Towards a better understanding of residential mobility and the environments in which adults reside: A nationwide geospatial study from Aotearoa New Zealand

MAREK, L <http://orcid.org/0000-0001-5473-8930>, HILLS, S <http://orcid.org/0000-0002-8622-4333>, WIKI, J, CAMPBELL, M <http://orcid.org/0000-0001-7975-4662> and HOBBS, Matthew <http://orcid.org/0000-0001-8398-7485>

Abstract

This nationwide geospatial study from Aotearoa New Zealand describes the frequency and spatial patterning of residential mobility and examines the interplay between patterns of residential mobility and the environments in which adults reside.

Data from the Integrated Data Infrastructure (n=4,781,268 adults) defined levels of residential mobility in 2016–2020. We then used nationwide environmental data included within the New Zealand Healthy Location Index to define access to a range of health-promoting and health-constraining features.

We identified 29 spatial clusters based on the mobility characteristics of the population living within selected administrative units that were further classified into five groups based on the similarity of residential mobility groups. Each group was described by its relation to the Healthy Location Index, urbanicity and ethnicity.

A greater proportion of residential mobility was related to metropolitan and large regional centres, and Māori, Pacific and Asian ethnicities. Areas with higher levels of vulnerable mobile population were identified in the North Island (Northland, Gisborne, Whanganui and urban pockets of Auckland, Hamilton, Napier and Hastings). While there was poor access to health-promoting features for the mobile population living in the inner cities, areas with higher residential mobility are associated with better access to health-promoting and neutral environments.

Keywords: Residential mobility, spatial patterns, socioeconomic disparities, New Zealand, linked individual-level data

Highlights

- The whole population linked individual-level microdata used to study residential mobility
- Residential mobility is spatially patterned on a national and local scale
- A significant proportion of New Zealanders are highly mobile with notable socioeconomic and demographic disparities
- We identified and mapped clusters of distinct residential mobility behaviours

1. Introduction

The environment within which a person resides and to which they are exposed is increasingly recognised as a potentially important contributor to their health behaviours and outcomes (Hobbs & Atlas, 2019). Broadly, these influences on health and behaviour can come from the built environment, features such as the location of liquor stores, fast-food outlets or physical activity facilities (Green et al., 2021; Hobbs et al., 2020; Hobbs, Green, et al., 2019), as well as the natural environment, such as the role of green spaces and parks (Richardson et al., 2013; Wolch et al., 2014). Different aspects of the built and natural environment may act together to influence health, both positively and negatively (Green et al., 2018; Sadler et al., 2019). Research accounting for their co-location or clustering may better capture the multifaceted nature of the environment, compared with considering any one feature in isolation (Hobbs et al., 2022; Mason et al., 2020).

Given the influence of these built and natural environmental features, the specific places where people live and their residential mobility (i.e., changes in their residential address over time) can play an important role in an individual's health behaviours and propensity to develop diseases (Boscoe, 2011; Liu et al., 2020). we use the term residential mobility to describe changing residential histories. However, although research on health disparities has long recognised the importance of 'place' (Morris et al., 2018), emphasis has often been on an individual or group's current place of residence. This approach overlooks any potential prior exposure to different environments over time, as occurs when changing residential addresses (Campbell et al., 2021).

Although cross-sectional studies dominate the current evidence base, there have been substantial developments in research documenting and contextualising residential mobility patterns (Elder & Shanahan, 2007; Morris et al., 2018; Mulder & Wagner, 1993). Whilst still relatively uncommon, studies are increasingly considering life-course environmental exposure and/or accounting for at least some aspect of an individual's residential mobility when linking the concepts of health and place (Jiang et al., 2019; Lomax et al., 2021; Morris et al., 2018). These are important steps in beginning to identify potential causal associations between the environments to which individuals are exposed, their health behaviours, and their health outcomes (Conner & Norman, 2017; Hobbs et al., 2021). Crucially, the ability to rigorously pursue such endeavours via high-quality research relies on the ability to adequately quantify residential mobility at an individual and/or population level.

Within the health-focused literature that has attempted to account for previous environmental exposure in some way, several limitations often affect evidential rigour. Firstly, the cross-sectional nature of many studies (e.g., census or survey data) is unable to capture the temporal dimension of mobility (Campbell et al., 2021; Quillian, 2003). Secondly, quantification of residential mobility has often relied on survey information or infrequent census data (Jiang et al., 2019). This has important implications as many of the risk factors for ill-health typically accumulate over time and/or display a time-lag from initial environmental exposure to manifestation (Ben-Shlomo & Kuh, 2002; Murray et al., 2021). Relying on such data sources also means that research has been unable to readily model mobility as a continuous variable because the number of observations decreases as the number of consecutive address changes increases. This precludes accurate quantification of residential mobility in highly mobility people (Morris et al., 2018), who may be at the greatest risk of poor health outcomes (Morris et al., 2017; Nathan et al., 2019). Thirdly, studies to date have often provided no clear theoretical basis for their categorization of mobility, the period they examined, and the implications of their findings (Stokols & Shumaker, 1982). Fourthly, Morris et al. (2018) highlighted that the majority of health and wellbeing studies have treated all address changes as equal, regardless of their context and/or motivation (Morris et al., 2018; Verropoulou et al., 2002). Finally, in practical terms, assessing whether or not a person has indeed changed address is complicated by the fact that much of the available data (e.g., such as census data) often only reports moves in which a person crosses an administrative boundary. Taken together, these factors indicate an overreliance on survey data or infrequent census information which builds an incomplete picture of residential mobility.

Emerging data sources may help to somewhat overcome the limitations of previous research by better documenting all known historical address changes to provide a fuller picture of nationwide residential mobility patterns. Once achieved, this information can be linked to robust data concerning environmental features to examine how access to the built and natural environment may differ depending on levels of residential mobility. Several improvements in data processing and storage capabilities mean that researchers can now access a range of novel data sources (Vogel et al., 2019).

In Aotearoa New Zealand (NZ), the Integrated Data Infrastructure (IDI) is one such advancement. The IDI is a large nationwide research database that stores linked individual and household-level microdata from a range of Government agencies such as housing, health and policing (Statistics New Zealand, 2022b). This IDI has been used within a range of research projects, such as developing national cohort studies to uniquely link health and education data (Bowden et al., 2022; Robertson et al., 2021). As (ideally) all address changes are notified in the IDI, it is possible to classify individuals based on the frequency and the sociodemographic or socioeconomic context of their movements (Jiang et al., 2019; Robertson et al., 2021). Such data can then be combined with other metrics such as access to features within the built and natural environment. This high-quality data will enable a better contextualisation of residential mobility alongside access to the built and natural environment. Other emergent sources of data include individual GPS location data from mobile phones or devices that attempt to better understand residential mobility also, including application in transport (Calabrese et al., 2013), and environmental exposures (Marek et al., 2016). Whilst this GPS data allows for more fidelity in understanding of residential mobility, it is not as comprehensive as administrative data, constraining its utility (Campbell et al., 2021).

This study aims firstly to describe and explore residential mobility by key sociodemographic and socioeconomic factors in a nationwide sample of adults, before identifying spatial clusters of some of the most and least mobile groups. We hypothesise that higher levels of residential mobility (i.e., greater population transience) will be in areas with higher levels of deprivation and that there will be significant spatial clusters of high residential mobility areas. Secondly, this study aimed to examine how residential mobility relates to characteristics of both the built and natural environment that an adult resides within.

2. Methods

The study uses three key data sources; the NZ Census, The Health location Index and the IDI. This data details residential mobility and transience of the NZ population, access to built and natural environments and socioeconomic demographic characteristics. Data used in this study are mix of area data (NZ Census and HLI) and aggregates of individual-based data (residential mobility and transience).

2.1 Geographical areas

Nationwide residential mobility and population transience data were derived on the individual-level using the IDI and aggregated into Statistical Area 2 (SA2) geographies to maintain confidentiality. The SA2 geography aims to reflect communities that interact together socially and economically with similar sized populations in populated areas (2,000–4,000 residents in cities, 1,000-3,000 in towns, and fewer than 1,000 in more sparsely populated but larger areas) (Stats NZ, 2018).

2.2 Study design

This study is a nationwide geospatial study. Aggregated population records and administrative data from the IDI (section 2.3), geospatial data on characteristics of the neighbourhood environment (section 2.4), and socioeconomic and demographic data from the New Zealand 2018 Census (Section 2.5) were used. Statistics NZ approved access to the IDI and also checked research results before they were released to make sure individuals cannot be identified.

2.3 Residential mobility and population transience

As people in NZ interact with various government agencies and services including healthcare, tax and income, social, and education the IDI records every change of residential address. These changes are stored as address notifications with anonymised addresses, meshblocks (the smallest geographic unit for which statistical data collected and processed by Stats NZ (Stats NZ, 2018)) within which the addresses are contained, and length time spent by the individual at the address. Whilst a recent study from NZ made significant progress in encapsulating residential mobility (Jiang, N., Pacheco, G., & Dasgupta, 2018; Robertson et al., 2021), capturing the type of environments that individuals are exposed to as they move is a crucial gap in current understanding. We built on existing methods (Jiang et al., 2019; Marek, Greenwell, et al., 2021) and assigned the level of residential mobility to each individual living in New Zealand during the 5-year reference period (2016–2020) by combining the frequency of address changes, death records, birth records, immigration records, overseas spell records, and the area-level socioeconomic deprivation (NZDep2018 (Atkinson et al., 2019)) of home address based on meshblock.

The categories of residential mobility were defined as *non-movement* (no address change during the reference period), *low movement* (1–2 address changes), *medium movement* (3–4 address changes), and *high movement* (five or more address changes). The latter was further broken into *vulnerable transient*, *transient*, and *high movement (upward)* based on the trajectory of socioeconomic deprivation related to former and current residential addresses (Table 1). However, *transient* and *high movement (upward)* classes were combined due to low counts of the latter Class names reflect previous research (Jiang, N., Pacheco, G., & Dasgupta, 2018) but the category assignment rules were adjusted to comply with a longer reference period and purpose of the study. A full description of the methodology can be found in (Marek, Greenwell, et al., 2021). To ensure data confidentiality and allow for geospatial data analysis and mapping to be completed, individual-level transience was then aggregated into sums and proportions of population in each mobility category for each SA2 area that allow for a low suppression of data counts (Mills et al., 2022).

Table 1. Classification rules used to define population transience.

Population transience	**Residential moves**	**Deprivation decile** (if applicable) (1-least deprived, 10-most deprived)
Non-movement	0	—
Low movement	1–2	—
Medium movement	3–4	—
High movement (upward)	5–9	Low (1–3) and decreasing to low
Transient	5–9	Medium (4–7) and increasing to medium
Vulnerable transient	5–9 ≥ 10	High (8–10) and increasing to high —

2.4 Environmental data

Data concerning features of the built and natural environment were obtained from The Healthy Location Index (HLI) (Marek, Hobbs, et al., 2021). This measure was designed as a composite measure of the accessibility of health-promoting and health-constraining environments. A range of environmental exposure data were compiled including ten measures of: national or international fast-food selling outlets, locally operated takeaways, dairy/convenience stores, fruit and vegetable outlets, supermarkets, physical activity facilities, alcohol outlets, gaming venues, green spaces, and blue spaces. The HLI consists of combined summed ranks of access from meshblock to SA2 area to health-constraining and health-promoting features (Marek, Hobbs, et al., 2021). Then deciles were assigned to final scores for both health-promoting and health-constraining features resulting in Decile 1 defined as the SA2 area with best accessibility while Decile 10 as the worst accessibility. For health-promoting features this meant that the greatest accessibility was healthy, for instance with greater access to health-promoting features such as green spaces. For health-constraining features, greater accessibility was considered a bad thing as this means greater accessibility to health-constraining environmental factors such as alcohol outlets. A detailed description of methodology and categorisation can be found in (Marek, Hobbs, et al., 2021).

