Mapping the food environment: The reliability of volunteered geographical information and institutional data sources in France

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Competing interests

The authors declare that they have no competing interests.

Authors' contribution

SV designed the study, performed ground-truthing, created figures and tables and interpreted results. SV drafted the article. CP critically revised the article. CP and CTS supervised the study, discussed the results, and worked on funding acquisition. CTS managed the research project. All authors read and approved the final manuscript.

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Abstract

The obesity epidemic and inequalities in access to food are prompting increasing numbers of food environment studies, which rely on secondary data sources for mapping. This article assesses the reliability of the two main food outlet data sources in France: the volunteered geographical information (VGI) collaborative map OpenStreetMap (OSM) and the national business register Sirene. Their information on food outlets was assessed through ground-truthing in the city-region of Montpellier. Sensitivity, positive predictive value, and concordance were computed for each database. We analyzed the socio-spatial variability of these measures according to households' income level. The sensitivity of Sirene is good and that of OSM moderate, while the opposite holds for positive predictive value, and the concordance of both OSM and Sirene is fair. Sirene provides more reliable data on deprived neighborhoods and OSM on wealthy neighborhoods. Caution is recommended regarding the classifications on which they are based, the time required to update the institutional database, and socially-influenced contributions to VGI.

Keywords

Field validation; OpenStreetMap; Sirene; Positive predictive value; Sensitivity; Concordance; Foodscape.

1 Introduction

The obesity epidemic (WHO, 2000) has turned scholars' attention to the food environment, individual exposure to food availability being considered one determinant of food choices

(HLPE, 2017). Studies have addressed the relationship between food environment and socioeconomic characteristics at neighborhood scale, seeking to identify impacts on diet (Caspi, Sorensen, Subramanian, & Kawachi, 2012) and obesity (Cobb et al., 2015; Gamba, Schuchter, Rutt, & Seto, 2015). A fine knowledge of the existing food supply in a given area is a necessary prerequisite both for research on inequalities in food access and for actions aimed at modifying the local food environment. Food outlets are considered the main component of the food environment (Glanz, Sallis, Saelens, & Frank, 2005), but mapping them at the scale of a city from exhaustive fieldwork is rarely feasible, due to both financial and time constraints. Many studies therefore employ secondary data (Lake, Burgoine, Greenhalgh, Stamp, & Tyrrell, 2010; Wilkins, Morris, Radley, & Griffiths, 2017), mainly from commercial and institutional databases (Fleischhacker, Evenson, Sharkey, Pitts, & Rodriguez, 2013; Gamba et al., 2015; Wilkins et al., 2019). Another source that offers significant potential for mapping food outlets is volunteered geographical information (VGI). However, to date, this collaborative data source's reliability for mapping food environments has never been evaluated. In fact, in France, despite the increasing number of food environment studies over the last decade (Casey et al., 2012; Chaix et al., 2012; Drewnowski et al., 2014; Salze et al., 2017), none of the various data sources has been assessed in terms of reliability.

Our paper contributes to filling these gaps by assessing and comparing the mapping reliability of two data sources: the VGI collaborative map OpenStreetMap and a national institutional database, the French national business register Sirene. The information they provide on location and type of food stores and restaurants was assessed through in-person validation (ground-truthing) in the city-region of Montpellier (France). This paper should therefore be useful to researchers and institutions interested in exploring the structural and institutional mechanisms behind food accessibility, offering guidance on both the potential and the limitations of these data sources.

2 State of the art

2.1 Mapping the food environment to address food access issues

For two decades, scholars have explored the impact of the food environment on diet and documented social inequalities in physical access to healthy food (Vonthron, Perrin, & Soulard, 2020). To assess food environments, most consider the density, diversity, and proximity of food outlets (Glanz et al., 2005). The concept of the food desert is employed to refer to areas or neighborhoods with very poor physical and economic access to “healthy food” (Beaulac, Kristjansson, & Cummins, 2009). Such food deserts are predominantly identified in socially disadvantaged areas, combining "unhealthy" food and a high prevalence of overweight. Thus, researchers have highlighted the possible links between inequalities in areas’ physical access to food and social and territorial inequalities in health (Walker, Keane, & Burke, 2010).

In France, the site of this study, 47% of adults in 2020 were overweight, and 17% of these obese (Ligue contre l’obésité, 2021). A strong social gradient is recognized to exist in the distribution of these prevalences (McLaren, 2007), with the prevalence of obesity decreasing as the level of education and income rises (de Saint Pol, 2007). These social inequalities in health are also spatial inequalities, since the relationship between socioeconomic status and body mass index varies spatially, particularly depending on the urban context (Feuillet et al., 2020). While diet and physical activity are acknowledged as the main determinants of overweight and obesity (Swinburn et al., 2011), there is less consensus regarding the relationships between food environment and food behaviors or overweight. Scholars have identified an effect of the food environment *surrounding schools* on overweight in children, but not on food purchases and consumption (Williams et al., 2014). According to the review by Lam, Vaartjes, Grobbee, Karssenberg, & Lakerveld (2021), most studies find no association between food environment and weight status, while the review of Turner, Green, Alae-Carew, & Dangour (2021) finds associations between food environment and consumption. Actually, this second review highlights an apparent link between the consumption of fruits and vegetables and the availability of food outlets selling fruits and vegetables, rather than the proximity and the density of these food outlets.

Different methods are used to perform these analyses, and this diversity may explain some of these mixed and even contradictory results (Lam et al., 2021; Titis, Procter, & Walasek, 2022; Turner et al., 2021). However, the articles do not provide enough details on the methods used to enable researchers to assess the effects of each method on the results (Wilkins et al., 2019). Such methodological choices include the data sources used to characterize the food environment, whose reliability needs to be ensured.

