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1 **Comparison of spatial approaches to assess the effect of residing**
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3

4 **Yang G, Thornton LE, Daniel M, Chaix B, Lamb KE.**

5

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8

9

10 **Keywords**

11 Built environment, urban planning, health-environment association, spatial analysis,
12 spatial autocorrelation

13

14

15 **Abbreviations**

16 BMI, body mass index; PA, physical activity; OLS, ordinary least squares; 20MN, 20-
17 minute neighbourhood; ProjectPLAN, Places and Locations for Activity and Nutrition
18 study; km, kilometre; SES, socioeconomic status; ABS, Australian Bureau of Statistics;
19 IRSAD, Index of Relative Socio-economic Advantage and Disadvantage; SA1,
20 Statistical Areas Level 1; SA2, Statistical Areas Level 2; kg, kilograms; m, metres; CI,
21 confidence interval; SD, standard deviation; IQR, interquartile range.

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26

28 **Abstract**

29 Beliefs that neighbourhood environments influence body mass index (BMI) assume
30 people residing proximally have similar outcomes. However, spatial relationships are
31 rarely examined. We considered spatial autocorrelation when estimating associations
32 between neighbourhood environments and BMI in two Australian cities. Using cross-
33 sectional data from 1329 participants (Melbourne=637, Adelaide=692), spatial
34 autocorrelation in BMI was examined for different spatial weights definitions. Spatial
35 and ordinary least squares regression were compared to assess how accounting for
36 spatial autocorrelation influenced model findings. Geocoded household addresses were
37 used to generate matrices based on distances between addresses. We found low positive
38 spatial autocorrelation in BMI; magnitudes differed by matrix choice, highlighting the
39 need for careful consideration of appropriate spatial weighting. Results indicated
40 statistical evidence of spatial autocorrelation in Adelaide but not Melbourne. Model
41 findings were comparable, with no residual spatial autocorrelation after adjustment for
42 confounders. Future neighbourhoods and BMI research should examine spatial
43 autocorrelation, accounting for this where necessary.

44

45 **1. Introduction**

46 Many health issues arise from having a high BMI (body mass index) and an enormous
47 research effort is placed on investigating the determinants of BMI. Research has shown
48 that BMI is geographically and spatially clustered, suggesting that people residing
49 proximally generally have a more similar BMI than to those residing further away
50 (Mills et al., 2020; Qiu et al., 2020; Kim et al., 2018; Guessous et al., 2014; Huang et
51 al., 2015; King et al., 2006). Explanations for this clustering have included geographical
52 variations in access to built environmental features considered health promoting (e.g.,
53 retailers selling fresh food, recreational facilities including open space) or health
54 harming (e.g., fast food retailers, car-dominant streetscapes) with these variations said
55 to influence diet and physical activity (PA) behaviours (Lam et al., 2021; Papas et al.,
56 2007). However, few studies investigating relationships between the neighbourhood
57 built environment and BMI have adequately accounted for spatial autocorrelation. This
58 is because commonly used methods like linear regression (Duncan et al., 2014; Hobbs
59 et al., 2018) assume spatial independence. Ignoring spatial autocorrelation can lead to
60 incorrect inference by not appropriately estimating standard errors when data are
61 spatially correlated (Chi and Zhu, 2007). Also, since in any real situation, sample sizes
62 will be finite, ordinary least squares (OLS) model parameters may be biased when
63 violations of independence occur (Keitt et al., 2002).

64

65 To handle potential spatial autocorrelation, some studies have accounted for the
66 clustering of participants living in the same neighbourhoods often defined by an
67 administrative unit boundary (Cunningham-Myrie et al., 2020; King et al., 2006; Mason
68 et al., 2020; Tseng et al., 2014; van Lenthe and Mackenbach, 2002; Feng and Wilson,
69 2015). However, accounting for clustering may be insufficient to explain all of the
70 spatial relationships in the data. This is because administrative units could be spatially
71 proximate (even sharing a common boundary), thus sharing common environmental
72 conditions, yet considered independent. Research has demonstrated that different
73 conclusions may be reached when comparing spatial regression and multilevel
74 regression analysis (Takagi et al., 2012; Takagi and Shimada, 2019; Chaix et al., 2005a;
75 Chaix et al., 2005b), implying that multilevel regression may not fully account for
76 spatial autocorrelation. As highlighted elsewhere, approaches exclusively based on
77 accounting for clustering according to geographical areas, rather than individual
78 neighbours, are insufficient to assess how neighbouring individuals affect one another
79 (Zangger, 2019). Spatial regression models based on distances between participant
80 locations, in contrast, enable a better reflection of the effects of neighbouring
81 individuals on one another (Zangger, 2019).

82

83 Policies and land use planning guidelines that advocate for health promoting built
84 environments are becoming increasingly popular (McKinnon et al., 2020; Kent and
85 Thompson, 2014). Originally proposed in Portland (City of Portland Bureau of

86 Planning and Sustainability, 2012), the 20-minute neighbourhood (20MN) concept has
87 since been adopted in Melbourne (State of Victoria Department of Environment, 2019).
88 Variations are now seen in European cities, including Paris (Paris En Commun, 2020).
89 In Melbourne, the written definition of a 20MN has undergone various iterations (State
90 of Victoria Department of Environment, 2019; State of Victoria Department of
91 Environment, 2017; State of Victoria Department of Transport, 2014; State of Victoria
92 Department of Environment, 2015). In brief, a 20MN is a setting that provides residents
93 with the services and resources to meet most of their daily needs (e.g., access to healthy
94 food stores, recreational facilities, health and education services) within a 20-minute
95 non-motorised transport trip from home (noting that in more recent versions of the
96 policy the mode of transport has been restricted to walking) (Victorian Government
97 Department of Environment Land Water and Planning, 2020). Urban renewal and
98 liveability policies that advocate for 20MNs do so under the assumption that these
99 encourage more physically active lifestyles that in turn lead to better population health.

