structures and relationships, including identifying those currently either on the periphery of a community or vulnerable family members who are currently, or could in the future be, left unsupported in the event of a hazard. Without understanding these changing social structures and implementing adequate DRR policy that addresses those that are becoming more isolated in light of these changes, the promised safety net of collective action is unlikely to exist for those most vulnerable in Nepal and put them at significant disaster risk in the case of a hazard occurring, as witnessed in the 2015 Gorkha earthquake.

4.4 The realities of disaster: the 2015 Gorkha earthquake

The impacts of 2015 Gorkha earthquake drew significant attention to the inadequacies of current DRR policy within Nepal, but also put into sharp focus that those most at risk and most vulnerable to these disasters and their long-term effects are those who are the poorest within the country. Whilst multiple narratives have emerged about the efficacy of the response and recovery operations from differing perspectives (e.g., Regmi, 2016 versus Paul, Acharya and Ghimire, 2017), across the literature one aspect is consistent: local social networks were critical to the success of the initial recovery operations, including search and rescue, as well the ongoing coordination of the substantial national and international aid efforts deployed to the affected areas (Devkota, Doberstein and Nepal, 2016; Ray, 2017; Carrero *et al.*, 2018). These networks were however not without fault, with reports emerging that aid was inequitably distributed as a direct and indirect result of the structural inequality that exists within the country (Cook, Shrestha and Htet, 2016; Hillig and Connell, 2018; Lam and Kuipers, 2018).

4.4.1 The 2015 Gorkha earthquake

At midday on the 25th April 2015, Nepal was struck by a 7.8 magnitude earthquake in the north of the central Gorkha region (Figure 4-1). The earthquake's shock propagated from west to east, with strong shaking experienced in Kathmandu. The shock caused significant damage, destroying buildings and infrastructure in both urban and rural areas, whilst also triggering several cascading hazards, including landslides and rock/boulder falls in the mountain areas. Aftershocks continued, including a further 6.8 magnitude aftershock followed on the 12th May 2015, causing additional damage to rural towns and villages in the northern part of central Nepal. In total, the earthquakes resulted in approximately 9,000 fatalities, 24,000 injuries and affected one third of Nepal's entire population (Government of Nepal, 2015).

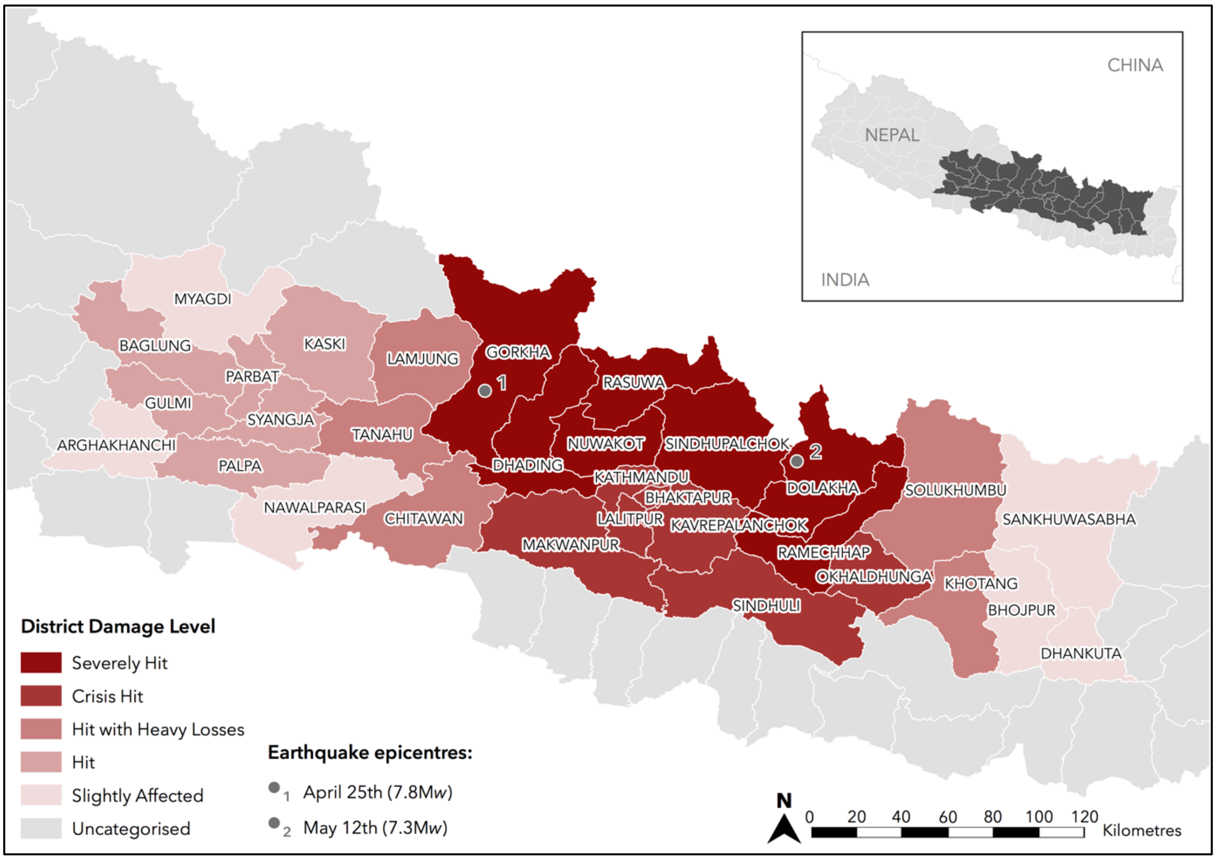


Figure 4-1. The location of the 2015 earthquakes and their damage impact on the nearby affected district, as classified by the Government of Nepal. *(Data: © 2018 GADM, Government of Nepal, United States Geological Survey).*

Out of the 75 districts, 31 were affected with 14 declared "severely hit" and "crisis hit" (Figure 4-1). According to the Government's Post Disaster Needs Assessment (PDNA), over half a million houses were damaged, as well as many government buildings, heritage sites, schools and health posts, rural roads, bridges, water supply systems, agricultural land, trekking routes, hydropower plants and sports facilities (Government of Nepal, 2015). Economically, reports suggest that the earthquake has cost approximately US$7-10 billion in economic loss and damage, about one half of Nepal's GDP, and will have serious and long-term socio-economic impacts on the people and communities in Nepal (Goda *et al.*, 2015).

4.4.2 Reports and research on the response: emerging key themes

With its significant impact and sizeable response, the earthquake has attracted substantial commentary from local and international researchers within the DRR field. Using Scopus, a bibliometric database, a search was made for articles on the earthquakes' response, looking for titles that included the keywords: "Nepal" AND "earthquake" AND "Disaster Response" AND "2015" OR "Gorkha" (on December 18th 2019). Articles were chosen that looked to evaluate the success of the response using primary and secondary data sources, including first-hand experiences or perspectives and field observations of the authors during the earthquake as well as the results of substantial primary data collection efforts, including post-earthquake interviews, surveys and workshops. Further articles and reports, such as the PDNA, a Save the Children report, an Amnesty International report and a HelpAge International/CBM/NDRC Nepal report were found through the cited references within the articles studied. Thirty-two studies were selected and summarised in Table 4-2 within the Supplementary Materials.

Across these thirty-two studies, four key themes about the response consistently emerged:

1) Disaster preparedness was not prioritised within the national development agenda, resulting in inadequate and insufficient response plans, and as a result, caused delays and deficiencies within the response (e.g., Bisri and Beniya, 2016; Cook, Shrestha and Htet, 2016; Wendelbo *et al.,* 2016; Basu *et al.,* 2017; Subedi and Bahadur Poudyal Chhetri, 2019).
2) The formal disaster response mechanism focused on a top-down approach, rather than engaging and working with the affected local communities, especially those most affected and vulnerable to the impact of the earthquakes (e.g., Baharmand *et al.*, 2016; Boersma *et al.,* 2016; Lam and Kuipers, 2018; Shrestha and Pathranarakul, 2018).
3) Aid provision was inequitable due to the direct and indirect effects of the structural inequality embedded within Nepal's social and political system and the lack of consultation with the affected local communities (e.g., Amnesty International, 2015; Barber, 2016; Cook, Shrestha and Htet, 2016).

4) The affected local communities relied on their networks with one another to coordinate local support, including SAR and longer-term relief and rebuilding activities (e.g., Devkota, Doberstein and Nepal, 2016; Mishra *et al.*, 2017; Ray, 2017; Adhikari *et al.*, 2018).

Whilst most international responses and parties in Nepal considered the immediate SAR and relief operations a success (Cook, Shrestha and Htet, 2016; Paul, Acharya and Ghimire, 2017), there was a clear combination of issues that resulted in a much-reported problem with the response: the inequitable distribution of (often ill-suited) relief. The problem arose due to failings prior to the earthquake of the Government to prioritise disaster preparedness within the NDRF (Bisri and Beniya, 2016), including no prior local level engagement to understand the vulnerabilities of the local population or who was at risk. There were also no local elected officials in place to advocate for those in need and to communicate to those responding what relief was needed and where (Neupane, 2015). This was further exacerbated by the external organisations involved reportedly not pro-actively engaging with the national or local organisations that represented the most vulnerable groups (Barber, 2016). This created a mismatch within the response between what was needed on the ground and what was delivered (Regmi, 2016) and resulted in many unnecessary, unsuitable, and at times offensive, items of aid being delivered (Cook, Shrestha and Htet, 2016; Shrestha and Pathranarakul, 2018). For example, the major need for those affected was secure shelter in the form of tents and tarpaulin, however the demand continuously outstripped the supply (Regmi, 2016; Basu *et al.*, 2017).

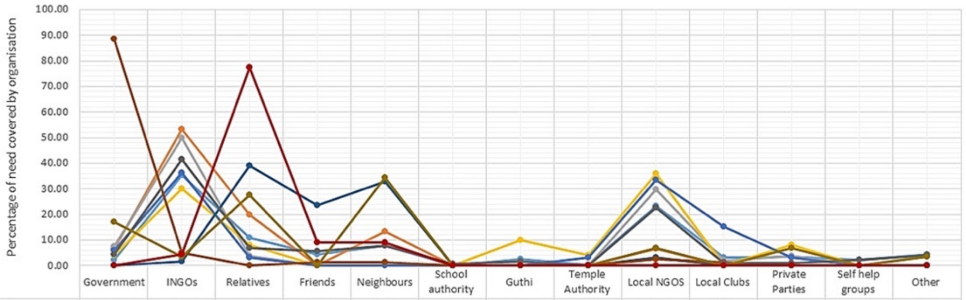
The reliance of the response on the international support also created direct and indirect opportunities for imbalances in where the aid was distributed. The preliminary assessment made by MoHA found that the earthquakes disproportionately affected the poorer, rural locations relative to the urban and less poor areas (Government of Nepal, 2015). However, without effective coordination during the response, there were some regions or disaster-affected areas which had multiple response teams while other areas had none (Cook, Shrestha and Htet, 2016). This disparity was further exacerbated by poor weather and accessibility to more remote areas, particularly as the second large aftershock damaged roads again (Government of Nepal, 2015; Billingsley, 2016; Sheppard and Landry, 2016; Basu *et al.*, 2017; Subedi and Bahadur Poudyal Chhetri, 2019).

The reliance on these international organisations removed the impetus for government agencies to be responsible and accountable, including identifying these areas where relief was yet to be delivered. With many of these agencies focusing their efforts within Kathmandu and its surrounding valley due to logistical and infrastructure issues, the most remote communities were at risk of not receiving any aid. This particularly affected the most vulnerable groups, such as women with young children, the elderly, the disabled and the Dalit communities, who were struggling to access aid through the main method of distributing aid to these communities, helicopter air drops, which were physically prohibitive to many of these vulnerable groups as they required walking significant distances (Billingsley, 2016).

To overcome this inequity, many communities, particularly those who were not well-connected or well-located, had to rely on their own wits and resources to survive (Neupane, 2015). Grassroots-level self-help movements occurred, engaging volunteers to conduct SAR, raise funds, share information as well as record losses and organise shelter building (Ray, 2017; Adhikari *et al.*, 2018); this collective action was facilitated by the strong social capital that had been created, maintained and sustained in everyday community life through their local social interactions (Devkota, Doberstein and Nepal, 2016) as well as traditional cultural practices (Ray, 2017).

The importance of these local responses was demonstrated by Carrero *et al. (*, who surveyed 160 houses within fifteen villages across four of the districts affected by the earthquake about the provision of different types of support from different need providers; their overall results are shown in Figure 4-2. Across their survey, they found that much crucial after-disaster care was catered for by local connections, including relatives, friends, neighbours, religious organisations and local clubs (Carrero *et al.*, 2018). This finding was present across many studies, with local volunteer groups often reaching affected areas way in advanced of any government or international help (Amnesty International, 2015; Devkota, Doberstein and Nepal, 2016). In comparison, Carrero *et al. (*, found that for most, the Government's main role was to provide financial support in the aftermath, whilst international NGOs were the key sources of basic relief materials, including shelter, water, medicine, and sleeping materials. With these findings, their study advocated for the revaluation of informal social networks as a crucial and not tacit part of disaster response; these networks covered almost any need in emergency relief and were especially important to some otherwise isolated households (Carrero *et al.*, 2018).

Table 1. Needs and needs providers.



	Government	INGOs	Relatives	Friends	Neighbours	School authority	Guthi	Temple Authority	Local NGOS	Local Clubs	Private Parties	Self help groups	Other
Food	2.18	35.37	10.92	4.37	7.86	0.00	2.62	0.44	23.14	3.06	3.49	2.18	4.37
Water	6.67	53.33	20.00	0.00	13.33	0.00	0.00	0.00	6.67	0.00	0.00	0.00	0.00
Medicines	7.41	50.00	3.70	0.00	0.00	0.00	0.00	0.00	29.63	1.85	3.70	0.00	3.70
Clothes	4.00	30.00	8.00	0.00	0.00	0.00	10.00	4.00	36.00	0.00	8.00	0.00	0.00
Sleeping materials	6.06	36.36	3.03	0.00	0.00	0.00	0.00	3.03	33.33	15.15	3.03	0.00	0.00
Rescue	0.00	1.56	39.06	23.44	32.81	0.00	0.00	0.00	3.13	0.00	0.00	0.00	0.00
Money	88.61	5.06	0.00	1.27	1.27	0.00	0.00	0.00	2.53	1.27	0.00	0.00	0.00
Shelter	4.55	41.48	6.82	5.68	7.95	0.57	1.70	0.00	22.73	1.14	1.14	2.27	3.98
Guidance	17.24	3.45	27.59	0.00	34.48	0.00	0.00	0.00	6.90	0.00	6.90	0.00	3.45
Emotional support	0.00	4.55	77.27	9.09	9.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure 4-2. The provision of support required post-earthquake by needs provider. Source: Carrero *et al.*, 2018.

The importance of local social networks within the response to cope with the inequity in aid provision was also found by two other studies that both focused on the most vulnerable strata of the population, the elderly and disabled people who were without, or in some cases had been left or even abandoned by, their immediate family in rural villages and areas (HelpAge International, CBM and NDRC Nepal, 2016; Speck, 2017). These groups struggled to access the much-needed humanitarian aid, either because of physical barriers (e.g., distance too far to travel) or social barriers (e.g., not able to access information or have the right political influence).

Despite losing their immediate social support, many of the case studies found that their neighbours were able to fulfil the roles often expected of their family (HelpAge International, CBM and NDRC Nepal, 2016). Furthermore, local help groups, such as older people's associations (OPAs), disabled people's organizations (DPOs), single women's group and age and disability task forces also helped these vulnerable groups access relief and materials during the recovery stage. Overall the studies concluded that strong social networks, caring neighbours and living with families are among the major coping capacities that help people manage emergencies, whilst the community and civil informal organizations were crucial to providing support for those most at risk (HelpAge International, CBM and NDRC Nepal, 2016; Speck, 2017).

One study however found that the reliance of social networks can sometimes have significant drawbacks. Many of the local NGOs had failed to plan adequately for such large earthquakes. With little cooperation from international organisations, they had minimal information on how to help and respond to the remote, and often most vulnerable, areas and so had to find alternative ways of identifying where and what help was needed. As a result, they relied on the social networks between themselves and the surrounding communities to find areas in need – however this prioritised those communities better placed socially and geographically as well as those areas that had well connected government officials (Hillig and Connell, 2018).

4.5 The need for social connectivity measurement in Nepal

As evident from the 2015 earthquakes, social networks between family, friends and neighbours are used by many individuals, households and communities as a critical resource to respond to and mitigate the impacts of a hazard occurring. However not everyone has these networks available or can rely on them in times of need; they are thus likely to be excluded from this benefit, which, due to Nepal's inadequate DRR policies, are often a key lifeline in the event a hazard becomes a disaster. Understanding the distribution of social connectivity in Nepal therefore should be a priority for those trying to enhance disaster resilience in the country.

In the case of the 2015 earthquake for example, by having data that detailed social connectivity, those responding to the earthquake could have used this data to proactively target areas lacking in substantial bonding, bridging and linking ties. These ties, as evident from the studies citied above, were instrumental in the delivery of aid by many smaller NGOs (Hillig and Connell, 2018). A social connectivity dataset could identify areas that were less likely to have these ties and could therefore help NGOs ensure that these areas are included within their distribution of aid. This prioritisation also is needed in areas where social cohesion is low, i.e., there is a lack of bonding social connectivity. In these areas, the data could be used to justify an increased focus on identifying those individuals who are either on the periphery of a community or even isolated from the overall community response and recovery activities.

In addition to operational decision-making, a social connectivity dataset for the country would be an essential resource for future DRR preparedness building. As identified in Chapter 3, social network mapping is an invaluable tool for practitioners to understand how to build community resilience from the bottom-up; without information on local social structures and connectivity, any top-down implementation of preparedness policy and procedures are likely to fail. A social connectivity dataset would be the first step to providing this mapping of community structures, including identifying the most isolated communities that could have resilience building programs tailored to increase their overall connectivity. The provision of a social connectivity dataset in Nepal could therefore have a significant impact in both the preparedness and operational aspects of resilience within DRR.

4.6 Summary

Through its geography and climate, Nepal is susceptible to natural hazards, however the vulnerability of its population is inherently tied to and exacerbated by the various social, economic and political processes that have created systemic structural inequalities across the country. Changing demographic structures, economic stagnation, and new pressures on existing livelihoods and coping strategies ensures that any shock is likely to have long lasting and cascading impacts.

Despite this high level of susceptibility and vulnerability to disasters, DRR policy in the country has been close to non-existent. Political instability has left many drafted policies and programmes unimplemented, whilst help for local communities have been subject to mixed agendas and priorities brought in by international governments and external NGOs. With no local elections for nearly two decades, there has been a disconnect between local government and communities, which has resulted in a lack of institutionalisation of DRR training and preparedness strategies. The local communities of Nepal are thus self-reliant: the social networks within and between communities continue to play an important role in helping members respond to and recover from a disaster, as evidenced in the 2015 Gorkha earthquake.

During the response, local social networks were critical to the success of the initial recovery operations, including SAR, as well the ongoing coordination of the substantial national and international aid efforts deployed to the affected areas (Devkota, Doberstein and Nepal, 2016). However, these social networks were limited by their geographic and social reach, particularly without local-level government to advocate for the communities that were not receiving adequate aid. As Bhandari (2014) summarises: strong bonding and bridging social capital can help mobilize pre-existing associations to help one other in the aftermath of disasters, but weak linking social capital can isolate vulnerable and powerless people from government disaster relief and recovery operations (Bhakta Bhandari, 2014).

These support systems are currently restricted in their efficacy, with geographically remote or socially isolated communities therefore at a higher risk of being missed by response organisations. This lack of connectivity within communities will only be further exacerbated as the wider social and economic processes at play in Nepal continue to change the traditional social landscape. Being able to identify these isolated households and communities to target them for specific resilience building interventions or additional support could help reduce their overall vulnerability before and during a hazard, particularly until the country is able to address the wider structural inequalities that have put them at greater risk in the first place. To enable this, a dataset that details social connectivity, preferably at least at a community scale, would be an essential resource.

4.7 Supplementary Material

Table 4-1. Province-level distribution of population, migrant permits and poverty in Nepal

	Province Percentage of Total Country Population[1]	Province Percentage of National Migrant Permits[2]	Percentage of Province in Multi-Dimensional Poverty[3]
Province 1	17	25	12
Province 2	20	24	35
Province 3	21	16	9
Province 4	9	13	8
Province 5	16	16	20
Province 6	6	3	8
Province 7	10	2	11

Data sources:
1. 2011 Nepal Census (Central Bureau of Statistics, 2012)
2. Nepal Ministry of Labour and Employment Report (Ministry of Labour and Employment, 2018)
3. Demographic and Health Surveys Program 2016 Nepal Survey Report (Ministry of Health and Population (MOHP) [Nepal], New ERA and ICF International Inc, 2017)

Table 4-2. Summary of the thirty-two case studies selected for use in the study site review

	Author	Year	Aim	Method
1	Adhikari et al	2018	Developed and tested a model of preparedness during the recovery phase of 2015 Nepal earthquake.	Based on 306 household surveys collected from Chainpur and Jeewanpur Village Development Committees, Dhading, Central Nepal during field visits in April/May 2016.
2	Amnesty International	2015	Review of the 2015 response from AI's human rights perspective	Field observations and review of emerging articles and media.
3	Baharmand et al	2016	Understand whether and how the humanitarian response enabled community resilience in the aftermath of the earthquake.	Field study six weeks after the earthquake, using open and semi-structured interviews with field observations. Interviewed 38 humanitarians involved in the response, as well as observed local communities and their interactions with the organisations.
4	Barber, for Save the Children)	2016	Evaluate the response in terms of its ability to help those most marginalized.	Consultations with affected communities and government and non-government actors focusing on the first 6 months of the response. Covered 5 districts and targeted different types of participants to ensure representation of advantaged and disadvantaged groups.
5	Basu et al	2017	Identify what the resource needs are during a major disaster through resource mapping.	Collection and analysis of WhatsApp messages between Doctors For You, a humanitarian organization of medical professionals.
6	Billingsley	2016	Outline the importance of structural inequality to the 2015 response.	Literature review of emerging reports from the earthquake.
7	Bisri and Beniya	2016	Identify structural gaps and on-the-ground inter-organizational cooperation previously undetected by the Nepali framework and/or stand-by arrangement of humanitarian organizations	A mixture of desk-study, fieldwork, and unstructured interviews with key informants in Nepal, to create a social network dataset on the cooperation between organisations and agencies working during the response.
8	Boersma et al	2016	Outline the dilemmas and challenges of the response faced by the NGOs the authors represented.	Field research in Kathmandu, Nuwakot and Rasuwa, four weeks after the second earthquake, visiting various organizations, from all levels, involved in the response.

9	Carrero et al	2019	Examine the mechanisms of aid provision in the aftermath of the 2015 earthquake.	Surveys with 160 households across 4 districts and 15 villages affected by the earthquake.
10	Cook et al	2016a	Detail the lessons learnt and observations from the 2015 earthquake response.	Literature review of emerging articles, reports, and publications on the search and rescue and immediate relief phases.
11	Cook et al	2016b	Details the recommendations and implications of the 2015 earthquake for future relief efforts.	Drawn from previous literature review (Cook, 2016a).
12	Daly et al	2017	Analysis of the post-reconstruction efforts and how local stakeholders are situated within national disaster structures.	Uses institutional ethnography to analyse post-earthquake framework as well as observations from five case study urban settlements in Kathmandu Valley.
13	Devkota et al	2017	Use social capital to explore how indigenous Newar communities in Kathmandu responded to the 2015 earthquake.	33 semi-structured interviews with local Newar inhabitants surrounding the three Durbar squares (Kathmandu, Lalitpur and Bhaktapur), plus secondary sources.
14	Dhakal	2018	Evaluates local and foreign news media coverage of the earthquake.	Literature review of 405 news media items using community capitals to frame discussion.
15	Epstein et al	2018	Investigated the impact of the earthquake on small householders.	Uses survey questionnaires (79 households), focus group discussions, 24 open ended interviews and observations. Respondents included affected households, community leaders, farmers, academics and aid workers.
16	Fitzgerald et al	2015	A review of the media's role in the response.	Literature review of published articles in the immediate response after the earthquake.
17	Government of Nepal / National Reconstruction Authority	2017	An update on the progress of building back better in Nepal, post-earthquake.	Review of government held data on the progress of the response, e.g., financial statements.
18	Government of Nepal Post-Disaster Needs Assessment,	2015	Updates on the current situation in Nepal.	Governmental data and field observations.

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19	Hall et al	2017	Review the learnings provided by a national workshop conducted to reflect on the response to the earthquake.	Workshop of 135 participants who had been directly involved in the response. Various stakeholders, including: Ministry of Health, NGOs, Health Practitioners, Academics, Community Practitioners
20	HelpAge International/CBM International	2016	Assesses the impact of the earthquake on older people and persons with disabilities in Nepal.	Cross-sectional survey of older people and persons with disabilities in seven several affected districts eight months after the earthquake. 1515 total respondents.
21	Hillig and Connell	2018	Study of the response of three NGOs during the earthquake and how they used social capital and networks to help their efforts.	Interviews with representatives from CARE Nepal, International Nepal Fellowship and Richa Bajimaya Memorial Foundation NGOs.
22	Lam and Kuipers	2019	Study how resilience has been operationalized and implemented in Nepal post-2015 earthquake context, with a focusing on housing reconstruction projects.	Mixed methods approach, including policy analysis and extensive field studies in the districts of Nuwakot and Dhading.
23	Mishra et al	2017	Identify factors which impact post-disaster recovery and contribute to building resilience in Nepal, particularly for mountain communities.	Analysis of 30 earthquake-affected mountain communities using Qualitative Comparative Analysis (QCA) of developed framework. Data collected through Focus Group Discussions.
24	Neupane	2015	Commentary on the immediate lessons learnt from the earthquake.	Commentary.
25	Paul et al	2017	Evaluates the performance and effectiveness of the relief operations.	Interviews with 302 respondents from 10 study sites in two earthquake-affected districted. Uses an additive composite score.
26	Ray	2017	Assesses the role of institutional initiatives in building resilient communities and their response to disasters, such as the 2015 earthquake.	Data collected from primary and secondary sources along with field observations.
27	Regmi	2016	A reflection on the political economy of the response.	Uses participatory approach of reconstruction as a theoretical framework, and reviews own personal experience (field notes, journal entries and emotions) during the response.

28	Sheppard & Landry	2015	Demonstrate the role of rehabilitation professionals in post-disaster relief and beyond in Nepal.	Experiential accounts for physiotherapists present during the earthquake and participating in post-disaster relief.
29	Shrestha and Pathranarakul	2018	Analyses the large-scale disaster response of the Nepal government's institutional system in the wake of the earthquake.	Interviewed 58 key individuals who participated in some form during within the response, including: Deputy Prime Minister, Military Air Service, Army Liaison Officers, Journalists, Medical Doctors, Paramedics, General Public, Volunteers, Victims Responders from NRCS and UNDP
30	Subedi et al	2019	Analyses and shows critical gaps and responsible factors that could help with DRR in Nepal from a seismic perspective.	Literature Review
31	Welton-Mitchell	2016	Assessing the cultural, psychological and social factors affecting recovery and disaster preparedness.	Semi-structured interviews with 80 community members shortly after the earthquake in five districts (Kathmandu, Lalitpur, Bhaktapur, Kavrepalanchok and Sindhulpalchowk).
32	Wendelbo et al	2016	Assesses the disaster resilience of Nepal leading up to the earthquakes and the response efforts.	Field observations, reviews of reports and articles emerging from the response.

Table 4-3: Chapter Data List (Map Creation)

Dataset	Source	Reference
Nepal Administrative Boundaries, Level 0 – 5	GADM 2018	© GADM www.gadm.org (https://gadm.org/download_country_v3.html, Accessed December 2018)
Priority Districts	Government of Nepal	Government of Nepal (2015) Nepal Earthquake 2015: Post Disaster Needs Assessment. Vol.B: Sector Reports. Kathmandu, Nepal. Available at: http://www.gfdrr.org/gfdrr/node/118.
Nepal Earthquake Data	United States Geological Survey	Data courtesy of the U.S. Geological Survey. Available: www.earthquake.usgs.gov https://earthquake.usgs.gov/earthquakes/eventpage/us20002926/ https://earthquake.usgs.gov/earthquakes/eventpage/us2000292y/ https://earthquake.usgs.gov/earthquakes/eventpage/us200029bt/ https://earthquake.usgs.gov/earthquakes/eventpage/us20002ejl/

Chapter 5 Changing geo-demographics of mobile phone ownership in Nepal 2006 – 2016

5.1 Overview

This chapter quantifies the accessibility of mobile phones within Nepal to provide evidence on the likely representativeness of the data generated by the use of mobile phones. Due to limitations in the availability of data to study mobile phone access, as discussed in the chapter, this accessibility is captured through the ownership of a mobile phone. The analysis is conducted at the household level over ten years to understand how mobile phone ownership has changed in Nepal and if ownership is equal across different socio-economic groups. Individual level ownership in 2016 is also assessed. The chapter validates the use of mobile phone data as a nationally representative dataset, as both household and individual level ownership of mobile phones are substantial across the different socio-economic groups by 2016.

5.2 Introduction

The total number of global unique mobile phone subscribers exceeded 5 billion in 2017 and is expected to reach nearly 6 billion by 2025, propelled by a shift in growth towards low- and middle-income countries, particularly in Asia and Sub-Saharan Africa (GSMA, 2018). This increase in mobile phone subscriptions is attributed to growing network coverage in rural areas (90% of the world's population is now covered by 3G networks) as well as the increasing affordability of both mobile devices and tariffs within these developing markets (GSMA, 2018). Despite being one of the poorest and slowest-growing economies in Asia (Cosic, Dahal and Kitzmuller, 2017), Nepal has been part of this growth, with the number of mobile phone subscriptions increasing from approximately 1 million at the end of 2006 (Nepal Telecom Authority, 2006) to over 32 million by the end of 2016 (Nepal Telecom Authority, 2017). The number of subscriptions now outnumbers Nepal's estimated population which stands at approximately 30 million (World Bank, 2018).

Whilst the mobile phone market appears saturated in Nepal when solely focusing on subscription numbers, there can in fact be a significant difference in the number of phones versus Subscriber Identity Module (SIM) cards owned per person (Gillet, 2014). In terms of access, a mobile phone subscription (or SIM card) does not equate to mobile phone ownership (MPO), nor does MPO consider the potential of device sharing (see Figure 5-1). For example, anecdotal evidence discussing mobile phone use during the 2015 Gorkha earthquake in Nepal suggested that the sharing of mobile phones, particularly smartphones, was common as not everyone owned a phone (Sattler, 2016). Furthermore, a recent small-scale qualitative study of MPO within indigenous populations in Nepal in 2015 found that several factors, including gender, literacy rate and employment, influenced who did or did not own a phone (Pradhan and Bajracharya, 2015). Despite the significant increase in mobile subscriptions, the actual accessibility of mobile phones in Nepal therefore cannot be understood through the subscription numbers alone.

Understanding mobile access and relevant terminology

Mobile subscription: A mobile connection, in the form of a SIM card. Connection and subscription are used interchangeably. Subscriptions can also be active or inactive, and can have the potential to be used by more than one person. Often an individual may have more than one subscription at one time (e.g., to receive better coverage in different areas) or may change subscriptions regularly to take advantage of new offers or products.

Unique mobile subscriber: An individual person, who may account for either a single or multiple mobile subscription(s). Unique mobile subscribers are calculated from creating a ratio between the total number of subscriptions against the average number of subscriptions (connections/SIMs) held by each subscriber. This ratio requires collecting data directly from the consumers about their mobile phone subscriptions and usage.

Mobile phone ownership: Physical ownership of a mobile phone device. The mobile phone may be used by a single person with one or multiple subscription(s); by multiple users using the same subscription(s); or by multiple unique subscribers (i.e., users who have their own SIM card(s) to insert into the device). Ownership only considers who owns the actual device.

Figure 5-2. Definitions of mobile phone access terminology.

Understanding who within a country has access to a mobile phone is of critical importance to those working within sustainable development. Reports, such as the

UNDP's 'Mobile Technologies and Empowerment', show that the technology is becoming intrinsic to many applications within various development sectors, from healthcare, agriculture, finance, and education (UNDP, 2012). Detailed information on accessibility provides evidence on who is likely to and who is likely to not benefit from these applications of the technology, and whether this can lead to existing inequalities, such as inaccessibility to financial services for the poor, illiterate or elderly, to still be perpetuated.

A growing field of research is also using the data generated by the use of mobile phones to provide insights into a country that can be used within sustainable development, including population and poverty estimates (Kang *et al.,* 2012; Steele *et al.,* 2017) as well as mobility and social network dynamics (Bengtsson *et al.,*2015; Wesolowski *et al.,* 2017). These insights are however only as accurate as the data used to provide them, with a heterogeneous population of mobile phone access having significant implications for these predictions by creating biases within the trends reported (Wesolowski *et al.,*2012). Whilst national ownership or subscription statistics are primarily used within these studies to account for mobile phone access, in-depth understanding of the actual representativeness of the data is rarely tested and assumptions are often made about the underlying population. For example, children are often missed within routine surveys that are primarily aimed at adult populations (aged 16 or 18 and over), despite contributing substantially to MPO; a 2015 GSMA international study in Bahrain, Japan and the Philippines, for example, found that on average 67% of children used a mobile phone, with 10 years old being the most common age for children to receive their first mobile device (GSMA and NTT DOCOMO, 2016). As a result, children and the complications or biases they may introduce into the analysis of the data are not usually accounted for nor addressed.

Already mobile phones have been used in Nepal for various sustainable development-related applications, including mobile banking (USAID, 2014), early warning systems for disasters (Ncell, 2018) and agricultural services (UNCDF, 2018). Furthermore, in 2015, mobile phone data were used by a team of researchers to provide population displacement estimates to the UN immediately after the Gorkha earthquake to help with the response. The speed at which the analysis was required meant that the biases in mobile phone ownership were not accounted for or explicitly addressed within the predictions (Wilson *et al.,* 2016). Detailed information on MPO from surveys was highlighted as a way to improve the estimates provided. However, there is currently no singular point of information to provide an understanding of mobile phone access within the country.

To help address this knowledge gap, this paper presents a temporal analysis of MPO in Nepal by key demographics and socio-characteristics that are expected to drive mobile phone accessibility within the country. Here access is captured through ownership due to the limited availability of data related to mobile phone access that includes socio-demographic characteristics. These driving factors and survey limitations are further explained in the following section on relevant mobile phone access literature. Data were extracted from three Demographic and Health Surveys (DHS) program surveys (2006, 2011 and 2016) and used within bivariate and multivariate logistic regression models to explore the selected variables and their influence on MPO at the household level (see 'Methods'). The DHS program surveys are nationally-representative household surveys, funded by US-AID, that collect data on a wide range of topics in areas of population, health and nutrition and can be used to generate monitoring and impact evaluation indicators (The DHS Program, 2018). The 'Results' section provides an overview of the most significant factors driving MPO and compares these factors over time to understand if and how they change. In addition to studying ownership at the household level over time, the study analyses MPO at the individual level in 2016, providing further detail on who in Nepal is most likely to own a mobile phone.

Overall, the analysis find that education and wealth are significant factors affecting household MPO in Nepal and continue to influence household MPO into 2016; at the individual level, gender in addition to education and wealth is also likely to mediate MPO. Through both descriptive and logistic analyses, the paper provides a clear understanding of how MPO has changed in Nepal and what current mobile phone access is likely to be within the country. These findings offer critical evidence needed for those wanting to use mobile phone technology or data within Nepal and can be used to help address potential biases surrounding the use of mobile phone data within future research.

5.3 Mobile Phone Access and Ownership

Research on mobile access, and access to information and communication technologies (ICT) in general, focuses on accounting for technological divides. A technological divide is a case of the 'haves' and 'have nots': those who have access to and are effectively using information and communication technologies (ICT) and those that do not (Stump, Wen Gong and Zhan Li, 2008). Over the last two decades empirical studies have sought to test the premise of technological divides by quantifying the impact of mediating factors, i.e., the demographic and socio-economic factors, as well as in some cases determining factors (i.e., perceived usefulness, social influence) on mobile phone access, summarised by van Biljon and Kotzé's (2007) extended Technology Adoption Model (TAM) in Figure 5-2.

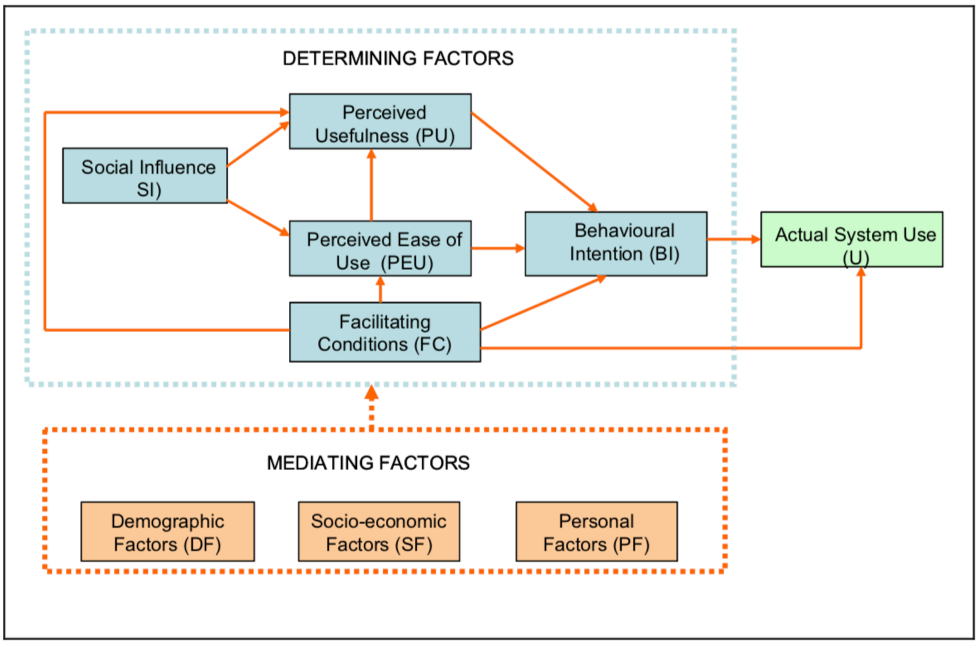


Figure 5-2. Van Biljon and Kotzé's proposed extended Technology Adoption Model (2007).