2.2 Common issues of reliability in commercial and institutional food outlet databases

Commercial and institutional data sources provide imperfect completeness and accuracy on the location of food outlets (Lake et al., 2010; Lebel et al., 2017; Lyseen & Hansen, 2014; Wilkins et al., 2019). This lack of data quality is often disregarded by users, leading to potential misuse (Devillers & Jeansoulin, 2006) and bias (Cobb et al., 2015; Gamba et al., 2015; Wilkins et al., 2019). For example, Ma *et al.* (2013) showed that measures of food accessibility could vary depending on the data source used to characterize the food environment. Results may also differ depending on the database used to consider associations between food store density and neighborhood sociodemographic characteristics (Mendez, Kim, Hardaway, & Fabio, 2016), as well as associations between number of food stores and body mass index (Hobbs et al., 2017).

Data source quality assessments have been performed in the United States, Canada, Northern European countries, and the United Kingdom. Database content quality is assessed against a reference (gold standard) like another database considered as reliable, or against field observations. These assessments consider excess data, i.e. food outlets listed in the databases but not the reference, and missing data, i.e. food outlets not listed in the databases but which exist according to the reference. Systematic literature reviews by Fleischhacker *et* *al.* (2013) and Lebel *et al.* (2017) found errors of both types in both commercial and administrative databases, but generally less missing data than excess data. In addition, Lebel *et al.* (2017) found that the reliability of the data sources evaluated in the United States, Canada, and the United Kingdom was comparable, while the reliability of the data sources evaluated in Denmark was higher, in terms of both excess and missing data. The greatest variability was observed in the United States, where most assessments were conducted. Most studies evaluated national databases, although some looked at local ones (Wilkins et al., 2017). More recently, a few studies following the example of Präger *et al.* (2019) have evaluated internationally available data sources: Google Maps and OpenStreetMap. However, there are not enough of these studies yet to extrapolate their results to a country other than the one where the evaluations were conducted.

2.3 Limitations and growing potential of volunteered geographical information

Volunteered geographical information offers significant and growing potential for research (Greg Brown & Kyttä, 2014; Goranson, Thihalolipavan, & di Tada, 2013; Kolak et al., 2020; Sui & DeLyser, 2012), particularly for food environment studies (Cervigni, Renton, Haslam McKenzie, Hickling, & Olaru, 2020; Fast & Rinner, 2018; Liu, Widener, Burgoine, & Hammond, 2020; Quinn & Yapa, 2016). As this geographical information is contributed by volunteers from the general public (Goodchild, 2007; Mericskay & Roche, 2011), it is a source of continuously updated data that is cost-effective and covers large areas not restricted by administrative boundaries (Goodchild, 2007; Sullivan et al., 2009; Zhang & Zhu, 2019). In their review of the literature, Zhang and Zhu (2018) identify three strands of work assessing the reliability of VGI and thus its potential for use: (i) work assessing the representativeness of VGI contributors (Gregory Brown, Kelly, & Whitall, 2014; Hecht & Stephens, 2014; Malik, Lamba, Nakos, & Pfeffer, 2015); (ii) work evaluating the completeness of VGI databases (Girres & Touya, 2010; Haklay, 2010); and (iii) work evaluating the representativeness of VGI databases for a specific use (Snäll, Kindvall, Nilsson, & Pärt, 2011).

The OpenStreetMap (OSM) collaborative map is one of the most widely assessed VGI projects (Senaratne, Mobasheri, Ali, Capineri, & Haklay, 2017). Scholars have highlighted the spatial heterogeneity of object/place location accuracy in OSM (Ciepłuch, Jacob, Mooney, & Winstanley, 2010; Fan, Zipf, Fu, & Neis, 2014), issues with map completeness, in particular missing data (Barron, Neis, & Zipf, 2014; Girres & Touya, 2010), and issues with object classification (Girres & Touya, 2010; Mooney & Corcoran, 2012). The latter showed that the misclassification of places in OSM was mainly due to contributors manually selecting ontology values and spelling them incorrectly, as well as to the lack of precision in the ontology. Finally, in their literature review of the methods used to assess VGI quality, Senaratne *et al.* (2017) identified a lack of use of ground-truth data, and suggested that such ground-truthing would enhance reliability assessment of data sources such as OSM.

Despite the warnings from this extensive literature, however, OSM is beginning to be used in food environments studies as a source of food outlet data (Kwate & Loh, 2016; Liu et al., 2020; Nguyen et al., 2017). Yet almost no research has, to our knowledge, specifically investigated OSM reliability regarding food outlets. In their study, Liu *et al.* (2020) simply mention a strong correlation between OSM data and an official Canadian database regarding the number of fast food outlets. While Präger *et al.* (2019) evaluated OSM for the study of obesogenic environments, including restaurants, they did not include food stores and their results on reliability did not distinguish restaurants from the other categories they considered (medical centers, schools, sports facilities, etc.). Therefore, OSM remains to be validated for food environment studies.

3 Methods

3.1 Area

The study area is the French city-region of Montpellier (465,000 inhabitants, 422 km²), which includes the core-city of Montpellier (280,000 inhabitants) and its periphery composed of 30 peri-urban municipalities. The high social deprivation and income inequalities between neighborhoods make this city-region particularly pertinent for food environment studies. In

2018 (INSEE), 19.8% of the population was living below the low-income threshold (60% of median disposable income). Individual annual median disposable income varies from €10,690 to €31,940 among the neighborhoods (Fig. 1 & 2).

While an Agroecological and Food Policy was initiated in 2015 by the city-region authority (Michel & Soulard, 2019), it does not consider the spatial distribution of food outlets as an issue requiring public attention, as there is no scientific evidence regarding how the local food environment and food practices are related.

