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Using kernel density estimation to understand the influence of neighbourhood destinations on BMI

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ABSTRACT

Objectives: Little is known about how the distribution of destinations in the local neighbourhood is related to body mass index (BMI). Kernel density estimation (KDE) is a spatial analysis technique that accounts for the location of features relative to each other. Using KDE, this study investigated whether individuals living near destinations (shops and service facilities) that are more intensely distributed rather than dispersed, have lower BMIs.

Study design and setting: A cross-sectional study of 2349 residents of 50 urban areas in metropolitan Melbourne, Australia.

Methods: Destinations were geocoded, and kernel density estimates of destination intensity were created using kernels of 400, 800 and 1200 m. Using multilevel linear regression, the association between destination intensity (classified in quintiles Q1(least)–Q5(most)) and BMI was estimated in models that adjusted for the following confounders: age, sex, country of birth, education, dominant household occupation, household type, disability/injury and area disadvantage. Separate models included a physical activity variable.

Results: For kernels of 800 and 1200 m, there was an inverse relationship between BMI and more intensely distributed destinations (compared to areas with least destination intensity). Effects were significant at 1200 m: Q4, β −0.86, 95% CI −1.58 to −0.13, p=0.022; Q5, β −1.03 95% CI −1.65 to −0.41, p=0.001. Inclusion of physical activity in the models attenuated effects, although effects remained marginally significant for Q5 at 1200 m: β −0.77 95% CI −1.52, −0.02, p=0.045.

Conclusions: This study conducted within urban Melbourne, Australia, found that participants living in areas of greater destination intensity within 1200 m of home had lower BMIs. Effects were partly explained by physical activity. The results suggest that increasing the intensity of destination distribution could reduce BMI levels by encouraging higher levels of physical activity.

INTRODUCTION

Obesity remains a growing problem in many Western countries including Australia, where 63% of the adult population is overweight or obese.[1] Among developed countries, the economic costs associated with overweight and obesity are significant.[2] There is growing interest in understanding how the neighbourhood environment may influence the risk of overweight and obesity by encouraging increased energy consumption and discouraging energy expenditure. While it seems plausible that the rise in obesity can be partly attributed to the built environment, the abundant literature examining aspects of the built environment in relation to weight status has yielded equivocal results, with calls for better metrics to evaluate associations.[3] Examination of destinations, an increasingly common focus of neighbourhood research, has yielded mixed results: inverse relationships between body mass index (BMI) and grocery or supermarket store availability have been observed in some research,[4–6] while positive relationships have been noted elsewhere between BMI and destinations such as small food stores and supermarkets,[7] and fast-food stores.[4 8]

The limitations of standard approaches in operationalising elements of the built environment may explain some of the contradictory findings. Most commonly, access to destinations in neighbourhoods has been measured in terms of the destinations present within a defined catchment or buffer (ie, a count of the number of destinations within a certain distance of home, or the presence of

destinations within a defined area). Such measures have been criticised on the basis of their binary or categorical classification: a feature (in this case destination) is simply classified as present or absent.[9 10] A destination located at the edge of the areal unit is not equivalent to a more proximal destination, however, typical binary measures do not accommodate this, and analyse them as if their effect is the same. Furthermore, such measures of destination accessibility do not take into account the location of destinations relative to each other (ie, they provide no indication of whether they are intensely distributed or dispersed).