100

101 Our study aimed to i) examine spatial autocorrelation in BMI using individual
102 household addresses, and ii) assess differences in BMI between people living in 20MNs
103 and non-20MNs, accounting for spatial autocorrelation. The statistical approach used
104 here is arguably an important advance over prior research exploring neighbourhood-
105 level influences on BMI where assumptions related to the spatial independence of
106 observations may be totally or partially violated. Advanced statistical modelling is vital

107 to create a more robust evidence base regarding the relationships between place and
108 health.

109

110 **2. Methods**

111 Our study used data from the cross-sectional Places and Locations for Activity and
112 Nutrition study (ProjectPLAN) which aimed to investigate the benefits of living in a
113 20MN on PA and dietary behaviors in two Australian cities, Melbourne, Victoria and
114 Adelaide, South Australia. Melbourne is the capital city of the state of Victoria located
115 in the south-east edge of Australia; Greater Melbourne covers an area of 9992.5km² and
116 has a population of almost 5 million (City of Melbourne, Last accessed June 2022;
117 Australian Bureau of Statistics, Last accessed June 2022). Adelaide is the capital city
118 of the state of South Australia located in the southern central part of Australia; Greater
119 Adelaide covers an area of 3259.8km² (Australian Bureau of Statistics, Last accessed
120 June 2022) with a population of approximately 1.3 million (Australian Bureau of
121 Statistics, Last accessed July 2022a). Cities were considered separately in the analysis
122 as the driving distance from the centre of Melbourne to the centre of Adelaide is over
123 700km. Data collection took place from October 2018 to May 2019. The study was
124 approved by the Deakin University Human Research Ethics Committee (HEAG-H
125 168_2017).

126

127 2.1. Neighbourhood characteristics

128 20MNs were conceived as address points having high-service and amenity provision,
129 with the particular services and amenities considered for inclusion based on 20MN
130 policy documents and a review of existing literature (State of Victoria Department of
131 Environment, 2019; Thornton et al., 2022). These services and amenities included
132 multiple attributes across five domains: 1) healthy food outlets (e.g., supermarkets), 2)
133 recreational resources (e.g., gyms), 3) community resources (e.g., primary schools,
134 general practitioners, pharmacies), 4) public open spaces, and 5) public transport access.
135 Attributes of the 20MN are described in Supplementary Table S1. Non-20MNs had low
136 service and amenity provision, defined as fewer than five individual attributes in
137 Melbourne and four individual attributes in Adelaide (due to different public transport
138 infrastructures). Full details of the approach to operationalise the 20MN are described
139 elsewhere (Thornton et al., 2022). In brief, geocoded services and amenities from a
140 combination of government and commercial sources were overlaid on a pedestrian
141 network layer. For healthy food outlets, recreational resources and community
142 resources, a 1.5-kilometre (km) distance pedestrian network service area, was created
143 using the service or amenity location as the start point. Different measures were used
144 for public open space and public transport, with accessibility to these domains guided
145 by literature or Australian planning guideline recommendations where available. Areas
146 of overlap between service areas could then be identified to determine 20MNs and non-
147 20MNs. The level of service and resource provision was determined across the whole

148 of the Melbourne and Adelaide metropolitan areas. This allowed the identification of
149 address points with access to all services and resources (these address points were
150 defined as having a 20MN) and addresses with low numbers of services and resources
151 (non-20MNs). This approach means we were not bound by a clustered study design
152 whereby participants needed to be within the same administrative units, typical of many
153 studies of neighbourhood effects. The distribution of 20MNs in both cities are shown
154 in Figures 4 and 5 of Thornton et al. (2022). In general, residential addresses that had a
155 20MN were commonly situated within inner and mid-suburban areas of Melbourne,
156 although they extended to the outer areas along the train lines. In Adelaide, residential
157 addresses with a 20MN were typically located centrally in the city, although they were
158 also found in townships extended through the middle and outer edges of the city.

159

160 Areas of low and high socioeconomic status (SES) were identified using the Australian
161 Bureau of Statistics (ABS) Index of Relative Socio-economic Advantage and
162 Disadvantage (IRSAD). Areas with low socioeconomic conditions were defined by
163 extracting deciles 1, 2 or 3 of the IRSAD at Statistical Areas Level 1 (SA1, i.e.,
164 geographical areas built from whole Mesh Blocks which are the smallest geographical
165 areas defined by the ABS) which were located within IRSAD deciles 1, 2 or 3 at the
166 larger Statistical Areas Level 2 (SA2). This approach was adopted to ensure that small
167 areas of low socioeconomic conditions were located within a larger community that

168 also had low socioeconomic conditions. The process was repeated for SA1s and SA2s
169 within deciles 8, 9 and 10 to represent areas with high socioeconomic conditions.

