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Geospatially-intelligent three-dimensional multivariate methods for multiscale dasymetric mapping of urban population: Application and performance in the Minneapolis-St. Paul metropolitan area

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GEOSPATIALLY-INTELLIGENT THREE-DIMENSIONAL MULTIVARIATE METHODS FOR MULTISCALE DASYMETRIC MAPPING OF URBAN POPULATION: APPLICATION AND PERFORMANCE IN THE MINNEAPOLIS-ST. PAUL METROPOLITAN AREA

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ABSTRACT

The wide availability of remote sensing data, the development of computer technology, and the accessibility of census data in the digital form created new opportunities for highly accurate population estimates. Of particular scientific interest is the method of dasymetric mapping, which can significantly improve the spatial accuracy of mapping socio-demographic processes. In addition to population density, the method has considerable potential in mapping the distribution of other social, economic and demographic variables, such as income level, crime, ethnicity, etc. Another significant gap in the existing studies is the development of three-dimensional dasymetric mapping methods.

This study is focused on developing intelligent dasymetric mapping methods to create algorithms for near real-time display demographic and other socio-economic parameters and assess their accuracy and their potential for geovisual analytics. The study is developed and tested in Minneapolis-Saint Paul area, Minnesota, USA as a key study site given the relative diversity of urban areas and the accessibility for field surveys.

The goal of this study is to develop and test an effective geospatially-intelligent method and GIS algorithm for the creation of multivariable three-dimensional dasymetric (3DM) geographic visualizations for the Twin Cities Metropolitan area.

2D and 3D binary dasymetric mapping methods, as well as floor fraction and intelligent dasymetric mapping method were used to identify the best performing method in terms of accuracy.

The 3D dasymetric mapping method yielded the best accuracy in estimation of population counts in conditions of the given study area. 3D dasymetric mapping method proved to improve the accuracy of population mapping in an urban environment compared to 2D methods. The improvement is more significant at a smaller scale of analysis that reflects a more heterogeneous residential building infrastructure. Finally, the additional socio-economic variables, such as aggregated income and three different types of spending(for food, household supplies, and apparel) were mapped.

The study faced the limitations of the inability to obtain data, perfectly synchronized in time between all the spatial layers, non-straightforward nature of the selection of residential/non-residential buildings and low height variance in the study area.

The future directions of the study are to integrate the developed methods with the existing web mapping platform, test the dasymetric mapping approach on the extended set of socioeconomic variables and explore the usefulness of the dasymetric mapping approach on the smaller scales of the enumeration units and dasymetric mapping polygons.

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CHAPTER 1

INTRODUCTION

Advancing Geospatial Data Science through Dasymetric Mapping

For a long time, geographers have shown an interest in increasing the accuracy of recording demographic parameters of population distribution and visualizing such results (Bracken & Martin, 1989; Langford, 2003). Multiple methods have been developed (MacEachren et al., 1998) to estimate and visualize the population distributions across space. The wide availability of remote sensing and other geospatial data and the accessibility of census data in the digital form created new opportunities for highly accurate population estimates (Wang et al., 2016). Of particular interest is the dasymetric mapping method. It can significantly improve the spatial accuracy of mapping socio-demographic phenomena (Mennis, 2009).

The method of dasymetric mapping (in translation from Greek "measuring density" (Kushnyr, 2015)) is an effective method of visualizing the distribution of people, which can show the spatial distribution of population density (Holt et al., 2004). Dasymetric mapping (DM) uses ancillary data to identify population distribution patterns and reorganize data that do not have an exact spatial reference to the spots of actual population distribution (Mennis, 2009; Petrov, 2012). DM requires integrating multiple datasets with diverse nature and characteristics. These datasets include population counts, digital topographic maps, building footprint and zoning datasets, remotely sensing, often high-resolution data, information from field observations and building surveys, as well as LiDAR and other heterogeneous sources of big geospatial data. DM could be computationally intensive as it assimilates these datasets, and increasing the precision, accuracy and efficiency of DM methods is an important consideration (Petrov, 2012).

Despite a potentially broad utility of the dasymetric mapping method to display any parameters associated with the uneven distribution of the investigated quantity under the influence of external factors, it often has a narrow focus. Most of the studies are concentrated on assessing the method's suitability for estimating the population distribution (Biljecki et al., 2016; Eicher & Brewer, 2001; Holt et al., 2004; Mennis, 2009). However, the method has considerable potential for mapping the distribution of other social, economic and demographic variables, such as income level, crime, ethnicity, etc. (Maantay et al., 2007).

Another emerging area of DM research is the development of three-dimensional dasymetric methods. Existing studies are mainly based on two-dimensional interpolation (Biljecki et al., 2016; Lwin & Murayama, 2009) even though the urban population exists in a distinctly 3D space (Moser et al., 2010).

Another shortcoming of existing dasymetric mapping applications is their orientation to work in the offline mode and lack of ability to effectively incorporate interactivity or real-time datasets (e.g Kim et al., 2013). Most studies focus on obtaining and processing auxiliary data, such as building footprints, zoning areas, and volumes of the structures (Biljecki et al., 2016; Lwin, 2010; Sleeter & Gould, 2007; Wang et al., 2016). As a part of emerging *Geospatial Data Science* (GDS), DM is overdue for algorithm improvement, incorporation of instant and near-real-time data flows, and interactive, user-driven geographic computation.

Goal, Research Questions, and Objectives

This study aims to test an effective geospatially intelligent method to create multivariable three-dimensional dasymetric (3DM) geographic visualizations for the Twin Cities, Minnesota Metropolitan area.

Hypothesis: 3DM improves the accuracy of population mapping in an urban environment compared to 2D methods. The improvement is more significant at a smaller scale of analysis that reflects a more heterogeneous residential building infrastructure.

Research Questions

- What is the most accurate method to introduce the 3rd dimension (3D) in dasymetric maps?
- What is the difference between the standard (2D) and 3D dasymetric mapping methods at different scales and levels of urban heterogeneity?
- What can additional social-economic variables be mapped using the 3D dasymetric method?

Objectives

- Identify the most accurate method to introduce the 3rd dimension in dasymetric maps.
- Examine the statistical difference between 2D and 3D dasymetric mapping methods at different scales and levels of urban heterogeneity.
- Apply the most accurate 3D dasymetric mapping method to additional social-economic variables.

The Significance of the Outcomes

This study improves processes, models, and algorithms, allowing accurate spatial data representations with relevant attributive information, thus contributing to urban geospatial data analytics. The low prevalence of algorithms for creating dasymetric visualizations, their orientation to a two-dimensional environment, and a small number of implementations related to the mapping non-population density variables are the deterrents to DM's integration into the modern decision support systems and geospatial data science. During the implementation of this project, dasymetric mapping technologies were developed to incorporate multiple variables that can be integrated into web-based spatial decision support systems. Such technologies will facilitate decision support and decrease the time needed for each decision, which is especially important for systems supporting emergency response decisions or decision-making in the rapidly changing business environment.

CHAPTER 2

LITERATURE REVIEW

Why Dasymetric Mapping?

Our rapidly changing world requires the adoption of quick and practical solutions. The majority of the world's population expected to live in cities soon (Vlahov et al., 2005). Cities are complex and dynamic human-natural systems that generate significant and heterogeneous data flows. Navigating through these big data volumes requires developing and implementing geovisually-advanced, data assimilation-effective, and often time-sensitive data analytics methods (e.g., "urban computing," (Zheng et al., 2014)). For example, cities are fragile systems susceptible to natural disasters and the impacts of climate change. To timely respond to emerging challenges, it could be beneficial to use decision support systems to provide accurate and timely answers during emergencies (National Research Council, 2010). Such solutions include calculating the location of situational centers, shelters, and warehouses with humanitarian aid (Lwin & Murayama, 2009). Other data-driven decisions are dependent on our ability to harness geospatial data in an urban environment to deal with public policy, real estate, business solutions, transportation, health care, crime, etc. (Rathore et al., 2016; Zheng et al., 2014). To promote evidence-based decision-making, the Decision Support Systems (DSS) must operate on various scales - from local governmental scale to global (Sugumaran & Degroote, 2010).

For effective operation, urban DSS systems require accurate and reliable information on the location of the population. It is necessary to know exactly how the population is distributed in space, including at different times and on different floors of buildings. Such information cannot be directly obtained from census data (Langford, 2003).

Census mapping generally shows population distributions only by generalized geographies such as census blocks, census block groups, and census tracts. In developed countries, this is done to protect the privacy of citizens. In developing countries, data is even more unreliable or detailed due to the lack of investment in the census infrastructure (Eicher & Brewer, 2001; Mennis, 2009). Census geographic units, such as block groups, reflect only the aggregate and/or indicative values and cannot be used to discern spatial patterns in the distribution of the population inside the census unit. In other words, this data collection technique operates as a low-pass filter, smoothing any variations in the data (Bielecka, 2005) and generates a phenomenon of spatial incongruity (Voss et al., 1999).

A significant task then is to reconstruct and reflect the patterns of the actual distribution of the population in a quantitative manner, based on a starting point of census data (Mennis, 2009). A practical method of visualizing the distribution of people, which can show the spatial distribution of population density, is the method of Dasymetric Mapping (DM) (in translation from Greek "measuring density," Kushnyr, 2015). Dasymetric mapping uses ancillary data to identify population distribution patterns and reorganize data that do not have an exact spatial reference to the spots of actual population distribution (Mennis, 2003; Petrov, 2012).

Russian scientist Benjamin Semenov Tian-Shansky first proposed the method in 1911 (Petrov, 2012). For various reasons, dasymetric techniques were not widely adopted in the pre-GIS era, although they were used in population research (e.g., Wright, 1936). The main reason was the high labor intensity of map production. Also, the difficulty in getting acquainted with the original materials was significant because they were published in Russian (Mennis, 2009; Petrov, 2012). However, with the advent of modern GIS technologies, dasymetric methods have become more commonly applied, as witnessed by increased published scientific literature (Mennis, 2009; Polyan, 2014).

The creation of effective dasymetric maps requires high-quality and reliable ancillary data. Historically, topographic maps have traditionally been used for dasymetric mapping (Petrov, 2012; Polyan, 2014). However, with the increased availability of remote sensing data, detailed address classifiers, LiDAR data, it becomes possible to create data processing technologies that will show the distribution of population across individual building spaces(Aubrecht et al., 2009). Having studied the spatial patterns of population distribution, it becomes possible even to evaluate and predict its population distribution, where there are no census data(Langford, 2003).

History of Dasymetric Mapping Methods

Most researchers agree that the earliest (implicit) example of dasymetric mapping is George Julius Poulett Scrope's population density map of 1833(MacEachren et al., 1998; McCleary, 1969; A. Robinson, 1982). He used the rudimentary method of dasymetric mapping to identify the differences between "populated," "insufficiently populated," and "not yet inhabited" parts of the Earth (Andrews, 1985).

In 1837, the British cartographer Henry Drury Harness created a map of the population density of Ireland, in which he used data on the features of the landscape to distinguish between densely populated and sparsely populated areas. In this work, the fundamental principle of dasymetric mapping was applied (A. Robinson, 1955). However, the methodology for creating maps was not transparent (Andrews, 1985; MacEachren et al., 1998; A. Robinson, 1955), and none of the researchers used the word "dasymetric."

The Russian geographer Benjamin Semenov-Tien-Shansky (1870-1942) first proposed the dasymetric mapping method concept as well as the term "dasymetric map." He first introduced the idea of dasymetric mapping in his report to the Russian Geographical Society in 1911. He translated the Russian words "measurement" and "density" into Greek, then transliterated the term into Russian as "dasymetric." (Petrov, 2008, 2012). The popularization of this term is connected with the project "Dasymetric map of European Russia," which Benjamin Semenov-Tian-Shansky began publishing in 1923 (Petrov, 2012).

Current Approaches to 3D Dasymetric Mapping and Geovisualization

Topographic maps were used as primary sources of auxiliary information for DM in the pre-GIS. There have been more studies based on remote sensing data, given wide remote sensing data availability. These studies are examining the relationship between the patterns of population distribution with the area of impervious surfaces, the intensity of the night glow, or even the NDVI indices (Bozheva et al., 2005). However, these methods are problematic in urban areas and exhibit a significant error due to the lack of homogeneity within the study area (Biljecki et al., 2016).

Later, building footprint areas were used as a proxy-value indicating the number of building inhabitants (Lwin, 2010). In addition to areas, it is also possible to use the number of buildings' stories to estimate the volume of premises inside the building (Greger, 2015; Järv et al., 2017). One could multiply the number of stories in the building to its footprint area and get the approximate volume of the building. The volume of the building and its type reflect the population of the structure relatively well (Lwin & Murayama, 2009). This work introduced the concept of three-dimensional dasymetric mapping (3DDM). Its disadvantages included an unnecessary simplified approach to assessing the residential volume— the entire volume is considered residential. In addition, the authors did not pay attention to the possibilities of using the three-dimensional dasymetric method proposed by them for the disaggregation of other variables that are not directly related to the population.

Literature suggests the need for a more accurate assessment of the volume of premises inside buildings with a variable number of stories (Biljecki et al., 2016). To date, the most elaborate technique to estimate the volume from remote sensing data seems to be a three-dimensional building reconstruction by calculating the size of building shadows from remote sensing data. Here, object classification in commercially available software such as eCognition, shadow recognition, and the subsequent calculation of building heights are pretty effective methods (Wang et al., 2016). However, despite the possibility of applying this method in areas that do not have LiDAR coverage, such a method probably does not represent such high accuracy of building volume estimation as methods using LiDAR data. Accuracy problems of volume estimation make it difficult to adapt this volume measurement method to its variation using multiple variables.

Estimates of building volume using multispectral remote sensing data provide a relatively approximate and rough estimate of building volumes. Some researchers suggest using LiDAR data (Aubrecht et al., 2009; Biljecki et al., 2016) as an effective way to calculate building volume to implement 3D volumetric methods effectively. These methods potentially give a much more accurate estimate of the volume of the building; however, they can be relatively expensive. Volume dasymetric methods can be used more efficiently if there is a publicly available statewide DEM, which in particular is available in Iowa. In the absence of such a detailed DEM, it is possible to use previous methods for calculating the volume of buildings. Unfortunately, despite the impressive size of the article (Biljecki et al., 2016) and the use of the three-dimensional dasymetric method, the discussion on how the dasymetric method can be used to disaggregate other variables that are not related to population estimates was out of the scope of the article

However, all the methods of estimating the volume of buildings described above do not consider local variations. For example, some structures may contain residential and non-residential premises occupied by various businesses. The work of Aubrecht et al., (2009) suggests using the detailed address classifiers with the description of the companies located in a particular building to estimate the population and take into account the local variations. The idea of using address classifiers was to understand, which apartments in the building belong to the residential and non-residential class, and exclude non-residential premises from the total livable volume of the building. However, despite the applied improvements of the classical three-dimensional dasymetric method to increase the accuracy of estimating the residential volume, the authors of this work focused on assessing the population. They did not consider the possibilities of the method for a more accurate assessment of other non-population variables.

Concerning visualization methods, most authors continue to use traditional two-dimensional maps. However, in the research by Tiede and Lang (2007), it is suggested how to display population estimates in the form of a 3D dasymetric map on the surface of a digital globe, which should facilitate a more natural perception of such information. Undoubtedly, the methods of web mapping are also actively used both for displaying traditional two-dimensional and three-dimensional maps. In this regard, we should note the already mentioned work of Lwin and Murayama (2009) and Tiede and Lang (2007).

One of the main gaps identified in the existing literature is that current studies are focused on finding out the exact quantitative distribution of the population. However, it does not pay enough attention to the spatial interpolation of socioeconomic indicators. In my work, I would like to pay attention to the applicability of the refined method of dasymetric mapping for calculating socioeconomic indicators, such as income distribution, etc. Such methods and datasets are expected to be of interest for more accurate and targeted marketing purposes. In particular, this will provide an opportunity to more accurately carry out advertising to households that meet the required socioeconomic metrics, such as total income and even more socially conscious programs instead of just advertising.

CHAPTER 3

METHODS

Overview of the Methodology

This study consists of the following main parts: (1) data preparation, development, and selection of the best (most accurate) algorithm for 3D dasymetric mapping; (2) 3DDM experiments with additional socio-economic variables. The choice of the algorithm has been made using the accuracy of the obtained dasymetric map. The accuracy of the resulting product relative to actual census data is evaluated. The main steps outlined above are depicted in Fig 1.

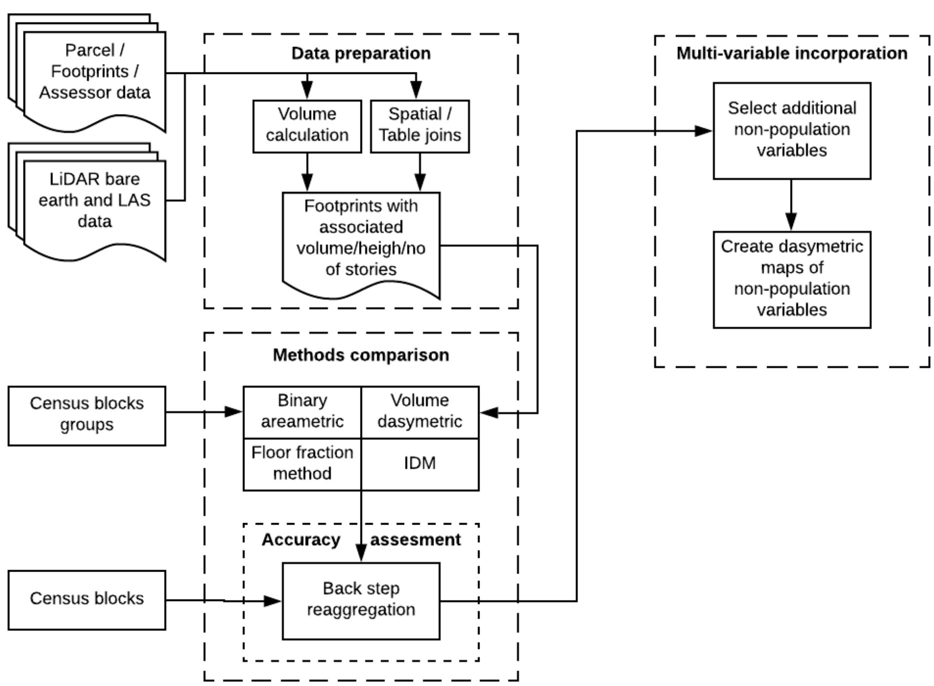

Figure 1 Process diagram, depicting the main steps of the research design

Study Area

The research area is located in the Twin Cities metropolitan area. This area is the largest metropolitan area in Minnesota, with an urban population of 3,112,117. The agglomeration area is 1,021.8 sq mi. and the population density is 515.4 / sq mi (199.0 / km²).

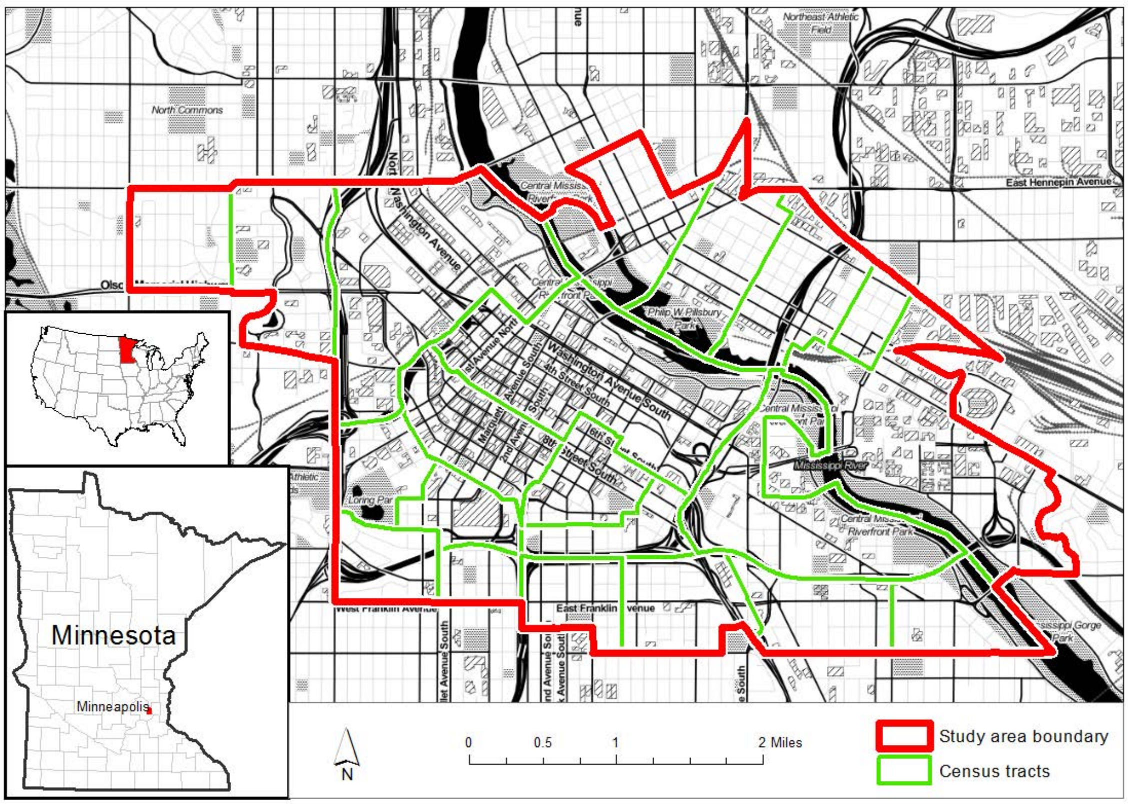

Figure 2 Map of the study area

When choosing a research area within the Twin Cities, urban areas with relatively high population density and residential housing with a variable number of stories were identified.

