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Improving Population Mapping and Exposure Assessment: Three-Dimensional Dasymetric Disaggregation in New York City and São Paulo, Brazil

Andrew Maroko[a], Juliana Maantay[a,b,c], Reinaldo Paul Pérez Machado[d], and Ligia Vizeu Barrozo[e]

[a]School of Public Health and Health Policy, Department of Environmental, Occupational, and Geospatial Health Sciences, City University of New York, New York, USA; [b]CUNY Graduate Center, New York, USA; [c]Department of Earth, Environmental, and Geospatial Sciences, Lehman College, City University of New York, Bronx, NY, USA; [d]Departamento de Geografia, Faculdade de Filosofia, Letras e Ciências Humanas da Universidade de São Paulo, São Paulo, Brazil; [e]Departamento de Geografia, Faculdade de Filosofia, Letras e Ciências Humanas e Instituto de Estudos Avançados da Universidade de São Paulo, Sao Paulo, Brazil

ABSTRACT

Dasymetric mapping is a process of disaggregating spatial data from a coarser to a finer unit of analysis, using additional (or "ancillary") data to refine the locations of population and achieve greater accuracy. Disaggregating population data reported by census tracts or other administrative or political geographic units can provide a more realistic depiction of actual population distribution and location. This is particularly important in assessing environmental exposures and impacts. Additionally, because exposures can occur in three dimensions (*e.g.,* air pollution is a three-dimensional phenomenon), modeling residential population in three dimensions might produce more reliable estimates of exposure. Population exposure estimates are improved through dasymetric disaggregation and 3D extrusion, using a combination of cadastral data (residential area by property tax lot), building footprint data, and building height data. Population in census units is dasymetrically disaggregated into individual buildings using residential area derived from property tax lots and then extruded vertically based on building height. This 3D dasymetric mapping technique is presented through a New York City–based case study, and contrasted with a case study of São Paulo, Brazil, to demonstrate the possibilities of using this technique in different settings of data availability.

KEYWORDS

Dasymetric; cadastral; population mapping; 3D mapping; environmental exposures; GIS; New York City; São Paulo

This study examines the importance of determining an accurate depiction of population distribution for urban areas to develop an improved "denominator," allowing for more correct rates in geographic information system (GIS) analyses involving public health and urban environmental planning. Rather than using data aggregated by arbitrary administrative boundaries such as census tracts, we use dasymetric mapping, an areal interpolation method using ancillary information to delineate areas of homogeneous values. The dasymetric method has been expanded in this study to incorporate three dimensions to better capture the actual population affected by three-dimensional (3D) impacts, such as air pollution. In a case study of Manhattan, New York City, a comparison is made among several residential population exposure estimation methods, such as traditional GIS spatial selection approaches (*e.g.,* intersection, centroid containment), two-

CONTACT Juliana Maantay Juliana.maantay@lehman.cuny.edu City University of New York, Lehman College, 250 Bedford Park Blvd. West, Bronx, NY 10468

dimensional (2D) dasymetric disaggregation (with lot-level cadastral data as the ancillary data set), and 3D dasymetric disaggregation. The results of the New York City case study are contrasted with another worked example, using São Paulo, Brazil, to illustrate the differences in the 3D disaggregation technique between locations with varying degrees of data availability, and to demonstrate the possibility of 3D dasymetric mapping improving the analysis in both types of areas. The study shows the impact that a more accurate estimation of population distribution has on current environmental and health research projects, and its potential for other GIS applications.

Exposure extent estimation methods

Environmental health and environmental justice studies require reliable estimates of exposed populations. Exposure extents can be modeled in many ways, including spatial coincidence, fixed-distance proximity buffers, network buffers, plume buffers, and contaminant fate and transport modeling (*e.g.,* air dispersion modeling), to ascertain the areas affected by the environmental impact. Using geographic information science (GIScience) as an analytical framework, population potentially affected within the exposure extents can then be estimated by methods such as centroid containment, spatial intersect, and areal weighting, which are explained later in this article. Although these methods have merit, and most have the advantage of being fairly simple to perform, dasymetric disaggregation techniques have the benefit of providing a more nuanced and accurate estimation of population distribution.

To be able to estimate the counts of vulnerable subpopulations that might be adversely affected by noxious land uses or events, it is necessary to have an accurate count of people potentially affected by environmental hazards, within the geographic extent of the hazardous conditions or at-risk locations. First, though, the geographic extent of the impact must be delineated.

Spatial coincidence method

The spatial coincidence method represents the simplest exposure assessment method (Maheswaran and Craglia 2004). This method assumes exposure to environmental hazards occurs within and is restricted to predefined geographic entities or administrative units such as postal codes or census enumeration units containing such hazards (Chakraborty and Maantay 2011). In other words, if a spatial unit contains an environmental hazard it is assumed that all people residing within this spatial unit are exposed to the adverse effects of the given hazard(s). For environmental justice studies, the socioeconomic and demographic characteristics of the exposed spatial units, also called host units, are then statistically compared to all other (nonhost) units that do not contain any hazards to evaluate if certain population groups are disproportionately exposed to environmental hazards. There are obvious limitations of this method, including the problem of edge effects, and the issue of respective locations of the hazard and the populations within both the host and the nonhost units. Populations outside the host unit might actually be more exposed to the hazard if they are closer to it than populations within the host unit that are far removed from the hazard.

