A best practice framework to measure spatial variation in alcohol availability

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Abstract

Alcohol outlet density (AOD) and alcohol related harms are an internationally reported phenomenon. There are multiple methods described in the literature to measure AOD, but with very little commentary on the geographical underpinnings of the methods. In this paper, we present a framework to help practitioners and researchers choose the most appropriate spatial method of measuring AOD. The framework includes components on theoretical geography, statistical implications and practical considerations, with an emphasis on population level exposure. We describe the CHALICE AOD measurement method which investigated the relationships between AOD and population harm (Fone et al. 2016). The CHALICE method is compared to four other methods found in the published literature. We demonstrate the impact of methodological choices (e.g. network vs. Euclidean distances) on resulting AOD scores. We conclude that wherever possible the best practice approach to modelling AOD should be used to facilitate flexibility in subsequent statistical analysis and improve the transparency of the results.

Keywords

Alcohol Outlet Density; GIS; Framework; Alcohol Related Harm; Public Health

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Introduction

The impact of alcohol outlet density (AOD) on health is an internationally reported phenomenon with recent studies reporting on density measures from New Zealand (Cameron et al., 2015), Australia (Livingston, 2014; Morrison et al., 2015), Scotland (Richardson et al. 2015), South Africa (Leslie et al., 2015) and the USA (Brenner et al., 2015; Cederbaum et al., 2015; Cook et al., 2014; Parker, 2014). Their aims are to better understand the link between AOD and the wide range of harms resulting from substantial levels of excess alcohol consumption (Anderson, 2011; Campbell et al., 2009; World Health Organisation, 2017). As the environment in which an individual resides has been demonstrated to be a key influencer on individual behaviour in relation to alcohol use (Dahlgren and Whitehead, 2007), AOD potentially impacts population health. Policy interventions which modify our environment to reduce AOD by restricting the number of alcohol outlets in a geographic area requires robust evidence to stand up to challenges from the retail sector and the multibillion pound alcohol industry (e.g. The Scottish Parliament 2014).

Producing robust evidence linking AOD and health outcomes is not straight-forward, in part because there is no agreed approach to measure AOD. Multiple approaches have been reported in the literature (e.g. Fone et al., 2016; Grubesic et al., 2016; Richardson et al., 2015). Two main issues can be identified here. The first is that any measure of AOD is based on models, which are necessarily simplifications of reality. Good quality research should include a statement of the limitations, or abstraction from reality but these statements are not always evident, particularly with regard to the limitations of underlying AOD measurements. The second is that alternative spatial models may produce different, and sometimes conflicting, results and are often chosen in relation to the outcomes under investigation (e.g. alcohol

related harms, violence or consumption) making comparisons of outcome measures difficult if not impossible. The limitations of AOD measurement methods need to be clearly understood to facilitate statistical analysis and interpretation of results when analysing the associations between AOD and outcomes.

In this paper, we present a best practice framework that will allow researchers and policy makers to decide what makes a good spatial model of AOD given the circumstances or setting of the research. Recent work by Grubesic et al. (2016) compares alcohol access in Seattle, finding gravity model-based approaches to modelling access the most balanced approach. We add to this work, through the development of a conceptual framework which can be used to decide which AOD measurement is the most appropriate and to help researchers to define the strengths and limitations of a method. We compare the different methods, like Grubesic et al. (2016), but at a national population-level and add stratification by urban-rural classifications and deprivation to investigate how the social and geographic morphologies may influence AOD measurements. We illustrate the framework by comparing the main measures of AOD reported in the literature to a high-resolution household level method developed as part of the CHALICE project, which investigated the relationships between AOD and population alcohol-related harm (Fone et al. 2016). We will focus on methods that produce consistent and theoretically sound spatial models, which best capture the environment in which an individual resides. Having a consistent spatial model is key to understanding the other social processes influencing alcohol related health.