2.5 Other relevant data

Data regarding the usually resident total population and population by self-reported ethnicity for each SA2 was sourced from the 2018 Census (Statistics New Zealand, 2022a). This census fell within the 5-year reference period for determining residential mobility and thus, whilst some discrepancies might exist between the aggregated population statistics from the IDI and 2018 census records, the recorded population characteristics of each area were expected to reflect the characteristics of the period as a whole.

Besides population and ethnicity, we further used the Functional urban areas classification describing the level of urbanicity of the area that was developed by Stats NZ (Statistics New Zealand, 2021). It classifies areas into five categories (Metropolitan area, Large/Medium/Small regional centre, Area outside functional urban area (here as Rural)) based on areas interconnectedness and size.

2.6 Geospatial and statistical analyses

Spatial scan statistics, processed using SaTScan 9.3 (Kulldorff & Information Management Services Inc, 2009) open-source software was used to identify spatial clusters of SA2s with unusual residential mobility characteristics. Input data (Fig. 1 - Step 1) were: 1) population counts for each category of residential mobility for each SA2 and 2) coordinates of SA2 population-weighted centroids. Clusters were identified based on a purely spatial multinomial scan statistics (Fig. 1 – Step 2) that identifies unusual population structures in the spatial data by taking into account all possible combinations of population characteristics and comparing their structure within and outside geographic areas defined by a dynamic window (Boscoe & Kulldorff, 2018).

A dynamic circular window in which up to 5% of the population were at risk was specified in SaTScan to detect clusters. This value was chosen, following sensitivity evaluation of circular windows with up to 3%, 5%, 10%, 20%, and 50% population (Marek et al., 2015) as it was deemed to best balance sensitivity in cluster detection with the need for the majority of clusters to be of sufficient size to allow meaningful interpretation.

Indirectly standardised rates (expressed as the relative risk) for each residential mobility category for each identified spatial cluster were estimated using the multinomial model, and only significant clusters (P values ≤ 0.001) were retained. Information about each cluster (e.g., relative risks for each residential mobility category, SA2s in each cluster, etc) were exported and attached to information (e.g., HLI, census data) about the SA2s contained therein.

Unlike SaTScan's ordinal or spatio-temporal models, multinomial model does not provide an additional classification of identified clusters [e.g., low/high-values (hot/cold spots)]. That is why a further classification using multivariate cluster analysis (Fig. 1 - Step 3) was further utilised to group spatial clusters by the similaritiy of their (non-spatial) characteristics (Relative Risk of transience groups), process similar to geodemographic classification (Brunsdon, Charlton & Rigby, 2018). We used Partitioning around medoids (PAM) algorithm from cluster package (Maechler et al., 2021) and categorised spatial clusters into five groups. The data were positionally standardised and Generalized

Distance Measure was used as input to PAM as suggested by analysis of determination of optimal clustering procedure (Walesiak & Dudek, 2006, 2020).

Analyses and visualisation of clusters and groups were completed in R (R Core Team, 2022) and QGIS (QGIS Development Team, 2022).

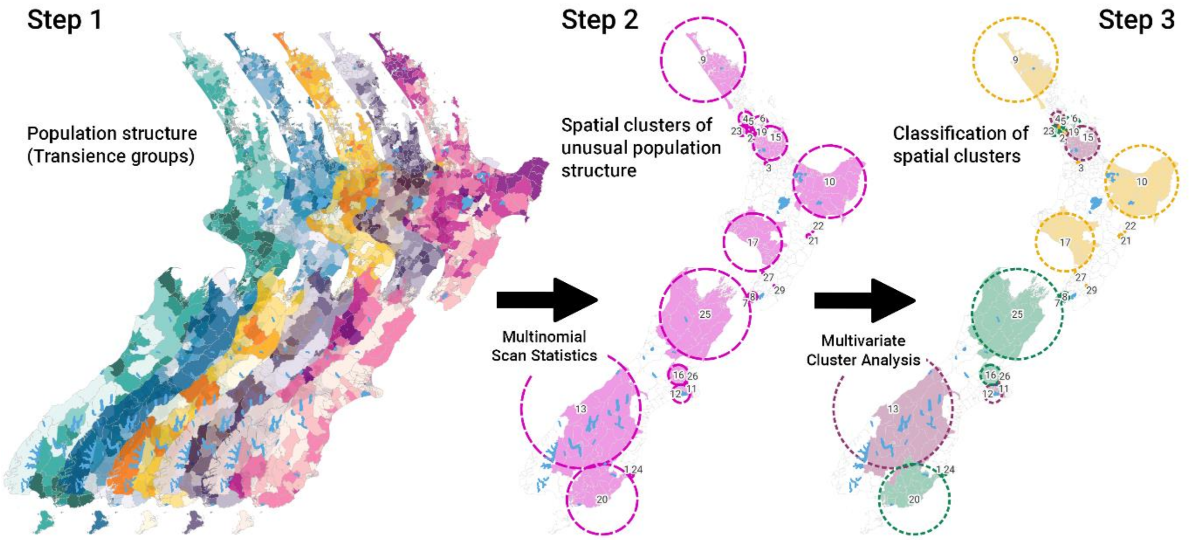

Figure 1. Workflow of geospatial and statistical analyses

3. Results

3.1 Descriptive statistics

Figure 2 shows the percentage of the New Zealand population by Statistical Area 2 classified as vulnerable transient population across Aotearoa New Zealand (NZ) with insets for the four major urban areas of Auckland, Christchurch, Wellington and Dunedin. The map shows five quintiles with quintile one containing the lowest percentage and quintile five the highest percentage. Vulnerable transient population was defined as people who moved at least 5 times (in the reference period) within the most deprived areas or 10- and more times regardless of the area's socioeconomic deprivation. A high percentage of vulnerably transient populations were seen within several of the urban areas of Tāmaki Makaurau (Auckland), Ōtautahi (Christchurch) and Te Whanganui-a-Tara (Wellington) as well as around Te Tai Tokerau (Northland), Tairāwhiti (the East Cape) and some areas of the Te Waipounamu (South Island). Table S1 shows the percentage of population by transience category and ethnicity (Māori and non-Māori). Overall, from an estimated population of 4.7 million New Zealanders, there were differences by transience category and by ethnicity.

A further spatial description of other residential mobility categories is outlined in the online supplementary materials. Figure S1 shows the percentage of transient and high movers (upward), Figure S2 shows the percentage of non-movers, Figure S3 shows the percentage of low-movers and Figure S4 shows the percentage of medium movers; all with insets for the three major urban areas of Tāmaki Makaurau (Auckland), Ōtautahi (Christchurch) and Whanganui-a-Tara (Wellington).

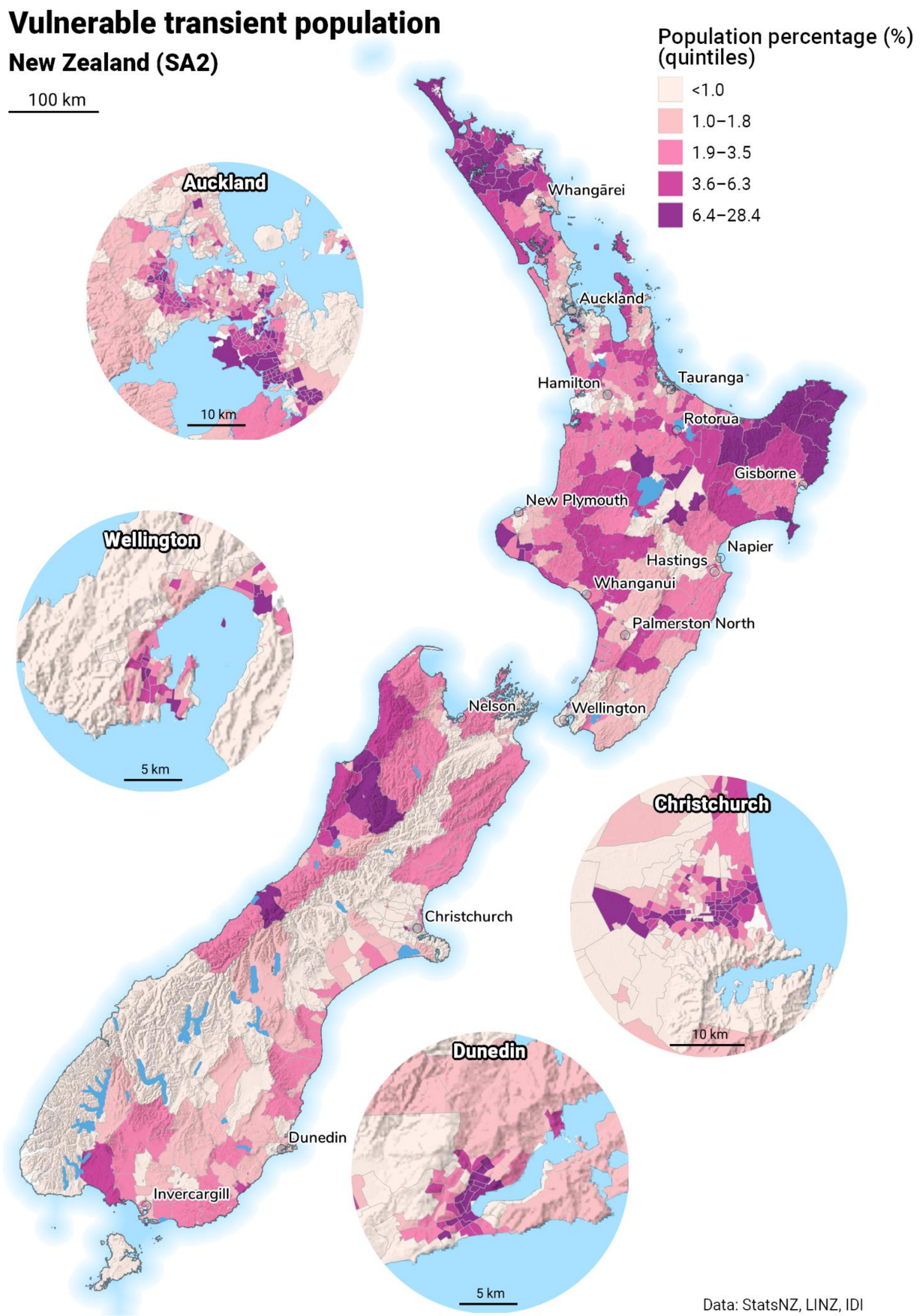

Figure 2. The percentage of the vulnerable transient population across New Zealand with insets for Auckland, Christchurch, Dunedin and Wellington (Quintile 1: lowest percentage and Quintile 5: highest percentage).

