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# Geographies of infections: built environment and COVID-19 pandemic in metropolitan Melbourne

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ABSTRACT

This paper uses spatial statistical techniques to reflect on geographies of COVID-19 infections in metropolitan Melbourne. We argue that the evolution of the COVID-19 pandemic, which has become widespread since early 2020 in Melbourne, typically proceeds through multiple built environment attributes – diversity, destination accessibility, distance to transit, design, and density. The spread of the contagion is institutionalised within local communities and postcodes, and reshapes movement practices, discourses, and structures of administrative politics. We demonstrate how a focus on spatial patterns of the built environment can inform scholarship on the spread of infections associated with COVID-19 pandemic and geographies of infections more broadly, by highlighting the consistency of built environment influences on COVID-19 infections across three waves of outbreaks. A focus on the built environment influence seeks to enact visions of the future as new variants emerge, illustrating the importance of understanding geographies of infections as global cities adapt to 'COVID-normal' living. We argue that understanding geographies of infections within cities could be a springboard for pursuing sustainable urban development via inclusive compact, mixed-use development and safe public transport.

## 1. Introduction

Notwithstanding a rapid rise of urban research on COVID-19 pandemic in recent times (Ahsan, 2020; Cornell et al., 2021; Dietz et al., 2020; Frumkin et al., 2004; Guan et al., 2020; Oldekop et al., 2020), investigations into geographies of infections – i.e. how the location and relative arrangement of places and physical features impact on contagion spread – in cities have been less apparent. While substantial attention has been directed towards how the pandemic has caused disruptions to businesses, national and regional economies, as well as human health and well-being (e.g., Cobbinah, 2021; Rojas-Rueda & Morales-Zamora, 2021), there is now a growing interest in understanding the spatial patterns of infections and the built environment influences across cities (Hamidi, et al., 2020; Huang et al., 2020; B. Li et al., 2021; Liu et al., 2021). This paper contributes to this emerging body of knowledge by offering an understanding of geographies of infections, highlighting the multiple influences of the built environment on the spread of the contagion in cities, and the widely reported devastating outcomes.

We acknowledge the positive outcomes such as reduction in waste generation, pollution, carbon emissions, and road traffic accidents (Benchrif et al., 2021; Basu et al., 2021). Other urban and household scale benefits including improved family relations, increased savings, and calmer environments due to reduced travel have been reported (Cornell et al., 2021). However, these occurred at the expense of significant disruptions to lifestyle, job losses and overall economic recessions (Rojas-Rueda & Morales-Zamora, 2021). Whereas the impacts of the COVID-19 pandemic have been experienced across the world, cities have inarguably witnessed the worst impacts and continue to remain the epicentres of outbreaks. And yet, earlier studies investigating the spread of infections and associated mortality heavily focused on urban variations at national scales (Chu et al., 2021; Aral & Bakir, 2022). Throughout, we focus on understanding the geographies of infections *within* cities which remains less explored (see Liu et al., 2021).

Analysis of spatial patterns of infections answers a call among urban studies researchers for groundwork on how COVID-19 infections are geographically constructed, discussed, imagined, lived, and defended in cities (Li, et al., 2021; Whittle & Diaz-Artiles, 2020). As Frumkin et al. (2004, p.57) noted "cities are the incubators of infectious diseases from their origins as early settlements… through their growth in [recent]

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centuries". History of urban planning suggests that serious respiratory infections, yellow fever, smallpox, and cholera outbreaks prompted rethinking of design guidelines for housing, sanitation systems and public spaces in Europe and the "New World" – i.e., North America – during the 19th century (Cobbinah, 2021; Frumkin et al., 2004). Similarly, global management responses of the recent COVID-19 pandemic have spurred built environment changes with the aim of reducing crowding, interactions, and movements across cities. These measures have renewed commentary about how the COVID-19 pandemic could influence the future of urban planning and the production of built environment modifications required to promote urban health outcomes and enhance the capacity of cities to cope with outbreak of contagion (Frumkin, 2021; Rojas-Rueda & Morales-Zamora, 2021). In this case, the COVID-19 pandemic calls into question many generations of established theses on the impacts of walkability, density, public transit use and other urban attributes on sustainability and health (Frank & Wali, 2021). A major concern in these discussions lies in the pandemic's potential to induce aversion towards sustainable urban development strategies such as compact and dense development, public transportation, and pedestrianised neighbourhood designs (Currie et al., 2021; Wali & Frank, 2021).

Within the context of the built environment, this paper highlights the similarities, differences, and connections between geographies of infections to pursue sustainable urban development futures aimed at creating effective contagion management. While the growing theme of built environment-infections link has framed public health response and urban planning and management interventions (e.g., Ahsan, 2020; Dietz et al., 2020; Huang et al., 2020; Li, et al., 2021; Whittle & Diaz-Artiles, 2020), there is no consensus in the literature on the specific directions or significance of the influence of different built environment attributes on COVID-19 infections. Similarly, studies based on cross-sectional data conducted during initial COVID-19 outbreak do not demonstrate the dynamism of this relationship in a pandemic that is still evolving through virus mutations and changes in public health measures. This paper demonstrates the value of reflecting across the city's geography on the extent to which built environment configuration characterises spread of infections over time. Using neighbourhood (postcode) level data in metropolitan Melbourne (Australia), this paper answers three questions: 1) What are the spatial patterns of COVID-19 infections during different outbreaks in metropolitan Melbourne? 2) What are the relationships between built environment attributes and COVID-19 infections across the different outbreaks in metropolitan Melbourne? and 3) How are these relationships distributed across metropolitan Melbourne? We address these questions using multiple regression, spatial autocorrelation, and geographically weighted regression to understand the geographies of spread and built environment relationship at both city and neighbourhood levels (Fotheringham & Oshan, 2016).

Metropolitan Melbourne offers a unique case for exploring these issues given its recent experiences of definable outbreaks characterised by distinct waves, responses, and outcomes. The Melbourne study provides understanding of how the built environment influences the spread of COVID-19 infections in three periods with different extenuating conditions – i.e., experimental management, stringent lockdown, and delta-vaccine period. The longitudinal approach is useful for verifying the consistency of results over successive outbreaks. As cities begin reopening, research addressing geographies of infections is timely and tenable, yet little is known about this, particularly in Australia. Such an understanding is critical for policymaking on how to interact with different aspects of our cities during the recovery phase, particularly regarding planning considerations for sustainable and healthy futures.

The paper is structured into five sections. Section 2 reviews current research on the influence of the built environment on the spread of the COVID-19 pandemic to consolidate the contributions of this present study in the literature. Section 3 presents the methods and approach adopted for the study including the data sources and methods of analysis. Section 4 presents the results and Section 5 discusses the results and presents the conclusions.

## 2. Built environment and health outcomes: exploring the Janus-faced relationships

Research (e.g., Frumkin et al., 2004) on the evolution of urban health has documented how cities historically grappled with infectious diseases in (pre-) industrial Europe and the early settlement of the Americas. From management of household garbage, industrial waste and pollutants, water and air contamination to substandard housing, developments in the built environment have long been associated with outbreaks of infectious diseases and its management (Cobbinah, 2021; Frumkin et al., 2004). These episodes influenced responses to declutter cities, reduce crowding and densities, to address persistent outbreaks of diseases such as cholera, yellow fever, smallpox, and typhoid. Consequently, urban density and settlement design were intensely scrutinised due to their roles in accelerating infection rates (McFarlane, 2021). Advancement in economic development and mobility technology contributed to the exodus of residents away from the city-cores igniting suburban development and urban sprawl and their associated urban health concerns. Complicating matters further, the de-densification of urban centres sparked noncommunicable diseases such as obesity, cardiovascular illnesses, asthma, diabetes, and mental health issues.

The COVID-19 pandemic was declared a pandemic by the World Health Organisation on 11 March 2020 and has since reignited interests among urban sustainability and public health scholars towards understanding the association of its outbreak with the built environment. A series of review studies have synthesised the empirical evidence suggesting that compact and dense urban environments with accessible greenspaces encourage interactions and promote physical activity that are essential for alleviating noncommunicable ailments (Jackson, 2003; Renalds et al., 2010). Yet, with recent infectious diseases such as SARS, H1N1, and COVID-19, the impacts of density and other built environment attributes on urban health outcomes have stimulated academic debate. While some studies (see Hamidi, et al., 2020; Liu et al., 2021) warn that dense urban environments promote more interactions and greater proximity among people thereby increasing the risk of spreading, others found negative or non-significant association with density (Wali & Frank, 2021; J. Wang et al., 2021).

