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A spatial interpretation of Australia’s COVID-vulnerability

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A R T I C L E   I N F O

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Social vulnerability
Disaster risk
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Australia
Sparsely populated area

A B S T R A C T

The school of social vulnerability in disaster sciences offers an alternative perspective on the current COVID-19 (coronavirus) pandemic crisis. Social vulnerability in general can be understood as a risk of exposure to hazard impacts, where vulnerability is embedded in the normal functioning of the society. The COVID-19 pandemic has exposed systemic (political and health care systems), demographic (aging, race) and, based on the results of our approach, spatial (spatial isolation and connectivity) vulnerabilities as well. In this paper, we develop a risk prediction model based on two composite indicators of social vulnerability. These indicators reflect the two main contrasting risks associated with COVID-19, demographic vulnerability and, as a consequence of the lockdowns, economic vulnerability. We conceptualise social vulnerability in the context of the extremely uneven spatial population distribution in Australia. Our approach helps extend understanding about the role of spatiality in the current pandemic disaster.

1. Introduction

The school of social vulnerability in disaster science offers valuable perspectives on the current COVID-19 (coronavirus) pandemic crisis [1]. Social vulnerability in general can be understood as a form of risk exposure to a disaster, where vulnerability is embedded in the normal functioning of the society. To date, social vulnerability in relation to the global COVID-19 pandemic has been interpreted in terms of its systemic (policy, political and health care systems [2–4]), demographic [5–7], inequality [8–10] and spatial dimensions [11–13].

A social vulnerability lens on the COVID-19 pandemic would postulate that, while its origins were the sudden and unanticipated transmission of the virus from animals to humans, and its subsequent spread, its impacts have propagated through populations according to the highest relative levels of social vulnerability. While both hazard and vulnerability related to risk exposure in disaster (see Cardona [14]), the main objective of this research is to develop and analyse social vulnerability composite indices for Australia to investigate the varying spatial risk from COVID-19 based on socio-cultural population determinants such as race, ethnicity, age and gender. It is our view that social vulnerability has not only a demographic-health component arising from the respiratory illness itself, but also a socio-economic dimension from the effects of lockdown efforts in disrupting normal economic activity and challenging the physical and mental wellbeing of those affected.

In Australia population distributions are highly uneven and characterised by significant urbanisation which is in contrast to the sparsely populated or ‘Outback’ areas of the nation. Demographic compositions are also highly diverse according to age, gender, race and other important variables [15,16]. While, relative to other areas, sparsely populated areas in Australia tend to have less per capita COVID-19 case numbers [17] they are also characterised by a significant proportion of vulnerable populations [18,19]. We argue, that the lower per capita case numbers could be explained by the spatial variation of social vulnerability, which is more complex in its composition than simply the difference in population densities. For these reasons we analyse social vulnerability using a human geographical approach, linking it to the spatial diversity of the population within Australia with a particular emphasis on its sparsely populated ‘edges’ to understand how spatial diversity in population compositions affect levels of social vulnerabilities.

In the first section of this paper we review the literature on social vulnerability and disasters. We then look at how social vulnerabilities expose risks in the current pandemic before developing a model for analysing the complex nature of these vulnerabilities, particularly in relation to their spatial diversity within Australia. Finally we discuss the results in relation to spatial analysis methods and disaster mitigation policies.
2. The effects of a disaster: when, where, and who is impacted?

In the initial global media coverage of the emergence of the COVID-19 pandemic, there was a great deal of discussion regarding the hazard event, with a focus on the role played by wet markets in Asia, particularly those in Wuhan, China [20–22]. Indeed, Parrish et al. [23]; Chan et al. [24] and Geoghegan et al. [25] argue that the risk of virus transmission by anthroponosis is globally increasing through the effects of habitat destruction, climate change, and the increase of populations living in hazard-prone areas, particularly the crowded megacities within developing nations [26–28].