The final study area with a total area of 18.84 km² includes a combination of one- and two-story buildings, small multi-story apartment buildings, and high-rise multi-story residential buildings. Twenty-one census tracts cover the research area with a total population of 76,558 people. The research area has a population density of 4,063 / km². The following high-rise buildings were identified within the study area; they are listed in Table 1.

Table 1 High-rise residential building landmarks inside the study area

Name	Address
The Carlyle	100 3rd Ave S, Minneapolis, MN 55401
LPM Apartments	1369 Spruce Pl, Minneapolis, MN 55403
365 Nicollet	365 Nicollet Mall, Minneapolis, MN 55401
Marquette Place Apartments	1314 S Marquette Ave, Minneapolis, MN 55403
110 Grant Apartments	110 W Grant St, Minneapolis, MN 55403
4Marq Apartments	400 Marquette Avenue South, Minneapolis, MN 55401
La Rive Condominiums	43 SE Main St, Minneapolis, MN 55414
Churchill Apartments	111 S Marquette Ave, Minneapolis, MN 55401
IVY Hotel + Residences	201 S. 11th Street, Minneapolis, MN 55403
Riverside Plaza(McKnight Tower Apartments)	1600 S 6th St, Minneapolis, MN 55454

The study area includes the downtown area of Minneapolis, enclosed between Broadway St, Lynda Ave, and Highway 35. The site contains most of the remarkable high-rise buildings in Twin cities.

Data

The study uses the following data: LiDAR for developing 3D dasymetric representations of population distributions, building footprints, zoning, and census data (multiple variables at the individual and household levels. Spatial data obtained from the Department of Natural Resources of Minnesota and other open sources, such as street layers and real estate databases. Social and Demographic data are obtained from the US Census Bureau and ESRI Demographic Data dataset. In addition, ground-truthing field observations (e.g., building characteristics, occupancy) were conducted in the selected Minneapolis neighborhoods to ascertain the accuracy of dasymetric mapping.

Table 2 List of the data sources

Data	Description	Source	Year
LiDAR(classified point clouds)	Elevation	Minnesota DNR	2011
Population counts by census block, block group, and tract	Multivariable population data	US Census Bureau, Decennial census 2010	2010
Income data by census block group and tract	Socioeconomic data	US Census Bureau, American Community Survey	2012
Spending data by census block group and tract	Socioeconomic data	ESRI Demographic data	2019
County assessor parcel data	Source of information about residential / non-residential areas	City of Minneapolis	2010
Building Footprints	Readily available building footprints	City of Minneapolis	2010

The LiDAR data in an open LAS format was used to obtain the building elevation and calculate the structures' volumes. It was mainly processed using FME Workbench software while calculating building heights and employing another method of calculating budging volumes by creating solids using ESRI ArcGIS 3D Analyst software. The depiction of the LiDAR data as a one-meter digital elevation model is provided in Figure 3.

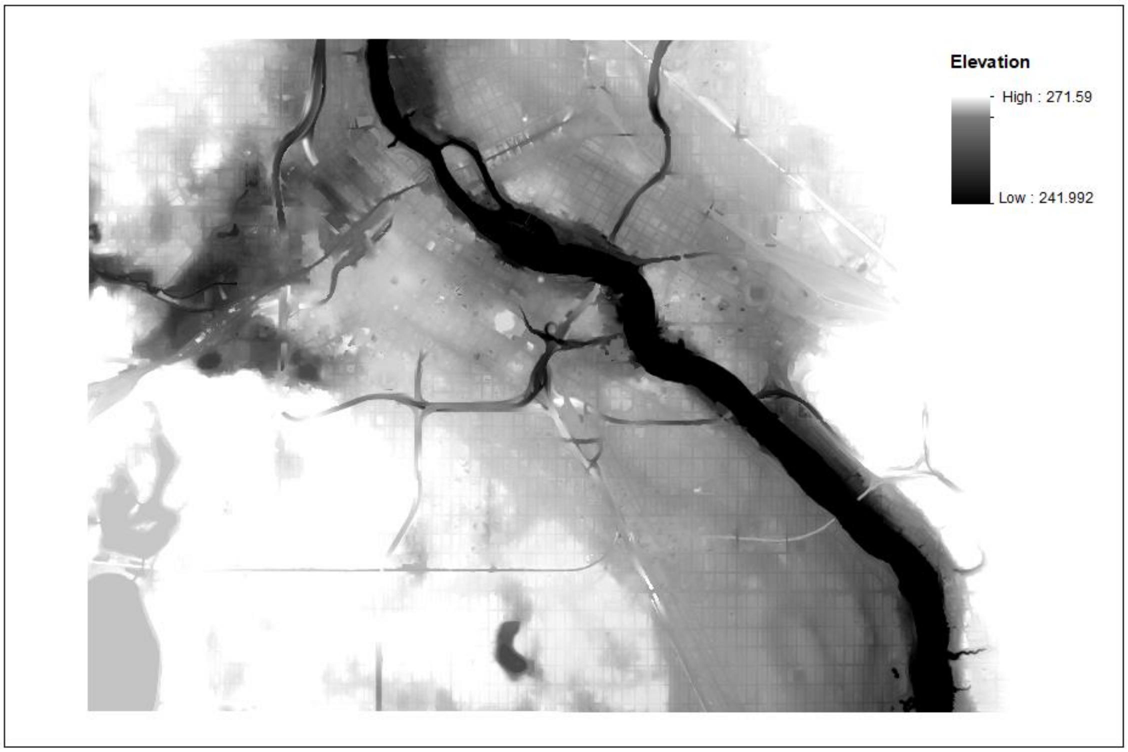

Figure 3 1 meter DEM LiDAR elevation data for the study area

The multiscale population counts data in a geodatabase format from US Census Bureau were used to create dasymetric maps of the population distribution, used to select the most accurate method of dasymetric mapping within the study area. The data on the census block group and census tract level was used for the actual disaggregation of the population counts, while the data on the census blocks level was used for accuracy assessment. The depiction of the multiscale population counts data on the census tract, block group, and block-level is provided in Figure 4.

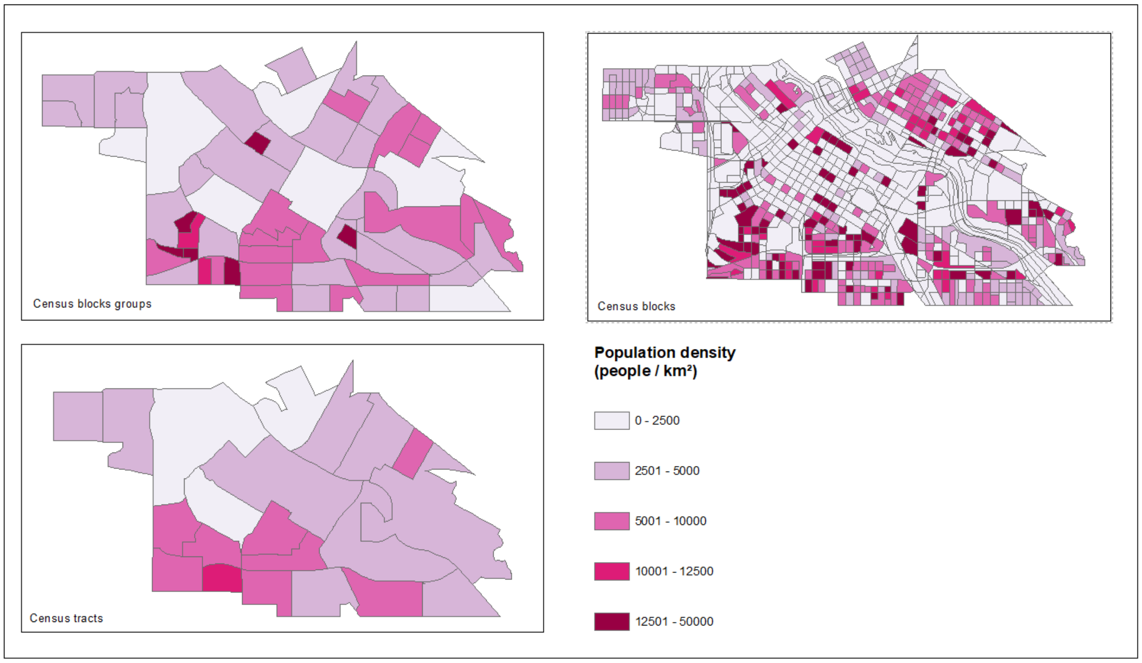

Figure 4 US Census 2010 population counts data on different scales

Income and spending data from the US Census Bureau, American Community Survey product in a geodatabase format, was used to create dasymetric maps of sociodemographic variables. In addition, the data on the tract level was used for disaggregation of socioeconomic variables and census block group data for accuracy assessment. The depiction of the source sociodemographic variables is provided in Figure 5 and Figure 6.

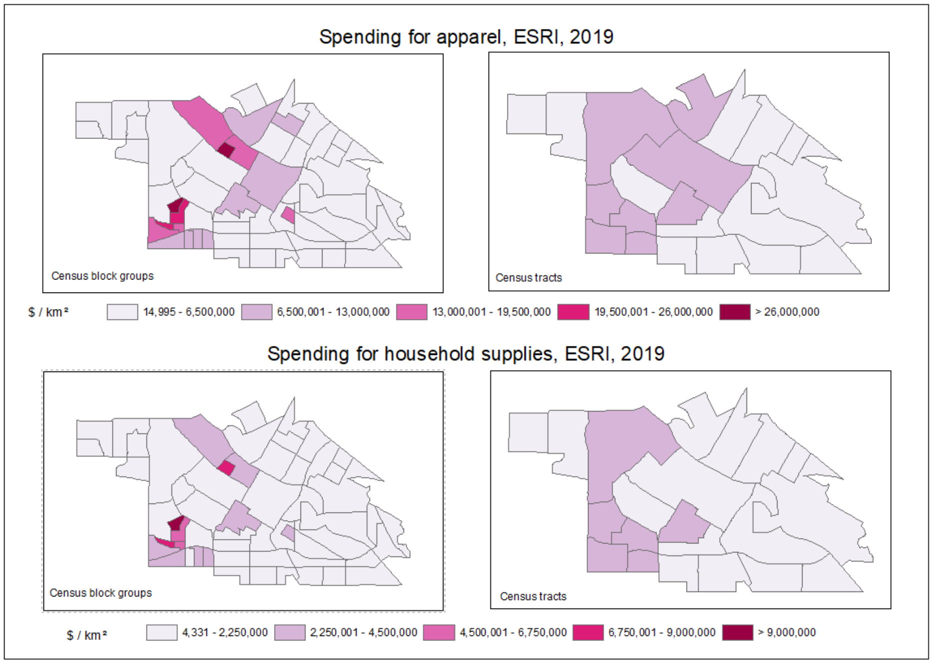

Figure 5 Sociodemographic variables – spending for apparel and household supplies

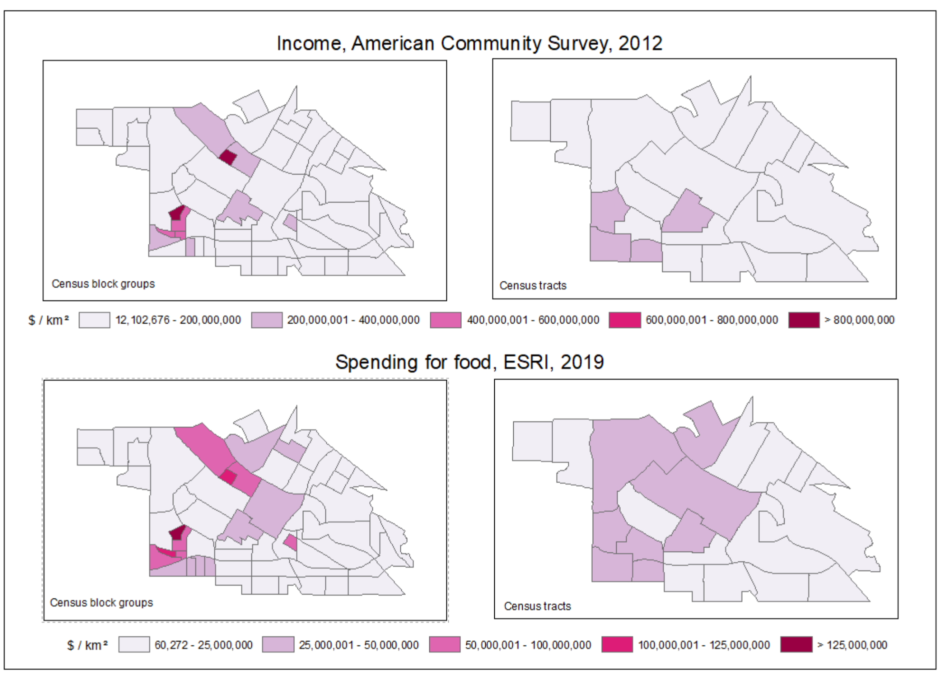

Figure 6 Sociodemographic variables – spending for apparel and household supplies

Finally, the county assessor parcel data (MetroGIS product) in a geodatabase format provides various building properties. It was used in this study to obtain information about the residential and non-residential status of the buildings. Building footprint layer in a shape file format was used to calculate areas and volumes of the building and as an essential data source to construct building solids for the volume calculation. The depiction of the different parcel types from the county assessor parcel data can be seen in Figure 7. The building footprint layer, provided by the City of Minneapolis Public Works department online contains readily available building footprints is depicted in Figure 8.

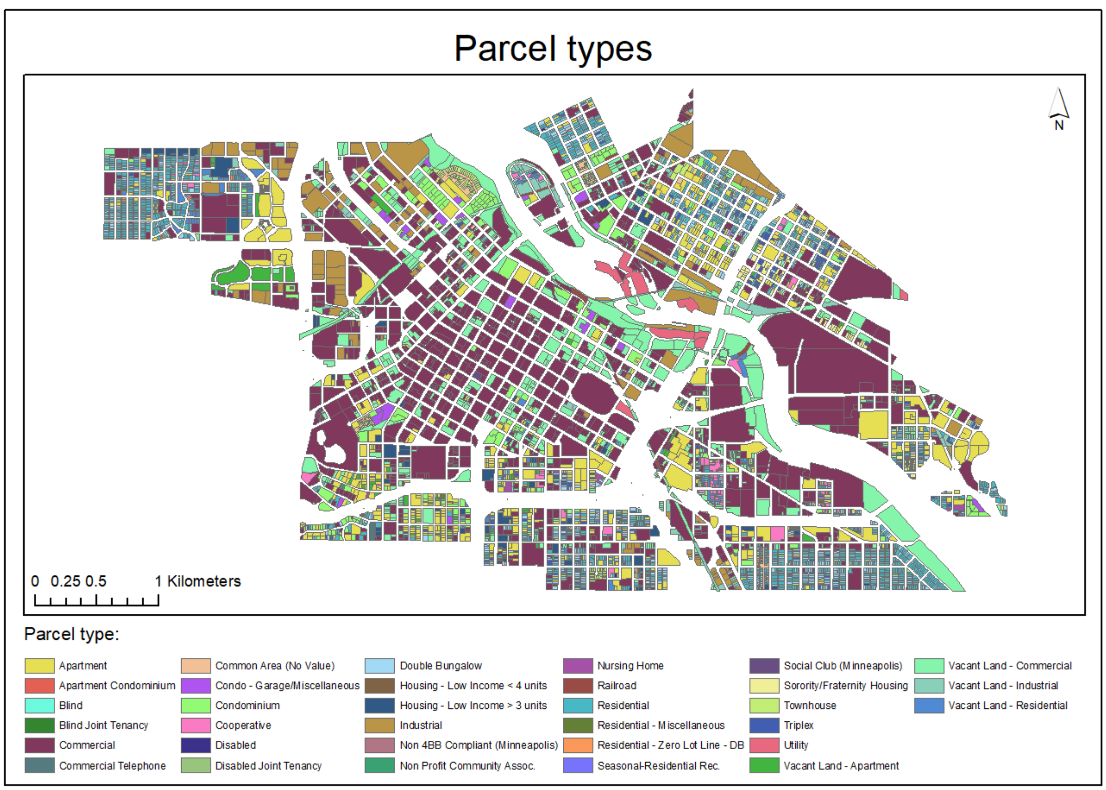

Figure 7 County assessor parcel dataset(MetroGIS) depicting parcel types

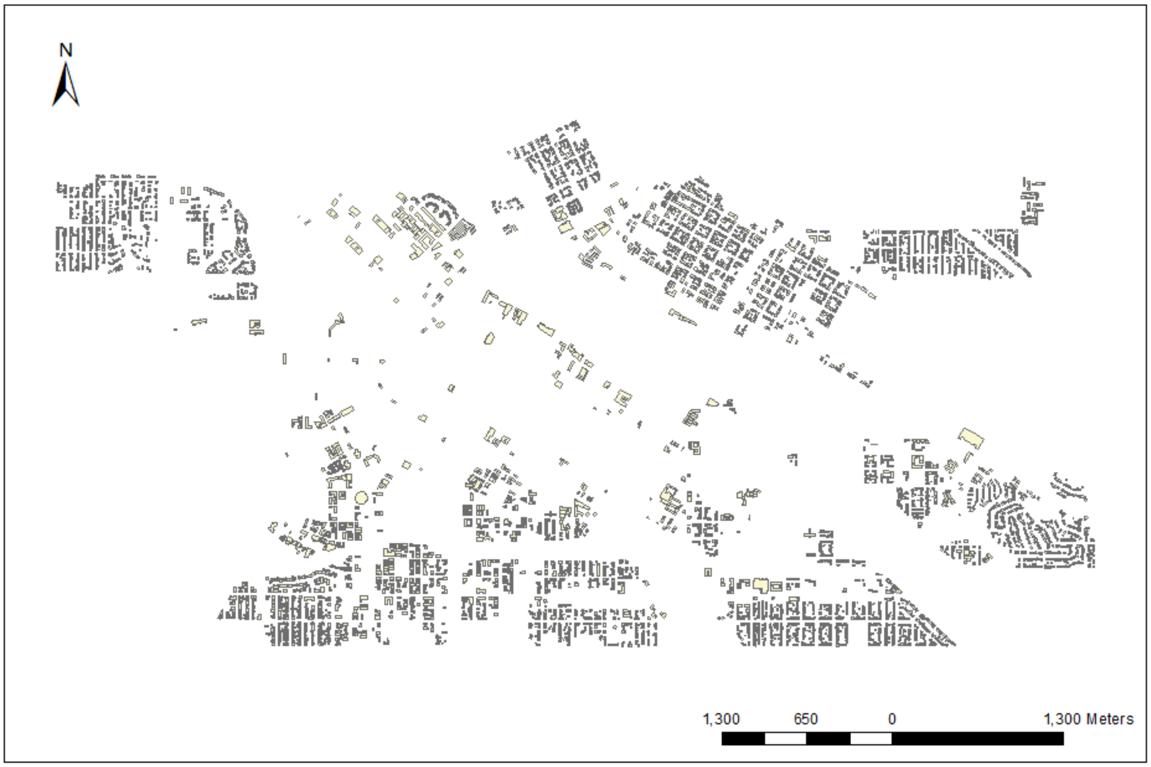

Figure 8 Building footprints

Data Preparation

As mentioned above, one of the intermediate steps of this study is to compare the performance of dasymetric mapping methods to identify the technique that gives the best result in the study area. The comparison stage consists of three sub-stages - preparation of the source data, creation of dasymetric maps, and comparison of the performance of the methods using the data set prepared in the first stage. As the primary tool for processing spatial data, FME Desktop software was used. 3D и 2D dasymetric mapping algorithms were also implemented using Python programming language to use them further in the development of the dasymetric mapping web application.