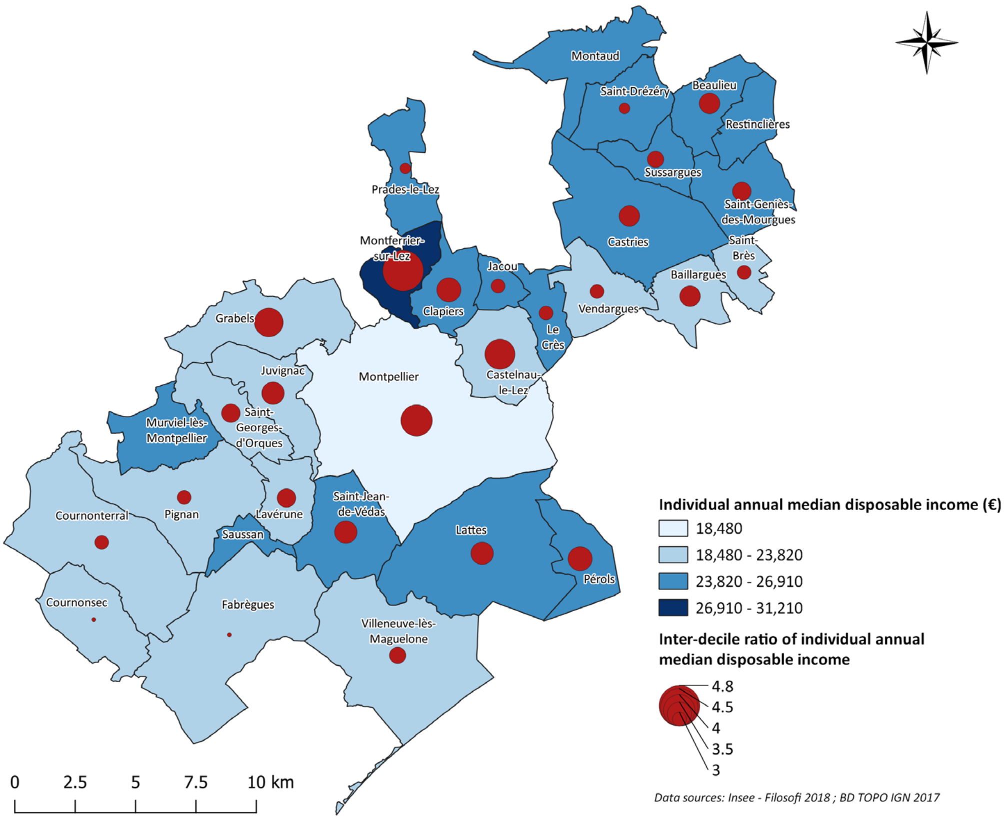

Fig 1: Individual disposable incomes in the municipalities of the Montpellier city-region in 2018

The inter-decile ratios of individual annual median disposable income of the municipalities of Cournonsec, Montaud, Murviel-lès-Montpellier, Restinclières and Saussan are not available due to statistical confidentiality.

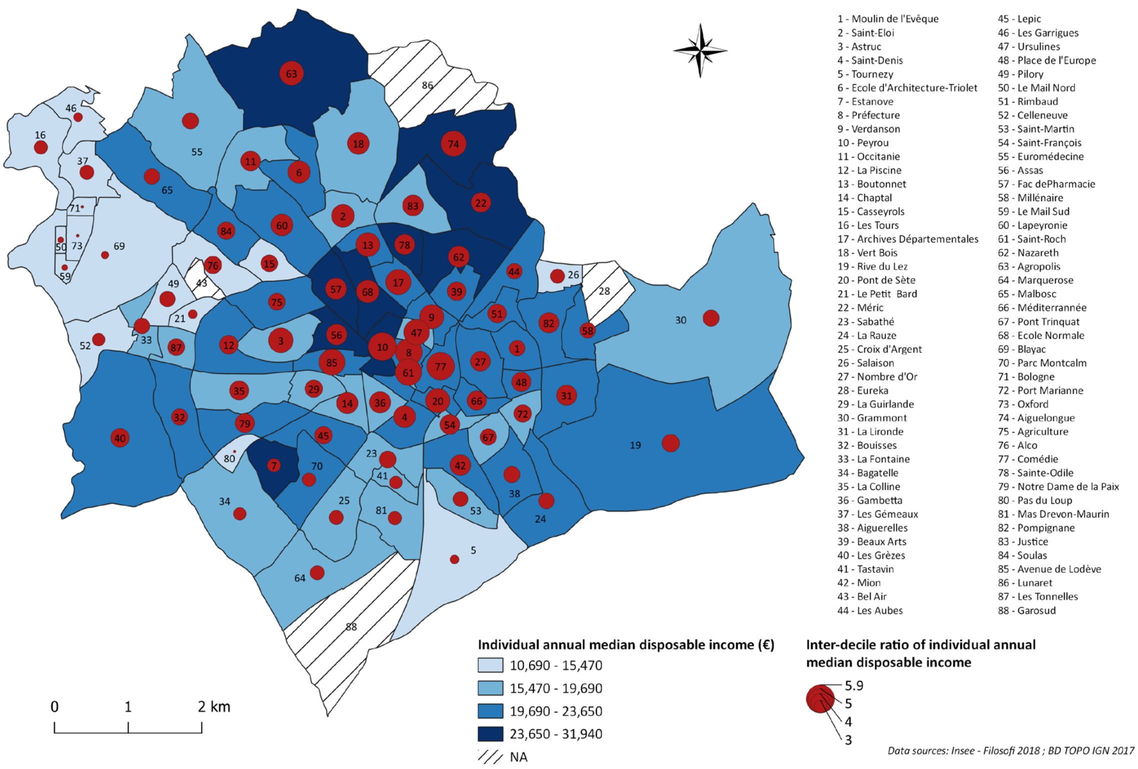

Fig. 2: Individual disposable incomes in the neighborhoods of Montpellier in 2018

3.2 Ground-truthing

Ground-truth data is key to assessing the completeness of data sources (Barron et al., 2014; Senaratne et al., 2017). Thus, to evaluate the reliability of the Sirene and OSM data sources, we compared their information on location and type of food stores and restaurants with observations we recorded in the field. As recommended by Fleischhacker *et al.* (2013), both missing and excess data were identified by ground-truthing rather than on-site verification (e.g. Rossen, Pollack, & Curriero, 2012; Svastisalee, Holstein, & Due, 2012), which only provides information about excess data. Our in-person field observations thus served as gold standard.