Distance-based methods

Distance-based methods of exposure assessment generally imply some sort of buffering function, and this rests on the basic principle that exposure declines with distance from the pollution source to a threshold beyond which the population is considered unexposed (Maheswaran and Craglia 2004). Buffer analysis is available for point, line, or polygon features depending on the geographic feature they represent—buffers around point features (*e.g.,* toxic facilities) are generally circular, whereas buffers around lines (e.g., roads, railroads, or power lines) and polygons (*e.g.*, noxious land uses, Superfund sites) are irregularly shaped.

Fixed-distance buffers are based on expert judgment of a threshold distance, whereby within the buffer the population is assumed exposed, but not exposed outside the buffer. This binary characteristic of buffer analysis is one of its weaknesses. One way to mitigate this is to use multiple buffers, often concentric, with various buffer distances away from the source, to illustrate varying degrees of exposure. Another way is the variable buffer, whereby the buffer distance itself varies depending on other characteristics of the landscape. For example, in developing a realistic buffer to indicate potential impacts from roadway vibration or noise, variability could be based on vehicular count. Wider, busier roads would have a larger impact buffer than secondary or local roads, and the buffer around each type of road would vary accordingly. A further refinement of this would be a buffer that varies in distance around each source, depending on adjacent conditions; for instance, different adjacent land uses might have an influence on how far the environmental impact is felt.

Network buffers are based on a linear network, usually streets or roads, giving the distance buffers a more realistic depiction of how people actually travel by vehicle or by foot, rather than an as-the-crow-flies distance. This is more often used in determining access and availability to an environmental "good," rather than developing an exposure extent to an environmental "bad."

Plume buffers can also be created based on pollutant fate and transport modeling of air or water contaminants. After modeling how the contaminants move through the air, water, or soil, a plume can be drawn to indicate the likely extent of the pollution. A plume buffer based on modeled outputs would show an approximation of the flow of air pollutants from a flue gas stack, for instance, using information about pollutant type, prevailing wind direction and wind speed at the site, exit velocity of the emissions from the stack, and other features of the pollutant and landscape morphology that would affect the geographic distribution of the pollutant. This is often thought to be more realistic than the more arbitrary fixed distance buffers, but still suffers from the binary mode of exposed or not exposed. Depending on the type of model used, however, the results might yield pollutant concentration levels that could then be used to have a more reliable accounting of the degrees of exposure. A plume buffer based on modeled outputs might be possible to examine in three dimensions.

Dasymetric mapping: Exposed population estimation

Once the potential exposure extent is established, the population and subpopulations within the exposure extent must be estimated. This is usually somewhat difficult to accomplish accurately, because population data are aggregated to preexisting administrative units like census tracts, postal codes, and so forth, and not to the boundaries of the exposure extent. Dasymetric mapping addresses this problem better than most commonly used methods.

Dasymetric mapping refers to a process of dividing spatial data into finer units of analysis, using ancillary data sets to better locate populations or other phenomena (Eicher and Brewer 2001; Holt, Lo, and Hodler 2004; Mennis and Hultgren 2006). This process seeks to create areas more closely resembling the actual "facts on the ground," rather than geographic units based on arbitrary administrative boundaries, such as postal codes or census enumeration units. Administrative boundaries are often created arbitrarily or for other purposes and generally do not relate to the underlying data pertaining to exposures. Population totals within a given geographic unit are assumed to be distributed evenly, when in fact they are usually much more heterogeneous, especially in densely developed urban areas (Maantay and Maroko 2009).

Two methods have been widely used to estimate populations in defined geographic districts: areal interpolation (Langford, Maguire, and Unwin 1991) and filtered areal weighting, a basic type of 2D dasymetric mapping (Goodchild and Lam 1980; Flowerdew and Green 1992). In this study, we are using an innovative approach, 3D dasymetric mapping, building on a previous method we designed, cadastral-based expert dasymetric system (CEDS), which uses census data in conjunction with cadastral (property lot) data to create a more precise picture of where people actually live (Maantay, Maroko, and Herrmann 2007; Maantay, Maroko, and Porter-Morgan 2008; Maantay and Maroko 2009). The CEDS method constitutes a refinement of 2D dasymetric disaggregation, and estimates populations better than areal interpolation and filtered areal weighting, calculating more accurate rates, and, thus, describes with more fidelity the spatial distribution and patterns of disease, risk from hazard, environmental exposures, and other issues.

In recent research by others, population estimation methods have incorporated some 3D data elements. In a study conducted by Wang *et al.* (2016), population distribution was estimated by 3D reconstruction of urban residential buildings through building detection and height retrieval with high-resolution (HR) images. Although this method used 3D information to perform the estimation, it still only yielded population distribution on the ground (2D), and not disaggregated in three dimensions. Other researchers (Petrov, Bozheva, and Sugumaran 2005; Xie 2006; Lwin and Murayama 2010, 2011; Biljecki *et al.* 2016; Pavía and Cantarino 2016) have undertaken similar studies, employing 3D building information from such sources as light detection and ranging (LiDAR) imagery and LiDAR-derived digital volume model (DVM), building footprint data, parcel-level data, digital orthophoto quarter quads (DOOQs), and DEIMOS-2 Very-High Resolution Multispectral Imagery. These studies resulted in improved 2D representations of population distribution, usually in the form of density surfaces, but did not actually place the population distribution in three dimensions. Sridharan and Qiu (2013) used LiDAR-derived building volumes as an ancillary variable to spatially disaggregate population, both horizontally and vertically, thus achieving the closest results to actual 3D population distribution so far. Our new method is an advancement on this, being based on more specific data than building volume alone, and taking into account 3D exposure assessment, in addition to population estimates.