170

171 2.2. Sampling and recruitment

172 Stratified random sampling was used to identify households within each city
173 (Melbourne or Adelaide), neighbourhood type (20MN or non-20MN), and level of
174 neighbourhood SES (low or high) to be sent an invitation letter with a URL and unique
175 password for accessing either a food or PA survey. The sampling approach allowed the
176 household location of participants to be captured which was necessary to account for
177 the spatial autocorrelation between participants. Only address points within residential
178 Mesh Blocks were included in the sampling frame to reduce the number of invitations
179 sent to non-residential addresses. Address point data were sourced from routinely
180 available government data sources (Department of Environment, 2021; Government of
181 South Australia, 2021). The total number of eligible addresses within each city by
182 neighbourhood type and SES are shown in Table 1. We aimed to recruit equal numbers
183 within each stratum. Higher numbers of letters were mailed to address points within
184 low SES areas in both cities due to lower anticipated response rates in these areas.
185 Reminder letters were also issued to some address points to increase response rates.

186

187 Given the sampling approach, there were eight combinations of city, neighbourhood
188 type and status (i.e., Melbourne 20MN low SES; Melbourne 20MN high SES;

189 Melbourne non-20MN low SES; Melbourne non-20MN high SES; Adelaide 20MN low
190 SES; Adelaide 20MN high SES; Adelaide non-20MN low SES; Adelaide non-20MN
191 high SES). Within each combination, randomly selected eligible households were
192 mailed an invitation to participate in either the online food or PA survey. Participants
193 aged 18 years or older were invited to complete the food survey if they were at least
194 jointly if not fully responsible for the household food shopping. The person (aged ≥ 18
195 years) in the household who had the most recent birthday was asked to complete the PA
196 survey. Participants were asked to confirm they lived at the address on file. In total, 782
197 participants (3.7% response rate) from Melbourne and 830 participants (4.2% response
198 rate) from Adelaide consented to complete either the food or PA survey (Table 1).

199

200 2.3. Variables

201 2.3.1. *Exposure*

202 The exposure was neighbourhood type (20MN or non-20MNs).

203

204 2.3.2. *Outcome*

205 BMI (weight [kilograms, kg]/height [metres, m]²) was calculated from self-reported
206 weight and height.

207

208 2.3.3. *Other covariates*

209 Potential confounders included gender (male; female), age, individual SES based on
210 highest qualification obtained (less than university; university) and self-rated financial
211 stress indicated by the ability to manage on household income (very difficult or difficult;
212 just getting by; comfortable or very comfortable).

213

214 2.4. Statistical analysis

215 Participants who were pregnant or who had missing or implausible BMI ($>50\text{kg/m}^2$ or
216 $<15\text{kg/m}^2$) were excluded, leaving 1382 (86%) participants from the original sample
217 eligible for analysis. The statistical analysis was conducted for eligible participants with
218 complete data for the exposure and potential confounding variables. A high percentage
219 of the eligible sample had complete data ($n=1329$, 96%). Descriptive characteristics for
220 the eligible, complete case and omitted samples are shown in Supplementary Table S2.

221

222 Analyses were conducted separately for Melbourne and Adelaide because there were
223 slightly different definitions of 20MN used (due to different public transport systems)
224 in each city. Food survey and PA survey participants were combined for analyses and a
225 parameter for survey type included in the models as these surveys had different target
226 populations; the food survey was completed by the primary or joint primary household
227 food purchaser and the PA survey was any adult in the household. The resulting sample
228 sizes were 637 for Melbourne (Melbourne Food Survey=287, Melbourne PA

229 Survey=350) and 692 for Adelaide (Adelaide Food Survey=351, Adelaide PA
230 Survey=341). Demographic characteristics for the two cities were compared to the 2016
231 Census data for Greater Melbourne (Australian Bureau of Statistics, Last accessed July
232 2022b) and Greater Adelaide (Australian Bureau of Statistics, Last accessed July
233 2022a).

234

235 *2.4.1. Global spatial autocorrelation*

236 Moran's I was calculated to assess spatial autocorrelation in BMI for both Melbourne
237 and Adelaide under different spatial weights definitions (Cliff and Ord, 1971; Cliff and
238 Ord, 1972). Moran's I is the most commonly used measure of spatial autocorrelation,
239 providing a measure of how related observations are based on the location at which
240 they are measured. The correlation ranges from values of -1, indicating negative spatial
241 autocorrelation or complete spatial dispersion, to 1, indicating high positive spatial
242 autocorrelation. A value of 0 indicates complete spatial randomness.

243

244 Eight spatial weights matrices were considered based on both the Euclidean and road
245 network distance between individual household addresses to investigate whether
246 findings were sensitive to the weight chosen. A 3-km bandwidth weight matrix was
247 considered as this distance was directly related to the 20MN exposure definition. Under
248 the assumption that people residing in 20MNs have similar health and behaviour
249 outcomes, it could be hypothesised that those living proximally (i.e., within the pre-

250 specified threshold of a 20MN) have correlated outcomes so this matrix choice enabled
251 us to assess this assumption. In this definition, participants were defined to be
252 neighbours (with a '1' entered in the matrix) if they lived within a 3-km distance of one
253 another; otherwise, participants were not considered neighbours ('0' in the matrix). It
254 was assumed that 1.5-km is the distance an adult can walk in 20 minutes, as discussed
255 previously, so participant pairs whose distances were less than 3-km could share the
256 same amenity or service, as illustrated in Figure 1. In addition, a 1.5-km bandwidth
257 weight matrix, corresponding to the assumed distance that can be travelled in a 20-
258 minute walk, was considered. Matrices were row-normalised, meaning each element in
259 row i (where i represents each study participant) was divided by the sum of the elements
260 of row i , meaning all weight elements took a value between 0 and 1. This means that
261 the spatial weight is shared among the total number of neighbours of participant i (e.g.,
262 for the 3-km bandwidth weight matrix, if participant i had 3 neighbours, each was
263 weighted by $1/3$).