Alcohol outlet density in the literature

AOD measurements can be broadly split into population-based measures and geography-based measures.. The main population-based measures are 1) counts of outlets per capita in a population-based administrative unit (Gruenewald & Remer 2006; Treno et al. 2007; Lapham et al. 2004; Cameron et al. 2015) and 2) counts of outlets per km^2 of a geographical unit (Morrison et al. 2015; Yu et al. 2008; Pollack et al. 2005). These methods are less concerned with local variation in AOD and more concerned with a per capita or per area unit measure of AOD and assume a) that access is equal across a study area and b) the population is unaffected by the constraints imposed by artificial boundaries (Richardson et al. 2015). The most widely reported geography-based measures are 1) counts per walking or driving neighbourhood ('buffer zone') (Huckle et al. 2008; Pollack et al. 2005) and 2) Kernel Density Estimate measures (KDE), which model distance decay within user-defined neighbourhoods (Richardson et al. 2015; Major et al. 2014; Berke et al. 2010). These methods measure AOD (to varying degrees of sophistication), modelling spatial heterogeneity as a fundamental component of the density measure. They typically use a Geographic Information System (GIS) to define a local neighbourhood around a population centre – either a household or a census tract centroid. Other measures of alcohol outlet availability described in previous research were calculated but are not presented here because they do not result in an area-based density score; for instance, outlets per road distance (e.g. Yu et al. 2008; Yu et al. 2009; Cohen et al. 2006) do not consider population distribution and assume equity of access across an area. Nearest outlet to a home or population centre (Day et al., 2012; Halonen et al., 2013) have also been excluded as they do not result in an outlet density measure. This literature

A best practice framework to measure spatial variation in alcohol availability and the development of an AOD methodology as part of the CHALICE project (Fone et al., 2016) forms the basis for the framework described here.

The Framework

The framework is underpinned by three conceptual requirements: theoretical geographical underpinnings; statistical soundness; and practical implementation and interpretation. The framework can be used to compare models of population-level exposure to alcohol outlets.

Theoretical geography components

Theoretical components comprise the core geographic principles underpinning AOD measurements. Simply put, AOD is a measure of geographic access based on spatial location of alcohol outlets, typically around where people live. The theoretical underpinnings of the measurement of geographic access are aimed at capturing an individual's propensity to participate or interact with aspects of their environment (Miller, 1999; Weibull, 1980). Geographic Information Systems (GIS) use digital map data to model human processes and interactions. It is underpinned by key theoretical principles of graph theory and topology (Curtin, 2007); population distribution modelling (Stewart and Warntz, 1958); and it informs spatial interaction modelling (Roy and Thill, 2003).

All GIS models are necessarily abstracts of reality including spatial dependence on related phenomena, ultimately aimed at capturing heterogeneity in geographic space. Spatial models of AOD can be broken down into four principal geographical components; topography, boundary effects, proximity and scale.

Topography describes how the natural and built environment features of an area are arranged. In geography and GIS this is often captured in a surveyed topographic (digital) map, precisely capturing features of the environment (for example rivers, roads, railways and canals). In GIS, network analysis is used to model how people are likely to move around and interact with their local environment using roads and footpaths. The use of a geographic network in analyses is an important component of measuring access to goods, services and places of interest as demonstrated by Apparicio et al. (2008); Higgs et al., (2012) and Mizen et al., (2015), which non-network approaches often resulting in significant variations in findings.

Boundary effects build on the first component by defining the maximum distance an individual is likely to travel to access goods and services. Many studies simply use standard statistical geographies to define small areas for analysis. These impose artificial boundaries on a population that are not necessarily related to the social process under investigation. Openshaw's (1984) definition of the Modifiable Areal Unit Problem (MAUP) and subsequent commentary by Wrigley (1995) and Arbia (1989) suggested that the only way to truly combat the problems associated with boundary effects is to perform the analysis at an individual or household level and use theoretically informed boundaries to capture the underlying social process.

The concept of proximity to related phenomena in spatial interaction models is classically described as Tobler's first law of geography (Tobler, 1970) - *"everything is related to everything else, but near things are more related than distant things."*. Gravity models are

traditionally used in GIS to model Tobler's first law of geography, as a predictor for how far people are willing to travel to access a service. Distances between an origin and destination may be distance decay weighted (Fotheringham, 1983; Halás et al., 2014). The further a person must travel, the smaller the weight assigned, and the less important the destination in the model.

The final theoretical component relates to the *scale* at which AOD is measured. As Goodchild (2001) comments, scale is used interchangeably depending on the discipline and often within disciplines. A cartographer understands scale as a ratio between the real world and a map representation, whereas to a GIS analyst scale may relate to spatial resolution or spatial extent of phenomena. We interpret scale as the spatial resolution at which spatial analysis is conducted. Scale impacts directly to how well the socio-environmental processes modelled are associated with individuals or groups of individuals. The larger the spatial unit of analysis the greater the potential for ecological fallacy (the extent to which assumptions about an individual may be incorrectly based on the group to which they belong - (Robinson, 1950). Scale influences the ability to aggregate to different spatial units, which may be required for subsequent linkage to other data for analysis, and to investigate some of the issues surrounding MAUP.