As computer power increases and data availability is improved, 3D modeling has become more practical. This study aims to compare the estimated affected population to a 3D exposure using four methods:

- Spatial intersect (census unit level).
- Centroid containment (census unit level).
- 2D dasymetric disaggregation (property lots—cadastral data—by residential area).
- 3D dasymetric disaggregation (buildings by residential volume).

Three-dimensional dasymetric disaggregation

In this study, we are expanding on the cadastral-based 2D dasymetric mapping method to incorporate 3D modeling of population distribution in New York City and São Paulo, using an extrusion technique, building heights information, and other ancillary data to obtain a more accurate estimation for population distribution. This then can be useful in assessing exposure to air pollution, noise impacts, urban heat islands (*e.g.*, adverse health effects from extreme heat events), and so forth. Three-dimensional dasymetric mapping improves on the 2D dasymetric method by including vertical data in mapped population distributions, thus allowing exposures that stem from 3D impacts to be taken into consideration.

In the New York City case study, American Community Survey population data (2014, five-year estimates) at the at the block group level were downloaded from the U.S. Bureau of the Census (2014). Cadastral data from 2014 were acquired at the tax lot level from the MapPLUTO spatial database provided by the New York City Department of City Planning (2014), which included information such as residential area. Building footprint and height data were downloaded from the New York City Department of Information Technology and

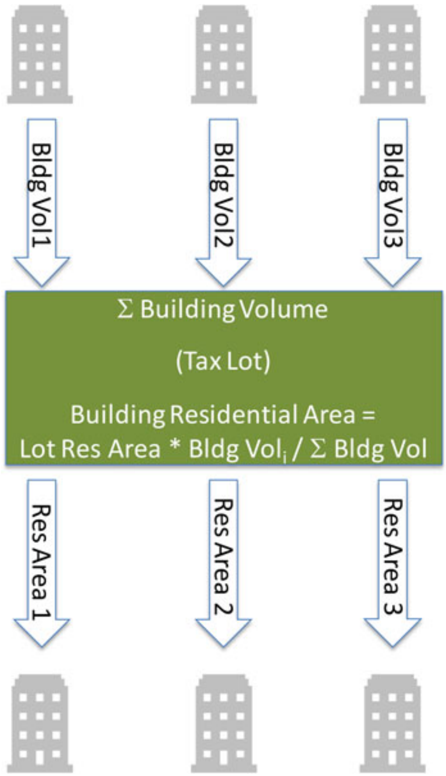

Figure 1. 3D dasymetric method: Residential area, New York City study. Residential area is estimated in each building by distributing the information from the tax lot to each building footprint based on building volume. Res Area = residential area; Bldg Vol = building-level volume.

Telecommunications' NYC Open Data (New York City Department of Technology and Telecommunications 2014).

To dasymetrically disaggregate census block group populations to individual buildings, a number of steps were executed. Building volumes are estimated using the footprint area and height information (area × height). The total building volume in each tax lot is calculated by summing the volumes of all the buildings contained by the lot. The amount of available residential area is then estimated in each building by distributing the information from the tax lot to each building footprint that is contained by that specific tax lot based on the ratio of building-level volume to tax lot-level volume. The total amount of residential area available per census block group is then calculated by aggregating the amount estimated in the buildings that fall within that specific block group (Figure 1). Census population estimates are then disaggregated to the buildings using the ratio of residential area per building divided by total available residential area in the census unit (Figure 2). An advantage to using building-level volumetric weighting is that there are some tax lots in New York City that not only contain multiple buildings, but sometimes also contain multiple census block groups. This is more common with large residential complexes such as public housing. The building-level population estimates are extruded to three dimensions based on the building's height (Figure 3).

A 3D exposure buffer was created to examine the differences between various methods of estimating exposed populations. In New York City, this buffer was specified in a six-block area of Amsterdam Avenue, from 104th Street to 110th Street, where the "impact zone" stretches 50 m from the center line of the street. Exposed population was quantified by first intersecting the 3D exposure buffer with the 3D population estimates, and then employing volumetric weighting to calculate the number of people exposed. For instance, if one quarter of the building's volume is

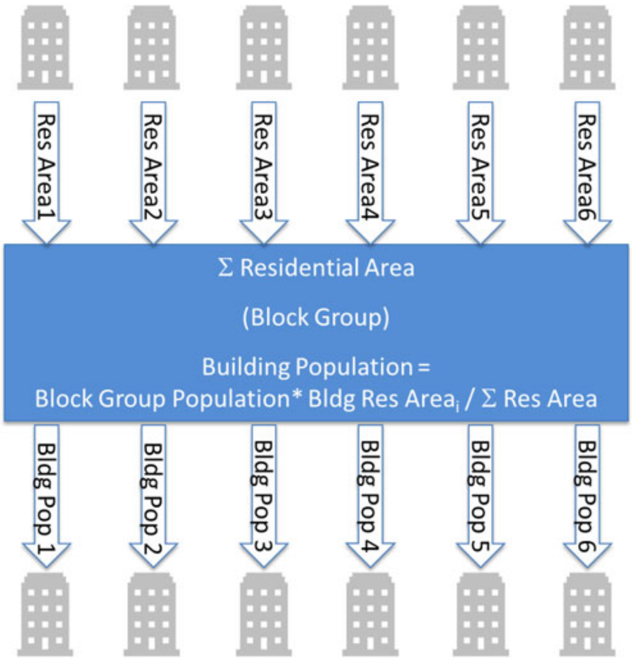

Figure 2. 3D dasymetric method: Population estimation, New York City study. Census population data are disaggregated to the buildings using the ratio of residential area per building divided by total available residential area in the census block group. Res Area = residential area; Bldg Pop = estimated building-level population.

