A Study of Homelessness and Migration in Northern Rural and Urban Centres in the Near North, Ontario, Canada, using GIS Techniques

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by

Rahat Naeem

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An Analysis of Pathways to Poverty, Homelessness and Migration in Northern Ontario, Canada

Approved by:

Professor Nigel Walford, Advisor
School of Natural and Built Environment
Department of Geography and Geology
Kingston University, UK

Dr. Annie Hughes
School of Natural and Built Environment
Department of Geography and Geology
Kingston University, UK

Co-Advisors:

Dr. Brad Blitz
Chair, Human and Political Geography (2019-2013)
Department of Geography and Geology
Kingston University, UK

Dr. Carol Kauppi
School of Social Work
Laurentian University, Canada

Dr. Henri Pallard
School of Law and Justice
Laurentian University, Canada

Date Approved: January 21, 2020

Abstract

Homelessness, migration and poverty in Northern Ontario, Canada are serious issues. In order to facilitate development of policy that effectively addresses these problems, a long-term Community-University Research Alliance at Laurentian University, Sudbury, Canada was initiated. The present research was conducted on the data gathered through this initiative with a goal of understanding pathways to homelessness in Northern Ontario. Data gathered in five communities (Sudbury, Timmins, Hearst, Cochrane, Moosonee) between the years 2001 and 2012 were analyzed. It was found that these communities, though located in the same province of Ontario, suffered from pathways to homelessness that were different from one another. These differences result from many factors including concentration of different ethnicities in different localities as well as non-uniform availability of education, employment and health facilities. For example, high rate of unemployment in Moosonee results in migration to larger cities such as Timmins and Sudbury, which sometimes leads to homelessness as these cities themselves do not have proper support structures and resources available to help these migrants. An interesting phenomenon observed during the analysis was that there is a trend of individuals migrating out in search of employment, becoming unsuccessful in securing employment, returning their home town and then becoming homeless. This was seen across the board in all five communities, which points to the scarcity of proper support structure and resources. An index of homelessness was also constructed during this study based on the variables that were seen to have the highest impact on homelessness. For this Fuzzy Cognitive Mapping approach was adopted. It resulted in separate equations for homelessness in the five communities studied and indicated the spatial dependence of pathways to homelessness. The main result that has come out of this study is that different communities in Northern Ontario, even though they are not very far apart from one another, have their unique challenges when it comes to homelessness, migration and poverty and therefore a uniform policy across the whole of Northern Ontario will not be an effective way to address these problems. The framework developed in this study to determine if a particular individual is at-risk of becoming homeless can be beneficial in formulating effective policy and strategy.

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List of Acronyms

CURA: Community-University Research Alliance

FCM: Fuzzy Cognitive Map

GIS: Geographical Information System

PHM: Poverty Homelessness and Migration

SPSS: Statistical Package for the Social Sciences

SSHRC: Social Sciences and Humanities Research Council of Canada

1 INTRODUCTION

1.1 Introduction

A CURA (Community-University Research Alliance) based initiative at Laurentian University, Sudbury (Ontario), Canada aims to develop practices and programs that will translate local concerns into effective strategies to address issues of migration out of northern rural communities, of homelessness, and of housing needs. This five-year project received a $1 000 000 grant from the Social Sciences and Humanities Research Council (SSHRC) of Canada. The study consists of the following five domains:

i. Gaining knowledge of the interconnections between social, economic, health, political, historical, and environmental forces as they relate to northern people's experiences of homelessness/housing needs and movements between remote rural communities and urban centers in near north.
ii. Studying the relationship between colonialism (including residential schools), discrimination, racism, and the social organization of homelessness amongst indigenous people and other northern groups.
iii. Understanding impacts of climate and other environmental changes on mobility, poverty, and homelessness in northern communities.
iv. Increasing knowledge and awareness about poverty, housing needs, homelessness, and migration in northern communities.
v. Coordinating evaluation of project activities and outcomes.

The first three domains mentioned above require collection of spatial and temporal data, thorough analyses of these data, and derivation of meaningful conclusions. Since Geographical Information Systems provide excellent techniques and tools to perform spatial and temporal analyses, such as correlation studies, it is natural to think about using them for this study. It is therefore proposed that a portion of this project be undertaken as a GIS PhD project as outlined in the following sections.

The main objective of this thesis is to study the spatial and temporal correlations between health, social, economic, political, historical, and environmental forces related to northern people's experiences of homelessness and movements between northern rural communities and urban centers in the near north of Ontario, Canada and draw inferences with help from GIS analysis and visualization techniques. An important aspect of this research is the development of indices for homelessness, migration and poverty by incorporating different variables based on data trends as well as prevalent theoretical knowledge of their inter-dependencies. These indices will help in developing strategies to quantify the risks associated with the issues being studied.

The research carried out was a subset of the larger CURA study being conducted at Laurentian University in Sudbury (Ontario), Canada. The CURA-based study is broader in respect that it goes far beyond data gathering and analyses and aims to lay foundations of positive change in society and environment by mobilizing local communities to address issues of deep poverty, housing need, and homelessness. The current study, however, restricted itself to gathering of data, development of indices based on data trends and unbiased spatial and temporal analyses using GIS techniques followed by framing of meaningful conclusions about the subject matter.

Hence this research focused on gaining in-depth understanding of impact of different health, social, political, economic, and environmental factors on the issues of poverty, homelessness, and migration in the near north of Ontario, Canada.

This study also explored the quantification of homelessness risk in the near north of Ontario, Canada by modeling the homelessness risk for different communities and its connection to the health of the individuals. This semi-empirical model was generated based on Fuzzy Cognitive Mapping and the distributions of homeless people in different regions.

Homelessness, poverty and migration in Northern Ontario, especially in First Nation communities, is a highly complex phenomena with dynamics controlled by a number of variables. Understanding these dynamics requires multi-dimensional studies, such as spatial and temporal correlations and time-series analyses. In the broader perspective, this research was geared towards understanding these dynamics using GIS techniques. Specifically, different quantitative and qualitative analyses on data were performed on migration with respect to age, community, gender, education level, poverty level, climatic conditions and family ties etc. The emphasis of these analyses was on understanding how these variables affected each other and contributed to the problems these communities were facing. These analyses helped in in-depth understanding of the underlying processes that result in homelessness, poverty and migration and provided insight on how these problems can be mitigated. These studies involved multi-variable analyses and development of techniques and algorithms to tackle the problem. The analyses performed and techniques developed in these studies will further help researchers and academics understand similar phenomena occurring in other communities as well.

The research approach adopted in the broader CURA-based initiative was based on a concurrent transformative design strategy (Creswell, 2007), which gave equal importance to both qualitative and quantitative approaches. Hence the data collected had both quantitative and qualitative components. Since this research was a subset of the broader CURA study, it also adopted the mixed-methods research methodology. The samples of population for this research mainly consisted of vulnerable and marginalized groups of people, such as the ones that have been traumatized by experiences of abuse and violence (Kauppi & Garg, 2003). Furthermore, the research utilized the principles and practices of Participatory Action Research or PAR (Wadsworth, 1998) since the ultimate objective of CURA is to promote positive social and environmental change.

1.2 The Communities

The Poverty, Homelessness and Migration Project has gathered data from 10 communities. Data for the PhD project was however limited to five communities: Sudbury, Timmins, Hearst, Moosonee and

Cochrane. The reason was that these communities were the largest and provided statistically significant data sets. Moosonee, population 3 500 is a northern community on the James Bay and only accessible by rail or air. Cochrane, population 5 500, is the southern terminus of the railway coming from Moosonee. Timmins, population 43 000, is the first large urban centre encountered after leaving Moosonee and Cochrane. Sudbury, population 158 000, is the largest community in northeastern Ontario. Figure 1.2.1 shows these study areas on a map.

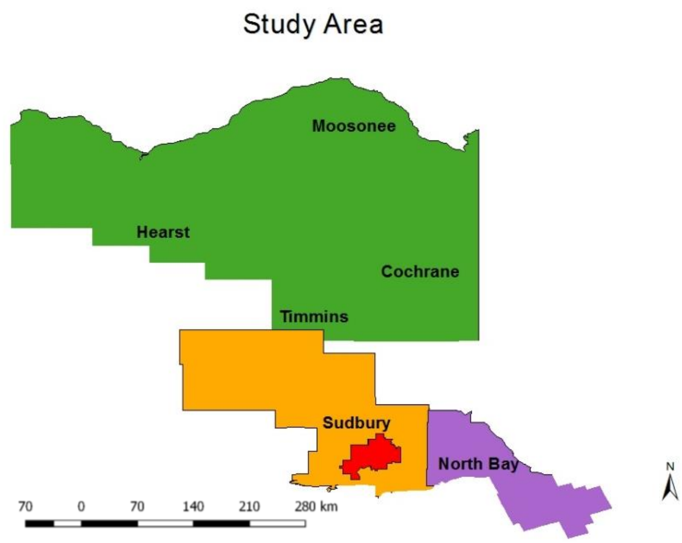

Figure 1.2.1: Five study communities in northern Ontario.

1.3 Data Gathering

Data gathering was performed in conjunction with the broader CURA study and was a collaborative effort between local service providers, homeless persons, formerly homeless persons, city planners and policy makers, students, and researchers at Laurentian University. Data were gathered through the following channels:

a. ***Census Data***

Census data was acquired from government agencies. These data were related to spatial and temporal movement of population.

b. ***Environmental Data***

In order to study the impacts of climate and other environmental factors on the prevalence of homelessness, poverty, and migration, environmental data was obtained from relevant governmental and non-governmental agencies.

c. ***Interviews***

Detailed semi-structured interviews were conducted with a wide array of participants, such as homeless persons, community leaders, and service providers.

d. ***Surveys***

Surveys were conducted to gather data on the experiences of the population on homelessness, poverty, migration, and other aspects related to the study.

1.4 Data Analysis

To draw meaningful results from this study, it is important to develop methodologies to quantify homelessness, poverty and migration. In the literature review part of this thesis it will become evident that the development of indices is highly dependent on the specificities of qualitative and quantitative nature of data. Therefore, the development of appropriate indices was performed based on data trends and interdependencies of different variables associated with those data.

An important point to note is that this study revolves around homelessness and poverty. The data gathered contain several variables that presumably have effects on homelessness and poverty. Understanding these effects has been accomplished in this study with the help of GIS analysis and Fuzzy Cognitive Maps, which will be introduced and discussed later in Chapter 3.

An important part of this study was to research the following hypothesis.

"There is a strong spatial dependence on pathways to homelessness in Northern Ontario due to multiple factors including ethnicity and access to health, education and social services."

This hypothesis was constructed after data from five northern communities (Sudbury, Timmins, Hearst, Moosonee, Cochrane) were analyzed and disparities in several parameter distributions were observed. To check this hypothesis, homelessness index equations for each community were developed using Fuzzy Cognitive Maps. The process has been discussed and presented in the chapter on data analysis. Another advantage of creating the homelessness index is that it can be used to determine if a certain individual is at risk of being homeless or not. This can help policy makers in developing strategies to minimize this risk. In this respect it can be stated that a very important part of this thesis was to develop homelessness index while utilizing homelessness data gathered from different communities.

GIS provides an excellent framework for analyzing spatial and temporal distribution of variables as well as generating visual representation of the data in the form of map layers based on data attributes. A large number of maps were generated during this study that helped with understanding spatial and temporal differences between parameter distributions.

2 LITERATURE REVIEW

2.1 Causes of Homelessness

Homelessness has been a serious issue in Canada for a number of years. The situation in 2006 was so bad that the United Nations Committee on Economic, Social, and Cultural Rights declared homelessness in Canada a national emergency (Czapska et. al, 2008). This can be appreciated from the observation made by Scott (2007) that there are as many as 100,000 homeless in Canada and about 1.7 million who cannot afford adequate and suitable shelter. Similarly, an organization called Homelessness Hub from Toronto estimates that on any given night there are about 30,000 homeless people just in Toronto, the largest city by population in Ontario (Gaetz et. al., 2013). The extent of this problem in a wealthy country like Canada raises a number of questions about the policy framework and efforts towards understanding and addressing the underlying issues. Unfortunately, homelessness is a highly complex problem and has been shown to depend on a number of variables. For example, Gaetz, Dej, Richter and Redman (2016) note that addiction and mental health issues are among the causes of homelessness in Canada and thus contribute to the overrepresentation of indigenous population in homelessness. Their argument is based on the observation that a large portion of indigenous population developed addictions to cope with trauma caused by residential schools. Similarly, Evans and Forsyth (2004) also argue that addiction and mental illness should be taken into consideration while analyzing this issue. Wenzel, Leake and Gelberg (2001) as well as Gearson, Bellack, Rachbeisel and Dixon (2001), on the other hand, point towards different kinds of abuses as prime causes for homelessness. Stock (2016) takes a somewhat different view and argues that shortage of affordable and social housing in Canada is one of the core causes of homelessness. In fact, this cause of homelessness in not typical of Canada as reported in the research published by National Alliance to End Homelessness (2016) in which the authors argue that affordable housing is difficult to access and maintain for a large portion of American population. This, together with insufficient and stagnant incomes, can lead to homelessness. This viewpoint can be related to the conservative policies, which can be viewed as a driving force in increasing homelessness in the marginalized but working classes. This has been pointed out by Hardill (2000) and Mallan (1998) who argue that the policies such as cuts to welfare, declining child and health care, unavailability of affordable housing and other shrinking social security measures lead to homelessness. In US, the incarceration of individuals has also been found to be one of the major causes of homelessness as reported by a research conducted by the United States Interagency Council on Homelessness (2018). It was found that about 25 to 50% of homeless individuals had a history of incarceration. Also, the people with mental health or substance use disorders were at higher risk of being incarcerated. In this sense incarceration can be seen as both cause and consequence of homelessness. Though this issue is prevalent in USA, it was not found to be a major cause of homelessness in Canada.

One of the causes of homelessness is abuse of women, which is not uncommon in northern communities of Canada. However, even though abuse of women is a major problem as noted by Rodgers (2000) and Tutty (1999) who mention that the abused women experience not only physical assault but also verbal taunting, stalking, marital rape and threats about custody, interestingly enough, it is generally not considered a major cause of homelessness. This is due to the fact that many women remain in abusive relationships since they know that if they leave, they and their children will plunge into poverty (Canadian Women's Foundation, 2017). Unfortunately, in case of abused women the issue is generally raised "why doesn't she leave?" Gelles (1972) points out that this idea is prevalent amongst academics as well. They seldom confront the perpetrator that why he engages in violent behavior and why he does not stop. The questions of whether or not he is arrested and charged are almost never asked. Also omitted are questions about whether the woman has the means to leave, whether she is in a position to take care of her dependent children, whether she has money, a job, or access to safe and affordable housing. Gelles (1972) says that if these alternate questions were asked, the most likely response would be "How could she leave?" According to Jones (1994), people who ask, "why doesn't she leave?" do not necessarily want an answer anyway. What they really want is to evaluate and judge the victims. As discussed in the OAITH report (1998), some women do not leave their abusive partners due to a number of reasons, such as funding shortage, shelter crowding, decline in social welfare measures and availability of affordable housing. A dire consequence of this may be delayed help seeking until a very serious injury to the woman or to her children occurs. Rodgers (1994) stresses on the "Violence against Women" survey, which found that only 13% of women who leave their abusive partners stay in a shelter. However, those who stay in shelters were more likely to have suffered a serious injury requiring medical attention. The report also elaborates on the fact that some women are left with no option but to return to their abusive partners after a short- or medium-length shelter stay due to lack of safe, affordable housing and jobs. This scenario is further explored by Metraux and Culhane (1999) who argue that the repeat shelter stays form a "cycle of homelessness" and are caused by repeated returns to the abusive partner.

Migration has been seen to be both a cause and consequence of homelessness. For example, Kauppi and Pallard (2015) note that a 2009 survey of homeless population in Northern Ontario suggests that migrants make up about one-fifth to a quarter of the homeless population. FEANTSA (2013), an organization working for the homeless people in Europe, notes that in European Union immigrants make up a significant portion of the homeless population. Most of the studies related to homelessness point to the selective nature of migration with respect to the earning capacity and level of income. For example, Fitchen (1995) arrives at this conclusion after analyzing how migration relates to spatial distribution of people with respect to their level of poverty. The relationship between low-income levels and low-cost places has been analyzed by Nord, Luloff and Jensen (1995) who find that low-income people tend to migrate to low-cost places over time. And as noted above, a significant percentage of these migrants end up becoming homeless. One of the issues directly related to immigration is employment, which is particularly low among immigrants. The occupational structure of the immigrant populations is also different from the average. On the whole immigrants are underrepresented in medium-skilled non-manual positions and overrepresented in non-skilled manual positions. This trend leads to social and economic marginalization, which is particularly adverse for women and young people. The employment and education statistics from various member states provide ample evidence for their effective marginalization from the mainstream. This may lead to anger and unrest among youth, as clearly shown during the riots in France in March 2006.

Poswa and Levy (2006) performed a study aimed to answer three questions: 1) What were the reasons for migrating? 2) What are the migrants' current living conditions?; and 3) Will the migrants' stay in Cape Town temporarily or permanently? The answers to these questions were obtained from a limited sample group consisting of eighteen interviewees – all newly arrived migrants living in the informal settlement of Monwabisi Park (Endlovini) in Khayelitsha. Poswa and Levy (2006) point out that even though the findings of this study deal with one pattern of migration, they apply well to other patterns of migration as well. For example, the cases in which the migrants were living in formal housing, had secure employment, had stayed in Cape Town for a longer period than one year, etc. The eighteen migrants that were interviewed a range of reasons for their decision to migrate to Cape Town. The majority of the migrants came to Cape Town in search of employment, while some migrated in search of better healthcare and education. Their existing social networks, primarily family members, provided them with further stimuli to migrate to Cape Town and not to other areas such as Johannesburg or Port Elizabeth. Poswa and Levy (2006) found that the interviewees had received positive feedback about employment opportunities, better education and good health care services in Cape Town from family members in the city. In most cases there appeared to be a gap between the migrants' expectations and the realities of their current living conditions in Endlovini. Most of the migrants remained either unemployed or poorly positioned in the labour market. This produced burden on their family members who supported them financially and through other means. The migrants who came to Cape Town for better education and better health care have been more successful, as they have gained access to these services due to their family members' payment of fees. Relatives paved the way for the few migrants who have obtained employment. One of the main concerns of the migrants is crime in Endlovini. Several migrants have had first-hand experience of crime and find Endlovini unsafe compared to their places of origin. In Endlovini the migrants live in shacks and without proper toilet facilities. In the Eastern Cape, the majority of the migrants lived in decent houses and with proper ablution facilities but they were willing to sacrifice more comfortable living conditions in exchange for employment.

Bekker (1999) points out that it is difficult to measure the permanency of the migrants' stay in Endlovini because migrants are often faced by uncertainty. The migrants' future depends on employment opportunities. Most of the migrants intend staying temporarily in Cape Town because the city is only a place to earn money and find a job, whereas the migrants regard the Eastern Cape as their home. However, the migrants may end up staying more permanently in Cape Town since their dream of returning to the Eastern Cape weakens over time.

This study re-emphasizes the problem of unemployment in Cape Town's informal settlements. According to Statistics South Africa (2001), the unemployment rate is as high as 58% in Endlovini. The eighteen migrants in Endlovini struggle due to unemployment and resultant poverty. Hadland (2006) has pointed out that such conditions reflect the general problem of urbanization in South Africa, with poverty shifting to the urban areas due to migration into cities and towns. De Swardt and others (2005) have therefore suggested that poverty must be understood within the context of migration, mainly from the Eastern Cape.

2.2 Plight of Homeless People and the Issues that Exacerbate the Likelihood of Homelessness

Many municipalities struggle to find resources to cope with growing number of homeless people. This results in significant number homeless people either on streets or living temporarily with others. For example, BC (2017) in its report mentions that only about 70% of the homeless could find shelters in 2017 in Vancouver, Canada. And the majority of the ones who were sheltered were there for only overnight stay. One of the reasons for this was the increase in homeless population, which in Vancouver saw an increase of 30% from 2014 to 2017.

Work towards sheltering the homeless people in Canada essentially began when the first shelter was opened in 1973 in Vancouver, as pointed out by Kenny and Magnussen (1993). They further argue that the Canadian shelter movement has experienced a number of dilemmas over the years. This has produced disagreements amongst the state and the civil society and has led to the drafting of Vancouver's Women's House Saving Action of 1985 for women as social claims makers and service users. Such disagreements can further dilute already scarce resources, leaving homeless people on the losing end.

It should be noted that even though the homeless people are already marginalized, their plight is further exacerbated by the treatment they receive from general population and government. Such a treatment occurs even if the person was in the working class before becoming homeless. Crowe, Hardill and Harding (2000) point out that unfortunately the moral and social outrage about such a treatment is limited. People fail to realize that there are a number of reasons that may have contributed towards homelessness of an individual or a family. For example, Main (1998) and Metraux and Culhane (1999) point out that a number of factors force the working poor out of their homes. These include poverty, job unavailability or insecurity, low wages and availability of insufficient or nonexistent social benefits especially during cyclical economic cycles.

The perception of homeless people in general population has not been very positive due to many factors. Hardill (2000) points out that this image of homeless individuals has negative effects on their well-being. They become homogenized, categorized, and often feared. They become the depersonalized "other" that more privileged people learn to dislike, dismiss, avoid, reject, and even blame for their own suffering. Boyle (2000) and Rankin (2000) raise similar points and argue that the further implication of such a negative perception is that they get declared as the "enemy" rather than "victims." On the practical side, the conservative governments round up the homeless, push and shove the poor, sweep them off the streets and parks as if they were inanimate pieces of refuse, and increasingly search ways to criminalize whatever it is that they do.

Breakey and Fischer (1990) call the issue of individuals and families living on streets one of the most somber and distressing social problems of current society. They contend that society needs to take this issue more seriously as the plight of the so-called "street people" has developed into a major problem. Therefore, it is imperative that the things that facilitate or hinder their transition from street to mainstream lifestyle are carefully examined and understood. The homeless population is in dire straits. Breakey and Fischer (1990) stress on the point that street people frequently live in dangerous accommodations where they are at high risk of being exposed to, and experiencing, physical and sexual violence. Alperstein and Arnstein (1988) and Miller and Lin (1988) have pointed out that not only immunization schedules for homeless children are neglected but care is also not taken to ensure that they receive proper protection from infectious diseases. Therefore, prevalence of such diseases in homeless is significantly more than in average citizens.

Wright (1989) claims that the chronically homeless do not constitute an overwhelming majority of any sample of a homeless population. However, Piliavin and others (1996) stress that there is only minimal research on those who make it back into the mainstream of society. Shlay (1994) also elaborates on this point and concludes that the results of research on homelessness has a number of noteworthy implications for social workers, counsellors, makers of social policies, and families who desire to help individuals abandon the street lifestyle. Furthermore, past research has revealed that transitioning street people to mainline society requires sustained intervention strategies that enable them to enter the labor market, maintain permanent housing, remain healthy and functional, and take care of their families. Creswell (1998) and Kvale (1994) have also elaborated in detail on this issue. They note that the current research affirms and extends what is known about the move of homeless people from street life to mainstream existence. They put forward practical suggestions for such a move as well and stress that the street people should be encouraged to permanently depart from their impoverished lifestyle to "(1) establish supportive relationships with mainstream role models or mentors, care-professionals, family members, and a meaningful spiritual reality; (2) separate from their street environment and their street peers by attending schools and rehabilitation programs away from the downtown core; (3) discover and develop their natural creative, scholastic, or leadership abilities to nurture self-confidence and self-esteem; (4) accept personal responsibility by addressing particular and family problems; (5) realize the significant nurturing role of parenthood (if they become parents); (6) gain accountability and sobriety by giving up dependency on alcohol and drugs; (7) become independent from welfare and social assistance

; (8) attend education programs that are structured and tailored for their needs; (9) engage in legitimate employment; (10) acknowledge their physical, emotional, spiritual, and moral deprivation." They, however, also point towards inherent limitations of a qualitative methodology in research needed to establish the above- mentioned implications. They report that during their own research participants' self-reports seemed to be affected by memory deficiencies or subjective bias.

Bandura (1995) argues that longitudinal studies that take into account quantitative measure of self-efficacy and compare categories of what facilitated people leaving the streets to what currently facilitates them from returning to the streets would be revealing. Furthermore, a thorough examination can be conducted on how individuals exited from the streets according to gender, level and type of mental illness and duration of the street.

2.3 Impact of Poverty and Homelessness

Several studies have shown direct link of homelessness with poverty. For example, Kneebone (2018) notes that "the great majority of people experiencing homelessness do so because of poverty". Due to this, most researchers include study on poverty in the corresponding population while studying homelessness. Employment status and income level are important parts of poverty level as well as homelessness, though different approaches have been incorporated by different authors to include them into a poverty index, which is a mathematical model that quantifies poverty in a certain population and area. For example, Rupasingha and Goetz (2003) use a variety of factors such as job growth, percentage of labour force and gender specificity in labour market to incorporate income level and employment in the poverty index. Crandall and Weber (2004), on the other hand incorporate job growth in their analyses. A similar methodology has been developed by Swaminathan and Findeis (2004) who use predicted employment growth.

Raphael (1999) wonders if the health sector has a role in raising the issue of how poverty and income inequality affect health. He contends that even though evidence-based perspective points towards poverty and income inequality being the key determinants of the health of Canadians, the policy directions of government threatens the health of Canadians. It is probably because those in the government are more concerned with the values being expressed by health institutions than by the research evidence. Raphael (2001) again suggests that examining and responding to the health impacts of poverty and income inequality can be justified as being part of the mandate of health institutions. But such examinations also need to consider the values associated with civil society and health promotion and the notion of shared responsibility. He notes that these are the values that provide a framework and justification for implementing actions needed to reduce poverty and income inequality. The perception that health is directly related to income inequality has been validated by many researchers. For example, Reutter, Neufeld, & Harrison (1999) found that a majority of Albertans were aware that poverty led to poor health. Raphael and Bryant (2000) argue that the efforts to address the causes and health impacts of poverty and income inequality must be rooted within the communities themselves. Williams and Popay (1997) also reach the same conclusion and point towards the emerging literature, which indicates that action to improve health is most effective when the participation and understandings of citizens are incorporated into such actions. Minkler (1995) and Raeburn and Rootman (1997) have also stressed upon the importance of carrying out local citizen involving activities to improving health. Raphael (2001) mentions that if citizens understand this point, they can identify policy issues that become the basis of efforts to influence government actions. There is a role for governments and health institutions to play in such efforts. At the city, provincial and national levels, governments and health institutions can support citizens in examination and discussion of the importance of the social determinants of health. According to Raphael (2001), it is these undertakings that can enhance civic involvement and participation to effectively reduce poverty and income inequality and improve the health of Canadians.

A number of researchers from North America (Combs-Orme and Cain 2006; Flores 2004; Kilty and Segal 2003), United Kingdom ((Bradshaw 2002b; Coles and Kenwright 2002; Hendrick 2005; Magadi and Middleton 2005) and other countries (Ansalone 2003; Bradshaw 2002a; Vleminckx and Smeeding 2001) have conducted extensive research on impact of poverty on children. All of them establish poverty has a profound impact on children and their families in myriad ways. Not only is there the daily uncertainty about survival, shelter, water, and food, but the effects of poverty extend into all areas of children's lives, including psycho-social and physical development and educational attainment. Balen, Cox and Jackson (2006) contend that in the 21st century, children's well-being is a major concern around the globe. Extreme poverty and social exclusion may lead to abandonment of children by parents, though few parents take that route to give their children a better life. Balen and others (2006) point out that there will always be some children in need of alternative care or protection and this should be provided whenever possible, whether it's in the child's family or in the community. However, they contend that there is no proof that institutionalization strengthens such traditional support networks. In fact, several case studies performed in Sri Lanka, Bulgaria and Moldova have shown how the use of institutional care has been a harmful response to poverty. These studies demonstrate the possibility of developing alternatives that are sensitive to the needs and problems of parents and families. In particular, they show the importance of engaging children, parents, and families in identifying the nature of their experiences and problems before making changes to policies or practice. Tolfree (2002) also reaches the same conclusions. However, he points out that this process is neither simple nor short-term and requires changes in philosophy and approach.

Moua and Kim (2006) argue that poverty, while quite low in the Twin Cities (Minneapolis and Saint Paul, Minnesota) when compared with nationwide statistics, is as highly disparitized as can be found nationwide. Single-mothers with children under the age of 18 are very likely to be stuck in poverty. Education can get a person out of poverty, but lack of education can be compensated for with good paying and low skill jobs. In today's economy, the most likely means of getting out of poverty is to get an education than to rely on hard work as an unskilled worker. The bigger a family is, the higher the chance a family will be in poverty. Race is not a strong factor to poverty, although racial discriminations may still exist. It can therefore be argued that anyone can get out of poverty regardless of race. Recent immigration is contributing to some poverty, but as time goes on, immigrants are able to get out of poverty. Lastly, families living in poverty are trapped in city neighbourhoods because that is where the affordable housing units are located.

Graves, Greenwell and Mark (2009) note that the 2008 homeless count provided policy makers with significant information on the characteristics of homelessness in Metro Vancouver. Medical issues have a similar prevalence among the street and sheltered homeless, with the exception of a much higher incidence of self-reported addiction from those who are street homeless. They further point out the following findings.

- The street homeless have a much higher reliance on binning and pan handling than those who are sheltered.
- The street homeless have been homeless for longer periods of time than the sheltered.
- The count identified a lack of knowledge concerning why Aboriginal people aren't accessing shelters and the need to determine what can be done to increase their access to homelessness programs and services.

They argue that although the 2008 Homeless Count does not give a complete picture of the extent and nature of homelessness in Metro Vancouver, it provides the best information available. The count has been able to identify trends over time as well as the characteristics and needs of the homeless people. The results have been used by provincial and municipal governments as well as non-profit agencies and foundations in program and funding decisions. The count also provided an opportunity for community engagement on an important social issue and for GIS technologies to help deal with a serious social problem.

2.4 Poverty Mapping and GIS

GIS provides an excellent platform to develop visual representations of spatial data as well as perform various kinds of analyses (Zahari et.al, 2018). However, one of the issues with incorporating the level of poverty in performing analyses is how to quantify it based on factors that have spatial variations. For example, the cost of living in urban and rural areas as well as within subsections of those areas are generally different. The main reason, as argued by Akinyemi (2010) is the unavailability of any generic poverty and homelessness related data model for database development. Different researchers have devised different methodologies to tackle this problem. For example, Nord (2000) argues that estimation of relative cost of living in two places can be performed by comparing nominal income-to-poverty ratios with a certain level of food insecurity corresponding to the assumption that households in different areas reporting equal levels of food insecurity are equally well off. On the other hand, Jolliffe (2004) simply uses differences in fair market rents to establish a price index. Joliffe (2003) in an earlier paper suggests a distribution-sensitive FosterGreerThorbecke poverty index (Foster et al., 2010) to examine spatial distribution of poverty incidence, depth and severity. His analysis raises an important point that the notion that poverty level in non-metropolitan areas is higher than in metropolitan areas is not substantiated. This finding has also been indicated in an earlier paper by Cushing and Zheng (2000).

Several researchers have recognized the effectiveness of GIS in areas of poverty and homelessness mapping. For example, Bitfocus (2016) in its white paper argues that this tool "can help communities better define and target geographic problems commonly faced when helping the homeless." Similarly, a UNESCO report (2005) has concluded that the GIS technology has many critical uses in statistical offices dealing with such issues. GIS provides an opportunity to integrate data from various sources and allows their visualization in causal relationships. This enhances analysis and understanding of complex data and phenomena, leading to easier and more accurate decision-making. The authors of the report further point out that poverty maps are becoming important tools for developing effective policies aimed at reducing disparities within a country, and in designing intervention schemes to reach the most-needy groups. Therefore, National Statistics Offices as custodians of socio-economic data should strengthen their capabilities in GIS so as to facilitate poverty mapping and poverty analysis.

Lobao and Murray (2005) note that although homelessness is an important social issue affecting cities around the world, often the provision of shelter and services to the homeless is undertaken by a loosely organized system of service providers and public officials who have a limited understanding of system-wide issues. At the same time, these people are directly involved in the system, and over time have developed perceptions regarding the system. Given the complexity involved in understanding a shelter system, an exploratory analysis involving the use of GIS-based techniques offers novel approach for examining the characteristics of such a system. In general, perceptions of the Columbus shelter system were supported by observed characteristics identified through spatial analysis. However, the particular finding that shelters are located in neighbourhoods with few residents cast doubt on the perceptions of planners and decision makers that shelters are located with the general support of the community. In addition, the aggregate number of employment opportunities found within shelter neighbourhoods contradicts perceptions that job opportunities are few within these areas. The development of policies and services towards the homeless often takes place with little analysis of the spatial and socio-economic conditions that define the shelter system. By exploring homeless shelter systems in a spatial manner, a more nuanced understanding of the shelter system can be reached by shelter operators and decision makers, one that is capable of distinguishing between reality and perception.

It is worth mentioning here that not much research has gone into use of GIS and fuzzy logic approaches to understand dynamics of homelessness, poverty and migration. Most research in this area has been performed only over the past decade. The effectiveness of this approach has however been demonstrated by several researchers. For example, Mogo et.al (2013) have argued that since homelessness is a complex social problem, fuzzy logic and fuzzy cognitive maps are useful modeling tools due to "their inherent ability to model, intricate, interactive systems often described in vague conceptual terms and then organize them into a specific, concrete form which can be readily understood by social scientists and others." Similarly, Pabuccu (2017) has demonstrated that since measurement of poverty requires "modeling of uncertainty in human thought using linguistic expressions," their numerical representations allow the use of fuzzy logic to measure the poverty. The scarcity of recent research papers in the areas of GIS and fuzzy logic applied to these issues has provided the necessary encouragement to develop new strategies of analyzing data and arriving at meaningful results.

3 DATA ANALYSIS METHODOLOGY

3.1 Introduction

The data collected during the broader PHM study spanned over several years and communities. The main object of this study was to understand the dynamics of homelessness and migration in Northern Ontario and develop index of homelessness that could be used to determine the risk factor of individuals becoming homeless. It was argued these dynamics in different communities differed from one another and therefore required their own specific homelessness index. The spatial dependence of homelessness index was hypothesized during this study and was thoroughly researched. In the following sections, the broader steps taken during this study are described.

Figure 3.1.1 shows a simplified analysis flow diagram followed during this study.

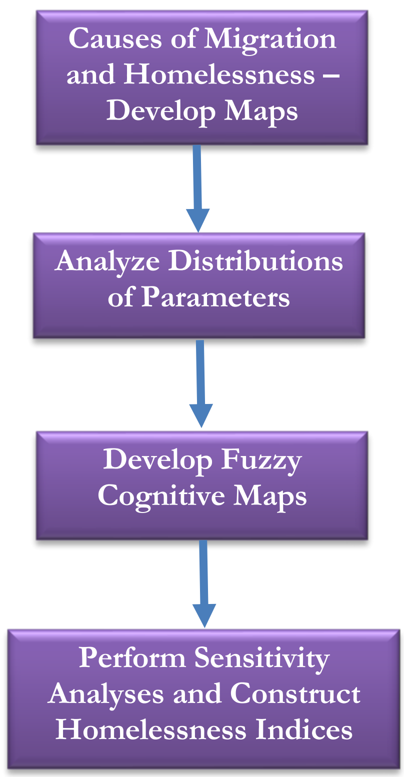

Figure 3.1.1: Simplified analysis flow diagram

Each of the steps in the above flow diagram as well as the datasets used in this study are discussed in the following sections.

3.2 Datasets

The data during the broader PHM study were gathered over a number of years between 1999 and 2011. The collection of data was performed through direct interviews of subjects in the chosen sample populations. A comprehensive questionnaire was followed for this purpose and the resulting data were entered in a SPSS database (see Appendix-B). There was no fact-checking routine performed to validate data and the answers given by the interviewees were assumed to be correct. For this study, data from five communities were analyzed: Sudbury, Timmins, Cochrane, Hearst and Moosonee.

As a part of the research, the author visited different communities in Northern Ontario to get a first-hand understanding of the living conditions there and to have discussions with the homeless as well as community leaders and government officials. Fig.3.2.1 shows a picture of one of those trips taken to Cochrane, Moosonee and Moose Factory. Some more pictures can be found in Appendix-C.

Figure 3.2.1: Author (left), Dr. Emily Faries (middle) and Dr. Carol Kauppi (right) while visiting Moose Factory.

3.3 Cities

The following five cities in Northern Ontario were selected for this study.

Sudbury

Sudbury is the largest city of Northern Ontario with a population of 161,531 as per 2016 Census (Statistics Canada, 2017). This region was inhabited by First Nations groups of Ojibwe and Algonquin as early as 9000 years ago (Saarinen, 2012). Currently, majority of Sudbury inhabitants are Caucasian with about 80% English-speaking and about 16% French-speaking (Statistics Canada, 2017). The economy of Sudbury is dominated by mining and the city is therefore affected by downturns in the commodity prices.

Timmins

Timmins is the fourth largest city of Northern Ontario with a population of 41,788 as per 2016 Census (Statistics Canada, 2017). Most of the Timmins inhabitants are Caucasian, out of which about 64% and English-speaking and about 36% French-speaking (Statistics Canada, 2017). The economy of the city is mostly dependent on mining.

Cochrane

Cochrane is situated northeast of Timmins and south of Moosonee. Though small, it is one of the major cities of the region with a population of a little over 5000 as per 2016 Census, half of which are anglophone and the other half francophone (Statistics Canada, 2017). The main industries in Cochrane are transportation, railway, tourism and forestry. However, due to lack of employment, its population is in decline.

Hearst

Hearst is a small town located about 935 km north of Toronto. As per 2016 Census, about 94% of the 5070 Hearst inhabitants are francophone (Statistics Canada, 2017). The main economy of Hearst is dependent on forestry products.

Moosonee

Moosonee is situated about 19 km south of James Bay on the Moose River. It is known as the gateway to the Arctic. As per 2016 Census, the population of Moosonee is 1405 (Statistics Canada, 2017). Moosonee has the largest First Nations population of about 15% amongst the five cities studied here (Statistics Canada, 2017).

3.4 Analyses on Causes of Homelessness

This involved performing trend analyses to understand major and minor causes of homelessness. It should be noted that these were single-variable analyses and did not account for inter-dependencies of variables. The objective of these analyses was to understand the broader picture of homelessness and migration in the study areas.

The data for Sudbury were collected during years 2009 to 2011. These data were used to perform time series analyses on some variables as well.

3.5 Migration Trends

An important issue is that there is a trend of individuals migrating from one community to another and then becoming homeless. And sometimes when migrants return to their home communities, they become homeless. To understand migration trends in the five communities, GIS techniques were employed due to their usefulness in analyzing spatial data, map generation as well as their visualization capabilities. This involved data filtration in SPSS software, constructing variable distributions and then developing raster map layers.

3.6 Parameter Distributions

Parameter distributions are very important in understanding how these parameters influenced homelessness. SPSS software was used to generate distributions of parameters.

3.7 Index of Homelessness

Homelessness and poverty are complex phenomena and depend on many variables that themselves have interdependencies [Fowler et.al. 2019]. A Fuzzy Cognitive Map or FCM provides an excellent means to analyze interdependencies between many variables [Dickerson and Kosko, 1994]. It was noted in the previous Chapter that the sensitivity analysis is important to understand the effects of different parameters on homelessness and poverty and an efficient way to perform sensitivity analyses is by generating Cognitive Maps. An FCM is simply a combination of fuzzy logic and cognitive mapping. It consists of interconnecting nodes, which are concepts representing individual parts of the whole system. The interconnections are labeled with fuzzy values between the two nodes. These values represent the strength of the relationship between the nodes [Gray, 2013]. Once the nodes and their interconnection fuzzy values have been established, the influences of the nodes on each other are calculated using an iterative procedure based on neural network approach. Once a stable solution has been obtained, the model can be used to determine the behaviour of the system as node values are changed. This is what is termed in this thesis as the sensitivity analysis. An FCM is constructed graphically with the help of causal relationships between variables by assigning fuzzy levels to the interconnections [Kosko, 1986]. In this study the following variables were initially used to generate the FCMs.

Access to Education – Access to Health – Age – Domestic Violence – Education Level – Employment Status – Ethnicity – Family Problems – Gender – Marital Status – Mental Health – Migration – Number of Children – Physical Health – Substance Abuse.

It should be noted that an FCM based on all these variables is very complex and difficult to draw inferences from. The situation is further complicated by the fact that the data collected from different regions revealed different interdependencies of variables. This was expected since distributions of variables had already hinted towards this issue. For example, the age distributions of homeless individuals in different regions showed some differences (see Figure 3.6.1). It was therefore necessary to develop FCM for each region and data collection period separately. It should be noted that there are no data shown for Hearst. This is due to the very low statistics available for some parameters for Hearst. In order to develop a framework to understand effects of different variables on homelessness, it was necessary to simplify these fuzzy cognitive models so that a common framework for comparison could be developed. It is worth noting that some of the above-mentioned variables are likely to have negligible impact on homelessness. However, instead of making a subjective decision, data analyses on all these variables were performed to determine which ones were most important with regard to development of simplified fuzzy cognitive maps.

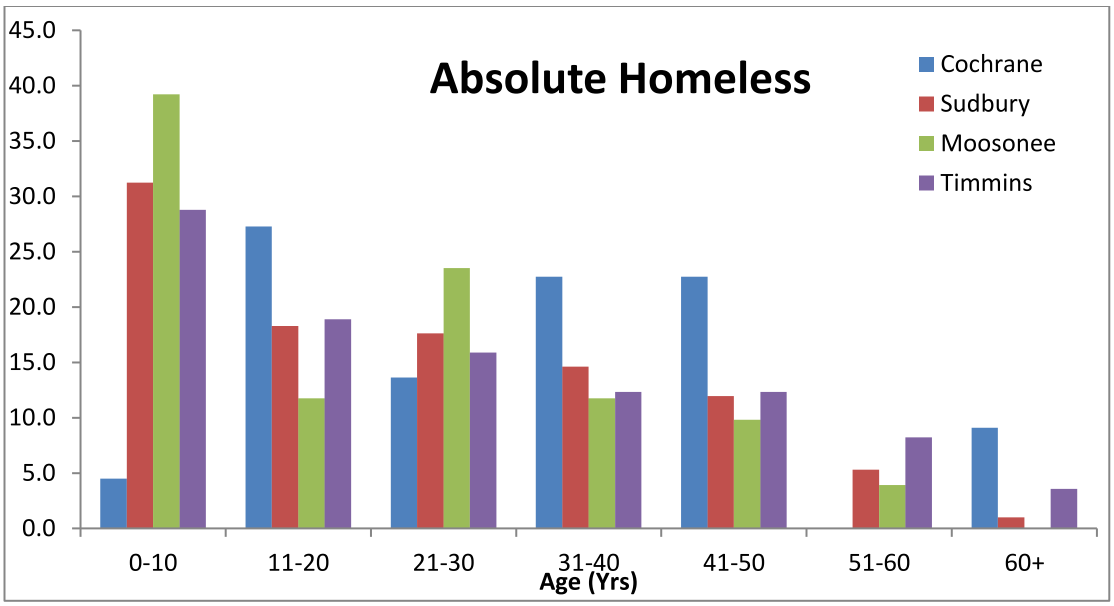

Figure 3.7.1: Age distribution of homeless individuals in different regions (% interviewed). Data for Hearst was not shown due to very low statistics available.

It can be noted that the fuzzy relationships (or weights) in a Fuzzy Cognitive Map are not necessarily crisp and should be deduced from the data collected during the study. In the context of fuzzy logic, a relationship can be positive or negative and can have any value between -1 and +1. For this study, the relationship levels as given in Table 3.6.1 were initially used since the FCM software available at that time only supported six values of logic levels. Later on, an update of the software became available that did not have this restriction and was subsequently used to complete the analyses.

Table 3.7.1: Fuzzy Logic Levels

Effect	Value
H+	1
M+	0.5
L+	0.25
L-	-0.25
M-	-0.5
H-	-1

In order to deduce the weight values from the data collected, filter and statistics functions available in SPSS were used. In the main database (SPSS) some of the variables were assigned numerical values, such as 1 for female and 2 for male. The variables, such as age, assumed the actual values while the ones that required yes or no answers were assigned some numerical value. For example, one of the questions was about the reason to leave hometown and the interviewee had to select one the of answers from a list of pre-defined answers, each of which was assigned a unique number. These and other variables as defined in SPSS are listed in Table 3.6.2.

As noted earlier, an important step in analyses was to determine interdependence of these variables so that an FCM could be constructed. An efficient way to determine such interdependencies is to calculate the Pearson's correlation coefficient, which assumes that the relationship between the variables is linear (Hall, G. 2015). This is a valid assumption since the range of values the variables assume are small and no strong non-linearities are expected within that range. As mentioned before, the earlier version of the MentalModeler software used to generate FCMs accepted only six discrete values of the fuzzy weights as given in Table 3.6.1. This meant that, to deduce the fuzzy weights, the correlation coefficients must be mapped onto the fuzzy logic weights listed in Table 3.6.1.

Table 3.7.2: Variable values as defined in SPSS.

Variable	**Assigned Values**
Access to Education	*A random unique value*
Access to Health	*A random unique value*
Age	Actual numerical values
Domestic Violence	*A random unique value*
Education Level	Less than high school = 1, ……., University = 7
Ethnicity	Caucasian = 1, First Nations = 2
Family Problems	*A random unique value*
Gender	Female = 1, Male = 2
Homeless	Yes = 1, No = 2
Marital Status	Married/Common Law = 1, Single/Divorced/Widowed = 2
Mental Health Problems	Yes = 1, No = 2
Migration	Yes = 1, No = 2
Number of Children	Actual numerical values
Physical Health Problems	Yes = 1, No = 2
Substance Abuse	*A random unique value*

In the theory of statistics, it is known that the correlation between two variables can be characterized by the following scheme (see, for example, Hall, G 2015 and references therein).

Weak positive correlation: $0 < r \leq 0.3$

Moderate positive correlation: $0.3 < r \leq 0.5$

Strong positive correlation: $0.5 < r \leq 1.0$

This correlation scheme is symmetric on the negative side. Using this scheme, the correlation values were mapped to the fuzzy logic levels as given in Table 3.6.3 below. Again, it should be noted that during the later stages of the analyses, the continuous fuzzy levels were used, which allowed direct 1:1 correspondence with the correlation coefficients.

Table 3.7.3: Fuzzy Logic Levels.

Correlation Coefficient	**Effect**	**Value**
$0.5 < r \leq 1.0$	H+	1
$0.3 < r \leq 0.5$	M+	0.5
$0 < r \leq 0.3$	L+	0.25
$-0.3 \leq r < 0$	L-	-0.25
$-0.5 \leq r < -0.3$	M-	-0.5
$-1.0 \leq r < -0.5$	H-	-1

A typical fuzzy weight matrix generated in this way is shown in Table 3.6.4 below.

Table 3.7.4: Fuzzy weight matrix for data collected in Sudbury in year 2009.

Sudbury 2009	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	No. of Kids	Homelessness	Migration
Gender										
Age	L+									
Ethnicity	L+	L-								
Education	L-	L-	L-							
Employment	L-	L-	L-	L-						
Mental Health	L+	L-	L-	L-	L-					
Physical Health	L+	M-	L-	L-	L-	M+				
No. of Kids	L-	L+	L+	L-	L-	L-	L-			
Homelessness	L+	L+	L-	L-	L-	L+	L+	**L-**		
Migration	L+	L+	L+	L-	L-	L-	L-	**L-**	L-	

Data Analysis Steps

The following steps were taken during data analyses.

Step-1: Perform statistical analysis to determine effects of individual variables on homelessness and calculate corresponding Pearson's correlation coefficients.

Step-2: Determine fuzzy levels from the correlation coefficients.

Step-3: Construct FCM.

Step-4: Perform sensitivity analysis.

Step-5: Determine variable - homelessness fuzzy levels

Step-6: Perform Steps 1-5 for all localities and data periods

Step-7: Construct homelessness index equations for all localities

Step-8: Perform analyses using homelessness index equations

The FCM is constructed by first building relationship map between all variables and then assigning weights to those variables in the weight value matrix. In order to determine the weights, distributions of different variables were generated. For example, let us look at the interplay between the eviction and gender in Sudbury between the years 2000 and 2009 as depicted in Table 3.6.5 below.

Table 3.7.5: Effect of eviction on gender in Sudbury between the years 2000 and 2009.

Location	Study Year	Female (%)	Male (%)	Transgender (%)	Subjects
Sudbury	2000	50	50		4
Sudbury	2001	44.4	55.6		27
Sudbury	2002	20	80		40
Sudbury	2003	34.8	65.2		69
Sudbury	2007	40.8	59.2		76
Sudbury	2009	43.2	55.4	1.4	74

To determine the FCM weight from this table, it should first be noted that females and males were assigned valued of 1 and 2 respectively. It should be mentioned that this assignment does not have any effect on the overall FCM analysis since if the assignment is reversed it will be reversed for all the factors. Keeping this assignment in view, it was noted that in year 2001, there was only a slight direct correlation between gender and eviction rate and therefore an FCM weight of 0.25 or L+ can be assigned. On the other hand, in year 2002, there seems to be a very strong bias in eviction rate toward males and therefore an FCM weight of +1 or H+ should be assigned.

It should be noted that in some cases the statistics are too low to draw any meaningful conclusions, such as for year 2000. In such a case, the interconnection in the FCM map between the respective variables was left open. During this study, the FCM weights of all variables were assigned based on this approach. Once all the weights have been assigned, the FCM map was generated with the help of Mental Modeler software package. Figure 3.6.2 shows a typical FCM map generated during this study.