The first step in the process of comparing the methods was to prepare the source data. The dasymetric mapping methods require two input spatial data layers. The first layer is the footprints layer with the height or volume of the buildings, and the second is the enumeration units layer with the associated population data. 2D-dasymetric mapping method, 3D dasymetric (volumetric) mapping method and 3D floor fraction method require the set of residential footprints (such as single-family houses and apartment complexes) non-residential such as shopping centers and factories should be removed from the data set. The intelligent dasymetric mapping method(Mennis & Hultgren, 2006) requires the residential-non residential binary classified footprint dataset and the classification between the different types of residential housing stock to assess the individual population densities for each class. Accurate building heights or volumes are necessary to test all dasymetric mapping methods besides the 2D method (Biljecki et al., 2016)

To obtain the data on population counts and selected socioeconomic variables such as per-capita income, spatial databases from US Census Bureau in GDB format on census block, block group, and a tract were used. Each of those databases contains a spatial layer and a set of non-spatial attribute tables. The spatial layer, population count table, and a table on income were joined and exported as shapefiles to facilitate further data processing.

To ensure that the layers representing three levels of the census hierarchy have the same extent, only those enumeration units(census blocks, census block groups, and census tracts) fully contained within the study area polygon were selected. Then the building footprints were filtered that fall into the extent of these census layers. Buildings of residential types were selected by overlaying the building footprints layer with the residential type parcels from the county Accessor parcel dataset (MetroGIS). Imagery from Google maps, such as photos and StreetView imagery, and field trips to the study area were used to determine if the particular buildings are residential or non-residential types.

The following parcel types were considered as residential: Apartment Condominium, Condo - Garage/Miscellaneous, Disabled Joint Tenancy, Double Bungalow, Housing - Low Income > 3 units, Non-4BB Compliant (Minneapolis), Non-Profit Community Assoc., Nursing Home, Residential - Miscellaneous, Residential - Zero Lot Line - DB, Social Club (Minneapolis), Sorority/Fraternity Housing, Apartment, Blind, Condominium, Cooperative, Disabled, Residential, Townhouse, Triplex. All the parcels in the parcel layers were filtered to include the only parcels of the aforementioned types. Then, all the building footprints were filtered to remove all buildings with an area less than 50m2 using AreaCalculator and Attribute Range Filter FME transformers.

The next important input variable for most of the dasymetric mapping method is building volume, which could be found by multiplying the area of the building footprints on the difference between roof and footprint elevation (building height). Another approach could be to calculate building volume by creating a 3d solids from the building footprints and LiDAR points located above the building footprints. During that stage, one could use either a readily available footprint layer, created from tracing aerial imagery, or create footprints right from the LiDAR data, or create the building footprints right from the LiDAR data. The advantage of the readily available footprints is their regular shape and reliability due to manual processing and verification involving human labor. On the other hand, such footprints could introduce a discrepancy between the existing LiDAR data and the footprints. By discrepancy, the author means that some of the buildings present in the footprint layer could not be present in the LiDAR data and vice versa. Such problems could arise when there is some temporal difference between the LiDAR and footprint data(for instance, footprints were created in a different year than the LiDAR data were acquired). During that study, both methods were tested, such as using the readily available footprints vs. creating the footprints right from LiDAR data.

To estimate building height and, subsequently, building volumes using the readily available footprints, one needs to calculate elevations of the building roof and the elevation of the building footprint. LiDAR points from the first return supplied in the LAS files were selected using the FME PointCloud Splitter transformer to calculate the roof elevation. These points have been clipped inside the building footprint to get the multiple individual points clouds, representing the roof elevations of separate buildings. Then a median value of LiDAR point elevations was calculated within each footprint. The median operator was considered preferable to Average or Max operators to reduce the consequences of possible skewness in the data and eliminate the influence of the antennas, chimneys, and other height anomalies in elevation calculation. The results of the calculations on this step were stored in the attribute *BldgRoofElevation.*

The bare earth data from the supplementary XYZI files were used to obtain the elevation of the bottom of the buildings. These files represent the bare earth surface, and the data producer software already removed the non-ground features, such as buildings and vegetation. Unlike the regular LiDAR point clouds, bare earth points exhibit irregular placement of the bare earth points caused by removed ground features. Due to that fact, it is not reliable to select bare earth points inside of the building polygon and then find the minimal elevation. One could get the building footprint elevation by creating a TIN surface using these bare earth points, “drape” (align all the points of the building footprints with the underlying TIN surface) the footprints to the surface and find the minimal elevation among the building footprint vertices. SurfaceDrapper transformer was used to align the buildings' footprints to the TIN surface, produced using XYZI files. Then the coordinates of all vertices of each footprint were extracted, the vertex with the lowest elevation for each footprint was found and stored to the attribute *BldgBaseElevation.* Finally, the individual building volume was obtained by subtracting the building bottom elevation from the rooftop elevation and multiplication of the result by the area of the building.

As it was mentioned above, another approach is to, instead of finding the median roof elevation is to create solids from the building footprints and the point clouds representing the roofs. The advantage of that approach is a more accurate volume calculation due to a more reliable portrayal of the complex shape of the roofs. Unlike the techniques explained above, which assume that all the roofs are flat, which is far to be true, all the complex roof features are preserved and participating in calculating the building volume. Building footprints were "draped" to the bare earth surface, as explained above. Their lowest elevation was recorded into an attribute during the first step to calculate volume from the solids. Then the ArcGIS Pro 3D Analyst module "Create building solids" was used to create the building solids using the footprint data and the LiDAR files. Finally, the volume of the buildings was calculated by using the "Add Surface measures" tool.

Objective 1: Identify the Most Effective (Accurate and Precise) Method to Introduce the 3rd Dimension in Dasymetric Maps.

This study uses existing and developed/improved new 3DDM methods and then compares them and tests for accuracy. Comparisons included the most traditional 2DDM (binary area metric) and two 3DDM (volumetric and floor fraction). The most accurate method was used in further parts of the study.

Dasymetric mapping methods have historically evolved from traditional two-dimensional methods. These methods estimate the distribution of a population on a flat surface, unlike the three-dimensional methods that use the height or volume of buildings as ancillary data and are more suitable for assessing the distribution of population in urban areas (Petrov, 2012).

Historically, the first method of dasymetric mapping was proposed by Benjamin Semenov Tyan-Shansky in 1911 (Petrov, 2012) and applied to create the map of the population of European Russia (Semenov-Tyan-Shansky, 1926). Later, the method was introduced and made more popular by Wright (1936), who created a map of the population of Cape Cod. The creation of a dasymetric mapping method is often mistakenly attributed to Wright (see Petrov, 2008). Eicher and Brewer (2001) presented three methods (binary, three-class, and limiting variable) for dasymetric mapping of population density.

Binary Areametric Method

The most straightforward method of dasymetric mapping is the binary areametric method. It will be used as a baseline for comparisons. A binary mask excludes "unoccupied" areas and highlighting the "occupied" areas. This "binary parametric dasymetric method" (Eicher & Brewer, 2001; Fisher & Langford, 1995) is widely described in the literature and is a simplified example of the "marginal variable" technique proposed by Wright (1936). This method uses the base area of buildings and does not use the third dimension (building height) in the calculations. Perhaps the binary areametric method is the most typical for estimation of population density.

As auxiliary data, often expressed as Land use/land cover(LULC) classes obtained by classifying satellite images or other methods are used. According to the analyst's ideas, the original set of LULC classes is reclassified into two classes - habitable (for instance, urban areas, villages) and non-habitable (for instance, water bodies, forests, parks) for the area being mapped. Non-habituated areas are excluded from the areas of the areal units. The population density for each unit of territorial division is calculated by dividing the number of inhabitants by the area remaining after excluding non-residential areas.

The advantages of the method include its simplicity. The disadvantages are the subjectivity of the classification since there are no clear criteria which particular classes should be classified as populated and which are non-populated.

Three-Class Method

The next method described in Eicher and Brewer, 2001 is the three-class method. The existing classes must be reclassified to the following set - urban, agricultural/woodland, and forested land to create a dasymetric map. Water class is considered as non-habituated. Then, within each enumeration unit, each class is assigned its share of the population - the urban class receives 70% of the total population, 20% - agricultural / woodland, 10% -forested land. The idea of weights (70–20–10) was taken by Redmond et al., 1996; however, the original coefficients (80-10-5) were modified to more accurately reflect the population density of more populated study area in Pennsylvania, while Redmond et al., 1996 used a study area in Montana, where most of the population lives in cities, unlike Pennsylvania.

Of the advantages of this method, one can note its relative ease of implementation in GIS. The main disadvantage of the method is that it does not consider the area occupied by the class inside the enumeration unit. In the extreme case, when one or two urbanized zones are present inside the enumeration unit, they will be assigned 70% of the population. These zones will have an unrealistically high population density, while the density of the remaining non-urban zones will be too low. Also, as was mentioned above, it’s up to the expert to choose the appropriate weights. One of the notable disadvantages of the method is the subjectivity of the choice of weights.

Limiting Variable Method

The next method is the limiting variable method. In the first step of the method, the population is assigned to all three populated classes in proportion to their area, so the population density is the same. Water zones are excluded from the calculation. Then "limits" are assigned - the values of the maximum population density for some (not all) populated classes. For example, population density in agricultural zones can be limited to 50 people / km2, and in forested areas, up to 15 people / km2. When the population density within the polygon exceeds a predetermined threshold value, the excess population is evenly distributed among the remaining classes.

When calculating the threshold values of population density, enumeration units are selected that fall entirely into a specific LULC class. There are often situations when it is impossible to find a sufficient number of zones to obtain the average threshold density that would fall into a particular single land-use class, complicating the use of the method.

Intelligent Dasymetric Mapping (IDM)

The other notable method of dasymetric mapping is the Intelligent Dasymetric Mapping (IDM) developed by Mennis and Hultgren (2006). As a source of data, this method uses a set of enumeration zones and a set of classified ancillary zones, similar to LULC classes. Zones overlap, and the polygons resulting from the intersection of enumeration units and ancillary zones are called target zones. For each target zone, the proportion of the target population of the total population of the zone is first calculated. This value is calculated as the product of the area of the target zone and the estimated population density divided by the sum of the area's products and the estimated population density within the original zone. Then the result of the division is multiplied by the number of people in the target zone.

Perhaps the main novelty of the IDM method is the three sub-methods proposed by the authors to find the estimated population density: “containment,” “centroid,” and “percent cover.” In the “containment” method, from the set of enumeration units, only those areas are selected that fall entirely into one or another type of ancillary zone. The “centroid” method selects those enumeration units whose centroids fall inside the ancillary zone.

In the “containment” method, it is not uncommon for some classes to find an enumeration unit entirely enclosed within an ancillary data polygon. Here comes the third sampling method, “percent cover,” which is a little more complicated than the previous two. It selects “enumeration units” having a given percentage of overlap with ancillary zones. Then, the population in the target zones that fall into the same enumeration unit as the zone with unknown density is calculated. The population in these target areas is estimated based on the density found by the “containment” method. The population density in an area of unknown density is calculated based on the difference between the population values already calculated, and the original population reported for the enumeration unit.

Volume Dasymetric method(VDM)

The volume method is the most commonly used in three-dimensional dasymetric mapping (Lwin & Murayama, 2011; Wu et al., 2008). First, the volume is calculated for each building, depending on its area and height. Then the number of people per unit of volume is calculated by adding the total population and then dividing it by the total volume of all buildings in the study area.

$$PV^j = pop^j / VT^j$$

PV is the number of people per unit of volume in region j (area of research), pop is the total population in area j, and VT is the total volume of buildings in region j.

After calculating the volume, population density is determined by multiplying PV by the individual volume of the building and dividing the result by the area of the building base.

$$PD_n^j = PV^j * V_n^j / A_n$$

PD is the population density of building n, where PV is the person per unit volume V, is the individual building volume of one building n in the area of interest j, and A is the base area. The broad overview of the volume dasymetric method is depicted in Fig. 2.

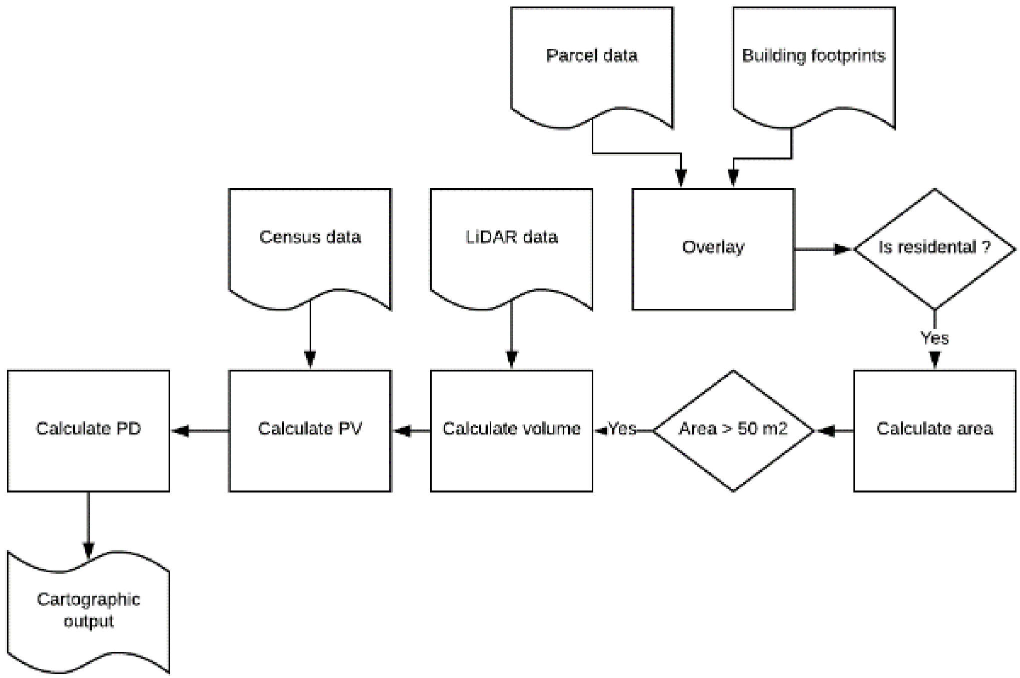

Figure 9 Process diagram of dasymetric map creation via 3D volumetric dasymetric mapping technique for urban areas.

As for source data to estimate building volume, one could use building footprints, LiDAR, and bare earth data. Also, the population counts from census per census block/tract are necessary. Then typical workflow including calculation of the volume of every residential building. Having calculated the volume, one could calculate the number of people per unit of volume(PV) and population density. Then the resulting data could be used for thematic map preparation.

Floor Fraction Method

The volumetric dasymetric method, which is the most comprehensive described in the literature, considers the entire volume of a residential building as an inhabited space. However, buildings are occupied unevenly, and some of the premises are uninhabited, for example, attics. The volume method simply adds the uninhabited area to the living space and, thus, may underestimate population densities. The floor fraction method proposed in the unpublished work of GeoTREE Center by Cavin et al. (2011) eliminates this problem by separating the volume of the building into floors and determining the population size only in living quarters.

First, an analysis of samples of residential buildings based on the in-person visual survey, panoramic imagery from the Google StreetView, and aerial photography to determine the average height of the floor is used. Then this parameter is used to determine the residential capacity of the building. This approach allows excluding the additional volume of non-residential premises.

The floor height threshold value is applied to the entire housing stock in the study area. For example, if the average floor height is approximately 3.5 meters, a building with a height of 4.5 meters will still be considered a one-story structure since the space above 3.5 meters is not enough to give an additional floor to the residents. Dwellings above 7.0 meters tall will be classified as two-story and so forth. The likelihood of inhabitance and expected population density on each floor are assumed to be identical. In other words, multistory structures are treated as ‘stacked’ single-story buildings.

Once all buildings are classified by the number of floors, the method applies the floor fraction technique to calculate the estimated population density. The floor fraction technique is based on the conventional population fraction method (Mennis, 2003), widely used in dasymetric mapping. However, instead of the typical urban, suburban, and rural classification, the floor fraction method uses floor classes, each about some floors present in the building dataset (one, two, three, four, etc., as needed within the study area).

The *population density fraction* is calculated by dividing the floor class's floors by the cumulative number of floors present in all floor classes. The population density fraction in effect expresses a relative propensity of people to reside (and different population densities to occur) in a floor class group. It is directly proportional to the number of available floors. This formulation may be given the following notation:

$$DF_n = FC_n / \sum_{n=1}^{k} FCj$$

Where DFn is the population density fraction of a classified floor class (n). FCn is the floor class or "stories" of n (typically starting from 1). The sum of FC is all floor classes within a study area j where k in some existing classes. This operation is computed for each aerial unit of analysis (e.g., block group).

After the population density fraction is found, we compute the *area ratio* to account for differences in total areas occupied by each floor class to accurately allocate the population to floor fraction classes. The area ratio represents the ratio of the actual percentage of total buildings' footprint area that belongs to a particular floor class to the theoretically expected percentage (i.e., equal distribution of all classes). The area ratio for the given floor class within a given block group is calculated by dividing the area of the floor class by the total building footprint area and dividing that result by the expected percentage. For example, in the case of three-floor classes:

$$AR_n^j = \left(\frac{a_n}{\sum_{n=1}^{3} a}\right)/0.33$$

Where AR is the area ratio of a floor class n within a study area (census block groups) j, a is the area of a floor class n, divided by the sum of the total building footprint area. Then this result is divided by the expected percentage of the area occupied by a single floor class in a three-class example.

Next, the total fraction is calculated by combining the population density fraction and the area ratio. Total Fraction represents the fraction of a given floor class in the total population. In other words, it determines the share of the population that should be distributed to the given floor class. Similarly to Mennis (2003), the Total Fraction is calculated by multiplying population density fraction by area ratio for a given floor class and then dividing the results by the outcome of the same expression for all floor classes:

$$TF_n^j = DF_n^j * AR_n^j / \sum_{n=1}^{j} (DF * AR)$$

TF is a total fraction of floor class n within region j, and DF is the population density fraction, AR is the area ratio for floor class n, divided by the sum of the total fractions for other classes within the region.

Lastly, we find the number of people to be apportioned to a given floor class. This is done by taking the total fraction multiplying it by the entire actual population of the area. Finally, we calculate population density by dividing the result of this that calculation by footprint area.

$$pop_n^j = (TF_n^j * pop_n^j)/a^j$$

Pop is population density assigned to floor class n within region j, TF is a total fraction of a floor class n within the region j, pop is the actual population of the region j, a is the total building footprint area j.

<u>Comparing Dasymetric Mapping Methods at Two Scales</u>

The dasymetric methods, such as 2D binary, 3D volumetric, floor fraction, and an intelligent dasymetric mapping method explained above, were implemented at the two spatial scales: census block groups and census tracts. The rationale was to test whether results will vary by scale, assuming that a smaller scale/larger unit (e.g., tract) will be internally more heterogeneous with respect to building heights and thus more sensitive to 3DDM improvements.

The study used FME Desktop 2018.1 software as FME Workspace (file with a *.fmw extension designed in FME Desktop). This approach resembles data processing using models created in the ArcGIS Model builder. Created models automate the process of dasymetric mapping using the selected method. This approach allows one to reuse the models further during the development of the web dasymetric system after minor changes to add support for variables not related to the assessment of the population. Some methods, such as 3D and 2D binary dasymetric mapping methods, were also implemented using Python 3.0 programming language and a GeoPandas module.

Dasymetic Methods Methods Accuracy Assessment and Comparisons

Maps of the population were created using the census block groups for disaggregation. The resulting population counts were compared with the reported population of the census blocks to facilitate the accuracy assessment. The second set of the population maps was created using the census tract data for disaggregation, and the resulting counts were compared against the census block groups to test the assumption that the homogeneity of the building heights affects the results.

Root square mean error was calculated for each dataset produced by the particular dasymetric method to access the accuracy of the dasymetric mapping methods. The general idea of the mapping method accuracy estimation is to create a dasymetric map based on a set of the larger enumeration units, aggregate the calculated building population by smaller enumeration units, and find the difference between the computed and reported values per enumeration unit. For instance, one can create the dasymetric map using the census block groups and then assess the accuracy of the resulting product, sum the computed population by census blocks and find the difference between the actual population, reported by the census for each census block and predicted population, aggregated within census blocks.

Then, to compare the results of the various methods between each other, root square mean error (RMSE). RMSE is a standardized measure to access the error in predicted quantitative data. It was calculated using the formula:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\widehat{y_i} - y_i)^2}{n}}$$

Where $\widehat{y_1},\ \widehat{y_2}, \dots, \widehat{y_n}$ are predicted values, $y_1,\ y_2, \dots, y_3$ are observed values, and n is the number of observations. RMSE was calculated for each resulting dasymetric map.