264

265 Inverse-distance weights using the calculated distance between each pair of
266 observations were also considered; this matrix allows all observations to have
267 neighbours, with those living nearer assumed to be more related than those living
268 further. The analysis using the inverse-distance matrix thus assumes that participants
269 would be more influenced by those who live closer to them than those who live further
270 away but enables all participants to have a spatial relationship with all other participants

271 within strata of city (Adelaide or Melbourne). In addition, the inverse-distance-squared
272 matrix was considered which allows the weights between neighbours to decrease
273 rapidly with increasing distance.

274 *2.4.2. Regression models*

275 Unadjusted and confounder-adjusted OLS linear regression models were fitted to
276 examine associations between having a 20MN (no/yes) and BMI in each of the two
277 cities. The Moran's *I* test was used to assess spatial autocorrelation in the residuals of
278 these models using all spatial weights definitions.

279

280 To account for potential residual spatial autocorrelation in the OLS regression models,
281 spatial error regression models were fitted to compare with results from the OLS
282 regression models. The spatial lag model was not considered because these models are
283 most suitable for situations where there is an intuitive or theoretical motivation that the
284 dependent variable will depend on its neighbours' values (e.g., housing price, local
285 government actions) (LeSage and Pace, 2009). The purpose of the spatial modelling in
286 this analysis was to avoid residual spatial autocorrelation where a spatial pattern in the
287 residuals could exist due to omitted random factors. Hence, spatial error models were
288 used in this study. The spatial error models do not assume the interdependence between
289 any two neighbouring observations operate in any particular way, meaning that the
290 outcome (i.e., BMI) of a given individual will be to some degree dependent on the
291 behaviours of their neighbours due to some unmeasured variables, thus accounting for

292 any unmeasured environmental exposures or individual characteristics shared by
293 neighbouring participants (Zangger, 2019). The spatial error model is expressed as
294 follows:

$$295 \quad y = \mathbf{X}\beta + \varepsilon$$

$$296 \quad \varepsilon = \lambda \mathbf{W}\varepsilon + u$$

297 where $u \sim N(0, \sigma^2 \mathbf{I})$ is the $N \times 1$ error vector, assumed to be independent and
298 identically distributed; \mathbf{W} is the $N \times N$ spatial weight matrix (either 3-km bandwidth
299 or inverse-distance) and $\lambda \mathbf{W}\varepsilon$ is the vector of the spatially weighted average of errors
300 (from the observation's neighbours, when the matrix is row-normalised); λ is the
301 spatial autoregressive coefficient, representing the spatial autocorrelation of the error
302 term ε . Since $\varepsilon = (\mathbf{I} - \lambda \mathbf{W})^{-1}u$, the error variance-covariance matrix is written as:

$$303 \quad \sigma^2 (\mathbf{I} - \lambda \mathbf{W})^{-1} (\mathbf{I} - \lambda \mathbf{W}^T)^{-1}$$

304 Once the variance-covariance matrix of error was obtained, after estimating λ by
305 maximum likelihood, the estimated parameters for the association between
306 neighbourhood type and BMI in the spatial error model were estimated by OLS method.
307 The coefficients of neighbourhood type and their 95% confidence intervals (CIs) can
308 be interpreted as the differences in mean BMI between participants residing in 20MNs
309 and non-20MNs.

310

311 *2.4.3. Sensitivity analyses*

312 Two additional types of spatial weights matrix were considered in sensitivity analyses
313 using both Euclidean and road network distances: an exponential decay weight matrix
314 with decay constant 1, which allows the weights between neighbours to decrease more
315 slowly with increasing distance, and an inverse-distance with 3-km bandwidth weight
316 matrix.

317

318 All analyses were conducted using R (version 3.5.3, The R Foundation) and RStudio
319 (version 1.1.463, RStudio, Inc.), with spatial analysis conducted using the “spdep”
320 package (Bivand and Wong, 2018).

321

322 **3. Results**

323 3.1. Descriptive analysis

324 Descriptive characteristics are shown in Table 2. The average age of participants was
325 50.6 (standard deviation [SD]=16.4) years in Melbourne and 57.3 (SD=15.7) years in
326 Adelaide. The ProjectPLAN participants reflect a demographic older than the general
327 populations of Greater Melbourne and Greater Adelaide (Supplementary Table S3).
328 There were higher percentages of women than men in each sample (57.3% in
329 Melbourne and 58.4% in Adelaide); both greater than the overall proportion (51%) of
330 women in the general population for each city. A much higher proportion of
331 ProjectPLAN participants had university education (46.4% in Adelaide and 60.4% in

332 Melbourne) than observed in the general population of these two cities (21-28%; see
333 Supplementary Table S3). Mean BMI was slightly higher in the Adelaide sample at
334 26.8kg/m² (SD=5.0) than in the Melbourne sample (25.4kg/m², SD=4.4). Just over half
335 of respondents in Adelaide (53.0%) resided in a 20MN. The percentage residing in a
336 20MN was lower in Melbourne (39.9%).

