Understanding vulnerability to COVID-19 in New Zealand: a nationwide cross-sectional study

WIKI, Jesse <http://orcid.org/0000-0002-1060-687X>, MAREK, Lukas, HOBBS, Matthew, KINGHAM, Simon and CAMPBELL, Malcolm

Citation:

WIKI, Jesse, MAREK, Lukas, HOBBS, Matthew, KINGHAM, Simon and CAMPBELL, Malcolm (2021). Understanding vulnerability to COVID-19 in New Zealand: a nationwide cross-sectional study. Journal of the Royal Society of New Zealand, 51 (sup1), S179-S196. [Article]

Taylor & Francis
Taylor & Francis Group

Journal of the Royal Society of New Zealand

ISSN: 0303-6758 (Print) 1175-8899 (Online) Journal homepage: www.tandfonline.com/journals/tnzr20

Understanding vulnerability to COVID-19 in New Zealand: a nationwide cross-sectional study

Jesse Wiki, Lukas Marek, Matthew Hobbs, Simon Kingham & Malcolm Campbell

To cite this article: Jesse Wiki, Lukas Marek, Matthew Hobbs, Simon Kingham & Malcolm Campbell (2021) Understanding vulnerability to COVID-19 in New Zealand: a nationwide cross-sectional study, Journal of the Royal Society of New Zealand, 51:sup1, S179-S196, DOI: 10.1080/03036758.2021.1900294

To link to this article: https://doi.org/10.1080/03036758.2021.1900294

Published online: 31 Mar 2021.

JOURNAL OF THE ROYAL SOCIETY OF NEW ZEALAND
2021, VOL. 51, NO. S1, S179–S196
https://doi.org/10.1080/03036758.2021.1900294

Taylor & Francis
Taylor & Francis Group

RESEARCH ARTICLE

OPEN ACCESS

Check for updates

Understanding vulnerability to COVID-19 in New Zealand: a nationwide cross-sectional study

Jesse Wiki [a], Lukas Marek[a], Matthew Hobbs[a,b], Simon Kingham[a,c] and Malcolm Campbell[a,c]

[a]GeoHealth Laboratory, Geospatial Research Institute, University of Canterbury, Christchurch, New Zealand; [b]Health Sciences, College of Education, Health and Human Development, University of Canterbury, Christchurch, New Zealand; [c]School of Earth and Environment, College of Science, University of Canterbury, Christchurch, New Zealand

ABSTRACT

COVID-19 can affect the entire population, but it poses an increased risk for particular population groups. Socioeconomic and demographic factors, as well as long-term health conditions, can make populations vulnerable to adverse health outcomes and mortality related to COVID-19. This study uses geospatial methods to visualise metrics of vulnerability to COVID-19 in New Zealand. Based on Ministry of Health guidelines, nationwide data on risk factors included age, ethnicity, population density, socioeconomic deprivation, smoking, long-term health conditions (cancer, cardiovascular conditions, diabetes, renal conditions, and respiratory illnesses), and health service awareness. Data were sourced from the Census (2018), the New Zealand Deprivation Index (NZDep2018), and the National Minimum Dataset (2011–2016). Factor analysis and bivariate mapping were used to identify areas of high vulnerability. Results demonstrate the unequal social and spatial vulnerabilities to COVID-19 across New Zealand. While some major cities were highlighted many areas also occurred outside of the major cities in smaller communities, which also typically have less access to healthcare and fewer resources. This study has generated data that may help mitigate potential inequality in our response to the COVID-19 pandemic, or indeed for future pandemics.

ARTICLE HISTORY
Received 15 September 2020
Accepted 2 March 2021

HANDLING EDITOR
Daniel Exeter

KEYWORDS
COVID-19; New Zealand; vulnerable populations; geospatial; mapping

Introduction

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has infected tens of millions of people around the globe (Lau et al. 2020). The resulting disease, named COVID-19 (coronavirus disease 2019) by the World Health Organization (Sohrabi et al. 2020), was declared a public health emergency of international concern in early 2020 (World Health Organization 2020) and is still ongoing. Compared to previous coronavirus outbreaks such as SARS-CoV in 2002 and MERS-CoV in 2012, COVID-19 has

CONTACT Jesse Wiki jesse.wiki@canterbury.ac.nz

spread at a much faster rate around the globe (Kamel Boulos and Geraghty 2020). Consequently, governments have enforced a mixture of border shutdowns, travel restrictions, social distancing, self-isolation, individual protective measures (face masks and increased hand washing), advised against unnecessary travel, and banned congregations (Nicola et al. 2020). New Zealand has been widely praised for its quick responses to COVID-19 including early implementation and rapid escalation of national COVID-19 suppression strategies that involved closing its borders to non-nationals (only permanent residents and citizens are allowed entry) and implementing one of the strictest lockdowns in the world (Jefferies et al. 2020; Ministry of Health 2020a).

Many long-term effects of the emergence of COVID-19 including social, economic and health consequences remain unknown; however, recent evidence has suggested a significant contraction (approximately 5%) in global GDP in 2020 (Stannard et al. 2020; The World Bank 2020a). Such economic downturns may reverse years of progress toward development goals, putting people back into extreme poverty (The World Bank 2020b). Other impacts include a reduced workforce across all economic sectors (Nicola et al. 2020), disruption to routine healthcare and a reduction in prevention, detection and management of conditions (Public Health England 2021), a decrease in the need for manufactured products (Nicola et al. 2020), and an increase in the need for medical supplies (Miller et al. 2020). The food sector is also facing increased demand due to panic buying and stockpiling of food products (Aday and Aday 2020) and there is some evidence that lockdown measures have increased rates of domestic violence (Bradbury-Jones and Isham 2020). While these are not exhaustive inevitably the impact is, and will be, significant and the gravity of the longer-term effects of COVID-19 are yet to be uncovered (Greenhalgh et al. 2020; National Institute for Health Research 2020).

Identifying vulnerable populations, meaning those that have a higher risk for adverse health outcomes and mortality related to COVID-19 because of barriers to social, economic, political and environmental resources as well as limitations due to illness or disability (National Collaborating Centre for Determinants of Health 2020), within specific areas or regions can help to prioritise interventions. In this context, Geographic Information Systems (GIS) can help monitor population movement, contact tracing across space and time, and are proving indispensable for timely and effective epidemic monitoring and response (Kamel Boulos and Geraghty 2020). GIS can also be used as a powerful tool to map specific areas that have a high prevalence of, for instance, elderly people or long-term health conditions alongside other risk factors such as deprivation. Such information would be immensely valuable to policymakers wishing to provide effective responses to any outbreak or indeed target resources to intervene. Despite this, to date, little if any evidence has provided such data and findings at a nationwide level in New Zealand.

