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Investigating Misclassification in Exposure to the Canterbury Earthquake Sequence Using a Birth Cohort Study

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Abstract

This study aimed to investigate exposure to a major disaster by developing a more accurate representation of the exact exposure that individuals in a birth cohort experienced using geospatial data. Individuals were categorised by their residential and non-residential locations at the time of the disaster. Our results revealed that over two-thirds of individuals were misclassified when compared to using residential address as their sole point of exposure. We provide new insight into post-disaster exposure research where it is evident that the location in which an individual was at the time of disaster matters in determining 'true' exposure.

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Disasters have been impacting the world for millennia (Smith et al., 2018; Svensen, 2009). More recently, it is apparent that the number of disasters occurring globally each year is increasing (Leaning & Guha-Sapir, 2013; Rayamajhee et al., 2020; Thurston et al., 2021). Studies show that disasters have increased from 44 events in 1960 to 611 in 2019, with the number of people being affected rising from 2.84 million to 100.17 million, respectively (Chen et al., 2021). As the number of events rises, it has become crucial to categorise these events. Enhanced recording helps in assembling a typology of disasters and explain potential patterns (Caldera & Wirasinghe, 2022; Wirasinghe et al., 2013). It has been suggested that disasters fall into three main categories: 1) extreme weather events, 2) seismic hazards and events, and 3) conflict and complex emergencies (Puttick et al., 2018). The first category refers to events such as hurricanes, cyclones, flooding and heat waves; the second to earthquakes and volcanoes; and the third to wars, outbreaks of violence and complex political situations (Puttick et al., 2018). Disasters that fall into the extreme weather and seismic hazards and events categories can often be difficult to predict due to their sudden timing, as are the effects that they have on the environment (March, 2002). Earthquakes in the 20th century have resulted in devastating disasters, partly due to their sudden and severe impacts, but also because the impacts of earthquakes – for example, financial loss, disruptions to social networks and worsening of general quality of life – can be felt over a long time period (Chou et al., 2004). Thirty major earthquakes were recorded in 2022, accounting for 9.34 per cent of major global disasters (Academy of Disaster Reduction and Emergency Management et al., 2023). The average number of earthquakes events in 2022 has increased from the annual averages seen in both the 10-year periods from 2002 to 2011 (29 major events) and 2012 to 2021 (25 major events)

(Academy of Disaster Reduction and Emergency Management et al., 2023).

The Canterbury earthquake sequence and context

On 4 September 2010 at 4:35 a.m., the Canterbury region in the South Island of New Zealand was struck by an earthquake measuring 7.1 magnitude, centred 38 kilometres west of Christchurch at a depth of 11 kilometres (Spittlehouse et al., 2014). The earthquake caused significant physical and structural damage, although there were no deaths, which may partly be due to the time at which the disaster struck, when the majority of the population were at home asleep (Dorahy & Kannis-Dymand, 2012). The 4 September earthquake saw the commencement of the *Canterbury earthquake sequence* (CES) which had a large impact on the region. The first earthquake was followed by a severe aftershock on 22 February 2011 at 12:51 p.m., measuring 6.2 magnitude (Kaiser et al., 2012).

The effects of the aftershocks from the 22 February earthquake were felt heavily throughout the region, with the destruction of several residential homes and buildings throughout Canterbury, specifically within the Christchurch central business district (CBD) (Kaiser et al., 2012). The 22 February aftershock was more violent due to its epicentre being just 10 kilometres southeast of the city centre of Christchurch, and at a shallower depth, of 5 kilometres (Ardagh et al., 2012). Furthermore, Canterbury was vulnerable to additional aftershocks due to the location of the city (Ministry of Civil Defence & Emergency Management [MCDEM], 2007), and the region experienced two further major shakes, on 13 June 2011, measuring 6.0 magnitude (Kaiser et al., 2012), and on 23 December 2011, measuring 5.9 magnitude (Chang et al., 2014). The effects seen in the aftermath of this sequence of seismic disasters caused extreme disruption to the built environment within Canterbury, and especially to the individuals living within the region. Within the Christchurch CBD, two multistorey buildings collapsed, with significant amounts of rubble falling to the streets from surrounding buildings (Ardagh et al., 2012). In the first 24 hours after the 22 February 2011 earthquake, 182 people died and 6659 were injured (Ardagh et al., 2012; New Zealand Police, 2012).

In the aftermath of the CES, people were displaced both throughout the region and nationally as a result of the damage caused, with approximately 17,000 properties deemed uninhabitable in the first 12 months following the 22 February earthquake (Ministry of Business, Innovation & Employment [MBIE], 2013a). The uninhabitable properties, along with the Christchurch CBD, were classified as ‘red zoned’ which meant that the land was not feasible to rebuild on at the present time. Additionally, the Christchurch CBD was deemed unsafe, uninhabitable or buildings required major repairs or rebuilds (King et al., 2014; MBIE, 2013a). By March 2011, 755 buildings in the Christchurch CBD and 5000 residential homes had been given a ‘red sticker’, stating that they had to be vacated by May 2013 (King et al., 2014). The red sticker designation meant that thousands of people were given just over two years to move out of their homes and relocate elsewhere (Dickinson, 2013). To highlight this, it has been noted that 20,000 residents redirected their mail to a new address within the Christchurch area, and an additional 5000 residents redirected their mail to outside the Christchurch area in the first few months after the 22 February earthquake (Price, 2011, as cited in Newell et al., 2012). These findings indicate the number of people affected by their exposure to the CES (Newell et al., 2012). The implementation of the ‘red zone’ effectively put pressure on the region’s housing market, creating uncertain futures for many (MBIE, 2013a). An estimated NZ$13 billion was required to repair and replace residential homes, with a further NZ$4 billion required for the reinstatement of commercial properties (Parker & Steenkamp, 2012).