Research has demonstrated that demographic and socio-economic variables including age, gender, income, literacy rate, and education, have in one way or another influenced the access of mobile phones (e.g., de Silva, Ratnadiwakara and Zainudeen, 2011; Deen-Swarray, Gillwald and Morrell, 2012; Alozie and Akpan-Obong, 2017), as well as their use (e.g., Blumenstock and Eagle, 2012; Wesolowski *et al.*,2012; Lee and Kim, 2014). Through the use of multivariate regression and model fitting, studies have shown that there is often a complex interplay between demographic and socio-economic factors that will determine mobile phone access, with local-specific factors providing a regulating effect, for example, cultural factors overriding or even exacerbating gender divides (Zainudeen, Iqbal and Samarajiva, 2010; FAO, 2016). The exact combination of factors that have emerged from each of these studies somewhat differ; for example, some strongly argue that gender is actually not a key digital divide (Hilbert, 2011), whilst others have tried to measure social influence and found little impact (Chabossou *et al.*,2009). Furthermore, Rice and Katz (2003) argued that the price of ICT would not serve as a substantial barrier when there is a suitable motive (Rice and Katz, 2003). However, across all of the studies, education and income play a clear and significant role, which suggests the costs entailed with purchasing and using a mobile phone remain a significant determining factor in mobile phone access (Rice and Katz, 2003).

Capturing mobile phone access is however not straight forward: is access the use of a phone in the last 24 hours sufficient to count as access? Or should only those who have and use their own SIM be considered to have access? Or should only mobile phone owners be represented? Whichever approach is taken to capture mobile phone access will require addressing these nuances directly. Here, this analysis captures access solely as MPO, i.e., the ownership of the physical device, constrained by the approach taken by the DHS program to survey mobile phone access: the questionnaires used in all three time points ask about household (and individual in 2016) ownership as a binary option (a yes or no) and not how many phones are owned or by whom. Ownership is likely to underestimate the overall accessibility of a population to mobile phones as it is unable to account for the sharing of the device between family, friends and even communities. For the purpose of this analysis, which is to provide an understanding of accessibility for sustainable development applications, this underestimation is preferable to an overestimation as it ensures that accessibility is not overexaggerated within different demographic and socio-economic groups.

Another motivation to focus on MPO is that there is limited availability of data that can robustly relate mobile phone access with these socio-demographic characteristics. Data on mobile phone access is usually acquired through one of three ways: firstly, through utilising external already available (and often publicly) general lifestyle, financial, or health surveys (see: Wesolowski *et al.,* 2012; Grzybowski 2015; Tran *et al.,* 2015; Alozie

& Akpan-Obong, 2017; Zhang 2017); secondly, through utilising external ICT-focused surveys e.g., the LIRNEasia survey from 2008 (used in de Silva, Ratnadiwakara and Zainudeen, 2011), or ResearchICT Africa from 2007/2008 (used in Chabossou *et al.,* 2009 and Hilbert, 2011) and 2012 (used by Deen-Swarray, Gillwald and Morrell, 2012); or through conducting study-specific fieldwork surveys (e.g., Zainudeen *et al.,* 2010; Blumenstock & Eagle 2012; Lee & Kim, 2014) and interviews (e.g., FAO, 2016; Pradhan & Bajracharya, 2015). Whilst these papers are not exhaustive of all empirical studies on mobile phone access, they do reveal many of the limitations on how mobile phone access can be studied.

In the majority of the external studies mentioned above, mobile phone access is presented as ownership as this is how it was captured by the surveys. In comparison, those studies that used their own surveys or in some cases, within the ICT-orientated surveys, there were more nuanced approaches to understanding access because of the questions asked within the survey e.g., the use of a mobile phone in the last three months or whether the interviewee had access to a shared device. Furthermore, the more general external surveys did not capture any of the determining factors cited within the TAM, restricting many of the studies in terms of the variables they can assess. The advantage of using data from ICT-orientated and study-specific surveys is that the majority of these studies cited previously were able to use variables that could represent all of the determining factors within the TAM.

Beyond determining how to capture access, an additional limitation arising from the majority of the studies is that their analyses are conducted at one time point; only a few studies have any temporal component to their analyses, all of which used external general datasets (Grzybowski, 2015; Tran *et al.,* 2015; Zhang, 2017). As a result, the majority of these studies have not actually tested the main hypothesis of technological divides: as overall access levels increase over time within a country, it is expected that associated technological divides will also narrow (Zainudeen, Iqbal and Samarajiva, 2010). Whilst this assumption is relatively straightforward, that an increase in access logically means those who were without should now have access, the rate of this equalisation has not been quantified nor has any variations between the longevity or influence of the different types of technological divides been studied. For example, does a divide in MPO created by wealth continue to have a greater or lengthier influence than education?

Furthermore, all of the studies lack any geographical analysis; assessment of mobile phone access at a subnational level was not present within any of the studies mentioned above.

This paper addresses these two limitations by studying MPO in a country over a ten-year period and adding a geographical variable to the demographic and socio-economic factors considered within the bivariate and multivariate models. To be able to address these limitations, data is drawn from the 2006, 2011 and 2016 Nepal DHS surveys (NDHS); the drawback of using these datasets is that accessibility is captured solely as device ownership and no data on determining factors are available.

5.4 Methods

5.4.1 Data

Household level datasets were extracted from the 2006, 2011 and 2016 Nepal DHS surveys (NDHS); this included the household recode (HR) dataset and household member recode (PR) dataset for each year. An additional individual level dataset was created from the men's (MR) and women's (IR) recodes from the 2016 NDHS survey. A list of these datasets can be found in the Chapter Data List found in the Supplementary Materials. The DHS program has helped run over 350 surveys in 90 countries since 1984. The majority of surveys generally fall into five categories including their main Demographic and Health Survey (DHS), AIDS Indicators Surveys (AIS), Service Provision Assessment (SPA), Malaria Indicator Surveys (MIS), and Key Indicator Surveys (KIS). The DHS surveys are the original survey tool for the DHS program, and are nationally and subnational representative surveys with large sample sizes of between 5,000 – 30,000 households, drawn from a stratified two-stage cluster design. The precise content of each survey changes with each phase of the DHS; as a result, there can be differences in the data collected for each round.

For Nepal, the surveys were, in the majority, consistent in the variables collected, however there were changes in administrative boundaries between 2015 and 2017 in Nepal which has resulted in spatial disparities with the 2016 Nepal DHS survey (NDHS-2016) (Figure 5-3). Prior to the changes, the smallest subnational unit accounted for by the NDHS-2006 and NDHS-2011 surveys sample design was the eco-development region; NDHS-2016 was instead designed around the newly created province level. As data from DHS surveys can only be used at the units at which they are representative (ICF International, 2012), the most refined geographic unit that could be used for comparison between the three surveys is the development region level, in addition to the national analysis.

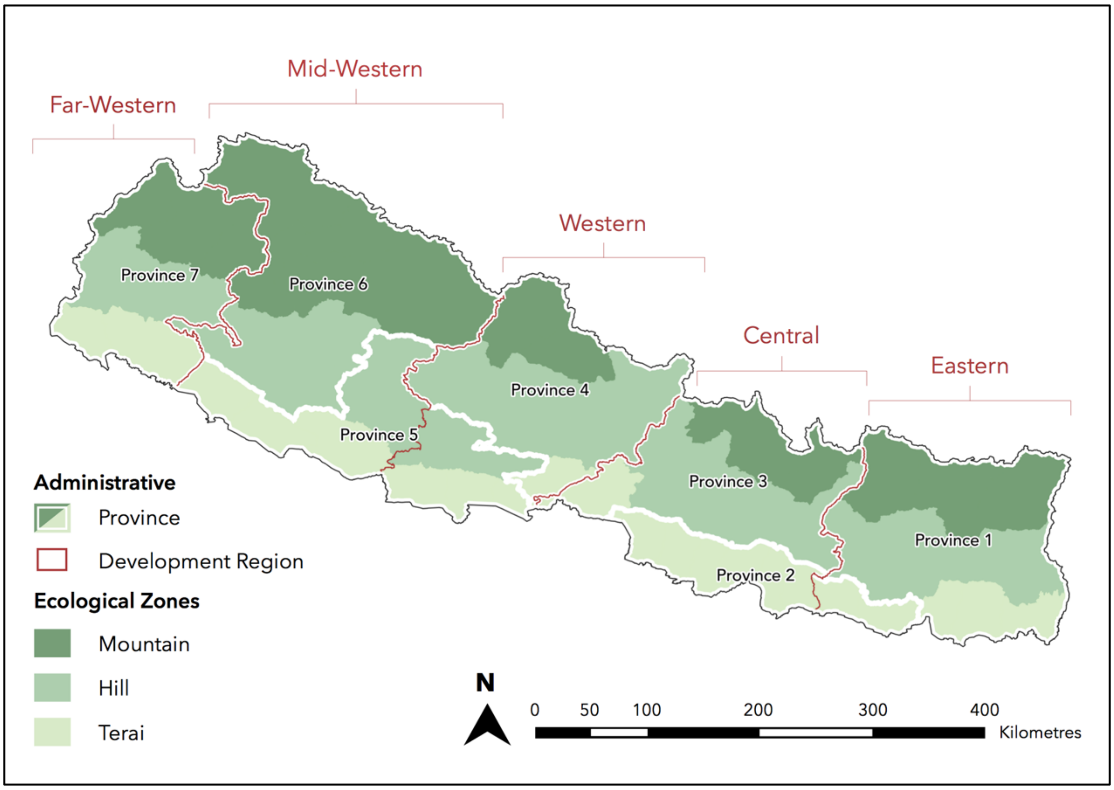


Figure 5-3. The various administrative levels used within past and current Nepal DHS survey sample designs *(Administrative Boundary Data: © 2018 GADM)*:

(a) The Development Region, representative across all three surveys and used within this analysis.
(b) The new Provinces, created in 2015 by grouping together existing districts (two were split between two provinces) and the most refined spatially representative unit within the 2016 data.
(c) The Eco-Development Regions: each Development Region is divided by three ecological zones (Terai, Hill and Mountain). The NDHS-2006 and NDHS-2011 sampling design used these five regions and three zones to create 13 domains at which the survey was representative. Due to low

population counts, the Far-Western, Mid-Western and Western Mountain regions are combined into one domain.

Each survey contains detailed information on ownership of goods at the household level, including the ownership of a mobile phone, which is clearly demarcated as a separate variable from the ownership of a landline telephone. NDHS-2016 also included the ownership of a mobile phone at the individual level. Data about living standards from the household survey, such as material and condition of floors, were used in the creation of the International Wealth Index (IWI) (Smits and Steendijk, 2015), a separate wealth index to that provided by the DHS. The IWI is an asset-based wealth index that utilises data for over 2.1 million households in 97 low- and middle-income countries to determine the appropriate weightings for the asset types used within the index (*ibid*); these assets include the type of toilet and flooring the house has, the number of rooms to sleep in, ownership of certain goods (car, bicycle, fridge) and how the household accesses water. It was chosen as the wealth index for analysis because of its focus on comparability across surveys as well as countries (for replicability of this investigation), its flexibility to omit mobile phones as an included variable and it can be constructed from the same DHS datasets used to assess MPO.

Demographic data about the household head were used to provide the demographic data for analysis at the household level, including gender, age and education information (as seen in Tadesse & Bahiigwa 2015). At the individual level, demographic data were specific to each individual within the survey dataset whereas the household IWI score was used to provide the wealth data.

5.4.2 Selected Variables

Utilising the finding of previous research on MPO both in Nepal (Pradhan and Bajracharya, 2015) and in other countries (Chabossou *et al.*, 2009; Zainudeen, Iqbal and Samarajiva, 2010; de Silva, Ratnadiwakara and Zainudeen, 2011), six variables were selected to assess the potential geo-demographic variability associated with MPO in Nepal (see Table 5-1); selection was informed by the previous MPO literature and the availability of data within the NDHS datasets. Stata Statistical Software (Version 15.1) (StataCorp., 2017) was used to perform both data management and analysis. Within the individual level dataset, in order to account for the subsampling of the men (men were only interviewed in one of every two of the households that women were interviewed within), the provided men's individual sampling weights were adjusted prior to analysis to provide a equivalent representation within the final dataset, as in accordance to DHS guidelines (DHS Forum, 2017). Also, within the individual level dataset, whilst age was also recoded into the same category bounding as the household, as the survey only collects data between the ages of 16-49, the final age group (61 years plus) was omitted from analysis.

Table 5-1: The six variables selected for analysis against MPO at the household level and their respective categories, used within the analysis. For each variable, the first category entry is the reference category used within the regression models. For the individual level analysis, the variables remain the same, however the gender, age and education of the individual is used instead of the household head.

Variable	Category
Development Region	Eastern, Central, Western, Mid-Western, Far-Western
Type of location	Urban, Rural
Household Head Gender	Female, Male
Household Head Age	Recoded into groups: 0 – 15 years old; 16 – 40 years old; 41 – 60 years old; 61 plus years old
Household Head Education	None, incomplete primary, primary, incomplete secondary, secondary, higher
International Wealth Index	Scored 0 – 100; recoded into quantiles to create wealth groups

The analysis aims to quantify the differences in household level and individual level mobile phone ownership relative to the expected technological and geographical divides at the national level. Using the selected variables, the analysis aims to answer:

- Are male-headed households [men] more or less likely to own a mobile phone than female-headed households [women]?
- Does MPO increase with the age of the household head [individual]?
- Are there geographical differences in household [individual] MPO across Nepal?

- Are households [individuals] in rural areas more or less likely to own a mobile phone than those in urban areas?
- Does MPO increase with the (higher) education of the household head [individual]?
- Does MPO increase with (greater) wealth of the household [individual's household]?

5.4.3 Statistical Analysis

Descriptive and regression analysis took into account the DHS survey design, including setting the *primary sampling unit*, the stratification *strata* and *pweights*, as according to DHS guidance (Croft *et al.*, 2018). Descriptive statistics were used to summarise each variable in relation to MPO. The chi-square test was then used to test the distribution of each variable against MPO in order to determine whether to include the variable within the logistic analysis (Table 5-5 in Supplementary Materials). The significance threshold level was set at $p<0.1$ to ensure a generous threshold that prevents any potential significant variables from being omitted within further analysis (Population Survey Analysis, 2014). Gender in 2011 exceeded the threshold, however was found significant in 2006 and 2016. To enable comparability across the logistic regression models (one for each time point), gender was kept as a variable for all three time points. These mixed findings correspond to several of the MPO studies cited above, where for some, gender was a significant factor (Zainudeen, Iqbal and Samarajiva, 2010; FAO, 2016) but for others, it did not affect ownership (Hilbert, 2011). For each year, variables were then checked for collinearity by using the Pearson's R statistic with a threshold of $r<0.5$ (Booth, Niccolucci and Schuster, 1994; Dormann *et al.*, 2013) to ensure that the likelihood of collinearity was low i.e., one variable would not be a proxy of another, particularly in the case of education and wealth. Development region, type of location and gender were not checked due to being nominal data.

Logistic regression was used due to the binary nature of the outcome variable (Chabossou *et al.*, 2009). First, the independent associations between each variable and MPO were tested through bivariate logistic regression for each year for the household analysis and for the 2016 individual analysis. Multivariate logistic analysis was then performed for each year for the household datasets as well as for the 2016 individual dataset. Reference categories were determined either by order (lowest for age, education and wealth), by fitting with the conceptual model (male owners, urban owners) or by examining the descriptive statistics over the three years (the Eastern region was both the median average and the closest to the national level overall across the three years).

5.5 Results

The following section details the descriptive, bivariate and multivariate analyses results at the household level. The individual level analyses results are also discussed, however the table containing the results can be found in Table 5-6 with the Supplementary Material.

5.5.1 Changing household ownership of mobile phones: demographic, socio-economic and geographic characteristics

National household MPO in Nepal has increased substantially from the NDHS-2006, at 5.5% to the NDHS-2016, at 92.8%. The percentage of mobile phone owners have increased across each of the demographic and socio-economic groups, whilst each region has also shown substantial percentage increases (Table 5-2).

Table 5-2. Household Mobile Phone Ownership in 2006, 2011 and 2016 across the different geographic and socio-economic groups. Counts (in parentheses) are weighted, whilst percentages are rounded to the nearest 1d.p.

	Owns mobile phone			Does not own mobile phone		
	2006	2011	2016	2006	2011	2016
National	5.5	74.7	92.8	94.5	25.3	7.2
Female	3.9	73.6	91.5	96.1	26.5	8.5
	(78)	*(2247)*	*(3155)*	*(1923)*	*(808)*	*(293)*
Male	6.1	75.1	93.5	93.9	24.9	6.5
	(400)	*(5817)*	*(7059)*	*(6148)*	*(1928)*	*(491)*
< 16	0	43.8	100	100	56.2	0
	-	*(6)*	*(3)*	*(21)*	*(8)*	*(0)*
16 – 40	6.9	77.3	95.6	93.0	22.3	4.4
	(268)	*(3588)*	*(4291)*	*(3607)*	*(1052)*	*(196)*
41 – 60	4.9	75.9	93.5	95.0	24.1	6.5
	(160)	*(3268)*	*(4221)*	*(3078)*	*(1038)*	*(293)*
61 +	3.5	65.3	85.2	96.5	34.7	14.8
	(49)	*(1203)*	*(1698)*	*(1364)*	*(639)*	*(296)*
Eastern	1.8	77.7	92.3	98.2	22.3	7.8
	(34)	*(2082)*	*(2386)*	*(1862)*	*(599)*	*(201)*
Central	11.1	77.5	94.0	89.0	22.5	6.0
	(333)	*(2800)*	*(3684)*	*(2678)*	*(813)*	*(235)*
Western	5.6	82.0	94.7	94.4	18.1	5.3
	(90)	*(1881)*	*(2125)*	*(1525)*	*(416)*	*(119)*

Mid-Western	1.6 *(17)*	60.7 *(753)*	90.9 *(1213)*	98.4 *(1022)*	39.3 *(487)*	9.1 *(122)*
Far-Western	0.4 *(4)*	56.6 *(548)*	88.1 *(806)*	99.6 *(984)*	43.4 *(421)*	11.9 *(109)*
Urban	22.7 *(327)*	91.7 *(1408)*	94.3 *(6370)*	77.3 *(1113)*	8.3 *(128)*	5.7 *(384)*
Rural	2.1 *(151)*	71.9 *(6656)*	90.6 *(3844)*	97.9 *(6959)*	28.2 *(2608)*	9.4 *(400)*
No education	1.4 *(58)*	61.4 *(2905)*	86.4 *(3717)*	98.6 *(4002)*	38.6 *(1830)*	13.6 *(583)*
Incomplete primary	3.6 *(52)*	72.7 *(1223)*	93.3 *(1620)*	96.4 *(1405)*	27.3 *(460)*	6.7 *(116)*
Complete primary	2.8 *(16)*	81.9 *(575)*	96.5 *(727)*	97.2 *(533)*	18.1 *(127)*	3.5 *(27)*
Incomplete secondary	7.2 *(102)*	86.3 *(1656)*	98.0 *(2005)*	92.8 *(1313)*	13.7 *(263)*	2.9 *(41)*
Complete secondary	12.2 *(62)*	94.6 *(827)*	98.5 *(882)*	87.8 *(451)*	5.4 *(47)*	1.6 *(14)*
Higher	33.8 *(188)*	98.9 *(188)*	99.7 *(1263)*	66.3 *(368)*	1.1 *(10)*	0.3 *(4)*
Lowest Quintile	0.1 *(1)*	34.6 *(784)*	79.0 *(1711)*	99.9 *(1642)*	65.5 *(1485)*	21.0 *(454)*
Second Quintile	0.1 *(1)*	66.4 *(1416)*	91.0 *(1854)*	99.9 *(1703)*	33.6 *(715)*	8.9 *(182)*
Middle Quintile	0.2 *(4)*	83.6 *(1845)*	95.1 *(2002)*	99.8 *(1816)*	16.4 *(362)*	4.9 *(103)*

Fourth Quintile	3.0 *(51)*	93.1 *(1968)*	98.4 *(2229)*	97.0 *(1625)*	6.9 *(147)*	1.6 *(36)*
Highest Quintile	24.6 *(420)*	98.7 *(2052)*	99.6 *(2417)*	75.4 *(1286)*	1.3 *(27)*	0.4 *(9)*

The most substantial growth across all variable groups (except for the lowest wealth quintile) occurred in the five years between 2006 and 2011, with an average increase of 68 percentage points (Figure 5-4). Between 2011 and 2016, growth slowed to an average increase in ownership of 18 percentage points. This deceleration in growth between 2011-2016 is however not applicable to all groups. The lowest owning groups in 2006 (the MWFW regions, those with a household head with Incomplete Education level and the households in the Poorest Wealth Quintile) continued to demonstrate strong growth after 2011, increasing in ownership by 20-44 percentage points. In comparison, the highest owning groups in 2011 (the Urban Households, households in the Highest and Second Wealth Quintiles, and those with a household head with Higher and Complete Secondary Education) have little further growth in ownership between 2011 and 2016 (<6% percentage points) although each of these groups had reached at least 91% ownership by 2011.

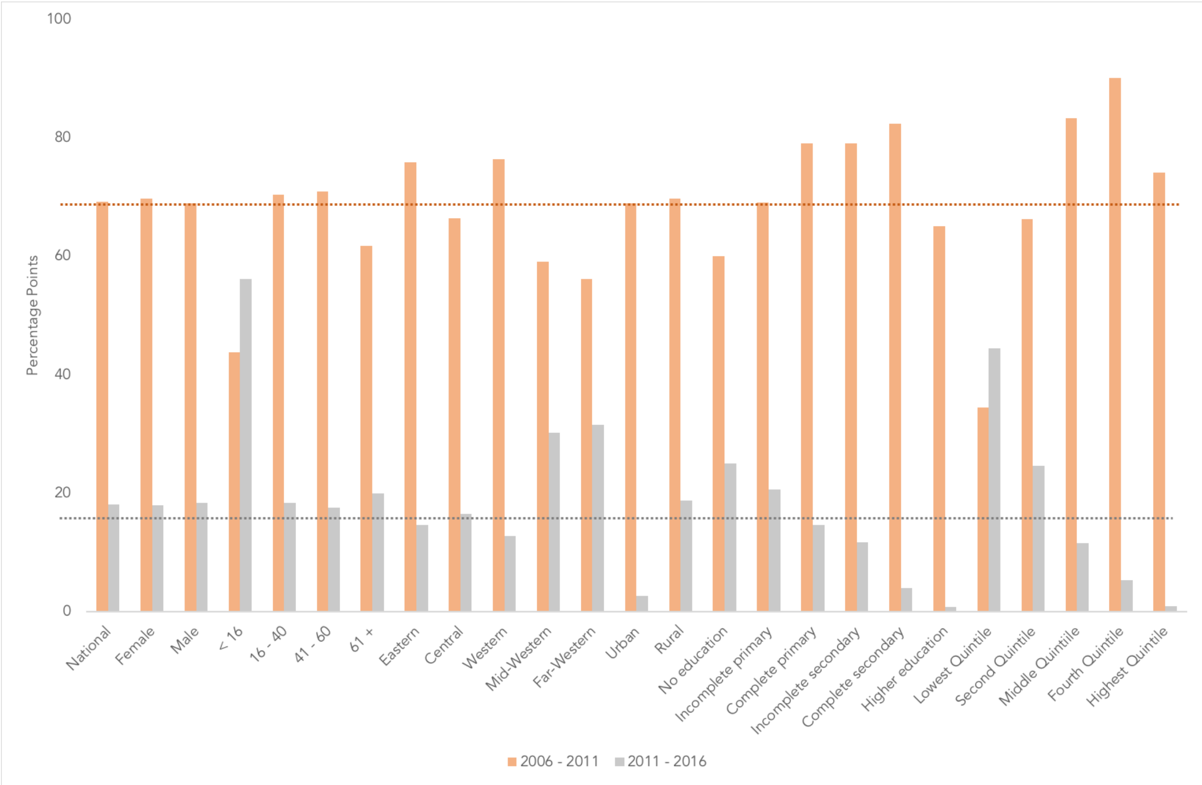


Figure 6-4. Percentage point change in household MPO for each group across the two time periods (2006-2011 and 2011-2016). Average percentage point change for each time period is shown by the dotted line in the respective colour. Quintile refers to the different wealth quintiles generated by the IWI.

There was also geographical disparity in ownership (Figure 5-5). Households within the Eastern, Western and Central (EWC) regions all displayed higher levels of MPO by 2011, than those households in the Mid-Western and Far-Western (MWFW) regions, despite most regions having similarly low ownership in 2006. On average, ownership was 20 percentage points higher in the EWC regions than the MWFW regions. Faster growth in the MWFW regions ensure that by 2016, overall household ownership levels within these regions were more aligned with the EWC regions.

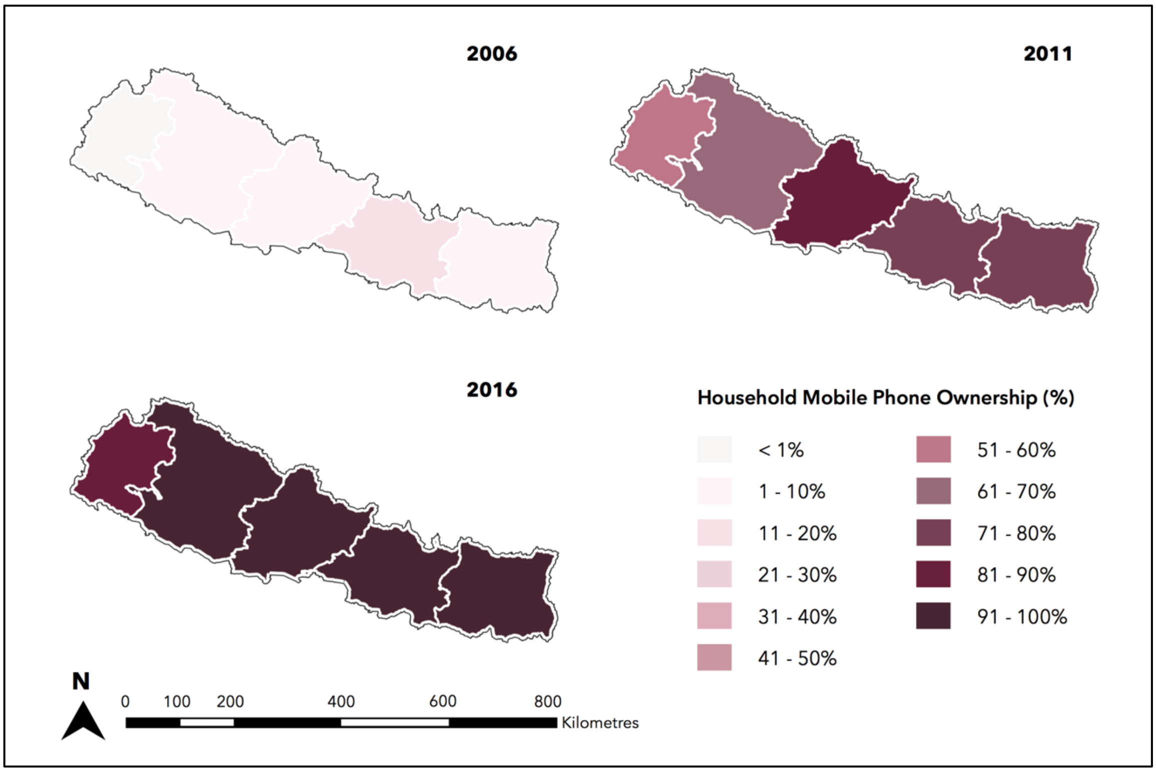


Figure 5-5. Household mobile phone ownership within the Development Regions for each survey: NDHS-2006, NDHS-2011 and NDHS-2016. *(Administrative Boundary Data: © 2018 GADM).*

5.5.2 Predictors of Household MPO: Bivariate Analysis

The results of the bivariate analysis are found in Table 5-3. Across all three time points, wealth is, in the majority, significantly associated with household MPO (p<0.001), indicating that greater wealth is likely to lead to increased odds of owning a mobile. Those households with the highest wealth (the two wealthiest quintiles) are significantly more likely to own a mobile phone than poorer households [OR: 44.51-463.79 in 2011; 25.40-143.47 in 2011; 16.36–71.69 in 2016; (p<0.001 across all three years)]. Despite an overall decrease in odds over the ten years, wealth remains the most influential category across all three time points, with the highest odds across the bivariate analysis for those in the Highest Wealth Quintile in 2006 [OR: 463.79, CI: 64.06, 3358.01, (p<0.001)].

A higher level of education also leads to a higher likelihood of MPO. For example, those households with a head who has minimal education (i.e., incomplete primary) were two and a half times more likely to own a mobile phone than those households with heads with no education, the baseline (and next) category [OR: 2.53, CI:1.59-4.02]. This influence remains consistent in 2011 and 2016, where households with heads with incomplete primary education are one and half [OR: 1.68, CI: 1.42-1.98] and two [OR: 2.19, CI: 1.71-2.82] times the odds more to own a phone than those households with uneducated heads, respectively for each year. Unlike wealth, the odds do not generally reduce over the ten years and, in some cases, marginally increase. For example, the odds for those households with a head who had Higher Education increased between 2006 and 2011 and remained substantially high. In 2016, a household with a head who had Higher Education was 52 times the odds more likely to own a mobile phone than those households with heads with no education [OR: 52.39, CI:19.96-137.57]. In comparison, for the next category, those households with heads with Complete Secondary were only 10 times more likely to own a phone than the those with no education [OR: 9.94, CI:5.80-17.03] in 2016.

The influence of the household head's gender and age was limited. For gender, only the results from 2016 suggested that male-headed households would have significant slightly higher odds of owning a mobile phone than female-headed households [OR: 1.33, CI:1.14-1.57]. The findings are also similar for age, where only in 2016, significant higher odds were found for those households of working age; those households with heads aged between 16-40 and then 41-60 were found to be 4 and 2.5 times more likely to own a mobile phone than those households with a head under 16 [OR: 3.81, CI:3.01-4.82] [OR: 2.51, CI:2.08-3.03] respectively.

From the geographical perspective, there is no single clear relationship between which Development Region a household is in and the likelihood of owning a mobile phone. Only two significant results are present. Firstly, in 2006, those households within the Central region were nearly 7 times more likely to own a mobile phone that those in the Eastern Region [OR: 6.82, CI:3.15-14.77]; no significant relationship was found between the Eastern and other three regions. This significant difference no longer exists by 2011. Instead, whilst there is no relationship between the Eastern and the Central and Western regions, the MWFW regions have less than half the odds as likely to own a mobile phone than the Eastern region, [Mid-Western – OR: 0.44, CI: 0.30-0.67] [Far-Western – OR: 0.37, CI: 0.27-0.53]. By 2016, no significant results are found. In contrast, when considering the type of location, there is a significant relationship in that a rural household is significantly less likely to own a mobile phone than an urban household although the odds do improve over the ten years. In 2006, a rural household was less than a tenth as likely to own a mobile phone than an urban household [OR: 0.07, CI: 0.036-0.15]. By 2016, rural households were just over half as likely to own a mobile phone as urban households [OR: 0.58, CI: 0.46-0.72].

Table 5-3. Household Mobile Phone Ownership in 2006, 2011, and 2016: Bivariate Analysis Results. Odds Ratios are rounded to the nearest 2d.p.

	2006		2011		2016	
	OR [95% CI]	Pr(>|t|)	**OR [95% CI]**	Pr(>|t|)	**OR [95% CI]**	Pr(>|t|)
Gender of household head (Ref: Female)						
Male	1.61 [1.18, 2.20]	0.003	1.09 [0.94, 1.25]	0.257	1.33 [1.14 – 1.57]	0.000
Age of household head (Ref: < 16)						
16 – 40	2.07 [1.31, 3.26]	0.002	4.37 [1.18, 16.27]	0.028	3.81 [3.01 – 4.82]	0.000
41 – 60	1.45 [0.89, 2.35]	0.137	4.04 [1.09, 15.00]	0.037	2.51 [2.08 -3.03]	0.000
61 +	-	-	2.41 [0.63, 9.25]	0.198	-	-
Development Region (Ref: Eastern)						
Central	6.82 [3.15, 14.77]	0.000	0.99 [0.69, 1.43]	0.956	1.32 [0.97 – 1.8]	0.081
Western	3.23 [1.40, 7.46]	0.006	1.30 [0.88, 1.92]	0.187	1.50 [1.12 – 2.02]	0.007
Mid-Western	0.90 [0.24, 3.37]	0.869	0.44 [0.30, 0.67]	0.000	0.84 [0.62 – 1.14]	0.259
Far-Western	0.25	0.005	0.37	0.000	0.62	0.003

	[0.09, 0.66]		[0.27, 0.53]		[0.46 – 0.85]	
Location Type **(Ref: Urban)**						
Rural	0.07 [0.036, 0.15]	0.000	0.23 [0.19, 0.29]	0.000	0.58 [0.46 – 0.72]	0.000
Education of household head **(Ref: No Education)**						
Incomplete Primary	2.53 [1.59, 4.02]	0.000	1.68 [1.42, 1.98]	0.000	2.19 [1.71 – 2.82]	0.000
Complete Primary	2.00 [0.81, 4.94]	0.132	2.86 [2.17, 3.77]	0.000	4.26 [2.81 – 6.47]	0.000
Incomplete Secondary	5.32 [3.58, 7.89]	0.000	3.96 [3.26, 4.82]	0.000	7.66 [5.50 – 10.68]	0.000
Complete Secondary	9.49 [6.11, 14.74]	0.000	11.13 [7.59, 16.30]	0.000	9.94 [5.80 – 17.03]	0.000
Higher Education	34.90 [23.96, 50.84]	0.000	55.90 [28.98, 107.83]	0.000	52.39 [19.96 – 137.57]	0.000
Wealth of household **(Ref: Lowest Quintile)**						
Second Quintile	0.98 [0.60, 16.11]	0.989	3.75 [3.12, 4.51]	0.000	2.71 [2.13 -3.44]	0.000
Middle Quintile	3.48 [0.40, 30.02]	0.255	9.67 [7.89, 11.84]	0.000	5.17 [4.03 – 6.63]	0.000
Fourth Quintile	44.51 [6.22, 318.69]	0.000	25.40 [19.48, 33.12]	0.000	16.36 [10.73 – 24.96]	0.000
Highest Quintile	463.79	0.000	143.47	0.000	71.69	0.000

	[64.06, 3358.01]	[84.73, 242.95]	[34.57 – 148.65]

5.5.3 Predictors of Household MPO: Multivariate analysis

The results of the multivariate analysis, presented in Table 5-4, corroborate with the main significant influencers found within the bivariate analysis (p<0.001). For each year, both wealth and education continue to be the most significant factors influencing MPO, although differences exist. Overall, the influence of wealth decreases substantially when other variables are considered. For example, in 2006, the odds of the Highest Quintile (against the Lowest Quintile) reduce to 102.68 [CI: 13.26 – 795.11] within the multivariate analysis, although as per the bivariate analysis, it is the only quintile that has a significant influence on the ownership of a mobile phone compared to those households with heads with No Education. The results also show a clear reduction in the influence of wealth over the ten years, as also found within the bivariate results.

The overall influence of household head education also decreased when included in the multivariate model, although it did not fall as substantially in odds as compared to wealth. For 2011 and 2016, those households with a head who had between either Complete Primary or Higher Education remained significantly more likely to own a mobile phone than those households with heads with No Education. Those households with heads with Higher Education continued to demonstrate higher odds of owning a mobile phone than the next category of Complete Secondary. In 2016, a household with a head who had Higher Education was 10 times the odds more likely to own a mobile phone than those households with heads with no education [OR: 10.03, CI: 3.73-26.96]. In comparison, those households with heads with Complete Secondary were only 3 times more likely to own a phone than the those with no education [OR: 2.71, CI:1.58-4.64] in 2016.Two noticeable differences between the bivariate and multivariate results are present. Firstly, in 2006 only households with a head with Higher Education had any significant influence on owning a mobile phone [OR: 5.77, CI: 3.73-8.93]; no other education category had any influence on ownership likelihood. Secondly, households with heads with Incomplete Education were no longer significantly more likely to own a mobile phone than those with No Education across all three time periods.

When other variables are considered, the gender of the household head is not a significant predictor, suggesting overall that gender has no significant influence on MPO. In contrast, the household head age presents the same significant association within the multivariate analysis as the bivariate analysis, with those of working age (16 – 60) in 2016 more likely to own a mobile phone than those under 16. Households with heads of 41-60 3.5 times and those of 41-60 2 times more likely to own a mobile phone than those under 16 [OR: 3.55, CI: 2.74-4.60] and [OR: 2.16, CI: 1.75-2.66]. Geographically, only two findings persist. In 2006, the households within the Central region are 4 times more likely to own a mobile phone than those in the Eastern region [OR: 4.09, CI: 2.13 – 7.87]. In 2011, households in the Far-Western region are half as likely to own a mobile phone as those in the Eastern region [OR: 0.52, CI: 0.38-0.71]; here the Mid-Western region odds are insignificant. The greatest contrast between the bivariate and multivariate analyses is the influence of the type of location: when other variables are considered, the type of location no longer has any significant influence on MPO across all three time periods.