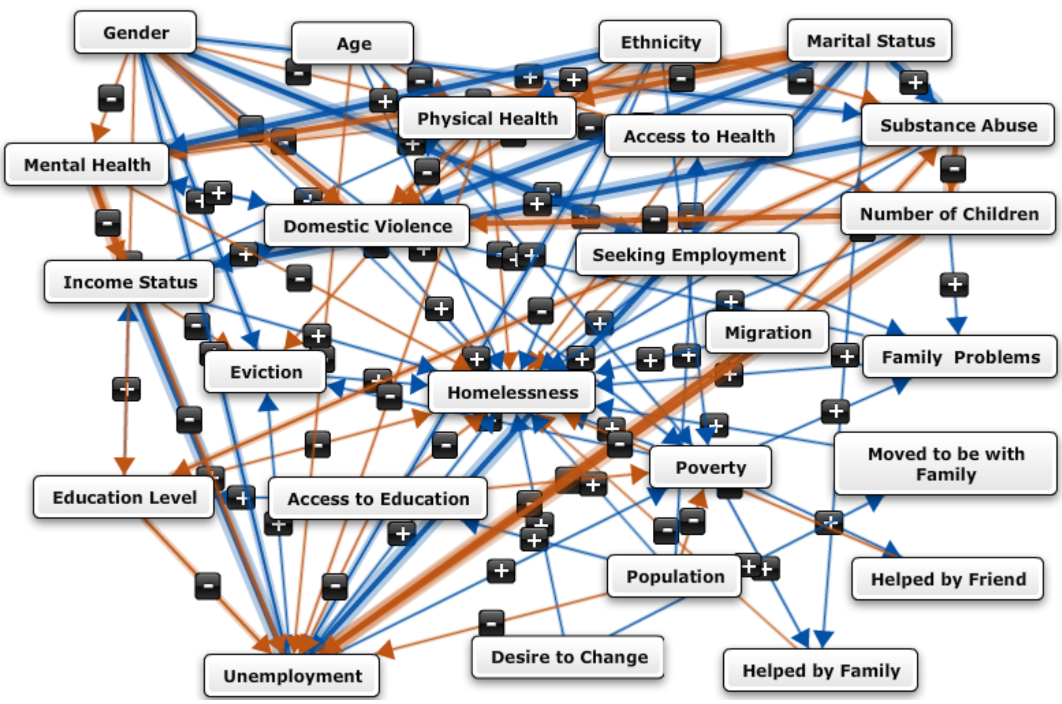

Figure 3.7.2: Typical Fuzzy Cognitive Map generated during this study.

The thickness of the interconnections represents the strength of correlation (positive or negative) between the variables. This FCM is very complex due to inter-relationships between the variables and therefore very difficult to use and interpret. In order to develop a simplified FCM for homelessness, sensitivity analyses were done on this model. To do this, artificial scenarios were created, such as increase in overall mental health of the population. Running the scenario showed its effect on different parameters. Figure 3.6.3 shows a typical scenario chart.

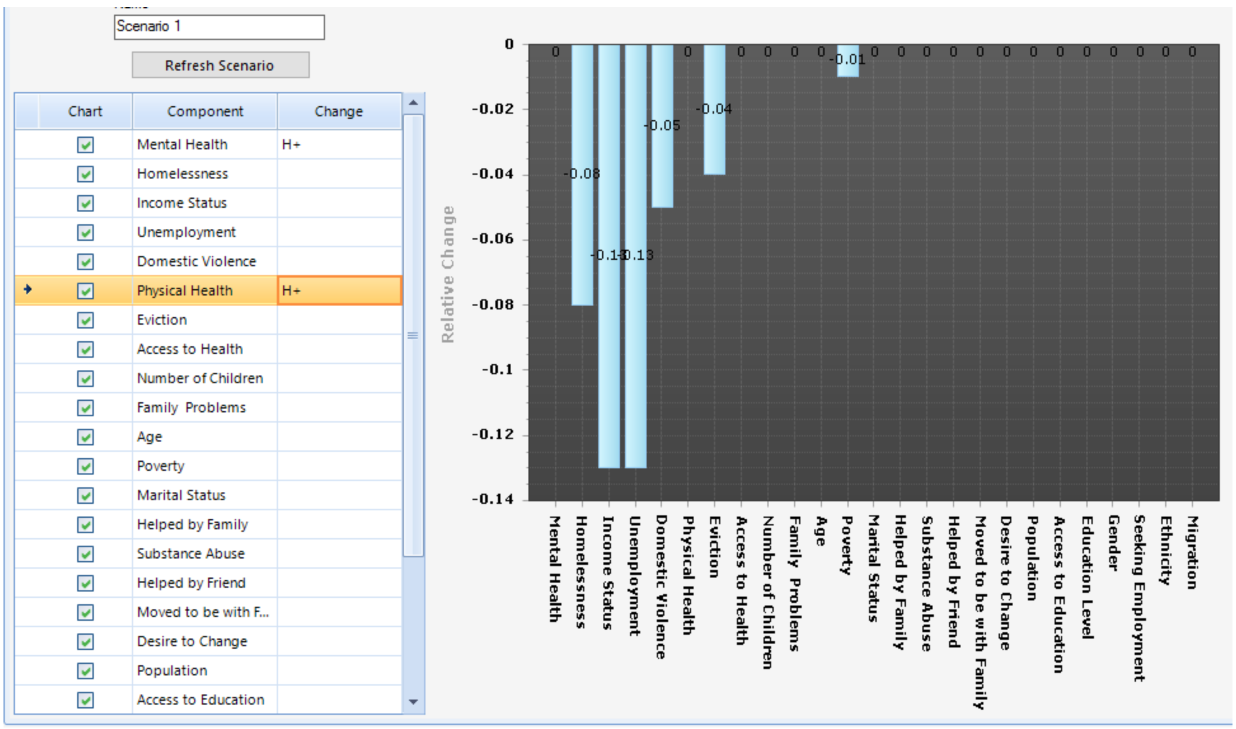

Figure 3.7.3: Typical FCM scenario chart.

In this scenario, the mental and physical health of the population was increased to the highest possible value (H+). This has reduced the homelessness by 8% and unemployment by 13%. Repeating this process for all six values for physical health from H+ to H- gave six values for change in unemployment. The relationship between the fuzzy levels and the corresponding change in homelessness gave a measure of direct relationship between that particular variable and homelessness. However, this gave six values, which means the relationship is not crisp and should therefore be handled in the framework of fuzzy logic. In order to get one value, these values were de-fuzzified using the centroid method (Wang, 2009) as explained below.

The first step is to normalize the values obtained from the above analysis. Let us denote the fuzzy value of the ith attribute and the jth value by x_i^j. Then the normalized fuzzy value for the ith attribute is given by

$$x_i = \frac{x_i^j}{\sum_{j=1}^{6} x_i^j}.$$

All the x_i values thus obtained, together form the so called fuzzy membership function $\mu(z)$ with z being the values at which the x_i^j are calculated. Once the fuzzy membership function has been obtained, the de-fuzzified value can be calculated using the following centroid formula.

$$\tilde{x}_i = \frac{\int \mu(z) \cdot z dz}{\int \mu(z) dz}$$

These de-fuzzified values were obtained for all attributes and used to generate the simplified FCM. Such fuzzy cognitive maps were generated for all areas.

As mentioned before, with the availability of the new version of the Mental Modeler software, this strategy was modified, though the underlying process remained the same. The new version of the software allowed any value of fuzzy weight between 0 and 1 instead of 6 levels as in the previous version. Hence, now it was possible to directly map the fuzzy weights on to the correlation coefficients. Now, instead of tables such as 3.6.4, the ones as shown in Table 3.6.6 were generated.

Table 3.7.6: Typical table generated for Pearson correlation coefficients between different variables.

	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	0.222								
Ethnicity	.025	0							
Education	0	0	0						
Employment	0	0	0	0					
Mental Health	0.198	-0.208	-0.104	0	0				
Physical Health	0.044	-0.376	-0.041	0	0	0.327			
Number of Kids	-0.231	0.218	0.242	0	0	-0.132	-0.207		
Homelessness	0.072	0.092	-0.152	0	0	0.059	0.135	-0.176	
Migration	0.040	0.068	0.096	0	0	0-.066	-0.162	0	-0.235

Using such tables, fuzzy cognitive maps were generated for each study area. These FCMs were then used to perform sensitivity analyses. For this the homelessness value was changed between -1 and +1 in steps of 0.25 and corresponding changes in other parameters were recorded. These were the raw fuzzy weights for the homelessness index. However, these could not be used directly in the homelessness index due to two reasons: the weights for each step of the homelessness value were not the same and they were not normalized. To normalize these weights, it was noted that some values were negative while others positive. Therefore, to normalize, the normalized exponential function was used as given below.

$$w_i = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$$

Here, w_i is the weight of the i^{th} variable, x_i is the sensitivity parameter of the i^{th} variable, and the n is the number of data points.

Once the normalized values had been obtained, averages for each parameter were calculated. These values were then used as the weights in the homelessness index equations. Naturally, there was one equation developed for each study area. These equations were then used to calculated minimum and maximum values of the homelessness index for each study area. Since each area had its own maximum and minimum value, it was not possible to compare result of one study area with another. To solve this problem, the following equation was used for rescaling such that the homelessness index value for each area remained between 0 and 1.

$$h^* = \frac{1.0}{h_{max} - h_{min}}(h - h_{max}) + 1.0$$

Here h is the calculated value, h_{min} and h_{max} are the minimum and maximum values of the homelessness index.

This allowed generation of new set of rescaled homelessness index equations. It was now possible to compare results from different study areas with same parameters. This was done in the next and final stage of data analysis. Several hypothetical scenarios were generated depicting typical individuals and their homelessness index values were calculated and compared. This allowed testing of the hypothesis that there are spatially-dependent pathways to homelessness in Northern Ontario and a single set of criteria cannot be used to form policy to reduce homelessness in all of Northern Ontario.

4 DATA ANALYSIS – CAUSES OF MIGATION AND HOMELESSNESS

In this Chapter, the causes of migration and homelessness in the five study areas will be explored using GIS techniques. Also, the spatial trends of migration will be studied using maps built from the gathered data.

4.1 Study Areas

Figure 4.1.1 below shows the study area in Northern Ontario in Canada for which data analyses in this study have been performed. Most of these areas have high concentrations of underground mines and are therefore affected by fluctuations in the commodity prices, such as Nickel and Copper. Sudbury and Timmins are the most important mining districts in this region and hold some of the largest underground mining operations in the world. Still, with such high concentration of mines and mining activities, homelessness, poverty and migration rates are a cause of concern.

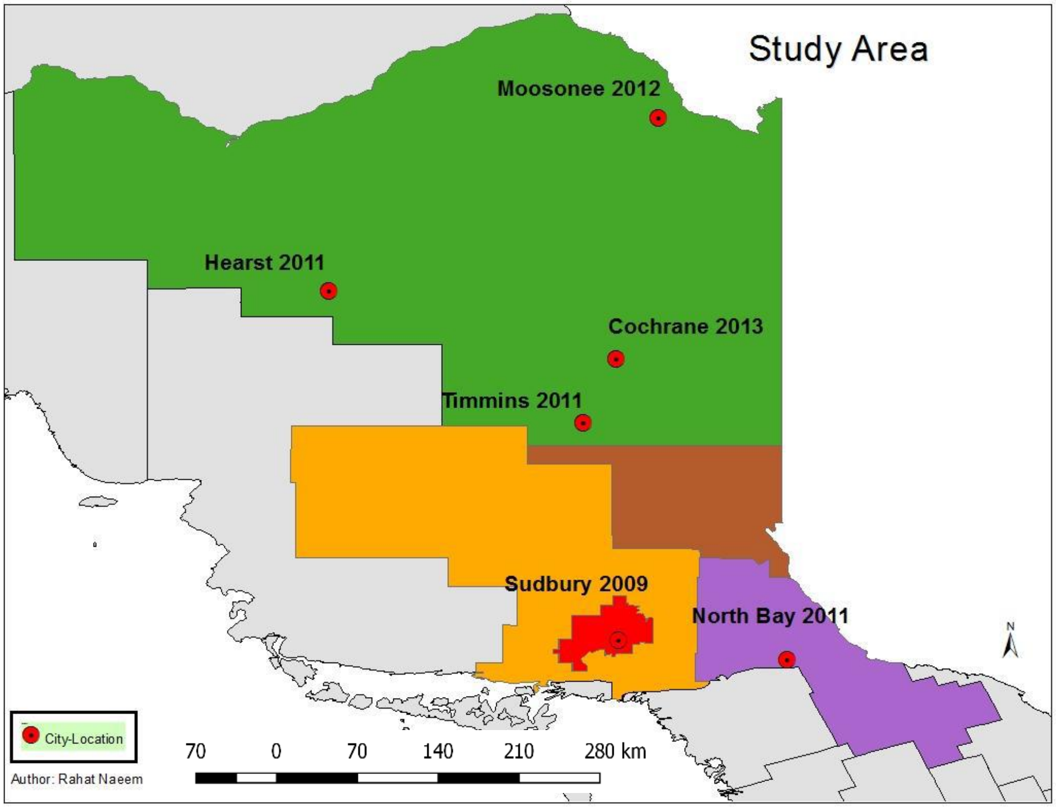

Figure 4.1.1: Map of the areas for which data analyses have been performed during this study along with the years of respective data acquisitions.

4.2 Causes of Migration and Homelessness

One of the objectives of the broader PHM study is to understand the causes of migration, especially when it leads to homelessness and poverty. Therefore, the interviews on which the data are based have been conducted on primarily homeless individuals. The persons interviewed were asked about the main causes of homelessness. Figure 4.2.1 shows the histogram for the data collected in Sudbury in 2009 and shows disparity between Caucasian and indigenous population in terms of different causes of homelessness. It can be seen that, although unemployment is the most important cause of migration leading to homelessness in both Caucasian and indigenous population, other causes cannot be ignored.

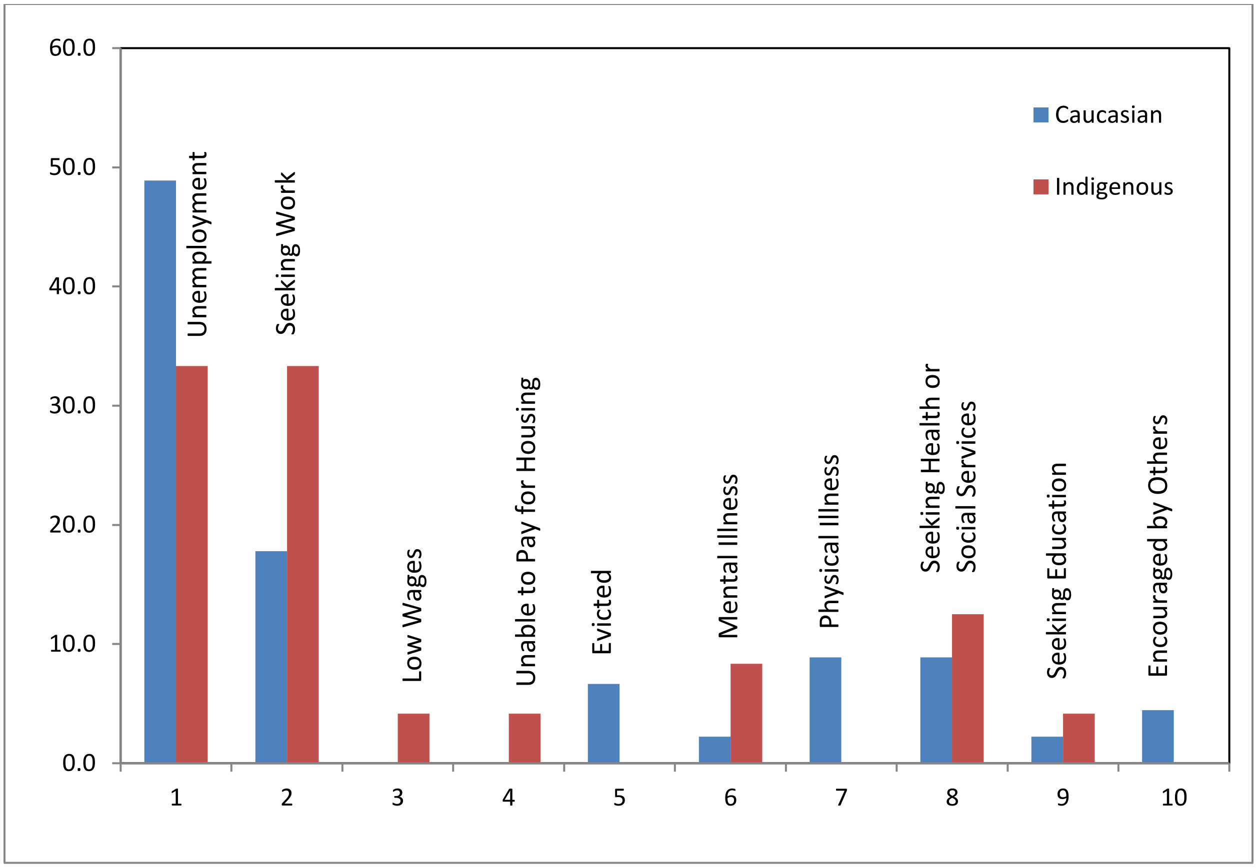

Figure 4.2.1: Causes of homelessness in 2009 in Sudbury for Caucasian and indigenous population (% interviewed).

It is important to note that illness and the need to seek health and social services were also found to be major causes of migration in indigenous population. What this means is that these individuals could not get proper employment or health care in their localities and therefore had to migrate to Sudbury. But this migration eventually led to homelessness. So, the problem is not only lack of services in their own communities but also lack of proper support structure in Sudbury.

During PHM study, data for Sudbury were gathered over several years between 2000 and 2011. Figure 4.2.2 depicts an interesting time series chart on major causes of homelessness in Sudbury. It can be seen here that for most individuals the major cause of homelessness was unemployment. The important thing to note here is that the relative number of individuals becoming homeless due to unemployment is steadily increasing over time.

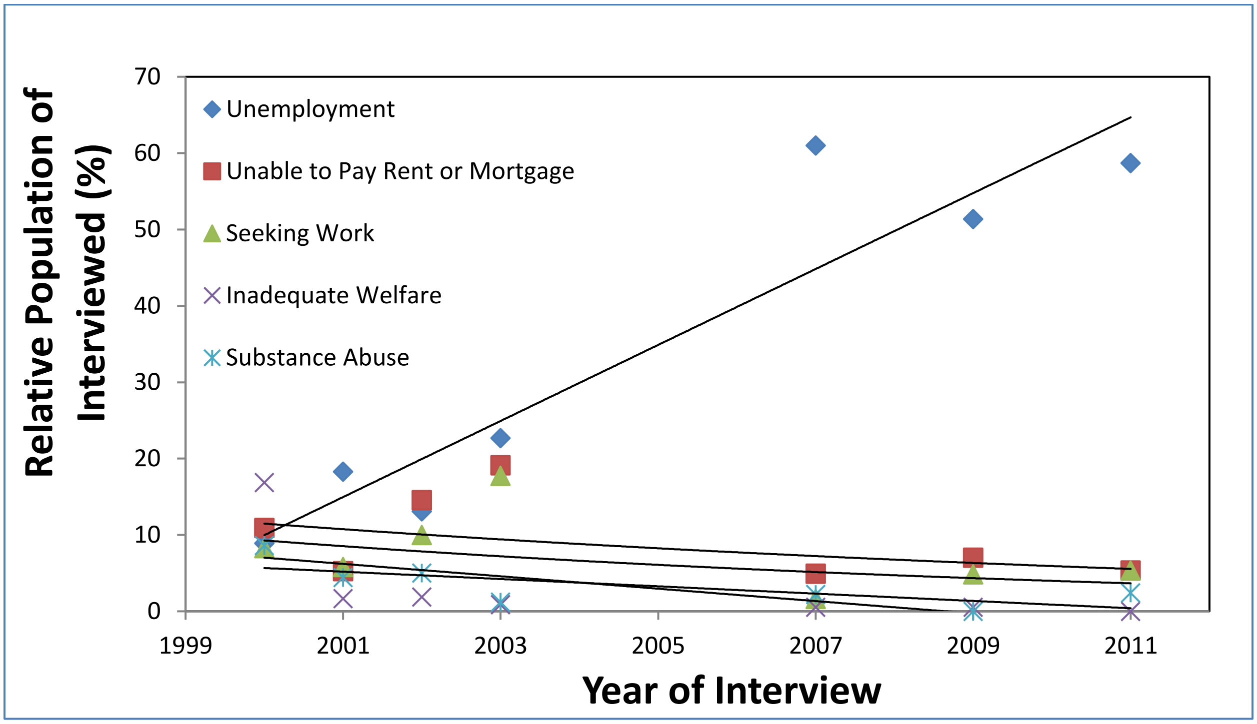

Figure 4.2.2: Time series of major causes of migration leading to homelessness in Sudbury.

Now, of course, the unemployment rate in general population is not constant over time either and therefore, a natural question to ask is if there is any correlation between the two. To study this, the unemployment data from Statistics Canada on unemployment rates in Sudbury during these years (see Table 4.2.1) were gathered. It can be seen in the second column that the percentage of homeless people in Sudbury in different years whose major cause of homelessness was unemployment. The third column shows the general unemployment rate in Sudbury in those years. The Pearson correlation coefficient between these two parameters came out to be -0.67. This shows that the homelessness due to unemployment does not follow the general population trend. This means that there are other factors at play as well. This strengthens the previous assertion that one needs to perform multivariate analyses to understand the phenomenon of homelessness in these communities.

Table 4.2.1: Homelessness due to unemployment and unemployment rates in Sudbury.

Year	**Homeless due to Unemployment (% interviewed)**	**Unemployment Rate in Sudbury (%)**
2000	8.9	8.4
2001	18.3	8.7
2002	13.1	9.4
2003	22.7	8.4
2007	61	5.8
2009	51.4	8.9

An important question to ask here is whether this trend is typical of other study areas or not. To understand this, similar histograms for Timmins for the data gathering year of 2011 (see Figure 4.2.3) were constructed. A trend similar to the one for Sudbury data was noticeable in these histograms. The major cause of migration is lack of job opportunities in their own communities. It was observed here that seeking education and family problems were also significant factors leading to migration and eventual homelessness. So, the lack of support structure for migrating individuals is not typical of Sudbury but is also clearly seen in Timmins. Still, it cannot be asserted that unemployment alone is the cause for homelessness in these communities. There are many factors that need to be studied and understood. Especially one must perform multivariate analyses on these factors and take into account their effects on each other to fully understand the mechanisms that lead to homelessness. As discussed in the previous chapter, fuzzy cognitive maps were used to perform these studies and arrive at meaningful results.

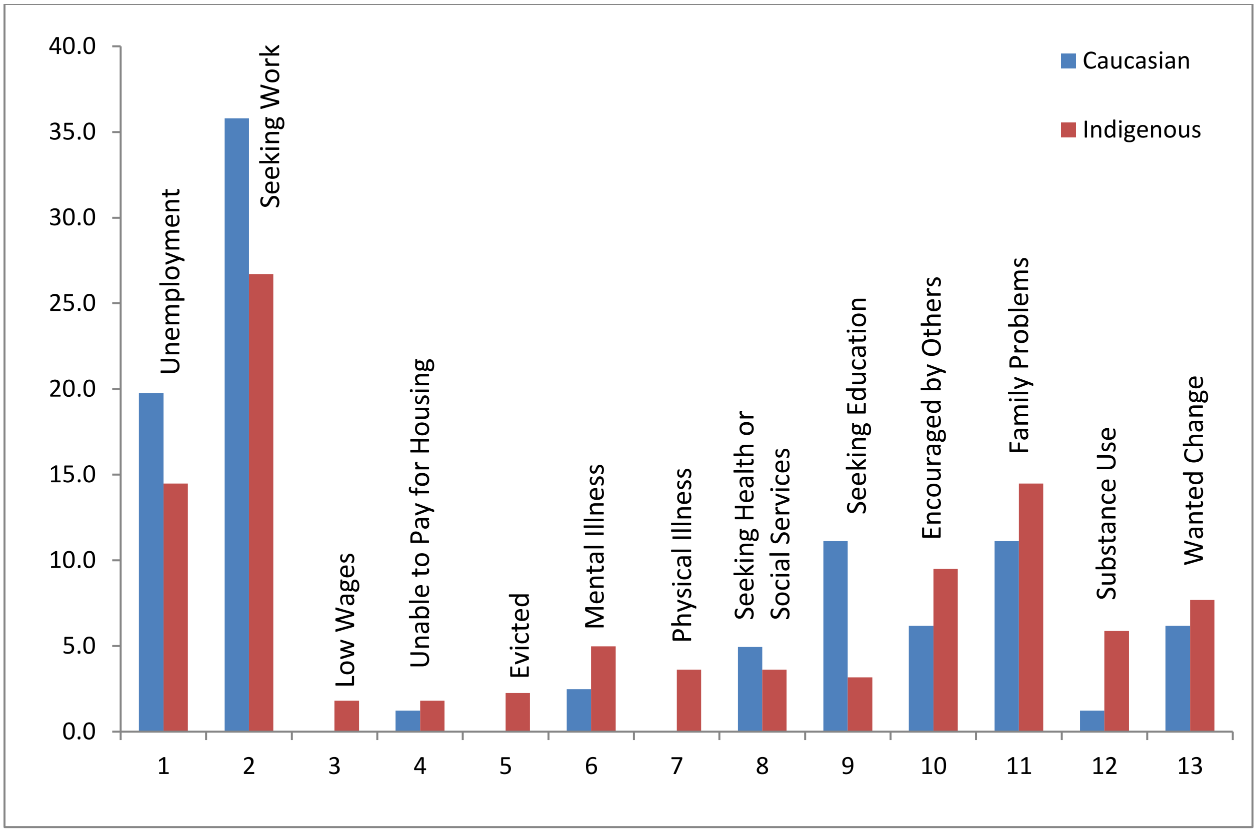

Figure 4.2.3: Causes of homelessness in 2011 in Timmins for Caucasian and indigenous population.

4.3 Migration Trends

One of the questions that was asked during the interviews was whether the town was their home town. Now, having Sudbury as home town does not mean that the person did not leave Sudbury at some point in time. In fact, the data suggests that in many cases a person migrated to another town to look for employment opportunities, could not find employment, returned to Sudbury and became homeless. This trend was seen not only for Sudbury but also for other towns, such as Timmins. Timmins, being primarily a mining town, has seen large migrations to the South of Ontario in search of employment.

Failing to find employment, when the individuals returned to Timmins, they became homeless. Also, an appreciable number of individuals from South of Ontario migrated to Timmins and Sudbury for employment and became homeless. This shows a disturbing issue of lack of proper support structure for migrants in these towns.

Figure 4.3.1 shows the trend of migration to Sudbury leading to homelessness. Red circles here show the areas from where these individuals migrated to Sudbury after leaving Sudbury for employment. The important thing to note is that these individuals had Sudbury as their hometown. They migrated to a different town to seek employment, could not find any meaningful employment, returned to Sudbury and became homeless.

It is apparent from the map in Figure 4.5 that the South of Ontario was the choice of migration destination for most individuals from Sudbury in search of employment opportunities. This is understandable since the South has larger cities, such as Toronto, with much larger population and industrial base than Sudbury. However, more opportunities in these cities and towns do not always translate into easier employment opportunities due mainly to high influx of highly qualified migrants from within and outside Canada. Hence, in many cases, the migrants from Sudbury remain unsuccessful in finding reasonable employment and are forced to return to Sudbury. However, return to Sudbury, as depicted in the above map, can lead to homelessness.

It is interesting to note that a large number of individuals from other areas including South of Ontario migrate to Sudbury and as a result become homeless. This is depicted in the map of Figure 4.3.2. This shows that a large number of individuals migrate to Sudbury even from larger cities in the South of Ontario in search of employment and become homeless.

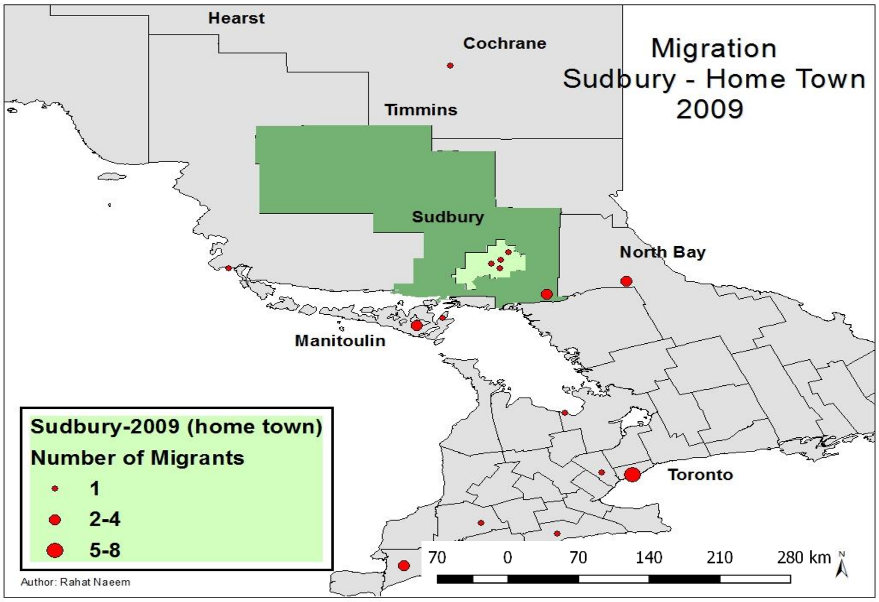

Figure 4.3.1: Trend of migration leading to homelessness in Sudbury in year 2009 for individuals having Sudbury as their hometown.

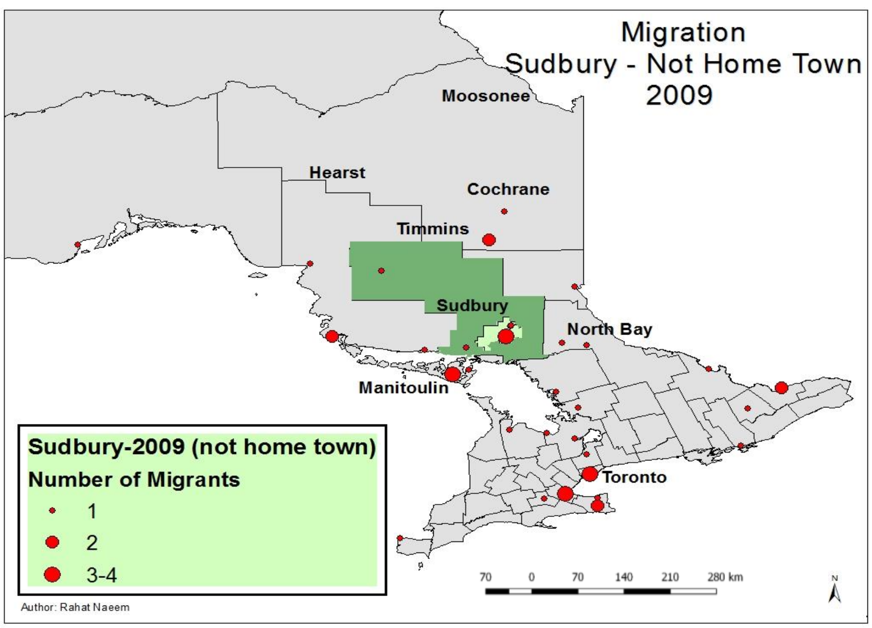

Figure 4.3.2: Trend of migration leading to homelessness in Sudbury in year 2009 with Sudbury not their hometown. The circles in Sudbury is for individuals who did not specify their hometown.

Actually, the maps in Figures 4.3.1 and 4.3.2 do not show the complete picture of homelessness trends in Sudbury. They were zoomed to show migrations between only North and South of Ontario. Figure 4.3.3 shows the complete map. Here, the complete migration data for Sudbury can be seen. It is interesting to note that there were also individuals from Quebec, Alberta, BC and the US, who came to Sudbury and became homeless. Still most of the emigrants to Sudbury were from Ontario.

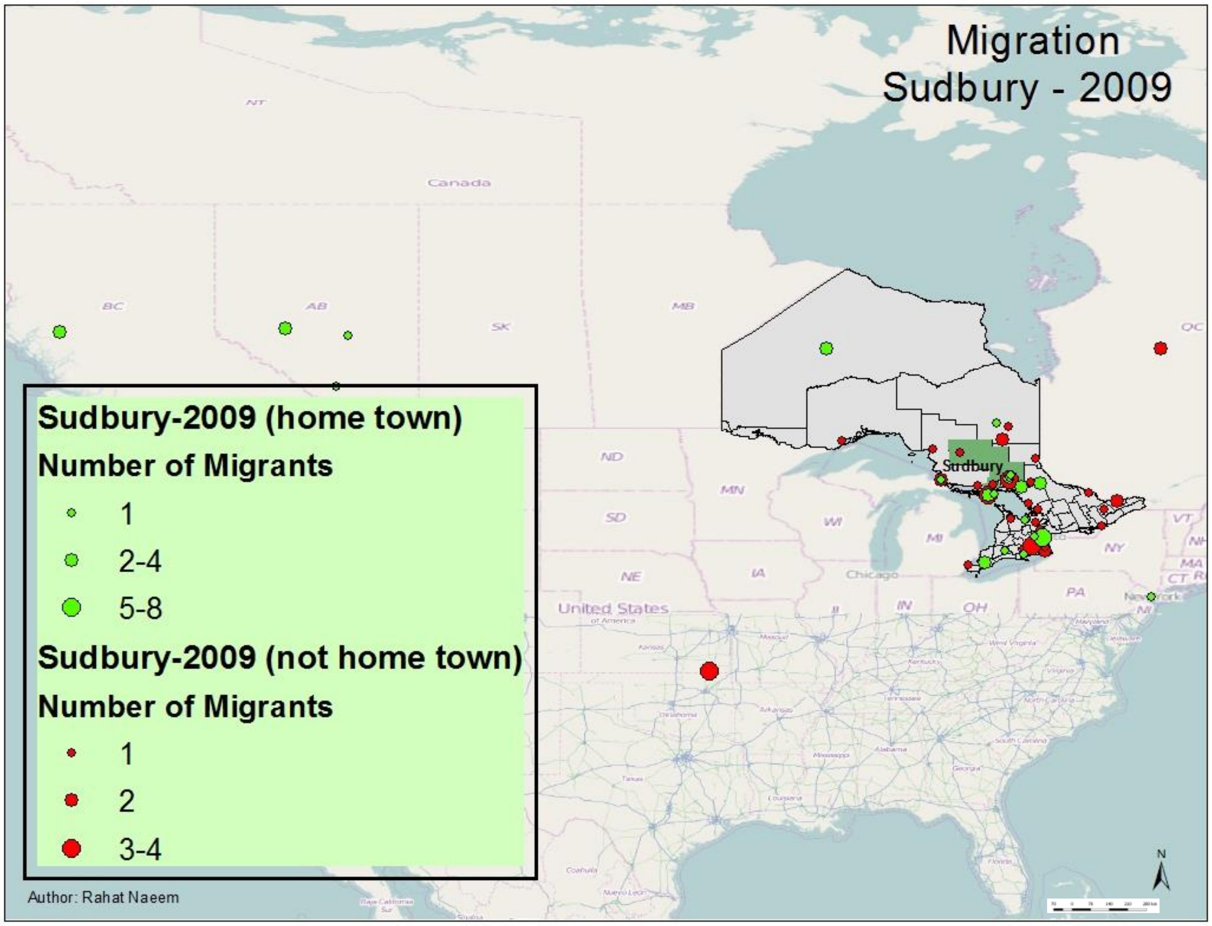

Figure 4.3.3: Trend of migration leading to homelessness in Sudbury in year 2009.

Of course, data for Sudbury should not be assumed to represent trends in other communities as well. Therefore, at the next step, similar maps for other localities were generated. Figure 4.3.4 shows the migration trend for Hearst for the data collected in 2011. This map shows the areas from where the individuals moved to Hearst with Hearst as their home town. A pattern similar to the one for Sudbury is obvious here. That is, people migrate out of their home town, probably in search for better employment opportunities, and then move back to their home town - and in the end become homeless.

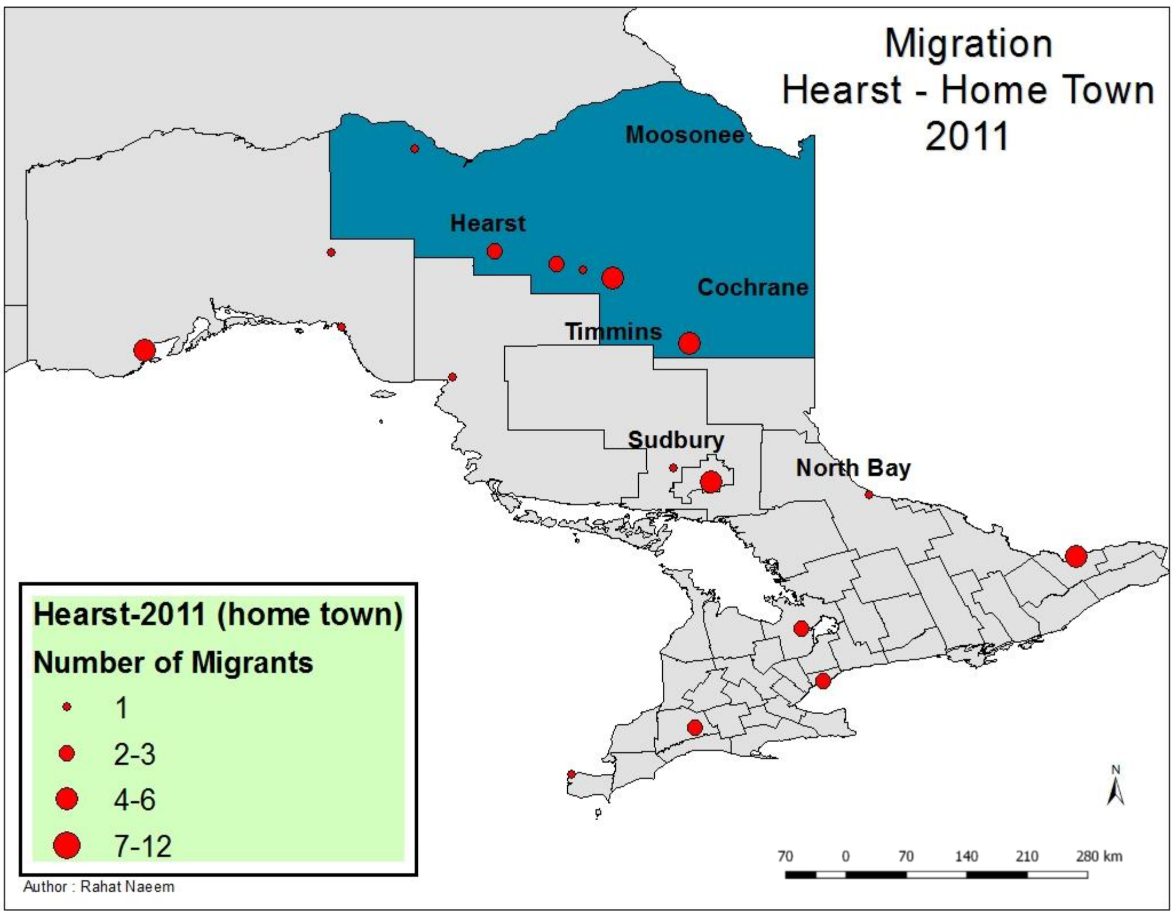

Figure 4.3.4: Trend of migration leading to homelessness in Hearst in year 2011 for individuals having Hearst as their hometown.

Figure 4.3.5 shows the map depicting migration trend for individuals having Hearst not their hometown. Unlike Sudbury, here migration seems to be taking place from nearby smaller towns instead of from the south. This is of course expected since there are larger cities in northern Ontario, such as Sudbury and North Bay, where people would prefer to go in search of opportunities.

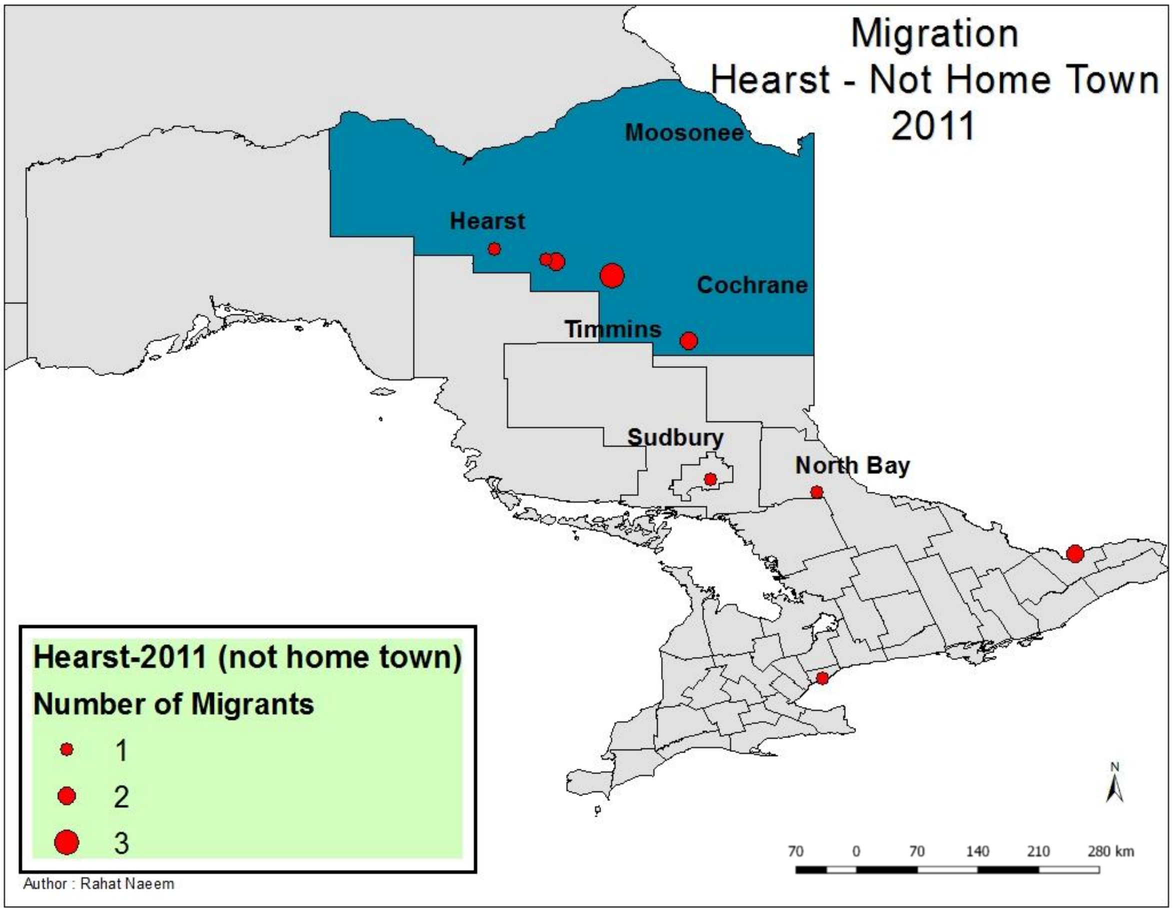

Figure 4.3.5: Trend of migration leading to homelessness in Hearst in year 2011 with Hearst not their hometown. The circle in Hearst is for individuals who did not specify their hometown.

The complete map of trends in migration to Hearst for the data collected in year 2011 is shown in Figure 4.3.6. It can be seen that some individuals moved to Hearst from Quebec, Alberta and BC but most of them were originally from Hearst. Most of the migrants to Hearst were from Ontario.

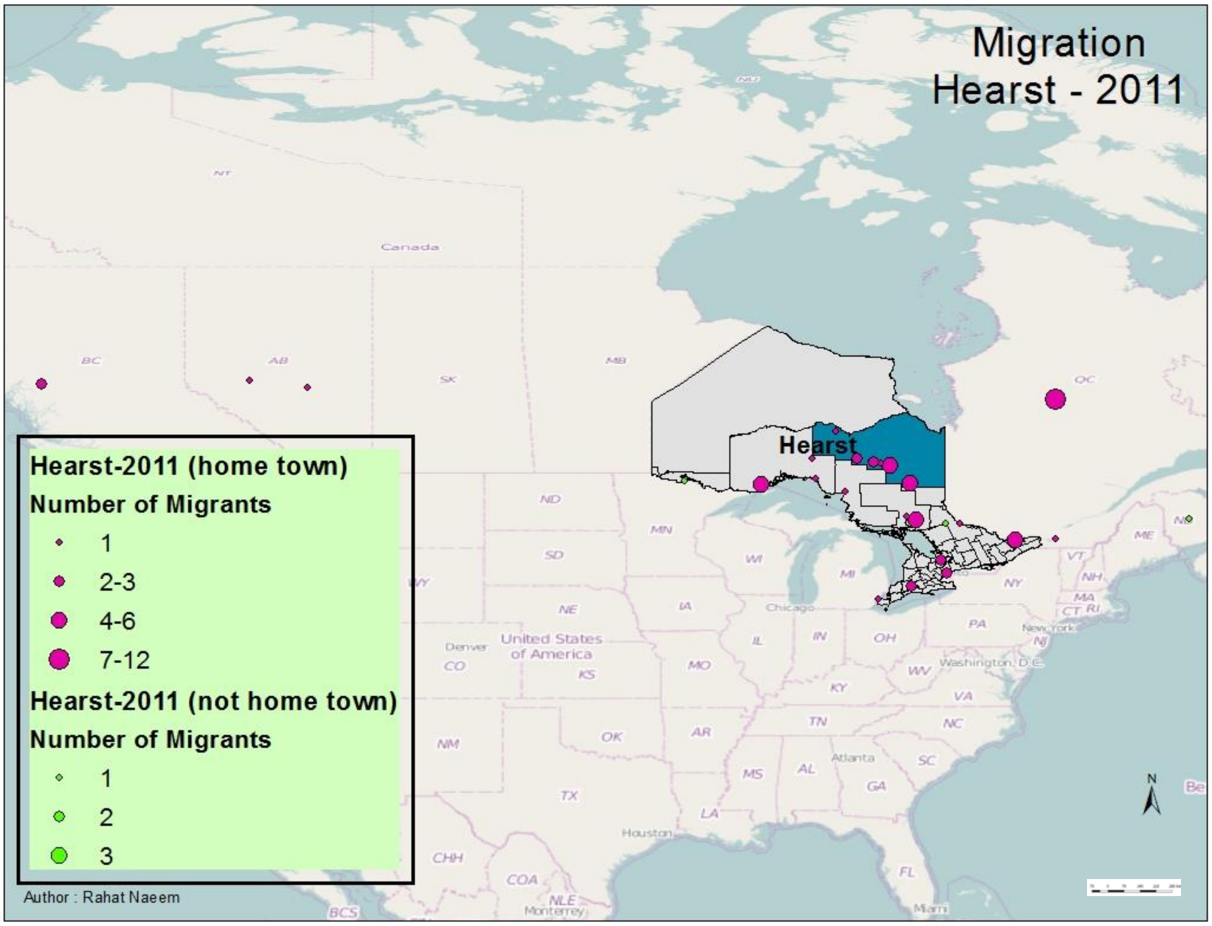

Figure 4.3.6: Trend of migration leading to homelessness in Hearst in year 2011.

Next, the migration trend in North Bay from the data collected in year 2011 (see Figure 4.3.7) were studied. It is interesting to note here a kind of pouring-down effect. It seems that individuals from North Bay moved to the South in large numbers in search of opportunities and became homeless when they returned to North Bay. Since North Bay is only about 100 km away from the much larger city, Sudbury, one would assume that most would go to Sudbury in search of employment. However, it is observed that most individuals actually move to southern Ontario instead. This can be due to a better understanding of the actual job market in Sudbury for the North Bay citizens. The more important issue here is that when these individuals return to North Bay, they become homeless. This indicates lack of proper support structure in North Bay for migrants.

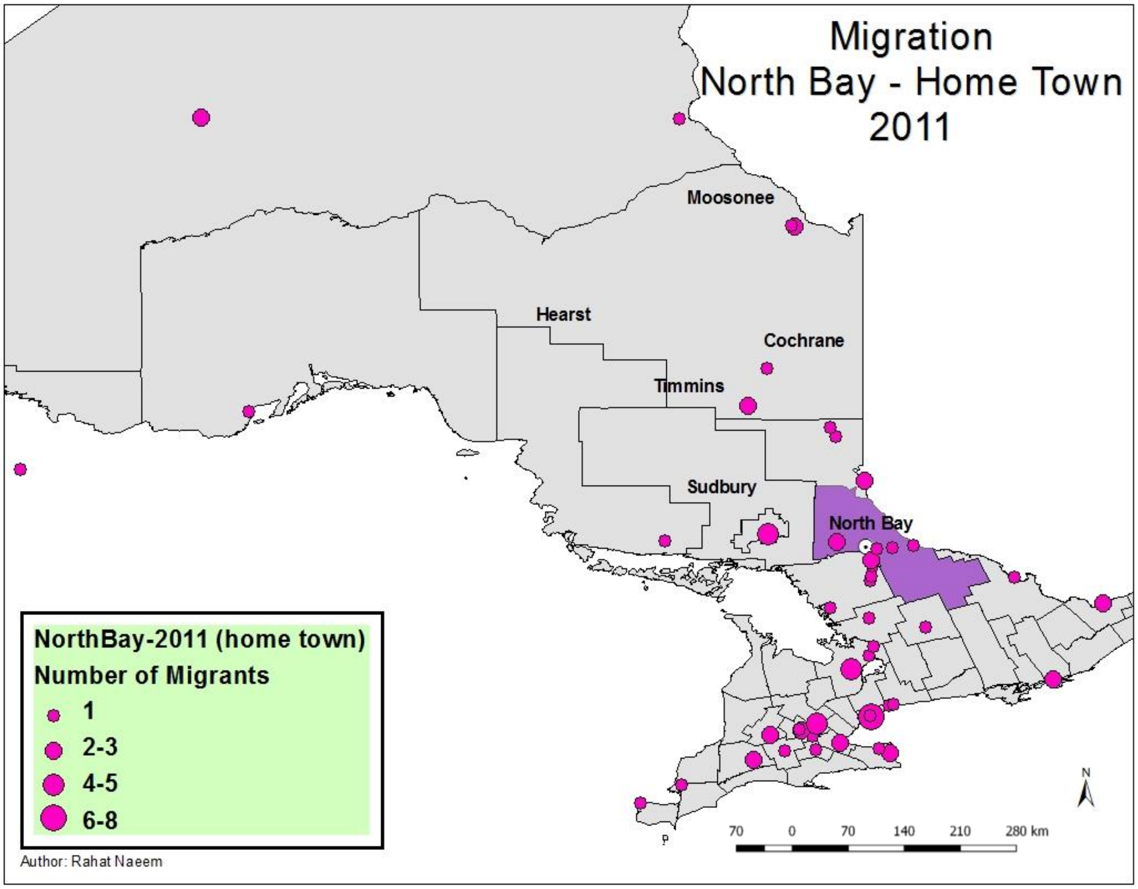

Figure 4.3.7: Trend of migration leading to homelessness in North Bay in year 2011 for individuals having North Bay as their hometown.