In fact, initial interests in understanding national and international hotspots shaped research on the influence of spatial and built environment factors in the diffusion of infections among countries, cities, and regions. For example, Sigler et al. (2021) examined global geographical diffusion across six early weeks of the pandemic and found spatial features such as population density and accessibility of smaller settlement to cities – used as proxies for human interactions – to positively affect infections across countries but the impacts declined in successive weeks. Li, et al. (2021) also examined the role of connection and mobility to the Hubei Province – reported as recording the first case in the world – by air and rail, centrality of and accessibility to railway stations, concentration of activities, and population density. Others have examined the influence of specific built environment features on COVID-19 infections within cities. For example, Tribby and Hartman (2021) arguing that parks and sidewalks offset crowding and density influences on infections found infections to be significantly inversely related with sidewalks but not parks. Frank and Wali (2021) in examining the role of chronic diseases in mediating the impacts of built and natural environment on COVID-19 mortality found that residential density and greenspace access mitigate deaths. Wali and Frank's (2021) assessments of neighbourhood-level active or sedentary travel confirmed that more walkable design can be useful for combating COVID-19 severity as it reduced hospitalisation and mortality. Some studies also explored the effect of medical and commercial facilities (B. Li et al., 2021), mobility and physical interactions (Manout & Ciari, 2021), land use diversity (Nguyen et al., 2020), nodal accessibility, greenspace access and density

(Huang et al., 2020; Tomasso et al., 2021), city size and density (Hamidi, et al., 2020) and governance capacity (Chu et al., 2021).

While findings from these past studies offer important insights into understanding the built environment influence on the novel coronavirus disease, they are limited in at least two ways. First, they mostly assume consistent relationship due to their focus on single outbreak. However, epidemiological evidence suggests that different mutations of the virus over time have led to different waves of outbreaks creating varying impacts even in the same locations (Herrero, 2021; Twohig et al., 2021). In each of these waves, many cities and countries have had to change their response measures due to the virulent impacts by successive variants. For example, Singapore and Vietnam which were among the global success cases of the initial pandemic management had to introduce stricter restrictions to slow subsequent infections. Second, these studies usually overlook the public health measures and conditions associated with the management of different outbreaks in cities. Since the pandemic began, cities around the world have adopted test and isolate, quarantining, social distancing, and complete lockdowns which may have yielded different results. Moreover, the steady roll-out of vaccinations may have varied the built environment impacts, the consistency of which has received limited research attention. At the time of this study only few studies have, to a limited extent, examined this pattern of consistency under different conditions. For example, Yip et al. (2021) examined the relationship between built environment and COVID-19 infections before and during social distancing measures in the initial outbreak in Hong Kong. Wang et al., (2021) undertook similar study under lockdown and reopening scenarios across several counties in the United States and found that in addition to population density, mobility significantly increased infections when lockdowns were eased in July 2020. While these studies offer enormous insights, they did not focus on different waves of outbreaks. Their results further necessitate the urgency to continue developing lessons across different waves of breaks over time.

In summary, while available literature has generated insights into the transmission influences of built environment and justifiably informed public health management responses in the early days of the pandemic, further research in other contexts is critical for deepening understanding about the association of built environment attributes on COVID-19 infections. Secondly, given the urgency with which research had to be undertaken to inform early responses, many of the empirical investigations focused on the initial outbreaks. Our research draws insights from three waves/outbreaks in Melbourne, two years since recording its first local case (10 March 2020), to examine the geographies of infections and to establish whether the association between built environment and COVID-19 is constant under different conditions and neighbourhoods.

## 3. Research methods

This research focuses on Melbourne, the second largest city in Australia and capital of the south-eastern state of Victoria (Figure 1). It has an estimated population of approximately 5.1 million residents and is projected to overtake the country's most populous city, Sydney, in the next two decades. Melbourne's attraction is partly influenced by its reputation as one of the most liveable cities in the world, winning the world's most liveable city accolade consecutively from 2011 to 2017. Victoria is the worst affected state in Australia recording 55.8% of the 194,119 cases and most COVID-related deaths in Australia as of 18 November 2021 (Australian Government Department of Health, 2021). Melbourne being the epicentre of the pandemic has endured numerous restrictions and arguably been described as the most locked down city in the world with stay-at-home orders lasting a total of 267 days since the pandemic (Bond, 2021). It recently ended its sixth lockdown amidst easing of restrictions – such as night curfew, limits on movements, shopping hours, social activities, among others – in what was a bold step in a road map towards reopening. Having endured the worst outbreaks


**Figure 1.** Context map of Metropolitan Melbourne
Source: Authors

in the country, Melbourne provides the best conditions for exploring the geographies of infections and built environment influences.

### 3.1. Research design

This research analyses the association of the built environment on COVID-19 infections under three outbreaks characterised by different infection rates, variants, and public health responses (Table 1). Phase 1 – experimental management phase - covers the initial outbreak beginning from 10 March 2020 when the first locally acquired cases were recorded. Public health responses were incremental primarily involving test, isolate, and quarantine. Some social housing buildings and postcode areas were locked down briefly, but life across the city was generally close to pre-pandemic normality. Phase 2 – the Second Wave – marks the period when stringent measures were imposed to restrict movements within one's local neighbourhood and for limited duration and purposes. Mask mandates, stay-at-home orders, night curfews, and movements restrictions were imposed with the state government essentially (though unofficially) targeting outright elimination. Phase 3 – the Delta/Vaccination Phase – is the third wave driven by the highly infectious Delta variant despite an initial take-up of vaccinations. Restrictions were similar to Phase 2 but the enforcement was limited and began easing as vaccination levels increased. This phase concluded on 21 October 2021 when the government announced the official end of the lockdown seeing management measures going off as vaccination rates increased despite rising cases. It is worth noting that periods in between these phases do not necessarily signify no cases. Rather a few outbreaks emerged but were quickly controlled with snap lockdowns lasting few days. Given the limited variability, these periods are excluded from the analysis.

### 3.2. Data collection and specification of variables

The built environment refers to the human-made surroundings that provide the setting for human activities and ranges from buildings, infrastructure, to parks (Kaklauskas & Gudauskas, 2016). We conceptualised different attributes of the built environment to have varying relationship with COVID-19 infections. Therefore, based on Ewing and Cervero's (2010) 5D framework, we selected eight built environment attributes including land-use mix *(Diversity)*, access to the central business district (CBD) and major activity centres (MAC) *(Destination accessibility)*, proximity to train station and bus stops *(Distance to transit)*, intersection density and greenspace access *(Design)* and population density *(Density)*.

We used infection cases per thousand population – case rate – as the dependent variable in our study. The COVID-19 infection data were obtained from the Victorian Department of Health and Human Services (DHHS) (2021) which publishes daily updates on de-identified case data with the date of diagnosis, source of acquisition (i.e., local, interstate, or foreign), residential postcode and local government area. Consequently, we used postcodes as the unit of analysis for this study. We analysed only locally acquired cases due to our interest in understanding spatial patterns and influence of built environment on infections within Melbourne. However, given that postcodes only indicate the residential location of cases, it cannot be assumed that infections were acquired within the specified postcodes. Actual places of infections are complicated to determine especially during major outbreaks and so were not collected by the DHHS.

The independent variables comprised built environment attributes and other control (socioeconomic) variables and were obtained from multiple sources. Population data which were used in calculating the case rates and densities involved the resident population recorded in the 2016 census by the Australian Bureau of Statistics (ABS). Urban (population) density is considered as a major determinant of infections, an argument that has intensified because of the devastating impacts of the COVID-19 pandemic in large cities across the world (Hamidi, et al., 2020). Recent studies have suggested that neighbourhoods with highly diversified land uses may foster greater congregation and interactions and therefore quickly spread COVID-19 (Nguyen et al., 2020). In this study, land use data were sourced from the Department of Environment, Land, Water and Planning (DELWP) through the state government's open data portal (DELWP, 2021). We then calculated land use mix/diversity based on the Shannon diversity index for each postcode. Shannon index is widely used in ecological studies to assess the diversity of species in a community but has been recently applied in urban studies (Brown et al., 2014). The land use categories include residential, commercial, educational, medical, industrial, greenspace, and others. The land use diversity was calculated as

$$H = -\sum pi * \ln pi \tag{1}$$

Where *pi* is the proportion of *i*th land use type and ln is the natural logarithm. The Shannon index ranges between 0 and 1, representing low to high diversity, respectively.

