



Building population mapping with aerial imagery and GIS data

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ABSTRACT

Geospatial distribution of population at a scale of individual buildings is needed for analysis of people's interaction with their local socio-economic and physical environments. High resolution aerial images are capable of capturing urban complexities and considered as a potential source for mapping urban features at this fine scale. This paper studies population mapping for individual buildings by using aerial imagery and other geographic data. Building footprints and heights are first determined from aerial images, digital terrain and surface models. City zoning maps allow the classification of the buildings as residential and non-residential. The use of additional ancillary geographic data further filters residential utility buildings out of the residential area and identifies houses and apartments. In the final step, census block population, which is publicly available from the U.S. Census, is disaggregated and mapped to individual residential buildings. This paper proposes a modified building population mapping model that takes into account the effects of different types of residential buildings. Detailed steps are described that lead to the identification of residential buildings from imagery and other GIS data layers. Estimated building populations are evaluated per census block with reference to the known census records. This paper presents and evaluates the results of building population mapping in areas of West Lafayette, Lafayette, and Wea Township, all in the state of Indiana, USA.

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1. Introduction

The census as applied in many countries is an attempt to gather basic information about the characteristics of the population. This is usually carried out at an interval of 5–10 years with the purpose of obtaining information on demographic, social, economic and housing characteristics and their variation over small areas (Martin, 2000, 2006; Boyle and Dorling, 2004). Apart from the great value of this important effort, one major aspect of population census is its spatial content.

Considering this spatial aspect, geographic aggregation is the most common way of releasing population and socioeconomic datasets. The census population, for instance, is usually publicly available in various geographic reporting zones depending on the policies applied by the country performing the census (Martin, 1996). Spatial analyses on these data may be performed for different purposes and by implementing methods with different assumptions and understanding. Thus, the specific areal unit in which the data are reported does not necessarily coincide with

the nature of the phenomena under investigation. The results of the correlation and regression analysis of spatial data may vary based on the size and configuration of the areal units used for the analysis (Flowerdew et al., 2001). Since the data reporting zones are not unique or fixed, it is possible to represent the same data using different aggregations for a more realistic presentation. This is known as the modifiable areal unit problem (MAUP) (Openshaw and Taylor, 1981). Indeed, representation of population in spatial units different from the census zoning may be essential for a better performance of various spatial applications. Some of these applications include criminal investigation, public health, natural hazards risk, environmental risk and accessibility analysis, facilities and retail planning, land use planning, resource allocation, emergency planning, and spatial interaction modeling (Chen, 2002; Langford, 2006; Mennis, 2009).

Representing data in different areal units requires interpolation from the initial source units to target units. One way to achieve this is by dasymetric mapping (Wright, 1936). This is basically a transform of data aggregated to one zone to some other desired zone so as to represent the underlying data distribution more realistically. Dasymetric maps discretize a continuous statistical surface into regions with minimum variation that are divided by boundaries approximating the steepest change (Langford and Unwin, 1994). Such maps aim to have a better depiction of the underlying statistical surface with more homogeneous zones (Eicher

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and Brewer, 2001; Mennis, 2009). In this respect, the information used to define homogeneous boundaries is of importance. In this study, building footprints are used to define the homogeneous zones.

Different approaches to dasymetric mapping have been used in various applications. Land use and land cover, soil type, geological unit or similar ancillary information may be used in dasymetric mapping. Eicher and Brewer (2001) provide detailed information and evaluation on major dasymetric mapping methods. Maantay et al. (2007) also provide a review on methods used for dasymetric mapping. Langford (2006) compares binary and 3-class dasymetric methods. Mennis (2003) describes a dasymetric mapping methodology that incorporates areal weighting and empirical sampling to determine the relation between the ancillary data and population distribution. In a later study by Mennis and Hultgren (2006), a flexible empirical sampling approach is introduced as an “intelligent” dasymetric mapping (IDM) technique that supports several ways to define the relationship between the ancillary data and the underlying statistical surface. At the finer scale, Lwin and Murayama (2009) introduce a GIS approach to the estimation of population for individual buildings.

This study explores population mapping for individual buildings. First, we determine building footprints and heights in residential zones from aerial images, digital terrain model (DTM), digital surface model (DSM) and zoning maps. Building address data, land use maps, and other ancillary information are further jointly used as supplemental data to categorize the extracted buildings as houses and apartments. In the final step, weighted areametric and volumetric models are used to disaggregate the population of census units to individual residential buildings. The rest of the paper is organized as follows. Section 2 introduces the weighted models for population disaggregation. The study areas and test data are described in Section 3. As an implementation of the object-based image classification technique, Section 4 discusses building extraction and evaluates its quality. Section 5 makes a combined use of zoning data, address data, land use maps, and other publicly accessible information to identify residential houses and apartments from the results of the previous section. Properties of different disaggregation models are evaluated in Section 6 by using census population data as the reference. Findings and concluding remarks are summarized in Section 7. Throughout the paper sample data and maps are presented from the cities of West Lafayette, Lafayette, and the Wea Township, in Indiana, USA.

2. Models for population mapping

Population data for a variety of geographic units are publicly available from the U.S. Census Bureau. Of importance for this study are four of these geographic units, from smallest to largest: census blocks, census block groups, census tracts, and townships. Census blocks are the smallest geographic units for which U.S. Census data are tabulated. Streets, roads, railroads, other physical features, legal boundaries, etc. may form the boundaries of census blocks. The next level units are census block groups. A census block group is a combination of several census blocks. Census tracts are geographic entities with more homogenous population characteristics, economic status and living conditions, usually having between 2500 and 8000 residents. The largest geographic unit for this study is the township, which is a minor civil division (MCD) defined as the primary sub-county governmental or administrative unit. (U.S. Bureau of the Census, 2005).

The objective of building population mapping is to distribute the publicly available population of a census unit to individual residential buildings therein. For this purpose, we modify the areametric

and volumetric models introduced by Lwin and Murayama (2009) through implementing a weighting scheme

$$P_i = \frac{w_i^S S_i}{\sum_{k=1}^n w_k^S S_k} P_c \quad (1)$$

where S_i : taking either A_i for the area or V_i for the volume of residential building i ; S_k : taking either A_k for the area or V_k for the volume of residential building k ; w_i^S, w_k^S : weighting factors for residential buildings i , and k ; P_i : population of residential building i ; P_c : population of a census unit; n : total number of buildings within the census unit.

In the above equation, the population of a census unit P_c is available from census. The weighting factor w_i^S represents the population per unit area or volume, which varies with the type of residential buildings. To apply the above model, we need to first find the buildings, recognize the residential ones, and then determine their weighting factors. These issues will be addressed in the following sections.

