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Enhancing Areal Interpolation Frameworks through Dasymetric Refinement to Create Consistent Population Estimates across Censuses

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Abstract

To assess micro-scale population dynamics effectively, demographic variables should be available over temporally consistent small area units. However, fine-resolution census boundaries often change between survey years. This research advances areal interpolation methods with dasymetric refinement to create accurate consistent population estimates in 1990 and 2000 (source zones) within tract boundaries of the 2010 census (target zones) for five demographically distinct counties in the U.S. Three levels of dasymetric refinement of source and target zones are evaluated. First, residential parcels are used as a binary ancillary variable prior to regular areal interpolation methods. Second, Expectation Maximization (EM) and its data-extended version leverage housing types of residential parcels as a related ancillary variable. Finally, a third refinement strategy to mitigate the overestimation effect of large residential parcels in rural areas uses road buffers and developed land cover classes. Results suggest the effectiveness of all three levels of dasymetric refinement in reducing estimation errors. They provide a first insight into the potential accuracy improvement achievable in varying geographic and demographic settings but also through the combination of different refinement strategies in parts of a study area. Such improved consistent population estimates are the basis for advanced spatio-temporal demographic research.

Keywords

areal interpolation; dasymetric modeling; population estimation; census data; spatial analysis

1. Introduction

Today's challenges in urban and rural planning efforts require the implementation of effective measures of development and population growth trends based on the evolution of demographic characteristics at local and regional scales. Therefore, there is an urgent need for fine-resolution population distributions aggregated within temporally consistent small-area reporting units. However, due to changing enumeration boundaries at the small-area level among census surveys (Schroeder 2007), the units are inconsistent, which impedes any meaningful temporal comparison and remains a persistent challenge in the field of GIScience.

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Recent research has begun to invest in the development of analytical solutions based on areal interpolation to produce fine-resolution population distributions for multiple points in time within temporally compatible analytical units (Schroeder 2007, Schroeder and Van Riper 2013). While applying dasymetric refinement to enhance areal interpolation has shown great potential in creating consistent units over time and population estimates of higher accuracy (Ruther et al. 2015, Zoraghein et al. 2016), these attempts are often constrained to the use of binary ancillary variables that simply limit where the population is expected to reside (Leyk et al. 2013), thereby assuming binary relationships between these ancillary variables and population characteristics. Such an assumption can lead to large estimation errors if population density shows high degrees of variability. Thus, more research is needed to identify methodological solutions that make more effective use of advanced dasymetric modeling techniques and employ related ancillary variables in order to reflect nuanced relationships between ancillary variables and population attributes for more accurate estimation. Related ancillary variables can amplify or curtail the likelihood of a place being populated (Leyk et al. 2013).

Dasymetric modeling employs ancillary datasets correlated with the variable of interest to map it from a set of aggregated source zones in a choropleth map to a set of target zones that reflect its statistical surface more precisely (Wright 1936, Fisher and Langford 1995, Eicher and Brewer 2001, Mennis 2003, Langford 2006). The methodology, which is covered extensively in the literature, is commonly used to downscale population from large aggregated census units to smaller target zones and has many applications, including crime analysis (Mennis 2016), environmental health justice (Maantay et al. 2007, Mennis 2015) and historical population estimation (Holt et al. 2004, Buttenfield et al. 2015, Ruther et al. 2015, Pavía and Cantarino 2016) to name a few. With widespread availability of various remote sensing products and growing analytical capabilities in geospatial software tools, dasymetric modeling has become a common spatial analytical approach for population reallocation and demographic small area estimation (Mennis 2009).

This study revisits the application of areal interpolation of dasymetrically refined census units to create temporally consistent population estimates and focuses on the integration of related ancillary data sources to improve the effectiveness of the dasymetric modeling step. These experiments build on recent research, in which the performance of areal interpolation methods such as areal weighting (AW) or target density weighting (TDW) could be improved by employing simple binary dasymetric refinement that geometrically adjusts source and target zones. While this research resulted in time series of more accurate and consistent population estimates, it still showed large errors in regions with rapid or unexpected population growth that may not be fully reflected by the expansion of developed land (Buttenfield et al. 2015, Ruther et al. 2015, Zoraghein et al. 2016). Given the effectiveness of related ancillary variables in dasymetric modeling in one point in time (Leyk et al. 2013, Nagle et al. 2014), it can be expected that the integration of related ancillary variables may also benefit the areal interpolation of census units from different points in time by overcoming limitations in using only binary ancillary variables to create consistent population estimates. The selection of ancillary variables, and how they are incorporated are key points that determine the performance of dasymetrically refined areal interpolation. This research establishes three refinement levels of increasing complexity, and for each, systematically reviews the performance of a selection of areal interpolation methods for creating consistent population estimates over time.

The findings of this research benefit disciplines such as demography, geography, economics, political science and sociology by providing more accurate delineations of how population has evolved using consistent micro-scale units. The approach is tested in five U.S. counties for both 1990–2010 and 2000–2010 time periods to transfer total population from census tracts in 1990 and 2000 (source zones) to census tract boundaries in 2010 (target zones), respectively.

2. Study Area and Data

2.1. Study Area

The five counties used in this study to test the methods represent different geographic and demographic settings that can be characterized by the urban/rural proportion of population, the extent and the population growth rate. They include Hennepin County, Minnesota, Mecklenburg County, North Carolina, Broward County, Florida, Hillsborough County, Florida and Worcester County, Massachusetts. Figure 1 depicts the five selected counties, the most recent boundaries of their seats, as well as their census tracts in 2010 with population densities of people per square kilometer.

Hennepin County includes the urban region of Minneapolis in the east and rural areas in the west. According to the U.S. Census, a low total population growth rate of 11% (from 1,032,431 to 1,146,195) has been observed between 1990 and 2010. Mecklenburg County includes the urban region of Charlotte at the center, which covers the majority of the county area, and rural census tracts on the fringe. The total population growth rate in this fast-growing county is 80%, an increase from 511,433 to 919,628 during the 1990–2010 time period.

Hillsborough County contains urban census tracts of Tampa in the west and rural areas in the east. Densely populated census tracts in this county are not limited to the city limit of Tampa but appear scattered all over the county except in the eastern parts. The population of the county has observed a rather fast growth rate of 47%, increasing from 834,027 to 1,229,226 during the 1990–2010 time period.

Most of Broward County is composed of census tracts with medium to high population density in the east. There is also a large sparsely populated census tract in the west. The population of the county has grown by 39%, an increase from 1,255,462 to 1,748,066 between 1990 and 2010.

Worcester is the county with the highest proportion of sparsely populated census tracts with only a few more densely populated tracts within the city limits of Worcester at the county center. The population of the county has grown by 12% and increased from 709,705 to 798,552 during the 1990–2010 time period.

The selected counties include different proportions of high and low population density areas, making them ideal case studies to evaluate the performance of each method under different conditions. More specifically, Mecklenburg, Hillsborough and Broward represent counties with fast population growth whereas Worcester and Hennepin indicate counties with a medium/low population growth rate. Testing the methods across these different histories of population development will help better understand their performance in different demographic settings.

2.2. Data

The boundaries of census tracts in 1990, 2000 and 2010 along with their total population counts found in the census summary files are the focus in this study. Census blocks represent the smallest enumeration units published by the Census. Therefore, blocks in 1990 and 2000 as well as their population values are used as reference data to evaluate the estimated total population counts at the tract level. The tract-level and block-level population values and boundaries for 1990 were retrieved from the National Historical Geographic Information System (NHGIS) (Minnesota Population Center 2016) whereas population counts and boundaries for 2000 and 2010 were extracted from U.S. Census Bureau (2016a) and U.S. Census Bureau (2016b), respectively.

Three ancillary variables associated with the distribution of total population are used in this study. They include residential parcels of each study area accessed from the corresponding county or state GIS data portal (Mecklenburg County GIS 2013, Hennepin County GIS 2016, MassGIS 2016, University of Florida GeoPlan Center 2016), the National Land Cover Database (NLCD) in 1992, 2001 and 2011 (Homer et al. 2015, Multi-Resolution Land Characteristics 2016) and TIGER/Line road networks in 2000 and 2010 (U.S. Census Bureau 2016b).

3. Methods

The areal interpolation methods for creating consistent population estimates at different points in time in this study are tested for three levels of dasymetric refinement, using different types of ancillary variables. The first-level refinement approach uses geometric footprints of residential parcels as the binary ancillary variable to spatially refine source and target zones to their developed subareas. The second approach incorporates housing characteristics found in parcel attributes as an additional dimension, employing them as a related ancillary variable to explore nuanced statistical associations between population density and different categories of residential parcels. Finally, the third approach extends the former two by integrating a composition of ancillary datasets, including parcels, NLCD developed classes and road buffers.

All areal interpolation methods and dasymetric refinement scenarios were implemented using Python scripts and ArcPy® geoprocessing functionalities. The scripts can be accessed at Zoraghein (2018) or requested from the corresponding author.

3.1. First-level dasymetric refinement using residential parcels as the binary ancillary variable

The first level of dasymetric refinement is employed through the use of binary ancillary variables such as residential parcel footprints. Well-known methods such as AW (Goodchild and Lam 1980) and TDW (Schroeder 2007) are adjusted to subareas of source and target zones (related to two different points in time) delineated by residential parcels of the five study areas following the approaches described in Zoraghein et al. (2016), in which accuracy improvements in population estimation were reported.

AW is the most basic areal interpolation method and assumes population density is constant within source zones. The method estimates source population in target zone boundaries based on the overlapping area between source and target zones (i.e., intersections or “atoms”). The population of each target zone is then simply calculated by summing population counts of all atoms within it.

Spatially refining source zones prior to areal interpolation is supported by different ancillary variables and modifies the underlying assumption as follows: population is homogeneously distributed within the developed land of a source zone, and no population is assigned to non-developed parts. This assumption is expected to be more realistic and generally results in more precise reapportionment of population counts from units in one time (source zones) to boundaries in another time (target zones).

Schroeder (2007) introduced TDW as an areal interpolation method appropriate for temporal analysis of census data. TDW is based on the assumption that the spatial distribution of population densities among atoms within a source zone in the source year remains proportionally the same over time. For example, if population density is distributed in a 2:1 ratio between two atoms in 2010, it is assumed that this ratio was the same in 2000.

Based on previous studies, TDW often outperforms AW (Schroeder 2007, Schroeder and Van Riper 2013), suggesting that it is more reasonable to assume that the ratio of population densities of atoms in one source zone remains constant than to assume that population is homogeneously distributed within source zones.

Refined TDW employs developed/built-up areas within both source and target zones (Buttenfield et al. 2015, Ruther et al. 2015, Zoraghein et al. 2016). This refinement implies that the underlying assumption of unrefined TDW be modified. In the first step, source and target zones are spatially refined using developed areas labeled by the ancillary variable. Then TDW is applied to these refined areas under the assumption that the ratio of refined population densities of atoms to refined population densities of source zones remains the same over time. While refined AW uses developed areas only in the source year, refined TDW incorporates this refinement in both source and target years. Zoraghein et al. (2016) provide a detailed description of the mathematical equations underlying AW, refined AW, TDW and refined TDW.