Kernel density estimation (KDE)—a spatial analysis technique that accounts for the location of features (ie, destinations) relative to each other—is an emerging spatial tool that has previously been applied to the examination of various aspects of the environment, such as park access,[10] health resources,[11] and recently, the food environment.[12 13] The ability to weight the distribution of destinations according to their proximity to a central feature or location is one of the key imperatives for the use of KDE. Further, by representing the distribution of activity or exposures on a continuous surface, KDE helps identify the presence of clusters and irregularities.[14] In plain terms, the use of KDE to examine the distribution of destinations in neighbourhoods enables researchers to see where destinations are sparsely distributed (dispersed), and where they are more intensely distributed (clustered). There is a paucity of studies that have used KDE to examine the relationship between destinations and BMI. In the USA, researchers have applied KDE methods to the examination of the relationship between the intensity/density of elements of the built environment and BMI, or obesity.[13 15] Among a sample of adults with diabetes, one study created a food environment score by subtracting the kernel density estimate of unhealthy food stores from that of healthy food stores, and examined associations between the food environment score and obesity.[15] They found that for higher income groups, a healthier food environment was associated with lower rates of obesity, but for lower income groups, higher rates of obesity were observed among those living in a healthier food environment.[15] These findings led them to conclude that the food environment can have differential effects on residents depending on the pressures placed on individual financial resources.[15] Also in the USA, food stores were classified as either BMI-healthy, BMI-intermediate, or BMI-unhealthy, and kernel density estimates of the distribution of each of these was examined in relation to BMI.[13] Greater density of BMI-healthy stores was found to be significantly associated with reduced BMI.[13] In reviewing the literature, we did not encounter any research examining the relationship between BMI and kernel density estimates of destination intensity in Australia. Furthermore, previous studies using kernel density estimates of destinations in relation to BMI have only examined food purchasing destinations.[13 15] We

contend that it is important to consider other neighbourhood destinations when examining the relationship between neighbourhood environments and BMI. Certainly the motivations for examining BMI in relation to food and recreational destinations are sound and logical: the intensity of healthy or unhealthy food stores may lead to greater consumption of healthy or unhealthy foods, and impact on BMI; the presence of recreational facilities could encourage greater levels of physical activity and lead to reduced BMI levels. However, we argue that many other destinations may also influence BMI by making active travel a viable option. The importance of other destinations is supported by our previous work on this data set. We have previously found strong associations between several specific destination types, such as community resources and small food stores, and both walking and physical activity.[16] Furthermore, in other analyses we used KDE to show that residents of areas with greater destination intensity (as measured by KDE) walked more frequently, and showed higher odds of being sufficiently active (this being largely explained by levels of walking).[17]

The impetus for broadening the focus to other destinations therefore, is thus: greater intensity of many destinations (not just food and recreational destinations) may present residents with more opportunities for active travel, and thereby encourage incidental physical activity. By encouraging more walking, cycling and physical activity, it is plausible that greater density of a range of destinations may be associated with lower BMI levels.

In this paper, we test whether the intensity of destinations near participants' homes is related to reduced BMIs, and assess whether this relationship is mediated by residents' overall physical activity levels. Based on our previous findings that an increased level of KDE is associated with higher levels of walking and greater odds of being sufficiently active,[17] we hypothesised that increasing levels of destination intensity, as measured by KDE, would be inversely associated with BMI, and that this would be mediated by physical activity.

METHODS

The analyses are based on individual and area-level data collected as part of the Victorian Lifestyle and Neighbourhood Environment Study (VicLANES) from 2349 individuals in 50 small areas in metropolitan Melbourne. Additional information on areas was also obtained from a range of different administrative geospatial data sets. The VicLANES project design was approved by the La Trobe University Human Ethics Committee (#02–130), and free and informed consent was obtained from all participants.

Study setting and design
VicLANES was a large, multilevel study conducted in 2003–2004 across the 21 innermost local government areas in Melbourne, Australia. The VicLANES methods

have been reported previously.[18][19] Briefly, CCDs (otherwise known as census collection districts; at the time of the study these were the smallest geographic unit of measurement used by the Australian Bureau of Statisics) were ranked according to a household measure of low income (<$A400/week), then stratified into septiles. Fifty CCDs were then randomly selected from the top (17), middle (16) and bottom (17) septile. Postal questionnaires were sent to 4005 residents over the age of 18 years, who were randomly selected from the electoral roll (voting is compulsory for all Australians over the age of 18 years, and it is estimated that 97.7% of those eligible to vote are enrolled do so).[20] The Tailored Design Method for Mail Surveys[21] was adopted to maximise response rates. A 58.7% valid completion rate was achieved, with 2349 participants returning a valid survey about their physical activity behaviour. Respondents were aged 18–75 years.

Outcome measure

The outcome variable, BMI, was based on self-reported height and weight and was modelled as a continuous outcome.