3. Study area and data

The selected study areas are parts of Lafayette and West Lafayette cities, and the entire Wea township, Indiana, USA. These twin cities are separated by the Wabash River, cover an area of 66.3 km², and have a total population of 85,175 based on the 2000 census data. The study area within the city of West Lafayette consists of two census tracts: 51 and 52. The Wea township, approximately 100 km² in area, overlaps in part with the city of Lafayette and includes both urban and suburban regions with multi residential, business, industrial and agricultural representative areas. These neighborhoods are relatively similar and comprise many typical residential land covers. There are three different types of major residential zoning observed in the neighborhoods of the study area. These include single family housing, single and two family housing, and single, two and multi-family housing. Single family housing neighborhoods include detached single family houses while single and two family housing neighborhoods include attached twin houses in addition to the single family houses. Neighborhoods of the third zoning class mainly include townhouses and apartment buildings in addition to the single and two-family houses. An overview of the study areas is illustrated in Fig. 1.

As summarized in Table 1, a variety of geographic data over the above study area is used in this work. They include 1 m resolution color infrared (CIR) aerial photos, acquired during March and April of 2005 in leaf off conditions, 1.5 m resolution DTM and DSM derived from the CIR image stereo pairs, current zoning maps, all for the entire study area; building footprints of 2000 and building address point data of 2009 for West Lafayette; land use maps of the Wea township; and 2000 census population data. The CIR images, DTM and DSM were acquired and created as a part of the 2005 IndianaMap Color Orthophotography project coordinated by the Indiana Geographic Information Council (IGIC), and are made publicly available online through a spatial data portal (<http://www.indiana.edu/~gisdata/>). Though the DSM was generated from the same image sources, it misses a number of buildings present in the imagery. The zoning maps are publicly available from the website of the Tippecanoe County Area Plan Commission (<http://www.tippecanoe.in.gov/apc/>). They show the boundaries of different zones of current and planned allowable uses, such as single-family residential, multi-family residential, business, industrial and agricultural. Both the building footprints and the address data are obtained from the Tippecanoe County GIS office. Building footprints include the building outlines combined from multiple sources and will be referred to as “county buildings” in the continuing sections. The address data consist of locations

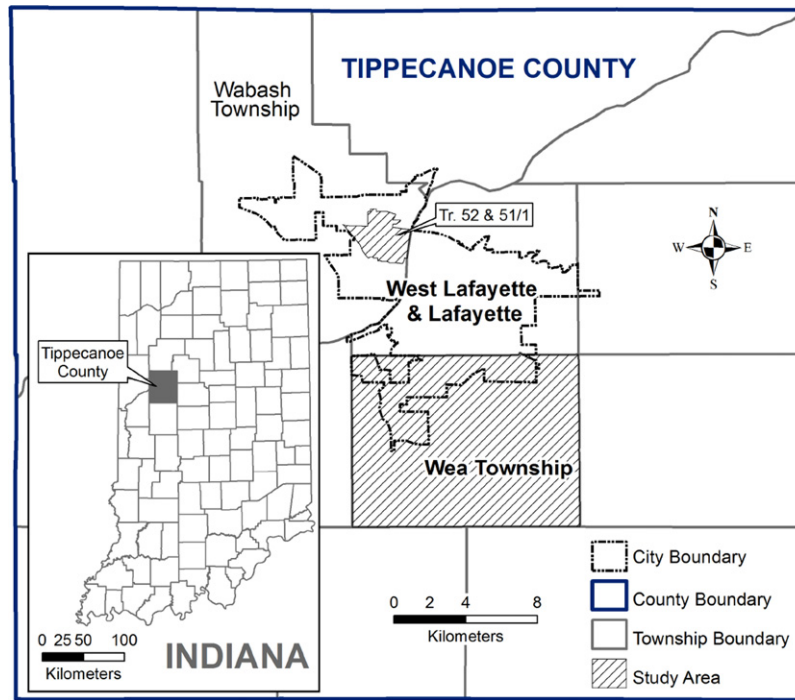


Fig. 1. Overview of the study areas in Indiana, USA.

of buildings and include information like house number, street address and building use. They do not cover all study areas and are not complete in terms of the information in their attribute tables, which justifies the need for additional data for appropriate building type classification. The land use map, available online at Tippecanoe County GIS website (<http://gis.tippecanoe.in.gov/public/>) has boundaries of actual land use, e.g., urban area, forest, farm buildings and home sites. Fig. 2 shows samples of data covering the area of census block group 1 of census tract 51 in West Lafayette.

Before proceeding to the implementation and testing, it is necessary to elaborate how these data will be utilized in the study. The 2005 images are first used to derive building footprints, which are then evaluated with reference to the county year 2000 buildings. Heights of buildings are acquired from the difference between DSM and DTM. Zoning maps, land use maps, and address points help further identify residential buildings. At the end, population of census block groups is disaggregated to individual residential buildings.

Based on the availability and quality of the datasets as well as the characteristics of the study area, implementation for other geographic areas may deviate from what is depicted in this paper. Proposed framework is established to provide guidelines. It may be necessary to adjust the process to account for deviations in resources and scope.

4. Building extraction from imagery

4.1. Object-based image classification

Buildings need to be extracted through image classification. In many instances, buildings have spectral reflectance very similar to roads, streets and parking lots. Urban areas are also often full of buildings with multi color roofs, of different shapes and sizes. At places, trees and their shadows partially or wholly cover buildings and hide them from the sensor. In such complex urban environments, conventional pixel-based image classification methods have limited capabilities in processing high resolution data (Thomas et al., 2003; Chen et al., 2004; Im et al., 2008), and often result in misclassification and low accuracy (Smith and Fuller, 2001). Object-based classification methods can produce better separation among spectrally similar classes with high accuracy (Blaschke and Strobl, 2001; Lu and Weng, 2007; Stow et al., 2007).

Object-based image analysis consists of two sequential steps: image segmentation and classification. Segmentation is performed to produce a hierarchical network of image objects at different levels, which closely resemble the real ground features (Blaschke and Strobl, 2001). This hierarchal network of objects allows defining their relations to other objects (segments), and also provides additional features such as spectral, spatial, size, and context to help the

Table 1
Summary of the data used.