Another measure besides RMSE that was used to evaluate the accuracy of the resulting dasymetric map products was the mean absolute error(MAE) measure. Mean absolute error represents the average difference between the set of predicted and actual values. In the scope of the study, population count estimates or income and spending values in dollars per individual building, aggregated per enumeration unit(census block or census block group) were considered as predicted values and values, reported by US census/ESRI were considered as actual values. Then to estimate the mean absolute error, one can find the difference in each pair of actual versus predicted observations and calculate the average of the absolute values of the difference.

$$MAE = \frac{\sum_{i=1}^{n} |\widehat{y_i} - y_i|}{n}$$

Where $\widehat{y_1},\ \widehat{y_2}, \dots, \widehat{y_n}$ are predicted values, $y_1,\ y_2, \dots, y_3$ are observed values, and n is the number of observations.

Both metrics are negatively oriented, so the lower value indicates a lower error. Both metrics express the error of prediction in the same units as it was for the source variable. The important difference that the RMSE penalizing the large errors more severely, so it's useful where the large errors are particularly undesirable (Wesner, 2016).

The paired t-test was used to test if there is a statistically significant difference between 2D and 3D mapping methods population estimates. The difficulty when using the t-test is that the mean value of two groups stays the same because the same census population is being redistributed between the same number of buildings, although in different ways. The resulting population counts dataset was subset to ten random groups, and the t-test was performed separately for each resulting sub-set to overcome that issue.

Incorporating Additional Socioeconomic Variables

The following variables were selected to demonstrate the dasymetric mapping approach for mapping the sociodemographic variables besides the population distribution – aggregated annual per-capita income and different categories of spending. These variables are highly correlated with each other and with population distribution, so the assumption was that they exhibit similar distribution assumptions of the population distribution. The assumptions were that the socioeconomic variable was defined for residential buildings only and assigned as a proportion of a building volume of the particular building out of the total volume of all residential buildings within the enumeration unit.

The American Community Survey(ACS) data was used to create the maps of the socioeconomic variables other than population. Since the smallest enumeration unit of the ACS is the census block group, socioeconomic variables were disaggregated from the census tracts, and the results were compared against the census block groups.

The 3D binary dasymetric mapping method was used to disaggregate the socioeconomic variables on the census tract level. The following variables were used to provide 'proof of the concept' of dasymetric disaggregation of the socioeconomic variables (other than population density): aggregated annual income from the American Community Survey (2012), and three types of spending: spending for food, household supplies and apparel from ESRI Demographic dataset (2019). The same FME workspace for the 3D dasymetric mapping method was used for data processing, but instead of population variable, socioeconomic variables on census tract level were used. The accuracy of the results was accessed by aggregating the results on the census block group level, finding the difference between the aggregated and reported values, and calculating the RMSE and MAE metrics for the map of each disaggregated variable.

CHAPTER 4:

RESULTS

What is the Most Accurate Method to Introduce the 3rd Dimension (3D) in Dasymetric Maps?

Using the methodology explained in Chapter 3 allowed me to create a set of dasymetric maps, modeling the population distribution on the building level. It was necessary to discover the best method for disaggregating the urban population to disaggregate the socioeconomic variables using the dasymetric mapping.

The first investigated dasymetric mapping method was the binary 2D dasymetric mapping method. During the first iteration of the method, census block groups were used for disaggregation of the population. The example map of the population density created using the 2D dasymetric mapping method is depicted in the Figure 10.

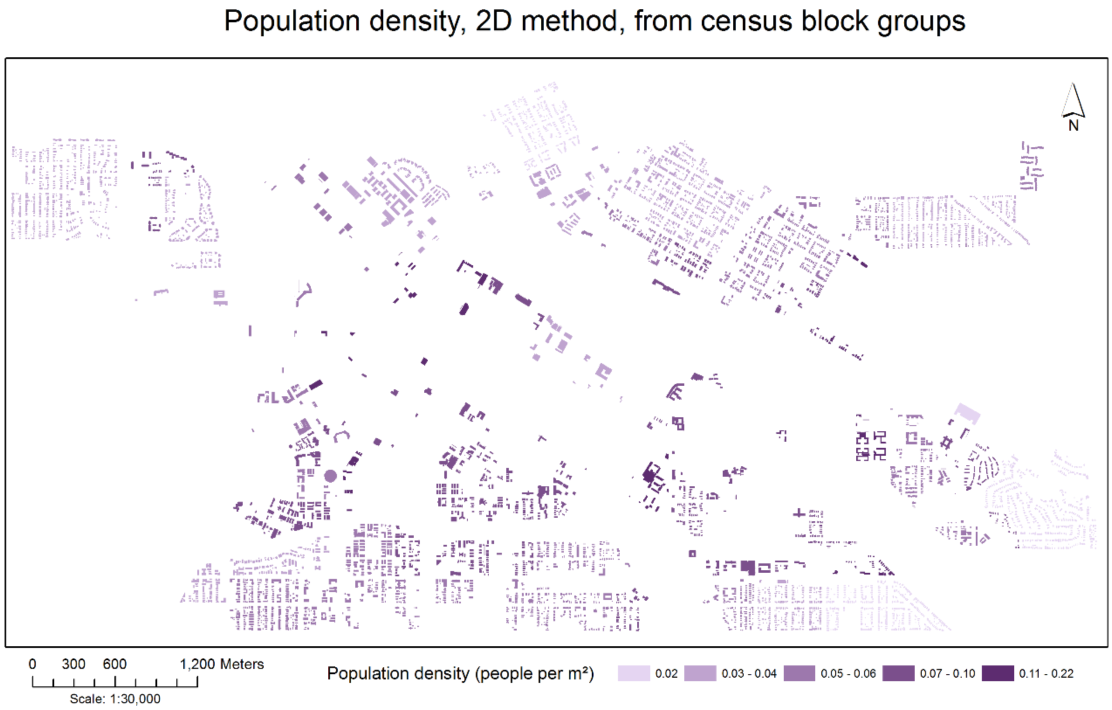

Figure 10 Population density, 2D mapping method, from census block groups

Then, the accuracy of the result was assessed against the census blocks. The different levels of the enumeration units were used in dasymetric disaggregation to test the assumption that the increased internal variance of the building heights within the enumeration units will unveil the superiority of the 3D dasymetric methods that use building volume/height in calculations versus 2D methods, that are not taking into account these measures.

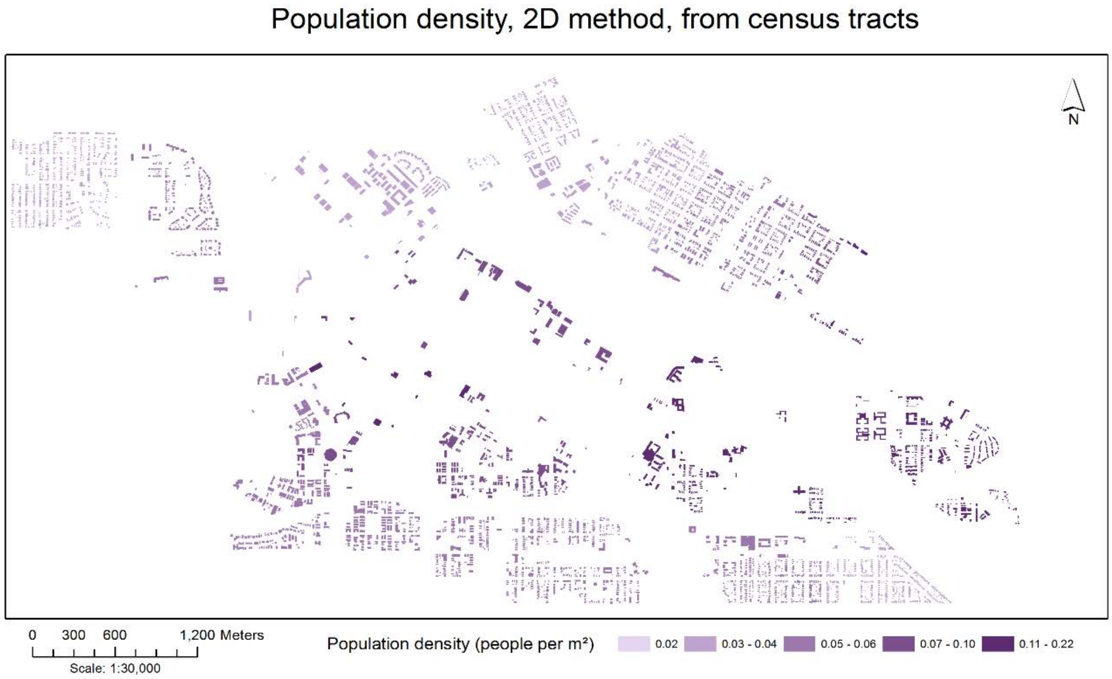

Figure 11 Population density, 2D mapping method, from census tracts

Then the same 2D binary dasymetric method was used to disaggregate the population reported on census tracts level (see Appendix 1, p. 74), and the accuracy was assessed against the census blocks and census block groups. The example map of the population density could be seen in the Figure 11. Another set of maps was created using the 3D volumetric mapping method. The resulting maps can be found in Appendix 1, pp. 73-76. Census block groups and census tract datasets were used for disaggregation and the accuracy of the results was accessed against the census blocks and census block groups as well.

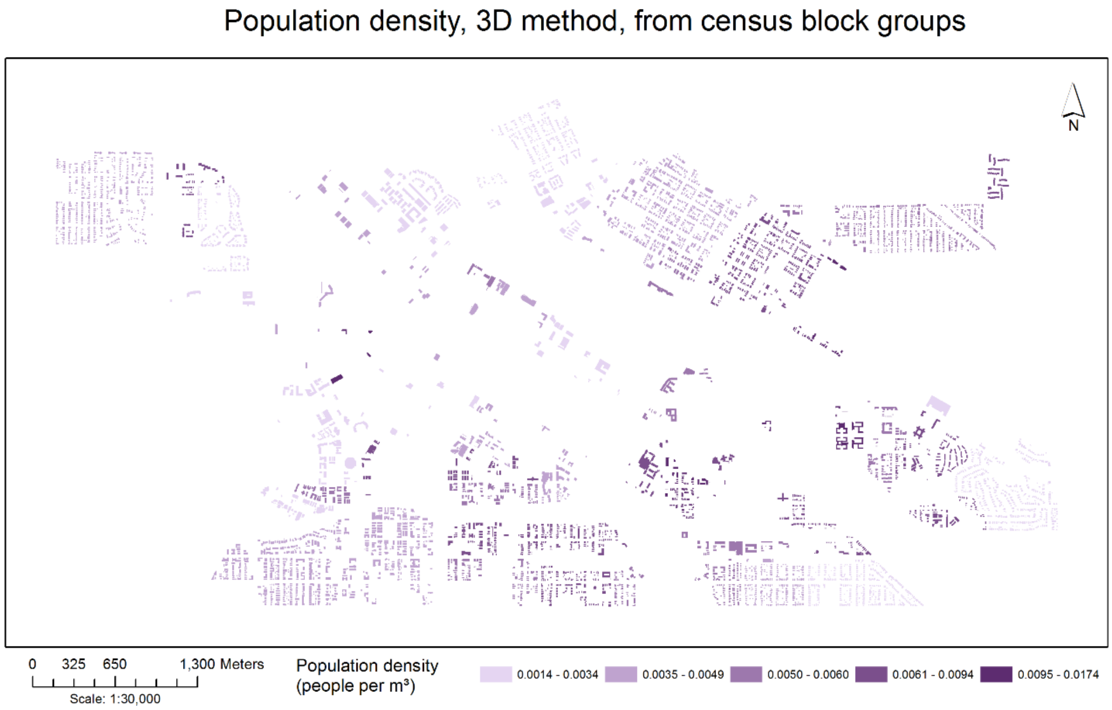

Figure 12 Population density, 3D method, from census block groups

To access the resulting accuracy of the dasymetric maps, the RMSE metric was calculated for each resulting map. Having created the dasymetric maps, the population counts for each building, obtained from disaggregation on the census block groups and census tracts level were re-aggregated by census block and census block group accordingly. That aggregated results were considered as predicted values $\widehat{y_1},\ \widehat{y_2}, \dots, \widehat{y_n}$, and the population counts per census block or per census block group were considered as observed values $y_1,\ y_2, \dots, y_3$in RMSE calculation. The results are provided in Table 2.

Table 3. Root Square Mean Error for 2D/3D dasymetric mapping methods.

Method	VS blocks		VS block groups	
	RMSE	MAE	RMSE	MAE
2d – from block groups	74.76	30.30	-	-
2d – from tracts	116.95	41.01	560.95	400.45
3d – from block groups	69.51	26.92	-	-
3d – from tracts	101.56	34.14	451.789	321.45

Note: Average population for census block is 84, census block group - 1309, tract - 3645

One can notice that the lowest RMSE was observed for the 3D dasymetric mapping method when disaggregating the fine-scale data from census block groups. The improvement in RMSE in the 3D method versus 2D DDM was relatively small - 74.76 people per block versus 69.51, which expresses in 7.27% difference. Although when disaggregating the data on the census tract level, the improvement was more significant – 116.95 for the 2D method vs. 101.56 for the 3D method, which expresses in 14% difference. When estimating the accuracy by aggregating the results of the tract disaggregation by block group, the 3D dasymetric mapping method exhibits significantly higher accuracy compared to its 2D counterpart – RMSE is 560.95 people per block group vs. 451.798 people per block group, which expresses in 21.55% difference. The difference between the methods could be explained in that the internal variation of building heights and their range within the census tracts are lower than in census tracts.

The average standard deviation and range of the building heights per census block group and per census tract were calculated for the building dataset to prove that point.

Table 4. Average standard deviation and range of the building heights.

Enumeration level	The standard deviation of height	Height range
Census blocks	3.263	7.74
Census block groups	5.622	25.91
Census tracts	5.89	41.82

Having estimated the results of the binary 2D and 3D dasymetric mapping, the more sophisticated mapping techniques were tested, such as the floor fraction method and the intelligent dasymetric mapping method. The floor fraction method was tested in multiple iterations, using different average floor height parameters. Census block group population was used for disaggregation, and the resulting RMS was calculated against the census blocks. The resulting RMS values are reported in Table 5.

Table 5. Resulting RMS for different average floor heights parameter in floor fraction method.

Average height	**Resulting RMS**
2.5	95.48
3.0	90.59
3.5	93.96
4.0	92.46
5.0	91.65
5.5	91.32

One can conclude that the RMS for the floor fraction method is significantly higher than for the binary 3D and even 2D dasymetric mapping. Therefore it should not be considered for further steps with disaggregating of socioeconomic variables.

Then the intelligent dasymetric mapping method was tested. The method requires a set of samples of the building of a particular property type to calculate a population density for each property type. The multiple sets of the census blocks, populated with a single type of residential buildings, were selected to calculate the population density of their respective type of residential property.

Table 6. Samples of building stock used in the Intelligent Dasymetric Mapping method

Property type	**Total sample population**	**No of blocks**	**Total volume**	**Density**
Apartment	19728	76	3891568.966	0.005069421
Condo - Garage/Miscellaneous	593	4	226124.7102	0.002622447
Condominium	4711	25	1836171.184	0.002565665
Cooperative	91	1	11979.07098	0.007596582
Double Bungalow	117	2	2984.647944	0.039200603
Housing - Low Income > 3 units	2700	12	320197.1419	0.008432305
Residential	418	22	156820.6745	0.002665465
Sorority/Fraternity Housing	334	3	37880.38178	0.008817229
Townhouse	326	7	175049.7771	0.001862327
Triplex	129	3	11048.28064	0.011676025

However, I could not calculate by this method a representative population density for all types of real estate, as most of the blocks contain multiple types of residential property. Therefore for the following property types: Apartment Condominium, Disabled Joint

Tenancy, Housing - Low Income < 4 units, Non-4BB Compliant (Minneapolis), Non-Profit Community Assoc., Nursing home, Sorority/Fraternity Housing, Blind, Social Club (Minneapolis), the average population density for entire dataset were used. Their properties compose about 1.4% of all housing units(88 buildings out of roughly 6,000 buildings)

The resulting map was created by disaggregating census blocks group population, and then RMSE was calculated against census blocks. The resulting RMSE is 251.39 is significantly higher than the other methods compared in the study, so one can conclude that they do not move forward with that method. In terms of resulting RMSE, the binary 3D dasymetric mapping method gave the best accuracy, followed by the Floor fraction methods.

Then the next goal was to check if the results of the 3D and 2D binary dasymetric methods, the best performing in terms of RMSE, were significantly statistically different. To accomplish that, the paired sample t-test was run over the multiple randomly selected groups of the building population estimates, produced using 3D and 2D dasymetric mapping methods. In this attempt, 1000 randomly selected samples were selected. Each sample contains approximately 10% of the records from the source dataset.

Table 7. Sample T-test results(first ten iterations) for the disaggregated population of census block groups and tracts

T-test for population, disaggregated from CBG		
Group	t-value	Significance
1	-2.379	0.018
2	0.124	0.901
3	-0.951	0.342
4	0.056	0.956
5	1.843	0.066
6	2.369	0.018
7	-0.871	0.384
8	-0.817	0.414
9	-1.525	0.128
10	-0.506	0.613

T-test for population, disaggregated from CT		
Group	t-value	Significance
1	-0.324	0.746
2	-1.435	0.152
3	1.973	0.049
4	-0.454	0.650
5	2.558	0.011
6	0.816	0.415
7	-0.749	0.454
8	0.985	0.325
9	-1.470	0.142
10	0.258	0.746

There were 42 statistically significant(with their $p = 0.05$ or less) groups for the dasymetric dataset created from census block groups. For the census tracts, there were 105 statistically significant groups. The complete list of t-test results is supplied in Appendix 2; statistically significant iterations are highlighted. As the statistical significance is more than 0.05, the null hypothesis of the lack of difference between the two groups can not be rejected. Thus, the results did not reveal a statistically significant difference between the results of both methods.

What is the Difference Between the Standard (2D) and 3D Dasymetric Mapping Methods at Different Scales and Levels of Urban Heterogeneity?

Differences in the height of buildings were compared on a small scale (at the level of census tracts), intermediate (at the level of census block groups), and at the largest, at the level of census blocks. Standard deviation averages vary significantly between the census block group and census block levels. However, their differences between census block groups and census tracts are not that significant. However, the building heights range within the enumeration unit values are more pronounced and vary significantly between large, intermediate, and small scale.

Scatter plots representing the relation between the absolute percentage error(APE) and variance of building heights were plotted.

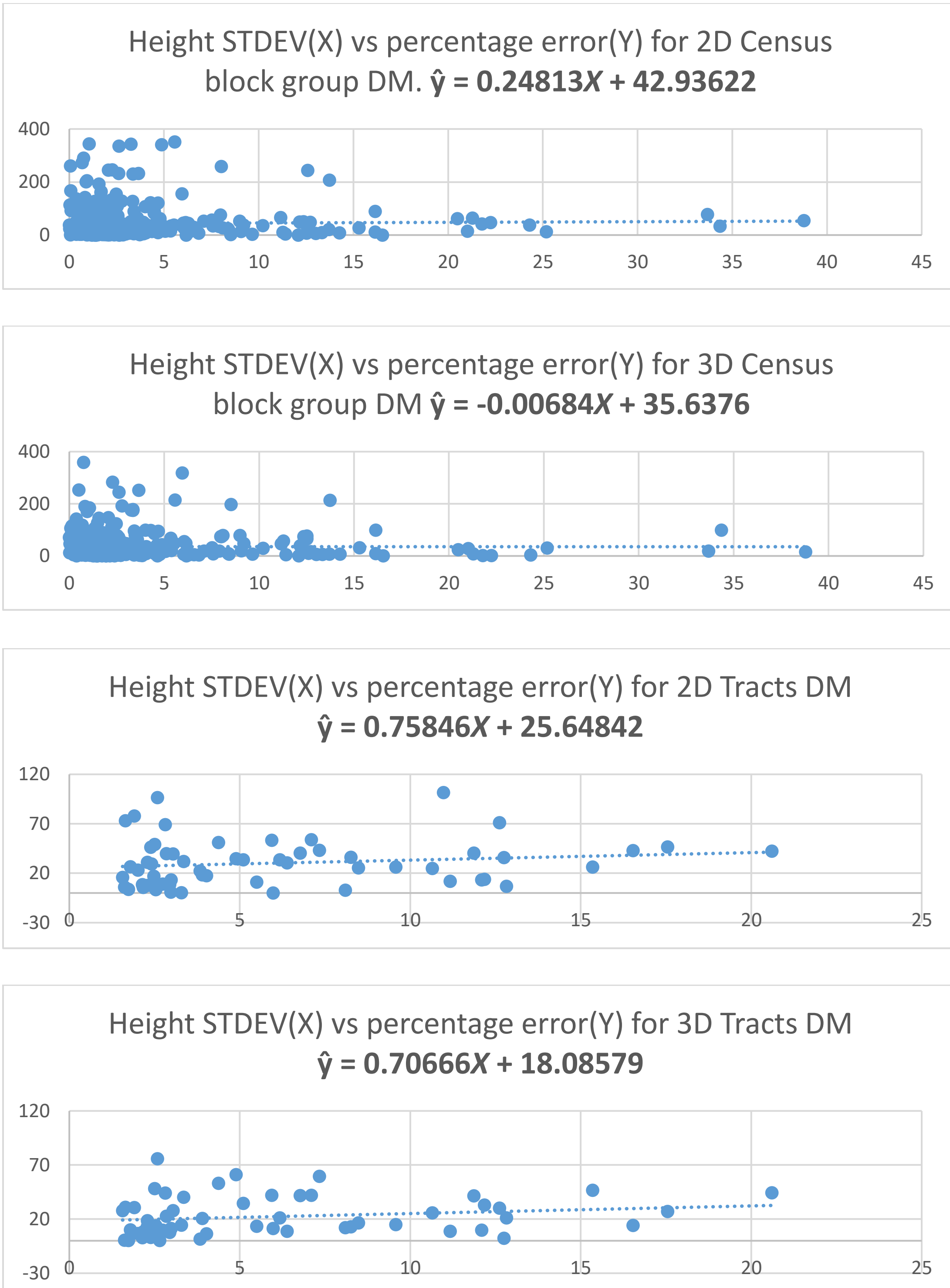

Figure 13 Scatter plots of errors

For the scatter plots representing the errors on census blocks level, most of the data points on the scatter plots tend to cluster in the left part of the graph due to the low variability of the building heights within the census block in the given study area. The point arrangement exhibits more scattered patterns for census tracts due to the larger size of enumeration units and, consequently, higher variability.