B. Li et al. (2021) observed that commercial vitality and access to economic centres were key drivers of flow and congregation of residents potentially driving up infections. They also found that transportation infrastructure which improves accessibility significantly influence infections clustering in the Huangzhou district of China. In a similar way, greenspace has a mixed association with infections as it may improve immunity to COVID-19 through physical activity but also the use of it during the pandemic may promote close contacts and increase the risk of infections (J. Wang et al., 2021; Frank & Wali, 2021). We therefore used data from Melbourne's strategic planning document – Plan Melbourne 2017-2050 – to specify the location of employment centres in the city [i.e., CBD and MAC] (Victoria State Government, 2017). We then estimated the average distance of residential parcels in each postcode to the economic centres as our measure of accessibility to CBD and MAC variables. MACs are designed as concentrations of activities offering goods and services at sub-metropolitan levels (Victoria State Government, 2017). We applied a similar approach to estimate the distance to public

**Table 1**
Summary of key features of the three outbreaks (phases)

| Phase | Phase 1 | Phase 2 | Phase 3 |
|---|---|---|---|
| Date | 10 March to 8 July 2020 | 9 July to 9 November 2020 | 16 July to 21 October 2021 |
| Total number of cases | 1,972 | 16,112 | 71,230 |
| Key features | First wave<br>Experimental responses; No sharp lockdowns; Generally unrestricted movements<br>Test, isolate and quarantine;<br>Short period of targeted lockdowns of buildings and neighbourhoods;<br>Lives close to pre-pandemic normal | Second wave with rapidly rising cases;<br>Strict enforcement of lockdowns and stay-at-home orders;<br>Only four permitted reasons to leave home (care or caregiving, exercises, essential shopping, and work/study that cannot be done from home);<br>Only two-hours for exercises and shopping;<br>Curfews imposed;<br>Elimination strategy largely pursued;<br>No vaccinations | Third wave driven by new 'Delta variant';<br>Vaccinations underway but strict lockdown like Phase 2 imposed;<br>Curfew imposed<br>Weaker enforcement of lockdown rules;<br>Gradual easing of restrictions as vaccinations increases despite rising cases |

Source: Authors

transport (i.e., bus stops and train stations) and greenspace access but the location data were sourced from PSMA Australia Transport and Topography dataset via the Australian Urban Research Infrastructure Network (AURIN) portal.

Intersection density improves connectivity and facilitates movements within neighbourhoods (Wali & Frank, 2021). Pedestrian-oriented intersections enhance walkability whereas auto-oriented intersections promote movements despite being barriers to active transportation. In Melbourne, sidewalks are integrated with most local roads ensuring shared access to motorists and pedestrians. We did not account for this distinction because our interest was in assessing how street connectivity design influences movements of people leading to the spread of COVID-19. Besides, car-dependency has increased in Australian cities even when smart mobility agenda intensified (Yigitcanlar & Kamruzzaman, 2019). We obtained intersection data from PSMA via AURIN and calculated the intersection density using the ESRI line and junction tool in ArcGIS. Only three-way intersections or above were used excluding dead-end junctions that do not enhance local connectivity.

### 3.3. Control variables

To improve the accuracy of our results, we controlled for socioeconomic status, median age, and household size, due to their reported associations with infectious outbreaks. We used the Index of Relative Socioeconomic Disadvantage (IRSD), an index created by the ABS to measure relative (dis)advantage of locations based on the economic and social conditions of residents as a proxy for socioeconomic status. We used the decile ranks for ease of interpretation. Together with the median age and average household sizes, the control variables were collected from the ABS community profiles on the 2016 census. Table 2 presents summary statistics on the variables. Appendix 1 illustrates the spatial distribution of the independent variables.

### 3.4. Data analysis

We used global spatial autocorrelation (Moran's I) and Local Indicators of Spatial Association (LISA) to assess for clustering in the spatial distributions of case rates. Both results confirmed spatial clustering with the LISA identifying hotspots and cold spots. As a result, we sought to understand the relationship between built environment and COVID-19 infections at both global (metropolitan) and local (postcode) scales. Metro-level analysis was conducted using multiple regression (MR) whereas local analysis was done using geographically weighted regression (GWR). While the MR model assumes that relations among variables are constant across the study area, the GWR examines the relations among variables in geographic space by conducting a regression model for individual observations located near each other in space (Yoon et al., 2016). The MR model was formulated as follows:

$$y = \beta_0 + \beta_1 BE + \beta_2 CV + \varepsilon \tag{2}$$

Where $y$ is COVID-19 case rate, $BE$ are the built environment variables, $CV$ are the control variables, $\beta_i$ denotes the regression coefficients for the intercept and independent variables and $\varepsilon$ is the random error.

The GWR model addresses the assumption of static relationship across the study area by accounting for spatial variations in the relationship between dependent and independent variables (Brunsdon et al., 1996; Fotheringham et al., 1998). The GWR constructs unique equations for each observation (postcode) as a function of the dependent and independent variables that is within the extent of each target feature's bandwidth (Mollalo et al., 2020; Oshan et al., 2020). We selected bandwidth based on fixed kernel that uses constant radius around each observation to select variables for the analysis, with the Akaike information criterion (AIC) used in determining the optimal bandwidth values. As per Fotheringham and Oshan (2016), the GWR model was formulated as follows:

$$y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_{ik} BE_{ik} + \beta_{ik} CV_{ik} + \varepsilon_i \tag{3}$$

where $y_i$ is the rate of Covid-19 case at postcode $i$, $\beta_{i0}$ represents the intercept, $\beta_{ik}$ denotes $k$th regression parameter, $BE_{ik}$ represents the $k$th of the independent variable, $CV_{ik}$ denotes $k$th control variable and $\varepsilon_i$ random error term. The parameter estimates were also derived as:

$$\widehat{\beta}(i) = (\mathrm{X}'\mathrm{W}(i)\mathrm{X})^{-1}\mathrm{X}'\mathrm{W}(i)\mathrm{y} \tag{4}$$

where X denotes the matrix of the chosen explanatory variable (n x k), $\widehat{\beta}(i)$ parameter estimate vector, $\mathrm{W}(i)$ denotes the diagonal weights of the matrix related to each observation as a function of distance.

## 4. Results

We address the research questions in the subsequent sections as follows: 1) the spatial patterns of infections; 2) relationship of infections with built environment attributes; and 3) the spatial variations of the relationships among the neighbourhoods. This helps to easily examine the consistency of results across the three outbreaks and determine the geographies of infections across metropolitan Melbourne.

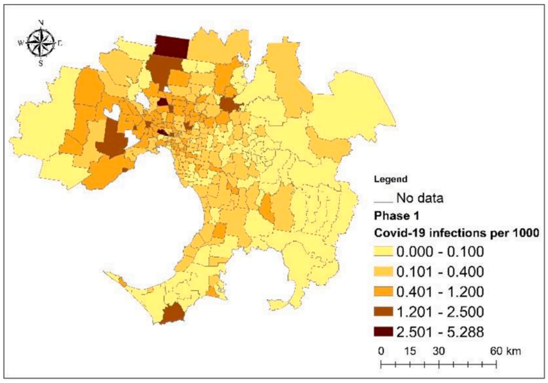
### 4.1. Spatial patterns of COVID-19 infections in metropolitan Melbourne

We explored the spatial distribution of COVID-19 infections in metropolitan Melbourne using choropleth (Figure 2) and the LISA cluster maps (Figure 3). As shown in Figure 2a, the neighbourhood – (i.e., North Melbourne) – with the highest infections (5.287 per thousand) during Phase 1 was located in inner Melbourne. However, most of the next highest case rates were found in the northern suburbs (e.g., Tullamarine, Gladstone Park, and Beveridge). Conversely, the lowest rate of infections could be found in the southern and eastern parts of the city. This result is reinforced by the LISA cluster analysis which shows the hotspots to be clustered in the inner and northern suburbs whereas the cold spots (i.e., lowest case rates) cluster in the eastern and southern areas (Figure 3a).

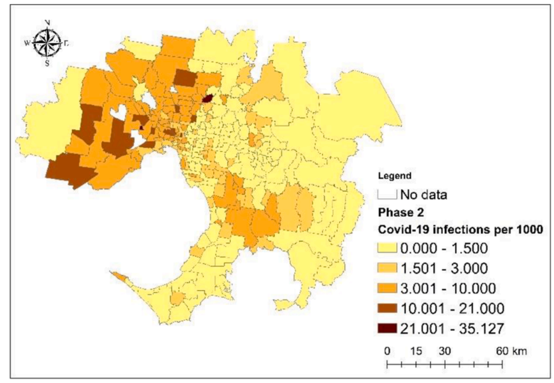
There was a more visible pattern during Phase 2 when most infections were recorded in the western and northern parts of the city (e.g., Ardeer and Plenty) with moderate incidence observed in the south and inner suburbs (Figure 2b). The eastern suburbs mainly showed low infection levels. The LISA cluster analysis confirms these results showing the hotspots of infections in the northern and western areas whereas