3.2. Second-level dasymetric refinement using residential parcels as the related ancillary variable

The first-level dasymetric refinement does not differentiate between different types or densities of residential units such as low-density single-family parcels as compared to high-density condominiums. Since it is well-known that associations between population and ancillary variables are not binary in nature, an approach to employ ancillary data to adjust and amplify population densities, appropriately, would have great potential to further improve the accuracy of population estimates. This type of association is addressed below by incorporating related ancillary variables into the dasymetric refinement for areal interpolation based on the Expectation Maximization (EM) algorithm. Housing characteristics of residential parcels, including single-family residential, multi-family residential and condominiums, were employed to establish nuanced associations between such housing types and population density.

3.2.1. EM with control zones based on residential types—The EM algorithm (Dempster et al. 1977) can be used as an iterative process to optimize population density weights under different conditions defined by the ancillary variable, thereby offering an appropriate framework for implementing the second-level dasymetric refinement.

The algorithm provides a robust framework for model fitting and maximum likelihood estimation in settings of incomplete data. First, the expectation (E) step "completes" the data by computing the conditional expectation for missing data, given a set of observed data and estimated model parameters. The maximization (M) step then fits the model, estimating model parameters by maximum likelihood given the "complete" data from the E step. A feedback loop between E and M steps is established and repeated until convergence (Schroeder and Van Riper 2013).

Flowerdew and Green (1994) demonstrated how the EM algorithm can be applied to areal interpolation applications, and Ruther et al. (2015) applied it to areal interpolation using land cover classes as the ancillary data to define control zones. In this study, control zones are defined by residential parcels that have the same housing type, and then EM is used to calculate a population density weight for each control zone. Finally, distinct population density weights of control zones are transferred to target zones. This approach is justified by the expectation that different housing characteristics relate to varying average population densities, and accounting for such variation is expected to improve resulting estimates for target zones.

In the E step, the algorithm estimates $\widehat{y_{sc}}$, i.e., the population count of the intersection between source zone s and control zone c:

$$\widehat{y_{sc}} = y_s\left(\frac{\widehat{\lambda_c} A_{sc}}{\sum_k \widehat{\lambda_k} A_{sk}}\right) \quad (1)$$

Where y_s is the population count of source zone s, $\widehat{\lambda_c}$ is the estimated density of control zone c, A_{sc} is the area of intersection between s and c, and k is a second control zone index, independent of c to reflect all control zones intersecting s. The first E step is essentially similar to AW and assumes equal weights for all housing types. Then, the M step re-estimates all λ_c values using the equation below:

$$\widehat{\lambda_c} = \frac{(\sum_s \widehat{y_{sc}})}{A_c} \quad (2)$$

Estimates of $\widehat{\lambda_c}$ from the M step are used to re-estimate $\widehat{y_{sc}}$ in the next E step, which is followed by another M step, and so on until the system converges. The algorithm stops when the maximum absolute difference between current population density weights and those calculated from the previous run is less than 0.001. Finally, $\widehat{y_{sc}}$ values are used to calculate the population count of target zone $t\,(\widehat{y_t})$:

$$\widehat{y_t} = \Sigma_s \; \Sigma_c \frac{(A_{tsc}\widehat{y_{sc}})}{A_{sc}} \quad (3)$$

Where A_{tsc} is the area of intersection between target zone *t*, source zone *s*, and control zone *c*.

3.2.2. Extending dasymetric refinement in EM to create more homogeneous control zones—EM assumes population density is constant within each control zone. However, this assumption can become problematic. For example, if residential parcels of the same type that form a control zone are diverse in area or number of units, the assumption of one constant population density for the whole control zone becomes unrealistic. This research extends the dasymetric refinement step in EM to address this issue.

In this extended refinement approach, control zones (parcels with the same housing type) are further divided into more similar and homogeneous sub-control zones based on the area of parcel units and unit density criteria within a parcel. First, those control zones with the highest number of residential parcels are identified to guarantee a sufficient number of parcels per sub-control zone. Those control zones with high degrees of variation in areal extents of their underlying parcels are divided into sub-control zones based on area quartiles. For some control zones such as condominiums, the number of units per parcel can be derived. Therefore, a unit density measure is computed by dividing the number of units by the area of the encompassing parcel, and then sub-control zones are created based on quartiles of unit density. This new set of more homogeneous sub-control zones is then input to the EM algorithm as described above.

In this study, the 6 most frequent housing types in each county and time period were selected as initial candidate control zones because they accounted for more than 98% of all parcel units in each county. Selecting more types would have increased the simulation time without any noticeable accuracy gain. All other housing types per county and time period remained unchanged. Out of those initial candidates, different combinations of 4 and 5 classes were iteratively selected for further categorization into more homogeneous sub-control zones based on similarity in either area or unit density. Among those 6 initial candidates, typically one or two control zones were identified as ineffective, minimizing the accuracy improvement in final population estimates. Using subsets of 4 and 5 control zones for further refinement facilitated the identification of the most effective class combinations.

To make an objective decision about control zones that should be further categorized and a reasonable number of subcategories per selected control zone, a simulation framework tested all combinations of 4 and 5 initial candidate control zones, as well as different numbers of subcategories (i.e., 5 to 7) per selected control zone to identify the optimum solution. Section 1 of the Appendix includes the selected control zones for further categorization (i.e., 4 or 5 from the 6 most frequent control zones per county) and their number of subcategories (i.e., 5 to 7) that resulted in the optimum solution in each county. Whereas a numerical and objective simulation was conducted, it is acknowledged that the number of selected control zones (4 or 5) and the tested number of subcategories (5 to 7) were subjective decisions, supported by exploratory tests, to prevent the simulation time from being excessively high. The optimum solution was the one that minimized the error metrics that will be introduced in Section 3.4. Figure 2 illustrates the workflow of this extended refinement approach for EM.

The processing time differed based on the method and study area. Generally, the processing time per method, time period and study area did not take longer than a few minutes on a common desktop computer. However, for the extended refinement approach for EM, the processing time multiplied because 2673 implementations of EM over various combinations of control zones and different numbers of categories had to be tested.

3.3. Third-level dasymetric refinement using a composition of ancillary variables

The third-level refinement strategy is not confined to only residential parcels and specifically targets rural settings, where large residential parcels are known to overestimate built-up land areas while developed land cover classes commonly underestimate development (Leyk et al. 2013, 2014). To mitigate these effects, this approach leverages additional complementary ancillary variables such as NLCD-derived developed classes and road buffer zones, assuming that population most likely resides where developed land can be found, or if developed land cannot be found, population would be expected close to roads. NLCD grids published in 1992, 2001 and 2011, which approximately match the three census years, and the available TIGER road networks in 2000 and 2010 are employed to derive additional ancillary variables. The largest residential parcels in each county, i.e., the upper 10%, are identified as candidate parcels that are more likely to be located in rural areas and potentially benefit from this compositional refinement. These candidate parcels are refined as follows: if a residential parcel contains developed land as classified by the NLCD, only those instances are used for dasymetric refinement, thereby geometrically adjusting the residential parcel. If no developed land exists, the intersection between the parcel and road buffers (using 50m buffer distance) is used to spatially constrain the area of the parcel. Figure 3 demonstrates the process of the third-level dasymetric refinement. Residential developed land is defined by classes 21 and 22 in NLCD 1992 and classes 21, 22 and 23 in NLCD 2001 and 2011, following recommendations in other studies (e.g., Ruther et al. 2015).

Once candidate residential parcels are spatially refined using developed lands and road buffers, the resulting dataset is input to AW, TDW and EM (indicated by the label "modified" before the abbreviation). It is expected that the accuracy of population estimates will improve because they are adjusted to more precise locations of likely human settlement in potential rural settings where errors are commonly high due to the large extent of residential parcels. This third-level dasymetric refinement cannot be implemented with the extended refinement approach for EM in its current form since area and density attributes are used for population weighting (i.e., as the related ancillary variables) in this method and must not be modified a posteriori. Integrating such a refinement in the extended approach for EM would require a priori implementation so that the changed area and density measures can be used for simulation and optimization. The results in this study will provide some indication of the potential benefit of this adjustment.

3.4. Validation

The validation of estimated tract-level results for each census year is done using census block statistics. After transferring population estimates from source zones (tracts in 1990 and 2000, respectively) to target zones (2010 tract boundaries), each 2010 census tract can be linked with its estimated population counts in 1990 and 2000. These estimates for target zones in 1990 and 2000 are compared to population counts of census blocks in 1990 and 2000 aggregated to target zone boundaries. Blocks are the finest resolution enumeration units used by the Census Bureau and are based on a full population count and thus are very useful for validation efforts. Different error measures are calculated such as the Mean Absolute Error (MAE), median absolute error, Root Mean Square Error (RMSE) and 90% percentile of absolute error. These error measures and error distributions can be compared across methods to characterize and evaluate their performance. For example, MAE and RMSE measures illustrate the overall behavior of the estimation error and are sensitive to outliers while the median absolute error and 90% percentile of absolute error can be used to describe the upper end of the error distribution and placement of extreme absolute error values.

4. Results

Table 1 shows the absolute error measures for each of the methods described, the two time periods (1990–2010 and 2000–2010) and each of the five counties. The number next to each method (i.e., 1st, 2nd and 3rd) shows what type of dasymetric refinement is applied to each method. Relative absolute errors, normalized by block-aggregated population values in the source year, are also presented in Table 6 of the Appendix. However, accuracy comparisons are mainly based on absolute error measures to make interpretations consistent with the relevant previous research (Buttenfield et al. 2015, Ruther et al. 2015, Zoraghein et al. 2016). Nevertheless, relative absolute error measures are referred to in some places to provide additional aspects of the error behavior.

Figures 4 and 5 show maps of absolute errors of the two best-performing methods found for each region and time period, but focusing on the first and second-level dasymetric refinement scenarios. In almost all cases except in Worcester for the time period 2000–2010, refined TDW and the extended refinement approach for EM outperform the other methods. Because third-level refinement methods require more specific analysis and interpretation with a focus on rural settings, they will be evaluated separately.

Figures 6 and 7 depict derived population maps in 1990 and 2000 from the two best-performing methods of the first and second-level dasymetric refinement scenarios compared to population maps resulting from aggregating block population counts to target tract boundaries in Hennepin County and Mecklenburg County, as two examples. These maps visualize the agreement between dasymetrically refined population estimates in 1990 and 2000, respectively, and corresponding ground-truth choropleth population maps based on block-level aggregates.

To evaluate how third-level dasymetric refinement methods perform in comparison to their first or second-level refinement equivalents in potentially rural areas, Table 2 presents the overall absolute error measures (i.e., MAE and RMSE) produced by all refined methods when applied to only candidate target tracts in each study area that are more likely to be rural. It is expected that the third-level dasymetric refinement methods are effective in rural areas because they further refine large parcels more frequently located in rural parts. To identify candidate target tracts, the number of rural households indicated by the Census is divided by the total number of households, and all tracts with a proportion of rural population greater than 10% are selected. Broward is excluded because this highly urbanized county includes only 1 target tract as such. Other thresholds for identifying candidate tracts (i.e., 5% and 15%) were also tested and yielded similar orders of results.