Statistical components

The statistical component relates to how AOD is interpreted and used as part of a wider analysis. The statistical component is inherently linked to the theoretical geography component described previously (robustness, sensitivity, ecological fallacy and MAUP). As

with all models, robust AOD measures should not be unduly affected by outliers, and have good performance when there are departures from the normal distribution (Huber and Ronchetti, 2009). This can be tested by the size of the interquartile range and a comparison of the median values when comparing density scores produced by different methods. The method should be sufficiently sensitive to measure AOD across all levels of geography as determined by the analysis plan. Raw data should be examined to assess if a resulting AOD score (for example, zero) is valid within different populations (e.g. rural areas). In addition, a method should be sensitive to a change in parameters (e.g. the distance used to define a local neighbourhood or distance decay function) and not be entirely a function of data availability.

Practical components

The final component of the framework considers the practicality of implementing and interpreting the results of an AOD measurement method. The practical component comprises: specialism; computational; data requirements, and interpretability.

Specialism, defines the specialised skills and software required to create an AOD measure. Some methods reported in the literature only require standard spreadsheet software (e.g. outlets per population and outlets per km^2) that are widely available and require no specialised training to use or implement. Other methods require a sophisticated skillset and specialist GIS software (e.g. Kernel Density Estimates and network-derived measures of AOD). Understanding these requirements prior to choosing a method is an important consideration. The *computational* requirements to calculate an AOD are intrinsically linked to the size of the study area and number of observations, the scale at which the analysis is being performed (see the theoretical geography section) and the specialism. These requirements may preclude

some methods from being implemented despite their sound geographical and statistical merits.

The *data requirements* reflect the availability of topographic, outlet and population data. Most developed nations are fortunate to have good data availability, with high precision up-to-date data detailing topography and home locations in digital map format. In the UK these data are contained in Ordnance Survey MasterMap (Ordnance Survey, 2017) and AddressBase Premium (Ordnance Survey, 2014) datasets respectively, that are available to researchers and government organisations under license. Details on the precise locations and type of outlets can be a difficult and time consuming process to collate (Fry et al., 2016) and may not always be available at the level of detail required. The final requirement relates to the *interpretability* of the AOD measure. An AOD measure that is difficult to interpret will make subsequent analysis difficult to design and implement and can impede the dissemination of findings to policy and practice. Conversely, an over-simplified AOD measure may lead to misinterpretation of the social process involved and misguided policy decisions.

In the rest of this paper, we present the CHALICE AOD method based on the theoretical geography, statistical and practical principles described in the framework. We then illustrate the conceptual differences using three commonly used methods from the literature. We compare each to the CHALICE method, evaluating how well they conform to the framework Finally, we use statistical analysis to highlight the similarities and differences.

Methods

The CHALICE Methodology

The CHALICE study was set in Wales, UK, with a total adult population of 2.5 million (Fone et al., 2016). The small-area geography used in CHALICE was the lower layer super output area defined by the 2001 Census (n=1896) (Office for National Statistics, 2001). We first compiled a dataset of alcohol outlets from Local Authority licensing records, described in detail elsewhere (Fone et al., 2016; Fry et al., 2016). Briefly, we located every alcohol outlet in Wales to address-level precision for each of the 24 yearly quarters during the study period from 2006 to 2011. We geo-located each household in Wales (n=1,420,354) using the Ordnance Survey (OS) AddressBase Premium (ABP) dataset (Ordnance Survey 2014). We calculated an AOD score for each household using a network dataset combining the Ordnance Survey (OS) Integrated Transport Network (ITN) and OS Urban Paths data (Ordnance Survey 2012). To calculate AOD, we created an origin-destination matrix using 10 minutes' walking time (833 metres, assuming a standard walking speed of 5 km/hr) as the cut-off value for every household in Wales. This has been widely reported as a definition of a localised neighbourhood and used extensively in previous research (eg Jiao et al., 2011; Poelman, 2016; Reyes et al., 2014). The conceptual framework for this is illustrated in figure 1.