Figure 3. Two-dimensional view of a six-block study area in Manhattan, New York City. Population density shown by census block group ($n = 7$) and building footprints shown as either having property tax-lot-derived residential area data (orange) or not (gray). Fifty-meter impact zone is shown along Amsterdam Avenue between 104th and 110th Streets.

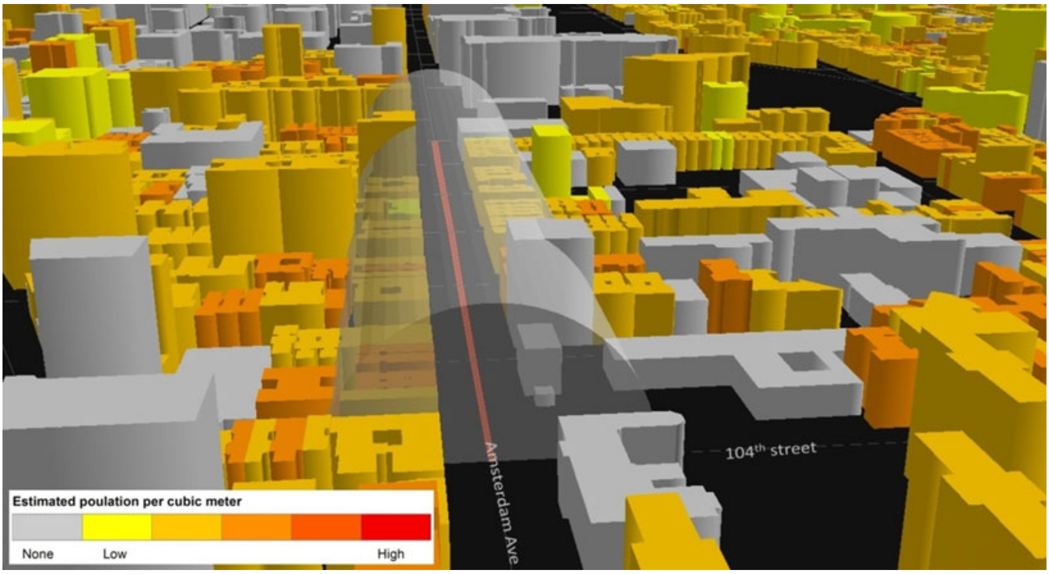

Figure 4. 3D depiction of population densities (by volume) and impact buffer for New York City study area. Three-dimensional oblique view of the Amsterdam Avenue study area. Impact zone is shown as a 3D 50-m buffer, and volumetric population density by building (people per cubic meter) is shown.

within the impact zone of exposure, then one quarter of the population estimated to reside in that particular building would be flagged as exposed (Figure 4).

To compare results of the 3D building-level dasymetric method, various 2D estimates were calculated using commonly used spatioanalytic techniques. The spatial intersect method identifies an area as "exposed" if any part of the geographic unit, in this case a census block group, is intersected by the impact zone. The centroid containment method determines if the geographic center of the census block group is contained within the impact zone. If it is, then the population of that unit is considered "exposed." Finally, 2D lot-level dasymetric disaggregation was employed. This disaggregates population from the census block groups into tax lots based on availability of residential area—similar to the 3D method described earlier but without using any building data or vertical information. If the tax lot polygon intersects the impact zone, it is considered exposed (Figure 5).

A similar 3D dasymetric disaggregation was conducted in a six-block area in the Jardim Paulista district in São Paulo, Brazil. Data from the Demographic Census (2010) by enumeration area (roughly equivalent to the census block group in the U.S. Census) were downloaded via the Brazilian Institute of Geography and Statistics (IBGE). A digital cartographic database of the city blocks and cadastral data (2017) was provided by the SP Secretariat of Finance and Economic Development of the City of São Paulo. Building footprint and height data (2004) were obtained from the SP Secretariat of Urbanism and Licensing. This area has a similar total population to the six-block area studied in New York City. Due to lack of access to comparable cadastral data, however, a different estimation method was used, where building volume is used as a proxy for residential area, assuming that residential area is proportional to the building volume (similar to Sridharan and Qiu 2013). Note that this assumption results in all buildings within a populated census unit to receive population estimates (which might include commercial, industrial, or otherwise nonresidential buildings). This was accomplished by first calculating the building volume based on footprint area and height, and then summing all the building volumes per census unit. The census population was then multiplied by the ratio of building volume and the sum of all building volumes in the tract (Figure 6).

