



Using Geographic Information Systems to measure retail food environments: Discussion of methodological considerations and a proposed reporting checklist (Geo-FERN)

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ABSTRACT

Geographic Information Systems (GIS) are widely used to measure retail food environments. However the methods used are heterogeneous, limiting collation and interpretation of evidence. This problem is amplified by unclear and incomplete reporting of methods. This discussion (i) identifies common dimensions of methodological diversity across GIS-based food environment research (data sources, data extraction methods, food outlet construct definitions, geocoding methods, and access metrics), (ii) reviews the impact of different methodological choices, and (iii) highlights areas where reporting is insufficient. On the basis of this discussion, the Geo-FERN reporting checklist is proposed to support methodological reporting and interpretation.

1. Introduction

The global prevalence of overweight and obesity is increasing, with rates approaching or exceeding 1 in 4 adults in numerous continents (International Food Policy Research Institute, 2016). The health, social and economic burden of obesity is well recognised (Dobbs et al., 2014; Kopelman, 2007; Reilly et al., 2003). In the UK, average intakes of sugar, saturated fat, and salt also exceed UK recommendations, and it is estimated that only 9% of 11–15 year olds and 29% of adults meet ‘five a day’ recommendations for fruits and vegetables (Public Health England, 2014). Strong calls have been made by numerous national and international organisations for policymakers to take robust action against obesity, and to help improve nutritional behaviours more generally (Government Office for Science, 2007; Institute of Medicine, 2012; World Health Organisation, 2016).

One area that has recently received attention from researchers and policymakers alike is the ‘retail food environment’ (RFE), and the link this may have with health and obesity-related behaviours. The RFE is characterised both by the ‘community nutrition environment’ (the local opportunities to acquire food) and the ‘consumer nutrition environment’ (the environment within and around food outlets (FO), comprising characteristics such as the price, acceptability and variety of food) (Swinburn et al., 2013). The concept that the RFE might be a driver for obesity is enticing, particularly to policymakers, because it suggests that it may be possible to transform environments from ‘obesogenic’

(i.e. promoting excessive energy intake, making obesity more likely) towards ‘leptogenic’ (i.e. deterring excessive energy intake through better access to healthful foods and/or fewer opportunities to obtain unhealthy foods).

Measures of the RFE are central to understanding its links with health and obesity. RFE measures broadly fall under three categories: (i) perception measures, which assess concepts like residents’ perceptions of the quality and availability of food provision; (ii) audit measures, which generally assess characteristics of the ‘consumer nutrition environment’, such as the variety and price of foods within an outlet; and (iii) Geographic Information Systems (GIS) measures, which measure the spatial accessibility of FO (see e.g. Kelly et al. (2011), Ohri-Vachaspati and Leviton (2010) and Caspi et al. (2012) for a review). These measures are typically used in isolation, although some studies incorporate multiple measures (Rose et al., 2010).

To date, GIS measures have been by far the most commonly employed. For example, a review by Caspi et al. (2012) examining the associations between the RFE and diet reported 68% of studies used GIS techniques. GIS techniques are also widely used by Town Planners and Local Authorities/Government Agencies in developing policy and making planning decisions (Glanz et al., 2016), making GIS-based research particularly relevant to policy development.

Several reviews have highlighted considerable heterogeneity in the methods used in GIS-RFE research (Charreire et al., 2010; Cobb et al., 2015; Forsyth et al., 2010; Ni Mhurchu et al., 2013). This heterogeneity

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makes the collation and interpretation of research findings difficult, and hinders effective translation of research into practice. While most authors acknowledge these limitations, an absence of best practices means the problems look set to persist. With such diversity in methods, accurate and transparent reporting is essential. However, various important methodological decisions are often insufficiently reported or omitted (including work by current authors).

Very little guidance exists to support authors in reporting GIS-RFE methods. Forsyth et al. (2006) propose a general framework for reporting GIS-based measures of the built environment, which calls for detailed reporting of the constructs measured, the GIS methods used, and any questions that arose during the measurement process. While this framework is useful, it is relatively general and does not consider issues specific to RFE measurement.

In view of the above, this paper seeks to (i) identify common dimensions of methodological diversity across GIS-RFE research, (ii) review the impact of different methodological choices, and (iii) highlight areas where reporting is often insufficient. On the basis of this discussion, the Geo-FERN (Geographic Information Systems Food Environment ReportiNg) checklist is proposed. Adoption of the reporting checklist will facilitate better reporting and critical evaluation of methods leading to a greater understanding of the links between the RFE, health and obesity, and improved translation of research evidence into practice. It should be noted that it is not the aim of this article to suggest ‘best practices’ for GIS-RFE methods; there is insufficient evidence on which to make such recommendations, and best practices are likely to vary depending on the specific study design and research question. However, it is hoped adoption of the Geo-FERN checklist will, enable appraisal of methods on a case-by-case basis.

2. Dimensions of methodological diversity

In GIS-based research, RFE are commonly operationalised in terms of the spatial accessibility of FO (Charreire et al., 2010; Cobb et al., 2015). While street audits are generally considered to be the ‘gold standard’ for FO location data (Paquet et al., 2008), they are costly, and time-consuming, particularly for large-scale studies required at the population level (Caspi and Friebur, 2016; Fleischhacker et al., 2012). Thus, the majority of studies instead use secondary FO data. Within this context, there are commonly five dimensions of methodological diversity: (i) the choice of FO data, (ii) the methods used to extract FO of interest, (iii) the ways that FO constructs (e.g. ‘supermarket’ or ‘fast food outlet’) are defined, (iv) the geocoding methods used, and (v) the ways that FO access is operationalised (Fig. 1). Discussion of each dimension is set out below.

3. Dimension one: food outlet data

FO data used in GIS-RFE research is usually either administrative (i.e. collected by governments, local councils etc.) or commercial (e.g. produced by companies such as InfoUSA, Dun and Bradstreet, or Yellow Pages) (Burgoine, 2010; Cobb et al., 2015). Other sources include data that is produced specifically for mapping purposes (e.g. by Ordnance Survey) (Fraser et al., 2012a; Harrison et al., 2011) and omnidirectional imaging such as Google Street View™ (Charreire et al., 2014). Considerations influencing choice of data source may include cost, accessibility, geographic scope, age and quality.

Secondary data has variable quality in terms of its completeness and accuracy (Clary and Kestens, 2013; Fleischhacker et al., 2013; Han et al., 2012; Liese et al., 2013, 2010; Lucan et al., 2013). A recent study (Mendez et al., 2016) has shown that the use of different data sources (InfoUSA and Dunn and Bradstreet) can lead to different conclusions regarding associations between FO density and area-level demographics, with both the number of significant associations and the strength of associations being greater for Dunn and Bradstreet data. Hobbs et al. (2016) also noted differences in the size of associations between food access and weight status when comparing Ordnance Survey Points of Interest (OS PoI) data and UK food hygiene data. However, these differences did not lead to substantively different conclusions (12/12 versus 11/12 of the tested associations were non-significant for the respective data sources).