Exposure variable: destinations

Destination information came from two principal sources: (1) the VicLANES environmental audit,[22][23] and (2) publicly available spatial data sets. We chose destinations that we thought people may use active travel to access in their neighbourhood. Destinations included in the analysis were: educational facilities (schools, kindergartens, universities), café/takeaway stores, transport stops and stations, supermarkets, sports facilities, community resources (such as libraries, maternal and child health centres, places of worship, community centres), small food stores (such as convenience stores, bakeries, butchers, green grocers). Online supplementary table S1 provides details of the destination types and the sources of this destination data.

KDE: constructing the exposure variable in ArcGIS

In ArcGIS 10.1,[24] all destinations were combined and merged into a single layer. The kernel density surface of destinations was estimated and extracted using the 'extract values to points' command in the Spatial Analyst toolbox in ArcGIS.[24]

The process of KDE commences with a continuous map surface divided into a grid of specified cell sizes. Across this map, KDE fits a series of cones or kernels centred over each point feature of interest (in this case destinations), creating a continuous map of feature density or intensity.[25] The radius of each cone/kernel is set to a distance that is estimated to reflect the service area/area of effect of that particular feature or resource. Each cell on the map surface is assigned a kernel density estimate such that cells at the centre of the cone receive higher estimates, and cells at the cone's periphery receive smaller estimates.[25] In effect, kernel density

estimates are inversely related to the distance from the feature that the cone is centred on (the centre of the cone).[25] KDE weights the effect of features such that a feature located closest to a point/location of interest is assigned greater weighting, while a feature located some distance away receives a negligible weighting.[14] The cones of different features/destinations overlap, often substantially. A smoothing function (bivariate Gaussian distribution) adds the estimates of overlapping kernels for each cell.[12][25] An example of the resultant image of KDE of the distribution of destinations using 1200 m kernels is presented in figure 1.

The kernel density values were extracted so that each participant's household location was assigned the kernel density value of the output cell in which they resided. While kernel density estimates are calculated on the basis of how close the destinations are to each other, the values extracted at each participant location provide an indication of the proximity and density of destinations in relation to the participant location. High kernel density estimates indicate high intensity or clustering of destinations, low kernel density estimates indicate negligible, highly dispersed destinations. Moderate kernel density estimates may indicate dispersed destinations, or they may result when a participant is located a greater distance from a set of highly clustered destinations.

In this analysis, kernel density estimates were calculated using kernel sizes of 400, 800 and 1200 m. We were interested in the extent to which physical activity might mediate any observed relationships between destinations and BMI. It is argued that 400 m is the distance that people may choose to walk rather than drive,[26] and this approximately equates to a 5 minute walk. Distances of 800 and 1200 m were also chosen, as they represent the distance that the average person could walk in 10 and 15 min, respectively.

Constructing the exposure variable for statistical analysis

Kernel density estimates were categorised into quintiles (quintile 1 representing areas of least intensely
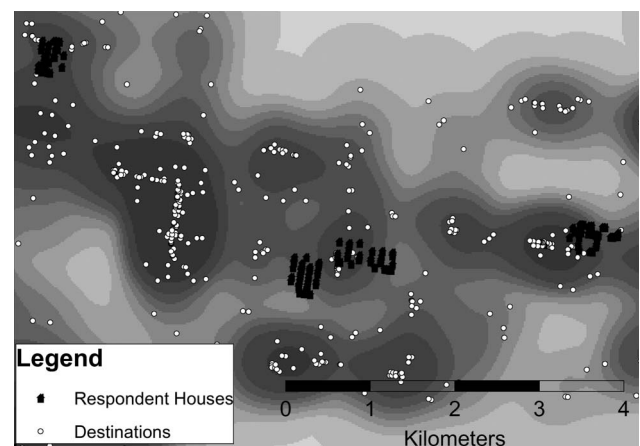

Figure 1 Raster representation of kernel density estimates of destination distribution using 1200 m kernels.

distributed destinations, and quintile 5 representing areas of most intensely distributed destinations). There are precedents for the use of quintiles to model the distribution of destinations, including research in the USA[13] and our own research.[16]