While some economic and environmental effects can be quantified, the extent of the impact that exposure to the CES had on the community is not fully understood (Ardagh et al., 2012; Dickinson, 2013; King et al., 2014; MBIE, 2013a; Newell et al., 2012; Parker & Steenkamp, 2012). Unknown information relating to precise location-based exposure of the population at the time of the event creates a gap in understanding of the nature of individual exposure to earthquake events.

To give a wider context, the Canterbury region is made up of ten district councils, which span as far north as the Kaikōura area and as far south as the Waitaki area. In 2011, approximately 370,000 people were living in Christchurch, the main city of Canterbury (Potter et al., 2015). Within the wider Canterbury area, and including Christchurch City, a total of 460,000 people were impacted by the earthquake sequence (Canterbury Earthquake Recovery Authority [CERA], 2012; Parker et al., 2012). With Canterbury spanning a large area, all individuals who were in the region at the time of the earthquake are categorised as having experienced the event.

The importance of location

An investigation into the exposure of individuals to the CES can be framed by the concept of the *Uncertain Geographic Context Problem* (UGCoP), where in a geographic setting, there is an issue with being able to accurately identify the effects of area-based attributes on individual outcomes (Kwan, 2012). The UGCoP arises due to our limited knowledge about precise spatial and temporal exposures of a given population, therefore the ‘true causal effect’ of a person’s interactions is unknown (Kwan, 2012). It is a convention within geography and public health research to use residential street addresses to assess an individual’s exposure to an outcome or event, mainly due to the convenience of accessing this data (Campbell et al., 2021; Chen et al., 2004; Kwan, 2009; Zhao et al., 2018). Using this method of defining exposure – an area-based approach – misses the specific location-based information. This conventional method of measuring exposure is referred to as 'static' exposure; for example, utilising census tracts, postcode areas or buffer zones surrounding residential addresses for indications of exposure (Bow et al., 2004; Campbell et al., 2021; Duncan et al., 2014; Healy & Gilliland, 2012; Zhao et al., 2018). This method has been effective in public health research to identify exposure to, for example, air pollution and greenspace (Letellier et al., 2022; Lu, 2021; Yoo & Roberts, 2022; Yu et al., 2018), although the literature suggests that simply using static exposure neglects a range of exposures during the day when time has been spent in other locations (Letellier et al., 2022). Therefore, in using this method, it is evident that there is an underestimation of the true effect of exposure. We can look to a more dynamic way of investigating population exposure (Campbell et al., 2021; Jiang et al., 2020; Yoo & Roberts, 2022). Considering the daily mobility of a population is important to completely understand exposure in any setting (Campbell et al., 2021; Jiang et al., 2020; Letellier et al., 2022; Lu, 2021; Yoo & Roberts, 2022; Yu et al., 2020). However, some studies investigate exposure bias (Campbell et al., 2021; Lu, 2021; Setton et al., 2011) where a common theme is an increase in bias for populations who have higher mobility levels (Lu, 2021). Researchers have identified the importance of not misclassifying a population (Dominici et al., 2005; Duncan et al., 2014; Freire & Aubrecht, 2012; Letellier et al., 2022; Lu, 2021; Yu et al., 2018). A key theme identified in the literature is the likelihood of misclassification error being applied when a home location alone is used (Yu et al., 2018).

The concept of the UGCoP has been utilised within a public health and geography setting to identify the role in which types of exposure can influence health outcomes

(Campbell et al., 2021; Letellier et al., 2022; Lu, 2021; Yoo & Roberts, 2022). However, within a disaster setting, researchers have recognised the importance of accounting for exact exposures, with studies stating there are methodological challenges that arise from the difficulties in being able to track exposures before, during and after a disaster (Dominici et al., 2005). Furthermore, these methodological challenges can be used to explain the importance of the type of data collected (Dominici et al., 2005). The advantage of accessing regularly collected longitudinal birth-cohort data is to identify historic characteristics that may influence the outcomes of individuals in later years (Gallagher et al., 2019; Matsuyama et al., 2016).

In a pre- and post-disaster setting, there is insufficient literature that investigates precise location-based data to measure exposure (Freire & Aubrecht, 2012; Yabe et al., 2016). Most post-disaster research uses the term 'exposure' to measure aspects such as health outcomes (Casacchia et al., 2012; Guo et al., 2022; Kiliç et al., 2011) or increased use of substances (Bianchini et al., 2015; Garfin et al., 2014; Kanehara et al., 2016; Kobayashi et al., 2019; Morishima et al., 2022; Shimizu et al., 2000), although the literature fails to recognise the influence that location-based exposure at the time of disaster has on their population. It is important to understand a population's exposure more fully in the aftermath of a disaster to better explain the outcomes observed within individuals who were exposed. Few studies have been able to accurately identify how to define exposure to health influences such as greenspace or air pollution (Campbell et al., 2021; Jiang et al., 2020; Letellier et al., 2022; Lu, 2021; Setton et al., 2011; Yoo & Roberts, 2022; Yu et al., 2018; Yu et al., 2020) where it is evident that using a dynamic method to assessing exposure is beneficial. Previous research investigating the CES found that individuals who were highly exposed to the event consequently had increased rates of major depression, post-traumatic stress disorder (PTSD) and nicotine dependence