Table 5-4. Household Mobile Phone Ownership in 2006, 2011, and 2016: Multivariate Analysis Results. Odds Ratios are rounded to the nearest 2d.p.

	2006		2011		2016	
	OR [95% CI]	**Pr(>|t|)**	**OR [95% CI]**	**Pr(>|t|)**	**OR [95% CI]**	**Pr(>|t|)**
Gender of household head (Ref: Female)						
Male	1.03 [0.68, 1.55]	0.906	0.85 [0.73, 0.99]	0.040	1.15 [0.96 – 1.38]	0.118
Age of household head (Ref: < 16)						
16 – 40	1.06 [0.60, 1.87]	0.852	4.92 [1.99, 12.15]	0.001	3.55 [2.74 – 4.60]	0.000
41 – 60	0.94	0.818	4.63 [1.89, 11.37]	0.001	2.16	0.000

	[0.57, 1.56]				[1.75 – 2.66]	
61 +	-	-	2.73 [1.08, 6.89]	0.034	-	-
Development Region (Ref: Eastern)						
Central	4.09 [2.13, 7.87]	0.000	0.96 [0.70, 1.33]	0.811	1.36 [0.97 – 1.90]	0.072
Western	2.86 [1.45, 5.62]	0.003	1.20 [0.87, 1.66]	0.262	1.18 [0.87 – 1.60]	0.291
Mid-Western	1.24 [0.39, 3.86]	0.715	0.62 [0.45, 0.84]	0.003	1.04 [0.77 – 1.40]	0.814
Far-Western	0.30 [0.14, 0.66]	0.003	0.52 [0.38, 0.71]	0.000	0.69 [0.51 – 0.93]	0.016
Location Type (Ref: Urban)						
Rural	0.36 [0.20, 0.64]	0.001	0.98 [0.77, 1.24]	0.855	1.07 [0.86 – 1.33]	0.546
Education of household head (Ref: No Education)						
Incomplete Primary	1.58 [0.97, 2.56]	0.066	1.17 [0.97, 1.42]	0.097	1.41 [1.08 – 1.85]	0.012
Complete Primary	1.30 [0.48, 3.49]	0.600	1.84 [1.33, 2.53]	0.000	2.32 [1.51 – 3.55]	0.000

Incomplete Secondary	2.00 [1.21, 3.31]	0.007	1.82 [1.44, 2.29]	0.000	3.05 [2.16 – 4.30]	0.000
Complete Secondary	2.25 [1.35, 3.75]	0.002	2.88 [1.84, 4.52]	0.000	2.71 [1.58 – 4.64]	0.000
Higher Education	5.77 [3.73, 8.93]	0.000	12.63 [6.22, 25.63]	0.000	10.03 [3.73 – 26.92]	0.000
Wealth of household (Ref: Lowest Quintile)						
Second Quintile	0.83 [0.05, 13.73]	0.895	3.40 [2.84, 4.08]	0.000	2.70 [2.10 – 3.46]	0.000
Middle Quintile	2.40 [0.28, 20.69]	0.424	8.07 [6.49, 10.05]	0.000	4.45 [3.45 – 5.73]	0.000
Fourth Quintile	18.47 [2.66, 127.96]	0.003	17.59 [13.19, 23.47]	0.000	13.42 [8.81 – 20.45]	0.000
Highest Quintile	102.68 [13.26, 795.11]	0.000	78.72 [45.79, 135.35]	0.000	45.39 [21.82 – 94.43]	0.000

5.5.4 Characteristics and predictors of individual MPO in 2016

The full results of the descriptive and logistic analyses of individual MPO in Nepal in 2016 are presented in Table 5-6 of the Supplementary Materials. Overall, individual MPO among men and women aged 16-49 in Nepal was 82.4%. There was higher ownership among men, standing at 89.3% compared to 72.6% for women. The three lowest owning groups amongst all variables and resulting categories were: those individuals aged under 16 (45.6%), those with no education (61.7%) and those who lived in a household within the Lowest Quintile of wealth (69.1%). In contrast, the three highest owning groups were those individuals with Higher Education (97.7%), or with Complete Secondary (93.6%) and those who lived in a household within the Highest Quintile of wealth (91.1%).

The individual-level analysis found that gender, age, education and wealth are significant predictors of MPO ($p<0.001$); the two geographical variables, Development Region and Location Type, are not. Unlike at the household level, gender is a significant influencer on individual MPO. The bivariate analysis found that men are 3 times more likely to own a mobile phone than women [OR: 3.15, CI: 2.75-3.61], whilst considered with other factors in the multivariate analysis, men are still 2.5 times more likely to own a mobile phone than women [OR: 2.61, CI: 2.20-3.10]. A second difference between the individual and household level analyses is that the education of the individual is a more significant predictor than their household wealth, for both bivariate and multivariate analyses. Within the multivariate model, for example, by being part of a household in the Highest Quintile of wealth, an individual is 2 times more likely to own a phone than someone within one of the poorest households [OR: 2.14, CI: 1.74-2.63]. In comparison, a person with Higher Education is 13 times more likely to own a mobile phone than someone with no education at all [OR: 13.18, CI: 9.64-18.03]. In addition, only Education shows the same trend at the individual level as in the household level analysis, where individuals with Higher Education once again have substantially higher odds of owning a mobile phone, than those within the next category (Complete Secondary) [OR: 5.25, CI: 4.04-6.82].

Age is found in both analyses to be a significant influence on individual MPO. In fact, when considered within the multivariate analysis, age becomes a more significant predictor than when considered solely on its own. For example, for those aged between 16-40, the probability of them owning a phone compared to someone aged under 16 increases from just over 7 times [OR: 7.24, CI: 5.72-9.16] to 8.5 more likely [OR: 8.47, CI: 6.49-11.05]. In terms of geography, Development Region overall was not found to be a significant predictor of individual MPO, whilst when considered with other variables, Location Type was also not a factor.

Finally, one additional analysis, presented in Figure 5-6, is a comparison of household and individual ownership levels in 2016. Overall, ownership of mobile phones at the individual level was 10 percentage points lower than the household estimate for the same year (92.8%). This lower level of ownership is reflected within the demographic, geographic and socio-economic variables groupings, where the individual-level estimates range between 2-55 percentage points lower than the household-level estimates. Overall, the widest gaps in ownership estimates are found in female ownership, those with no education, and those individuals under 16.

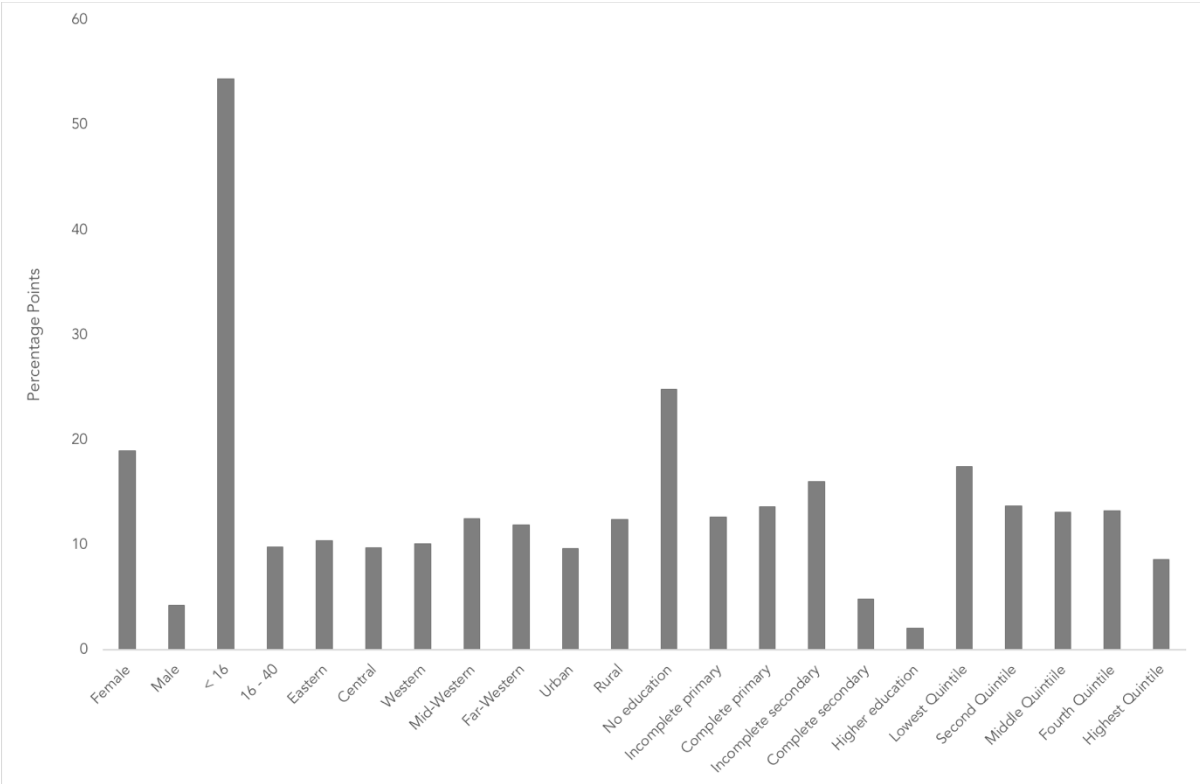


Figure 5-6. Percentage point difference between household and individual MPO in 2016.

5.6 Discussion

Household MPO increased substantially between 2006 and 2016 in Nepal. As part of this growth, there was a shift in ownership from being primarily concentrated in wealthy or urban households, or in households where the household head has a high level of education, or households within the EWC regions, towards a more similar level of ownership across the different demographic and socio-economic groups and geographical regions studied. Despite these increases, a small divide in ownership continued to exist into 2016; the poorest households, those households with either elderly or uneducated heads, as well as those households located in the Far Western had yet to reach the 90% ownership level. However, considering that these groups showed above average levels of growth between 2011 and 2016, it is likely that ownership will only continue to increase within these groups, resulting in an (near-)equalization across

Nepal in terms of what type of households will own a mobile phone, in line with Zainudeen *et al.'s* (2010) hypothesis (Zainudeen, Iqbal and Samarajiva, 2010). As Nepal shifts towards a 100% household MPO, it is likely that these technological divides will continue to decrease.

This analysis provides clear evidence on specific influential factors and how they correlate with increases in household MPO over the ten-year period studied. Education and wealth were found to be the most significant factors influencing household MPO in Nepal, corresponding to the majority of literature on digital divides (Chabossou *et al.*, 2009; de Silva, Ratnadiwakara and Zainudeen, 2011; FAO, 2016). In addition, different 'baselines' were found for both wealth and education which further contribute to the divides of who would or would not own a mobile phone. In 2006, it is evident that only those in the wealthiest households had a likelihood of owning a mobile phone, whilst by 2016 only the poorest households were significantly less likely to own a mobile phone than the other households. In 2006, there was a baseline wealth needed in order to consider purchasing a mobile phone but by 2016, a "competitive market place has made mobile phones an affordable commodity, rather than a luxury item for only the most affluent" (Pradhan and Bajracharya, 2015, pg. 227), enabling ownership to spread further into households of considerably less wealth who recognise the importance of mobile phones for work as well as communicating with distant family (Pradhan and Bajracharya, 2015). The liberalisation policies of the Nepalese government over the last decade has seen the entrance of new private sector operators into the telecom market; these operators are able to offer mobile phones at better prices (Gautam, 2017). These prices however remain somewhat prohibitive for the poorest households, where a mobile phone is likely to still be an expensive or luxury possession and require a significant portion of income which could otherwise be spent on basic needs (FAO, 2016).

Education on the other hand appears to have two opposing influences on MPO. Firstly, those households with at least complete primary education and above were more likely to own a phone than those households who had a head with incomplete primary or no education. This suggests that there may be certain entry barriers for those with little or no education, irrespective of wealth, to own a mobile phone in Nepal; in their 2015 study, Pradhan and Bajracharya suggested this may be because these households are not as exposed to new technology as those more educated and thus not as eager to adopt

(Pradhan and Bajracharya, 2015). This exposure is likely to be one of the reasons why those households with higher education were substantially more likely to own a mobile phone than those in the next education category throughout the ten-year period, whilst at individual level, having Higher Education was the most influential factor in driving MPO, irrespective of wealth. For these households and individuals, the increasing role of and exposure to mobile phones in the workplace is likely to drive the high level of ownership: mobile phones help provide prompt communication, improve access to information and can expand business opportunities (Pradhan and Bajracharya, 2015). Furthermore, in the modern jobs market in Nepal, mobile phones are an essential tool for gaining employment (FAO, 2016), with high-skilled roles increasingly requiring mobile phone and internet use (Pradhan and Bajracharya, 2015). For many of these jobs, such as within the Civil Service, a bachelor's degree is often required (Gautam, 2017); as a result, for those households and individuals with higher education, owning a mobile is becoming a necessity rather than a luxury.

The exposure to mobile phones through work, mass media and everyday life, may also contribute to the underlying factors that confound the influence of gender. At the household level, female-headed households did not seem less likely to own a mobile phone when considered with other variables. However, at the individual level in 2016, men were significantly more likely to own a mobile phone than women, suggesting that women, whilst head of the household, may not be the individual who owned the mobile phone. Consequently, our findings suggest that gender does influence MPO in Nepal, even when controlling for income and education. Milek *et al. (*2011) stated the most intractable limitations to equitable access and use of ICTs lie in the cultural and social dimensions of normal social practices, but such norms are often what discriminate against women and girls (Milek, Stork and Gillwald, 2011).

For Nepal, it is proposed here that this is likely to be employment. Research indicates that women in rural areas, despite education levels equal to men or women in urban areas, have less opportunity to find regular employment and are faced with large wage discrimination (Gautam, 2017). Such factors have precluded women searching for employment (Gautam, 2017; Yamamoto and Kaneko, 2017; Chen, 2018) and lower participation in the labour force has led to higher levels of domesticity, despite having high education levels (Alozie and Akpan-Obong, 2017), and therefore less exposure to technology. The changing social structures, identified in Chapter 4, in terms of outmigration of predominantly young men internationally for work is also likely to exacerbate these inequalities (Speck, 2017), leaving their female counterparts to continue with domestic and familial duties. The 2016 DHS survey, for example, found that only 54% of women in the highest wealth quintile had ever used the internet, in comparison to 79% of men (Ministry of Health and Population (MOHP) [Nepal], New ERA and ICF International Inc, 2017).

The addition of the individual analysis in 2016 reveals nuances in ownership that focusing solely on the household misses when it comes to the role of gender. It also provides confirmation of the many trends found in the household analysis but whilst the factors affecting ownership are similar, household level ownership is considerably higher than individual level ownership overall and across each demographic and socio-economic grouping. This finding is important when considering how the results are interpreted, particularly when it comes to evaluating the potential access of mobile phones within Nepal. At the household level, the main limitation is that the data answers solely one question: is someone within a household of a certain demographic or socio-economic standing likely to own a mobile phone. The data are unable to attribute to whom the mobile phone belongs or whether the demographics and education of the household head is actually reflective of the owner. The lower ownership levels of the individual analysis, particularly for the lowest owning groups, suggest that the latter is not always consistent. The results of the individual analysis therefore help refine our understanding of who exactly is likely to own a mobile phone.

Neither dataset however is able to capture a more nuanced understanding of access, such as who uses the phone and whether it is shared within the household, due to how mobile access was captured through the DHS Program questionnaires. The findings of this study are therefore only related to the ownership of the physical device, which is one aspect of overall access, and must be interpreted as such. Using household and individual results together provides a complimentary and greater understanding of who is likely to benefit from mobile technology. To help improve this understanding, we suggest that additional data on usage, sharing behaviours and subscription numbers is required: however this requires the use of more detailed technology orientated surveys, such as seen in Blumenstock and Eagle (2010) and Wesolowski *et al.* (. Understanding who currently has a subscription (and how many and why), how often they use the service and if they own the device they currently use could therefore lead to a more holistic understanding of mobile phone access.

5.7 Summary

The study has found that, in Nepal, there are several technological divides in MPO at the household and the individual level. Whilst there is no significant difference in the likelihood of a male-headed household owning a mobile phone than a female-headed household, between individual men and women, a divide does exist. Men are two to three times more likely to own a mobile phone, even when other factors are included. In terms of age, at both the household and individual level, mobile phone ownership is more likely for those of working age rather than those entering or within retirement age. There are also geographical differences to the level of ownership within Nepal, with the Central, Eastern and Western regions continuously having higher ownership that the Mid- and Far-Westerns regions; however, these differences are not significant, particularly when accounting for other factors. Furthermore, by 2016, ownership in the latter two regions had substantially caught up with the rest of Nepal. The type of location, rural versus urban, also had no significant influence on MPO. The two most significant factors were education and wealth for household and individual MPO. For both, MPO increases with an increase in education level and an increase in wealth. Education was found to be the more significant predictor of ownership at the individual level, whilst wealth was the most influential at household level.

Overall, the findings of this study conform to the expectations of the TAM model, that MPO is a complex interplay among a number of factors that determine and mediate ownership (van Biljon and Kotzé, 2007). A second key finding of this paper is the initial validation of Zainudeen et al.'s (2010) hypothesis: that technological divides decrease as ownership increases. As the first paper to complete a temporal analysis of MPO changes within a country using DHS data, the paper shows how the technological divides have over time weakened as the ownership of mobile phones has increased in Nepal and the differences within the longevity of these divides. Household ownership is nearing 100% whilst individual ownership has exceeded 80%; however, it is evident in both the household and individual analyses that the poorest and the least educated, and in some cases women, are less likely to own a mobile phone.

Extending this study to other countries that have seen such considerable growth in MPO is an area of future work that can help to further validate Zainudeen et al.'s (2010) hypothesis, and the findings of this study (there are approximately 32 other countries within the DHS Program that have multiple surveys, of which at least one has individual level data). Utilising both household and individual level datasets also provided the study with a better understanding of access from a MPO perspective; it is therefore advocated that both household- and individual-level data are assessed concurrently to provide a robust methodology for future MPO studies in other countries.

5.8 Supplementary Material

Table 5-5: Chi-square results for household analysis

Results of the Chi-Square analysis of the household level datasets from the 2006, 2011 and 2016 Nepal DHS Surveys (NDHS).

	2006	2011	2016
Household Head Gender	0.003	0.2570	0.0004
Household Head Age	0.0263	<0.0001	<0.0001
Development Region	<0.0001	<0.0001	<0.0001
Location (Rural/Urban)	<0.0001	<0.0001	<0.0001
Household Head Education	<0.0001	<0.0001	<0.0001
Household Head Wealth	<0.0001	<0.0001	<0.0001

Table 5-6: Individual Mobile Phone Ownership Results

Descriptive and logistic analyses of individual level MPO in Nepal in 2016. Counts (in parentheses) are weighted, whilst percentages are rounded to the nearest 1d.p. Odds Ratios are rounded to the nearest 2d.p. Reference category for bivariate and multivariate analyses is denoted by *.

			Bivariate		**Multivariate**	
	Does own mobile phone	**Does not own mobile phone**	**OR [95% CI]**	**Pr(>|t|)**	**OR [95% CI]**	**Pr(>|t|)**
National	82.4%	17.6%	-	-	-	-
Gender						
Female*	72.6 (9308)	27.4 (3554)	-	-	-	-
Male	89.3 (3508)	10.69 (483)	3.15 [2.75, 3.61]	0.000	2.61 [2.20, 3.10]	0.000
Age						
< 16*	45.6 (268)	54.4 (436)	-	-	-	-
16 – 40	85.9 (10738)	14.1 (2553)	7.24 [5.72, 9.16]	0.000	8.47 [6.49, 11.05]	0.000
41 – 50	75.9 (1882)	24.1 (1048)	3.75 [2.87, 4.9]	0.000	5.65 [4.19, 7.62]	0.000
Development Region						
Eastern*	81.8 (736)	18.1 (736)	-	-	-	-
Central	84.3 (1014)	15.7 (1014)	1.19 [0.96, 1.48]	0.109	1.10 [0.89, 1.36]	0.376
Western	84.6 (666)	15.4 (666)	1.22 [0.92, 1.61]	0.161	1.15 [0.89, 1.50]	0.290
Mid-Western	78.4 (916)	21.6 (916)	0.81 [0.64, 1.01]	0.060	0.96 [0.76, 1.21]	0.722

Far-Western	76.2	23.8	0.71	0.002	0.77	0.028
	(705)	(705)	[0.57, 0.89]		[0.61, 0.97]	
Location Type						
Urban*	84.8	15.2	-	-	-	-
	(8594)	(2352)				
Rural	78.2	21.8	0.65	0.000	0.95	0.515
	(4294)	(1685)	[0.55, 0.75]		[0.81, 1.11]	
Education Level						
No Education*	61.7	38.3	-	-	-	-
	(2781)	(1966)				
Incomplete Primary	80.8	19.3	2.61	0.000	1.91	0.000
	(1427)	(459)	[2.15, 3.16]		[1.53, 2.37]	
Complete Primary	82.8	17.2	3	0.000	2.12	0.000
	(776)	(209)	[2.35, 3.81]		[1.61, 2.79]	
Incomplete	82	18.1	2.82	0.000	2.22	0.000
Secondary	(3754)	(1105)	[2.43, 3.28]		[1.82, 2.69]	
Complete Secondary	93.6	6.4	9.10	0.000	5.25	0.000
	(1618)	(193)	[7.17, 11.54]		[4.04, 6.82]	
Higher Education	97.7	2.3	26.92	0.000	13.18	0.000
	(2532)	(105)	[20.10, 36.06]		[9.64, 18.03]	
Wealth of Household						
Lowest Quintile*	69.1	30.9	-	-	-	-
	(1685)	(1026)				
Second Quintile	77.4	22.6	1.53	0.000	1.36	0.002
	(2305)	(891)	[1.28, 1.82]		[1.13, 1.65]	
Middle Quintile	82.1	18	2.04	0.000	1.60	0.000
	(2597)	(841)	[1.74, 2.4]		[1.34, 1.90]	
Fourth Quintile	85.2	14.8	2.57	0.000	1.63	0.000
	(2931)	(759)	[2.16, 3.05]		[1.35, 1.97]	
Highest Quintile	91.1	8.9	4.55	0.000	2.14	0.000
	(3336)	(509)	[3.81, 5.43]		[1.74, 2.63]	

Table 5-7: Chapter Data List

Dataset	Source	Reference
NPHR51.DTA 2006 NDHS Household Survey	The DHS Program	Ministry of Health and Population (MOHP) [Nepal], New ERA, and Macro International. 2007. Nepal Demographic and Health Survey 2006 [Dataset]. NPHR51.DTA. Kathmandu, Nepal. Ministry of Health and Population, New ERA, and Macro International [Producers]. ICF International [Distributor], 2007.
NPPR51.DTA 2006 NDHS Household Member Survey	The DHS Program	Ministry of Health and Population (MOHP) [Nepal], New ERA, and Macro International. 2007. Nepal Demographic and Health Survey 2006 [Dataset]. NPPR51.DTA. Kathmandu, Nepal. Ministry of Health and Population, New ERA, and Macro International [Producers]. ICF International [Distributor], 2007.
NPHR60.DTA 2011 NDHS Household Survey	The DHS Program	Ministry of Health and Population (MOHP) [Nepal], New ERA, and ICF International. 2012. Nepal Demographic and Health Survey 2011 [Dataset]. NPHR60.DTA. Kathmandu, Nepal. Ministry of Health and Population, New ERA, and ICF International [Producers]. ICF International [Distributor], 2012.
NPPR60.DTA 2011 NDHS Household Member Survey	The DHS Program	Ministry of Health and Population (MOHP) [Nepal], New ERA, and ICF International. 2012. Nepal Demographic and Health Survey 2011 [Dataset]. NPPR60.DTA. Kathmandu, Nepal. Ministry of Health and Population, New ERA, and ICF International [Producers]. ICF International [Distributor], 2012.
NPHR7H.DTA 2016 NDHS Household Survey	The DHS Program	Ministry of Health and Population (MOHP) [Nepal], New ERA, and ICF International. 2017. Nepal Demographic and Health Survey 2016 [Dataset]. NPHR7H.DTA. Kathmandu, Nepal. Ministry of Health and Population, New ERA, and ICF International [Producers]. ICF International [Distributor], 2017.
NPPR7H.DTA 2016 NDHS Household Member Survey	The DHS Program	Ministry of Health and Population (MOHP) [Nepal], New ERA, and ICF International. 2017. Nepal Demographic and Health Survey 2016 [Dataset]. NPPR7H.DTA. Kathmandu, Nepal. Ministry of Health and Population, New ERA, and ICF International [Producers]. ICF International [Distributor], 2017.
NPIR7H.DTA 2016 NDHS Individual Survey	The DHS Program	Ministry of Health and Population (MOHP) [Nepal], New ERA, and ICF International. 2017. Nepal Demographic and Health Survey 2016 [Dataset]. NPMR7H.DTA. Kathmandu, Nepal. Ministry of Health and Population, New ERA, and ICF International [Producers]. ICF International [Distributor], 2017.
NPMR7H.DTA 2016 NDHS Men's Survey	The DHS Program	Ministry of Health and Population (MOHP) [Nepal], New ERA, and ICF International. 2017. Nepal Demographic and Health Survey 2016 [Dataset]. NPIR7H.DTA. Kathmandu, Nepal.

		Ministry of Health and Population, New ERA, and ICF International [Producers]. ICF International [Distributor], 2017.
Nepal Administrative Boundaries, Level 0 – 5	GADM 2018	© GADM www.gadm.org (https://gadm.org/download_country_v3.html, Accessed December 2018)

Chapter 6 Detecting geographic communities in Nepal using CDRs

6.1 Chapter Overview

This chapter uses a combination of complex network analysis and GIS techniques to explore whether the connections between subscribers within a mobile phone network are likely to represent their real-world social networks. The chapter investigates whether the social communities that are detected within the CDR dataset network are spatially constrained, i.e., occupy a certain geographic area. This investigation is based on the theory of the role of space and homophily on the formation of geographic communities. The investigation not only confirms that the social networks found within the CDR dataset are likely to be representative of real-world social networks, but also that precise geographic communities can be found within the dataset.

6.2 Introduction

Geographic communities – the villages, towns, and neighbourhoods within cities that constitute our human landscape – are important building blocks for sustainable development. Primarily forming through the co-location of people who often have similar interests and goals as well as strong social ties, these communities will share the benefits and gains of community-level economic development and sustainability (Blakely and Leigh, 2013; International Federation of Red Cross and Red Crescent Societies, 2016), as highlighted by Goal 11 of the 2015 Sustainable Development Goals (SDGs) (UN General Assembly, 2015b). Analysing up-to-date demographic as well as socio-economic data about these communities is essential to inform and target policy and programmes that aim to enhance the economic development and sustainability of these communities. Furthermore, these data are required to provide a baseline from which to measure and monitor progress (Lu *et al.*, 2015), a key mechanism to quantify and evaluate whether the SDGs are making the impact they promise (Peters *et al.*, 2016) as well as more generally understand and keep track of a country's overall socio-economic wellbeing (Durand, 2015). Despite this critical need, these types of data are often scarce, either non-existent or difficult to obtain, or sparse, limited in temporal or spatial coverage. The data required for more than half of the global indicators are not regularly collected, even at a national level, resulting in a significant lack of information to help with community monitoring (Report of the Secretary-General, 2019).

To combat this data scarcity and sparsity, scientific and financial investment is being made in novel data sources for monitoring changing socio-demographic conditions, which hold the promise of offering near real-time data that are collected automatically, often without any additional costs (UN, 2018). Call Detail Records (CDRs), the metadata generated through the use of mobile phones, are one of these promising datasets, having already been used to provide displacement predictions (Wilson *et al.*, 2016), build disease models (Tatem *et al.*, 2009; Buckee *et al.*, 2013), and support poverty estimation (Blumenstock, Cadamuro and On, 2015; Steele *et al.*, 2017) for sustainable development and humanitarian applications.

CDRs hold promise for monitoring geographic communities, as they are typically collected in near real-time, and carry valuable information that could inform economic development and resilience, such as downward trends in expenditure or unusual movement patterns suggesting the community is or has experienced some type of shock. Thus far, however, CDR-based analyses have generally grouped individual subscriber behaviour by the cell tower at which they are calculated to live nearby, often known as their 'home location', and aggregating to an appropriate administrative region. Currently, there is no methodology to provide these analyses at the community scale, rendering CDRs impractical for community monitoring unless a new approach can be found. Consequently, it is important to ascertain whether CDRs can be used to provide community-scale data in order to consider the opportunities and limitations the dataset faces in its future use within SDG-oriented applications.

Using CDRs for community monitoring requires that geographic communities can be identified within the dataset. This involves finding communities of people that are connected both socially and spatially in one place (Sarkar, Sieber and Sengupta, 2016). The first step to identifying geographic communities within CDR data therefore is to determine whether the CDR-based social network can be partitioned into communities that represent social closeness. As mobile phone communication is strongly correlated with friendship networks and represents a significant portion of an individual's social network (Eagle, Pentland and Lazer, 2009), it is likely that these communities created using CDR data represent real social groupings, such as a social community. The detection of communities relies on using a Community Detection Algorithm (CDAs) to partition the network into groups of subscribers (see Methods). Mobile phone networks have already been tested with CDAs and been shown to partition well (Blondel *et al.*, 2008; Onnela *et al.*, 2011).

The second step is to confirm that these detected social communities are spatially concentrated, i.e., the members all live in one place, and correlate with known real-world geographic communities, such as cities, towns and villages. From the outset, as mobile phones enable communication regardless of time or distance (Cairncross, 2002), it would seem unlikely that the social communities within a mobile phone network would exist in concentrated spatial areas. Yet studies have determined that communities detected within CDR-based networks do have specific local geographies, with contact numbers and frequency decreasing over distance (Onnela *et al.*, 2011; Sobolevsky *et al.*, 2013; Madhawa *et al.*, 2015). Even mobile networks are constrained by geography, abiding by the basic principles of Tobler's First Law of Geography (those who are closer together are likely to be more similar) and homophily (those more similar are more likely to interact), which work together to promote spatial propinquity, co-location, and thus community formation (Caughlin *et al.*, 2013; Sarkar, Sieber and Sengupta, 2016).

This research sets out to test whether these spatially concentrated social communities correspond to real-world geographic communities, such as cities, towns and villages. By identifying these real-world geographic communities, this paper provides a significant step towards using CDRs to provide the required datasets for community monitoring. Instead of providing analysis at the Voronoi scale, this work could enable these communities to be used as units at which to aggregate future analyses, such as food security (Decuyper and Rutherford, 2014) or resilience estimates (as advocated in Chapter 3). This aggregation scale would enable these analyses to be compared directly with other pre-existing spatial and demographic data used in monitoring and evaluation, substantially enhancing the overall value of these CDR analyses and increase their utility for helping to address the data gaps faced by initiatives such as the SDGs.

To support this novel approach, we look to find geographic communities within eleven districts in the country of Nepal using pseudonymised CDR data provided by

Ncell (Figure 6-1). These districts cover a range of settings within Nepal, from the urbanised Kathmandu Valley, its surrounding peri-urban areas, several other regional urban areas as well as more rural areas across the Terai, Hill and Mountain ecological regions. We reconstruct the social networks of approximately 1.69 million subscribers from these 11 districts; this represents approximately a quarter of the population of 7.6 million, counted at the last census (2011). With individual (adult) mobile phone ownership at 82.4% (Ministry of Health and Population (MOHP) [Nepal], New ERA and ICF International Inc, 2017), and similar level of ownership found across the different demographic and socio-economic groups (according to the previous Chapter), it is likely that these 1.69 million subscribers represent a substantial cross-section of the Nepalese population, however the poorest and least educated persons and/or households may be underrepresented within the dataset. We use the metadata from all calls made between January and April 2015 and partition the network using the Louvain CDA. We adapt Shi et al.'s (2015) Kernel Density Estimation (KDE) methodology to map the spatial distribution of the resulting communities and check the resulting density maps for community centres. From these centres, we find over thirty geographic communities within the CDR data although several limitations to their use and application become apparent when we validate these centres against existing census data.

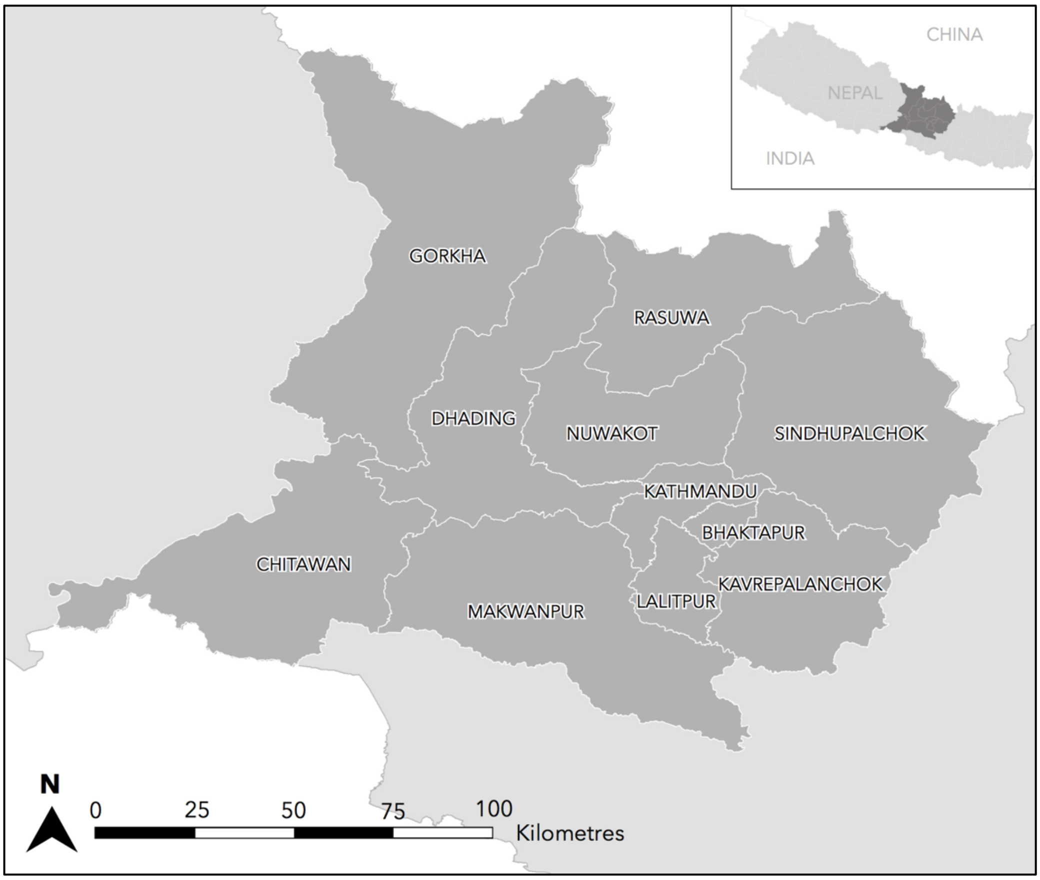


Figure 6-1. The eleven districts of interest in Nepal. (Administrative Boundary Data: © 2018 GADM).

6.3 Data and Methods

The CDR dataset was provided by Ncell, a leading Mobile Network Operator (MNO) in Nepal, and processed in partnership with the Flowminder Foundation. The Ncell subscriber base accounts for nearly 50% of the Nepalese mobile phone market. In order to preserve subscriber anonymity, a data governance framework and privacy safeguards were implemented prior to the CDR dataset being processed. The safeguarding steps included:

- the CDR data were retained within the premises, and under the control, of the operator, and were analysed via secure remote access
- only aggregated data were extracted from the secure system
- the CDR data were pseudonymised by the operator so that sensitive fields, such as mobile phone numbers, were replaced with pseudonyms generated using an industry standard cryptographic process

Home locations for all subscribers (11.15 million) in Nepal were first assigned by calculating the most common cell tower connected to by a subscriber during their last call of the day within the selected time period, January 1st 2015 – April 24th 2015. This approach is one of several common methods used within CDR analyses to determine a home or reference location for an individual, others include determining the tower connected to most often by the subscriber, or the tower with the maximal number of distinct days with phone activities. Previous studies have shown that location of the last call of the day can predict a subscriber's home location with good accuracy (Calabrese *et al.,* 2013; Tatem *et al.,* 2014).

The social contacts for each subscriber were then reconstructed and the total number of contacts for each subscriber were calculated (known as the contact degree). The home locations were then used to filter subscribers to only those that resided within the eleven districts of interest, a total of 2.78 million subscribers. The remaining subscribers were filtered further by their contact degree, with a minimum of 10 and maximum of 100 contacts used to reduce the likelihood of including inactive or business-orientated subscribers within the analysis.

From the remaining subscribers (1.69 million), an undirected network graph was constructed using the NetworkX package (Hagberg, Swart and Chult, 2008). The general form of a network graph is G = (V, E), where G is the graph, V is the set of vertices, and E, the set of edges that represent the connectivity between these vertices. In CDR networks, a vertex represents a single mobile subscriber and an edge between two vertices is some type of contact between them, for example a phone call or text message (Teng and Chou, 2007). These edges can be weighted by the frequency, duration or even cost of the overall contact. The resulting graph can then be analysed to extract certain properties about the network, such as using a CDA. The aim of a community detection algorithm is to identify groups of vertices that have higher concentrations of edges than to those surrounding them, resulting in tightly-knit groups which then have a low concentration of edges between them (Brunsdon *et al.,* 2012). By identifying these groupings, the CDA is able to partition the network into communities. The degree to which a network can be partitioned is known as the network modularity; a high value of modularity indicates a more robust community structure (Shi *et al.,* 2015).