Beyond the mitigation of impacts of the hazard event, in this case the transmission and the subsequent spread of the coronavirus [29], there exists an additional factor determining risk exposure; namely social vulnerability, and its variations according to demographic and social composition of the populations at different locations. Furthermore, instead of viewing disasters as ‘non-routine events’ (see Drabek [30] creating non-routine social problems, Blaikie et al. [31] and Wisner et al. [32] argue that disasters are embedded in the ‘normal’ functioning of society and are rooted in social inequalities. For these reasons, they emphasise the role which social, political and economic structures play in different levels of vulnerability. Their work has helped shift the understanding of disasters as extreme and unusual events to an expression of the vulnerability of human-social systems which themselves vary across space. As Cutter [33] has stated, disasters are not events but a reflection of society’s vulnerability to environmental threats and extreme shocks. Oliver-Smith [34] similarly argued that “…social systems generate the conditions that place people […] at different levels of risk from the same hazard and subject to different forms of suffering from the same event” (p. 120).

Social vulnerability perspectives in the analysis of disasters emphasise that the scale and timing of impacts are inherently a function of social circumstances, which in turn determine who (individuals, social groups, communities etc.) is at risk and who is impacted [31,32]. Thus, the hazard event is a trigger which exposes pre-existing vulnerabilities generated by power-law relationships as well as underlying social and economic inequalities [32,35].

This paper is therefore premised on the view that the course of the current COVID-19 pandemic is strongly influenced by spatially-determined vulnerabilities which are a result of diversity in the demographic and geographic composition of Australia’s population. In this respect, the COVID-19 pandemic has exacerbated pre-existing social inequalities [36], exposed systemic (political and health care systems), population (aging) and spatial (isolation and connectivity) vulnerabilities which have strongly influenced varying mortality rates between and within individual nations [37]. From this perspective, clinical and biomedical efforts to prevent, monitor and understand the transmission and mortality effects of the coronavirus can be seen as secondary responses to the primary effect of systemic social and economic vulnerabilities [38]. For example, health systems which, in the lead-up to 2020 had relatively less funding on which they could modernised or increased capacity to deal with caseloads [3,4]. In contrast, nations which are more vulnerable to COVID-19 have long exhibited lower health outcomes than for city-based residents [19]. In Australia, many remote regions are also characterised by highly mobile populations, including mobile Indigenous residents [58,59], mobile populations, including mobile Indigenous residents [19]. In Australia, many remote regions are also characterised by highly mobile populations, including mobile Indigenous residents [58,59], mobile populations, including mobile Indigenous residents [19]. In Australia, many remote regions are also characterised by highly mobile populations, including mobile Indigenous residents [58,59], mobile populations, including mobile Indigenous residents [19]. 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mean that the data on per capita infection rates within small-area units are too ‘noisy’ to apply a post-event analysis of social vulnerability using methods such as multivariate regression. Consequently, in this paper, we have developed a spatially focused social vulnerability model to predict risk exposures by creating two composite indicators of social vulnerability to COVID-19 using Australian data. In the following section we outline the methods and data applied to developing this model.

3. Data and methods

Our approach was to collect a set of indicators (see Table 2) to describe social vulnerabilities based on existing scientific reports (Table 1) and data available from the Australian Bureau of Statistics (ABS) and then reduce this set to a small number of factors as the basis for a COVID-19 risk prediction model. Even though there are a large number of variables, some are correlated, and it is therefore possible to significantly reduce the dimensions while retaining a large amount of variation of the initial data set. To do this we used principal component analysis (PCA) which is a multi-variable method of dimension reduction to perform a linear decomposition of the initial variables into a set of uncorrelated dimensions of vulnerability.

We used ABS estimated resident population data for 2018 and ABS census population data for 2016, both published as ‘Data by Region, 2013–2018’ by the ABS [73] for our small-area population compositions. To understand the spatial distribution of vulnerable populations, we first collected indicators related to probable vulnerable groups based on the availability of indicators and the existing literature we discussed in the previous section which highlights the most vulnerable groups in the population as being the elderly, Indigenous people, non-citizens and people on the move. The spatial distribution of each of these groups