Even though North Bay was not one of the towns included in this study, to better understand the migration trend, similar analyses were performed on out-of-town individuals leading to homelessness. Figure 4.3.8 shows the map thus generated. Here, migration from heavily populated areas in the south including greater Toronto can be observed. This is a healthy trend in general and policy makers encourage such migrations. However, in this case the migrations have led to individuals becoming homeless. This further depletes already scarce resources of small towns, such as North Bay, and eventually leads to higher levels of poverty in the society.

North Bay is not an industrial or mining town, though it has a large number of government offices. Most individuals are therefore government employees or associated with contracting companies working for the government. The employment opportunities are therefore limited and prone to long application assessment times and delays. This results in many individuals in North Bay seek employment opportunities elsewhere. It is apparent from the map in Figure 4.3.8 that, being located in about the middle of Ontario, the North Bay sees migrations from both North and South of Ontario with higher numbers coming from southern parts.

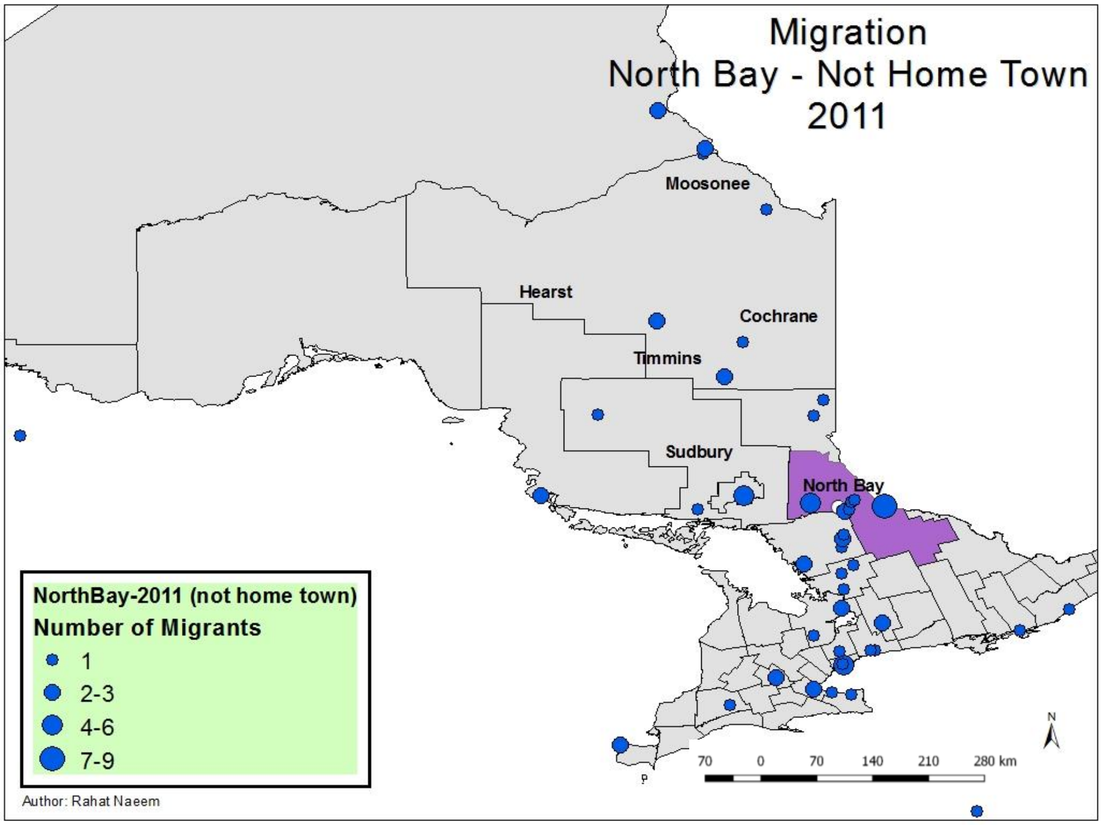

Figure 4.3.8: Trend of migration leading to homelessness in North Bay in year 2011 with North Bay not their hometown. The circles in North Bay are for individuals who did not specify their hometown.

Figure 4.3.9 shows the overall migration trend in North Bay during 2011. As discussed earlier, North Bay is a small town with few industries and mainly housing government offices. Migration to North Bay is therefore by individuals who are mainly looking for work in the government sector or who already have job offers. In the event of job loss in North Bay in the government sector, finding another job in the sector is difficult with long processing times and delays. Such issues are generally faced by individuals who are hired on contract basis. After the contract is over, they find it hard to secure another contract or employment. This can lead to either another migration out of North Bay or eventual homelessness.

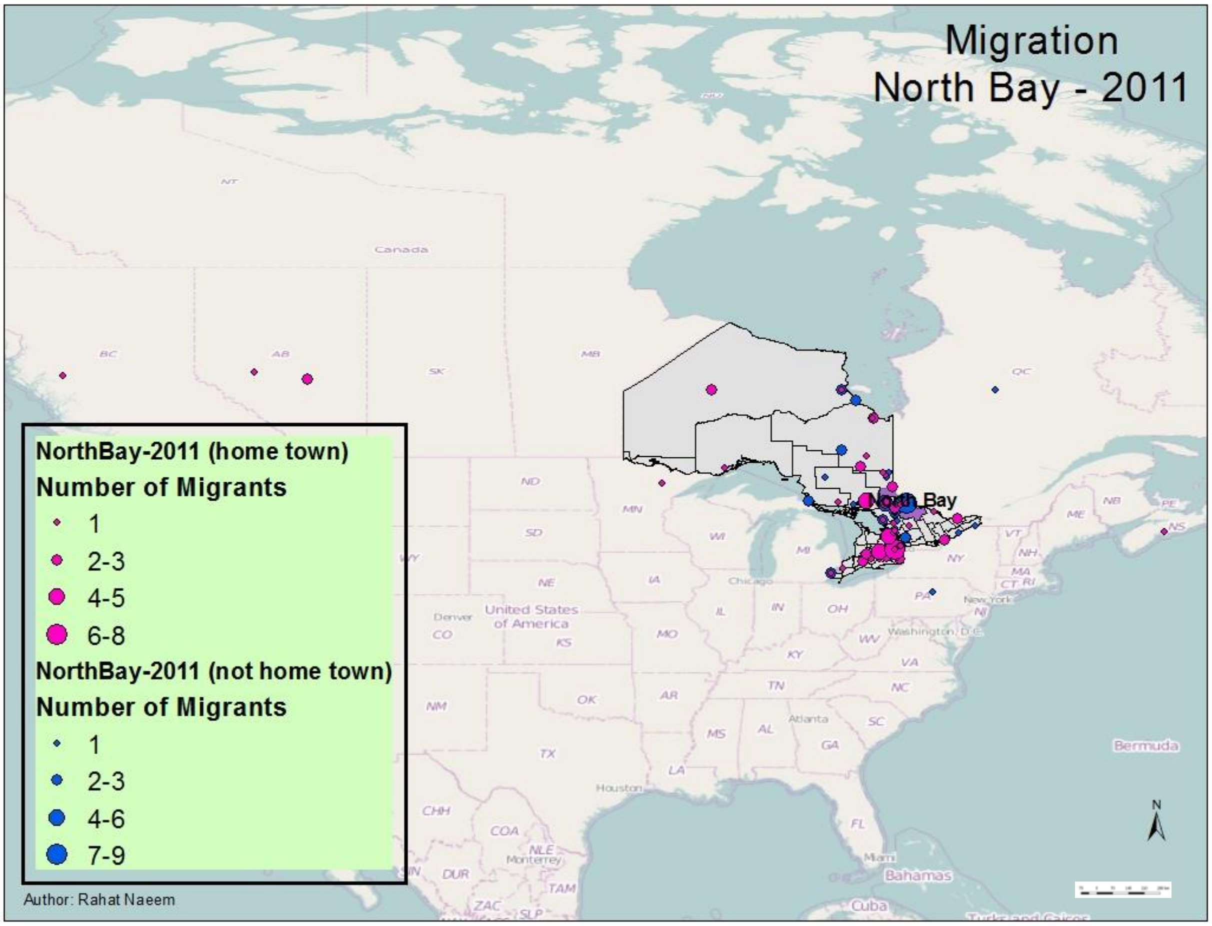

Figure 4.3.9: Trend of migration leading to homelessness in North Bay in year 2011.

Data in Moosonee were collected during year 2012. Moosonee is the northmost town of Ontario studied during this project. The only access to the town is either by air or by ice roads, which make the transportation costs extremely high. Hence the common grocery items, such as milk, are sold at prices that are three to four times their prices in larger cities, such as Sudbury. This, together with virtually non-existing industrial base, has made the city rampant in poverty and homelessness. Most individuals in Moosonee belong to First Nations communities with low education levels. Many are afraid of leaving their communities as then they would have to forego the government assistance they get. Due to these factors, migration out of Moosonee are not as common as in other cities in the North. Figure 4.3.10 shows the migration trend for individuals with Moosonee as their hometown. It seems that most individuals migrated to nearby towns especially Timmins. This is understandable since Timmins is a mining town with higher job prospects.

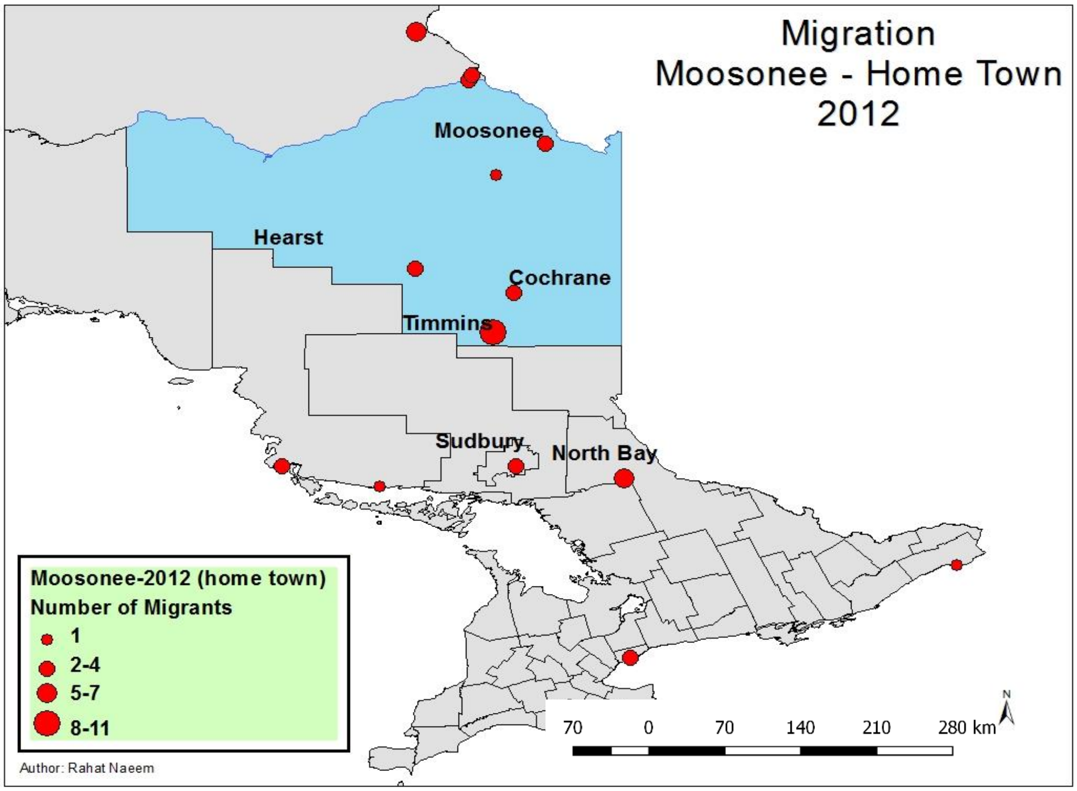

Figure 4.3.10: Trend of migration leading to homelessness in Moosonee in year 2012 for individuals having Moosonee as their hometown.

The map in Figure 4.3.11 depicts the migration trend of individuals whose home town was not Moosonee. These individuals came to Moosonee and then became homeless. As discussed earlier, Moosonee does not have an industrial base and the employment opportunities are very minimal. The cost of living is very high due to high transportation costs. As can be seen here, most of the migrants were from areas North of Moosonee. This is expected and understandable since for individuals further North, Moosonee is the first town they can go in search for work or medical attention.

The complete migration trend for Moosonee is depicted in Figure 4.3.12. Of course, one should not expect anyone from far reaches in Canada to migrate to Moosonee unless there is a compelling reason, such as family. Hence, almost negligible migration to Moosonee from outside Ontario is observed.

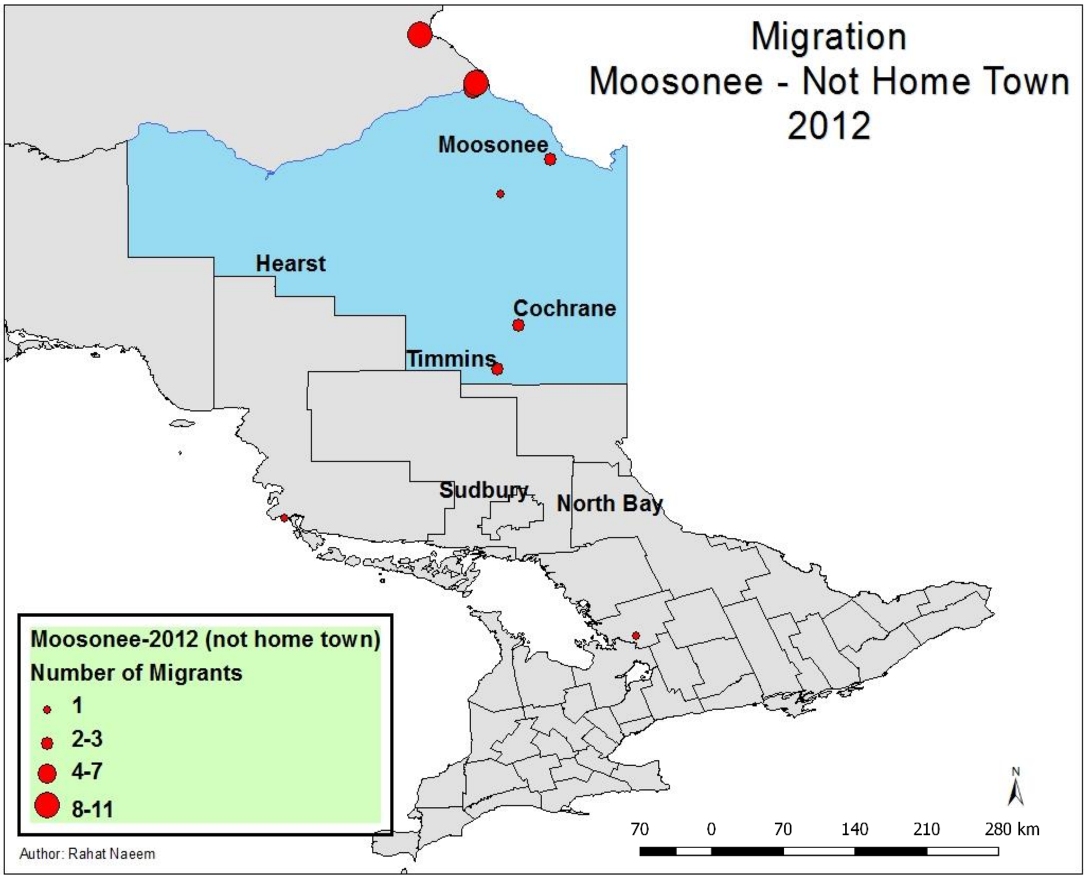

Figure 4.3.11: Trend of migration leading to homelessness in Moosonee in year 2012 with Moosonee not their hometown. The circles in Moosonee are for individuals who did not specify their hometown.

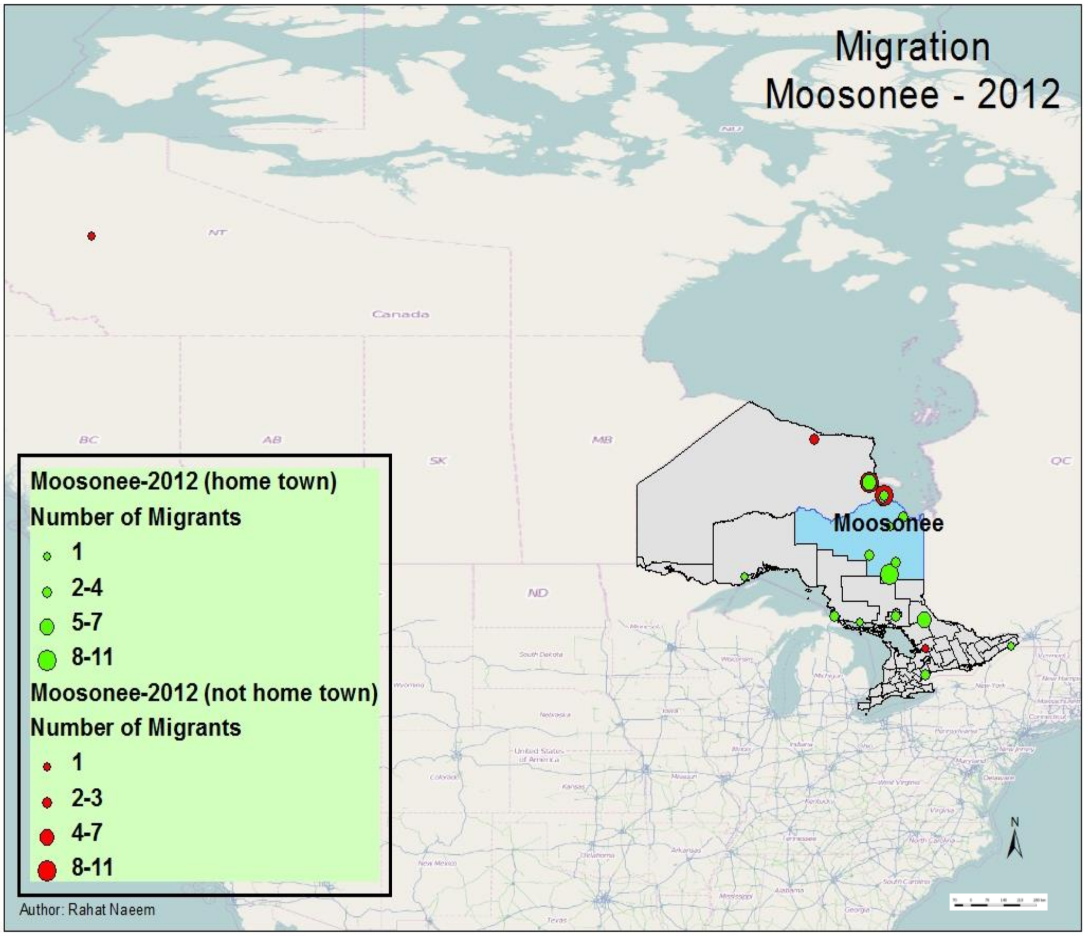

Figure 4.3.12: Trend of migration leading to homelessness in Moosonee in year 2012.

Cochrane is a small town near Timmins in Northern Ontario. Data were collected in Cochrane in year 2013. Figure 4.3.13 shows a map depicting migration trend in Cochrane for individuals who stated Cochrane as their hometown. It is interesting to note that an appreciable number of individuals from Cochrane migrated to northern and southern Ontario and became homeless after returning to their hometown. Cochrane, being a very small town, does not have many employment opportunities. This also means that migration into Cochrane from other communities should not be expected. However, as can be seen in Figure 4.3.14, an appreciable number of individuals did actually migrate to Cochrane from the North and the South of Ontario. And after migration they became homeless.

Figure 4.3.15 shows the complete picture of migration trend in Cochrane in 2013. As expected the bulk of migration in Cochrane remained from within Ontario.

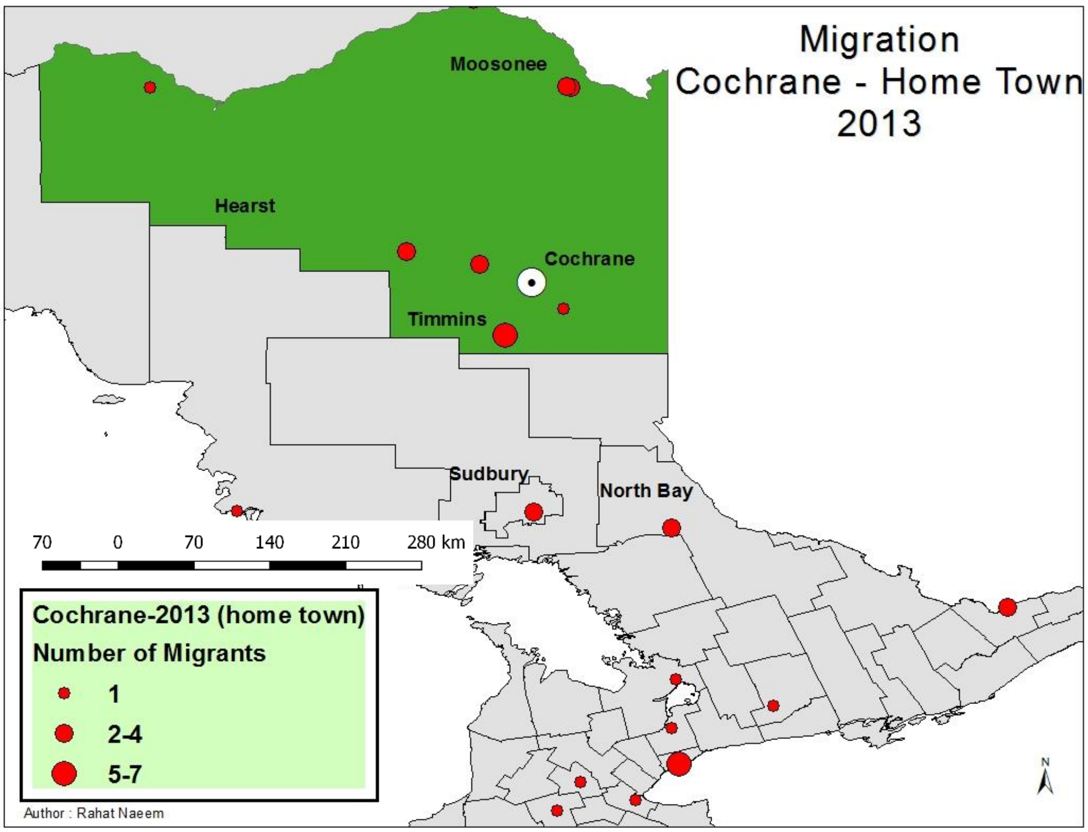

Figure 4.3.13: Trend of migration leading to homelessness in Cochrane in year 2013 for individuals having Cochrane as their hometown.

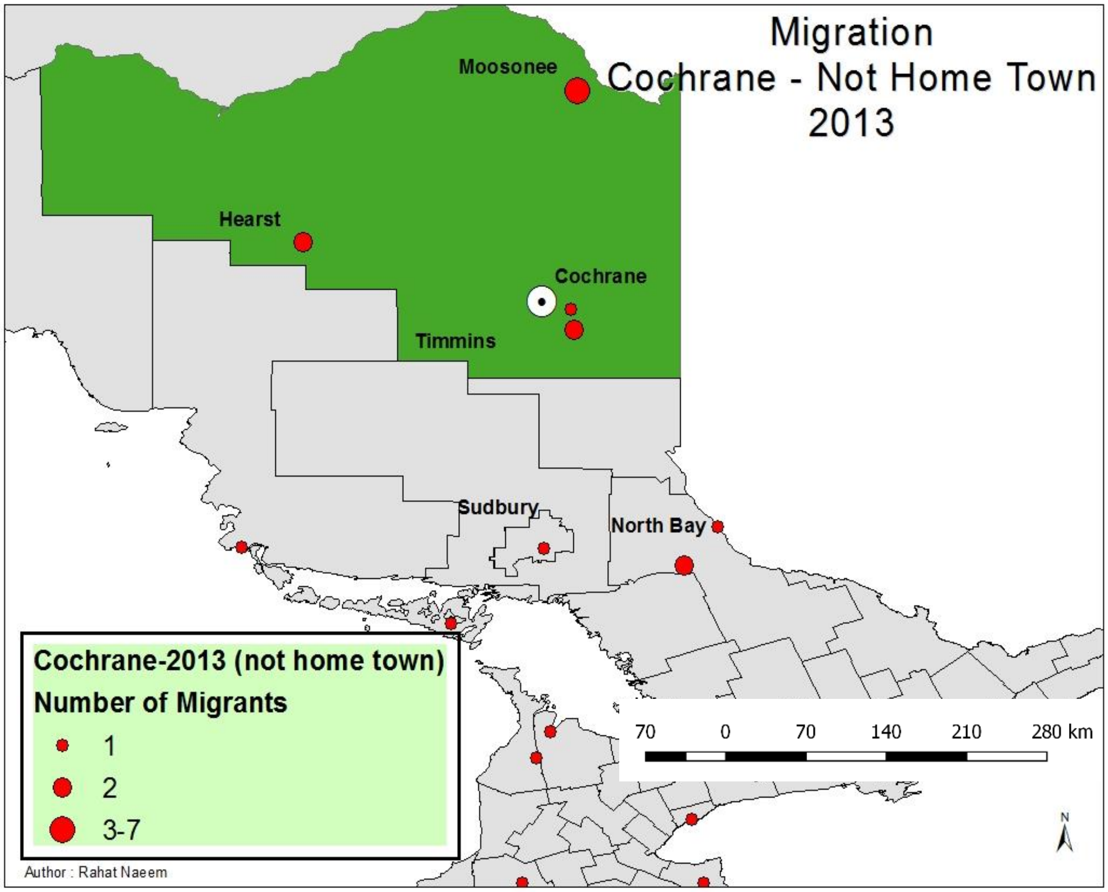

Figure 4.3.14: Trend of migration leading to homelessness in Cochrane in year 2013 with Cochrane not their hometown. The circles in Cochrane are for individuals who did not specify their hometown.

Timmins is an important town in northern Ontario with some of the deepest and oldest underground mines in the world. Though the mining operations in Timmins are of smaller scale as compared to Sudbury, the town does see influx of migrants from other parts of Ontario in search for employment opportunities. A point worth mentioning is that even with such large mining operations, the town has widespread poverty and homelessness problems.

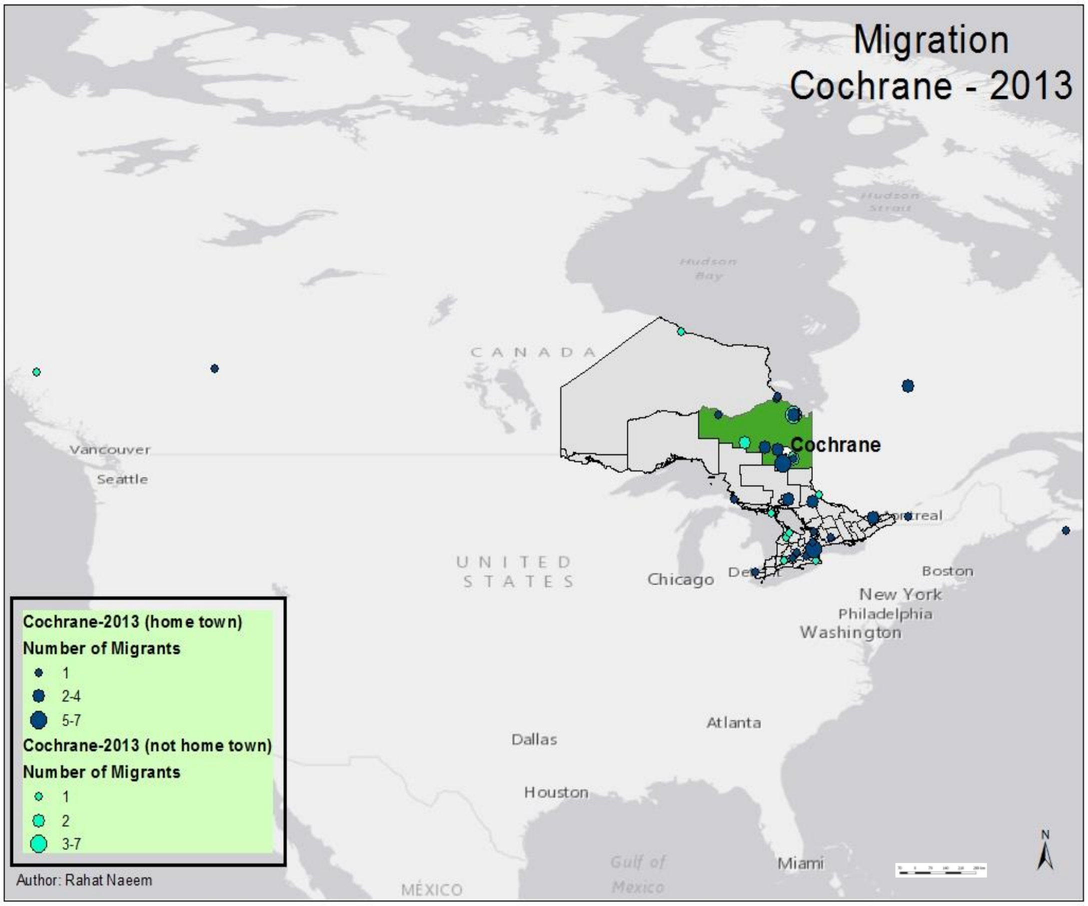

Figure 4.3.15: Trend of migration leading to homelessness in Cochrane in year 2013.

Figure 4.3.16 shows the map for the trend of migration in Timmins in year 2011 by individuals who identified Timmins as their hometown. A good mix of movement from both North and South in Ontario can be observed here. These individuals moved out of Timmins, returned and became homeless. Figure 4.3.17 shows a similar map but for individuals who did not identify Timmins as their hometown. As expected, most of the migrants in this case were from upper parts of Ontario and from areas that are near to Timmins.

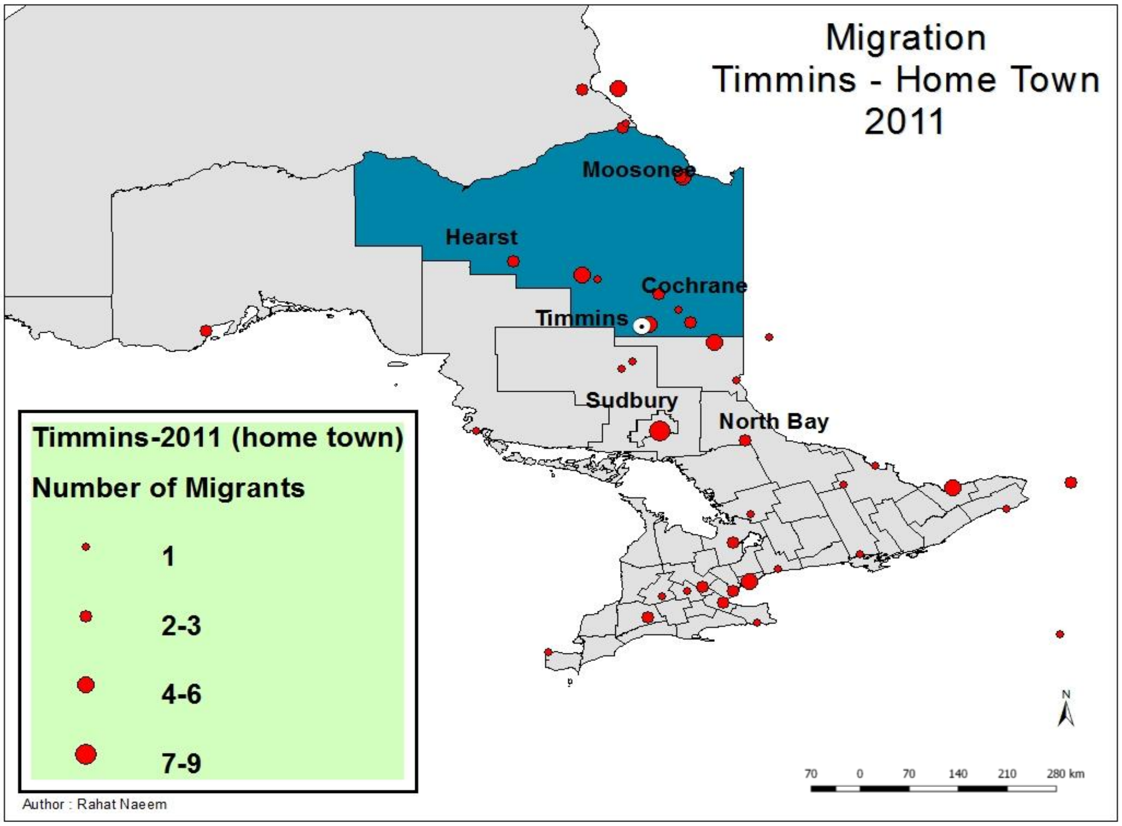

Figure 4.3.16: Trend of migration leading to homelessness in Timmins in year 2011 for individuals having Timmins as their hometown.

Timmins being a known mining town, sees migration from other parts of Canada as well (see Figure 4.3.18). Unlike maps for other communities, here it can be seen that a sizable number of individuals from eastern and western Canadian regions migrated to Timmins, probably in search of better opportunities, and as a result becoming homeless.

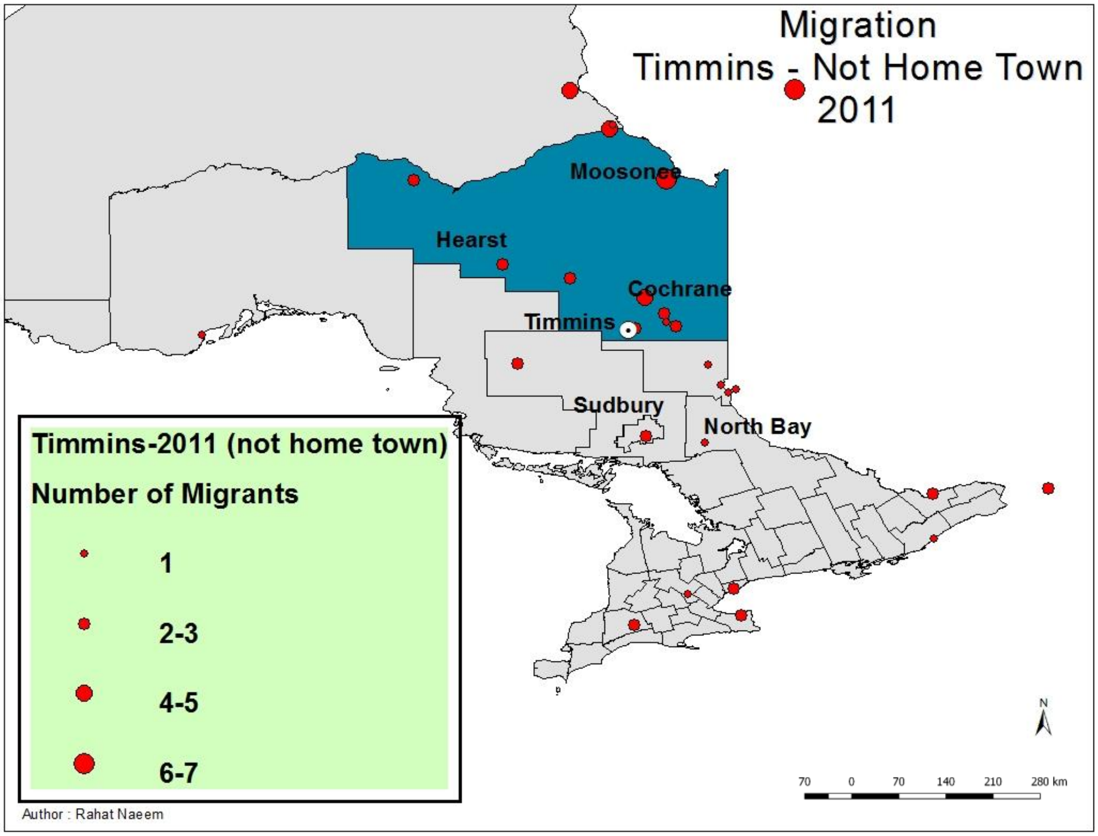

Figure 4.3.17: Trend of migration leading to homelessness in Timmins in year 2011 with Timmins not their hometown. The circles in Timmins are for individuals who did not specify their hometown.

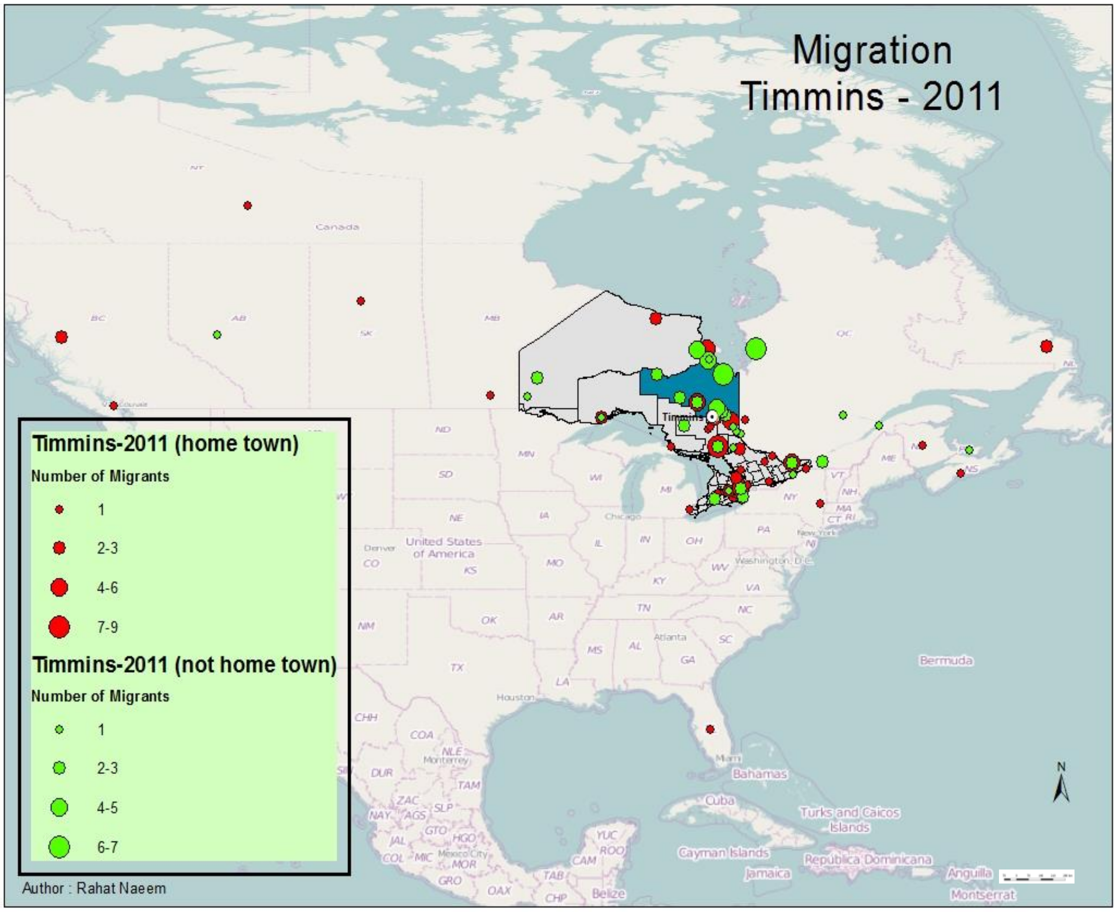

Figure 4.3.18: Trend of migration leading to homelessness in Timmins in year 2011.

A number of important conclusions can be arrived at from the above analyses. One is that in many cases migration actually leads to homelessness. This happens to those who migrate to another town in search of better employment or health services but also to those who migrate out and then come back to their home towns. There are larger towns in the south of Ontario where most from the north migrate to. And due to highly competitive and saturated job markets in these cities, many of them go back to their home towns and then become homeless after spending whatever they had possessed before migration.

Another important result is that the predominant migration route is from north to south. This is due to the fact that economies of most of the cities in the north are dependent on mining or lumber and get severely affected whenever there is economic downturn in these industries. This leave many unemployed for longer periods of time and hence migrate to southern part of Ontario in search of employment. This is a serious issue as it leaves many in severe poverty and become homeless.

5 DATA ANALYSIS – DISTRIBUTION OF PARAMETERS

5.1 Distribution of Parameters

In this Chapter, the distribution of different parameters will be individually studied. This is important in order to understand how different parameter distributions vary between the study areas.

5.1.1 Gender Distribution

It was observed in the data acquired that in general there were more females than males in the homeless population. To look at it more closely, the cumulative gender distributions in different localities were generated. Figure 5.1.1 shows the pie charts depicting gender distributions in different cities and towns. It is worth nothing that, except for Sudbury and North Bay, the female homeless population in other towns is higher than male population. This situation is much more pronounced in Moosonee and Hearst.

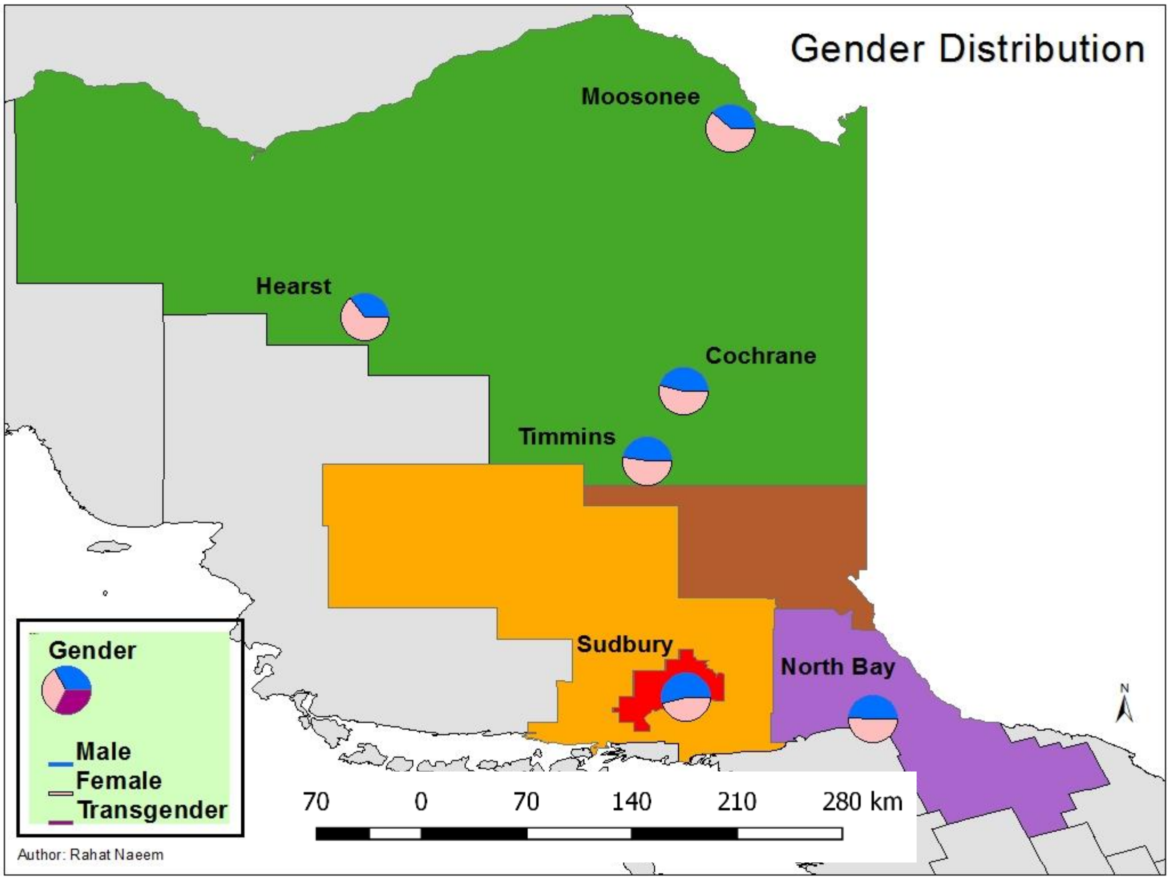

Figure 5.1.1: Cumulative gender distributions of homeless in different communities.

5.1.2 Age Distribution

The cumulative age distributions of homeless people in different communities are shown in Figure 5.1.2. Here the light blue colour represents the age group of 21 to 40 years. It can be seen that in all cities, except for Moosonee, this age group dominates. In Moosonee, the largest number of homeless individuals are children of up to 10 years of age. As it will become evident later, this is actually due to larger number of children per individual in Moosonee. Another interesting thing is that in Sudbury and

North Bay the homeless population of 60+ individuals is very small. Hearst and Cochrane show the most evenly distributed population of homeless with respect to age.

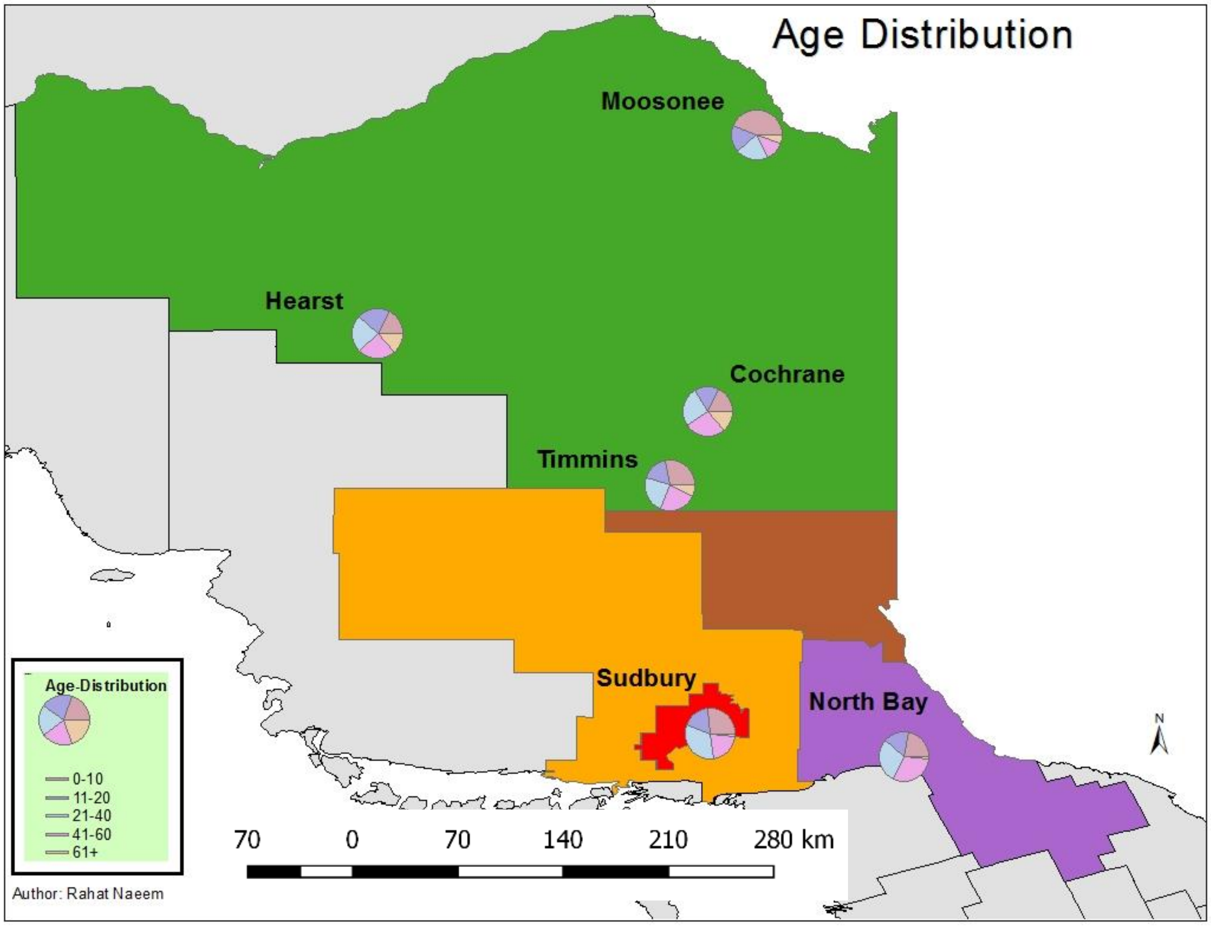

Figure 5.1.2: Cumulative age distributions of homeless in different communities.

5.1.3 Absolute Homelessness Distribution

Figure 5.1.3 shows the distributions of individuals who do and do not meet the definition of absolute homelessness. Note that meeting the criteria does not mean that the person is not at the risk of becoming homeless. Sudbury shows a much larger population of individuals who meet this definition followed by North Bay and Timmins.

