Trends in Endocrinology & Metabolism

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Review

Spatial Technologies in Obesity Research: Current Applications and Future Promise

Peng Jia,[1,2,*] Hong Xue,[3] Li Yin,[4] Alfred Stein,[1] Minqi Wang,[5] and Youfa Wang[6,*]

Geographic Information Systems (GIS), Global Positioning Systems (GPS), and remote sensing (RS) are revolutionizing obesity-related research. The primary applications of GIS have included visualizing obesity outcomes and risk factors, constructing obesogenic environmental indicators, and detecting geographical patterns of obesity prevalence and obesogenic environmental features. GPS was mainly used to delineate individual activity space and combined with other devices to measure obesogenic behaviors. RS has been understated for its role as important sources of data about natural and built environments. These spatial technologies, collectively called the 3S technologies, will be useful in measuring more facets of obesogenic environments and individual environmental exposure at finer levels and studying obesity etiology and interventions.

Highlights

Geographic information systems (GIS) has been used for visualizing and studying spatial patterns of obesity outcomes and risk factors, and developing obesogenic environmental indicators.

Global positioning systems (GPS) has been used for delineating individual activity space and combined with other devices to measure obesogenic behaviors.

Remote sensing (RS), although rarely mentioned in obesity literature, has been used for acquiring environment measures and can potentially delineate obesogenic environmental features in a high spatial resolution.

The use of the *3S technologies* should be leveraged to harness synergistic power of the family of spatial technologies, which should further work with systems approaches to address multifactorial complexity of obesity problems.

While we see growing interdisciplinary collaboration between 3S experts and traditional public health researchers, many challenges exist. We made recommendations for future research.

Growing Obesity Prevalence and Developing *3S* Technology

Over the past three decades, new developments in technologies and services, including those based on spatial technologies and mobile devices, have greatly changed peoples' daily lives as well as health research, particularly on obesity related lifestyles and health problems [1]. Obesity has been widespread, with the global prevalence (including overweight) increasing from 28.8% to 36.9% for men and from 29.8% to 38.0% for women during 1980–2013 [2]. In recent years, the spatial dimension of obesity epidemiology has been increasingly investigated [3,4]. A complex spatial and temporal heterogeneity has been observed in both the distribution of and risk factors for obesity, especially those modifiable risk factors that are termed **obesogenic environmental** (see Glossary) factors [5]. A variety of obesity and obesogenic environmental research themes have demonstrated the demand for technologies that can handle and integrate spatial information from voluminous data sources, especially in the big data era [6–8].

Emerging spatial technologies have facilitated the progress of obesity research, primarily focusing around **geographic information systems (GIS)**, **global positioning systems (GPS)**, and **remote sensing (RS)**, collectively named the *3S* technologies. On a broad scale, these technologies have profoundly affected peoples' daily lives in regard to health problems such as obesity and how research related to them could be conducted. On the one hand, they have changed peoples' lifestyles; for example, how people find destinations and commute between places, some of which can lead to less physical activity (PA), more energy intake, and thus increased obesity risk [9]. On the other hand, *3S* technologies enable the collection of related data to study individual lifestyles, behaviors, and health outcomes and, more broadly, neighborhood and urban metabolism, at affordable costs for researchers [10,11].

Although being interlinked and commonly applied in many health research areas, including obesity research, *3S* technologies are still being used in relative isolation in most studies, with GPS and RS being used less frequently than GIS. A recent review examined the applications of

[1]Department of Earth Observation Science, Faculty of Geo-information Science and Earth Observation (ITC), University of Twente, Enschede, 7500, The Netherlands
[2]International Initiative on Spatial Lifecourse Epidemiology (ISLE), Enschede, 7500, The Netherlands
[3]Department of Health Behavior and Policy, School of Medicine, Virginia Commonwealth University, Richmond, VA 23298, USA
[4]Department of Urban and Regional

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spatial data/methods in obesity research for the first time and found that applications of GIS data and methods in obesity research were limited [3]. Also, as reflected in recent consortium research projects that focus on obesity, reviews and recommendations on the applications of *3S* technologies in obesity research are urgently warranted to facilitate more advanced and innovative use of spatial technologies for better understanding and prevention of causal risk factors of obesity [12]. However, a review of the applications of GPS or RS in this area is missing from the existing literature.

To fill this gap, this review seeks to lay out the current landscape and guide future cooperative use of *3S* technologies in obesity research by investigating major applications of *3S* technologies in the field, identifying current gaps and challenges, and making recommendations for the applications of the technologies in future obesity research. A framework was developed that attempted to incorporate major spatial obesity research questions and recommendations for future endeavors (Figure 1). With the increasing availability of portable scientific equipment and spatial data/methods, this review could help researchers and other relevant stakeholders with a limited spatial science background to understand the roles of *3S* technologies in obesity research. Such endeavors will also bring more fundamental and critical spatial thinking into obesity research, which holds the potential to revolutionize obesity epidemiology research and steer present urban landscape patterns towards a leptogenic environment. Many of these

Planning, University at Buffalo, The State University of New York, Buffalo, NY 14214, USA
[5]Department of Behavioral and Community Health, University of Maryland at College Park, College Park, MD 20742, USA
[6]Global Health Institute, Department of Epidemiology and Biostatistics, School of Public Health, Xi'an Jiaotong University Health Science Center, Xi'an, Shaanxi, 710061, China

*Correspondence:
youfawang@gmail.com (Y. Wang) and
jiapengff@hotmail.com (P. Jia).

