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Exploring the impact of dasymetric refinement on spatiotemporal small area estimates

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Comparing demographic small area estimates across multiple time periods is hindered by boundary changes in census enumeration units. Areal interpolation can resolve temporal incompatibilities, but underlying assumptions of uniform population density within units is sometimes flawed and results in distorted estimates. Dasymetric modeling refines spatial precision by limiting areal interpolation to the most likely residential areas. Here, a systematic examination of the impacts of dasymetric refinement on temporal interpolation accuracy compares errors that emerge as a consequence of differing time spans. This paper compares the accuracy of three commonly utilized methods of areal interpolation for temporal analysis of population data over the 1990–2010 decades. It examines whether multi-temporal dasymetric refinement prior to areal interpolation improves the accuracy of small area estimates, comparing two different demographic contexts. Data sets include tract-level demography exhibiting dramatic growth (Las Vegas, Nevada), and relative stability (Pittsburgh, Pennsylvania). Areal interpolation with and without the dasymetric refinement is validated using block level data. The dasymetrically refined target density weighting (TDW) provides the overall best performance for the 2000 source data and the expectation maximization (EM) method gives the overall best performance for the 1990 source data; effects of refinement are more prominent in areas of faster population change.

Keywords: spatiotemporal analysis; dasymetric modeling; demography; land cover

Small area estimations of demographic data through time

Temporal estimation of census data informs descriptions of population structure, growth, and decline. Temporal analysis can support generation of new information about patterns of demographic processes as they occur in urban and rural areas. However, the comparison of small area estimates of population across multiple time periods can be complicated or hindered by frequent changes in data enumeration zones such as census tracts. This research examines the impacts of dasymetric refinement prior to temporal estimation of population characteristics. Dasymetric refinement refers to a type of areal interpolation wherein ancillary data are utilized to refine enumeration areas and thus to better approximate the underlying population distribution (Mennis 2003). The question to be addressed in this study is whether multi-temporal dasymetric refinement will improve the performance of areal interpolation methods to generate more accurate and compatible temporal small area estimates of population. The sensitivities of such interpolations to the duration of the study period and the demographic setting will be investigated as they can provide important insights for future work.

Previous work

Schroeder (2007) states that more than half of the tracts enumerated in the 1990 Decennial Census underwent boundary changes prior to the 2000 Decennial Census. When tract boundaries change, extra processing steps are required to resolve spatially incompatible estimates of population counts or densities prior to estimation or analysis. Complicating this is the fact that in many census tracts, residential areas and thus population are not uniformly distributed. The coexistence of various structure and housing types, mixed-use zoning, and urban modernization or decline can increase heterogeneity within a tract, and tracts often contain areas, such as parks or industrial zones, in which residential population is not expected. As a consequence, it is unreasonable to expect that population density is homogeneous within tract-level enumeration units. Yet the most commonly utilized method for resolving boundary incompatibilities through time, the areal weighting (AW) method, assumes uniform population distribution within the small areas used for estimation. In places where census boundaries are modified as a consequence of demographic change, the assumption of homogeneity in areal interpolation can invoke considerable estimation error and uncertainty (Gregory 2002).

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Previous work applies various areal interpolation methods to compare demographic estimates over time. Examples of commonly utilized methods include AW (Markoff and Shapiro 1973; Goodchild and Lam 1980), Dempster et al.'s (1977) regression-based expectation maximization (EM) model used by Flowerdew and Green (1994), and the target density weighting (TDW) method devised by Schroeder (2007). Each approach has the advantage of preserving data volumes locally, which Tobler (1979) states is an important property in any interpolation method. In most methods, the central assumption remains that population density is homogeneous within enumeration zones or ancillary data zones, and must be compensated or corrected.

Areal interpolation methods may integrate ancillary data by dasymetric refinement (Semenov-Tian-Shansky 1928; Wright 1936) to improve estimation accuracy for a single point in time (Eicher and Brewer 2001; Mennis and Hultgren 2006; Langford 2007; Lin, Cromley, and Zhang 2011). Dasymetric refinements are commonly based on remotely sensed imagery or classified land cover data (Mennis 2003; Holt, Lo, and Hodler 2004; Reibel and Agrawal 2007; Kim and Yao 2010) or street network densities (Reibel and Bufalino 2005), other cadastral data (Leyk et al. 2014; Tapp 2010), or both (Leyk et al. 2013). Areal interpolation methods that incorporate ancillary refinement by dasymetry have been shown to improve the accuracy of interpolated small area estimates, relative to areal interpolation methods which do not use ancillary data (Mrozinski and Cromley 1999; Gregory 2002). Dasymetric methods have been shown to outperform regression-based statistical models in generating accurate small area estimates of population (Fisher and Langford 1995; Lin, Cromley, and Zhang 2011).