Incomplete secondary data is also a concern. For example, UK food hygiene records typically do not include information on the locations of market stalls; instead recording the home addresses of stall owners (Burgoine, 2010; Burgoine and Harrison, 2013). However, market stalls may be an important food source among certain communities (Bader et al., 2010), and excluding these sources could underestimate food access in such groups. Any secondary data should be cited in order to enable critical appraisal and to recognise and reward the scientific contribution of the data creators. While best practices in data citation are still in their infancy, the Economic and Social Research Council (ESRC) suggest that as a minimum citations should provide an identifier (i.e. a web address or ideally a Digital Object Identifier (DOI)), the name of the data creator, the title of the dataset, the publisher of the dataset and the publication year (Economic and Social Research Council, 2016). However, numerous authors (e.g. Abbott et al., 2014; Griffiths et al., 2014; Fraser et al., 2012b; Jennings et al., 2011) do not meet these criteria. The age of FO data may be particularly important to report, as this may affect the validity of food access measures e.g. if there is a temporal mismatch between the FO data and any linked data. However, the age of secondary data may not always be known. If this is the case, then it should be stated as a limitation.

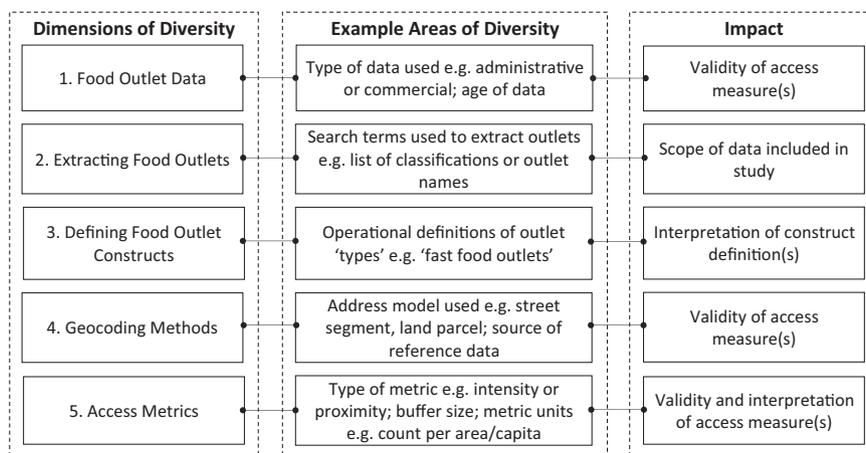


Fig. 1. The five dimensions of methodological diversity in GIS-based retail food environment research, and corresponding impact.

As data sources are often unique to specific countries, and in some cases even regions, reader familiarity with the data should not be assumed, and a brief description of the data is warranted. Description could usefully include e.g. the purpose for which the data was originally collected, the methods of data collection, the scope of the data (in terms of both the geographic coverage of the data and the range of business types included in the data) and the data fields used in analyses. Further details that could usefully be reported to support appraisal of data quality include information on the accuracy of FO data (e.g. via reference to a validation study) and provision of information on the prevalence of missing attribute data (or acknowledgement that the level of missing data is unknown).

4. Dimension two: extracting food outlets

Once a data source has been selected, the next methodological step usually involves extracting data of interest (Fig. 1). Data extraction is performed primarily to extract FO from a larger dataset of more general businesses and/or to exclude FO that are not of relevance to the research question.

Extracting FO is not as simple as may be assumed. One method is to extract outlets on the basis of proprietary classification codes (Boone-Heinonen et al., 2013; Carroll-Scott et al., 2013; Gibson, 2011; Jennings et al., 2011; Macdonald et al., 2011; Shier et al., 2012). Such codes may conform to nationally or internationally recognised classifications schemes (e.g. the North American Industry Classification System (NAICS) or Standard Industrial Classifications (SIC)), or may be unique to a data provider (e.g. OS PoI classifications).

One challenge with this method of data extraction is in deciding which classifications to retain/exclude. As an example, OS PoI data includes spatially coded data on businesses in the UK, with business being associated with one of 616 possible classifications (Ordnance Survey, 2016a). However, while some classifications such as 'Cafes, Snack Bars and Tea Rooms', 'Fish and Chip Shops' and 'Supermarkets' are obviously food retailers, other classifications are less clear. For example, the classifications 'Department Store' and 'Chemists and Pharmacies' may include some stores that sell food and others that do not (Farley et al., 2010). The researcher must therefore decide whether to include outlets falling within these 'peripheral' classifications (possibly applying further techniques to extract those selling food), or whether to exclude all 'peripheral' classifications.

A second extraction method involves searching other attributes in the data (Block et al., 2004; Forsyth et al., 2012a; Hurvitz et al., 2009; Thornton et al., 2012). For example, Thornton et al. (2012) extracted supermarkets by searching for the names of main chain supermarkets, and Forsyth et al. (2012a) extracted fast food outlets using a combination of chain names, and search terms such as "pizza", "taco", "burger", etc. The choice of extraction method will affect the scope of FOs extracted. For example, the method of Forsyth et al. (2012a) would omit non-chain FO whose name is not descriptive of the foods sold.

Despite varied approaches to data extraction, many studies (e.g. Abbott et al., 2014; Griffiths et al., 2014; Bloodworth et al., 2014; Harrison et al., 2011; Smith et al., 2013; Williams et al., 2015) provide no description of the methods used. Of those that do, some still fall short of providing a complete description of extraction methods. For example, where outlets are reported to be extracted on the basis of proprietary classifications, extraction methods can still remain opaque because authors (e.g. Carroll-Scott et al., 2013; Jennings et al., 2011) do not give an exhaustive list of codes/categories that were extracted, or if a list of categories is given, authors (e.g. Casey et al., 2012; Jennings et al., 2011) do not clearly state whether these correspond to the proprietary categories, as opposed to e.g. researcher-defined categories. This makes it difficult for the reader to identify which types of outlets have been included, and which have been excluded; a detail that is important for informing FE-related policy, and for replicating research in different regions.

Extraction methods have been well reported in several papers (e.g. Bodicoat et al., 2015; Boone-Heinonen et al., 2013; Forsyth et al., 2012a; Shier et al., 2012), wherein exhaustive lists of codes/search terms have been provided either within the text or within supplementary material. Where outlets are extracted on the basis of proprietary classifications specifically, it may also be helpful for the classification scheme to be included within supplementary material, or for any 'peripheral categories' to be highlighted so that the reader can evaluate whether any important outlets have been omitted. Fraser et al. (2012b) provide a good example of this practice, by highlighting pubs as a peripheral category, and providing rationale for their exclusion.

5. Dimension three: defining food outlet constructs

Many studies examine access to specific outlet types, such as 'supermarkets', 'fast food outlets' and 'convenience stores' or to larger groupings of outlets considered more generically to be either 'healthy' or 'unhealthy' (Charreire et al., 2010; Cobb et al., 2015). These FO constructs are frequently used as a proxy for the availability of certain types of food (Cobb et al., 2015). For example, supermarkets are often taken to represent healthy food sources, and fast food outlets to represent unhealthy food sources (Moudon et al., 2013; Rundle et al., 2009).

Clear construct definitions are necessary to enable appraisal of a construct as a proxy for food availability. For example, taking supermarkets to represent a source of healthy food may not be entirely valid, as supermarkets also offer a wide range of unhealthy foods; particularly in smaller local supermarkets, where a much greater proportion of store space may be devoted to unhealthy foods (Farley et al., 2009). Clear construct definitions are also imperative to enable translation of research into practice; without this it is impossible for policymakers to take evidence-based action in respect of outlet types determined to have an (un)favourable influence on health/obesity.