Moreover, Section 3 of the Appendix includes another approach for defining candidate target tracts that considers both their population density and their intersection area with census-defined urban areas in 1990 and 2000, respectively. The results show a similar order of accuracy improvement compared to the approach based on rural household proportions, described above.

Figures 8 and 9 demonstrate the effectiveness of third-level refinement methods in comparison to their first or second-level refinement counterparts, particularly in potentially rural areas, for both time periods. This is visualized at the target tract level, and candidate rural tracts are emphasized in the maps. Although the emphasis of third-level refinement methods is on potentially rural tracts, absolute error values of other tracts might change as well due to the existence of some large parcels in urban areas.

If the third-level refinement (labeled “modified” refined AW, refined TDW and EM, respectively) applied to a method results in a lower error for a target tract compared to the first or second-level refinements, that tract is shown in green. For example, in Figure 8(a) all green tracts represent those for which modified refined AW leads to lower absolute errors than refined AW in estimating the population in 1990 within target tract boundaries from 2010 in Hennepin County. Tracts shown in orange and grey indicate those where refined AW outperforms modified refined AW and results in equal error measures, respectively.

5. Discussion

As Table 1 implies, the first-level dasymetric refinement (i.e., refined AW and refined TDW) often reduces absolute error measures in comparison to regular implementations of AW and TDW. Table 6 of the Appendix suggests a very similar pattern based on relative absolute error measures. These re-confirm the great potential of using residential parcels for the dasymetric refinement in creating temporally consistent population estimates as described in earlier research (Zoraghein et al. 2016). Notably, the quality of the ancillary variable and the degree to which underlying assumptions hold greatly influence the effectiveness of the spatially refined interpolation. For instance, the overestimation of developed land through residential parcels can be one major reason why population can be allocated disproportionally in refined AW. In refined TDW, that overestimation may invalidate the underlying assumption of proportionally equal population densities within source unit boundaries at different points in time, leading to biased estimates and increased errors. The very few instances in which errors are higher in the first-level dasymetric refinement methods than their unrefined counterparts can be attributed to those issues. For example, the reason why the RMSE of refined TDW is higher than TDW in Mecklenburg County for 2000–2010 relates to the existence of very few target tracts with high absolute errors in the upper 10% of the error distribution, possibly pointing to the above-mentioned problem.

Although EM uses the housing type attribute of residential parcels in addition to their geometric footprints for the second-level refinement, the computed error measures are rather high. A possible reason is the considerable variation within individual residential control zones across a county, which cannot be reflected by this method. However, the accuracy level of its extended refinement approach is much higher than EM as verified in all 10 cases and according to both absolute error measures in Table 1 and relative absolute error measures in Table 6 of the Appendix. Consequently, the additional refinement of residential control zones based on area and density measures appears to be a useful approach to reflect and partially account for within-class variations, ultimately resulting in further error reduction. Whereas definitions of housing types are not consistent among the counties, Tables 1 to 5 of the Appendix indicate that single family residential, as the most frequent control zone in each county, should be further categorized to make the extended refinement approach for EM effective.

The results demonstrate the efficacy of the extended refinement approach for EM as an accurate method for temporally consistent estimation of population, especially over longer time periods where the assumptions of refined TDW begin to fall apart. For 1990–2010, the extended approach is the best-performing method in all study areas except Broward. For 2000–2010, however, neither the extended approach nor refined TDW dominates as the most accurate method over the five study areas. For shorter time periods, the assumptions of refined TDW appear to be realistic enough, explaining its robust performance in Hillsborough, Broward and Worcester Counties. However, in regions where the assumptions of refined TDW are not reliable even over short time periods, the extended refinement approach for EM can be more accurate than refined TDW such as in Mecklenburg and Hennepin Counties. The extended approach is computationally expensive, and running the simulation to find the best combination of eligible control zones and the optimum number of subcategories per control zone is time-demanding. Nevertheless, the current results suggest that the methodology carries great potential to be implemented in cases where the accuracy levels of simpler refined methods such as refined AW and refined TDW are not satisfactory, which can especially be true over long time periods. This is an important point as the approach is expected to be more efficient once parcel-derived demographic or property databases become available for larger regions that contain more consistent, broadly defined residential classes, thus eliminating the need for expensive simulation, optimization and exploratory analysis. If these large-scale parcel and housing databases carry consistent temporal information for residential development, this will open new possibilities to model small area population estimates over very long time periods, nationally, once historical census data become also available. Another advantage of the extended refinement approach for EM over refined TDW is that it is pycnophylactic; that is, it preserves population values of source zones as opposed to refined TDW.

It should be mentioned that if the comparisons were based on relative absolute error measures, the findings would not have been necessarily the same. Instead, they would depend on how the methods perform for scarcely-populated target tracts. For example, while refined TDW is more accurate than refined AW according to the absolute error measures in Hillsborough and for the 1990–2010 time period (Table 1), there is a reverse order according to the relative absolute error measures (Table 6 of the Appendix), suggesting that refined TDW was more effective in error reduction for populous target tracts whereas refined AW was more effective for those with low population.

According to Figures 4 and 5, target tracts with higher absolute errors are more frequent and pervasive outside highly urbanized areas and city boundaries. This effect is consistent with the explanations provided before, suggesting that the overestimation of developed lands through large residential parcels in less urbanized areas contributes to a decrease in accuracy of dasymetric refinement in those areas.

Figures 6 and 7 demonstrate that the population maps in 1990 and 2000 resulting from the two best-performing methods closely match the ground-truth maps. Derived population estimates of almost all target tracts from the two methods, particularly the extended refinement approach for EM, and their corresponding ground-truth values belong to the same population categories in both 1990 and 2000.

The third-level dasymetric refinement approaches (i.e., modified refined AW, modified refined TDW and modified EM) further increase the accuracy of population estimates compared to the first (i.e., refined AW and refined TDW) and second-level refinement scenarios (i.e., EM) in most cases as can be observed in Table 1 and Table 6 of the Appendix. The overall absolute and relative absolute error measures are mostly lower for AW, TDW and EM when refined using the composite ancillary dataset compared to using only residential parcels. The main focus of this additional refinement step, however, is on rural settings where land cover databases typically underestimate developed lands, and parcel units overestimate residential areas. Table 2 demonstrates that the improvement effect of the third-level dasymetric refinement is more consistent in potentially rural target tracts. In almost all cases, the overall error measures of the methods using the third-level refinement are lower, and in some cases, the improvement is substantial. A similar pattern is also observed in Table 7 of the Appendix, in which the criteria based on population density and census-defined urban areas in 1990 and 2000 were used to locate candidate rural target tracts. The reason why the error metrics in Hennepin County for 2000–2010 are very low is because the boundaries of selected tracts are almost unchanged during the period. Only in Worcester and for the time period 2000–2010, the overall absolute error metric of a third-level refinement is greater than its first-level refinement counterpart (i.e., modified refined TDW vs. refined TDW). Figures 8 and 9 illustrate that absolute error values of the majority of potentially rural target tracts are reduced by the third-level dasymetric refinement approaches. The only cases where such an effect is not observed are TDW for 1990–2010 and 2000–2010 in Worcester and EM for 2000–2010 in Hillsborough. However, according to Table 4, even for two of those three cases, the MAE values decrease, meaning that error reduction is greater for those tracts where the third-level dasymetric refinement is effective. These slight performance variations can be explained, to some degree, by the quality of the ancillary variables used for the third-level refinement. Both developed land classes in NLCD and road network data are imperfect data sources and have locational errors as well as classification issues that can impact population estimation, resulting in some higher errors in some parts of the study areas. Notably, the assumption that population is located close to roads may not always hold true, especially in rural areas where long driveways off of roads are common. Nonetheless, the results in this study show that this assumption was effective in reducing estimation errors in rural areas using the third-level dasymetric refinement strategy.

According to Table 1 and Table 6 of the Appendix, absolute and relative absolute error measures are generally lower for 2000–2010 than for 1990–2010. This complies with observations reported by Schroeder (2007) that lower degrees of boundary changes during the shorter time period typically relate to smaller estimation errors. The only exception is observed for Mecklenburg County, possibly because of a highly increasing population growth in the area between 2000 and 2010, making boundary changes significant even for the short time period. However, as mentioned before, quality issues related to the ancillary variables can affect population estimates, and this is generally more aggravated over longer time periods, thereby adding to generally higher absolute error measures for the 1990–2010 time period. For example, no road networks could be found for 1990, and thus the dataset for 2000 was utilized instead. Also, the classification accuracy of NLCD is known to be lower in 1992 (Wickham et al. 2010), and the developed land categories were classified under a different scheme in 1992 than in the other two years (i.e., three classes instead of four).

6. Conclusions

This research applied different levels of dasymetric refinement to areal interpolation techniques to estimate total population values within temporally consistent small area census units. The second-level refinement, in which related ancillary variables were employed through extending the refinement approach for the EM algorithm, improved the accuracy of population estimates by effectively leveraging nuanced statistical associations between population distribution and housing types. Moreover, at the third level of refinement, a composite ancillary dataset was tested to more accurately model population distribution in potentially rural areas, where estimation errors remained persistently high in the first and second level refinements. These findings demonstrate the importance of the choice of the ancillary data, their categorization and their integration for the performance of interpolation methods in different settings. The findings will be of direct benefit to researchers in demography and migration studies, crime analysis, economics, health studies and integrated assessment modeling, where accurate and temporally consistent demographic estimates represent a precondition for an objective analysis of changes in underlying populations.

Future research will assess the combination of different refinement scenarios. While this approach may be computationally expensive and more complex, each of the utilized refinement levels and interpolation techniques has its own strengths under different circumstances, justifying initial efforts for the development of a hybrid refinement approach. The incorporation of new global data products such as the recently introduced Global Human Settlement Layer (GHSL) that indicates built-up land for four points in time (1975–2014) (Pesaresi et al. 2016), represents a promising research avenue to apply similar approaches to areas that are less data-rich. Despite remaining uncertainties in rural settings (Leyk et al. 2018), such global ancillary variables provide new opportunities to apply dasymetrically-refined areal interpolation methods to any region in the world where census data are available for different points in time.

Acknowledgments

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Appendix

1.: Categorization of the extended refinement approach for EM per county and time period

Table 1.

Categorization of the extended refinement approach for EM in Hennepin.

Initial candidate control zone (6 types)	Selected for categorization	Number of subcategories (5 to 7)
	1990–2010	
Single Family	Included	7
Double Bungalow	Included	6
Townhouse	Included	5
Apartment	Included	6
Condo	Excluded	-
Triplex	Excluded	-

Initial candidate control zone (6 types)	**Selected for categorization**	**Number of subcategories (5 to 7)**
	2000–2010	
Single Family	Included	7
Double Bungalow	Included	7
Townhouse	Included	5
Apartment	Included	6
Condo	Included	6
Triplex	Excluded	-

Table 2.