Although the perimeter of our study is the Montpellier city-region, it was not feasible to conduct exhaustive systematic field surveys over this whole area, and we therefore selected a spatial sample. This approach to ground-truthing has frequently been used to focus on a few neighborhoods or census tracks (Clary & Kestens, 2013; Lake et al., 2010). To address potential inter-neighborhood differences in data source completeness, we opted for a random sampling of survey units, similar to the protocol used by Lyseen and Hansen (2014) in Aalborg, Denmark.

Our survey unit is the smallest made available by the French national institute of statistics: 200 x 200 m inhabited grid cells. The ground-truthing was performed on 10% of the city of Montpellier in 103 cells, and in another 103 cells spread over the 30 other municipalities of the metropolitan area, for a total of 206 cells (Fig. 3). The grid cells were selected through a random spatial sampling method using QGIS 2.18.

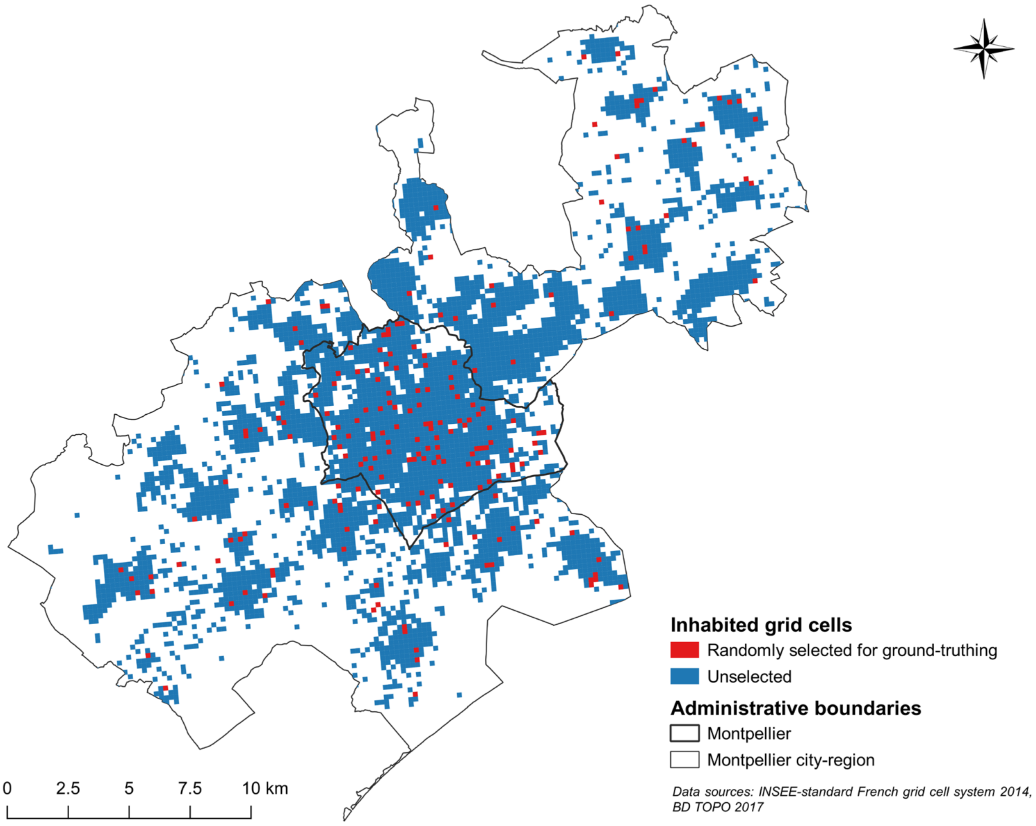

Fig.3: Spatial distribution of 206 randomly selected grid cells within the Montpellier city-region

3.3 Data sources

3.3.1 The French national business register: Sirene

The French National Institute of Statistics and Economic Studies (INSEE) produces the national business register, called Sirene, which records and collects economic and legal information on all new businesses, including food outlets. A person declaring a new business suggests an APE code (type of Principal Activity Exercised). The final APE code is chosen by INSEE based on a classification (NAF Rev.2) that is defined by decree. INSEE updates the Sirene register every day.

We chose the institutional Sirene database for this study for three reasons. First, it is the reference for official statistics on the number of shops in all French municipalities (Insee, 2021). Second, it is free and publicly available, and third, it is the data source used in the latest French studies on food environments (Charreire et al., 2017; Salze et al., 2017). We extracted from Sirene the commercial establishments with a predominantly food activity, according to their APE code (Table 1). The definition of each category is available on the INSEE website[1]. We used a free geocoded version of the Sirene register (Quest, 2017) and extracted data from April 2018 to match our OSM data extraction date.

3.3.2 OpenStreetMap

OpenStreetMap is a collaborative project based on volunteered geographical information. The data is updated by a community of contributors on an ongoing basis. OSM's contributors use tags to describe features of map elements. Tags are described in a wiki[2], which states: “the community agrees on certain key and value combinations for the most commonly used tags, which act as informal standards.” For example, a supermarket is described by the tag ‘shop=supermarket’ where ‘shop’ is the key and ‘supermarket’ the value. However, tags are

[1] https://www.insee.fr/fr/metadonnees/nafr2/
[2] https://wiki.openstreetmap.org/wiki/Map_features

free format text fields, so contributors can also create new tags and definitions are not standardized.

The OSM data are free and under open-content license. We extracted OSM data using the QuickOSM plugin in QGIS 2.18 on April 18, 2018.