The re-emergence of COVID-19 within New Zealand (Ministry of Health 2020b) and worldwide highlights the need to better understand where vulnerable populations are located and if there are areas of high vulnerability within New Zealand. Pandemics do not affect all populations or individuals equally and many factors make populations vulnerable to adverse health outcomes including socioeconomic and demographic factors as well as underlying medical conditions (Flanagan et al. 2018; Li et al. 2020; Williamson et al. 2020; Yang et al. 2020). Previous studies and current data have documented inequality and inequity in previous pandemics (Gray et al. 2020), for instance within the 1918 Spanish influenza (Mamelund 2006; Murray et al. 2006) or more recently in the 2009 H1N1 influenza pandemic (Charu et al. 2011; Rutter et al. 2012). Inequalities in COVID-19 infection and mortality rates are said to arise because of the syndemic of COVID-19 (Bambra et al. 2020). Indeed, as outlined in New Zealand Ministry of Health guidance, people at risk of severe illness from COVID-19 include older populations as well as populations with underlying medical conditions such as cardiovascular conditions, diabetes, hypertension, and chronic obstructive pulmonary disease and compromised immunity (Ministry of Health 2020c). Other factors such as ethnicity, smoking, pregnancy and obesity are also associated with deleterious outcomes of COVID-19 (Ministry of Health 2020c). This is concerning as there are known health inequities in care (Hobbs et al. 2019) and access to healthcare (Bowie et al. 2013) in New Zealand as well as health-related environmental exposures (Wiki et al. 2019). COVID-19 therefore has the potential to interact with, and exacerbate, pre-existing health and social conditions, which compound the effects of vulnerability based on known risk factors.

This study aims to develop measures of vulnerability for COVID-19 in New Zealand by considering populations at higher risk of adverse health outcomes and mortality related to COVID-19 and visualising this at a nationwide level. Identifying where areas of high vulnerability are located allows for better targeting of resources and generates information that can mitigate potential inequality in our response to the COVID-19 pandemic or future pandemics as in the case of UK-based studies (Daras and Barr 2020; Thomas and Gordon 2021).

Materials and methods

Based on New Zealand Ministry of Health guidance (Ministry of Health 2020c) this study used the most recent nationwide data available on geographic boundaries (Section Geographical areas), demographic variables (Section Demographics), socioeconomic deprivation, long-term health conditions and health behaviours, and linguistic barriers and health service awareness in order to understand population vulnerability in New Zealand. The following sections introduce the data used (Sections Geographical areas, Demographics, socioeconomic deprivation, Long-term health conditions and health behaviours, Linguistic barriers and health service awareness) and describe the analysis (Section Analysis).

Geographical areas

For all analyses, Statistical Area 2 (SA2) boundaries were used to define geographic areas, reflecting communities that interact both socially and economically (Stats NZ 2018a); usually with a shared road network, shared community facilities, shared historical or social links, or socioeconomic similarity. SA2 boundaries vary in size and are the second smallest geography at which census data is publicly available. There are 2171 SA2 areas based on boundaries that are clipped to the New Zealand coastline, with SA2s in city council areas having a population range of 2000–4000 residents and SA2s in smaller district council areas generally having a population between 1000–3000 residents. Some rural SA2s have fewer than 1000 residents due to sparse populations and large geographic areas (Stats NZ 2018a). Population size is based on the usual resident population (2018) and inland water, inlets or oceanic areas represented by SA2s that contained nil or nominal resident populations as well as the Chatham Islands were excluded from this study, leaving a total of 2148 SA2s for further analyses.

Demographics

Demographic variables include population size and density, age, and ethnicity. Population size is based on the usually resident population of each SA2, as outlined above, and used to calculate population density as the number of people per square kilometre. For the purpose of this study, age was defined as a binary variable; either below 65 years of age or 65 and over (65+). This aligns with the Centers for Disease Control and Prevention social vulnerability index (Flanagan et al. 2018; Pereira 2020) and New Zealand Ministry of Health guidelines, which note that older people have a higher risk of developing a severe illness from COVID-19, particularly if they have underlying health conditions (Ministry of Health 2020c). In general, the risk increases with age and is a particularly important factor in identifying vulnerable populations. Ethnicity, based on broad category definitions (Stats NZ 2018b) is also included. This is an important consideration as Māori and Pacific populations are likely to experience higher levels of risk at an earlier age than European/Other ethnic groups (Plank et al. 2020). This is, in part, because chronic health conditions and co-morbidities are often experienced at an earlier age for these ethnic groups (Ministry of Health 2020c). All population groups were sourced from the Census (2018). The count in each population group and the usually resident population count were used to calculate the percentage of the above population groups in each SA2 area.

Socioeconomic deprivation

Socioeconomic deprivation was based on the deprivation decile provided by the New Zealand Deprivation Index (NZDep2018) (Atkinson et al. 2019). NZDep2018 combines several variables from the 2018 census that reflect dimensions of material and social deprivation (Atkinson et al. 2019). Specifically, these reflect a lack of income, employment, communication, support, qualifications, owned home, living space, and dry living conditions. Importantly, this captures living conditions, as it measures bedroom occupancy threshold i.e. overcrowding and damp/mould, which are known contributors to a higher risk of COVID-19 mortality (Ministry of Health 2020c; Institute of Health Equity 2021).

Long-term health conditions and health behaviours

Long-term health conditions (LTCs) were sourced from the National Minimum Dataset (NMDS) for the period 2011–2016, supplied by the Ministry of Health. The NMDS is a national collection of public and private hospital discharge information, including clinical information, for inpatients and day patients with a valid National Health Index number (Ministry of Health 2019). LTCs included in this study were cancer, cardiovascular conditions, diabetes, renal conditions, and respiratory illnesses. Records were selected from the NMDS if they contained a corresponding ICD-10 diagnosis code, regardless of the diagnosis rank. Where multiple LTC diagnoses were recorded for a hospitalisation (e.g. patient diagnosed with cancer and diabetes), these records were counted as a single event. Of the 6,714,606 total NMDS records provided, 4,690,108 had no associated LTC code and 144,123 had no spatial reference. These were removed, leaving a remainder of 1,880,375 records for analysis, which were then aggregated to SA2 areas. These were standardised as a percentage of the total population for each SA2 area based on the Census (2018) usually resident population. Regarding health behaviours, data on regular smokers was sourced from the Census (2018). The count of regular smokers (aged 15+ years) and the usually resident population (aged 15+ years) were used to calculate the percentage of regular smokers in each SA2 area.