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Aim</th>
<th>Methods</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acharya, Porwal [61]</td>
<td>Identification of vulnerable regions in India</td>
<td>Creating composite index by percentile ranking</td>
<td>There are some unclear connections between predicted vulnerabilities and actual spread</td>
</tr>
<tr>
<td>Bamweyana et al. [63]</td>
<td>Vulnerability index for parishes in Kampala (Uganda)</td>
<td>Composite index using socio-economic indicators and pre-existing health conditions, densities and transport hubs</td>
<td>Composite vulnerability indicator based on adaptive capacity, exposure and susceptibility</td>
</tr>
<tr>
<td>Santos et al. [64]</td>
<td>Vulnerability in Río de Janeiro, Brazil</td>
<td>Weighted composite indicator of vulnerability based on census data</td>
<td>Identification of vulnerable city neighbourhoods</td>
</tr>
<tr>
<td>Cuadros et al. [11]</td>
<td>Spatio-temporal transmission dynamics</td>
<td>Mathematical spatial simulation of virus spread estimating case numbers</td>
<td>Spatially uneven disease diffusion when urbanised, connected areas are compared with rural areas</td>
</tr>
<tr>
<td>Savini et al. [65]</td>
<td>Modelling COVID-19 susceptibility in Italy</td>
<td>Municipality level modelling of contact rates by using census and commuting network data</td>
<td>Geographically detailed scenarios for risk prediction</td>
</tr>
<tr>
<td>Esteve et al. [66]</td>
<td>Vulnerability based on age and household structure</td>
<td>Country level global simulation based on census microdata</td>
<td>Estimation of possible infection rates</td>
</tr>
<tr>
<td>Fortaleza et al. [67]</td>
<td>Spatial and demographic factors of vulnerability in Sao Paulo State, Brazil</td>
<td>Typology of the municipalities based on socio-demographic data than modelling the spread of the virus</td>
<td>Reinforce of hypothesis on spatial hierarchical spread of the virus</td>
</tr>
<tr>
<td>Lakhaní [68]</td>
<td>Identifying vulnerable areas in Melbourne</td>
<td>Hotspot analysis of ageing population, disability and low access areas to health services</td>
<td>Identifying priority areas for health service development</td>
</tr>
<tr>
<td>Mishra et al. [69]</td>
<td>Identifying social factors jeopardising lockdown measures</td>
<td>Aggregation of weighted scores of selected variables for sub-city-level areas of Mumbai, Delhi, Kolkata and Chennai in India</td>
<td>Identifying vulnerable sub-city areas where social factors jeopardising lockdown measures</td>
</tr>
<tr>
<td>Kim, Bostwick [45]</td>
<td>Vulnerability and racial inequality in Chicago</td>
<td>Hotspot analysis of COVID-19 deaths, social vulnerability index, health risks and percentage of African Americans based on community areas</td>
<td>Significant overlap between African American population and COVID-19 death rate</td>
</tr>
<tr>
<td>Bertocchi, Dimico [42]</td>
<td>Relationship between COVID-19 mortality and race (Cook County, Illinois, USA)</td>
<td>Correlation between COVID-19 mortality and the four sub-indices of vulnerability (socio-economic status, household composition, minority status, housing)</td>
<td>Higher mortality among African Americans through lower socioeconomic status and household composition</td>
</tr>
<tr>
<td>Harris [13]</td>
<td>Correlates of COVID-19 deaths in London</td>
<td>Regression between COVID-19 mortality and socio-economic predictor variables considering neighbourhood connectivity</td>
<td>Mortality is influenced by age, wealth and ethnicity</td>
</tr>
<tr>
<td>Hamidí et al. [12]</td>
<td>Connection between development density and COVID-19 infection rate</td>
<td>Regression modelling (Multilevel linear modelling) of density and infection rate and mortality rate</td>
<td>High density areas have significantly higher infection and mortality rates</td>
</tr>
<tr>
<td>Khazanchi et al. [70]</td>
<td>County-level analysis of COVID-19 cases and death rates in the USA</td>
<td>Regression analysis of positive COVID-19 test and COVID-19 death per capita</td>
<td>Minority and socioeconomic status were associated with differential risk, while household composition and disability was not COVID-19 cases connected to ethnicity, crime and income factors while COVID-19 deaths are connected to deaths, migration and income factors. These connections highly vary across space and time.</td>
</tr>
<tr>
<td>Maiti et al. [71]</td>
<td>Casual association between explanatory variables and COVID-19 transmission in the USA</td>
<td>Global and locally, geographically weighted spatial regression model at county level</td>
<td>Social inequalities strongly influence COVID-19 outcomes.</td>
</tr>
<tr>
<td>Chen, Krieger [72]</td>
<td>Provide estimate on unequal social and economic burden of COVID-19</td>
<td>Rate differences in COVID-19 deaths, cases and positive tests at county and zip-code area levels</td>
<td></td>
</tr>
</tbody>
</table>