Regarding the scatter plots of building heights standard deviation versus absolute percentage error, there is a slight visible upward trend on the graph representing the 2D method on the census block group level. The graph for the 3D methods on the census block group level is straight and does not exhibit any trend. Both graphs exhibit an upward trend on the census block tract level, so APE rises with an increase of variability. The rise of APE is slower for the 3D method. The trend lines on the plots of errors for the 3D method are lower, indicating the better performance of the 3D dasymetric method in terms of accuracy. This is consistent with RMSE and MAE metrics for the maps created with the 3D binary dasymetric method.

What can Additional Socio-Economic Variables Be Mapped Using the 3D Dasymetric Method?

Finally, the proof of the concept of using the dasymetric mapping to disaggregate the socioeconomic variables was produced. The 3D dasymetric mapping was used to disaggregate aggregated income – ACS variable called *"B19313e1 - Aggregate income in the past 12 months (in 2012 inflation-adjusted dollars): Population 15 years and over -- (Estimate)"* on the tract level, and then the results were verified against the census block groups. It was not feasible to disaggregate the population on the finer scale due to the fact that American Community Survey reports all the sociodemographic variables only on census block level only. The RMSE metric was calculated to compare the dasymetric disaggregation result of the tract income with the reported income of the block level. The resulting RMS was \$ 15 212 247, and the resulting MAE was \$ 8 290 862. The 2D dasymetric method yielded RMSE \$ 17 932 711 and MAE \$ 11 475 825. The resulting maps for both(3D and 2D) methods, disaggregated from census block groups and census tracts, are provided in Appendix 1, pp. 77-80.

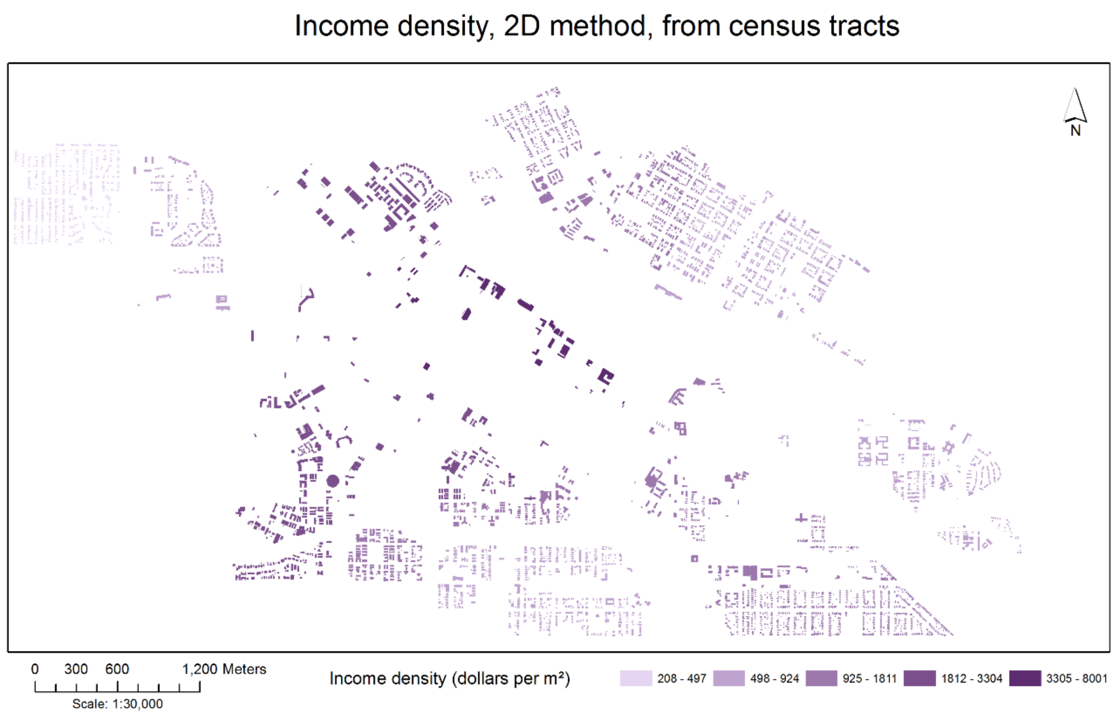

Figure 14 Income density, 2D method, from census tracts

Regarding the other sociodemographic variables, the following variables from the Esri Demographics data, 2019 release were disaggregated on the tract level and compared with the census block groups level:

2019 Food, Variable: X1002_X, Source: Esri and Bureau of Labor Statistics. Vintage: 2019. Definition: The total amount spent on Food includes food at home or away from home. Total spending represents the aggregate amount spent by all households in an area annually.

2019 Housekeeping Supplies, Variable: X4033_X, Source: Esri and Bureau of Labor Statistics, Vintage: 2019. Definition: Total amount spent on Housekeeping Supplies includes soaps and detergents, other laundry and cleaning products, cleansing and toilet tissue/paper towels/napkins, miscellaneous household products including paper/plastic/foil products, stationery/gift wrap supplies, and postage and delivery services. Total spending represents the aggregate amount spent by households in an area annually.

2019 Apparel & Services, Variable: X5001_X, Source: Esri and Bureau of Labor Statistics, Vintage: 2019

Definition: Total amount spent on Apparel & Services includes men’s and women's apparel, children's: apparel, footwear, apparel products and services, and watches and jewelry. Total spending represents the aggregate amount spent by all households in an area annually.

Table 8. Error estimates for the three socioeconomic variables.

Metric / Variable	**2010 Income** B19313e1	**2019 Food** X1002_X	**2019 Housekeeping Supplies** X4033_X	**2019 Apparel & Services** X5001_X
Average value for census block group($)	34 154 143	6 091 696	472 113	1 529 296
Average value for census tract($)	94 330 480	16 935 233	1 319 750	4 236 060
Average value for building($)	392 654	70 493	5 493	17 632
RMSE	15 212 247	2 169 517	164 271	548 495
MAE	8 290 862	1 313 670	102 069	329 690

The resulting maps for these three variables(spending for food, household supplies, and apparel) for both(3D and 2D) methods, disaggregated from census block groups and census tracts, are provided in Appendix 1, pp. 79-83. The maps of the differences between 2D and 3D dasymetric methods are provided in Figure 15

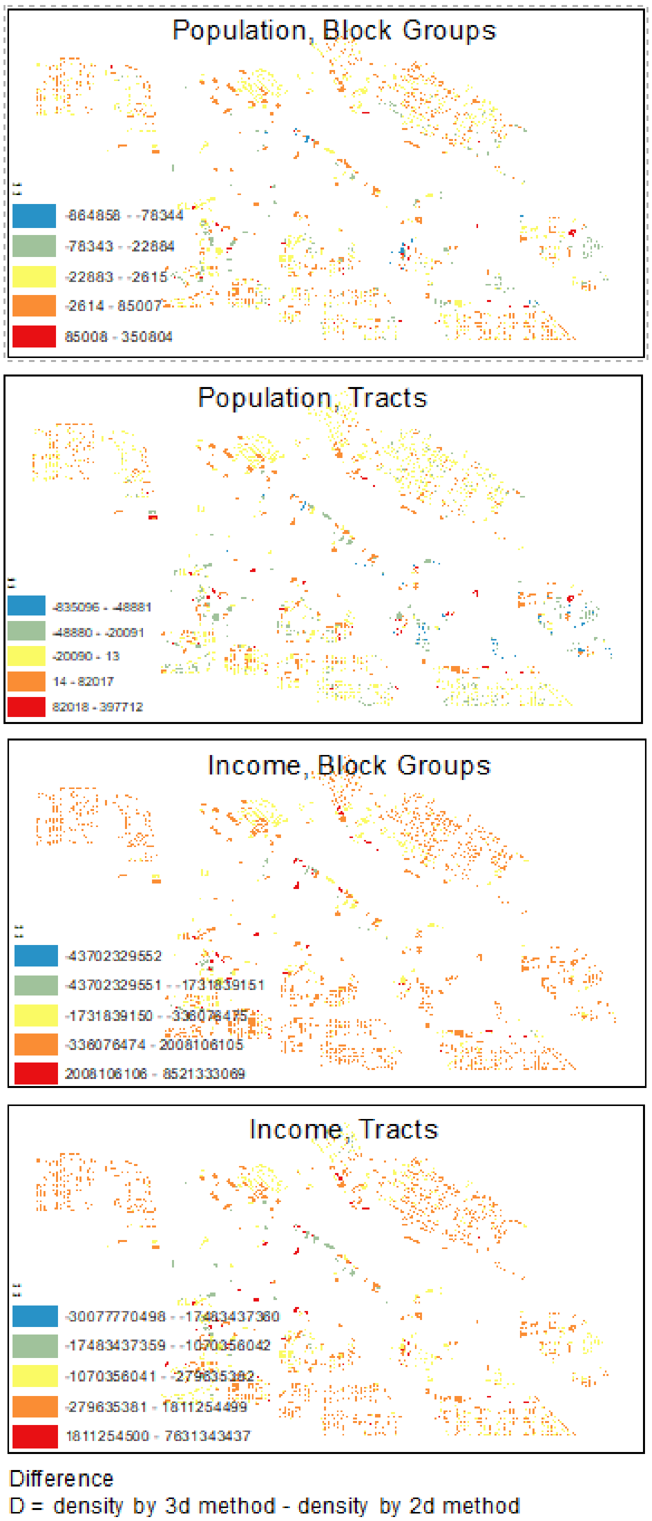

Figure 15 Differences between the results of the mapping methods

CHAPTER 5:

DISCUSSION

A comparison of the dasymetric mapping methods demonstrates that the binary 3D dasymetric mapping method yields the best accuracy in terms of RMSE and MAE metrics. Other more complicated dasymetric methods, such as the intelligent dasymetric mapping method suggested by Mennis and Hultgren (2006) and the floor fraction method (Cavin & Petrov, n/d), did not demonstrate much improvement. The 2D binary dasymetric mapping method is one of the most discussed methods in the existing literature. The 3D dasymetric method emerged in recent years (Biljecki et al., 2016); it is tailored mostly for urban environments and did not discuss in the existing literature extensively (Lu et al., 2011). By claim of its authors, Lwin and Murayama (2009), it demonstrates better results in urban environments in comparison with other methods according to their test results on the study area in Tokyo, Japan, which exhibits an extremely diverse set of residential high-rise buildings.

During the experiment conducted on the study area in Minneapolis, Minnesota, the 3D dasymetric method demonstrated an approximately 10% improvement in terms of RMSE when disaggregating the data for the census block groups level, and approximately a 20% increase when disaggregating the data on the census tract level. That finding could be explained by a higher diversity in the residential building stock heights at the census tract levels in comparison with the census block group level. In other words, it's more likely that the high-rise and low-rise buildings could fall in the same census tract, and it's a less frequent occurrence in the census block groups (as the latter tend to be more homogenous). Due to the increased diversity in building heights and subsequently their volume, it becomes more difficult to assign an appropriate number of inhabitants by using conventional 2D methods due to their use of the footprints of the buildings only and failure to consider the volume/height of the buildings.

Both methods (2D and 3D binary dasymetric mapping, population density maps are provided in Appendix 1, pp. 73-76) tend to overestimate the population density in the multi-family buildings surrounded by single-family buildings. In that situation, one can observe significant overestimation of the population counts in the block with the multi-family/apartment buildings and underestimation in the blocks populated with single-family buildings.

Regarding the other dasymetric mapping methods (Floor Fraction and Intelligent Dasymetric Mapping), they exhibit more significant errors. For the floor fraction method, the most significant limitation is that it uses the constant value for floor height for the entire study area. In case when the supplied floor height is too high for the particular building, one can get the number of the floors less than in reality, and when the supplied average floor height is too low, it will create additional floors. It could lead to a significant overestimation of the population counts in that building where the actual floor height is more than the supplied average floor height and an underestimation where the actual floor height is less than the specified value. As for the 3D Intelligent dasymetric mapping method, the biggest shortcoming is the lack of census enumeration units populated with a single property type. That fact leads to an inability to accurately calculate the representative population densities for the particular classes (9 out of 19), so the average value was used, which leads to the high inaccuracies during the calculation of the population counts.

Based on the analysis of the relationship between DM accuracy and building height heterogeneity, one can conclude that both methods(2D and 3D binary methods) demonstrate an increase of absolute percentage errors of predicted results with an increase of building height variability within the enumeration unit. On the other hand, the 3D binary dasymetric method demonstrates relatively better accuracy of predicting population counts with an increase of building height variability in comparison with its 2D counterpart.

T-test results were utilized to reveal the statistically significant difference between the datasets produced by 2D and 2D binary dasymetric mapping methods. There is no evidence that the results significantly vary between the methods. As the literature suggests (Biljecki et al., 2016), the 3D method should work better in the conditions, exhibiting a high degree of height variability. The findings of this study partially support that point. The number of iterations with the statistically significant difference in results was higher for the maps derived from the census tracts (smaller scale, more diverse housing stock, i.e., the higher standard deviation of building heights) versus those derived from the census block groups(larger scale).

Regarding the particular study area, located in the typical Midwestern urban environment, the results demonstrated that at a smaller scale, the differences between dasymetric mapping methods are more pronounced, although still exhibited relatively weak statistical significance. Thus, using the 3D dasymetric method in these urban environments, one should exercise caution, as it may not give a satisfactory increase in accuracy over the conventional dasymetric method in the conditions with the subtle building height variability. One can conclude that the 3D dasymetric method is best used in conditions of significant differences in the height of buildings in the study area.

Finally, the dasymetric maps of four socioeconomic variables were created. The resulting maps are provided in Appendix 1, pp. 77-83. Their visual appearance is closely resembling each other. It is mainly because the socioeconomic variables are strongly correlated (see Table 9), so the units and scale of the depicted phenomena could be different, but using the same classification scheme and cartographic approach, they will look very similar. That property could be helpful to more accurately spatially distribute the variables that are typically highly correlated with population distribution based on the assumption that these variables exhibit similar distribution patterns and principles as the distribution of the population.

Table 9. Correlation coefficients between the variables, census block group level

	1	2	3	4	5
1. Population	-				
2. Income	0.273177	-			
3. Food	0.210203	0.908829	-		
4. Household	0.210314	0.911319	0.999511	-	
5. Apparel	0.21049	0.906519	0.999746	0.998954	-

Table 10. Correlation coefficients between the variables, census tract level

	1	2	3	4	5
1. Population	-				
2. Income	0.25737	-			
3. Food	0.175349	0.959087	-		
4. Household	0.170257	0.963076	0.999526	-	
5. Apparel	0.175906	0.958281	0.999919	0.999256	-

These maps of socioeconomic variables(Appendix 1, pp 77-83) provide valuable insight into the distribution of the socioeconomic phenomena by providing a disaggregated values of the income and spending on a much finer scale than that provided by the census – instead of the census block groups, one can see the distribution of the variable on the building level. In particular, using the economic data on the income and spending aggregated on the building level could be beneficial in deciding the location of the retail outlets and conduct more effective and precisely targeted advertising campaigns.

CONCLUSION

The following hypothesis was examined in the research: 3D dasymetric mapping improves the accuracy of population mapping in an urban environment compared to 2D methods. The improvement is more significant at a smaller scale of analysis that reflects a more heterogeneous residential building infrastructure. The research supported the hypothesis despite some discrepancy between confidence in the results for the first and for the second part of the hypothesis.

This study demonstrates that the most accurate method to introduce the 3rd dimension in the dasymetric map was the 3D binary dasymetric (volumetric) mapping method. The difference in the accuracy between the 2D and 3D dasymetric method in terms of RMSE at the larger scale(census block groups) was significantly smaller than at, the larger scale (7.27 % difference versus 21.55% difference). Thus one can conclude that the 3D dasymetric mapping method gives more evident accuracy improvement on smaller scales of enumeration units, which exhibits more variation in building heights. Regarding the difference between the 2D and 3D dasymetric mapping methods at the different scales and levels of urban heterogeneity, the 3D dasymetric mapping method shows more significant improvement when using the enumeration units of larger size due to increased diversity in building heights within the enumeration units. In heterogeneous residential building infrastructure settings, the 3D dasymetric mapping method does not provide significant accuracy improvement. One of the implications explaining the weak statistical difference between 2D and 3D dasymetric mapping results could be difficulties in methods used in the typical Mid-Western urban conditions that do not exhibit significant variability in building heights.

The 3D dasymetric method was successfully applied to produce detailed maps of income and spending to expand DM beyond purely population mapping. These maps are providing valuable insight into the fine-scale distribution of these socioeconomic variables. The economic data on income and spending, aggregated on the building level, could be beneficial in deciding the location of the retail outlets and to conduct more effective and precisely targeted advertising campaigns.

Limitations

This study had several limitations. Despite the best efforts, it was not possible to select layers that were synchronized entirely in time. This is due to the frequency of data collection. In particular, the population layer was taken from the 2010 census, the height of buildings was calculated from the 2011 LiDAR data, layers with sociodemographic indicators were dated 2012 for income and 2019 for spending data. Data on the census block population is available for the decennial census only, which was conducted almost ten years ago. To produce the optimal results, one needs to use the building footprint and LiDAR data, synchronized with each other and with the census data. Otherwise, one could face the situation when some of the buildings have zero or negative heights. If the LiDAR data was collected before the particular building was erected, there are no corresponding non-ground points inside the corresponding footprint, so the average bare earth height instead of true building height will be assigned. Considering that

Minneapolis is updating the parcel and footprint data on an annual basis, it is possible to obtain the parcel and building footprint data synchronized with the census.

Regarding the LiDAR data, it is much more expensive to update it regularly, and in turn, it exists only at a single point of time – 2011, so some discrepancy exists between the LiDAR and the other spatial layers are inevitable. Considering the looming urban sprawl and city development, the use of such old data significantly obstructs the fieldwork nowadays to determine which buildings are residential and which are not, as some new buildings were constructed, and some of the buildings do not exist anymore. These limitations are especially significant for the disaggregation of the spending data for 2019 using the ancillary data from 2010-2011.

The next group of limitations is related to the selection process of residential and non-residential buildings. Filtering residential buildings by their minimum area does not allow to unambiguously separate residential buildings from non-residential buildings, because even inside those lots marked as residential, there are separate buildings, such as garages with a sufficiently large area, which leads to the erroneous designation of a specific population to such buildings and the underestimation of population density in residential buildings.

Finally, the study area location's choice imposed limitations in testing hypotheses about the different performance of 2D and 3D methods under conditions of varying scales and level of building heights homogeneity. The Mid-Western urban landscape with a small number of high-rise buildings does not allow to achieve a significant degree of differences in variability of building heights at different scales of enumeration units, which makes it difficult to obtain convincing results in this study.

Future Directions

The following future directions were identified to continue and extend the study on dasymetric disaggregation of socioeconomic variables. The feature to calculate population and sociodemographic indicators at the building level using dasymetric mapping can be a useful addition to the popular web mapping platforms such as ArcGIS Online or other web geospatial platforms. Taking into account the availability of the source data necessary for dasymetric mapping, such as footprints with the associated building height, census data, and partially data on residential and non-residential lots within the ArcGIS Online platform itself, it seems feasible to implement the calculation of various sociodemographic indicators based on this platform. The dasymetric mapping feature can be implemented either in a dynamic approach, in the form of a web tool that will disaggregate selected variables at the user's request, and as a set of static layers on the territory of interest, for example, covering some large cities with a limited set of sociodemographic indicators.