**Table 2**
Summary statistics of dependent and independent variables

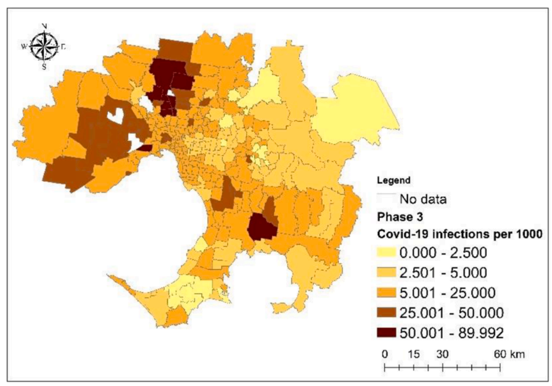
| Variable | Mean | Min | Max |
|---|---|---|---|
| ***Dependent variables*** | | | |
| Case rate (per 1,000 population) | | | |
| Phase 1 | 0.368 | 0.000 | 5.287 |
| Phase 2 | 2.966 | 0.000 | 35.127 |
| Phase 3 | 13.068 | 0.000 | 89.992 |
| ***Independent variables*** | | | |
| *BE attributes* | | | |
| Land use mix (0-1) | 0.379 | 0.152 | 0.696 |
| Accessibility to CBD (km) | 26.490 | 0.681 | 84.886 |
| Accessibility to major activity centres (km) | 4.36 | 0.405 | 33.003 |
| Distance to train station (km) | 3.195 | 0.355 | 31.043 |
| Distance to bus stop (km) | 1.019 | 0.132 | 28.746 |
| Intersection density (n/ha) | 0.026 | 0.000 | 0.465 |
| Distance to parks, open space, playgrounds (km) | 0.316 | 0.091 | 6.758 |
| Population density (p/ha) | 17.393 | 0.032 | 152.475 |
| *Control variables* | | | |
| Median age (yrs.) | 38.99 | 22 | 67 |
| Socioeconomic status (IRSD decile) | 7.06 | 1 | 10 |
| Average household size | 2.64 | 1.8 | 3.5 |




**a. Phase 1**




**b. Phase 2**




**c. Phase 3**

**Figure 2.** Spatial distribution of COVID-19 infection in Melbourne (per 1,000 residents)

cold spots emerged in the eastern and southernmost suburbs (e.g., Mornington Peninsula areas; Figure 3b).

The pattern of cases distribution in Phase 3 largely follows what was observed in Phase 2 but there was more obvious concentration in the northern suburbs with areas such as Broadmeadows, Meadow Heights, and Campbellfield ranked at the top. Interestingly, a postcode in the southern region (i.e., 3978 – Clyde, Clyde North and Cardinia) – also recorded high cases (Figure 2c). However, the cluster analysis showed this was isolated. The hotspot of the infections still emerged in the northern and western regions, with the eastern and southernmost areas mainly being the cold spots (Figure 3c).

### *4.2. The built environment drivers of COVID-19 infections in metropolitan Melbourne*

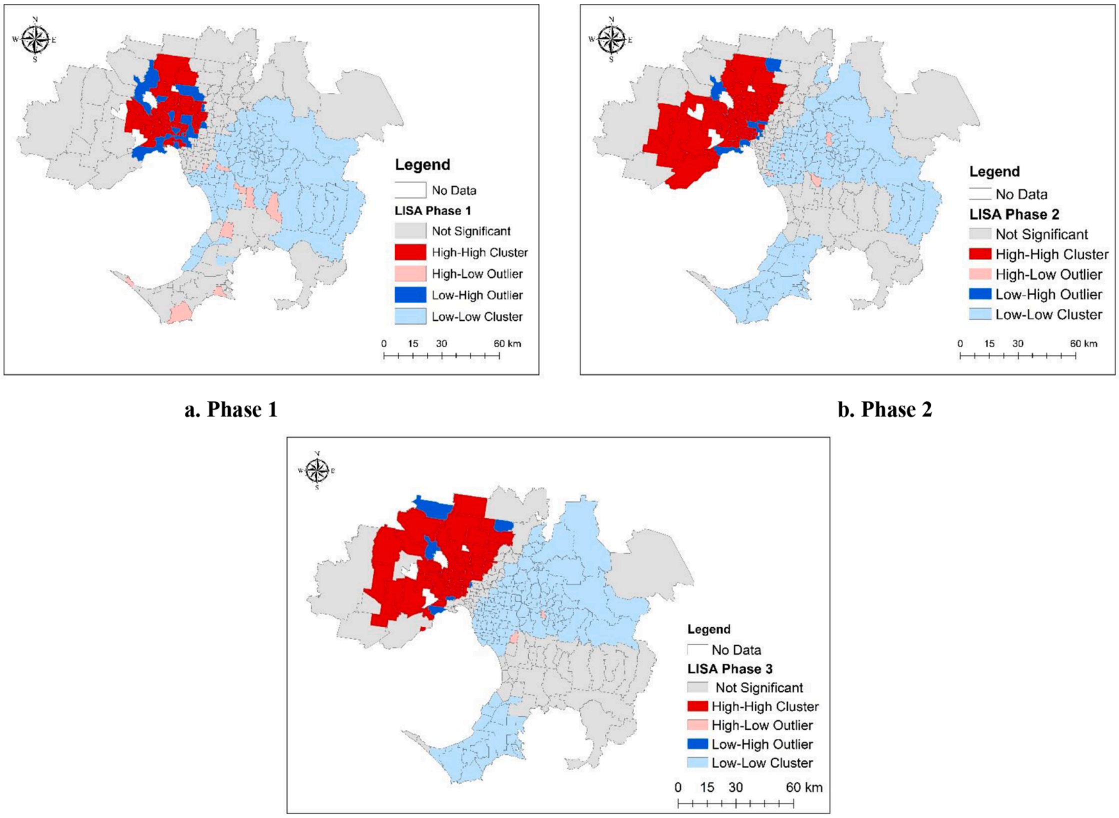
As earlier indicated, we focused on testing the association between built environment attributes and COVID-19 infections across the three different outbreaks. As a result, we developed three MR models with each modelling one outbreak/phase (Table 3). A check of the model diagnostics indicated no problems with multicollinearity given that none of the variance inflation factors (VIF) exceeded the 5 to 10 cut off range (Chatterjee & Yilmaz, 1992).

The results indicate that only three of the nine built environment features had statistically significant relationships with COVID-19 infection rate during Phase 1. Population density and distance to train stations had a positive relationship with case rate whereas accessibility to CBD showed an inverse association. Thus, neighbourhoods with longer distances from train stations or more densely populated recorded more infections of COVID-19. In other words, neighbourhoods with better access to train transportation were less likely at risk of COVID-19 infections. The negative coefficient estimate for access to CBD indicates that the farther a neighbourhood is from the CBD, the less cases they recorded. This result is intuitive given the assumption that greater accessibility to activity centres fostered more interactions which were likely to expose residents to more infections (B. Li et al., 2021).

The built environment effect was observed for only one attribute during Phase 2. Only accessibility to the CBD maintained a statistically significant association with COVID-19 infections, similarly, showing that neighbourhoods close to the CBD had higher risks of infections. Unlike Phase 1, distance to the train station and population density did not have statistically significant associations with cases during this outbreak.

On the contrary, as observed during the first outbreak, the original three built environment variables had significant associations with infections during Phase 3 outbreak. The distance to train station still had positive association with infections, suggesting that the easier a neighbourhood could access public transport, the less likely it recorded COVID-19 infections. Also, the same relationship was recorded for accessibility to CBD in this phase as it was during the first and second waves (Phases 1 and 2). In contrast, the relationship with population density changed during the third wave. Unlike Phase 1, findings indicate that dense neighbourhoods were less likely to record more cases. The results suggest that the impacts of built environment attributes on COVID-19 infections may not be constant across different outbreaks.

These findings are intriguing considering the increased aversions of urban populace and commentators to public transportation use (Rahimi et al., 2021), density (Hamidi, et al., 2020; McFarlane, 2021) and economic centres (B. Li et al., 2021) during the pandemic. Increasingly, urban observers have lamented about rethinking public transportation, urban density, and activity clustering in post-pandemic urban development planning. Our results indicate that there might not be a straightforward implication of these built environment attributes for health promotion, infection control and healthy city development. We investigated the geographic differentiation (in Section 4.3) briefly after




**a. Phase 1** **b. Phase 2**

**c. Phase 3**

**Figure 3.** LISA cluster map of COVID-19 infections across the phases of outbreaks

discussing the role of socioeconomic features.

#### 4.2.1. *The impacts of socioeconomic features on infections*

Our analysis revealed some intriguing results regarding the association between socioeconomic characteristics of Melbourne neighbourhoods and COVID-19 infections (Table 3) which offer insights for urban planning and public health policy. It shows that socioeconomic advantage (i.e., IRSD index) negatively correlated with COVID-19 infections. Thus, in the study area, socioeconomically disadvantaged neighbourhoods were highly likely to record more COVID-19 infections. And this result was consistent across all three outbreaks of COVID-19 in the city. Similarly, household size also had consistent association across all outbreaks with larger households more likely to have driven far more infections than expected in their neighbourhoods. This result is intuitive considering the highly contagious nature of the coronavirus which makes households highly susceptible once a member contracts the disease. Interestingly, the impact of age was only observed during the delta outbreak (Phase 3) where neighbourhoods with relatively younger population experienced more infections. This may be partly explained by the fact that vaccination rates (where initial eligibility was based on age) were lower in localities with more youthful population. However, it might also indicate the exuberance of younger people in being less careful which may have driven up infections of the more virulent variant of the virus.