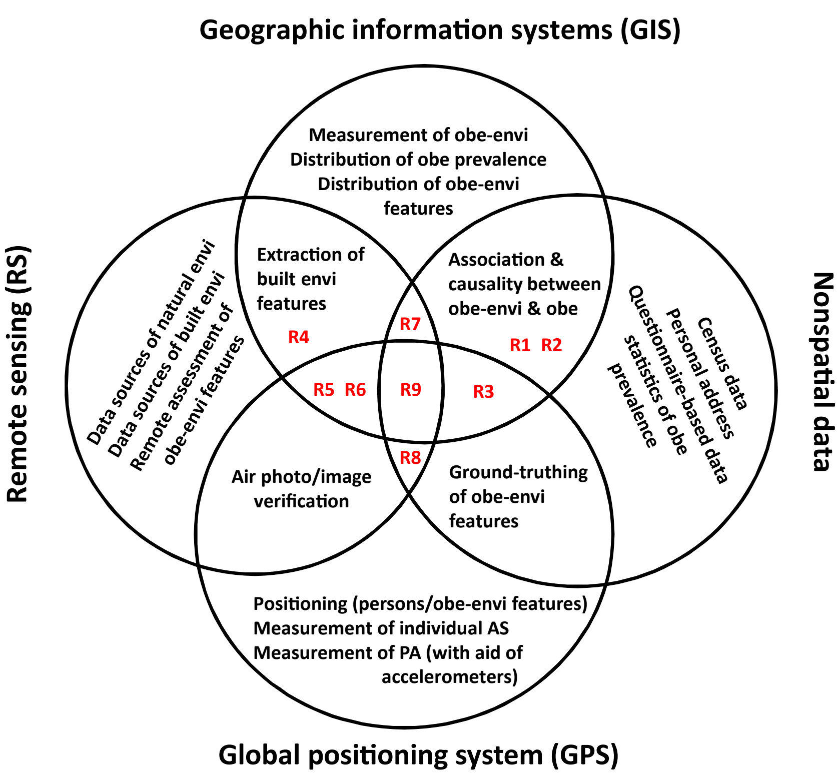

Figure 1. Framework of Applications of Spatial Technologies in Obesity Research. Abbreviations: AS, activity space; obe, obesity; obe-envi, obesogenic environment; PA, physical activity; R1–R9, recommendation 1–9 (see Recommendations for Future Research section in the main text).

perspectives can be adapted to study other health outcomes as well, especially noncommunicable, chronic diseases.

GIS Applications in Obesity Research

Visualizing Obesity Related Health Outcomes and Risk Factors

GIS-based interactive maps have been officially employed in the US to visualize the distribution of obesity prevalence (Figure 2) and PA indicators at a state level over time [13] (https://www.cdc.gov/nccdphp/dnpao/data-trends-maps/index.html). At a county level, the distribution of adult obesity prevalence and an array of health behavior factors was mapped in annual *County Health Rankings* reports (http://www.countyhealthrankings.org/) [14]. In addition, a number of studies on the spatial distribution of obesity rates have emerged over the past decade, with the geographic scale ranging from state [15] to census block levels [16].

Constructing Obesogenic Environmental Indices

Prior to the use of GIS, the obesogenic environment was subjectively perceived by participants in surveys and recorded by questionnaires. For example, participants were typically asked questions regarding the presence and/or numbers of one or more types of food outlets within their neighborhoods or walking distance. The collection of food environmental data used to be conducted in such ways rather than being measured using GIS when GIS-based data are not available, such as measurement of the food environment in the China Health and Nutrition Survey [17]. However, these traditional methods proved insufficient to provide an objective and complete measurement of obesogenic environmental factors [18].

GIS has advanced the measurement of the obesogenic environment to a less biased level, with obesogenic environmental indices now being objectively developed in a way that complements the surveyed data [19]. The four most frequent types of GIS-based and obesity related metrics are the presence of, density of, proximity to, and distribution pattern of obesogenic environmental features. Example questions answered by these metrics include 'Is there any fast-food (FF) restaurant within ten minutes' walk from your home?' (presence), 'What is the density of street intersections within your ZIP code' (density), 'How long does it take you to walk to the closest park?' (proximity), and 'Do you feel that grocery stores are evenly distributed across your city?' (pattern). These four types of metrics are primarily at areal and individual levels [20]. Most of the areal-level exposures are often calculated based on traditional administrative units (e.g., ZIP code or census units, such as census tract) or **straight-line buffers**. The former is officially provided in the form of a spatial database and regularly updated by the US Census Bureau [21], while the latter is often created by research teams using GIS, based on the context-specific demand for their projects [22]. When individual addresses and road networks are available, **road-network buffers**, taking into consideration realistic road conditions and sometimes speed limits, are oftentimes used to more accurately represent spatial accessibility of obesogenic environmental features. These GIS-based measures have been further incorporated into regression analyses for examining how environmental factors are associated with obesogenic behaviors and obesity outcomes [23–27].