Confounders

Based on the literature, several covariates were included in the analysis as potential confounders.[13 27] These were: age (grouped into six categories: 18–24; 25–34; 35–44; 45–54; 55–64; 64 years and over), sex, country of birth (born in Australia; born in a country other than Australia), education (bachelor degree or higher; diploma; vocational training; and no postschool qualification), household type (single adult-no children; single adult with children; two or more adults-no children; two or more adults with children), dominant household occupation (professional; white-collar employee; blue-collar employee; not in labour force–including retirees, students, unemployed, those not looking for, or unable to work), and disability/injury that prevents exercise (yes, no). Area disadvantage was also included as a potential confounder. The three septiles used to set the sample frame (see 'Study settings and design' above) were used as an indicator of area disadvantage, and were defined as least disadvantaged, mid-disadvantaged and most disadvantaged.

Physical activity sufficiency

Using items from the Active Australia Survey, participants were asked to indicate the frequency and duration of their participation in walking, vigorous physical activity, moderate physical activity, vigorous garden or yard work. These items were then used to produce a measure of overall physical activity sufficiency. The Active Australia Survey has been used in national surveys, and demonstrates very good reliability and validity.[28]

Australian and international guidelines recommend that a person needs to participate in at least 30 min of moderate to vigorous intensity activity most days of the week, for a total of at least 150 min of activity per week.[28–30] According to the Active Australia Survey guidelines, physical activity sufficiency for health can be measured in two ways[28]: (1) measured as total time engaged in physical activity (at least 150 min for sufficiency); (2) measured as total time across total number of sessions (at least 150 min across at least five sessions). The combined measure of time and number of sessions (at least 150 min of at least moderate intensity activity across at least five session week)[31 32] was chosen for this analysis, because it most closely matches guidelines for physical activity sufficiency.[29]

In accordance with the Active Australia Survey administration and implementation guidelines, VicLANES responses were converted to total amount of time (minutes) engaged in each activity, and summed, with vigorous activity weighted by a factor of 2.[28 33] Participants were then categorised into one of two

groups: those reporting less than 150 min of at least moderate activity across five sessions a week were classified as insufficiently active; those with at least 150 min of at least moderate activity across five sessions or more were classified as sufficiently active.

Statistical analysis

Pregnant women (n=22) were excluded because their BMI may have been altered by their pregnancy status. One CCD from just outside the central business district of Melbourne was omitted from the final analysis (n=14) as this CCD's catchment area encapsulated almost the entire central business district, and the number of features and destinations contained in this catchment area was irregularly high. We also excluded 150 participants for whom BMI data were missing, resulting in an analytical sample of 2163 participants, and 49 CCDs. There was no missing data for sex, age group or level of area disadvantage. Missing data for the other variables ranged from 0.1% to 2.1%, with the exception of the disability item and the physical activity item, for which missing data amounted to 5.6% and 14.2%, respectively.

All analyses were conducted in Stata IC 10.0. The referent category for the exposure was quintile 1 (Q1, lowest destination clustering). Descriptive analyses included cross-tabulations between BMI and both individual covariates and kernel density estimates. Multilevel linear regression was performed (with CCDs at level 2 and individuals at level 1) to examine the associations between BMI and the three kernel density measures (400, 800 and 1200 m). More specifically, we used mixed-effects multilevel models with robust SEs. All models were adjusted for confounders. Finally, physical activity was included in the models to test whether it attenuated associations between kernel density estimates and BMI. ORs and 95% CIs are reported for all estimates.

RESULTS

Descriptive statistics

Summary statistics for the outcome by different covariates are presented in table 1. Higher BMIs were reported among men, those aged 55–64 years and over 65 years, those living in the most disadvantaged areas, and those missing data for education (while the BMI for those missing information on country of birth was high, this group only constituted two participants). Lower BMIs were reported among women, those with a bachelor degree or higher, those in the least disadvantaged areas, and younger participants (aged 18–24 and 25–34 years).