The use of ancillary data to improve temporal analysis commonly involves land cover information (Fisher and Langford 1995; Cockings, Fisher, and Langford 1997; Holt, Lo, and Hodler 2004; Reibel and Bufalino 2005; Reibel and Agrawal 2007; Schroeder and Van Riper 2013). Dasymetric refinement determines population density based on ancillary landscape information classified according to predefined rules (Eicher and Brewer 2001) that may involve binary distinctions (residential vs. nonresidential areas), arbitrary classification, or empirical sampling (Mennis and Hultgren 2006).

Regression-based refinement has also been examined and found to offer no great advantage to straightforward dasymetric modeling with limiting ancillary variables (Fisher and Langford 1995). Cromley, Hanink, and Bentley (2012) found that quantile classification brings only slight accuracy gains over binary classification of ancillary data. Lin, Cromley, and Zhang (2011) applied geographically weighted regression to localize the parametric estimation of population densities within ancillary data classes, and Schroeder and Van Riper (2013) applied a spatial weighting to EM regression, with similar results (only modest gains in accuracy). Dasymetric modeling using limiting variables (Wright 1936) is computationally simpler than regression modeling, and is a more logical choice for areal estimation, in that limiting variables can be localized more readily and more precisely than globally applied classifications or geographic weighting strategies (Lin, Cromley, and Zhang 2011).

The paper extends knowledge gained in these other studies, exploring the impacts of spatial refinement using land cover data on the three areal interpolation methods listed to estimate population at different points in time, studying two different demographic contexts in which differences in model performance might emerge. The study areas include one metropolitan area that exhibits dramatic growth (Las Vegas, Nevada) during the study period (1990–2010), and another metropolitan area that maintains a relatively stable population (Pittsburgh, Pennsylvania) over the same period. Areal interpolation will be performed with and without dasymetric refinement, and the results compared statistically and validated against estimates using block level data, which is the finest resolution population data available from the U.S. Census Bureau. Understanding more about the choice among interpolation methods for different demographic contexts can inform decisions about which method will provide the highest accuracy in temporal analyses when shifting enumeration boundaries confound assessment of demographic change.

Data and sources

Census tract boundary files and decadal census population data were obtained from the National Historical Geographic Information System (Minnesota Population Center 2011). In a metropolitan area such as Pittsburgh, where population has been relatively stable for the past two decades, few tract boundaries are expected to change. In counterpoint, Las Vegas population has experienced a period of rapid growth in the same time frame, with a higher frequency of boundary changes.

Tracts will be analyzed for entire counties in both cases to study the entire geographic context of each metropolitan area, working with Allegheny County, Pennsylvania (surrounding Pittsburgh), and with Clark County, Nevada (surrounding Las Vegas). Comparing interpolation outcomes for counties with distinct demographic patterns should provide important insights into method effects, that is, the sensitivity of each interpolation method in the context of having many tracts that split versus the context of tracts that tend not to change or that merge. The use of two different source zones (1990 and 2000) and a single target zone (2010) is intended to demonstrate whether interpolating across longer periods of time introduces additional error regardless of the interpolation method.

Ancillary land cover data are taken from the USGS National Land Cover Dataset (NLCD) using versions distributed in 1992, 2001, and 2011. NLCD provides the only public domain source of national coverage of land cover information for 5–10-year periods over the past two decades. It is derived from Landsat 30-meter imagery and characterizes thematic land use, amount of impervious surface, and tree cover (http://pubs.usgs.gov/fs/2012/3020/). The thematic land use layer will be utilized in this research to identify which parts of census tracts in the two metropolitan areas can be considered residential.

A potential problem arises in using it over the entire 20-year span. The attribution categories vary from one NLCD version to the next; this has been remedied by aggregating the NLCD classification into developed or residential land (classes 21 and 22 in NLCD 1992 and classes 21–23 in NLCD 2001/2011) and nondeveloped or nonresidential (all other classes) land. Two classes, showing high-intensity developed land from NLCD 2001/2011, and commercial land from NLCD 1992, respectively, were determined to be nonresidential for this analysis, as pixels in these classes are unlikely to contain large populations.

Figure 1 shows how dasymetric refinement can improve the precision and accuracy of area interpolation methods. The figure shows NLCD developed land classes for 1992 (classes 21–22) and 2001 (classes 21–23), overlaid on census tract boundaries for 1990 or 2000 source zones, respectively, and tract boundaries used as target zones in 2010. Notice in the figure that some boundaries are conflated, as for example, the boundary running east–west immediately beneath the "1992" label. Boundary conflation is assumed to be a consequence of printing technology, and will not be considered as an actual census tract change. In the southeast corner of the 1992 panel however, one can see a 1990 tract that was eliminated by 2010 (and in fact by 2001), comparing with the 2001 panel. This is not due to conflation, but to actual census tract change, and will be treated as such in the analysis.