The methods used to define FO constructs are highly variable. Constructs have been defined, for example, based on proprietary classifications (see e.g. Griffiths et al., 2014; Cetateanu and Jones, 2014; Macdonald et al., 2011) and/or criteria such as floor space (see e.g. Gilliland et al., 2012), number of employees (see e.g. Fiechtner et al., 2013; Fiechtner et al., 2015; Gibson, 2011) or annual sales (see e.g. Shier et al., 2012). Yet others have replaced proprietary classification schemes with secondary schemes in order to group FO into constructs (e.g. Burgoine et al., 2014; Williams et al., 2015). Some methods rely exclusively on information available within the FO data source to group outlets (e.g. Griffiths et al., 2014; Cetateanu and Jones, 2014; Macdonald et al., 2011), whereas others use supplementary information (e.g. Block et al., 2011; Burgoine and Monsivais, 2013; Carroll-Scott et al., 2013; Fraser et al., 2012b; Hurvitz et al., 2009; Williams et al., 2015). For example, Fraser et al. (2012b) used a combination of proprietary classifications, outlet names and local knowledge to group outlets.

As a result of differing construct definitions, the scope of similarly-named constructs is diverse. While the construct 'fast food outlets' has in some cases been defined narrowly to include e.g. only 'traditional' hot food takeaways (Block et al., 2004; Burgoine et al., 2014; Burgoine and Monsivais, 2013; Hurvitz et al., 2009; Skidmore et al., 2010), others have adopted broader definitions including e.g. cafes, sandwich shops and bakeries (Williams et al., 2015). Broad construct definitions may include outlets with varied food provision, which may not conform to the type of food provision the construct is supposed to represent.

The use of different construct definitions can lead to very different findings, meaning the collation of similarly-named, but differently-defined constructs may give rise to heterogeneous, and overall null or misleading results. For example, Moudon et al. (2013) applied three different 'healthy' and 'unhealthy' outlet definitions to the same data. All outlets were first classified according to their proprietary classification code and then divided into 'healthy' and 'unhealthy' outlets such

that (i) outlets classified as ‘broad selection’ food stores and ‘limited service’ restaurants were ‘healthy’, and all other outlets were ‘unhealthy’; (ii) outlets classified as ‘supermarkets’ were ‘healthy’, and ‘convenience stores’ and ‘fast food restaurants’ were unhealthy; and (iii) outlets classified as ‘supermarkets’ and ‘fruit and vegetable markets’ were healthy, and ‘fast food restaurants’, ‘convenience stores’, ‘bakeries’, and ‘meat markets’ were unhealthy. Under the three schemes, the percentage of outlets classified as ‘healthy’ ranged from 3% to 34%, and ‘unhealthy’ ranged from 16% to 66%. In spite of these problems, reviewers have nevertheless collated studies examining similarly-named, but differently defined constructs in order to simplify the wildly heterogeneous evidence base (Casey et al., 2014; Cobb et al., 2015; Feng et al., 2010; Fleischhacker et al., 2011).

In spite of the diversity of construct definitions, frequently studies go no further in defining constructs than providing construct names (e.g. Abbott et al., 2014; Griffiths et al., 2014; Bloodworth et al., 2014; Carroll-Scott et al., 2013). Although some other authors do state the method used to define outlets (e.g. use of proprietary codes), important methodological details necessary to understand the construct scope are still missing (e.g. the proprietary classifications making up each construct) (see e.g. Casey et al., 2012; Fiechtner et al., 2013; Fiechtner et al., 2015).

Where proprietary classifications, store names or other objective criteria have been used to define outlet constructs similar guidance as for Dimension Two applies; briefly, authors should provide an exhaustive list of categories/names/criteria making up each construct, with a copy of the proprietary classification scheme (where used) preferably being provided in supplementary materials. Where citable categorisation schemes, such as those developed specifically for RFE research, have been used (i.e. replacing proprietary classifications), these should ideally be cited and the methods used to apply the secondary classifications described. For example, Burgoine and Monsivais (2013) report use of a validated RFE classification scheme (Lake et al., 2010) to define constructs, and describe use of “[t]he internet, Google Street View, phone calls, some ground truthing and local knowledge” to apply the classifications to FO data.

In any case, it is suggested that authors list some exemplary (ideally well-known) outlets falling within each construct such that the scope of each construct can be more readily interpreted. For example, if the construct ‘fast food outlet’ includes ‘traditional’ burger and fried chicken outlets, and also coffee shops and sandwich shops, then well-known chains falling within each such sub-type could be listed. This is recommended even when an exhaustive list of proprietary classifications defining the scope of constructs is provided, because classification schemes may be applied inconsistently by data providers. For instance, for two data providers both applying the NAICS classification scheme, the number of outlets that were classified as ‘supermarkets and other grocery stores’ differed by 40% (Forsyth et al., 2010). Data providers may also not apply classifications consistently over time. For example, Ordnance Survey classified McDonald’s as a ‘restaurant’ in the 2006 version of their Points of Interest data, and as a ‘fast food and takeaway outlet’ in their 2016 version (Ordnance Survey, 2006, 2016b).

As there is presently little evidence to guide construct definitions (and the most appropriate definitions are likely to vary depending on the research question), as a minimum it is suggested authors seek to use established definitions to facilitate comparability between studies. It may also be helpful for authors to set out the conceptual basis for their constructs, e.g. via reference to audit-based studies evidencing an association between a construct and a certain type of food availability/environment.

6. Dimension four: geocoding methods

Geocoding is the process of converting address data into coordinates or other geographic identifiers by matching the address data to spatially coded reference data. It is a common methodological step in

many GIS-RFE studies (Fig. 1), and is used to map FOs, residential addresses, schools, workplaces or geographic covariates. Geocoding is a complex process carried out by algorithms. Possibly for this reason, many authors (e.g. Abbott et al., 2014; Block et al., 2011; Bloodworth et al., 2014; Bodicoat et al., 2015; Fiechtner et al., 2013; Fiechtner et al., 2015) provide very little detail about the geocoding methods used. However, while detailed knowledge of these algorithms is not essential for geocoding to be performed, nor for the results to be understood, there are numerous decisions and processes that require human intervention, and which may affect the quality of the geocoding process. Reporting of these human processes, and recognition of the ways in which they may affect geocoding quality is therefore important.

The quality of the geocoding process can broadly be defined in terms of the spatial accuracy of geocoded address points and the percentage of addresses that are successfully geocoded (the ‘match rate’) (Jacquez, 2012). Reviews of geocoding errors have noted typical positional errors of 25–614 m (Jacquez, 2012; Zandbergen, 2008). However, larger positional errors are quite common, with Cayo and Talbot (2003) reporting that in rural areas, 10% of addresses were geocoded with errors > 1.5 km. This is substantially larger than commonly used buffer sizes and could lead to invalid access measures. Positional errors in geocoding can also lead to issues such as biased regression coefficients, inflated standard errors and reduced statistical power (Griffith et al., 2007; Jacquez, 2012; Rushton et al., 2006; Zandbergen, 2008). Low match rates can lead to unrepresentative access measures, and match rates that vary geographically in a non-random manner can lead to confounded results; a phenomenon known as ‘cartographic confounding’ (Oliver et al., 2005).