Image	Time/year	Bands	Resolution	Projection	Coverage
CIR orthophoto	Spring/2005	G, R, IR	1 m	UTM, Zone 16, NAD 83	L, WL, Wea
DEM, DSM	Spring/2005	1	1.5 m	State plane, NAD83	L, WL, Wea
GIS data	Description	Year	Coverage		
Building footprints	Footprints of all buildings	2000	WL		
Address points	House numbers, building categories, street addresses	2009	WL		
Zoning map	Zoning boundaries	2009	L, WL, Wea		
Land use map	Land use classes	Recent	Wea		
Census data	Population counts, census block boundaries	2000	L, WL, Wea		
Roads and streets	Road, street lines and names	2005	L, WL, Wea		

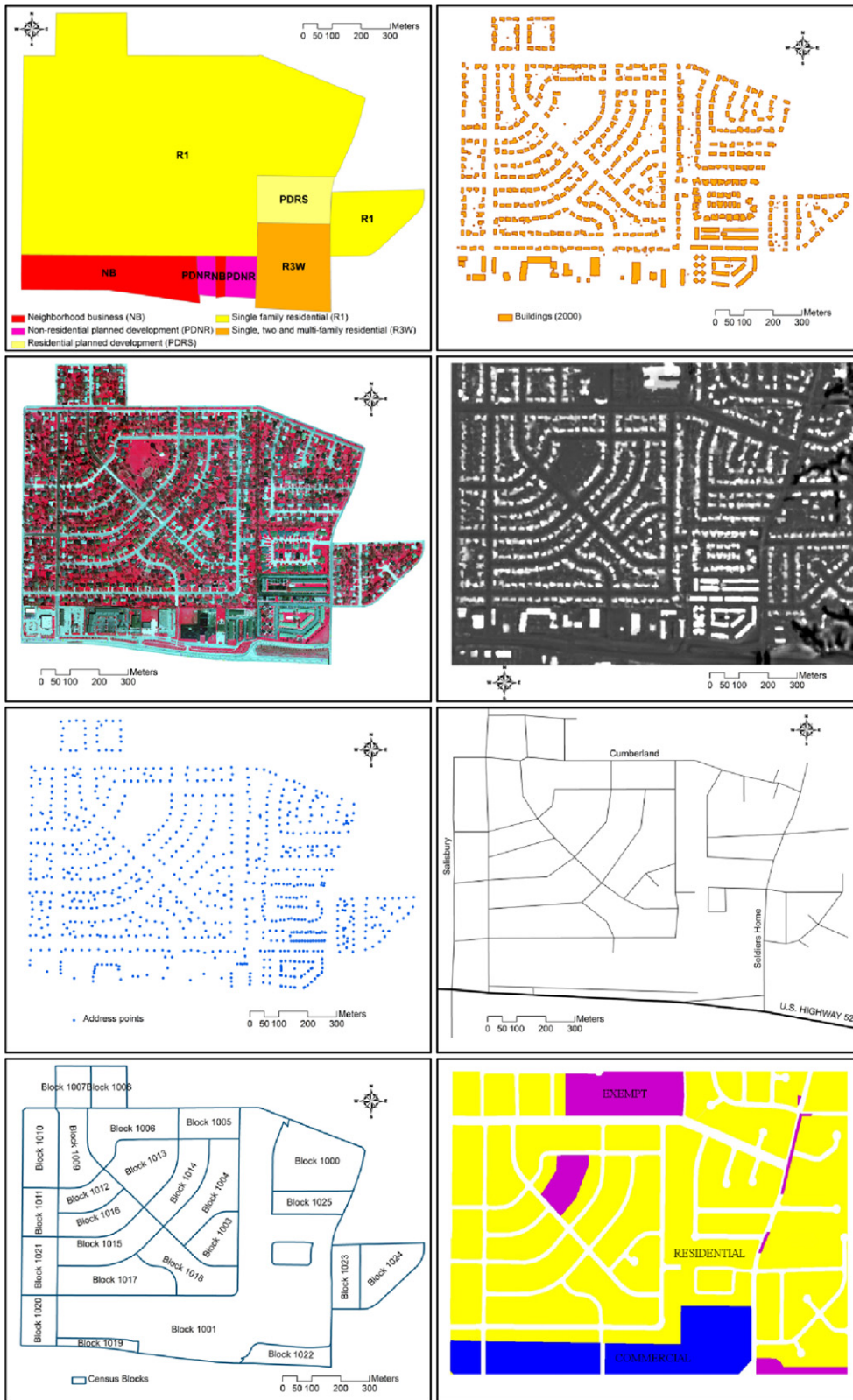


Fig. 2. Sample data for census block group 1 of tract 51. From left to right and top to bottom: zoning map, building footprints of 2000, 1 m resolution CIR aerial photo, nDSM = DSM-DEM, address points, roads, census block boundaries, and land use. The size of the area is approximately 0.8 km north-south and 1 km east-west.

classification (Baatz and Schäpe, 2000). The subsequent step classifies image objects (rather than pixels) based on their spectral and spatial characteristics and context. As a result, thematic classes are more homogenous since all the pixels within an object are classified as one class even in the presence of certain spectral variations.

4.2. Land cover classification

Land cover image classification has been performed to extract buildings using the CIR images, nDSM, and zoning map. After image segmentation, classification rules are developed using



Fig. 3. Land cover classification map of census tract 51.

different combinations of object features and expressed with fuzzy membership functions. Building extraction is initially performed over two small areas equivalent to census tracts 51 and 52, and then over the entire Wea township. Census tract 51 is fully developed, whereas census tract 52 has seen both addition and demolition of a few buildings between 2000 and 2005. For these two census tracts, the classification is performed hierarchically with seven classes: roads–streets and parking lots, shadow, water, grass, trees, buildings in residential zones, and buildings in non-residential zones. Since the Wea township includes both urban and suburban areas, bare land is added as the eighth class for this area. The classification images for census tract 51 and Wea Township are shown in Figs. 3 and 4 respectively. Initially, buildings are classified based on their heights. However, this could not pick up a few buildings whose height information is missing in the DSM. Therefore, rules based on additional object features, such as shape and their context to other objects are added to classify such remaining buildings (Hussain and Shan, 2010). At a few places, shadow cast by the higher part of a building over its lower part separates the building to two different parts. In order to correctly merge such building objects, height thresholds are used. The shadow of a building has no height over the ground, but has

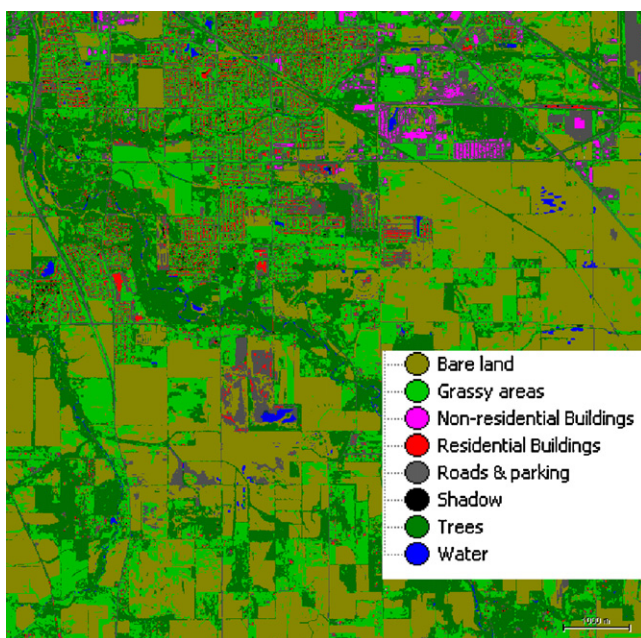


Fig. 4. Land cover classification map of the Wea township.

on the lower roof. Therefore, the context of shadow segments with the height feature are used for their reclassification as buildings and then such split building objects are merged to form one building.