3.2 Identifying spatial clusters and groups of residential mobility patterns

Figure 3 shows 29 significant spatial clusters of residential mobility patterns across NZ further classified to five groups which shared common residential mobility patterns. Group 1 was defined as *"mobile inner city"* (n=142,188; 66 SA2s) located largely in inner city and central areas of cities such as Auckland, Wellington, Christchurch and Dunedin. Group 2 were defined as *"mobile vulnerable"* (n=773,826; 410 SA2s) which included a large swathe of rural North Island locales as well as some parts of Auckland, Hamilton, Napier and Hastings, Whanganui, and Gisborne. Group 3 were defined as *"mobile non-vulnerable"* (n=540,864; 269 SA2s) which included some outskirts of Auckland, southwest of Christchurch plus a large part of the central and west South Island. Group 4 were the largest cluster and were defined as *"stayers"* (n=1,140,468; 505 SA2s) including the southeast of South Island (excluding the centre of Dunedin), the northern outskirts of Christchurch and a large portion of the north of the South Island. Other areas included in group 4 were several areas outside Wellington and outside the centre of Auckland. Finally, group 5 was the smallest cluster and was defined as *"urban outliers"* (n=3,924; 2 SA2s) identified in areas of both Auckland and Christchurch. Table S2 shows relative risks and details of each identified cluster.

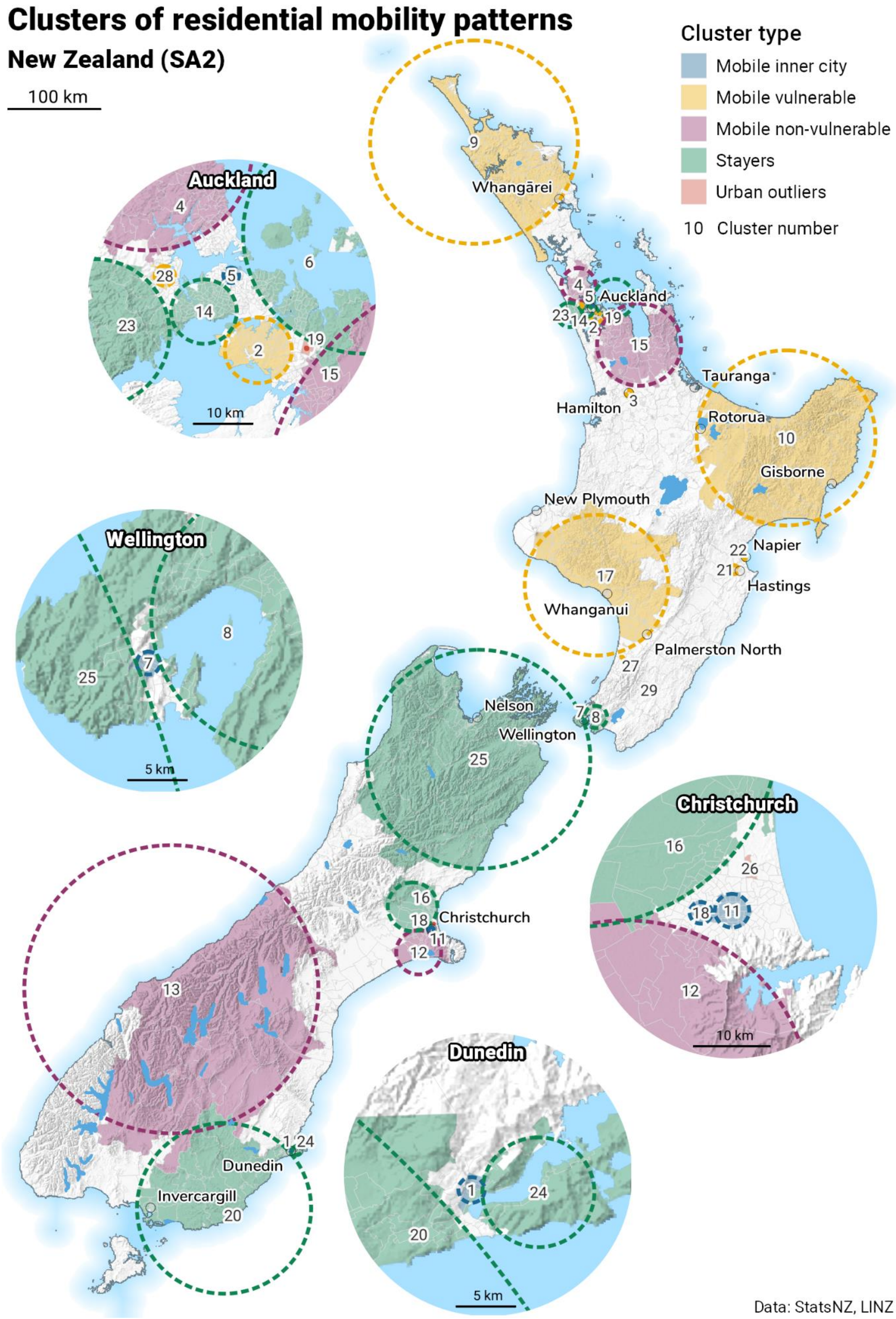

Figure 3. Map of clusters/groups from SaTScan (details of clusters in the online supplementary materials)

Figure 4 shows the median relative risk (indirectly standardised rate estimated by multinomial scan statisitics) of the five original residential mobility categories for each group of the spatial clusters identified. The *“mobile inner city”* group contained very few non-movers, with lots of moderate movement, high-movement (upward) and a very high vulnerable transient population. The *“mobile vulnerable”* group was characterised by very low numbers of transient and high-movement (upward) but a very high relative risk of being vulnerable transient. Conversely, the *“mobile non-vulnerable”* group contained a very low vulnerable transient population but a high relative risk for the transient and high-movement (upward) category. *“Stayers”* also had a low relative risk of vulnerable transience, but had the highest relative risk for non-movers, the lowest relative risk for medium movement and relative risk values ~1 for the transient and medium movement categories. Finally, *“urban outliers”* had very low relative risk values for the non-movement and vulnerable transient categories, but a high proportion of this group population fell into low movement, moderate movement and transient.

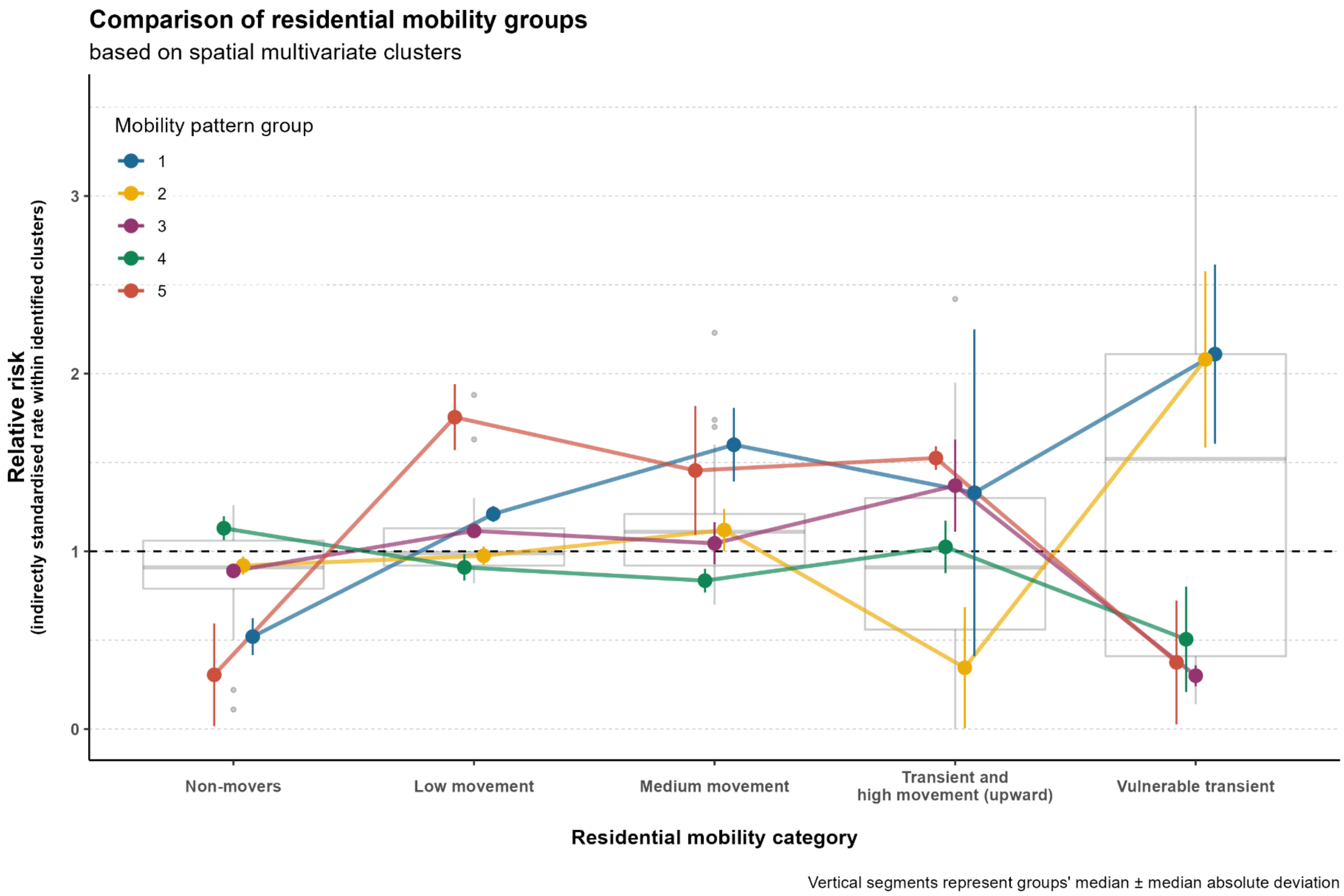

Figure 4. A comparison of residential mobility groups based on spatial multivariate clusters.

When comparing groups according to the ethnicity of their population and the functional urban area classification of the SA2s contained within them, the *"mobile inner city"* group had by far the highest proportion of Asians and only contained metropolitan areas. The *"mobile vulnerable"* had the highest proportion of Maori/Pacific residents and the lowest proportion of Europeans/other ethnicities. *This group* covered a mixture of area types, but contained the largest proportion of regional centre and rural SA2s of any group. The groups with the highest proportion of Europeans/other ethnicities were the *"mobile non-vulnerable"* and *"urban outliers"*, with *"urban outliers"* also containing the second largest proportion of Asians. *"Stayers"* contained a mix of ethnicities, ~87% of whom resided in metropolitan areas or large regional centres, whilst *"urban outliers"* were entirely located in metropolitan areas and reflected new housing developments in these areas.

The mobile inner city group mostly had very high access to both health-promoting and health-constraining features (Figure 6). However, ~30% of the population in this group resided in more health-constraining environments (i.e, with greater access to environmental bads than environmental goods). There were similar HLI characteristics between mobile vulnerable, mobile non-vulnerable, and stayers groups. Each of these groups included areas with very good access to environmental goods and poor access to bads, as well as areas with the opposite patterns of access and areas that are neither health-promoting nor health-constraining. Urban outliers were either neutral or had relatively poor access to environmental goods and bads (albeit with slightly better access to goods). Table S3 contains data on which Figures 5 and 6 are based.