337

338 The median Euclidean distance between participants was lower in Adelaide (16.7-km,
339 interquartile range [IQR]: 9.5-26.3) than in Melbourne (20.6km, IQR: 12.5-23.4).
340 Similarly, participants had a lower median network distance in Adelaide (22.1-km,
341 IQR:11.8-30.8) than in Melbourne (26.8-km, IQR: 15.1-38.1). The median number of
342 neighbours within 3-km was higher in Adelaide (38.5, IQR: 24-61) than Melbourne (22,
343 IQR: 12-33). Further details are shown in Supplementary Table S4.

344

345 3.2. Spatial autocorrelation in BMI

346 The Moran's *I* values for BMI based on the eight spatial weights definitions are shown
347 in Table 3.

348

349 3.2.1 Euclidean distance

350 The estimated spatial autocorrelation in BMI was low and positive for all types of
351 Euclidean spatial matrix, ranging from 0.008 (Melbourne: inverse-distance spatial
352 matrix) to 0.059 (Adelaide: 1.5-km bandwidth spatial matrix). The estimated spatial

353 autocorrelation was lower in Melbourne than Adelaide for all spatial weight definitions.
354 Analyses showed no evidence against the null hypothesis of spatial randomness for
355 almost all spatial weight definitions in Melbourne, although the Moran's I test based
356 on the Euclidean 3-km bandwidth spatial weights on the Melbourne sample had a small
357 p -value (Moran's $I=0.032$, $p=0.029$). In contrast, three of four Euclidean spatial
358 matrices in the Adelaide sample showed strong evidence against the null hypothesis of
359 spatial randomness in BMI.

360

361 The Moran's I values based on the 3-km bandwidth weights matrices and the 1.5-km
362 bandwidth weights matrices were slightly larger than the inverse-distance or the
363 inverse-distance-squared weights matrices in both cities.

364

365 *3.2.2 Network distance*

366 Findings using network distances were comparable to those using Euclidean distances.
367 The spatial autocorrelation in BMI ranged from 0.004 (Melbourne: inverse-distance
368 spatial matrix) to 0.051 (Adelaide: 3-km bandwidth spatial matrix). Similar to the
369 Euclidean-distance-based matrices, there was no evidence against the null hypothesis
370 of spatial randomness for all spatial weight definitions in Melbourne, while three of
371 four network spatial matrices in Adelaide showed strong evidence to suggest the
372 presence of positive spatial autocorrelation in BMI. Generally, the values of Moran's I
373 derived from network distances were smaller than those derived from Euclidean

374 distances.

375

376 3.2. Comparison of regression models

377 The difference in mean BMI between residents of 20MN and non-20MN and the
378 corresponding CIs for each model are shown in Figure 2. The results show that
379 adjustment for covariates affected the estimated differences, indicating potential bias in
380 the unadjusted estimates due to confounding. The estimated mean difference in BMI
381 was positive for all models, indicating a higher mean BMI in people living in non-
382 20MNs than 20MNs. However, after adjustment for potential confounders, differences
383 in mean BMI attenuated in both Melbourne (0.22kg/m^2 , 95% CI=-0.48-0.93; Model 2
384 Supplementary Table S5) and Adelaide (0.71kg/m^2 , 95% CI=-0.04-1.45; Model 2
385 Supplementary Table S6).

386

387 Moran's *I* values for the residuals of the unadjusted models were smaller than those
388 observed for BMI in all the samples (Table 3). There was no residual spatial
389 autocorrelation in Melbourne after adjusting for living in 20MN (unadjusted OLS
390 model). Findings for Adelaide were mixed and dependent on the spatial matrix
391 considered. There was strong evidence of residual spatial autocorrelation in Adelaide
392 for all but one (the inverse-distance-squared) Euclidean distance spatial matrices.
393 However, there was only evidence of positive residual spatial autocorrelation for the 3-
394 km bandwidth matrix when considering the network distance. After accounting for

395 potential confounders in the OLS models, the spatial autocorrelation attenuated to close
396 to zero in both Melbourne and Adelaide for all spatial weights matrices (Table 3),
397 indicating complete spatial randomness.

398

399 There was little discrepancy in inference assessing the difference in BMI between
400 20MN and non-20MNs comparing the OLS regression models with the spatial
401 regression models, irrespective of which spatial matrix or type of distance was used.

402

403 3.3 Sensitivity analyses

404 Sensitivity analyses are presented in Supplementary Table S7. Similar to the results
405 presented in Table 3, there was strong evidence of spatial autocorrelation in BMI in
406 Adelaide considering the inverse-distance with 3-km bandwidth spatial weight or
407 Exponential decay weight, with Moran's I ranging from 0.044 ($p=0.042$; inverse-
408 distance with 3-km bandwidth network distance matrix) to 0.055 ($p<0.001$; Exponential
409 decay network distance matrix). Estimated spatial autocorrelation in Melbourne was
410 lower (0.021 to 0.029) and there was only strong statistical evidence of spatial
411 autocorrelation using the exponential decay Euclidean distance matrix (Moran's
412 $I=0.032$, $p=0.037$). As with the other spatial matrices considered, the estimated residual
413 spatial autocorrelation in both Melbourne and Adelaide attenuated to close to zero after
414 accounting for potential confounders in the OLS regression models.