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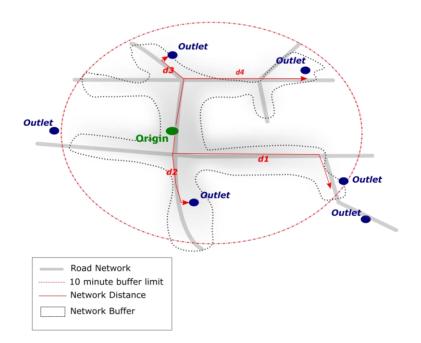

Figure 1: CHALICE method conceptual framework

We re-scaled the adjusted distances to give a value between 0 and 1 (1 high access, 0 poorer access) using a Butterworth filter gravity model (Langford et al., 2012), thus giving closer outlets a higher weighting than those further away from a residence. The Butterworth filter produces a small zone of zero impedance directly around the measurement point followed by a smooth decay so that zero weighting is realised at maximum threshold distance (Langford et al., 2012). We repeated distance calculations for each origin-destination and summed the values to calculate an AOD score for each household. In the CHALICE study, some of the outcome data we used were only available at LSOA level (crime rate data; consumption data) and therefore this became our unit of analysis. To compute an LSOA score we took the mean of the density scores for every residence in an LSOA.

Alcohol outlet density comparisons

We compared the AOD measure developed for CHALICE to three other methods described in the literature: (1) outlet counts per 1000 population – population based on our cohort of

adults in Wales extracted from the SAIL databank (Ford et al., 2009; Jones et al., 2014; Lyons et al., 2009) (2) outlet counts per km^2, and (3) KDE AOD using the method described in Richardson et al. (2015) using each LSOA population weighted centroid (PWC) as the density measurement point. We also included a fifth AOD method following the CHALICE method, but using the PWC as the origin to create an AOD measure for the LSOA as a whole rather than basing this on an aggregation of individual household AOD measures. We wanted to know whether the PWC-based CHALICE method produced comparable results to the full CHALICE household derived measure of AOD at LSOA level, thus potentially reducing the complexity and number of calculations required.

We mapped each method against the framework, derived descriptive statistics (counts of LSOAs with a score of zero AOD (#LSOAs -0), interquartile range (IQR), min, max, mean and median) for the five methods and plotted the density scores as Dorling pseudo-cartograms (Dorling, 1996) to visualise the differences. Finally, we used Bland-Altman plots (Bland and Altman 1986) to plot the difference in values between the CHALICE method and each of the other methods separately (y-axis) against the means of the two methods being compared. Each density score was transformed to a z-score so that the scale of measurement was the same for all five methods. We then stratified each plot by the ONS Rural-Urban settlement type (ONS Geography, 2004) and by quintiles of multiple deprivation derived from the WIMD 2011 (Welsh Government, 2012) comparing the two most deprived quintiles with the two least deprived.

Results

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The framework allowed us to compare each method using a scoring system we developed as part of this research (Table 1). The idea of providing a scoring system has also appeared in a recent report published by the Center for Disease Control and Prevention (CDC) (2017) - a guide to inform practitioners in alcohol outlet research in the USA. Our scoring system, developed as part of the CHALICE project (Fone et al., 2016, 2012), compares various AOD methods, ranking them from low (1 dot) to high (3 dots) based on how well they address each component of the framework. For example, a method including a gravity model will score higher than one using a simpler measure of proximity. A visual representation of the resultant scoring matrix is presented in Table 1.

		CHALICE	CHALICE (PWC)	KDE	OUTLETS PER 1000	OUTLETS PER KM²
THEORETICAL	*TOPOGRAPHY*	●●●	●●●	●●○	●○○	●○○
	BOUNDARY EFFECTS	●●●	●●○	●●○	●●○	●○○
	PROXIMITY	●●●	●●●	●●●	●○○	●○○
	SCALE	●●●	●●○	●●○	●●○	●○○
STATISTICAL	*ROBUSTNESS*	●●●	●●○	●●○	●●○	●○○
	SENSITIVITY	●●●	●○○	●○○	●●○	●●○
	ECOLOGICAL FALLACY	●●●	●●○	●●○	●○○	●○○
	MAUP	●●●	●●○	●●○	●●○	●●○
PRACTICAL	*SPECIALISM*	●○○	●○○	●●○	●●●	●●●
	COMPUTATIONAL	●○○	●●○	●●○	●●●	●●●
	DATA REQUIREMENTS	●○○	●○○	●●○	●●●	●●●
	INTERPRETABILITY	●●○	●●○	●○○	●●●	●●●

Table 1: Framework scores for five AOD methods. The CHALICE method ('CHALICE Density'); the CHALICE methodology using a population weighted centroid as the access measure point ('CHALICE (PWC)'), Kernel density estimates ('*KDE*'); Outlet counts per 1000 LSOA population ('*Outlets per 1000*'); Outlet counts per geographical area ('*Outlets per km²*').