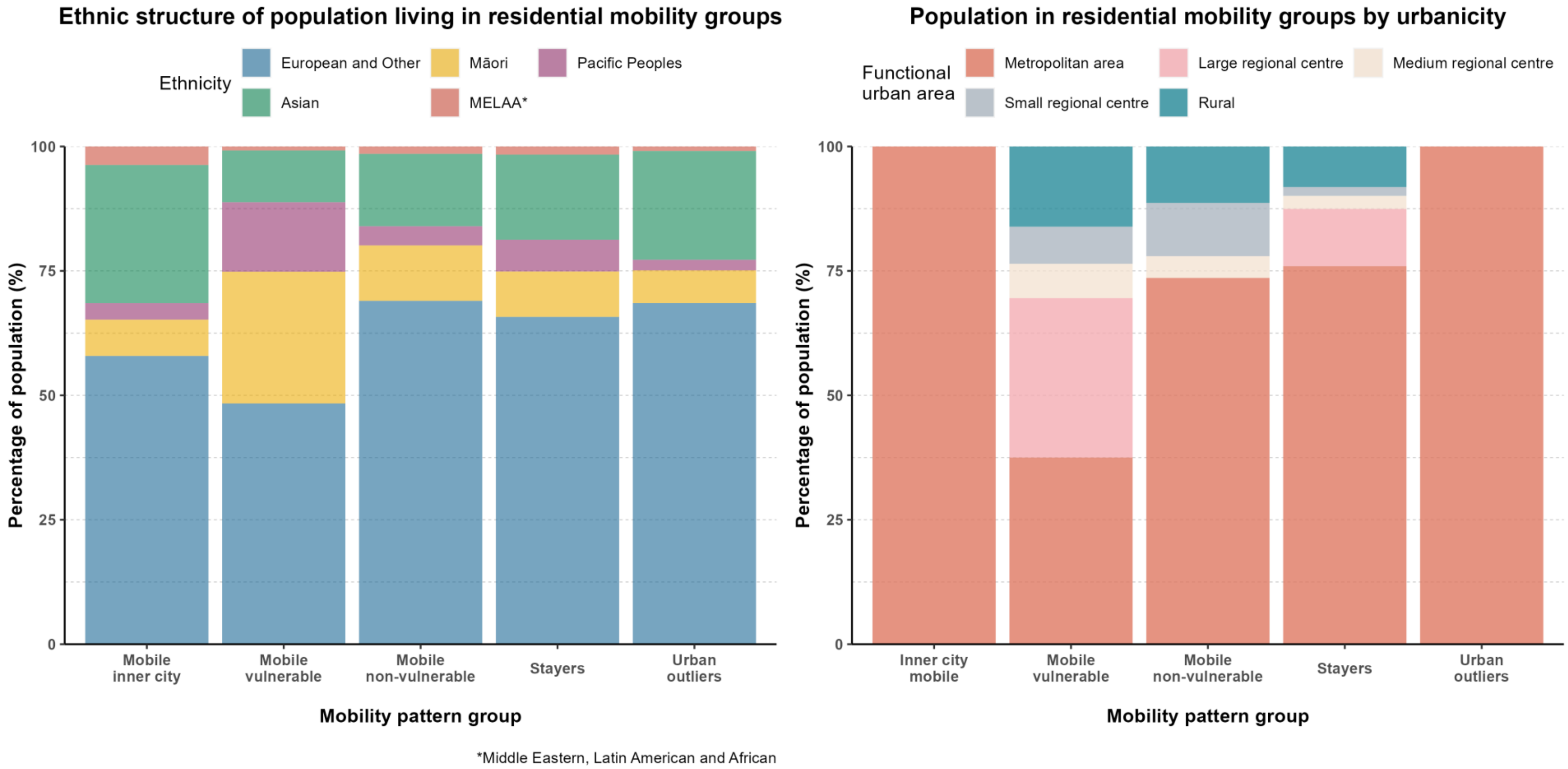

Figure 5. The ethnicity structure and urbanicity of each of the residential mobility groups.

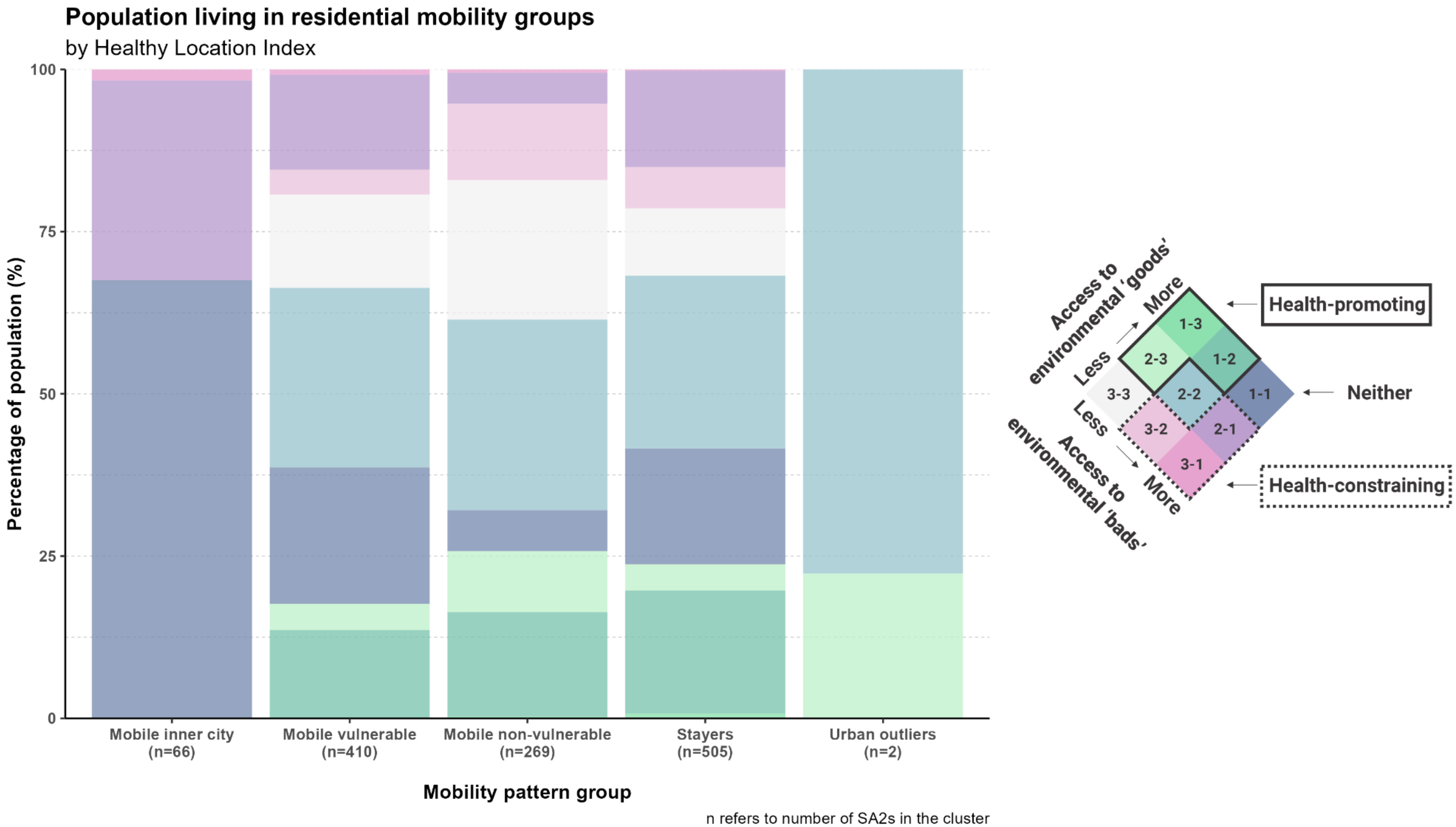

Figure 6. The proportion of each residential mobility group and their access to both health-promoting and health-constraining features by Healthy Location Index category.

4. Discussion

This is one of the first, to the authors knowledge, nationwide and geospatial investigations of residential mobility and population transience combined with environmental exposures. This study first spatially described levels of population transience in Aotearoa New Zealand (NZ) from 2016-2020. It then examined links between levels of residential mobility and population transience and the characteristics of the environments in which an individual resides in terms of access to features of the built and natural environment. Our findings showed that a large proportion of the NZ population was classified as transient or vulnerably transient. Therefore, we add to evidence by demonstrating how these populations cluster together spatially. Findings also provide insight into the access of health-promoting and health-constraining environments and associations these hold with regional geographies and the ethnic structure of populations. Recent studies have demonstrated the potential utility of residential histories collected from sources such as electronic medical records and administrative databases (Campbell et al., 2021; Jacquez et al., 2011; Wheeler & Wang, 2015; Wiese et al., 2020) however, rarely do studies use complete residential address records to capture prior exposures to the environment over time.

Our findings highlight significant groups of clusters with similar population characteristics based on similar patterns of residential mobility. Principally, our results highlight three distinct patterns of residential mobility: populations who may move to areas of newly built housing developments, populations who may be reliant on the social housing system, and populations who may move due to educational and work opportunities. Regarding populations who may move to areas of newly built housing developments, this is most evident within the mobile non-vulnerable group. This group contains a high proportion of European, Other and Asian ethnicities (Figure 5), who have been shown to have higher rates of home ownership in Aotearoa New Zealand than other ethnic groups (Statistics New Zealand, 2020). Spatial patterns for this group are visible within the south and west of Christchurch as well as the lakes districts of the South Island and north of Auckland (Figure 3), all of which are notable areas of new housing developments. Such developments attract more affluent home-buyers and may also offer new areas for holiday homes and retirement opportunities. This aligns with Figure 4, which shows that the driving group behind this is the high-movement (upward) group.

Our study also highlighted significant areas of NZ classified as vulnerable transient and transient populations which were clustered by area. There are distinct patterns when considering the mobile vulnerable group however, which is most visible in areas of high deprivation (Figure 3). This group may have some or sole reliance on the social welfare system and the linked social housing provision. For instance, previous research has demonstrated that many families and individuals who are reliant on social housing have little agency over their housing conditions (Rolfe et al., 2020) and are often moved around numerous accommodations due to a myriad of lifecourse or legislative changes. For example, the building of new social housing developments and possible removal or destruction of others, short-term tenancies, particularly for individuals without families, short-to-medium-term incarceration of tenants, particularly in areas that have a high gang presence, and even school zoning requirements for those social housing tenants that have young children (Pollio, 1997). This is an important consideration given the areas of spatial clustering for the mobile vulnerable group, including South Auckland, Northland, East Cape and Whanganui/New Plymouth areas (Figure 3). These are areas of high deprivation, meaning much of the population is likely reliant on social welfare and therefore social housing (Rolfe et al., 2020; Welfare Expert Advisory Group Kia Piki Ake, 2018). This highlights long-standing concerns regarding the availability and instability of social housing for highly deprived population groups (Mills et al., 2015). Moreover, this is also supported by Figure 5 where there is the largest proportion of Māori in this group than any other group, with recent data from Aotearoa New Zealand demonstrating that Māori are overrepresented within the social welfare system (Welfare Expert Advisory Group Kia Piki Ake, 2018). Prior work has demonstrated the magnitude of these persistent inequities (Christopher Bowie et al., 2013; Hobbs, Ahuriri-Driscoll, et al., 2019).