Categorization of the extended refinement approach for EM in Mecklenburg.

Initial candidate control zone (6 types)	**Selected for categorization**	**Number of subcategories (5 to 7)**
	1990–2010	
Single Family	Included	7
Townhouse	Included	6
Apartment	Included	7
Condo	Included	5
Patio Home	Excluded	-
Assisted Living	Excluded	-
	2000–2010	
Single Family	Included	7
Townhouse	Included	5
Apartment	Included	7
Condo	Included	5
Patio Home	Excluded	-
Assisted Living	Excluded	-

Table 3.

Categorization of the extended refinement approach for EM in Broward.

Initial candidate control zone (6 types)	**Selected for categorization**	**Number of subcategories (5 to 7)**
	1990–2010	
Single Family	Included	7
Multi Family < 10 Units	Included	5
Condo	Included	5

Initial candidate control zone (6 types)	Selected for categorization	Number of subcategories (5 to 7)
Mobile Homes	Excluded	-
Multi Family	Included	7
Boarding Homes	Excluded	-
	2000–2010	
Single Family	Included	7
Multi Family < 10 Units	Included	5
Condo	Included	7
Mobile Homes	Included	5
Multi Family	Included	5
Boarding Homes	Excluded	-

Table 4.

Categorization of the extended refinement approach for EM in Hillsborough.

Initial candidate control zone (6 types)	Selected for categorization	Number of subcategories (5 to 7)
	1990–2010	
Single Family	Included	7
Mobile Homes	Included	6
Multi Family < 10 Units	Included	6
Multi Family	Included	7
Condo	Included	7
Orphanages	Excluded	-
	2000–2010	
Single Family	Included	7
Mobile Homes	Included	5
Multi Family < 10 Units	Included	5
Multi Family	Included	6
Condo	Included	5
Orphanages	Excluded	-

Table 5.

Categorization of the extended refinement approach for EM in Worcester.

Initial candidate control zone (6 types)	Selected for categorization	Number of subcategories (5 to 7)
	1990–2010	

Initial candidate control zone (6 types)	Selected for categorization	Number of subcategories (5 to 7)
Single Family	Included	7
Two Family	Included	6
Three Family	Included	7
Apartment 4–8 Units	Excluded	-
Mixed Residential	Included	5
Condo	Excluded	-
	2000–2010	
Single Family	Included	5
Two Family	Excluded	-
Three Family	Included	5
Apartment 4–8 Units	Included	6
Mixed Residential	Included	5
Condo	Excluded	-

2.: Relative absolute error measures

Table 6.

Relative Absolute error measures of unrefined and refined methods in all counties.

Method	AW	Refined AW (1st)	Modified Refined AW (3rd)	TDW	Refined TDW (1st)	Modified Refined TDW (3rd)	EM (2nd)	Modified EM (3rd)	Extended EM (2nd)
				Hennepin: 1990–2010					
MAE	0.09	0.07	0.06	0.08	0.05	0.05	0.07	0.05	0.04
Median Abs Error	0.02	0.01	0.01	0.02	0.02	0.01	0.02	0.02	0.01
RMSE	0.29	0.19	0.13	0.22	0.15	0.12	0.17	0.11	0.10
90th Percent Error	0.21	0.17	0.17	0.21	0.11	0.13	0.24	0.15	0.11
				Hennepin: 2000–2010					
MAE	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.01
Median Abs Error	0	0	0	0	0	0	0	0	0
RMSE	0.09	0.08	0.07	0.03	0.03	0.03	0.07	0.04	0.03
90th Percent Error	0.03	0.01	0.01	0.02	0.01	0	0.01	0	0.01
				Mecklenburg: 1990–2010					
MAE	2.85	0.4	0.26	0.92	0.43	0.3	0.38	0.24	0.17
Median Abs Error	0.27	0.18	0.11	0.16	0.11	0.1	0.2	0.11	0.07
RMSE	32.46	0.92	0.51	3.26	1.44	0.93	0.7	0.47	0.31

Method	**AW**	**Refined AW (1st)**	**Modified Refined AW (3rd)**	**TDW**	**Refined TDW (1st)**	**Modified Refined TDW (3rd)**	**EM (2nd)**	**Modified EM (3rd)**	**Extended EM (2nd)**
90th Percent Error	1.71	0.93	0.7	1.5	0.93	0.71	0.93	0.59	0.46
				Mecklenburg: 2000–2010					
MAE	3.9	0.46	0.37	1.96	1.82	1.7	0.35	0.3	0.09
Median Abs Error	0.09	0.08	0.06	0.07	0.05	0.04	0.11	0.06	0.04
RMSE	46.67	3.1	3.4	26.69	25.05	24.16	1.77	2.64	0.17
90th Percent Error	0.68	0.61	0.37	0.47	0.36	0.26	0.53	0.31	0.23
				Broward: 1990–2010					
MAE	9.08	0.3	0.29	10.42	0.18	0.19	0.26	0.24	0.19
Median Abs Error	0.18	0.12	0.14	0.1	0.07	0.07	0.09	0.11	0.08
RMSE	95.45	0.8	0.66	113.2	0.4	0.38	0.63	0.51	0.4
90th Percent Error	1.14	0.67	0.71	0.69	0.35	0.43	0.63	0.55	0.5
				Broward: 2000–2010					
MAE	0.14	0.08	0.09	0.04	0.03	0.03	0.07	0.07	0.05
Median Abs Error	0.01	0.01	0	0	0	0	0.01	0.01	0
RMSE	0.3	0.17	0.18	0.1	0.06	0.06	0.14	0.15	0.09
90th Percent Error	0.42	0.26	0.28	0.13	0.09	0.1	0.21	0.23	0.14
				Hillsborough: 1990–2010					
MAE	1.84	0.27	0.23	1.96	0.84	0.85	0.31	0.24	0.22
Median Abs Error	0.16	0.09	0.09	0.1	0.07	0.07	0.12	0.09	0.07
RMSE	8.68	0.58	0.45	15.43	10.72	10.7	0.64	0.45	0.49
90thPercent Error	1.35	0.72	0.65	0.99	0.77	0.67	0.82	0.7	0.58
				Hillsborough: 2000–2010					
MAE	0.59	0.16	0.14	0.18	0.1	0.09	0.13	0.1	0.08
Median Abs Error	0	0	0	0	0	0	0	0	0
RMSE	4.71	0.47	0.36	0.73	0.27	0.25	0.37	0.26	0.21
90thPercent Error	0.68	0.46	0.45	0.41	0.27	0.25	0.37	0.31	0.25
				Worcester: 1990–2010					
MAE	0.09	0.07	0.05	0.04	0.04	0.04	0.08	0.05	0.04
Median Abs Error	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.01
RMSE	0.23	0.19	0.12	0.08	0.1	0.11	0.18	0.12	0.1
90th Percent Error	0.22	0.2	0.11	0.1	0.1	0.09	0.26	0.1	0.08

Method	AW	Refined AW (1st)	Modified Refined AW (3rd)	TDW	Refined TDW (1st)	Modified Refined TDW (3rd)	EM (2nd)	Modified EM (3rd)	Extended EM (2nd)
				Worcester: 2000–2010					
MAE	0.06	0.05	0.03	0.01	0.01	0.01	0.06	0.02	0.02
Median Abs Error	0	0	0	0	0	0	0	0	0
RMSE	0.21	0.17	0.12	0.03	0.08	0.08	0.16	0.09	0.08
90th Percent Error	0.15	0.18	0.06	0.02	0.02	0.02	0.15	0.06	0.03

3.: Accuracy measures of potentially rural target tracts identified using an alternative approach

As another approach to define potentially rural target tracts that are supposed to benefit the most from the third dasymetric refinement, we first selected tracts with population density lower than 1000 people per square mile. Next, we identified tracts whose overlapping area with census-defined urban areas in 1990 and 2000 was less than 50%. Finally, we identified tracts that belonged to both sets as candidate rural target tracts. Table 7 summarizes the overall absolute error measures resulting from applying the methods to this set of potentially rural tracts. We also tested population density of 500 people per square mile and the results showed the same order.

Table 7.

Absolute error measures of all refined methods applied to potentially rural target tracts in four study areas.

Method	Refined AW(1st)	Modified Refined AW (3rd)	Refined TDW (1st)	Modified Refined TDW (3rd)	EM (2nd)	Modified EM (3rd)
		Hennepin: 1990–2010				
MAE	276	161	541	395	233	173
RMSE	401	245	959	629	374	242
		Hennepin: 2000–2010				
MAE	4	1	2	1	1	1
RMSE	7	1	3	2	3	2
		Mecklenburg: 1990–2010				
MAE	680	307	388	330	515	238
RMSE	972	398	540	468	774	326
		Mecklenburg: 2000–2010				
MAE	732	218	401	254	689	254

Method	Refined AW(1st)	Modified Refined AW (3rd)	Refined TDW (1st)	Modified Refined TDW (3rd)	EM (2nd)	Modified EM (3rd)
RMSE	1194	319	540	335	1066	382
		Hillsborough: 1990–2010				
MAE	447	345	369	324	457	362
RMSE	759	620	645	615	749	637
		Hillsborough: 2000–2010				
MAE	255	222	181	164	162	160
RMSE	663	606	464	441	448	430
		Worcester: 1990–2010				
MAE	267	118	147	128	290	173
RMSE	517	205	282	272	588	482
		Worcester: 2000–2010				
MAE	191	72	36	34	184	61
RMSE	451	185	70	100	431	144

References

Buttenfield BP, Ruther M, and Leyk S, 2015 Exploring the impact of dasymetric refinement on spatiotemporal small area estimates. Cartography and Geographic Information Science, 42 (5), 449–459.

Dempster A, Laird N, and Rubin D, 1977 Maximum likelihood from incomplete data via the EM algorithm. Journal of the Royal Statistical Society. Series B (Methodological), 39 (1), 1–38.

Eicher CL and Brewer CA, 2001 Dasymetric mapping and areal interpolation: Implementation and evaluation. Cartography and Geographic Information Science, 28 (2), 125–138.

Fisher P and Langford M, 1995 Modelling the errors in areal interpolation between zonal systems by Monte Carlo simulation. Environment and Planning A, 27 (2), 211–224.

Flowerdew R and Green M, 1994 Areal interpolation and types of data. *In*: Fotheringham S and Rogerson P, eds. Spatial analysis and GIS London: Taylor & Francis, 121–145.

Goodchild M and Lam NSN, 1980 Areal interpolation: a variant of the traditional spatial problem. Geo-processing, 1, 297–312.

Hennepin County GIS, 2016 Hennepin County Geographic information systems [online] Hennepin County Available from: http://www.hennepin.us/gisopendata [Accessed 3 Dec 2016].

Holt JB, Lo CP, and Hodler TW, 2004 Dasymetric estimation of population density and areal interpolation of census data. Cartography and Geographic Information Science, 31 (2), 103–121.