One methodological decision that is often not reported, and which can impact geocoding quality is the address model used (Jacquez, 2012; Zandbergen, 2008). There are four commonly used models, which respectively match addresses to (i) areal units, (ii) street segments, (iii) land parcels and (iv) address points (Goldberg et al., 2007; Zandbergen, 2008). Areal units can include postcode/ZIP code zones, counties, cities etc. An exemplary geocoded point (Point A) is shown in Fig. 2 for a postcode zone areal unit. In the street segment model, an address is matched to a street segment, and each segment is associated with an address range, with odd and even numbers usually being assumed to reside on opposite sides of the street. The position of an address along the street is then estimated, assuming addresses are linearly dispersed within the address range (Fig. 2, Point B). In the land parcel model, addresses are geocoded to a matched land parcel (usually the parcel centroid) (Fig. 2, Point C). Finally, in the address point model, addresses are matched to individual point data, which is typically located at the centroid of the building to which the address corresponds (Fig. 2, Point D).

The areal unit model is generally the least spatially accurate because all addresses within a unit are geocoded to the unit centroid (Goldberg et al., 2007). Amongst the other three models, street segment geocoding is commonly the least accurate (Zandbergen, 2008). For example, Cayo and Talbot (2003) found the respective mean positional errors of street network and land parcel models to be 143 m and 15 m respectively in suburban areas. In contrast, the areal unit model tends to have the highest match rate because it only requires a match for the areal unit identifier within the address (e.g. postcode or county) (Zandbergen, 2008). Among the other three, street network geocoding usually has the highest match rate (70.9–97.4%), as matches are only required for the street segment; followed by address point (48.0–80.7%) and land parcel (24.1–78.2%) models, which require matches across all address fields (Zandbergen, 2008). In general there is a trade-off between high match rates and high spatial accuracy.

A second methodological decision is the choice of reference data (or the choice of geocoding software, which may dictate the reference data used). Different sources of reference data are known to have variable accuracy and completeness (Frizzelle et al., 2009; Jacquez, 2012; Rushton et al., 2006), which may impact both positional accuracy

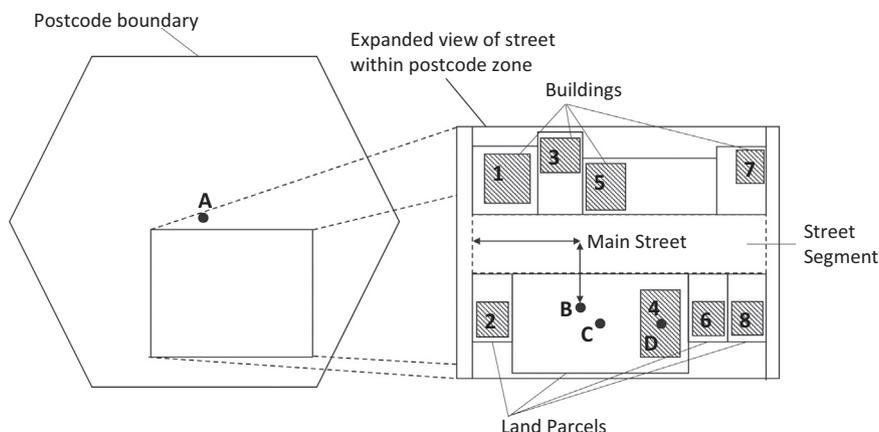


Fig. 2. Diagram of an exemplary postcode zone, and expanded view of a street segment within the postcode zone illustrating the geocoded locations of building Number 4, Main Street under four geocoding methods. Point A was geocoded by postcode unit matching, Point B by street segment interpolation, Point C by land parcel matching, and Point D by address point matching.

and match rate (Bell et al., 2012). For example, where street segment geocoding is used, the spatial accuracy of the street network data will impact the positional accuracy of geocoded addresses. The age of the reference data may be of particular pertinence, as development of new roads and/or buildings could reduce geocoding quality.

Environmental context is another factor which, although not a methodological step, nonetheless requires reporting because it is associated both with spatial accuracy and match rate. More specifically, positional errors are higher in rural areas compared to urban and suburban areas (Jacquez, 2012; Schootman et al., 2007; Zandbergen, 2008). Cayo and Talbot (2003), for instance, reported a mean positional error of 614 m in rural areas versus only 58 m in urban areas. Oliver et al. (2005) also found match rates to be associated with county-level demographics, leading to ‘cartographic confounding’. When reporting environmental context, the operational definition should be stated, as various definitions can be employed. For example, in the UK the Office for National Statistics employ different urban/rural definitions depending on the level of geography being classified (Department for Environment and Rural Affairs, 2016).

Other factors that may affect geocoding quality include the particular software (i.e. algorithm) used to perform the geocoding operation and any user-modifiable parameters, such as the minimum match score (i.e. the level of agreement required between the input and reference addresses to determine a match) and the street network offset (Rushton et al., 2006).

To facilitate critical appraisal of geocoding methods, it is proposed that as a minimum authors report the address model, percentage match rate and environmental context of the study (e.g. whether the environment was urban or rural, including the operational definition used). Additional useful details include the geocoding software used and the source of reference data, including publication date. Knowledge of a particular reference dataset should not be assumed, as international readers are unlikely to be familiar with foreign reference data. If the geocoding method is unknown (e.g. because data was already geocoded by the data provider), then this should be clearly stated.

7. Dimension five: access metrics

Once geocoded, the final step is to compute access metrics (Fig. 1). There are numerous methods for operationalising access, the most common of which can broadly be classified as either intensity metrics, proximity metrics, and gravity metrics (Charreire et al., 2010; Cobb et al., 2015).

Intensity metrics are indicative of the number or density of outlets within a zone (usually an aerial or a buffer zone). Aerial zones are

regions that have usually been pre-defined for purposes other than RFE research e.g. census tracts, healthcare districts, or local government districts. Buffer zones can be formed around a point, line or polygon (i.e. 2D shape), and can be defined either using Euclidian (straight line) distances, or network (street length) distances. There is no consensus on the appropriate zone size for defining RFE, and a variety of sizes have been used, ranging from 100 m to 6 mile buffer radii (Charreire et al., 2010; Cobb et al., 2015).

Different zoning systems have various limitations. For example, while aerial units may be highly relevant to governments and other policymakers, their arbitrary size and scale can lead to bias; a problem known as the Modifiable Areal Unit Problem (Fotheringham and Wong, 1991). All zoning methods are also limited in that they are unlikely to represent the true extent of an environment with which a person interacts (Crawford et al., 2014; Zenk et al., 2011); a problem termed the ‘uncertain geographic context problem’ (Kwan, 2012). Recent research has begun using GPS tracking to define environments (Ni Mhurchu et al., 2013). However, such methods may be flawed by reverse causality arguments, with GPS routes being dependent on an individual’s motivation to access certain FOs (Chaix et al., 2013). For these reasons, authors are encouraged to provide a rationale for their choice of zone type and size and to clearly define the ‘type’ of environment(s) being measured e.g. home, school or work environments, such that the conceptual basis for their zoning definition can be appraised.

Irrespective of how zones are defined, it is important that zoning methods are well described. In relation to aerial zones, any aerial boundary data used should be cited, including a date or other version identifier. This is because aerial zones (e.g. administrative zones) may change over time (Office for National Statistics, 2012), and because different sources of areal unit boundary data may have differing accuracy (Rushton et al., 2006).

Euclidian buffer zoning methods are generally well reported. However, where buffers are formed around a point, the methods for defining this point are not always clear due to lack of clarity in geocoding methods (see Dimension Four). The accuracy of the location of the buffer centroid may be an important consideration e.g. in studies involving small buffer sizes (~400 m) around large buildings. This is because, depending on where the centroid is located, parts of the true environment around the building may not be captured.