There are multiple CDAs available that take differing approaches to grouping vertices. This is because each algorithm created is dependent on the background and aims of those who have developed it, as well as their interpretation of how to define a community (Yang, Algesheimer and Tessone, 2016) and how this translates into an objective function (Decuyper *et al.,* 2018). Ultimately, all methods aim to identify meaningful communities, whilst keeping the computational complexity of the underlying algorithm as low as possible (Yang, Algesheimer and Tessone, 2016), to ensure it runs efficiently. For geographic networks, certain CDAs are less suited for detecting communities; primarily this is any algorithm that introduces a random replacement element into the partition as it will violate the topological properties of the network and produce spatially inconsistent merges (Comber, Brunsdon and Farmer, 2012). Here we utilised the Louvain CDA which has been previously deployed efficiently and effectively on mobile phone datasets (Blondel *et al.,* 2008). The Louvain CDA works in two steps: it first optimises the modularity locally on all nodes and then each small community is grouped into one. This step is repeated until the network is unable to be partitioned further, maximising modularity. The algorithm does have its limitations, with a tendency to over group nodes resulting in a loss of smaller scale communities; an issue faced by modularity optimization algorithms.

The Louvain CDA, available with the open-source Python-based FlowKit toolbox (Gray *et al.*, 2020), which leverages the python-louvain Python library (Aynaud, 2020), was run on the resulting graph, with the number of events between subscribers used as a weighting. The CDA was run with several parameters, with the minimum community size set at five members and the maximum as infinite; these parameters aimed to capture a variety of community sizes. The resulting detected social communities were then used to produce a final output file, which listed for each social community, the total count of members for each cell tower (with none as a possibility). In total, there were 675 cell towers within the eleven districts. All cell towers registered at least once as a potential home location for a subscriber. To produce the density maps, the spatial distribution of each social community was first mapped using the home cell towers for the community and their respective count. Figure 6-2 shows the distribution of cell towers for one community, symbolised by the number of subscribers registered at each tower.

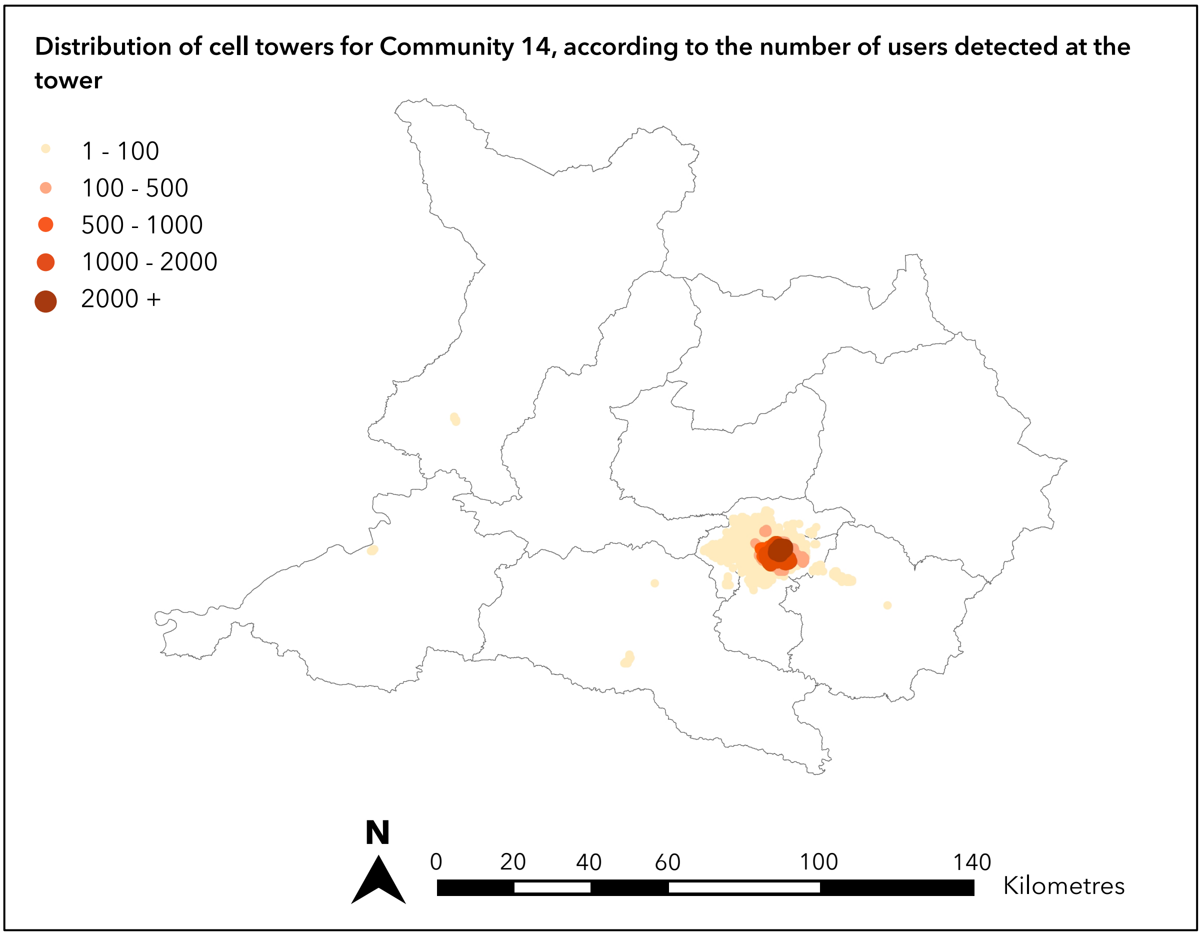


Figure 6-2. Cell tower distribution for one community. (Administrative Boundary Data: © 2018 GADM).

Shi et al.'s (2015) approach to distributing community members was then utilised in order to weaken the impact of the uneven distribution of the cells. Instead of using the cell tower location within the KDE methodology, the subscriber count at each location is distributed across the tower's predicted network coverage area, also known as the cell tower Voronoi, using a 0.5 x 0.5 km grid, (Shi *et al.*, 2015). This approach can also enable a better geographic representation of how the community would be distributed; community members, for example, would not all be located at a single point (i.e., the cell tower) but would be distributed in some pattern across the geographic area around the cell tower.

To match this distribution closely to real-world distributions and improve on Shi et al.'s (2015) methodology, the WorldPop 2015 population raster dataset of Nepal (Tatem, 2017) was utilised to weight the grid cells before allocating community members (Figure 6-3): zonal statistics (sum) were used to extract the 2015 population for each grid cell or polygon within the Voronois. This was then used to calculate the proportion of the total Voronoi population each grid cell/polygon contained to provide the distribution weight. Community members for each cell tower were then distributed across the weighted Voronoi grid, according to this proportion. The motivation was to further refine and improve the accuracy of the spatial coverage for each community and aid the extraction of a likely geographic community. Once each community was distributed across the cell Voronoi grid, the KDE was run to calculate the expected counts of community members across the eleven districts. In keeping with Shi et al.'s (2015) approach, a bandwidth, also known as the search radius, of 1.5 km (three times the grid size) was used to ensure the resulting distributions were appropriate (Shi *et al.*, 2015) and the cell size was designated as 500m to match the distribution grid.

The resulting density maps were then visually and quantitatively assessed. The hotspots from the density maps were then extracted and used to identify the geographic centre(s) of each of the social communities. Each extracted area was visually compared with OpenStreetMap (OSM) and Municipality/Village Development Committee (VDC) administrative data from Nepal to derive names for geographic communities based on nearby settlements. OSM is a freely accessible open-content online map created through formal (institutional open data uploads, such as the US Census Bureau TIGER dataset) and non-formal (crowd-sourcing and volunteer editing) methods (Antoniou, 2017). As

OSM provides openly available and accessible geographic reference data, using it ensures that the methodology used in this Chapter can be translated to other countries (subject to CDR access). The VDC data were used as a secondary dataset for validation of OSM, particularly to check inaccuracies within OSM in the official spelling of the names for smaller towns and villages. The VDC data also were from 2015 which coincides with the dates of the CDR data; since September 2015, the administrative regions in Nepal have changed.

To provide an initial validation of our detected geographic communities, population statistics for each municipality/VDC were extracted from the 2011 census data (Central Bureau of Statistics, 2012). To provide a quantification of the community distribution, for all communities a central point of the community was identified by selecting the pixel with the highest community membership. Distance from this pixel was then computed for the remaining populated pixels, with the cumulative community population calculated as the distance increased. For the zonal community distributions, their spatial orientation and spread were estimated by calculating their elliptical standard deviation distribution.

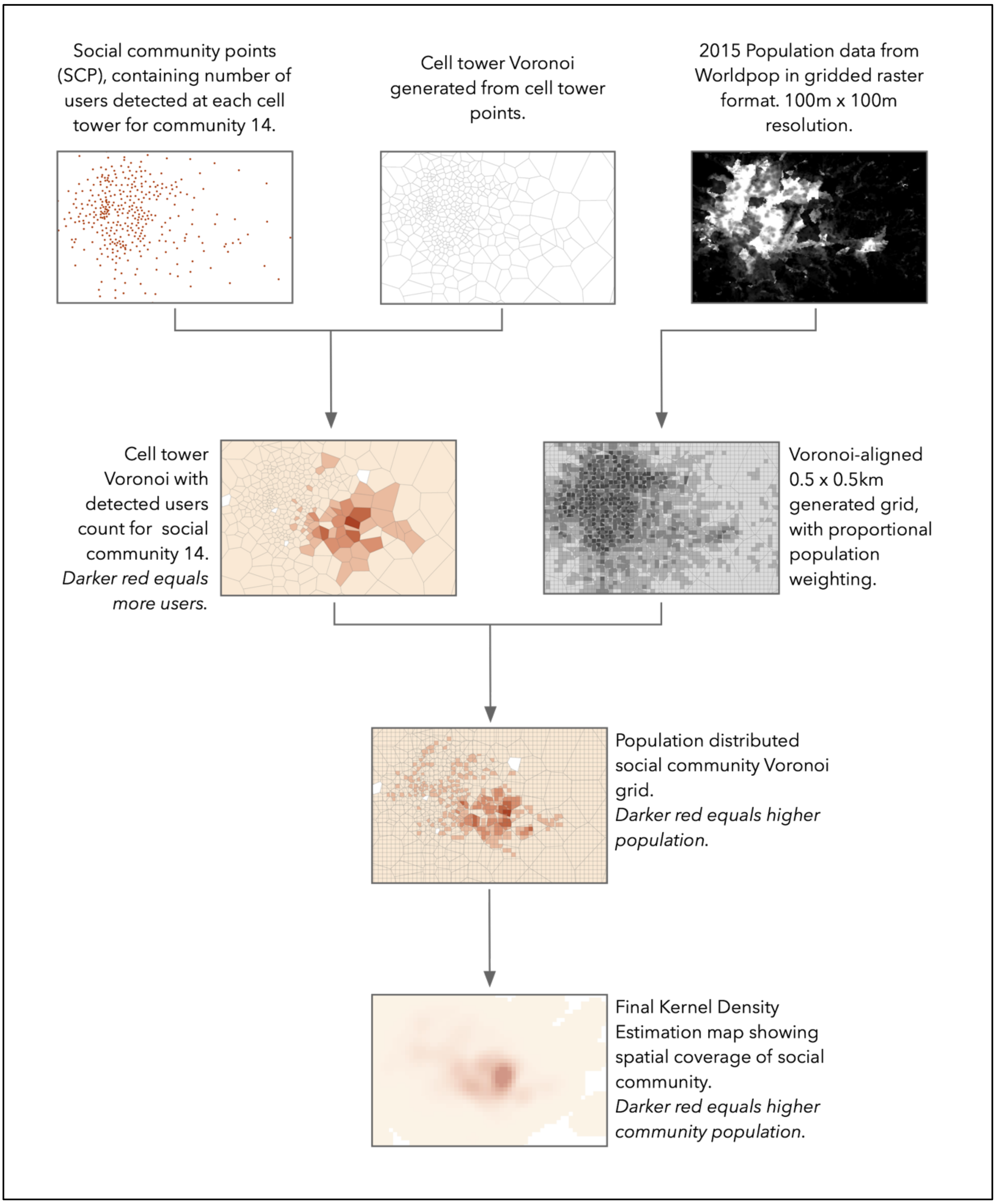


Figure 6-3. Producing density maps for each social community, using the population-weighted cell tower Voronoi grid. (Administrative Boundary Data: © 2018 GADM; Population Data: WorldPop).

6.4 Results

6.4.1 Community Detection

In total, 54 social communities were detected within the dataset, ranging from 5 to 247,790 members. The twenty-four communities which had 5-100 members were processed, however their resulting density maps were unusable as the resulting expected counts of people, for the majority, were under 1 person per pixel. As a result, these communities were removed from further analysis. Overall, there were 30 communities with more than 100 members that were suitable for analysis: 13 communities with 100-5,000 members; 9 communities with 5,000-100,000 members; and 8 communities with over 100,000 members. These 30 communities represented 99.97% of the subscribers within the CDR dataset.

6.4.2 Identification of Community Centres

Density maps were produced for each social community, reflecting the overall spatial distribution as well as providing a hotspot for the core geographic areas (examples: Figure 6-4; all communities: Figure 6-8 in the Supplementary Materials). As the communities are clustered based on their social proximity and the CDA is not constrained to achieve geographically contiguous areas (Zhong *et al.,* 2014), different patterns have emerged within the density maps. Each community density map shows at least one hotspot, confirming that the social communities found within the Nepal CDR dataset are spatially concentrated. However just under half of the communities have either two or three hotspots; whilst these communities are spatially concentrated, they are concentrated in more than one location.

For Shi *et al. (*2015), who had very similar results, these density patterns result from the effect of social phenomena, such as commuting, which have split social communities into multiple geographic locations (Kok and Veldkamp, 2011). Here we use Shi et al.'s (2015) qualitative approach of categorising these patterns into three types of distributions to identify our community centres. The implications of these different distributions for using CDRs to map geographic communities are explored further in our Discussion.

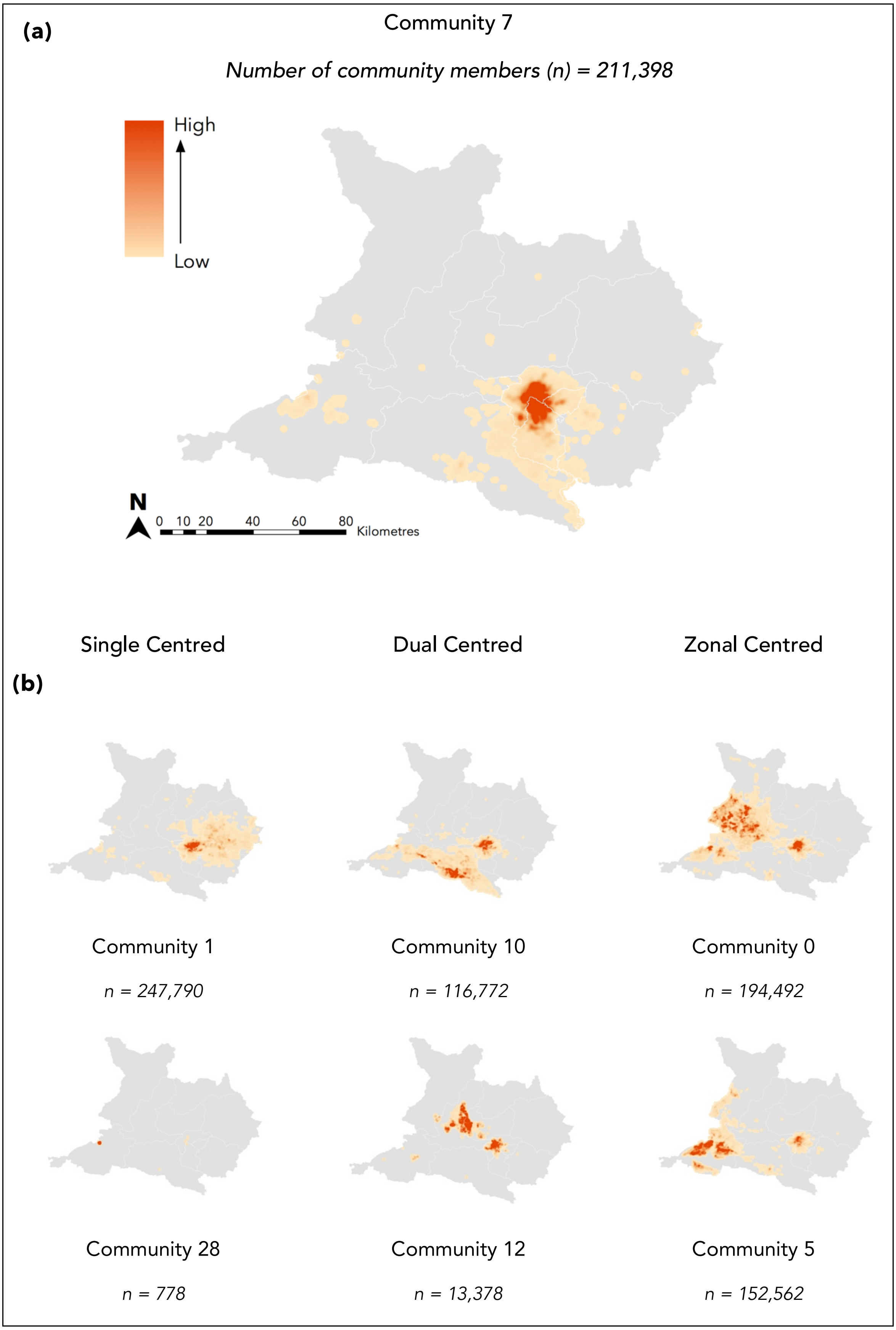


Figure 6-4. Kernel Density Estimation community maps of relative population distribution. a) Community 7, a single distribution community. b) Further examples of the single, dual and zonal centre distributions. (Administrative Boundary Data: © 2018 GADM).

In total, the majority of our communities (17) showed a single-centre distribution, where there was either a single contiguous hotspot or, in several cases, a set of close hotspots that created almost continuous coverage. For our dataset, the size of these singular distributions varied from the size of a neighbourhood within a city up to the size of a city or incorporating several towns or villages (large single-centred); the hotspot-centres themselves remained relatively small, at the size of a neighbourhood or village. The majority (16 out of 17) of these single centre communities were located in one of two districts, Kathmandu or Lalitpur. Eight communities displayed a dual-centred pattern, which is when there are two distinct spatial locations where community members cluster. The distance between these two spatial clusters varies from local (e.g., between a city or nearby village) to regional, stretching across several districts. These communities were distributed more evenly across the eleven districts, although for each community, at least one of the centres was in either the Kathmandu or Lalitpur district.

The remaining five communities showed a zonal distribution, which is an intermediate pattern between single and dual-centred patterns, where there can be multiple centres (Shi *et al.*, 2015). The directional distribution of these communities in relation to Kathmandu is shown in Figure 6-5, using weighted standard deviation ellipses (weighted by the expected community population from the KDE maps). The ellipses show the central tendency, dispersion and directional trends of each community. Four of the five communities extend radially out from Kathmandu whereas Community 5 is primarily spread around the city of Bharatpur. Those communities closer to Kathmandu (within 40km) are more concentrated in their dispersal and, for Communities 19 and 2, appear to create corridors towards other district capitals. This corridor effect is apparent for Community 0, as it extends over 60km between the capitals of the Gorkha (Gorkha) and Dhading (Nilkantha) districts towards Kathmandu. Community 0 and Community 5 are less concentrated than those communities nearer Kathmandu. Community 17 does not connect to any other district capital, instead extending into nearby towns of Chandragiri and Bajrabarahi.

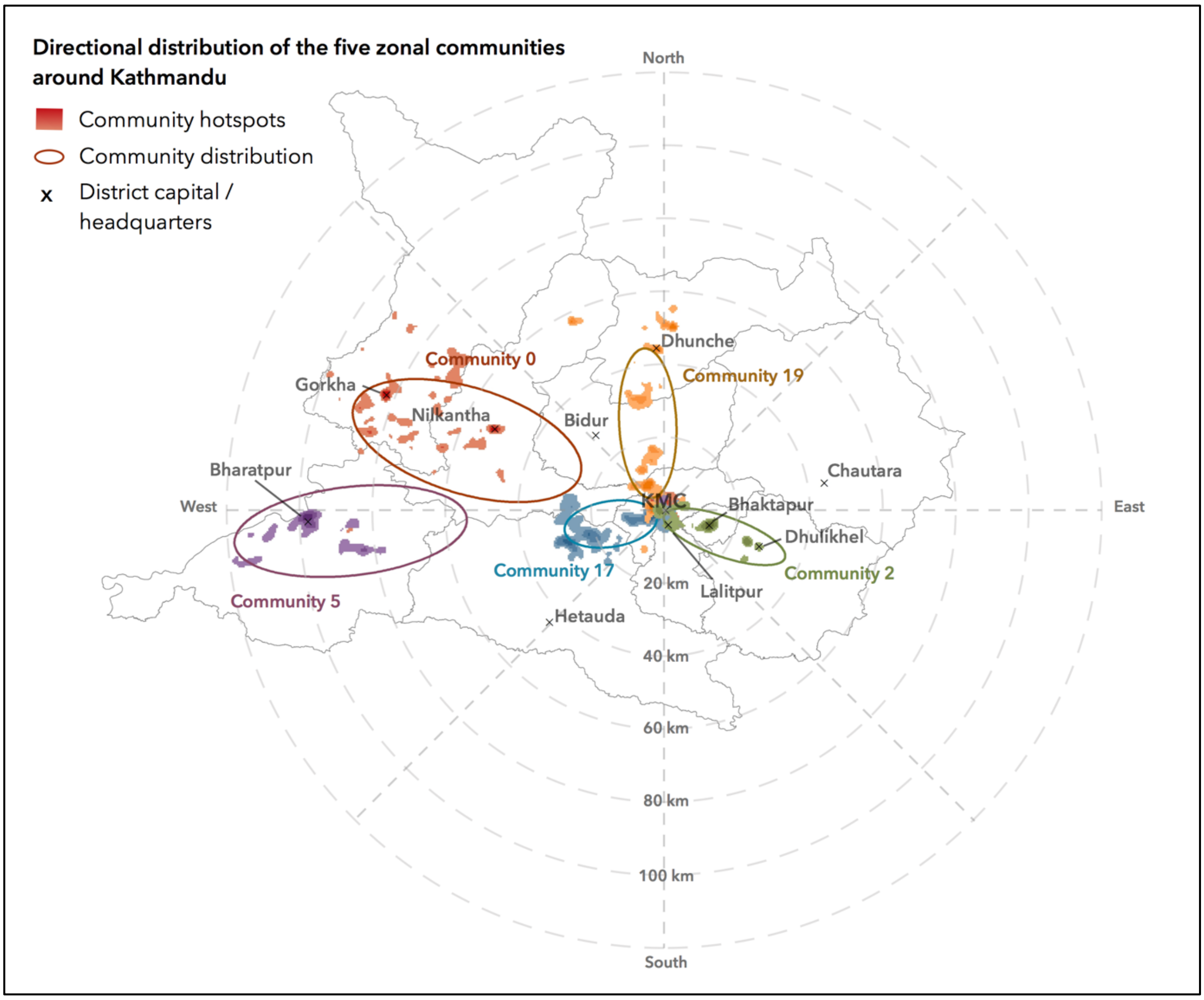


Figure 6-5. Directional distribution of the five zonal communities around Kathmandu Metropolitan City and the other district headquarters. (Administrative Boundary Data: © 2018 GADM; District Place Data: © OpenStreetMap contributors).

To measure the concentration of the community members, the spatial distributions were then quantitively assessed by plotting the cumulative community population against the distance away from the centre point of the community, here assigned to the pixel with the highest population (Figure 6-6). The three centre distributions resulted in three distinct patterns of slope, which helped provide confirmation of the initial visual classification of each of the communities.

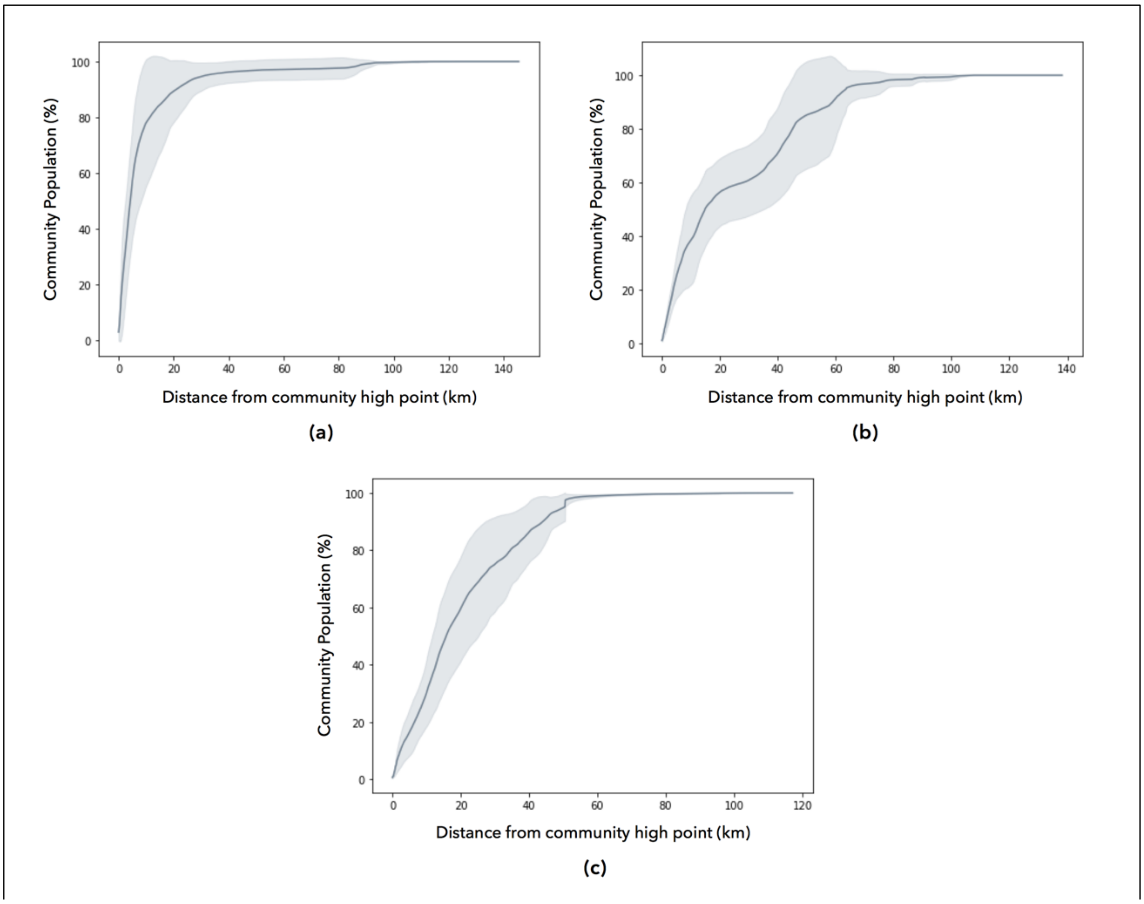


Figure 6-6. Average and standard deviation of the cumulative distribution of community population as distance increases from the community centre point for each zonal type: a) single; b) dual; and c) zonal.

Single centred communities produced a steep slope, with the majority (60-80%) of each community's population living within 20km of the community centre. In comparison, dual centred communities demonstrated a distinct step pattern, where community population peaked between 35-80% within the first 20km, and then plateaued (or showed very gradual increases) until the next centre was found (between 10-60km away). At the next centre, the cumulative population increased again, gaining another 15-45%. As with the visual representation, the slopes produced for the zonal communities were an intermediary between the single and dual distributions, with the step pattern no longer visible, however a more gradual slope was present, showing the transition between the two. The majority of each community's population (60-80%) was found between 10 to 45 km away from the centre point.

6.4.3 Assigning Community Geographic Locations

The community density maps and cumulative population graphs confirm that the social communities detected within the Nepal CDR data are spatially concentrated; for some communities, the spatial concentration may occur in several places. Reducing the density maps to their classified centres enables their comparison with spatial reference data to identify potential geographic locations. Using a combination of OpenStreetMap and VDC administrative data, each centre was assigned a geographic location. In total, 35 separate geographic communities were identified from the 30 CDR-detected communities (Figure 6-7).

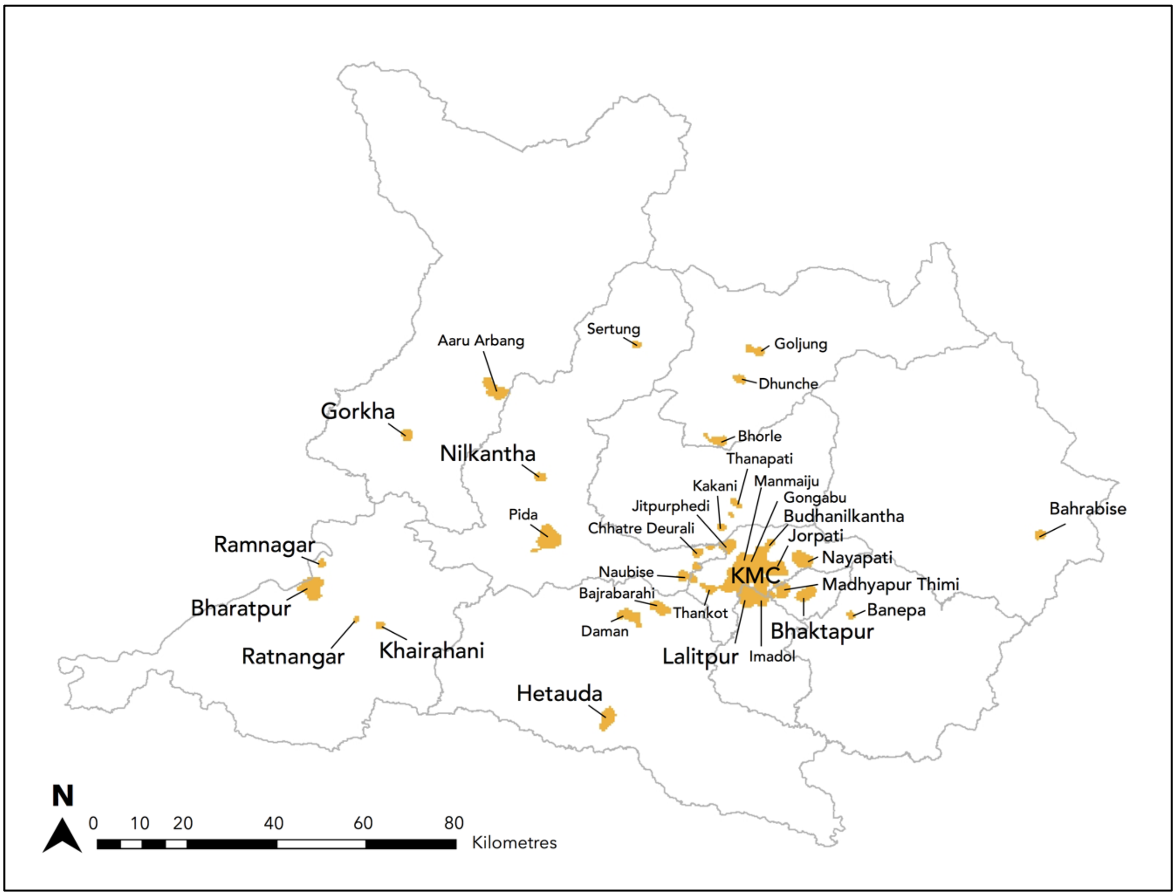


Figure 6-7. Community centres and their respective geographic locations. Community centres are extracted by reclassifying the density maps to show only the hotspot areas.

The full list of detected communities and their respective geographic locations are listed in Table 6-2 in the Supplementary Materials. Kathmandu Metropolitan City (KMC) was the most prevalent location identified (13 times), home to six single centred communities as well as part of four dual and three zonal centre communities. The areas surrounding KMC, including the cities of Lalitpur and Bhaktapur, and the smaller neighbourhoods of Manmaiju and Gongabu, as well as other major cities including Bharatpur, Nilkantha and Hetauda also matched with the detected social communities more than once. For all the dual communities, one of the two centres matched with KMC or a nearby neighbourhood (Jorpati, Manmaiju and Imadol). Three of the five zonal communities also had a centre that matched with the KMC, as well as one that had a centre in nearby Thankot. Of all the dual and zonal centre distributions, only Community 5 had no individual centre within the Kathmandu district; instead it included the major city of Bharatpur and its surrounding municipalities of Ratnangar and Khairahani.

6.4.4 Community census validation

Census population data at the lowest administrative level (municipality or VDC) from the 2011 national census (Central Bureau of Statistics, 2012) were used to provide an initial validation of the number and size of geographic communities that were found through our methodology. Census data were used instead of WorldPop population data to prevent issues with cross-validation. Overall, our analysis detected thirteen of the fifteen largest (population > 25,000) municipalities within the eleven districts (Table 6-1). In addition, we detected 21 smaller VDCs registered on the census. The village of Ramnagar (Community 27) is incorporated within the Bharatpur municipality and not present within the census.

Table 6-1. Detected communities versus census municipalities and Village Development Committees

Census Population Size	No. of Municipalities/VDCs in Census	No. of Municipalities/VDCs in CDR data	Percentage (%)
> 250,000	1	1	100
100,000 – 250,000	2	2	100
50,000 – 100,000	6	5	83.3
25,000-50,000	9	5	55.6
10,000 – 25,000	63	8	12.7
< 10,000	486	13	2.7

There were five larger urban areas, Kirtipur (50,000-100,000), Bidur and Panauti municipalities as well as Kapan and Gothatar VDCs (25,000-50,000), missing from our detection.

6.5 Discussion

By exhibiting concentrated spatial patterns, our detected geographic communities adhere to the basic principles, explained previously, of how space influences the formation of social relationships: each community's social networks have remained predominantly local. Consequently, the detection of these geographic communities provides substantial evidence that the CDRs in Nepal are representative of real-world social networks. The importance of this is that CDRs can be used more confidently as novel dataset for social network analysis (SNA), which is advocated as a critical tool for future community resilience policy planning (see Chapter 3).

Our multi-centred distributions also provide substantial insight into ongoing social processes that could be of use for those working in sustainable development. In Shi *et al. (*2015), the patterns of these distributed communities (along with information on mobility) provided a first step towards discovering spatial interaction communities based on CDRs (Gao *et al.*, 2013), where the impact of daily commuting as well as large-scale migration could be examined. Here, our addition of a geographic location to our communities offers new detail in which to interpret the latter of these processes. Internal migration has been an integral part of socio-economic transformation within Nepal, particularly from the mid-Hills to Terai regions and from rural to urban areas (Thapa, Adhikari and Budhathoki, 2019), with KMC experiencing the highest population growth rate at 4.78% (United Nations Population Fund, 2017). This migration is reflected in the majority of our dual centred communities, where KMC or a close municipality (e.g., Gongabu, Manmaiju) were present as one of the two community centres. As a result, there has been a spatial split in previously tight-knit socially based geographic communities into two locations, with KMC and its surrounding metropolis a primary destination for many of the migrants. This is even evident in the rural or peri-urban communities, including smaller sub-metropolitan cities, with communities in both Hetauda and Nilkantha split with a centre in KMC.

Discovering these spatial interaction communities within our dataset could provide significant insight for those working in disaster response, as well as other fields such as epidemiology, by revealing the connections between communities that could help predict population movement, as seen previously for individuals in CDR data (Lu, Bengtsson and Holme, 2012; Bengtsson *et al.,* 2015). Adding the same mobility analysis of Shi *et al.* (2015) alongside any available data on migration patterns in Nepal could also help understand the longevity of these connections, including whether they reflect daily or seasonal commuting patterns or long-term migratory changes. CDRs can also provide the capability to monitor and track these patterns, with opportunity to repeat the same analysis over other time periods or successively, if their collection and sharing permit future analyses. Repeating the same community mapping could enable the study of community dynamics, including membership (formation and retention) and spatial extent, over time. With Nepal experiencing significant shocks, such the 2015 Gorkha earthquake, CDRs could therefore help study the impact of these events on a community, including their resilience by monitoring these dynamics post-event (as advocated in Chapter 3). Furthermore, with many telecom operators also providing information on calls from overseas destinations, additional social network mapping from the detected communities to other countries may reveal specific geographic patterns, that could help further refine the current mapping and tracking of remittance flows.

There are however limitations already presented to using CDR data for individual community monitoring. Whilst over half of our communities were concentrated in a single geographic location, the remainder demonstrated either a dual or zonal centre distribution. For these communities, whilst the individual centres themselves were spatially concentrated, the community was distributed over several geographic locations through less local but socially-strong connections. To use these social communities within any further geographic CDR analyses would require further disaggregation, for example, assigning community members to the geographic community to which their home location is closest. Several geographic communities were also missing from detection within our CDR dataset. This could be the result of a lack of data covering these areas due to either a preference in the area to use another telecom operator or low network coverage. For areas with data, there may be an insufficient number of relationships between people to signal clustering within the Louvain CDA, resulting in these communities being assigned to other larger communities. For now, as the dataset is unable to capture every community, it is unlikely that CDRs can be aggregated at the community scale in future analyses that could be used for community monitoring.