Multilevel analysis: KDE

Table 2 shows the adjusted results of the multilevel analyses that tested the association between BMI and the kernel density estimates for destination intensity at kernel sizes of 400, 800 and 1200 m. There was no

Table 1 Sample descriptive statistics (unweighted)

	Sample n=2163		BMI Mean (SD)
	n	%	
Sex			
Male	961	44.4	26.1 (3.8)
Female	1202	55.6	25.0 (4.9)
Missing	0	0	n/a
Country of birth			
Australia	1531	70.8	25.5 (4.5)
Elsewhere	630	29.1	25.6 (4.3)
Missing	2	0.1	31.6 (1.8)
Age (years)			
18–24	170	7.9	23.5 (4.6)
25–34	374	17.3	24.8 (4.5)
35–44	468	21.6	25.6 (4.3)
45–54	459	21.2	25.9 (4.6)
55–64	369	17.1	26.0 (4.0)
Over 65	323	14.9	26.3 (4.5)
Missing	0	0	n/a
Dominant occupation (household)			
Professionals	1016	47.0	25.3 (4.1)
White collar	327	15.1	25.7 (5.1)
Blue collar	224	10.4	25.5 (4.1)
Not in labour force	551	25.5	25.8 (4.7)
Missing	45	2.1	25.9 (6.2)
Education			
Bachelor degree or higher	695	32.1	24.8 (4.1)
Diploma	242	11.2	26.0 (4.5)
Vocational	405	18.7	26.0 (4.4)
No postschool qualifications	776	35.9	25.7 (4.7)
Missing	45	2.1	27.0 (5.3)
Household type			
Single adult, no children	370	17.1	25.8 (4.8)
Single adult, children	125	5.8	26.0 (5.0)
Two or more adults, no children	898	41.5	25.2 (4.3)
Two or more adults, children	730	33.8	25.7 (4.3)
Missing	40	1.9	25.8 (5.4)
Level of area disadvantage			
Least disadvantaged	789	36.5	25.0 (3.9)
Mid-disadvantaged	725	33.5	25.5 (4.6)
Most disadvantaged	649	30.0	26.1 (4.8)
Missing	0	0	n/a
Disability or injury			
Yes	457	21.1	26.7 (5.0)
No	1578	73.0	25.2 (4.3)
Missing	128	5.9	25.4 (4.2)
Physical activity sufficiency			
Insufficiently active	1011	46.7	25.8 (4.7)
Sufficiently active	845	39.1	25.1 (3.9)
Missing	307	14.2	25.6 (4.9)

BMI, body mass index.

association between kernel density estimates and BMI for the 400 m kernel size. For both the 800 and 1200 m kernels, however, increasing kernel density estimates were associated with a reduced BMI, with significant results observed at 1200 m. Evidence was strongest for quintiles 4 and 5 relative to quintile 1 at 1200 m

(quintile 4, $-0.86 \, \text{kg/m}^2$, quintile 5, $-1.03 \, \text{kg/m}^2$). Inclusion of physical activity attenuated these effects (quintile 4, $-0.75 \, \text{kg/m}^2$; quintile 5, $-0.77 \, \text{kg/m}^2$).

Sensitivity analysis

Results remained substantively unchanged in models that excluded transport destinations. We also ran models in which kernel density estimates were modelled as continuous variables, rather than categorical. These results supported those presented in table 2, with significant effects observed for 1200 m, but not other distances.

DISCUSSION

In the analysis presented in this paper, the intensity of destinations was associated with BMI at 1200 m kernels. Specifically, as the intensity of destinations increased, the BMI of participants decreased, this being significant at 1200 m for quintiles 4 and 5 (the quintiles with the most intensely distributed destinations). This effect was attenuated with the inclusion of physical activity in the multilevel regression models.