Data source: Authors’ collection.
across Australia and the share of each of these groups as a proportion of the total estimated resident populations within each area determines the level of vulnerability of the population (see Figs. 1–4).

To contextualise the importance of the four sub-groups outlined above, in Fig. 1, we observe elderly people make up a higher proportion of residents in regional (relatively densely populated rural) Australia, outside greater capital city areas, even though their absolute numbers are the highest within capital (e.g. in Sydney) and other large cities (e.g. in Cairns). Meanwhile, Fig. 2 shows that the Indigenous population has the highest share in remote sparsely populated areas of Australia, particularly in Northern Australia (Kimberley in Western Australia, Northern Territory ex-Darwin, and Northern Queensland) and a low share but high number in Australia’s largest cities. Fig. 3 shows that the absolute size of the non-citizen population is high in greater capital cities where its share is relatively high. On the other hand, the shares of non-citizen populations are the highest in those sparsely populated regions where the mining or tourism sectors are significant (e.g. the Pilbara and Alice Springs regions) while in other sparsely populated regions the shares of these people remain very low (e.g. Tanami Desert, East Arnhem, Queensland or New South Wales Outback). Both non-citizen and Indigenous populations have a lower level of English proficiency (in general) which increases their vulnerability. Fig. 4, meanwhile, shows the population churn rate as an indicator of population mobility. High churn rates are related to sparsely populated regions with remote mining towns and to Darwin with a significant fly-in-fly-out workforce.

We also included economic variables in our approach to vulnerability since the economic consequences of lockdown efforts impacted employees and businesses differentially across sectors. Economic vulnerability to the COVID-19 pandemic is represented by indicators of those industries particularly impacted when lockdown efforts are imposed [74–78]. These included non-essential small business services (pubs, coffee shops, restaurants, gyms etc.), businesses with a highly mobile fly-in-fly-out labour force (mining, construction) or a seasonal migrant worker labour force (agriculture). Economic and demographic dimensions are often overlapped by mobility-related variables. For instance, as a result of the international travel ban, the education and horticulture sectors have been particularly hard hit due to the loss of overseas students, working holiday makers and seasonal migrant workers from Pacific islands nations (see also [79,80]. Small businesses and service businesses make up a relatively high proportion in regional areas close to large cities where there is a relatively high proportion of older residents [81,82]. Farming related businesses tend to be in outer regional areas, especially those related to cattle and sheep grazing [83]. Mining and construction sectors employing mobile fly-in-fly-out populations [16], are concentrated in sparsely populated areas where large mine sites are located (Fig. 5).

Based on the assumption that a lower socio-economic status leads to a higher vulnerability to any kind of hazard, we have included the variables of unemployment and labour force participation rates, the share of people earning less than $500AUD per week, per capita passenger vehicles and average incomes (see Table 2). While a high unemployment is clearly related to those sparsely populated remote areas with high proportions of Indigenous people [84], the share of people earning less than 500AUD is also high in inner regional areas with significant elderly populations.

It should be added that the ABS also provides small area estimates of populations at risk to the COVID-19 pandemic disaster based on the National Health Survey 2017–18. These estimates include people with chronic conditions such as cardiovascular diseases, diabetes and asthma [85,86]. However, this data is not published for most very remote areas for reasons of confidentiality related to these areas’ small population numbers. For this reason, we used data on the share of people living with disabilities taken from the 2016 census.