Detecting Spatial Patterns of Obesity and Obesogenic Environmental Features

Obesogenic environmental features, including different types of food outlets and PA facilities, not only influence body weight individually but also spatially interact with one another to produce synergistic effects. In a GIS environment, spatial statistical methods that have thus far been used for exploring spatial patterns of obesity prevalence and obesogenic environmental features include *Moran's I* for measuring global spatial autocorrelation [28], and *Local Moran's I*, *Getis* G_i^*, and *K-function* for testing local spatial autocorrelation [29,30] (Box 1). For example, the

Glossary

Geographic information systems (GIS): technology that can capture, store, check, and display data with location information. Unlike traditional methods that lack the ability to handle spatial information, GIS have provided opportunities to public health researchers to integrate and analyze spatial and nonspatial data from multiple sources. They can show many different types of data simultaneously in one map, which enables people to more easily see, analyze, and understand patterns of, and relationships between, phenomena. Using spatial data and methods, the associations between environmental factors and obesity can be examined at an unprecedented level.

Global positioning systems (GPS): technology that provides accurate location (geographic coordinates), speed, and time data to a user anywhere in the world and under any weather condition by receiving signals from multiple satellites simultaneously. GPS technology enables the measurement of actual human–environment interaction, which can deepen our understanding of how humans perceive and are influenced by their surrounding environment. The GPS units, both handheld previously and wearable recently, have also been increasingly used in health-related studies, such as capturing individual routine activities.

Obesogenic environment: environment in which one is more susceptible to weight gain, primarily encompassing built and food environments.

Raster data: geographic data in a format of regular square grids, with each grid representing aggregated information over the corresponding area on the surface of the Earth (e.g., high-resolution aerial photos and satellite images). In addition to being converted from radiation recorded by sensors, they can also be produced through GIS-based interpolation techniques based on discrete data from observation stations.

Remote sensing (RS): technology that, in contrast to on-site observation, acquires information by space-borne satellites or airborne sensors without making physical bivariate *K-function* was used to estimate spatial dependence between FF restaurants and schools and concluded that there were three to four times as many FF restaurants within 1.5 km from schools than would be expected if restaurants were dispersed in a way unrelated to schools [31]. Global (*Moran's I*) and local clustering detection (*Local Moran's I*) methods were compared to identify the clustering patterns of obesity prevalence and moderate PA [18].

GPS Applications in Obesity Research

Tracking Individual Activity Space

Although a wide variety of obesity related studies have been conducted at the community and neighborhood levels [32], definitions of both community and neighborhood remain ambiguous or inconsistent across studies. This may make the studies that involve individual exposure to obesogenic environments problematic and incomparable with one another. Although the use of GIS has significantly improved the ability to describe obesogenic environments, GIS-based indices only measure assumed individual exposure, which is normally static and rarely realistic. For example, individuals are assumed to have equal access or be evenly exposed to all food outlets within the straight-line buffers centered on their residence.

GPS enables the refining of GIS-based all-direction measurement by recording individual real-time positions, which can be exported to computers in the form of points, comprise outdoor moving trajectories (e.g., playing, walking, biking, and driving), and be overlaid with other GIS-based obesogenic environmental features. For example, it was found that youth do not play within a uniform radius around their homes equally in all directions [35]. A youth's routine activity space tended to focus on only one or two directions within a circled neighborhood. Despite the ability of conducting network analysis in a GIS environment, GIS-modeled routes between home and school were found not to be representative of children's routine school journeys mapped by wearable GPS [33]. Thus, integration of GPS devices with measurement of exposure to obesogenic environments may prevent deviation from true situations, especially for those children who walk home [33].

Combining with Other Devices to Measure Obesogenic Behaviors

The use of GPS is often accompanied by other types of devices for fulfilling specific health-related aims [34]. For example, an accelerometer is used to record the amount and intensity of individual movement, which, linked with GPS data by a shared attribute of time, could not only complement but also cross-reference and verify GPS data [35,36]. Such combinations have been increasingly developed into various types of health-tracking applications for smartphones for monitoring individual dietary intakes and PA, given that numerous types of sensors, such as GPS receiver, accelerometer, and gyroscope, are nowadays incorporated in smartphones [37–39].

Remote Sensing Applications in Obesity Research

High-Resolution Representation of Obesity Related Features

RS data are usually stored as **raster data**, which, in contrast to **vector data**, provide an efficient way to describe obesity risk spatially. A recent research effort integrated the National Health and Nutrition Examination Survey and census demographic data to produce the estimated percentage of obese adults across the US, which is represented in the form of 250-meter grids (Figure 3). This effort may lead to more high-resolution representation of obesity facts/estimates and obesity related features as both obesity and other ancillary spatial data become increasingly available.