Calculating a network buffer has been made relatively easy through advances in GIS software. However, the relative ease of performing this procedure hides the complexity of algorithms underpinning the process, which as discussed by Forsyth et al. (2012b) vary between software providers and even between versions of software from the same provider. This can lead to differently defined buffers, and

reinforces the requirement to cite the geocoding software used or to describe buffering methods in detail.

Creating network buffers requires access to network data representing the positions of roads, paths, public transportation routes, and/or cycle routes. The quality and age of this data have bearing on the spatial accuracy of street network data, as mentioned above. Additionally, the type(s) of network included is also an important consideration because different network types (e.g. footpaths and motorways) will have variable applicability depending on whether the buffer is intended to represent e.g. a walking or driving distance. It is not uncommon for studies (e.g. Cerin et al., 2011; Jennings et al., 2011; Williams et al., 2015) to omit details on the network data used, or the types of route (e.g. footpath, cycle path, motorways) that were included.

In addition to reporting zoning method, it is also important to clearly report the units of the intensity metric. Intensity metrics have been measured as raw counts, or as normalised metrics ('densities'), which include count per capita, count per unit area, or count per unit length for buffers around a line (Burgoine et al., 2014; Cobb et al., 2015). Other studies have also included relative intensity metrics (e.g. the number of 'healthy' outlets relative to the number of 'unhealthy' outlets) (e.g. Clary et al., 2015; Cobb et al., 2015; Shier et al., 2012). It is not uncommon for authors (e.g. Abbott et al., 2014; Carroll-Scott et al., 2013; Fraser et al., 2012b) to use the word 'density', when the metric that is reported is actually a simple raw count. This leads to confusion and should be avoided. Clarity with regard to the operational definition of outlet intensity may be especially important for town planners who may be interested in setting maximum/minimum allowable outlet densities, for example.

Proximity metrics measure the 'accessibility' of foods, and can be calculated, e.g. as a Euclidian (straight line) distance, a network (street length) distance, a Manhattan distance (distance along perpendicular axes), or a travel time (Charreire et al., 2010; Cobb et al., 2015; Ni Mhurchu et al., 2013). Again, proximity metrics have various limitations. Notably, while proximity metrics may give a reasonable measure of food access in rural areas, they may under-estimate food access in urban areas, where a high number of similarly proximate food sources is likely (Guagliardo, 2004). This adds further basis to the argument that environmental context should always be reported. Other factors that should be reported are the same as for buffer methods i.e. clear definition of origin and destination locations, and specification of any network data, including network types included in analyses. Additionally, where travel time is calculated, the parameters used for calculating this (e.g. speed limits, public transport scheduling etc.) should be reported.

Gravity metrics are combined measures of accessibility and availability, wherein FO that are more proximal to a zone centroid are weighted more highly than those that are further away (Guagliardo, 2004). A common example is the kernel density metric (Cobb et al., 2015). Gravity metrics include a decay coefficient dictating how rapidly the weighting of FO falls with increasing distance (Guagliardo, 2004), and a zone radius (Thornton et al., 2010). To facilitate comparison between metrics, these parameters should be reported.

8. Geo-FERN (Geographic Information System Food Environment Reporting)

Based on the discussions above, a reporting framework is proposed (Supplementary Materials). To ensure that the framework is pragmatic, the suggestions are divided into those deemed essential to facilitate a minimum understanding and comparability between studies, and those which provide desirable supplementary information, enabling a higher level of critical appraisal, closer replicability of the study methods and/or more in-depth understanding of the study outcomes. One limitation of the proposed framework is that, when word limits are tight, authors may need to prioritise results and discussion sections and may not be able to meet all of the GeoFERN criteria. It is hoped however that at

least the 'essential' criteria will be achievable within most word limits, and that supplementary materials are used to provide additional methodological detail when this is not the case.

9. Future directions

Future research should continue to explore the impact of different methodological choices, and to work towards developing best practices for GIS-RFE. While the present framework focusses on the most commonly used methods in RFE research, new spatial methods for measuring RFE are emerging, such as use of omnidirectional imaging and GPS tracking, and future protocols may need to be developed for reporting these methods, if they become adopted widely.

10. Conclusion

Measures of the RFE are central to understanding the links between the RFE, health and obesity, with GIS-based measures being used by both researchers and practitioners. Absence of best practices for GIS-RFE research has led to highly diverse methods across multiple dimensions including data sources, data extraction methods, FO construct definitions, geocoding methods, and access metrics. This diversity makes it difficult - if not impossible - to collate research and reach a consensus on whether and how the RFE influences health and obesity. This problem is compounded by unclear and incomplete reporting, which at best makes it difficult to review evidence with a critical eye, and at worst precludes the interpretation of research in a meaningful way (i.e. one that supports policy).

GIS-RFE methods are typically complex, and the reporting of methods is not as simple as may be assumed. It is hoped that this discussion and proposed reporting framework provide support to authors in setting out the most salient details of their methods clearly and accurately. These materials are also intended to assist academics, policymakers and other practitioners in the critical appraisal of RFE research. It is our intention that adoption of the framework will go some way to helping to clarify and synthesise RFE research, enabling policymakers to make evidence-based choices.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.healthplace.2017.01.008.

References

- Abbott, G., Backholer, K., Peeters, A., Thornton, L., Crawford, D., Ball, K., 2014. Explaining educational disparities in adiposity: the role of neighborhood environments. *Obesity* 22 (11), 2413–2419.
- Bader, M.D.M., Ailshire, J.A., Morenoff, J.D., House, J.S., 2010. Measurement of the local food environment: a comparison of existing data sources. *Am. J. Epidemiol.* 171 (5), 609–617.
- Bell, S., Wilson, K., Shah, T.I., Gensher, S., Elliott, T., 2012. Investigating impacts of positional error on potential health care accessibility. *Spat. spatio-tempo. Epidemiol.* 3 (1), 17–29.
- Block, J.P., Christakis, N.A., O'Malley, A.J., Subramanian, S.V., 2011. Proximity to food establishments and body mass index in the Framingham heart study offspring cohort over 30 years. *Am. J. Epidemiol.* 174 (10), 1108–1114.
- Block, J.P., Scribner, R.A., DeSalvo, K.B., 2004. Fast food, race/ethnicity, and income: a geographic analysis. *Am. J. Prev. Med.* 27 (3), 211–217.
- Bloodworth, R.F., Ward, K.D., Relyea, G.E., Cashion, A.K., 2014. Food availability as a determinant of weight gain among renal transplant recipients. *Res. Nurs. Health* 37 (3), 253–259.
- Bodicoat, D.H., Carter, P., Comber, A., Edwardson, C., Gray, L.J., Hill, S., Webb, D.,