According to these results for BMI (unadjusted for physical activity), using 1200 m kernels, the BMI of a 65 kg woman of 1.65 m height (BMI=23.9), living in an area of greatest destination intensity (quintile 5), would be $1.03 \, \text{kg/m}^2$ less than if she was living in an area of least destination intensity (quintile 1)—or 2.9 kg lighter. A male of 1.75 metres in height, and 75 kg (with a BMI of 24.5) living in the quintile of most destination intensity compared to least destination intensity, would be 3.2 kg lighter. As we have previously pointed out,[18] while such a shift in individual weight may not have a substantial impact on individual health and mortality, it may reduce the overall burden of obesity-related disease at a population level.[34]

The observed association between destination distribution and BMI at 1200 m is consistent with our hypothesis that more intensely distributed destinations would be associated with reduced BMI. We presupposed that any relationship between destination intensity and BMI would operate through increased physical activity: more destinations would increase residents' opportunities for physical activity (principally through active travel), and lead to reduced BMIs. Supporting this, the inclusion of physical activity sufficiency in the analytical models attenuated findings. These results are broadly consistent with several other studies revealing inverse associations between BMI and destinations, such as grocery stores or supermarkets,[4–6 13] and bus and transit stops.[35] It is difficult to place these results within the literature given there are scant studies examining associations between kernel density estimates of destination density and BMI. Both the studies that we are aware of that have examined the association between KDE and BMI distinguished between healthy and unhealthy food destinations.[13 15] Rundle et al[13] found that the KDE of healthy destinations was inversely associated with BMI. In The Diabetes

Table 2 Multilevel linear regression: β coefficients for association between destination intensity and BMI

Kernel distance	Quintile of kernel density estimates of destination intensity	Beta coefficient for change in BMI	
		Model 1† n=1927 Resp/CCD§=39.3	**Model 2‡** n=1675 Resp/CCD§=34.2
400 m	Quintile 1	Referent	Referent
	Quintile 2	−0.23 (−0.76 to 0.30)	−0.04 (−0.59 to 0.50)
	Quintile 3	0.13 (−0.56 to 0.82)	0.21 (−0.58 to 1.00)
	Quintile 4	−0.07 (−0.69 to 0.82)	−0.19 (−0.61 to 0.99)
	Quintile 5	0.18 (−0.51 to 0.87)	0.22 (−0.53 to 0.96)
	Area-level variance	0.237	0.275
	ICC	1.34%	1.64%
800 m	Quintile 1	Referent	Referent
	Quintile 2	−0.38 (−0.92 to 0.16)	−0.41 (−1.03 to 0.22)
	Quintile 3	−0.31 (−0.95 to 0.33)	−0.30 (−1.03 to 0.43)
	Quintile 4	−0.63 (−1.42 to 0.16)	−0.48 (−1.38 to 0.42)
	Quintile 5	−0.61 (−1.41 to 0.18)	−0.32 (−1.22 to 0.58)
	Area-level variance	0.164	0.232
	ICC	0.93%	1.39%
1200 m	Quintile 1	Referent	Referent
	Quintile 2	−0.42 (−0.92 to 0.10)	−0.53 (−1.11 to 0.05)
	Quintile 3	−0.42 (−1.03 to 0.19)	−0.48 (−1.19 to 0.24)
	Quintile 4	−0.86 (−1.58 to −0.13)*	−0.75 (−1.59 to 0.09)
	Quintile 5	−1.03 (−1.65 to −0.41)**	−0.77 (−1.52 to −0.17)*
	Area-level variance	0.100	0.189
	ICC	0.57%	1.13%

Estimates adjusted for: age, sex, country of birth, education, household, dominant household occupation, level of area disadvantage, injury/disability.
*p<0.05.
**p<0.01.
†Model 1: adjusted model; outcome is BMI.
‡Model 2: Model 1+physical activity.
§Resp/CCD denotes the mean number of respondents in each CCD.

Study of Northern California (DISTANCE), however, the relationship varied by income bracket and race: for all ethnic groups in the high-income bracket, greater density (KDE) of healthy food destinations was associated with reduced odds of being overweight or obese; while for those in the lower income category, having greater intensity of healthy food destinations (as measured by KDE) was associated with greater odds of being overweight or obese, although this was only statistically significant for African–Americans.[15] The association between destinations and physical activity at 1200 m in our analysis is noteworthy. It may be explained by the fact that, if the association between destination intensity and BMI operates through increased levels of physical activity, then it is likely that stronger associations would be observed at distances such as 1200 m, rather than 400 or 800 m. In order to attain sufficiency in physical activity (and receive the health benefits, such as reduced levels of obesity), people need to be active more often, for longer periods of time. While intensely distributed or clustered destinations at 400 and 800 m may still encourage physical activity, this may be insufficient to enact effects on BMI, whereas, 1200 m may be of adequate distance to exert an effect on BMI.