### 4.3. *Spatial variations of built environment association with COVID-19 infections*

The foregoing analysis revealed that some built environment features were associated with COVID-19 infections in metropolitan Melbourne. However, these MR results assume that the associations are constant across all neighbourhoods (i.e., postcodes). As the LISA maps suggest, the clustering of infections at certain areas may indicate spatial variations of association. The Moran's I test confirmed that all the dependent and independent variables (except greenspace) were not randomly distributed (Table 4). Consequently, we conducted GWR analyses to explore the spatial variations in the association between the built environment and COVID-19 infections.

The percentage of explained variances in COVID-19 outbreak models increased in the GWR compared with the MR (see Table 3). The explained variances increased from 17.6% to 21.8% in Phase 1, 30.8% to 34.5% in Phase 2, and 46.7% to 52.4% in Phase 3. The corrected Akaike Information Criterion (AICc) factors decreasing in the GWR models also confirm that they outperform the MR models. Figures 4 to 6 mapping the GWR results reveal spatial variations of the coefficient estimates of the independent variables that had statistically significant association with case rates.

#### 4.3.1. *Phase 1*

Population density had positive coefficients across all postcodes confirming the MR results that the denser neighbourhoods recorded more cases of infections in Phase 1 (Figure 4a). The strongest was, however, found in the southernmost areas followed by the western suburbs. In contrast, the north-eastern areas recorded the weakest influence. While proximity to train station showed positive associations with infections in all postcodes (Figure 4b), this impact was strongest in the western suburbs (0.023) and declined as one moved towards the southern suburbs (0.016). The suburbs surrounding the CBD recorded a moderately strong association with proximity to train station.

Figure 4c illustrates the distribution of the coefficients of the accessibility to CBD in Phase 1 depicting a north-south gradual decline in the significance of the relationships with COVID-19 infections. All the neighbourhoods recorded negative coefficients confirming the results of the MR that neighbourhoods with better access to the CBD tended to

**Table 3**
Estimation results of multiple regression and geographically weighted regression models

| | | Phase 1 | | | | Phase 2 | | | | Phase 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | MR | GWR Coefficient | | | MR | GWR Coefficient | | | MR | GWR Coefficient | | |
| | VIF | Coefficient | Median | Min | Max | Coefficient | Median | Min | Max | Coefficient | Median | Min | Max |
| Intercept | | 0.216 | 0.246 | 0.205 | 0.285 | 2.963 | 3.107 | 2.681 | 3.711 | 7.768 | 8.370 | 6.725 | 10.725 |
| *Built environment variables* | | | | | | | | | | | | | |
| Land use diversity | 1.677 | 0.507 | 0.539 | 0.498 | 0.590 | 2.705 | 3.101 | 2.407 | 3.385 | -2.244 | -1.249 | -2.982 | 0.574 |
| Population density | 2.579 | 0.007** | 0.006 | 0.006 | 0.007 | -0.018 | -0.018 | -0.019 | -0.016 | -0.103* | -0.100 | -0.111 | -0.087 |
| Distance to bus stop | 2.129 | -0.011 | -0.009 | -0.023 | 0.002 | 0.056 | 0.068 | 0.009 | 0.120 | -0.008 | -0.006 | -0.238 | 0.170 |
| Distance to train station | 2.695 | 0.020* | 0.021 | 0.016 | 0.022 | 0.105 | 0.099 | 0.072 | 0.108 | 0.500** | 0.476 | 0.323 | 0.515 |
| Accessibility to CBD | 3.588 | -0.011*** | -0.013 | -0.015 | -0.009 | -0.093*** | -0.096 | -0.107 | -0077 | -0.347*** | -0.366 | -0.427 | -0.261 |
| Accessibility to MAC | 4.015 | 0.013 | 0.014 | 0.004 | 0.025 | -0.005 | 0.003 | -0.028 | 0.068 | 0.257 | 0.326 | -0.001 | 0.722 |
| Intersection density | 2.234 | -1.391 | -1.430 | -1.483 | -1.334 | 6.450 | 5.924 | 5.552 | 6.878 | 39.135 | 37.633 | 34.006 | 40.518 |
| Proximity to greenspace | 1.113 | 0.00 | 0 | 0 | 1.0e6 | 1.1e5 | 1.2e5 | 1.0e5 | 1.5e5 | 2.6e5 | 3.1e5 | 1.7e5 | 4.4e5 |
| *Control variables* | | | | | | | | | | | | | |
| IRSD | 1.411 | -0.044*** | -0.047 | -0.053 | -0.033 | -0.536*** | -0.547 | -0.619 | -0.446 | -2.600*** | -2.654 | -2.887 | -2.176 |
| Median Age | 2.694 | -0.007 | -0.008 | -0.012 | -0.004 | -0.059 | -0.064 | -0.079 | -0.047 | -0.291** | -0.314 | -0.375 | -0.252 |
| Household size | 1.483 | 0.245*** | 0.263 | 0.139 | 0.347 | 2.736*** | 2.761 | 2.164 | 3.147 | 16.238*** | 16.383 | 12.771 | 18.949 |
| $R^2$ | | 0.176 | 0.218 | | | 0.308 | 0.345 | | | 0.467 | 0.524 | | |
| Adjusted $R^2$ | | 0.141 | 0.175 | | | 0.278 | 0.308 | | | 0.444 | 0.497 | | |
| AICc | | 455.265 | 445.195 | | | 1437.295 | 1426.437 | | | 2085.943 | 2059.329 | | |
| Bandwidth | | | 124.401 | | | | 124.401 | | | | 124.401 | | |
| N | | 271 | 271 | | | 271 | 271 | | | 271 | 271 | | |

Notes:
* $p < 0.10$
** $p < 0.05$
*** $p < 0.01$, bandwidth in km

**Table 4**
Summary of spatial autocorrelation results

| Variable | Moran's Index | *z*-score | *p*-value |
|---|---|---|---|
| Infection rate: phase 1 | 0.181 | 16.857 | <0.001 |
| Infection rate: phase 2 | 0.208 | 19.067 | <0.001 |
| Infection rate: phase 3 | 0.265 | 23.859 | <0.001 |
| *BE variables* | | | |
| Land use diversity | 0.089 | 8.159 | <0.001 |
| Population density | 0.758 | 67.935 | <0.001 |
| Distance to bus stop | 0.085 | 8.193 | <0.001 |
| Distance to train station | 0.213 | 19.376 | <0.001 |
| Accessibility to CBD | 0.683 | 60.124 | <0.001 |
| Accessibility to MAC | 0.257 | 23.080 | <0.001 |
| Intersection density | 0.523 | 49.826 | <0.001 |
| Proximity to greenspace | 0.002 | 1.140 | 0.254 |
| *Control variables* | | | |
| IRSD | 0.224 | 19.952 | <0.001 |
| Median age | 0.160 | 14.560 | <0.001 |
| Household size | 0.216 | 19.582 | <0.001 |

report higher cases of infections. However, the magnitude of this influence was stronger in the northern than the southern suburbs. Thus, at a similar change in distance from the CBD, suburbs in the northern part were likely to record more cases than in the south.

The spatial pattern of the impact of socioeconomic status (IRSD) is depicted in Figure 4d which shows the strongest inverse relationship with infections to be found in the western suburbs (-0.053) but weak in the southern part (-0.034). Also, the strongest influence of household size on infections were found in the north and north-western parts (0.346) which declined gradually towards the south (0.139) (Figure 4e).