4.3. Classification accuracy

Classification accuracy is assessed using selected test samples. The test samples for all the classes were selected interactively from the segmented images of the respective test areas. These test samples were subsequently used to create confusion matrices to assess the classification accuracies. The achieved overall accuracy and kappa are 98% and 0.97, 93% and 0.89, 98% and 0.90, respectively for census tracts 51, 52 and Wea township. Furthermore, the provided (year) 2000 county building footprints are used as reference to evaluate the extracted buildings for census tracts 51 and 52. This comparison helps to find changes to buildings between 2000 and 2005. It is shown that census tract 51 has no change to buildings in the residential zones, except one building missed during the classification. In census tract 52, however, 12 buildings in residential zones are missed and two are false detections out of 1,685. Missing buildings are caused by occlusion by trees and lack of significant height values in the nDSM, while the falsely detected buildings are objects that are spectrally similar to real buildings. The statistics of the extracted buildings in comparison with the 2000 county buildings for census tracts 51 and 52 are listed in Table 2. It should be noted that the assessment for Wea township cannot be performed due to lack of independent building data.

5. Identification of residential buildings

5.1. Procedure

Buildings extracted in the previous step consist of buildings in non-residential and residential zones. The latter includes residential utility buildings, such as garages, sheds and barns, as well as residential activity buildings, such as churches and schools, none of which is directly for dwelling purposes. To exclude schools and churches, we used the address data, or their large footprint sizes and heights when address information was not available. Using an area threshold for these large buildings works well within single-family and two-family residential zones but ambiguity may occur for buildings within multi-family residential zones where such non-residential buildings may have similar sizes to apartment buildings. Such conflicts are clarified by using land use maps. Address points or footprint sizes are also used to exclude residential utility buildings. The area threshold applied is 60 m², which is determined by analyzing the size of such utility buildings identified by using the address points.

Once the residential buildings are obtained, they are further classified as apartment buildings and houses. These two building types are typical and most representative in the U.S., and have clear distinction in population density. Fig. 5 shows the procedure of identifying houses and apartments for final population mapping. Zoning maps in combination with either address points or building sizes are used to identify houses and apartment buildings. Problems

Table 2
Buildings derived from 2005 images in comparison to 2000 county data.

Tract#	Zone category	Total detected	Missed	False	New	Demolished
51	Residential	591	1	0	0	0
	Non-residential	14	0	0	3	5
52	Residential	1685	12	2	23	30
	Non-residential	36	1	0	6	3

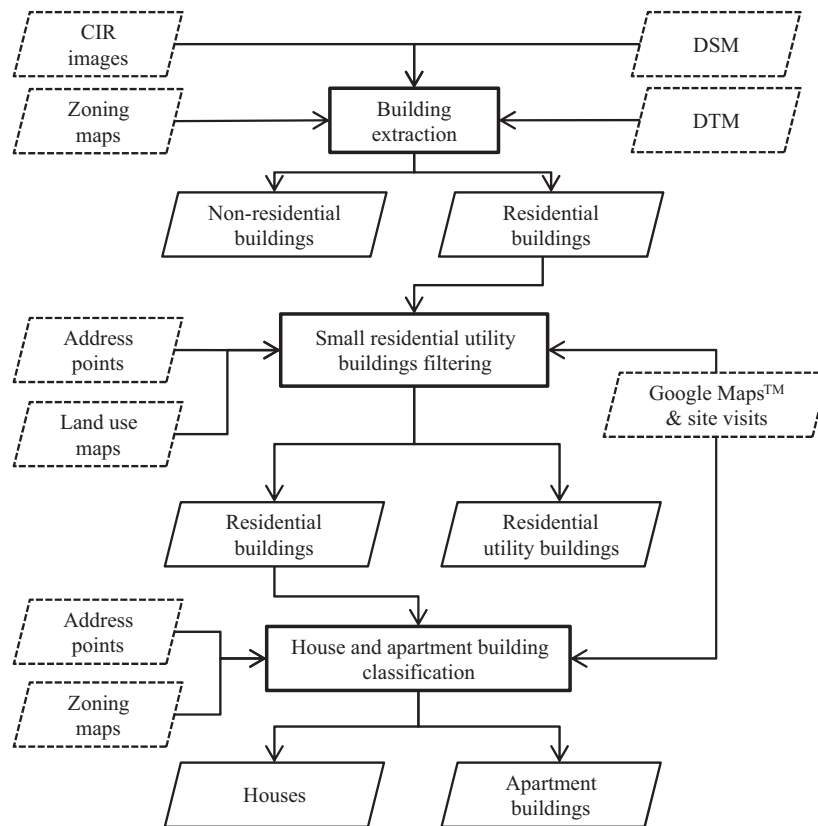


Fig. 5. Flowchart for house and apartment identification.

associated with the process are discussed in detail with examples in the following section.

Height information is associated with buildings as an attribute. The mean of the nDSM values within each building footprint is taken as the building height. For the buildings that were demolished between 2000 and 2005, average of the height values of three nearest buildings of same type are used. The same process is applied for buildings that are missed in the elevation data.

5.2. Problems and solutions

Since the Wea township covers a large area, identification of the residential buildings brings up some difficulties. For example, its southern part has an agricultural landscape with scattered residential and farm buildings. The zoning map does not provide any categorical information regarding such farm buildings within the agricultural zones. Such buildings are classified by using the land use map.

Another issue for accurate population mapping is identification of apartment buildings. It is not possible to distinguish apartment buildings from single- or multi-family houses based only on the zoning map since they may all coexist in the same zone; e.g. "Single, two and multi-family residential". Address point data are helpful to solve this problem up to certain extent. Apartment buildings usually have more than one address point assigned to them. However, duplexes or multi-family houses may also have more than one address point while some apartments may have just one. Fig. 6 shows an area with such examples and the Street View image for one of the apartment buildings in that area.