Comparison of the methods shows that there is a trade-off between theoretical groundings and practical implementation. The CHALICE method at household-level scores highly on the theoretical components due to its use of network distances, household defined boundaries, a gravity model and the ability to be aggregated easily to different units of analysis. As a result, it also scores highly against the statistical components (reflected in the descriptive statistics

in Table 2) resulting from the robustness and analytical flexibility of calculating AOD at household level. The AOD score is conceptually relatively easily to comprehend - the average count of outlets within 10 minutes' walk of all households within an LSOA. However, the method requires expertise and above average computational and data requirements to derive AOD.

The CHALICE (PWC) method is an adaptation of the CHALICE method that uses a PWC as a proxy for all household locations in an LSOA. This introduces bias to the analysis, which is reflected in the theoretical scores and subsequent statistical scores. The method is less computationally intensive and therefore scores higher than the household CHALICE method for practical components. The KDE method scores lower because it introduces boundary effects and limitations of scale by using a PWC as the point of measurement for AOD. These limitations are also reflected in the statistical component scores and supported by the descriptive statistics (Table 2). Interpretation of the KDE method is the most complex as the AOD at the measurement point is result of a distance weighted interpolation of distances to outlets over the study area. The KDE method is a relatively simple method to implement with fewer data requirements and is available in many GIS and statistical software packages. The models of outlets per 1000 people and the outlets per km^2 both have low theoretical scores due to the lack of inclusion of any theoretical geography beyond the grouping of outlets by small area geographies. Correspondingly the statistical component scores are lower, but the methods are simple to implement and interpret and therefore score highly in the practical components.

Statistical comparisons

Only the CHALICE method has a density score recorded for each of the 1896 LSOAs; there are no zero values (Table 2). Methods relying on a population weighted centroid (CHALICE (PWC) and KDE) resulted in the most LSOAs with a score of zero (n=323 and n=311 respectively), generally found in rural (Table 3) and least deprived areas (Table 4). Distributions of all measures were positively skewed (mean > median), with most LSOAs for all methods returning low values, accompanied by some very high outlying AOD values. The interquartile ranges (IQR) for all methods showed that the CHALICE methods (IQR = 2.4, IQR = 2.7) produced a smaller range of values. Differences in the IQR were dominated by variation in density scores in urban areas (Table 3). Rural IQRs for the CHALICE method (0.64) and the KDE method (0.56) were broadly similar, whilst the IQRs for the other methods were much smaller, suggesting little variation. Stratification of the density measures by deprivation revealed that the most deprived areas of Wales had the biggest range of IQR values. Outlets per km^2 (IQR = 8.6) and the KDE (IQR = 7.9) models produced the largest IQR. CHALICE methods produced smaller ranges in the most deprived areas (CHALICE density: IQR = 2.7, CHALICE density (PWC): IQR = 3.1).

	CHALICE	CHALICE (PWC)	KDE	OUTLETS PER 1000	OUTLETS PER KM^2
#LSOAs - 0	0	323	311	164	164
IQR	2.40	2.74	6.66	3.95	6.42
MIN	0.0003	0	0	0	0
MAX	56.72	42.62	197.83	64.36	273.68

Mean	2.95	2.77	6.52	4.35	7.42
Median	1.55	1.26	2.36	2.89	2.00

Table 2: Descriptive statistics for five measures of AOD at LSOA-level (n=1896).

	CHALICE		CHALICE (PWC)		KDE		OUTLETS PER 1000		OUTLETS PER KM2	
	U	R	U	R	U	R	U	R	U	R
#LSOAs - 0	0	0	61	231	79	171	141	0	141	0
IQR	2.87	0.64	2.99	0.12	8.34	0.56	3.34	4.17	8.39	0.29
Min	0.0003	0.06	0	0	0	0.01	0	0.67	0	0.01
Max	56.72	4.22	42.62	15.75	176.92	5.18	64.36	27.29	176.92	5.19
Mean	3.47	0.777	3.27	0.27	8.83	0.52	3.60	5.59	9.94	0.38
Median	1.77	0.54	1.66	0	4.16	0	2.24	4.82	3.57	0.18

Table 3: Descriptive statistics for five measures of AOD at LSOA-level. <u>Urban-Rural</u> Split LSOA's (Urban (U) n=1238, Rural (R) n =321)