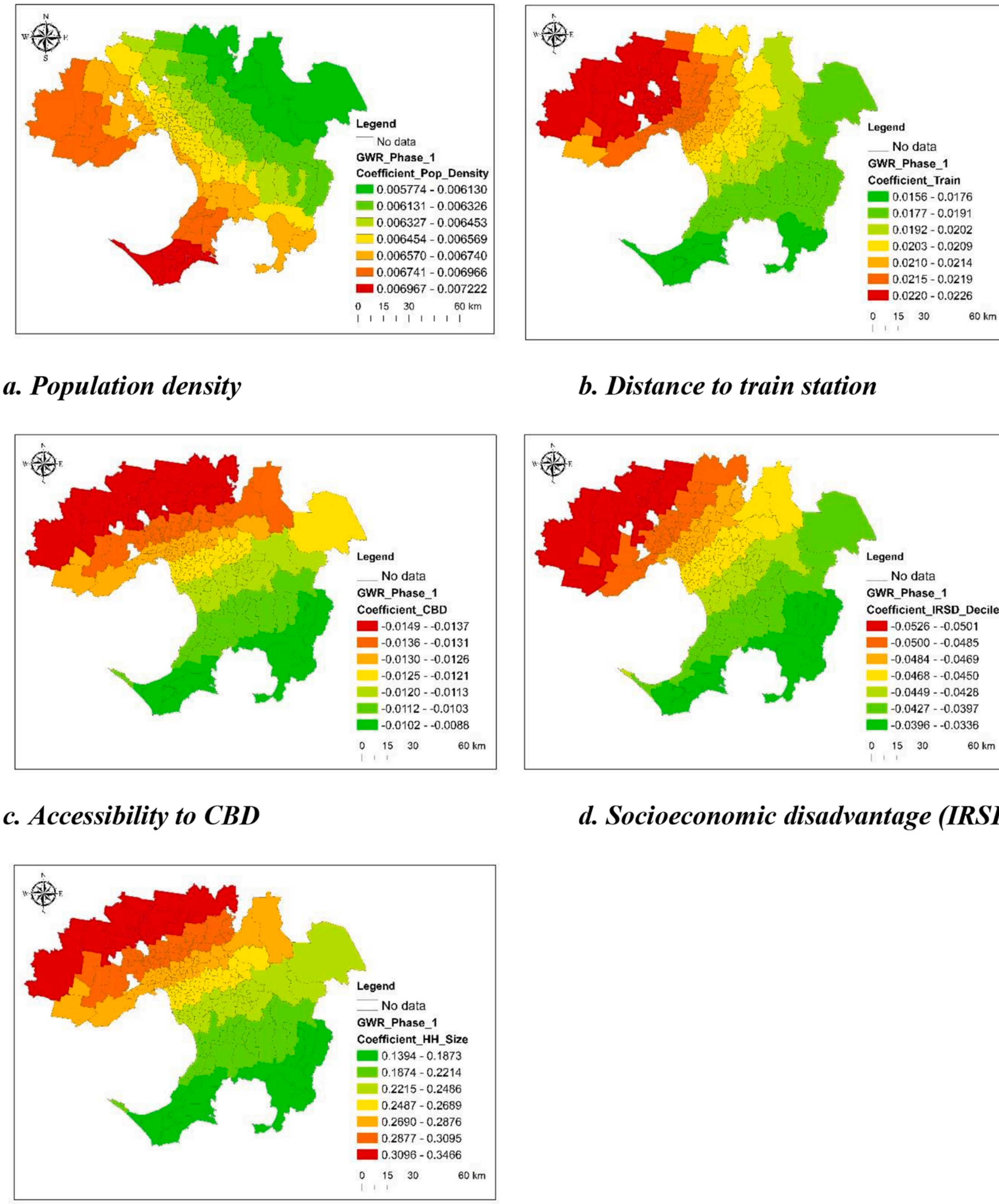
### 4.3.2. Phase 2

Since accessibility to CBD was the only built environment feature significantly associated with COVID-19 infections in Phase 2, the GWR analysis was restricted to that. As shown in Figure 5a, access to CBD although had negative coefficients across all suburbs, the impacts were stronger in the west (-0.107) and lowest in south-easternmost region (-0.077). This pattern differs from Phase 1 where a north-south decline was primarily observed.

Figure 5b depicts the spatial distribution of the coefficients of the IRSD and reveals a similar pattern as the accessibility to CBD. The western suburbs appear to have far stronger inverse coefficients (-0.619) and declining to the lowest levels in the south-easternmost area (-0.446). This indicates that given a similar degree of change in socioeconomic status, suburbs in the west were likely to record more cases of COVID-19 than any other areas. Thus, while the western suburbs are generally poor (i.e., suburbs have lower IRSD scores), differences in socioeconomic status created greater influence on infections when compared with the relatively well-to-do southern suburbs. The positive coefficients of household sizes were stronger in the western and northern suburbs (3.147) declining to the lowest in the southern areas (2.164; Figure 5c). This spatial pattern is similar to what was observed in Phase 1 (see Figure 4e).

### 4.3.3. Phase 3

Unlike Phase 1, population density was inversely related with COVID-19 infections in Phase 3 indicating that in all neighbourhoods, dense populations led to lower infections. But this impact was strongest in the north-eastern part (0.111) and weakest in the southernmost suburbs in the Mornington Peninsula (0.087; Figure 6a). The impacts in the western and central belt (including areas around the CBD) was closer




*a. Population density*

*b. Distance to train station*

*c. Accessibility to CBD*

*d. Socioeconomic disadvantage (IRSD)*

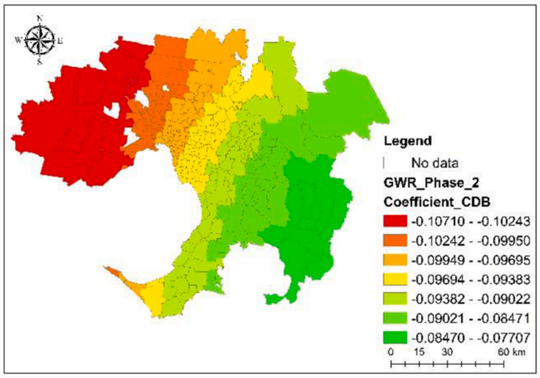
*e. Household size*

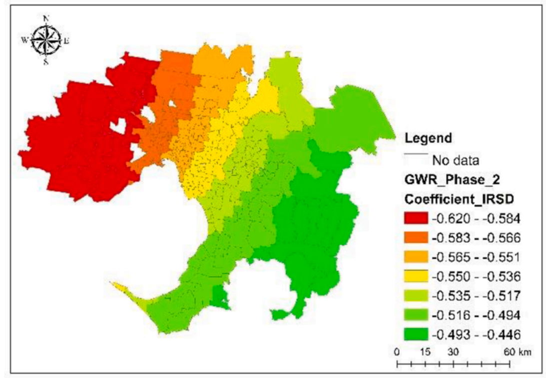
**Figure 4.** Spatial variation of the coefficients of the statistically significant variables in Phase 1

to the median coefficient. The differences in the direction and distribution of the coefficients in Phases 1 and 2 suggest that the influence of population density on COVID-19 infections is not simply defined.

While the MR revealed that a kilometre-long change in distance to a train station was associated with 0.5 per thousand increases in infections in Phase 3, the magnitude ranged from 0.32 to 0.52 per thousand across the neighbourhoods. This degree of influence increased in an east-west direction (see Figure 6b), with western suburbs more likely to record more cases if they had poor access to train service compared to the eastern suburbs. The influence of accessibility to the CBD on COVID-19 infections in Phase 3 (Figure 6c) depicts a north to south decline, generally like the pattern observed in Phase 1. The negative coefficients in the northwest suburbs appear stronger (-0.427) than that in the southeasternmost areas (-0.261). However, unlike Phase 1 where the southernmost area (i.e., Mornington Peninsula) had a weak association, the association is moderate in Phase 3.

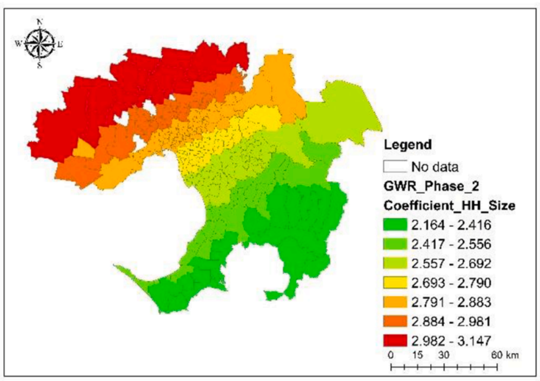
The spatial pattern of coefficient estimates of IRSD in Phase 3 is identical to what was observed in Phase 1 showing higher influences in the northwest (-2.886) and declining to -2.176 in the southern areas (Figure 6d). This differed slightly from Phase 2 where the strongest relationships were more obvious in the western suburbs and the weakest found in the southeast (the southernmost areas had modest weak coefficients). Household size also depicted a pattern similar to the IRSD in Phase 3 although their relationship with infections was positive across all suburbs. A unit increase in household size resulted in 18.949 per thousand more cases in the northwest compared to about 12.771 cases




*a. Accessibility to CBD (IRSD)*

*b. Socioeconomic disadvantage*




*c. Household size*

**Figure 5.** Spatial variation of the coefficients of the statistically significant variables in Phase 2

in the southern regions (Figure 6f). Also, it was only during this outbreak that median age had a statistically significant influence on COVID-19 infections. Figure 6e illustrates the distribution of coefficients of median age depicting the northern suburbs with stronger inverse association (-0.375) compared with the southernmost area (Mornington Peninsula) where the effect was the weakest (-0.252). Thus, neighbourhoods with younger population recorded more cases during the delta outbreak in Phase 3, but this effect was more seriously felt in the northern part of Melbourne.

## 5. Discussion and conclusion

### *5.1. Future of cities: complexities of built environment influence in COVID-19 spread*

This paper explored COVID-19 infections in metropolitan Melbourne during three different outbreaks, and the implications on the city's sustainable future. The research design reflecting distinctive waves of outbreaks, public health measures and associated conditions of living in the city allowed for understanding the consistency in geographies of infections, the spatial patterns and relationships with built environment and socioeconomic features. This understanding is paramount in responding and adapting to current and future pandemics, recognising that the city-scape is not a homogenous space. During Phase 1 (the initial outbreak), management responses were mainly experimental involving testing, isolation, and quarantine, with residents' interaction with built environment largely uncurtailed. On the contrary, Phases 2 and 3 involved more substantial waves with more decisive restrictions, significantly altering urban life. Phase 3 differs from Phase 2 mainly for being driven by a more infectious Delta variant, vaccinations, and less enforced *albeit* similar stringent restrictions. What do these mean for the built environment and for developing sustainable cities?