Linguistic barriers and health service awareness

Data on linguistic barriers and health service awareness was also included as linguistic isolation may create an important barrier to healthcare literacy and access (Field 2000; Pegasus Health 2013; de Moissac and Bowen 2019). Moreover, lower educational attainment may be associated with lower service awareness and utilisation (Field 2000), and both are factors that may make populations more vulnerable. Populations that are linguistically isolated were used to represent populations with linguistic barriers. The Census (2018) official language indicator was used to identify populations that are linguistically isolated. The variable 'Other languages only (neither Māori, English nor NZ Sign Language)' and the usually resident population count were used to calculate the percentage of people in each SA2 area that are linguistically isolated. Populations without a high-school qualification were used to represent populations that may have limited service awareness (Field 2000). Data on the highest qualification was sourced from the Census (2018), the number of people with 'No Qualification' and the census usually resident population aged 15 years and over were used to calculate the percentage of people (aged 15+) in each SA2 area that do not have a high-school qualification.

Analysis

Statistical analysis

First, descriptive statistics were used to understand the range and distribution of all variables. Factor analysis was then used to group variables into a smaller number of factors, which has the benefit of not only consolidating multiple variables into a fewer number of factors for ease of interpretation but also indicates the relative importance of different factors. It describes variability among observed, correlated variables and assumes that total variance can be partitioned into common and unique variance. The result is a reduction of multiple individual variables into fewer dimensions called factors. The Kaiser–Meyer–Olkin Measure of Sampling Adequacy was used to indicate the proportion of variance that may be caused by underlying factors, where a value of 0.6 is a commonly suggested minimum. Additionally, Bartlett's Test of Sphericity was used to test whether the variables are unrelated and therefore not suitable for structure detection.

Principal axis factoring was used for extraction, and when deciding upon the number of factors for inclusion we follow the common understanding that only eigenvalues greater than 1 are of importance (Griffith and Amrhein 1997) while also assessing the scree plot. Varimax rotation (an orthogonal rotation) was then applied to estimate the unique contribution of each factor and maximise the loading of a variable on one factor while also minimising the loadings on all others. This helps to identify which data variables are important for which factor, with scores greater than 0.4 considered stable (Guadagnoli and Velicer 1988; Field 2013).

Kaiser Normalisation was used to obtain stability of solutions across samples, as communalities are high across all items. Given that a factor is by nature unobserved, we generate plausible factor scores using the regression method in order to maximise validity and enable mapping of factors. All analysis was conducted using R 3.6.3 (R Core Team 2017) and SPSS version 26.

Spatial analysis

Bivariate mapping was then utilised to identify geographic areas of New Zealand that have a high level of vulnerability based on differing combinations of variables (older age alongside the factors outlined in the previous step). Bivariate mapping is a cartographic visualisation technique that builds on univariate choropleth maps by simultaneously depicting two separate variables (Leonowicz 2006). This allows the reader to see areas that have, for example, both high numbers of older populations and high sociocultural barriers. In this regard, it has the potential to reveal geographic phenomena more effectively by demonstrating the relationship between multiple spatially distributed variables. As noted previously, older age (65+) is the key focus of this study and given that it did not have a high loading coefficient for any of the three factors considered, it was used as the primary variable in all analyses; secondary variables include the factors resulting from factor analysis. These were grouped by tertile – into three groups of similar size – to ensure that each class had a relatively equal number of areas and results were comparable. These tertiles were combined to form bivariate classifications (an example is shown in Figure 1). The spatial distribution

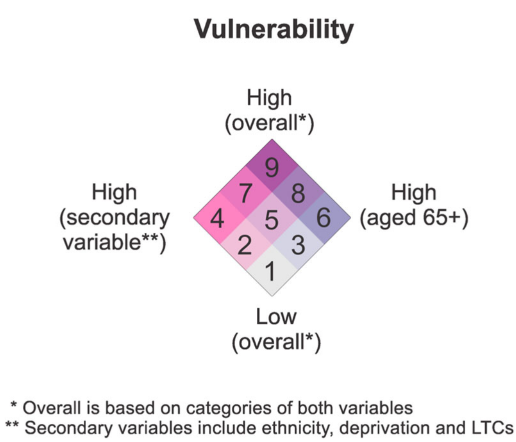

Figure 1. Bivariate categorisation of vulnerability.

was then investigated by assigning each SA2 area a bivariate classification and displaying the colours in a map. All analysis was conducted using R 3.6.3 (R Core Team 2017) and QGIS 3.8.0.

Results

Factor analysis

Within New Zealand, the population aged 65+ comprised 15.22% ($n = 715{,}128$) of the usually resident population in 2018. European was the predominant ethnic group (70.17%, $n = 3{,}297{,}864$), followed by Māori (16.51%, $n = 775{,}836$), Asian (15.06%, $n = 707{,}598$), Pacific Peoples (8.12%, $n = 381{,}642$), Middle Eastern/Latin American/African (MELAA) (1.50%, $n = 70{,}332$), and Other ethnic groups (1.24%, $n = 58{,}053$). However, it should be noted that one person can identify as belonging to multiple ethnic groups in New Zealand.

Results for both the Kaiser–Meyer–Olkin Measure of Sampling Adequacy, with a value of 0.749, and Bartlett's Test of Sphericity, with a significance value of 0.000, indicate that factor analysis is a suitable analytical method for the data. In deciding upon the number of factors for inclusion, we follow the common understanding that only eigenvalues greater than 1 are of importance while also assessing the scree plot (Griffith and Amrhein 1997). Table 1 indicates that there are four variables with eigenvalues greater than 1, however, after examining the scree plot it is concluded that variable 4, although having an eigenvalue of 1.006, will not be included in the further analysis as its contribution to the total variance explained is negligible when compared to first three factors. Therefore, three factors are retained which explain 70.38% of the total variance (Table 1). Table 2 presents the rotated factor structure, with variables that have a high loading (>0.4) highlighted in bold and the three factors labelled to reflect major variables captured by each factor.

Factor 1 is identified as being a comprehensive indicator of health. It explains 28.38% of the total variance and 40.80% of the variance explained by the three factors. It includes

Table 1. Eigenvalues from principal axis factoring.

Variable	Eigenvalue	% of variance	Cumulative %
1	4.824	28.38	28.38
2	3.849	22.64	51.02
3	3.292	19.36	70.38
4	1.006	5.92	76.30
5	0.885	5.21	81.51
6	0.721	4.24	85.75
7	0.718	4.22	89.97
8	0.529	3.11	93.08
9	0.334	1.96	95.05
10	0.239	1.41	96.45
11	0.156	0.92	97.373
12	0.118	0.69	98.07
13	0.113	0.67	98.73
14	0.081	0.48	99.21
15	0.053	0.31	99.52
16	0.047	0.28	99.79
17	0.035	0.21	100.00

Table 2. Rotated factor structure.