(Fergusson et al., 2014). Relative to residential location, a study determined that two and a half years following an earthquake in Iceland in 2000, individuals were still suffering from ongoing fear and anxiety as a direct consequence to high exposure to the epicentre of the event (Akason et al., 2006). Likewise, some individuals who were displaced from their homes following an earthquake in Nepal in 2015 had increased symptoms of depression and PTSD, which correlated to the number of earthquakes experienced (Schwind et al., 2018). While it is evident that individuals who experience earthquakes are at risk to develop adverse health outcomes, knowing their exact exposure and how this can impact longer-term outcomes is yet to be fully investigated. This suggests that there is no significant research that has been able to identify how the UGCoP could influence the outcomes measured in a disaster setting. It is important to recognise the difficulty in recording this type of data. As mentioned earlier, the timing of the February 2011 Canterbury earthquake was in the middle of a usual workday. The timing of this disaster can explain the uncertainty in which individuals experienced exposure, which ultimately leads to and demonstrates the UGCoP (Alexander 1996; Kwan, 2012).

It is generally understood that disasters occur randomly, making it difficult to be able to ascertain specific exposure data on a population. However, researchers recognise that there is a difference in people’s experiences when they are exposed to earthquakes at night compared with during the day. This can be partially explained by daily shifts in population distribution based on daytime activities, such as work or education, for example (Freire & Aubrecht, 2012). The 12:51 p.m. timing of the earthquake on 22 February 2011 earthquake suggests that the population would have been dispersed throughout the region, as opposed to prior earthquakes that occurred during the night. We suggest that the timing of a disaster could be critical to understanding when, where and how exposure to an earthquake unfolds.

More fully understanding how a population was exposed to a disaster as it struck contributes to the range of post-disaster literature about the temporal impacts of disasters. This understanding is created by identifying where individuals were, identifying the level of damage to the area, and determining if their exposure was worse, better or the same as their residential address. In doing this, researchers can predict the percentage of the population who, under the typical way of identifying a person's exposure through public health or disaster research (i.e., by residential address), would be misclassified.

Study aim

Our study aims to investigate exposure misclassification to a major disaster by developing a more accurate representation of the degree of exposure experienced by a birth cohort at the precise moment a disaster strikes. Individuals will be determined as either not misclassified or misclassified, and by their degree of exposure (severity of damage at residential and non-residential addresses), which will quantify how and to what extent a population can be misclassified. This extends ongoing debates by utilising a birth cohort who experienced a major earthquake on 22 February 2011. The possible effect that socio-economic variables have on misclassification will also be explored.

Methods

Study design and participants

Data

The Christchurch Health and Development Study (CHDS) is a longitudinal study that follows a cohort of people who were born in Christchurch, New Zealand between April and August 1977; the 1265 participants in the study represent 98 per cent of all births that occurred in Christchurch over that four-month period. The cohort has now been studied on 24 occasions, from birth to age 40 (Buchanan et al., 2023; Fergusson & Horwood, 2013). Data from the CHDS has been used to investigate a range of topics relating to health, education and life progress as the participants have advanced from childhood to adulthood. All data were gathered subject to the signed consent of the research participants, and all phases of the study received approval from the regional Health and Disability Ethics Committee. The study sample was based on the CHDS cohort members who were exposed to the CES, which was recorded in the age 35 wave of data collection (in 2012). Of the overall exposed population, a sample size of $n = 362$ (71 per cent) had valid data appropriate for this study.

Exclusion criteria

Exclusion criteria were created to develop the final sample. First, individuals who had experienced the 22 February earthquake but who opted not to complete the earthquake-specific interview were removed from the data set. Second, individuals who stated they had been exposed to the CES but not to the 22 February earthquake were removed. Third, individuals who had experienced the 22 February earthquake but did not to complete the earthquake-specific interview were removed. Finally, as the data are from the CHDS, individuals from the wider Canterbury area were included in this study. We are observing the exposures of individuals to the 22 February earthquake disaster across a wider geographical area (Canterbury) than only the immediate city area (Christchurch). So, fourth, individuals who did not have accurate address data, meaning their degree of exposure to the earthquake was unidentifiable, were removed. Refer to Figure 1 for further details.