Data on estimated resident population is published for both ABS (Australian Statistical Geography Standard - ASGS) and non-ABS (Local Government Areas) regions. The former allows exploration of vulnerabilities at different spatial levels. The ASGS has four Statistical Area (SA) levels; SA1 is the smallest but most detailed geographical unit. However, the ABS only provides estimated resident population data at the higher SA levels of SA2, SA3 and SA4. When working with the ASGS geography we faced some challenges. For example, the ASGS statistical area levels are designed to reflect units of equal demographic or economic weight (e.g. communities or labour markets) rather than equal spatial weight, and as a result within a given level there can be a large variation in areal size. The high variation of areal sizes is closely related to the modifiable areal unit problem [87] which Openshaw [88,89] highlights the results of a spatial analysis can be different based on the scale and pattern (zonation) of the spatial units used. To overcome this limitation and to have a greater emphasis on the regional variation of COVID-19 vulnerabilities, we created our own geography based on ASGS at the SA2 level, where those SA2 units located in metropolitan areas have been aggregated into larger units. This resulted in 191 units out of the original 2239 ASGS 2016 SA2 units, with a reduced variation in area size and population density, and a slightly increased relative variation in population size (Table 3). As a by-product of this aggregation our geography is easier to interpret visually because its units are more equally weighted by areal size.

Finally in relation to geography, we extracted composite components of vulnerability according to both the ASGS SA2 and our adjusted geographies by using PCA (see a simplified workflow in Fig. 6). Comparing our results for the two different geographies helped us to understand the size effect due to the modifiable areal unit problem, and to validate our adjusted geography. During the selection of variables from the initial

### Table 2
The pool of available indicators related to social vulnerabilities in Australia.

<table>
<thead>
<tr>
<th>Code of the indicator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>IND_SH</td>
<td>Share of Indigenous and Torres Strait Islander people from total population, 2016 (%)</td>
</tr>
<tr>
<td>NCIT_SH</td>
<td>Share of non-citizen from total population, 2016 (%)</td>
</tr>
<tr>
<td>NOENGS</td>
<td>Share of population not speaking English at home from total population, 2016 (%)</td>
</tr>
<tr>
<td>OPO_SH</td>
<td>Share of people aged 65 or older from total population (%)</td>
</tr>
<tr>
<td>CHURN</td>
<td>Churn rate (total arrivals and departures per estimated resident population) 2018 (%)</td>
</tr>
<tr>
<td>AG_SH</td>
<td>Employment in agriculture and forestry, 2016 (%)</td>
</tr>
<tr>
<td>ED_SH</td>
<td>Employment in education and training, 2016 (%)</td>
</tr>
<tr>
<td>HEALTH_SH</td>
<td>Employment in health care and social assistance, 2016 (%)</td>
</tr>
<tr>
<td>MIN_CO_SH</td>
<td>Employment in mining and construction, 2016 (%)</td>
</tr>
<tr>
<td>SERV_SH</td>
<td>Employment in wholesale and retail trade, accommodation and food services, rental, hiring and real estate services, arts and recreation and other services, 2016 (%)</td>
</tr>
<tr>
<td>SMALL_BUS_SH</td>
<td>Share of non-employing businesses or businesses employing less than 5 employees from total number of businesses, 2018 (%)</td>
</tr>
<tr>
<td>PEREMP_SM_BUS</td>
<td>Number of non-employing businesses or businesses employing less than 5 employees per total number of employees (%)</td>
</tr>
<tr>
<td>PEREMP_SERV_BUS</td>
<td>Number of businesses in wholesale and retail trade, accommodation and food services, rental, hiring and real estate services, arts and recreation and other services per total number of employees, 2018 (%)</td>
</tr>
<tr>
<td>PEREMP_AGRIBUS</td>
<td>Number of agriculture and forestry businesses per total number of employees (%)</td>
</tr>
<tr>
<td>PCAP_DWELL</td>
<td>Total dwelling units approvals per estimated resident population, 2018</td>
</tr>
<tr>
<td>PERCAP_VEH</td>
<td>Registered passenger vehicles per estimated resident population, 2018</td>
</tr>
<tr>
<td>PERCAP_INC</td>
<td>Total income per estimated resident population, 2018</td>
</tr>
<tr>
<td>PEREMP_INCOM</td>
<td>Total employee income per number of employees, 2016</td>
</tr>
<tr>
<td>POOR_RAD</td>
<td>Persons earning less than $500 per week, 2016 (%)</td>
</tr>
<tr>
<td>UNEMP_R</td>
<td>Unemployment rate, 2016 (%)</td>
</tr>
<tr>
<td>PARTICIP</td>
<td>Participation rate, 2016 (%)</td>
</tr>
<tr>
<td>DISAB</td>
<td>Persons who have need for assistance with core activities, 2016 (%)</td>
</tr>
</tbody>
</table>

Fig. 1. Distribution and share of elderly people.