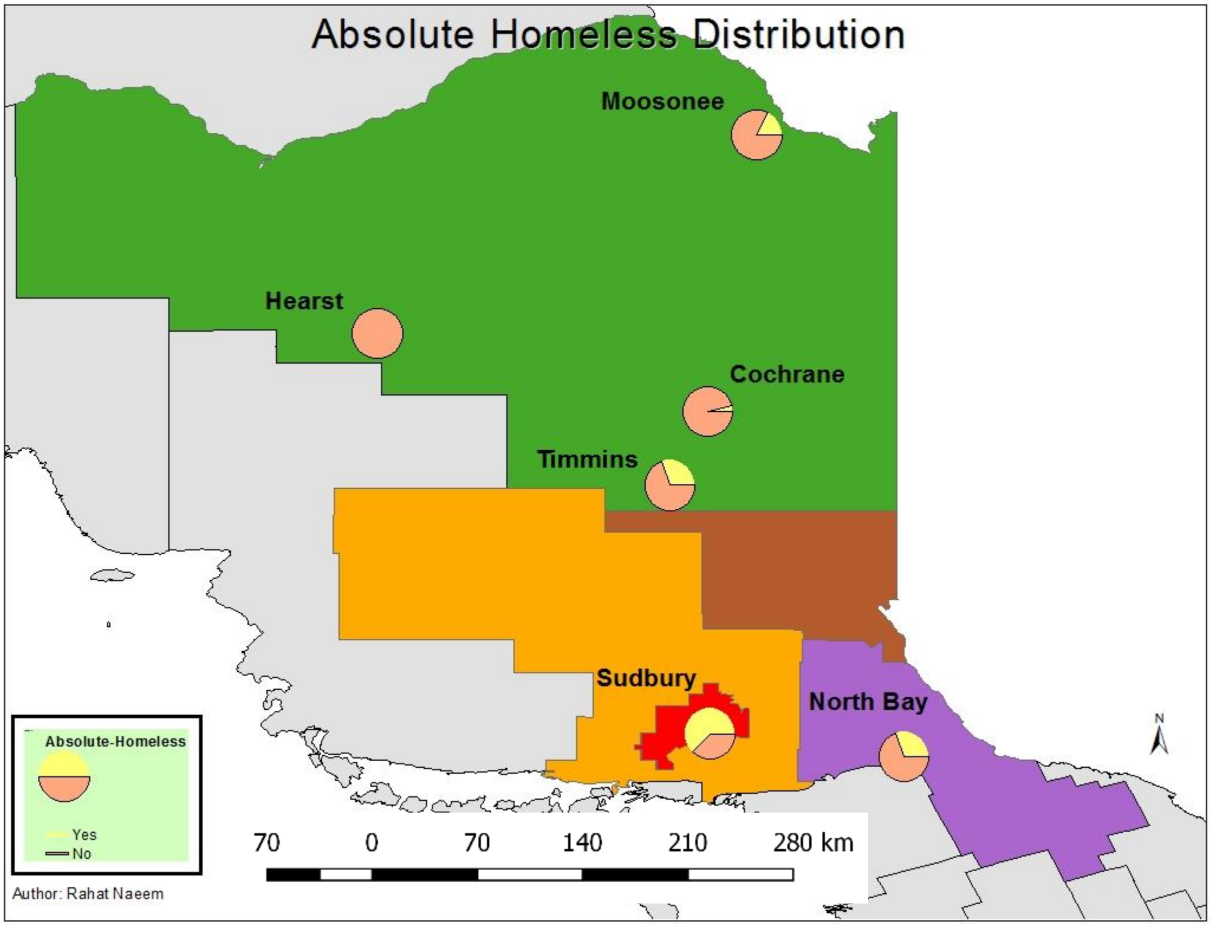

Figure 5.1.3: Cumulative distributions of absolute homeless in different communities.

5.1.4 At Risk of Homelessness Distribution

Figure 5.1.4 depicts a map for the percentage of individuals who are at risk of becoming homeless. Note that even though Sudbury has the highest proportion of individuals who meet the definition of absolute homelessness, the proportion of at-risk individuals is lower than cities in upper north. North Bay has the lowest proportion of at-risk individuals.

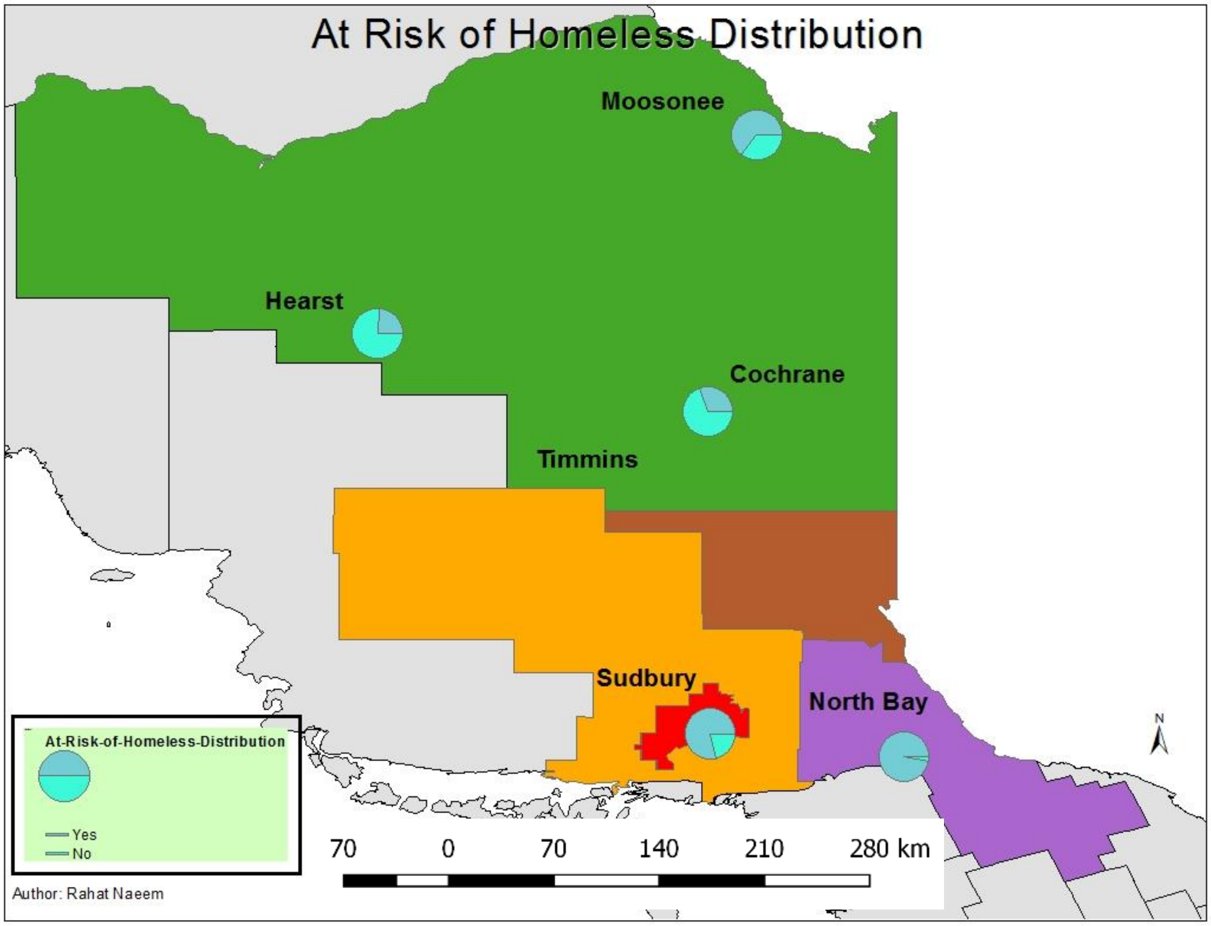

Figure 5.1.4: Cumulative distributions of individuals at risk of becoming homeless in different communities.

5.1.5 Distribution of Accompanied Children

Earlier it was observed that Moosonee had the highest relative number of children up to the age of 10. The reason for that can be observed in map of Figure 5.1.5. That is, the number of homeless individuals in Moosonee with three or more children is higher than in any other city. Sudbury shows the highest population of homeless individuals with no children.

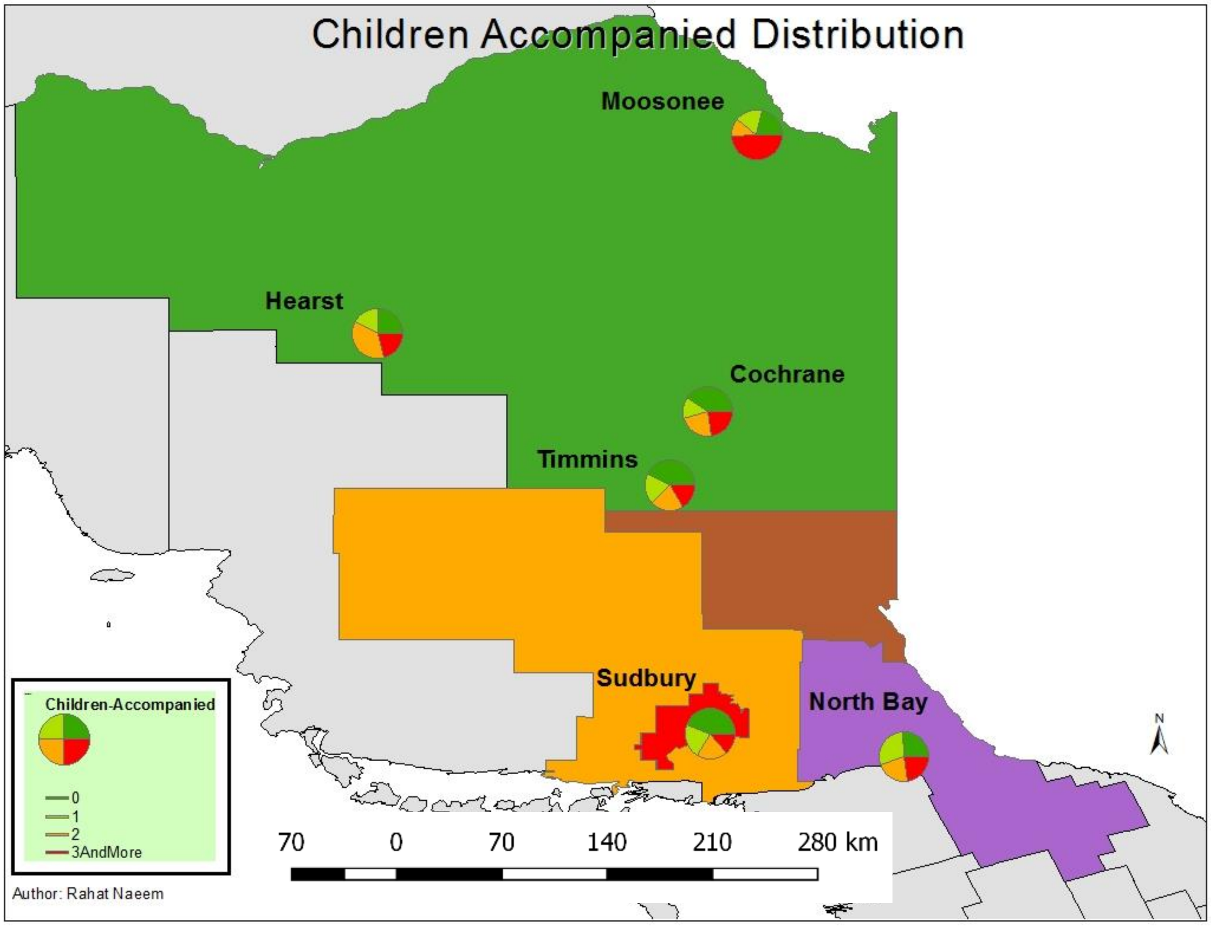

Figure 5.1.5: Cumulative distributions of homeless with accompanied children in different communities.

5.1.6 Ethnic Distribution

This map in Figure 5.1.6 shows the ethnic distribution in different communities. As expected, the highest population of aboriginal homeless individuals is in Moosonee. All other cities have Caucasians as the dominant proportion of homeless individuals.

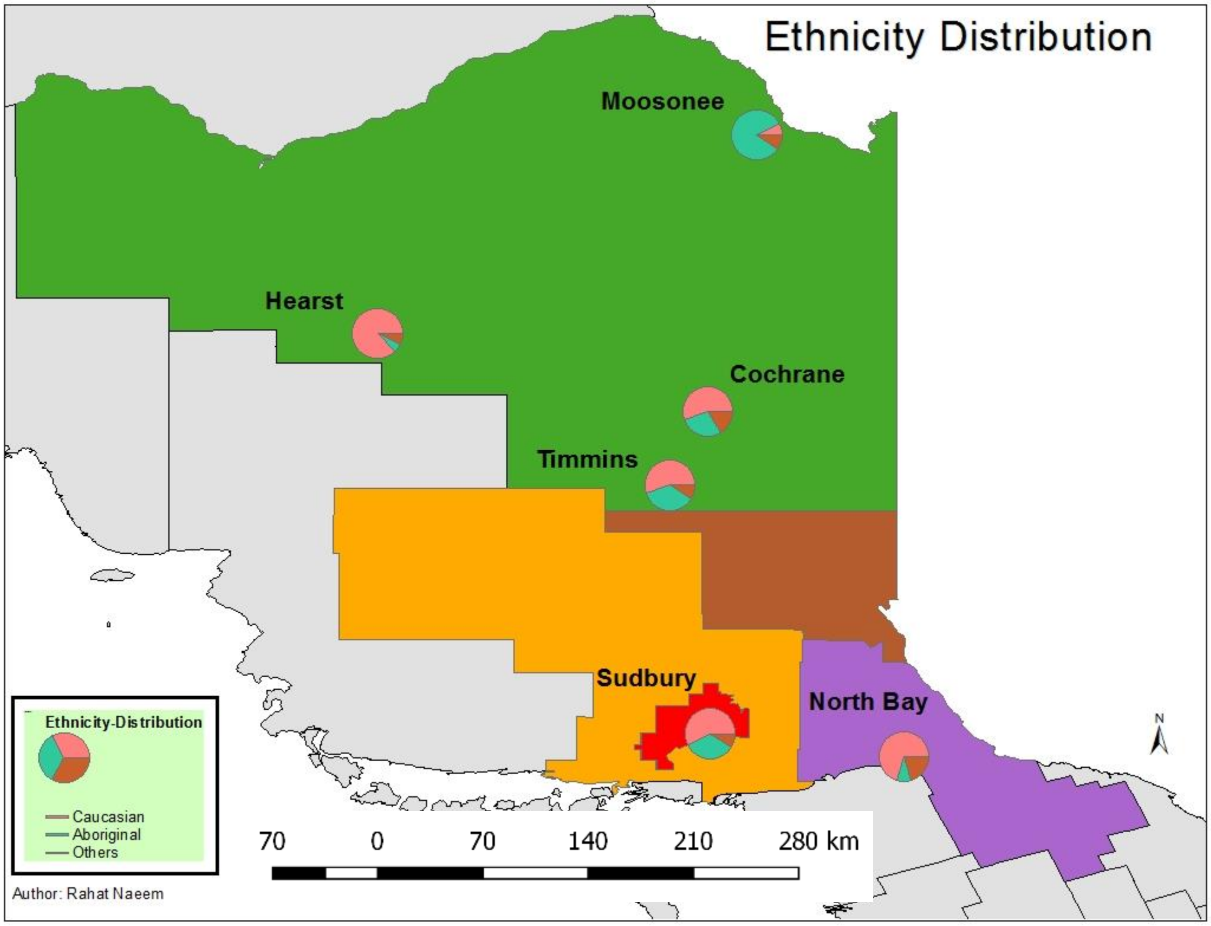

Figure 5.1.6: Cumulative distributions of ethnicity in different communities.

5.1.7 Income Status Distribution

The distribution of income status is shown in Figure 5.1.7. It is apparent that in Sudbury and North Bay most individuals are on Ontario Disability Support Program (ODSP) or welfare. In Hearst, Cochrane, Timmins and Moosonee, most individuals are on Canada Pension Plan (CPP). A sizable population in Moosonee is on welfare.

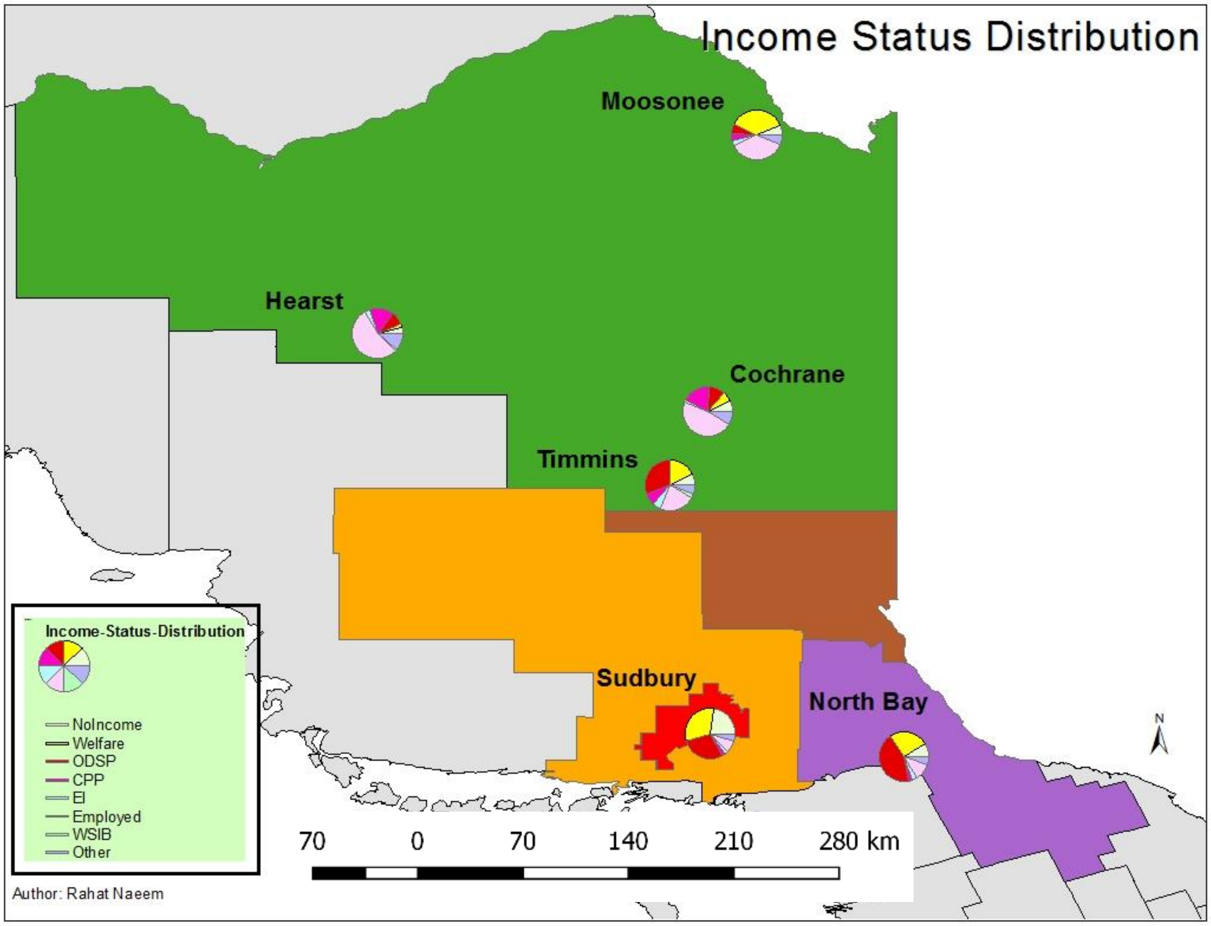

Figure 5.1.7: Cumulative income status distributions of homeless in different communities.

5.1.8 Spoken Language Distribution

Figure 5.1.8 shows the cumulative distributions of languages spoken by homeless individuals in different communities. In Moosonee most individuals speak either English or Cree. In Hearst, English and French languages dominate. In Sudbury, North Bay, Cochrane and Timmins, English is spoken more frequently than any other language.

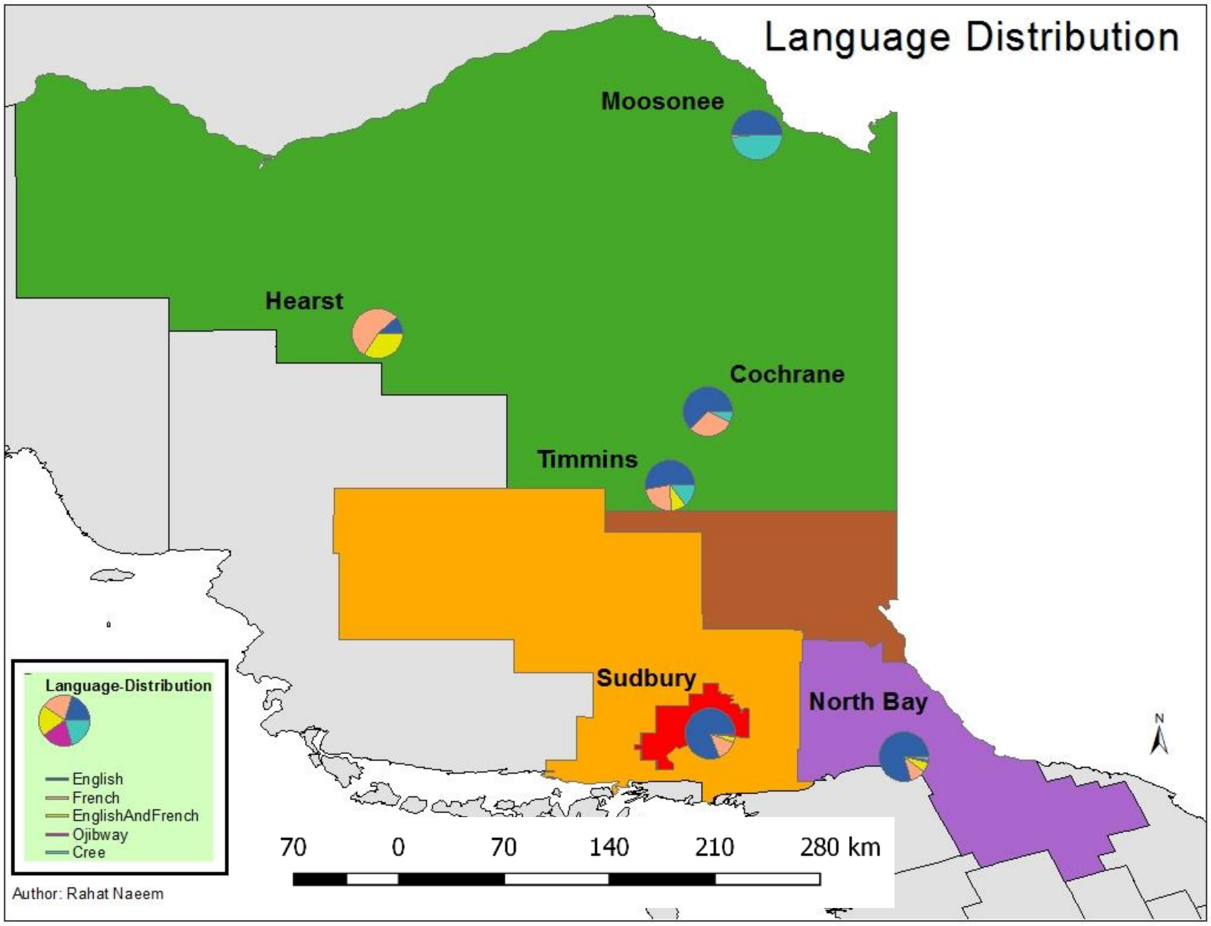

Figure 5.1.8: Cumulative distributions of languages spoken by homeless in different communities.

5.1.9 Marital Status Distribution

The map in Figure 5.1.9 shows the marital status distributions of homeless in different cities. It is apparent that, except for Sudbury and North Bay, most individuals in other cities are married or are in common law relationships. A sizable population of individuals in North Bay and Sudbury are single.

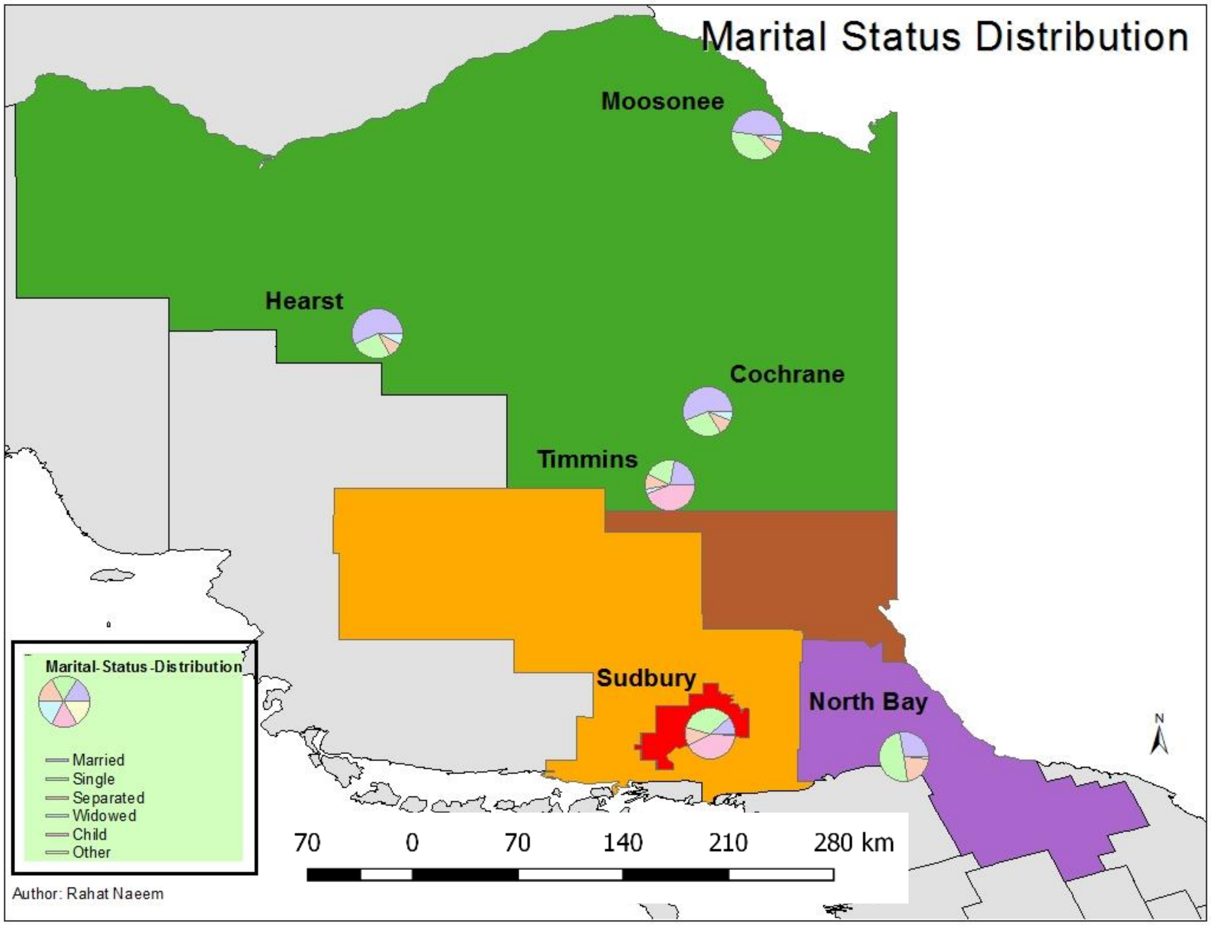

Figure 5.1.9: Cumulative marital status distributions of homeless in different communities.

5.1.10 Mental Health Status Distribution

During this study, the persons interviewed were asked if they thought they had any mental health conditions. The resulting distributions are shown in Figure 5.1.10. It is interesting to note that large proportion of individuals in Sudbury, North Bay and Timmins identified themselves as dealing with mental health issues.

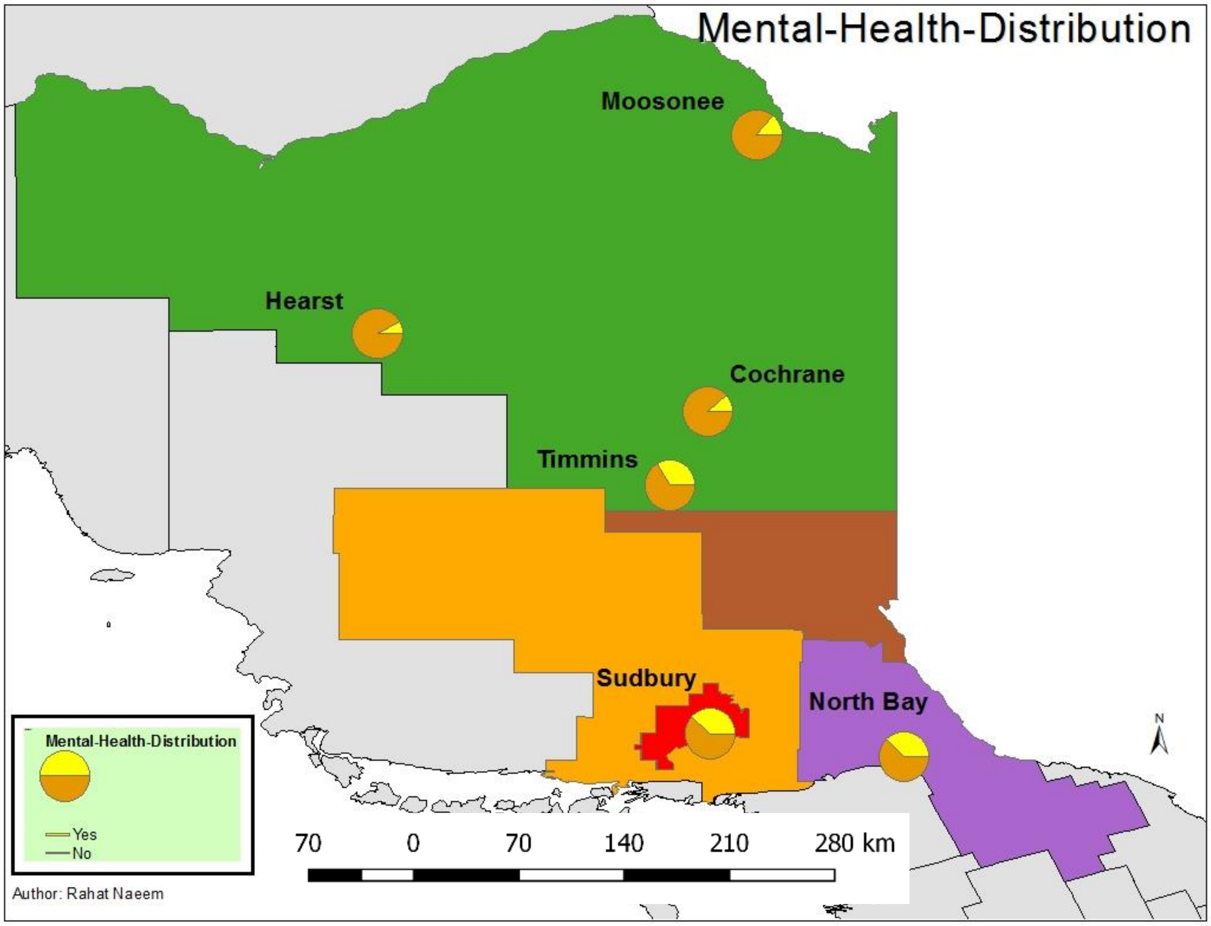

Figure 5.1.10: Cumulative distributions of mental health for homeless in different communities.

5.1.11 Mental Health Problem Distribution

Figure 5.1.11 shows the distributions of mental health problems in different communities. In most of the cases, depression and anxiety were identified as the major causes of mental issues.

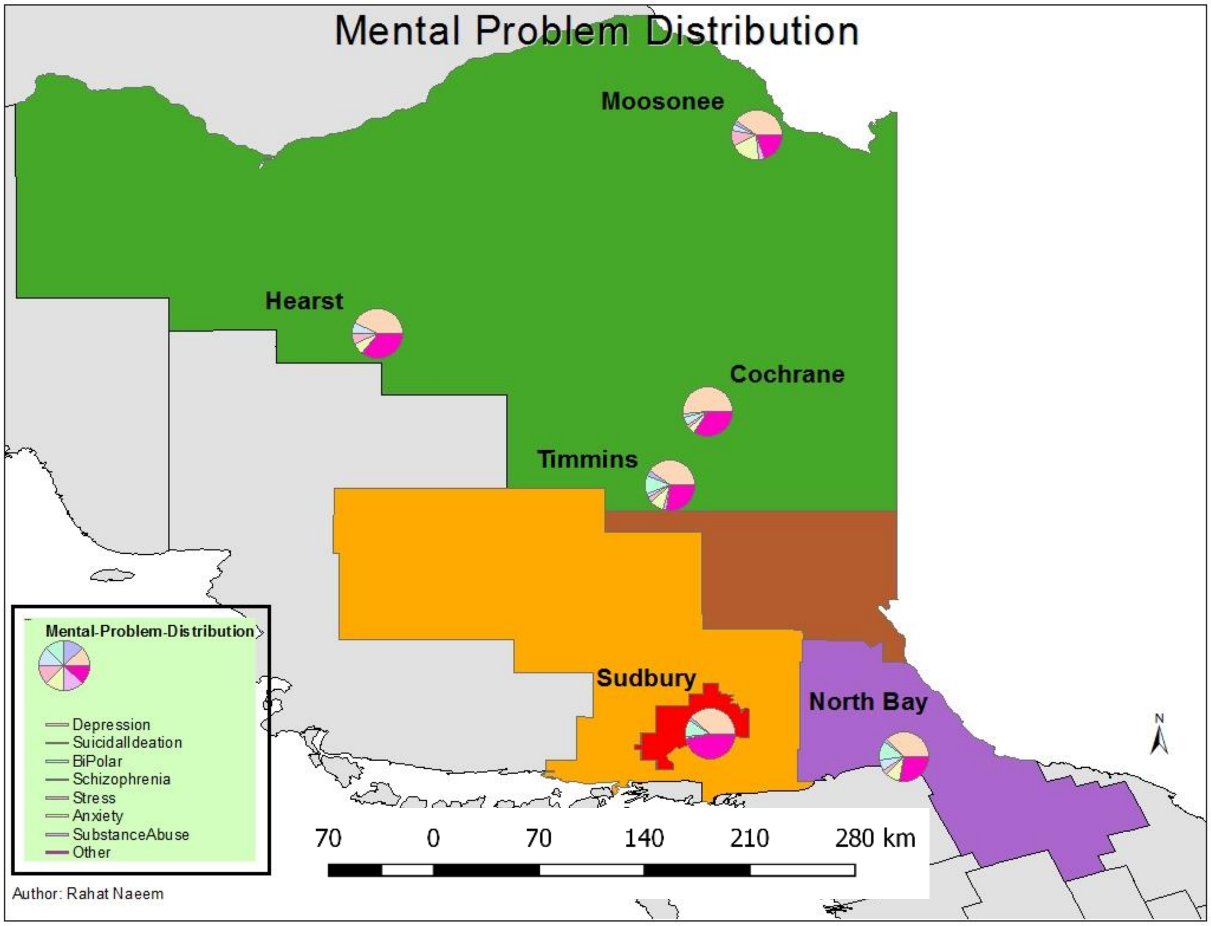

Figure 5.1.11: Cumulative distributions of mental health problems for homeless in different communities.

5.1.12 Physical Health Status Distribution

The map in Figure 5.1.12 shows the distributions generated from the responses of individuals to the question whether they had any physical health issues or not. It is apparent that in all communities most of the individuals identified themselves as having no physical health problems. This is in sharp contrast to the mental health question.

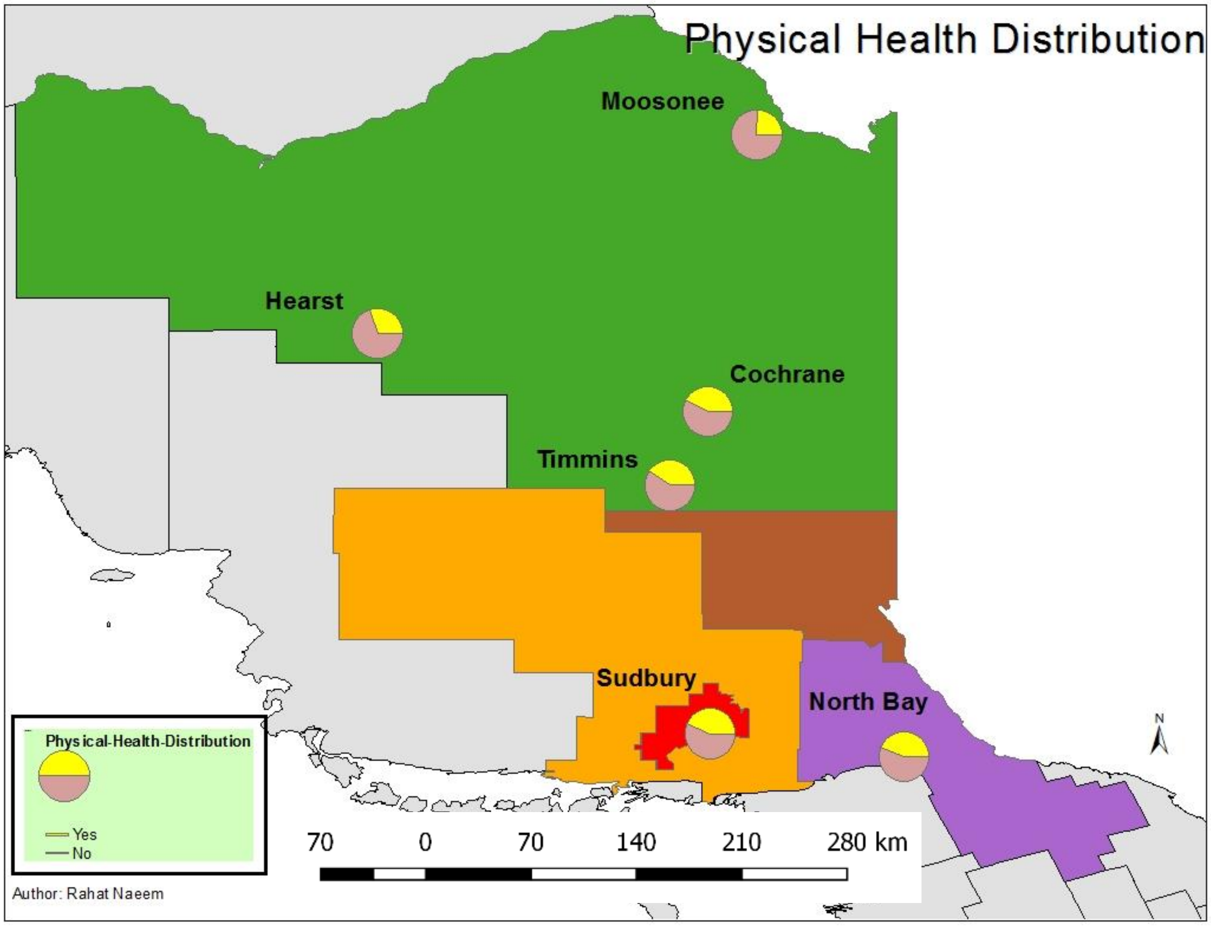

Figure 5.1.12: Cumulative distributions of physical health status for homeless in different communities.

6 DATA ANALYSIS – FUZZY COGNITIVE MAPS

6.1 Fuzzy Cognitive Maps

As discussed earlier, a major part of this research was to understand pathways to homelessness and their spatial dependence through Fuzzy Cognitive Maps for different regions. A Fuzzy Cognitive Map or FCM is simply a combination of fuzzy logic and cognitive mapping. An FCM consists of interconnecting nodes, which are concepts representing individual parts of the whole system. The interconnections are labeled with fuzzy values between the two nodes. These values represent the strength of the relationship between the nodes. Once the nodes and their interconnected fuzzy values have been established, the influence of the nodes on each other is calculated using an iterative procedure based on neural network approach. Once a stable solution has been obtained, the model can be used to determine the behaviour of the system as node values are changed. Up until now there has not been much research carried out in terms of spatial dependence on pathways to homelessness in Northern Ontario. Most of the inquiries have been static studies performed in different localities. However, looking at the data gathered during this study, it can be observed that migration has played a strong role in homelessness in different communities. For example, it has been seen that there is a trend that people from South (such as from Greater Toronto) migrate to Northern communities (such as Timmins) in search of better employment but in turn become homeless. Similarly, it has been observed that there is a strong tendency of individuals from Northern communities to become homeless after their return from South where they would go to seek better employment opportunities. In view of these observations, there are spatial dependencies that must be taken into consideration to understand pathways to homelessness. Therefore, for this study the following hypothesis was tested. There is a strong spatial dependence on pathways to homelessness in Northern Ontario due to multiple factors including ethnicity and access to health, education and social services.

Testing this hypothesis would greatly help in understanding homelessness and its dependence on different variables, such as migration and scarcity of certain resources in different communities leading directly to homelessness as well as migration and subsequent homelessness. These findings will help the policy makers to intelligently allocate resources within different communities to minimize homelessness in Northern Ontario.

Testing the above-mentioned hypothesis requires understanding of interplay between different variables. For example, what is the relationship between mental illness and gender or how education level is related to unemployment. The data distributions presented earlier show that homelessness has both intrinsic and extrinsic dependence on different variables. Therefore, looking at variables individually does not have much value in terms of understanding homelessness in Northern Ontario. It is imperative that different variables and their inter-dependence must be taken into consideration in order to accurately understand their effects on homelessness. One approach to understand these relationships is to develop and analyze a Fuzzy Cognitive Map or FCM. For this study the Mental Modeler software was used (Gray, S.A. et. al., 2013). As discusses in the previous Chapter, the fuzzy relationships (or weights) in a Fuzzy Cognitive Map are not necessarily crisp and can be deduced from the data collected during the study. In the context of fuzzy logic, a relationship can be positive or negative and can have any value between -1 and +1.

6.1.1 FCM from Collective Distributions

Though, from previous analyses it was concluded that there were temporal and spatial variations between dependences of different variables but it was important to understand how significant those variations were. This step was absolutely necessary to understand spatial dependence on pathways to homelessness. At the same time, this was necessary to quantify the fuzzy logic weights that are needed to develop the fuzzy cognitive map. As the first step, the dependence of eviction on gender in different communities and in different years were looked at. The results are shown in Table 6.1.1. It can be seen from this table that there are differences between the parameters during different years and in different communities. However, looking at the collective numbers it can be deduced that a male individual is almost twice as likely to be evicted and become homeless as compared to a female individual. Therefore, on a fuzzy logic scale the Gender-Eviction relationship has been assigned a value of "M+". Note that Gender = 1 refers to female and Gender = 2 refers to male.

Table 6.1.1: Dependence of eviction on gender in different communities.

Location	Study Year	Female (%)	Male (%)	Transgender (%)	Subjects	Comments
Sudbury	2000	50	50		4	Low statistics
Sudbury	2001	44.4	55.6		27	
Sudbury	2002	20	80		40	
Sudbury	2003	34.8	65.2		69	
Sudbury	2007	40.8	59.2		76	
Sudbury	2009	43.2	55.4	1.4	74	
Timmins	2011	45.3	54.7		86	
Hearst	2011	0	100		1	Low statistics
Moosonee	2012	52.6	47.4		19	
Cochrane	2013	31.3	68.7		16	
	Collective	**39.6**	**60.2**	**0.2**		

Table 6.1.2 shows the dependence of unemployment on gender in different communities.

Table 6.1.2: Dependence of unemployment on gender in different communities.

Location	Study Year	Female (%)	Male (%)	Transgender (%)	Subjects	Comments
Sudbury	2000	30.3	69.7		33	
Sudbury	2001	20.9	79.1		91	
Sudbury	2002	33.6	66.4		113	
Sudbury	2003	31.3	68.7		278	
Sudbury	2007	42.2	57.8		218	
Sudbury	2009	33.7	65.7	0.6	169	
Timmins	2011	49.3	50.7		288	
Hearst	2011		100		1	Low statistics
Moosonee	2012	40	60		20	
Cochrane	2013	26.7	73.3		15	
	Collective	**37.3**	**62.6**	**0.1**		

Here again significant differences between variable dependencies during different years and in different communities are observed. Collectively, this shows that a male individual is almost twice as likely to be unemployed and become homeless as compared to a female individual. Therefore, on a fuzzy logic scale the Gender-Unemployment relationship has been assigned a value of "M+".

The dependence of seeking employment on gender can be seen in Table 6.1.3. This table shows significant differences in variable dependencies especially for data collected in Sudbury in different years. Looking at the data collectively, it is obvious that a male individual is almost three times as likely to become homeless while seeking employment as compared to a female individual. Therefore, on a fuzzy logic scale the Gender-Unemployment relationship has been assigned a value of "H+".

Table 6.1.3: Dependence of seeking employment on gender in different communities.

Location	Study Year	Female (%)	Male (%)	Subjects
Sudbury	2000	46.7	53.3	45
Sudbury	2001	28.1	71.9	57
Sudbury	2002	16.6	83.4	193
Sudbury	2003	17.6	82.4	403
Sudbury	2007	31.6	68.4	95
Sudbury	2009	33.3	66.7	102
Timmins	2011	41.5	58.5	193
Hearst	2011	45.5	54.5	11
Moosonee	2012	46.7	53.3	30
Cochrane	2013	40.9	59.1	22
	Collective	**27.1**	**72.9**	**1151**

In Table 6.1.4 the dependence of substance abuse on gender can be observed.

Table 6.1.4: Dependence of substance abuse on gender in different communities.

Location	Study Year	Female (%)	Male (%)	Subjects
Sudbury	2000	18.8	81.3	32
Sudbury	2001	39.6	60.4	53
Sudbury	2002	45.9	54.1	74
Sudbury	2003	32.5	67.5	154
Sudbury	2007	38	62	129
Sudbury	2009	37.8	62.2	98
Timmins	2011	42.1	57.9	126
Hearst	2011	33.3	66.7	6
Moosonee	2012	45.5	54.5	22
Cochrane	2013	40	60	10
	Collective	**37.8**	**62.2**	**704**

For gender-substance abuse relationship one would expect the distribution to be highly skewed toward male population. However, this does not seem to be true in all localities and during different years. For example, in Moosonee the gender ratio is almost 1. This shows how important it is to analyze data for different localities separately. However, the objective of these studies is to look at the data collectively. In the next step, data will be analyzed separately for each location and for different years. Looking at the data collectively, it can be deduced that a male individual is almost twice as likely to become homeless while using controlled substances as compared to a female individual. Therefore, on a fuzzy logic scale the Gender-Substance Abuse relationship has been assigned a value of "M+".

Table 6.1.5 shows the prevalence of domestic violence for females and males. Here, one would expect the distribution to be highly skewed toward the female population. That is exactly what is observed here. It should be noted that domestic violence is either not highly prevalent or it is not well reported. This information is part of the data collected during interviews and therefore it is not expected that the interviewees will hold up information. It is therefore highly probable that the domestic violence is not the leading cause of homelessness in many of the Northern communities.

Table 6.1.5: Dependence domestic violence on gender in different communities.

Location	Study Year	Female (%)	Male (%)	Subjects	Comments
Sudbury	2000	82.5	17.5	40	
Sudbury	2001	74.2	25.8	62	
Sudbury	2002	84.1	15.9	63	
Sudbury	2003	96	4	25	
Sudbury	2007	100	0	20	
Sudbury	2009	100	0	1	Low statistics
Timmins	2011	100	0	2	Low statistics
Hearst	2011	0	0	0	Low statistics
Moosonee	2012	0	100	1	Low statistics
Cochrane	2013	0	0	0	Low statistics
	Collective	**83.6**	**16.4**	**214**	

The collective distribution in Table 6.1.5 shows that a female individual is almost three times as likely to become homeless as a result of domestic violence as compared to a male individual. Therefore, on a fuzzy logic scale the Gender-Domestic Violence relationship has been assigned a value of "H-". Next, the dependence of mental illness on gender in different communities was studies. The results are shown in Table 6.1.6.

Table 6.1.6: Dependence of mental illness on gender in different communities.

Location	Study Year	Female (%)	Male (%)	Subjects	Comments
Sudbury	2000	0	100	1	Low statistics
Sudbury	2001	65.2	34.8	23	
Sudbury	2002	43.5	56.5	85	
Sudbury	2003	49.6	50.4	125	
Sudbury	2007	43.2	56.8	162	
Sudbury	2009	37.1	62.9	89	
Timmins	2011	53.4	46.6	148	
Hearst	2011	40	60	5	Low statistics
Moosonee	2012	66.7	33.3	9	
Cochrane	2013	58.8	41.2	17	
	Collective	**47.3**	**52.7**	**664**	

The above table indicates substantial differences between data collected during different time frames and in different communities. Collectively, it shows that a male individual is slightly more likely to become homeless as a result of being mentally ill as compared to a female individual. Therefore, on a fuzzy logic scale the Gender-Mental Health relationship has been assigned a value of "L-".

Next, the dependence of physical illness on gender was studies. The results are shown in Table 6.1.7.

Table 6.1.7: Dependence of physical illness on gender in different communities.

Location	**Study Year**	**Female (%)**	**Male (%)**	**Subjects**	**Comments**
Sudbury	2000	70	30	10	
Sudbury	2001	31	69	29	
Sudbury	2002	37.1	62.9	35	
Sudbury	2003	42.1	57.9	19	
Sudbury	2007	43.8	56.3	96	
Sudbury	2009	0	0	0	Low statistics
Timmins	2011	0	0	0	Low statistics
Hearst	2011	0	0	0	Low statistics
Moosonee	2012	0	0	0	Low statistics
Cochrane	2013	0	0	0	Low statistics
	Collective	**41.8**	**58.2**	**189**	

The above table shows large disparities in variable dependencies during different study periods in Sudbury. However, collectively this shows that a male individual is slightly more likely to become homeless as a result of being physically ill as compared to a female individual. Therefore, on a fuzzy logic scale the Gender-Physical Health relationship has been assigned a value of "L-". The collective distribution of unemployed with respect to ethnicity is shown in Table 6.1.8. This shows that a Caucasian person is more than twice as likely to become homeless as a result of being unemployed as compared to a person belonging to First Nations. Therefore, on a fuzzy logic scale the Ethnic Group - Unemployment relationship has been assigned a value of "M+".

Table 6.1.8: Unemployed - Ethnicity distribution (collective).

Ethnic Group	Percent Unemployed
Caucasian	61
First Nations	27.1
Others	11.9

The graph in Figure 6.1.1 shows the age distribution of unemployed. The above distribution indicates a weak negative relationship between age of individuals and unemployment leading to homelessness. Therefore, on a fuzzy logic scale the Age - Unemployment relationship has been assigned a value of "L-".