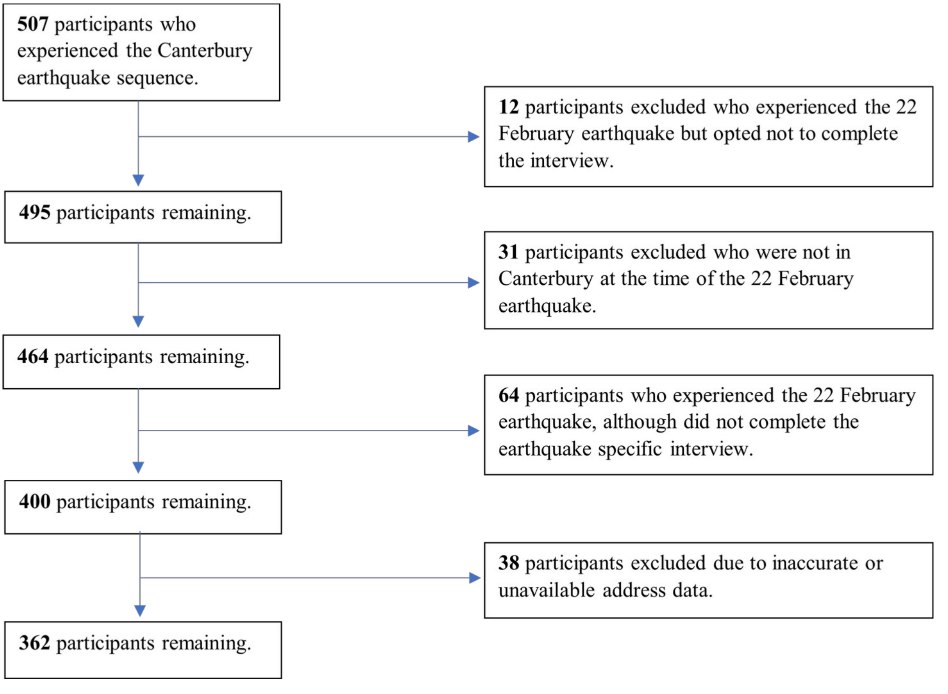
Outcome

Exposure event

The degree of exposure to the CES was initially measured by those in the CHDS birth cohort who were present in the Canterbury region at the time of any of the four major earthquakes that comprise the CES (i.e., 4 September 2010, 22 February 2011, 13 June 2011 and 23 December 2011). These data were recorded in 2012, 20 to 24 months following the onset of the CES. Individuals who had experienced the CES were asked questions about the immediate impacts of the disaster using questions derived from the Modified Mercalli Earthquake Intensity Scale (Beaglehole et al., 2023; Dowrick, 1996).

The 22 February 2011 earthquake was chosen as the main focus for this study due to temporal considerations. Although several individuals experienced one or more of the three remaining earthquakes that make up the CES, only those who had also experienced

Figure 1: Exclusion criteria for the CHDS population exposed to the 2011 Canterbury earthquake



the 22 February earthquake were included. The focus of the individuals who experienced the 22 February 2011 major earthquake is because the environmental, social and economic effects of that earthquake were much more intense than those of the other three earthquakes in the CES. Furthermore, the 22 February 2011 earthquake occurred at midday, during a working week, meaning that a significant proportion of the population were likely be at a non-residential address. In contrast, the 4 September 2010 earthquake occurred at 4:35 a.m., where it can be assumed that the majority of the population were at residential addresses. It has been shown that a greater proportion of the population is likely to be impacted by a daytime disaster (Freire & Aubrecht, 2012). As our main aim is linked to misclassification of the degree of exposure, the focus is on the population who were exposed to

the midday 22 February 2011 earthquake. For the purpose of this analysis, exposure to an earthquake is simply defined by whether an individual was in the Canterbury region at the time of the event and state they experienced the event. Going forward, the following categories were used to describe the degree of exposure of the cohort:

- *Exposed at home* (same risk category, same location) – this represents the proportion of the cohort who were at their residential address at the time of the event.
- *Not misclassified* (same risk category, different location) – this represents the proportion of the cohort who were at a non-residential address at the time of the event, although the location they were in was at the same level of risk as their residential address.
- *Misclassified high* – this represents the proportion of the cohort who were at a non-residential address at the time of the event, and that non-residential address was in a higher risk category than their residential address.
- *Misclassified low* – this represents the proportion of the cohort who were at a non-residential address at the time of the event and that non-residential address was in a lower risk category than their residential address.
- *Address* – divided into two subcategories:
    - *Residential address* – defined as the location at which the individual resided on the day of the event (22 February 2011).
    - *Non-residential address* – defined by any location where the individual stated they were at the exact moment the earthquake struck (12:51 p.m. on 22 February 2011) that is not their residential address.

Protocol to assign exposure

To investigate the degree of exposure to the 22 February 2011 earthquake, address data were required for each individual. Data in categories such as which suburb the individual was living in and/or was present in at the time of the disaster, the nature of surroundings at the time of the disaster, and their residential addresses were required. To be included in the population sample, a valid residential address was required. In order to determine the exposure at the time of the event, either a statement of being at their residential address or evidence of being at a non-residential address was required. The inclusion of both addresses was paramount to data matching. Previously inputted data on residential and non-residential addresses were used to match where the individual stated they were at the time the 22 February earthquake occurred in order to then assign degree of exposure to the disaster.

Area-based damage to determine exposure

In the aftermath of the 22 February 2011 earthquake, MBIE developed technical categories (TC) throughout the Christchurch urban region (MBIE, 2013). The TCs were established to illustrate the observed land damage, property damage, groundwater information and soil conditions (MBIE, 2013a). Research completed by geotechnical consultants, research groups and engineers determined the boundaries of these TCs throughout the urban region. The categories that were established were TC1 (little damage), TC2 (moderate damage) and TC3 (severe damage). Further to this, the CERA developed the red zone, which were the areas of the Christchurch urban area that were most severely damaged.