The capabilities of the method of dasymetric mapping in this paper were demonstrated using a minimal set of variables, namely, population, income, and three categories of spending. In the future, it is planned to expand the range of socioeconomic variables and test the possibility of using the method of dasymetric mapping on their example. Despite the demonstrated potential of the DM technique for the disaggregation of socioeconomic variables, the decomposition of variables in rural conditions, not necessarily at the building level, but at the level of, for example, census blocks using classical 2D dasymetric mapping techniques such as limiting variable, has not been investigated in the study. Another area of future research is the use of dasymetric mapping methods to disaggregate sociodemographic parameters at a smaller scale, not at the building level.

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APPENDIX 1

DASYMETRIC MAPS OF THE POPULATION DENSITY AND DISAGGREGATED SOCIOECONOMIC VARIABLES

Population density, 2D method, from census block groups

Population density, 2D method, from census tracts

Population density, 3D method, from census block groups

Population density, 3D method, from census tracts

Income density, 2D method, from census tracts

Income density, 3D method, from census block groups

Income density, 2D method, from census block groups

Income density, 2D method, from census tracts

Spending density(food), 3D method, from census tracts

Spending density(household supplies), 3D method, from census tracts

Spending density(apparel), 3D method, from census tracts

APPENDIX 2

RESULTS OF THE T-TEST TO COMPARE POPULATION MEANS BETWEEN 3DDM AND 2DDM ON TWO SCALES – ON CENSUS BLOCKS GROUP AND CENSUS TRACTS LEVELS

Statistically significant iterations($p < 0.05$) are highlighted.

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
1	0.321756	0.7477428	-0.32357	0.74640235
2	1.426107	0.1542998	-1.43518	0.15183668
3	0.101848	0.9189063	1.972817	0.04907127
4	-0.98971	0.3226837	-0.45367	0.65026399
5	-0.69928	0.4846267	2.557632	0.01084052
6	-1.37248	0.170406	0.815749	0.41500425
7	-0.97622	0.3293244	-0.74869	0.45439661
8	-0.78159	0.4347431	0.985493	0.32486028
9	0.110333	0.9121821	-1.46991	0.14222845
10	-1.14111	0.2542237	0.25771	0.79673906
11	-1.96258	0.0501152	-0.91631	0.35995878
12	0.244338	0.8070481	2.420781	0.01584377
13	0.819567	0.4127785	0.631008	0.5283199
14	-0.19712	0.8438021	0.356424	0.7216714
15	-0.55639	0.5781375	-0.78156	0.43485404
16	0.913195	0.3614586	1.429525	0.15347062
17	-0.6955	0.4869803	-0.3907	0.69620244
18	0.814454	0.4156837	-1.04072	0.2984597
19	-0.60208	0.5473279	1.275086	0.202902
20	0.625539	0.5318376	0.020019	0.9840365
21	-0.3033	0.7617585	0.650845	0.51541323
22	0.587403	0.5571335	1.857779	0.06376331
23	-1.00926	0.3132347	-1.02537	0.30568282
24	0.560032	0.5756722	1.179807	0.23861042
25	0.511196	0.6093952	1.487868	0.13741618
26	-0.80761	0.4196108	-0.52354	0.60082794
27	-0.10146	0.9192129	0.849839	0.39580854
28	1.434107	0.1520308	-0.65902	0.5101813
29	0.527625	0.5979424	1.038635	0.29948677
30	1.217158	0.2239886	-0.77082	0.44117557
31	0.426493	0.6698904	-0.10773	0.91425088
32	-0.23868	0.8114286	-0.43676	0.66248117

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
33	-0.44345	0.6575806	0.227931	0.81979545
34	-0.36103	0.7181953	0.670741	0.50269241
35	1.376989	0.1689833	-0.76233	0.44622903
36	-1.56301	0.1185283	1.311398	0.19030314
37	-0.25574	0.798226	0.773971	0.43931728
38	0.98786	0.3235865	-0.05913	0.95286981
39	0.584008	0.5594199	0.735223	0.46254629
40	1.482402	0.1387143	-0.13009	0.89654722
41	-0.13003	0.8965813	1.106104	0.26917293
42	-0.66859	0.5039846	2.353614	0.01898758
43	-1.02516	0.3056711	-0.97053	0.33222384
44	-1.87569	0.0611294	-0.3114	0.7556192
45	-0.63108	0.5281973	1.541558	0.12384559
46	1.503024	0.133334	-1.1323	0.25807057
47	0.328101	0.7429401	-0.33333	0.73902514
48	0.225103	0.8219677	0.99966	0.31799724
49	0.011886	0.9905202	1.522378	0.12862144
50	-0.43071	0.6668273	-0.29766	0.76608538
51	-1.78612	0.0745274	-0.74251	0.45812514
52	-0.46588	0.641445	1.251991	0.21115734
53	0.158788	0.8738866	-0.95155	0.34177318
54	-0.42924	0.6678895	-0.00658	0.99475418
55	-1.08069	0.2802591	-0.66077	0.50905715
56	-1.02161	0.3073377	-1.45717	0.14568993
57	0.437398	0.6619609	0.002851	0.99772641
58	-1.19987	0.2306195	0.366468	0.71416705
59	-0.65767	0.5109898	1.606113	0.10887163
60	-0.05898	0.9529869	3.129897	0.00184884
61	0.075253	0.9400368	1.052334	0.29316078
62	0.104334	0.9169382	-1.19446	0.23286185
63	-0.46444	0.6424907	1.408069	0.15971872
64	-0.90184	0.3674587	-0.1875	0.85134685
65	-2.04937	0.0408232	2.297036	0.02202336
66	-0.47828	0.6326202	0.136171	0.8917443
67	0.67526	0.4997362	-0.81743	0.41408152
68	-0.59532	0.5518274	0.213269	0.83120496
69	1.274651	0.2029125	-0.65178	0.51484831
70	1.837707	0.0665335	0.388993	0.69746295
71	-0.03481	0.9722428	2.699941	0.00717956
72	-1.36526	0.17265	-1.00165	0.31701395
73	-0.09525	0.9241458	0.324547	0.74566418
74	1.556601	0.1200173	0.076361	0.93916028
75	1.314884	0.1890296	0.444041	0.65721365
76	-1.57054	0.1167555	0.365559	0.71484884

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
77	-0.44245	0.6583109	-0.87898	0.37984325
78	-0.19384	0.846368	-0.79957	0.42434499
79	0.592884	0.5534643	1.222259	0.22216889
80	-1.02751	0.304563	-1.43847	0.15093869
81	0.614415	0.5391529	-0.4728	0.63656028
82	-1.08098	0.2800908	-1.72755	0.08469116
83	2.507576	0.0123974	0.085451	0.93193502
84	1.492137	0.1361637	1.014249	0.31092249
85	-0.31258	0.7546956	1.012162	0.31193148
86	-0.09697	0.9227824	1.838377	0.06658261
87	-0.46518	0.6419527	-0.26596	0.79037902
88	1.142184	0.2537994	0.491487	0.62328402
89	1.071014	0.2845372	-0.70987	0.47808734
90	0.688007	0.4916812	0.604862	0.54554155
91	-1.37081	0.1709346	-1.02475	0.30600682
92	0.048467	0.9613604	-0.47834	0.63259244
93	1.430197	0.1531538	-0.98541	0.32488989
94	0.31538	0.752578	-0.93087	0.35242295
95	0.220197	0.8257854	-0.41272	0.67998925
96	0.86939	0.3849469	2.247781	0.02499515
97	-0.80177	0.4229861	0.58895	0.55616111
98	1.055096	0.2917601	0.065186	0.94805199
99	2.191526	0.0288073	0.606524	0.54443007
100	-1.88624	0.0597377	-0.07501	0.94023244
101	-1.02364	0.306386	-1.01041	0.31277463
102	0.568099	0.5701632	1.160498	0.24641006
103	1.102535	0.2706374	-0.10958	0.91278747
104	-0.92253	0.3566137	-0.76326	0.44568137
105	0.29208	0.7703167	-1.23845	0.21613186
106	0.039985	0.9681172	0.848387	0.3966554
107	1.991562	0.0468484	0.843754	0.39922305
108	2.51183	0.0122426	-1.44594	0.14876971
109	-0.92759	0.3539689	1.447019	0.14854302
110	-0.21009	0.8336642	-0.32519	0.74517294
111	1.544756	0.1229131	0.090819	0.92767337
112	0.003708	0.9970429	0.561069	0.57499306
113	0.246802	0.8051372	0.799898	0.42412515
114	0.470321	0.6382755	0.319765	0.74927209
115	0.284739	0.775934	0.92111	0.35742831
116	-0.42084	0.6740139	0.143566	0.8859017
117	-0.0717	0.9428616	2.995544	0.00287521
118	0.554933	0.579122	-0.13727	0.89087655
119	-0.36722	0.7135697	2.88527	0.0040744
120	-1.83128	0.0674781	-0.0557	0.95560156

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
121	1.104615	0.2697416	-0.55664	0.57802113
122	0.576998	0.5641361	1.949888	0.05174464
123	-0.4746	0.6352373	0.020895	0.98333756
124	2.170246	0.0303772	-0.88974	0.37402679
125	-0.0058	0.9953743	0.909608	0.36344923
126	-0.05547	0.9557796	-0.12991	0.89669267
127	1.346793	0.1785099	0.016522	0.9868251
128	-0.46729	0.6404499	1.362695	0.1735741
129	-0.29409	0.7687845	-1.16273	0.24545779
130	-0.78799	0.4309954	0.724593	0.46902601
131	-1.17319	0.2411396	0.445065	0.65645663
132	-0.59922	0.5492281	0.982143	0.32650347
133	-0.51948	0.6036086	-0.43001	0.66737236
134	1.581612	0.1142465	0.212896	0.83148787
135	-0.67537	0.4996911	-0.74372	0.4573798
136	-0.64395	0.5198486	-1.27215	0.20391419
137	0.320615	0.7486033	0.778281	0.43676485
138	0.81656	0.4144673	-0.15569	0.87634365
139	0.377961	0.7055762	-0.20572	0.83709325
140	-0.32372	0.7462536	1.198636	0.23120942
141	0.322501	0.7471806	1.260789	0.20799748
142	-1.39772	0.1626674	-1.34765	0.17837176
143	-1.85075	0.0646472	-1.34744	0.17844981
144	-1.48047	0.1392436	-1.32445	0.18598728
145	1.313718	0.1894202	1.959821	0.05056308
146	-0.35749	0.7208434	-0.24976	0.80288824
147	1.910651	0.0564939	0.975665	0.32968308
148	-0.04339	0.9654014	-0.48481	0.62804497
149	-0.55808	0.5769766	0.622132	0.53414305
150	0.033991	0.9728952	-0.05897	0.95299843
151	0.195828	0.8448077	1.69845	0.09004505
152	0.77945	0.4359957	1.899483	0.05809639
153	1.829864	0.0676978	0.061174	0.95124467
154	1.234275	0.2175464	-0.49876	0.61817585
155	0.204764	0.8378199	1.8727	0.06170502
156	0.275138	0.7832942	1.841719	0.06609225
157	1.825035	0.068461	0.771097	0.44099847
158	0.358463	0.7201124	0.298241	0.76563668
159	-0.15468	0.8771258	1.932866	0.05381825
160	0.035861	0.9714041	-1.33708	0.18178388
161	0.416086	0.6774839	-0.23661	0.81305204
162	0.941702	0.3466889	0.465825	0.64155541
163	-2.0538	0.0403913	-1.2889	0.19800831
164	0.808309	0.4192087	2.125804	0.0340013

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
165	0.081175	0.9353287	1.253966	0.21041135
166	-1.16014	0.2464308	2.416499	0.01600934
167	-1.73602	0.0830329	0.247283	0.80479532
168	-1.10264	0.2705732	1.033193	0.30198281
169	-1.23311	0.2179762	-1.12907	0.25942263
170	-0.15323	0.8782668	-0.68056	0.49646255
171	0.733997	0.4632039	0.610775	0.54160636
172	-1.98932	0.0470883	-0.79434	0.42738394
173	0.231751	0.8168063	1.240899	0.21524283
174	0.888686	0.3744783	-0.01227	0.99021653
175	0.833936	0.4046032	1.261847	0.20757719
176	0.992239	0.3214431	0.775546	0.43838822
177	0.068654	0.9452854	-0.88007	0.37923611
178	-0.54008	0.5893294	-1.01242	0.31180459
179	-0.03391	0.9729588	0.273563	0.78453777
180	-0.43171	0.6661042	-0.11775	0.9063153
181	0.63583	0.5251132	2.616111	0.00917576
182	1.902082	0.0575989	-1.18811	0.23536039
183	-1.73397	0.0833944	1.140839	0.25448312
184	-0.00811	0.9935279	2.19359	0.02873105
185	-0.01994	0.9840961	0.360398	0.71869884
186	3.274571	0.0011202	1.011936	0.31206195
187	-0.64106	0.5217163	-0.30064	0.76381664
188	0.034067	0.9728333	-0.31913	0.74975054
189	0.658646	0.5103628	2.271594	0.02354469
190	1.434891	0.1517753	2.45115	0.01458761
191	2.90475	0.0038106	1.946993	0.05205747
192	1.079076	0.2809561	0.751338	0.45279243
193	0.124324	0.9010949	0.784468	0.43310285
194	-0.10301	0.9179838	1.226423	0.2205722
195	0.646409	0.5182403	-0.61119	0.54134582
196	-0.85853	0.3909172	-0.39919	0.68993125
197	-1.65948	0.0974877	-1.21964	0.22315926
198	-0.8374	0.4026793	0.921018	0.35747371
199	0.046427	0.962984	-0.87132	0.38398605
200	0.174212	0.8617567	3.434553	0.00064075
201	-1.49552	0.1352814	0.805305	0.42100371
202	0.23332	0.8155881	-1.31714	0.18839036
203	0.723038	0.4699048	3.182514	0.00155051
204	-0.7345	0.4629009	1.141337	0.25423448
205	0.973523	0.3306516	3.704236	0.00023459
206	0.752113	0.452247	1.624657	0.10491464
207	-0.89506	0.3710732	-0.11269	0.91031956
208	1.392252	0.1643221	0.569462	0.56929889

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
209	1.131582	0.2582128	-1.27638	0.20238726
210	-0.81376	0.4160705	1.740325	0.08246357
211	-0.06504	0.9481638	-0.9427	0.34625796
212	-0.17702	0.8595523	-0.9485	0.34334374
213	0.34706	0.7286552	-0.61768	0.53706698
214	-0.54803	0.5838645	0.647446	0.51764937
215	-1.17643	0.2398461	1.065822	0.28700429
216	-0.13371	0.8936693	1.34954	0.17776944
217	-0.51906	0.6038896	0.747077	0.45536696
218	-0.74029	0.4593791	0.161763	0.87156223
219	0.258543	0.7960657	0.46133	0.64476052
220	-0.06937	0.9447131	-0.10205	0.91875825
221	-0.94565	0.3446902	0.148883	0.88170087
222	1.792756	0.0734834	-0.59444	0.55248436
223	1.253412	0.2104878	-0.94211	0.34659663
224	-1.01075	0.3125518	0.894263	0.37159341
225	0.1364	0.8915504	-0.67624	0.4992014
226	0.069401	0.9446909	2.139553	0.03283202
227	0.490125	0.6242135	-0.32756	0.74339573
228	2.628074	0.008781	2.376883	0.01781366
229	-1.02179	0.3072461	-0.6957	0.48692735
230	0.556868	0.5778012	0.284667	0.77601556
231	-0.72133	0.4709776	0.812004	0.41718549
232	1.307173	0.19163	0.820494	0.41231045
233	0.178219	0.8586076	0.549761	0.58273015
234	0.678218	0.4978811	1.371277	0.17086681
235	-0.37293	0.7093145	0.497082	0.6193444
236	-0.72549	0.468404	-0.26058	0.79452564
237	-0.36721	0.7135874	0.023086	0.98159043
238	0.541043	0.5886715	1.89256	0.05894999
239	3.043821	0.0024333	-0.91433	0.36098599
240	0.723591	0.4695696	-0.0202	0.98389373
241	1.902737	0.0575052	0.626587	0.5312244
242	-0.80858	0.4190431	-1.88709	0.05972487
243	0.473354	0.6361147	0.328968	0.7423208
244	0.676515	0.4989494	1.668443	0.09584526
245	1.325547	0.1854435	-0.64737	0.51768626
246	1.286542	0.1986872	-0.34682	0.72887839
247	-0.46992	0.638573	0.342365	0.73222134
248	-0.09785	0.9220806	0.65515	0.51266388
249	-1.15883	0.2469613	0.85729	0.39171451
250	-0.58444	0.5591351	0.707055	0.47986229
251	1.947146	0.0519469	-0.53325	0.59410019
252	-1.17035	0.2422922	0.151922	0.87930709

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
253	-1.79891	0.0724999	-0.0471	0.96245137
254	3.112644	0.0019393	-0.51081	0.60969056
255	-0.83111	0.4062333	-0.17315	0.86260112
256	0.37235	0.7097499	-0.62021	0.53539883
257	1.620663	0.1055683	0.108824	0.91338812
258	-1.04034	0.2985691	0.329648	0.74179848
259	-1.32053	0.187133	2.169752	0.03046258
260	-0.50851	0.6112621	-0.82171	0.41164057
261	0.411518	0.6808406	2.120553	0.03443401
262	0.495914	0.6201343	-0.99853	0.31850999
263	-0.07766	0.9381237	0.425766	0.67045892
264	0.949178	0.342911	0.645533	0.51887431
265	0.756755	0.4494706	-0.11539	0.90818618
266	0.759574	0.4477894	2.410679	0.0162969
267	1.426211	0.1542831	0.126604	0.89930585
268	-1.72945	0.0842083	0.004412	0.99648137
269	-1.25672	0.2093254	-0.66881	0.5039443
270	-1.20168	0.2299353	0.459085	0.6463751
271	-0.28066	0.7790612	-1.16179	0.24590411
272	1.054108	0.2922459	1.852473	0.06457932
273	-1.04013	0.2986572	-0.71759	0.47331372
274	0.154978	0.8768876	-0.60836	0.54322323
275	-0.64589	0.5185754	1.499901	0.13424805
276	0.073541	0.9413988	0.364615	0.71556139
277	-0.30155	0.7630844	1.020112	0.30819796
278	0.035521	0.9716759	1.092893	0.27498573
279	-0.47411	0.6355757	-0.27834	0.78086232
280	0.255231	0.79863	1.437756	0.15110932
281	1.676466	0.0941212	-0.00896	0.99285785
282	0.528824	0.5971107	-0.3623	0.7172739
283	0.994995	0.3201154	-0.66822	0.50430217
284	-1.3676	0.171855	1.382557	0.16740005
285	1.553725	0.1207287	-0.556	0.57845669
286	0.510969	0.6095464	-0.30454	0.76084716
287	0.850265	0.3954798	0.849508	0.39597605
288	1.750909	0.0804276	0.933436	0.35103735
289	-0.1791	0.857915	-1.20277	0.22964928
290	0.695527	0.4869651	0.540287	0.58922928
291	1.40529	0.1604174	0.287705	0.77368529
292	-0.46459	0.642389	-0.52273	0.60139913
293	1.471307	0.1416982	-0.37171	0.71025763
294	0.139314	0.8892446	0.602344	0.54722154
295	0.553699	0.5799776	1.447044	0.14849406
296	0.73491	0.4626628	3.077346	0.00220403