Despite this there is still significant utility in detecting geographic communities within CDR data, which reaches beyond humanitarian and sustainable development applications. Key questions continue to be asked within the CDR literature on the best approaches to allocate subscribers, delineate the space they cover and whether aggregation is necessary and if so, how (Vanhoof, Ploetz and Smoreda, 2018). At each step, error can be introduced resulting in uncertainty in the analysis and resulting data and indicators produced. One contributor to this uncertainty is the misallocation of subscribers in urban areas, where cell tower density is at its highest: in these areas, subscribers may be allocated to one tower, but ultimately live equidistance from several others. Their allocation is determined by identifying their most likely home location. For this study, the most frequent last call of the day was used, however other options exist, including the tower most connected to by the subscriber, or the maximal number of distinct days with phone activities. Recent research suggests that the latter may slightly outperform (although not significantly) the most frequent last call of the day (Vanhoof *et al.,* 2018) in allocating subscribers with better spatial certainty. The main recommendation from the study is to try multiple approaches together, to determine if there any substantial differences (Vanhoof *et al.,* 2018).

The misallocation of subscribers may create noise within the data, such as a subscriber appearing to continuously be on the move from their home location, when in fact, they are in the same location and pinging to other nearby towers. In these cases, aggregating cell Voronois may help reduce this noise. Here, our social-spatial communities could be used to identify the cell Voronois that are most suitable for aggregation, selecting those cell Voronois that form clear and distinct geographic communities. This potential application would also be a significant contribution towards the formal integration of social network and spatial analytic strategies, which currently remains relatively underdeveloped (Adams, Faust and Lovasi, 2012). With the identification of socio-geographic based activity spaces vital to the understanding of human behaviour (Hannigan *et al.,* 2013), the integration of social network data with GIS is likely to be an increasingly popular area of research, highlighted by the emerging field of spatialised-social networks (Sarkar, Sieber and Sengupta, 2016).

6.6 Summary

This chapter has explored the possibility of refining the spatial resolution of CDRs to the community scale, using emerging literature on social spatial networks, where communities "adhere to the old-school definition encompassing shared area and based on social ties" (Sarkar *et al*., 2016, pg.1). Building upon kernel density community mapping methods used by Comber *et al.* (2012), Gao *et al.* (2013) and Shi *et al.* (2015), the chapter mapped the spatial distribution of 30 social communities detected within the CDR dataset. The results found that these social communities were spatially concentrated and took the form of three types of spatial distributions: single, dual and zonal. Furthermore, through these distributions, geographic communities could be identified and assigned. This finding could have significant implications for future work in the technical processing of CDRs as it demonstrates the potential of refining the scale of CDR analysis to the community scale; more work is however required to achieve the necessary detail needed. The dual and zonal distributions also offer new insight into the geographic spread of social communities within these eleven districts, which would be advantageous for any field of research that requires an understanding of how different geographic communities and spatial regions are socially connected.

6.7 Supplementary Material

Figure 6-8: Density maps for all communities

Single-Centred Communities

Community 1

n = 247,790

Community 7

n = 211,398

Community 6

n = 184,435

Community 9

n = 103,387

Community 3

n = 89,166

Community 8

n = 60,431

Community 14

n = 28,007

Community 4

n = 6,213

Community 21

n = 5,687

Community 11

n = 4,935

Community 26

n = 4,138

Community 24

n = 1,486

Community 16

n = 1,335

Community 15

n = 1,121

Community 27

n = 888

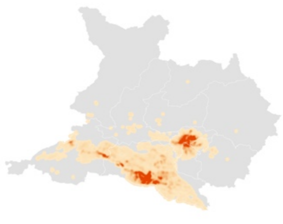
Community 28

n = 778

Community 34

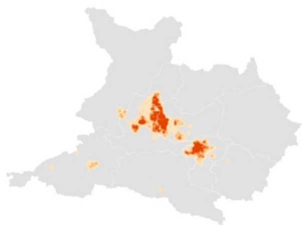
n = 144

Dual-centred Communities



Community 10

n = 116,772



Community 12

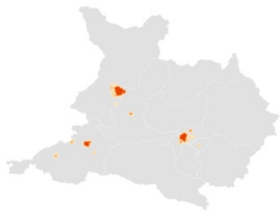
n = 13,378

Community 13

n = 8,401

Community 18

n = 4,526



Community 20

n = 2,188

Community 23

n = 1,287

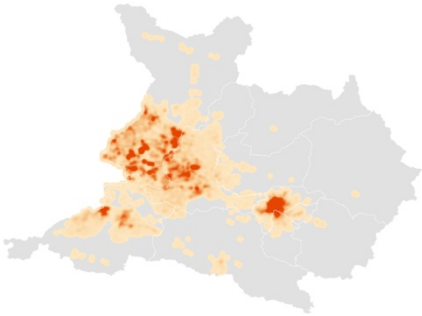
Community 29

n = 1,253

Community 25

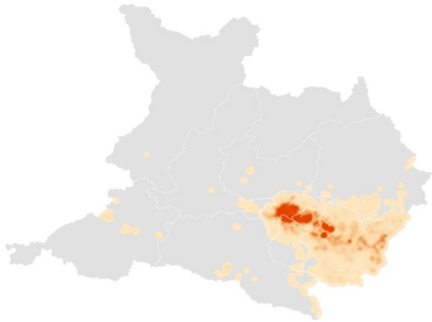
n = 745

Zonal Communities



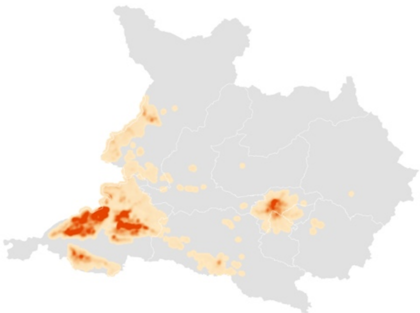
Community 0

n = 194,492



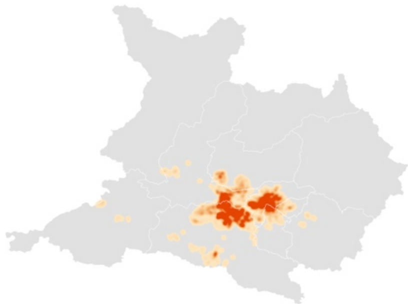
Community 2

n = 183,161



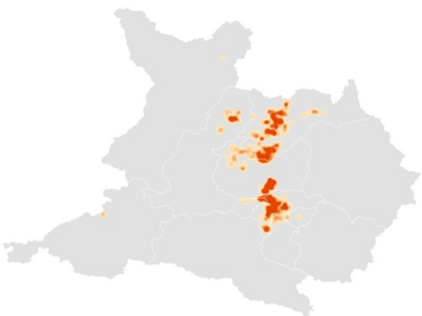
Community 5

n = 152,562



Community 17

n = 29,366



Community 19

n = 7,917

Table 6-2. Detected communities listed with their identified geographic centres.

Community	Size	Centre	Geographic Location(s) *(in alphabetical order)*			
Community 0	194492	Zonal	Gorkha	KMC	Nilkantha	
Community 1	247790	Single	KMC			
Community 2	183161	Zonal	Banepa	Bhaktapur	KMC	
Community 3	89166	Single	KMC			
Community 4	6213	Single	Bhaktapur			
Community 5	152562	Zonal	Bharatpur	Khairahani	Ratnangar	
Community 6	184435	Single	Manmaiju			
Community 7	211398	Single	Lalitpur			
Community 8	60431	Single	Gongabu (plus Dhapasi & Khadka Bhadrakali)			
Community 9	103387	Single	KMC			
Community 10	116772	Dual	Hetauda	Jorpati		
Community 11	4935	Single	Lalitpur			
Community 12	13378	Dual	Manmaiju	Nilkantha		
Community 13	8401	Dual	Banepa	KMC		
Community 14	28007	Single	Madhyapur Thimi			
Community 15	1121	Single	Nayapati			
Community 16	1335	Single	Jorpati			
Community 17	29366	Zonal	Bajrabarahi	Daman	Thankôt	
Community 18	4526	Dual	Hetauda	KMC		
Community 19	7917	Zonal	Bhorle	Dhunche	Goljung	Jitpurphedi
			Kakani	KMC	Sertung	Thanapati
Community 20	2188	Dual	Aaru Arbang	Manmaiju		
Community 21	5687	Single	KMC			
Community 23	1287	Dual	Bahrabise	Imadol		
Community 24	1486	Single	KMC			
Community 25	745	Dual	Chhatre Deurali	KMC	Naubise	
Community 26	4138	Single	Budanilkantha			
Community 27	888	Single	Ramnagar			
Community 28	778	Single	Bharatpur			
Community 29	1253	Dual	KMC	Pida		
Community 34	144	Single	KMC			

Table 6-3: Chapter Data List

Dataset	Source	Reference
Nepal Administrative Boundaries, Level 0 – 5	GADM 2018	© GADM www.gadm.org (https://gadm.org/download_country_v3.html, Accessed December 2018)
Ncell Cell Tower Locations	Flowminder	N/A
Ncell Call Detail Records, January 1st – April 24th 2015	Flowminder	N/A
2015 Nepal 100m Population PPP Raster	WorldPop	WorldPop. 2017. Nepal 100m Population, Version 2. University of Southampton. DOI: 10.5258/SOTON/WP00531.
Nepal Map	OpenStreetMap	OpenStreetMap data is provided under the Open Database License (www.openstreetmap.org/copyright), and has the attribution of ©OpenStreetMap contributors, https://www.openstreetmap.org.
2011 VDC Census Data	Government of Nepal	Central Bureau of Statistics. National Population and Housing Census 2011 (Village Development Committee/Municipality). Kathmandu, Nepal; 2012.

Chapter 7 Measurement of social connectivity using CDRs in Nepal for disaster resilience estimation

7.1 Overview

This Chapter explores, through the creation of a social connectivity index (SCI) dataset, how social connectivity varies within the eleven districts in Nepal according to CDR data. To enable this analysis, the Chapter establishes the theoretical and technical foundations behind the SCI methodology including how to assess social connectivity as well as how to process CDR data to provide a proxy-community level analysis. The Chapter proposes the use of several different social network analysis measures to analyse the presence and the strength of the different network types. It then identifies how data generated from the previous Chapter can be used to refine the mapping of these connections at a proxy-community scale. This community delineation is used to calculate specific measurements for each community's respective bonding and bridging networks. An overall SCI is then calculated for the resulting cell tower communities using these measures.

7.2 Introduction

Whilst traditional DRR efforts have focused on improving the physical, financial and infrastructure components that are believed to enhance resilience (Aldrich and Meyer, 2014), recent disasters worldwide have highlighted the role of social connectivity in the immediate response and ongoing longer-term recovery of populations, e.g., the 2015 Gorkha earthquake (Carrero *et al.*, 2018), the 2015 floods in US (Meyer *et al.*, 2020) and the 2011 tsunami in Japan (2011 tsunami) (Ye and Aldrich, 2019) as well as the 2013 and 2014 typhoons in the Philippines (Han, Howe and Park, 2019). As one of the primary resources the poor use to manage their risk (Woolcock and Narayan, 2000), understanding the social connectivity, i.e., the presence and durability of social networks, within a population can provide insight into their capability and capacity to respond to a shock, including natural hazards (Misra *et al.*, 2017). As a result, a growing discourse of research is aiming to quantify this role, specifically by investigating and measuring connectivity through social networks as a core component of resilience (as evidenced in

Chapter 3). To quantify this connectivity, empirical studies have increasingly employed a structural or network-based approach that uses social network analysis (SNA) to assess the number, strength and value of these networks (see Chapter 3). These measurements are then related to aspects of resilience, such as using the degree centrality (i.e., the number of connections) of individuals to identify those most connected (e.g., Misra *et al.*, 2017), or the betweenness centrality (i.e., the number of times an individual connects others) to find leaders within the network who could act as coordinators for the dissemination of information and resources (e.g., Guarnacci, 2016). The measurements can be evaluated independently (e.g., Guarnacci, 2016) or can be combined to create a connectivity index (e.g., Cueto, Villalta and Bernal, 2017) or even a connectivity profile (e.g., Tobin *et al.,* 2014).

To extend the application of these studies to provide resilience estimations that could be used to inform policy and project programming, SNA for DRR would benefit from the development of a singular analytical approach. Using SNA for resilience estimation relies on having a substantial amount of data on the connections between the actors in question, such as individuals, households, or communities. The current approach to collecting these data is through the use of interviews and workshops; as a result, there is no standardised method for data collection or analysis although certain measures are consistently used (as identified in Chapter 3). Furthermore, the majority of studies have been conducted within a single community, between individuals and households, and at only one point of time. These network studies result in a snapshot of a potentially wider social system in both time and conceptualisation, presenting resilience solely as a property and not as an ongoing process subject to change, which is fundamental to how resilience is understood (as explained in Chapter 2). There is a need therefore to extend these analyses beyond the immediate community and over longer time spans, as identified in Misra *et al. (*2017), to capture how these networks change during and after a shock and how this impacts resilience.

As such, in this study we demonstrate how novel large-scale datasets, such as those championed by the UN in their 'data revolution' (UN Data Revolution Group, 2014), could be used to address these limitations. Work has already begun in this field, with two very recent DRR-related pieces of research that have employed SNA using data extracted from social media platforms. One study utilised data from over 1.5 million people on

Facebook, an online social network site, to understand how social ties influence evacuation behaviour across three different hurricanes within the US (rather than resilience) (Metaxa-Kakavouli, Maas and Aldrich, 2018). Higher connectivity correlated strongly with evacuation; greater bonding connections encouraging users to stay home, whilst greater bridging or linking connections encourage users to evacuate (Metaxa-Kakavouli, Maas and Aldrich, 2018). Another study utilised data from Nextdoor, an online social network organised by real-world local neighbourhoods, to track how users utilised their connections with one another to engage in protective activities, such as searching for information, during the onset of Hurricane Harvey in the US (Fan, Jiang and Mostafavi, 2020). The study found that bridging ties, the connections between the neighbourhoods, scaled up during the onset of the hurricane and led to greater social cohesion. Whilst both studies illustrate the possibilities of using novel sources of social network data within DRR, neither consider how to relate their findings directly to a measure of resilience. Furthermore, there are distinct limitations with extending their methodologies to other countries; Nextdoor is currently only used in eleven countries (Nextdoor, 2020), whilst Facebook use varies considerably across countries, particularly when accounting for different demographics (Gil-Clavel and Zagheni, 2019).

Here, it is proposed that Call Detail Records (CDRs), the metadata generated by the use of mobile phones, have multiple attributes that present them as a potential new data source for dynamic social connectivity measurement specifically for resilience estimation for DRR. First, as addressed in the Introduction and in Chapter 5, mobile phone penetration across the world has grown substantially, with the total number of unique mobile phone subscribers exceeding 5 billion users (GSMA, 2020). The lowest penetration rate currently is in Sub-Saharan Africa at 45%, although this is expected to grow to 50% by 2025 equating to approximately 500 million users (GSMA, 2020; The World Bank, 2020). Facebook, in comparison, stands at 1.59 billion daily global active users (Facebook, 2019), and not all of these users allow the company to track or harvest their location. Secondly, by containing data on the contact between individual mobile phone subscribers, CDRs have been shown to represent a substantial portion of a subscriber's social network (Eagle, Pentland and Lazer, 2009). Furthermore, the addition of location information (the cell tower in which subscribers are connected to when making or receiving calls and texts) enables the mapping of these networks to geographic areas (as evident in the previous chapter). Finally, CDRs are collected as part of routine billing, resulting not only in a low cost but also regularly updated and maintained historic dataset that could enable both repeat and near-real time analyses. Consequently, CDRs offer a unique opportunity to measure social connectivity at significantly greater spatial and temporal scales than currently evident within DRR research, plus providing the potential for a standardised quantitative approach for comparison across future studies.

CDRs have already been used post-hoc to study the social behaviour of populations in response to disasters (Bagrow, Wang and Barabasi, 2011; Lin and Lazer, 2011; Moumni, Frias-Martinez and Frias-Martinez, 2013) as well as provide operational information, such as displacement estimates (Wilson *et al.,* 2016), to disaster response agencies during real-world events. However, the application of CDRs to measure social connectivity for disaster resilience is as yet untested. This study addresses this gap using the constructed social networks of 1.69 million subscribers across eleven districts in Nepal (as produced in Chapter 6) within a SNA approach informed by previous studies. CDR data generated between 1 January 2015 and 24 April 2015 (the day before the 2015 Gorkha earthquake, which resulted in nearly 9,000 fatalities and displaced over 95,000 people (Ray, 2017)) were used to establish a pre-shock snapshot of social connectivity for eleven districts in Nepal; it is highlighted that this could then be compared with following time periods within further research. The results highlight that social connectivity does vary across our districts, with the most rural and isolated areas and cities lacking in high levels of social connectivity.

7.3 Measuring social connectivity for DRR

There has been an evolving focus on the role of social networks within disaster resilience (Misra *et al.,* 2017). Tiernan et al.'s (2019) review on the practice and research trends in disaster resilience, for example, found that across the 150 related papers published between 2012 – 2017, one of the three most prominent research themes was the socialisation of responsibility for risk and resilience (Tiernan *et al.,* 2019), where various case studies have shown that individuals and communities often had to be self-sufficient and self-reliant to recover in the aftermath of a shock.

At the forefront of this research has been the concept of social capital, where individuals and communities expect to have access to help and support from those they are connected to, facilitated by the tacit understanding that this help would be reciprocated if and when needed by the other party, creating a sense of goodwill. This cooperation and/or collective action is assisted by the investment and trust they have instilled in these networks, promoted by similar norms and beliefs. Social capital therefore is primarily understood from two perspectives: firstly, the structural approach, where it is "the aggregate of the actual or potential resources which are linked to possession of a durable network" (Bourdieu, 1986, pg.21) and secondly, a cognitive approach where the "features of social organization, such as trust, norms and networks that can improve the efficiency of society by facilitating coordinated actions" (Putnam, Leonardi and Nanetti, 1994, pg.167) . Social capital is seen as a key element of resilience (Barrios, 2014), underpinning all other aspects and essential for the agency and collective action required for adaptation within resilience (Berkes and Ross, 2013).

The quantification of social capital from both perspectives is a challenge, with no solid singular ground in its measurement (Carrillo Álvarez and Riera Romaní, 2017). As a result, there are significant epistemological and logistical challenges to operationalising social capital within resilience measurement, particularly under one clear and consistent method for its use within policy and practice (as evidenced in Chapter 3). To overcome these limitations, it has been advocated that research needs to move beyond social capital to focus more on the structure, geography and content of social networks, to theorise and analyse resilience (MacGillivray, 2018). As Chapter 3 outlined, a growing body of literature is emerging, focusing solely on social networks and their role in providing connectivity i.e., acting as a form of coordination, through connecting people, or as a pipe, by connecting flows of resources, information and knowledge. Here, the premise is that connectivity i.e., the presence, strength and effectiveness of the social networks – will directly influence resilience and network properties can be assessed using SNA (Misra *et al.*, 2017).

The measurement of connectivity and social networks through SNA for disaster resilience is still relatively new (Misra *et al.*, 2017) and not currently prioritised within research or practitioner circles. However, across the studies that do exist, a robust methodology is developing with the use of similar measurements to quantify connectivity, as evidenced in Chapter 3. When applied to social networks, connectedness and connectivity can be understood through the properties of the social distance between persons as well as through the number of connections between them (Barnes, 1969). These properties translate to several key centrality measures already established within the wider SNA methodology: degree, closeness, betweenness and eigenvector centrality. Table 7-1 outlines these measures, how they correspond to different characteristics of connectivity and the implication of these characteristics for disaster resilience.

Table 7-1. Common Social Network Analysis measures and their relationship with resilience

Measure	**Description**	**Connectivity characteristic**	**Relation to disaster resilience**
Degree centrality (Count/Density)	The number of connections held by the actor (*or can be calculated as a proportion of the network*).	A higher number of connections, the higher overall connectivity.	A greater and likely more diverse pool of resources to access and utilise.
Closeness centrality	The average of the shortest path length from the actor to every other actor in the network.	Shorter averages lead to faster contact across all connections – more efficient connectivity.	Better chance of receiving information and/or resources in a timely manner.
Betweenness centrality	The number of times an actor occurs along the shortest path between two other nodes.	Greater cohesiveness of the network, more robust connectivity – identifies those centrally connected, versus those on the outside.	A lack of cohesivity can result in those on the outside being marginalized or excluded. Those actors more central will have a greater opportunity for more diversity in information and resources but can also act as a gatekeeper or control point. Cohesion will encourage collective action and collaboration.
Eigenvector centrality	The number of connections an actor's connections are connected to.	Expansivity of connectivity – identifies how many additional connections a subscriber may have through their bridging networks.	Increases the size and diversity of the resource pool further.

These measures can be calculated for each individual actor within a network. For the various DRR studies using SNA this has primarily been the individual(s) or household(s) within a single community. More recently, one study applied SNA at a wider scale: looking at connections within and between neighbourhoods across a single city (Cueto, Villalta and Bernal, 2017).

Distinguishing different networks based on the type of connection is also an important aspect of evaluating social networks for resilience as not all relationships contribute to resilience in the same way (Cueto, Villalta and Bernal, 2017). As Table 7-2 explains, the three types of network commonly identified, bonding, bridging and linking, take on different roles during the various stages of a disaster (Nakagawa and Shaw, 2004). Furthermore, the presence and strength of these network varies, playing a dual role in disaster recovery, enhancing recovery for some but hampering it for others (Rahill *et al.*, 2014). As a result, a balance between bonding, bridging and linking connections is necessary to enhance resilience (Cueto, Villalta and Bernal, 2017). Accounting for these three networks is therefore important for the evaluation of social networks in relation to disaster resilience. One approach to achieve this balance is through the creation of an index that incorporates the various benefits of the different types of connections through using particular SNA measures. This was demonstrated in the neighbourhood study, where they combined a value for each type of relationship to create a single value for evaluation (Cueto, Villalta and Bernal, 2017). This approach requires those creating the index to determine which social network measurements are the most suitable to quantify the benefits derived from the presence and strength of these different network types.

Table 7-2. Different types of social networks and their role in disaster support

Network Type	Description	Disaster Support	Network Operation
Bonding	The strong connections within a group of individuals, that may constitute a family, a friendship group, or even a community.	At the onset of a disaster, likely to provide help in the initial response such as rescue efforts as well as immediate medical attention. Afterwards, these networks continue to play a significant role in supporting those most affected, including providing shelter, as well as financial and psychological support.	Bonding and bridging networks operate through collaborative efforts and collective action
Bridging	The weaker connections between different groups, such as those between communities.	Act as a similar support mechanism to bonding in the aftermath of a disaster, particularly if the bonding networks are unable to act due to being affected by the impact. Can also provide a more diverse range of resources, such as channelling aid and information.	
Linking	The weak connections from individuals and groups to more 'formal' actors, such as government agencies or non-governmental or community-based organisations.	Organise large-scale response and recovery efforts and provide longer term financial assistance through rehabilitation or rebuilding schemes. Longer term assistance could lead to enhanced resilience building schemes to help with mitigation pre-hazard.	Linking networks operate through a formalised duty and responsibility to respond

7.4 The need for novel datasets in social connectivity measurement

To conduct a connectivity analysis across these three network types involves extending the network dataset beyond a single community or neighbourhood. However, this extension is difficult due to the traditional collection of social network data: using individual or household interviews and questionnaires to create a matrix of connections between actors. Capturing social network data for multiple communities through traditional survey approaches therefore will require significant investment in time, logistics and cost. For example, in the case of a multi-neighbourhood study, the bonding dataset was collected during organised neighbourhood assemblies by using family attendance as a proxy for their social connection (Cueto, Villalta and Bernal, 2017). With the researchers attending at least one assembly for each neighbourhood (and up to three) and 18 neighbourhoods in total, this could lead to approximately 50 – 100 hours of data collection. Furthermore, the bridging and linking datasets were created through structured interviews with leaders of the neighbourhood association, adding further investment in time. Repeating this type of data collection beyond a single city is not likely to be scalable; furthermore, the time required to implement this data collection is likely to be detrimental to the currency of the dataset. As a result, alternative methods of collecting data or sourcing it from different datasets is required to ensure connectivity measurement through SNA can become a viable dataset with disaster resilience estimation.

7.4.1 Call Detail Records as a source of social network data for resilience estimation

Researchers have shown that CDRs are able to reconstruct key human behaviours, including mobility, social contact and expenditure, at fine spatial and temporal resolutions, at national spatial coverages and over extensive time periods (Blondel, Decuyper and Krings, 2015). These insights have been used for multiple sustainable development and humanitarian applications, including population mapping (Deville *et al.*, 2014), poverty estimation (Steele *et al.*, 2017) and disease tracking (Bengtsson *et al.*, 2015).

To use CDRs as a source of social network data for disaster resilience estimation, there are several data- and methodology-based issues that need to be accounted for or addressed. First the extent to which the dataset can represent real social relationships should be understood and quantified; CDRs only contain the social contacts of subscribers that are identified through phone calls (and messages) and thus miss out other types of social interactions (Blondel, Decuyper and Krings, 2015). Quantifying the extent to which mobile phone social networks represent real social networks however requires an alternative source of detailed social network data, which if available at the scale and resolution of CDR data would make the need of CDRs for disaster resilience redundant.

Several studies have tried to estimate this representation by comparing self-reported social network data to CDR social network data at very small scales. A study by Eagle *et al. (*2009), for example, of 94 participants comparing call logs with self-reported relational data on friendships showed that 95% of an individual's contacts could be inferred by the CDR data alone (Eagle, Pentland and Lazer, 2009). Another larger study (n=200) by Stopczynski *et al. (*2014) comparing multiple network data sources (e.g., calls, Facebook contacts), found that the strongest 10% of face-to-face interactions between users accounted for 90% of call ties, suggesting that the contacts within CDR data primarily represent the closest of real social network relationships (Stopczynski *et al.*, 2014). These studies were conducted in very similar spatial and social settings (conducted at universities in the US and Denmark respectively). As a result, extrapolating these findings to countries of potentially different social and technological practices and behaviours, such has Nepal, should be cautious; as Eagle *et al. (*2009, pg.15277) explain, "the specific results are surely embedded within the social milieu in which the study was grounded, the critical next question is how much these patterns vary from context to context".

A second data-related consideration is the underlying issue of inclusion and exclusion of certain population groups within the dataset. The CDR dataset will only include those who can afford to use a mobile phone; utilising CDR data for any analysis needs to consider the ownership and usage of mobile phones in the area of study carefully. Evidence on mobile phone ownership and usage as well as network coverage can provide an understanding of whether the CDR dataset is likely to be representative of the overall population (such as the analysis provided in Chapter 5).

From a methodological perspective, CDRs also present a challenge in determining a scale at which the relationships can be aggregated and assessed. Whilst predominantly social networks have been studied at the geographic community scale for resilience estimation, this is currently not possible with CDRs. There has been recent work to detect and identify geographic communities within CDRs to reduce the spatial scale at which CDR analyses can be provided, however this is not yet ready for use (outlined in Chapter 6). As a result, the spatial scale of aggregation is restricted to the network's spatial resolution, i.e., at the individual cell tower calls and texts are routed through (Vanhoof, Ploetz and Smoreda, 2018). To use the cell towers as the spatial scale of aggregation, each individual subscriber needs to be assigned to a tower, which will depend on a pre-determined approach e.g., identifying a tower as the subscriber's most likely home location, which may introduce a level of spatial bias into the dataset, such as mis-allocating subscribers to an incorrect spatial location (Vanhoof, Ploetz and Smoreda, 2018).

This also has implications for using the tower scale as the scale of analysis. As a proxy for a person's geographic location, those subscribers at the same tower are likely to be in the same physical location and thus geographic community. This assumption can be used to categorise the CDR connections into two of the types of social connectivity i.e., looking at the bonding connectivity of the subscribers within each tower and then the bridging connectivity between these subscribers to subscribers at all other towers. This assumption relies on those subscribers being part of a community that exists within each tower's network coverage. For now, whilst the mapping of geographic communities is currently in its infancy (as illustrated in Chapter 6), this is the most spatially refined way to assign and map different types of connections using CDRs. This approach also does not facilitate studying linking connectivity, which is likely to prove difficult with CDRs without any further external data about who the subscriber is and if they have a formal role in DRR within the country of interest.

Another issue with using cell towers for aggregation is that the location of each cell tower is chosen by the network operator and generally guided by population, resulting in a higher density of antennas in more densely population areas (e.g., cities and coastlines) and a lower density in rural regions, including mountains or nature reserve areas (Vanhoof, Ploetz and Smoreda, 2018); as a result, any network analyses needs to take into account the differences in population likely to occur across the cell towers. Those cell towers with a higher subscriber population may have more network connections, simply through having more subscribers to have the connections. There are also additional 'tower effects' that may need to be considered, including the direction and strength of the tower signal and its resulting spatial coverage; a tower coverage map can help account for and address these effects.

When a tower coverage map is not available, researchers have utilised Voronoi tessellations generated from the locations of the cell tower within the network to capture the likely coverage of each tower. These tessellations are also used to create the most spatially refined mappable outputs from CDR analyses. However, the resulting delineated polygons typically have different boundaries to administrative regions, resulting in translation and comparisons problems (Vanhoof, Ploetz and Smoreda, 2018), such as combining the data with other datasets that might be used in DRR policy analyses.

A final methodological consideration of using CDRs as a dataset for disaster resilience estimation is the ethical implications of using an individual's data without their specific consent. This requires the creation and enforcement of suitable regulation and protocols to ensure that a subscriber is never identified nor their individual data at risk of falling into the wrong hands. Aggregation of datasets and strict data management policies are just two examples of strategies to ensuring the use of CDRs does not exploit those behind the data (Jones *et al.*, 2018).

Overall, CDRs do have key advantages for DRR research in that they can be: provided over extensive spatial and temporal scales; accessed both post hoc and in near-real time; and used remotely, not requiring those using the data to be 'on the ground' and potentially disturbing the response efforts. Furthermore, despite not potentially accounting for the entire friendship network, which even self-reported data also struggles to achieve (Eagle, Pentland and Lazer, 2009), recent studies have shown that the friendships within mobile phone social networks are important, particularly in the event that a disaster occurs (e.g., Bagrow, Wang and Barabasi, 2011; Lu, Bengtsson and Holme, 2012; Moumni, Frias-Martinez and Frias-Martinez, 2013; Wang, Lin and Bagrow, 2014).

These studies have found that mobile phones are 'sociometers' to disasters, providing evidence and insight into several social behaviours and processes that occur during a response (Wang, Lin and Bagrow, 2014). For example, Bagrow *et al.* (2011) and Moumni *et al.* (2013) showed how the number of contacts people called in the aftermath of a shock or disaster grew, but the time spent talking to them decreased, suggesting that there was an initial need to 'check in' on one another and offer help (Bagrow, Wang and Barabasi, 2011; Moumni, Frias-Martinez and Frias-Martinez, 2013). In addition, Lu *et al.* (2012) showed that in the aftermath of the Haiti earthquake, the displacement of the population was highly correlated with people's social networks; people moved to areas they had either been before or had previous contact in. As a result, with Stopczynski's *et al.* (2014) findings in mind, it is likely that the relationships within mobile phone networks are those that are most important and most likely to contribute direct support and information in the event of a disaster. Utilizing CDR data as a source of social network data has the potential to prioritize the most useful connections for resilience building.

7.5 Data and methods

To measure social connectivity using Call Detail Records for disaster resilience estimation, first a suitable methodology must be established. This methodology needs to:

- Identify and account for the technical aspects of constructing and processing the CDR data in order to use it for social network mapping at the community level.
- Define the relevant measures used to assess the different community bonding and bridging networks to create the final Social Connectivity Index.

With CDRs as yet unused in social network mapping at this scale, the following section outlines in detail the devised methodology.

7.5.1 Nepal CDR dataset

Nepal was chosen as the country of interest due to a combination of factors, including its vulnerability to hazards through its geographic location (including earthquakes and floods) and lack of DRR policy (as evidenced in Chapter 4). The country has also experienced a substantial increase in the ownership of mobile phones, with 92.8% of households having access to a mobile phone as of 2016 (Ministry of Health and

Population (MOHP) [Nepal], New ERA and ICF International Inc, 2017), which suggests CDRs are likely to represent a significant proportion of the population (as assessed in Chapter 5). For the purpose of this research, eleven districts in Nepal were selected for the focus of this analysis (Figure 7-1), chosen for their proximity to the 2015 Gorkha earthquake and its aftershocks.

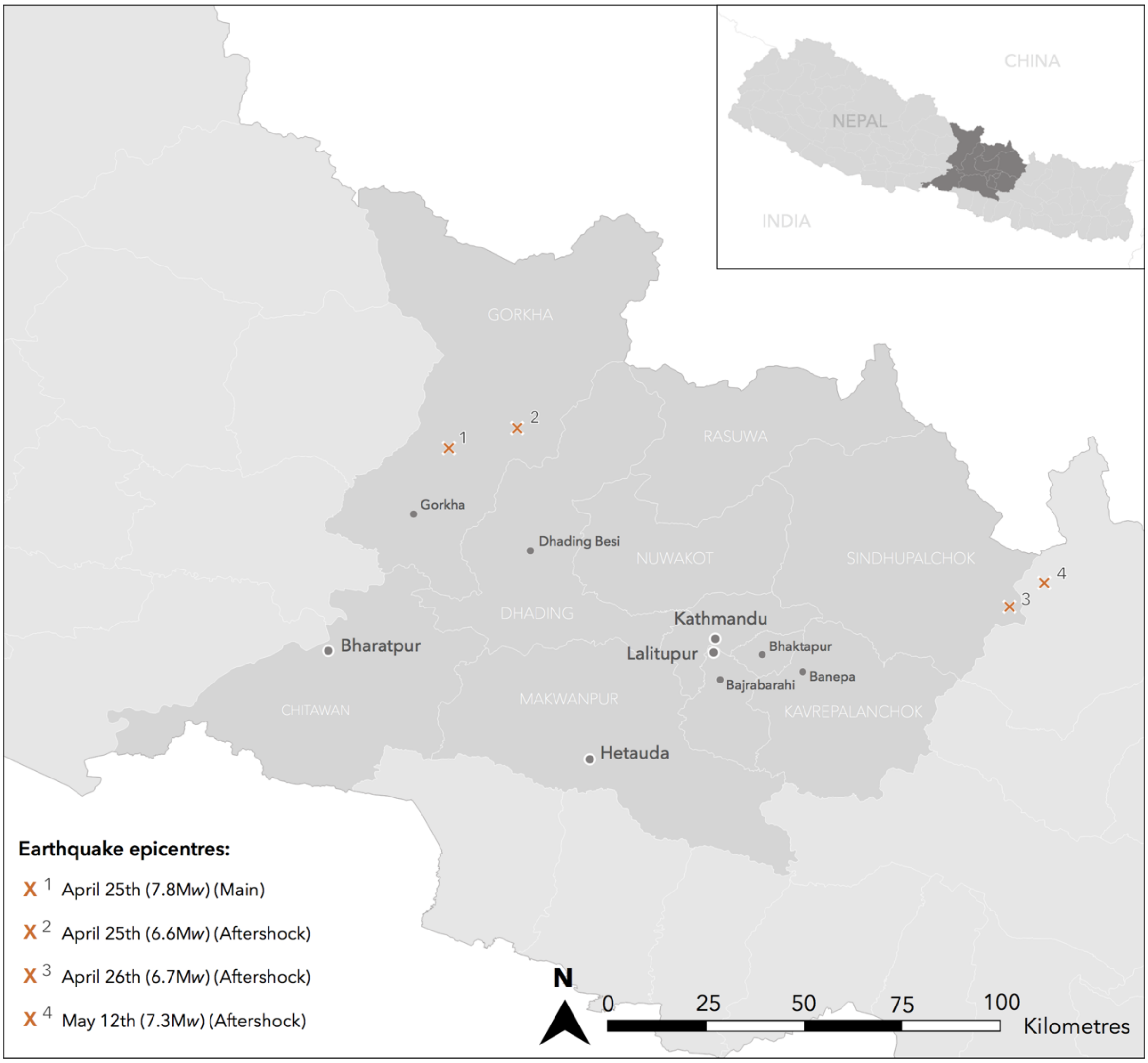


Figure 7-1. The eleven districts selected for analysis, their major cities and towns, and the location of the 2015 earthquakes. *Note, Kathmandu, Lalitpur and Bhaktapur are also the names of the districts in which they are located.* (Administrative Boundary Data: © 2018 GADM; District Place Data: © OpenStreetMap contributors; Earthquake Data: USGS).

7.5.2 Scale of analysis: using home location towers as a proxy for geographic communities

The aim of this research was to map and measure social connectivity at the community level. As shown in Chapter 6, the identification of geographic communities from CDR data is not yet feasible with current methods and is an area identified for further research. The decision was therefore made to map social networks at a proxy-community scale, where the home location cell tower was used as a spatial proxy for the subscriber's community. To improve the accuracy of these cell towers representing proxy-communities, the information on social community distributions from Chapter 6 was used to combine those towers where a strong social community signal was detected across multiple towers. To enable this, each social community's density distribution was visually evaluated against predicted cell tower coverage represented by a Voronoi tessellation (Figure 7-2).