Alternatively, considering the footprint size or height threshold for identification has some exceptions when the apartment buildings have similar footprint size or height with multi-family houses. To assure the quality, apartment building candidates that are initially identified using address points, footprint size and height

thresholds are checked visually from aerial images, Google Maps™ images, and Google Maps™ Street View images. Use of publicly available information and images is beneficial and can significantly reduce the requirement for onsite visits. Two instances regarding a total of eight apartment buildings in census tract 52 required onsite visit when interpretation with Google Maps™ was not possible.

The area threshold used for filtering out residential utility buildings, such as detached garages, sheds, and barns may also filter out some of the trailer houses. This situation happens because the trailer houses are either very small or partially covered by trees or shadow. To resolve this problem, a separate threshold is applied to filter out residential utility buildings within these regions.

In another area, a large number of railway wagons parking along the rail line near an industrial installation are classified as residential buildings, as shown in Fig. 7 (upper left and upper right). This location falls within the industrial zone (lower left), however, it is wrongly shown as residential area (R1) in the zoning map (lower left). This confusion is clarified and corrected using the land use map shown in Fig. 7 (lower right) and further confirmed visually from Google Maps™.

The above discussions demonstrate that combined use of zoning map, building address data, land use map, and other publicly available data can minimize the difficulties in identifying the building use, such as houses and apartments for population mapping. Nevertheless, certain confusion may still remain. For example, buildings used as amenities for apartment complexes are hard to determine, unless the address point data relevant to those buildings are available. This will affect population distribution since this type of buildings has large footprints and may also be as high as their neighboring apartments. Through this identification process of integrating data sources, out of 11,448 image-derived buildings in the Wea township, 8240 are houses and 132 are apartments.

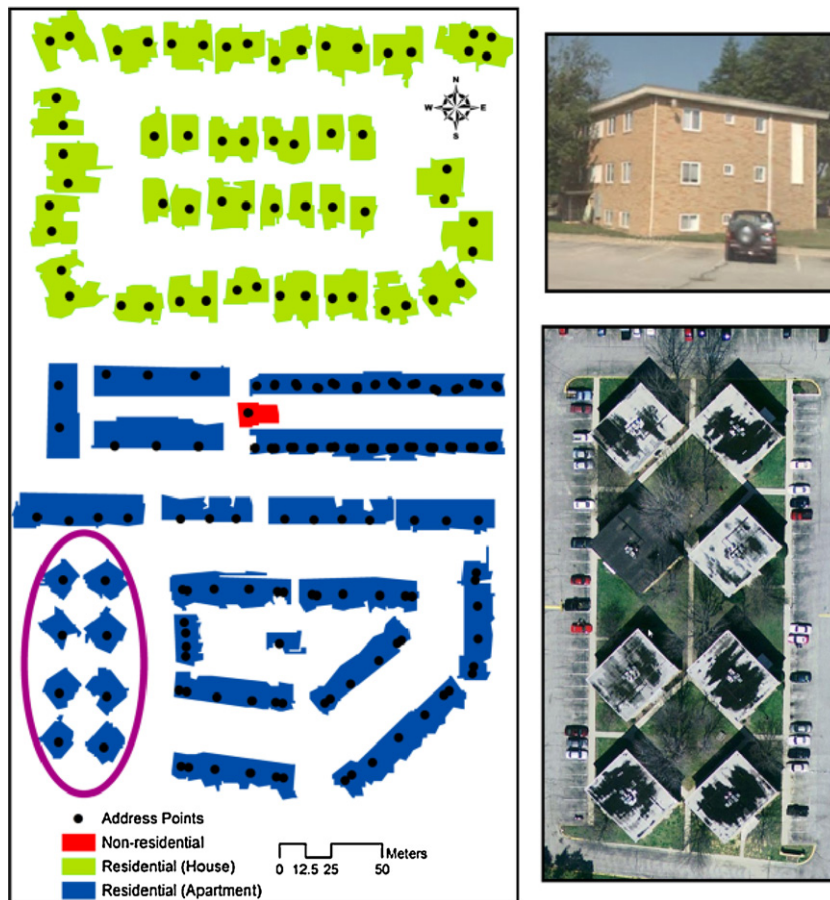


Fig. 6. Diversity of single-, multi-family houses and apartment buildings: single-, multi-family houses and apartment buildings overlaid with address points (left), apartment buildings of small footprint with only one address point as seen on the image in Google Maps™ (bottom right), and one of these apartment buildings from Google Maps™ Street View (top right) (©2010 Google, Images – ©2010 DigitalGlobe, USDA Farm Service Agency, IndianaMap Framework Data, GeoEye).

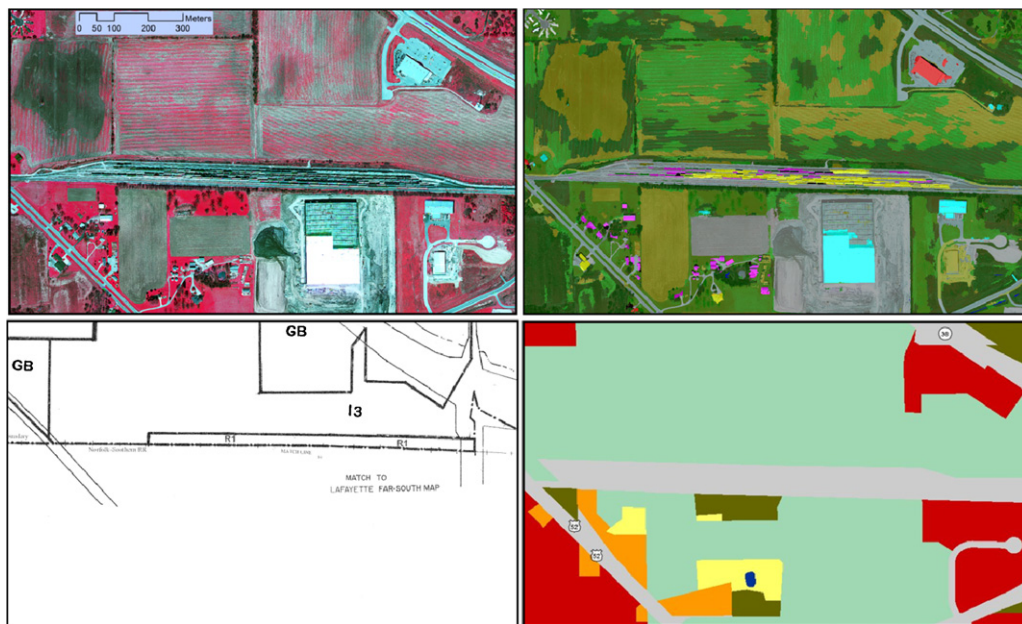


Fig. 7. Railway wagons shown in aerial image (upper left), classified as buildings (upper right), shown as residential area (R1) in the zoning map (lower left), and shown as rail line (gray) in the land use map (lower right).