3.3.3 Fieldwork

We systematically recorded the name, category and GPS coordinates of each food store and food service establishment observed in the streets, using the Epicollect 5 smartphone application. Information was collected by walking, cycling or driving through all the streets of the selected grid cells between May 2018 and January 2019.

We standardized the categories from the different data sources for purposes of comparison with fieldwork results (Table 1). This yielded 11 food outlet categories, 9 of which are food stores and 2 restaurants. We excluded food outlets such as bars, liquor stores or event caterers. We also excluded open-air food markets because of their absence from the Sirene register and their limited opening hours (one to two half-days per week).

Outlets observed in the field were classified in categories according first, to what the front of the outlet indicated and second, to the definitions in the OSM wiki, intended for use by non-specialist contributors. The Sirene definitions of categories, although more precise, did not seem applicable in the field – for instance, definitions of general food stores (grocery store, supermarket, etc.) are based on store size. All field observations were made by a single person in order to ensure homogeneity in choice of categories.

Table 1: Food outlet categories. Matching between Sirene and OpenStreetMap

Sirene (APE code)	**OpenStreetMap**		**Standardized category**
	Amenity	**Shop**	
Other specialized food store (47.29Z)		Coffee	Other

		Cheese	
Butcher shop (47.22Z)		Butcher	Butcher shop
Baked goods shop (10.71B) Bakery (10.71C) Patisserie (10.71D)		Bakery	Bakeries
Shop selling candy, chocolate, bread and pastry not self-produced (47.24Z)		Chocolate	Chocolate and candy shops
General food (47.11B) Grocery store (47.11C)		Convenience	Grocery store
Cafeterias and buffets (56.10B) Fast food restaurants (56.10C)	Fast food		Fast food restaurant
Supermarket (47.11D; 47/11E) Bigger supermarkets (47.11F)		Supermarket	Supermarket
Fish shop (47.23Z)		Seafood	Fish shop
Greengrocer (47.21Z)		Greengrocer	Greengrocer
Traditional restaurant (56.10A)	Restaurant		Restaurant
Frozen food store (47.11A)		Frozen food	Frozen food store

3.4 Validity measures

To assess the reliability of databases, the scientific literature uses three validity measures: sensitivity (S), positive predictive value (PPV), and concordance (C) (Table 2) (Fleischhacker et al., 2013; Lebel et al., 2017). We adapted these measures of databases' completeness and object classification to our objective: to determine how reliably these databases depict the food environment, defined as individuals' exposure to particular food availability depending on the spatial distribution of food outlets. This is what Devillers (2004) calls 'fitness-for-use': in the food environment case, errors related to i) the name of a shop or ii) the takeover of a shop by another person selling the same products do not impact food availability, nor physical access to food. Traditional assessment methods are therefore likely to underestimate the databases' potential to characterize food environments (Lebel et al., 2017). Thus, we decided not to take into account the name of the outlet when defining a true or false positive, which Clary and Kestens (2013) call “relaxed measures”. A true positive was defined as the correspondence between a database and the field based on only two criteria: the category of the food outlet (same category) and its location (same street and same grid cell).

Table 2: Calculation of validity measures

		Fieldwork	
		Outlet present	Outlet absent
Database	Outlet present	True positive (TP)	False positive (FP)
	Outlet absent	False negative (FN)	True negative (TN)

(1) Positive prediction value (PPV) = TP / (TP + FP)

(2) Sensitivity (S) = TP / (TP + FN)

(3) Concordance (C) = TP / (TP + FP + FN)

We computed these validity measures (S, PPV, and C) both in aggregate for each database and by category for the categories with the most outlets.

Finally, we analyzed the socio-spatial variability of these measures, stratifying our sample according to the income level of households living in each grid cell. We assigned to each cell the median income of the census tract in which the cell is included. The two strata thus correspond to the grid cells in which the median annual disposable income is below (resp. above) that of all the inhabitants of the Montpellier city-region, i.e. €20,036 per inhabitant in 2015 (Fig. 4). The income data come from INSEE (Filosofi database).