	CHALICE		CHALICE (PWC)		KDE		OUTLETS PER 1000		OUTLETS PER KM^2	
	Most	*Least*	*Most*	*Least*	*Most*	*Least*	*Most*	*Least*	*Most*	*Least*
#LSOAs - 0	0	0	40	156	69	191	68	79	68	79
IQR	2.70	1.58	3.15	4.47	7.87	1.91	3.62	3.84	8.56	3.48
Min	0.060	0.0003	0.89	0	0	0	0	0	0	0
Max	42.37	31.16	4.04	30.76	111.87	76.67	46.09	31.78	169.70	176.92
Mean	3.60	2.16	3.43	4.36	8.62	1.97	4.25	3.89	9.91	4.72
Median	1.99	1.02	1.85	1.29	4.09	0.67	2.63	2.67	3.59	1.08

Table 4: Descriptive statistics for five measures of AOD at LSOA-level. Most deprived (n=759), least deprived (n=758)

Cartograms of the outlet densities (Figure 2 and 3) show that the urban areas of Wales had proportionally much larger density values, particularly when measured using the KDE method and Outlets per km^2. The Outlets per 1000 population method resulted in higher density in rural areas – represented by dark blue LSOAs being visible in the cartogram - suggesting an over inflation of rural AOD using this method. Comparing the same cartograms, but split into three categories - least deprived, middle, and most deprived - revealed little systematic difference between least deprived and the most deprived LSOAs (Figure 3). The KDE and Outlets per km^2 methods had higher densities in urbanised areas compared to the CHALICE

methods, but proportionally the differences between least deprived and most deprived were
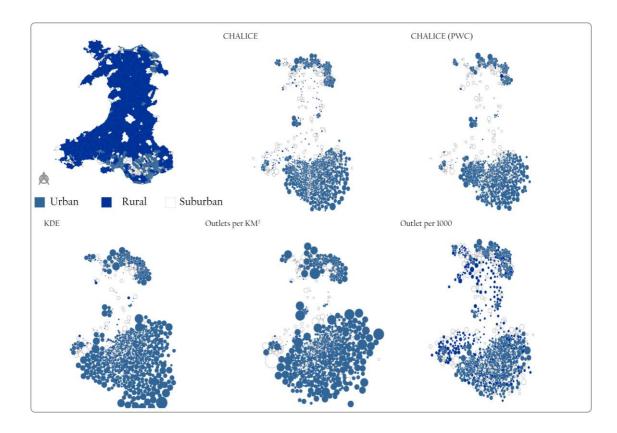
comparable.

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Figure 2: Density scores stratified by rural urban classification.
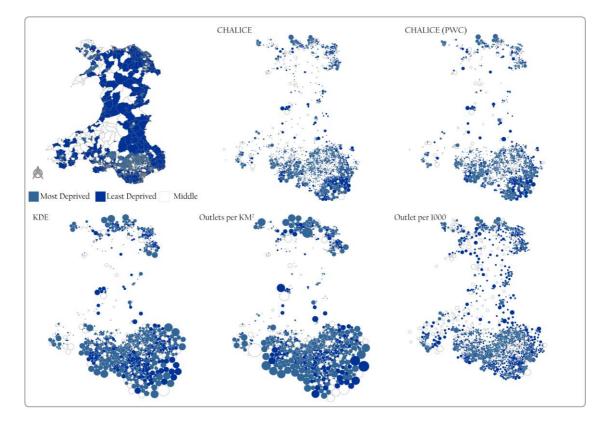

Figure 3: Density scores stratified by deprivation.

Using Bland-Altman (BA) plots we found little evidence of systematic differences in the three methods compared to the CHALICE method (Figure 4), however, there was considerable scatter in the differences between the values as AOD increased.
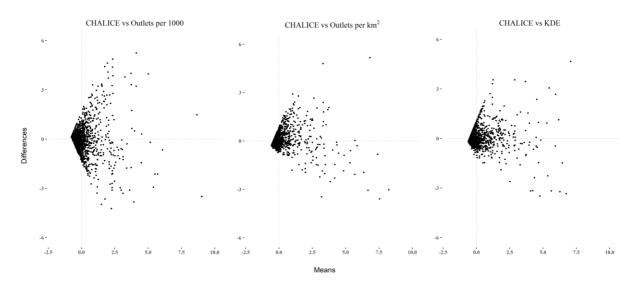

Figure 4: BA plots showing the difference in values between the CHALICE density method and Outlets per 1000 population, Outlets per km^2 and KDE.