These TC areas throughout the Christchurch urban areas were used as a baseline for determining the degree of exposure of the CHDS population. For this study, and due to the small sample size, three disaster exposure categories were created: those who had an address in TC3 or in the red zone area (as established by the CERA) fell into the high disaster exposure category; those who had an address in TC2 fell into the medium disaster exposure category; and those who had an address in TC1 fell into the low disaster exposure category.

The TC zones developed by MBIE and the red zone developed by the CERA failed to categorise the city centre of Christchurch. This is the area within the four avenues of

Christchurch: Deans Avenue, Fitzgerald Avenue, Bealey Avenue and Moorhouse Avenue. It is evident through literature and aerial imagery that this area can be classified as severely damaged, meaning addresses in this area fit into the high disaster exposure category. Furthermore, some unmapped North Canterbury locations that surrounded TC2 zones closely were classified as medium exposure. Unmapped locations to the south of the Christchurch urban area were classified as low exposure.

Some inconsistencies in the reporting of address data meant that protocols were required to prevent inaccuracies. Where possible, addresses were matched to be suburb-specific. This meant that some individuals did not have an exact street address as their exposure. Where it was unlikely to be able to determine a suburb-specific address, the individual was removed from the study population.

Misclassification

Data on the misclassification of individuals were derived from a combination of residential and non-residential address data. Residential addresses at the time of the disaster were collected in the aftermath during the age 35 wave of data collection through earthquake-specific interviews (conducted from 2011 to 2012). Non-residential addresses were defined by a combination of workplace names and compiling their earthquake-specific data on location at the time the disaster struck. Workplace addresses were collected in the age 35 main interview (in 2012), identified as valid through using the Yellow Pages and the New Zealand Companies Register, and mapped to assign a street address. Both residential and non-residential addresses were inputted and geocoded to create *x* and *y* coordinates. It is important to note that these data were self-reported through an interview process, which leaves room for error in reporting of residential and workplace addresses. After analysing the address data to determine the location of individuals at the time of the 22 February earthquake, a measure was then created to determine the differences in their residential and non-residential address exposure. Individuals who stated their location to be away from their residential address were included in this measure of potential misclassification. Individuals who were not at their residential address but were within the same risk category as their residential address at the time of the earthquake were subsequently determined to be not misclassified as their degree of exposure did not change. It is important to add that not all individuals were at a physical street address – some were in a vehicle and others walking on the footpath. Data were available on whether individuals were indoors, outdoors or in a vehicle; however, for the purpose of this analysis, these data were excluded due to small sample size. In this instance, these individuals were categorised due to the severity of damage in their surroundings as they stated the given suburb or location that they were in at the time of the earthquake, rather than a specific street address.

Individuals were first grouped by damage at their residential address. The grouped categories were High, Medium and Low, based on the severity of damage at this address. Next, individuals were grouped by their non-residential address, being the location they were at when the earthquake struck. Again, the categories High, Medium and Low were used for this process. This produced a two-dimensional scale measuring both the damage at an individual's residential address and the damage of the location where they actually were when the earthquake struck.

Where individuals fell into the same damage category for both their residential and non-residential addresses (High-High, Medium-Medium, Low-Low), they were classed as Not Misclassified. Where individuals had higher damage levels for their non-residential address than for their residential address (Medium-High, Low-High, Low-Medium), they were classed as

Misclassified High. And finally, where individuals had lower damage levels for their non-residential address than for their residential address (High-Medium, High-Low, Medium-Low), they were classed as Misclassified Low.

Other relevant CHDS data

Other variables extracted from the CHDS birth cohort database which are of relevance include sex, socio-economic index, education, and welfare status. These have been included due to relevant literature that suggests sociodemographic characteristics can influence an individual's outcomes linked to exposure within health literature (Guo et al., 2022).

Statistical analysis

Descriptive statistical analysis was used in this study to determine the effect that misclassification has on the exposed population. Percentages and a Sankey diagram were used to show misclassification throughout the population. Descriptive statistics including percentages were used to determine the influence that sociodemographic factors had on a misclassified population's degree of exposure. All percentages presented in this analysis have been rounded to whole numbers, which may create a margin of error. A stacked bar chart was used to show the significance of the findings. One-way ANOVA was conducted to determine the relationship between the demographic and socio-economic factors and misclassification. All analyses were conducted using Microsoft Excel, SPSS or the statistical software RStudio.

Results

Descriptive statistics

As outlined in Table 1, it is evident that just over a third of the total exposed population were at their residential home address at the time of the earthquake. Excluding individuals who were at home at the time of the earthquake, 58.5 per cent of the exposed CHDS population were misclassified. This result can be seen more clearly in the Sankey diagram (Figure 2). Individuals who were not misclassified were evenly spread between the three categories (High-High, Med-Med and Low-Low). Notably, 32.1 per cent of the total population were misclassified low, where most individuals were misclassified from a medium residential degree of exposure to a low non-residential degree of exposure. The same trend is seen for individuals who were misclassified high. The largest proportion (18.3 per cent) of the misclassified high group had a medium residential degree of exposure and moved to a high non-residential degree of exposure category.

The scale derived from others on earthquake severity (Fergusson et al., 2014) was used to prove if misclassification was accurate. Table 2 reflects this result where it is evident that individuals who were not misclassified have stable numbers within each of the categories, while individuals who were misclassified high are mostly in the highest two categories (3 and 4). Furthermore, Figure 3 solidifies the earlier results where those in the middle two categories (2 and 3) have the highest percentage in misclassified groups.