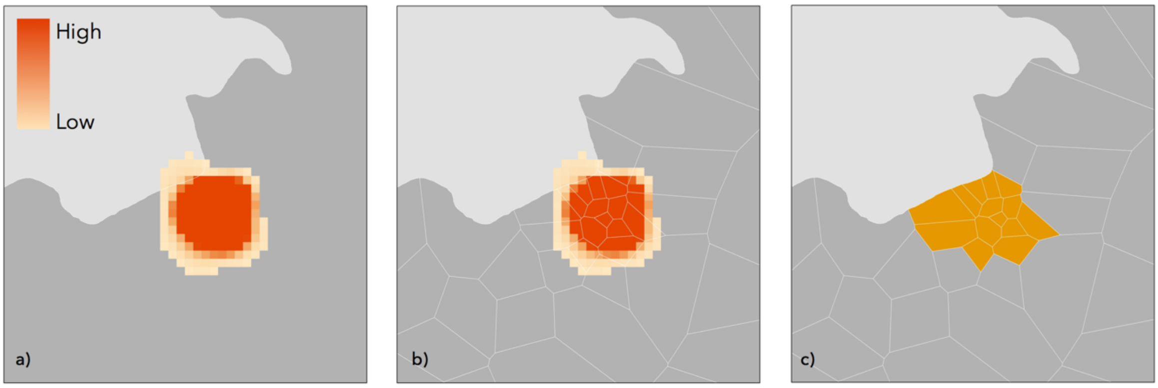


Figure 7-2. Aggregating cell towers based on social community distributions across the cell tower Voronois: a) predicted density distribution of a social community; b) overlaid within cell Voronois; c) selected cell Voronois aggregated based on the community distribution. (Administrative Boundary Data: © 2018 GADM)

Those cell towers which had Voronois fall substantially within a community's coverage were assigned to that community. The subscribers that were registered previously at these individual cell towers were then aggregated to a single overall cell tower home location for analysis. Without this aggregation, potential bonding relationships would be assessed as bridging connections and thus create inaccuracies and noise within the results. To facilitate visualising the results of the analysis, each of the resulting Voronoi community groupings were also dissolved to create a single spatial unit (Figure 7-3).

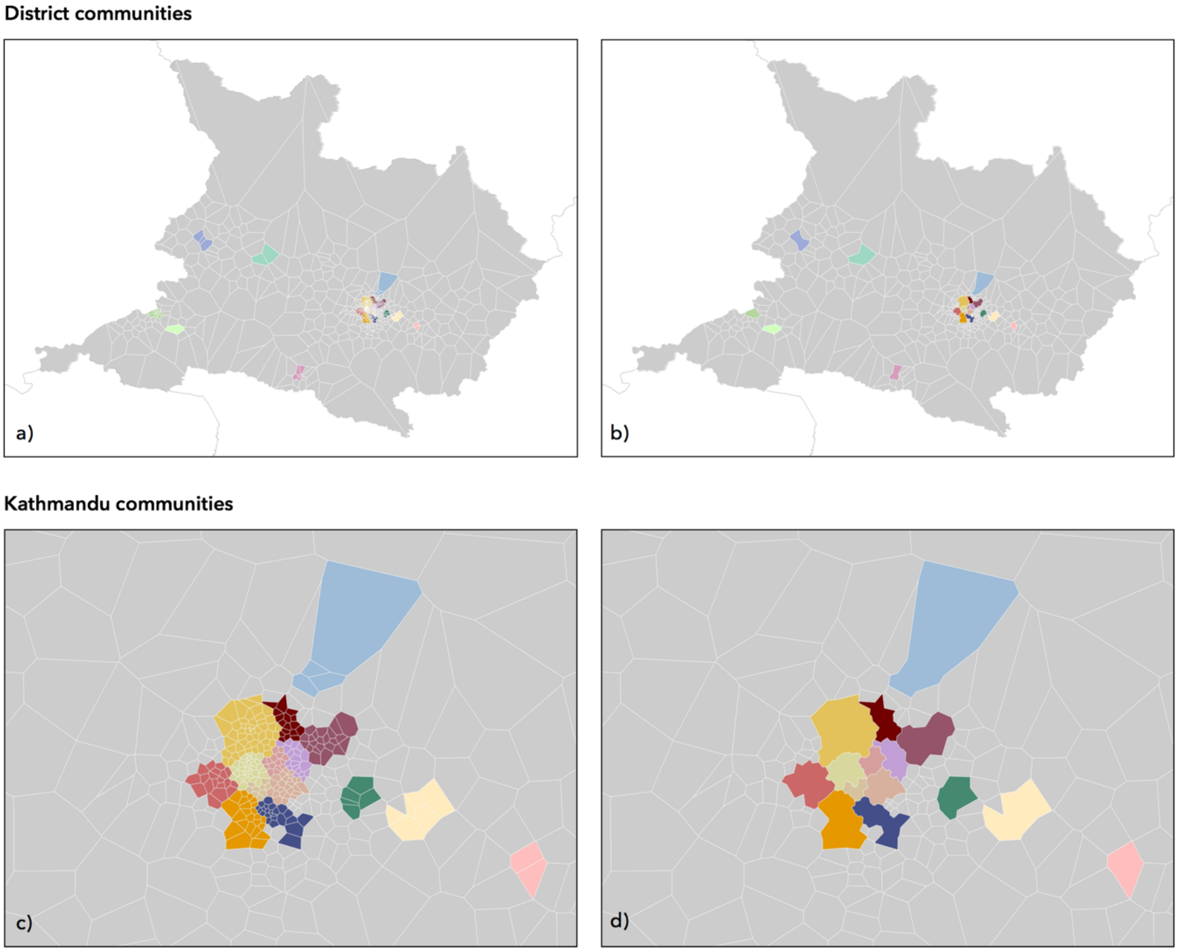


Figure 7-3. Dissolving cell tower Voronois into single spatial units based on social community distributions: a) cell tower Voronois with the same social community, by different social community; b) resulting aggregated cell tower Voronois; c) as above, for Kathmandu Metropolitan City area; d) as above, for Kathmandu Metropolitan City area. (Administrative Boundary Data: © 2018 GADM).

7.5.3 Evaluating Social Connectivity within the CDR dataset using SNA measures

The study used the CDR social network dataset constructed in Chapter 6 for analysis, with the home location also detected in Chapter 6 used to assign each subscriber to a 'tower-community'. For each of these tower-communities, the presence and strength of their bonding (internal) and bridging (external) connections were assessed (Table 7-2). For both connection types, the degree centrality, i.e., the number of connections that a subscriber had, was used to quantify the presence of these networks. The number of connections a person has is likely to correspond to the size and the diversity of the support and resources available to them within the respective networks (Burt, 2000)

Table 7-3. Network measures used to assess community social connectivity for bonding and bridging networks.

Network Type	Network Property	SNA Measure	Implementation
Bonding	Presence	Degree Centrality	Average number of internal contacts per subscriber.
	Strength	Closeness Centrality	Average shortest path distance between a subscriber to all other subscribers. *Inversed, where higher values indicate higher centrality.*
		Betweenness Centrality	Standard deviation of: the number of times a subscriber will connect two other subscribers on their shortest path.
Bridging	Presence	Degree Centrality	Average number of external contacts per subscriber.
	Strength	Eigenvector Centrality	Average number of external contacts a subscriber's external contacts connects them to.

For each tower-community's bonding network, strength was quantified using closeness and betweenness centrality measures, as these two measures are likely to directly relate to whether the perceived benefits of bonding networks would materialise. For example, whilst the degree centrality is likely to determine the size and variety of resources available, a greater closeness centrality (i.e., shorter paths) within the community suggests that all subscribers can access these resources quickly and therefore benefit from its presence. In addition, less variation in the betweenness centrality of subscribers suggests that everyone in the communities is as likely to receive help as one another, ensuring that no one is excluded or likely to become marginalized or isolated in the event of a disaster.

For each tower-community's bridging network, strength was quantified using one measure, the eigenvector centrality. Beyond adding directly to the size of resources a community can access, the key strength of bonding networks is the ability of these networks to indirectly diversify resources through their own linkages. The eigenvector centrality measure captures this strength by quantifying the number of connections the subscriber's connections are connected to through these external linkages.

To calculate these measures for the CDR data, two types of social matrices were generated. Firstly, for the bonding measures, a social matrix was generated for each tower-community that detailed only the connections between subscribers located at that tower i.e., the internal contacts. This matrix was used to count the number of contacts each subscriber had within the tower-community and then calculate the overall average for the tower-community to provide the degree centrality. This matrix was then transformed into a NetworkX graph; NetworkX is a freely available SNA library used within Python programming for the creation, manipulation and study of the structure, dynamics and functions of complex networks (Hagberg, Swart and Chult, 2008). The closeness and betweenness centrality functions from the NetworkX package were used to compute the respective measures for every subscriber within each tower-community internal matrix. These values were then used to calculate for each tower-community, the average subscriber closeness centrality and the standard deviation of its subscribers betweenness centrality. The standard deviation was used to assess the level of variability in the interlinkages between the connections, with a larger range indicating lower cohesivity within the tower-community.

For tower-communities with more than 20,000 members (a total number of 13 tower-communities), the NetworkX calculations were too computationally intensive to run. As a result, in these cases, the NetworkX-based centrality measures were run on a sample of the subscribers at the tower-community. To determine a suitable sample size, a sensitivity analysis was first conducted on eleven of these tower-communities (those which ranged between 37,000 to 73,000 subscribers) as well as a selection of smaller towers (n=10), the results of which can be found in Table 7-5 within the Supplementary Materials. Comparing the results at the different sample sizes across both tower sizes, it was that determined that a sample size of 5000 would be appropriate to be used when calculating the NetworkX based bonding measures for the oversized tower-communities. The sample size was deemed precise enough for calculating the betweenness and closeness centralities, whilst reduced the degree of computation required (see Supplementary Materials).

For bridging measures, an overall social matrix was created, constructed for all subscribers within the dataset. For each subscriber, the number of external contacts (i.e., contacts located at a different tower-community) was computed and an average degree centrality for each tower-community then calculated. The same approach was used to compute the eigenvector values for each subscriber, where the indirect (or additional) external contacts a subscriber was connected to by their direct external contacts were counted and then averaged for the tower-community.

These measures were then assessed individually as well as combined into a single connectivity index. Due to the dataset being anonymised, identifying those connections from subscribers which are likely to be to formal connections is not possible, therefore linking connectivity was not assessed, a key limitation of the dataset. As a result, unlike Cueto, Villalta and Bernal *(*2017), who captured social connectivity using an index-approach with three values, here only the measures associated with bonding and bridging connectivity for each tower-community could be combined.

To create an overall social connectivity index, the five measures of centrality were first normalised using range scaling. The inverse of the bonding betweenness measurement was then calculated as smaller deviations inferred a stronger, more cohesive connectivity. The inverse bonding betweenness and closeness values were then averaged to provide only a single strength measure for the bonding networks. These final four measures were summed to provide a single connectivity value (Equation 7-1); the tower-communities with a higher combined overall social connectivity are understood to be those with a high level in each of the two connectivity types, thereby making them more resilient (Cueto, Villalta and Bernal, 2017).

$$SCI = bonding_{DC} + bonding_{\frac{IBC+CC}{2}} + bridging_{DC} + bonding_{EGV}$$

Equation 7-1. Creation of a Social Connectivity Index (SCI)

7.6 Results

7.6.1 Tower-community composition

In total, there were 385 tower-communities, ranging from 64 to 193,026 subscribers in size (Figure 7-4). Two tower-communities were removed from the analyses as these tower-communities did not contain any internal connections, resulting in 383 tower-communities. Given the substantial difference in subscribers assigned to each tower, our analysis first sought to account for whether the overall tower-community size would have a significant influence on the resulting number of connections a subscriber may have. For a tower with a smaller number of subscribers, the opportunity for multiple internal connections is reduced by the lack of other subscribers registered at that tower to make these connections with. No relationships between tower-community size and our chosen variables were found.

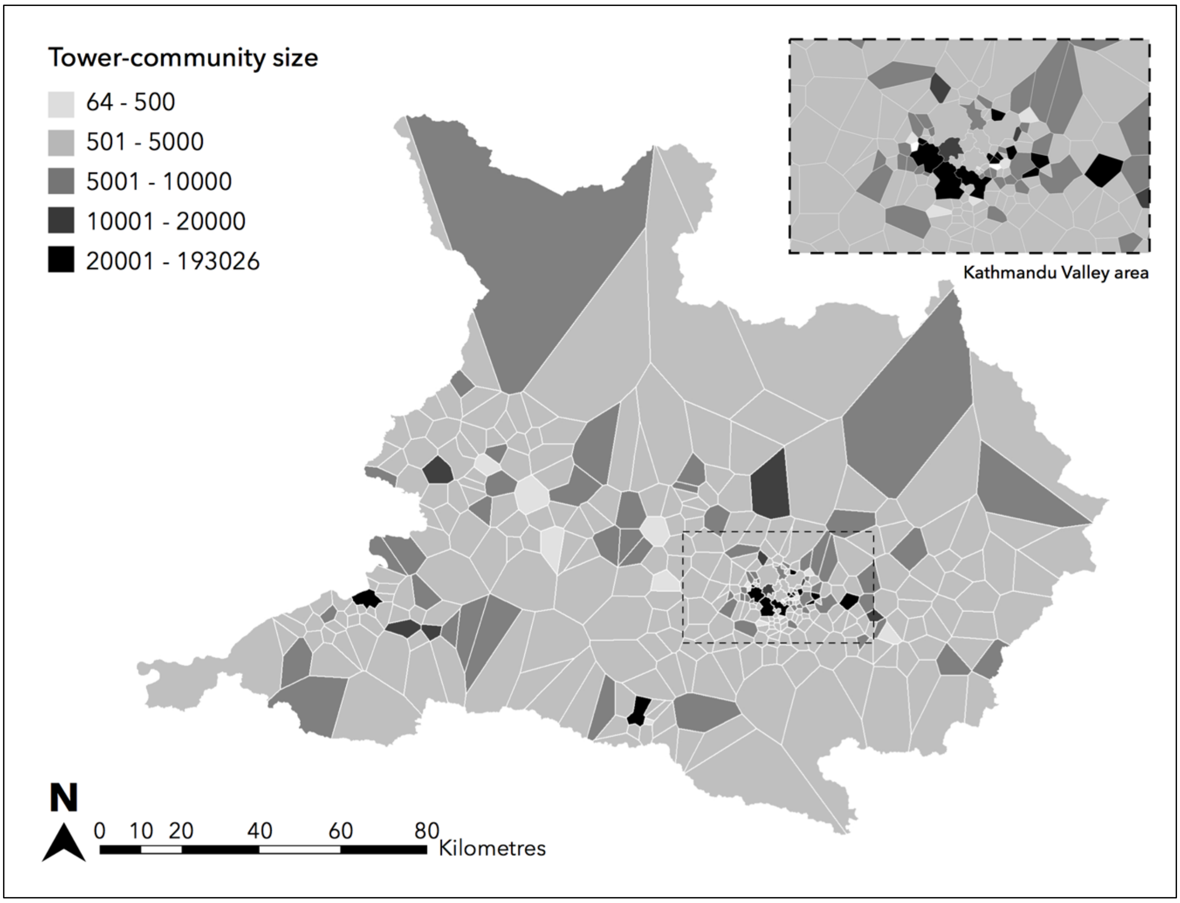


Figure 7-4. The number of subscribers at each tower-community. (Administrative Boundary Data: © 2018 GADM).

7.6.2 Bonding Connectivity

The average number of bonding connections per subscriber across all tower-communities within our dataset was 5 connections, with a range of 1 to 13 connections. The majority of subscribers held 3 – 6 bonding connections. The distribution of the average number of bonding connections at each tower community scale is shown in Figure 7-8 in the Supplementary Materials. Overall, a lower average number of bonding connections are primarily found in tower-communities located in or nearby major cities and towns, such as Kathmandu (as shown in the subset map), Bharatpur, Gorkha and Hetauda (see Figure 7-1 for location of main cities/towns within the eleven districts). In comparison, higher average number of bonding connections are found in tower-communities within peri-urban (or semi-rural) areas between cities and towns in lower Hills and Terai areas, such as between the city of Gorkha and town of Dhading Besi, as well as between Bharatpur and Hetauda (see Figure 7-10a in the Supplementary Materials for city/town locations mapped to the ecological zones). This spatial pattern suggests that the presence of bonding connections varies across the different geographies in Nepal.

The strength of these connections (Figure 7-8 in the Supplementary Materials) show a similar spatial pattern, particularly for the closeness centrality of the tower-communities. Closeness centrality was higher across similar peri-urban areas, with the average path lengths to connect all subscribers to one another within these tower-communities shorter than for any other areas. This suggests that connectivity within these tower-communities is likely to be more efficient, with subscribers able to contact one another through short internal chains of contact. Within the general area of Kathmandu Metropolitan City (KMC), the level of closeness centrality varies considerably, with certain tower-communities particularly on the outskirts demonstrating high levels of closeness that coincide with smaller historical cities of Patan (Lalitpur) and Bhaktapur. For tower-communities on the eastern side of the city, in comparison, coinciding with more industrial areas of Nepal such as Tribhuvan International Airport, closeness centrality was low (see Figure 7-10b in the Supplementary Materials for an OpenStreetMap excerpt detailing the features within the eleven districts/Kathamndu). This variability is also seen, although to less extremes, in tower-communities around the cities of Bharatpur, Hetuada and Gorkha, suggesting subscribers in some areas within and around these cities are well connected to one another, whilst others are more detached from each other.

Betweenness centrality across the tower-communities demonstrated a more variegated spatial pattern; tower-communities in the peri-urban areas showed the smallest deviations in their cohesivity of connectivity. Across the majority of KMC, deviation in connectivity was also low suggesting subscribers in these areas were likely to be as well as connected to each other as another. In comparison, greater deviation was found in tower-communities within more rural areas, such as in the north-western mountain areas, or to the south-west of KMC. In these cases, subscribers in these tower-communities will have less cohesion in their connectivity between subscribers i.e., some subscribers will be well connected to other subscribers in their tower-community, whilst other subscribers are likely to be more isolated.

Combining these three measures, the resulting overall bonding connectivity across the tower communities in the eleven districts is highly varied (Figure 7-5). Presented using quantiles, it is evident that higher levels of bonding connectivity are more common in the more rural areas, both in the Mountain, lower Hills and Terai regions. These areas as a result contain a suitable balance between the presence and strength of the connections between their subscribers. In comparison, there are various 'hotspots' of tower communities where bonding connectivity is low, including to the south-east of the city of Gorkha, the south/south-west of KMC, and as evident in the subset, various cell-tower communities across KMC, predominantly in the Eastern side of the city. Despite the tower-communities in these areas having an average presence of connections, the strength of their connections, particularly in the efficiency of their connectivity, is lacking.

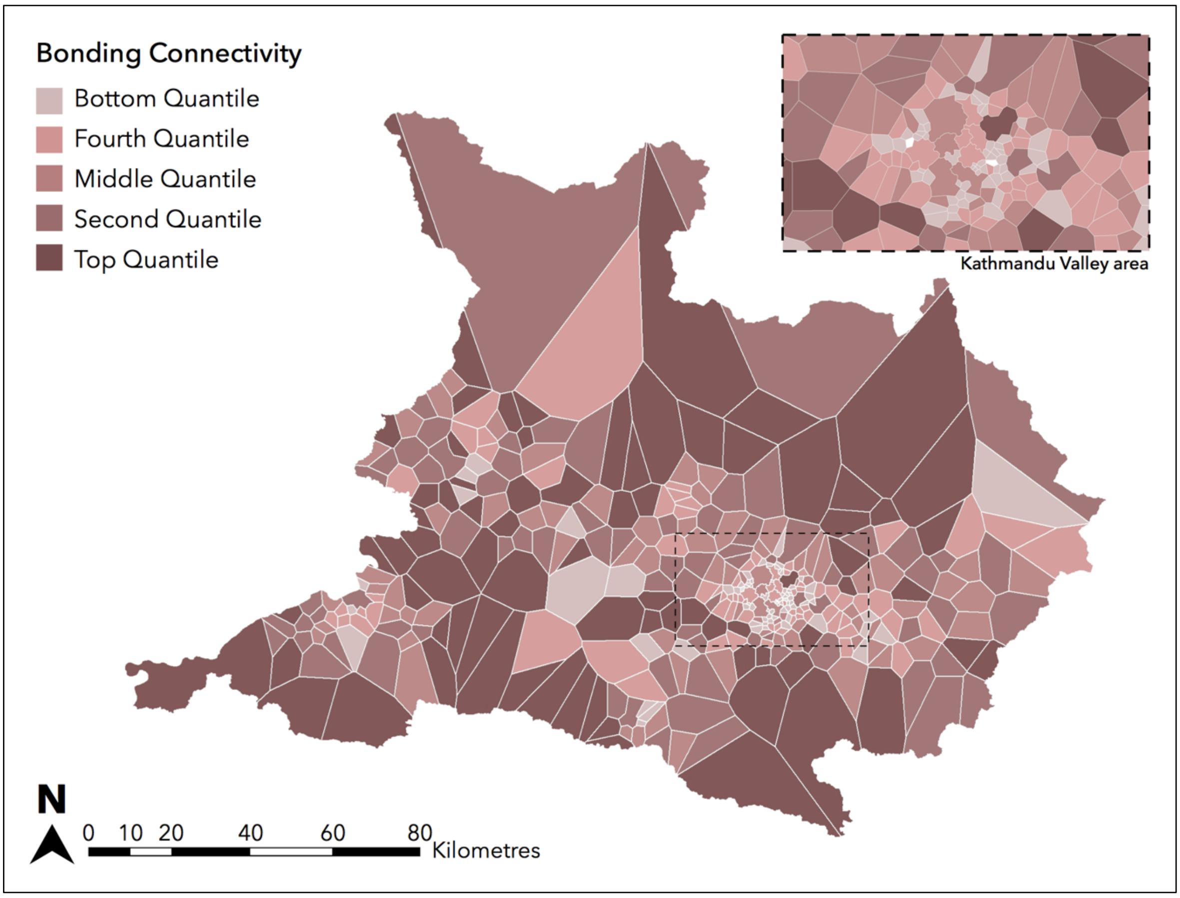


Figure 7-5. Overall bonding connectivity for each tower-community within the eleven districts, as calculated from the bonding presence and strength variables (Figure 7-8). The bottom quantile are the tower-communities with the lowest level of bonding connectivity, relative to the other tower-communities. The top quantile are the tower-communities with the highest level of bonding connectivity, relative to the other tower-communities.

7.6.3 Bridging Connectivity

The average number of bridging connections per subscriber across all tower-communities was 9 connections, with a range of 3 – 15 connections. The majority of subscribers had between 7 – 12 external connections. These numbers are approximately double those calculated for bonding connectivity. The distribution of the average number of bridging connections at each tower-community is shown in Figure 7-9 within the Supplementary Materials. A higher average number of bridging connections are found across several peri-urban areas along the middle of our eleven districts, which also extends partially southwards from KMC towards Hetauda. This high presence of bridging connections however is not found within the city-based cell tower-communities themselves. The tower-communities within the main cities (KMC, Bharatpur, Bhaktapur, Lalitpur and Hetauda) overall demonstrate a lower number of bridging connections than the peri-urban areas. These low numbers of connections are also found in the tower-communities in the most Western and Eastern (and thus more remote) areas in the mountain and Terai regions. Overall the tower-communities in the peri-urban areas between the cities possess an average number of bridging connections.

The strength of these connections (Figure 7-9 within the Supplementary Materials), assessed through the eigenvector centrality, follow a similar but subtler pattern. Overall, tower-community subscribers are connected to between 49 – 421 other external subscribers through their external connections, with an average of 198 connections. In the majority, subscribers are connected to approximately 140 and 235 additional subscribers through their external connections, although this high level of expansivity is primarily located in this ‘belt’ across the middle of our districts. Again, the cities show a much lower eigenvector centrality, suggesting what external contacts they do have, do not connect them to many additional contacts.

The combination of both high presence and strength of connections in the tower-communities within these specific areas translate into a very distinct spatial pattern for overall bridging connectivity. As shown in Figure 7-6, for bridging connectivity when presented as quantiles, there is apparent belt of higher bridging connectivity along the middle of our eleven districts, which also extends southwards from KMC towards Hetauda. The tower-communities in these peri-urban areas, primarily on the outskirts of the major cities, have the highest bridging connectivity. In comparison, the tower-communities in the far-east mountain region in the north and the far western and eastern areas in Terai within the eleven districts have the lowest overall bridging connectivity, alongside the tower-communities within the major cities.

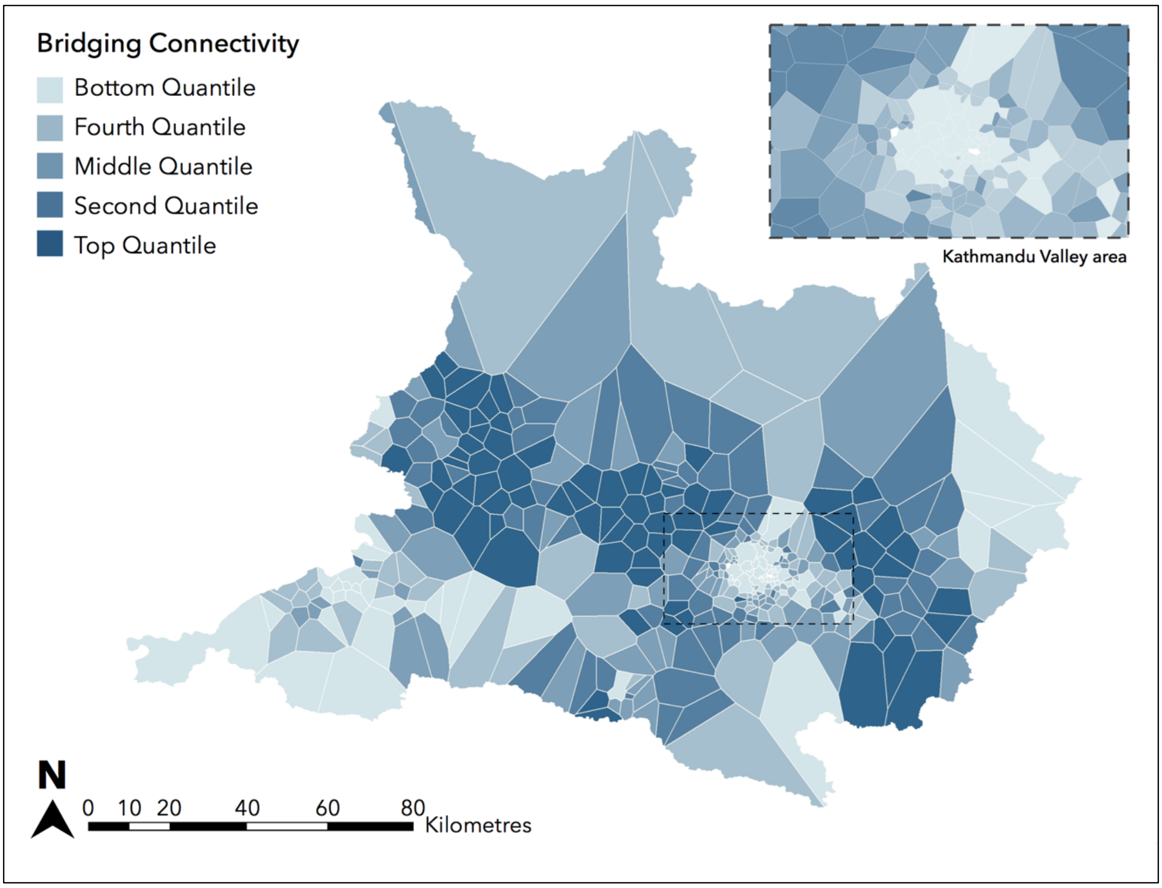


Figure 7-6. Overall bridging connectivity for each tower-community within the eleven districts, as calculated from the bridging presence and strength variables (Figure 7-9). The bottom quantile are the tower-communities with the lowest level of bridging connectivity, relative to the other tower-communities. The top quantile are the tower-communities with the highest level of bridging connectivity, relative to the other tower-communities. (Administrative Boundary Data: © 2018 GADM).

7.6.4 Overall Social Connectivity

Through combining the overall bonding and bridging connectivity results, the final social connectivity index (SCI) is presented in Figure 7-7 and again uses quantiles to identify differences between high and low areas of social connectivity. Overall tower-communities in the peri-urban areas continue to demonstrate the highest level of social connectivity; as evident from the previous results, these areas balance both high levels of bonding and bridging connectivity. The influence of low bridging connectivity can be seen in the low overall connectivity exhibited in the more rural Mountain and Terai regions as well as within the major cities of KMC and Bharatpur. Low levels of bonding connectivity in comparison create small pockets of low social connectivity, such as around the city of

Bharatpur, the areas west and east of KMC and north of the city of Hetauda. Overall the SCI clearly identifies regions of higher and lower social connectivity.

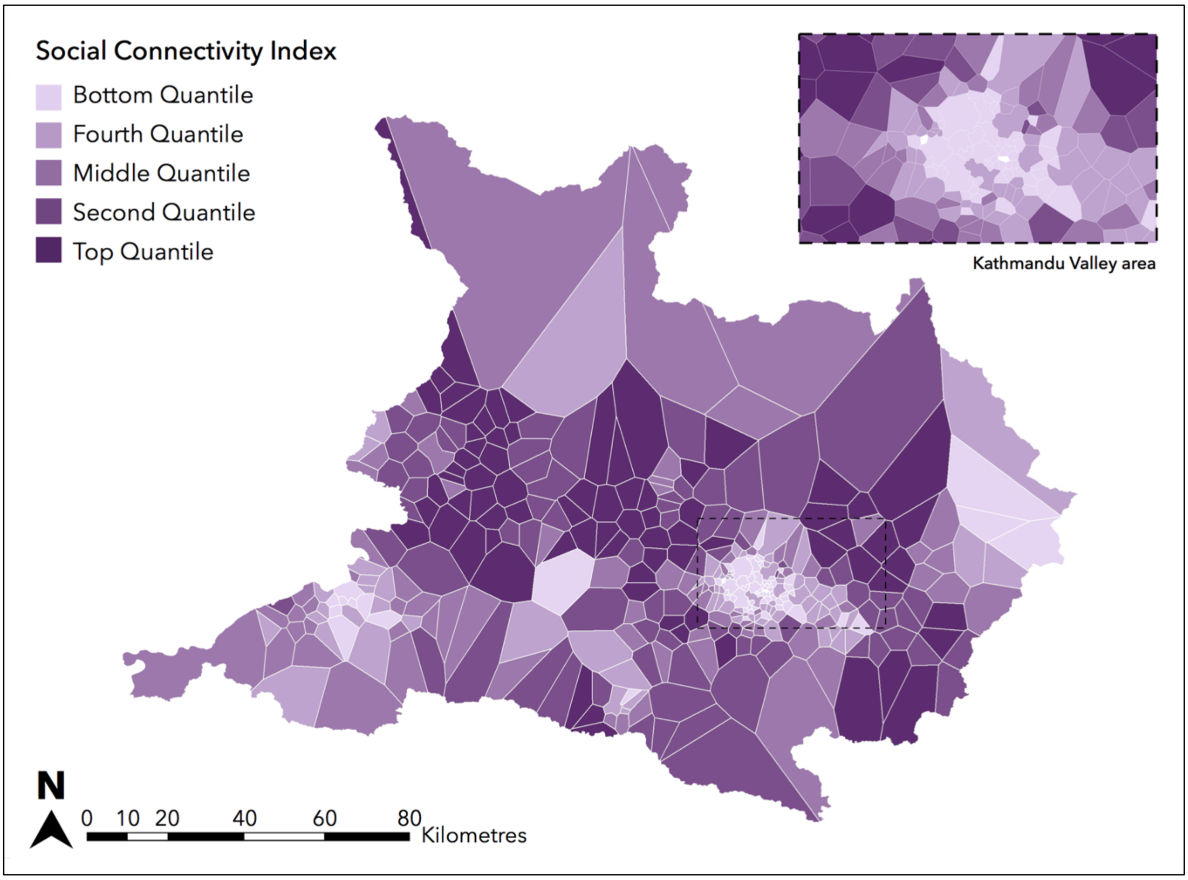


Figure 7-7. Overall social connectivity for each tower-community within the eleven districts, as calculated from the bonding and bridging variables. The bottom quantile are the tower-communities with the lowest level of overall social connectivity, relative to the other tower-communities. The top quantile are the tower-communities with the highest level of overall social connectivity, relative to the other tower-communities. (Administrative Boundary Data: © 2018 GADM).

7.7 Discussion

The mapping and measurement of social networks (SNMM) for DRR remains largely-unexplored, despite the general understanding of social networks as the 'main engine' within the immediate response of populations to disasters and their following longer-term recovery (Carrero *et al.*, 2018). One of the main issues and likely reasons for this lack of action in SNMM is that whilst "it is relatively easy to find representative data showing that individuals in developing countries have a great need for social networks, it is harder to find evidence from such representative datasets that these individuals use social networks because many of the largest household surveys do not contain social network data" (Chuang and Schechter, 2015, pg.452-453). Without this data, there is a lack of evidence substantiating these ad hoc or tacit understandings of the importance of local community structures and social networks for DRR (Carrero *et al.,* 2018). The impact is that, even with global DRR frameworks such as the SFDRR calling for the decentralisation of DRR governance and the empowerment of local communities (Wahlstrom, 2017; Han, Howe and Park, 2019), the role of local support networks are overlooked (Sanyal and Routray, 2016), or worse, are readily dismissed in the face of a real emergency (Carrero *et al.,* 2018).

To address this data scarcity and to support the inclusion and prioritisation of SNMM as a tool by DRR practitioners and national governments, there is an emerging body of research that demonstrates how social networks can be assessed in relation to community resilience (outlined in Chapter 3). Whilst studies continue to emerge e.g., Sakshi and Kumar, 2020, SNMM is still relatively new (Guarnacci, 2016) and lacks a singular methodology. This, akin to the issues with the operationalisation of social capital, results in disparate and localised methodologies and datasets (MacGillivray, 2018), which are likely to prevent the progression of social connectivity into a recognisable and indispensable indicator of resilience estimation. This Chapter answers this need by presenting a literature-informed methodology to create a Social Connectivity Index, using several SNA measures to quantify the presence and strength of social networks across two of the three types of networks shown to be critical during a disaster. Furthermore, the Chapter achieves this by using an innovative dataset, CDRs, which has the coverage and detail to extend this methodology and thus index well beyond these eleven districts, not only to the entirety of Nepal but to other countries as well.

The potential utility of a multi-country SCI dataset for DRR is evident within our findings for the eleven districts. Across this subnational area, it is evident that there is a geographic variation to the levels of bonding, bridging and overall social connectivity a tower-community is likely to possess. This is to be expected as, MacGillivray highlights, social networks have a placed nature, where they are spatially patterned with their form and effects modified by other background variables that are unevenly distributed across space (MacGillivray, 2018). In the case of the eleven districts, those subscribers located in tower-communities within peri-urban areas have the highest connectivity, with a good balance between their bonding and bridging connections. In comparison, those subscribers located in tower-communities within cities and in more rural areas possess fewer bridging connections, which in turn reduces their overall social connectivity. Both these geographies appear to be relatively insular, demonstrating reasonable levels of bonding connectivity, but substantially low bridging connectivity.

By approximating these connections as real-world social networks, it is proposed here that the subscribers in the peri-urban areas are likely to be the most resilient, as they have access to both immediate support and resources through their bonding networks as well as ongoing and more diverse help through the bridging networks (Carrero *et al.*, 2018). For city-based tower-communities, despite being surrounded by other neighbourhoods, bridging connectivity is as weak as those subscribers in tower-communities in more rural areas. As a result, both of these tower-community geographies will rely more strongly on their higher bonding connections and have less access to the diverse benefits provided by bridging connections.

Another clear spatial pattern to the connectivity is the localised differences between the central tower-communities in KMC and those tower-communities on the outskirts. The latter possess higher levels of bridging but lower bonding connectivity. Here, it is proposed that these tower-communities may be located in areas associated with high (and recent) migration, where subscribers continue to maintain their connections with their previous (tower-communities, but are yet to establish substantial connections within their new surrounding tower-communities. To confirm this hypothesis, future work could look to assess the direction and volume of the bridging connections originating from these tower-communities, as well as data on local demographics. This demographic data could include migration information for the areas in question, including when individuals or households had migrated and where they had moved from; The expected percentage of migrant households for each could then compared to the bonding connectivity score, whilst the relocation of these migrants could be mapped against the bridging flows to evaluate whether migration is a likely contributor to the social connectivity differences. Access to current migration data at this scale is however limited; the recent 2018 Surveys for Urban Equity program may provide an insight into these processes, but the 1600 household survey, conducted in the Kathmandu Valley, is not representative enough to draw formal conclusions (Elsey *et al.*, 2018). An analysis of this type is likely to require waiting until the release of next year's (2021) census data (i.e. 2022).

Being able to identifying these differences in the distribution of the two different types of social network on a subnational basis across multiple countries could have significant implications for DRR. For example, for those areas where bonding connectivity is strong but bridging weak (i.e., rural areas and within city centres), during preparedness time, focus must be made on improving the diversity and range of support they can access. During a response these areas should be identified as highly vulnerable to mid- to long-term effects of a shock, such as decreasing access to food supplies, building materials and even financial help in the weeks following a shock. In comparison, those areas with strong bridging but weak bonding areas should be targeted differently (e.g., city outskirts, migratory areas); here, preparedness efforts should focus on the development of internal connections, such as encouraging engagement between local neighbours, particularly those who would be considered as highly vulnerable (e.g., the elderly). During a response, it is likely that in these areas, the most vulnerable will be at a high risk of not being included in immediate response efforts as well as long term recovery and rebuilding. The SCI and use of CDRs provides an unprecedented opportunity to understand social connectivity across a range of countries at a subnational scale.