Another example of RS data that are frequently used in obesity research is high-resolution images seen on the Google website or in Google Earth, which have also been transformed into a vector version: Google Street View (GSV). A recent study developed a virtual audit tool to use

contact with the object. The sensors record the intensity of radiation reflected or emitted by objects, and then convert the data into different land surface (e.g., vegetation) and meteorological (e.g., temperature) properties for easy use by end users. RS technologies also have been playing a key role in a wide variety of application fields from environmental monitoring (e.g., air quality, land cover/use, sea level, coastal line, forestry, crop, and glacier) to climate-sensitive disease risk modeling (e.g., malaria, dengue fever, Lyme disease, and Ebola) by providing a large amount of environmental data. An example of passive sensor data that may be most familiar to a broad audience is Google satellite images.

Road-network buffer: an irregular zone around a given address where it covers the same distance to travel from that address to any point on the boundary of the zone along the shortest road network path.

Straight-line buffer: a zone around an address that extends to a specified distance (e.g., circular zone with a specified radius), to represent a catchment area of that address.

Vector data: points, lines, and polygons that are the same as drawing elements in computer-aided drafting programs, but with geographic coordinates.

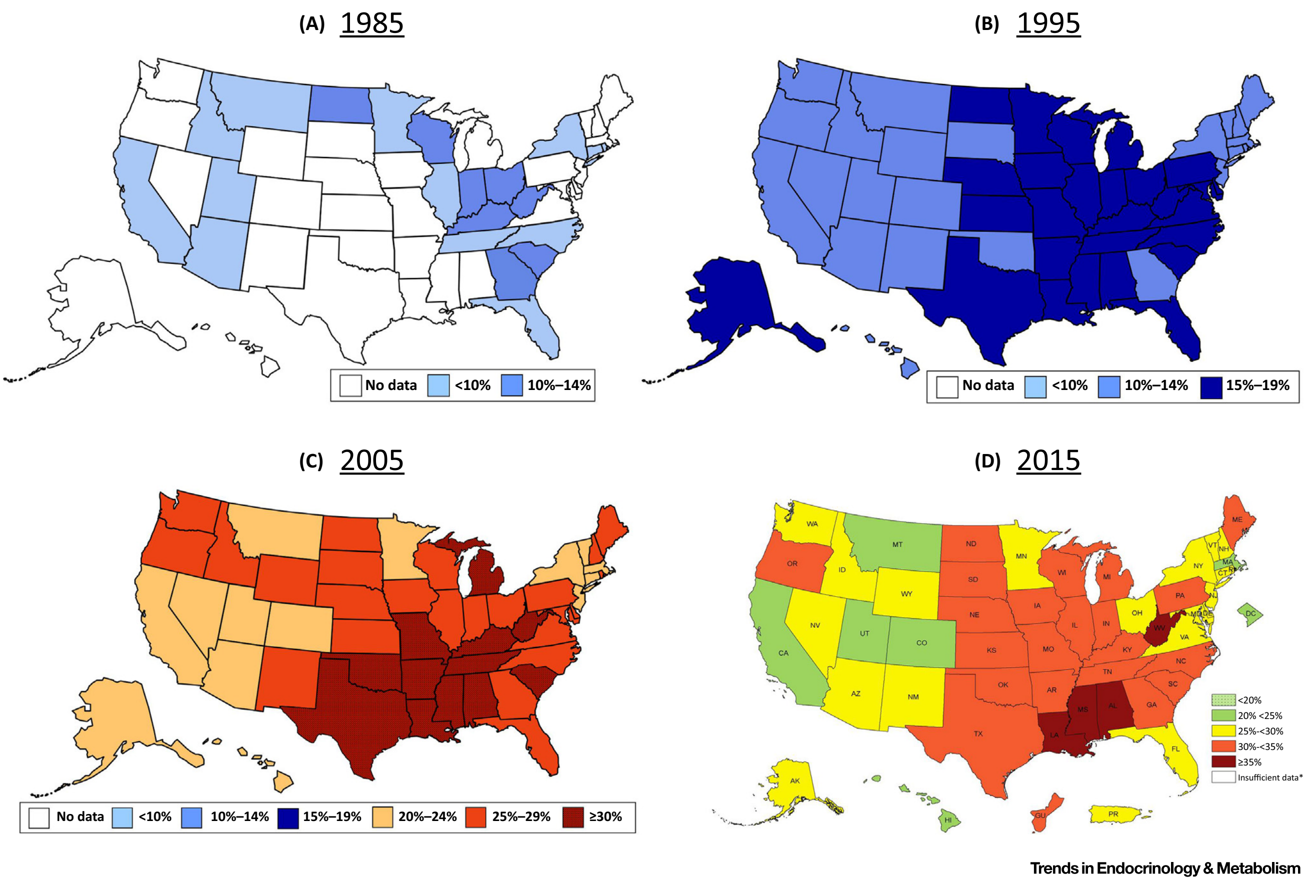

Figure 2. Time Trends and Regional Differences in Prevalence (%) of Obesity (BMI $\geq$ 30) in US Adults, BRFSS 1985 to 2016. BMI of study participants was calculated based on reported weight and height. The improvement changes to the BRFSS affect obesity prevalence estimates and mean that estimates from data collected in 2010 and before cannot be compared with estimates collected from 2011 onwards. Obesity was defined as BMI $\geq$ 30 kg/m^2. Data source: Centers for Disease Control (CDC). Prevalence of self-reported obesity among US adults by state and territory, BRFSS. Abbreviations: BMI, body mass index; BRFSS, behavioral risk factor surveillance system.