Fig. 2. Distribution and share of Indigenous population.
dataset (Table 2) we aimed to exclude those indicators having low communalities (not contributing to either components) or high factor weights on more than one component. This was undertaken to extract the best-fit model with the lowest possible number of composite dimensions which still have an explanatory strength (sums of squares) more than 1.

4. Results

Principal component analysis (PCA) based on the adjusted SA2 geography allows us to factor the selected 12 standardised measures of vulnerability given in Table 4 into two dominant composite indicators which together explained 72.2% of the variation of the initial data set, the first encompassing 47.3% and the second 24.9%. The first component is weighted more on the share of Indigenous population, share of aged population, indicators related to service businesses, and the unemployment rate. The second dimension is weighted more on average income, mining and construction sectors, and the mobility related indicators. Based on these factor loadings we called the first dimension ‘demographic vulnerability’ and the second dimension ‘economic vulnerability’.

High (positive) scores of demographic vulnerability can be found mostly in regional Australia with its higher share of old people, higher importance of small and service-related businesses which is also connected to the older population in regional areas. Negative scores are mostly found in remote, Indigenous Australia, where along with the high share of Indigenous people who have (in general) a significantly higher unemployment rate than for the rest of the population, particularly in remote areas [84] (Fig. 7). It is important to clarify, that both negative and positive ‘extremes’ of that dimension represent a higher vulnerability, characterised either by high share of Indigenous or elderly population, and that the opposite signs simply indicate that where one is present the other tends to be absent.

High (positive) scores of the economic vulnerability dimension correspond to greater capital city areas as well as mining areas in remote Australia (Fig. 8). These areas are characterised by high employee incomes, high shares of mining and construction workers and a high migration turnover, which together imply a high risk exposure to the negative economic impacts of lockdowns on businesses.

A PCA based on the original ASGS SA2 geography and the selected 10 standardised variables yielded three components which together explained the 79.9% of the variation of the initial variables, the first explaining only 36.9% (Table 5). The first component in this model we called the ‘household economic dimension’ because of the high factor loadings on those indicators related to economic performance and disability. The second component we called the ‘minority dimension’ because it had greater weights on overseas and Indigenous populations and high overseas migration turnover. These are all related to a higher share of non-English speaking populations. The third component we called the ‘business economic’ dimension because it is almost exclusively related to small and service-related businesses.

The first dimension of this model has its highest values in the CBDs of greater capital cities while certain suburbs have very low factor values. This spatial variation is repeated in regional and remote Australia where high scores in mining areas are contrasted with the low scores of predominantly farming and Indigenous areas. The second dimension has its highest scores where there is a higher share of non-citizens in metropolitan suburbs. High scores are also found in sparse, remote units where the Indigenous population makes up a higher proportion. Hence two different phenomena are combined in that single component: foreigners in urban areas, and Indigenous Australians in remote areas. The third dimension reflects small and service businesses which have low score values in residential suburbs and in remote sparsely populated areas.

On comparing the two models from the two different geographies,
Fig. 4. Population churn rate by region in Australia, 2018. Note: The churn rate is the sum of total in and out-migration as a proportion of the estimated resident population.