When stratified by rural-urban classification (Figure 5) the BA analysis showed in rural areas there is a systematic difference between methods. The methods of Outlets per km^2 and the KDE produce much smaller density values in rural areas compared to the CHALICE method. The differences increased as the density values increased (x-axis); differences between the measures became more scattered. Inversely, Outlets per 1000 population produced higher values when compared to the CHALICE method resulting in a negative trend in the BA plots. The differences also increased as the density values increased suggesting a systematic difference between the methods. The BA analysis showed no systematic difference between the methods for urban areas, with scatter increasing with density.
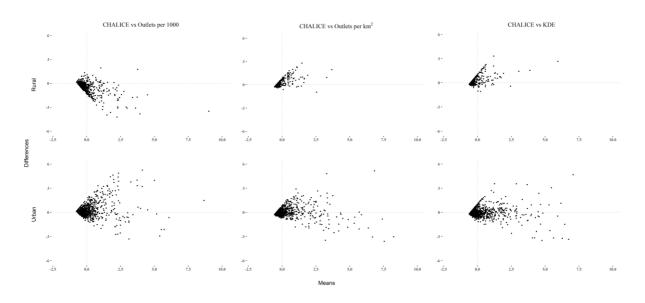
Figure 5: BA plots showing the difference in values between the CHALICE density method and Outlets per 1000 population, Outlets per KM² and KDE. Stratified by Rural (n=321) Urban (n=1238) classification

Repeating the BA analysis and stratifying the results by deprivation showed no systematic differences between the methods (Figure 6) with large scatter of differences for density per 1000 population and the KDE methods compared with Outlets per km².
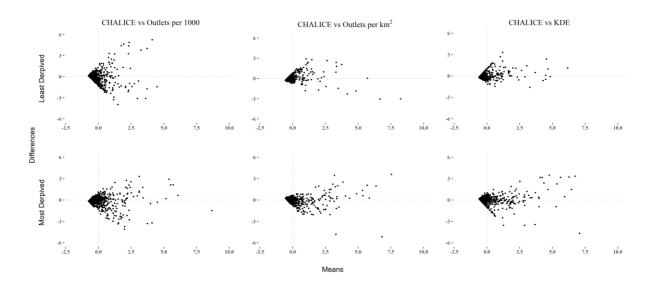

Figure 6: BA plots showing the difference in values between the CHALICE density method and: Outlets per 1000 population, Outlets per KM2 and KDE. Stratified by Least Deprived (n=758) and Most Deprived (n=759) using the WIMD.

Discussion

The method used to measure AOD is important because resultant statistical analysis on the associations between AOD and health is used to inform policy areas related to alcohol abuse. This paper describes the method used in the CHALICE project (Fone et al. 2012, Fone et al. 2016) to measure AOD. The results from this paper show that the CHALICE method conforms to current theoretical geography best practice when compared to other methods found in the literature but is limited by expertise, data and computational requirements. The CHALICE method is not without limitations; the use of 10 minutes walking time to define a local neighbourhood is widely reported in the literature (Hewko et al., 2002; Langford et al., 2012; McGrail, 2012; Poelman, 2016). However, this unit of time does introduce an arbitrary boundary, and therefore is subject to its own MAUP, which arguably may not be representative of access in all contexts, and rural areas in particular. The impact of MAUP should be tested and minimised by performing multi-scale analysis to explore how AOD changes with scale. The CHALICE project also calculated AOD for 10 minutes driving time (Fone et al. 2016). This produced a smoothing in AOD scores resulting in fewer significant associations with health outcomes and smaller effect sizes. A more sophisticated approach would to be to introduce a dynamic bandwidth; however, this would be at the expense of computational ease, interpretability and complicates follow on statistical analysis. The interactions between multi-scale AOD and health and social outcomes are an important area for future work.

Other methods introduce geographical bias to an AOD measure, which may influence follow on analysis. For example, from examining the raw outlet locations, we know that at least one