This paper makes the following contributions. First, the patterns of infections and the built environment influence are complex and do not show a simple predictable direction across outbreaks/waves despite commonalities of urban features in the city. The complexity of the built environment's influence on infections implies that for policy responses to be effective and sustainable, they need to be tailor-made for the different communities within the cities rather than a city-wide wholesale approach. For example, while more cases were recorded in the northern and western suburbs during all three outbreaks, locations in the southern region only experienced high case rates during the third wave. That notwithstanding, the northern region emerged as a hotspot during all outbreaks whereas the western areas became hotspots during Phases 2 and 3. On the contrary, the eastern suburbs became the cold spots but exhibiting slightly distinct spatial patterns across outbreaks. Apart from Phase 1, the southernmost suburbs (e.g., in the Mornington Peninsula) also showed significant cluster of lower cases. The spatial patterns of infections are important for controlling and reducing spread during a pandemic (Aral & Bakir, 2022). However, our findings show that these patterns differ in separate outbreaks necessitating contextual responses in different episodes to guarantee effectiveness and ensure that the city continues to thrive in a sustainable manner. This is a major contribution from our research highlighting the dynamism of different waves of the COVID-19 pandemic, in terms infections, management responses and how the built environment responded to this evolving

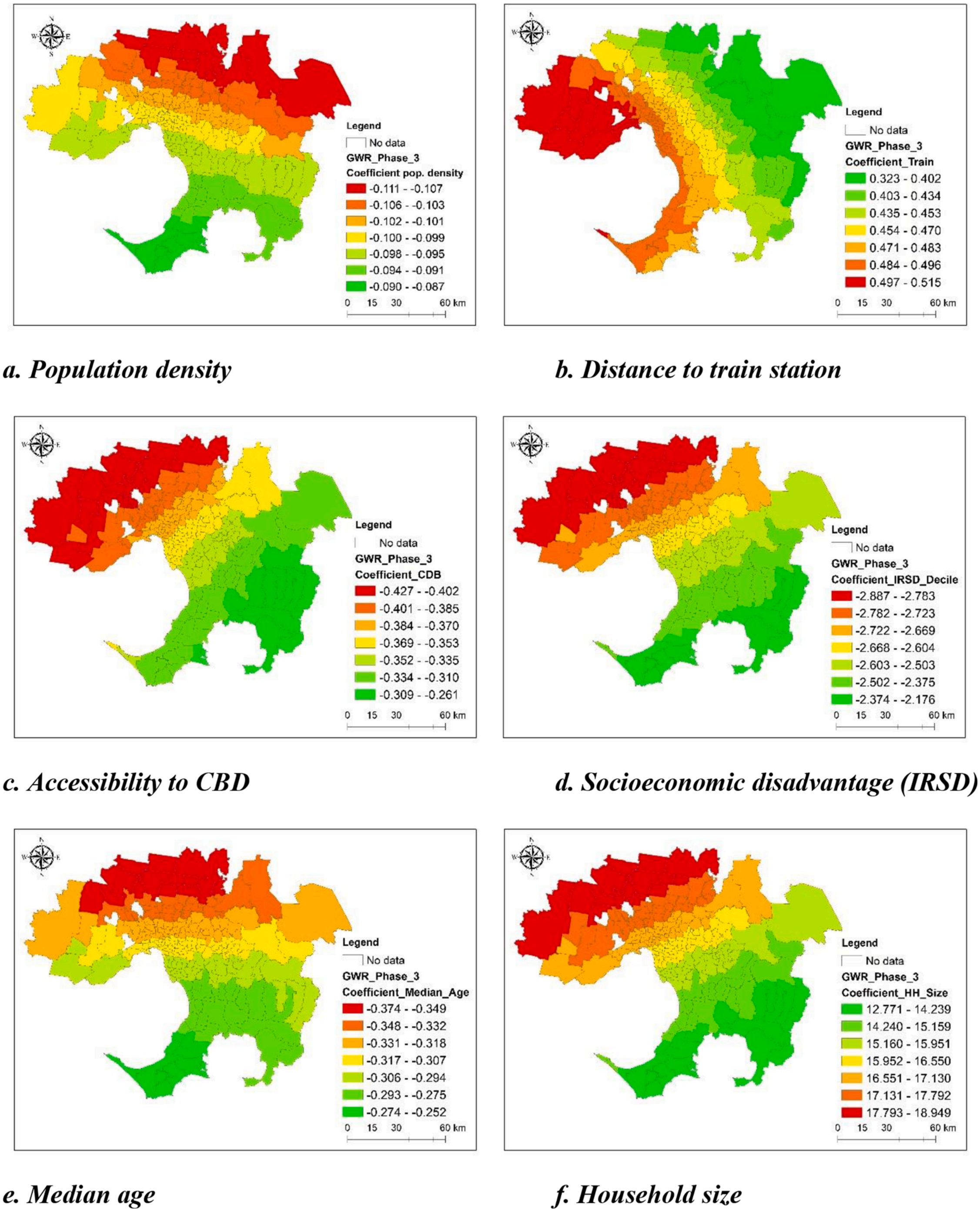



**Figure 6.** Spatial variation of the coefficients of the statistically significant variables in Phase 3

situation. In fact, this contextualised understanding based on the dynamism of different waves of the contagion is even more relevant considering the inconsistency of the built environment influences on COVID-19 infection rates. This research shows that the built environment can not only have contrasting impacts in different outbreaks (as was evident with population density) but also spatial variation of associations in different neighbourhoods during the same outbreak (see Li, et al., 2021; Liu et al., 2021). Within this context, for any policy response to be sustainable and effective, it needs to reflect the built environment requirements considering neighbourhood dynamics.

Second, our analysis shows that population density had the most complicated relationship with case rates by registering positive association during Phase 1, non-significant in Phase 2 and negative during Phase 3. This result confirms findings from earlier studies showing contrasting relationships between urban density and COVID-19 infection rates in different regions. For example, higher population density were found to be positively correlated with infection rates in India (Bhadra et al., 2021) and Germany (Ehlert, 2021) whereas the reverse was observed during the early outbreaks in China (Liu, 2020). Other findings show no significant relationship as in the case of the United States (Hamidi, et al., 2020). Our results further add that even in the same city, this relationship can differ depending on prevailing outbreak and accompanying public health measures. During Melbourne's first wave, physical distancing measures were generally absent which allowed greater interactions explaining how infections in dense neighbourhoods soared. However, on the two occasions where lockdowns were introduced to enforce physical distancing, the impacts were either non-significant (phase 2) or inverse (phase 3). Thus, density in itself may not be a problem in driving infectious diseases. Rather, crowding defined as many people gathering close together may be the critical driver as confirmed by Hamidi and Hamidi (2021) in their study comparing the density with crowding. In general, densely populated areas have better access to services and facilities such as bars, restaurants, etc. and so without restrictions, it is expected for these areas to be more crowded and become exposure sites for infections.

Third, while this research did not focus on the mitigatory role of physical distancing measures in relation to the potential effect of public transport on spread of infection, the findings suggest that public transport usage may not necessarily drive infections contrary to recent concerns. This finding is important for public policy and sustainable future of cities as during Phases 1 and 3, neighbourhoods with improved access to train services recorded less infections. It is possible that access to public transport service may not necessarily equate actual usage, but evidence elsewhere suggests that proximity to service drives usage (Badland et al., 2014; Murray, 2001). The fact that public transport service relationship with infections was similar during the two outbreaks suggests the different management conditions did not impact infection spread through this means. This finding contradicts expectations and results from earlier studies suggesting that public transport use is associated with higher infections (Liu, 2020), highlighting the importance of recognising diversity of cities in policy responses. It is true that public transportation use declined during the pandemic (Curie et al., 2021) due to concerns that it fostered more contacts, interactions, crowding and had shared surfaces which increased infections. Nonetheless, we speculate that even in this general decline, areas with improved public transport access still used more train services than the areas with lower access. Thus, the results offer key insights into concerns of aversion to public transport usage which is expected to persist post-pandemic and remains a threat to sustainable urban transport development. In a recent study, Currie et al. (2021) suggested that while 'working-from-home' is expected to slow recovery of public transport ridership, some commuters expressed their resolve for modal shifts due to public health concerns. In this situation, our finding showing that better access to trains is related to lower cases in both normal and lockdown periods in Melbourne may boost public confidence in the safety of public transport use and spur public policy response that encourages the use of sustainable forms of transport, particularly public transport. This finding is strongly supported by the non-significant relationships of access to bus services with infections. Moreover, the result reveals that with necessary control measures, public transport will still be an important feature of sustainable post-pandemic cities.