Homer CG, Dewitz JA, Yang L, Jin S, Danielson P, Xian G, Coulston J, Herold ND, Wickham JD, and Megown K, 2015 Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information. Photogrammetric Engineering and Remote Sensing, 81 (5), 345–354.

Langford M, 2006 Obtaining population estimates in non-census reporting zones: An evaluation of the 3-class dasymetric method. Computers, Environment and Urban Systems, 30 (2), 161–180.

Leyk S, Buttenfield BP, Nagle NN, and Stum AK, 2013 Establishing relationships between parcel data and land cover for demographic small area estimation. Cartography and Geographic Information Science, 40 (4), 305–315.

Leyk S, Ruther M, Buttenfield BP, Nagle NN, and Stum AK, 2014 Modeling residential developed land in rural areas: A size-restricted approach using parcel data. Applied Geography, 47, 33–45.

Leyk S, Uhl JH, Balk D, and Jones B, 2018 Assessing the accuracy of multi-temporal built-up land layers across rural-urban trajectories in the United States. Remote Sensing of Environment, 204, 898–917. [PubMed: 29599568]

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

MassGIS, 2016 MassGIS Data Download - Level 3 Assessor's Parcels [online]. Office of Geographic Information (MassGIS), Commonwealth of Massachusetts, MassIT Available from: http://www.mass.gov/anf/research-and-tech/it-serv-and-support/application-serv/office-of-geographic-information-massgis/datalayers/download-level3-parcels.html [Accessed 3 Dec 2016].

Mecklenburg County GIS, 2013 Data - Open Mapping - Mecklenburg County GIS [online] Available from: http://maps.co.mecklenburg.nc.us/openmapping/data.html [Accessed 3 Dec 2016].

Mennis J, 2003 Generating Surface Models of Population Using Dasymetric Mapping. The Professional Geographer, 55 (1), 31–42.

Mennis J, 2009 Dasymetric mapping for estimating population in small areas. Geography Compass, 3 (2), 727–745.

Mennis J, 2015 Increasing the accuracy of urban population analysis with dasymetric mapping. Cityscape, 17 (1), 115–126.

Mennis J, 2016 Dasymetric spatiotemporal interpolation. The Professional Geographer, 68 (1), 92–102.

Minnesota Population Center, 2016 National Historical Geographic Information System: Version 11.0 [Database] University of Minnesota.

Multi-Resolution Land Characteristics, 2016 Multi-Resolution Land Characteristics Consortium (MRLC) [online] Available from: https://www.mrlc.gov/index.php [Accessed 3 Dec 2016].

Nagle N, Buttenfield B, Leyk S, and Spielman S, 2014 Dasymetric modeling and uncertainty. Annals of the Association of American Geographers, 104 (1), 80–95. [PubMed: 25067846]

Pavía J and Cantarino I, 2016 Can Dasymetric Mapping Significantly Improve Population Data Reallocation in a Dense Urban Area? Geographical Analysis

Pesaresi M, Ehrlich D, Ferri S, Florczyk A, Freire S, Halkia M, Julea A, Kemper T, Soille P, and Syrris V, 2016 Operating procedure for the production of the Global Human Settlement Layer from Landsat data of the epochs 1975, 1990, 2000, and 2014 JRC Technical Report; European Commission, Joint Research Centre, Institute for the Protection and Security of the Citizen: Ispra, Italy.

Ruther M, Leyk S, and Buttenfield BP, 2015 Comparing the Effects of an NLCD-derived Dasymetric Refinement on Estimation Accuracies for Multiple Areal Interpolation Methods. GIScience & Remote Sensing, 52 (2), 158–178.

Schroeder JP, 2007 Target density weighting interpolation and uncertainty evaluation for temporal analysis of census data. Geographical Analysis, 39 (3), 311–335.

Schroeder JP and Van Riper DC, 2013 Because Muncie's densities are not Manhattan's: Using geographical weighting in the EM algorithm for areal interpolation. Geographical analysis, 45 (3), 216–237. [PubMed: 24653524]

U.S. Census Bureau, 2016a American FactFinder - Download Center [online] Available from: https://factfinder.census.gov [Accessed 26 Nov 2016].

U.S. Census Bureau, 2016b TIGER/Line Shapefiles and TIGER/Line Files [online]. Census.gov, Maps and Data, TIGER Products Available from: https://www.census.gov/geo/maps-data/data/tiger-line.html [Accessed 25 Nov 2016].

University of Florida GeoPlan Center, 2016 The Florida Geographic Data Library - FGDL [online]. University of Florida GeoPlan Center Available from: http://www.fgdl.org/download/ [Accessed 3 Dec 2016].

Wickham J, Stehman S, Fry J, Smith JH, and Homer CG, 2010 Thematic accuracy of the NLCD 2001 land cover for the conterminous United States. Remote Sensing of Environment, 114 (6), 1286–1296.

Wright J, 1936 A method of mapping densities of population: With Cape Cod as an example. Geographical Review, 26 (1), 103–110.

Zoraghein H, 2018 Areal interpolation code. Harvard Dataverse Available from: 10.7910/DVN/UBNNQS

Zoraghein H, Leyk S, Ruther M, and Buttenfield BP, 2016 Exploiting temporal information in parcel data to refine small area population estimates. Computers, Environment and Urban Systems, 58, 19–28.

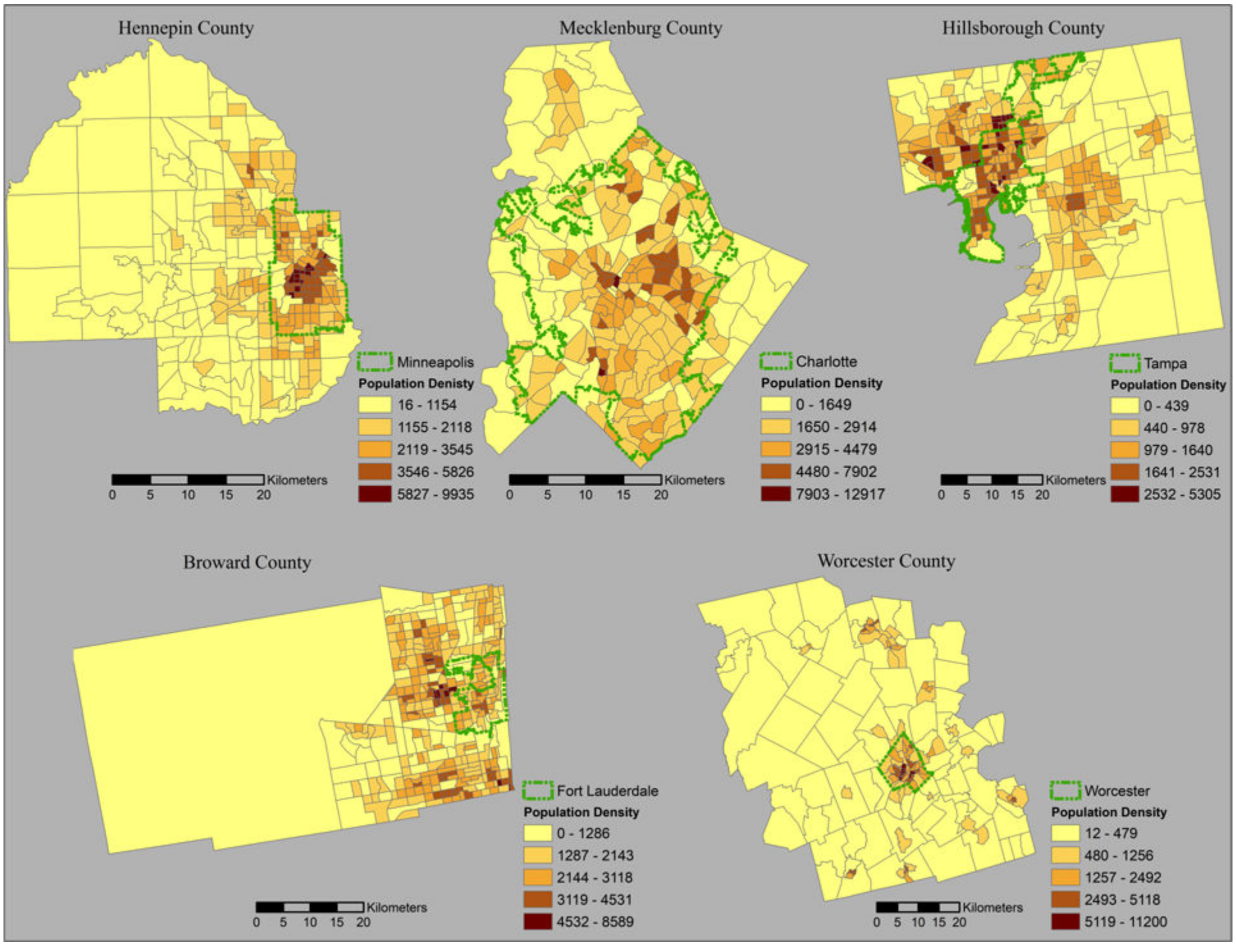

Figure 1.
The study areas and target census tracts.

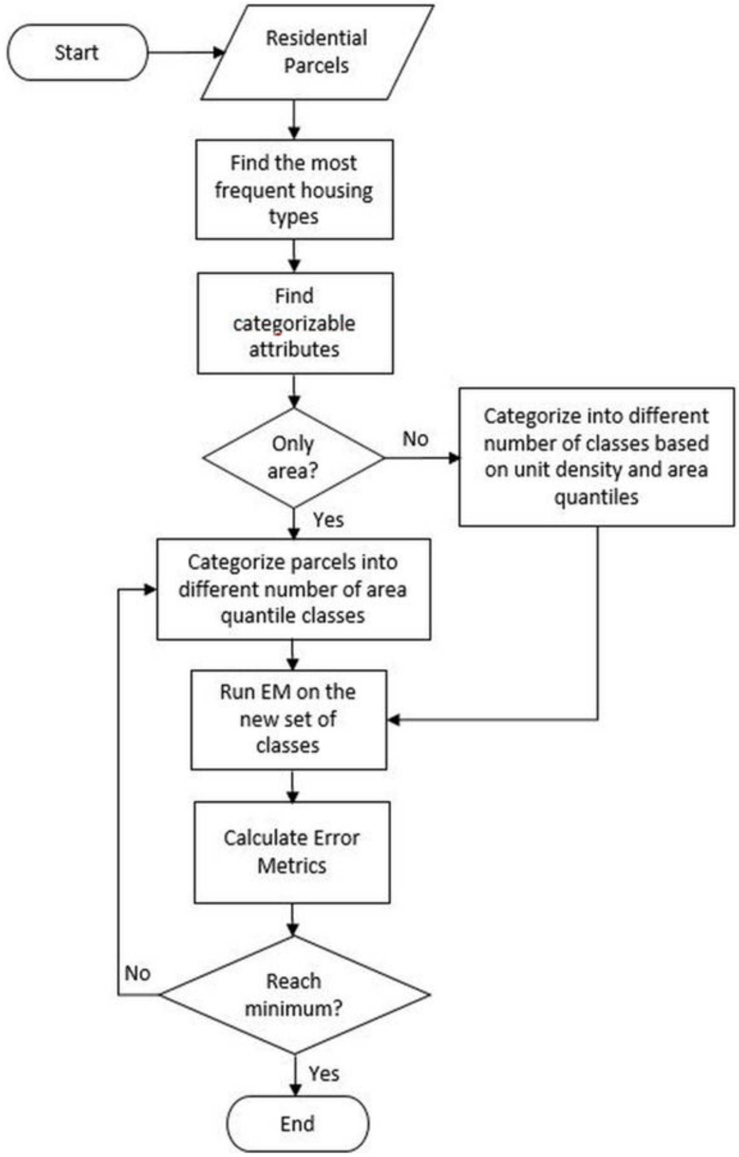

Figure 2.