415

416 **4. Discussion**

417 Our study found some evidence of positive global spatial autocorrelation in BMI in
418 Adelaide for almost all types of spatial weights matrices considered. However, this was
419 of a low level, with estimated correlations below 0.1. This is accordant with some
420 previous studies that considered area-level measures to define spatial matrices (Laraia
421 et al., 2014; Han et al., 2018; Paquet et al., 2016) but in contrast to others that
422 demonstrate spatial randomness or spatial dispersion (Penney et al., 2014; Schuurman
423 et al., 2009). Only the inverse-distance-squared weight matrix provided no statistical
424 evidence of spatial autocorrelation in BMI in Adelaide. Generally, there was no
425 evidence of spatial autocorrelation in BMI in Melbourne, where estimated spatial
426 autocorrelation was consistently lower than in Adelaide for all spatial matrices
427 considered. However, our results do show differences in the magnitude of spatial
428 autocorrelation depending on the choice of spatial weights matrix, with positive
429 correlations in BMI ranging from 0.008 to 0.040 in Melbourne and 0.021 to 0.059 in
430 Adelaide. This highlights the importance of the choice of spatial weights matrix in the
431 analysis.

432

433 Estimated spatial autocorrelation in BMI was found to be lower using the inverse-
434 distance weights than the bandwidth weights. The use of the inverse-distance weight is
435 appealing as it does not enforce an arbitrary threshold on distances when defining

436 neighbours. However, by not imposing any distance limits, the inverse-distance matrix
437 considers weighting between pairs even if they reside very far from one another. In this
438 approach, two participants residing 50-km and 51-km from participant i would have
439 different weights, even though arguably these participants reside too far for either to
440 have an impact on participant i . Therefore, perhaps the inverse-distance weights
441 become meaningless beyond certain distances. Interestingly, the estimated spatial
442 autocorrelations in BMI from sensitivity analysis using combined inverse-distance and
443 threshold weights were more comparable to those of the bandwidth only approach than
444 the inverse-distance only approach.

445

446 Comparison of adjusted OLS and spatial regression models examining BMI by
447 neighbourhood type showed little difference in findings when accounting for spatial
448 autocorrelation using any of the spatial weights matrix definitions. After adjustment for
449 potential confounders in the OLS models, there was no evidence of residual spatial
450 autocorrelation in either city. This suggests the spatial autocorrelation in BMI observed
451 in Adelaide may be due to the shared environment or characteristics of the neighbours.
452 Of course, these findings are study- and context-specific, and our results in no way
453 negate a need to appropriately consider spatial relationships in research in this area. Our
454 results provide some indication that mean BMI was higher in non-20MNs than 20MNs,
455 with the estimated mean difference higher in Adelaide than Melbourne. All observed
456 differences were subsequently attenuated, however, after adjustment for confounders.

457 This was so even for Adelaide, where CIs included the null, though with minimal
458 overlap. Importantly, as our samples were older and more highly educated than the
459 general population of Greater Melbourne and Greater Adelaide, our findings may not
460 be generalisable as representative of the broader population. No other studies have
461 examined the effect of having a 20MN on BMI. However, studies examining composite
462 neighbourhood environment measures have yielded mixed findings. In Australia, Tseng
463 et al. (2014) did not find meaningful correlations in the relationship between an index
464 of neighbourhood access to food resources, PA facilities and transport and BMI among
465 women living in socioeconomically disadvantaged areas. In the UK, Hobbs et al. (2018)
466 found that a combination of access to both food and PA environmental facilities may be
467 important for BMI and that the richness of environmental attributes is not necessarily
468 linearly associated with BMI. Future research on liveable environments, considering
469 multiple measures of neighbourhood attributes, is required to understand built
470 environment relationships with BMI.

471

472 Choosing a spatial weights matrix is challenging but critical for spatial analysis as it
473 proposes the spatial dependence structure imposed and can affect both the spatial
474 autocorrelation test and the estimates of spatial regression models (Anselin, 2002;
475 Fingleton, 2003). In research conducted elsewhere examining the ability to estimate
476 area-level relative risk of birth defects in Australia, the researchers found that models
477 incorporating distance-based spatial weights matrices performed better than adjacency-

478 based weights (Earnest et al., 2007). One reason Earnest et al. cited for this is that
479 adjacency matrices are likely to perform better with more regular shaped areas than
480 obtained when dealing with administrative data and they argue the need for careful
481 consideration of appropriate spatial matrices. In addition to the methods used in the
482 present study, a spatial weight matrix could be chosen through an exploratory analysis
483 to assess the degree of spatial autocorrelation (Earnest et al., 2007). One approach to
484 reduce the arbitrariness of the choice is to select from a set of predefined matrices by
485 criterion, such as comparison of values of Moran's I , AIC or model boosting method
486 (Kostov, 2010).