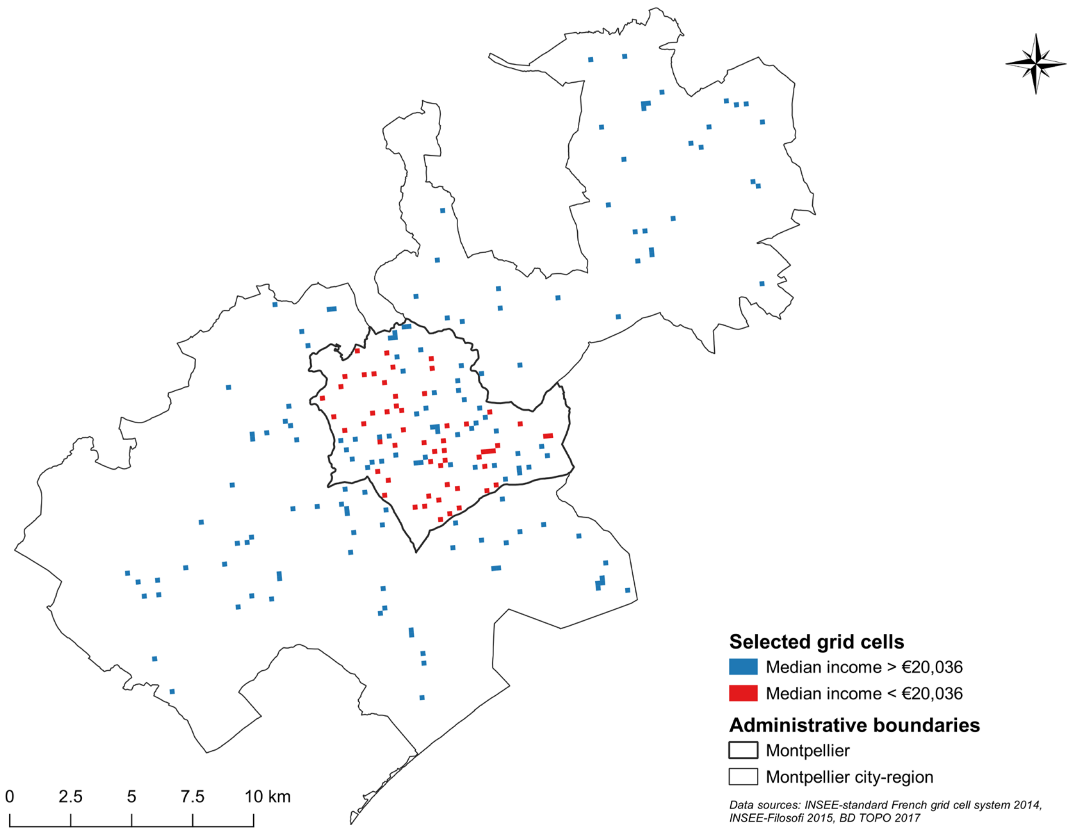

Fig.4: Spatial distribution of income in the randomly selected grid cells

The validity measures are interpreted according to the scale proposed by Paquet *et al.* (2008): below 0.30 is considered poor, from 0.31 to 0.50 fair, from 0.51 to 0.70 moderate, from 0.71 to 0.90 good, and above 0.91 excellent. Although using this scale is controversial (Lebel et al., 2017), since it was developed in a different context (Janse et al., 2004), it allows us to compare our measures to those of other reliability assessment studies, almost all of which use this scale.

4 Results

4.1 Overall reliability of Sirene and OSM

Of the 192 food outlets we recorded in the field, 72% are food service establishments: 80 traditional restaurants and 59 fast food restaurants (Table 3). Overall, the Sirene register over-records (228 food outlets), while OSM under-records (130 food outlets). The true positives consist of 137 food outlets listed in the Sirene register (respectively 101 in OSM) that are also observed in the field. The false positives consist of 91 food outlets listed in Sirene (resp. 29 in OSM) that do not, or no longer, exist in the field. The false negatives consist of 55 food outlets recorded in the field but missing from the Sirene register (resp. 89 in OSM).

Sensitivity measures reveal that Sirene is more exhaustive than OSM. However, positive predictive values show that OSM contains fewer establishments that do not, or no longer, exist than Sirene. Finally, concordance is higher for Sirene than for OSM.

Thus, according to the interpretation scale of Paquet *et al.* (2008), the sensitivity of the Sirene register is good (0.71) and that of OSM moderate (0.53). Conversely, positive predictive value is good for OSM (0.78) and moderate for Sirene (0.60). Concordance for both OSM and Sirene is fair (0.46-0.48).

Table 3: Validity measures computed for Sirene and OpenStreetMap

	Number of food outlets			**Sensitivity**		**Positive predictive value**		**Concordance**	
	Fieldwork	**Sirene**	**OSM**	**Sirene**	**OSM**	**Sirene**	**OSM**	**Sirene**	**OSM**
Total	192	228	130	0.71	0.53	0.60	0.78	0.48	0.46
Category									
Other	4	6	1	0.5	0.25	0.33	1.00	0.25	0.25
Butcher shop	3	4	3	1.00	1.00	0.75	1.00	0.75	1.00
Bakeries	12	15	8	0.92	0.67	0.73	1.00	0.69	0.67
Chocolate and candy shops	1	2	0	0	0	0	NA	0	0
Grocery store	16	22	6	0.75	0.38	0.55	1.00	0.46	0.38
Fast food restaurant	59	69	29	0.71	0.44	0.61	0.86	0.49	0.41
Supermarket	6	2	4	0.17	0.67	0.50	1.00	0.14	0.67

Fish shop	2	1	2	0.50	1.00	1.00	1.00	0.50	1.00
Greengrocer	1	2	1	0	0	0	0	0	0
Restaurant	80	91	74	0.75	0.63	0.66	0.68	0.54	0.48
Frozen food store	4	2	2	0.50	0.50	1.00	1.00	0.50	0.50

Table 3 shows that the number of outlets per category is too small to allow the validity measures to be interpreted for most categories. We restrict our analysis here to the largest categories, namely restaurants, fast food outlets, grocery stores, and bakeries. For these categories, results from validity measures are consistent with our general findings listed above: the sensitivity and concordance of Sirene are systematically higher than those of OSM, while the positive predictive value of OSM is systematically higher than that of Sirene.

4.2 Reliability by neighborhood income level

The reliability of the two databases varies according to the income level of the neighborhood. In the poorest areas, Sirene's sensitivity is good (0.77) while OSM's sensitivity is fair (0.48) (Table 4). In the wealthiest areas, Sirene and OSM show the same moderate sensitivity (0.62). Positive predictive values are good (0.71-0.88) for OSM regardless of income level, while they are moderate (0.51-0.66) for Sirene. In terms of concordance, PPV is higher for Sirene (0.55) than for OSM (0.40) in the poorest areas, and vice-versa in the wealthiest areas. Moreover, the differences in sensitivity between the wealthiest and poorest sectors are of the same order for Sirene and OSM (0.15 and 0.14 respectively), as are their differences in positive predictive value and concordance.

Hence, our results indicate that the Sirene database offers better reliability in the poorest neighborhoods, while the OSM database offers better reliability in the richest neighborhoods. Thus, given the income geography of the Montpellier city-region, Sirene is more robust in the core-city of Montpellier and OSM is more robust in peri-urban areas, because the income level per neighborhood is lower in Montpellier than in peri-urban areas (Fig. 4).