Workflow of the extended refinement approach for EM.

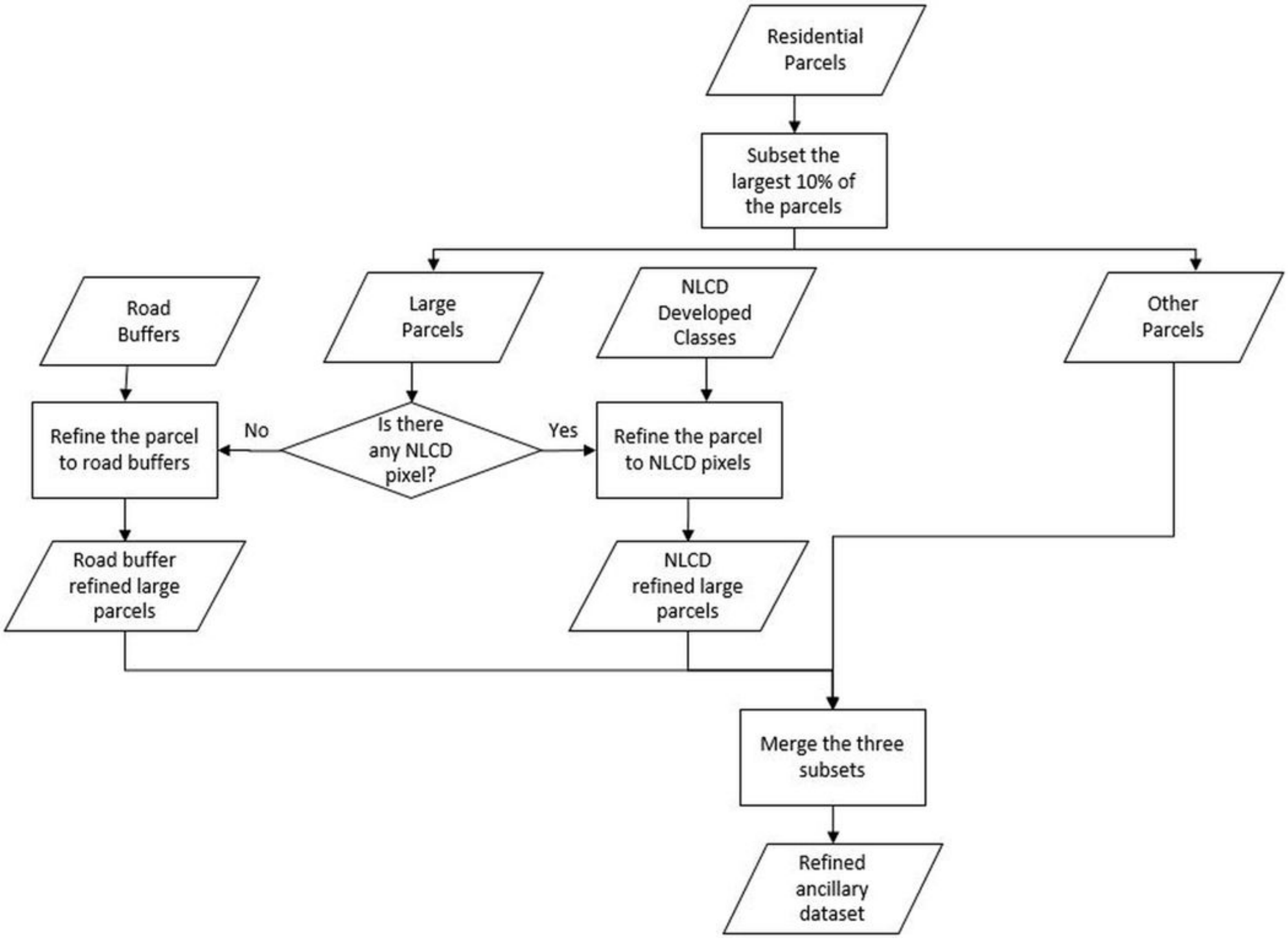

Figure 3.
Workflow of the third-level dasymetric refinement.

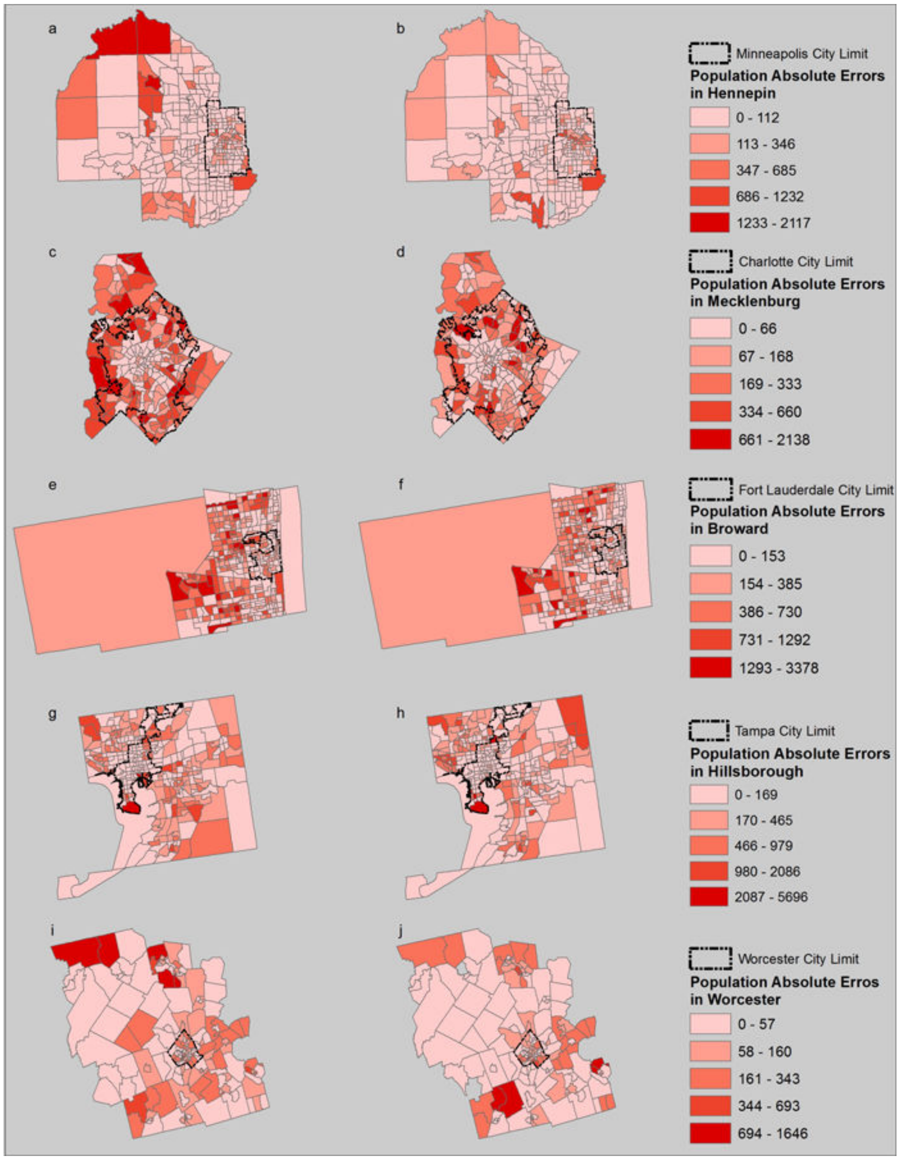

Figure 4.

Error maps of the five counties (1990–2010), Hennepin: Refined TDW (a), Extended Refinement for EM (b), Mecklenburg: Refined TDW (c), Extended Refinement for EM (d), Broward: Extended Refinement for EM (e), Refined TDW (f), Hillsborough: Refined TDW (g), Extended Refinement for EM (h), Worcester: Refined TDW (i), Extended Refinement for EM (j).

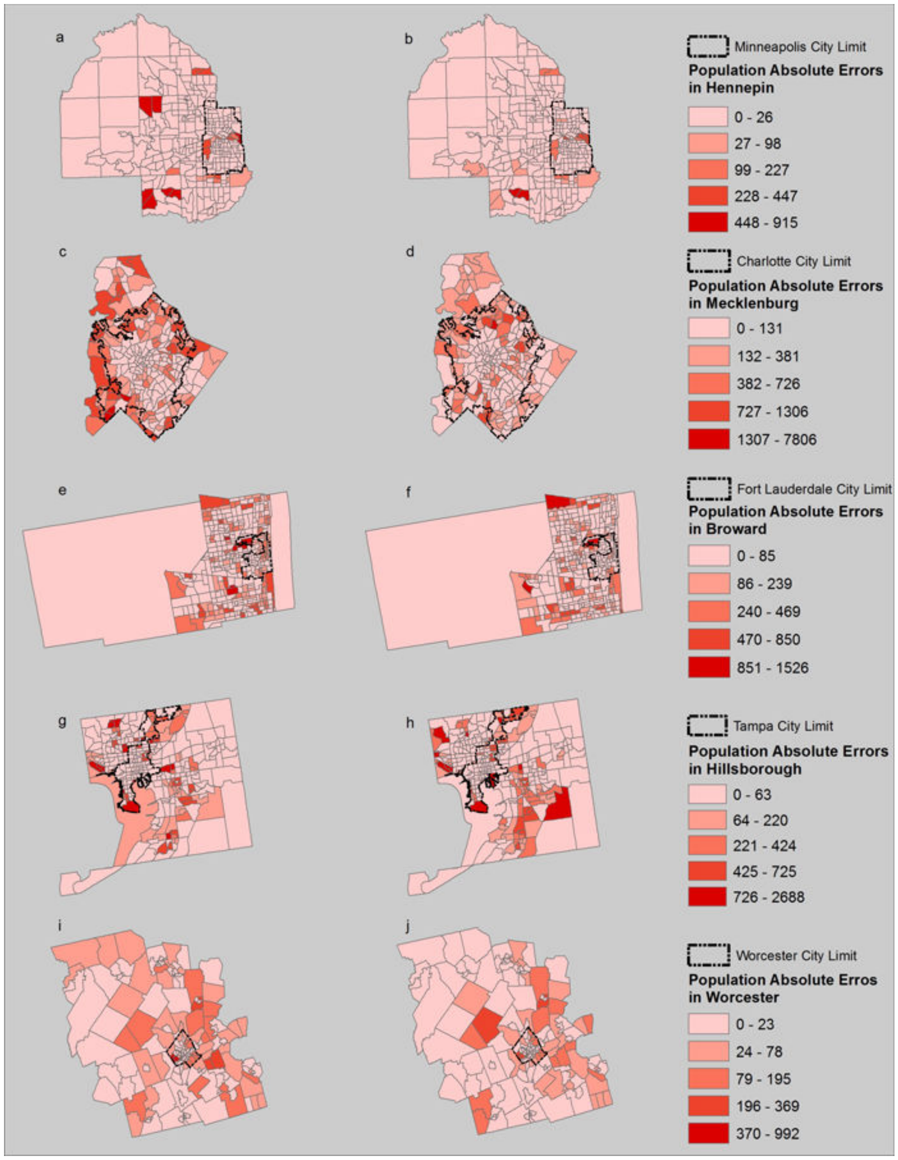

Figure 5.