Box 1. Spatial Statistical Methods Commonly Used in Current Obesity Research

Moran's I measures the overall spatial autocorrelation of all objects in a data set. In the context of obesity, it measures how the obesity prevalence or obesogenic environment in one region is similar to the one in other surrounding regions, with a value ranging from −1 (dissimilar values cluster geographically) to 1 (similar values cluster geographically).

Local Moran's I detects local clusters and spatial outliers. In contrast to *Moran's I*, which only measures global spatial autocorrelation, it can identify spatial clusters of high values and low values, as well as high-low (high value surrounded by low values) and low-high spatial outliers (low value surrounded by high values).

Getis G_i^* also detects local spatial autocorrelation, with positive and negative values indicating spatial clusters of high and low values, respectively. Different from *Local Moran's I*, it does not consider spatial outliers (i.e., high-low and low-high outliers).

K-function determines whether the features of interest (e.g., an obesogenic environmental feature, such as fast-food restaurant and recreational facility) appear to be dispersed, clustered, or randomly distributed throughout the study area. It is similar to *Moran's I*, but can describe clustering patterns at multiple user-defined scales. It can be calculated in a univariate form (i.e., spatial pattern of only one type of feature) or in a bivariate form (i.e., spatial pattern of one type of feature compared with another type of feature).

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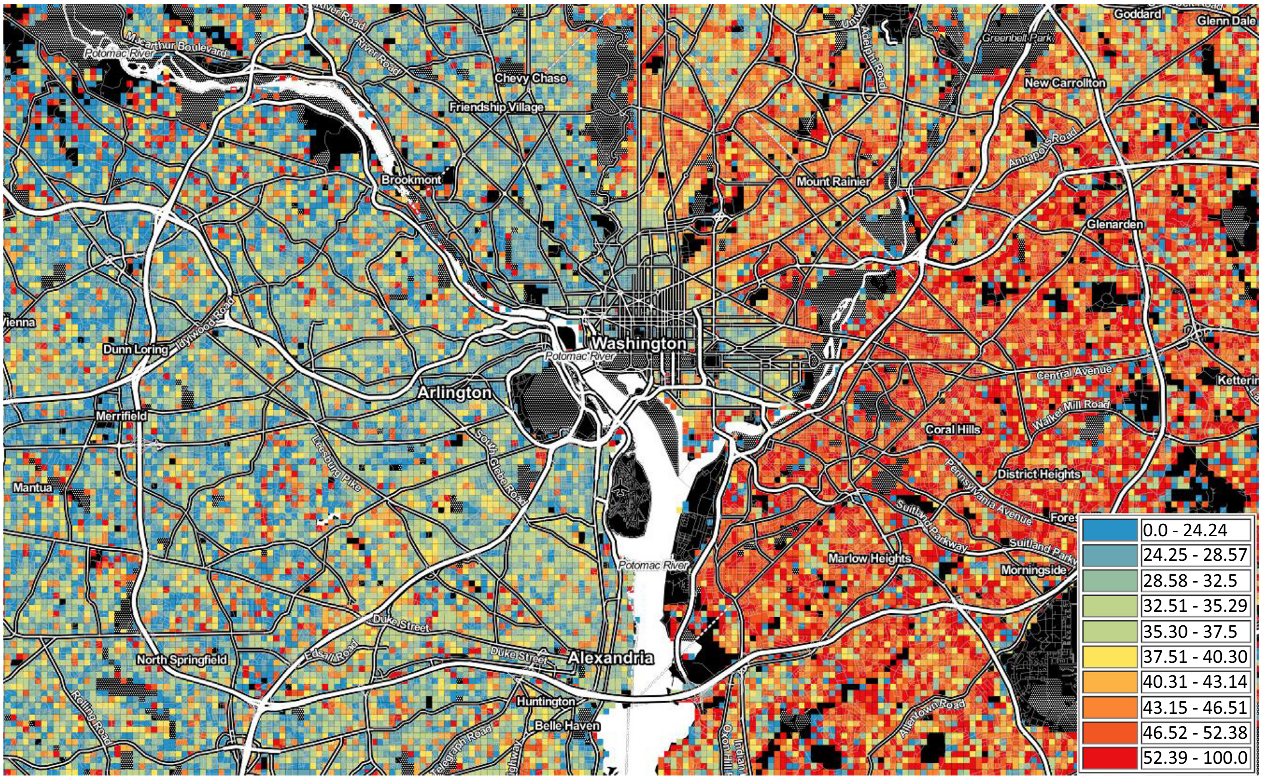

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Figure 3. Estimated Percentage of Obese Adults within Each 250 m Grid in the Washington D.C. Area, USA. Maps were created based on the National Health and Nutrition Examination Survey (NHANES) 2011–2012, 2010 Decennial Census data, and 2007–2011 American Community Survey (ACS) data (https://www.rti.org/newsroom/news.cfm?obj=F9A58485-EEF0-29D8-941A682B86B0F868).