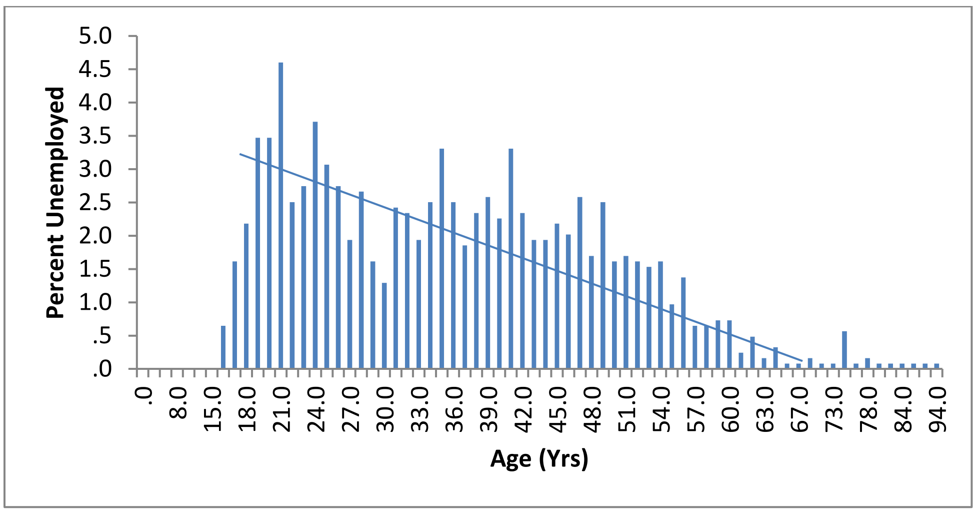

Figure 6.1.1: Distribution of unemployed individuals who became homeless (collective).

Table 6.1.9 indicates a very strong relationship between married and single individuals with respect to becoming homeless due to unemployment. Therefore, on a fuzzy logic scale the Marital Status - Unemployment relationship has been assigned a value of "H+".

Table 6.1.9:Unemployed - Marital Status distribution (collective).

Marital Status	**Percent Unemployed**
Married or Common Law	19.3
Single/Divorced/Widowed	80.7

Table 6.1.10 indicates a very strong negative relationship between unemployment leading to homelessness and the number of children. Therefore, on a fuzzy logic scale the Number of Children - Unemployment relationship has been assigned a value of "H-".

Table 6.1.10: Unemployed - Number of Children relationship (collective).

Number of Children	**Percent Unemployed**
0	41.2
1	21.7
2	19.4
3	8.1
4	4.6
5	2.4
>6	2.5

Table 6.1.11 shows a very strong positive relationship between unemployment leading to homelessness and the person's income status. Therefore, on a fuzzy logic scale the Income Status - Unemployment relationship has been assigned a value of "H+".

Table 6.1.11: Unemployed - Income Status distribution (collective).

Income Status	**Percent Unemployed**
No income	26.2
Welfare	73.8

Table 6.1.12 indicates a negative relationship between unemployment leading to homelessness and the person's highest level of education. Therefore, on a fuzzy logic scale the Education Level - Unemployment relationship has been assigned a value of "M-".

Table 6.1.12: Unemployed - Education Level relationship (collective).

Highest Level of Education	**Percent Unemployed**
Less than high school	11.5
Some high school	40.1
High school diploma	23
Some community college	15.7
Community college diploma	4.8
University degree	1.8

Table 6.1.13 depicts a very strong negative relationship between unemployment leading to homelessness and migration. A person is almost three times as likely to become unemployed and homeless as compared to a person who has migrated to that community. Therefore, on a fuzzy logic scale the Migration - Unemployment relationship has been assigned a value of "H-".

Table 6.1.13: Unemployed - Migration relationship (collective).

Migration	**Percent Unemployed**
No	71
Yes	29

Table 6.1.14 indicates a moderately negative relationship between unemployment leading to homelessness and the person's mental health status. Therefore, on a fuzzy logic scale the Mental Health - Unemployment relationship has been assigned a value of "M-".

Table 6.1.14: Unemployed - Mental Health Problems relationship (collective).

Mental Health Problems	Percent Unemployed
No	61.6
Yes	38.4

Table 6.1.15 shows a weakly negative relationship between unemployment leading to homelessness and the person's physical health status. Therefore, on a fuzzy logic scale the Physical Health - Unemployment relationship has been assigned a value of "L-"

Table 6.1.15: Unemployed - Physical Health Problems relationship (collective).

Physical Health Problems	Percent Unemployed
No	56.6
Yes	43.4

Table 6.1.16 shows that a Caucasian person is more likely to become homeless due to substance abuse as compared to a person belonging to First Nations. Therefore, on a fuzzy logic scale the Ethnic Group - Substance Abuse relationship has been assigned a value of "L-".

Table 6.1.16: Substance Abuse - Ethnic Group relationship (collective).

Ethnic Group	Percent
Caucasian	49.3
First Nations	39.3
Others	11.4

Table 6.1.17 depicts a very strong positive relationship between substance abuse leading to homelessness and the person's marital status. Therefore, on a fuzzy logic scale the Marital Status - Substance Abuse relationship has been assigned a value of "H+".

Table 6.1.17: Substance Abuse - Marital Status relationship (collective).

Marital Status	Percent
Married or Common Law	18.6
Single/Divorced/Widowed	81.4

Table 6.1.18 indicates a very strong negative relationship between substance abuse leading to homelessness and the number of children. Therefore, on a fuzzy logic scale the Number of Children - Substance Abuse relationship has been assigned a value of "H-".

Table 6.1.18: Substance Abuse - Number of Children relationship (collective).

Number of Children	Percent
0	47.3
1	17.6
2	16.8
3	7.5
4	6.0
5	2.4
>=6	2.4

Table 6.1.19 indicates a very strong positive relationship between substance abuse leading to homelessness and the person's income status. Therefore, on a fuzzy logic scale the Income Status - Unemployment relationship has been assigned a value of "H+".

Table 6.1.19: Substance Abuse - Income Status.

Income Status	Percent
No income	21.5
Welfare	78.5

Table 6.1.20 shows a moderately strong relationship between substance abuse leading to homelessness and the person's highest level of education. Therefore, on a fuzzy logic scale the Education Level - Unemployment relationship has been assigned a value of "M-".

Table 6.1.20: Substance Abuse - Education Level relationship (collective).

Highest Level of Education	**Percent**
Less than high school	11.3
Some high school	38.3
High school diploma	24.1
Some community college	9.8
Community college diploma	12.0
University degree	4.6

Table 6.1.21 indicates a person is twice as likely to become homeless as a result of substance abuse as compared to a person who has migrated. Therefore, on a fuzzy logic scale the Migration - Unemployment relationship has been assigned a value of "M-".

Table 6.1.21: Substance Abuse - Migration relationship (collective).

Migration	**Percent Unemployed**
No	66.7
Yes	33.3

Table 6.1.22 shows that a Caucasian person is much more likely to become homeless as a result of domestic violence as compared to a person belonging to First Nations. Therefore, on a fuzzy logic scale the Ethnic Group - Substance Abuse relationship has been assigned a value of "M-".

Table 6.1.22: Domestic Violence - Ethnic Group relationship (collective).

Ethnic Group	**Percent**
Caucasian	66.5
First Nations	27.8
Others	5.7

Table 6.1.23 indicates a very strong positive relationship between domestic violence leading to homelessness and the person's marital status. Therefore, on a fuzzy logic scale the Marital Status - Domestic Violence relationship has been assigned a value of "H+".

Table 6.1.23: Domestic Violence - Marital Status relationship (collective).

Marital Status	**Percent**
Married or Common Law	25.6
Single/Divorced/Widowed	74.4

Figure 6.1.2 shows the age distribution of individuals who became homeless due to domestic violence. The distribution is more or less even and therefore on a fuzzy logic scale the Domestic Violence - Age relationship has not been assigned any value.

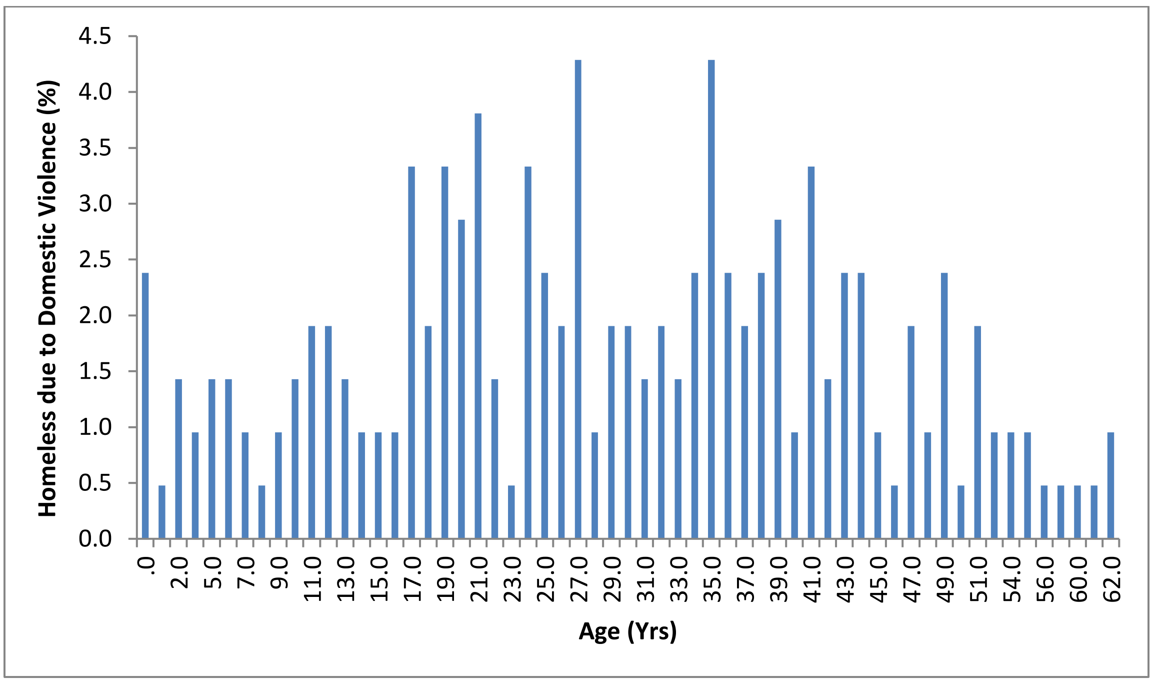

Figure 6.1.2: Collective age distribution of individuals who became homeless due to domestic violence.

Table 6.1.24 indicates a very strong negative relationship between domestic violence leading to homelessness and the number of children. Therefore, on a fuzzy logic scale the Number of Children - Domestic Violence relationship has been assigned a value of "H-".

Table 6.1.24: Domestic Violence - Number of Children relationship (collective).

Number of Children	Percent
0	61.6
1	13.8
2	13.8
3	9.4
>=4	1.2

Table 6.1.25 indicates a slightly positive relationship between domestic violence leading to homelessness and the person's income status. Therefore, on a fuzzy logic scale, the Income Status - Domestic Violence relationship has been assigned a value of "L+".

Table 6.1.25: Domestic Violence - Income Status relationship (collective).

Income Status	Percent
No income	43.3
Welfare	56.7

Table 6.1.26 shows a slightly positive relationship between domestic violence leading to homelessness and the person's mental health status. Therefore, on a fuzzy logic scale the Mental Health - Unemployment relationship has been assigned a value of "L+".

Table 6.1.26: Domestic Violence - Mental Health Problems relationship (collective).

Mental Health Problems	Percent
No	52.4
Yes	47.6

Table 6.1.27 depicts a moderately negative relationship between unemployment leading to homelessness and the person's physical health status. Therefore, on a fuzzy logic scale the Physical Health - Domestic Violence relationship has been assigned a value of "M-".

Table 6.1.27: Domestic Violence - Physical Health Problems relationship (collective).

Physical Health Problems	Percent
No	34.1
Yes	65.9

Table 6.1.28 shows that a Caucasian person is much more likely to become homeless as a result of being mentally ill as compared to a person belonging to First Nations. Therefore, on a fuzzy logic scale the Ethnic Group - Mental Health relationship has been assigned a value of "H+".

Table 6.1.28: Mental Illness - Ethnic Group relationship (collective).

Ethnic Group	Percent
Caucasian	63.5
First Nations	23.5
Others	13.0

Figure 6.1.3 shows the age distribution of individuals who became homeless due to mental illness. Even though there seem to be some dependence on age specially after 50 years but the change is very small. Therefore, on a fuzzy logic scale, the Age - Mental Health relationship has not been assigned a value.

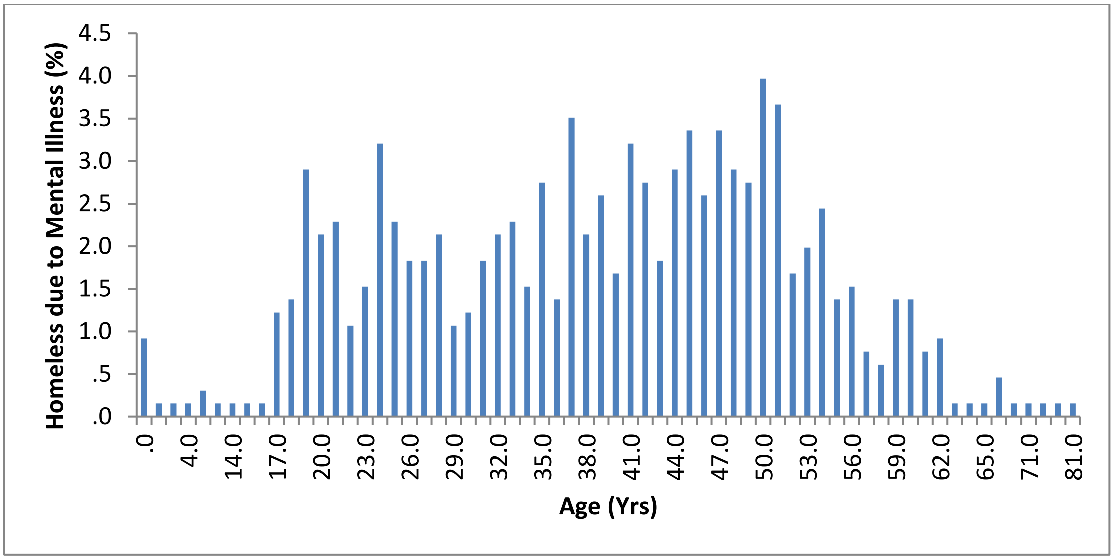

Figure 6.1.3: Age distribution of individuals with mental illness who became homeless.

Table 6.1.29 indicates a very strong positive relationship between mental illness leading to homelessness and the person's marital status. Therefore, on a fuzzy logic scale the Marital Status - Mental Health relationship has been assigned a value of "H-".

Table 6.1.29: Mental Illness - Marital Status relationship (collective).

Marital Status	**Percent**
Married or Common Law	19.4
Single/Divorced/Widowed	80.6

Table 6.1.30 indicates a strong positive relationship between mental illness leading to homelessness and the person's income status. Therefore, on a fuzzy logic scale, the Income Status - Mental Health relationship has been assigned a value of "H-".

Table 6.1.30: Mental Illness - Income Status relationship (collective).

Income Status	**Percent**
No income	13.8
Welfare	86.2

Table 6.1.31 shows that a Caucasian person is much more likely to become homeless as a result of being physically ill as compared to a person belonging to First Nations. Therefore, on a fuzzy logic scale the Ethnic Group - Physical Health relationship has been assigned a value of "M+".

Table 6.1.31: Physical Illness - Ethnic Group relationship (collective).

Ethnic Group	**Percent**
Caucasian	60.8
First Nations	29.6
Others	9.6

Table 6.1.32 indicates a very strong positive relationship between physical illness leading to homelessness and the person's marital status. Therefore, on a fuzzy logic scale the Marital Status - Physical Health relationship has been assigned a value of "H-".

Table 6.1.32: Physical Illness - Marital Status relationship (collective).

Marital Status	**Percent**
Married or Common Law	18.0
Single/Divorced/Widowed	82.0

Now that the most important parameter pairs have been studied and their weights have been generated, the Fuzzy Cognitive Map can be generated. The FCM thus generated is shown in Figure 4.5.4. Here blue and brown lines show positive and negative relationships respectively. The widths of the lines represent the weights. The corresponding weight grid is shown in Figure 6.1.5.

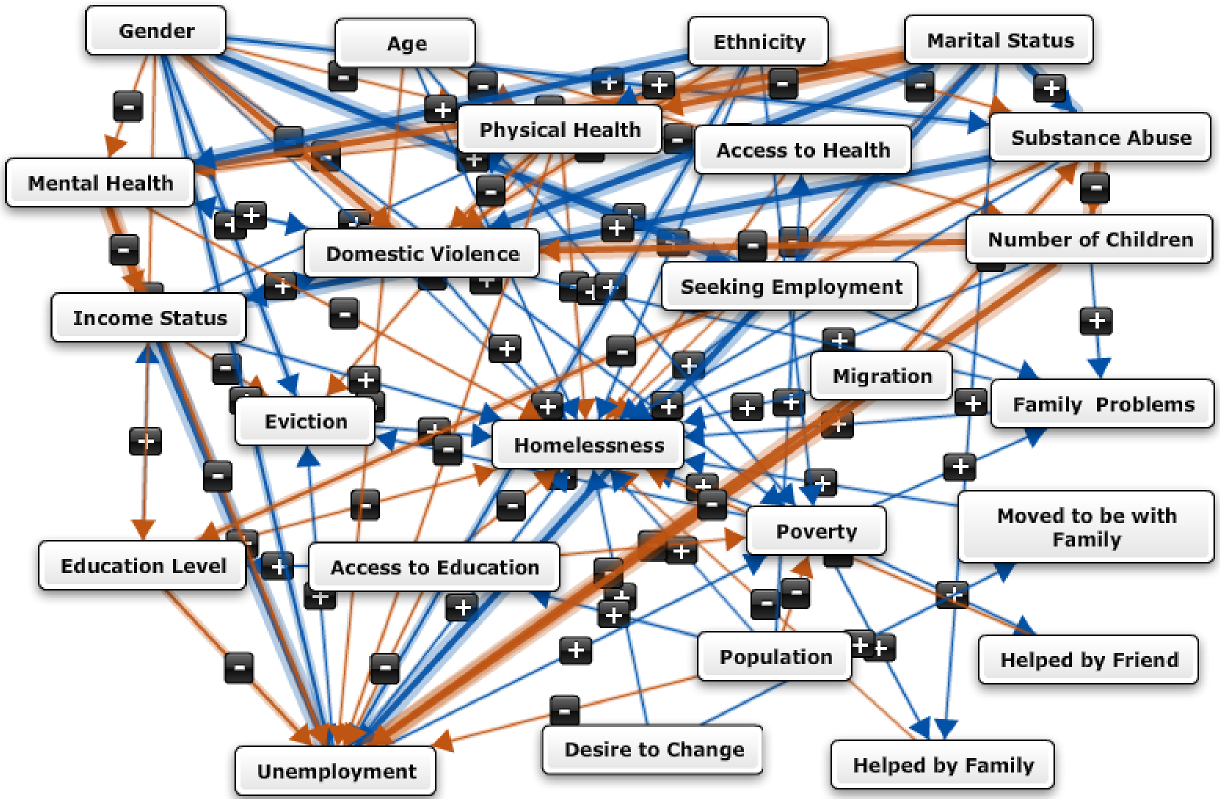

Figure 6.1.4: FCM generated from collective distributions.

	Effect	Value
	H+	1
	M+	0.5
	L+	0.25
		0
	L-	-0.25
	M-	-0.5
➔	H-	-1

	Me...	Ho...	Inc...	Un...	Do...	Ph...	Evi...	Ac...	Nu...	Fa...	Age	Po...	Ma...	He...	Su...	He...	M...	De...	Po...	Ac...	Ed...	Ge...	Se...	Eth...	M...
H...																									
In...		L+		H+	L+	L+	L-																		
Un...		L+					L+					L+													
D...		L+																							
Ph...	L-	L-		L-	M-		L-																		
Evi...		L+																							
Ac...		L-				L-																			
N...		L+		H-	H-					L+															
Fa...	L+	L+																							
Age		L+		L-		L-			L-			L+													
Po...		L+					L+			L+				L+		L+									
M...	H-	L-		H+	H+	H-								L+	H+										
He...		L-																							
Su...		L+	H+						H-												M-				
He...		L-																							
M...		L+																							
De...		L+															L+								
Po...		L+		L-				L+				L-								L+					
Ac...		L-		L-								L-									L+				
Ed...		L-	L+	M-																					
Ge...	L-	L+		M+	H-	L-	M+			L+		L+			M+						L-		H+		
Se...		L+																							
Et...	H+	L+		M+	M-	L+						L+			L-										
➔ Mi...		L+		H-											M-										

Figure 6.1.5: Weight grid of the FCM generated from collective distributions.

The effects of different parameters on homelessness can now be studied. Figure 6.1.6 shows the effect of increasing physical and mental health of individuals. It can be seen that betterment in physical and mental health has a significant impact on reducing homelessness (8% reduction).

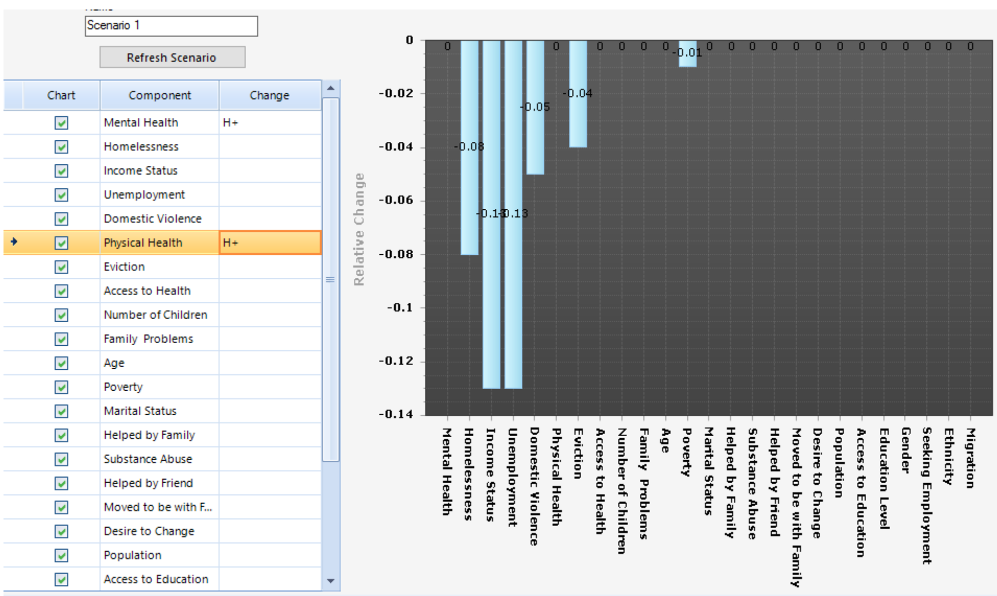

Figure 6.1.6: Effects of betterment in physical and mental health of individuals.

Figure 6.1.7 shows that lowering unemployment is expected to decrease homelessness by about 5%. At the same time, it also has positive effects of reducing poverty and eviction.

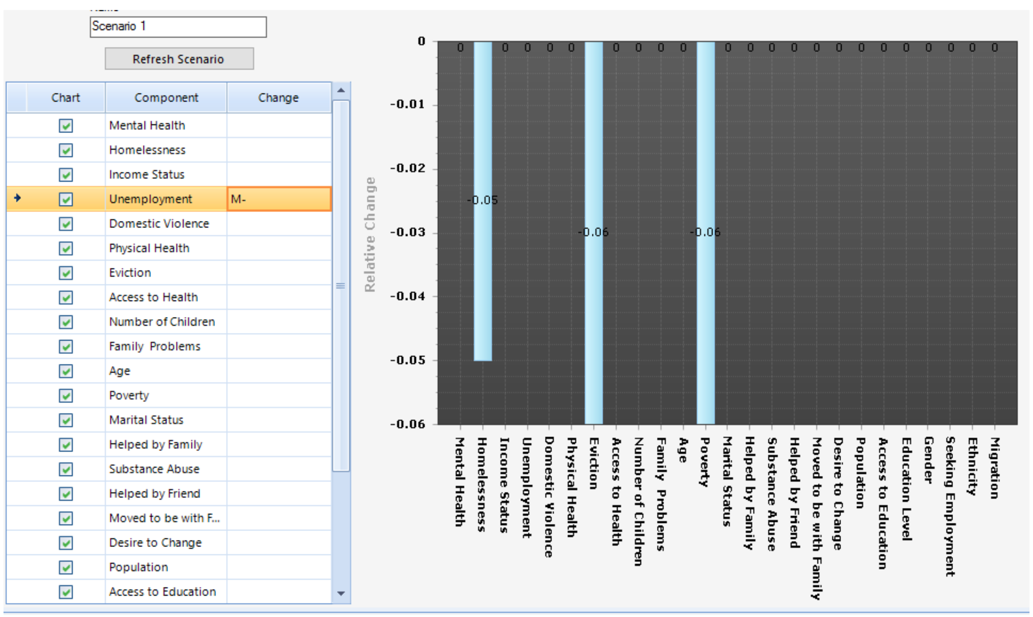

Figure 6.1.7: Effects of lowering unemployment.

Figure 6.1.8 depicts that decreasing family problems has a positive impact on reducing homelessness as much as 5%. This indicates usefulness of family counseling and related services.

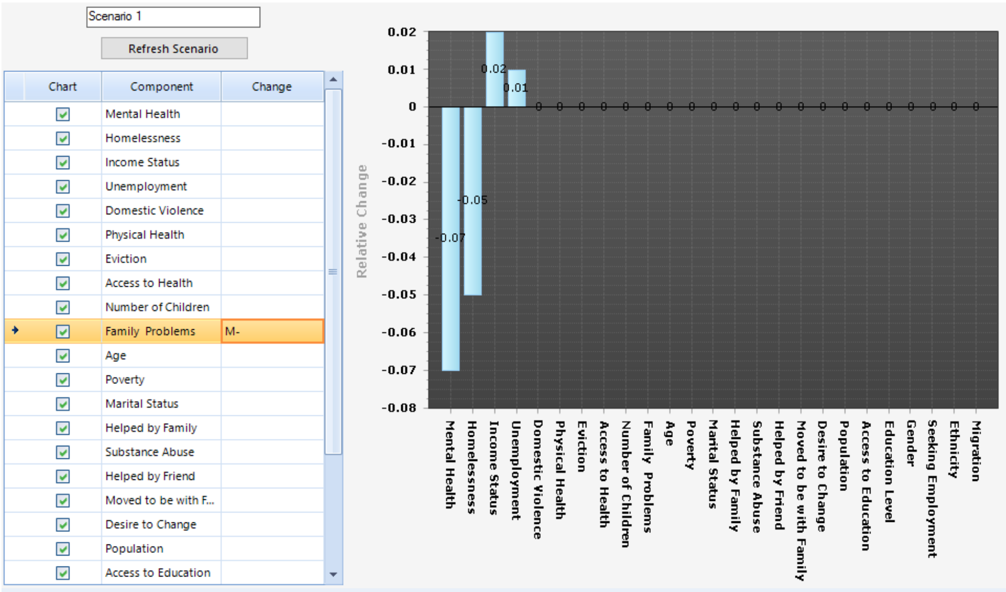

Figure 6.1.8: Effects of decrease in family issues.

Figure 6.1.9 shows that increasing access to education has a positive impact of reducing homelessness by as much as 3%.

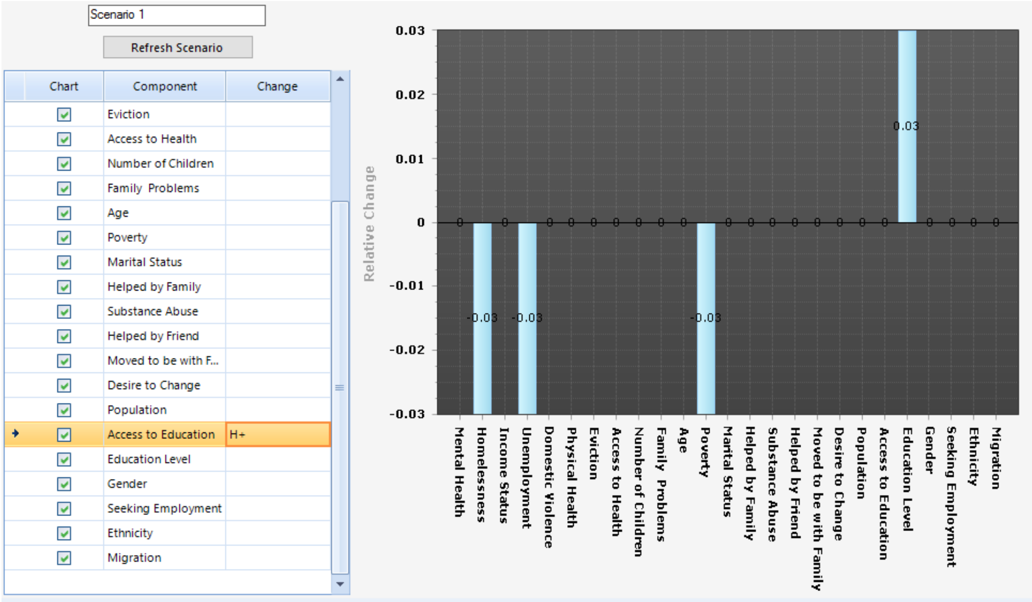

Figure 6.1.9: Effects of increasing access to education.

6.2 Spatial Analyses

6.2.1 Spatial Variation of Variables

The analyses carried out in the previous section were based on collective distributions of all areas and all data gathering periods. It was hypothesized earlier that the paths to homelessness have strong spatial dependence, which means that the values of the variables should also show significant spatial variations. In order to see if there are significant differences between values of variables in different locations and times as compared to collective values, their relative differences were calculated using the following formula.

$$Relative\ Difference\ (\%) = \frac{Local\ Value - Collective\ Value}{Local\ Value} \times 100$$

Table 6.2.1 shows the relative differences calculated for the eviction-gender relationships in different communities. The resulting graph is shown in Figure 6.2.1. It is clear that there are significant variations in relative differences across different communities.

Table 6.2.1: Eviction - Gender relationships in different communities and their relative differences as compared to collective values.

Location	**Study Year**	**Female (%)**	**Male (%)**	**Relative Difference Female (%)**	**Relative Difference Male (%)**	**Comments**
Sudbury	2009	43.2	55.4	8.3	-8.7	
Timmins	2011	45.3	54.7	12.6	-10.1	
Hearst	2011	0	100			Low statistics - Excluded
Moosonee	2012	52.6	47.4	24.7	-27.0	
Cochrane	2013	31.3	68.7	-26.5	12.4	
	Collective	**39.6**	**60.2**			

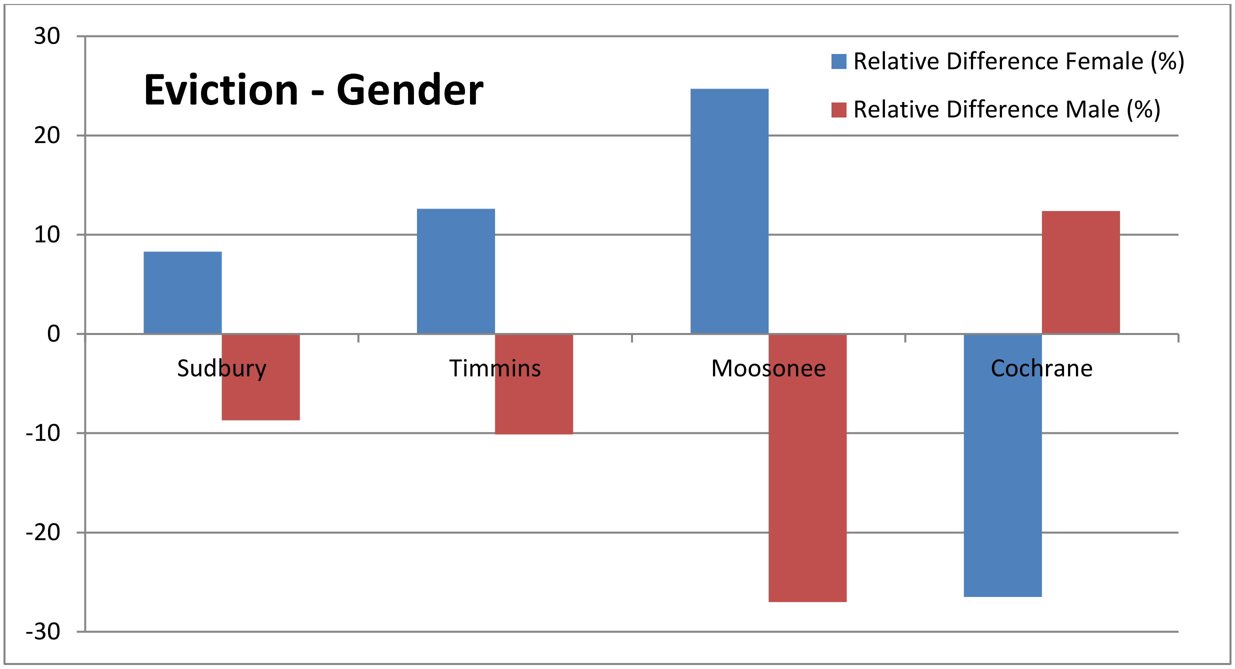

Figure 6.2.1: Relative differences as compared to collective distributions for eviction-gender relationships in different communities.

Table 6.2.2 shows the relative differences for the unemployment-gender relationships in different communities. The graph of relative differences is shown in Figure 6.2.2.

Table 6.2.2: Unemployment - Gender relationships in different communities and their relative differences as compared to collective values.

Location	Study Year	Female (%)	Male (%)	Relative Difference Female (%)	Relative Difference Male (%)	Comments
Sudbury	2009	33.7	65.7	-10.7	4.7	
Timmins	2011	49.3	50.7	24.3	-23.5	
Hearst	2011		100			Low statistics
Moosonee	2012	40	60	6.8	-4.3	
Cochrane	2013	26.7	73.3	-39.7	14.6	
	Collective	**37.3**	**62.6**			

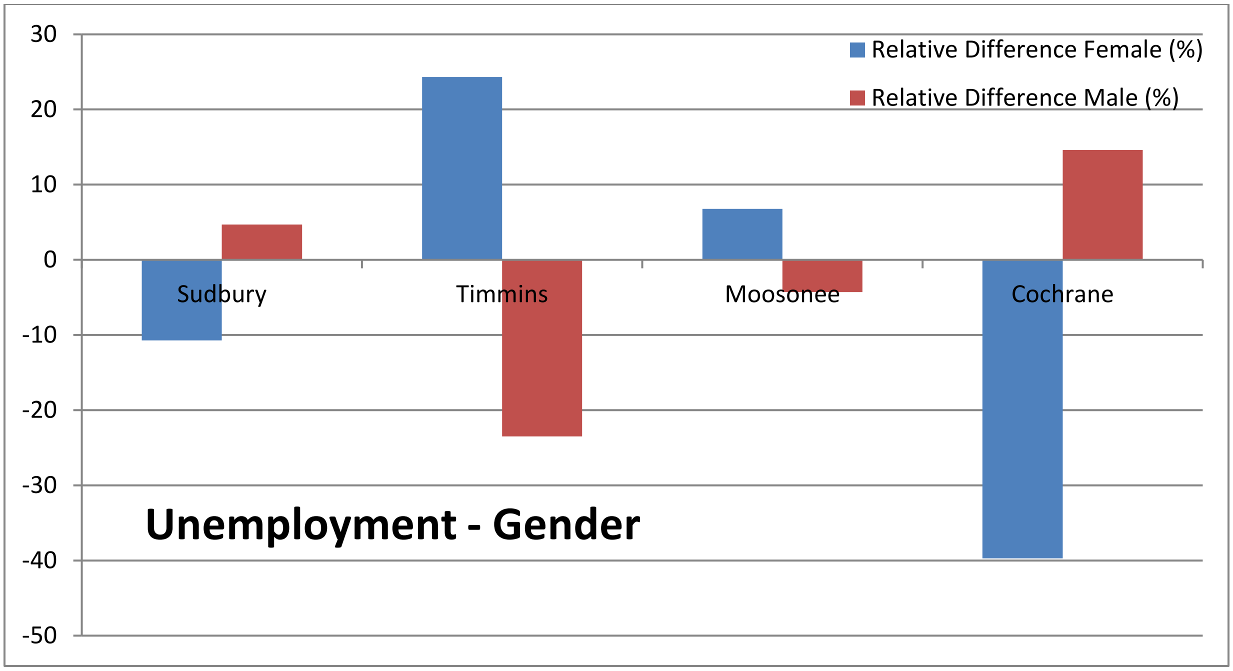

Figure 6.2.2: Relative differences as compared to collective distributions for unemployment-gender relationships in different communities.

The relative differences for the seeking employment-gender relationships are shown in Table 6.2.3 and the corresponding chart in Figure 6.2.3.

Table 6.2.3: Seeking Employment - Gender relationships in different communities and their relative differences as compared to collective values.

Location	Study Year	Female (%)	Male (%)	Relative Difference Female (%)	Relative Difference Male (%)	Comments
Sudbury	2009	33.3	66.7	18.6	-9.3	
Timmins	2011	41.5	58.5	34.7	-24.6	
Hearst	2011	45.5	54.5	40.4	-33.8	
Moosonee	2012	46.7	53.3	42.0	-36.8	
Cochrane	2013	40.9	59.1	33.7	-23.4	
	Collective	**27.1**	**72.9**			

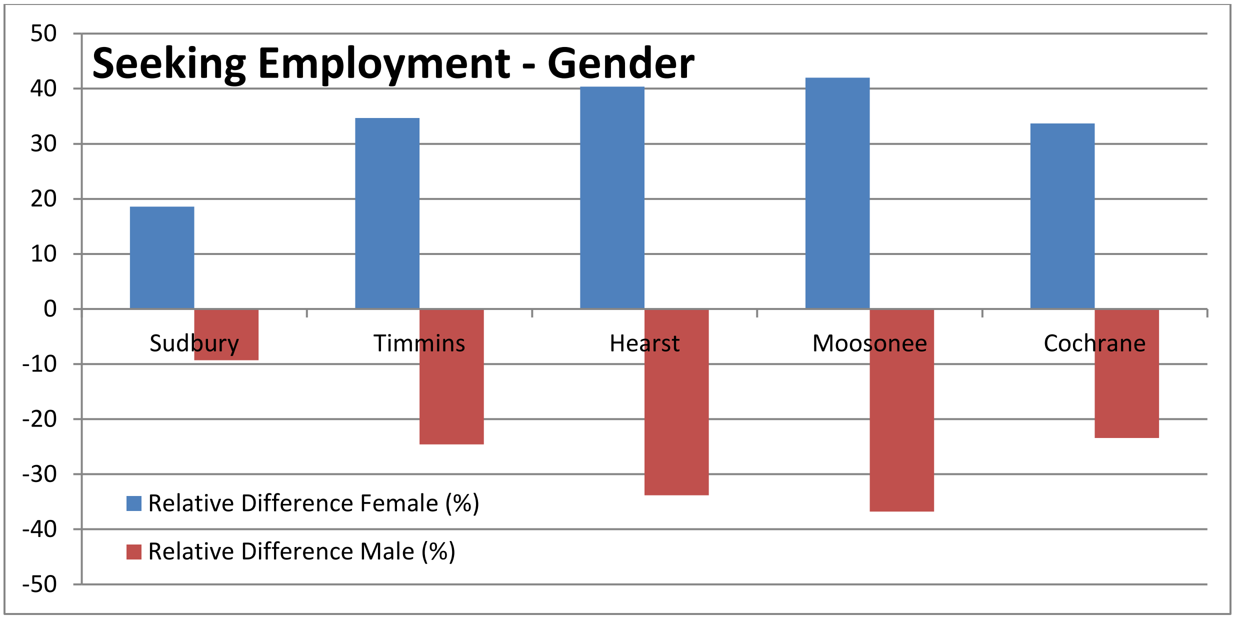

Figure 6.2.3: Relative differences as compared to collective distributions for seeking employment-gender relationships in different communities.

Table 6.2.4 shows the relative differences for the substance abuse-gender relationships in different communities. The corresponding relative difference chart is shown in Figure 6.2.4.

Table 6.2.4: Substance Abuse - Gender relationships in different communities and their relative differences as compared to collective values.

Location	**Study Year**	**Female (%)**	**Male (%)**	**Relative Difference Female (%)**	**Relative Difference Male (%)**	**Comments**
Sudbury	2009	37.8	62.2	0	0	
Timmins	2011	42.1	57.9	10.2	-7.4	
Hearst	2011	33.3	66.7	-13.5	6.7	
Moosonee	2012	45.5	54.5	16.9	-14.1	
Cochrane	2013	40	60	5.5	-3.7	
	Collective	**37.8**	**62.2**			

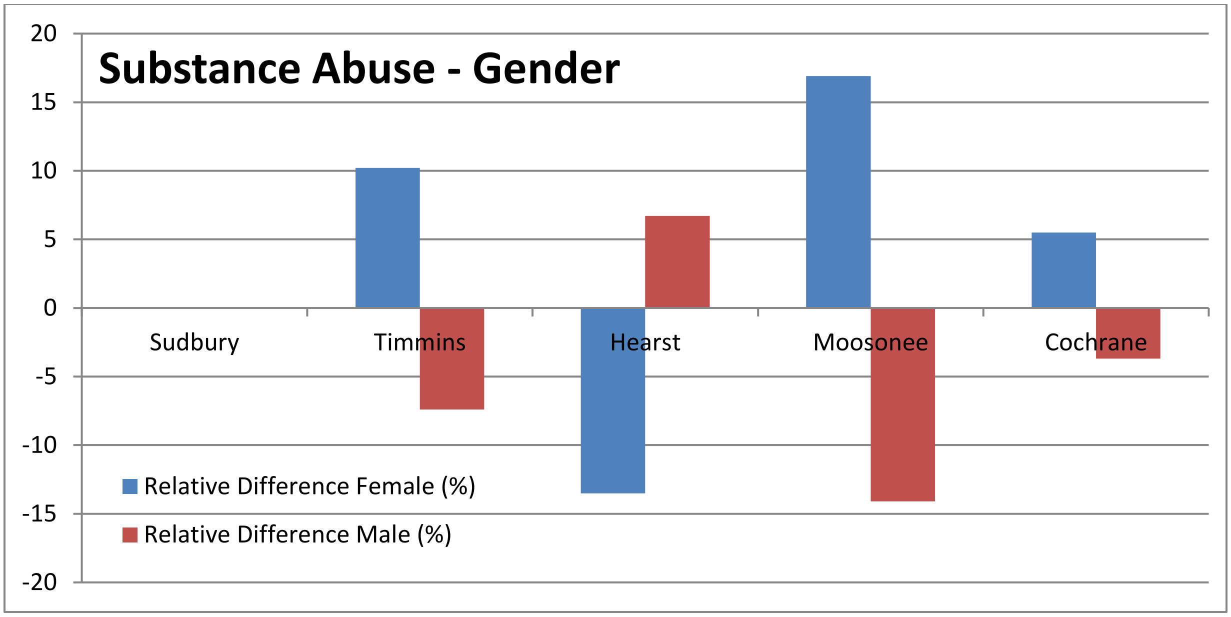

Figure 6.2.4: Relative differences as compared to collective distributions for substance abuse-gender relationships in different communities.

Table 6.2.5 shows the relative differences for mental illness-gender relationships in different communities and the respective chart is depicted in Figure 6.2.5.

Table 6.2.5: Mental Illness - Gender relationships in different communities and their relative differences as compared to collective values.

Location	Study Year	Female (%)	Male (%)	Relative Difference Female (%)	Relative Difference Male (%)	Comments
Sudbury	2009	37.1	62.9	-27.5	16.2	
Timmins	2011	53.4	46.6	11.4	-13.1	
Hearst	2011	40	60	-18.3	12.2	Low statistics
Moosonee	2012	66.7	33.3	29.1	-58.3	
Cochrane	2013	58.8	41.2	19.6	-27.9	
	Collective	**47.3**	**52.7**			

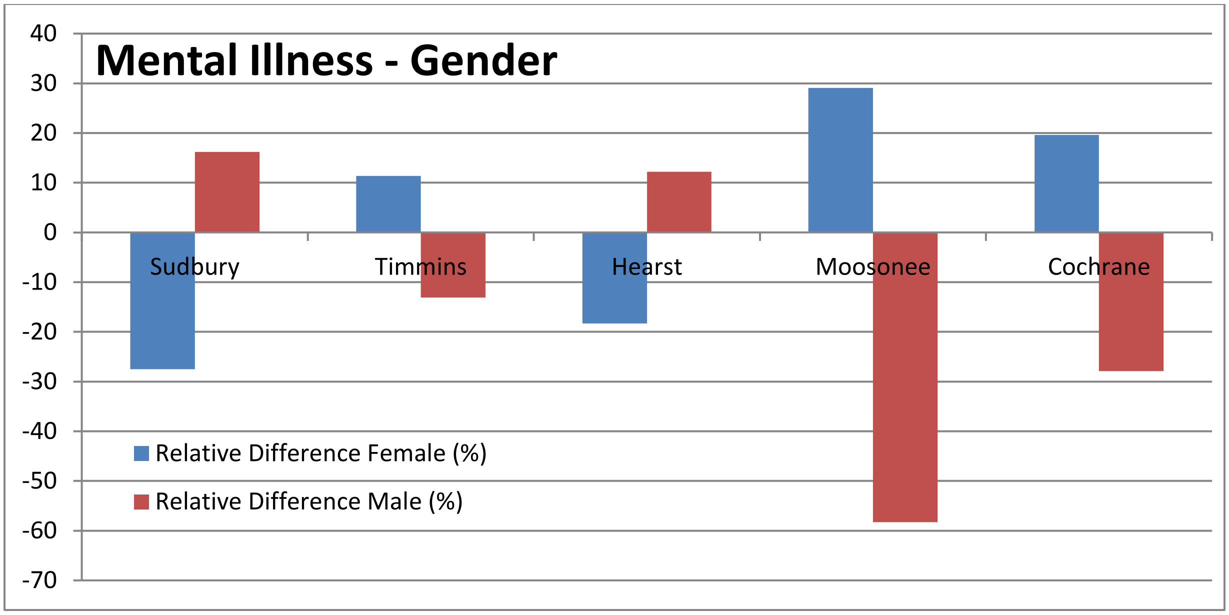

Figure 6.2.5: Relative differences as compared to collective distributions for mental illness-gender relationships in different communities.

It is apparent from all of the above relative difference tables and charts that the values of parameters show significant differences in different locations. Therefore, it is safe to conclude that using collective values will not faithfully represent all of Northern Ontario. Hence the hypothesis is correct and the parameters at different locations should be studied individually.

6.2.2 Absolute Homelessness

During the interviewing phase, it was also established whether the interviewee met the definition of absolute homeless or not. To further understand spatial variations, the distributions of different variables for individuals who were termed as absolute homeless were analyzed. The rationale for this analysis was to determine if the conclusion about significant variation in parameters with respect to location was correct or not. It is important to note that the distributions generated and shown in the first part of this Chapter were not generated with the filter for absolute homelessness.

Figure 6.2.6 shows the age distributions of individuals in different communities who passed the criteria of absolute homelessness. It is clear that the distributions show significant spatial variations.

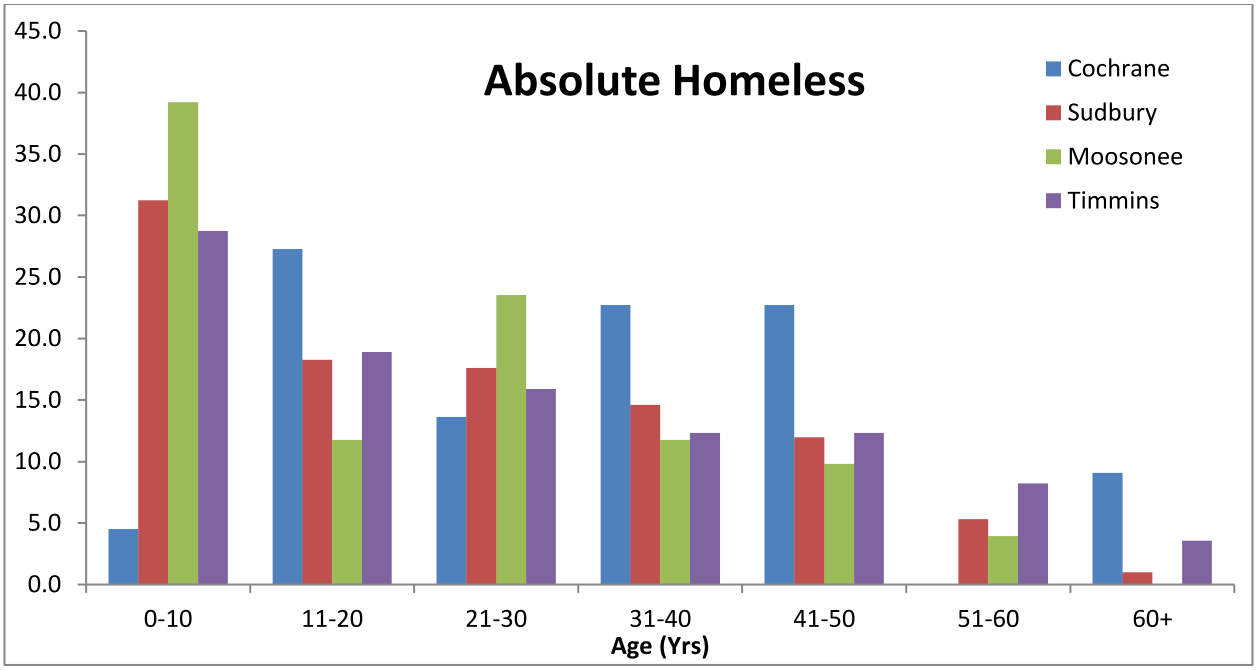

Figure 6.2.6: Age distributions of individuals deemed to be absolute homeless in different communities.