Error maps of the five counties (2000–2010), Hennepin: Refined TDW (a), Extended Refinement for EM (b), Mecklenburg: Refined TDW (c), Extended Refinement for EM (d), Broward: Extended Refinement for EM (e), Refined TDW (f), Hillsborough: Extended Refinement for EM (g), Refined TDW (h), Worcester: TDW (i), Refined TDW (j).

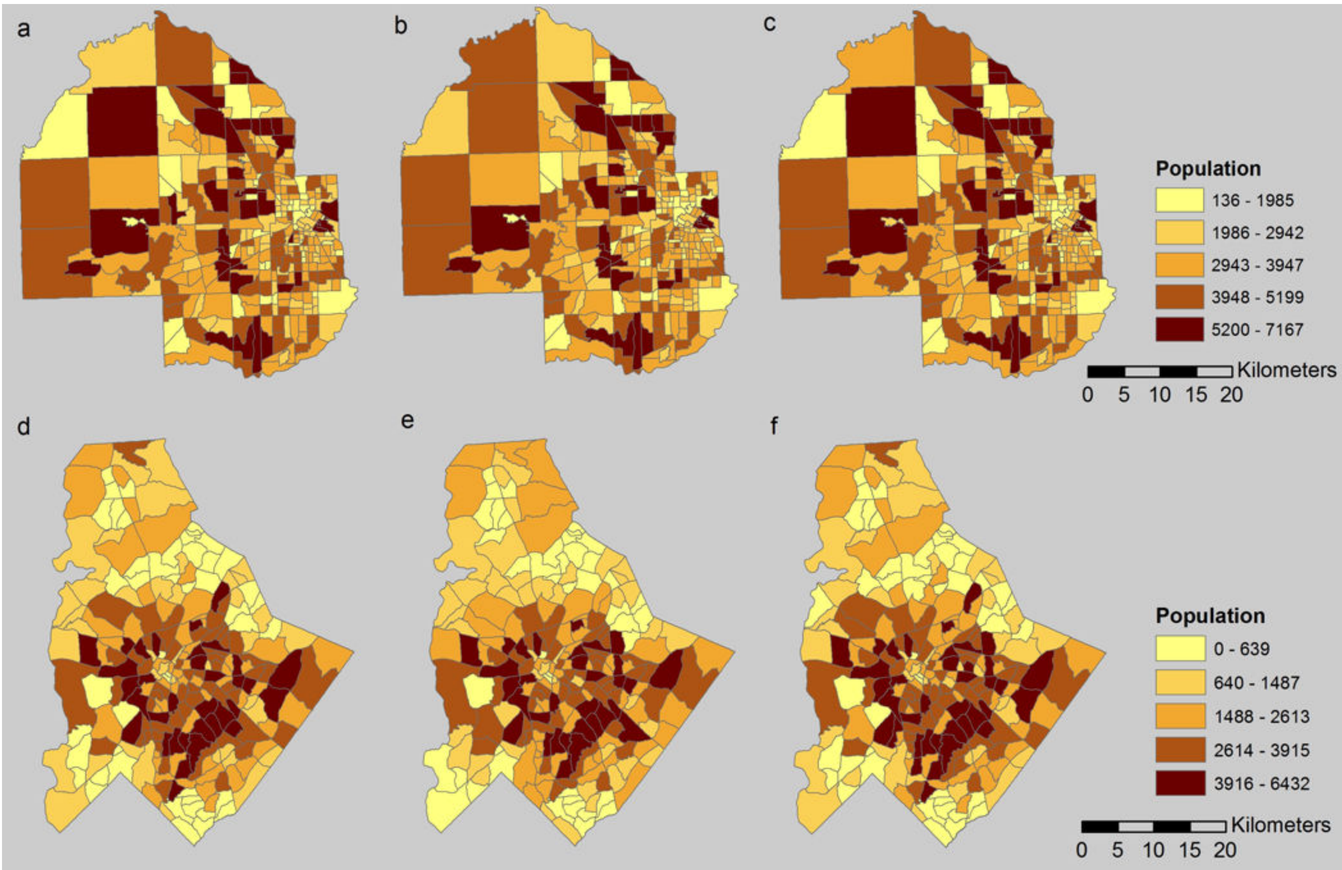

Figure 6.

Population maps in 1990 at the target tract level, Hennepin: block-aggregated (a), Refined TDW (b), Extended Refinement for EM (c), Mecklenburg: block-aggregated (d), Refined TDW (e), Extended Refinement for EM (f).

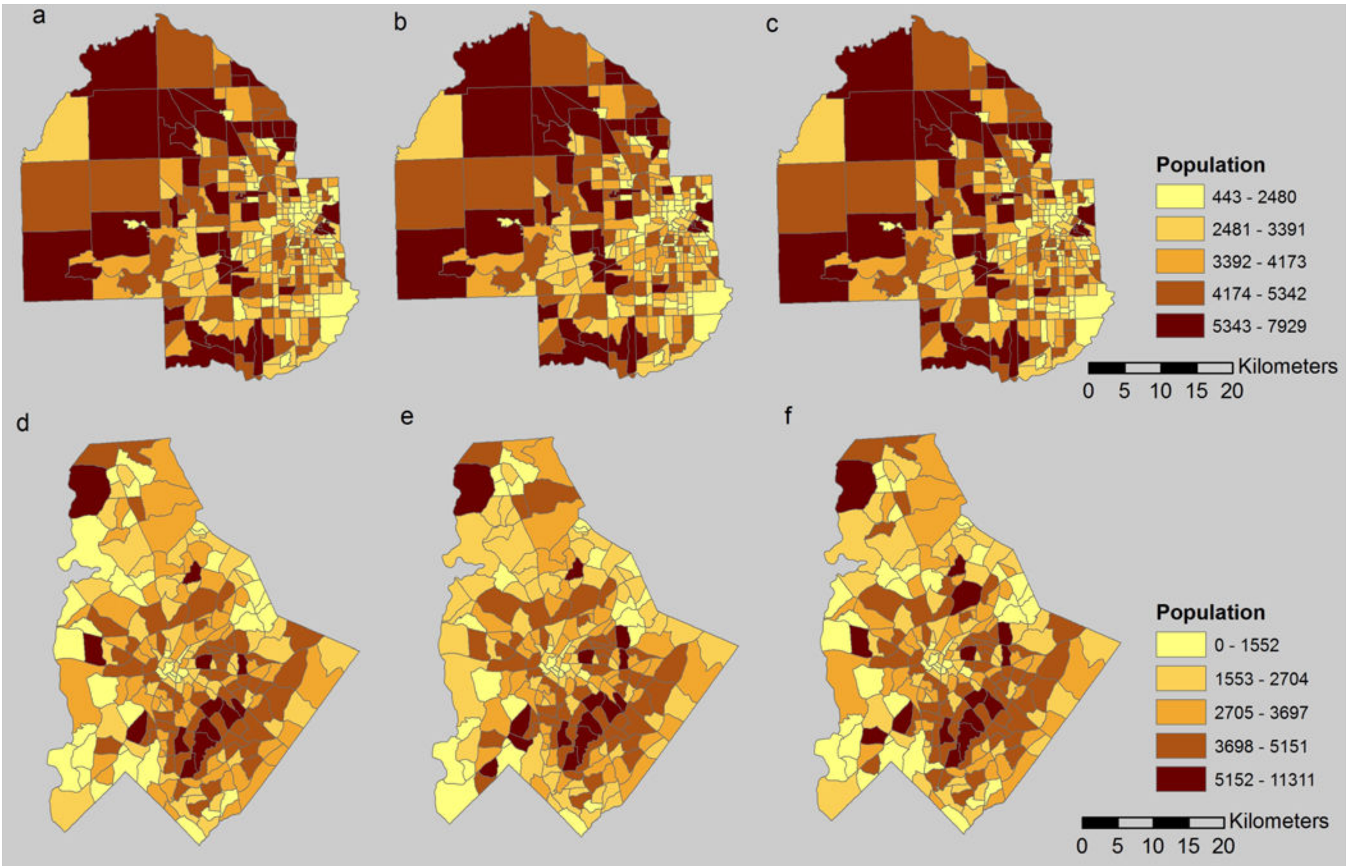

Figure 7.
Population maps in 2000 at the target tract level, Hennepin: block-aggregated (a), Refined TDW (b), Extended Refinement for EM (c), Mecklenburg: block-aggregated (d), Refined TDW (e), Extended Refinement for EM (f).