	Health	Sociocultural	Socioeconomic
Deprivation (decile)	0.045	0.210	**0.827**
Cancer	**0.945**	−0.090	−0.037
Cardiovascular conditions	**0.982**	−0.050	−0.003
Diabetes	**0.958**	0.045	0.090
Renal conditions	**0.911**	0.015	0.083
Respiratory illness	**0.967**	0.048	0.130
Regular smoker	0.074	−0.056	**0.938**
European	−0.094	−0.861	−0.404
Māori	0.024	−0.102	**0.776**
Pacific Peoples	0.052	**0.490**	**0.410**
Asian	−0.028	**0.837**	−0.230
MELAA[a]	−0.032	**0.594**	−0.215
Other ethnic groups	−0.062	−0.214	−0.187
Aged 65+	0.028	−0.466	−0.036
No qualification	0.030	−0.332	**0.702**
Linguistically isolated	−0.001	**0.831**	−0.090
Population density	−0.042	**0.543**	−0.041
% of total variance explained	*28.38*	*22.64*	*19.36*
% of variance explained by the 3 factors	*40.80*	*30.92*	*28.28*

Notes: Bold values indicate variables with a high loading (>0.4) on each factor and italicised values describe the percentage of variance explained.
[a]Middle Eastern/Latin American/African.

the following five variables, listed in order of relative loadings: cardiovascular conditions, respiratory illnesses, diabetes, cancer, and renal conditions. Factor 2 is identified as being a comprehensive indicator of sociocultural factors. It explains 22.64% of the total variance and 30.92% of the variance explained by the three factors. It includes the following five variables, listed in order of relative loadings: Asian, populations that are linguistically isolated, Middle Eastern/Latin American/African (MELAA) populations, population density, and Pacific Peoples. Factor 3 is identified as being a comprehensive indicator of socioeconomic factors. It explains 19.36% of the total variance and 28.28% of the variance explained by the three factors. It includes the following four variables, listed in order of relative loadings: regular smokers, deprivation, Māori, populations with no qualification, and Pacific Peoples.

A notable point here is that the loading coefficient for the variables European, Other ethnic groups, and populations aged 65+ are not significant contributors to any of the three factors. Being of older age is outlined as one of the most significant factors for vulnerability to pandemics such as COVID-19, however (Ministry of Health 2020c). Therefore, we proceed by mapping this against each of the three factors identified above in order to visualise potentially vulnerable populations in New Zealand.

Nationwide population vulnerability

We use the New Zealand Ministry of Health guidelines (Ministry of Health 2020c) to identify vulnerable populations based on people at-risk of severe illness. Nationwide population vulnerability was mapped using those aged 65+ as the primary variable (as old age is the most important factor contributing to COVID-19 infection and mortality (Williamson et al. 2020)) in combination with (i) Factor 1 – health, (ii) Factor 2 – sociocultural, and (iii) Factor 3 – socioeconomic as secondary variables. Each variable was grouped by tertile (tertile 1 being the lowest and tertile 3 being the highest).

The tertiles for each variable were then combined to form bivariate classifications (Figure 1). As shown in Figure 1, the vulnerability of the area increases alongside the hue and saturation of colour. For instance, the lightest areas (category 1) were classified as being the lowest level of vulnerability and the darkest areas (category 9) the highest level of vulnerability. Areas of moderate vulnerability are within category 5, in the middle of the diamond (Figure 1). Category 4, to the far left of the diamond, indicates areas that have a high level of vulnerability based on the secondary variable considered, but not in terms of populations aged 65+ years. In contrast, category 6, on the far right of the diamond, shows that vulnerability is high based on those aged 65+ years but not the secondary variable. The remaining categories (2, 3, 7, and 8) demonstrate vulnerability within these extremes, again with the level of vulnerability represented by hue and saturation.

Table 3 shows the distribution of vulnerability based on the count of SA2 areas and the percentage of the population, reflecting the bivariate classification of vulnerability. When considering the count of areas within each vulnerability category, results show a relatively even distribution for the socioeconomic factor. For the health factor, however, there is a larger number of SA2 areas in categories 1 (low overall), 5 (moderate overall), and 9 (high overall), with the largest number of SA2 areas in the most extreme categories (categories 1 and 9). In contrast, when considering the sociocultural factor the extreme categories have the least areas and the largest concentration of SA2s is within categories 4, 5, and 6. This is largely reflected in the percentage of the population within each category for each factor.

As shown in Figure 2 and Figure 3 there are notable spatial variations in vulnerability. Otago, Tasman, Wellington particularly around Wairarapa, and the Coromandel area of the Waikato region are shown to have a high vulnerability based on populations aged 65 +, as indicated in all three maps (Figure 2). Vulnerability based on the health factor is generally higher in cities than rural areas with the exception of the Northland region and pockets of high vulnerability in the East Cape of the North Island (around the Bay of Plenty and Gisborne regions) and the central South Island. When considering the combination of high vulnerability based on both populations aged 65+ and the health factor, there are few areas of high vulnerability overall. These are primarily located in cities and the Northland region, with additional pockets in the East Cape,

Table 3. Count of SA2 areas and percentage of the population in each bivariate vulnerability category.[a]

	Health		Sociocultural		Socioeconomic	
	SA2 (*n*)	Population (%)	SA2 (*n*)	Population (%)	SA2 (*n*)	Population (%)
1 (Low overall)	335	14.66	87	2.44	244	12.6
2	182	10.68	172	7.49	212	10.36
3	249	9.37	272	9.38	270	13.32
4 (High independent)	201	11.16	459	26.57	262	13.54
5 (Moderate overall)	305	14.87	273	13.01	228	9.94
6 (High constant)	132	4.57	357	13.93	202	9.78
7	163	7.99	172	9.85	219	8.97
8	229	10.34	271	12.99	276	11.99
9 (High overall)	352	16.36	85	4.35	235	9.49

[a]All categories include the population aged 65+ as the dependent variable and the factors listed along the column headers as the independent variable.