The marital status distributions of individuals in different communities that were found to be absolute homeless are shown in Figure 6.2.7.

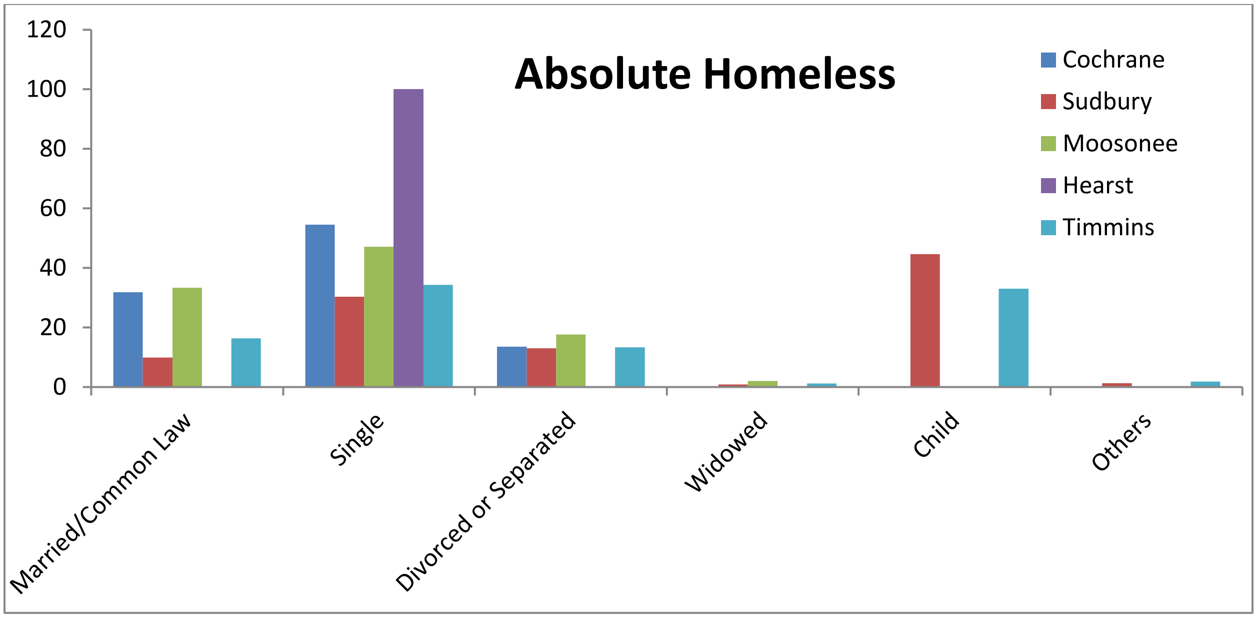

Figure 6.2.7: Marital status distributions of individuals deemed to be absolute homeless in different communities.

Figure 6.2.8 shows the ethnicity distributions of the individuals termed as absolute homeless in different communities.

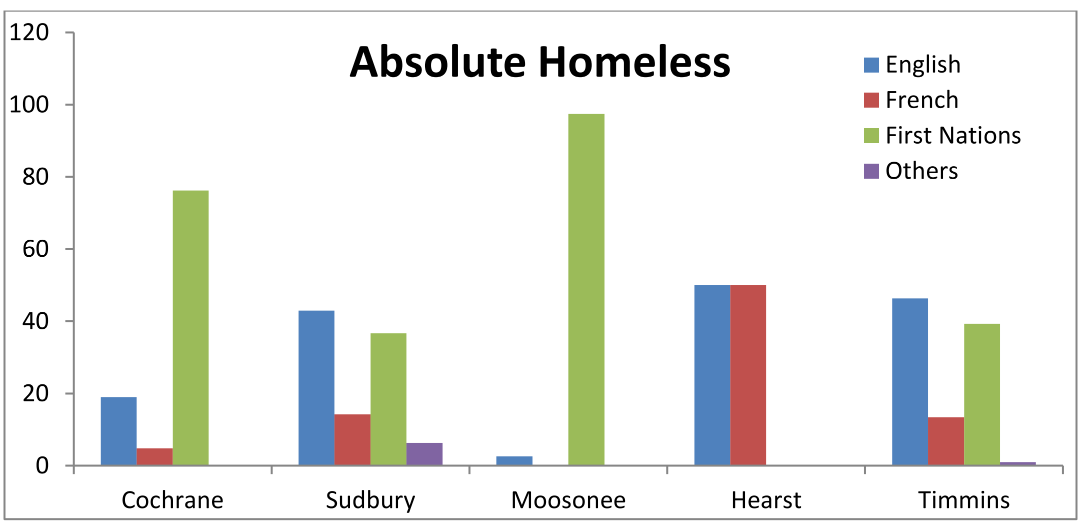

Figure 6.2.8: Ethnicity distributions of individuals deemed to be absolute homeless in different communities.

It is apparent from these distributions that the right approach would be to analyze data for different localities and for different time periods separately.

6.3 Fuzzy Cognitive Maps from Individual Distributions

The necessity to perform FCM-based analyses on individual communities has now been established. For this the following datasets were individually analyzed.

- Moosonee - 2012
- Cochrane - 2013
- Timmins - 2011
- Hearst - 2011
- Sudbury - 2009

The reason for choosing Sudbury 2009 dataset was to minimize effect of temporal change in parameters since all other data for Sudbury belonged to previous years. The data were filtered through the built-in functions in SPSS and then manually entered into spread sheets. The fuzzy logic levels for each scenario were then estimated using the same methodology that was used for collective distributions. The tables thus generated for different communities are given below.

6.3.1 Fuzzy Logic Levels

At this stage of the study the Mental Modeler software had been further developed and allowed the fuzzy logic levels to assume any value between -1 and +1. Therefore, instead of using the previous approach of constructing distributions and assigning one of six discrete levels, the Pearson correlation coefficient value was used instead. Incidentally the correlation coefficient assumes a value between -1 and +1 as well and thus the value could be directly assigned to build the FCM. The Pearson correlation coefficients between different variables were calculated in the SPSS software. The matrices below show their values for different localities.

Table 6.3.1: Pearson correlation coefficients between different variables in Sudbury for data collected in 2009.

Sudbury 2009	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	0.222								
Ethnicity	.025	0							
Education	0	0	0						
Employment	0	0	0	0					
Mental Health	0.198	-0.208	-0.104	0	0				
Physical Health	0.044	-0.376	-0.041	0	0	0.327			
Number of Kids	-0.231	0.218	0.242	0	0	-0.132	-0.207		
Homelessness	0.072	0.092	-0.152	0	0	0.059	0.135	-0.176	
Migration	0.040	0.068	0.096	0	0	0-.066	-0.162	0	-0.235

Table 6.3.2: Pearson correlation coefficients between different variables in Timmins for data collected in 2011.

Timmins 2011	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	-0.023								
Ethnicity	-0.009	-0.136							
Education	-0.097	0.033	-0.110						
Employment	-0.026	-0.021	-0.015	-0.134					
Mental Health	0.030	-0.050	0.088	-0.067	0.021				
Physical Health	-0.021	-0.302	0.052	-0.014	0.019	0.262			
Number of Kids	-0.145	0.043	0.105	-0.103	0	0.050	-0.006		
Homelessness	-0.027	0.104	-0.086	0.079	0.015	0.022	-0.045	-0.013	
Migration	0.064	-0.016	0.083	0.041	-0.027	0.087	0.09	0.013	-0.123

Table 6.3.3: Pearson correlation coefficients between different variables in Hearst for data collected in 2011.

Hearst 2011	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	-0.039								
Ethnicity	0.018	-0.111							
Education	-0.085	-0.247	-0.084						
Employment	0.069	0.425	0.110	-0.323					
Mental Health	-0.001	0.113	-0.035	0.088	-0.111				
Physical Health	0.077	-0.321	-0.017	0.121	-0.363	0.155			
Number of Kids	-0.222	0.424	0.030	-.101	0	0.105	-0.143		
Homelessness	-0.112	0.014	-0.161	0.035	-0.018	-0.030	-0.071	0.090	
Migration	0.048	0.033	-0.059	-0.036	0.094	-0.010	-0.032	-0.107	-0.083

Table 6.3.4: Pearson correlation coefficients between different variables in Moosonee for data collected in 2012.

Moosonee 2012	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	0.060								
Ethnicity	0.057	-0.086							
Education	0.060	-0.123	-0.252						
Employment	-0.081	0.128	0.19	-0.409					
Mental Health	0.013	-0.050	-0.036	0.048	-0.182				
Physical Health	-0.063	-0.098	-0.042	-0.008	-0.023	0.353			
Number of Kids	-0.064	0.285	0.099	-0.18	0	-0.031	-0.054		
Homelessness	-0.092	0.020	-0.023	0.051	-0.106	0.139	0.162	-0.015	
Migration	0.101	-0.007	0.070	-0.002	0.054	-0.128	-0.114	-0.060	-0.053

Table 6.3.5: Pearson correlation coefficients between different variables in Cochrane for data collected in 2009.

Cochrane 2013	**Gender**	**Age**	**Ethnicity**	**Education**	**Employment**	**Mental Health**	**Physical Health**	**Number of Kids**	**Homelessness**
Age	-0.144								
Ethnicity	0.067	-0.283							
Education	0.008	-0.151	-0.020						
Employment	-0.024	0.307	-0.021	-0.361					
Mental Health	0.107	0.061	-0.002	0.034	-0.073				
Physical Health	0.088	-0.247	0.012	-0.011	-0.197	0.196			
Number of Kids	-0.021	0.040	0.194	0.032	0	0.047	-0.037		
Homelessness	-0.060	0.021	-0.07	0.113	-0.122	0.038	-0.061	-0.003	
Migration	0.023	-0.127	0.198	0.055	-0.041	-0.055	-0.002	0.021	-0.087

As mentioned before, there is a 1:1 correspondence between correlation coefficients and fuzzy logic levels. Both represent the influence of one parameter on the other with a value between -1 and +1. Therefore, the correlation coefficient values can be directly used as fuzzy logic values in the Mental Modeler software after rounding the numbers to two significant digits as per data input requirements of the software. The following tables thus represent the fuzzy logic levels deduced from the correlation coefficient tables.

Table 6.3.6: Fuzzy logic levels between different variables in Sudbury for data collected in 2009.

Sudbury 2009	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	0.22								
Ethnicity	0.03	0							
Education	0	0	0						
Employment	0	0	0	0					
Mental Health	0.20	-0.21	-0.10	0	0				
Physical Health	0.04	-0.38	-0.04	0	0	0.33			
Number of Kids	-0.23	0.22	0.24	0	0	-0.13	-0.21		
Homelessness	0.07	0.09	-0.15	0	0	0.06	0.14	-0.18	
Migration	0.04	0.07	0.10	0	0	-0.07	-0.16	0	-0.24

Table 6.3.7: Fuzzy logic levels between different variables in Timmins for data collected in 2011.

Timmins 2011	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	-0.02								
Ethnicity	-0.01	-0.14							
Education	-0.10	0.03	-0.11						
Employment	-0.03	-0.02	-0.06	-0.13					
Mental Health	0.03	-0.05	0.09	-0.07	0.02				
Physical Health	-0.02	-0.30	0.05	-0.01	0.02	0.26			
Number of Kids	-0.15	0.04	0.11	-0.10	0	0.05	-0.01		
Homelessness	-0.03	0.10	-0.09	0.08	0.02	0.02	-0.05	-0.01	
Migration	0.06	-0.02	0.08	0.04	-0.03	0.09	0.09	0.01	-0.12

Table 6.3.8: Fuzzy logic levels between different variables in Hearst for data collected in 2011.

Hearst 2011	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	-0.04								
Ethnicity	0.02	-0.11							
Education	-0.09	-0.25	-0.08						
Employment	0.07	0.43	0.11	-0.32					
Mental Health	0	0.11	-0.04	0.09	-0.11				
Physical Health	0.08	-0.32	-0.02	0.12	-0.36	0.16			
Number of Kids	-0.22	0.42	0.03	-0.10	0	0.11	-0.14		
Homelessness	-0.11	0.01	-0.16	0.04	-0.02	-0.03	-0.07	0.09	
Migration	0.05	0.03	-0.06	-0.04	0.09	-0.01	-0.03	-0.11	-0.08

Table 6.3.9: Fuzzy logic levels between different variables in Moosonee for data collected in 2012.

Moosonee 2012	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	0.06								
Ethnicity	0.06	-0.09							
Education	0.06	-0.12	-0.25						
Employment	-0.08	0.13	0.19	-0.41					
Mental Health	0.01	-0.05	-0.04	0.05	-0.18				
Physical Health	-0.06	-0.10	-0.04	-0.01	-0.02	0.35			
Number of Kids	-0.06	0.29	0.10	-0.18	0	-0.03	-0.05		
Homelessness	-0.09	0.02	-0.02	0.05	-0.11	0.14	0.16	-0.02	
Migration	0.10	-0.01	0.07	0	0.05	-0.13	-0.11	-0.06	-0.05

Table 6.3.10: Fuzzy logic levels between different variables in Cochrane for data collected in 2009.

Cochrane 2013	Gender	Age	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Homelessness
Age	-0.14								
Ethnicity	0.07	-0.28							
Education	0.01	-0.15	-0.02						
Employment	-0.02	0.31	-0.02	-0.36					
Mental Health	0.11	0.06	0	0.03	-0.07				
Physical Health	0.09	-0.25	0.01	-0.01	-0.20	0.20			
Number of Kids	-0.02	0.04	0.19	0.03	0	0.05	-0.04		
Homelessness	-0.06	0.02	-0.07	0.11	-0.12	0.04	-0.06	0	
Migration	0.02	-0.13	0.20	0.06	-0.04	-0.06	0	0.02	-0.09

Looking at the above tables it becomes apparent that the correlation coefficients and fuzzy levels for different localities show significant variations. To understand this visually, maps of some of these variables were generated. Figure 6.3.1 shows the map of correlation coefficients between age and homelessness. The first thing worth noting here is that there is fairly weak positive correlation in all areas. The second is that there seems to be lower correlation in the upper north as compared to the lower north. This indicates that an individual in the upper north is more likely to become homeless as compared to an individual of the same age in lower north.

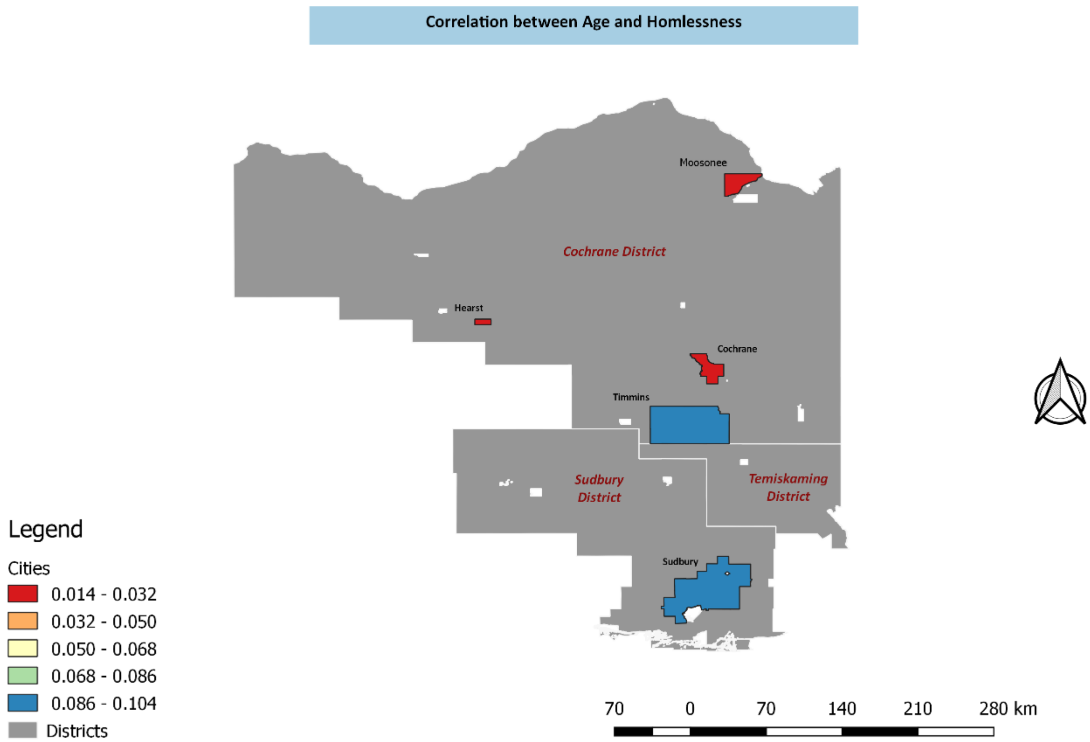

Figure 6.3.1: Map of correlation coefficient between age and homelessness in different cities.

Figure 6.3.2 shows the map of correlation coefficients between ethnicity and homelessness. Note that here Caucasians were assigned a value of 1 and First Nations a value of 2. This means that a Native person in all of these areas is more likely to become homeless as compared to a Caucasian person. The other important thing to note here is that there does not seem to be any spatial dependence on the correlation coefficient. The values seem to be spread over all cities randomly.

The map in Figure 6.3.3 shows very weak positive correlation between gender and homelessness in Sudbury and very weak negative correlation in all the other areas. Also, the values seem to be randomly distributed.

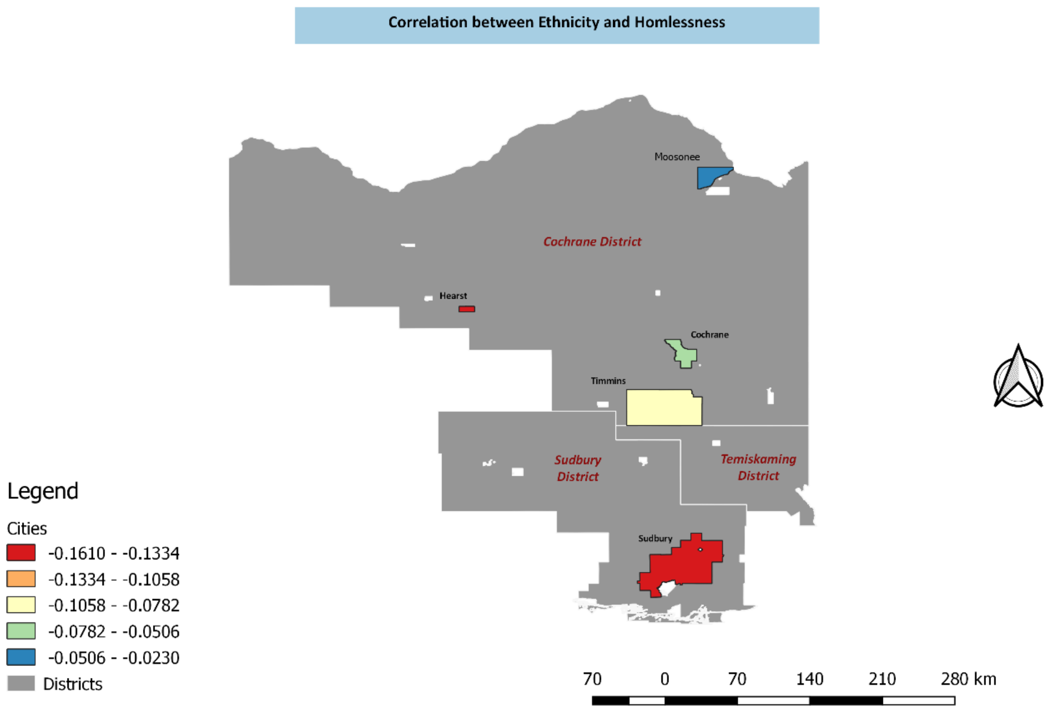

Figure 6.3.2: Map of correlation coefficient between ethnicity and homelessness in different cities.

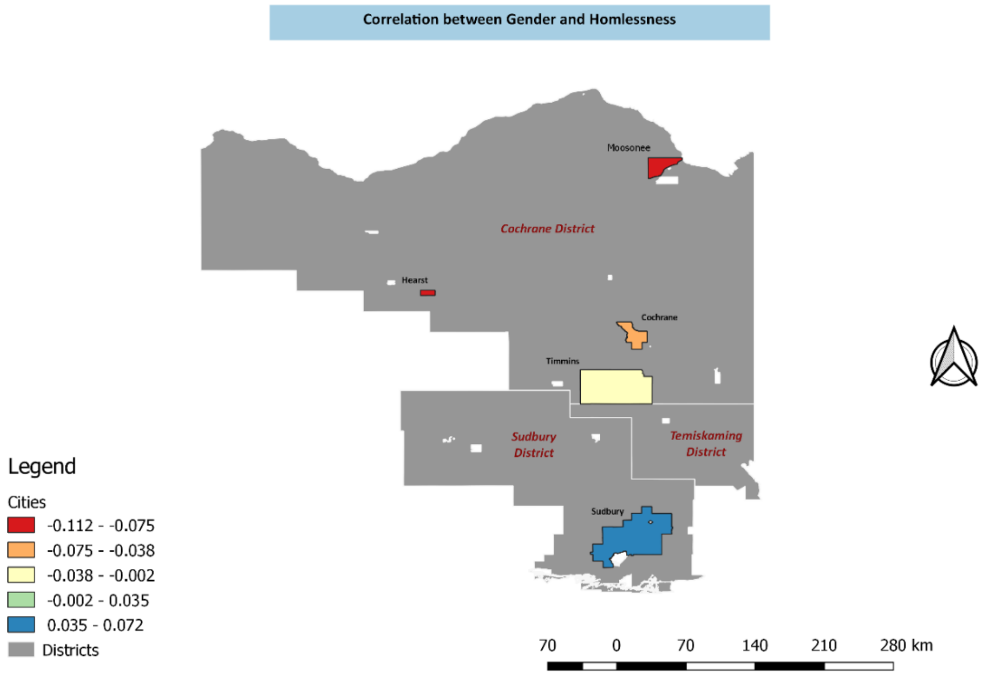

Figure 6.3.3: Map of correlation coefficient between gender and homelessness in different cities.

The map in Figure 6.3.4 depicts the correlation between mental health issues and homelessness. Here a significant positive correlation can be observed in the Moosonee area, which is located in the far upper north. There can be many factors causing this including overall social and financial conditions as well as lack of proper mental health facilities. The correlation coefficient in Hearst is very weakly negative while in all other areas it is weakly positive.

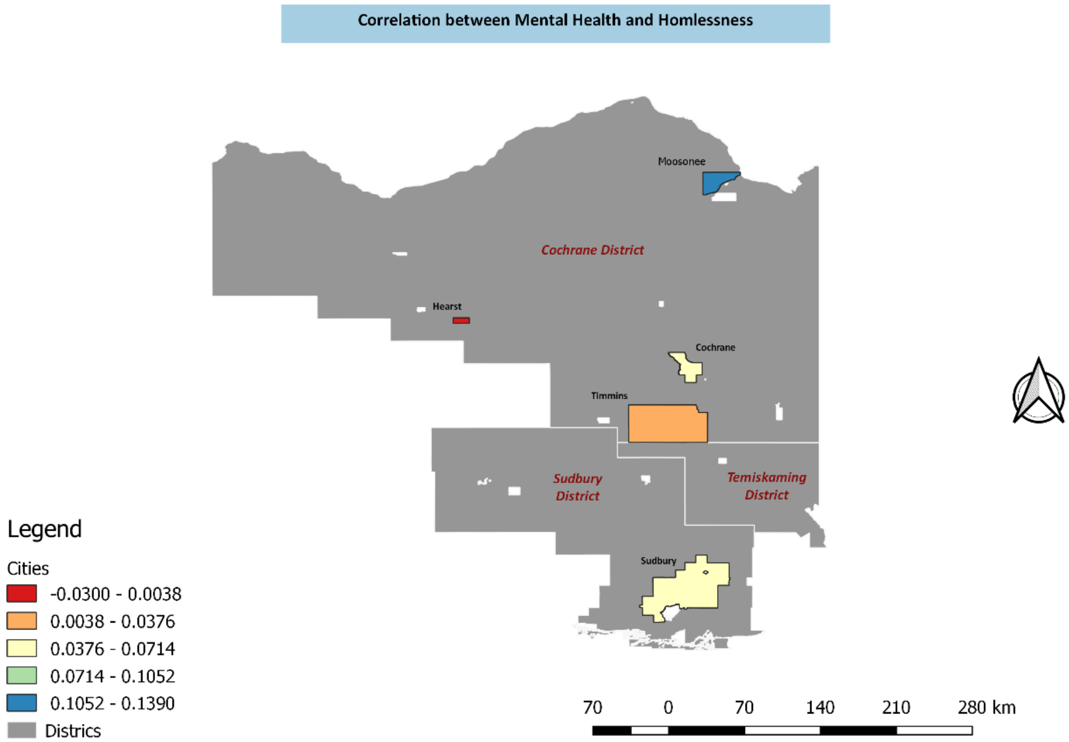

Figure 6.3.4: Map of correlation coefficient between mental health and homelessness in different cities.

The correlation between migration and homelessness is depicted in the map of Figure 6.3.5. Though the correlation is negative in all areas, the degree of anti-correlation seems to decrease from south to north with highest negative value in Sudbury and lowest in Moosonee.

Figure 6.3.6 shows the map of the correlation coefficient between physical health and homelessness. It is obvious that there is weak negative correlation in the mid north while significant positive correlation in the lower and upper north, that is in Sudbury and Moosonee.

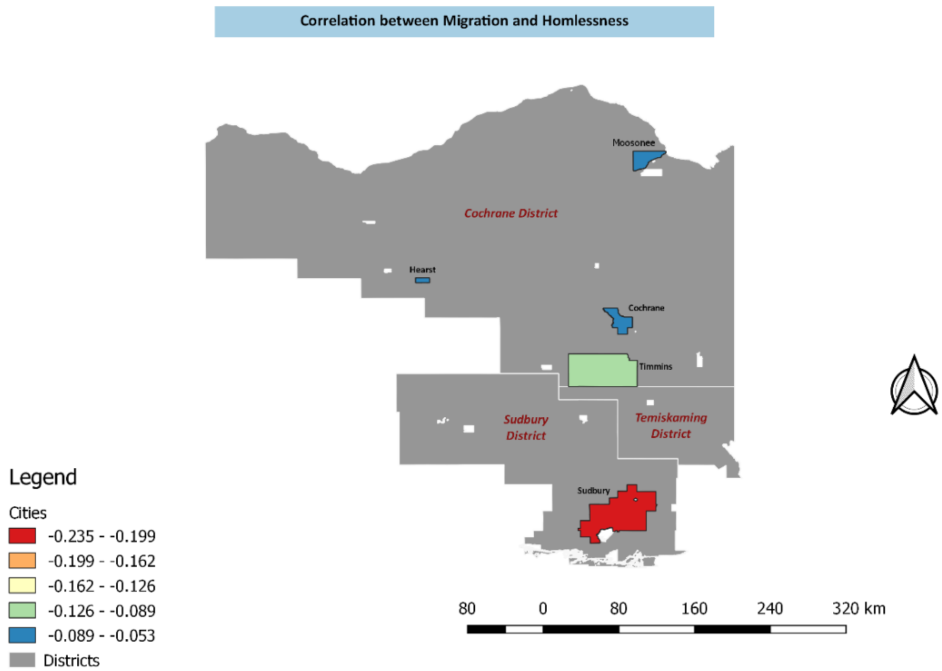

Figure 6.3.5: Map of correlation coefficient between migration and homelessness in different cities.

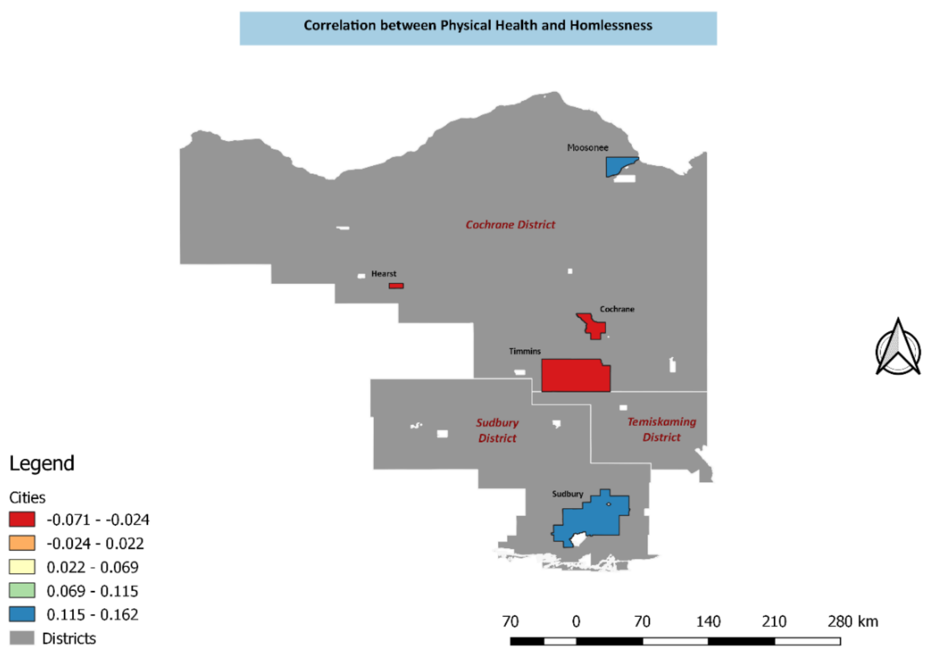

Figure 6.3.6: Map of correlation coefficient between physical health and homelessness in different cities.

6.3.2 Fuzzy Cognitive Maps

The Fuzzy Cognitive Maps were generated in the Mental Modeler software using the fuzzy levels listed in Tables 6.3.6 to 6.3.10. These FCMs are shown below in Figures 6.3.7 to Figure 6.3.11. It should be noted that the map for Sudbury has smaller number of variables as compared to the maps of other areas. Those are the variables which showed no correlation with other variables.

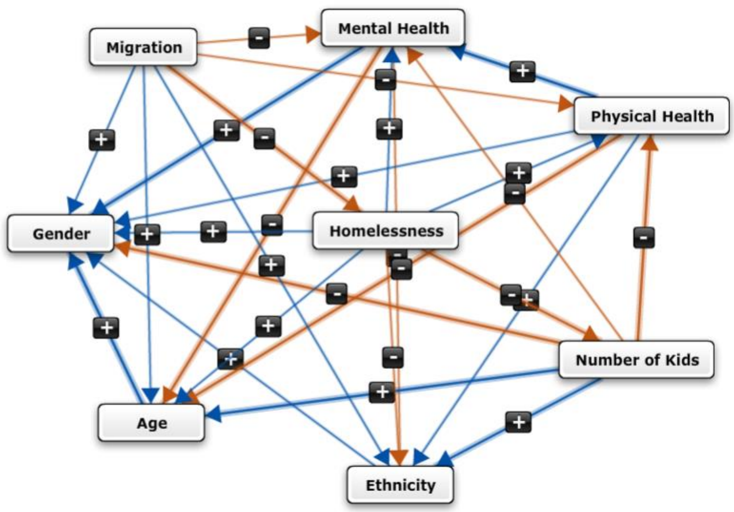

Figure 6.3.7: Fuzzy cognitive map for Sudbury for data gathered in 2009. Here blue and brown lines show positive and negative relationships respectively. The widths of the lines represent the fuzzy levels.

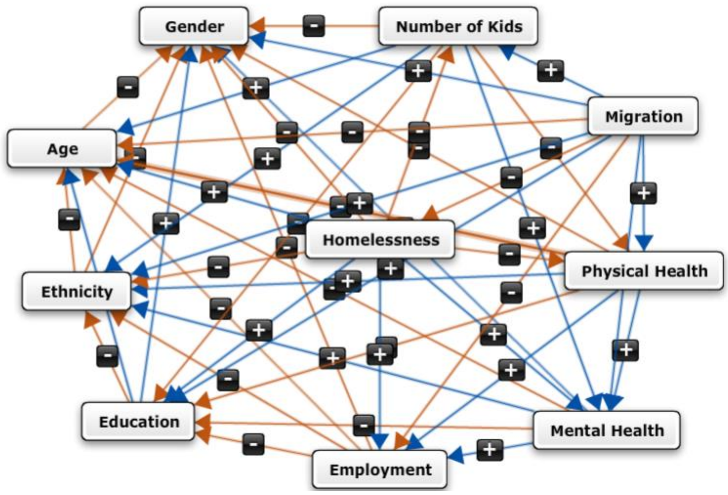

Figure 6.3.8: Fuzzy cognitive map for Timmins for data gathered in 2011. Here blue and brown lines show positive and negative relationships respectively. The widths of the lines represent the fuzzy levels.

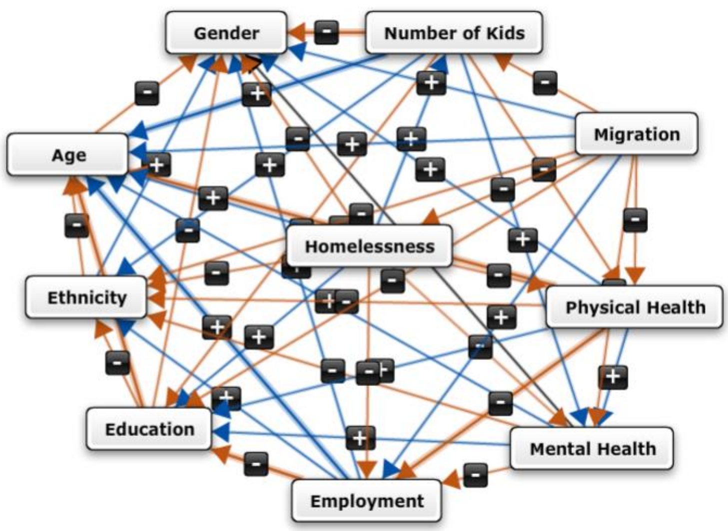

Figure 6.3.9: Fuzzy cognitive map for Hearst for data gathered in 2011. Here blue and brown lines show positive and negative relationships respectively. The widths of the lines represent the fuzzy levels.

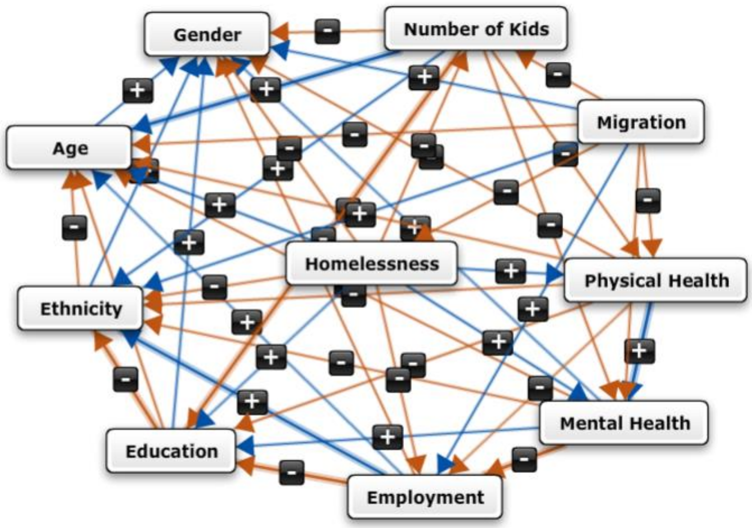

Figure 6.3.10: Fuzzy cognitive map for Moosonee for data gathered in 2012. Here blue and brown lines show positive and negative relationships respectively. The widths of the lines represent the fuzzy levels.

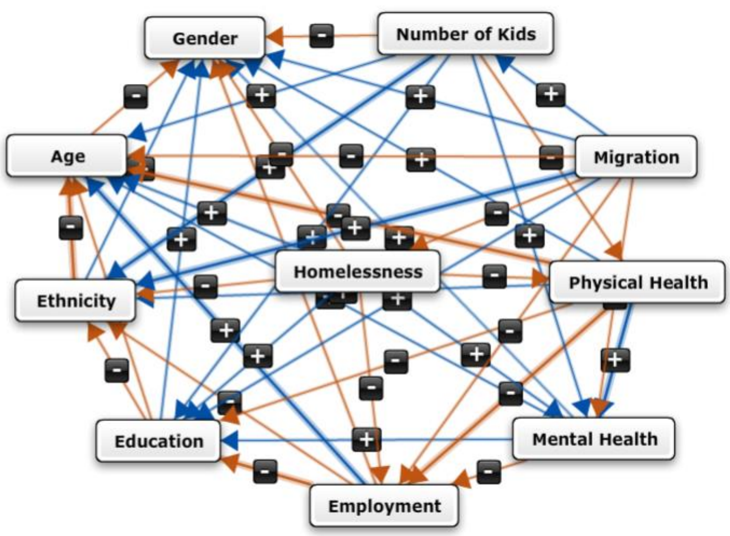

Figure 6.3.11: Fuzzy cognitive map for Cochrane for data gathered in 2009. Here blue and brown lines show positive and negative relationships respectively. The widths of the lines represent the fuzzy levels.

In the next Chapter, these Fuzzy Cognitive Maps will be used to perform sensitivity analyses needed to establish indices of homelessness for the study areas and to determine if the pathways to homelessness have any spatial dependence.

7 DATA ANALYSIS – SENSITIVITY ANALYSIS AND HOMELESSNESS INDEX

7.1 Sensitivity Analyses

To perform the sensitivity analyses, the "Scenario" function of the Mental Modeler software was used. This function allowed calculation of change in different variables with respect to the change in a variable. For this analysis, homelessness was used as the central variable and effects on other variables on changing homelessness were determined. The software allowed the parameter values to change from -1 to +1, with -1 being the extreme negative change and +1 as the extreme positive change. Figure 7.1.1 shows the changes in different variables for Sudbury when the homelessness was increased to 0.5 from 0. To understand this, it is first noted that the mental and physical health variables represent mental and physical health problems and increase in gender means there are more males than females. This means that if there are more males with mental and physical health issues in lower age group having smaller number of kids of predominantly Caucasian ethnicity, homelessness will increase.

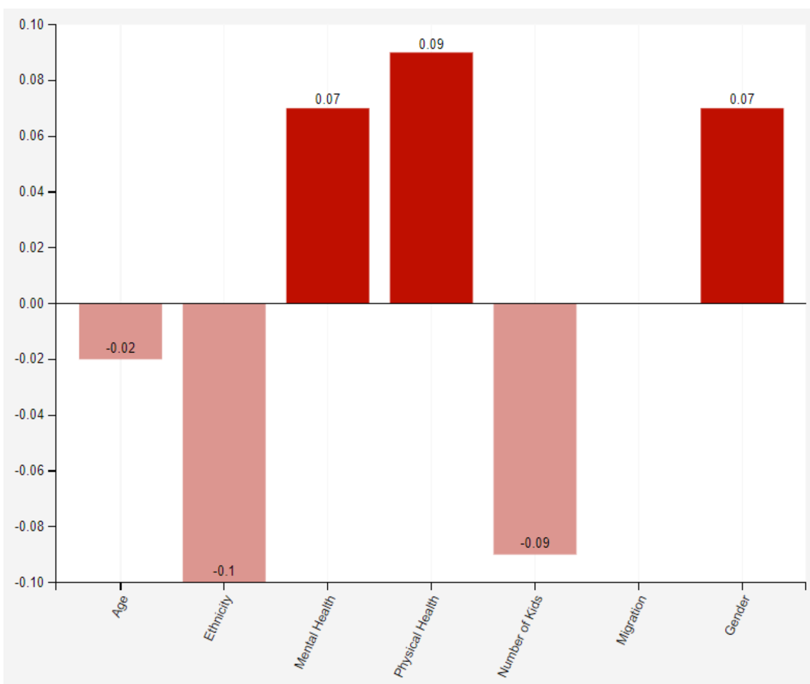

Figure 7.1.1: Change in different parameters with increase in homelessness to 0.5 for FCM from data collected in Sudbury in 2009.

This analysis was repeated for homelessness values of -1, -0.75, -0.5, 0.5, 0.75 and 1.0. The resulting changes in other variables are listed in Table 7.1.1.

Table 7.1.1: Change in different parameters with increase in homelessness from -1.0 to +1.0 for FCM from data collected in Sudbury in 2009.

Homelessness	Age	Gender	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Migration
-1.00	0.05	-0.13	0.20	0.00	0.00	-0.14	-0.18	0.18	0.00
-0.75	0.03	-0.10	0.15	0.00	0.00	-0.11	-0.13	0.13	0.00
-0.50	0.02	-0.07	0.10	0.00	0.00	-0.07	-0.09	0.09	0.00
-0.25	0.01	-0.03	0.05	0.00	0.00	-0.04	-0.04	0.04	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.25	-0.01	0.03	-0.05	0.00	0.00	0.04	0.04	-0.04	0.00
0.50	-0.02	0.07	-0.10	0.00	0.00	0.07	0.09	-0.09	0.00
0.75	-0.03	0.10	-0.15	0.00	0.00	0.11	0.13	-0.13	0.00
1.00	-0.05	0.13	-0.20	0.00	0.00	0.14	0.18	-0.18	0.00

It is apparent from Table 7.1.1 that the trend in change of parameter values is linear for all variables. This can also be seen in the charts in Figures 7.1.2 and 7.1.3.

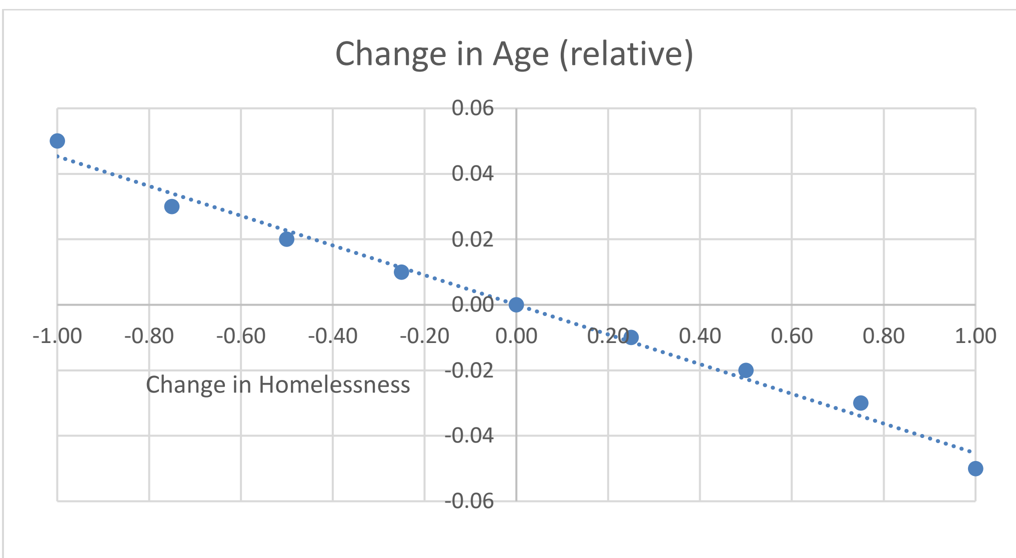

Figure 7.1.2: Relationship of change in age with change in homelessness for FCM from data collected in Sudbury in 2009.

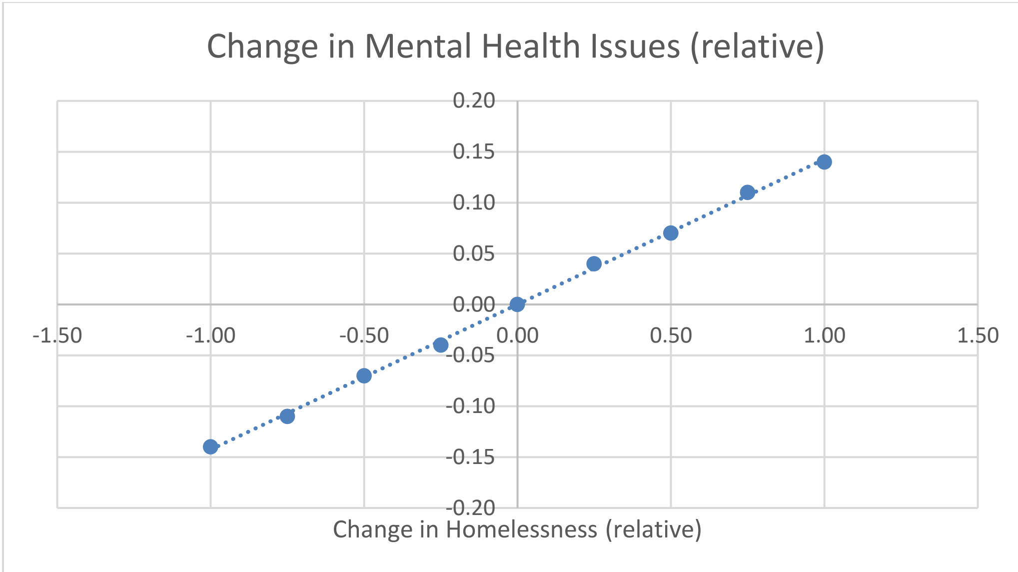

Figure 7.1.3: Relationship of change in mental health issues with change in homelessness for FCM from data collected in Sudbury in 2009.

Since the relationship is linear on negative and positive sides, it is sufficient to calculate the weights using only positive side of the data. For this the data were first written with rows and columns interchanged and then the values were normalized. Since the values contained both positive and negative numbers, the normalized exponential function was used for normalization.

$$w_i = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$$

Here, w_i is the weight of the i^{th} variable, x_i is the sensitivity parameter of the i^{th} variable, and the n is the number of data points.

Table 7.1.2 lists the raw and normalized sensitivity values (or weights) deduced from the FCM for Sudbury. Looking at this table it is apparent that the normalized weights remain almost constant throughout the range of change in homelessness. This means that one can effectively use an average value for the weights.

Table 7.1.2: Raw and normalized weights calculated from sensitivity analyses of FCM from data collected in Sudbury in 2009.

Change in Homelessness	0.25		0.50		0.75		1.00		Average
	Raw	Normalized	Raw	Normalized	Raw	Normalized	Raw	Normalized	
Age	-0.01	0.1098	-0.02	0.1085	-0.03	0.1070	-0.05	0.1046	0.1075
Gender	0.03	0.1143	0.07	0.1187	0.10	0.1219	0.13	0.1253	0.1200
Ethnicity	-0.05	0.1055	-0.10	0.1001	-0.15	0.0949	-0.20	0.0901	0.0976
Education	0.00	0.1109	0.00	0.1106	0.00	0.1103	0.00	0.1100	0.1105
Employment	0.00	0.1109	0.00	0.1106	0.00	0.1103	0.00	0.1100	0.1105
Mental Health	0.04	0.1155	0.07	0.1187	0.11	0.1231	0.14	0.1265	0.1209
Physical Health	0.04	0.1155	0.09	0.1211	0.13	0.1256	0.18	0.1317	0.1234
Number of Kids	-0.04	0.1066	-0.09	0.1011	-0.13	0.0968	-0.18	0.0919	0.0991
Migration	0.00	0.1109	0.00	0.1106	0.00	0.1103	0.00	0.1100	0.1105

Similar analyses were performed on data from other communities. The changes in different parameters for data for all the other communities and their raw and normalized weights are given in Tables 7.1.3 to 7.1.10.

Table 7.1.3: Change in different parameters with increase in homelessness from -1.0 to +1.0 for FCM from data collected in Timmins in 2011.

Homelessness	Age	Gender	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Migration
-1.00	-0.13	0.02	0.10	-0.08	-0.02	-0.02	0.05	0.01	0.00
-0.75	-0.10	0.02	0.08	-0.06	-0.01	-0.01	0.04	0.01	0.00
-0.50	-0.06	0.01	0.05	-0.04	-0.01	-0.01	0.02	0.00	0.00
-0.25	-0.03	0.01	0.03	-0.02	0.00	0.00	0.01	0.00	0.00
0.00	0.03	-0.01	-0.03	0.02	0.00	0.00	-0.01	0.00	0.00
0.25	0.03	-0.01	-0.03	0.02	0.00	0.00	-0.01	0.00	0.00
0.50	0.06	-0.01	-0.05	0.04	0.01	0.01	-0.02	0.00	0.00
0.75	0.10	-0.02	-0.08	0.06	0.01	0.01	-0.04	-0.01	0.00
1.00	0.13	-0.02	-0.10	0.08	0.02	0.02	-0.05	-0.01	0.00

Table 7.1.4: Raw and normalized weights calculated from sensitivity analyses of FCM from data collected in Timmins in 2011.

Change in Homelessness	0.25		0.5		0.75		1		Average
	Raw	Normalized	Raw	Normalized	Raw	Normalized	Raw	Normalized	
Age	0.03	0.1145	0.06	0.1174	0.10	0.1222	0.13	0.1253	0.1199
Gender	-0.01	0.1100	-0.01	0.1095	-0.02	0.1084	-0.02	0.1078	0.1089
Ethnicity	-0.03	0.1078	-0.05	0.1052	-0.08	0.1021	-0.10	0.0996	0.1037
Education	0.02	0.1133	0.04	0.1151	0.06	0.1174	0.08	0.1192	0.1163
Employment	0.00	0.1111	0.01	0.1117	0.01	0.1117	0.02	0.1122	0.1117
Mental Health	0.00	0.1111	0.01	0.1117	0.01	0.1117	0.02	0.1122	0.1117
Physical Health	-0.01	0.1100	-0.02	0.1084	-0.04	0.1063	-0.05	0.1047	0.1073
Number of Kids	0.00	0.1111	0.00	0.1106	-0.01	0.1095	-0.01	0.1089	0.1100
Migration	0.00	0.1111	0.00	0.1106	0.00	0.1106	0.00	0.1100	0.1106

Table 7.1.5: Change in different parameters with increase in homelessness from -1.0 to +1.0 for FCM from data collected in Hearst in 2011.