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
297	0.143759	0.885734	-1.46443	0.14373011
298	0.114039	0.9092427	1.837634	0.06673688
299	-0.09523	0.9241585	-0.92981	0.35294224
300	-1.19685	0.2317985	2.276916	0.0232038
301	-0.2187	0.8269486	0.525629	0.59935455
302	-1.33674	0.1817626	-0.85224	0.39447647
303	-0.19859	0.8426413	0.550094	0.5824928
304	0.334387	0.7381977	-0.6819	0.49562673
305	0.677113	0.4985672	-0.99895	0.31828776
306	0.180053	0.8571657	-0.02972	0.97630332
307	1.259659	0.2082558	0.918335	0.35887499
308	-1.15198	0.2497702	1.998902	0.04614608
309	1.305832	0.1920834	-0.57748	0.56386295
310	-0.3331	0.7391613	2.748358	0.00621413
311	-0.2186	0.8270263	-0.89499	0.3712102
312	1.598491	0.1104101	1.47238	0.14152917
313	0.617045	0.5374183	1.299443	0.19438365
314	0.795061	0.4268753	-0.675	0.50000346
315	-1.59905	0.1103079	0.568825	0.56971109
316	1.104899	0.2696123	0.566442	0.57134646
317	0.230256	0.8179616	0.906351	0.36516288
318	-0.49428	0.621264	3.868202	0.0001242
319	0.800375	0.4238024	1.4286	0.15376157
320	-0.54897	0.5832067	-0.18943	0.84983358
321	1.925013	0.0546338	-0.3962	0.69211561
322	-0.33977	0.734141	-0.71351	0.47585942
323	1.811361	0.0705294	-0.03985	0.96823112
324	1.54242	0.1234606	1.212776	0.22580832
325	-1.09268	0.2749245	-1.6111	0.10779843
326	-0.88559	0.3761709	1.334816	0.18256532
327	-0.09397	0.9251612	1.27877	0.20156176
328	1.731684	0.0837841	-0.12645	0.89942375
329	-0.76975	0.4417144	0.862663	0.38873969
330	1.031634	0.3026148	-0.92073	0.35765733
331	1.362796	0.1734215	-0.49522	0.62064648
332	-1.24823	0.2124132	-0.55123	0.58174501
333	-0.23323	0.8156525	0.838344	0.40225668
334	0.618851	0.5362259	0.526529	0.59874595
335	-0.52052	0.6028784	-1.47073	0.14195351
336	0.144362	0.8852588	1.151773	0.24999751
337	-1.84468	0.0655497	-0.22498	0.82208318
338	0.673114	0.5011287	2.352861	0.01900922
339	0.236939	0.8127756	-1.13046	0.25882257
340	-0.3136	0.753931	0.251308	0.80167298

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
341	-0.88742	0.3751678	-0.4745	0.63534775
342	1.461982	0.1442192	-0.12839	0.89789217
343	1.595173	0.111159	-0.26835	0.78853911
344	0.872864	0.3830383	-0.00976	0.99221296
345	1.038932	0.2992306	1.492597	0.13620111
346	-0.63763	0.5239435	-0.83495	0.40415274
347	0.259451	0.7953726	0.406245	0.68473785
348	0.726536	0.4677761	1.123303	0.26181434
349	0.902137	0.3673222	1.519498	0.12928087
350	-0.61715	0.5373522	2.717532	0.00680807
351	1.506106	0.1325127	-1.57221	0.11650326
352	-1.83582	0.0668376	0.858336	0.39110625
353	0.649096	0.5164954	-0.00321	0.9974375
354	0.403519	0.6867125	-0.13734	0.89081407
355	-0.52145	0.6022451	-0.01896	0.98488379
356	-1.32029	0.187186	0.065188	0.94804858
357	0.923852	0.3559094	-0.17925	0.85781598
358	-1.04924	0.294431	-0.64673	0.51811782
359	0.391623	0.6954664	-0.0912	0.92736797
360	-0.41578	0.6777063	-0.84874	0.39639317
361	1.531596	0.1260786	0.424771	0.67118315
362	0.992581	0.3212792	-0.21344	0.83107197
363	1.18739	0.235507	0.932892	0.35135076
364	0.728281	0.4667214	0.996036	0.31972125
365	-0.29324	0.7694316	2.060902	0.03983003
366	0.593777	0.5528717	0.642638	0.52075142
367	0.132842	0.8943573	1.072052	0.28419684
368	-0.41079	0.6813668	-0.03267	0.97395378
369	1.025146	0.3056575	-0.40624	0.68474917
370	-0.79033	0.4296296	-0.23558	0.81385279
371	-0.27325	0.784744	1.439735	0.15055941
372	0.63908	0.5229911	1.678784	0.09378806
373	-1.16586	0.2441023	-0.31618	0.75200027
374	-0.45658	0.6481326	1.574472	0.11599594
375	0.56999	0.5688774	-0.23315	0.81574665
376	-1.44132	0.1499681	0.541096	0.58867478
377	-0.06227	0.9503703	-0.05199	0.95855491
378	-1.3693	0.1713609	-0.07351	0.94142921
379	1.19569	0.2322682	1.534042	0.12569501
380	2.294527	0.0220705	1.308584	0.19125126
381	-1.13117	0.2584047	-0.14686	0.88330405
382	-0.62372	0.5330278	0.457089	0.64780178
383	1.933753	0.0535676	0.851096	0.39512498
384	-0.63163	0.527855	0.381283	0.70315532

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
385	-0.00223	0.9982252	0.400843	0.68869548
386	0.678783	0.4975047	-0.17019	0.86493031
387	1.184104	0.2368128	-0.55968	0.57594684
388	-0.93911	0.348021	1.377825	0.16888001
389	0.24768	0.8044602	0.611316	0.5412817
390	0.546197	0.5851279	-0.06301	0.94978653
391	-1.05155	0.2934046	-0.329	0.74229543
392	-1.651	0.0992397	-0.57763	0.56375149
393	1.58128	0.1142846	-0.31117	0.7558006
394	-1.12532	0.2608541	-0.43819	0.66144273
395	-0.3998	0.6894232	-1.11146	0.26687347
396	-1.39317	0.1640339	0.301532	0.76313459
397	-1.17244	0.2414461	-0.65709	0.51145045
398	2.859358	0.0043859	0.433838	0.66458574
399	-0.86498	0.3873861	0.705679	0.48071264
400	0.436292	0.6627675	1.200407	0.23052165
401	0.691664	0.4893861	-0.95936	0.33789102
402	-2.07433	0.0384558	0.198086	0.84305199
403	-0.54361	0.586894	1.141325	0.25426704
404	-0.70902	0.478557	0.528782	0.59718893
405	-0.19486	0.8455667	1.1403	0.25469013
406	-1.43861	0.1507433	0.1383	0.89006027
407	1.352259	0.1767415	-0.99119	0.32205021
408	0.132876	0.8943343	1.136093	0.25648832
409	-0.06272	0.950012	1.311726	0.19019919
410	-0.43302	0.6651432	0.608048	0.54344551
411	1.719863	0.0859356	2.278705	0.02310881
412	1.534433	0.1254251	-0.33038	0.74125555
413	-0.09333	0.9256642	-1.40373	0.16106149
414	-0.62233	0.5339602	0.910504	0.36299093
415	0.335361	0.7374571	-0.81885	0.41325295
416	0.017949	0.9856853	-0.82997	0.40692307
417	1.121796	0.26235	-0.63828	0.52359195
418	-0.23637	0.8132256	-0.59502	0.55209555
419	0.354137	0.7233545	-0.19548	0.8450998
420	0.806975	0.4199811	-0.84203	0.40016141
421	0.826618	0.408753	-0.72178	0.47078057
422	0.549276	0.5830028	2.384562	0.01745694
423	-0.38416	0.7009858	0.052759	0.95794417
424	0.652094	0.5145676	-1.01341	0.31134037
425	1.953414	0.0511858	-0.74004	0.4596097
426	1.517108	0.1297559	1.045736	0.29619111
427	-1.16981	0.2425227	0.635806	0.52521077
428	-1.44713	0.1483449	-0.78588	0.43230664

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
429	0.613272	0.5399289	-1.59845	0.11057873
430	1.424547	0.1547384	0.165303	0.86877084
431	1.202958	0.22943	-0.24389	0.80741041
432	1.322179	0.1865583	-0.65583	0.51220257
433	1.412938	0.1581702	1.949182	0.0517969
434	2.176644	0.029868	1.128194	0.25976953
435	0.230999	0.8173853	1.352235	0.17687364
436	-0.36423	0.7157942	0.476513	0.63391127
437	0.003543	0.9971744	0.364028	0.71599479
438	1.665163	0.0963271	-1.36934	0.1715136
439	-0.40449	0.685993	0.615043	0.53880031
440	0.089083	0.929043	-0.35576	0.72216209
441	-0.25615	0.7979141	-1.068	0.28601541
442	1.97342	0.0488529	2.036746	0.04217105
443	-0.23501	0.8142717	0.776316	0.43793414
444	1.587646	0.1129022	1.274862	0.20295509
445	-0.51903	0.6039122	0.731684	0.4646899
446	-0.30301	0.7619812	2.065183	0.03941648
447	0.061535	0.9509537	2.484186	0.01331512
448	-0.17732	0.8593134	0.960731	0.33719668
449	-1.1469	0.2518346	2.185511	0.02930824
450	-0.46098	0.644969	1.811031	0.07070207
451	0.607318	0.5438562	-0.04356	0.96527303
452	-0.02369	0.9811038	0.783255	0.43382577
453	0.273852	0.7842809	2.31899	0.02080022
454	-1.04896	0.2946209	1.689199	0.0918376
455	-0.92974	0.3528454	2.526451	0.0118172
456	1.306274	0.1918835	-1.09217	0.27523309
457	-0.20293	0.8392563	0.996547	0.31946922
458	2.661612	0.0079729	0.064921	0.94826301
459	1.030976	0.3029181	-0.6216	0.53449199
460	0.278682	0.7805725	-1.10434	0.27000047
461	-1.33245	0.1831782	1.468242	0.14268269
462	1.355214	0.1758407	1.779827	0.07576867
463	-0.32208	0.7474918	3.02511	0.00261544
464	1.646005	0.1002536	3.2708	0.00115126
465	1.381035	0.1677436	-1.61176	0.10764316
466	-1.21844	0.2235117	0.384782	0.70055026
467	0.988558	0.3232388	-0.42144	0.67362524
468	1.488831	0.1369868	-0.65239	0.51444185
469	0.582464	0.5604437	-0.66103	0.50889437
470	1.434766	0.1518491	0.708776	0.47877967
471	1.169662	0.2425923	0.583406	0.55988295
472	1.587442	0.1128681	0.275411	0.78310774

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
473	0.413961	0.6790394	0.343422	0.73141881
474	1.001779	0.3168309	1.494674	0.13559019
475	1.361359	0.1738823	-0.53275	0.5944297
476	0.439966	0.6601108	-0.49203	0.62291381
477	-0.0532	0.9575868	-0.88974	0.37402773
478	1.265393	0.2061607	-0.7406	0.45928169
479	-1.3248	0.185713	-0.21454	0.8302191
480	-0.6753	0.4997217	-0.64662	0.51817991
481	-1.01346	0.3112008	-0.34266	0.73199398
482	0.337724	0.7356823	2.326009	0.02039799
483	1.208568	0.2272436	0.886654	0.37570647
484	0.58173	0.5609421	-2.09564	0.03665585
485	-0.27521	0.7832406	-0.20693	0.8361555
486	0.020342	0.9837774	1.738958	0.08268202
487	-1.31415	0.1892967	0.617094	0.53746151
488	-0.19233	0.8475451	-0.23581	0.81367798
489	-0.47282	0.6365	1.363731	0.17324678
490	1.60757	0.1084164	1.872985	0.0616334
491	2.090895	0.036946	-0.31191	0.75522476
492	0.439046	0.6607707	-1.57187	0.11660741
493	-0.68549	0.4932902	-1.10215	0.27091262
494	-0.39224	0.6950102	2.271375	0.02356992
495	-0.96018	0.3373265	-1.01843	0.30897203
496	0.27258	0.7852636	-0.6306	0.52857327
497	0.614162	0.5393184	-0.1375	0.89068941
498	-0.01219	0.9902744	2.363341	0.01848963
499	-1.144	0.2530635	0.259457	0.79538007
500	0.377215	0.7061392	-0.00263	0.99790534
501	0.236076	0.8134492	0.360591	0.71854838
502	-0.79193	0.4286776	-0.68426	0.49411743
503	-1.03605	0.3005687	0.831553	0.40604616
504	-0.53555	0.592457	1.998631	0.04618174
505	-1.10978	0.2674972	0.929905	0.35288573
506	-1.14365	0.2531757	0.086791	0.93087188
507	0.433073	0.6651039	-0.03582	0.97144276
508	-0.65526	0.512516	-0.12226	0.90274614
509	1.018287	0.3089379	-1.48595	0.13797478
510	-0.25825	0.7962873	0.830123	0.40688455
511	-0.34773	0.7281526	-0.33008	0.74147628
512	-0.84589	0.3979523	-0.22729	0.82029135
513	2.151333	0.0318177	-0.26317	0.79252648
514	-0.36439	0.7156845	-1.19706	0.23188973
515	0.051066	0.9592894	-0.12591	0.89986078
516	-0.31089	0.7559783	-1.04799	0.2951292

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
517	0.409165	0.6825469	-1.28695	0.19864561
518	-1.3918	0.164423	3.077416	0.00220897
519	0.516503	0.6056892	0.377762	0.70575873
520	-0.83716	0.4028162	0.562768	0.57381621
521	0.975535	0.3296635	0.874646	0.3822013
522	1.534088	0.1255013	-0.15638	0.87579341
523	-0.92421	0.3557551	-0.03929	0.9686738
524	0.145989	0.8839735	0.11392	0.90934429
525	-0.00491	0.9960842	-0.35696	0.7212812
526	2.640689	0.0084607	-0.22924	0.81877022
527	1.317108	0.1882759	0.691247	0.48970464
528	0.039248	0.9687041	-1.28702	0.19872194
529	-0.61151	0.5410676	-0.73918	0.46014239
530	-0.17032	0.8648134	0.041262	0.96710223
531	-0.41559	0.6778412	-0.07616	0.93932562
532	-0.08368	0.9333384	-1.81661	0.0698847
533	0.669544	0.5033953	-1.42545	0.1546113
534	0.160305	0.8726902	1.308978	0.19113957
535	0.664497	0.506618	2.079772	0.0380615
536	-1.00741	0.3141047	0.487989	0.62577562
537	-0.42859	0.6683538	-0.49894	0.61803033
538	-0.27429	0.783948	1.251348	0.21135766
539	-0.62651	0.5311744	1.45682	0.14579259
540	-1.25278	0.2107283	-1.10294	0.27057226
541	0.065369	0.9479006	0.04872	0.96116192
542	-1.1489	0.2510172	-0.46544	0.64181473
543	-0.46059	0.6452467	2.348502	0.01920675
544	1.056019	0.2913356	-0.21862	0.8270348
545	0.940432	0.3473529	2.713492	0.00688216
546	2.457678	0.0142305	-0.92838	0.35367874
547	0.010045	0.9919888	0.317649	0.7508854
548	0.460827	0.6450739	-0.21699	0.82830682
549	-1.02854	0.3040421	-0.31046	0.75634392
550	1.826193	0.0682614	0.544193	0.58654346
551	0.337104	0.7361448	0.795335	0.42679929
552	-0.47988	0.6314637	3.408542	0.00070695
553	1.269027	0.2048871	-1.35744	0.17523947
554	-0.0349	0.9721702	-1.01969	0.30839683
555	-0.52919	0.5968555	1.036292	0.30058463
556	-1.75128	0.0803689	-1.19815	0.23144918
557	-0.71672	0.4738155	1.354892	0.17606888
558	-0.24492	0.8065922	2.023809	0.04352653
559	0.574734	0.5656762	-1.33937	0.18104522
560	0.404931	0.6856654	-0.22503	0.82205531

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
561	-0.41047	0.6815903	0.522234	0.60172999
562	-0.95857	0.3381279	-1.23522	0.2173614
563	0.018175	0.985505	0.248107	0.80415504
564	0.450365	0.6525922	0.039935	0.96815981
565	-0.48214	0.6298676	-0.4288	0.66824769
566	0.432914	0.6652215	-0.76881	0.44236303
567	0.543763	0.5867842	-0.71465	0.47515424
568	-0.51824	0.6044801	-1.16978	0.24264527
569	-1.20229	0.2296602	0.108066	0.91398578
570	-0.03874	0.9691125	-0.32497	0.74534193
571	1.30501	0.1923607	-0.6067	0.54430824
572	-0.98884	0.3231157	0.743074	0.45779437
573	1.375278	0.169505	1.821337	0.06914369
574	-0.48587	0.6272156	0.71159	0.47704596
575	-2.36508	0.0183124	-1.18728	0.23567392
576	-0.6642	0.5068086	-0.45825	0.64695661
577	-0.38279	0.7020021	-0.75257	0.45206589
578	-0.19414	0.8461208	0.794584	0.42720864
579	-1.14295	0.2535058	2.019944	0.04389663
580	-0.34148	0.7328498	0.360762	0.71842236
581	0.607733	0.5435793	-0.07672	0.93888067
582	-0.37573	0.7072444	1.079861	0.28073655
583	0.851543	0.3947746	1.657879	0.09794157
584	-1.76097	0.0786906	1.206705	0.22810626
585	1.176048	0.2400063	-0.15073	0.88024626
586	0.523784	0.6005965	-0.77103	0.4410734
587	-0.49416	0.6213555	-0.46939	0.63898161
588	0.407138	0.6840414	1.033371	0.30193704
589	1.072621	0.2838403	-0.26527	0.79091734
590	-0.54369	0.5868403	0.017868	0.98575165
591	0.880579	0.3788515	-0.77891	0.43641284
592	-0.74189	0.4584229	0.814139	0.41594526
593	1.703428	0.088966	-0.17513	0.86104091
594	2.102339	0.0358951	1.351408	0.1771467
595	1.897254	0.0582508	0.186909	0.85180724
596	-0.97158	0.3316111	-0.71824	0.47295317
597	0.408859	0.6827781	0.112915	0.91014266
598	-0.28887	0.7727709	1.888143	0.05960342
599	1.010797	0.3124879	0.287041	0.7741976
600	2.39915	0.0167142	-0.80462	0.42142189
601	-0.22552	0.8216381	0.039631	0.96840301
602	-0.28415	0.776384	-1.28712	0.19863559
603	0.542228	0.5878478	0.769221	0.44212853
604	-1.50131	0.1337813	0.369332	0.71203225

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
605	-0.77987	0.4357546	-0.49007	0.62430673
606	-0.93844	0.3483508	2.698051	0.0072267
607	1.888774	0.0593591	-0.7015	0.48329096
608	-0.04052	0.9676895	1.222262	0.22217883
609	0.633632	0.5265445	-1.34785	0.1782819
610	0.161364	0.8718575	-0.72167	0.47082705
611	0.008025	0.9935995	0.446492	0.65542681
612	0.013264	0.9894214	-0.55803	0.57707571
613	1.038118	0.2996071	-0.36849	0.7126742
614	-1.44647	0.1485247	-1.12997	0.25902253
615	0.124238	0.901167	-0.79154	0.42901329
616	-0.05611	0.9552711	0.552838	0.5806359
617	1.412437	0.1582727	1.508643	0.13202159
618	0.719564	0.4720578	-0.10978	0.91263389
619	1.03428	0.3013779	1.602228	0.10971253
620	0.279734	0.779767	1.282907	0.20010859
621	0.347785	0.7281255	-0.37012	0.71144464
622	1.19043	0.2343041	-0.62099	0.53488589
623	0.564562	0.5725598	-0.43691	0.66236949
624	-1.05454	0.2920221	1.453075	0.14683157
625	1.58153	0.1142628	1.704828	0.08883556
626	-0.19836	0.8428212	0.790113	0.42983766
627	-1.22563	0.2208149	-0.21108	0.83290809
628	1.856878	0.0637944	2.239819	0.02553188
629	-0.18008	0.857145	-0.50436	0.61423741
630	-0.19103	0.8485595	0.459862	0.64582123
631	0.304098	0.7611519	-0.73114	0.46505678
632	-0.19686	0.8439961	-0.39745	0.69119821
633	-1.27341	0.2033276	0.475936	0.6343391
634	-0.5272	0.5982348	0.320697	0.74857716
635	0.295532	0.7676811	1.91773	0.05567838
636	-0.16823	0.8664571	-0.64793	0.51733264
637	1.192229	0.2336217	-0.3944	0.69344732
638	-0.10253	0.9183681	-1.0359	0.30076307
639	-1.10304	0.270415	-1.15148	0.25005781
640	1.121542	0.2624441	2.176808	0.02993722
641	-0.34717	0.7285806	-0.93137	0.35210615
642	-0.94737	0.343782	-0.01337	0.98933432
643	-1.33393	0.1826883	2.179036	0.02980177
644	1.668502	0.0956912	0.386467	0.6993149
645	-0.306	0.7596993	-1.90639	0.05716115
646	-0.98372	0.3256456	0.769016	0.44223938
647	0.115307	0.9082353	-0.78316	0.43391766
648	-0.43984	0.660201	0.597911	0.55015251