- Yates, T., Davies, M.J., Khunti, K., 2015. Is the number of fast-food outlets in the neighbourhood related to screen-detected type 2 diabetes mellitus and associated risk factors? *Public Health Nutr.* 18 (9), 1698–1705.
- Boone-Heinonen, J., Diez-Roux, A.V., Goff, D.C., Loria, C.M., Kiefe, C.I., Popkin, B.M., Gordon-Larsen, P., 2013. The neighborhood energy balance equation: does neighborhood food retail environment + physical activity environment=obesity? The CARDIA study. *PLoS One* 8 (12), (e85141-e85141).
- Burgoine, T., 2010. Collecting accurate secondary foodscape data. *A Reflect. Trials Tribul. Appetite* 55 (3), 522–527.
- Burgoine, T., Forouhi, N.G., Griffin, S.J., Wareham, N.J., Monsivais, P., 2014. Associations between exposure to takeaway food outlets, takeaway food consumption, and body weight in Cambridgeshire, UK: population based, cross sectional study. *BMJ* 348, 1–10.
- Burgoine, T., Harrison, F., 2013. Comparing the accuracy of two secondary food environment data sources in the UK across socio-economic and urban/rural divides. *Int. J. Health Geogr.* 12 (1), 1–8.
- Burgoine, T., Monsivais, P., 2013. Characterising food environment exposure at home, at work, and along commuting journeys using data on adults in the UK. *Int. J. Behav. Nutr. Phys. Act.* 10 (1), 85–95.
- Carroll-Scott, A., Gilstad-Hayden, K., Rosenthal, L., Peters, S.M., McCaslin, C., Joyce, R., Ickovics, J.R., 2013. Disentangling neighborhood contextual associations with child body mass index, diet, and physical activity: the role of built, socioeconomic, and social environments. *Soc. Sci. Med.* 95, 106–114.
- Casey, R., Chaix, B., Weber, C., Schweitzer, B., Charreire, H., Salze, P., Badariotti, D., Banos, A., Oppert, J.M., Simon, C., 2012. Spatial accessibility to physical activity facilities and to food outlets and overweight in French youth. *Int. J. Obes.* 36 (7), 914–919.
- Casey, R., Oppert, J.-M., Weber, C., Charreire, H., Salze, P., Badariotti, D., Banos, A., Fischler, C., Hernandez, C.G., Chaix, B., 2014. Determinants of childhood obesity: what can we learn from built environment studies? *Food Qual. Prefer.* 31, 164–172.
- Caspi, C.E., Frieber, R., 2016. Modified ground-truthing: an accurate and cost-effective food environment validation method for town and rural areas. *Int. J. Behav. Nutr. Phys. Act.* 13, 1–8.
- Caspi, C.E., Sorensen, G., Subramanian, S., Kawachi, I., 2012. The local food environment and diet: a systematic review. *Health Place* 18 (5), 1172–1187.
- Cayo, M.R., Talbot, T.O., 2003. Positional error in automated geocoding of residential addresses. *Int. J. Health Geogr.* 2 (10), 1–12.
- Cerin, E., Frank, L.D., Sallis, J.F., Saelens, B.E., Conway, T.L., Chapman, J.E., Glanz, K., 2011. From neighborhood design and food options to residents' weight status. *Appetite* 56 (3), 693–703.
- Cetateanu, A., Jones, A., 2014. Understanding the relationship between food environments, deprivation and childhood overweight and obesity: evidence from a cross sectional England-wide study. *Health Place* 27, 68–76.
- Chaix, B., Meline, J., Duncan, S., Merrien, C., Karusisi, N., Perchoux, C., Lewin, A., Labadi, K., Kestens, Y., 2013. GPS tracking in neighborhood and health studies: a step forward for environmental exposure assessment, a step backward for causal inference. *Health Place* 21, 46–51.
- Charreire, H., Casey, R., Salze, P., Simon, C., Chaix, B., Banos, A., Badariotti, D., Weber, C., Oppert, J.M., 2010. Measuring the food environment using geographical information systems: a methodological review. *Public Health Nutr.* 13 (11), 1773–1785.
- Charreire, H., Mackenbach, J.D., Ouasti, M., Lakerveld, J., Compernelle, S., Ben-Rebah, M., McKee, M., Brug, J., Rutter, H., Oppert, J.M., 2014. Using remote sensing to define environmental characteristics related to physical activity and dietary behaviours: a systematic review (the SPOTLIGHT project). *Health Place* 25, 1–9.
- Clary, C.M., Kestens, Y., 2013. Field validation of secondary data sources: a novel measure of representativity applied to a Canadian food outlet database. *Int. J. Behav. Nutr. Phys. Act.* 10 (77), 1–9.
- Clary, C.M., Ramos, Y., Shareck, M., Kestens, Y., 2015. Should we use absolute or relative measures when assessing foodscape exposure in relation to fruit and vegetable intake? Evidence from a wide-scale Canadian study. *Prev. Med.* 71, 83–87.
- Cobb, L.K., Appel, L.J., Franco, M., Jones-Smith, J.C., Nur, A., Anderson, C.A., 2015. The relationship of the local food environment with obesity: a systematic review of methods, study quality, and results. *Obesity* 23 (7), 1331–1344.
- Crawford, T.W., Jilcott Pitts, S.B., McGuirt, J.T., Keyserling, T.C., Ammerman, A.S., 2014. Conceptualizing and comparing neighborhood and activity space measures for food environment research. *Health Place* 30, 215–225.
- Department for Environment and Rural Affairs, 2016. Guide to applying the Rural Urban Classification to data [Internet]. Available from: (https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/539241/Guide_to_applying_the_rural_urban_classification_to_data.pdf) (accessed 26.08.16), 2016).
- Dobbs, R., Sawers, C., Thompson, F., Manyika, J., Woetzel, J.R., Child, P., McKenna, S., Spatharou, A., 2014. Overcoming obesity: an initial economic analysis. McKinsey Global Institute.
- Economic and Social Research Council. Data Citation. What you need to know. [Internet]. Available from: (https://www.ukdataservice.ac.uk/media/104397/data_citation_online.pdf) (accessed 29.06.16).
- Farley, T.A., Baker, E.T., Futrell, L., Rice, J.C., 2010. The ubiquity of energy-dense snack foods: a national multicity study. *Am. J. Public Health* 100 (2), 306–311.
- Farley, T.A., Rice, J., Bodor, J.N., Cohen, D.A., Bluthenthal, R.N., Rose, D., 2009. Measuring the food environment: shelf space of fruits, vegetables, and snack foods in stores. *J. Urban Health* 86 (5), 672–682.
- Feng, J., Glass, T.A., Curriero, F.C., Stewart, W.F., Schwartz, B.S., 2010. The built environment and obesity: a systematic review of the epidemiologic evidence. *Health Place* 16 (2), 175–190.