Homelessness	Age	Gender	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Migration
-1.00	0.14	-0.09	0.15	-0.01	-0.01	0.03	0.08	-0.09	0.00
-0.75	0.11	-0.07	0.11	-0.01	-0.01	0.02	0.06	-0.07	0.00
-0.50	0.07	-0.04	0.08	-0.01	-0.01	0.02	0.04	-0.04	0.00
-0.25	0.04	-0.02	0.04	0.00	0.00	0.01	0.02	-0.02	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.25	-0.04	0.02	-0.04	0.00	0.00	-0.01	-0.02	0.02	0.00
0.50	-0.07	0.04	-0.08	0.01	0.01	-0.02	-0.04	0.04	0.00
0.75	-0.11	0.07	-0.11	0.01	0.01	-0.02	-0.06	0.07	0.00
1.00	-0.14	0.09	-0.15	0.01	0.01	-0.03	-0.08	0.09	0.00

Table 7.1.6: Raw and normalized weights calculated from sensitivity analyses of FCM from data collected in Hearst in 2011.

Change in Homelessness	0.25		0.5		0.75		1		Average
	Raw	Normalized	Raw	Normalized	Raw	Normalized	Raw	Normalized	
Age	-0.04	0.1076	-0.07	0.1048	-0.11	0.1009	-0.14	0.0984	0.1029
Gender	0.02	0.1142	0.04	0.1170	0.07	0.1208	0.09	0.1239	0.1190
Ethnicity	-0.04	0.1076	-0.08	0.1037	-0.11	0.1009	-0.15	0.0975	0.1024
Education	0.00	0.1120	0.01	0.1135	0.01	0.1138	0.01	0.1144	0.1134
Employment	0.00	0.1120	0.01	0.1135	0.01	0.1138	0.01	0.1144	0.1134
Mental Health	-0.01	0.1108	-0.02	0.1102	-0.02	0.1104	-0.03	0.1099	0.1103
Physical Health	-0.02	0.1097	-0.04	0.1080	-0.06	0.1061	-0.08	0.1045	0.1071
Number of Kids	0.02	0.1142	0.04	0.1170	0.07	0.1208	0.09	0.1239	0.1190
Migration	0.00	0.1120	0.00	0.1124	0.00	0.1126	0.00	0.1132	0.1125

Table 7.1.7: Change in different parameters with increase in homelessness from -1.0 to +1.0 for FCM from data collected in Moosonee in 2012.

Homelessness	**Age**	**Gender**	**Ethnicit y**	**Educatio n**	**Employmen t**	**Mental Health**	**Physical Health**	**Numbe r of Kids**	**Migration**
-1.00	0.09	0.04	0.09	-0.12	0.15	-0.19	-0.16	0.02	0.00
-0.75	0.06	0.03	0.07	-0.09	0.11	-0.15	-0.12	0.01	0.00
-0.50	0.04	0.02	0.05	-0.06	0.07	-0.10	-0.08	0.01	0.00
-0.25	0.02	0.01	0.02	-0.03	0.04	-0.05	-0.04	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.25	-0.02	-0.01	-0.02	0.03	-0.04	0.05	0.04	0.00	0.00
0.50	-0.04	-0.02	-0.05	0.06	-0.07	0.01	0.08	-0.01	0.00
0.75	-0.06	-0.03	-0.07	0.09	-0.11	0.15	0.12	-0.01	0.00
1.00	-0.09	-0.04	-0.09	0.12	-0.15	0.19	0.16	-0.02	0.00

Table 7.1.8: Raw and normalized weights calculated from sensitivity analyses of FCM from data collected in Moosonee in 2012.

Change in Homelessness	**0.25**		**0.5**		**0.75**		**1**		**Average**
	Raw	**Normalized**	**Raw**	**Normalized**	**Raw**	**Normalized**	**Raw**	**Normalized**	
Age	-0.02	0.1085	-0.04	0.1071	-0.06	0.1033	-0.09	0.1000	0.1047
Gender	-0.01	0.1096	-0.02	0.1093	-0.03	0.1065	-0.04	0.1051	0.1076
Ethnicity	-0.02	0.1085	-0.05	0.1060	-0.07	0.1023	-0.09	0.1000	0.1042
Education	0.03	0.1141	0.06	0.1184	0.09	0.1201	0.12	0.1234	0.1190
Employment	-0.04	0.1064	-0.07	0.1039	-0.11	0.0983	-0.15	0.0942	0.1007
Mental Health	0.05	0.1164	0.01	0.1126	0.15	0.1275	0.19	0.1323	0.1222
Physical Health	0.04	0.1152	0.08	0.1208	0.12	0.1237	0.16	0.1284	0.1220
Number of Kids	0.00	0.1107	-0.01	0.1104	-0.01	0.1086	-0.02	0.1072	0.1092
Migration	0.00	0.1107	0.00	0.1115	0.00	0.1097	0.00	0.1094	0.1103

Table 7.1.9: Change in different parameters with increase in homelessness from -1.0 to +1.0 for FCM from data collected in Cochrane in 2013.

Homelessness	Age	Gender	Ethnicity	Education	Employment	Mental Health	Physical Health	Number of Kids	Migration
-1.00	0.06	0.00	0.07	-0.15	0.11	-0.03	0.06	0.00	0.00
-0.75	0.05	0.00	0.05	-0.11	0.08	-0.02	0.04	0.00	0.00
-0.50	0.03	0.00	0.04	-0.08	0.05	-0.01	0.03	0.00	0.00
-0.25	0.02	0.00	0.02	-0.04	0.03	-0.01	0.01	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.25	-0.02	0.00	-0.02	0.04	-0.03	0.01	-0.01	0.00	0.00
0.50	-0.03	0.00	-0.04	0.08	-0.05	0.01	-0.03	0.00	0.00
0.75	-0.05	0.00	-0.05	0.11	-0.08	0.02	-0.04	0.00	0.00
1.00	-0.06	0.00	-0.07	0.15	-0.11	0.03	-0.06	0.00	0.00

Table 7.1.10: Raw and normalized weights calculated from sensitivity analyses of FCM from data collected in Cochrane in 2013.

Change in Homelessness	0.25		0.5		0.75		1		Average
	Raw	Normalized	Raw	Normalized	Raw	Normalized	Raw	Normalized	
Age	-0.02	0.1093	-0.03	0.1085	-0.05	0.1066	-0.06	0.1058	0.1075
Gender	0.00	0.1115	0.00	0.1118	0.00	0.1121	0.00	0.1123	0.1119
Ethnicity	-0.02	0.1093	-0.04	0.1074	-0.05	0.1066	-0.07	0.1047	0.1070
Education	0.04	0.1160	0.08	0.1211	0.11	0.1251	0.15	0.1305	0.1232
Employment	-0.03	0.1082	-0.05	0.1063	-0.08	0.1035	-0.11	0.1006	0.1046
Mental Health	0.01	0.1126	0.01	0.1129	0.02	0.1143	0.03	0.1157	0.1139
Physical Health	-0.01	0.1104	-0.03	0.1085	-0.04	0.1077	-0.06	0.1058	0.1081
Number of Kids	0.00	0.1115	0.00	0.1118	0.00	0.1121	0.00	0.1123	0.1119
Migration	0.00	0.1115	0.00	0.1118	0.00	0.1121	0.00	0.1123	0.1119

The sensitivity analyses have provided the weights needed to compute the homelessness indices.

7.1.1 Homelessness Indices

The weights as calculated in the previous section are given in Table 7.1.11 together with spread or standard deviation amongst various communities. It is worth noting that the spreads in weight values for all the communities are fairly small. In this table, the weight parameters have also been assigned symbols.

Table 7.1.11: Average normalized weights for different communities with standard deviations.

	Weight Parameter	Weight					Spread (Standard Deviation)
		Sudbury	Timmins	Hearst	Moosonee	Cochrane	
Age	w_{ag}	0.1075	0.1199	0.1029	0.1047	0.1075	0.0066
Gender	w_{ge}	0.1200	0.1089	0.1190	0.1076	0.1119	0.0057
Ethnicity	w_{et}	0.0976	0.1037	0.1024	0.1042	0.1070	0.0034
Education	w_{ed}	0.1105	0.1163	0.1134	0.1190	0.1232	0.0049
Employment	w_{em}	0.1105	0.1117	0.1134	0.1007	0.1046	0.0053
Mental Health	w_{mh}	0.1209	0.1117	0.1103	0.1222	0.1139	0.0054
Physical Health	w_{ph}	0.1234	0.1073	0.1071	0.1220	0.1081	0.0084
Number of Kids	w_{nk}	0.0991	0.1100	0.1190	0.1092	0.1119	0.0071
Migration	w_{mi}	0.1105	0.1106	0.1125	0.1103	0.1119	0.0010

The homelessness index determines the likelihood of a person becoming homeless and can be defined as follows.

$$h = s_1 p_{ag} w_{ag} + s_2 p_{ge} w_{ge} + s_3 p_{et} w_{et} + s_4 p_{ed} w_{ed} + s_5 p_{em} w_{em} + s_6 p_{mh} w_{mh} + s_7 p_{ph} w_{ph} + s_8 p_{nk} w_{nk} + s_9 p_{mi} w_{mi}$$

Here the sign parameters (s) determine whether the trend is positive or negative. These have been derived from the correlation matrices and are listed in Table 7.1.12. The weights (w) are as defined in Table 7.1.11 and the parameter (p) are defined as in Table 7.1.13below. The table also lists the minimum and maximum values assigned to these parameters. It is worth mentioning here that since the assignment of these values is arbitrary, the homelessness index as calculated from the above equation is relative.

Table 7.1.12: Sign parameters representing parameter trends in different communities.

	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8	s_9
Sudbury	-1	1	-1	1	1	1	1	-1	1
Timmins	1	-1	-1	1	1	1	-1	-1	1
Hearst	-1	1	-1	1	1	-1	-1	1	1
Moosonee	-1	-1	-1	1	-1	1	1	-1	1
Chochrane	-1	1	-1	1	-1	1	-1	1	1

Table 7.1.13: Boundary values assigned to the parameters.

	Parameter	**Assigned Values**
Age	p_{ag}	0-10 Y: 0.1; 11-20 Y: 0.2; 21-30 Y: 0.3; ……. ;81-90 Y: 0.9; >91 Y: 1.0
Gender	p_{ge}	Female: 0.5; Male: 1.0
Ethnicity	p_{et}	Caucasian: 0.5; Native: 1.0
Education	p_{ed}	No – Primary: 0.1; High School: 0.5; College/Trade: 0.75; University: 1.0
Employment	p_{em}	Unemployed: 0.5; Employed 1.0
Mental Health	p_{mh}	No Mental Health Issues: 0.0; Mental Health Issues: 1.0
Physical Health	p_{ph}	No Physical Health Issues: 0.0; Physical Health Issues: 1.0
Number of Kids	p_{nk}	No Kids: 0.0; 1-2: 0.5; >=3: 1.0
Migration	p_{mi}	No Migration: 0.0; Migration: 1.0

The minimum and maximum values of the homelessness index for all localities can now be calculated. For this the homelessness index equations for all the regions with sign parameters from Table 6.3.4.1 are given below.

$$h_{Sudbury} = -p_{ag}w_{ag} + p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} + p_{em}w_{em} + p_{mh}w_{mh} + p_{ph}w_{ph} - p_{nk}w_{nk} + p_{mi}w_{mi}$$

$$h_{Timmins} = p_{ag}w_{ag} - p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} + p_{em}w_{em} + p_{mh}w_{mh} - p_{ph}w_{ph} - p_{nk}w_{nk} + p_{mi}w_{mi}$$

$$h_{Hearst} = -p_{ag}w_{ag} + p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} + p_{em}w_{em} - p_{mh}w_{mh} - p_{ph}w_{ph} + p_{nk}w_{nk} + p_{mi}w_{mi}$$

$$h_{Moosonee} = -p_{ag}w_{ag} - p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} - p_{em}w_{em} + p_{mh}w_{mh} + p_{ph}w_{ph} - p_{nk}w_{nk} + p_{mi}w_{mi}$$

$$h_{Cochrane} = -p_{ag}w_{ag} + p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} - p_{em}w_{em} + p_{mh}w_{mh} - p_{ph}w_{ph} + p_{nk}w_{nk} + p_{mi}w_{mi}$$

The parameter weights and the assigned parameter bounds were then used to calculate the minimum and maximum indices from these equations for all localities as given in Table 7.1.14 below.

Table 7.1.14: Boundary values for homelessness index.

	h	
	Minimum	Maximum
Sudbury	-0.177939	0.636202
Timmins	-0.350480	0.463766
Hearst	-0.295210	0.515775
Moosonee	-0.514600	0.306771
Cochrane	-0.358960	0.456204

Since the boundary values for different localities as given in Table 7.1.14 are different from one another, the calculated values cannot be directly compared. To make any meaningful comparison, these ranges must be rescaled between common end points, such as 0 and 1. The following rescaling formula was therefore used to rescale these between 0 and 1.

$$h^* = \frac{1.0}{h_{max} - h_{min}}(h - h_{max}) + 1.0$$

Here h is the calculated value, h_{min} and h_{max} are the minimum and maximum values as given in Table 6.3.4.4 and h^* is the rescaled value of homelessness index. Using this formula, the equations for rescaled homelessness index for all five localities can be written as follows.

$$h^*_{Sudbury} = 1.228288\{-p_{ag}w_{ag} + p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} + p_{em}w_{em} + p_{mh}w_{mh} + p_{ph}w_{ph} - p_{nk}w_{nk} + p_{mi}w_{mi} - 0.636202\} + 1.0$$

$$h^*_{Timmins} = 1.228123\{p_{ag}w_{ag} - p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} + p_{em}w_{em} + p_{mh}w_{mh} - p_{ph}w_{ph} - p_{nk}w_{nk} + p_{mi}w_{mi} - 0.463766\} + 1.0$$

$$h^*_{Hearst} = 1.233076\{-p_{ag}w_{ag} + p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} + p_{em}w_{em} - p_{mh}w_{mh} - p_{ph}w_{ph} + p_{nk}w_{nk} + p_{mi}w_{mi} - 0.515775\} + 1.0$$

$$h^*_{Moosonee} = 1.21748\{-p_{ag}w_{ag} - p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} - p_{em}w_{em} + p_{mh}w_{mh} + p_{ph}w_{ph} - p_{nk}w_{nk} + p_{mi}w_{mi} - 0.306771\} + 1.0$$

$$h^*_{Cochrane} = 1.226751\{-p_{ag}w_{ag} + p_{ge}w_{ge} - p_{et}w_{et} + p_{ed}w_{ed} - p_{em}w_{em} + p_{mh}w_{mh} - p_{ph}w_{ph} + p_{nk}w_{nk} + p_{mi}w_{mi} - 0.456204\} + 1.0$$

Of course, the question here arises that how the rescaled homelessness index between 0 and 1 can be understood and labeled. One important point to note is that here fuzzy logic has been used to construct this index and therefore there is no reason to believe that the corresponding values will be crisp. It is obvious that a value of 0 should correspond to no risk and a value of 1 should correspond to highest risk. Therefore, the following labeling scheme for the homelessness index is proposed.

$h^* = 0$: No risk of homelessness

$0 < h^* \leq 0.3$: Low risk of homelessness

$0.3 < h^* \leq 0.7$: Medium risk of homelessness

$0.7 < h^* \leq 1.0$: High risk of homelessness

7.1.2 Calculations of Homelessness Indices

The rescaled homelessness index equations developed in the previous section can be termed to represent probability that how likely a certain individual is to become homeless with $h^* = 0$ representing not likely and $h^* = 1$ representing highly probable. Since each locality had its unique index equation, it was found to be instructive to compare the values calculated for all five areas. For this, four scenarios were constructed as given in Table 7.1.15.

Table 7.1.15: Four scenarios constructed to calculate homelessness index.

	Scenario-1		Scenario-2		Scenario-3		Scenario-4	
	State	p	**State**	p	**State**	p	**State**	p
Age	18.00	0.2	35.00	0.4	45.00	0.5	25.00	0.3
Gender	Male	1.0	Female	0.5	Female	1.0	Male	1.0
Ethnicity	Caucasian	0.5	Caucasian	0.5	Native	1.0	Native	1.0
Education	High School	0.5	High School	0.5	Primary School	0.1	Primary School	0.1
Employment	Unemployed	0.5	Unemployed	0.5	Unemployed	0.5	Unemployed	0.5
Mental Health Issues	No	0.0	Yes	1.0	Yes	1.0	No	0.5
Physical Health Issues	No	0.0	Yes	1.0	No	0.0	Yes	1.0
Number of Kids	None	0.0	3	1.0	2	0.5	3	1.0
Migration	Yes	1.0	No	1.0	Yes	1.0	Yes	1.0

Figure 7.1.4 to Figure 7.1.8 show the homelessness indices calculated for these four scenarios.

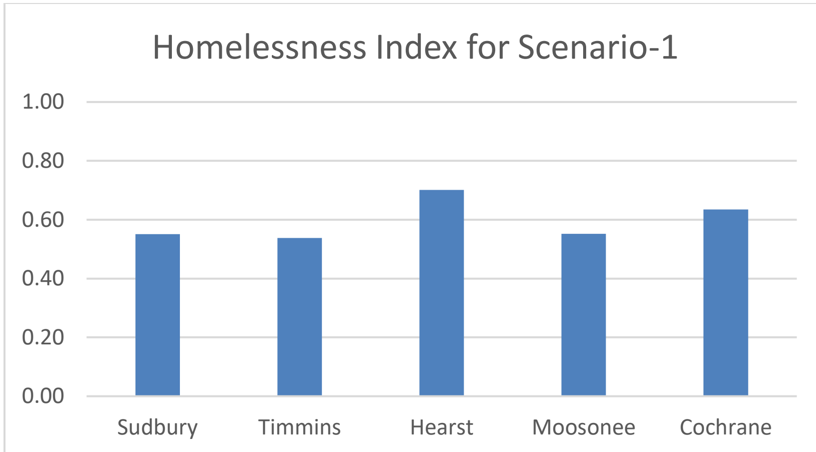

Figure 7.1.4: Homelessness indices calculated for scaneario-1 in the study communities.

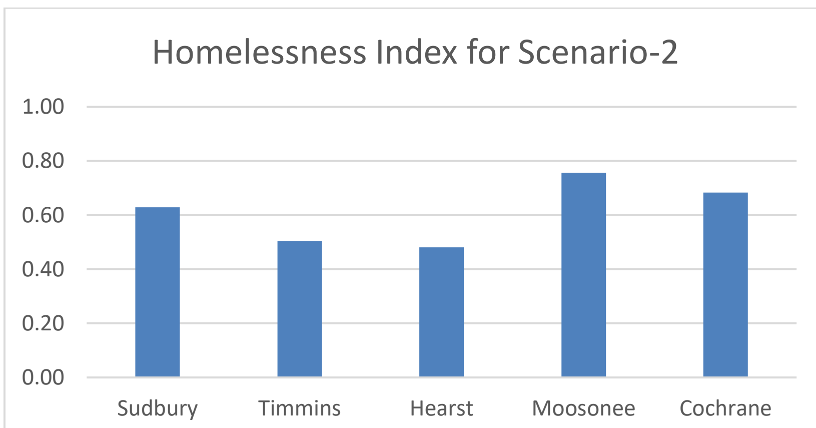

Figure 7.1.5: Homelessness indices calculated for scaneario-2 in the study communities.

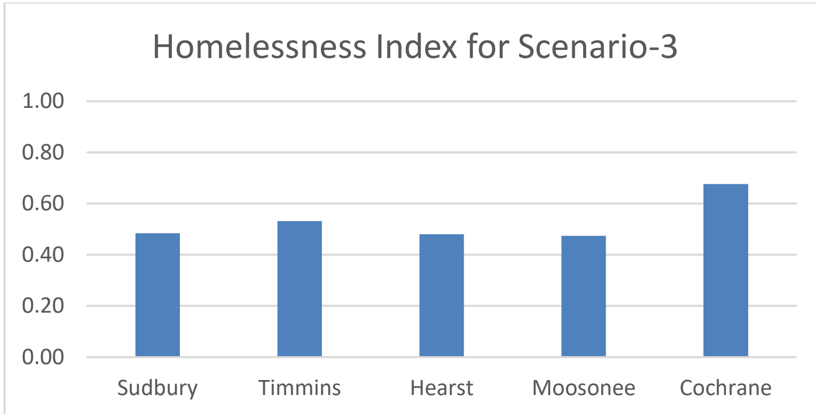

Figure 7.1.6: Homelessness indices calculated for scaneario-3 in the study communities.

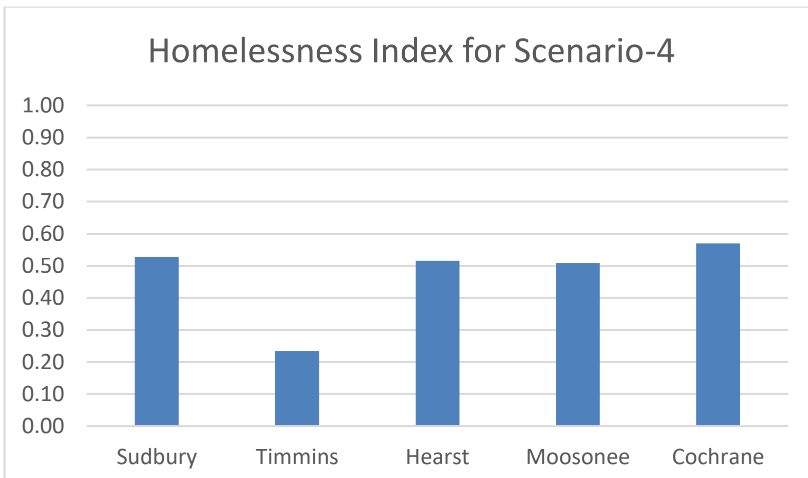

Figure 7.1.7: Homelessness indices calculated for scaneario-4 in the study communities.

In order to understand the differences in values of homelessness index the five communities, the differences with respect to respective averages were calculated using the following formula.

$$\Delta h^* = \frac{\left|h^* - \overline{h^*}\right|}{\overline{h^*}} \times 100$$

Here $\overline{h^*}$ is the average for that particular scenario. The resulting histogram is shown in Figure 7.18.

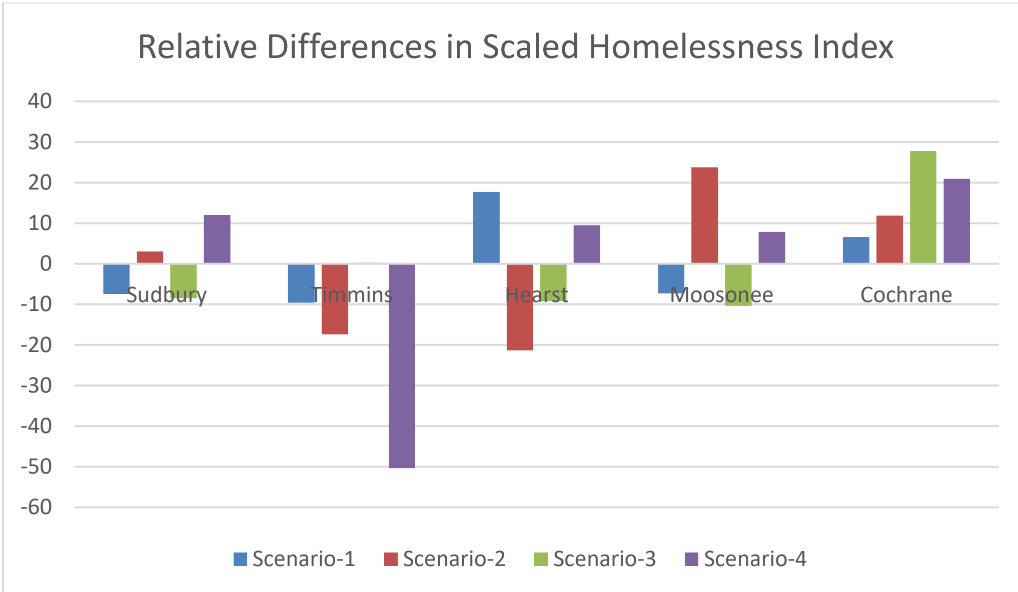

Figure 7.1.8: Relative change in scaled homelessness index for different scenarios.

It is apparent from the above histogram that the homelessness index values are generally different in different communities for exactly same individuals. It confirms the hypothesis that one homelessness index cannot be used to understand risk of homelessness in all of Northern Ontario. This concludes data analysis for this study. In the next Chapter, the results are discussed and concluded.

8 DISCUSSIONS AND CONCLUSIONS

In this study, the complex issues related to homelessness in Northern Ontario were investigated. The data that were generated over several years in Sudbury, Timmins, Hearst, Cochrane and Moosonee were thoroughly analyzed using GIS techniques and Fuzzy Cognitive Maps. Parameter distributions were generated and maps developed to understand pathways to homelessness. A very important result that came out of this study was the marked differences between homelessness dynamics in the five study areas. Therefore, a single policy to reduce homelessness in Northern Ontario will yield limited success. A better approach will be to develop policy for each area separately depending on its particular issues. The results of this study will help make such policies. The quantitative approach used in this study would allow the policy makers and stakeholders to make more informed decisions. In the following, the main results of this study are discussed.

It is worth noting that even though the areas studied during this research spanned a large part of Northern Ontario from Sudbury in the lower north to Moosonee in the upper north, the communities themselves were not very large except for Sudbury. For example, Moosonee had a population of a little over 1500 during the study year. Compared to this the population of Hearst was 5,500 and that of Timmins just over 41,000. Cochrane had a population of a little over 25,000. The Sudbury, the most populous of all five, had a population over 160,000. The data gathered in smaller population areas were therefore more representative of the conditions there as compared to areas with larger population. Table 8.1 below shows the populations of different areas and the respective number of individuals interviewed there. The fourth column in this table gives the ratio of the number of interviewees and the respective population.

Table 8.1: Approximate population and number of interviewees in study areas.

	Approximate Population	Number of Interviewees
Sudbury (2009)	160,000	588
Timmins (2011)	41,000	1268
Hearst (2011)	5,500	292
Moosonee (2012)	1,500	597
Cochrane (2013)	26,000	1495

The largest amount of data gathered were for Sudbury since the interviews in Sudbury were conducted in seven years from 1999 to 2011. However, in 2009, only 588 interviews were conducted in Sudbury. Time series analyses were performed to understand how different variables changed over the years. It was found that the many variables did not change significantly. However, homelessness due to unemployment seemed to steadily increase over time (see Figure 4.2.2). It is important to understand that this does not necessarily mean that the unemployment rate increased with time. In fact, looking at Table 4.2.1 it is apparent that there is no correlation between homelessness due ot unemployment and unemployment rate. This points to the issue of possible deterioration of support structure and available resources with time or just stagnation of those resources. The availability of such support structures and resources must increase with increase in population, which does not seem to be the case for Sudbury.

During the initial stage of this research a large number of parameters were looked at individually as possible causes of homelessness. Of course, these single-variable analyses were not supposed to provide an accurate description of the situation as these did not include effects of one variable on other variables. Still the distributions thus generated provided a good understanding of homelessness in different communities. For example, Figure 4.2.3 showed that most of the interviewees in Timmins mentioned unemployment and seeking work as the dominant reasons for homelessness.

A very clear result that has come out of this study is that the migration in and out of Northern Ontario may lead to homelessness. In many instances, the individuals migrated out of their hometowns, generally in search of employment, failed to find appropriate employments and became homeless after returning to their hometown. This is a disturbing trend and points towards lack of proper guidance and support structures available in these communities. The usual migration into the towns leading to homelessness was also observed in the data analyzed.

Sudbury is the largest city out of the five cities studied. It has a large base of mining operations and therefore is attractive in terms of employment opportunities. However, the town also gets hit by scaling down of mining operations during periods of low commodity prices. This leads to massive lay-offs and subsequent migrations out of Sudbury. It was observed that many individuals who thus migrated out of Sudbury in search of employment, were unsuccessful and became homeless when they came back to Sudbury. Also, many individuals who migrated in Sudbury from upper North and South, became homeless. This points to issues with employment opportunities as well as available support structure in Sudbury.

Timmins is the second largest city after Sudbury with a population of a little over 40,000. This is also primarily a mining town and is one of the largest producers of gold in the world. Still, the homelessness in Timmins in rampant. As in the case for Sudbury, the issue of individuals becoming homeless after migration into the city in search of employment was observed here as well. The difference that was observed for Timmins was that here sizable migration from Eastern and Western parts of Canada was observed as well. This is perhaps mainly due to the perception of high employment opportunities in the town, which is not generally the case. Also, many individuals leave Timmins to search for employment to Sudbury and Southern cities, such as Toronto. In many cases, they fail to secure employment, return to Timmins and then become homeless. This indicates the problems of low employment opportunities as well as availability of proper support structure in Timmins.

With a population of a little over 26,000, the third largest town in this study is Cochrane. Its main industries include transportation, tourism and forestry. Migration out of town is not uncommon in Cochrane, primarily due to low employment opportunities. The migrants not only go to nearby towns, such as Timmins and Sudbury, but also to town in far South, such as Toronto. As in other towns, it was observed that the individuals become homeless after returning to Cochrane. Cochrane, being a relatively larger town in upper North, also sees influx of migrant from other towns in the North and South of Ontario. The largest number of migrants to Cochrane were seen to have migrated from Moosonee, which is a much smaller town in upper North. There is a tendency of these migrants to become homeless due to lower employment opportunities in Cochrane.

Hearst and Moosonee are much smaller towns as compared to Sudbury, Timmins and Cochrane. Hearst, with a population of about 5,500, has lumber as its main industry. It sees very little migration from other towns but has a much higher rate of migration out of the town. And, as in other towns, there is a tendency of both types of migrants to become homeless in Hearst. Moosonee, with a population of a little over 1,500, is the smallest town studied. The main industry is tourism and employment opportunities are rare. Therefore, Moosonee sees sizable migration out of town not only in search of employment but also to seek medical help. The town also receives migrants from other communities specially in far upper North. Homelessness after migration is fairly common in Moosonee.

North Bay is a town about 100 km East of Sudbury. Even though it was not one of the five cities studied, it was felt important to look at migration trends in this town as well. The same issues were seen in North Bay as well.

It should be noted that seeking employment has been a major motive for most of migrants out of their home towns. However, there have been other causes of migration as well, such as lack of proper medical and education facilities in town and family problems. In order to understand what parameters influenced migration and homelessness, their distributions were generated. Note that these distributions were generated for homeless individuals, which means that it is a given that these are related directly to homelessness.

It was observed that, except for Sudbury, in all other towns female homeless outnumbered male homeless. Hearst was seen to have the largest relative proportion of female homeless, followed by Moosonee, Cochrane, Timmins and Sudbury. This shows an interesting trend of the number of female homeless being inversely proportional to the population. The larger the town, the higher is the relative number of homeless men. This could be due to the higher number of men who migrate in and out of larger towns in search of employment and become homeless as a result.

Moosonee had the largest proportion of homeless older men as compared to other four communities. The population in this town is mainly indigenous and it is understandable that older individuals do not tend to migrate out of town in search of better social services. There is also a tendency of indigenous people to remain in or near their hometowns. The age distribution of other towns was found to be fairly evenly distributed except for Sudbury which showed the lowest proportion of homeless in the age group of less than 10 years old. These mostly even age distributions of homeless points toward scarcity of social services and support structures in these towns, as it shows that the homelessness is being faced by all age groups.

In smaller towns, there were less individuals who could be categorized as absolute homeless. The proportions of absolute homeless individuals in Timmins and Sudbury were much higher, pointing toward much more severe problems in larger cities as compared to smaller towns. This result was contrary to the expectation since one would assume the larger cities to have better social support network and resources available. However, it seemed as if the smaller cities were doing a better job in providing social services to the needy. This is also evident from the distribution of individuals who are deemed to be at-risk of becoming homeless. In Sudbury, the proportion of such individuals was the highest. In smaller towns, there were less individuals at-risk of becoming homeless.

Moosonee had the highest number of homeless individuals with three or more accompanied children. This situation should be addressed by policy makers since extreme poverty in this community together with higher population of children may lead to larger problems in the long run. Proper social services are absolutely needed in such towns. In Sudbury, Timmins, Cochrane and Hearst most homeless did not have any children.

Moosonee was the only town with highest number of Aboriginal homeless population. In other towns, most homeless were Caucasian. Hearst had the largest proportion of homeless Caucasians while in Sudbury, Timmins and Cochrane the population of homeless Caucasian was higher than that of homeless Aboriginal. It is important to note that only in Moosonee the general population is predominantly Aboriginal while in other towns the population of Caucasians is much higher than that of Aboriginal. A direct inference on the probability of a certain individual to become homeless just based on ethnicity should therefore not be made without taking into consideration the spatial factor. This again points toward spatial dependence of pathways to homelessness, which was also explored during this study and discussed later in this Chapter.

Except for Sudbury, in all other localities most of the homeless individuals did not have any source of income, with the rest on some kind of government support. In Sudbury, most were either receiving some kind of government support or were living on employment insurance or Canada Pension Plan payments. This points toward a more developed process and structure of government assistance in Sudbury as compared to other towns. This may be due to the much larger number of homeless individuals seeking assistance in Sudbury and simply availability of larger sums of funding, leading to development of a better support structure. Other towns may therefore benefit from this experience in Sudbury.

English was seen as the dominant mode of communication in all towns except for Hearst where the population is predominantly francophone. It should be noted that some Aboriginal individuals, especially young ones, also mark English as their language. Therefore, language is not an indication of ethnicity. For example, even though the predominant population in Moosonee is Aboriginal but there too most aboriginals stated English as their language.

Most homeless individuals in Hearst, Cochrane and Moosonee were found to be married. However, in Sudbury and Timmins most homeless were single.

Very few homeless individuals from Hearts, Cochrane and Moosonee mentioned that they had any kind of mental illness. The proportions in Timmins and Sudbury were much higher, though. It is interesting to note that the main mental issue reported by interviewees in all five study areas was depression. The reasons for depression were not studied during this research. It would be of value to look at the causes of depression and ways to mitigate those. The issue of physical health was found to be almost even. That is, almost 50% of all interviewees indicated having physical health problems.

To look at the overall picture, the cumulative fuzzy cognitive maps were generated during the early part of analysis. These maps allowed sensitivity analyses to be performed. However, it was soon realized that the spatial dependence of variables must be taken into consideration since there were marked differences between various variable distributions for different study areas. Therefore, in the next step the maps for all areas were individually constructed and analyzed. The parameter weights used to connect variables in these FCMs were determined from correlation analyses on the data. A point worth noting is that during the cumulative analysis a large number of variables were included in the FCM. However, in order to simplify the analysis and homelessness index, during the later stages only nine variables were selected based on their much higher importance. As expected, the fuzzy cognitive maps thus generated for different areas showed differences in fuzzy weights obtained from sensitivity analyses. This pointed to the fact that a single homelessness index will not be appropriate for all five study areas and there is spatial dependence on pathways to homelessness in Northern Ontario.

The homelessness index is an equation that can be used to quantify the risk a certain individual is at of becoming homeless. As mentioned earlier, a separate equation for each area was generated. In the next step, four different scenarios were analyzed with the help of these equations. Marked differences in the scaled homelessness index were noted for different areas. This again established the hypothesis that there is spatial dependence on pathways to homelessness in Northern Ontario.

From the results obtained from this study, it is clear that every locality has its own unique challenges and issues when it comes to homelessness, poverty and migration. Therefore, a unified and common approach at the provincial or state level will not likely bring acceptable and positive results. It is important that stakeholders, policy makers, researchers, academics and community members work together to understand the dynamics of homelessness, poverty and migration in their community and bring forward an approach unique to the challenges there. In this respect, the empirical approach of understanding the interplay between different variables developed here leading to formation of indices of homelessness can be of value. The fuzzy cognitive approach provides an excellent means to determine the importance of different variables on homelessness.

The last batch of data analyzed during this thesis was from 2011, which makes the results obtained here somewhat outdated. However, the methodology developed here can be easily used to analyze new datasets as they become available. It is expected that this methodology will be used and further developed to encompass more variables and applied to new datasets not only from northern Ontario but also from other communities from within Canada and other countries.

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10 APPENDIX-A

Correlation Matrices (a subset of all matrices generated)

Sudbury 2009

Correlations

		Age at time of study	Mental Health Problems?
Age at time of study	Pearson Correlation	1	-.208**
	Sig. (2-tailed)		.000
	N	293	293
Mental Health Problems?	Pearson Correlation	-.208**	1
	Sig. (2-tailed)	.000	
	N	293	308

**. Correlation is significant at the 0.01 level (2-tailed).

Timmins2011

Correlations

		Age at time of study	Mental Health Problems?
Age at time of study	Pearson Correlation	1	-.050
	Sig. (2-tailed)		.180
	N	708	708
Mental Health Problems?	Pearson Correlation	-.050	1
	Sig. (2-tailed)	.180	
	N	708	727

Hearst 2011

Correlations

		Age at time of study	Mental Health Problems?
Age at time of study	Pearson Correlation	1	.113
	Sig. (2-tailed)		.124
	N	188	188
Mental Health Problems?	Pearson Correlation	.113	1
	Sig. (2-tailed)	.124	
	N	188	189

Moosonee 2012

Correlations

		Age at time of study	Mental Health Problems?
Age at time of study	Pearson Correlation	1	-.050
	Sig. (2-tailed)		.530
	N	161	161
Mental Health Problems?	Pearson Correlation	-.050	1
	Sig. (2-tailed)	.530	
	N	161	299

Cochrane 2013

Correlations

		Age at time of study	Mental Health Problems?
Age at time of study	Pearson Correlation	1	.061
	Sig. (2-tailed)		.122
	N	635	635
Mental Health Problems?	Pearson Correlation	.061	1
	Sig. (2-tailed)	.122	
	N	635	648

Sudbury 2009

Correlations

		Age at time of study	Any Problems With Health?
Age at time of study	Pearson Correlation	1	-.376**
	Sig. (2-tailed)		.000
	N	297	297
Any Problems With Health?	Pearson Correlation	-.376**	1
	Sig. (2-tailed)	.000	
	N	297	313

**. Correlation is significant at the 0.01 level (2-tailed).

Timmins 2011

Correlations

		Age at time of study	Any Problems With Health?
Age at time of study	Pearson Correlation	1	-.302**
	Sig. (2-tailed)		.000
	N	700	700
Any Problems With Health?	Pearson Correlation	-.302**	1
	Sig. (2-tailed)	.000	
	N	700	718

**. Correlation is significant at the 0.01 level (2-tailed).

Hearst 2011

Correlations

		Age at time of study	Any Problems With Health?
Age at time of study	Pearson Correlation	1	-.321**
	Sig. (2-tailed)		.000
	N	171	171
Any Problems With Health?	Pearson Correlation	-.321**	1
	Sig. (2-tailed)	.000	
	N	171	172

**. Correlation is significant at the 0.01 level (2-tailed).

Moosonee 2012

Correlations

		Age at time of study	Any Problems With Health?
Age at time of study	Pearson Correlation	1	-.098
	Sig. (2-tailed)		.215
	N	161	161
Any Problems With Health?	Pearson Correlation	-.098	1
	Sig. (2-tailed)	.215	
	N	161	300

Cochrane 2013

Correlations

		Age at time of study	Any Problems With Health?
Age at time of study	Pearson Correlation	1	-.247**
	Sig. (2-tailed)		.000
	N	636	636
Any Problems With Health?	Pearson Correlation	-.247**	1
	Sig. (2-tailed)	.000	
	N	636	649

**. Correlation is significant at the 0.01 level (2-tailed).

Sudbury 2009

Correlations

		Age at time of study	Number of children
Age at time of study	Pearson Correlation	1	.218**
	Sig. (2-tailed)		.000
	N	532	255
Number of children	Pearson Correlation	.218**	1
	Sig. (2-tailed)	.000	
	N	255	267

**. Correlation is significant at the 0.01 level (2-tailed).

Timmins 2011

Correlations

		Age at time of study	Number of children
Age at time of study	Pearson Correlation	1	.043
	Sig. (2-tailed)		.276
	N	1209	659
Number of children	Pearson Correlation	.043	1
	Sig. (2-tailed)	.276	
	N	659	677

Hearst 2011

Correlations

		Age at time of study	Number of children
Age at time of study	Pearson Correlation	1	.424**
	Sig. (2-tailed)		.000
	N	285	179
Number of children	Pearson Correlation	.424**	1
	Sig. (2-tailed)	.000	
	N	179	180

**. Correlation is significant at the 0.01 level (2-tailed).

Moosonee 2012

Correlations

		Age at time of study	Number of children
Age at time of study	Pearson Correlation	1	.285**
	Sig. (2-tailed)		.001
	N	392	123
Number of children	Pearson Correlation	.285**	1
	Sig. (2-tailed)	.001	
	N	123	243

**. Correlation is significant at the 0.01 level (2-tailed).

Cochrane 2013

Correlations

		Age at time of study	Number of children
Age at time of study	Pearson Correlation	1	.040
	Sig. (2-tailed)		.312
	N	1465	636
Number of children	Pearson Correlation	.040	1
	Sig. (2-tailed)	.312	
	N	636	649

Sudbury 2009

Correlations

		Age at time of study	Meet the definition of absolute homelessness?
Age at time of study	Pearson Correlation	1	.092*
	Sig. (2-tailed)		.043
	N	532	485
Meet the definition of absolute homelessness?	Pearson Correlation	.092*	1
	Sig. (2-tailed)	.043	
	N	485	524

*. Correlation is significant at the 0.05 level (2-tailed).

Timmins 2011

Correlations

		Age at time of study	Meet the definition of absolute homelessness?
Age at time of study	Pearson Correlation	1	.104**
	Sig. (2-tailed)		.000
	N	1209	1209
Meet the definition of absolute homelessness?	Pearson Correlation	.104**	1
	Sig. (2-tailed)	.000	
	N	1209	1269

**. Correlation is significant at the 0.01 level (2-tailed).

Hearst 2011

Correlations

		Age at time of study	Meet the definition of absolute homelessness?
Age at time of study	Pearson Correlation	1	.014
	Sig. (2-tailed)		.814
	N	285	285
Meet the definition of absolute homelessness?	Pearson Correlation	.014	1
	Sig. (2-tailed)	.814	
	N	285	292

Moosonee 2012

Correlations

		Age at time of study	Meet the definition of absolute homelessness?
Age at time of study	Pearson Correlation	1	.020
	Sig. (2-tailed)		.699
	N	392	392
Meet the definition of absolute homelessness?	Pearson Correlation	.020	1
	Sig. (2-tailed)	.699	
	N	392	598

Cochrane 2013

Correlations

		Age at time of study	Meet the definition of absolute homelessness?
Age at time of study	Pearson Correlation	1	.021
	Sig. (2-tailed)		.509
	N	1465	1031
Meet the definition of absolute homelessness?	Pearson Correlation	.021	1
	Sig. (2-tailed)	.509	
	N	1031	1047

Sudbury 2009

Correlations

		Age at time of study	study community is home community?
Age at time of study	Pearson Correlation	1	.068
	Sig. (2-tailed)		.436
	N	132	132
study community is home community?	Pearson Correlation	.068	1
	Sig. (2-tailed)	.436	
	N	132	141

Timmins 2011

Correlations

		Age at time of study	study community is home community?
Age at time of study	Pearson Correlation	1	-.016
	Sig. (2-tailed)		.686
	N	663	663
study community is home community?	Pearson Correlation	-.016	1
	Sig. (2-tailed)	.686	
	N	663	679

Hearst 2011

Correlations

		Age at time of study	study community is home community?
Age at time of study	Pearson Correlation	1	.033
	Sig. (2-tailed)		.678
	N	163	163
study community is home community?	Pearson Correlation	.033	1
	Sig. (2-tailed)	.678	
	N	163	164

Moosonee 2012

Correlations

		Age at time of study	study community is home community?
Age at time of study	Pearson Correlation	1	-.007
	Sig. (2-tailed)		.927
	N	161	161
study community is home community?	Pearson Correlation	-.007	1
	Sig. (2-tailed)	.927	
	N	161	304

Cochrane 2013

Correlations

		Age at time of study	study community is home community?
Age at time of study	Pearson Correlation	1	-.127**
	Sig. (2-tailed)		.001
	N	638	638
study community is home community?	Pearson Correlation	-.127**	1
	Sig. (2-tailed)	.001	
	N	638	651

**. Correlation is significant at the 0.01 level (2-tailed).

Sudbury 2009

Correlations

		Highest level of education obtained	Currently employed?
Highest level of education obtained	Pearson Correlation	.[a]	.[a]
	Sig. (2-tailed)		
	N	0	0
Currently employed?	Pearson Correlation	.[a]	.[a]
	Sig. (2-tailed)		
	N	0	0

a. Cannot be computed because at least one of the variables is constant.

Timmins 2011

Correlations

		Highest level of education obtained	Currently employed?
Highest level of education obtained	Pearson Correlation	1	-.134*
	Sig. (2-tailed)		.015
	N	332	326
Currently employed?	Pearson Correlation	-.134*	1
	Sig. (2-tailed)	.015	
	N	326	327

*. Correlation is significant at the 0.05 level (2-tailed).

Hearst 2011

Correlations

		Highest level of education obtained	Currently employed?
Highest level of education obtained	Pearson Correlation	1	-.323**
	Sig. (2-tailed)		.000
	N	188	187
Currently employed?	Pearson Correlation	-.323**	1
	Sig. (2-tailed)	.000	
	N	187	188

**. Correlation is significant at the 0.01 level (2-tailed).

Moosonee 2012

Correlations

		Highest level of education obtained	Currently employed?
Highest level of education obtained	Pearson Correlation	1	-.409**
	Sig. (2-tailed)		.000
	N	302	297
Currently employed?	Pearson Correlation	-.409**	1
	Sig. (2-tailed)	.000	
	N	297	304

**. Correlation is significant at the 0.01 level (2-tailed).

Cochrane 2013

Correlations

		Highest level of education obtained	Currently employed?
Highest level of education obtained	Pearson Correlation	1	-.361**
	Sig. (2-tailed)		.000
	N	1049	1049
Currently employed?	Pearson Correlation	-.361**	1
	Sig. (2-tailed)	.000	
	N	1049	1051

**. Correlation is significant at the 0.01 level (2-tailed).

Sudbury 2009

Correlations

		Highest level of education obtained	Age at time of study
Highest level of education obtained	Pearson Correlation	.[a]	.[a]
	Sig. (2-tailed)		
	N	0	0
Age at time of study	Pearson Correlation	.[a]	1
	Sig. (2-tailed)		
	N	0	532

a. Cannot be computed because at least one of the variables is constant.

Timmins 2011

Correlations

		Highest level of education obtained	Age at time of study
Highest level of education obtained	Pearson Correlation	1	.033
	Sig. (2-tailed)		.556
	N	332	326
Age at time of study	Pearson Correlation	.033	1
	Sig. (2-tailed)	.556	
	N	326	1209

Hearst 2011

Correlations

		Highest level of education obtained	Age at time of study
Highest level of education obtained	Pearson Correlation	1	-.247**
	Sig. (2-tailed)		.001
	N	188	187
Age at time of study	Pearson Correlation	-.247**	1
	Sig. (2-tailed)	.001	
	N	187	285

**. Correlation is significant at the 0.01 level (2-tailed).

Moosonee 2012

Correlations

		Highest level of education obtained	Age at time of study
Highest level of education obtained	Pearson Correlation	1	-.123
	Sig. (2-tailed)		.119
	N	302	161
Age at time of study	Pearson Correlation	-.123	1
	Sig. (2-tailed)	.119	
	N	161	392

Cochrane 2013

Correlations

		Highest level of education obtained	Age at time of study
Highest level of education obtained	Pearson Correlation	1	-.151**
	Sig. (2-tailed)		.000
	N	1049	1033
Age at time of study	Pearson Correlation	-.151**	1
	Sig. (2-tailed)	.000	
	N	1033	1465

**. Correlation is significant at the 0.01 level (2-tailed).

Sudbury 2009

Correlations

		Highest level of education obtained	Mental Health Problems?
Highest level of education obtained	Pearson Correlation	.[a]	.[a]
	Sig. (2-tailed)		
	N	0	0
Mental Health Problems?	Pearson Correlation	.[a]	1
	Sig. (2-tailed)		
	N	0	308

a. Cannot be computed because at least one of the variables is constant.

Timmins 2011

Correlations

		Highest level of education obtained	Mental Health Problems?
Highest level of education obtained	Pearson Correlation	1	-.067
	Sig. (2-tailed)		.225
	N	327	327
Mental Health Problems?	Pearson Correlation	-.067	1
	Sig. (2-tailed)	.225	
	N	327	727

Hearst 2011

Correlations

		Highest level of education obtained	Mental Health Problems?
Highest level of education obtained	Pearson Correlation	1	.088
	Sig. (2-tailed)		.230
	N	188	188
Mental Health Problems?	Pearson Correlation	.088	1
	Sig. (2-tailed)	.230	
	N	188	189

Moosonee 2012

Correlations

		Highest level of education obtained	Mental Health Problems?
Highest level of education obtained	Pearson Correlation	1	.048
	Sig. (2-tailed)		.412
	N	294	294
Mental Health Problems?	Pearson Correlation	.048	1
	Sig. (2-tailed)	.412	
	N	294	299

Cochrane 2013

Correlations

		Highest level of education obtained	Mental Health Problems?
Highest level of education obtained	Pearson Correlation	1	.034
	Sig. (2-tailed)		.389
	N	646	646
Mental Health Problems?	Pearson Correlation	.034	1
	Sig. (2-tailed)	.389	
	N	646	648

Sudbury 2009

Correlations

		Highest level of education obtained	Any Problems With Health?
Highest level of education obtained	Pearson Correlation	.[a]	.[a]
	Sig. (2-tailed)		
	N	0	0
Any Problems With Health?	Pearson Correlation	.[a]	1
	Sig. (2-tailed)		
	N	0	313

a. Cannot be computed because at least one of the variables is constant.