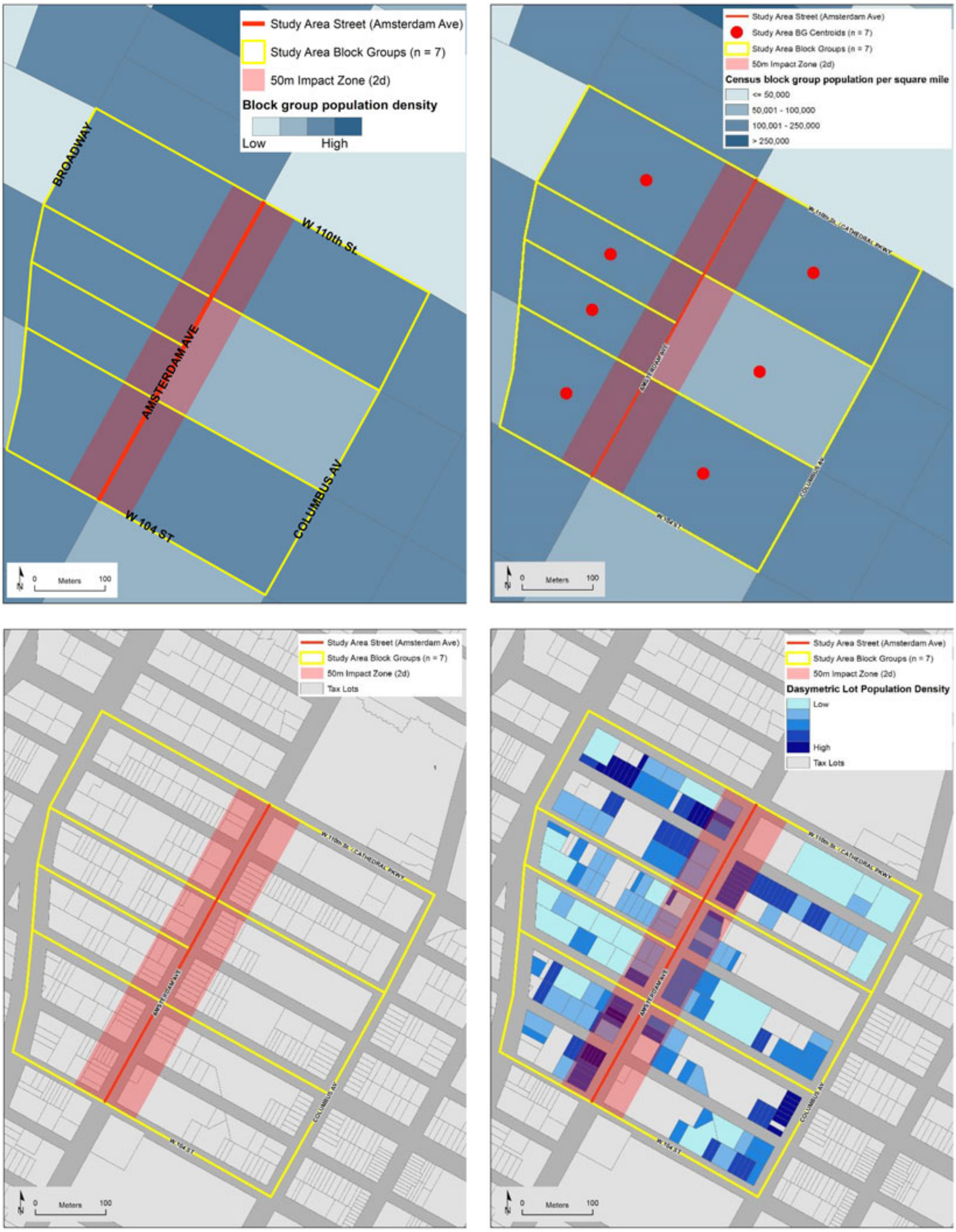

Figure 5. Spatial selection methods. Top left: Block group intersect (all block groups are identified as exposed). Top right: Block group centroid containment (no block groups are identified as exposed). Bottom left: Tax lots in the study area. Bottom right: 2D dasymetric method (estimated tax lot populations intersecting the buffer as estimated as exposed).

Exposed populations were estimated similarly to the methods used in the New York City example, but this case did not include a 2D dasymetric lot-level comparison—again due to the lack of comparable cadastral data (Figures 7 and 8).

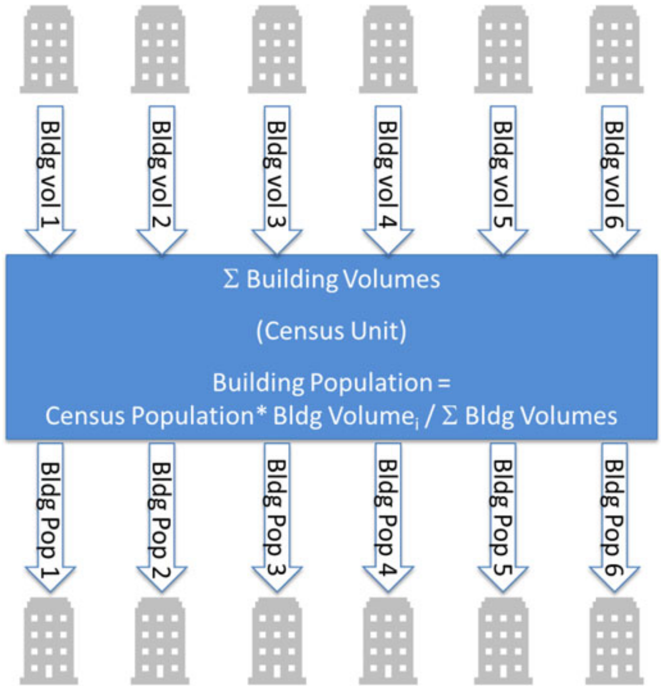

Figure 6. 3D dasymetric method: Population estimation, São Paulo study. Building volume was calculated based on building footprint areas and height, then summing all the building volumes per census tract. The census population was then multiplied by the ratio of building volume and the sum of all building volumes in the tract. Bldg Vol = building volume; Bldg Pop = estimated building population.