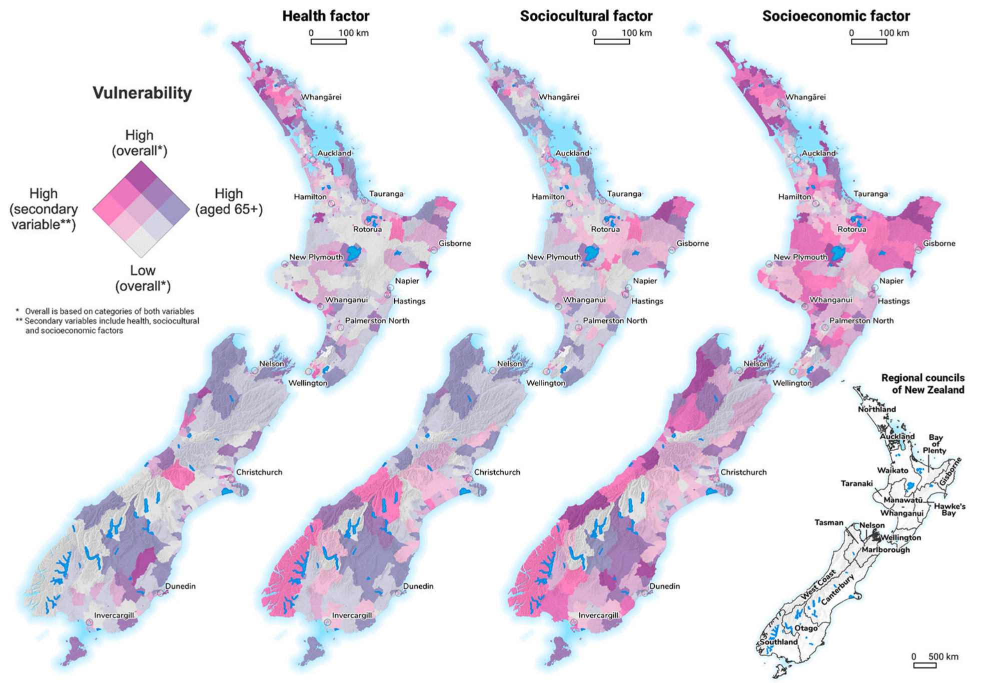

Figure 2. Nationwide area-level vulnerability for adults aged 65+ years in New Zealand by health, sociocultural, and socioeconomic factors.

Coromandel, and Manawatū-Whanganui regions of the North Island and a few isolated areas in the South Island (Figure 2).

Vulnerability based on the sociocultural factor is high in the East Cape region and major cities of the North Island, particularly Auckland, as well as Southland and parts of the West Coast and Christchurch city in the South Island (Figure 2). When considering the combination of high vulnerability based on both populations aged 65+ and the sociocultural factor, there are notably few areas. There are pockets of high vulnerability in the Coromandel and Northland regions; however, the largest concentration of high vulnerability based on both of these factors is around central and north Auckland and west Christchurch (Figure 3).

When considering the socioeconomic factor, results show an increase in areas that are high in vulnerability particularly in Northland, the East Cape and central North Island and the West Coast of the South Island (Figure 2). While some major cities such as Wellington show few areas of high vulnerability based on this factor, others such as South Auckland, Porirua and the east of Christchurch demonstrate areas of high vulnerability (Figure 3). Vulnerability based on this factor in combination with populations aged 65+ is shown to be high in the Northland, Coromandel and East Cape regions of the North Island. There are also additional pockets of high vulnerability in rural areas of the South Island, largely the West Coast and Otago regions (Figure 2). Interestingly, there were few areas of high vulnerability based on this combination of factors in major cities (Figure 3).

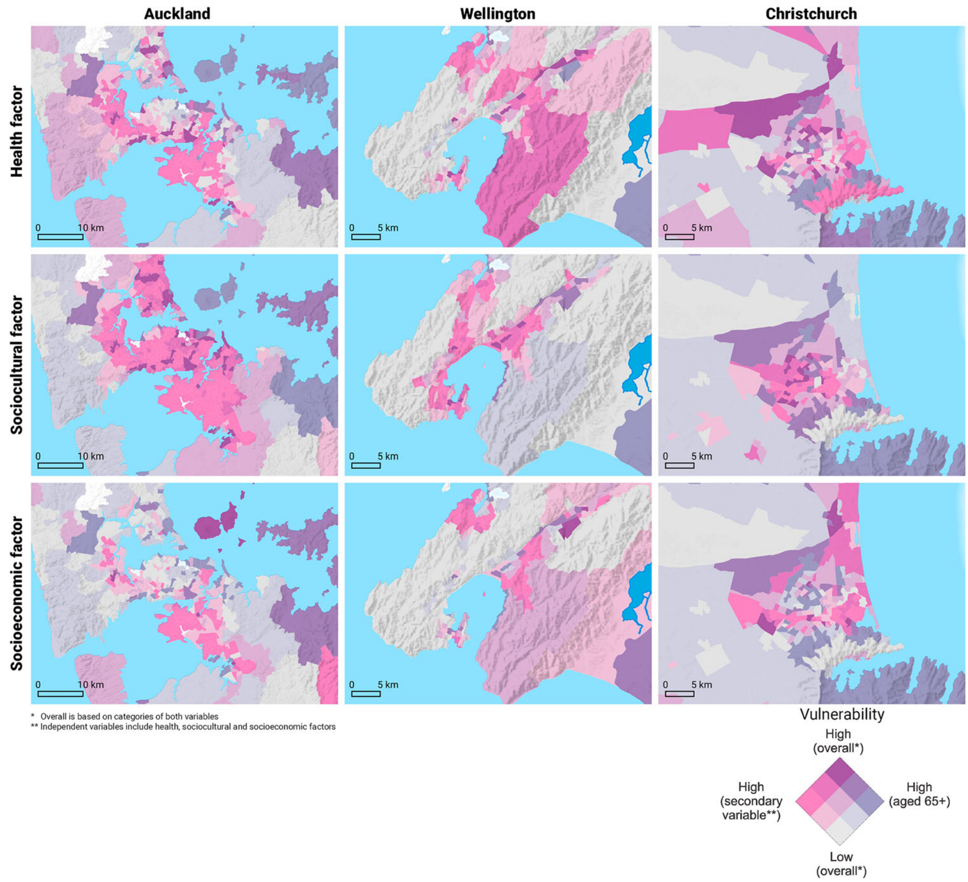

Figure 3. Population vulnerability for adults aged 65+ years in Auckland, Wellington and Christchurch by health, sociocultural, and socioeconomic factors.

Discussion

This study aims to develop measures of vulnerability for COVID-19 in New Zealand by considering populations at higher risk of adverse health outcomes and mortality, particularly in regard to COVID-19. Specifically, it adds to evidence by investigating and visualising vulnerability to health outbreaks, such as pandemics, in New Zealand based on a range of known risk factors such as population density, age, ethnicity, deprivation, health service awareness, health behaviours and long-term health conditions. Previous research shows that the spatial differences in socioeconomic and demographic impacts on health are important, with a wealth of evidence supporting this proposition in New Zealand (Bowie et al. 2013). This is also particularly true for COVID-19, as international evidence shows that the virus has potential to interact with, and exacerbate pre-existing chronic health conditions (Sanyaolu et al. 2020; Ssentongo et al. 2020), and social conditions (Baqui et al. 2020; Iacobucci 2020; Williamson et al. 2020). This compounds the effects of vulnerability in terms of adverse health consequences in regard to COVID-19 based on other known risk factors for pandemics such as COVID-19 including older age or the presence of underlying health conditions. Such associations need to be considered with caution as much of the research in this field is based on emerging evidence and lacks definitive conclusions based on high-quality longitudinal or experimental studies.

We used spatially aggregated data that represents communities rather than focusing on individuals to demonstrate spatial variations in areas of high vulnerability. Identifying where these areas are is crucial as it allows for better targeting of resources and generates information that can mitigate potential inequality in government response. Such findings also provide support for the idea of targeted protective measures and precautions that can be effective locally.