Timmins 2011

Correlations

		Highest level of education obtained	Any Problems With Health?
Highest level of education obtained	Pearson Correlation	1	-.014
	Sig. (2-tailed)		.801
	N	323	323
Any Problems With Health?	Pearson Correlation	-.014	1
	Sig. (2-tailed)	.801	
	N	323	718

Hearst 2011

Correlations

		Highest level of education obtained	Any Problems With Health?
Highest level of education obtained	Pearson Correlation	1	.121
	Sig. (2-tailed)		.116
	N	171	171
Any Problems With Health?	Pearson Correlation	.121	1
	Sig. (2-tailed)	.116	
	N	171	172

Moosonee 2012

Correlations

		Highest level of education obtained	Any Problems With Health?
Highest level of education obtained	Pearson Correlation	1	-.008
	Sig. (2-tailed)		.891
	N	295	295
Any Problems With Health?	Pearson Correlation	-.008	1
	Sig. (2-tailed)	.891	
	N	295	300

Cochrane 2013

Correlations

		Highest level of education obtained	Any Problems With Health?
Highest level of education obtained	Pearson Correlation	1	-.011
	Sig. (2-tailed)		.772
	N	647	647
Any Problems With Health?	Pearson Correlation	-.011	1
	Sig. (2-tailed)	.772	
	N	647	649

Sudbury 2009

Correlations

		Highest level of education obtained	Number of children
Highest level of education obtained	Pearson Correlation	.[a]	.[a]
	Sig. (2-tailed)		
	N	0	0
Number of children	Pearson Correlation	.[a]	1
	Sig. (2-tailed)		
	N	0	267

a. Cannot be computed because at least one of the variables is constant.

Timmins 2011

Correlations

		Highest level of education obtained	Number of children
Highest level of education obtained	Pearson Correlation	1	-.103
	Sig. (2-tailed)		.098
	N	332	259
Number of children	Pearson Correlation	-.103	1
	Sig. (2-tailed)	.098	
	N	259	677

Hearst 2011

Correlations

		Highest level of education obtained	Number of children
Highest level of education obtained	Pearson Correlation	1	-.101
	Sig. (2-tailed)		.180
	N	188	179
Number of children	Pearson Correlation	-.101	1
	Sig. (2-tailed)	.180	
	N	179	180

Moosonee 2012

Correlations

		Highest level of education obtained	Number of children
Highest level of education obtained	Pearson Correlation	1	-.180**
	Sig. (2-tailed)		.005
	N	302	240
Number of children	Pearson Correlation	-.180**	1
	Sig. (2-tailed)	.005	
	N	240	243

**. Correlation is significant at the 0.01 level (2-tailed).

Cochrane 2013

Correlations

		Highest level of education obtained	Number of children
Highest level of education obtained	Pearson Correlation	1	.032
	Sig. (2-tailed)		.418
	N	1049	647
Number of children	Pearson Correlation	.032	1
	Sig. (2-tailed)	.418	
	N	647	649

Sudbury 2009

Correlations

		Highest level of education obtained	Meet the definition of absolute homelessness?
Highest level of education obtained	Pearson Correlation	.[a]	.[a]
	Sig. (2-tailed)		
	N	0	0
Meet the definition of absolute homelessness?	Pearson Correlation	.[a]	1
	Sig. (2-tailed)		
	N	0	524

a. Cannot be computed because at least one of the variables is constant.

Timmins 2011

Correlations

		Highest level of education obtained	Meet the definition of absolute homelessness?
Highest level of education obtained	Pearson Correlation	1	.079
	Sig. (2-tailed)		.152
	N	332	332
Meet the definition of absolute homelessness?	Pearson Correlation	.079	1
	Sig. (2-tailed)	.152	
	N	332	1269

Hearst 2011

Correlations

		Highest level of education obtained	Meet the definition of absolute homelessness?
Highest level of education obtained	Pearson Correlation	1	.035
	Sig. (2-tailed)		.630
	N	188	188
Meet the definition of absolute homelessness?	Pearson Correlation	.035	1
	Sig. (2-tailed)	.630	
	N	188	292

Moosonee 2012

Correlations

		Highest level of education obtained	Meet the definition of absolute homelessness?
Highest level of education obtained	Pearson Correlation	1	.051
	Sig. (2-tailed)		.374
	N	302	302
Meet the definition of absolute homelessness?	Pearson Correlation	.051	1
	Sig. (2-tailed)	.374	
	N	302	598

Cochrane 2013

Correlations

		Highest level of education obtained	Meet the definition of absolute homelessness?
Highest level of education obtained	Pearson Correlation	1	.113**
	Sig. (2-tailed)		.000
	N	1049	1045
Meet the definition of absolute homelessness?	Pearson Correlation	.113**	1
	Sig. (2-tailed)	.000	
	N	1045	1047

**. Correlation is significant at the 0.01 level (2-tailed).

Sudbury 2009

Correlations

		Highest level of education obtained	study community is home community?
Highest level of education obtained	Pearson Correlation	.[a]	.[a]
	Sig. (2-tailed)		
	N	0	0
study community is home community?	Pearson Correlation	.[a]	1
	Sig. (2-tailed)		
	N	0	141

a. Cannot be computed because at least one of the variables is constant.

Timmins 2011

Correlations

		Highest level of education obtained	study community is home community?
Highest level of education obtained	Pearson Correlation	1	.041
	Sig. (2-tailed)		.463
	N	324	324
study community is home community?	Pearson Correlation	.041	1
	Sig. (2-tailed)	.463	
	N	324	679

Hearst 2011

Correlations

		Highest level of education obtained	study community is home community?
Highest level of education obtained	Pearson Correlation	1	-.036
	Sig. (2-tailed)		.645
	N	163	163
study community is home community?	Pearson Correlation	-.036	1
	Sig. (2-tailed)	.645	
	N	163	164

Moosonee 2012

Correlations

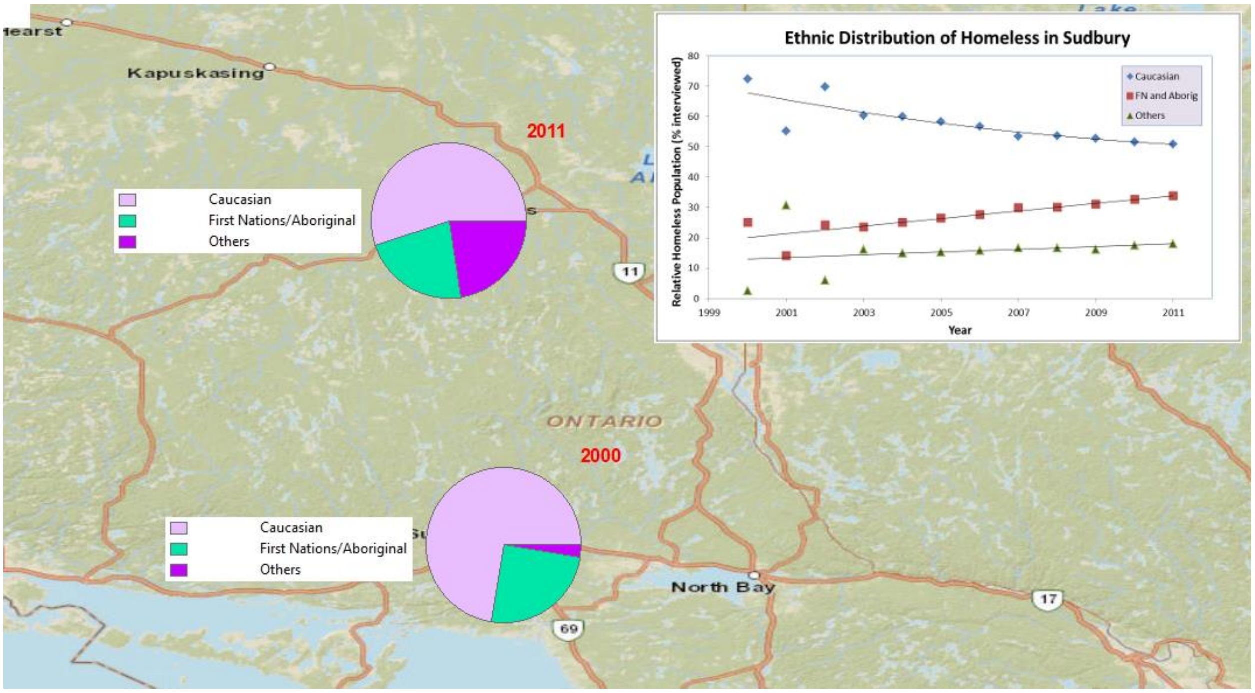
		Highest level of education obtained	study community is home community?
Highest level of education obtained	Pearson Correlation	1	-.002
	Sig. (2-tailed)		.973
	N	299	299
study community is home community?	Pearson Correlation	-.002	1
	Sig. (2-tailed)	.973	
	N	299	304

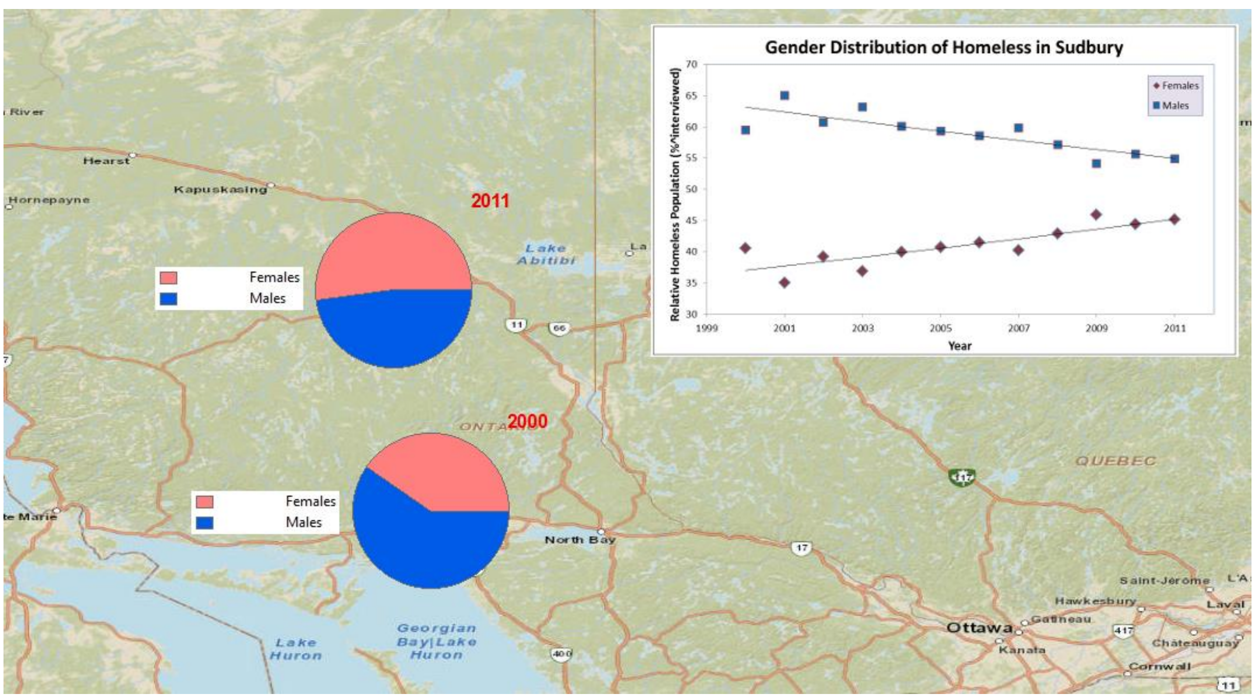
Cochrane 2013

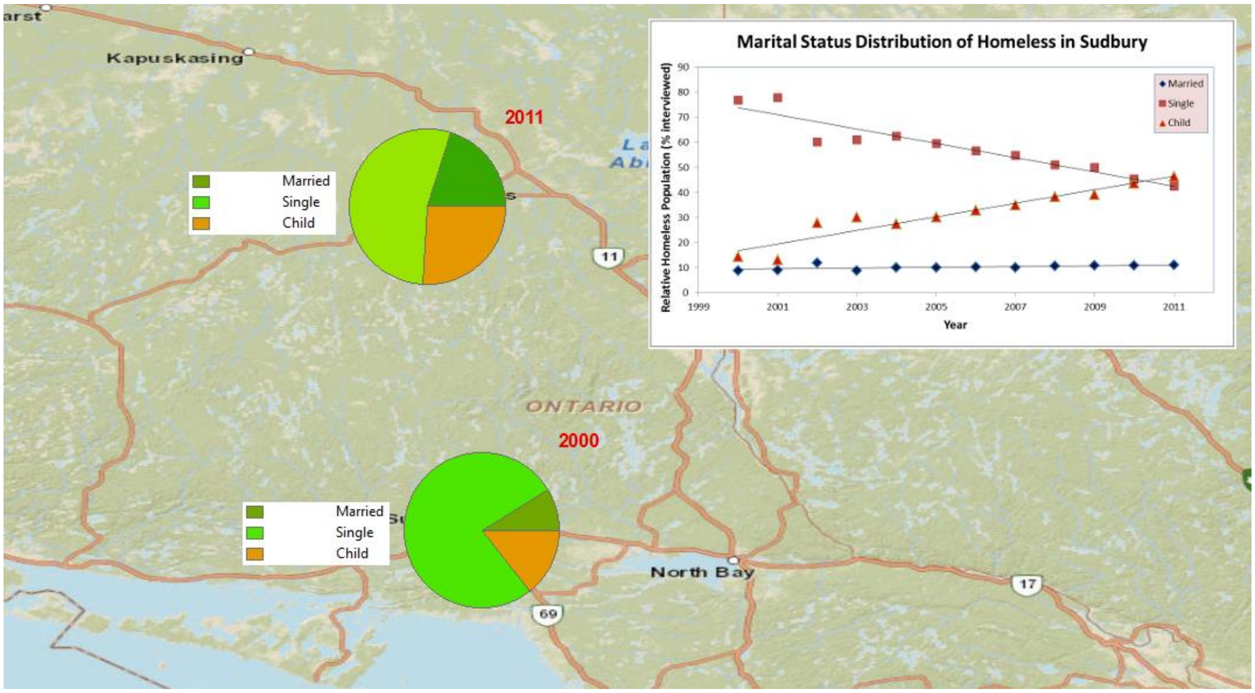
Correlations

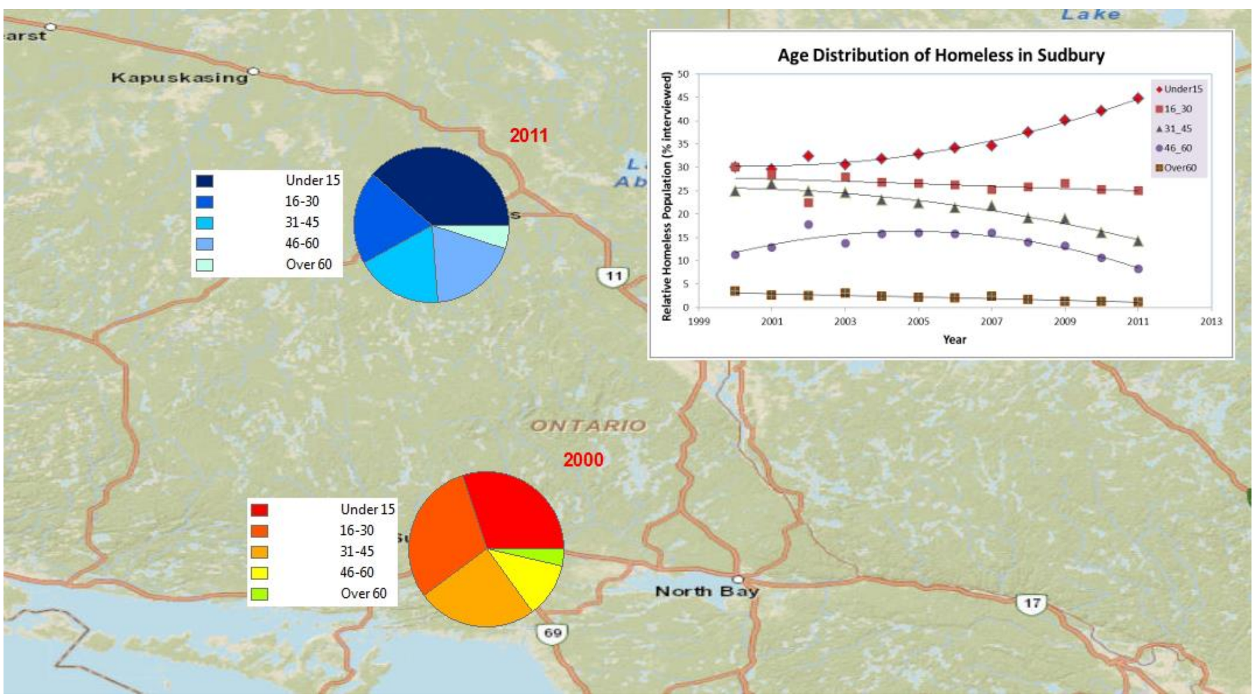
		Highest level of education obtained	study community is home community?
Highest level of education obtained	Pearson Correlation	1	.055
	Sig. (2-tailed)		.159
	N	649	649
study community is home community?	Pearson Correlation	.055	1
	Sig. (2-tailed)	.159	
	N	649	651

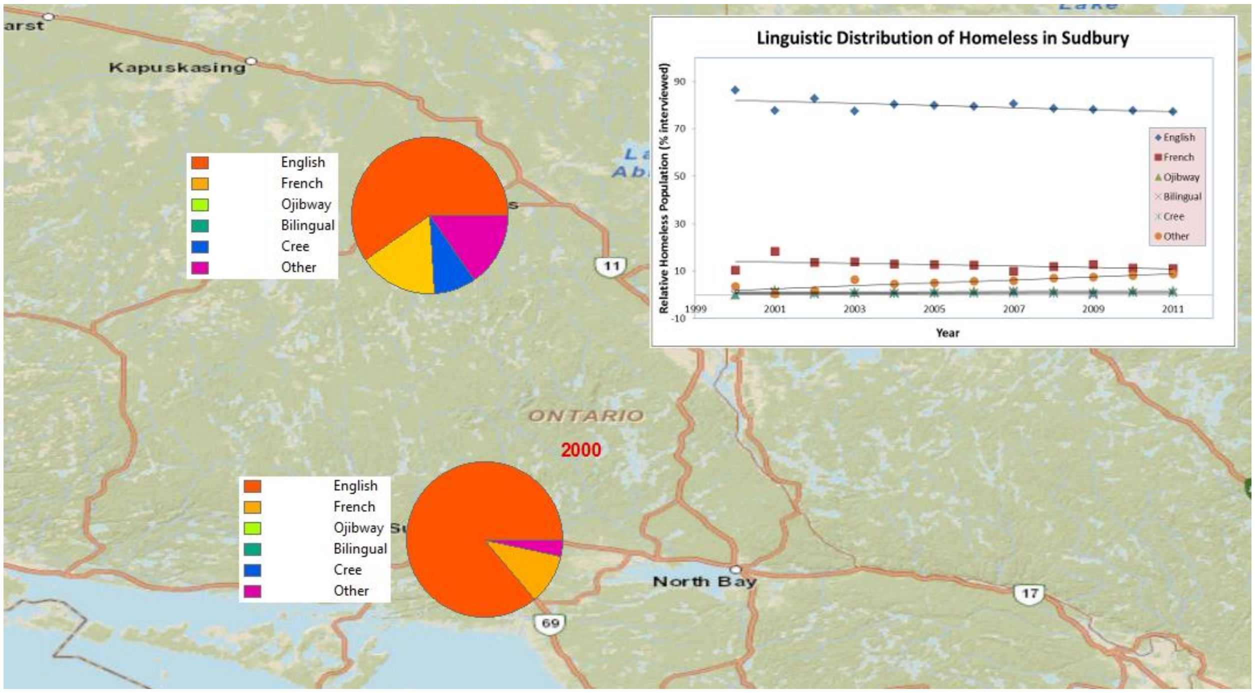
Parameter Distributions for Sudbury between Years 2000 and 2011



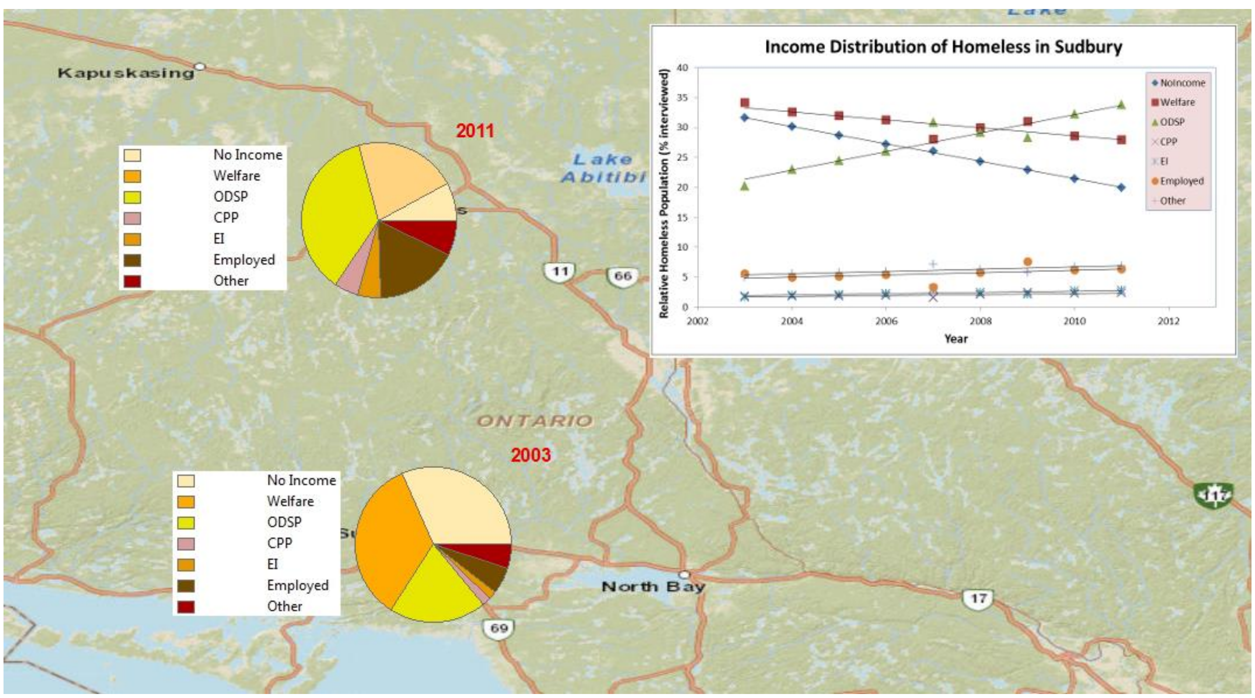



Marital Status Distribution of Homeless in Sudbury
Relative Homeless Population (% interviewed)
Year
Married
Single
Child
2011
2000
Kapuskasing
ONTARIO
North Bay


Age Distribution of Homeless in Sudbury
Relative Homeless Population (% interviewed)
Year
Under15
16_30
31_45
46_60
Over60
2011
2000
Under 15
16-30
31-45
46-60
Over 60
Kapuskasing
ONTARIO
North Bay



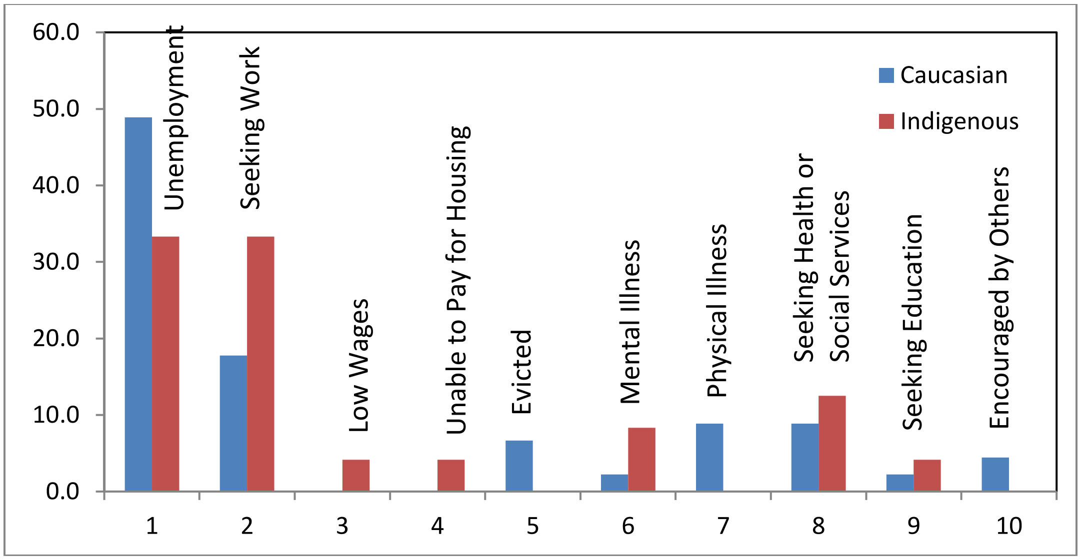
Linguistic Distribution of Homeless in Sudbury
Relative Homeless Population (% interviewed)
Year
English
French
Ojibway
Bilingual
Cree
Other
2000
ONTARIO
Kapuskasing
North Bay



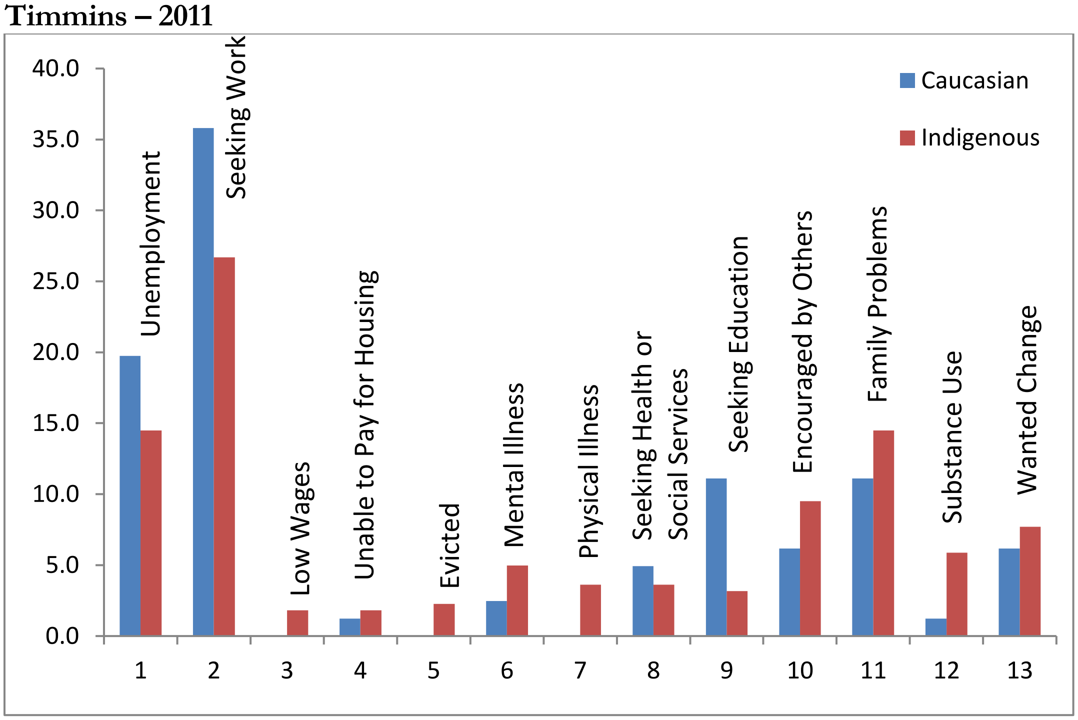
Income Distribution of Homeless in Sudbury
Relative Homeless Population (% interviewed)
Year
NoIncome
Welfare
ODSP
CPP
EI
Employed
Other
No Income
2011
2003
ONTARIO
Kapuskasing
Lake Abitibi
North Bay

Histograms (subsample of all histograms generated)

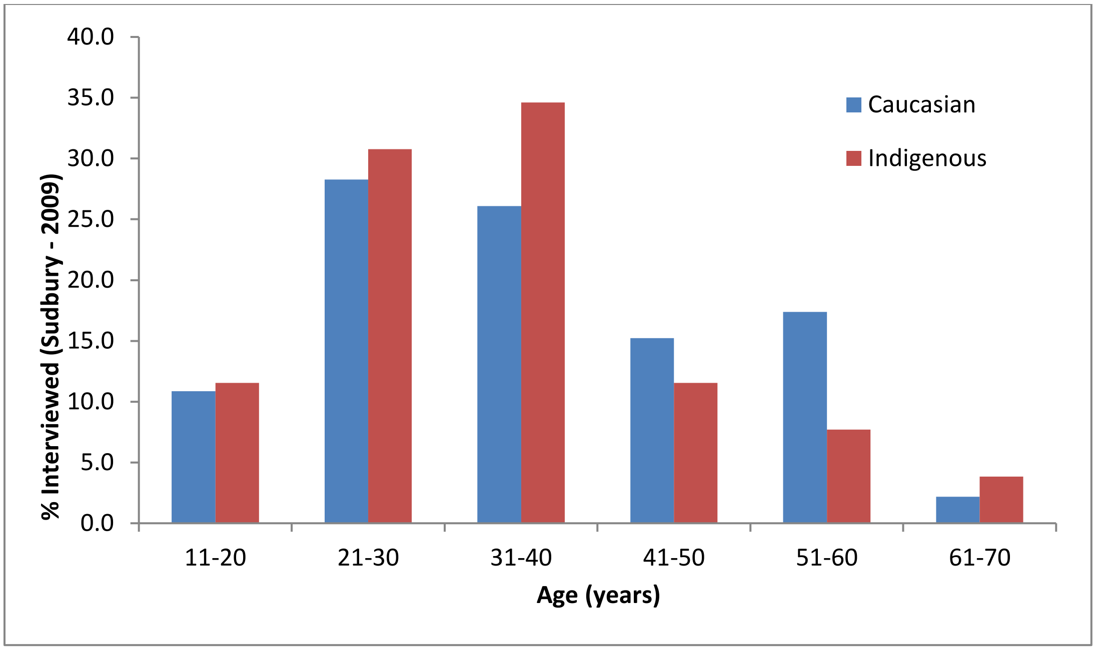
Sudbury - 2009



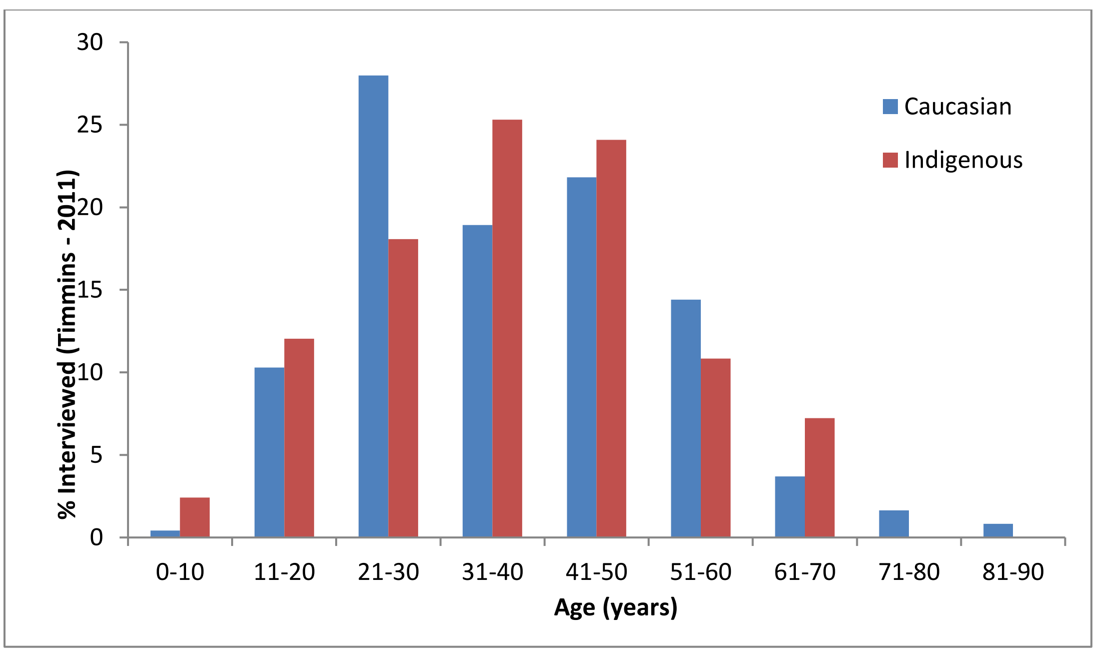
Timmins – 2011



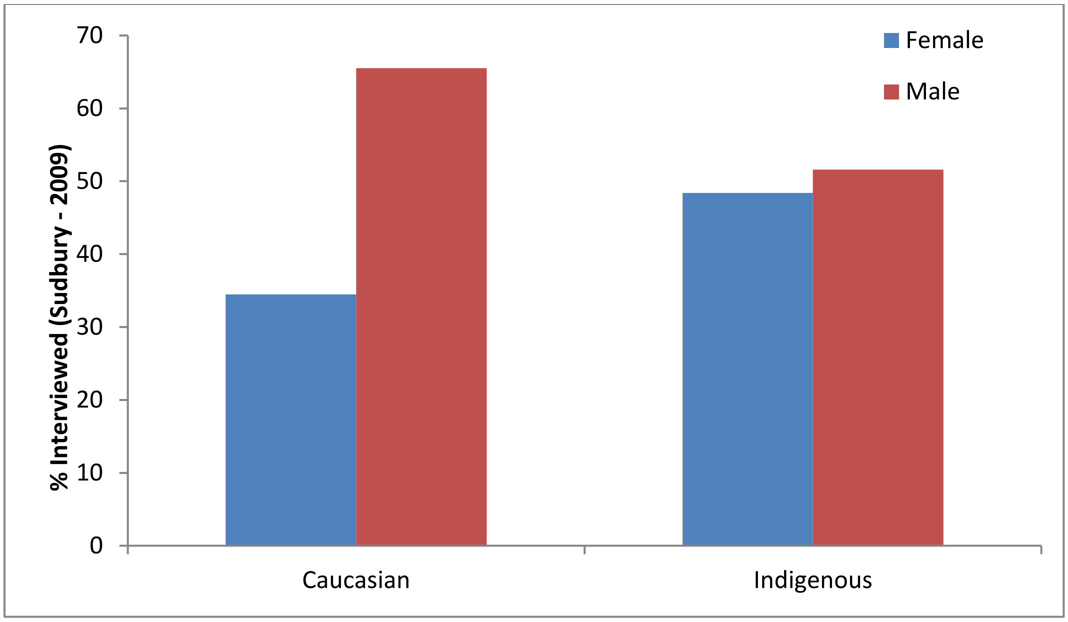
Age Distribution for Sudbury (2009)



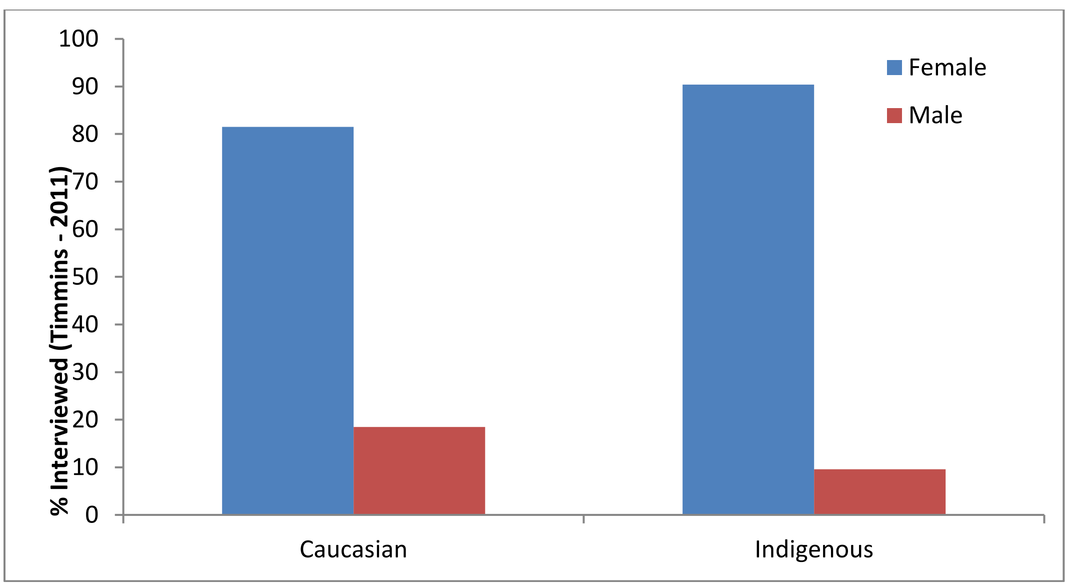
Age Distribution for Timmins (2011)



Gender Distribution for Sudbury (2009)



Gender Distribution for Timmins (2011)



City-Wide Distributions to Generate Maps (subsample of all distributions generated)

Latitude	Longitude	Male	Female	Transgender	City	Year
46.49	-81.01	53.9	45.7	0.2	Sudbury	2009
48.47582	-81.330495	47.1	52.9	0	Timmins	2011
49.06503	-81.02993	46.3	53.4	0.1	Cochrane	2013
51.27309	-80.640049	38.1	61.7	0.2	Moosonee	2012
49.68802	-83.666955	35.9	64.1	0	Hearst	2011
46.30912	-79.46082	49	51	0	North Bay	2011

City	Year	Latitude	Longitude	Caucasian	Aboriginal	Others
Sudbury	2009	46.49	-81.01	57.5	33.9	8.6
Timmins	2011	48.47582	-81.3305	50	32.3	8.6
Cochrane	2013	49.06503	-81.0299	55.3	28.5	16.2
Moosonee	2012	51.27309	-80.64	7.2	83.5	9.3
Hearst	2011	49.68802	-83.667	87.2	5.6	7.2
North Bay	2011	46.30912	-79.4608	70.7	9	20.3

Latitude	Longitude	English	French	EnglishAndFrench	Ojibway	Cree	Other
46.49	-81.01	78	12.7	4.2	1.3	0.5	3.3
48.47582	-81.3305	47.8	20.2	9.1	0	13	9.9
49.06503	-81.0299	59.3	28.4	0.9	0	6.7	4.7
51.27309	-80.64	48.3	1.9	0.5	0	47	2.3
49.68802	-83.667	10.6	52.7	32.9	0	0.7	3.1
46.30912	-79.4608	76.9	9.6	6.6	1.2	2.2	3.5

Year	Latitude	Longitude	Married	Single	Separated	Widowed	Child	Other
2009	46.49	-81.01	11.3	34.2	12	0.5	40.9	1.1
2011	48.47582	-81.3305	22.2	20.2	10.1	2.7	44.1	0.7
2013	49.06503	-81.0299	56.1	27	10.5	6.1	0	0.3
2012	51.27309	-80.64	47.1	39.3	8.1	4.7	0.7	0.1
2011	49.68802	-83.667	56.9	26.1	9.6	6.9	0	0.5
2011	46.30912	-79.4608	27.7	48.2	21.3	0.9	0.3	1.6

Longitude	NoIncome	Welfare	ODSP	CPP	EI	Employed	WSIB	Other
-81.01	22.9	31	28.3	2.4	2.1	7.5	0.9	4.9
-81.3305	7.1	17.6	31.2	7.3	5.6	22.7	2.7	5.8
-81.0299	6.8	7	10.3	17.8	2.2	46.9	0.2	8.8
-80.64	6.3	36.5	6	5	3.3	36.9	0	6
-83.667	3.8	2.7	8.1	15.1	3.8	54.3	1.1	11.1
-79.4608	8.8	25.8	43.2	2.1	4	10.6	0	5.5

Age

Latitude	Longitude	0-10	11-20	21-40	41-60	61+	City	Year
46.49	-81.01	26.7	17.7	32.7	21.6	1.3	Sudbury	2009
48.47582	-81.3305	28.3	17	23.4	23.4	7.8	Timmins	2011
49.06503	-81.0299	17.6	16.2	25.4	26.8	13.9	Cochrane	2013
51.27309	-80.64	43.9	17.8	20.7	12	5.6	Moosonee	2012
49.68802	-83.667	16.8	21.4	23.9	24.9	13	Hearst	2011
46.30912	-79.4608	21.8	17.2	28.9	30.7	1.4	North Bay	2011

Number of Children

City	Year	Latitude	Longitude	0	1	2	3AndMore
Sudbury	2009	46.49	-81.01	43.8	22.5	19.9	13.8
Timmins	2011	48.47582	-81.3305	42.6	19.6	21.1	16.7
Cochrane	2013	49.06503	-81.0299	40.7	13.9	23	22.4
Moosonee	2012	51.27309	-80.64	21.4	17.7	11.5	49.4
Hearst	2011	49.68802	-83.667	25	17.2	37.2	20.6
North Bay	2011	46.30912	-79.4608	25.5	30.1	21.2	23.2

Physical Health Problems

City	Year	Latitude	Longitude	Yes	No
Sudbury	2009	46.49	-81.01	43.5	56.5
Timmins	2011	48.47582	-81.3305	40.4	59.6
Cochrane	2013	49.06503	-81.0299	42.5	57.5
Moosonee	2012	51.27309	-80.64	24.3	75.7
Hearst	2011	49.68802	-83.667	30.2	69.8
North Bay	2011	46.30912	-79.4608	44.1	55.9

11 APPENDIX-B

LaurentianUniversity
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Homelessness in Cochrane: Period Prevalence Count (24 to 30 July, 2013)

Name of Agency:________________________________ Date:______________

Definitions of homelessness and migration/transience
Absolute homelessness: A homeless person does not have a place that he/she considers to be home or a place where he/she sleeps regularly.
Longer definition:

You are homeless if

- You have no place to call home OR
- Your home is neither a room, an apartment, nor a house, OR
- Your room, apartment or house is not your own OR
- You either stay there **four times** a week or less OR
- You have no arrangement to sleep there regularly.

At-risk for homelessness: Due to particular circumstances, a person is at an elevated risk for homelessness (i.e. pending eviction, extremely low income, familial abuse, inability to pay rent, existing medical condition with no benefits etc.).

Migration/transience A homeless person has moved or travelled to Cochrane from another location or another community.

1. Initials: ____ ____ ____ (Last, middle, and first initials of your name)
Last Middle First

2. Date of Birth_______(Day) ______________(Month) ________(Year)

3. Gender: 1.....Female 2.....Male 3.....Transgender

* This information is <u>NOT</u> used to identify individuals but as a way to eliminate duplicate cases in the count.

4a. What are the reason(s) why you are at-risk of homelessness ***AND/OR*** absolutely homeless?

Please check (√) all that apply: REASONS FOR BEING AT-RISK FOR HOMELESSNESS:			*Please check (√) all that apply:* REASONS FOR BEING ABSOLUTELY HOMELESS		
1	____	Unemployment	1	____	Unemployment
2	____	Seeking work	2	____	Seeking work
3	____	Low wages	3	____	Low wages
4	____	Unable to pay rent or mortgage	4	____	Unable to pay rent or mortgage
5	____	Evicted	5	____	Evicted
6	____	Mental illness	6	____	Mental illness
7	____	Physical illness or disability	7	____	Physical illness or disability
8	____	Social Assistance (welfare) cheque late	8	____	Social Assistance (welfare) cheque late
9	____	Social Assistance (welfare) payment is inadequate/low	9	____	Social Assistance (welfare) payment is inadequate/low
10	____	Social Assistance (welfare) cut-off	10	____	Social Assistance (welfare) cut-off
11	____	Don't qualify for welfare benefits	11	____	Don't qualify for welfare benefits
12	____	Family events or problems	12	____	Family events or problems
13	____	Divorce	13	____	Divorce
14	____	Out of jail/incarceration	14	____	Out of jail/incarceration
15	____	Substance abuse	15	____	Substance abuse
16	____	Transient or migrant	16	____	Transient or migrant
17	____	Other (please specify):	17	____	Other (please specify):

4b. Do you meet the definition of ***absolute homelessness***? 1.....YES 2.....NO (see definition above)

4c. Do you meet the definition of being ***at-risk for homelessness***? 1.....YES 2.....NO (see definition above)

5. Ethnic/racial/cultural Group:
1.....European origin (Caucasian/White)
2.....Aboriginal (specify): ______________________
3.....Visible minority (specify): ______________________
4.....Other (specify): ______________________

6. What language was first learned as a child and is still spoken?
1.....English
2.....French
3.....Cree or other First Nation language (specify): ____________
4.....Other (specify): ____________

6a. Do you still speak this language? 1.....YES 2.....NO

7a. Income Status: (List all sources)
1.....Have no income
2.....OW (Ontario Works/Welfare)
3.....ODSP (Ontario Disability Support Program)
4.....CPP (Canada Pension Plan)
5.....EI (Employment Insurance)
6.....OAS (Old Age Security)
7.....WSIB (Workers Compensation)
8.....War Veterans Allowance
9.....Private pension
10...Employment (please specify type): ____________
11...Other (specify): ____________

7b. Are you employed right now? 1...YES 2...NO

7c. If YES, how long have you been doing this job (or working for that employer)? ____________

7d. IF YES, what do you do (or where do you work? ____________

8. Are you able to read and write? 1...YES 2...NO

8a. IF YES, where did you learn to read and write? ____________

9. What is the highest level of education you have obtained?
1.....Less than high school
2.....Some high school
3.....High school diploma
4.....Some community college
5.....Community college diploma
6.....University degree

10. Marital/ Family Status:
1.....Married/ Common Law
2.....Single
3.....Divorced/Separated
4.....Widowed
5.....Other (specify): ____________

11. Number of children or other dependents: ____________

12. Do you have any children who:
are accompanying you? 1...YES 2...NO
are in your custody? 1...YES 2...NO

12a. Please provide the information about the gender and age of each of your children:

	Gender			Age in Years
Child #1	1.....Female	2......Male	3......Transgender	____
Child #2	1.....Female	2......Male	3......Transgender	____
Child #3	1.....Female	2......Male	3......Transgender	____
Child #4	1.....Female	2......Male	3......Transgender	____
Child #5	1.....Female	2......Male	3......Transgender	____

13. Are you being referred to another service provider? 1...YES 2...NO

13a. IF YES, please specify what type of agency/service: ____________

13b. Please specify the reason for the referral: ____________

14. In the last year, have you had any ***mental health*** problems? 1...YES 2... NO
Please describe ____________

15. In the last year, have you had any ***physical health*** problems? 1...YES 2... NO
Please describe ____________

16. Have you:
been ***absolutely*** homeless in your lifetime? 1...YES 2...NO
been ***absolutely*** homeless in the last year? 1...YES 2...NO
in the last year, slept outdoors/on the streets because you had nowhere to go? 1...YES 2... NO

17. Where did you sleep last night? 1...your home 2...with family/friends 3...shelter 4...streets 5...other

Please explain ____________

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Turn to page 3 ➥

Questions on *transience* and *migration*

18. Were you born in Cochrane? 1.....YES 2.....NO

19. Is Cochrane your home community? 1.....YES 2.....NO

19a. **IF Cochrane IS NOT your home community,** please specify your home community:
(circle the letter and then write the name of the community)

a.....in the Cochrane area →
b.....other North-eastern Ontario area →
c.....in North-western Ontario →
d.....in Eastern Ontario →
e.....in Western Ontario →
e.....in Southern Ontario →
f..... in another province or territory →
g.....in another country →

For all areas (a to g) specify the community / country ______________________

19b. **IF Cochrane IS your home community,** have you recently returned to Cochrane after living somewhere else? Where?
(circle the letter and then write the name of the community)

a.....in the Cochrane area →
b.....other North-eastern Ontario area →
c.....in North-western Ontario →
d.....in Eastern Ontario →
e.....in Western Ontario →
e.....in Southern Ontario →
f..... in another province or territory →
g.....in another country →

For all areas (a to g) specify the community / country ______________________

19c. How long have you been in Cochrane? # days________ or # months________ or # years ________

20. How many times have you moved to a different community in the last year? ________

21. How many times have you moved to a different community in the last 5 years? ________

22. Why did you leave another community to come to Cochrane? Please give the reason(s) for leaving, using the categories below:

Reasons for leaving another community to come to Cochrane:
Please check (√) all that apply:

1	____	Unemployment	15	____	Divorce
2	____	Seeking work in Cochrane	16	____	Family violence
3	____	Low wages	17	____	Out of jail/prison
4	____	Unable to pay rent or mortgage	18	____	Substance use (alcohol or drugs)
5	____	Evicted	19	____	Wanted a change
6	____	Mental illness	20	____	Encouraged/helped to come to Cochrane
7	____	Physical illness or disability	20a	____	➡ Who helped? (please circle):
8	____	To access health or social services		a	family
9	____	To access education		b	friends/ acquaintances
10	____	Unable to obtain welfare/didn't qualify		c	services
11	____	Social Assistance (welfare) cheque late	21	____	Other reasons (please specify):
12	____	Social Assistance (welfare) payment is inadequate/low			____
13	____	Social Assistance (welfare) cut-off			____
14	____	Family events or problems			____

23. Did you come to Cochrane with someone else? 1.....YES 2.....NO
IF YES, who (e.g. family, friends, children etc.) ______________________

24. Did circumstances improve when you came to Cochrane? 1.....YES 2.....NO

25. Where are you currently staying in Cochrane? 1..own place 2..family 3..friends 4..a shelter 5..streets

26. Has anyone in Cochrane helped you with challenges or difficulties? 1.....YES 2....NO
IF YES, who (e.g. family, friends, services etc.) ______________________

27. Are you planning to stay in Cochrane? 1.....YES 2.....NO

28. IF NO, IF LEAVING COCHRANE, where will you go? ______________________

29). What do you need right now? ______________________

Thank you for assisting with this study on Homelessness in Cochrane! If you have any questions about the study, please call Dr. Carol KAUPPI (1-705-675-1151, ext. 5058) or Kayla Sayler 1-705-491-2882) or email us at homeless@laurentian.ca

12 APPENDIX-C

Road Trips to Northern Ontario

At Cochrane train station

Waiting for Polar Bear Express in Cochrane

In Moose Factory. Author (left), Dr. Emily Faries (middle), Dr. Carol Kauppi (right)

Author with other researchers in Cochrane.

Driving on ice roads from Moose Factory to Moosonee.

Natives in Moosonee can be seen traveling on skidoos


Because of housing problem in Moose Factory, people are living in sheds as well.


Hospital in Moose Factory which covers 60 communities around James Bay area with only 2 duty doctors.

Sweat lodge near the hospital in Moose Factory.

Monument for the natives in Moose Factory who were killed in the 2^{nd} world war.

Common household items being sold in Moose Factory. The prices are 2 to 3 times more expensive than in larger cities, such as Sudbury.