Table 1: Misclassified CHDS cohort members

Classification	**%**
Exposed at home (same risk category, same location)	n = 138 (38%)
High	n = 32
Med	n = 23
Low	n = 83
Not Misclassified (same risk category, different location)	n = 93 (26%)
High-High	n = 32
Med-Med	n = 30
Low-Low	n = 31
Misclassified High	n = 59 (16%)
Med-High	n = 41

Low-High	n = 10
Low-Med	n = 8
Misclassified Low	n = 72 (20%)
High-Med	n = 12
High-Low	n = 13
Med-Low	n = 47

Figure 2: Sankey diagram to represent misclassification of CHDS cohort members

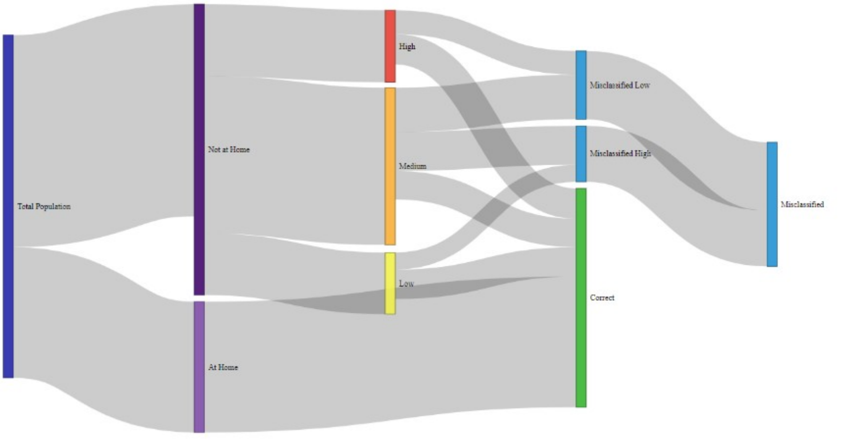
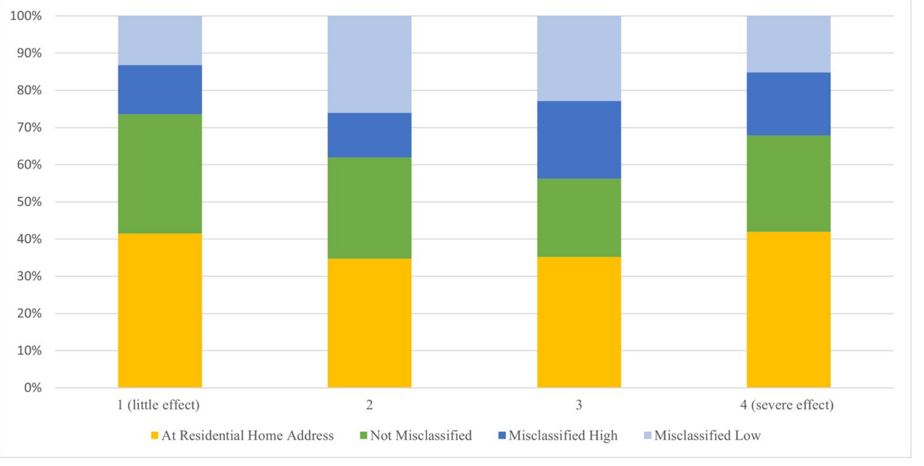


Table 2: Proving the categorical measure by misclassification of CHDS cohort members

	Scale	**1 (Little effect)**	**2**	**3**	**4 (Severe effect)**	**Total**
At home	At residential home address	22 (16%)	32 (23%)	37 (275)	47 (34%)	138 (100%)
Not at home	Not Misclassified	17 (18%)	25 (27%)	22 (24%)	29 (31%)	93 (100%)
	Misclassified High	7 (12%)	11 (19)	22 (37%)	19 (32%)	59 (100%)
	Misclassified Low	7 (10%)	24 (33%)	24 (33%)	17 (24%)	72 (100%)
	Total	**53 (15%)**	**92 (25%)**	**105 (29%)**	**112 (31%)**	**362 (100%)**

Figure 3: Percentage exposure of misclassification based on effect level



Socio-economic variables were used to determine the effect on misclassification (Table 3). Females were more likely to be at home at the time of the event (49 per cent compared with 29 per cent of males). Of the population who were not at home at the time of the event, males were more likely to be misclassified (42 per cent compared with 30 per cent of females), with 15 per cent of males being misclassified low and 27 per cent misclassified high. This compares with 17 per cent of females not at home being misclassified high and 13 per cent misclassified low. A large percentage of the population (30 per cent) who had the highest socio-economic status (Index 4) were misclassified low, meaning that their location at the time of the disaster was in a less severely damaged area to their residential address. It is important to state that there is no statistically significant difference between the population groups. Interestingly, those who were on a welfare benefit were equally as likely to be misclassified either high or low.