487

488 Our use of the 3-km bandwidth is appealing as it is linked to the distance deemed
489 important for our 20MN exposure definition. However, this approach places an
490 arbitrary threshold on the definition of 'neighbours' through this dichotomisation (e.g.,
491 participants located within 2.99-km of one another are classified as neighbours while
492 those 3.01-km apart are not). Defining participants as neighbours (an entry of 1 in the
493 matrix) or not (0) using the 3-km bandwidth is analogous to the common approach used
494 when considering administrative boundaries where areas (e.g., postal areas or ZIP codes)
495 are defined as neighbourhoods if they share a common boundary. Although attractive
496 due to simplicity, the common approach using administrative boundaries does not allow
497 for vastly varying sizes typical of administrative units. For example, in Australia inner
498 city administrative units are much smaller than those in regional or rural areas. This

499 means the distance between participants deemed ‘neighbours’ in remote areas can be
500 much greater than the distances considered between neighbours in more urban areas.
501 While understandable as administrative units are created based on the number of
502 households and population density, the implications of this are that within the same
503 study, the distance used to represent neighbours can vary extensively.

504

505 The use of distance-based spatial weights in built environment and health research
506 avoids this issue. The inverse-distance spatial matrix, or variations of this matrix (e.g.,
507 inverse-distance-squared), allows the relative distance between *all* participants to be
508 considered, avoiding the specification of arbitrary boundaries and administrative
509 neighbouring areas of varying size, whether distance-based (e.g., the 3-km bandwidth)
510 or not (e.g., defining administrative areas as neighbours if they share common
511 boundaries). However, it should be noted that the inverse-distance spatial matrix is
512 typically calculated based on Euclidean distances. Although Euclidean distances often
513 work well in the context of highly urbanised areas where the underlying level of
514 connectivity is high (Thornton et al., 2012), this means that barriers (e.g., highways or
515 bodies of water) between participants are not accounted for when defining neighbours.
516 This has important implications when considering built environment and health
517 research where increasingly exposure measures, such as access to retail or public open
518 space, are defined based on pedestrian street network distances. Therefore, to better
519 reflect neighbours in this context, spatial matrices should also be based on a network

520 distance measure, as considered in this study, to represent the walking or driving
521 distance between study participants as this may better reflect accessibility between
522 participants. Our findings show that the magnitude of spatial autocorrelation can differ
523 when using Euclidean or network distances, although our inference regarding the
524 relationship between 20MNs and BMI was not affected by which type of distance was
525 used.

526

527 Importantly, it should be noted that our study was able to consider distances based on
528 participant location as our sample sizes were modest at less than 700 in each sample.
529 Larger studies may encounter difficulties in fitting spatial models considering between
530 participant distances. In Stata, for example, the maximum possible matrix size is
531 currently 11,000. Therefore, large studies could either incorporate weighted averages
532 of the response as model covariates as shown in spatial modelling elsewhere (Lee and
533 Neocleous, 2010) or define neighbours based on areal units.

534

535 Strengths of our study include our approach to create spatial matrices considering the
536 precise spatial location of participants through geocoded home addresses. This enabled
537 greater specification of spatial relationships than the use of arbitrary boundaries. While
538 research in this area is often hampered by a lack of access to sensitive spatial location
539 data, particularly if using secondary data sources to examine neighbourhood effects on
540 health, our project greatly reduced the risk of participant identification by analysts by

541 separately creating spatial matrices before merging only the spatial matrices, not the
542 address data, to anonymised participant characteristic data. This demonstrates the
543 possibility of spatial matrices being created externally without the need to release
544 participant data with geocoded addresses. This is an approach that may be considered
545 by other researchers wishing to take spatial relationships into account who are unable
546 to access participant locations. It may be possible for data custodians to create these
547 matrices using open-source software to be linked to participant characteristic data
548 without the geocoded locations.

549

550 Although we considered a number of different spatial matrices in this analysis, future
551 research could consider other types of spatial matrix, including different distance decay
552 functions or exploring different thresholds in a mixed approach combining distance
553 decay with different distance cut-points. Our choice of a 3-km cut-point was based on
554 accessible distances related to the 20MN definition. However, across different contexts,
555 there will be questions about what this threshold distance should be. The choice of the
556 spatial matrices used in the primary analysis for this study was based on common matrix
557 types likely to be adopted by behavioural researchers in neighbourhoods and health
558 wishing to undertake spatial analysis and is by no means exhaustive. However, our
559 findings suggest that spatial autocorrelation values are relatively low and have minimal
560 impact on modelling findings.

561

562 The lack of consideration of spatial models in most studies of the environment and BMI
563 could be attributable to several reasons. Researchers may be unfamiliar with these
564 approaches, or the diverse and complex nature of spatial models may be off-putting.
565 However, the analysis conducted in this study was undertaken using open source
566 statistical and geographical tools, demonstrating that these methods are becoming more
567 accessible to researchers. Although the findings from ProjectPLAN suggest little need
568 for spatial regression models when examining differences in BMI by neighbourhood
569 type after adjustment for individual characteristics, it is important to acknowledge that
570 these findings are context specific. Therefore, future studies of the built environment
571 on BMI, or other health outcomes, should take care to examine and appropriately
572 account for spatial autocorrelation.
573

Authors' contributions

GY and KL led the writing of the article with input from all authors (LT, MD, BC). GY conducted the statistical analysis. KL and LT led the conceptualisation of the study. All authors provided critical feedback on the article drafts and approved the final manuscript.