Table 4: Validity measures for Sirene and OpenStreetMap by neighborhood income level

	Number of food outlets			Sensitivity		Positive predictive value		Concordance	
	Fieldwork	**Sirene**	**OSM**	**Sirene**	**OSM**	**Sirene**	**OSM**	**Sirene**	**OSM**
Total	192	228	130	0.71	0.53	0.60	0.78	0.48	0.46
Disposable income									
< Median	119	139	79	0.77	0.48	0.66	0.71	0.55	0.40
> Median	73	89	51	0.62	0.62	0.51	0.88	0.38	0.57

5 Discussion

Our assessment of the reliability of the data sources available for food environment studies is, to our knowledge, the first performed in France and the first to evaluate a data source based on volunteered geographical information. However, the many similar evaluations that have been carried out in other countries provide a useful point of comparison with our results.

5.1 Sirene's reliability is similar to other commercial and institutional databases

For Sirene, our analyses show sensitivity, positive predictive value, and concordance of between 0.45 and 0.71. Based on the meta-analysis of Lebel *et al.* (2017), these values are in the same range as those found in most international studies, with the exception of the consistently higher validity measures reported for Denmark (Svastisalee et al., 2012; Toft, Erbs-Maibing, & Glümer, 2011).

More precisely, comparing our results for Sirene with the results obtained from the evaluation of other national and institutional data sources, we observe that:

- Sensitivity is clearly higher than the median of sensitivities calculated in Canada, the UK, and the US;
- Positive predictive value is clearly lower than the median obtained in these three countries;
- Concordance is clearly higher than the median obtained in Canada and the US and very slightly lower than in the UK.

Three hypotheses may explain these discrepancies, in particular regarding positive predictive value.

First, misclassifications could be more numerous in Sirene than in other assessed databases. For example, some businesses classified in Sirene as fast food restaurants were actually found in the field to be private homes. The name we found on the letter box was often the name of the registrant in Sirene. In addition, the names of home delivery companies appeared in Sirene’s comment fields for some of these false fast food restaurants. We thus hypothesize that some food delivery services have registered themselves as fast food restaurants in Sirene.

Second, the classifications used by national business registers are not consistent. For example, the NAF Rev.2 classification used in Sirene includes mobile food services in its 'fast food restaurant' category, whereas the NCAIS (North American Industry Classification System) used by InfoUSA distinguishes between them. These differences in classification may explain the higher positive predictive values for data sources using NCAIS than for those using NAF Rev.2.

Third, this lower positive predictive value for Sirene may also be explained by an issue related to the completeness of the database: the lapse of time between the date of a business’s permanent closure and the date of its deletion from the database. While declaring a new business to INSEE is compulsory, declaring business closure is not. Future evaluations could compare the Sirene database at several dates, more or less distant from the field observation period, to estimate the proportion of errors due to this delay in deleting food outlets from the Sirene database.

Finally, Sirene's data quality appears to be better in the poorest neighborhoods. Liese *et al.* (2013) found similar results for InfoUSA, a commercial data source, although other studies did not find significant differences in data quality according to income level (Lebel et al., 2017). We have no explanation for this socio-spatial heterogeneity in the reliability of Sirene, although we can explain it for OSM.

5.2 The challenge of diversifying the OSM community to enhance data quality

Our results show that the overall reliability of the VGI collaborative map OpenStreetMap is equivalent to that of commercial and institutional databases used in the academic literature. However, we do not have a reference frame allowing us to compare these results to a data source with an equivalent data acquisition mode (i.e. collaborative), as we believe our study is the first to evaluate a collaborative map for food environment studies, and given the systematic reviews of Fleischhacker *et al.* (2013) and Lebel *et al.* (2017).

Nevertheless, the limitations found here regarding OSM completeness are in line with other OSM studies addressing fields other than food environments (Barron et al., 2014; Mobasheri, Zipf, & Francis, 2018). OSM's moderate sensitivity in Montpellier highlights its incompleteness, while the differences in validity measure values between areas confirm that the reliability of OSM is spatially heterogeneous. In particular, our results show lower OSM reliability in the poorest neighborhoods. These findings are in line with those of Präger *et al.* (2019) who show, in Germany, that OSM's sensitivity in characterizing obesogenic environments[3] varies greatly according to type of neighborhood. Consistent with recent research (Gardner, Mooney, De Sabbata, & Dowthwaite, 2020; Mullen et al., 2015), we suggest that the mode of data

[3] The categories of places used by Präger et al. (Präger et al., 2019) only partially overlap with those used in this paper. Notably, they did not include food stores. These differences mean that our results cannot be further compared to their validity assessments.

acquisition (volunteer contribution) and the profile of contributors may explain such limited completeness.

In France, the profile of OSM contributors is relatively homogeneous. Moreover, Duféal and Noucher (2017) showed that city dwellers, men, and thirty-year-olds are over-represented. In addition, more than 60% of the contributors who responded to their survey had a university degree or post-graduate qualification. These results raise questions about the neighborhoods contributors live in or frequent, and therefore about their knowledge of other areas.

First, the reliability of OSM is higher where contributors reside. Our results confirm that the spatial density of data in OSM depends on the density of contributors in the same area. Girres and Touya (2010), who examined the topography of OSM in different regions of France, found that the areas best mapped in OSM are those with wealthy and/or young populations, while data on certain aging-population rural areas is particularly scarce. It is true that in France, OSM was still underdeveloped in 2010, or at least considerably less developed than it is today - the number of contributors doubled between 2010 and 2016 (Duféal & Noucher, 2017) - limiting the scope of their study. Nevertheless, Haklay (2010) highlighted similar results in the United Kingdom, a country where the contribution of citizens to data collection and knowledge creation was already widespread in 2010 (Mericskay & Roche, 2011).