Table 3
Differences of estimated building populations between the image-based buildings and county buildings.

Model	Building type	#Buildings w/pop. diff.	Total pop. diff.	Min.	Mean	Max.
Areametric	House	-292	-118.5	-2.62	-0.41	-0.01
		248	118.6	0.01	0.48	2.64
	Apartment	-12	-10.0	-2.82	-0.85	-0.09
		14	9.9	0.06	0.70	2.10
Volumetric	House	-283	-104.9	-3.03	-0.37	-0.01
		255	101.3	0.01	0.40	2.35
	Apartment	-12	-12.6	-2.62	-1.05	-0.15
		14	16.2	0.13	1.15	2.69
Weighted areametric	House	-286	-82.6	-1.83	-0.29	-0.01
		245	83.1	0.01	0.34	1.85
	Apartment	-12	-34.6	-9.72	-2.88	-0.28
		14	34.1	0.22	2.44	7.25
Weighted volumetric	House	-288	-83.2	-2.36	-0.29	-0.01
		251	77.3	0.01	0.31	1.83
	Apartment	-12	-27.2	-5.65	-2.72	-0.33
		14	33.1	0.13	2.36	5.59

5.3. Errors of building size

Errors in building size will cause uncertainties in estimated population using Eq. (1). This section uses the county building footprints as a reference to evaluate the buildings extracted from aerial images. Census block group 1 of tract 51 (cf. Fig. 3), an area with no change in residential buildings between 2000 and 2005, is selected for this purpose. It is found that the average and median of the footprint size differences for a total of 570 buildings are 18.96 m² and 14.44 m², respectively. The statistics show that 80% of buildings have a size error of less than 25% of their size and also less than 60 m², which is the threshold used for excluding small buildings like sheds and garages.

6. Mapping census population to buildings

6.1. Weight determination

Two most common, general types of residential buildings are considered: houses and apartments. To calculate their weight factors, sample census blocks that have only one type of residential buildings are selected. The average population per area and volume within these sample blocks are then obtained. For houses, the average population density is 1.07 people/100 m² and 2.66 people/1000 m³, respectively. For apartments, these numbers are 5.29 people/100 m² and 7.18 people/1000 m³. Taking the unit weight for houses, the apartment buildings are then weighted 4.94 (5.29/1.07) in the areametric model and 2.70 (7.18/2.66) in the volumetric model.

6.2. Effect of building dimension errors

Results of population mapping from county buildings and image-derived buildings are compared for a selected census block group. A summary of the population differences between county buildings and image-based buildings for all four model options are provided in Table 3. Because of the differences in area and volume of buildings, the same building in the two building datasets may receive different populations. The number of such buildings are listed in the column “#Buildings w/pop. diff.”. The “Total pop. diff.” column counts the population differences in these buildings, with the “+” sign being for population increase and “-” for population decrease, both with reference to the results from the county buildings. The other columns are for the minimum, mean, and maximum of the population differences between the two building data sets. It is seen that the areametric models and volumetric models

have similarly small sensitivity to building dimensions, whereas apartments may receive large population change (up to 10 people) under the weighted models. The test shows 90% of population differences between the two building data sets are not more than one (1) person for a house and five (5) for an apartment. Since apartments have a much higher population density, this difference is reasonable. The estimated building populations from image-based buildings are practically acceptable.

6.3. Evaluation of disaggregation models

Since there were no population data available for the study area at the level of individual buildings, we set up a scheme to evaluate the four different model options in Eq. (1). We first distribute the population of a census block group to all of its individual buildings. Then, the total estimated population of each census block within the census block group is compared with its census population. The difference then indicates the errors in population mapping.

These census block groups have a total of 89 census blocks in census tracts 51 and 52. Two census blocks are pre-excluded from the analysis since they have no population reported but contain a total of three buildings. Fig. 8 shows the estimated number of people for individual buildings in part of this area.

Since the population in a census block is known for 2000, it is used to evaluate the above disaggregation results. After initial analysis, five census blocks (four in tract 52 and one in tract 51) are found to have large differences between the estimated populations and the actual census. Fig. 9 maps the actual and percent errors of the population estimates in each census block. The shaded erroneous census blocks 4000, 4001, 4002, and 4006 of census tract 52 and census block 1002 of tract 51 on the map show large differences between the estimated population and the actual census population. It is observed that the actual census counts do not match the number of residential buildings at the time of census for these blocks. For example, block 4000 contains just one single house whereas its census count is 51 people. On the other hand, the neighboring census block 4001 has a census count of only 3 people, but 19 residential buildings. Census block 4006 of tract 52 and block 1002 of tract 51 also have similar conflicts. The census population record for block 4006 is 139 people whereas there were only five single-family houses in this block at that time. These observations suggest possible inconsistencies in census data and care should be exercised for quality control. Population is re-mapped in Fig. 9 after removing these five outlier census blocks and re-



Fig. 8. Estimated building population for 2000 with the weighted areametric model (a portion of the census tracts 51 and 52).

distributing the remaining population to buildings in the rest of the study area.

The selected 84 census blocks are quite diverse, with an average population 76, minimum 7, maximum 934, standard deviation 123, and total 6,347. The errors of the estimated population with reference to the actual census block records are listed in Table 4. As is shown, applying weights significantly improves the estimation quality for both models, with RMSE of areametric model being reduced from 51 to 23 (55% decrease), and volumetric model from 38 to 24 (37% decrease). The results also show that the introduction of building volume improves the estimation when no weighting scheme is applied (51 vs. 38). Weighted volumetric and areametric models yield, practically the same results (23 vs. 24). Besides, the RMSEs and Mean Absolute Error (MAEs) as well as the distribution of the percent errors of the two weighted models are very close to each other. Hence, it is practical to utilize buildings extracted from high resolution images for implementing the weighted areametric model when elevation data are not available.

Fig. 10 shows the histograms of the errors of estimated population for all four models, whereas Fig. 11 plots the percent errors

for both weighted areametric and volumetric models with respect to the actual census block populations. These two figures demonstrate that all model options yield centralized errors for most census blocks (>90%). Blocks with small populations (<20) may have large percent errors of up to 60%, whereas the percent errors of large blocks (>100 persons) are mostly less than 20%. A few census blocks have estimation blunders of more than 100 persons in magnitude. Significant underestimation (estimated values < census values) of such cases occurs to blocks whose actual population density is higher than average and whose buildings are partially covered by trees and thus could not be extracted completely from the imagery. Significant overestimation at some census blocks is due to their actual population density being less than the neighboring blocks. Some buildings with larger size tend to amplify this effect. For example, connected houses may be wrongly classified as apartments, which yields overestimated population for these buildings.