GSV for identifying and comparing obesogenic environmental characteristics in European neighborhoods in terms of land use mix (e.g., types of residential buildings), aesthetics (e.g., maintenance of green areas), and presence of walking-related items, cycling-related items, public transport, grocery stores, food outlets, and PA facilities [40]. GSV was also used to objectively measure street-level urban design features for walkability [41,42]. More recently, a study conducted in four US urban areas utilized a deep learning approach (an advanced machine-learning method) to extract built environmental features (i.e., human-made features that provide the setting for human activity, such as buildings and roads) directly from Google high-resolution satellite images [43]. RS has made it possible to implement such procedures at a large scale anytime and anywhere, with better standardization and quality control, with less time and resources spent than in typical field audits, and without incurring travel expenses or facing the risks of working in unsafe neighborhoods [40].

Acquiring Natural Environmental Variables

RS provides an economical way to acquire a massive amount of data for measuring natural environments. Evidence has shown that natural environmental factors could affect obesity through several mechanisms, primarily by impacting dietary and PA behaviors [44,45]. For example, activity may increase in response to appropriate temperature and sunlight; people in cold climates may consume more calories to generate more heat than their counterparts in the tropics. Residents in high climate-amenity US counties tended to have a lower BMI [45]. Similarly, obesity prevalence at the county level was positively associated with summer temperatures and negatively associated with winter sunlight duration and temperatures [44,46].

Another study found a positive correlation at the county level between indices for natural amenities and outdoor recreational opportunities, where both indices were associated with a higher propensity for PA and a low prevalence of obesity among adults living in nonmetropolitan areas [47]. Seven out of eight variables used for constructing the natural amenity index were derived from RS products, including winter sunlight hours, winter and summer mean temperature, summer relative humidity, topographic relief, water area, and forest cover.

Producing Built Environmental Variables

Associations between obesity and built environmental factors have been a major research area in obesity related research. In contrast to natural environment data, most of the built environmental data are stored and represented in a vector format. Vector data can be collected by: (i) ground surveying and GPS; (ii) drawing elements based on surveys or observations in a nongeographic setting, and later assigning them real-world geographic coordinates based on reference maps; and (iii) drawing elements along the boundaries of objects on top of base maps in a GIS setting, also termed digitalization. Nevertheless, a considerable number of public health researchers might not realize that large quantities of built environmental data are originally derived from RS data.

RS images have been used to construct obesity related built environmental variables, such as green space [48] and artificial light at night [49]. Those that have high spatial resolution (e.g., aerial photos in Google Earth images) have been used to extract man-made structures and constructs, such as street intersection density [50,51]. Theoretically, most geographic features with a larger size than the sensor/imagery resolution can handle can be identified and converted into vector features (e.g., polygon). In some cases, they can be simplified and represented by lines and points for ease of use. For example, when an area can be ignored in certain contexts, roads and buildings therein can be represented by lines and points, respectively. More built environmental features and indices can be further produced from these basic features through GIS spatial operations, such as street intersection and Walk Scores (https://www.walkscore.com/methodology.shtml) [52]. Some features may not be directly recognized because they have a smaller size than the sensor/imagery resolution can detect, but can be added manually later if they are important landmarks or matter to specific goals.

Current Gaps and Challenges

Great progress has been made in the application of *3S* technologies in obesity research over the past two decades. However, there is more promise and opportunity for interdisciplinary research and intervention efforts tackling the obesity epidemic [53,54]. Some options have been conceptualized, but have yet to be applied [19]. For example, objectively measured obesogenic environments were more studied than actual individual-environment interactions. This limits the detailed assessment of an individual's real-world exposure to obesogenic environments. Furthermore, despite an expanding number of separate applications of GIS, GPS, and RS in the obesity context, there is a paucity in the literature of integrative applications of *3S* technologies in obesity research. This may prevent the introduction of advanced geographical thinking and methodologies to facilitate in-depth applications of *3S* technologies.

Recommendations and Future Perspectives

Based on our experiences of conducting multidisciplinary research in this field, we have identified current gaps and made recommendations for future research (Table 1; i.e., improving

Table 1. Recommendations for Future Applications of Spatial Technologies in Obesity and Obesogenic Environmental Research.

Category	No.	Recommendations
Measurement of built environments	R1	Improving measurement of food environments, such as food affordability, accommodation, and acceptability
	R2	Defining neighborhood boundaries for measuring individual exposure to the built environment
	R3	Refining individuals' environmental exposures using spatial approaches, such as geographical modeling and movement tracking approaches
	R4	Counting environmental exposure at multiple locales, such as home, school, and workplace
Measurement of natural environments	R5	Exploring effects of natural environmental variables on obesogenic behaviors and obesity
Measurement of individual behaviors	R6	Measuring food purchasing behaviors for measuring individual exposure to the food environment
Innovative and dynamic measurement	R7	Increasing the use of spatial regression modeling approaches for exploring spatially varying effects of obesogenic environmental variables
	R8	Integrating spatial technologies with systems science approaches for addressing the multifactorial complexity of obesity problems
Staffing and operation	R9	Fostering interdisciplinary collaboration and using team science approaches for tackling complex problems and approaching reality scientifically

the measurement of built environments (recommendations 1–4, R1–R4), the natural environment (R5), and individual behaviors (R6), the use of innovative and dynamic approaches (R7–R8), and staffing and operation (R9)].