Additionally, while the largest proportion of Māori are shown to be within the mobile vulnerable group, this is followed by the mobile non-vulnerable group (Figure 5). Both of these groups are also those highly represented in rural and regional centres rather than central metropolitan areas which contain predominantly European, Other and Asian ethnicities (Figure 5). This demonstrates that Māori have high access to health-promoting environments due to a high proportion of this ethnic group living outside of central metropolitan areas, instead residing in rural and regional centres. Such areas can also be those of high deprivation however, and previous research has demonstrated that they are areas which often lack health services and have increased odds of worse health outcomes (Marek et al., 2020).

Furthermore, even when shown in Figure 6 that the HLI for areas with clusters of mobile vulnerable groups is relatively health-promoting, or neutral, with few health-constraining environments, such instability can influence the capacity to feel a part of the community and interact positively with the surrounding environment.

Finally, when considering populations who are moving due to educational and work opportunities, this is most clearly shown within the mobile inner city group. This reflects the influence of mobile student populations, moving to the inner city for studies and potentially moving multiple times due to movement patterns between home (out of city) and city coinciding with the start or end of academic terms. This pattern is most prominent in Dunedin, an area with a high student population, but can also be observed in mobile inner city populations in other major cities as well, such as the clusters seen in the central/west of Christchurch and central Wellington and Auckland (Figure 3). Additionally, Figure 5 shows that Asian populations are highly represented within the mobile inner city group, reinforcing a strong link to educational activities as many universities in Aotearoa New Zealand have a high proportion of Asian students (Education Counts, 2022a). Furthermore, Figure 4 highlights the transient and high movement upward group within the mobile inner city group. There is potential that this could also represent the student population, with a possible explanation of high movement upward after graduation and upon entering the workforce (Education Counts, 2022b). In stark contrast to a potentially thriving population seeking educational and work opportunities within the mobile inner city group, the vulnerable transient group is also highlighted here (Figure 4). This may tie in with the social housing aspect discussed previously, reflecting this group within an urban context, as well as potentially reflecting populations that experience intermittent homelessness.

The mobile inner city group is also shown to have the highest access to health-constraining environments while stayers, mobile non-vulnerable, and mobile vulnerable groups have the highest access to health-promoting environments (Figure 6). This may reflect the abundance of health-constraining exposures within central metropolitan areas, where there is high population density and a suitable environment for the establishment of businesses (Jiang et al., 2019; Marek, Hobbs, et al., 2021). Due to lower population density in other functional urban areas such as regional centres and rural areas it may not be as profitable to locate businesses in these areas, therefore reducing the total number of health-constraining environmental exposures (Hood et al., 2016). Additionally, such areas have a different urban structure, allowing for more availability of greenspace than central metropolitan areas and therefore increasing the likelihood of health-promoting environments.

Our study is cross-sectional and therefore, causality cannot be inferred. Furthermore, it is also plausible that in our study, some transient individuals may not be picked up in the IDI for instance if they do not interact with social agencies or do not have an existing residential address. While we progress evidence by using the IDI to capture address changes, and while we consider residential mobility at multiple time points, the temporal aspect of the HLI is fixed and thus we assume that the environment has remained static from 2016–2020. We have already demonstrated the existing inequities in NZ (Marek et al., 2020) by rural-urban classification, highlighting those minor urban areas with worse health outcomes. Our study confirms the importance of urbanicity as a key component in better understanding residential mobility and exposure to environmental factors. Despite this, we did not use socioeconomic deprivation as one of the measures as it is part of the residential mobility classification employed within this study. While the percentage of individual transience groups in SA2s were derived using the IDI, we have used official statistics data (census) to describe these population groups in relation to ethnicity and urbanicity and the HLI as this level of detail (by SA2) would possibly allow for identification of individuals and consequently prevent public release of the data (Mills et al., 2022). Another limitation of census data (and HLI) is that they capture population and its characteristics at one point in time versus the IDI 2016–2020, but overlaps in mid-period. Due to usage of the administrative data, we also miss a qualitative aspect describing individual perception of the environment, neighbourhood and individual socioeconomic position that are important factors in individual residential mobility and willingness to move (He et al., 2022; Kim et al., 2015). Finally, both SaTScan and multivariate clustering are heavily dependent on the initial settings of parameters that can often be subjective. We attempted to overcame the subjectivity by sensitivity analysis, which meant running and evaluating multiple circular windows sizes (3–50% population) for SaTScan and using simulation of cluster results for multivariate clustering.

5. Conclusion

Our study builds on existing evidence to provide a comprehensive spatial examination of residential mobility using a nationwide dataset in New Zealand. We highlight links between levels of residential mobility and population transience and the characteristics of the environments in which an individual resides in terms of access to features of the built and natural environment. Our study adds to evidence by highlighting significant groups of clusters with similar population characteristics based on similar patterns of residential mobility.

DISCLAIMER

6. References

Atkinson, J., Salmond, C., & Crampton, P. (2019). *NZDep2018 Index of Deprivation Interim Research Report*. *5541*(December), 1–65. https://www.otago.ac.nz/wellington/otago730394.pdf

Ben-Shlomo, Y., & Kuh, D. (2002). A life course approach to chronic disease epidemiology: conceptual models, empirical challenges and interdisciplinary perspectives. *International Journal of Epidemiology*, *31*(2), 285–293. https://doi.org/10.1093/ije/31.2.285

Boscoe, F. P. (2011). The Use of Residential History in Environmental Health Studies. In *Geospatial Analysis of Environmental Health* (pp. 93–110). Springer Netherlands. https://doi.org/10.1007/978-94-007-0329-2_4

Boscoe, F.P., & Kulldorff, M. (2018). *Multinomial Scan Statistic for Identifying Unusual Population Age Structures.* https://www.satscan.org/tutorials/unusualpopulationage/SaTScanUnusualPopulationAge.pdf

Bowden, N., Gibb, S., Audas, R., Clendon, S., Dacombe, J., Kokaua, J., Milne, B. J., Mujoo, H., Murray, S. W., Smiler, K., Stace, H., van der Meer, L., & Taylor, B. J. (2022). Association Between High-Need Education-Based Funding and School Suspension Rates for Autistic Students in New Zealand. *JAMA Pediatrics*, *176*(7), 664. https://doi.org/10.1001/jamapediatrics.2022.1296

Brunsdon, C, Charlton, M. & Rigby, J.E. (2018). An Open Source Geodemographic Classification of Small Areas in the Republic of Ireland. *Applied Spatial Analysis and Policy*, *11*, 183–204

Calabrese, F., Diao, M., di Lorenzo, G., Ferreira, J., & Ratti, C. (2013). Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. *Transportation Research Part C: Emerging Technologies*, *26*, 301–313. https://doi.org/10.1016/j.trc.2012.09.009

Campbell, M., Marek, L., & Hobbs, M. (2021). Reconsidering movement and exposure: Towards a more dynamic health geography. *Geography Compass*, *15*(6). https://doi.org/10.1111/gec3.12566

Christopher Bowie, Beere, P., Griffin, E., Campbell, M., & Kingham, S. (2013). Variation in health and social equity in the spaces where we live: A review of previous literature from the GeoHealth Laboratory. *New Zealand Sociology*, *28*(3), 164–191. https://doi.org/10.3316/informit.829523802993020

Conner, M., & Norman, P. (2017). Health behaviour: Current issues and challenges. *Psychology & Health*, *32*(8), 895–906. https://doi.org/10.1080/08870446.2017.1336240

Education Counts. (2022a). *International students in New Zealand*. https://www.educationcounts.govt.nz/statistics/international-students-in-new-zealand

Education Counts. (2022b). *What young graduates earn when they leave study*. https://www.educationcounts.govt.nz/publications/tertiary_education/education-outcomes/income-and-earnings/what-young-graduates-earn-when-they-leave-study

Elder, G. H., & Shanahan, M. J. (2007). The Life Course and Human Development. In *Handbook of Child Psychology*. John Wiley & Sons, Inc. https://doi.org/10.1002/9780470147658.chpsy0112

Green, M. A., Daras, K., Davies, A., Barr, B., & Singleton, A. (2018). Developing an openly accessible multi-dimensional small area index of 'Access to Healthy Assets and Hazards' for Great Britain, 2016. *Health & Place*, *54*, 11–19. https://doi.org/10.1016/j.healthplace.2018.08.019

Green, M. A., Hobbs, M., Ding, D., Widener, M., Murray, J., Reece, L., & Singleton, A. (2021). The Association between Fast Food Outlets and Overweight in Adolescents Is Confounded by Neighbourhood Deprivation: A Longitudinal Analysis of the Millennium Cohort Study. *International Journal of Environmental Research and Public Health*, *18*(24), 13212. https://doi.org/10.3390/ijerph182413212

He, Q., Boterman, W., Musterd, S., & Wang, Y. (2022). Perceived social distance, socioeconomic status and adaptive residential mobility in urban China. *Habitat International*, *120*, 102500.

Hobbs, M., Ahuriri-Driscoll, A., Marek, L., Campbell, M., Tomintz, M., & Kingham, S. (2019). Reducing health inequity for Māori people in New Zealand. *The Lancet*, *394*(10209), 1613–1614. https://doi.org/10.1016/S0140-6736(19)30044-3

Hobbs, M., & Atlas, J. (2019). Environmental influences on behaviour and health: a call for creativity and radical shifts in thinking within contemporary research. *The New Zealand Medical Journal*, *132*(1505), 97–99. http://www.ncbi.nlm.nih.gov/pubmed/31697670

Hobbs, M., Green, M., Roberts, K., Griffiths, C., & McKenna, J. (2019). Reconsidering the relationship between fast-food outlets, area-level deprivation, diet quality and body mass index: an exploratory structural equation modelling approach. *Journal of Epidemiology and Community Health*, *73*(9), 861–866. https://doi.org/10.1136/jech-2018-211798

Hobbs, M., Mackenbach, J. D., Wiki, J., Marek, L., McLeod, G. F. H., & Boden, J. M. (2021). Investigating change in the food environment over 10 years in urban New Zealand: A longitudinal and nationwide geospatial study. *Social Science & Medicine*, *269*, 113522. https://doi.org/10.1016/j.socscimed.2020.113522

Hobbs, M., Marek, L., Wiki, J., Campbell, M., Deng, B. Y., Sharpe, H., McCarthy, J., & Kingham, S. (2020). Close proximity to alcohol outlets is associated with increased crime and hazardous drinking: Pooled nationally representative data from New Zealand. *Health & Place*, *65*, 102397. https://doi.org/10.1016/j.healthplace.2020.102397

Hobbs, M., Milfont, T. L., Marek, L., Yogeeswaran, K., & Sibley, C. G. (2022). The environment an adult resides within is associated with their health behaviours, and their mental and physical health outcomes: a nationwide geospatial study. *Social Science & Medicine*, *301*, 114801. https://doi.org/10.1016/j.socscimed.2022.114801

Hood, N., Clarke, G., & Clarke, M. (2016). Segmenting the growing UK convenience store market for retail location planning. *The International Review of Retail, Distribution and Consumer Research*, *26*(2), 113–136. https://doi.org/10.1080/09593969.2015.1086403

Jacquez, G. M., Slotnick, M. J., Meliker, J. R., AvRuskin, G., Copeland, G., & Nriagu, J. (2011). Accuracy of Commercially Available Residential Histories for Epidemiologic Studies. *American Journal of Epidemiology*, *173*(2), 236–243. https://doi.org/10.1093/aje/kwq350

Jiang, N., Pacheco, G., & Dasgupta, K. (2018). *Residential movement within New Zealand: Quantifying and characterising the transient population*. https://workresearch.aut.ac.nz/__data/assets/pdf_file/0020/350606/Transient-population-report-FINAL.pdf

Jiang, N., Pacheco, G., & Dasgupta, K. (2019). Understanding the transient population: insights from linked administrative data. *Journal of Population Research*, *36*(2), 111–136. https://doi.org/10.1007/s12546-019-09223-y

Kim, H., Woosnam, K. M., Marcouiller, D. W., Aleshinloye, K. D., & Choi, Y. (2015). Residential mobility, urban preference, and human settlement: A South Korean case study. *Habitat International*, *49*, 497-507.