New Zealand, similar to many other developed countries, is experiencing an ageing population. This places increasing pressure on the health system, a situation potentially aggravated during epidemic and pandemic states. As older age is also one of the most significant predictors of COVID-19 deaths, especially when combined with other socioeconomic and cultural factors (Williamson et al. 2020), this study focused on the population aged 65+ in combination with health and sociodemographic characteristics of the population highlighted with New Zealand Ministry of Health guidance (Ministry of Health 2020c) in order to understand area-level vulnerability.

Results demonstrate that vulnerability based on the health factor in combination with populations aged 65+ is generally higher in cities than rural areas with the exception of the Northland region. This may be due to higher demand for healthcare in cities, resulting from larger populations (Oladipo 2014). Vulnerability based on the sociocultural factor and populations aged 65+ is high in areas such as the East Cape region and major cities of the North Island, influenced by significant proportions of ethnic minorities in these areas. Being a bi-cultural country with an indigenous Māori population and mix of ethnicities living in both population centres and outside of them, adds to the complexities of defining what vulnerable populations are and where they reside. This is important, as such differences have previously been shown to have implications for health inequity and health outcomes in New Zealand (Hefford et al. 2005; Hobbs et al. 2019; Wiki et al. 2020; Marek et al. 2020a). The largest concentration of high vulnerability based on the combination of this factor and populations aged 65+ is around central and north Auckland and west Christchurch. This is likely influenced by the Asian ethnic group, which was shown to have a high loading on this factor and have high population numbers in these areas.

There was a significant increase in areas of high vulnerability based on the socioeconomic factor particularly in rural areas of the North Island, South Auckland and the east of Christchurch. This is reflective of increased deprivation, negative health behaviours such as smoking, larger Māori populations and lower service awareness in these areas, all variables that were shown to load highly on this factor and can significantly influence health outcomes. There were notably few areas of high vulnerability based on this combination of factors in major cities demonstrating that vulnerability based on this combination of factors may be more influential in rural areas of New Zealand, particularly those with large Māori populations. This is an unexpected pattern compared to common findings that study the overall population and often identify worse health and well-being outcomes in urban settings (Bowie et al. 2013). Such findings may be due to higher concentrations of younger populations living in socioeconomically deprived areas of cities compared to deprived rural areas, which is in line with the Ministry of Health guidelines (Ministry of Health 2020c) where young people are not considered vulnerable.

There has been other preliminary work that models vulnerability to COVID-19, particularly within the UK. Daras and Barr (2020) focused on the creation of index that describes an increase in risk related to the population vulnerability while Thomas and Gordon (2021) utilised machine learning in order to classify vulnerability Our research in this study is distinct from other research worldwide given the bivariate approach and uniqueness of the New Zealand context. Importantly, New Zealand has a bi-cultural context, low population density and is geographically isolated. These factors are particularly important as New Zealand is often compared with other OECD countries, or western European nations, with distinct social and physical geographies.

This study confirms important distinctions in vulnerability measures based on health, sociocultural and socioeconomic factors. It demonstrates that many areas of high vulnerability, particularly when considering combinations of older populations and populations with socioeconomic barriers, are outside of the major cities and in smaller communities of New Zealand, which typically have less access to healthcare and fewer resources (Fearnley et al. 2016; Health and Disability System Review 2019) and also attract less attention (Marek et al. 2020b). This finding is also in line with international research suggesting COVID-19 can potentially affect smaller communities more than urban areas (Peters 2020; Ribeiro et al. 2020), even though population density can affect the timing of outbreaks through higher connectedness of denser location (Carozzi et al. 2020). Interestingly, this offers some support for the actions taken by some local communities who, recognising their vulnerability, implemented protective measures (additional to nationwide lockdown) such as road barriers, to protect their populations (Groenstein and Mitchell 2020; Johnsen 2020; O'Connor 2020).

This is the first study that uses geospatial analysis to develop a nationwide vulnerability metric (in the health context) for New Zealand. It identified areas of high vulnerability where populations may be at greater risk of adverse health outcomes, particularly COVID-19, using comprehensive nationwide data on sociodemographic characteristics, socioeconomic status, health outcomes and behaviours, and health service awareness from several robust contemporary sources. It also combines this data to investigate vulnerability, providing a more nuanced understanding than considering isolated datasets and variables. Despite this, the results of this study should be interpreted with consideration of its limitations. Firstly, as this study is of cross-sectional design and ecological in nature it can only provide a limited measure of vulnerability at a given time period and may be prone to issues of ecological fallacy as a result of spatial aggregation. This is because our data are presented at area-level, so no association between risk factors and COVID-19 at the individual level can be inferred and no causal association is sought. Aggregating data for visualisation also means that some information may be lost through grouping and categorisation; however, this is necessary to ensure that the results are understandable to a wide audience. In addition, many variables in this study were analysed in terms of relative rather than absolute numbers. This demonstrates areas with a higher proportion of vulnerable populations however it may also be appropriate in many cases to focus on areas with a high absolute number of people at-risk. Future research should consider the implications of this carefully and may gain value from including variable weightings. Finally, vulnerability itself can be understood in many ways and may mean different things to different people. We only capture some aspects of what being vulnerable means due to data availability and more work is needed to examine how different population groups interpret the understanding of this.

Overall, the current study is intended to be exploratory in nature, aiding in the detection of broad spatial patterns and associations. Further assessment of vulnerability, specific populations and mobility patterns among other compositional and societal norms through detailed longitudinal or experimental studies are needed to fully understand the relationships discussed within this study. Despite these limitations, spatial intelligence is a useful tool for policy makers and those who need geographically specific information and data to target disease management and resource allocation. It can be argued that there is utility in this type of research, as results can guide health-focused policy responses to areas where interventions are likely to be needed. Our results will be of interest to policy makers due to the multi-dimensional description of vulnerability and visualisation of areas that have high vulnerability, an important consideration in the overall policy response.

Conclusions

Currently, COVID-19 disproportionately affects particular population groups including older people and those with compromised health among other factors. While these populations are at greater risk of adverse health outcomes and mortality from COVID-19, there are also known health inequities in care and access across New Zealand, particularly for ethnic minorities and those living in socioeconomically deprived areas. This study visualised metrics of vulnerability to adverse health outcomes, such as COVID-19, in New Zealand using geospatial tools for modelling, analysis and presentation of spatial data. Through mapping, it identified areas that may experience disproportionately negative impacts of disease outbreaks based on age, underlying health conditions, sociocultural factors, socioeconomic factors, and a combination of these. Identifying where these areas of high vulnerability are located allows for better targeting of resources and generates information that can mitigate potential inequality in our response to the COVID-19 pandemic, or indeed for future pandemics.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The GeoHealth Laboratory is funded by the New Zealand Ministry of Health.