Table 3: Exposure misclassification by selected demographic and socio-economic factors

	At home	**Not at home**			***p-value***	**Total exposed population**
	At residential address	*Not Misclassified*	*Misclassified High*	*Misclassified Low*		
Gender						
1 (male)	43 (25%)	54 (32%)	26 (15%)	46 (27%)	<.001	169 (47%)
2 (female)	95 (49%)	39 (30%)	33 (17%)	26 (13%)		193 (53%)
Socio-economic Index						
1 (low)	63 (45%)	36 (26%)	15 (11%)	27 (19%)	.338	141(39%)
2	38 (32%)	34 (29%)	26 (22%)	19 (16%)		117 (32%)
3	17 (33%)	11(22%)	13 (25%)	10 (20%)		51 (14%)
4 (high)	20 (38%)	12 (23%)	5 (9%)	16 (30%)		53 (15%)
Education status						
0 (no education)	10 (42%)	2 (8%)	4 (16%)	8 (33%)	.459	24 (7%)
1	84 (40%)	59 (28%)	28 (13%)	38 (18%)		209 (58%)
2	10 (23%)	17 (39%)	12 (27%)	5 (1%1)		44 (12%)
3	31 (42%)	13 (18%)	14 (19%)	16 (22%)		74 (20%)
4 (high)	3 (27%)	2 (18%)	1 (9%)	5 (45%)		11 (3%)
Welfare						
0 (no)	101 (34%)	82 (28%)	50 (17%)	62 (21%)	.014	295 (81%)
1 (yes)	37(55%)	11 (16%)	9 (13%)	10 (15%)		67 (19%)

Discussion

Our study aimed to more precisely investigate the degree of exposure misclassification to a major disaster in Christchurch, New Zealand, by employing detailed spatio-temporal data from a birth cohort study to determine a precise exposure location. The study established individual residential exposure, as well as non-residential exposure, based on the severity of damage to the land. This study adds to the evidence on understanding spatio-temporal exposure to disasters by determining: 1) if individuals were misclassified, and 2) the degree of misclassification if only their residential address were used to assign degree of exposure to disaster.

Our study demonstrates that approximately two out of three people who were not at their residential address at the time of the event would be misclassified if residential address were used as the only measure of exposure. This finding itself is significant. No meaningful patterns in degree of exposure misclassification were found when investigating the socio-economic characteristics of the population. This is one of the first studies that has been able to more accurately identify where a population was located at the time a disaster struck (Dominici et al., 2005). This means that this study can make conclusions about the instantaneous or ongoing impacts based on exposure location at the instant of a disaster. Our results demonstrate the only a limited proportion of a population (one in three) were correctly classified based on known degree of exposure location. It could be argued that this might have profound implications for subsequent analysis, results and conclusions. Our study supports previous literature in that issues such as the UGCoP outline how limited knowledge of the precise spatial and temporal exposures of given populations (Kwan, 2012) can have important consequences for research endeavours. Furthermore, previous literature has suggested that investigating misclassification creates an underestimation of individuals' true degree of exposure (Duncan et al., 2014). It is plausible that an exact address can be far from the centroid of a spatially aggregated unit such as a census tract (Duncan et al., 2014). Moreover, the literature discusses that analysing individual exposure based on census data alone in the aftermath of a daytime disaster may result in misestimation (Freire & Aubrecht, 2012). Our study builds on previous literature, demonstrating that if residential address is used as the only measure, two-thirds of the population would be misclassified by their exposures if the disaster were to occur in the middle of the day. Furthermore, we have demonstrated that relying on areal-level exposure metrics and assuming residential address exposure can have important limitations in understanding the impact of earthquakes on populations.

Our findings support previous research and policy that have suggested that in a public health setting, disregarding spatial variability could lead to differential exposure misclassification and, therefore, biased health risk assessments (Letellier et al., 2022; Lu, 2021; Yu et al., 2018). Applying this method can generalise results to a disaster setting, where it is likely to have biased health assessments of exposed populations in the aftermath if we do not know the true extent of their exposure. Moreover, Campbell et al. (2021), in their work on dynamic exposures, have argued that there are important implications in understanding how their findings can be generalised by expanding the size of the cohorts to see the degree to which their findings can be applied across different people, places and application domains. Our study engages with this prior limitation, using a cohort study to further illuminate the misclassification of a larger cohort study.

Research suggests risk of injury, and therefore the severity of felt damage, varies significantly between night and day, implying that exposure should be measured temporally (Alexander, 1996). Additionally, literature recognises that population distribution based on daytime activities can significantly influence the number of people exposed to a disaster, with more people likely to be exposed to daytime events (Freire & Aubrecht, 2012). While three of the four major earthquakes in the CES occurred during the daytime, as noted earlier, the most intense effects were seen in the 22 February 2011 earthquake, which is why the decision was made to make that earthquake the focus of this study. The critical importance of the temporal aspect of the disaster is highlighted by the finding that a significant proportion of individuals were away from their residential address at the time of the disaster. Thus, the importance of both temporal and spatial fidelity is highlighted in our study.

While there is not a great wealth of literature that investigates exact location-based exposure to a disaster, our study does support the plethora of previous research that has investigated the benefits of using dynamic data to analyse exposures (Campbell et al., 2021; Jiang et al., 2020; Letellier et al., 2022; Lu, 2021; Yoo & Roberts, 2022; Yu et al., 2018). Our study highlights the importance of identifying how individuals can be misclassified using a residential address as their perceived exposure to an event, which can be applied to a range of settings. Research has identified that establishing a precise definition of exposure is imperative to reduce the risk of misclassification (Stricker & Stijnen, 2010). Our study addresses the risk by illustrating our understanding of exposure.