Kulldorff, M., & Information Management Services Inc. (2009). SaTScan v9.3: Software for the spatial and space-time scan statistics. In *StatScan, Boston, USA* (p. 109). http://www.satscan.org/

Liu, B., Lee, F. F., & Boscoe, F. (2020). Residential mobility among adult cancer survivors in the United States. *BMC Public Health*, *20*(1), 1601. https://doi.org/10.1186/s12889-020-09686-2

Lomax, N., Norman, P., & Darlington-Pollock, F. (2021). Defining distance thresholds for migration research. *Population, Space and Place*, *27*(4). https://doi.org/10.1002/psp.2440

Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., & Hornik, K. (2021). *cluster: Cluster Analysis Basics and Extensions. R package version 2.1.2.*

Marek, L., Campbell, M., Epton, M., Storer, M., & Kingham, S. (2016). Real-time environmental sensors to improve health in the Sensing City. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLI-B2*(July), 729–733. https://doi.org/10.5194/isprsarchives-XLI-B2-729-2016

Marek, L., Greenwell, J., Hobbs, M., McCarthy, J., Wiki, J., Campbell, M., Kingham, S., & Tomintz, M. (2021). Combining large linked social service microdata and geospatial data to identify vulnerable populations in New Zealand. *Big Data Applications in Geography and Planning*, 52–63. https://doi.org/10.4337/9781789909791.00010

Marek, L., Hobbs, M., Wiki, J., Kingham, S., & Campbell, M. (2021). The good, the bad, and the environment: developing an area - based measure of access to health - promoting and health - constraining environments in New Zealand. *International Journal of Health Geographics*, 1–20. https://doi.org/10.1186/s12942-021-00269-x

Marek, L., Tuček, P., & Pászto, V. (2015). Using geovisual analytics in Google Earth to understand disease distribution: a case study of campylobacteriosis in the Czech Republic. *International Journal of Health Geographics*, *14*(7), 1–13. https://doi.org/10.1186/1476-072X-14-7

Marek, L., Wiki, J., Campbell, M., Kingham, S., Sabel, C., Tomintz, M., & Hobbs, M. (2020). Slipping under the radar: worsened health outcomes in semi-urban areas of New Zealand. *New Zealand Medical Journal*, *133*(1519), 121–125.

Mason, K. E., Pearce, N., & Cummins, S. (2020). Do neighbourhood characteristics act together to influence BMI? A cross-sectional study of urban parks and takeaway/fast-food stores as modifiers of the effect of physical activity facilities. *Social Science & Medicine*, *261*, 113242. https://doi.org/10.1016/j.socscimed.2020.113242

Mills, A., Thom, K., Maynard, A., Meehan, C., Kidd, J., Newcombe, D., & Widdowson, D. (2015). *Meeting the housing needs of vulnerable populations in New Zealand.* https://researchspace.auckland.ac.nz/bitstream/handle/2292/27386/

Mills, O., Shackleton, N., Colbert, J., Zhao, J., Norman, P., & Exeter, D. J. (2022). Inter-relationships between geographical scale, socio-economic data suppression and population homogeneity. *Applied Spatial Analysis and Policy*, 1075–1091. https://doi.org/10.1007/s12061-021-09430-2

Morris, T., Manley, D., Northstone, K., & Sabel, C. E. (2017). How do moving and other major life events impact mental health? A longitudinal analysis of UK children. *Health & Place*, *46*, 257–266. https://doi.org/10.1016/j.healthplace.2017.06.004

Morris, T., Manley, D., & Sabel, C. E. (2018). Residential mobility. *Progress in Human Geography*, *42*(1), 112–133. https://doi.org/10.1177/0309132516649454

Mulder, C. H., & Wagner, M. (1993). Migration and marriage in the life course: a method for studying synchronized events. *European Journal of Population / Revue Européenne de Démographie*, *9*, 55–76.

Murray, E. T., Nicholas, O., Norman, P., & Jivraj, S. (2021). Life Course Neighborhood Deprivation Effects on Body Mass Index: Quantifying the Importance of Selective Migration. *International Journal of Environmental Research and Public Health*, *18*(16), 8339. https://doi.org/10.3390/ijerph18168339

Nathan, K., Robertson, O., Atatoa Carr, P., Howden-Chapman, P., & Pierse, N. (2019). Residential mobility and socioemotional and behavioural difficulties in a preschool population cohort of New Zealand children. *Journal of Epidemiology and Community Health*, *73*(10), 947–953. https://doi.org/10.1136/jech-2019-212436

Pollio, D. E. (1997). The Relationship between Transience and Current Life Situation in the Homeless Services-Using Population. *Social Work*, *42*(6), 541–551. https://doi.org/10.1093/sw/42.6.541

QGIS Development Team. (2022). QGIS Geographic Information System. In *Open Source Geospatial Foundation Project*. http://qgis.osgeo.org

Quillian, L. (2003). How Long are Exposures to Poor Neighborhoods? The Long-Term Dynamics of Entry and Exit from Poor Neighborhoods. *Population Research and Policy Review*, *22*, 221–249. https://doi.org/10.1023/A:1026077008571

R Core Team. (2022). R: A language and environment for statistical computing. In *R Foundation For Statistical Computing*. R Foundation for Statistical Computing. http://www.r-project.org/

Richardson, E. A., Pearce, J., Mitchell, R., & Kingham, S. (2013). Role of physical activity in the relationship between urban green space and health. *Public Health*, *127*(4), 318–324. https://doi.org/10.1016/j.puhe.2013.01.004

Robertson, O., Nathan, K., Howden-Chapman, P., Baker, M. G., Atatoa Carr, P., & Pierse, N. (2021). Residential mobility for a national cohort of New Zealand-born children by area socioeconomic deprivation level and ethnic group. *BMJ Open*, *11*(1), e039706. https://doi.org/10.1136/bmjopen-2020-039706

Rolfe, S., Garnham, L., Godwin, J., Anderson, I., Seaman, P., & Donaldson, C. (2020). Housing as a social determinant of health and wellbeing: developing an empirically-informed realist theoretical framework. *BMC Public Health*, *20*(1), 1138. https://doi.org/10.1186/s12889-020-09224-0

Sadler, R. C., Hippensteel, C., Nelson, V., Greene-Moton, E., & Furr-Holden, C. D. (2019). Community-engaged development of a GIS-based healthfulness index to shape health equity solutions. *Social Science & Medicine*, *227*, 63–75. https://doi.org/10.1016/j.socscimed.2018.07.030

Statistics New Zealand. (2020). *Housing in Aotearoa: 2020*. https://www.stats.govt.nz/assets/Uploads/Reports/Housing-in-Aotearoa-2020/Download-data/housing-in-aotearoa-2020.pdf

Statistics New Zealand. (2021). *Functional urban areas – methodology and classification*. https://www.stats.govt.nz/methods/functional-urban-areas-methodology-and-classification/

Statistics New Zealand. (2022a). *Age and sex by ethnic group (grouped total responses), for census usually resident population counts, 2006, 2013, and 2018 Censuses (RC, TA, SA2, DHB)*. https://nzdotstat.stats.govt.nz/wbos/Index.aspx?DataSetCode=TABLECODE8277

Statistics New Zealand. (2022b). *Integrated Data Infrastructure*. https://www.stats.govt.nz/integrated-data/integrated-data-infrastructure/

Stats NZ. (2018). *Statistical standard for geographic areas 2018*. http://archive.stats.govt.nz/methods/classifications-and-standards/classification-related-stats-standards/geographic-areas/pg4.aspx

Stokols, D., & Shumaker, S. A. (1982). The Psychological Context of Residential Mobility and Weil-Being. *Journal of Social Issues*, *38*(3), 149–171. https://doi.org/10.1111/j.1540-4560.1982.tb01776.x

Verropoulou, G., Joshi, H., & Wiggins, R. D. (2002). Migration, family structure and children's well-being: a multi-level analysis of the second generation of the 1958 Birth Cohort Study. *Children & Society*, *16*(4), 219–231. https://doi.org/10.1002/chi.700

Vogel, C., Zwolinsky, S., Griffiths, C., Hobbs, M., Henderson, E., & Wilkins, E. (2019). A Delphi study to build consensus on the definition and use of big data in obesity research. *International Journal of Obesity*, *43*(12), 2573–2586. https://doi.org/10.1038/s41366-018-0313-9

Walesiak, M., & Dudek, A. (2006). Symulacyjna optymalizacja wyboru procedury klasyfikacyjnej dla danego typu danych - charakterystyka problemu (Determination of optimal clustering procedure for a data set - The characterisation of the problem). *Zeszyty Naukowe Uniwersytetu Szczecinskiego*, *450*.

Walesiak, M., & Dudek, A. (2020). The Choice of Variable Normalization Method in Cluster Analysis. In K. Soliman (Ed.), *Education Excellence and Innovation Management: A 2025 Vision to Sustain Economic Development During Global Challenges* (pp. 325–340).