ORCID

Jesse Wiki http://orcid.org/0000-0002-1060-687X

References

Aday S, Aday MS. 2020. Impacts of COVID-19 on food supply chain. Food Quality and Safety. 4 (4):167–180. https://doi.org/10.1093/fqsafe/fyaa024

Atkinson J, Salmond C, Crampton P. 2019. NZDep2018 index of deprivation. Wellington: University of Otago.

Bambra C, Riordan R, Ford J, Matthews F. 2020. The COVID-19 pandemic and health inequalities. Journal of Epidemiology and Community Health (1979). 74(11):964-968.

Baqui P, Bica I, Marra V, Ercole A, van der Schaar M. 2020. Ethnic and regional variations in hospital mortality from COVID-19 in Brazil: a cross-sectional observational study. The Lancet Global Health. 8(8):e1018–e1026.

Bowie C, 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.

Bradbury-Jones C, Isham L. 2020. The pandemic paradox: the consequences of COVID-19 on domestic violence. Journal of Clinical Nursing. 29(13–14):2047–2049.

Carozzi F, Provenzano S, Roth S. 2020. Urban density and COVID-19, IZA Discussion Papers, No. 13440, Institute of Labor Economics (IZA). Bonn. https://www.econstor.eu/bitstream/10419/223882/1/dp13440.pdf.

Charu V, Chowell G, Mejia LSP, Echevarría-Zuno S, Borja-Aburto VH, Simonsen L, Miller MA, Viboud C. 2011. Mortality burden of the A/H1N1 pandemic in Mexico: a comparison of deaths and years of life lost to seasonal influenza. Clinical Infectious Diseases. 53(10):985–993.

Daras K, Barr B. 2020. Exploring the vulnerability to COVID19 between communities in England. University of Liverpool. https://pldr.org/2020/06/18/exploring-the-vulnerability-to-covid19-between-communities-in-england/.

de Moissac D, Bowen S. 2019. Impact of language barriers on quality of care and patient safety for official language minority francophones in Canada. Journal of Patient Experience. 6(1):24–32.

Fearnley D, Lawrenson R, Nixon G. 2016. ‘Poorly defined’: unknown unknowns in New Zealand rural health. New Zealand Medical Journal. 129(1439):77–81.

Field A. 2013. Discovering statistics using SPSS. 4th ed. London: SAGE.

Field K. 2000. Measuring the need for primary health care: An index of relative disadvantage. Applied Geography. 20(4):305–332.

Flanagan BE, Hallisey EJ, Adams E, Lavery A. 2018. Measuring community vulnerability to natural and anthropogenic hazards: The centers for disease control and prevention’s social vulnerability index. Journal of Environmental Health. 80(10):34–36.

Gray DM, Anyane-Yeboa A, Balzora S, Issaka RB, May FP. 2020. COVID-19 and the other pandemic: populations made vulnerable by systemic inequity. Nature Reviews Gastroenterology & Hepatology. 17(9):520.

Greenhalgh T, Knight M, A’Court C, Buxton M, Husain L. 2020. Management of post-acute Covid-19 in primary care. BMJ (Clinical Research Ed.). 370:m3026.

Griffith DA, Amrhein CG. 1997. Multivariate statistical analysis for geographers. Upper Saddle River, NJ: Prentice Hall.

Groenstein C, Mitchell P. 2020. Coronavirus: isolated East Cape community takes matters into its own hands. Stuff. [accessed 2020 Sep 14]. https://www.stuff.co.nz/national/health/coronavirus/120470952/sweeping-measures-including-stay-home-edict-for-most-vulnerable-as-covid-cases-rise?rm=m.

Guadagnoli E, Velicer WF. 1988. Relation of sample size to the stability of component patterns. Psychological Bulletin. 103(2):265–275.

Health and Disability System Review. 2019. Health and disability system review – interim report. Hauora Manaaki ki Aotearoa Whānui – Pūrongo mō Tēnei Wā. Wellington: HDSR. www.systemreview.health.govt.nz/interim-report.

Hefford M, Crampton P, Foley J. 2005. Reducing health disparities through primary care reform: The New Zealand experiment. Health Policy (Amsterdam). 72(1):9–23.

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 (British Edition). 394 (10209):1613–1614.
Iacobucci G. 2020. Covid-19: deprived areas have the highest death rates in England and Wales. British Medical Journal. 369:1.
Institute of Health Equity. 2021. Build back fairer: the COVID-19 Marmot review. http://www.instituteofhealthequity.org/.
Jefferies S, French N, Gilkison C, Graham G, Hope V, Marshall J, McElnay C, McNeil A, Muellner P, Paint S, et al. 2020. COVID-19 in New Zealand and the impact of the national response: a descriptive epidemiological study. The Lancet Public Health. 5(11):e612–e623.
Johnsen M. 2020. Covid-19: Remote communities in Far North want checkpoints to remain in level 2. Radio New Zealand. [accessed 2020 Sep 14]. https://www.rnz.co.nz/news/te-manu-korihi/416492/covid-19-remote-communities-in-far-north-want-checkpoints-to-remain-in-level-2.
Kamel Boulos MN, Geraghty EM. 2020. Geographical tracking and mapping of coronavirus disease COVID-19/severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic and associated events around the world: How 21st century GIS technologies are supporting the global fight against outbreaks and epidemics. International Journal of Health Geographics. 19(1):8–12.
Lau H, Khosrawipour T, Kocbach P, Ichii H, Bania J, Khosrawipour V. 2020. Evaluating the massive underreporting and undertesting of COVID-19 cases in multiple global epicenters. Pulmonology. 27(2): 110-115.
Leonowicz A. 2006. Two-variable choropleth maps as a useful tool for visualization of geographical relationship. Geografija. 42(1):33–37.
Li Q, Guan X, Wu P, Wang X, Zhou L, Tong Y, Ren R, Leung KSM, Lau EHY, Wong JY et al. 2020. Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. The New England Journal of Medicine. 382:1199–1207.
Mamelund S. 2006. A socially neutral disease? individual social class, household wealth and mortality from Spanish influenza in two socially contrasting parishes in Kristiania 1918–19. Social Science & Medicine. 62(4):923–940.
Marek L, Hobbs M, McCarthy J, Wiki J, Tomintz M, Campbell M, Kingham S. 2020a. Investigating spatial variation and change (2006–2017) in childhood immunisation coverage in New Zealand. Social Science & Medicine. 264:113292.
Marek L, Wiki J, Campbell M, Kingham S, Sabel C, Tomintz M, Hobbs M. 2020b. Slipping under the radar: worsened health outcomes in semi-urban areas of New Zealand. The New Zealand Medical Journal. 133(1519):121–125.
Miller FA, Young SB, Dobrow M, Shojania K. 2020. Vulnerability of the medical product supply chain: the wake-up call of COVID-19. BMJ Quality & Safety. Published Online First: 02 November 2020. Epub ahead of print. PMID: 33139342. doi: 10.1136/bmjqs-2020-012133.
Ministry of Health. 2019. National minimum dataset. https://www.health.govt.nz/nz-health-statistics/national-collections-and-surveys/collections/national-minimum-dataset-hospital-events.
Ministry of Health. 2020a. COVID-19 health and disability system response plan. Wellington: Ministry of Health.
Ministry of Health. 2020b. 1 new case of COVID-19. Media release. 11 Aug 2020. https://www.health.govt.nz/news-media/media-releases/1-new-case-covid-19-16.
Ministry of Health. 2020c. COVID-19: Advice for higher risk people. https://www.health.govt.nz/our-work/diseases-and-conditions/covid-19-novel-coronavirus/covid-19-information-specific-audiences/covid-19-advice-higher-risk-people#risk.
Murray CJ, Lopez AD, Chin B, Feehan D, Hill KH. 2006. Estimation of potential global pandemic influenza mortality on the basis of vital registry data from the 1918–20 pandemic: A quantitative analysis. The Lancet (British Edition). 368(9554):2211–2218.
National Collaborating Centre for Determinants of Health. 2020. Vulnerable populations. https://nccdh.ca/glossary/entry/vulnerable-populations.