6.4. Mapping predicted population

Since the census in US takes place every 10 years, the actual population counts for a year in between are not available. To map the population distribution of 2005, an estimation on its total population is needed. U.S. Census Bureau provides yearly estimated population at the township level. Therefore, the U.S. Census estimated 2005 population of Wea township is distributed to the residential buildings extracted from 2005 high resolution images. As shown in Fig. 12, the estimated building populations of 2005 present a distribution similar to year 2000.

Table 4
Population estimation errors for different model options.

Models	RMSE	%Mean	%MAE
Areametric	51.0	7.07%	22.7%
Weighted areametric	23.3	-2.81%	16.6%
Volumetric	38.7	2.70%	19.4%
Weighted volumetric	24.3	-3.83%	15.8%

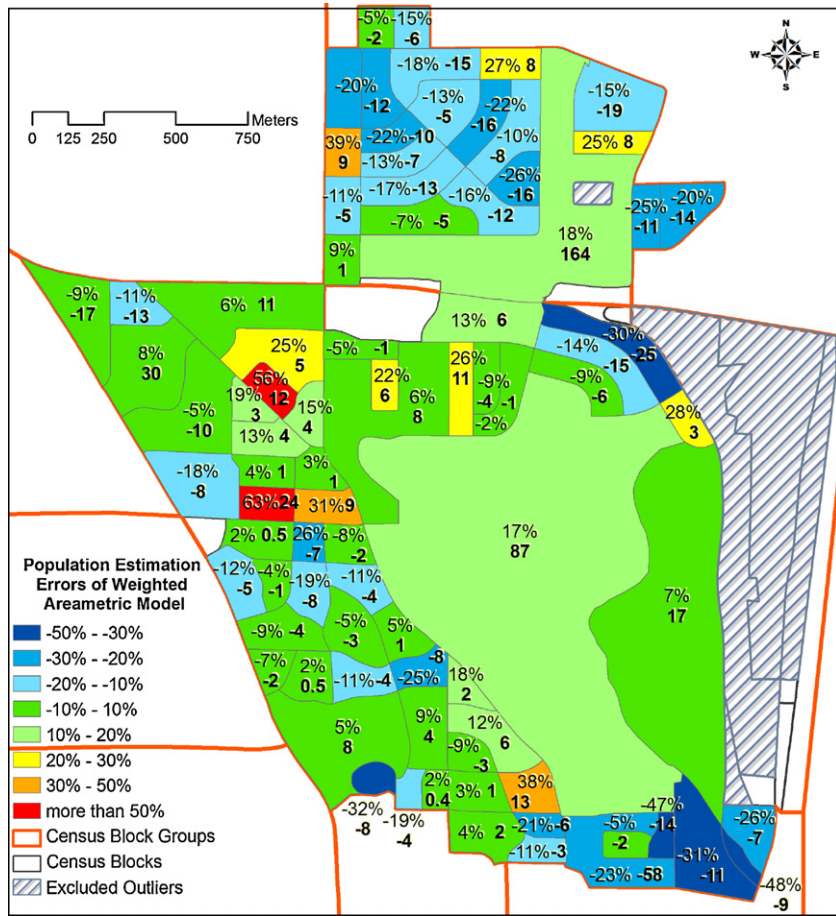


Fig. 9. Errors of population estimation in 2000 with the weighted areametric model for 84 census blocks. Each block is labeled with its actual estimation error and the percent error with respect to 2000 census data.

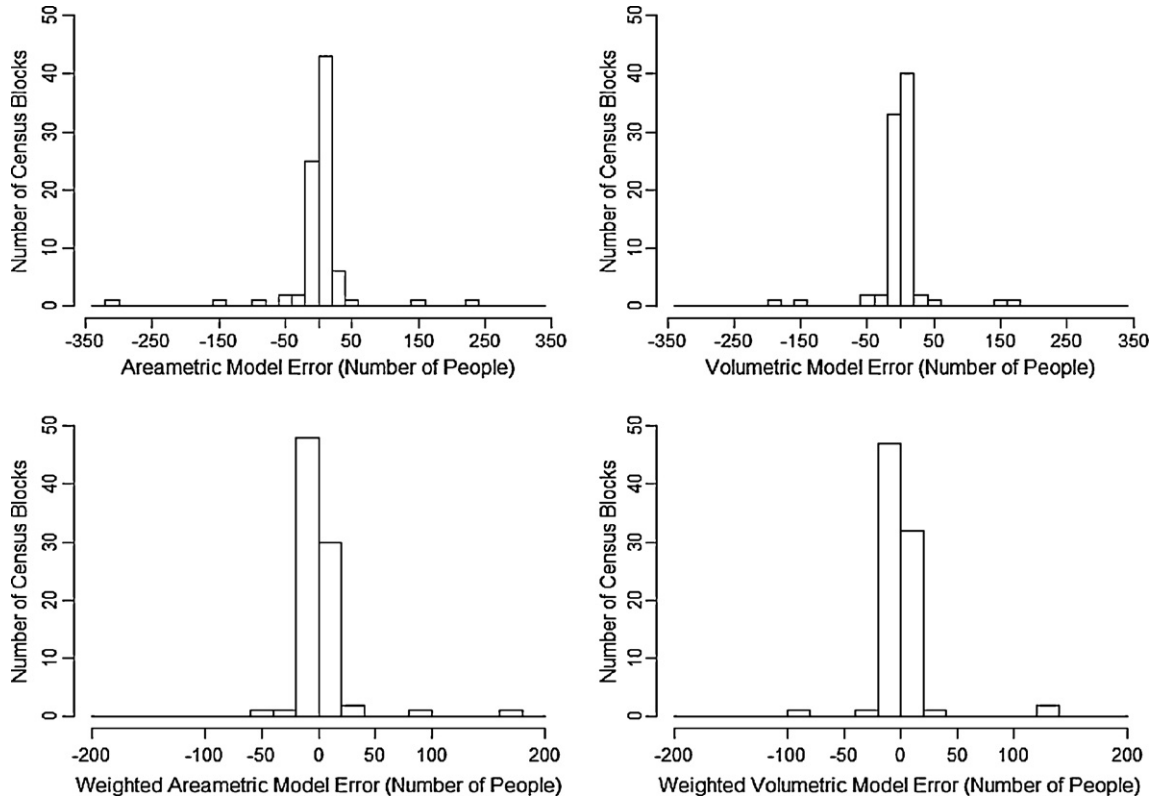


Fig. 10. Histograms of errors of estimated population for 2000 census blocks.