Fig. 5. Remoteness and sparseness in Australia. Note: Remoteness Structure is based on ABS [103].
we see that the model based on the ASGS SA2 geography reflects intra-urban issues related to the location of wealth (economic participation, incomes and efficiency), segregation (overseas and Indigenous) and service sector concentration. These ‘urban’ dimensions are repeated in remote sparsely populated areas where high income inequalities (see Taylor et al. [90]) and spatial segregation (Indigenous vs. mining communities, spatial diversity, see Carson et al. [15,84]) are also present. On the other hand, when these results are compared to the adjusted geography we notice that the demographic-aging dimension contrasting vulnerability explaining 47.3% of the total variance. Additionally, while the first two components in the model based on the ASGS SA2 geography explain only 59.7% of the total variation, the two dimensional model based on the adjusted geography explains 72.2%. Hence the adjustment of SA2 spatial units allows us to better characterise Australia’s COVID-19 vulnerability by removing the confounding effect of intra-urban spatial variations. These are the reasons why we decided to use the two-dimensional model based on the adjusted geography.

5. Discussion and conclusions

The two composite measures of demographic and economic vulnerability in our model reflect the two main contrasting risks from the COVID-19 pandemic disaster. The first dimension, demographic vulnerability, is related to the individual’s socio-demographic status and highlights those jurisdictions which would be highly exposed to risk in the event of an uncontrolled spread of the virus. Demographic vulnerability, particularly the ethnic composition of the population, has been identified by the literature as the most important risk factor for COVID-19. Empirical studies by Kim, Bostwick [43]; Bertocci, Dimico Bertocci, Dimico [42] and Maiti et al. [71] revealed a strong interrelation between ethnicity and COVID-19 cases. It should be emphasised however that, according to Maiti et al. [71] while COVID-19 cases are related to both ethnicity and income factors, COVID-19 caused deaths are empirically connected only to income factors, hence socio-economic status and ethnicity are connected only in relation to the likelihood of contracting the virus. According to our risk prediction model, Indigenous Australians are particularly vulnerable in remote regions where the low socio-economic status is strongly related to ethnicity because Indigenous Australians make up the majority of unemployed there. Hence, Indigenous Australians are most at risk as a result of both their minority and income status.

It is important to add, however, that these demographic vulnerabilities were, thankfully, not clearly evident in Australia to date because of the very low level of community transmissions. Transmission in Australia has been almost exclusively within the geographic bounds of the greater capital cities which have hosted returning Australian residents from overseas in hotel quarantine. Several clusters in Melbourne,
Fig. 7. Scores of the 1st principal component (demographic vulnerability).

Fig. 8. Scores of the 2nd principal component (economic vulnerability).
Sydney and Brisbane have emerged from the virus being ‘transported’ out from hotel quarantine positive cases by security guards, health worker and others. Fortunately, in regional and remote Australia the numbers have been just a handful of people who had contact with people in city-originating clusters. This pattern is demonstrated by Hamidi et al. [12] and Mishra et al. [69] who highlighted that the COVID-19 pandemic is strongly connected to densely populated urban core areas where the risk of community transmission is higher due to the physical proximity of residents. They also suggest that the current COVID-19 pandemic is challenging the concept of compact urban development as a sustainable model when future pandemics seem likely. In contrast, Cuadros et al. [11] emphasised that critical health care infrastructure unlike in large metropolitan areas, may lack the necessary capacity in rural and remote areas despite the lower case numbers as a result of sparsity, and hence put the residents there in a more vulnerable situation.

In contrast to demographic vulnerability, the second dimension, economic vulnerability, is related to the impacts of lockdowns and border closures on businesses and their employees. Until recently this dimension has not been widely studied empirically. Nevertheless, Kikuchi et al. [91] examined declining household expenditures in Japan at the initial stage of the pandemic, which, as a result of lockdowns, will likely be the most serious consequence of the pandemic in Australia as well. To mitigate this impact the Australian Government implemented the Job Keeper program [92] and tax relief policies in order to maintain household expenditures and reduce business failures. Despite this, measures to prevent the spread of and totally eliminate the virus have hit metropolitan cores particularly hard and put at risk mining sites and the tourism sector in sparsely populated areas.