- Fiechtner, L., Block, J., Duncan, D.T., Gillman, M.W., Gortmaker, S.L., Melly, S.J., Rifas-Shiman, S.L., Taveras, E.M., 2013. Proximity to supermarkets associated with higher body mass index among overweight and obese preschool-age children. *Prev. Med.* 56 (3–4), 218–221.
- Fiechtner, L., Mona, S., Sequist, T., Block, J., Duncan, D.T., Melly, S.J., Rifas-Shiman, S.L., Taveras, E.M., 2015. Food environments and childhood weight status: effects of neighborhood median income. *Child. Obes.* 11 (3), 260–268.
- Fleischhacker, S., Evenson, K.R., Rodriguez, D.A., Ammerman, A.S., 2011. A systematic review of fast food access studies. *Obes. Rev.* 12 (5), e460–e471.
- Fleischhacker, S.E., Evenson, K.R., Sharkey, J., Pitts, S.B.J., Rodriguez, D.A., 2013. Validity of secondary retail food outlet data: a systematic review. *Am. J. Prev. Med.* 45 (4), 462–473.
- Fleischhacker, S.E., Rodriguez, D.A., Evenson, K.R., Henley, A., Gizlice, Z., Soto, D., Ramachandran, G., 2012. Evidence for validity of five secondary data sources for enumerating retail food outlets in seven American Indian Communities in North Carolina. *Int. J. Behav. Nutr. Phys. Act.* 9 (137), 1–14.
- Forsyth, A., Larson, N., Lytle, L., Mishra, N., Neumark-Sztainer, D., Noble, P., Van Riper, D., 2012a. LEAN-GIS Protocols (Local Environment for Activity and Nutrition Geographic Information Systems) Version 2.1, January 2012 [Internet]. Available from: (http://designforhealth.net/wp-content/uploads/2012/12/LEAN_Protocol_V2_1_010112rev.pdf) (accessed 22 July 2016).
- Forsyth, A., Lytle, L., Van Riper, D., 2010. Finding food: issues and challenges in using Geographic Information Systems to measure food access. *J. Transp. Land Use* 3 (1), 43–65.
- Forsyth, A., Schmitz, K.H., Oakes, M., Zimmerman, J., Koeppe, J., 2006. Standards for environmental measurement using GIS: toward a protocol for protocols. *J. Phys. Act. Health* 3 (Suppl 1), S241–S257.
- Forsyth, A., Van Riper, D., Larson, N., Wall, M., Neumark-Sztainer, D., 2012b. Creating a replicable, valid cross-platform buffering technique: the sausage network buffer for measuring food and physical activity built environments. *Int. J. Health Geogr.* 11 (14), 1–9.
- Fotheringham, A.S., Wong, D.W., 1991. The modifiable areal unit problem in multivariate statistical analysis. *Environ. Plan. A* 23 (7), 1025–1044.
- Fraser, L.K., Clarke, G.P., Cade, J.E., Edwards, K.L., 2012a. Fast food and obesity: a spatial analysis in a large United Kingdom population of children aged 13–15. *Am. J. Prev. Med.* 42 (5), e77–e85.
- Fraser, L.K., Edwards, K.L., Tomnitz, M., Clarke, G.P., Hill, A.J., 2012b. Food outlet availability, deprivation and obesity in a multi-ethnic sample of pregnant women in Bradford, UK. *Soc. Sci. Med.* 75 (6), 1048–1056.
- Frizzelle, B.G., Evenson, K.R., Rodriguez, D.A., Laraia, B.A., 2009. The importance of accurate road data for spatial applications in public health: customizing a road network. *Int. J. Health Geogr.* 8 (24), 1–11.
- Gibson, D.M., 2011. The neighborhood food environment and adult weight status: estimates from longitudinal data. *Am. J. Public Health* 101 (1), 71–78.
- Gilliland, J.A., Rangel, C.Y., Healy, M.A., Tucker, P., Loebach, J.E., Hess, P.M., He, M., Irwin, J.D., Wilk, P., 2012. Linking childhood obesity to the built environment: a multi-level analysis of home and school neighbourhood factors associated with body mass index. *Can. J. Public Health* 103 (9), (eS15-eS21).
- Glanz, K., Handy, S.L., Henderson, K.E., Slater, S.J., Davis, E.L., Powell, L.M., 2016. Built environment assessment: multidisciplinary perspectives. *SSM-Popul. Health* 2, 24–31.
- Goldberg, D.W., Wilson, J.P., Knoblock, C.A., 2007. From text to geographic coordinates: the current state of geocoding. *J. Urban Reg. Inf. Syst. Assoc.* 19 (1), 33–46.
- Government Office for Science, 2007. Foresight. Tackling Obesity: Future Choices-Project Report [Internet]. Available from: (https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/287937/07-1184x-tackling-obesity-future-choices-report.pdf) (accessed 4.08.16).
- Griffith, D.A., Millones, M., Vincent, M., Johnson, D.L., Hunt, A., 2007. Impacts of positional error on spatial regression analysis: a case study of address locations in Syracuse, New York. *Trans. GIS* 11 (5), 655–679.
- Griffiths, C., Frearson, A., Taylor, A., Radley, D., Cooke, C., 2014. A cross sectional study investigating the association between exposure to food outlets and childhood obesity in Leeds, UK. *Int. J. Behav. Nutr. Phys. Act.* 11 (1), 1–10.
- Guagliardo, M.F., 2004. Spatial accessibility of primary care: concepts, methods and challenges. *Int. J. Health Geogr.* 3 (1), 1–13.
- Han, E., Powell, L.M., Zenk, S.N., Rinkus, L., Ohri-Vachaspati, P., Chaloupka, F.J., 2012. Classification bias in commercial business lists for retail food stores in the US. *Int. J. Behav. Nutr. Phys. Act.* 9 (1), 1–9.
- Harrison, F., Jones, A.P., van Sluijs, E.M.F., Cassidy, A., Bentham, G., Griffin, S.J., 2011. Environmental correlates of adiposity in 9–10 year old children: considering home and school neighbourhoods and routes to school. *Soc. Sci. Med.* 72 (9), 1411–1419.
- Hobbs, M., Green, M., Griffiths, C., Jordan, H., McKenna, J., 2016. How different data sources and definitions of neighbourhood influence the association between food outlet availability and body mass index: a cross-sectional study. *Perspectives in Public Health*, [Online] Available at: (<https://www.ncbi.nlm.nih.gov/pubmed/27282516>) (accessed 1 Sept 2016).
- Hurvitz, P.M., Moudon, A.V., Rehm, C.D., Streichert, L.C., Drewnowski, A., 2009. Arterial roads and area socioeconomic status are predictors of fast food restaurant density in King County, WA. *Int. J. Behav. Nutr. Phys. Act.* 6 (1), 1–8.
- Institute of Medicine, 2012. Accelerating Progress in Obesity Prevention. Solving the Weight of the Nation. [Internet]. Available from: (<http://www.nationalacademies.org/hmd/Reports/2012/Accelerating-Progress-in-Obesity-Prevention.aspx>) (accessed 09.06.16).
- International Food Policy Research Institute, 2016. Global Nutrition Report 2016: From Promise to Impact: Ending Malnutrition by 2030. Washington, DC.
- Jacquez, G.M., 2012. A research agenda: does geocoding positional error matter in health GIS studies? *Spat. Spatio-Tempo. Epidemiol.* 3 (1), 7–16.