Welfare Expert Advisory Group Kia Piki Ake. (2018). *Welfare and Housing Interface: Evidence and policy options*. http://www.weag.govt.nz/assets/documents/WEAG-report/background-documents/5327c4530e/Welfare-housing-interface-evidence-010419.pdf

Wheeler, D., & Wang, A. (2015). Assessment of Residential History Generation Using a Public-Record Database. *International Journal of Environmental Research and Public Health*, *12*(9), 11670–11682. https://doi.org/10.3390/ijerph120911670

Wiese, D., Stroup, A. M., Maiti, A., Harris, G., Lynch, S. M., Vucetic, S., & Henry, K. A. (2020). Residential Mobility and Geospatial Disparities in Colon Cancer Survival. *Cancer Epidemiology, Biomarkers & Prevention*, *29*(11), 2119–2125. https://doi.org/10.1158/1055-9965.EPI-20-0772

Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough.' *Landscape and Urban Planning*, *125*, 234–244. https://doi.org/10.1016/j.landurbplan.2014.01.017

7. Online supplementary materials

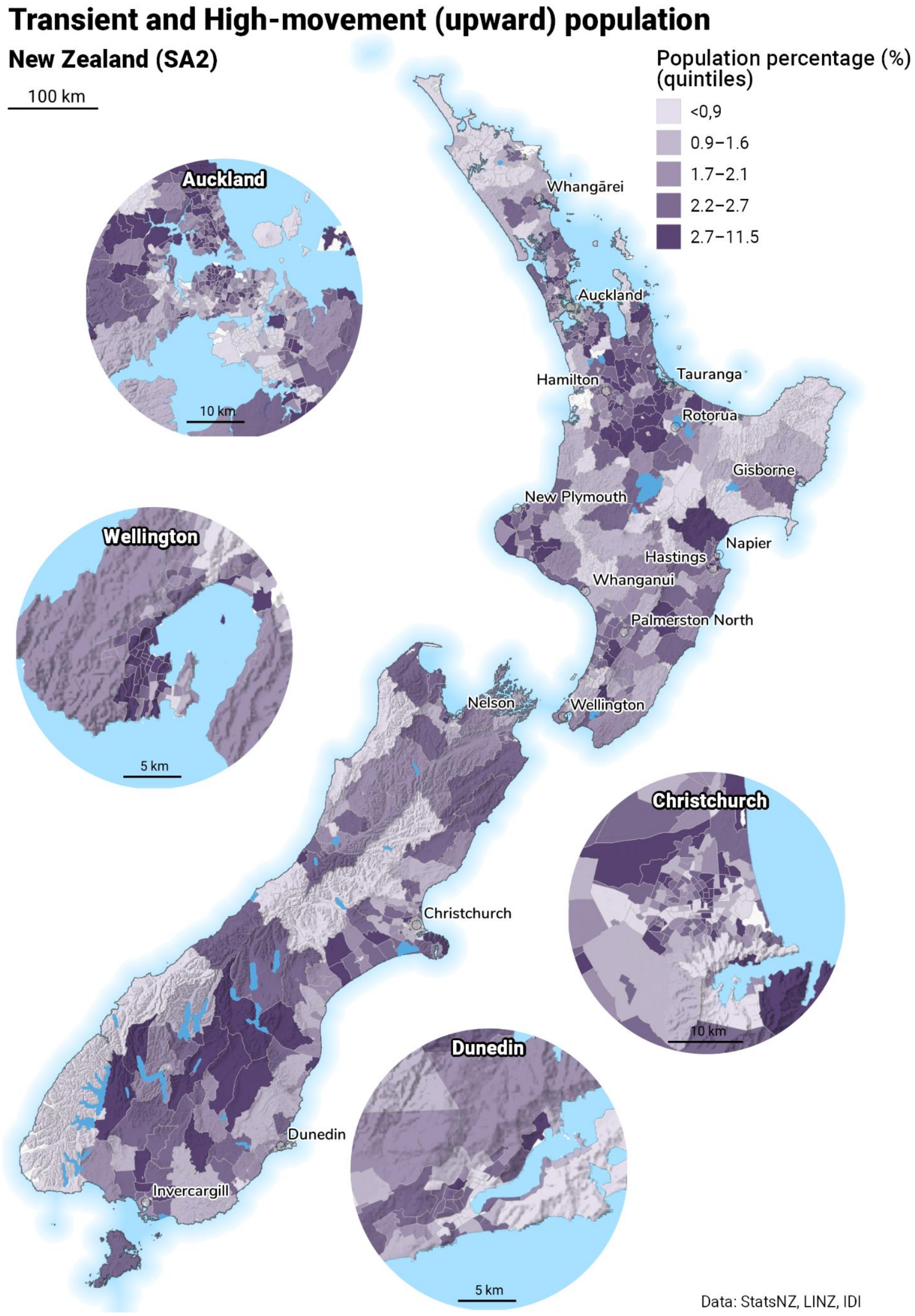

Figure S1. The percentage of the transient and high movers (upward) population across New Zealand with insets for Auckland, Christchurch, Dunedin and Wellington (Quintile 1: lowest percentage and Quintile 5: highest percentage).

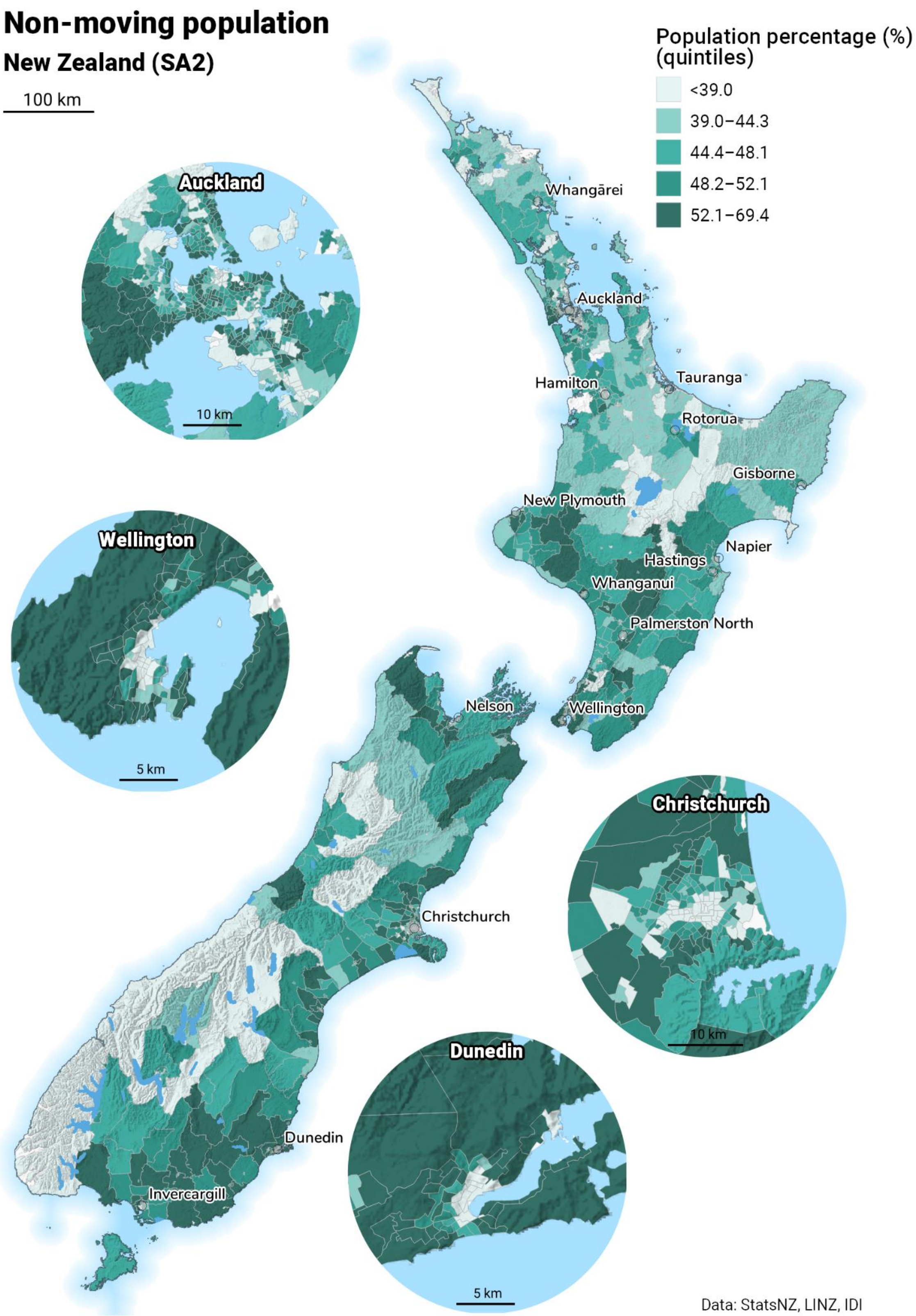

Figure S2. The percentage of non-movers across New Zealand with insets for Auckland, Christchurch, Dunedin and Wellington (Quintile 1: lowest percentage and Quintile 5: highest percentage).

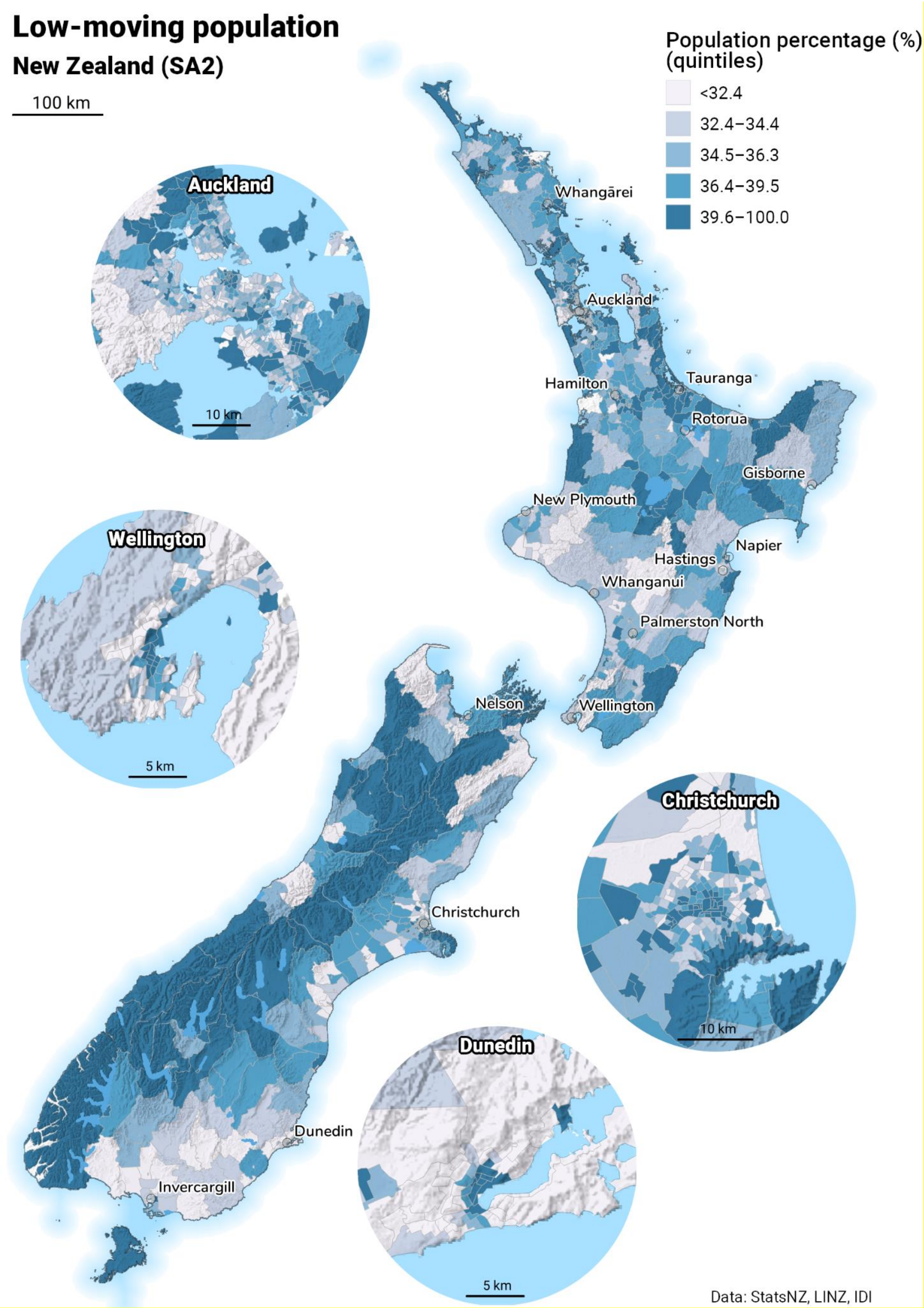

Figure S3. The percentage of low-movers across New Zealand with insets for Auckland, Christchurch, Dunedin and Wellington (Quintile 1: lowest percentage and Quintile 5: highest percentage).