Our two dimensions are at the core of most policy debates around the pandemic as well: whether to accept a level of virus spread in order to save the economy and possibly achieve some kind of herd immunity this way (or since early 2021, through vaccination), or whether to totally eliminate the virus first in order to ease pressure on the health care system, save lives and ultimately re-open the economy. For example, Western Australia, a state particularly exposed to risk in the economic dimension (Fig. 8) followed the second approach by enacting and maintaining very strict border controls; a move which not only prevented transmission but also delivered a political whitewash for the standing government in the 2021 Western Australian state elections [93]. Of course, the policies which seek to balance both risks could create different outcomes, similar to the effects of scale in policy response emphasised by Delaney [40] in the context of the federalist USA and the more centralised Ireland. Both the WHO and the Australian federal government have often emphasised the lack of universal policies among nations, states and territories, but our work suggests such a universal recipe might never work. Australia in particular is an example of where states and territories have taken different approaches to overcoming the obstacles posed by the pandemic. We should probably expect further regional variations in lockdown policies, maintained or re-imposed border restrictions, and migration bubbles until a global herd immunity is achieved through vaccination in the coming years.

Along with the spatial variation of mitigation policy measures during the COVID-19 pandemic, geography has exerted a significant impact on societies through a ‘territorial trap’ [94] (p. 154) in the form of border closures, travel bans and zoning of regions and hot spot areas [106] where “time has been annihilated by space” [95] (p. 191). This is challenging the pre-pandemic view of an increasingly hyper connected global society [96,97]. According to Fortaleza et al. [67] large metropolitan areas are playing a significant role through their global connectedness and the virus spreading from these centres down the settlement hierarchy and into the adjacent rural peripheries through commuting networks. Harris [15] also emphasised the role of neighbourhood connectivity at the intra-urban level. Adding to this, the variation in outcomes by scale shows that social vulnerabilities are also influenced by the geography along with health and social status. Thus, the spread of the virus is potentially influenced not only by spatially varying mitigation policies, population densities and connectivity, but also by spatial variations in social vulnerability.

Table 5

<table>
<thead>
<tr>
<th>PC 1</th>
<th>PC 2</th>
<th>PC 3</th>
<th>Communalities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zscore(NCT, SH)</td>
<td>0.431</td>
<td>0.849</td>
<td>0.090</td>
</tr>
<tr>
<td>Zscore(NOEGNS)</td>
<td>0.177</td>
<td>0.825</td>
<td>0.004</td>
</tr>
<tr>
<td>Zscore(O, CHURN)</td>
<td>0.476</td>
<td>0.763</td>
<td>0.010</td>
</tr>
<tr>
<td>Zscore(PEREMP, SM, BUS)</td>
<td>0.028</td>
<td>-0.023</td>
<td>0.997</td>
</tr>
<tr>
<td>Zscore(PEREMP, SERV, BUS)</td>
<td>0.029</td>
<td>-0.015</td>
<td>0.997</td>
</tr>
<tr>
<td>Zscore(PERCAP, INC)</td>
<td>0.806</td>
<td>-0.210</td>
<td>0.131</td>
</tr>
<tr>
<td>Zscore(PEREMP, INCOME)</td>
<td>0.835</td>
<td>-0.226</td>
<td>0.017</td>
</tr>
<tr>
<td>Zscore(PORR, S)</td>
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<td>0.382</td>
<td>0.048</td>
</tr>
<tr>
<td>Zscore(PARTICIP)</td>
<td>0.791</td>
<td>-0.207</td>
<td>-0.108</td>
</tr>
<tr>
<td>Zscore(DISAB)</td>
<td>-0.779</td>
<td>0.051</td>
<td>0.043</td>
</tr>
<tr>
<td>% of Variance explained</td>
<td>36.9</td>
<td>22.7</td>
<td>20.2</td>
</tr>
</tbody>
</table>
considered using geographically weighted PCA (GWPCA) [101,102] to better understand the spatially varying nature of social vulnerability which Maiti et al. [71] utilised explaining casual associations between explanatory variables and COVID-19 cases and deaths, but considered this as an extension of, rather than an integral part within our study. Lastly, validation of the two dimensional risk prediction model is also an important consideration, but the lack of large scale community transmission in Australia, and the corresponding lack of data against which validation methods might be applied, prevent this. There is an opportunity, therefore, to utilise international comparisons to extend this study and address this and other limitations.

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Declaration of competing interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References