These findings and this potential however should be interpreted in the context in which they were created and not be extrapolated beyond what they can represent: mobile phone subscribers' connections as a proxy for social networks at the tower-community scale. Overall, this is the first dataset of its kind that aims to measure and map social connectivity at a substantial spatial scale and, as a result, is not without issue. From a conceptual perspective, for example, our current methodology is unable to capture the linking connectivity of our cell-tower communities, the third type of social networks identified as important within DRR. The SCI therefore cannot provide fully an understanding behind the balance between bonding, bridging and linking connections necessary to enhance resilience (Cueto, Villalta and Bernal, 2017). Alternative or additional data will be needed to measure these relationships, a key area of future work required to take this methodology further.

Whilst there is also work to improve the technical CDR processing aspects of the methodology (refining the mapping of geographic communities, outlined in Chapter 6), this initial methodology and the results already illustrate the capacity for CDRs to provide a much-needed singular approach to social connectivity measurement. This approach can then be supplemented with traditional disaster work, such as interviews or surveys, which can provide further critical context and information on the role of social networks for disaster resilience (Metaxa-Kakavouli, Maas and Aldrich, 2018). Combining these methodologies is a likely pathway forward, as CDRs also offer the opportunity to repeat the analysis across multiple time periods and thus generate new temporal understandings of disaster resilience (explored in more detail in Chapter 8). These findings will need to be grounded in local context, as advocated and demonstrated within this thesis through the inclusion of Chapter 4.

7.8 Summary

It is anticipated that a full understanding of social networks will enhance disaster response and build community resilience (Tobin, 2014). Despite the limitations mentioned, this Chapter provides a robust and repeatable methodology for the use of CDRs to measure social connectivity for disaster risk reduction. The outputs from the SCI details the overall presence and strength of mobile phone-based social networks across proxy-communities in Nepal, and as a result, offers new insight into how different regions across the eleven districts are likely to be able to cope with disaster events (Misra *et al.*, 2017). This ability to measure social connectivity is a small but nonetheless significant step towards using SNMM to estimate disaster resilience, itself the first step towards achieving DRR (Burton, 2015).

7.9 Supplementary Material

Table 7-4. Sensitivity analysis to determine sample size, using the betweenness centrality standard deviation as a sample test. Various sample sizes, *k*, were used when running the betweenness centrality function for each tower. For larger towers, *k*=2000, 5000, 10000, 15000 or 20000. For the smaller towers, these same sample sizes were also used until *k* exceeded the total number, *n*, of subscribers registered at that tower. The output for these *k* sizes are provided in the Between Standard Deviation (SD) Score column.

Large Towers

Tower	Sample Size	Betweenness SD Score
1655	2000	0.00021958
1655	5000	0.0002097
1655	10000	0.00020585
1655	15000	0.00020454
1655	20000	0.00020449
1829	2000	0.00018575
1829	5000	0.000178
1829	10000	0.00017323
1829	15000	0.00017297
1829	20000	0.00017191
1888	2000	0.00025141
1888	5000	0.0002429
1888	10000	0.00023685
1888	15000	0.00023733
1888	20000	0.00023727
1962	2000	0.00026423
1962	5000	0.00025455
1962	10000	0.00025212
1962	15000	0.00024975
1962	20000	0.00025064
2098	2000	0.00023265
2098	5000	0.00022266
2098	10000	0.00021971
2098	15000	0.00021833
2098	20000	0.00021797
2278	2000	0.00028451
2278	5000	0.00027688
2278	10000	0.00027123
2278	15000	0.00027227
2278	20000	0.00027158

Small Towers

Tower	Sample Size	Betweenness SD Score
1384	2000	0.00071202
1384	5000	0.00070721
1384	8283	0.00070432
1601	2000	0.00087256
1601	5000	0.00085769
1601	9862	0.00085914
1602	2000	0.00088679
1602	5000	0.00086776
1602	9483	0.00086169
2085	2000	0.00144008
2085	5000	0.00145546
2085	7343	0.00144136
2185	2000	0.00108597
2185	5000	0.00110246
2185	10000	0.00109005
2185	10269	0.0010913
2738	2000	0.00146376
2738	5000	0.00146752
2738	8202	0.00145897
2801	2000	0.00065939
2801	5000	0.00065079
2801	10000	0.00064493
2801	14253	0.0006437
2904	2000	0.00067548
2904	5000	0.00064887
2904	10000	0.00064912
2904	11367	0.00064758
3026	2000	0.00116701
3026	5000	0.00116997
3026	9822	0.00116677

2299	2000	0.00055369
2299	5000	0.00053927
2299	10000	0.00053462
2299	15000	0.00053509
2299	20000	0.000533
2480	2000	0.00039412
2480	5000	0.00037902
2480	10000	0.00037638
2480	15000	0.00037372
2480	20000	0.0003737
2648	2000	0.00040793
2648	5000	0.00040375
2648	10000	0.00039483
2648	15000	0.00039554
2648	20000	0.00039478

3882	2000	0.00096894
3882	5000	0.00095978
3882	7896	0.00095381

Figure 7-8. Bonding connectivity variables

(Administrative Boundary Data: © 2018 GADM).

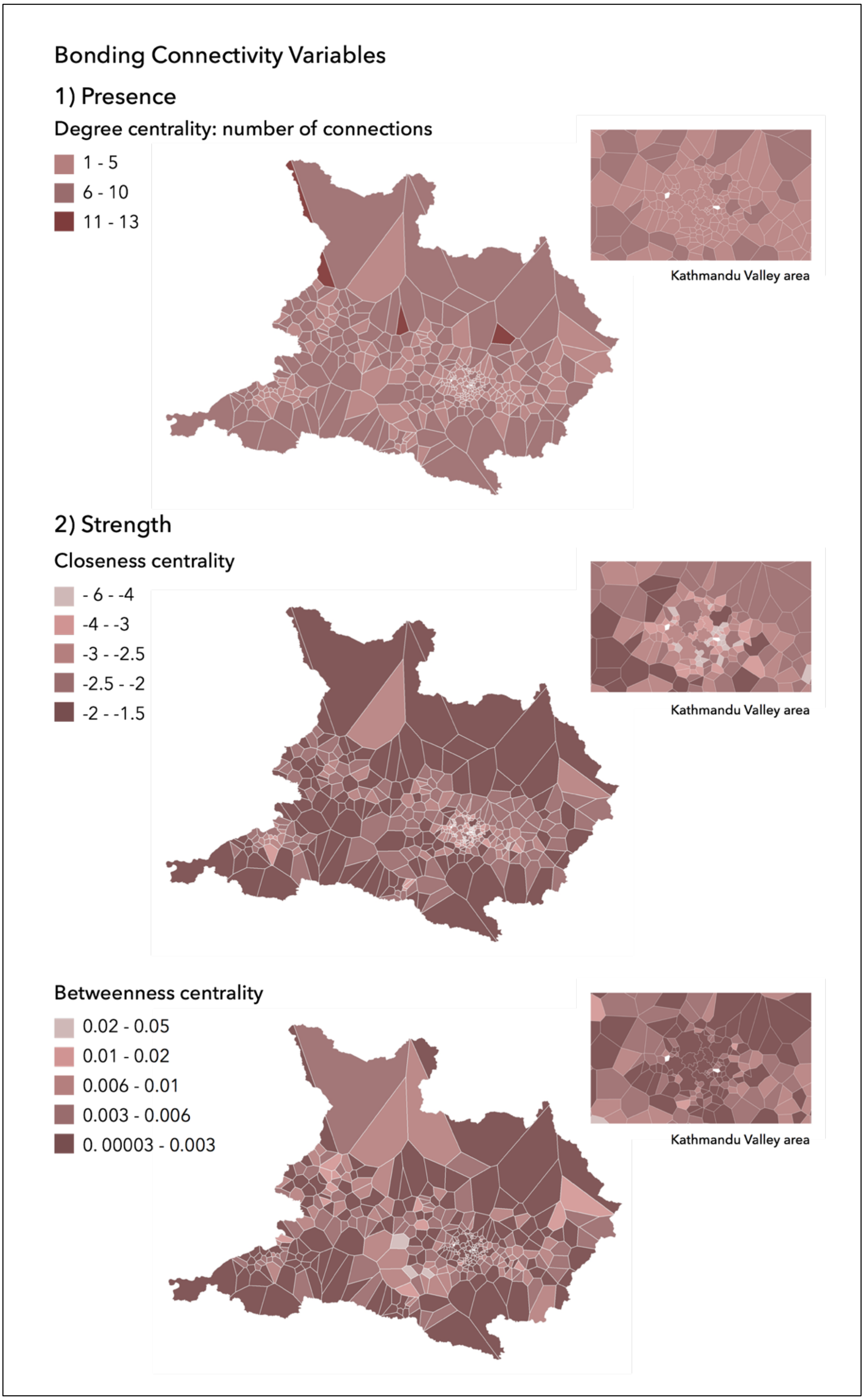


Figure 7-9. Bridging connectivity variables

(Administrative Boundary Data: © 2018 GADM).

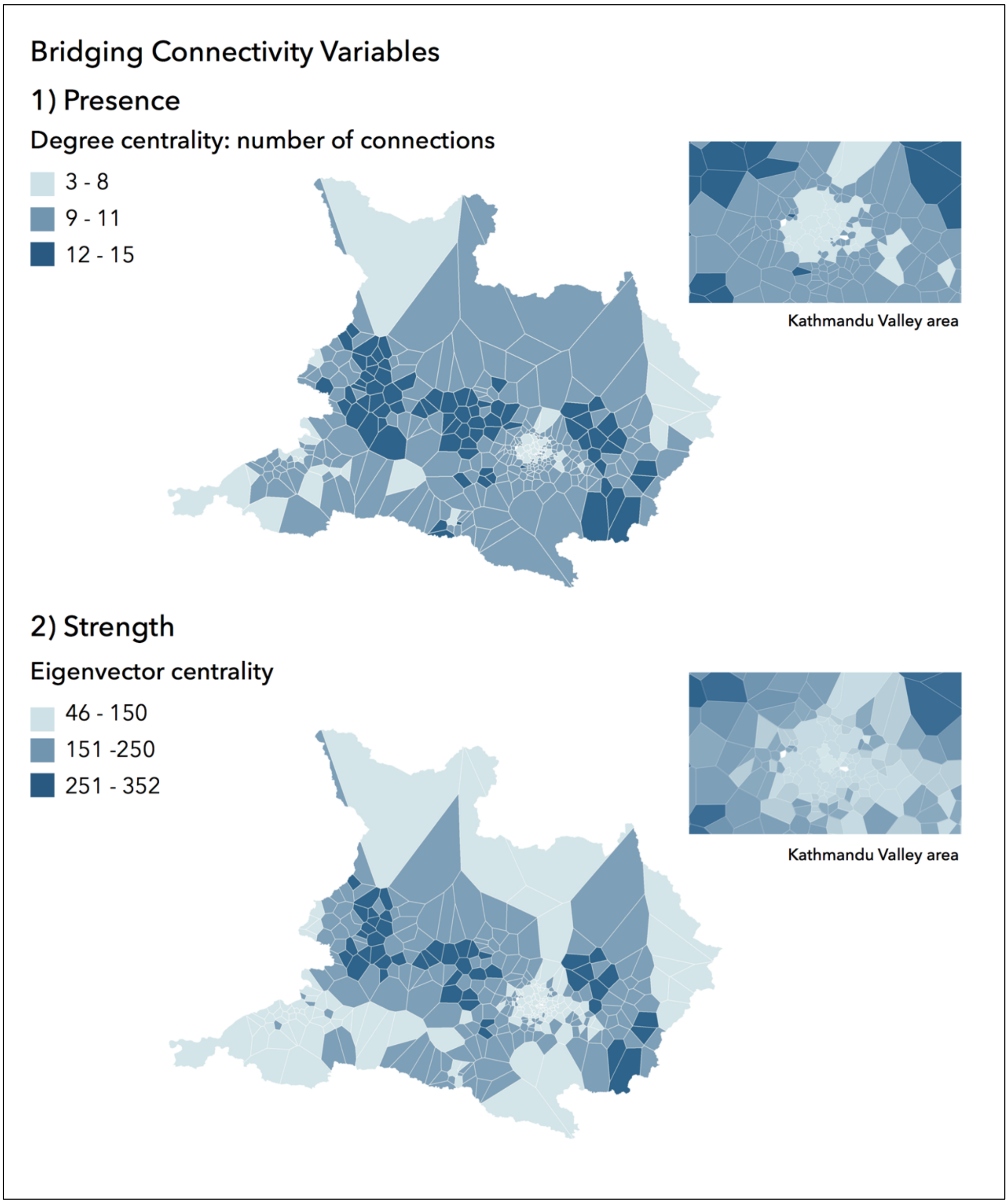


Figure 7-10. References maps of the eleven districts used within discussion: a) Ecological region distribution across the eleven districts and b) OpenStreetMap excerpt for the eleven districts *(Note, Tribhuvan International Airport in the Kathmandu Metropolitan City subset in the centre-east, identifiable from the long grey runway).* (Administrative Boundary Data: © 2018 GADM; District Place & Reference Data: © OpenStreetMap contributors.)

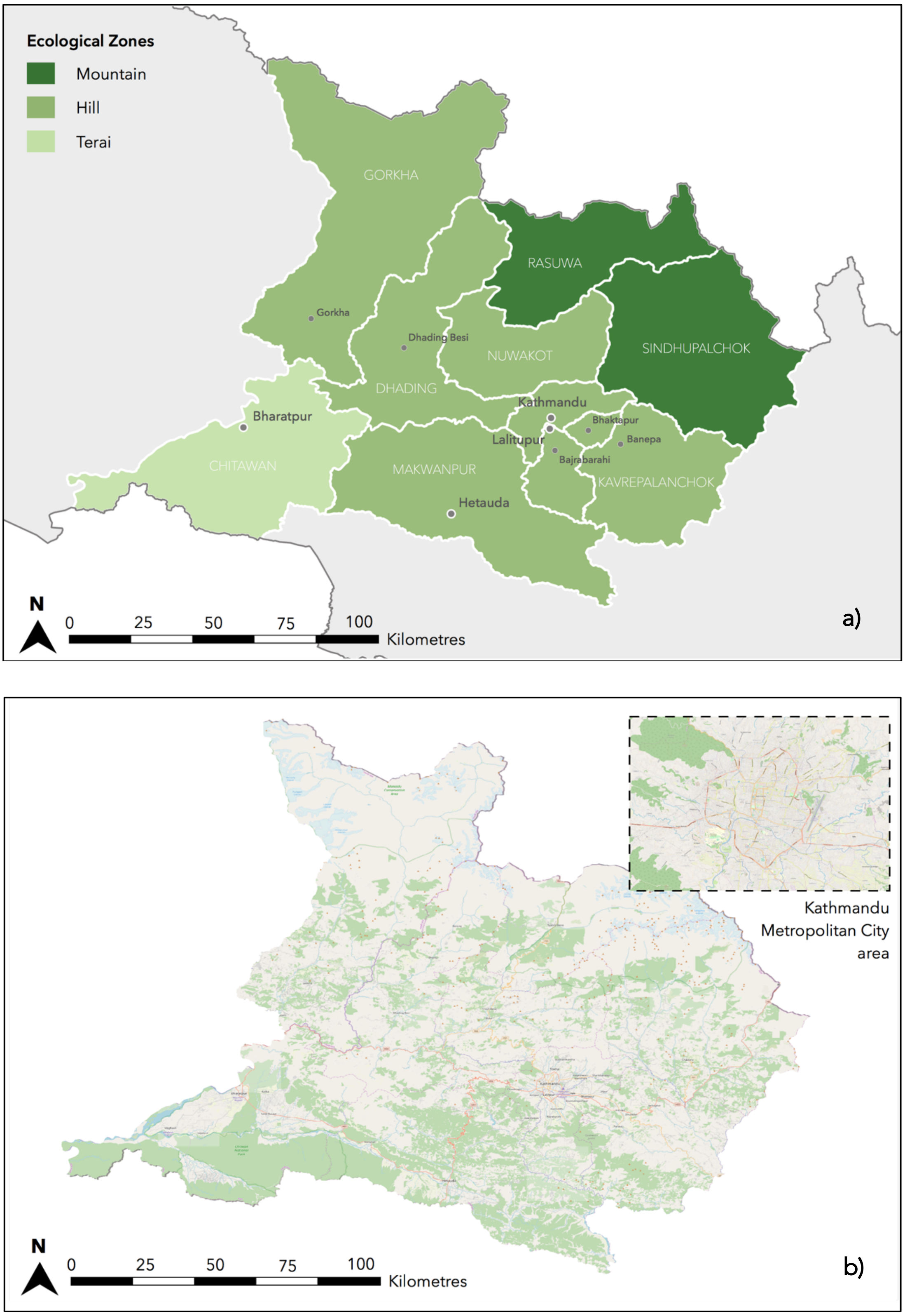


Table 7-5: Chapter Data List

Dataset	Source	Reference
Nepal Administrative Boundaries, Level 0 – 5	GADM 2018	© GADM www.gadm.org (https://gadm.org/download_country_v3.html, Accessed December 2018)
Ncell Cell Tower Locations	Flowminder	N/A
Ncell Call Detail Records, January 1st – April 24th 2015	Flowminder	N/A
Nepal City Locations	OpenStreetMap	OpenStreetMap data is provided under the Open Database License (www.openstreetmap.org/copyright), and has the attribution of ©OpenStreetMap contributors, https://www.openstreetmap.org.
Nepal Earthquake Data	United States Geological Survey	Data courtesy of the U.S. Geological Survey. www.earthquake.usgs.gov https://earthquake.usgs.gov/earthquakes/eventpage/us20002926/ https://earthquake.usgs.gov/earthquakes/eventpage/us2000292y/ https://earthquake.usgs.gov/earthquakes/eventpage/us200029bt/ https://earthquake.usgs.gov/earthquakes/eventpage/us20002ejl/

Chapter 8 Utilising Call Detail Records for improved mapping and measurement of social connectivity for disaster resilience: opportunities and challenges

8.1 The significance of the Social Connectivity Index

The importance of reducing the risk of populations to disaster is a key aim for those working within sustainable development and its related fields. For example, the Sendai Framework for Disaster Risk Reduction (SFDRR) is often cross-referenced within the revision of ongoing climate change and humanitarian policies and agreements (Collins, 2018). It is also recognized as a key driver for achieving the SDGs within the policy sphere; after all, Target 1.5. of the SDGs aims to "build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters"(United Nations, 2015). Whilst DRR activities have long focused on enhancement of physical infrastructure and encouraged residents to prepare in purely materialistic ways (Aldrich and Meyer, 2014), major international organisations and academia are paying increasing attention to the social dimension in DRR (Carrero *et al.*, 2018).

Within this context, a small but growing canon of research is demonstrating that how people are connected and interact and how they support each other (or not) within a network can significantly influence the ability of communities to cope with disaster and will influence their recovery and eventual outcomes (Tobin *et al.*, 2014; Misra *et al.*, 2017). Whilst the consensus throughout the literature is that there needs to be a better understanding of these roles, social networks remain under-explored, under-researched and under-conceptualised within resilience literature (Rockenbauch and Sakdapolrak, 2017; Carrero *et al.*, 2018). Very few systematic empirical studies have actually used social network analysis (SNA) as a methodology to investigate how communities are structured and cope with disasters (Guarnacci, 2016), as ultimately, it is difficult to find comparable cross-country evidence regarding households use of social networks (Chuang and Schechter, 2015). To help address this, and raise the prominence and recognition of social networks as a critical driver of resilience and a key component to understanding disaster risk, this thesis has provided a novel approach using an innovative dataset that could quantify social connectivity across substantial spatial and temporal scales.

Using the theoretical frameworks established in chapters 2 and 3 and the contextual and technical justifications provided by chapters 4, 5 and 6 (Table 8-1), chapter 7 devised and implemented the creation of a Social Connectivity Index (SCI) for eleven districts in Nepal. The SCI was deemed to be the most suitable operational methodology to measure social connectivity for disaster resilience estimation. The resulting dataset has shown clear spatial patterns to the distribution of bonding, bridging and overall social connectivity across the tower-communities within eleven districts In Nepal. These results could provide practical evidence to help more effectively target different types of DRR policy as well as potentially be used during a response to plan and prioritise aid distribution. In the case of the 2015 Gorkha earthquake, for example, this dataset could have enabled local NGOs to identify the most isolated areas that were likely to be missing aid and support (Hillig and Connell, 2018). In case of the future hazards, using the SCI, those tower-communities with the lowest overall social connectivity would be prioritised for any aid or support that an NGO can provide, whilst search and rescue and immediate response activities would be focused in areas with low bonding connections. Comparatively, tower-communities with low bridging connections would be targeted by longer-term recovery operations; NGOs would also need to establish direct lines of communication within these areas to ensure that response and recovery-related information is delivered with efficacy.

Beyond this use as an operational dataset within disaster response, the SCI has substantial potential to help assess the risk of these areas to future hazards. The SCI could be used either as a single proxy for resilience or as a variable within a resilience indicator, which would then be incorporated within an overall risk assessment. As a result, the SCI dataset could have significant benefits for the ongoing challenges faced within the wider DRR field of quantifying and assessing the distribution of risk.

Table 8-1. Key findings from Chapters 2-6 of the thesis used within Chapter 7.

Chapter	Objective	Main Finding(s)
Chapter 2	Provide an understanding of resilience, including how it is measured, situated within the context of the research.	There is no singular definition or operationalisation of resilience. There is a need to find a dynamic way of measuring resilience to understand it as a process, as well as a property.
Chapter 3	Consolidate literature to provide guidance on developing an appropriate methodology for analyzing social connectivity.	A growing area of research that seeks an alternative approach to measuring resilience through the analysis of social networks, primarily at the community scale. Within this research, a robust methodology utilising social network analysis is emerging, which offers opportunity for research cross-comparability and potential dynamic measurement.
Chapter 4	Evidence the importance of social networks for disaster risk reduction in Nepal	The social networks within and between communities continue to play an important role in helping members respond to and recover from a disaster, as exemplified in Nepal. Each of the network types, i.e., bonding, bridging and linking, play a different role in disaster response, as evidenced by the 2015 Gorkha earthquake.
Chapter 5	Quantify the representativeness of the CDR dataset of the population at study	Mobile phone ownership in Nepal has been influenced by a complex interplay among a number of factors. By 2016, the technological divides have weakened as the ownership has increased. Household ownership is nearing 100% whilst individual ownership has exceeded 80%.
Chapter 6	Evaluate the validity of using CDRs to map social networks at the community scale	Each community's social networks have remained predominantly local. Detection of geographic communities provides substantial evidence that the CDRs in Nepal are representative of real-world social networks.

The importance of this CDR-informed SCI is highlighted by many of the disasters that have occurred over the last ten years, in which civilians, such as friends, family and neighbours have been involved in the immediate response as well as help with longer term recovery. These responses have occurred across a variety of socio-economic settings, from the 'Cajun Navy' that gained attention during the 2016 Louisiana floods and 2017 Texan floods in the US (Lohr and Bellware, 2017; Plott, 2017) to the 2015 Gorkha earthquake (as evidenced in this thesis). The availability of this SCI dataset could enable comparison of levels of risk and resilience across communities within and between countries from this social connectivity perspective, which is yet to be achieved within the current more static approaches that measure resilience. The dataset could therefore help DRR practitioners to make decisions and recommendations on the most appropriate risk reduction activities and strategies across an entire population. Whilst practitioners may want to include other aspects of a community's resilience within this decision-making, such as whether a community possess and practice emergency response plans, the SCI provides the groundwork to measuring resilience at this scale.

The construction of the SCI also attempts to directly address some of the downsides associated with social networks. As MacGillivray (2018) explains, bonding networks are by definition exclusionary in nature and can be used in ways that harm the interests of those not within the network, such as when there are ethnic or racial identity tensions within a community. To account for this, the betweenness centrality measurement was used to ensure that the bonding connections were only considered to be 'strong' if everyone was as well connected as each other. Another alternative approach could have been to look at clique formation within the towers (Figure 3-2/Table 3-1), but this would have likely added further computational complexity to the SCI. Overall, as Guarnacci (2016) highlights, analysing resilience through the lens of SNA can be used to overcome the potential issues of unequal distributions of power (and relationships) within communities that resilience estimation often faces. It achieves this by trying to understand and evaluate the social networks of a system, the community, as a whole - an application of Aristotle's well-quoted "the whole is greater than the sum of its parts". For example, by having this single variable calculated for the tower-communities, those areas where there appears to be a high variability in the cohesiveness of bonding connections decision-makers can prioritise their investment in programs that build bridges across groups in communities (Aldrich and Meyer, 2014). As outlined in Chapters 2, 3 and 4, adaptation and transformation in the face of disaster relies on the ability of the community to act collectively.

The final advantage of the SCI presented in this thesis is the ability to extend the SCI into multiple time periods that stretch across disasters that have already occurred, subject to the availability of the data. Currently, research on social networks and resilience during disasters remains sparse due to the methodological challenges to collecting data during this periods; it is however an important phase that deserves to be understood to the same degree as "before" and the "after" (Nilsen, Haavik and Almklov, 2019). After all, it is the point at which a disaster's impact is likely to be the greatest and thus when strengthening of social networks could potentially have a huge impact (Nilsen, Haavik and Almklov, 2019). Using CDRs that have already been collected during a previous disaster, the SCI could seek to analyse the changes of social connectivity over time in response to the shock; for example, mapping the connections in Nepal over several time periods following on from the Gorkha earthquake in 2015. This approach could also enable measuring the impact of chronic exposure to ongoing disasters on social network structures, which in turn are likely to shape individuals' abilities to adapt to hazardous conditions (Tobin *et al.*, 2014).

This knowledge on changing social connectivity could have significant practical benefits within DRR, including reducing the psychological impacts a disaster may have. To respond to and recover from a disaster, communities need to be able to make choices that are well informed (Twigg *et al.*, 2017); as a result, a lack of information is a critical contributor to poor mental health during and after a disaster (McFarlane and Williams, 2012; Roudini, Khankeh and Witruk, 2017; Lee and Lee, 2019). As communities using their weak ties (and the ties of their ties) to search for information (Carrero *et al.*, 2018), studying the levels and flows of connectivity between communities could therefore simulate how information is likely to be disseminated and where it is less likely to be received (as seen in Fan, Jiang and Mostafavi, (2020), and discussed further in Future Research). These areas could then be proactively targeted with information in the likelihood of a hazard to reduce the anxiety and distress caused by the impact of the disaster. The SCI therefore provides multiple possibilities for future and further analysis.

By measuring social connectivity through the disaster management cycle, the SCI could be one of the first studies to provide a dynamic temporal dimension to connectivity in relation to resilience. The capability and almost immediate capacity to do so (as explained in Section 8.3) is likely to be unique to this thesis and its research. Furthermore, this potential ability to measure resilience as a process is a significant innovation not only in terms of methodological advancement but also in terms of pushing the boundaries of current academic resilience thinking forward. Whilst static resilience studies continue to be published using outdated data (e.g. Aksha and Emrich, 2020, explained below), this thesis demonstrates that there are novel datasets that are able to provide a dynamic insight into resilience. As a result, it provides a small but significant theoretical advancement on how to operationalise resilience as a process within DRR. To support this progress, this thesis has concomitantly provided substantial evidence and a novel contribution (i.e., Chapter 3) to advance the current discourse that aims to prioritise social networks within DRR.

8.2 Advancing the discourse on measuring social networks for resilience estimation

Context-bound networks in disaster-hit communities are of serious academic interest because, apart from being strategically important for managing disasters (Misra *et al.*, 2017), they offer a real-world stage on which to test novel theories. In this case, whilst SNA is starting to catch up in the field of disaster research, the study of network evolution and their characterization has remained extremely limited (Misra *et al.*, 2017). The CDR-enabled SCI could enable the study communities in their entirety, across the impact of a disaster under Rockenbauch and Sakdapolrak's (2017) 'translocal lens'.

The hope of pursing this research would be to help address the disconnect between those researchers continuing to focus on inherent resilience measures (predominantly composite indices) and those who seek an innovative approach to the measurement of resilience (Cutter, 2016a). A key example of this is that two weeks prior to the submission of this thesis, a paper was recently published (March 2020) on developing a Community Disaster Resilience Index for Nepal. Despite the fact the data used for the index construction was from the 2011 census, the paper advocates that its findings could be used to inform current policymaking, resource allocation, and disaster management among government officials and non-governmental organizations (Aksha and Emrich, 2020). In light of the significant damage by 2015 Gorkha earthquake and the ongoing socio-economic processes that are substantially changing Nepal's social landscape (as outlined in Chapter 4), the accuracy and validity of the resulting index is questionable, particularly when reviewed in the context of the findings presented in Chapters 1, 2, 3 and 4 of the thesis.

To this end, the provision of this SCI and thesis is to encourage the uptake of researchers to focus on new and innovative ways of measuring resilience and to focus on the importance of social networks. After all, there is significant demand from researchers for international DRR agencies and countries to place more emphasis on building social capital when developing DRR frameworks and supporting national-level DRR programs e.g., Han, Howe and Park (2019). But the potential role and contribution of local-level social organizing enabled by social capital is often overlooked (Sanyal and Routray, 2016). A key factor behind this, as identified by Chapter 3, is that many researchers still focus on the definition and measurement of the concept of social capital, which continues to be challenging and contested (MacGillivray, 2018). Empirical work has not yet widely adopted a standardised approach and, as suggested in Chapter 3, it is likely that practitioners are still unsure on how to engage with concept. This thesis therefore puts a firm stake in the ground from the outset, and has advocated for the progression of the focus from social capital to social connectivity. Chapter 3 outlined the increasingly overlapping and similar methodologies on social network measurement as motivation to move towards this focus on structure and geography of these networks as a priority (MacGillivray, 2018).

Whilst this is likely to receive criticism from those working within the social capital as a concept, many of the key 'social capital' building interventions advocated by researchers ultimately aim to maximize social interactions, such as time banking (where people volunteer labour or skills in exchange for incentives or rewards , focus groups and social events (Aldrich and Meyer, 2014). Essentially the notion is to create strong ties with neighbours and the local community, or even across communities. Whether a source, form or consequence of this 'social capital', the outcome can still be captured through the presence and strength of the resulting social networks.

Ultimately, whether conceptualising the role of bonding and bridging networks through social connectivity or social capital, the most intrinsic part to encouraging the uptake of either concept within practitioner circles is to change the narrative around how disasters are viewed. As Tierney (2014) advocated:

> …to fully comprehend how disasters are socially produced, it requires a departure from current and historical ways in which disasters are been characterised. Ultimately both risk and resilience have roots existing within the social order itself, whilst societies, communities and organisations have the power to reduce risk and become more resilient. But to help them, researchers need to help better understand the social forces that produce these disasters and act to address those forces and strengthen capacity for resilience of future threats. There will inevitably be impacts that will be out of the control of a response, but these can be greatly reduced through a broad range of risk reduction and resilience enhancing activities.
>
> (Summarised from Tierney, 2014, pg.4-6).

Here, in agreement with Carrero *et al. (*2018) it is advocated that the way forward is to highlight how informal networks, consisting of informal actors and connections, are in fact crucial and central elements of governance of DRR and not, as perceived by some, a secondary dimension. To do so, requires "a more systematic and data-driven look at the value of informal social networks in DRR…" in order to evidence that "disaster response should be more effectively engaged with local and informal processes" (Carrero *et al.,* 2018, pg.565). The SCI provides a small but nonetheless significant contribution towards providing this understanding. With the proviso of having access to CDR data (discussed in more detail below), it is scalable and repeatable for any country and as a result could provide a global database on social connectivity at a detailed spatial resolution. It would as a result enable on substantial scales, the re-valuation of informal disaster networks as a crucial, not tacit, component of disaster response (Carrero *et al.*, 2018). By providing this evidence at such a scale, it could help promote the importance of social networks as a key source of a community's resilience and thus encourage their recognition and utilisation by practitioners and policy-makers, particularly in times of disaster when they are needed most.

8.3 Creating a Social Connectivity Index from Call Detail Records

As identified in the Introduction of this thesis, one of the key challenges in the use of novel datasets is understanding what relevant information can be extracted and how. Through the extensive review of social connectivity literature, evident in Chapter 3, the decision was made early on in the process of this thesis to transform the social networks present within the CDR dataset into a Social Connectivity Index, using the methodology described in Chapter 7. Indicators are a primary way to measure aspects of resilience (Copeland *et al.*, 2020), particularly as those with a spatial component enable their integration with other datasets. The creation of indices of social connectivity however is not as established, with Cueto, Villalta and Bernal (2017) one of the first papers to provide a potential methodology from which an index is created. As outlined in Chapter 3, data challenges have significantly limited researchers' ability to empirically study the geography of present-day social networks and connections (Bailey *et al.*, 2018a), and, as a result, have likely hindered the conceptual and practical development of an index representing social connectivity.

Of significant interest to this thesis therefore is that in the latter stages of its development, a "Social Connectedness Index" (FBSCI) was published by Facebook (Bailey *et al.*, 2018a). Following a similar methodology to the SCI, the FBSCI captures the relative frequency of Facebook links of its US user base within counties, between counties, and to every foreign country (Bailey *et al.*, 2018a). With the platform's scale as well as the relative representativeness of its user body (for the US), the dataset provides a comprehensive measure of friendship networks at a national level (Bailey *et al.*, 2018a). The FBSCI has been used to study economic effects of network structure (Bailey *et al.*, 2018b) as well as the impact of social connectedness on the spread of viruses, such as the 2020 Coronavirus pandemic (Kuchler, Russel and Stroebel, 2020). The FBSCI has also been used as a proxy for social capital (Wachs *et al.*, 2019). The FBSCI marks a methodological development to the network quantification used in Metaxa-Kakavouli *et al.* (2018), which also utilised Facebook data and was developed with Facebook to assess social capital and connections.

The creation of an index to represent social connectedness by a globally recognised technology company highlights that understanding social connectivity is of significant interest to applications and industries, beyond its potential within resilience estimation and disaster risk reduction. However, whilst Facebook advertises its FBSCI as providing the "first comprehensive measure of social networks at an international level"(Facebook, 2020), the use of the online social network – and as a result, the representativeness of data behind the FBSCI - varies considerably across countries, particularly when accounting for different demographics (Gil-Clavel and Zagheni, 2019). Conversely, with subscriber penetration rates nearing or above 50%, and also continuing to rise, in regions such as Latin America, the Middle East, North and Sub-Saharan Africa, and Asia Pacific (GSMA, 2020), CDRs may offer a more representative dataset of the social networks within countries where Facebook's reach is inconsistent or limited across a country's population, particularly when trying to understand social connectivity for sustainable development applications.

The SCI and its respective methodology presented in this thesis therefore represents a first attempt to utilise CDRs to provide a comprehensive measure of social networks across a more representative population base; the SCI can also be expanded to an international scale - with the right data access and motivations. For Facebook, these requirements are a non-issue; the individual-level data is owned by the company, and with its "Data for Good" program, it provides the resulting FBSCI free to researchers and non-profits and promotes its use within published works (Facebook, 2020). For CDRs, with the datasets maintained and owned across multiple MNOs, it will require significant brokerage by researchers or through an NGO such as Flowminder, to gain access to develop the SCI at an international scale. The motivation to do so may hopefully increase as more researchers realise the potential of CDRs in providing detailed geographical understandings of social connectivity (e.g. Erlström, Grillitsch and Hall, 2020). In addition, MNOs may see the potential applications and corporate social responsibility advantages of supporting the SCI development; within the current COVID-19 pandemic, the FBSCI is providing innovative insights into the virus's spread and ineffective response mechanisms (e.g. Holtz *et al.*, 2020; Kuchler, Russel and Stroebel, 2020).

Whilst this conceptual development and application corroboration from the FBSCI provides considerable impetus to further expand the SCI, the SCI does face several specific methodological challenges that should be highlighted and addressed prior to this expansion. The first challenge is conducting further validation that CDRs are able to represent a person's social network effectively. In this thesis, Chapter 6 was utilised to investigate into the dataset's network representativeness, based on the premise that if the relationships present within the CDRs were reflective of those in the real world, then geographic communities would be identifiable within the data (adhering to the cited geographical and sociological theory).

A potentially more reliable method would be to conduct a small-scale survey that asks subscribers about their mobile social networks versus those within the real world and then also compare to these networks to their individual CDRs records, e.g., Eagle *et al.* (2009), Blumenstock and Eagle (2010). The issue with conducting these types of studies is that the latter step requires both the participants and the MNOs to grant researchers with permission to access identifiable CDR records. This arrangement is likely to require considerable ethical consideration and approval, which is less likely than ten years ago, given the changing privacy and regulatory environment, such as General Data Protection Regulation in the European Union. An alternative is to only focus on the first step and initial question of whether mobile phone users see their mobile contacts as representative of their real-world social networks – however, as Eagle *et al. (2009)* found, this type of self-reported social network data often has errors, with individual's memories of their interactions degrading after approximately a week.

A second methodological challenge is to identify a way in which to incorporate a betweenness measurement within bridging connectivity. In this SCI, betweenness was only used to measure the strength of the bonding network present within each community. The notion here was that less variation in the betweenness centrality of subscribers suggests that everyone in the communities is as likely to receive help as one another, ensuring that no one is excluded or likely to become marginalized or isolated in the event of a disaster. Bonding connections were only considered to be 'strong' if everyone was as well connected as each other, hence the inclusion of betweenness centrality within the strength component of the bonding connectivity. This inclusion also aimed to address the downsides of social capital including its exclusionary nature, as discussed further in Rahil *et al.* (2014).