R1: Improving Measurement of Food Environments

Most of the current food environmental indices center on accessibility and availability, as they are inherently geographic and can be easily measured by GIS. However, these two dimensions only measure objective facts and are insufficient to associate food environments with actual dietary and obesity outcomes, such as a weak relationship between FF outlets and consumption [55]. The literature suggests that there are multiple dimensions of measures of food access that also include affordability, acceptability, and accommodation [19], which may potentially serve as mediating variables to bridge food environments and dietary and obesity outcomes, and hence should be studied more in future endeavors. Traditionally, affordability, acceptability, and accommodation of the food environment were measured by methods such as participant surveys (e.g., interviews and questionnaires) and store audits (e.g., researcher visits to stores to assess/rate various aspects of stores and products). With abundant demographic and geographical data nowadays, a practical strategy could be to link measurable features of food outlets relevant to those dimensions with areal or individual characteristics. For example, within census units, we may: (i) link food price with median household income to measure affordability; (ii) link employment rate with opening hours of food outlets to measure acceptability; and (iii) link types of food (outlets) with demographic characteristics to measure accommodation (e.g., kids like McDonald's due to the play place).

R2: Defining Neighborhood Boundaries

From subjective perception or recall to objective indices, GIS has expanded the measurement of individual exposure to obesogenic environments. However, many commonly used indices are based on administrative and census units, which are originally designed for the purposes of administration, representation of census data, or mail delivery. A growing number of studies have suggested that taking them for granted as basic units to calculate the density of obesogenic environmental features does not always result in measurements that can accurately represent the extent of individual exposure to the surroundings [32]. Innovative combinations of spatial data and methods are needed to measure individual activity space and define more realistic neighborhood boundaries.

Some studies imply population- and area-specific radii and directions of individual activity spaces estimated from GPS measurement [56,57]. These individual measurements can be further aggregated over small areas (e.g., census tracts) and overlaid with GIS- and RS-based environmental data to elucidate individual-environment interactions and delineate functional and dynamic neighborhood boundaries. In addition, in this era of big data, shopping flows/patterns of most individuals could be potentially obtained from business databases to depict individual routine shopping areas. Such individual-centered business trade areas may be cross-referenced with individual activity space by GPS measurements. Relevant experiences may also be borrowed from other regionalization fields, such as hospital service areas in health care research, which are created based on patients' travel flows to hospitals [58]. In addition, it would save plenty of effort in the future if the realistic radius and direction of individual activity space could be generalized as a function of individual and environmental characteristics.

R3: Refining Individuals' Environmental Exposures

At present, most of the GIS-based indicators for obesogenic environments are areal-based, and residents living in a certain area are often assumed to be equally exposed to all obesogenic environmental features within that area [35]. However, this assumption is rarely valid in reality. As the influence between two objects normally decreases with increasing geographic distance, the extent of individual exposure at any location to a given obesogenic environmental feature can be estimated by distance-decay functions, which have been successfully adopted to measure the attractiveness between two destinations in a GIS environment [59]. Moreover, wearable GPS can record individuals' frequency of visiting each destination, based upon which various destinations could be differently weighted in terms of their actual attractiveness to residents. Also, the raster data format could be used to store the measurement of individual exposure, where each grid could be individually assigned based on the exposure or weight at that location.

R4: Counting Environmental Exposure at Multiple Locales

Home, school, and workplace have been separately studied in a large volume of past studies. Individual routine exposure should be estimated based on obesogenic environmental features surrounding all these locales that apply. It was also suggested that food exposure should be what a child may encounter over the course of a day, instead of those around school or residence only [60]. Hence, all food outlets along the routes from residence to work/school and other frequently visited destinations should be considered. Also, age matters in the measurement of children's realistic interaction with food environments, as some factors affecting food affordability and accessibility may vary with age, such as degree of independence and availability of pocket money.

R5: Exploring Roles of Natural Environment Variables on Obesity

A number of meteorological (e.g., rainfall and temperature) and climatological factors (e.g., season and daylight length), previously identified as important health indicators, may influence the obesity epidemic via dietary behaviors and PA [44,45]. However, some of them were simply aggregated at a coarse level and entered into statistical models, while others were insufficiently investigated in existing studies. As spatial technologies advance, the natural environment is being more accurately measured spatially, temporally, and dimensionally, and hence should be integrated cohesively with individual locational and behavioral data for producing more precise individual exposures to the environment.

A growing number of RS products, including natural environment variables, have been derived for direct use, such as: monthly mean, minimum, and maximum temperature and rainfall, and some bioclimatic variables from the WorldClim [61]; middle infrared radiation, land surface temperature, and enhanced vegetation index images produced by Temporal Fourier Analysis [62]; and daily climate variables, including total precipitation, mean dew point temperature, minimum and maximum temperature, and vapor pressure deficit from the Parameter-elevation Regressions on Independent Slopes Model Climate Group. End users may further implement GIS analysis to customize specific products on the basis of the existing products, such as producing annual minimum, maximum, and mean precipitation variables by implementing raster math calculations based on monthly total precipitation datasets [63,64].