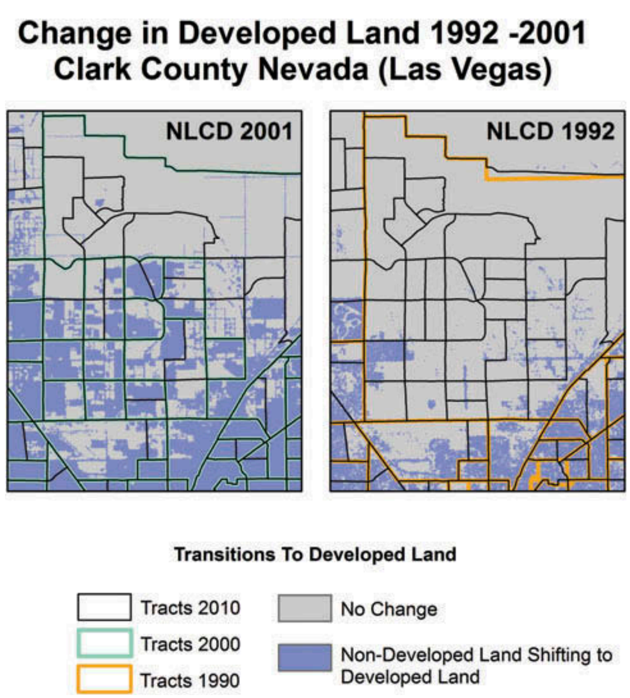

Figure 1. Population densities computed from entire census tracts do not reflect actual residential (developed) land area. The two panels show developed land as shown in 1992 and 2001 NLCD, with tract boundaries for 1990, 2000, and 2010.

Without spatial refinement, the entire tract is assumed to be populated and population estimates are based on the area of the entire tract. Tract boundary changes do not necessarily modify area values in the estimates. With refinement however, only land classified as residential development (blue) is assumed to contain population within a tract. In situations of dramatic population growth or decline, residential land pixels may also change dramatically and have an equally dramatic effect on population densities. Because the refinement improves the precision of area values, derived small area estimates are expected to improve in accuracy.

Areal interpolation methods

Three methods will be applied to the two urban study areas to interpolate census tract population densities from 1990 to 2010, and from 2000 to 2010. The three interpolation methods include AW, the EM algorithm, and TDW. Each method has been applied to small area estimation for areas with changing tract boundaries, and each is an exact or nearly exact interpolator as defined by Burrough and McDonnell (1998), and will preserve population densities pycnophylactically, which Tobler (1979) maintains is an important goal for interpolation. Detailed descriptions and equations for each method are introduced below.

Interpolation method 1: AW

Computationally, AW provides the simplest method (Markoff and Shapiro 1973; Goodchild and Lam 1980). A spatial intersection on source and target zones subsets the enumeration units. The proportion of area within each newly created polygon is used to assign an equivalent proportion of population, thus meeting the assumption of uniform population described above. Counts are tallied for all pixels within source zones situated within each target zone. Revised population counts are then calculated:

$$\hat{y}_t = \sum_s \frac{A_{st}}{A_s} y_s \tag{1}$$

where, $\hat{y}_t$ is the estimated count of population in target zone t, y_s is the observed count of the population in source zone s, A_s is the area of source zone s, and A_{st} is the area of the intersection of zones s and t.

Interpolation method 2: TDW

In TDW, as in AW, source and target zones are spatially intersected forming new enumeration polygons. The density of the source zone population within each intersected polygon at the source time is considered to be proportional to the population density found in the entire target zone for the target time period (Schroeder 2007). This assumption is pragmatic, because the population densities within each intersected polygon in the target year are not usually known. This assumption forces the population density to be uniform for all polygons within one target zone. Population counts of the source year within each target zone are calculated as follows:

$$\hat{y}_t = \sum_s \frac{\left(\frac{A_{st}}{A_t}\right) z_t}{\sum_\tau \left(\frac{A_{s\tau}}{A_\tau}\right) z_\tau} y_s \tag{2}$$

where y_s is the population count in source zone s, z_t is the population count in the target year within the target zone t, A_t is the area of the target zone, and A_{st} is the area of the new polygon formed by intersection of source (s) and target (t) zones. The parameter τ indexes the individual zones that intersect with a given target zone.