Our findings support previous literature that suggests that workers are more likely to have higher exposure-estimation bias than non-workers (Lu, 2021). The current research found that those who were not at home were more likely to be misclassified. It is also recognised that exposure levels are likely to be over- or underestimated in some circumstances depending on neighbourhood factors; for example, the level of air pollutants at home in comparison with when travelling (Lu, 2021). Populations who are likely to have higher mobility are, therefore, more likely to be misclassified by their exposure. Our study highlights this phenomenon through our finding that the more mobile population was most likely to have misclassified exposure.

In future research, considerations of health outcomes could be relevant with regard to the location-based exposure data collected. Relationships between residential and non-residential exposures to determine health outcomes would be established. While investigating the influence of socio-economic factors was not a main aim of this study, it is recognised that future research might further focus on the importance of these aspects. In a disaster setting, it is paramount that we investigate associated outcomes that could influence this field of literature. Future research might identify various impacts from an earthquake that could influence the way exposure is defined and conceptualised. Future research might also focus on the medium- to longer-term movements and associated damages of a population, which will provide an interesting insight into how knowledge of location-based data can influence a population over time. It is evident that future research needs to be conducted to identify exact exposures. Typical research investigating exposure to an earthquake uses census-based resident population, which fails to recognise the spatial distribution of real-time data (Freire & Aubrecht, 2012). Outcomes in disaster research can be more reliant on using location-based data as an exposure measure as we can then be confident that populations are not being misclassified. When a location-specific exposure is known, this changes how we determine the effect of the disaster on a population. Populations can be more prepared with this knowledge to supply resources more rapidly to those who are most severely affected by a disaster based on their location-based data.

Policy should, therefore, focus on efforts to obtain both spatial and temporally accurate representations of the exposure of populations in disaster-prone environments. In other words, the time of disaster is critical, but so is an individual's precise location. Knowing location through time will then lead to much more precise and accurate responses to disaster by those tasked with both disaster prevention and recovery.

Strengths and limitations

This study used data from a birth cohort that has been studied over the course of 40 years, which is a rare form of data collection to be used in a post-disaster setting. Specific location-based data were self-reported in the age 35 wave of data collection by individuals of the birth cohort, and the data were collected 20 to 24 months after the onset of the CES.

Since the location-based data were self-reported, and due to the likely stressful disaster that many experienced, recollections could be inaccurate (Krayem et al., 2021), which is the first potential limitation of the study. It is also important to note that the birth cohort is restricted to age. The effects of experiencing the CES likely vary with age and the effects of the degree of exposure on younger or older populations may differ from those found within this cohort.

The definition of exposure created through this investigation was simply to determine where individuals were at the time of the 22 February 2011 earthquake within the Canterbury region. It is recognised that this definition does not account for the multiple facets and influences that may arise during this type of event. Defining exposure to an event such as this is a complex process, and future research could use this definition as a starting point to create more exact outcomes post disaster.

As the data collected were self-reported through an interview style, inaccuracies with the reporting of address data could likely lead to recall bias. Some locations used within this study were suburb-specific rather than street-specific, leading to less precision than desired. The inclusion of census data was considered, although this type of data would be unable to account for particular patterns of travel on the day of the earthquake (22 February 2011), whereas we have specific data on the day of the event. It has been recognised in literature that when specifically investigating the effects of an earthquake, census data will not be able to account for the required information when you consider individuals may be away from their homes (Dominici et al., 2005).

Protocols were assigned to ensure that there was an accurate representation of all location data (as reported in the methods section). It is recognised that the use of the TC categorisations could lead to problematic inaccuracies when determining the level of damage in each location, specifically within the city centre. A number of options were considered including creating a new measure of damage based on GeoNet's earthquake intensity scale and shaking map (Dowrick, 1996; GeoNet, n.d.) and mean building damage per household (as a percentage of property value), which was used in a study on cardiovascular disease risk and earthquake damage (Teng et al., 2017). The options explored, however, did not appear to give a reasonable explanation of the levels of damage that were seen throughout the Canterbury region, so the decision was made to use the TC categories to explain damage. While using this method may provide some inconsistencies with data, determining the level of damage was not the primary aim of this study; rather, the study sought to determine the difference in the degree of exposure of a cohort. The decision to classify the city centre as TC3 (most severely damaged) was due to the severe damage, with loss of buildings and lives, and the degree of distress that was felt throughout the city from that given location. North Canterbury, southern areas of Christchurch and greater Canterbury were categorised per their closest TC. As these were unmapped areas and a TC was provided based upon assumption, this could provide inconsistencies with the level of damage among these locations.

Despite these limitations, the present study suggests that determining the differences between residential addresses in comparison to non-residential addresses does imply misclassification exists. As this birth cohort was followed during a major disaster, using this data is invaluable.

Conclusion

Our study suggests that misclassification is both present and an important consideration within exposure research. Our analysis represents the first stage of a larger analysis investigating the degree of exposure to the Canterbury earthquake sequence. Future studies could examine the influence that precise location-based exposure has on determining mental health outcomes among a birth cohort in the aftermath of a disaster. Moreover, future research on the degree of exposure after a disaster would benefit from using a comprehensive measure of exposure such as the one used in this study. More precise location information is likely to be useful in identifying individuals who require immediate resources in the initial post-disaster period as well as signalling people who may need long-term help in the aftermath of a disaster. In conclusion, we have demonstrated that two in three people were misclassified when a conventional static exposure approach was used and that the timing of a disaster is likely to be a critical factor that determines how many people will be misclassified.

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