National Institute for Health Research. 2020. Living with Covid 19. doi:10.3310/themedreview_41169.
Nicola M, Alsafi Z, Sohrabi C, Kerwan A, Al-Jabir A, Iosifidis C, Agha M, Agha R. 2020. The socio-economic implications of the coronavirus pandemic (COVID-19): a review. International Journal of Surgery (London, England). 78:185.
O'Connor M. 2020 Apr 25. Checkpoint concerns. Gisborne Herald. [accessed 2020 Sep 14]. http://www.gisborneherald.co.nz/local-news/20200425/checkpoint-concerns/.
Oladipo JA. 2014. Utilization of health care services in rural and urban areas: a determinant factor in planning and managing health care delivery systems. African Health Sciences. 14(2):322–333.
Pegasus Health. 2013. Culturally and linguistically diverse populations and health in Canterbury. Occasional Paper No. 1. https://www.pegasus.health.nz/wp-content/uploads/2018/05/Culturally-and-linguistically-diverse-populations-in-health.pdf.
Pereira E. 2020. COVID-19 risk maps – identifying high risk communities across the City of Los Angeles. https://storymaps.arcgis.com/stories/72dfb48fb6714e80b302710bf13378e1.
Peters DJ. 2020. Rural areas face higher and distinct risks of serious COVID-19 outcomes than urban areas. Technical Report, Iowa State University. Retrieved from: https://ruralopioids.soc.iastate.edu/wp-content/uploads/sites/210/2020/04/STR1059_covid19.pdf.
Plank M, Sporle A, Hannah K, McLeod M, Steyn N. 2020. Research shows Māori are more likely to die from COVID-19 than other New Zealanders. The Conversation. https://theconversation.com/research-shows-maori-are-more-likely-to-die-from-covid-19-than-other-new-zealanders-145453.
Public Health England. 2021. Wider impacts of COVID-19 on health. Public Health Profiles 2021. https://fingertips.phe.org.uk.
R Core Team. 2017. R: a language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing.
Ribeiro HV, Sunahara AS, Sutton J, Perc M, Hanley QS. 2020. City size and the spreading of COVID-19 in Brazil. PloS one. 15(9):e0239699.
Rutter PD, Mytton OT, Mak M, Donaldson LJ. 2012. Socio-economic disparities in mortality due to pandemic influenza in England. International Journal of Public Health. 57(4):745–750.
Sanyaolu A, Okorie C, Marinkovic A, Patidar R, Younis K, Desai P, Hosein Z, Padda I, Mangat J. 2020. Comorbidity and its impact on patients with COVID-19. SN Comprehensive Clinical Medicine. 2 (8):1069–1076.
Sohrabi C, Alsafi Z, O'Neill N, Khan M, Kerwan A, Al-Jabir A, Iosifidis C, Agha R. 2020. World health organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). International Journal of Surgery (London, England). 76:71.
Ssentongo P, Ssentongo AE, Heilbrunn ES, Ba DM, Chinchilli VM. 2020. Association of cardiovascular disease and 10 other pre-existing comorbidities with COVID-19 mortality: A systematic review and meta-analysis. PloS One. 15(8):e0238215.
Stannard T, Steven G, McDonald C, Reserve Bank of New Zealand. 2020. Economic impacts of COVID-19 containment measures. Wellington: Reserve Bank of New Zealand.
Stats NZ [Statistics New Zealand]. 2018a. Statistical area 2 2018 [Data file]. https://datafinder.stats.govt.nz/layer/92213-statistical-area-2-2018-clipped-generalised/.
Stats NZ [Statistics New Zealand]. 2018b. 2018 census of population and dwellings [Data file]. http://nzdotstat.stats.govt.nz/wbos/Index.aspx.
Thomas M, Gordon E. 2021. British Red Cross Covid-19 vulnerability index. https://britishredcrosssociety.github.io/covid-19-vulnerability/.
Wiki J, Kingham S, Campbell M. 2020. A geospatial analysis of type 2 diabetes mellitus and the food environment in urban New Zealand. Social Science & Medicine.(1982): 113231-113231.
Wiki J, Kingham S, Campbell M. 2019. Accessibility to food retailers and socioeconomic deprivation in urban New Zealand. New Zealand Geographer. 75(1):3–11. doi:10.1111/nzg.12201.
Williamson EJ, Walker AJ, Bhaskaran K, Bacon S, Bates C, Morton CE, Curtis HJ, Mehrkar A, Evans D, Inglesby P, et al. 2020. Factors associated with COVID-19-related death using OpenSAFELY. Nature (London). 584(7821):430–436.

The World Bank. 2020a. Pandemic, recession: the global economy in crisis. https://www.worldbank.org/en/publication/global-economic-prospects.

The World Bank. 2020b. The global economic outlook during the COVID-19 pandemic: a changed world. https://www.worldbank.org/en/news/feature/2020/06/08/the-global-economic-outlook-during-the-covid-19-pandemic-a-changed-world.

World Health Organization. 2020 Jan. Statement on the second meeting of the International Health Regulations Emergency Committee regarding the outbreak of novel coronavirus (2019-nCoV), Geneva, Switzerland. https://www.who.int/news-room/detail/30-01-2020-statement-on-the-second-meeting-of-the-international-health-regulations-(2005)-emergency-committee-regarding-the-outbreak-of-novel-coronavirus-(2019-ncov).

Yang J, Zheng Y, Gou X, Pu K, Chen Z, Guo Q, Ji R, Wang H, Wang Y, Zhou Y. 2020. Prevalence of comorbidities and its effects in patients infected with SARS-CoV-2: a systematic review and meta-analysis. International Journal of Infectious Diseases. 94:91–95.