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
649	-0.61388	0.5395029	0.437954	0.66161361
650	0.996931	0.3191952	-1.06509	0.28736634
651	-0.60564	0.5449659	0.756278	0.44982119
652	0.148303	0.8821466	-0.17712	0.85948869
653	-0.42986	0.6674504	-0.91611	0.360043
654	-0.70328	0.4821556	1.04835	0.29501637
655	-1.67081	0.0952446	-0.04874	0.96114355
656	0.817622	0.4138689	0.31733	0.75113278
657	2.262008	0.0240165	-0.09094	0.92757622
658	0.222514	0.8239808	0.206697	0.83633045
659	1.502436	0.1335081	0.195784	0.84486068
660	-1.61848	0.1060599	-1.1086	0.26811213
661	2.991024	0.0028901	0.209586	0.83407565
662	1.479359	0.1395109	-0.67381	0.50073291
663	-0.43409	0.6643576	0.692519	0.4889179
664	-0.89648	0.3703429	2.343648	0.01948694
665	-1.25718	0.2091478	-1.0652	0.28728445
666	0.433028	0.6651378	1.333079	0.18312536
667	1.54059	0.1239546	0.38617	0.69952776
668	-0.50942	0.6106398	-0.70333	0.48216989
669	-0.78792	0.4310338	-1.43322	0.15246549
670	-0.8779	0.3803118	0.508336	0.61145262
671	0.283898	0.7765807	-0.11725	0.90670948
672	1.116188	0.2647404	0.068634	0.94530683
673	-0.72186	0.4706372	0.439567	0.66044658
674	1.944354	0.0522954	0.949049	0.3430765
675	1.278654	0.2014404	1.105889	0.26932499
676	-0.61582	0.5382304	-0.73875	0.46040797
677	-0.88932	0.3741493	0.108509	0.91363511
678	-0.40355	0.6866739	0.893887	0.37182752
679	-1.20631	0.2281307	0.012175	0.99029027
680	-0.82474	0.4098213	1.762396	0.07861464
681	1.788607	0.0741792	2.382309	0.01757733
682	0.776462	0.4377625	-0.04587	0.96343095
683	-0.09941	0.9208442	0.122885	0.90224296
684	-0.91855	0.3586537	1.000135	0.3177166
685	-1.95273	0.0513277	-0.60566	0.54503839
686	1.247277	0.2127545	-0.52142	0.60231072
687	-0.31199	0.7551529	-0.99908	0.31824103
688	-0.39856	0.6903492	-0.56999	0.56891838
689	-0.32005	0.749024	2.477364	0.01355236
690	0.790658	0.4294089	0.428581	0.66841509
691	-0.77136	0.4407829	0.631907	0.52773917
692	0.794052	0.4274574	-1.06423	0.28776678

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
693	-0.70853	0.4788719	1.799862	0.07250121
694	-0.69061	0.4900687	-0.01046	0.99165854
695	0.562003	0.5743117	-0.23561	0.81383216
696	-0.78918	0.4302973	1.491201	0.1365381
697	-0.38009	0.7040031	0.72915	0.46627688
698	1.337589	0.1815004	0.85509	0.39287043
699	1.1547	0.2486411	0.000173	0.99986187
700	1.877605	0.0608746	-0.04381	0.96507708
701	-0.84635	0.3976672	-0.58569	0.55834302
702	-0.26737	0.789271	0.151827	0.8793895
703	2.128343	0.0336746	-0.51028	0.6100747
704	-0.89904	0.3689683	2.298779	0.0219186
705	1.449895	0.1475687	-0.47459	0.63528799
706	-0.51004	0.6102002	0.578058	0.5634974
707	0.072862	0.9419377	0.67496	0.50001571
708	0.080919	0.9355296	2.969495	0.00312794
709	1.157194	0.2476358	1.527945	0.12716611
710	-0.38885	0.6975204	1.577168	0.11536502
711	1.14967	0.250719	1.171115	0.24211128
712	-0.80738	0.4197241	2.836384	0.00473826
713	-0.33719	0.7360888	-1.03781	0.29985723
714	0.532022	0.5948998	0.176922	0.85963834
715	-1.00287	0.3163085	-0.56692	0.57104137
716	-0.57871	0.5629985	-0.94377	0.34572403
717	-1.19331	0.2332023	-0.19074	0.84880481
718	-0.27629	0.7824136	0.163986	0.86980518
719	1.483024	0.1385931	1.476802	0.14035316
720	1.217597	0.2238464	-1.46179	0.1444114
721	-1.25329	0.2105481	0.747663	0.45502265
722	-1.32876	0.1843784	-0.56448	0.57267419
723	1.372379	0.1704095	1.542526	0.12355425
724	1.223098	0.2217523	2.183765	0.02944725
725	0.20976	0.8339161	0.802383	0.4226879
726	-0.75473	0.4506692	0.779464	0.43606473
727	-1.29657	0.1952054	1.630063	0.10372945
728	0.164568	0.8693344	-0.51314	0.60809299
729	1.340856	0.18044	-1.03633	0.30055345
730	-0.4434	0.6576281	-1.13299	0.25774824
731	1.756884	0.0794077	0.654456	0.51312473
732	-1.02651	0.3050441	-0.72355	0.46968166
733	-1.2752	0.202715	-0.60498	0.54548863
734	-0.45132	0.6519062	0.388177	0.69806089
735	0.040258	0.9678994	1.003028	0.31632286
736	0.411921	0.6805265	2.538742	0.0114225

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
737	-1.05786	0.2905282	0.783962	0.43343815
738	0.914954	0.3605396	3.033371	0.00255025
739	1.625777	0.1045248	-0.20042	0.84122988
740	0.549135	0.5831025	-1.28038	0.20098869
741	1.013663	0.3111366	1.411623	0.15865574
742	0.324469	0.7456821	2.966615	0.00315002
743	-1.20187	0.2298182	1.287104	0.1986157
744	-1.19473	0.2326223	0.06097	0.95140918
745	0.353834	0.7235844	1.404949	0.16064896
746	-0.61355	0.5397215	-0.00388	0.99690684
747	1.399905	0.162022	1.389294	0.16534386
748	1.174692	0.240541	1.65662	0.09821862
749	0.042202	0.9663495	2.2192	0.02690724
750	2.317616	0.0207756	0.439422	0.66055594
751	0.627878	0.5302964	1.812339	0.07052646
752	-1.16499	0.2444569	0.020475	0.98367283
753	-0.74473	0.4567046	0.157596	0.87483976
754	1.469536	0.1421721	-0.75318	0.45170293
755	2.369641	0.018089	-1.36652	0.17240024
756	0.919503	0.3581829	1.211334	0.22632736
757	-0.23457	0.8146197	-0.13015	0.89649957
758	0.659076	0.5100827	0.926238	0.35475051
759	-0.36253	0.7170784	0.900843	0.36810801
760	0.426304	0.6700265	1.001837	0.31689754
761	-0.01059	0.9915544	-0.79313	0.42807073
762	1.325755	0.1854107	-0.74326	0.45766907
763	-1.37897	0.1683671	0.115353	0.90820799
764	1.887915	0.0595117	0.579487	0.56251006
765	-0.71661	0.4738678	-1.70715	0.08842559
766	-0.60605	0.5446885	-0.80913	0.41881982
767	0.433449	0.6648312	0.562428	0.57407292
768	-0.26394	0.7919098	1.570746	0.11688974
769	0.603499	0.5464082	1.753802	0.08005931
770	-1.54979	0.1216637	-0.53772	0.59103797
771	-0.61825	0.5366102	-1.05522	0.29182391
772	0.706351	0.4802371	1.453722	0.14666223
773	-0.63974	0.5225524	0.605726	0.5449693
774	-0.05305	0.9577118	2.707585	0.00699839
775	1.911959	0.0563102	1.438366	0.15094487
776	0.156897	0.8753757	0.484306	0.62838151
777	-1.1714	0.2418566	-0.88296	0.37768201
778	0.072202	0.942464	-0.30557	0.76005813
779	-0.99235	0.3214038	-0.14886	0.88172202
780	1.162641	0.2453954	1.207505	0.22775127

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
781	0.152153	0.879112	1.686473	0.09233229
782	-0.8862	0.3758637	-0.28231	0.7778328
783	-0.469	0.6392189	4.802319	2.0184E-06
784	0.267551	0.7891273	1.238237	0.21615359
785	-0.32458	0.7456052	0.04455	0.96448374
786	-0.61027	0.5419058	-1.33791	0.18151628
787	1.231929	0.2184289	-0.08301	0.93387487
788	-0.44125	0.659185	-0.58154	0.56113702
789	0.174634	0.8614209	-0.52684	0.59855988
790	-0.5239	0.6005358	-0.25205	0.80110657
791	-0.40373	0.686538	1.071117	0.2846017
792	-0.68312	0.4947689	-0.631	0.52833841
793	0.34201	0.7324531	-0.64227	0.52099157
794	0.334147	0.7383716	-0.27872	0.78057902
795	-0.78388	0.4333929	-0.45327	0.65054562
796	1.273298	0.2033668	2.686711	0.0074596
797	-0.95453	0.3401755	1.862648	0.06310637
798	-0.40475	0.6857902	0.705949	0.48057208
799	1.494067	0.135629	-0.49678	0.61955656
800	-0.13947	0.8891203	1.877511	0.06101641
801	0.0393	0.9686633	-0.01998	0.9840678
802	-0.87452	0.3821437	1.06776	0.28609402
803	0.064383	0.9486842	0.861097	0.38960834
804	-0.20911	0.8344317	0.415857	0.67769179
805	0.754965	0.4505378	-0.16593	0.86827694
806	-0.34798	0.7279692	1.315194	0.18904385
807	0.301558	0.7630833	-0.52385	0.60060699
808	1.022537	0.3069049	0.428217	0.66868208
809	1.85435	0.0641001	-0.40259	0.68740377
810	-0.81514	0.4152835	0.151401	0.8797169
811	0.900879	0.3679717	-1.20902	0.2272336
812	0.277308	0.7816352	-0.34737	0.72845856
813	-1.44909	0.1477946	-0.71864	0.4726972
814	1.049285	0.2944348	1.672354	0.09508512
815	-0.32572	0.7447487	1.464954	0.14356205
816	-1.71532	0.0867505	-0.08176	0.93487301
817	-0.3638	0.7161203	-0.67667	0.49893876
818	-0.20482	0.8377807	-0.25865	0.79601198
819	0.046466	0.962952	-0.80931	0.41873721
820	0.54102	0.5886992	-1.54667	0.12252441
821	-0.0352	0.9719315	0.58178	0.56097594
822	0.360913	0.718277	1.175279	0.24043027
823	-0.97854	0.3281669	2.631863	0.0087516
824	-0.2948	0.7682405	0.05302	0.95773671

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
825	-0.12814	0.8980795	0.027542	0.97803823
826	1.065015	0.2872486	0.947596	0.34379382
827	0.673177	0.5010857	0.470718	0.63804559
828	-0.77932	0.4360801	-0.57081	0.56837862
829	-1.37538	0.1695006	-1.1304	0.2588756
830	1.152039	0.2497535	-0.2279	0.81982353
831	0.494698	0.6209786	1.416511	0.15726277
832	0.17365	0.8621925	0.452424	0.65116081
833	-1.01768	0.3091901	-1.10666	0.2689346
834	0.367488	0.7133831	2.219108	0.02695415
835	0.262577	0.7929615	-1.0811	0.28020381
836	-0.21899	0.8267321	2.363111	0.01849214
837	-1.50985	0.1315622	-0.16584	0.86834798
838	0.162658	0.8708407	0.366952	0.71380192
839	1.369721	0.1712377	-1.04313	0.29737409
840	-0.31709	0.7512799	0.384952	0.70044865
841	-0.39527	0.6927687	1.747711	0.08114293
842	0.898705	0.3691554	-0.05682	0.95470719
843	1.770758	0.0770732	-0.18778	0.85112852
844	-1.2272	0.2201874	-0.38758	0.69847817
845	0.253016	0.8003362	-0.19981	0.84171184
846	-1.16673	0.2437421	-0.86005	0.39015982
847	0.195619	0.8449712	0.172656	0.86298985
848	-1.5725	0.1163143	0.11625	0.90749934
849	-0.57436	0.5659355	3.824532	0.00014721
850	1.97808	0.0483448	-0.32669	0.74404364
851	0.970017	0.3324081	0.417275	0.6766576
852	-0.92426	0.3556824	1.33341	0.18304468
853	-0.69592	0.4867371	-1.18315	0.23730125
854	0.473502	0.6360006	-0.79151	0.42903623
855	1.062538	0.2884054	0.627687	0.53051034
856	-1.27857	0.2014792	1.206781	0.22805875
857	1.403297	0.1610036	-0.41795	0.67617966
858	0.547636	0.5841292	0.243197	0.80795059
859	-0.04896	0.9609702	3.621619	0.00032347
860	0.468263	0.6397488	1.602112	0.10972563
861	-0.44181	0.6587699	-0.25223	0.80096474
862	-1.091	0.2756921	-1.22846	0.21984352
863	1.099629	0.2718986	2.29396	0.02220006
864	-0.78743	0.4313287	0.837361	0.40279036
865	0.418131	0.6759894	0.624864	0.53235033
866	3.312368	0.0009784	-1.52333	0.12831095
867	-0.84737	0.3971065	1.05432	0.29226238
868	-0.9419	0.3465853	-0.82373	0.41047926

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
869	0.40544	0.6852926	0.164707	0.86924057
870	-0.62015	0.5353735	-0.13167	0.89530011
871	-1.21331	0.225448	2.524822	0.01186695
872	-0.60922	0.5426085	1.483173	0.1386487
873	0.648959	0.5166059	-0.79755	0.42551799
874	-1.51938	0.129142	-1.0581	0.29053977
875	0.63113	0.5281823	-1.41012	0.15911152
876	1.71433	0.0869327	0.793743	0.42772075
877	-1.02289	0.3067429	-1.14794	0.25154442
878	0.310761	0.7560808	-0.24141	0.80933979
879	-0.72727	0.4673331	0.857004	0.39181137
880	3.308548	0.0009901	-0.50438	0.61420355
881	0.375229	0.7076132	0.849512	0.39600149
882	3.361325	0.000819	-0.52534	0.59958398
883	1.325076	0.1855863	1.067991	0.28604703
884	-0.90635	0.3650852	0.118054	0.90607207
885	1.305822	0.192089	-1.53669	0.12498102
886	0.816184	0.4147061	-0.79005	0.42985486
887	-0.7084	0.4789485	1.349594	0.17773797
888	1.050454	0.2938953	-0.12832	0.8979451
889	-0.08615	0.9313763	-0.92543	0.35519079
890	1.158493	0.2471026	1.555974	0.12040798
891	-0.74896	0.4541546	-0.26853	0.78840766
892	0.844267	0.3988325	0.061629	0.95088175
893	0.656936	0.5114496	0.000769	0.99938688
894	-0.74742	0.4550799	-0.36356	0.71633554
895	1.91888	0.0554384	-1.15662	0.2479431
896	2.006782	0.0451847	0.830614	0.40659061
897	2.088877	0.037128	-1.24318	0.21437266
898	-0.74131	0.4587747	0.147488	0.8828086
899	0.997416	0.3189351	0.136138	0.89176455
900	1.191137	0.2340166	-1.38601	0.16631402
901	0.186516	0.8520965	-1.24283	0.21450113
902	-0.37068	0.7110006	-0.30194	0.76282647
903	1.791647	0.073644	-0.35156	0.72530257
904	-1.65877	0.0976511	-0.63986	0.52253767
905	-0.43866	0.6610548	-0.5543	0.5796272
906	-0.36716	0.7136232	2.016689	0.04425779
907	0.161902	0.8714382	-1.27464	0.20303143
908	0.6643	0.5067432	0.354995	0.72274499
909	0.419365	0.6750915	0.097583	0.9223019
910	-0.73379	0.4633461	-0.01623	0.98705498
911	-0.12033	0.9042621	0.677575	0.49835705
912	0.022812	0.981807	-0.31201	0.75516211

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
913	0.717592	0.4732743	1.945087	0.05232247
914	0.940445	0.3473445	-0.56091	0.57512829
915	0.250865	0.8020035	-0.92553	0.3551617
916	-0.12965	0.8968884	0.693136	0.48853771
917	-0.45078	0.652294	-0.00279	0.99777234
918	-0.23835	0.8116808	2.462731	0.01410767
919	-0.99673	0.3192431	1.842095	0.06607536
920	-0.55201	0.5811205	0.309763	0.75686263
921	1.132792	0.2577168	-0.15417	0.87754247
922	-0.77199	0.4403873	0.383508	0.70148952
923	-0.77898	0.4362686	-0.45711	0.64777786
924	1.60246	0.1095324	-1.03561	0.30088805
925	0.029263	0.9766641	-0.66112	0.5088352
926	-0.23391	0.8151205	0.587938	0.55685244
927	0.537248	0.5912769	-1.31691	0.18848085
928	-0.41592	0.6776033	0.667189	0.50496213
929	-0.00973	0.9922433	0.459121	0.64636393
930	0.988784	0.3231132	0.248465	0.8038697
931	-1.17374	0.2409129	-0.63306	0.52698408
932	0.132897	0.8943193	-0.32277	0.747003
933	0.790923	0.4292785	0.023911	0.98093291
934	0.839987	0.4012503	0.370364	0.71127172
935	0.263793	0.7920193	-0.98402	0.32558214
936	0.540426	0.5890963	1.073497	0.28358649
937	0.201289	0.8405364	-0.5509	0.58195017
938	-1.07317	0.2835935	2.142843	0.03258393
939	-1.40772	0.1596972	0.311051	0.75590372
940	0.557686	0.5772562	-0.40735	0.68391842
941	0.506852	0.612431	0.592042	0.55408878
942	1.585831	0.1132426	-0.37802	0.70557232
943	-0.74524	0.4564037	-0.96113	0.33693949
944	0.656735	0.5116151	-0.4868	0.62659919
945	0.686452	0.4926725	-1.65554	0.09842965
946	1.810008	0.0707252	-1.36133	0.17403073
947	-0.7759	0.4380953	-1.09328	0.27482744
948	0.421204	0.6737417	-0.23161	0.81693246
949	-1.15938	0.2467145	4.027649	6.526E-05
950	-0.54448	0.586296	-0.42633	0.67004597
951	0.194323	0.8459856	0.666621	0.50530142
952	-0.60168	0.5476109	-0.57809	0.56346176
953	-0.49021	0.6241502	-0.3643	0.71579403
954	0.179635	0.8575003	1.404555	0.16080302
955	2.157255	0.0313349	1.898509	0.05823227
956	0.443148	0.6578156	-0.89198	0.37283504

	Block groups		Census tracts	
Iteration	t-value	significance	t-value	significance
957	0.812536	0.4167743	-0.92825	0.35371171
958	-1.05439	0.2920649	0.184819	0.85345218
959	-0.71952	0.4720712	0.156262	0.87589088
960	0.878026	0.3802453	1.406806	0.16013338
961	-1.3005	0.1939023	-0.18777	0.85112491
962	0.660203	0.509352	1.018378	0.30903621
963	0.183424	0.854521	0.837255	0.40283254
964	1.902959	0.0574755	0.126698	0.89923101
965	1.994867	0.0464688	-0.04789	0.96182598
966	1.193404	0.2331454	0.674972	0.49998693
967	-0.30244	0.7624148	-0.73412	0.46320588
968	-0.83917	0.4016661	-1.3856	0.16646306
969	4.844571	1.589E-06	0.692544	0.48892439
970	0.424322	0.671466	0.540008	0.58942509
971	-1.21922	0.2232437	0.406663	0.68443964
972	-0.56169	0.5745204	0.090637	0.92781799
973	-1.51593	0.1300204	-0.42053	0.67428392
974	-0.21181	0.8323185	-0.81925	0.41303542
975	-0.45658	0.6481215	-0.35508	0.72267945
976	-0.45195	0.6514522	0.212201	0.83203579
977	-0.56968	0.5690889	1.64126	0.10132148
978	-1.23784	0.2162279	0.232106	0.81655693
979	1.830084	0.0676937	-0.68625	0.49286887
980	-1.61973	0.1057624	0.40178	0.68801259
981	-0.50731	0.6121062	1.190281	0.23447498
982	-1.29227	0.1967276	1.018534	0.30897155
983	0.598175	0.5499215	1.585173	0.11354555
984	-0.86652	0.3865189	0.698141	0.48542286
985	-1.01113	0.3123258	0.088306	0.92967011
986	1.641784	0.1011193	-1.08789	0.27718702
987	-1.27367	0.2032456	-0.53396	0.59360268
988	-0.04936	0.960647	-0.14272	0.88656607
989	-0.23223	0.8164249	0.635889	0.5251185
990	2.108551	0.0353801	-0.37375	0.70874934
991	1.651013	0.0992017	2.386976	0.01735246
992	0.249141	0.8033313	-0.89773	0.3697616
993	1.381668	0.1675712	0.613019	0.54012963
994	-1.09496	0.2739346	2.13239	0.03349035
995	-0.66552	0.5059476	0.798397	0.42504098
996	-0.73801	0.4607599	-0.02956	0.97642721
997	-0.16388	0.869879	0.461047	0.64496307
998	0.241701	0.8090898	0.721128	0.47113331
999	0.502719	0.6153267	0.403057	0.68706654
1000	0.818214	0.4135288	1.642915	0.10101092