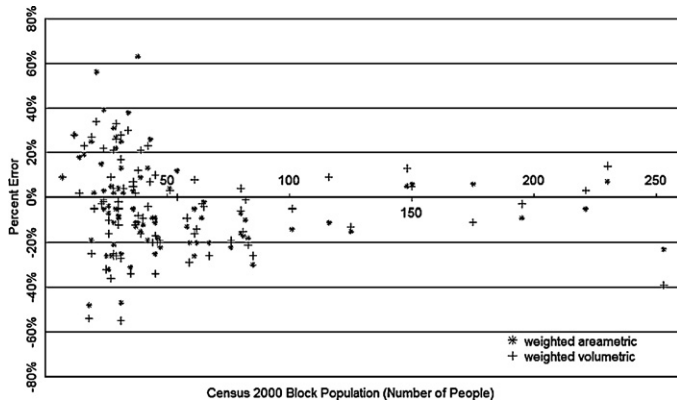


Fig. 11. Percent errors of estimated population for 2000 census blocks with weighted areametric and weighted volumetric models.

7. Conclusion

As the first step towards micro population mapping at the level of individual buildings, building extraction can be effectively carried out with object-based image classification. An overall accuracy of 98% has been achieved through combined use of high resolution imagery and elevation data. Integration of city zoning maps within the image classification process helps to categorize the buildings to their actual use. The availability and use of zoning maps, address data, land use maps, street maps, and other publicly available information proves to be necessary and effective to identify residential buildings. This process consists of following three steps: determining the buildings in residential and non-residential zones, filtering out the utility buildings within the residential zones, and finally determining different types of residential buildings. Due to the complexity of land use and land cover, care should be exercised during this process and sometimes field visiting and knowledge on the neighborhood would be necessary and helpful in resolving ambiguity and confusion of detected buildings.

Weighting factors should be considered in the population disaggregation models. Applying proper weights for different types of

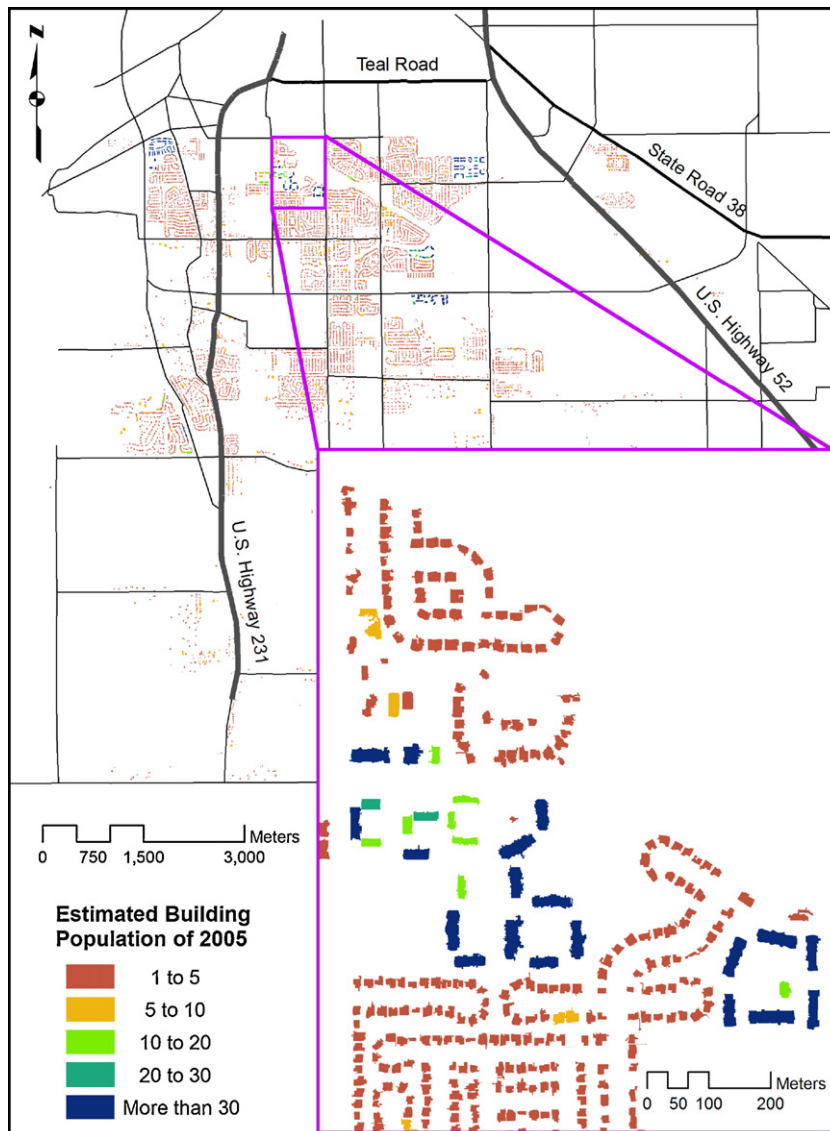


Fig. 12. Estimated building populations of 2005 for Wea township with the weighted areametric model.

buildings requires sampling of population densities for each building class, mostly houses and apartments. It is important to consider the weights of building types that are representative of the study area. The weighting factors for houses and apartments in this study are found to be 1:4.94 for the areametric model and 1:2.70 for the volumetric model. As an extension to the earlier work of Lwin and Murayama (2009), the introduction of weighting factors reduces the estimation uncertainty of census block populations by 55% for the areametric model and 37% for the volumetric model. On the other hand, weighted areametric and weighted volumetric models present close results, which suggests that satisfactory building population estimation can be achieved without using elevation data. Evaluation of the results at the scale of individual buildings may provide more insight on the accuracy of the models in case of building population data are available for testing. It should be noted that the population mapping results also rely on the quality of the input census data, which may sometimes have rather significant inconsistency or mistakes.

Buildings extracted from high resolution imagery and other GIS data can be used for population mapping with satisfactory results. Comparing with mapping results from county building data, majority (90%) of the differences is less than one person for a house and five for an apartment, which is at a level that satisfies practical applications. Supporting this assertion, buildings extracted from high resolution imagery can be used for population estimation when buildings from other sources are not available or not up to date. Moreover, this enables mapping predicted population over a census unit with up-to-date individual buildings obtained from high resolution images.

In this study, population mapping at residential building level has to go through three major steps: obtaining the building footprints, identifying the residential buildings, and estimating the residential building populations. Lack of up-to-date and complete building footprints may be considered as a common difficulty. Our study intends to acquire such information by using high resolution aerial images, which are often collected every two years by each state in the US. Identification of residential buildings is another major challenge. Since the type and availability of data that can be utilized for this purpose may vary from the areas of interest, one may need to defer from the framework for cities outside the US. Nevertheless, different countries often provide similar or alternative datasets that allow identifying residential buildings at various details. Zoning maps or equivalent ones, for example, are commonly available in many countries for urban development. Similarly, one must note that census data also vary in availability, intervals, and details around the world.

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