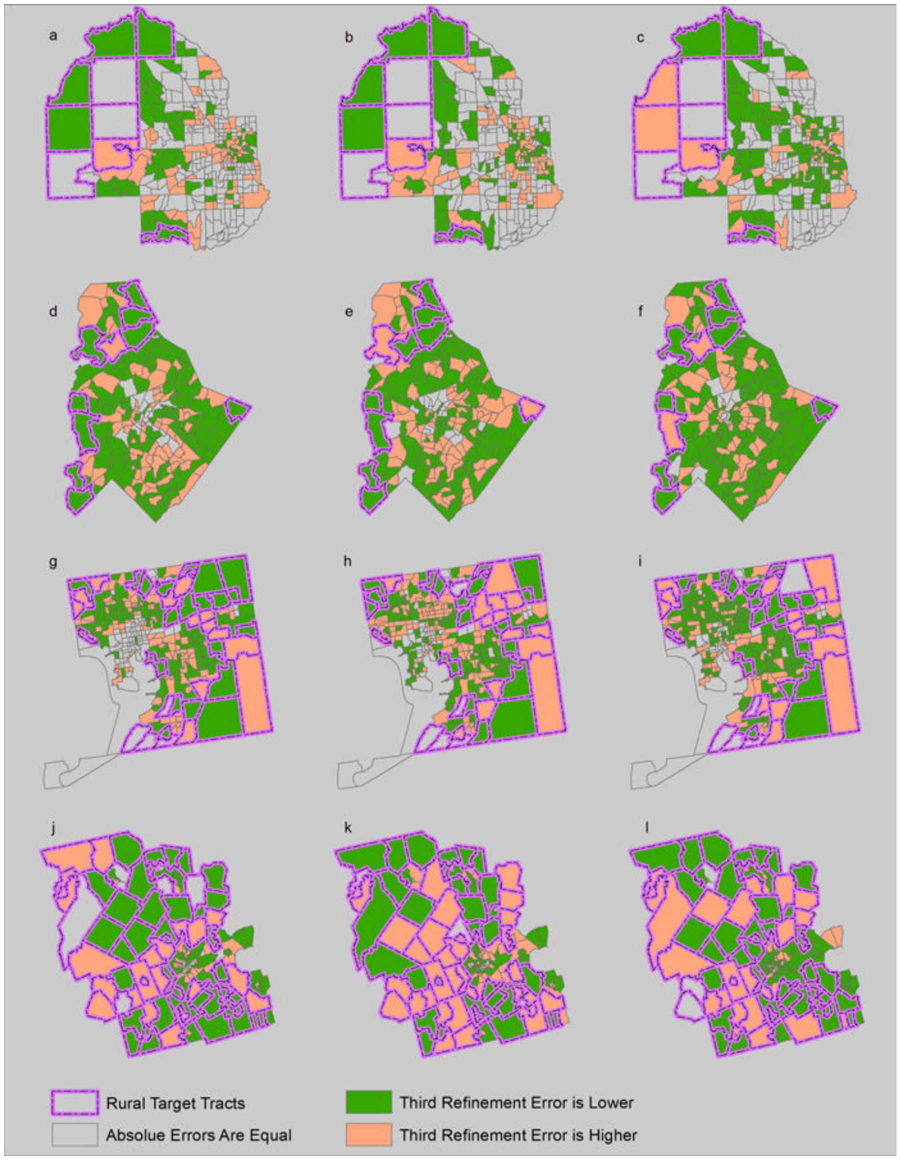

Figure 8.

Third dasymetric refinement methods in comparison to their first or second refinement equivalents in 1990–2010, Hennepin: modified refined AW vs. refined AW (a), modified refined TDW vs. refined TDW (b), modified EM vs. EM (c), Mecklenburg: modified refined AW vs. refined AW (d), modified refined TDW vs. refined TDW (e), modified EM vs. EM (f), Hillsborough: modified refined AW vs. refined AW (g), modified refined TDW vs. refined TDW (h), modified EM vs. EM (i), Worcester: modified refined AW vs. refined AW (j), modified refined TDW vs. refined TDW (k), modified EM vs. EM (l).

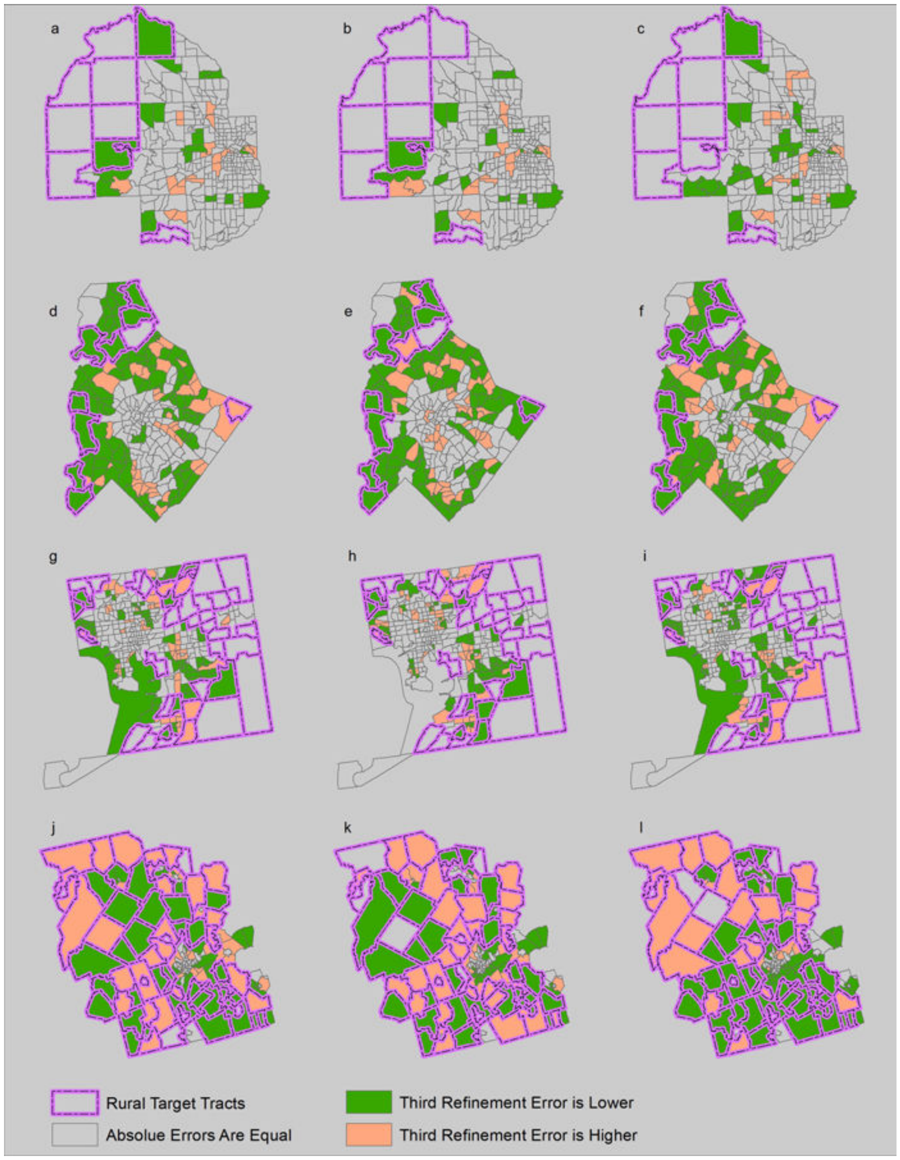

Figure 9.

Third dasymetric refinement methods in comparison to their first or second refinement equivalents in 2000–2010, Hennepin: modified refined AW vs. refined AW (a), modified refined TDW vs. refined TDW (b), modified EM vs. EM (c), Mecklenburg: modified refined AW vs. refined AW (d), modified refined TDW vs. refined TDW (e), modified EM vs. EM (f), Hillsborough: modified refined AW vs. refined AW (g), modified refined TDW vs. refined TDW (h), modified EM vs. EM (i), Worcester: modified refined AW vs. refined AW (j), modified refined TDW vs. refined TDW (k), modified EM vs. EM (l).

Table 1.

Absolute error measures of unrefined and refined methods in all counties.

Method	AW	Refined AW (1^{st})	Modified Refined AW (3^{rd})	TDW	Refined TDW (1^{st})	Modified Refined TDW (3^{rd})	EM (2^{nd})	Modified EM (3^{rd})	Extended EM (2^{nd})
Hennepin: 1990–2010									
MAE	219	158	148	201	132	117	203	139	110
Median Abs Error	57	47	50	56	47	48	60	58	44
RMSE	487	342	310	420	294	234	402	262	222
90^{th} Percent Error	646	429	464	650	368	306	616	291	270
Hennepin: 2000–2010									
MAE	58	53	44	36	24	21	49	31	18
Median Abs Error	0	0	0	0	0	0	0	0	0
RMSE	214	248	201	127	95	86	217	159	89
90^{th} Percent Error	97	16	17	88	19	17	24	14	23
Mecklenburg: 1990–2010									
MAE	546	384	261	387	263	220	443	251	178
Median Abs Error	346	212	130	255	168	129	240	125	91
RMSE	832	624	427	575	407	360	743	412	297
90^{th} Percent Error	1477	974	684	829	588	493	1094	628	455
Mecklenburg: 2000–2010									
MAE	613	465	290	330	309	228	464	246	183
Median Abs Error	213	210	135	138	116	115	240	141	79
RMSE	1012	793	502	531	720	490	741	394	309
90^{th} Percent Error	1728	1294	796	931	808	548	1294	630	478
Broward: 1990–2010									
MAE	1016	610	623	630	312	365	499	481	374
Median Abs Error	584	310	322	309	197	194	256	284	207
RMSE	1699	1012	978	1075	489	609	854	764	576
90^{th} Percent Error	2460	1499	1667	1566	738	907	1235	1140	914
Broward: 2000–2010									
MAE	560	282	290	151	100	101	227	232	151
Median Abs Error	47	29	17	14	13	13	33	28	14
RMSE	1654	538	555	375	204	197	457	468	297

Method	AW	Refined AW (1st)	Modified Refined AW (3rd)	TDW	Refined TDW (1st)	Modified Refined TDW (3rd)	EM (2nd)	Modified EM (3rd)	Extended EM (2nd)
90th Percent Error	1619	845	863	439	324	333	709	700	449
				Hillsborough: 1990–2010					
MAE	633	357	321	431	293	327	425	334	276
Median Abs Error	300	178	168	234	148	143	220	157	114
RMSE	1000	615	569	667	560	909	674	550	500
90th Percent Error	1807	901	765	1230	726	688	1118	894	697
				Hillsborough: 2000–2010					
MAE	574	231	228	178	130	121	213	162	133
Median Abs Error	5	0	0	3	0	0	0	0	0
RMSE	2513	501	491	363	298	287	493	380	313
90th Percent Error	1741	862	776	689	426	401	679	606	477
				Worcester: 1990–2010					
MAE	275	221	146	147	138	129	290	155	129
Median Abs Error	52	51	46	77	56	45	72	46	46
RMSE	598	446	298	287	272	266	596	382	288
90th Percent Error	892	803	379	299	290	326	845	319	269
				Worcester: 2000–2010					
MAE	184	150	101	37	37	36	184	75	40
Median Abs Error	9	8	7	13	6	7	8	6	5
RMSE	530	402	301	74	100	110	473	196	112
90th Percent Error	568	748	240	104	103	89	745	297	87

Table 2.

Absolute error measures of all refined methods applied to potentially rural target tracts in four study areas.

Method	Refined AW(1st)	Modified Refined AW(3rd)	Refined TDW (1st)	Modified Refined TDW (3rd)	EM (2nd)	Modified EM (3rd)
		Hennepin: 1990–2010				
MAE	282	153	575	360	209	137
RMSE	405	243	966	613	331	198
		Hennepin: 2000–2010				
MAE	3	0	1	1	1	1
RMSE	6	1	2	2	2	1
		Mecklenburg: 1990–2010				
MAE	841	355	573	443	616	264
RMSE	1106	447	694	510	857	346
		Mecklenburg: 2000–2010				
MAE	1003	246	577	284	819	208
RMSE	1276	328	678	340	1003	349
		Hillsborough: 1990–2010				
MAE	494	353	312	273	507	398
RMSE	754	512	470	437	733	561
		Hillsborough: 2000–2010				
MAE	303	237	137	111	186	154
RMSE	730	620	342	286	425	334
		Worcester: 1990–2010				
MAE	238	102	147	122	268	178
RMSE	495	195	300	284	579	520
		Worcester: 2000–2010				
MAE	173	54	36	35	137	49
RMSE	442	131	73	105	316	125