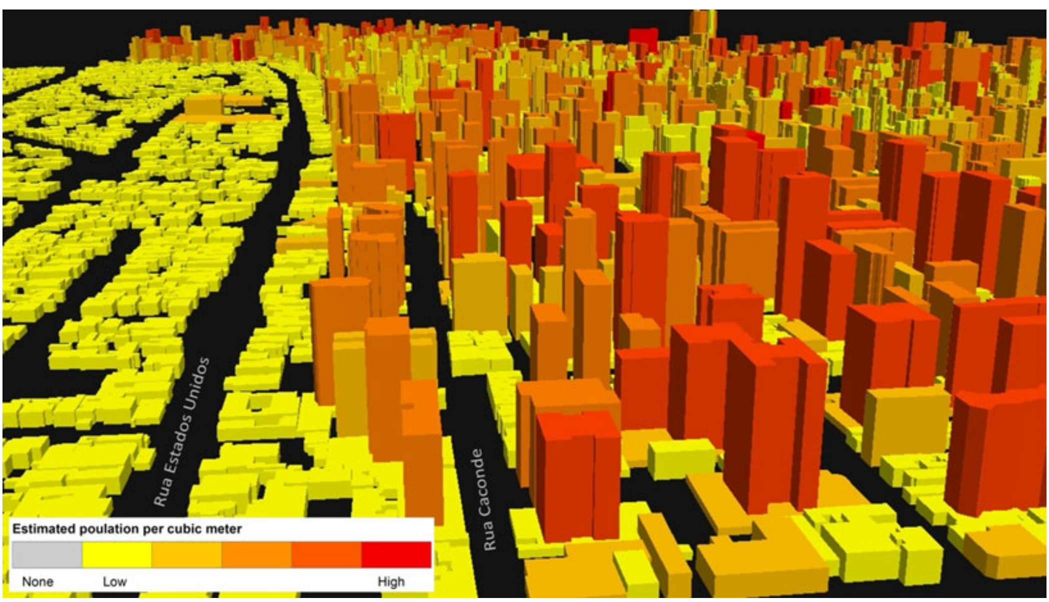

Figure 7. The Jardim Paulista district in São Paulo, Brazil: Estimated population per cubic meter of building volume. Note that both sides of Rua Estados Unidos show a sharp contrasted boundary among the horizontal wealthy residential part of the Jardim Paulista neighborhood and the high-rise buildings normally occupied by businesses and mixed-use residential land uses.

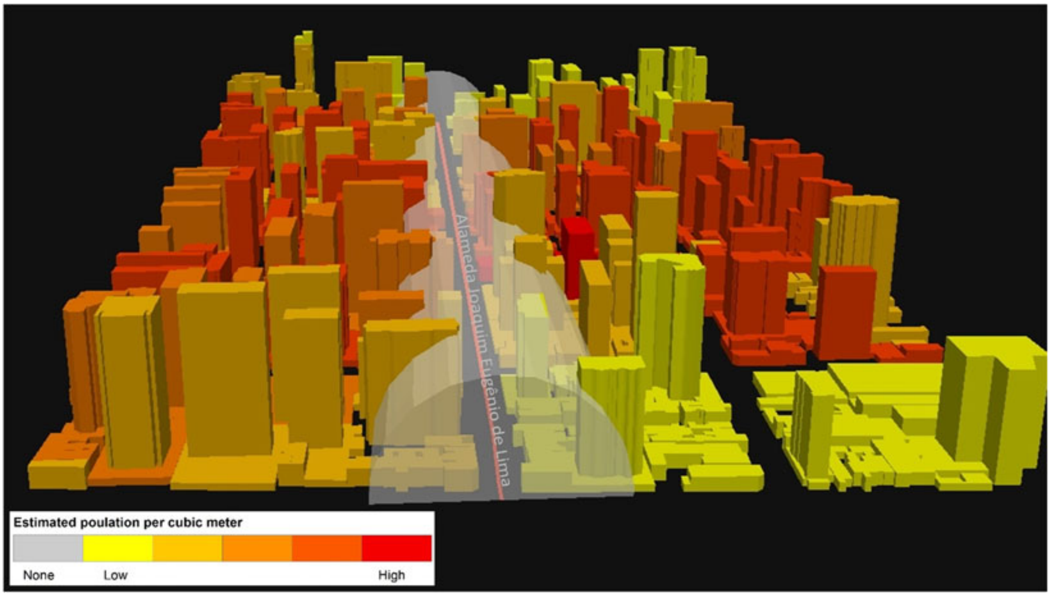

Figure 8. 3D depiction of population densities (by volume) and impact buffer for São Paulo study area. Three-dimensional oblique view of the Alameda Joaquim Eugênio de Lima study area. Impact zone is shown as a 3D 50-m buffer, and volumetric population density by building (people per cubic meter) is shown.

Results

The outputs from the various exposure estimation techniques were compared in both absolute numbers and proportions of the study population identified as "exposed." Four methods were used in the New York City study area: (1) census unit intersect, (2) census unit centroid containment, (3) lot-level (2D) intersect, and (4) 3D building-level volumetric weighting. Three methods were used in the São Paulo study area: (1) census unit intersect, (2) census unit centroid, and (3) 3D building-level volumetric weighting (Table 1 and Figure 9). The results of the comparison in both study areas illustrate the benefits of 3D dasymetric disaggregation.