This research also showed that neighbourhoods with better access (in terms of proximity) to the CBD recorded highest infection rates and this was consistent across all three outbreaks. In contrast, access to major activity centres which decentralise jobs across Melbourne was not significantly related to infections. Better access to services from economic centres relating to higher infections is validated in the literature (B. Li et al., 2021). Yet, during the outbreaks in Melbourne, the legal enforcement of working-from-home resulted in less movements in the CBD and other employment centres. Therefore, the consistent association during outbreaks with lax restrictions (Phase 1) and stringent lockdowns (Phases 2 and 3) was unexpected. Perhaps, examining the relationship with different sectoral employment clusters (i.e., manufacturing, service, retail, and commerce) may help to decompose the relationship with infections, but this remains a subject for further research.

Relatedly, this research revealed the implications of socioeconomic inequality for COVID-19 spreading. The results support studies indicating that socioeconomic disadvantages were significantly related to infections (Whittle & Diaz-Artiles, 2020; Liu et al., 2021). In the same way, neighbourhoods with large household sizes were found to be having more cases during all three waves of outbreaks (see Liu et al., 2021). As argued by Leach et al. (2021), this pandemic has exposed the shortcomings of the unruly economic goals that entrench inequality across multiple scales of society. The fact that poor neighbourhoods in Melbourne persistently recorded the worst cases during all three waves of outbreaks underscores the urgency for radical public policy transformation towards promoting sustainable and inclusive development at all levels. The GWR analysis confirmed that where some built environment variables (e.g., population density) were associated with more cases, the impacts were stronger for the more disadvantaged neighbourhoods in the west and north, questioning the inclusive and sustainable urban development policy agenda for the city. Age only became an influential factor during Phase 3 which was driven by more infectious variant and vaccination eligibility. Unlike observations elsewhere (e.g., Frank & Wali, 2021), neighbourhoods with younger population experienced more infections but this might be because they were last to be vaccinated in Australia.

### 5.2. Conclusion

This study provides interesting perspective for sustainable urban planning and development in post-pandemic period. Using the unique quasi-experimental conditions presented by three different COVID-19 outbreaks in metropolitan Melbourne, we studied the geographies of infections to examine the consistency of built environment influences on infections. The results provide evidence to continue supporting advocacy of sustainable design practices such as compact, dense, walkable, and mixed-use development as well as public transportation investments that promote liveable and healthy cities. The understanding that these features do not necessarily drive infections is important in a post-COVID world where serious rethinking of the ways cities are designed and organised is being pursued. However, as previously discussed, any efforts for urban sustainability cannot overlook the systemic socioeconomic inequalities existing in major cities.

Finally, we acknowledge the following limitations. While the different public health measures allowed for longitudinal analysis in this study, the phasing (start and end dates of waves of outbreaks) were artificially bounded depending on prevailing government policies and may not necessarily match the natural end or transition from one wave to another. Further studies may address this concern. Also, future studies exploring the consistency of built environment influences on COVID-19 infections could include variables such as air quality, density of bars and restaurants that have been found to have significant influences in cross-sectional studies (Travaglio et al., 2021; Yip, et al., 2021). The recommended future research is critical to unravel the relationships as new waves (such as Omicron) emerge and cities and countries reopen to 'COVID-normal' living.

## 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.

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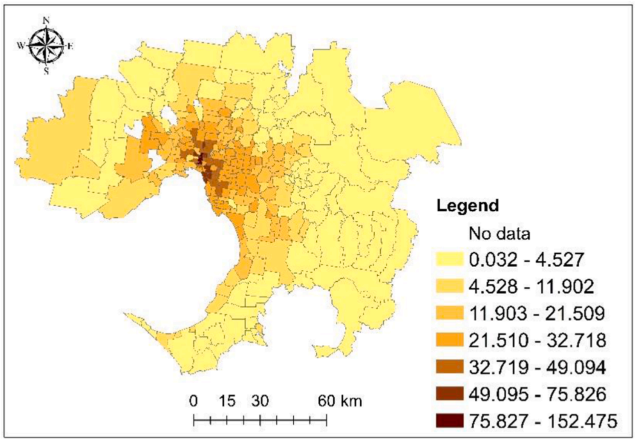
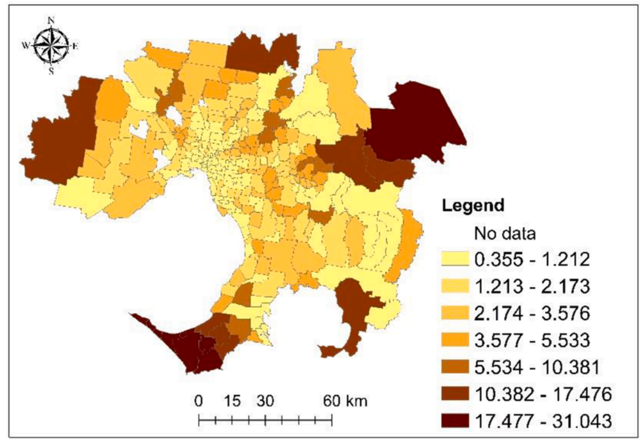
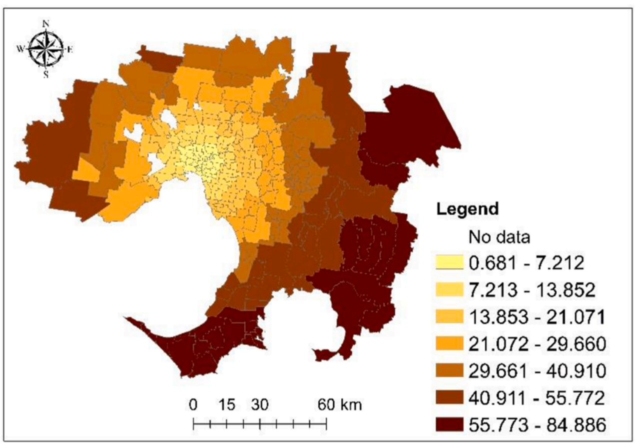
**Appendix 1. Spatial distribution of built environment and socioeconomic varaibles in metropolitan Melbourne**



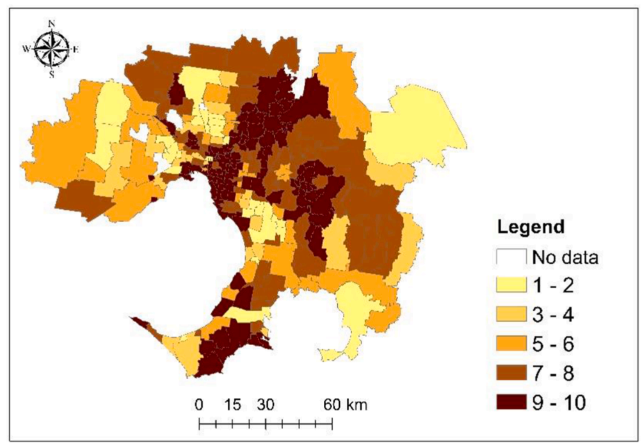

**a. Population density (per hectare)**



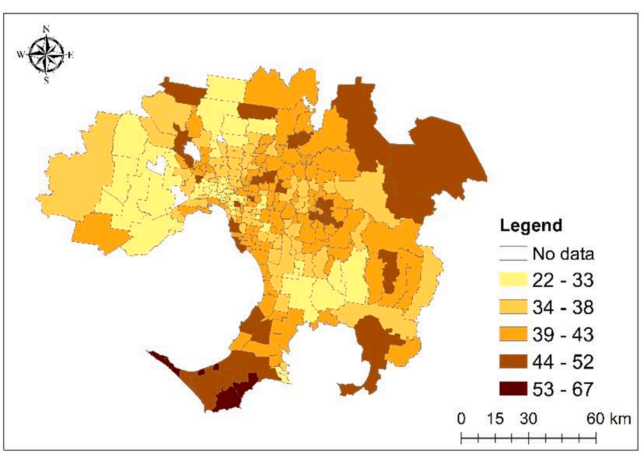

**b. Distance to train station (km)**



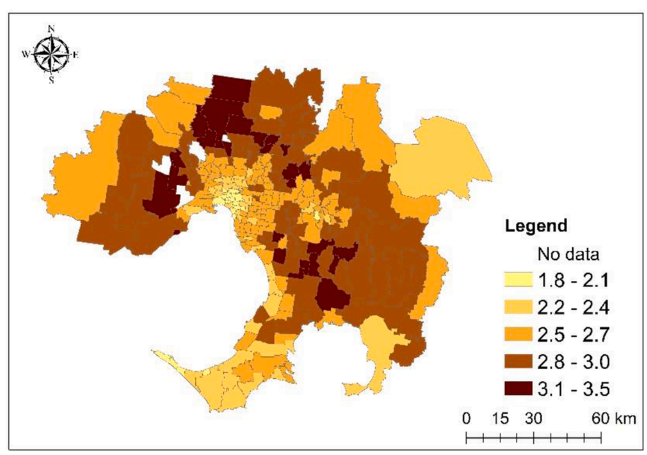

**c. Accessibility to CBD (km)**




**d. Socioeconomic disadvantage (IRSD Score Decile)**




**e. Median age (years)**




**f. Average household size**

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