- Jennings, A., Welch, A., Jones, A.P., Harrison, F., Bentham, G., van Sluijs, E.M.F., Griffin, S.J., Cassidy, A., 2011. Local food outlets, weight status, and dietary intake: associations in children aged 9–10 years. *Am. J. Prev. Med.* 40 (4), 405–410.
- Kelly, B., Flood, V.M., Yeatman, H., 2011. Measuring local food environments: an overview of available methods and measures. *Health Place* 17 (6), 1284–1293.
- Kopelman, P., 2007. Health risks associated with overweight and obesity. *Obes. Rev.* 8 (s1), 13–17.
- Kwan, M.-P., 2012. The uncertain geographic context problem. *Ann. Assoc. Am. Geogr.* 102 (5), 958–968.
- Lake, A.A., Burgoine, T., Greenhalgh, F., Stamp, E., Tyrrell, R., 2010. The foodscape: classification and field validation of secondary data sources. *Health Place* 16 (4), 666–673.
- Liese, A.D., Barnes, T.L., Lamichhane, A.P., Hibbert, J.D., Colabianchi, N., Lawson, A.B., 2013. Characterizing the food retail environment: impact of count, type, and geospatial error in 2 secondary data sources. *J. Nutr. Educ. Behav.* 45 (5), 435–442.
- Liese, A.D., Colabianchi, N., Lamichhane, A.P., Barnes, T.L., Hibbert, J.D., Porter, D.E., Nichols, M.D., Lawson, A.B., 2010. Validation of 3 food outlet databases: Completeness and geospatial accuracy in rural and urban food environments. *Am. J. Epidemiol.* 172 (11), 1324–1333.
- Lucan, S.C., Maroko, A.R., Bumol, J., Torrens, L., Varona, M., Berke, E.M., 2013. Business list vs ground observation for measuring a food environment: saving time or waste of time (or worse)? *J. Acad. Nutr. Diet.* 113 (10), 1332–1339.
- Macdonald, L., Ellaway, A., Ball, K., Macintyre, S., 2011. Is proximity to a food retail store associated with diet and BMI in Glasgow, Scotland? *BMC Public Health* 11 (1), 1–9.
- Mendez, D.D., Kim, K.H., Hardaway, C.R., Fabio, A., 2016. Neighborhood racial and socioeconomic disparities in the food and alcohol environment: are there differences by commercial data sources? *J. Racial Ethn. Health Disparities* 3 (1), 108–116.
- Moudon, A.V., Drewnowski, A., Duncan, G.E., Hurvitz, P.M., Saelens, B.E., Scharnhorst, E., 2013. Characterizing the food environment: pitfalls and future directions. *Public Health Nutr.* 16 (7), 1238–1243.
- Ni Mhurchu, C., Vandevijvere, S., Waterlander, W., Thornton, L.E., Kelly, B., Cameron, A.J., Snowdon, W., Swinburn, B., 2013. Monitoring the availability of healthy and unhealthy foods and non-alcoholic beverages in community and consumer retail food environments globally. *Obes. Rev.: Off. J. Int. Assoc. Study Obes.* 14 (Suppl 1), 108–119.
- Office for National Statistics, 2012. Changes to Output Areas and Super Output Areas in England and Wales, 2001 to 2011 [Internet]. Available from: <https://data.gov.uk/data/resource_cache/84/845565bb-26d7-4894-af29-083f4a7fa0e5/report-changes-to-output-areas-and-super-output-areas-in-england-and-wales--2001-to-2011.pdf> (accessed 30.05.16).
- Ohri-Vachaspati, P., Leviton, L.C., 2010. Measuring food environments: a guide to available instruments. *Am. J. Health Promot.* 24 (6), 410–426.
- Oliver, M.N., Matthews, K.A., Siadaty, M., Hauck, F.R., Pickle, L.W., 2005. Geographic bias related to geocoding in epidemiologic studies. *Int. J. Health Geogr.* 4 (29), 1–9.
- Ordnance Survey, 2006. Points of Interest, May–September 2006 Ordnance Survey [CD-ROM].
- Ordnance Survey, 2016a. Points of Interest [Internet]. Available from: (<https://www.ordnancesurvey.co.uk/business-and-government/products/points-of-interest.html>) (accessed 28.06.16).
- Ordnance Survey, 2016b. Points of Interest March 2016 version. EDINA Digimap [distributor] [Internet]. Available from: (<http://edina.ac.uk/digimap>) (accessed 15.07.16).
- Paquet, C., Daniel, M., Kestens, Y., Leger, K., Gauvin, L., 2008. Field validation of listings of food stores and commercial physical activity establishments from secondary data. *Int. J. Behav. Nutr. Phys. Act.* 5 (58), 1–7.
- Public Health England, 2014. National Diet and Nutrition Survey Results from Years 1, 2, 3 and 4 (combined) of the Rolling Programme (2008/2009–2011/2012) [Internet]. Available from: (https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/310995/NDNS_Y1_to_4_UK_report.pdf) (accessed 26.08.16).
- Reilly, J.J., Methven, E., McDowell, Z.C., Hacking, B., Alexander, D., Stewart, L., Kelnar, C.J., 2003. Health consequences of obesity. *Arch. Dis. Child.* 88 (9), 748–752.
- Rose, D., Bodor, J.N., Hutchinson, P.L., Swalm, C.M., 2010. The importance of a multi-dimensional approach for studying the links between food access and consumption. *J. Nutr.* 140 (6), 1170–1174.
- Rundle, A., Neckerman, K.M., Freeman, L., Lovasi, G.S., Purciel, M., Quinn, J., Richards, C., Sircar, N., Weiss, C., 2009. Neighborhood food environment and walkability predict obesity in New York City. *Environ. Health Perspect.* 117 (3), 442–447.
- Rushton, G., Armstrong, M.P., Gittler, J., Greene, B.R., Pavlik, C.E., West, M.M., Zimmerman, D.L., 2006. Geocoding in cancer research: a review. *Am. J. Prev. Med.* 30 (2), S16–S24.
- Schootman, M., Sterling, D.A., Struthers, J., Yan, Y., Laboube, T., Emo, B., Higgs, G., 2007. Positional accuracy and geographic bias of four methods of geocoding in epidemiologic research. *Ann. Epidemiol.* 17 (6), 464–470.
- Shier, V., An, R., Sturm, R., 2012. Is there a robust relationship between neighbourhood food environment and childhood obesity in the USA? *Public Health* 126 (9), 723–730.
- Skidmore, P., Welch, A., Sluijs, E. v., Jones, A., Harvey, I., Harrison, F., Griffin, S., Cassidy, A., 2010. Impact of neighbourhood food environment on food consumption in children aged 9–10 years in the UK SPEEDY (Sport, Physical Activity and Eating behaviour: Environmental Determinants in Young people) study. *Public Health Nutrition* 13, 1022–1030.
- Smith, D., Cummins, S., Clark, C., Stansfeld, S., 2013. Does the local food environment around schools affect diet? Longitudinal associations in adolescents attending secondary schools in East London. *BMC Public Health* 13 (70), 1–10.
- Swinburn, B., Sacks, G., Vandevijvere, S., Kumanyika, S., Lobstein, T., Neal, B., Barquera, S., Friel, S., Hawkes, C., Kelly, B., 2013. INFORMAS (International Network for food and Obesity/non-communicable diseases Research, Monitoring and Action Support): overview and key principles. *Obes. Rev.* 14 (S1), 1–12.
- Thornton, L.E., Crawford, D.A., Ball, K., 2010. Neighbourhood-socioeconomic variation in women's diet: the role of nutrition environments. *Eur. J. Clin. Nutr.* 64 (12), 1423–1432.
- Thornton, L.E., Pearce, J.R., Macdonald, L., Lamb, K.E., Ellaway, A., 2012. Does the choice of neighbourhood supermarket access measure influence associations with individual-level fruit and vegetable consumption? A case study from Glasgow. *Int. J. Health Geogr.* 11 (29), 1–12.
- Williams, J., Scarborough, P., Townsend, N., Matthews, A., Burgoine, T., Mumtaz, L., Rayner, M., 2015. Associations between food outlets around schools and bmi among primary students in England: a cross-classified multi-level analysis. *PLoS One* 10 (7), 1–17.
- World Health Organisation, 2016. Report of the commission on ending childhood obesity. WHO Press, Geneva, Switzerland.
- Zandbergen, P.A., 2008. A comparison of address point, parcel and street geocoding techniques. *Comput., Environ. Urban Syst.* 32 (3), 214–232.
- Zenk, S.N., Schulz, A.J., Matthews, S.A., Odoms-Young, A., Wilbur, J., Wegrzyn, L., Gibbs, K., Braunschweig, C., Stokes, C., 2011. Activity space environment and dietary and physical activity behaviors: a pilot study. *Health Place* 17 (5), 1150–1161.