In both the New York City and São Paulo examples, the techniques were comparable, the proportions of the populations estimated to be exposed were similar, with the intersect method being the most inclusive, and the centroid containment method being most conservative, which tend to reflect the results typically obtained in other studies (Maantay, Maroko, and Herrmann 2007; Maantay and Maroko 2009; Maantay, Maroko, and Culp 2010). Therefore, the intersect method gave the highest number of potentially affected or exposed population, followed by the 2D lot-level dasymetric intersect (in New York City only, because this method was not possible in São Palo due to data constraints), then the 3D method. The centroid containment method (showing zero exposed populations in both cases) had the lowest estimate of exposed population.

Discussion and conclusions

Population estimates derived from the 3D dasymetric method are shown to perform differently from other more commonly used techniques when examining exposures in three dimensions. The findings suggest that if researchers have access to highly accurate impact zone models, such as dispersion modeling outputs for air pollutants, this method might create a more realistic estimate of exposed populations. The smaller the impact zone, particularly in the Z (height) dimension, the more the differences in estimates could be between 2D and 3D estimates. For instance, if the exposure only reaches a few meters off the ground, a 2D estimate might wildly overestimate

Table 1. Comparison of results for the New York City and the São Paulo case study areas.

Method	Population in 6-block study area		Estimated exposed population		Estimated percent exposed population	
	New York City	São Paulo	New York City	São Paulo	New York City	São Paulo
Census intersect	12,487	11,786	12,487	9,830	100.0	83.4
Census centroid	12,487	11,786	0	0	0.0	0.0
Lot-level dasymetric intersect	12,487	11,786	3,209	—	25.7	—
3D building volumetric weighting	12,487	11,786	1,971	1,157	15.8	9.8

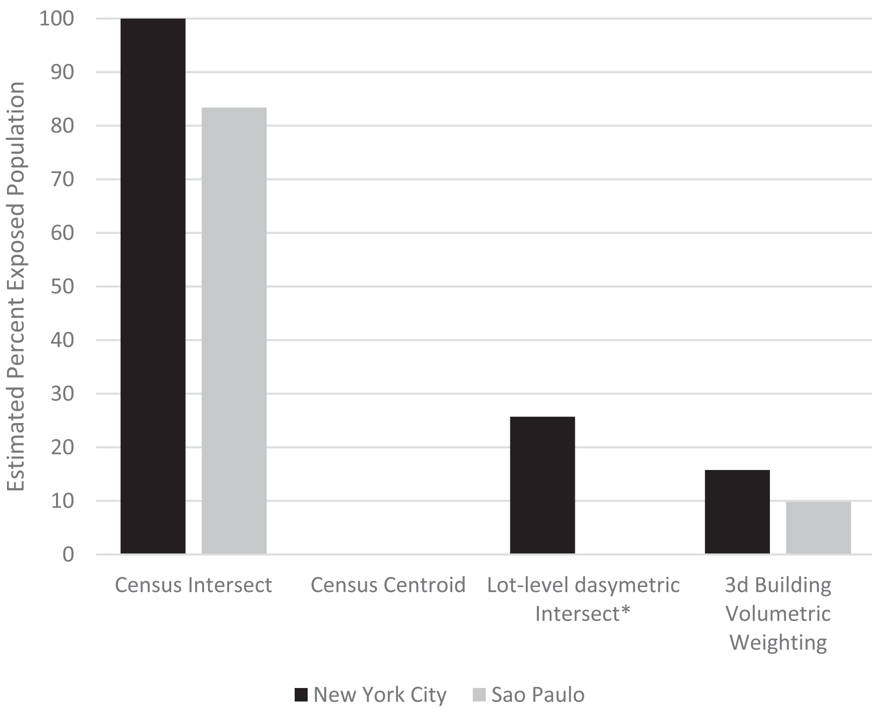

Figure 9. Comparison of results for New York City and São Paulo. *São Paulo study area did not include the lot-level dasymetric intersect method.

the population impact in a high-rise residential building. The converse is also true, however: Very large impact zones, such as ones that encompass an entire neighborhood and extend upward to the tops of the residential structures, will likely have less variation among the methods to estimate affected populations. As such, if the study area has only low residential structures, such as single-family homes, then 3D disaggregation might not add meaningfully to the analyses. If there is significant heterogeneity in the land use patterns in the area of interest, however, then some sort of dasymetric disaggregation is still recommended. Other limitations to the 3D dasymetric method include reliance on a number of data sets (*e.g.*, building volume data, cadastral data, census population data), all of which might contain both attribute and locational errors. The 3D method also assumes a homogeneous distribution of residents within the buildings, which might not always be the case (*e.g.*, a commercial storefront on the first floor of a mixed-use residential building or parking facilities within the building).

We have established the usefulness of the 3D dasymetric method for analyses employing population-based rates, as is commonly the case with public health and epidemiological research and hazard and risk assessment, but the 3D dasymetric method is not limited to improving the development of rates alone. These methods will be useful in many disparate fields and serve many purposes. For instance, one can improve emergency management operations and implementation by providing more precise information about actual positions of vulnerable or susceptible populations, thereby increasing the quality of functions such as evacuation route planning, optimal site selection for emergency shelter locations, and critical rescue and recovery prioritization for first responders.

As the morphology of cities becomes increasingly complex, the need continues to grow for immediate and well-informed decision making, regarding both catastrophic events and chronic conditions. We anticipate that advances in dasymetric mapping, such as the 3D dasymetric, will help us to "perfect the denominator" and better our understanding of the human–urban project.