R6: Measuring Food Purchasing Behaviors

Food affordability, accommodation, and acceptability could influence residents' shopping decision-making, which ultimately shapes the way they actually interact with their surrounding food environment. However, food purchasing behaviors that actually bridge food environments and dietary intake and body weight have been little studied. It is feasible to utilize advanced GIS-based methods to model residents' purchasing behaviors with increasing availability of ancillary data, including retailer loyalty card data and some household panel data, such as HomeScan (http://www.nielsen.com/id/en/solutions/measurement/consumer-panels.html) [65] and Consumer Network data (https://www.iriworldwide.com/) [66]. Additionally, psychosocial variables related to how residents perceive their surrounding food environment should be measured, as they also affect residents' shopping decision-making.

R7: Increasing Use of Spatial Regression Modeling Approaches

The use of spatial regression methods has been limited and insufficient to date. With an increasing volume of GIS data and RS images, they should be utilized more in obesity research, such as geographically (and temporally) weighted regression, spatial lag models, and spatial error models [4]. Despite the prolific utilization of multilevel regression models in current obesity research, they have been used separately from single-level spatial regression [67]. Conventional and spatial statistical methods should be used in conjunction, such as spatial multilevel modeling, to explore spatially varying effects of environmental variables on obesogenic behaviors and obesity [68].

R8: Incoporating Spatial Technologies with Systems Science Approaches (SSAs)

Obesity is a result of the complex interplay of many biological, behavioral, environmental, social, and economic factors, which requires SSAs to disentangle this complexity [69]. The SSAs focus on the dynamic and nonlinear interactions among agents, environments, and systems components at different levels in a complex system. Natural, built, food, and economic environments have been changing dramatically. With the explosion of environmental data (e.g., real-time data collected from satellites and location-aware technologies), this information should be incorporated in systems modeling (e.g., agent-based modeling, network analysis) for analyzing unstructured real-time data, overlaying multiple data layers from heterogeneous sources, mining huge spatio-temporal data, and validating constructed simulation models. Integrating RS and GPS with systems approaches provides a promising future for exploring complex spatio-temporal distribution and environmental determinants of obesity (i.e., obesity etiology and problem scope) and for evaluating obesity interventions.

R9: Fostering Interdisciplinary Collaboration and Using Team Science Approaches

Although some research involved a large amount of RS data, the term 'remote sensing' has not appeared throughout the texts reporting these studies [36]. This might imply that professional geospatial scholars were missing from many of the current team configurations. A growing number of RS data sources are expected to be the most promising tool for addressing two major issues that haunt most of the current obesity related studies: 1) data mismatch between individual measurement and environmental exposure, and 2) neglected influences of weather and climate on outdoor PA. Although possibly encountering short-term disharmony among different disciplines, working as an interdisciplinary research team, such as the International Initiative on Spatial Lifecourse Epidemiology (ISLE) [70], is definitely a sustainable way of approaching reality scientifically.

Concluding Remarks

The 3S technologies have become increasingly accessible and affordable, and their use has grown in health research fields over the past decade. These spatial technologies have advanced obesity research to a new level, and the demands and challenges for obesity research have allowed for the progression of those technologies in turn. The awareness and appreciation of the importance of these technologies have been growing steadily among the obesity research communities. However, there are still many challenges and limitations (see Outstanding Questions). Even with greater recognition across a wide range of disciplines, integration of GIS and GPS in the context of obesity studies is still at an early stage. RS was used in only a very small number of studies and has so far not been fully credited, which has hindered the advance of GIS and GPS applications as well. We should realize that RS can provide a significant amount of obesogenic environmental data [71], which could potentially refine measurements of obesogenic environments and behaviors, and be integrated with GPS for more accurate measurements of personalized exposure. This can facilitate more advanced GIS analyses for a better understanding of the prevalence and determinants of obesity, and explain the mechanisms behind what one can observe (e.g., the association between environmental factors and obesity). This review concludes that the use of 3S technologies should be leveraged in order to harness the synergistic power of this family of spatial technologies. These technologies should further work with systems approaches to address the multifactorial complexity of obesity problems. The nine specific recommendations made in this review have clearly pointed the way forward.

Outstanding Questions

Can we use spatial data and methods to delineate a full dimension of food environments and accessibility? How can we examine individuals' exposure to food environments more accurately? Can we model the realistic radius and direction of individuals' activity space based on individual and environmental characteristics?

How can we disentangle the effects of intercorrelated environmental factors on individuals' dietary behaviors, physical activity patterns, and obesity risk? Can we link the data collected by different location-aware applications to track processes from food distribution, purchasing, and consumption to individuals' weight status?

How should we integrate spatial epidemiology and nutritional epidemiology for a better understanding of the pathways from environmental factors to individuals' risks of developing obesity? How can advanced statistical modeling approaches help to detect, quantify and reduce uncertainties in the pathways?

How should we develop remote sensing-based products that are of immediate use for understanding, modeling, and predicting obesity risk? How may public health interventionists and policy makers use the 3S technologies in future practices to fight the global obesity and chronic disease epidemic?

Can we incorporate spatial data in dynamic and systems science research approaches to study various obesity-related research questions, mainly in terms of testing causal relationships and studying food consumption, physical activity and weight outcomes, and then deducing energy balance at population and individual levels?

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