Betweenness centrality however is also used for bridging connectivity as it details how integrated a community is within the wider network (Granovetter, 1973; Freeman, 1977; Everett and Valente, 2016). By having a higher betweenness centrality, i.e. occurring often along the shortest path between two other nodes, a community is likely to have many close relationships with these weaker ties. In the case of DRR, it is likely that these communities will have access to a greater diversity of information and resources first-hand from the communities to which they are connected. They are also likely to hold what is often known as a gatekeeper role, which can either be used positively to instil and encourage collective action, or negatively, as a point of control, particularly in the flow of information and resources. As a result, incorporating betweenness centrality within the strength aspect of the bridging connectivity could help improve its quantification, and ensures the SCI better adheres to previous and ongoing research on bridging connectivity.

The main challenge of adding betweenness centrality to the bridging connectivity component is its computation. Using the current tower proxy-community approach (calculation at the subscriber level and then aggregation at the tower level), it is likely to be incredibly complex. To calculate the bridging betweenness centrality of each subscriber involves: for each subscriber, (1) remove any subscribers within the same cell tower community from the dataset, (2) then construct the graph network, and (3) then run the betweenness centrality calculation. This process would then run 1.69 million times – for every single subscriber – to enable averages to be calculated for each proxy-tower community. To understand the computational complexity, the eigenvector calculation, used as the sole measure of strength for bridging connectivity, relied on a similar iterative removal process seen in (1), but did not require the complex network graph analysis of (2) and (3). Instead, the calculation used a more computationally simple approach of using querying, look-up tables and addition. Despite this relative simplicity, the calculation still took 2.5 weeks to complete. Additional computational resources will therefore be needed to integrate betweenness centrality – or a sample-based approach, as used for those tower communities over 20,000 subscribers in the bonding connectivity calculations, could be taken – in this case, taking samples for all tower communities.

The third challenge of creating the SCI was and continues to be determining the appropriate approach to allocate subscribers into communities in order to define and delimit bonding versus bridging connections. Here the decision was made to use the cell towers that subscribers were registered at as a home location as proxy-communities; the cell towers are, for now, the smallest geographical scale to which CDRs can be georeferenced. This approach therefore assigns, delineates, and aggregates subscribers and their respective social networks to the respective geography and geographical area (i.e. Voronoi) of the cell tower, rather than to their actual geographical community (which is currently impossible without additional personal data linked to their CDRs). To improve on this delineation as a representation of local communities, the findings of Chapter 6 were used to aggregate certain cell towers (and their respective Voronois) into larger proxy-communities and to try to prevent bonding networks from being counted as bridging networks. As improvements are made in the methodology used by Chapter 6, it is hoped that these aggregations can become more representative of the geographical coverage and delineation of the local communities.

This approach however does not account for one of the other findings present within the Chapter, which is the spread of communities across multiple spatial centres, by. As a result, what may be counted as a bridging connection through the current approach to delineation may in fact be considered a bonding connection by those subscribers behind the data. To address this, these dual and zonal communities could be used to provide additional criteria to assign subscribers into non-spatial bonding communities, either as a subset of the SCI or as an addition to it. One counter argument to this is that one of the key benefits of bonding connectivity within DRR is the immediate Search and Rescue efforts these networks often provide, as well as the initial tools for survival (e.g., shelter, food, medical assistance) in the first few days after a hazard's impact. Any bonding networks that are located further away are unlikely to provide these key benefits in a timely matter, therefore allocating subscribers and their social networks according to the geography of the cell tower at least attempts to capture these spatial constraints.

In addition to this local delineation, the SCI currently does not incorporate any information on international bridging connections. In the case of the 2015 Gorkha earthquake, Nepalese migrants across the world collectively organised to send and distribute aid and financial assistance to their close connections (Carrero *et al.*, 2018).

Adding this international component into the SCI could reveal geographical nuances into the role of bridging connectivity beyond the national scale.

The use of geography to define relationships within the CDR network also resulted in the compromise of not accounting for linking connections. As addressed in Chapter 7, linking connections are an essential component of social connectivity for DRR (Cueto, Villalta and Bernal, 2017). However, with phone numbers within the CDRs pseudonymised, there is no direct way to determine whether a subscriber could represent an NGO or government agency. Alternative approaches to adding in linking connections are discussed in 8.6, but fundamentally, the SCI could be supplemented with additional quantitative or even qualitative data to capture these linkages.

This addition of qualitative and quantitative datasets across the various aspects of the SCI reflects how this key challenge of novel datasets - what relevant information can be extracted and how – cannot be solved solely by the data itself, and instead requires an integrative approach ("CDR-plus[5]") with pre-existing knowledge and relevant data sets. As Blumenstock wrote in 2018, "new sources of data should complement, not replace, old ones. Conventional datasets are essential to calibrate and validate big-data applications". One immediate improvement for the current SCI is to aggregate its results to an administrative level to facilitate its comparison and integration with more traditional datasets; this would also enable a cross-validation with the FBSCI, if available for Nepal. Overall, the creation of a Social Connectivity Index from Call Detail Records is a key step in utilising novel datasets to help promote the importance of social networks in disaster risk reduction, rather than a single silver bullet to transform resilience measurement.

8.4 Methodological transferability

To capitalise on the potential of the SCI and enable this global comparison, it is essential that the dataset can be replicated and extended both in spatial and temporal coverage. This involves repeating the analysis presented across different countries, as well as over

[5] This term was used by the external examiner (Professor Daniel Aldrich) during the candidate's viva voce and, as such, should be accredited to them.

multiple time periods. To enable this, there is a fundamental question on the availability of and accessibility to CDR data; ultimately this the main restriction in the ability to transfer and apply the methodologies outlined in both Chapter 6 and 7.

In the case of this thesis, access to the Nepal CDR dataset was managed by the Flowminder Foundation, a registered NGO, through their agreement with Ncell, the Nepalese Mobile Network Operator (MNO). Flowminder has agreements with MNOs in multiple low- and middle-income countries and works with researchers, relief agencies and national governments to produce datasets for use within disaster response, sustainable development and epidemiology. Flowminder was formally founded six years ago, after it was clear through various research projects (Tatem *et al.,* 2009; Bengtsson *et al.,* 2011; Buckee *et al.,* 2013), that there was a distinct utility in the analysis of CDRs for the practical applications mentioned above. At this time, accessibility to CDRs was primarily granted to individual researchers on a case-by-case basis by MNOs; in addition, various research competitions using CDRs were also run, such as Orange's 'Data for Development' challenges (Blondel *et al.,* 2012).

Since Flowminder's inception, there have been ongoing changes in expectations on the use of CDRs, including more discussion and awareness of the ethical use of these datasets[6], including privacy security concerns, particularly within the research community (Taylor, 2016; de Montjoye *et al.,* 2018). For example, it was found that four data points containing the approximate places and times of where an individual was present was enough to re-identify them 95% of the time within a CDR dataset of 1.5 million users (De Montjoye *et al.,* 2013), despite the theoretical 'de-anonymisation' of the dataset. As a result, the likelihood of an independent researcher gaining access to individual level CDR data is more ethically and even technically complicated than five years ago. In the case of the latter, the introduction of General Data Protection Regulation prevents most researchers based in institutions in Europe from being able to use the data directly (such as the case in this thesis) as the data are required to be stored on the University servers,

[6] The ongoing pandemic situation in which this thesis is being submitted (i.e., the global COVID-19 pandemic of 2019/2020) has drawn significant attention to the need for regulation in regard to the accessibility of CDRs and if and whether MNOs should be forced by governments to hand over their data for use in population surveillance and tracking.

which most MNOs will no longer allow. The impact of these changes and restrictions means that whilst the repetition of this analysis is theoretically possible, it is likely to require access through a third-party which has a history with the MNO and the security safeguards in place to use the data (i.e., remote access to data), such as Flowminder or the UN's Global Pulse.

This approach is one of the four models advocated by the CDR community for the privacy-conscientious use of mobile phone data (de Montjoye *et al.*, 2018) (Figure 8-1). The notion here is that the SCI will become a pre-computed indicator that can be requested from Flowminder (or other MNO data broker) for a specific country (if the data are available). In this case, it is likely that there will be financial costs involved to account for the labour required by the data broker to adapt and implement the code that was created as part of this thesis. These costs may be addressed through the application for and use of relevant research grants. For those researchers who are able to access CDR data, the code created during this thesis will be added to Flowminder's online and openly available repository, FlowKit (https://flowminder.github.io/FlowKit/); as a result, the SCI can be recomputed using this code, following through with the Methods outlined in Chapter 7.

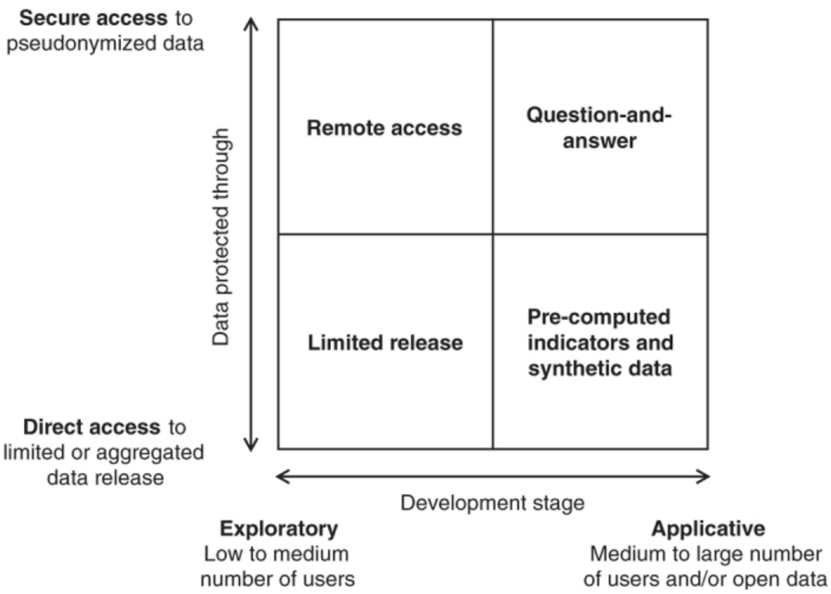


Figure 8-1. The four models for the privacy-conscientious use of mobile phone data. Source: de Montjoye *et al.*, 2018.

Beyond this restriction, all the remaining datasets used within the two CDR analysis chapters were openly available, with data lists provided at the end of each chapter and a final acknowledgements section provided in the Appendix of this thesis. In terms of analysis, the thesis used a variety of proprietary and open-source software, although all proprietary software could be replaced by open-source alternatives. The following outlines the precise methodological transferability of each analysis Chapter, exclusive of the issues regarding access to CDR data.

The analysis of MPO provided in Chapter 5 utilised survey data obtained through the WorldPop account with the Demographic and Health Surveys (DHS) program. Access to these data requires users to register with the DHS program and explain their use of the datasets they wish to access. Once registered, the survey data are freely accessible. There are approximately 32 other countries within the DHS Program that have multiple surveys that contain MPO information, of which at least one (the most recent) will have individual level data. As a result, it is possible to conduct this analysis for a range of countries, and it would be recommended for those looking to use CDR datasets within these countries.

To conduct the descriptive statistics and regression analysis, access to statistical software is preferable. Whilst for this analysis Stata Statistical Software (Version 15.1) (StataCorp., 2017) was used under a University licence, it is possible to complete all data management and analysis using open-source software such as *R*, its user-friendly interface *R-Studio* (Allaire, 2012) and its survey library (Lumley, 2020). Furthermore, with the addition of many mapping libraries to *R*, such as *tmap* (Tennekes, 2018), it would be preferable to use *R* to repeat this analysis in order to create the MPO maps also provided within the analysis. In the case of this Chapter, maps were produced using open administrative data from the GADM (https://gadm.org) with QGIS (Version 3.8), an opensource GIS program (QGIS Development Team, 2019).

With supposed access to a CDR dataset granted, the transferability of Chapter 6 is relatively straight-forward for those familiar with both Python programming and GIS modelling. The initial CDR analysis, as described in the Methods section of the Chapter, used the openly available NetworkX Python package (Hagberg, Swart and S Chult, 2008) (graph creation) and Bandicoot toolbox (contained the Louvain Community Detection algorithm). The Voronoi tessellation to which these data were joined was created from the cell tower locations using the ‘Create Thiessen Polygons’ tool within ArcGIS (version 10.7); a proprietary GIS software from Esri (Environmental Systems Research Institute, 2019). Both QGIS and the *scipy* python library (Virtanen *et al.,* 2020) also have the capacity to create the same tessellation.

The community distribution processing (outlined in Figure 6-3) then used openly available python libraries, such as *numpy* (Oliphant, 2006), *pandas* (McKinney, 2012), *geopandas* (Jordahl, 2014) and *rasterio* (Gillies, Ward and Petersen, 2013), to create the resulting community point distribution files (the code for which will be available online after submission). This process also involved the use of a raster-based population dataset, in this case, provided by WorldPop (Tatem, 2017). This dataset was chosen as it predicted population distribution for the same year as the CDR data was generated: 2015. Other open raster-based population datasets are available, such as Facebook and Columbia University's Centre for International Earth Science Information Network High Resolution Settlement Layer (Facebook Connectivty Labs and Center for International Earth Science Information Network - CIESIN - Columbia University, 2016), that may offer different spatial resolutions as well as temporal coverages.

The Kernel Density Estimation (KDE) processing was run in ArcGIS due to the author's familiarity with using ArcPy, Esri's own Python library, to automate GIS processing. This analysis could be repeated and automated using QGIS, if preferred using the Heatmap tool and python scripting. The resulting KDEs were mapped in ArcGIS alongside GADM data, and validated using openly available census data as well as OpenStreetMap. The standard deviation ellipses were created using the Directional Distribution tool, again within ArcGIS whilst city reference data was extracted from OpenStreetmap.

For Chapter 7, again with supposed access to a CDR dataset granted, the basic methodology required the knowledge of Python programming and GIS modelling/map creation; to expediate the calculation of many of the measures, the use of Structured Query Language (SQL) was used by the analyst at Flowminder. Before the measures were calculated, the towers were first aggregated by using a visual approach to identifying community distributions and dissolving the Voronois as appropriate (as illustrated in Figure 7-2 and 7-3), which required the use of a GIS. Once the measures were calculated, they were processed using *R* and then mapped using ArcGIS.

As evident from the explanations provided above, beyond the need to access and process CDR data, the remaining processing and analysis of the data is possible using openly available data and software. A key factor in the development of the various methodologies presented in this thesis was the substantial availability of online learning materials and guidance. For example, the DHS Program runs a comprehensive forum that can either be searched to identify topics of interest (e.g., how to weight samples correctly) or questions can be posted that will be answered by a DHS Program specialist as well as the user community. For GIS or programming related questions, a range of online documentation is available, from Esri's own well-maintained documentation (https://desktop.arcgis.com/en/arcmap/) to community forums, such as StackOverflow (https://stackoverflow.com) or GIS stack exchange (https://gis.stackexchange.com). Furthermore, the python libraries citied above also contain substantial documentation, whilst multiple online courses exist to teach basic python programming (e.g., Code Academy) as well as Python for GIS analysis (such as those provided by the University of Helsinki: https://automating-gis-processes.github.io). Ultimately, the training, software and data (exclusive of CDR data) are easily available which makes the research within this thesis highly repeatable for any researcher interested in social connectivity measurement. The key restriction as identified at the start of this section is and will be the accessibility of CDR data.

8.5 Critical challenges: current and future

The accessibility to the CDR dataset posed the most significant challenge in the completion of this thesis, with the raw data processing reliant on and subject to Flowminder staff and server availability and constraints. For the final SCI, for example, the complexity of many of the SNA measure queries required substantial processing time, including two weeks to calculate the Eigenvector Centrality measure. Beyond these technical issues, the author was challenged by their own personal reflections on the ethical question of whether it is appropriate to analyse the data in the first place, even with the security and privacy safeguards put in place. The use of novel datasets for sustainable development, as outlined in the introduction, has at many times over the last few years received substantial criticism and negative feedback questioning the integrity of using such data without the user's consent and whether it really is 'data for good' (e.g., Maxmen, 2019). To this end, the author hopes that by putting the connections within and between communities at the forefront of the SCI, this methodology focuses on the agency of these users involved and ensures that the people that are behind these datasets are not forgotten (Blumenstock, 2018).

In terms of creating the SCI with CDRs within future research, there are likely to be three critical challenges. The first is the validation of the current dataset, as highlighted in Section 8.3. One of the key challenges of using novel datasets within DRR and sustainable development applications is to ensure that the results are somehow validated (Blumenstock, 2018); in many cases, such as this, little to no validation data exist and as a result alternative approaches to validation are sought. In this thesis, potential biases or issues with the dataset were primarily addressed through the first two analysis chapters, however, ultimately the SCI and its relation to resilience is still untested. One option to validate the SCI is to seek out other innovative datasets that can also offer a similar measure of connectivity, such as online social networks, i.e. the FBSCI (if these datasets can provide representative coverage), or, considering Nepal's mobile phone market is dominated by two networks, extract the same connectivity dataset using CDR data from the other MNO. To test the SCI, following on from the findings by Metaxa-Kakavouli *et al. (*2018), on evacuation behaviours in relation to social networks, it is proposed that a displacement analysis using CDRs, as demonstrated in Li *et al. (*2019), could be a first step to providing a demonstrable connection between the SCI and community recovery.

The second challenge is created through the changing mainstream understanding of how CDR data are used. Prior to the last few weeks, the use of CDR data for research was not a widely discussed in the public sphere. For example, a study on the use of CDRs for public health in the UK found that only 3% of users knew that their CDR data were being used for research (Jones *et al.,* 2019a). However over the last two weeks, there have been substantial reporting within the mainstream media about the use of CDRs for population tracking and monitoring (Flowminder Foundation, 2020), which has raised substantial concerns within privacy watchdog organisations (Kirchgaessner, 2020). Whilst, the study by Jones *et al. (*2019a), highlighted that 62% were content for these data to be analysed (and this increased to 80% when the participants were informed of the safeguards in place), the current discourse on the use of CDRs (as well as other sources of mobile phone data) and the invasion of privacy for surveillance applications may sway public opinion against their use.

The potential fallout is that researchers and responders are either discouraged or even prohibited to use these types of data, such as seen during the Ebola crisis in 2014 where a blanket ban was placed on using CDRs for the same type of population tracking. Furthermore, there is a worry that a rushed response due to the current climate may result in the abuse of the dataset and could cause future impediments to the continued establishment of formal regulation, as well as the creation of an ethically founded framework research for their use in research (Jones *et al.*, 2019b). At the moment, the availability of CDR data as a research dataset, particularly via Flowminder, are likely to continue.

The final identified future challenge to the use of CDR in the future is the currency of CDRs as the spread of 4G and 5G networks facilitate the predominant use of data-enabled services, such as iMessage and WhatsApp as well as Wi-Fi-calling, rather than using traditional SMS and telephone lines. To ensure the SCI can be generated in future years, there is a need to understand the implications of changing mobile phone use and whether these types of messaging and calling behaviours can also be recorded and analysed using the same methodologies and approaches. The ethics of using these datasets must also be considered.

8.6 Limitations

Each analysis chapter has been presented with its associated limiting factors, primarily specific to the datasets used or methodology chosen, whilst Section 8.3 has presented key limitations of the current SCI and its respective methodology. These limitations are summarised in this following section.

For Chapter 5, the main limitation is in the confidence of extrapolating the analysis of household and even individual level MPO to understand the likely socio-economic demographics of the persons generating the CDR data. As explained in the Chapter, a mobile phone subscription (or SIM card) is not equal to MPO, whilst MPO does not consider the potential of device sharing or the ownership of multiple phones or SIMs. As a result, it cannot be assumed that for the 1.69 million users within the CDR dataset, a certain percentage is likely to be female, whilst the rest are male. The precise socio-economic demographics of the CDR dataset are still relatively unknown, and instead the MPO analysis can only guide the likelihood of its representation. Furthermore, the spatial resolution of these data at the province level are too coarse to understand the potential variations in ownership that may occur at the district level.

For Chapter 6, the main limitation is that, for now, the approach is unable to detect and visualise every geographic community in the eleven selected districts. As explained, a lack of data, network coverage or contact between users could be the cause, or a different community detection algorithm (CDA) may need to be used in order to find smaller clusters. One of the key limitations with the Louvain CDA, despite its fast computation, is that it often fails to detect smaller scale community structures (Lee and Cunningham, 2014). Furthermore, in light of more recently published CDR research, it would be prudent to re-run the home location algorithm with different parameters to validate the overall accuracy of the subscriber's assigned home tower (Vanhoof *et al.*, 2018). Despite these technical issues, the resulting spatial distributions do provide enough data that it can be used to help with ongoing wider issues facing the use of CDRs to generate indicator-based datasets (such as the SCI) in terms of the aggregation and delineation of subscribers to cell towers and their respective spatial coverage, i.e., the cell tower Voronoi (Vanhoof, Ploetz and Smoreda, 2018), as evidenced in Chapter 7.

The limitations of Chapter 6 directly contribute to the limitations faced within Chapter 7. At the outset of this thesis, the aim was to map and measure social connectivity at the community scale, where community membership of users would be used to distinguish between two of the different types of connections, bonding and bridging, that were identified within the DRR literature to build resilience (Hawkins and Maurer, 2010). To enable this, geographic communities would need to be identified within the network data and studied; however, whilst several geographic communities were found (Chapter 6), the resolution was not sufficient enough to focus at the community scale when creating SCI created in Chapter 7. As a result, communities are represented at the smallest spatial resolution possible, at the cell tower level (or aggregated cell tower, informed by the spatial distributions from Chapter 6). The implications of this type of geographic approach have been explained in detail in Section 8.3. Overall, before the methodology is expanded to additional countries, more work is required to improve on the current methodology presented in Chapter 6 and refine further the detection of geographic communities in order to map the social connections and measure social connectivity at the geographic community scale. Until then, despite the positive and interesting findings the SCI offers, any interpretation has to be realistic about what these results show – connectivity within and between users at cell towers within a CDR network dataset.

This links to the second limitation of the SCI dataset and methodology presented in Chapter 7. As identified earlier, the current approach is unable to quantify the linking networks of the cell-tower communities, an essential third part to understanding social connectivity for resilience building (Cueto, Villalta and Bernal, 2017). Linking networks are considered to be the connections between individuals, households and communities with local government, NGOs, and other community-based organisations (Islam and Walkerden, 2015). A key piece of future work would be to determine ways in which these linkages could be added, for example, supplementing the analysis with external datasets, such as obtaining the contact data directly from NGOs that may work in the area, or from the local elected officials responsible for engaging with them. These relationships will involve fewer data points than the overall community level analysis and thus more feasible to collect using traditional methods e.g., Islam and Walkerden (2015), and Matin et al. (2015). The need for this additional data is important; a recent study found that trust in an NGO will rely on how long and how close they have been working with the community, requiring a certain level of previous contact to be established prior to emergency situations for them to be accepted (Han, Howe and Park, 2019).

8.7 Future research

Through outlining the various limitations this research has faced, the previous sections have also identified various avenues of future research. In addition to this, the various findings arising particularly from the last two analysis chapters have also created and leaves many questions unexplored. From a technical perspective, there is need to pursue more technical CDR analysis refining the allocation of users to home locations as well as the mapping of the networks further to community scale. Within the sociological and geographical context, the zonal distributions (Chapter 6) and bridging relationships between tower-communities (Chapter 7) show at a fine level of detail, which different geographic areas are connected through social networks in both Chapters 6 and 7.

For Nepal, this raises interesting questions regarding the impact of ongoing socio-economic processes, such as migration, on the formation and distribution of communities as well as the development of urban systems. In this case, the direction and volume of bridging flows may offer additional insight into these processes. These flow data can be easily extracted within the social network constructed and analysed within Chapters 6 and 7 and would be a relatively straightforward piece of follow-on research after the submission of this thesis. Furthermore, in light of the current virus pandemic and the speed to which COVID-19 has spread, these methodologies may provide additional approaches to using CDRs for epidemiological studies, beyond only population tracking, such as seen in Bengtsson *et al. (*2015) to assess likely risk factors behind the virus spread.

For DRR research specifically, as identified in Chapter 2, one of the most pressing challenges within resilience research is to find an approach to measuring resilience dynamically (Cutter, 2016a). From the outset of this thesis it was proposed the integration of social networks and analyses using novel data sources has the potential to revolutionise how resilience is measured, through the measurement of social connectivity through the disaster management cycle. As yet, the current research only prevents an SCI for a single snapshot in time: the social connectivity of users in the three months leading up to the 2015 Gorkha earthquake. As a result, the relationship between resilience as a property and as a process remains theoretical and yet to be tested (Cutter, 2016b).

The main emphasis for future research is therefore the repetition of this current analysis for at least another three time points directly after the earthquake, such as the first day, the first week, and the first three months. The aim of this analysis would be to understand how different networks are used and activated in response to a hazard. For example, a recently published study that focused on social media posts prior to and during the impact of a disaster (Hurricane Harvey in 2017) showed that disaster events give rise to emergent social cohesion, including the formation of new links (Fan, Jiang and Mostafavi, 2020). The repetition of the methodology presented in this thesis for CDRs could provide a more detailed reflection on how networks are used and activated in a response, for example, calculating the rise in average number of bridging connections over the following weeks. After all, CDRs have been proven to be a 'sociometer' to disasters (Bagrow, Wang and Barabasi, 2011).These further analyses could provide new insight into how different communities may or may not use their social networks to respond to a shock and, as a result, could significantly shape the theory behind understanding resilience as a dynamic process.

A final addition to this dynamic study would be to extend the analysis to include international ties within the CDR dataset. This ability to look at cross-country networks would be one of the first attempts to engage with Rockenbauch and Sakdapolrak's (2017) 'translocal lens' perspective, which highlights that these community connections are not necessarily bounded to the geographical understanding of what a community is, but can extend into a multi-dimension concept of global-scale social ties (as also advocated in Guarnacci, 2016). The creation of this 'trans-local' lens, they advocate, will help researchers truly understand the realities of resilience (Rockenbauch and Sakdapolrak, 2017).

8.8 Summary

The aim of this discussion has been, in the context of the entire thesis, to evaluate the suitability and potential of Call Detail Records for measuring social connectivity to support resilience estimation for disaster risk reduction. To do so, this discussion has focused on two significant areas of novel contributions that this research has made. First it has outlined the current challenges in social network mapping and measurement that the CDR-generated Social Connectivity Index addresses, with Section 8.3 outlining the underlying limitations of the final index. The second area of focus was to highlight the key opportunity to extend the dataset across unprecedented spatial and temporal scales. The second half of the discussion has focused on the feasibility of this, with Section 8.4 illustrating the relative ease of extending the methodology, granted CDR or similar data is available and the required technical expertise is present. Section 8.5 highlights that this data access is the main critical challenge current researchers are likely to face, although determining alternative approaches to validation (beyond those achieved in Chapters 5 and 6) will also be necessary. Section 8.6 continues on this theme, with more work required to map connections and measure connectivity more precisely as well as the need to find alternative datasets to integrate linking connectivity into the dataset. Despite these limitations, as advocated by Section 8.7, the future potential applications of the SCI dataset are substantial and could lead to insights beyond the original application, to estimate resilience and help with disaster risk quantification.

In the evaluation of the SCI, the discussion has also highlighted the second major contribution of this thesis (Section 8.2), where in its totality, the thesis has sought to advance the current discourse on resilience estimation and demonstrate that, through social network measurement and the use of CDRs, there is a potential methodology to measure resilience as a process. To support this methodology, the thesis advocates how the focus on social capital has stalled resilience researchers from fully appreciating the primary role social networks have in building and driving resilience. Without this recognition within academia, the importance of social networks and this bottom-up approach to resilience in policy-maker and practitioner circles are often ignored, but often to great consequence. Without considering resilience building from the bottom-up, DRR policies are likely to fail.

The thesis promotes strongly the measurement of social connectivity to advance current resilience thinking, particularly in search of this dynamic understanding and measurement. Ultimately taking these two contributions into account, the final contribution of this thesis can be outlined. As Carrero *et al. (*2018) state clearly: to truly evidence the importance of social networks within DRR, there needs to be a data-driven and systematic approach to their valuation. The SCI, and its use of an innovative dataset, is an avenue in which to pursue this, with substantial potential to raise the prominence and recognition of social networks as a critical driver of resilience and a key component to understanding disaster risk.

In light of everything articulated within this discussion, there are four clear pathways for future work:

1) Validation of current methodology;
2) Improvement on current scale of mapping;
3) Repetition of analysis at multiple temporal periods to understand the use of social networks during and after the 2015 Gorkha earthquake;
4) Analysis of the direction and volume of bridging flows.

Chapter 9 Conclusion

The aim of this research has been to quantify and evaluate the potential of Call Detail Records (CDRs) for measuring social connectivity to support resilience estimation for disaster risk reduction (DRR). With CDRs containing the social network data of each individual subscriber, the premise was that the connections between these subscribers could be mapped at the community scale to create a Social Connectivity Index (SCI) for use in resilience estimation for DRR. It was theorised that this would provide significant opportunity to measure social connectivity across unprecedented spatial and temporal scales that could help facilitate the quantification of resilience and disaster risk across multiple countries and enable their comparison. To substantiate these theories, the theoretical framework behind the methodology and the feasibility and validity of using CDRs within the devised SCI has constituted the majority of the thesis objectives, with Chapter 7 providing the inaugural connectivity dataset. The discussion then sought to critically assess the suitability and validity of CDRs as a source of social network data for resilience estimation.

The research presented within this thesis establishes that there is significant impetus for the creation of such a dataset and demonstrates how CDRs have the potential to fulfil this need. Through an appraisal of emerging literature on social network measurement within resilience estimation, the thesis exemplified how social networks are a fundamental component to resilience, which until recently have often been ignored in preference to more tangible or measurable aspects of resilience e.g. local infrastructure (Objective 1 and 2). Synthesising this literature also revealed how a robust singular approach to their measurement is emerging through the use of social network analysis. However, for these approaches to gain momentum within disaster resilience research, as the thesis firmly advocates, requires a rethinking of social networks from their traditional conceptualisation as social capital to a focus on the role of social connectivity (Objective 2). These theoretical findings were reinforced within the exploration of the role of social networks in Nepal, where substantial evidence was collated from multiple reviews to confirm how social connections within and between communities in Nepal are critical to their routine and emergency needs (Objective 3).

To scrutinise the feasibility of using CDRs as a potential source of social network data in Nepal, and without the availability of ground truth data on social networks to validate the resulting index, the dataset's likely population coverage and the conformity of the networks within the dataset to expected sociological norms were investigated. It found that ownership in Nepal by 2016 was substantial (82% for individuals, 93% for households) and as a result, could be concluded that the 2015 CDR dataset was likely to be representative of a substantial cross-section of Nepal's population (Objective 4). The second analysis chapter mapped the spatial distributions of the social communities detected within the CDR dataset and demonstrated how the social networks within the CDR data adhered to the key sociological principles of homophily and Tobler's First Law of Geography. This observance of these 'digital' social networks to these social principles provided the necessary justification that CDRs can represent real-world social connectivity (Objective 5).

The final chapter then engaged with both DRR and CDR literature and to develop a operational methodology to map and measure social connectivity across the eleven districts within Nepal (Objective 6). The study revealed that there were evident spatial differences in the levels of bonding, bridging and overall social connectivity across the eleven districts. These results could provide significant insight into the resilience of these districts that could be used by those working to understand disaster risk within the country. Consolidating these individual findings and as outlined in the final discussion, the thesis overall finds that there is a feasible and practical method to map and measure social connectivity using CDRs, which could be used as an innovative dataset for disaster resilience estimation within DRR.

As with any analysis of what is ultimately a proxy dataset of a specific phenomenon, the social connectivity indicated by CDRs must be interpreted as such. In this context, social connectivity should not be the sole or single dataset to understand resilience or global disaster risk, but one that should be integrated with other measurements to further improve on the current understanding of risk and resilience: a CDR-plus approach. Whilst our CDR-based SCI may provide a single perspective to understanding resilience, our findings across our analyses show that this is likely to be a significantly important one, with the CDR social networks revealing in precise detail the impact of large-scale ongoing socio-economic processes within the country e.g., the zonal distributions presented in Chapter 6. Even the detail in the complexity of the relationships across our eleven districts reveal that the CDRs are able to capture differences in local 'mobile-based' social networks.

Ultimately this thesis shows that through the emerging body of literature on social connectivity and social network analysis, and the utilisation of an innovative dataset, such as CDRs, there is significant opportunity to rethink the current methods of resilience estimation for disaster risk reduction. To do so, the thesis has shown that the creation of a cross-country dataset for resilience and risk estimation and comparison is not only feasible but possible in the immediate future. As such, this thesis challenges the current status quo on resilience measurement and adds to the growing canon of research that aims to refocus on, what is proposed here to actually be, one of the most tangible aspects of a community's resilience to disasters: social networks.

The provision of this thesis in its entirety is provided as a pertinent and substantive document of evidence that hopes to add to the growing and rigorous research that calls to prioritise and promote the pivotal role of social networks within disaster resilience.

Appendix A PhD Logistics and further activities

Supervisor capacity

The primary supervisor for this PhD thesis is Andrew J Tatem, who is a Professor of spatial demography and epidemiology within Geography and Environmental Science at the University of Southampton.

The secondary supervisor for the thesis is Dr Eloise Biggs, who is a Lecturer in Geographical Information Science (GIS) within the University of Western Australia's School of Agriculture and Environment.

Data provision and code implementation from the Flowminder foundation

Access to the mobile phone data was provided by the Flowminder foundation, through Prof Tatem's role as Director. The Flowminder foundation did not provide any advice or support during the PhD in terms of research context, methodology or analysis. The organisation is supportive of the research and managed the relationship with Ncell, the Nepal MNO, to enable the use and analysis of the data and authorise the publication of the research results. The two CDR-based papers emerging from the thesis are undergoing approval by Ncell in order to be submitted. An update on the status of this approval can be provided by the time of the Viva.

Project Ethics Approval

Ethical approval for this project was granted in March 2017 (prior to any analysis beginning), under the submission ID: 23964 – Secondary Data Analysis: Developing a methodology to use Call Detail Records (CDRs) to help map community resilience in Nepal. The application detailed the expected use of both the CDR dataset and the DHS program survey data within the PhD programme. Approval is granted until December 2020.

Conference presentations and attendance

The thesis details the research outputs resulting from the PhD to fulfil the main academic requirements. In addition to this thesis, the research from the PhD has been presented at two conferences.

1) Geo4Dev 2018, University of Berkeley, California, USA, *'Geospatial Data and Community Resilience'*, 15/11/2019. (Chapters 2 and 3)
2) NetMob 2019, University of Oxford, United Kingdom, *'Mapping Geographic Communities using CDRs and OpenStreetMap'*, 08/07/2019 (Chapter 6)

Grants and Awards

During the PhD programme, Joanna was a recipient of external funding for travel and internal and external awards for her contribution to teaching in the University.

<u>Travel Grant</u>

2017 World University Network Research Mobility Grant for extension to a research trip to UWA, Perth, Australia

<u>Awards</u>

2019 Esri UK Young Scholar Prize and 2019 University of Southampton Doctoral College Director's Award for Education for the 'Geography Programming Bootcamp'

In addition to the Esri Young Scholar of the Year Award 2019, the Bootcamp was nominated for and won a University of Southampton's Doctoral College Director's Award in Teaching.

Appendix B Data acknowledgements and copyright statements

The acknowledgement and copyright statements listed here are provided in order of appearance/use throughout this thesis.

Hazard Dataset (Chapter 1)

Access to the EM-DAT database is made available free of charge by the UCL. The reproduction and communication of the information from EM-DAT is authorized by any means and in all forms, provided that the source is clearly mentioned as follows:

> EM-DAT: The Emergency Events Database - Université catholique de Louvain (UCL) - CRED, D. Guha-Sapir - www.emdat.be, Brussels, Belgium.

Administrative Boundary Dataset (Nepal, India, China) (Used throughout)

GADM data are freely available for academic use and other non-commercial use, with credit to GADM, © 2018 GADM. Data is available at www.gadm.org .

Needs and needs providers figure by Carrero *et al.* (2018).

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Nepal 2015 Earthquake Data (Chapters 4 and 7)

USGS-authored or produced data and information are considered to be in the U.S. Public Domain. and may be used without restriction. Data is provided under the courtesy of the U.S Geological Survey at www.usgs.gov.

2011 Nepal Census (Chapters 4 and 7)

Nepal Census data was extracted directly from the official National Population and Housing Census Report 2011, found at: https://unstats.un.org/unsd/demographic-social/census/documents/Nepal/Nepal-Census-2011-Vol1.pdf .

The Demographic Health Surveys Program Datasets (Chapters 4 and 5)

The DHS Program is authorized to distribute, at no cost, unrestricted survey data files for legitimate academic research. Registration is required for access to data. Access to the data can be found at: https://dhsprogram.com/data ; Chapter 5 Supplementary Material contains detail references for the individual datasets.

The Technology Adoption Model figure by Van Biljon and Kotzé (2008) (Chapter 5)

OpenStreetMap data (Used throughout)

Open street map data were provided under the Open Database License (www.openstreetmap.org/copyright), and has the attribution of © OpenStreetMap contributors, https://www.openstreetmap.org.

WorldPop population dataset (Chapter 6)

WorldPop data is licensed under the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0). Data can be downloaded at www.worldpop.org .

Ncell CDR dataset (Chapter 6 and 7)

The Ncell CDR dataset was provided under a Memorandum of Understanding with Flowminder. Permission was sought and granted for access and use of the data, including publication of the final results, under recognition of Ncell within all work. The dataset is not available to other users.

Matrix of the four models for the privacy-conscientious use of mobile phone data figure by Montjoye *et al.* (2018) (Chapter 8)

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