ORCID

Andrew Maroko http://orcid.org/0000-0002-9398-2386
Juliana Maantay https://orcid.org/0000-0002-2449-0345
Reinaldo Paul Pérez Machado https://orcid.org/0000-0001-5608-6286
Ligia Vizeu Barrozo http://orcid.org/0000-0001-7322-6789

References

Biljecki, F., K. A. Ohori, H. Ledoux, R. Peters, and J. Stoter. 2016. Population estimation using a 3D city model: A multi-scale country-wide study in the Netherlands. *PLoS One* 11(6):e0156808. doi: 10.1371/journal.pone.0156808.

Brazilian Institute of Geography and Statistics (IBGE). 2010. Demographic Census Data downloaded.

Chakraborty, J., and Maantay, J. A. 2011. Proximity Analysis for Exposure Assessment in Environmental Health Justice Research. In Maantay, and McLafferty (Eds.), Geospatial Analysis of Environmental Health (pp. 111–138). Heidelberg London New York: Springer.

Eicher, C. L., and C. A. Brewer. 2001. Dasymetric mapping and areal interpolation: Implementation and evaluation. *Cartography and Geographic Information Science* 28(2):125–38. doi: 10.1559/152304001782173727.

Flowerdew, R., and M. Green. 1992. Developments in areal interpolation methods and GIS. *The Annals of Regional Science* 26(1):67–78. doi: 10.1007/BF01581481.

Goodchild, M., and N. S.-N. Lam. 1980. Areal interpolation: A variant of the traditional spatial problem. *Geo-Processing* 1:297–312.

Holt, J. B., C. P. Lo, and T. W. Hodler. 2004. Dasymetric estimation of population density and areal interpolation of census data. *Cartography and Geographic Information Science* 31(2):103–21. doi: 10.1559/1523040041649407.

Langford, M., D. J. Maguire, and D. Unwin. 1991. The areal interpolation problem: Estimating population using remote sensing in a GIS framework. In *Handling geographic information: Methodology and potential applications*, ed. I. Masser and M. Blakemore. London: Longman.

Lwin, K. K., and Y. Murayama. 2010. Development of GIS tool for dasymetric mapping. *International Journal of Geoinformatics* 6(1):11–8.

Lwin, K. K., and Y. Murayama. 2011. Estimation of building population from LiDAR derived digital volume model. In *Spatial analysis and modeling in geographical transformation process*, ed. Y. Murayama and R. B. Thapa, 87–9. Berlin: Springer.

Maantay, J. A., and A. R. Maroko. 2009. Mapping urban risk: Flood hazards, race, & environmental justice in New York. *Applied Geography* (Sevenoaks, England) 29(1):111–24. doi: 10.1016/j.apgeog.2008.08.002.

Maantay, J. A., A. R. Maroko, and G. Culp. 2010. Using geographic information science to estimate vulnerable urban populations for flood hazard and risk assessment in New York City. In *Geotechnical contributions to urban hazard and disaster analysis*, ed. P. Showalter and Y. Lu, Ch. 5, 71–97. Berlin: Springer-Verlag.

Maantay, J. A., A. R. Maroko, and C. Herrmann. 2007. Mapping population distribution in the urban environment: The cadastral-based expert dasymetric system (CEDS). *Cartography and Geographic Information Science* 34(2):77–102. doi: 10.1559/152304007781002190.

Maantay, J. A., A. R. Maroko, and H. Porter-Morgan. 2008. A new method for population mapping and understanding the spatial dynamics of disease in urban areas. *Urban Geography* 29(7):724–38. doi: 10.2747/0272-3638.29.7.724.

Maheswaran, and Craglia. 2004. Using GIS for Exposure Assessment: Experience from the Small Area Health Statistics Unit. In K. de Hoogh, D. Briggs, S. Cookings, A. Bottle, R. Maheswaran, and M. Craglia (Eds.), GIS in Public Health Practice (pp. 109–124). CRC Press.

Mennis, J., and T. Hultgren. 2006. Intelligent dasymetric mapping and its application to areal interpolation. *Cartography and Geographic Information Science* 33(3):179–94. doi: 10.1559/152304006779077309.

New York City Department of City Planning. 2014. Bytes of the big apple archive. https://www1.nyc.gov/site/planning/data-maps/open-data/bytes-archive.page?sorts[year]=0

New York City Department of Technology and Telecommunications. 2014. NYC open data (building footprints). https://data.cityofnewyork.us/Housing-Development/Building-Footprints/nqwf-w8eh

Pavía, J. M., and I. Cantarino. 2016. Can dasymetric mapping significantly improve population data reallocation in a dense urban area? *Geographical Analysis* 49(2):155–194. doi: 10.1111/gean.12112.

Petrov, A., A. Bozheva, and R. Sugumaran. 2005. The effect of spatial resolution of remotely sensed data in dasymetric mapping of residential areas. *GIScience and Remote Sensing* 42(2):113–30. doi: 10.2747/1548-1603.42.2.113.

Sridharan, H., and F. Qiu. 2013. A spatially disaggregated areal interpolation model using light detection and ranging-derived building volumes. *Geographical Analysis* 45(3):238–58. doi: 10.1111/gean.12010.

U.S. Bureau of the Census. 2014. American factfinder. https://factfinder.census.gov/

Wang, S., Y. Tian, Y. Zhou, W. Liu, and C. Lin. 2016. Fine-scale population estimation by 3D reconstruction of urban residential buildings. *Sensors* 16(10):pii: E1755. doi: 10.3390/s16101755.

Xie, Z. 2006. A framework for interpolating the population surface at the residential-housing-unit level. *GIScience and Remote Sensing* 43(3):233–51. doi: 10.2747/1548-1603.43.3.233.