household in each LSOA has access to at least one alcohol outlet within a 10-minute walk. Crucially, from a methodological perspective, the outlet may not be located in the same LSOA as the household – this resulted in significant differences between the methods in the numbers of LSOAs which had a *zero* AOD score. For example, in one of the LSOAs with a *zero* value there are 16 outlets within the LSOA (but beyond 10 minutes walk of the PWC), and a further 6 outlets in an adjacent LSOA but close enough to the boundary to be accessible. The population for this LSOA is approximately 1,070 people, all of whom were assigned a zero-AOD score using the CHALICE (PWC) or KDE methods. This is a classic example of ecological fallacy; where a density score at a median location within a geographic area is used to assign AOD to the total resident population (Figure 7).
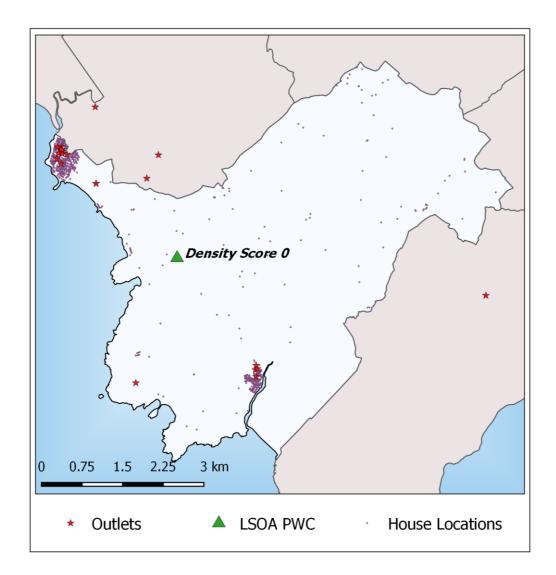
Figure 7: Population location estimates using PWC resulting in *null* values for density calculations

Although a *zero* AOD is conceptually a valid measure, particularly for smaller geographic units or at household level, these *zeros* should be evaluated in conjunction with the spatial distribution of the outlets to ensure that the *zero* is a true reflection of the spatial distribution of outlets and not a construct of the choice of method. Methods that rely on fixed units of analysis (density per km^2 and outlets per 1000) represent a naïve implementation of spatial theory and do not truly model how people could access alcohol. In comparison, methods that use network defined neighbourhoods and small base geographies to define localised AOD

arguably better model spatial interactions between people and their surroundings and reduce the impacts of MAUP in subsequent analysis.

One of the strengths of the CHALICE method is the ability to aggregate from household level to higher units of analysis as required. This is exemplified by the smallest reported IQR (2.4) for the CHALICE method, which indicates that aggregation from household to LSOA results in a more stable measure of AOD when compared with the other methods. This allows for the investigation of MAUP, as described in the theoretical framework, to see how AOD changes in relation to the unit of analysis. Furthermore, using anonymised linked data methods such as those found in the SAIL databank (Lyons et al. 2009; Ford et al. 2009; Rodgers, et al. 2009; Jones et al. 2014), hyper-local AOD measures can be linked to individual households to examine the impacts of AOD on health and other societal problems such as crime and domestic violence.

Results we present here have demonstrated that small geographic area measures of density and methods, without network measures, produce significantly different AOD values when compared to sophisticated GIS methods. This concurs with Grubesic et al. (2016) who found similar trends in Seattle. However, we further demonstrate that this problem is exacerbated when the results are examined over a whole country with stratification by rural-urban classification revealing over and under inflation of AOD. The fundamental theoretical and methodological differences which underpin the non-network and non-spatial methods are significant and their effects have been clearly demonstrated in other work. Research has

shown that omission of network routes can result in falsely assigning places as accessible (Higgs et al. 2012; Apparicio & Seguin 2006; Mizen et al. 2015). The topography of an area, and the barriers to access contained within, whether built (e.g. roads, railways, canal) or naturally occurring (rivers, mountains), fundamentally change how an individual or population can move around their locality.

Data availability and quality, in respect to outlet type and location, is a crucial element to measuring AOD. Other outlet attribute data (e.g. type, opening times and trading dates) are also important to collect as detailed in Fry et al (2016). These attributes are not considered in this paper, as the aim is to focus on the spatial measurement of AOD. However the principles of the framework presented in this paper can be applied with AOD stratified by type or temporally modelled to examine changes in AOD over a 24-hour period or a number of years as detailed in the CHALICE project (Fone et al., 2016)

Conclusion

The use of the framework described in this paper will help researchers determine the best approach to measuring AOD and to understand the limitations of a chosen method whether it be theoretical, statistical or practical. The framework will help improve the understanding of the relationship between AOD and alcohol use at the community level, particularly in rural areas, as identified by Bryden (2013). Recent research on modelling the complexity of the relationships between environmental exposures and health has suggested that the most effective way of developing interventions at the population level is to target the modifiable aspects of the environment in which people reside (Brown et al., 2017) . Moreover, the framework is not limited to AOD and could be applied to any scenario where measuring exposure to some socio-environmental phenomena is required (e.g. tobacco, fast food, urban

green space). Finally, but perhaps most importantly, understanding the bias and limitations

of a method using the framework will also allow policy to more effectively implement

licencing restrictions in relation to the oversupply of alcohol, an issue which is continually

disputed by the alcohol industry as being a causal factor in public health

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