Second, it is not only OSM contributors' home neighborhoods but also the areas they frequent, their spatial mobility practices, which may explain the limited completeness of OSM. Numerous studies have shown that individuals' spatial practices differ depending on their socio-economic status (Chen & Akar, 2016; Hirsch, Winters, Clarke, & McKay, 2014; Vich, Marquet, & Miralles-Guasch, 2017). For instance, the wealthiest individuals could choose routes that enable them to avoid seeing poverty or feeling unsafe (Atkinson, 2016). In France, social geographers and environmental psychologists have highlighted differing spatial practices and space representations among individuals according to their level of education (Dias & Ramadier, 2018), their gender (Di Méo, 2012), their age (Perchoux et al., 2014), or the built environment of their neighborhood (Lamatkhanova, Raux, & Grassot, 2019). The relatively homogeneous socioeconomic and demographic profile of OSM contributors is therefore likely to restrict the areas they frequent and map. This may therefore constitute a knowledge filter and, ultimately, prevent exhaustive cartographic representation of a city-region in OSM.

Thus, although exhaustive, up-to-date, and accurate representation of the area constitutes a leitmotiv for OSM contributors (Duféal & Noucher, 2017), their spatial practices and interests may generate spatial heterogeneity in the quality of the data available in OSM. While the overall quality of OSM today matches that of the commercial or institutional data sources used in the literature on food environments, the socio-spatial heterogeneity of the data quality needs to be reduced before food outlets can reliably be mapped at city-region scale. The challenge for the OSM community is hence to attract contributors from other socioeconomic categories, particularly female contributors. This conclusion mirrors those of other studies on the reliability of OSM outside the food environment field of research (Basiri, Haklay, Foody, & Mooney, 2019; Yan et al., 2020).

5.3 Limitations and perspectives

5.3.1 Assessing the reliability of data sources for food environment studies

The number of outlets per category in our sample proved to be too small to calculate food environment indicators per spatial unit (grid cell) or per category. Even though we performed on-site observations on 206 grid cells spread over 31 municipalities, many cells did not include any food service establishment or food stores. We recommend using spatial units larger than our 200m grid cells for future evaluations.

Moreover, our results are not equally generic for both data sources. The mode of data acquisition for Sirene is homogeneous in France, enabling us to consider our results applicable to all large French cities. In contrast, because OSM data acquisition relies on volunteer contributions, similar studies will need to be conducted in other cities to better assess the reliability of OSM and its variability.

Finally, our analysis of the varying reliability of OSM and Sirene data was based on the income level of neighborhoods. However, as inhabitants move around, their socioeconomic characteristics alone cannot explain spatial variability in the quality of OSM data. Future research should address the relationship between the reliability of OSM data and the spaces visited daily by the contributors, their activity space (Patterson & Farber, 2015).

5.3.2 Recommendations for building a reliable database

The differences in reliability found for Sirene and OSM suggest that the choice between these two databases should depend on the area under study. Thus, for studies focusing on specific types of neighborhoods or populations, Sirene should be used when assessing deprived neighborhoods and OSM for wealthy neighborhoods, or at least those frequented or inhabited by its main contributors. For analyses at meso or macro scales (one municipality and larger areas), we recommend choosing the most robust data source for deprived neighborhoods, i.e. Sirene. Actually, one of the main objectives of studies on food environments is to address social inequalities regarding access to food, as confirmed by the rising number of studies on food deserts.

However, we suggest methodological adjustments to mitigate the limitations encountered here, particularly regarding food outlets listed in the Sirene database but non-existent in the field. Concerning fast food restaurants in particular, we recommend deleting any establishments whose contact details correspond to those of a company's head office or a residence and not to a food outlet. Moreover, because not all places where food is purchased are covered in Sirene, we suggest supplementing the database from other data sources. In particular, OSM can provide data regarding markets. Google Street View can be used to validate data (Rundle, Bader, Richards, Neckerman, & Teitler, 2011), as can websites of major supermarket companies and municipalities. Finally, qualitative approaches can be used to improve the reliability of databases: for example, organizing participatory mapping workshops and learning from counter mapping (Collective, Dalton, & Mason-Deese, 2012).

In addition, OSM should be chosen only after considering the number of local contributors, which varies greatly from one country to another. In 2016, Germany had the largest number of contributors (84,000), followed by the United States (69,000) and France (40,000), while Canada had only 13,000 for a much larger area to be mapped (Laboratoire d'Analyse et de Décryptage du Numérique, 2017).

6 Conclusion

To our knowledge, this is the first evaluation of the reliability of secondary data sources for mapping the food environment in France. In addition, it is the first evaluation worldwide addressing this use of a volunteered geographical information database. Our results show that the OSM collaborative map and the French national business register Sirene offer reliability similar to that assessed for equivalent data sources in other countries. The socio-spatial heterogeneity in reliability that we found in the Montpellier city-region suggests that Sirene should be preferred for the study of deprived neighborhoods and OSM for wealthy neighborhoods. We invite scholars to reevaluate these two data sources in other areas of France, in order to specify their conditions of validity and precautions for use. In particular, since OSM coverage depends on local contributors, its reliability needs to be studied in regions with varying levels of urbanization. In addition, our results confirm the need for systematic cross-referencing of food outlet data with spatialized socioeconomic data in future evaluations of data sources for food environment studies. Finally, researchers should weigh carefully the limitations of each source, in terms of the formal and informal classifications on which the data sources are based, the time required to update the institutional bases, or the socially-influenced contributions of VGIs.

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Availability of data and materials

The French national business register Sirene is publicly available at https://www.data.gouv.fr/fr/datasets/base-sirene-des-entreprises-et-de-leurs-etablissements-siren-siret/. The URL for geocoded versions of the Sirene register varies, and is therefore not provided here. Geocoded versions are available at the bottom of the above web page. OSM data are freely available and can be extracted using the QGIS QuickOSM plugin. The datasets generated during the ground-truthing are available from the corresponding author on reasonable request. Income data are publicly available at https://www.insee.fr/fr/statistiques/5055909. GIS data from the INSEE-standard French grid cell system are publicly available at https://www.insee.fr/fr/statistiques/2520034.