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TABLES

Table 1. Number of eligible addresses by city and neighbourhood type.

Melbourne	Number of eligible addresses	Total number of mailed letters*	Total number of reminder letters issued	Total number of letters sent to unique address points**	Number of consenting participants (% response**)
20MN Low SES	4365	7973	3860	4113	112 (2.7%)
20MN High SES	61187	4039	500	3539	204 (5.8%)
Non-20MN Low SES	30064	9786	0	9786	239 (2.4%)
Non-20MN High SES	24653	4292	500	3792	227 (6.0%)
Overall	120269	26090	4860	21230	782 (3.7%)
Adelaide					
20MN Low SES	4537	5701	1600	4101	147 (3.6%)
20MN High SES	24799	4200	0	4200	290 (6.9%)
Non-20MN Low SES	18118	7606	0	7606	216 (2.8%)
Non-20MN High SES	32333	2403	0	2403	177 (7.4%)
Overall	79787	19910	1600	18310	830 (4.5%)

*Including reminder letters. **From total number of mailed letters subtracting the number of reminder letters.

Table 2. Descriptive characteristics of ProjectPLAN participants by city.

	Melbourne (N=637)	Adelaide (N=692)	Overall (N=1329)
Neighbourhood Status			
20MN	254 (39.9%)	367 (53.0%)	621 (46.7%)
non-20MN	383 (60.1%)	325 (47.0%)	708 (53.3%)
Neighbourhood SES			
High	367 (57.6%)	401 (57.9%)	768 (57.8%)
Low	270 (42.4%)	291 (42.1%)	561 (42.2%)
Gender			
Female	365 (57.3%)	404 (58.4%)	769 (57.9%)
Male	272 (42.7%)	288 (41.6%)	560 (42.1%)
Education			
Less than university education	252 (39.6%)	371 (53.6%)	623 (46.9%)
University education	385 (60.4%)	321 (46.4%)	706 (53.1%)
Ability to manage on income			
Comfortable/Very Comfortable	416 (65.3%)	462 (66.8%)	878 (66.1%)
Just getting by	160 (25.1%)	162 (23.4%)	322 (24.2%)
Very difficult/Difficult	61 (9.6%)	68 (9.8%)	129 (9.7%)
Age (years)			
Mean (SD)	50.6 (16.4)	57.3 (15.7)	54.1 (16.4)
Survey Type			
Food	287 (45.1%)	351 (50.7%)	638 (48.0%)
Physical Activity	350 (54.9%)	341 (49.3%)	691 (52.0%)
BMI (kg/m²)			
Mean (SD)	25.4 (4.4)	26.8 (5.0)	26.2 (4.8)

Table 3. Moran's *I* test of spatial autocorrelation in BMI and the OLS model residuals.

		Melbourne (N = 637)		Adelaide (N =692)		
	Distance type	Weight type	Moran's <i>I</i>	<i>p</i> -value	Moran's <i>I</i>	<i>p</i> -value
BMI	Euclidean	Inverse-distance	0.008	0.357	0.026	0.001
		3-km bandwidth	0.032	0.029	0.051	<0.001
		Inverse-distance-squared	0.019	0.504	0.037	0.170
		1.5-km bandwidth	0.031	0.183	0.059	0.001
	Network	Inverse-distance	0.004	0.691	0.021	0.022
		3-km bandwidth	0.026	0.163	0.051	0.001
		Inverse-distance-squared	0.022	0.420	0.026	0.329
		1.5-km bandwidth	0.040	0.164	0.049	0.040
Residual of unadjusted OLS regression model	Euclidean	Inverse-distance	0.004	0.558	0.015	0.027
		3-km bandwidth	0.024	0.078	0.034	0.001
		Inverse-distance-squared	0.014	0.586	0.027	0.290
		1.5-km bandwidth	0.025	0.248	0.045	0.009
	Network	Inverse-distance	0.000	0.877	0.012	0.153
		3-km bandwidth	0.018	0.304	0.032	0.033
		Inverse-distance-squared	0.018	0.473	0.016	0.504
		1.5-km bandwidth	0.034	0.210	0.033	0.147
Residual of adjusted OLS regression model*	Euclidean	Inverse-distance	0.000	0.748	0.003	0.481
		3-km bandwidth	0.000	0.888	0.000	0.707
		Inverse-distance-squared	0.006	0.496	-0.002	0.939
		1.5-km bandwidth	-0.008	0.876	0.013	0.355
	Network	Inverse-distance	-0.003	0.993	0.004	0.511
		3-km bandwidth	-0.007	0.749	0.002	0.721
		Inverse-distance-squared	0.005	0.896	-0.007	0.922
		1.5-km bandwidth	-0.004	0.970	0.005	0.688

*Models adjusted for neighbourhood SES, gender, age, education, ability to manage on income and survey type.

FIGURES

Figure 1. Concept of the 3-km bandwidth spatial weight matrix.

It is assumed that 1.5-km is the distance an adult can walk in 20 minutes, so participant pairs whose distances were less than 3-km may share the same facility.

Figure 2. Estimated difference in mean BMI with 95% confidence intervals by neighbourhood status from OLS regression and spatial error regression models by city.

OLS adjusted and all spatial weights models presented adjusted for neighbourhood SES, gender, age, education, ability to manage on income and survey type.