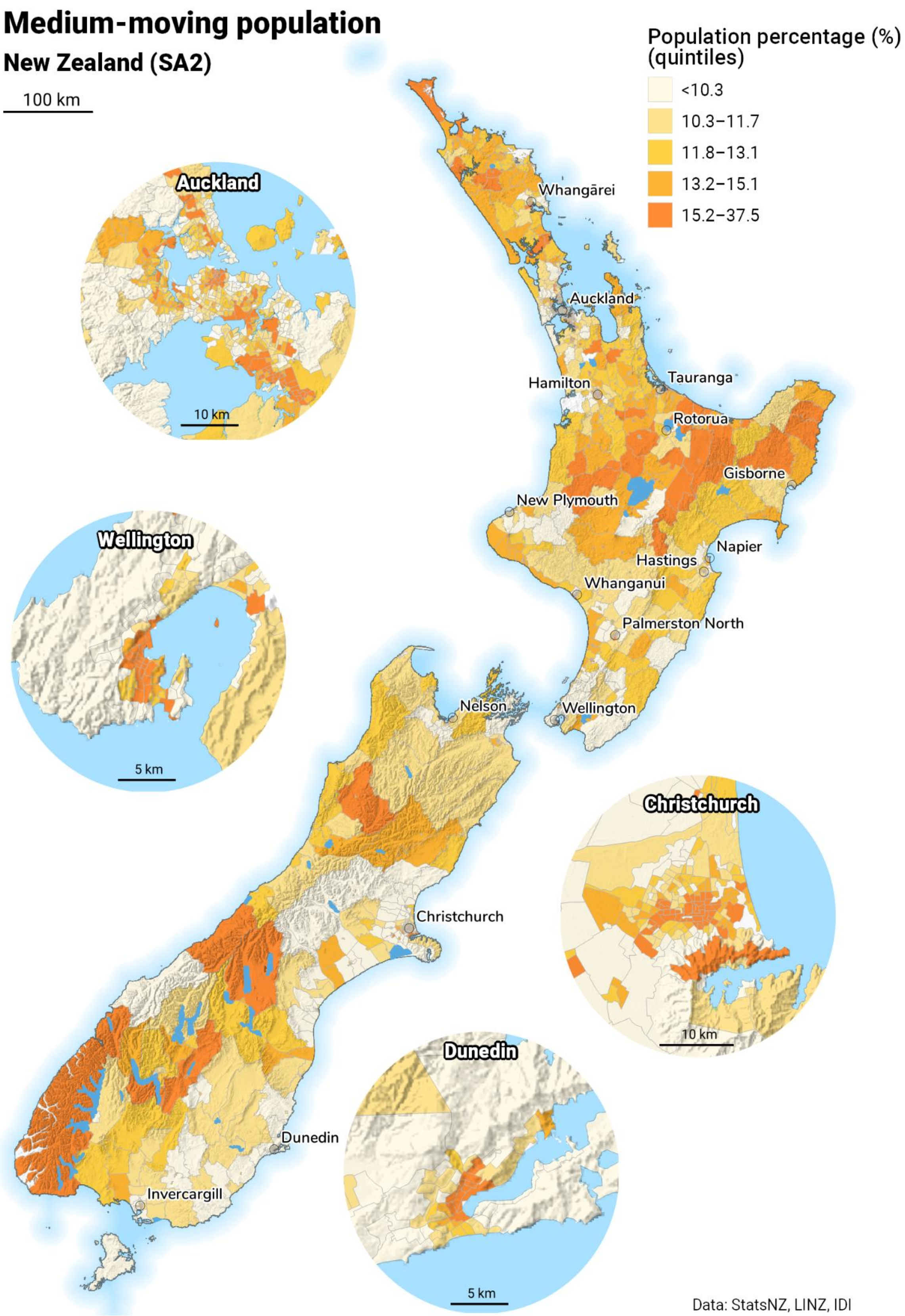

Figure S4. The percentage of medium movers across New Zealand with insets for Auckland, Christchurch, Dunedin and Wellington (Quintile 1: lowest percentage and Quintile 5: highest percentage).

Table S1. The percentage of the total population by residential mobility category and ethnicity.

	New Zealand		
	Overall	**Māori**	**Non-Māori**
Non-movers	45.4%	35.3%	47.7%
Low movement	34.9%	34.9%	34.9%
Medium movement	13.7%	17.9%	12.7%
High movement upward	0.3%	0.2%	0.3%
Transient	1.9%	2.8%	1.7%
Vulnerable transient	3.8%	9.0%	2.6%
Population	4,781,268	890,517	3,890,751

Table S2. Relative risks and details of each identified cluster. All clusters significant at the p <0.001 level

Cluster number	Number of SA2s	Total population (Census 2018)	Total cases (Based on the IDI)	RR non-movers	RR low-movement	RR medium movement	RR transient and high movement (upward)	RR vulnerable transient	Group number
1	6	13,716	10,587	0.22	1.3	2.23	0.21	3.51	1
2	60	136,725	201,483	1.06	0.92	0.96	0.19	1.66	2
3	36	99,096	100,863	0.79	1.03	1.29	0.78	2.32	2
4	87	224,736	232,596	0.98	1.1	0.97	1.44	0.3	3
5	20	44,988	33,429	0.52	1.24	1.6	1.95	1.77	1
6	82	229,410	223,932	1.14	0.96	0.82	0.98	0.39	4
7	9	26,937	23,721	0.5	1.19	1.74	2.42	1.65	1
8	83	198,270	202,116	1.18	0.89	0.82	0.84	0.6	4
9	76	127,539	141,441	0.87	1.04	1.17	0.56	1.91	2
10	107	164,727	201,858	0.91	0.99	1.13	0.75	1.84	2
11	24	43,020	41,136	0.68	1.09	1.46	1.33	2.18	1
12	36	73,602	79,986	0.91	1.2	0.96	1.3	0.22	3
13	61	73,041	69,759	0.87	1.13	1.15	1.92	0.3	3
14	78	234,237	235,740	1.12	0.92	0.89	0.91	0.74	4
15	88	169,485	197,766	0.87	1.08	1.12	1.09	1.31	3
16	59	106,077	109,686	1.09	1	0.85	1.11	0.41	4
17	104	176,130	186,741	0.97	0.97	1.04	0.75	1.61	2
18	7	13,527	11,394	0.59	1.21	1.54	0.83	2.11	1
19	1	876	2,292	0.11	1.88	1.7	1.57	0.61	5
20	88	153,780	157,182	1.12	0.9	0.87	0.86	0.96	4
21	9	17,856	18,816	0.94	0.92	1.11	0.23	2.49	2
22	3	8,523	9,015	0.91	0.87	1.2	0	3.12	2
23	10	18,465	18,504	1.26	0.86	0.7	1.09	0.24	4
24	12	16,320	16,593	1.26	0.82	0.76	1.07	0.34	4
25	110	183,927	200,820	1.06	0.97	0.92	1.14	0.74	4
26	1	3,048	3,771	0.5	1.63	1.21	1.48	0.14	5
27	8	13,284	13,926	0.9	0.99	1.14	0.1	2.25	2
28	11	23,382	35,280	1	0.97	1.02	0.42	1.52	2
29	4	6,564	6,969	0.93	0.98	1.04	0.27	2.34	2

Table S3. The population characteristics per group (5 groups) (% (n)) by ethnicity and urban/rural classification

	Mobile inner city	Mobile vulnerable	Mobile non-vulnerable	Stayers	Urban outliers
Total population	142,188	773,826	540,864	1,140,468	3,924
Ethnicity					
European	61.3 (87,195)	58.0 (448,449)	74.4 (402,318)	70.9 (809,076)	72.1 (2,829)
Maori	8.0 (11,376)	32.0 (247,425)	12.1 (65,427)	10.2 (115,989)	7.3 (285)
Pasifika	3.6 (5,157)	13.5 (104,808)	4.3 (23,289)	7.1 (80,877)	2.4 (93)
Asian	30.5 (43,323)	12.0 (93,132)	16.5 (89,478)	19.2 (219,471)	24.2 (948)
MELAA	4.1 (5,802)	1.0 (7,485)	1.7 (9,120)	1.8 (20,880)	1.0 (39)
Other	1.1 (1,599)	1.1 (8,229)	1.3 (6,975)	1.3 (15,045)	1.8 (69)
FUA					
Metropolitan area	100.0 (142,188)	37.5 (329,097)	73.6 (412,653)	76.0 (883,245)	100.0 (3,924)
Large regional centre	0.0 (0)	32.0 (280,917)	0.0 (0)	11.5 (133,833)	0.0 (0)
Medium regional centre	0.0 (0)	6.9 (60,579)	4.4 (24,492)	2.6 (30,465)	0.0 (0)
Small regional centre	0.0 (0)	7.5 (65,436)	10.7 (60,024)	1.8 (20,532)	0.0 (0)
Rural	0.0 (0)	16.1 (141,297)	11.3 (63,504)	8.2 (94,827)	0.0 (0)
HLI					
1-3	0.0 (0)	0.0 (0)	0.2 (1,338)	0.7 (8,604)	0.0 (0)
1-2	0.0 (0)	13.6 (119,331)	16.1 (90,525)	19 (220,494)	0.0 (0)
2-3	0.0 (0)	4.0 (35,517)	9.4 (52,569)	4.0 (47,016)	22.3 (876)
1-1	67.5 (95,985)	21.0 (184,239)	6.3 (35,424)	17.8 (207,546)	0.0 (0)
2-2	0.0 (0)	27.7 (242,925)	29.4 (164,679)	26.6 (309,849)	77.7 (3,048)
3-3	0.0 (0)	14.4 (126,288)	21.5 (120,480)	10.4 (120,390)	0.0 (0)
3-2	0.0 (0)	3.8 (33,429)	11.8 (66,129)	6.4 (74,040)	0.0 (0)

2-1	30.8 (43,794)	14.6 (128,406)	4.8 (26,649)	14.9 (172,731)	0.0 (0)
3-1	1.7 (2,409)	0.8 (7,191)	0.5 (2,880)	0.2 (2,232)	0.0 (0)