Strengths and limitations

This present analysis using KDE of destination distribution represents an important advancement in the study of the relationship between the built environment and BMI. KDE expresses the distance and density of destinations.[15] By using KDE, this study was able to weight or grade destination access, and accommodate the fact that: (1) a set of destinations close to a house is likely to have greater influence on a person than destinations some distance away; and (2) a set of intensely distributed destinations is likely to have greater influence than dispersed destinations.

Another important strength of this research is the way we optimised the specificity of exposure measures by creating exposure areas specific to each individual, rather than creating neighbourhood exposures based on territorially defined area units.

The comprehensive data collection methods (individual surveys, objective environmental audits by trained staff, and the use of publicly available spatial datasets) represent an important strength, and the simultaneous collection of individual and environmental data reduced the risk of bias associated with the misclassification of environmental exposures.

The use of multiple kernel distances is notable, as it enables the comparison of distance effects, and thereby offers greater ability to observe and understand the complexities of the relationship between destination distribution and BMI. Few previous studies have examined such a wide-ranging list of destinations, particularly in relation to BMI. Of those using KDE to examine the relationship between destinations and BMI, we are not aware of any that have looked beyond food and recreational destinations. While not exhaustive, the wide-ranging list of destinations used here represents an important strength.

There are some limitations that must be acknowledged. First, physical activity and BMI outcome measures are based on self-reported information, and are thus subject to measurement error.[36 37] Comparisons between self-reported and objectively measured BMI show that across the population, height tends to be overestimated and weight underestimated,[37 38] although this varies by population subgroups. For example, overestimation of height is more common in groups of low socioeconomic status and people with higher BMI,[36] while weight is more likely to be underestimated by men.[39] Among women, overestimation of weight has been observed,[39] however, in the USA, there is some evidence that under-reporting of weight is more prevalent among white, well-educated women.[40] Self-reported physical activity is also associated with misclassification and systematic error.[41 42] Underestimation of physical activity is more likely for people engaging in high levels of physical activity.[42] Misclassification of the mediator (in this case physical activity) can severely attenuate estimates of the effects of mediation. Furthermore, as with all such mediation analysis, the model assumes there are no unmeasured confounders, and that there is no misspecification of the causal order. It is also important to acknowledge that 14.2% of responses were missing for the physical activity variable which may have introduced some bias.

As this is a cross-sectional study, reverse causation is possible. However, we believe that BMI is unlikely to cause destination intensity and that it is more plausible that the direction of effect is from the neighbourhood environment to BMI. It is also true that this analysis is predicated on the assumption that destinations that are more intensely distributed, or clustered, lead to reduced incidence of overweight and obesity. However, it is likely that not all destinations exert healthful effects on BMI; fast-food restaurants, for example, are unlikely to positively improve health. Importantly, however, while it is commonly assumed that the availability of fast-food restaurants is associated with higher BMI, evidence is somewhat mixed: some studies have found positive associations,[4 8 22] and others have found no relationship.[13 43] Future analysis of this data set could distinguish between destinations on the basis of their hypothesised relationship with BMI.

It is also important to acknowledge that the participants in this study were adults, so the extent to which the results can be generalised to other populations, such as children and the elderly, is limited. Finally, we have only considered the home environment here. Other environments, such as work and social environments may have important influences on overweight and obesity.

CONCLUSIONS

This is the first study that we are aware of to assess the relationship between destination intensity and BMI using a wide-ranging set of destinations. We demonstrate that intensely distributed destinations are associated with reduced BMI, most particularly at 1200 m from home, and that physical activity, at least partly, explains this association. These results have important implications for policy and planning, as they suggest that increasing the density of destinations may lead to reduced levels of obesity by increasing the physical activity of residents.

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