Interpolation method 3: EM

The EM algorithm is an iterative fitting procedure that relies on ancillary information found within target zones to allocate source zone population counts to target zones (Green 1989; Flowerdew, Green, and Kehris 1991). It is the most complex method from a computational standpoint. Earlier implementations operated similar to the first two interpolation methods, estimating population for intersected source and target zones, under the assumption that the distribution of the populations within different source zones follows a Poisson distribution (Green 1989; Flowerdew, Green, and Kehris 1991). The analysis reported here will follow that implementation, along with the re-specification proposed by Schroeder and Van Riper (2013), estimating population counts for source zones positioned within each land cover class as follows:

$$\hat{y}_{sc} = y_s \left(\frac{\hat{\lambda}_c A_{sc}}{\sum_k \hat{\lambda}_k A_{sk}} \right) \tag{3}$$

where $\hat{y}_{sc}$ is the expected population for land cover class c in source zone s, y_s is the source zone population, A_{sc} is the area of intersection of source zone s and the given land cover class c, $\hat{\lambda}_c$ is the population density within the given land cover class, and k indexes the different land cover classes within s (Schroeder and Van Riper 2013). Following initial estimates of $\hat{y}_{sc}$, iterative maximization takes place to revise population density estimates for each land cover class:

$$\hat{\lambda}_c = \frac{\sum_s \hat{y}_{sc}}{A_c} \tag{4}$$

The new density estimate is returned to Equation (3) to estimate populations within each land cover class, for each source zone. Iterations continue until estimates of $\hat{\lambda}_c$ stabilize. At this point, the estimated values for $\hat{y}_{sc}$ are input to estimate population counts for the source year for each target zone:

$$\hat{y}_t = \sum_s \sum_c \frac{A_{tsc} \hat{y}_{sc}}{A_{sc}} \tag{5}$$

where $\hat{y}_t$ is the estimated population attribute in target zone t, A_{tsc} is the area of class c within the intersection of source zone s and target zone t. In this analysis, 1000 iterations were carried out, at which point the individual population densities within land cover classes given in Equation (4) stabilized to 0.0001.

Whereas the other two methods assume uniform densities within source and/or target zones, it can be seen that EM assumes uniform densities within land cover classes. A recent variation (Schroeder and Van Riper 2013) estimates values for the intersection of source zones with a set of control zones, characterized by different land cover classes, acting as a kind of training set for subsequent interpolation.

Analysis and validation

Interpolation by each method will be run twice, once incorporating dasymetric refinement and once using unrefined tract boundaries. Binary dasymetric refinement (classifying ancillary data into residential and nonresidential classes) is used in this study following research findings (Fisher and Langford 1995; Eicher and Brewer 2001) demonstrating that more sophisticated classifications do not improve interpolation accuracies substantially.

Each interpolation method incorporates dasymetric refinement in a unique manner. For the AW interpolations, refinement will be incorporated for the source year alone. The TDW method incorporates refinement for both source and target zones, working with only those land cover pixels classified as developed (residential) in both source and target decades. The refinement of the target zones in the TDW method is based upon the fact that the population densities of the target zones, which will change as a result of the refinement, are an input into the interpolation method; the same is not true for the AW method. Dasymetric refinement is inherent in the EM model. The land cover ancillary data, including both developed and undeveloped classes for the source year, are the basis for the iterative fitting process. Comparing the three types of refinement can illuminate discussions about its application in source years, target years, or both.

Validation of tract level estimates will rely upon census block data, as proposed by Schroeder (2007), because the tract-level population estimates in 1990 and 2000 are calculated for the target zone boundaries of a different census decade (2010) and will not align with known population or attribute counts from census-produced summary tables in either source year. Interpolation error will be quantified using census block data from 1990 and 2000, which nests exactly within the source year zones and approximately within the 2010 target zones. Where census blocks in 1990 and 2000 do not nest entirely within a single 2010 target zone, simple AW will allocate block validation data to the appropriate target zone. This happens in only a few cases and is not expected to fundamentally alter the results.

Error metrics to be computed include mean and median errors, 90th percentile error and the root mean square error (RMSE) of population estimates. Metrics will be calculated for tracts characterized by substantial boundary change between decades, defined as an area difference of at least 50 pixels (at 30 m resolution) between a target zone and the source zone with which it has the largest areal intersection. Of Clark County's 487 tracts in 2010, 49.49% of the tracts exhibited substantial boundary changes since 2000, and 97.54% exhibited substantial boundary changes since 1990. Allegheny County's 402 tracts in 2010 exhibited a much lower rate of change, specifically 37.56% change from 2000, and 51.24% change from 1990 (Figures 2 and 3).

Visual inspection of the two figures shows clear differences in census tract boundaries for Las Vegas, with mostly stable boundaries in Pittsburgh. Legends are standardized in each figure to the year of highest densities (2010 in Las Vegas and 1990 in Pittsburgh). Population density is highly concentrated in Las Vegas in all three

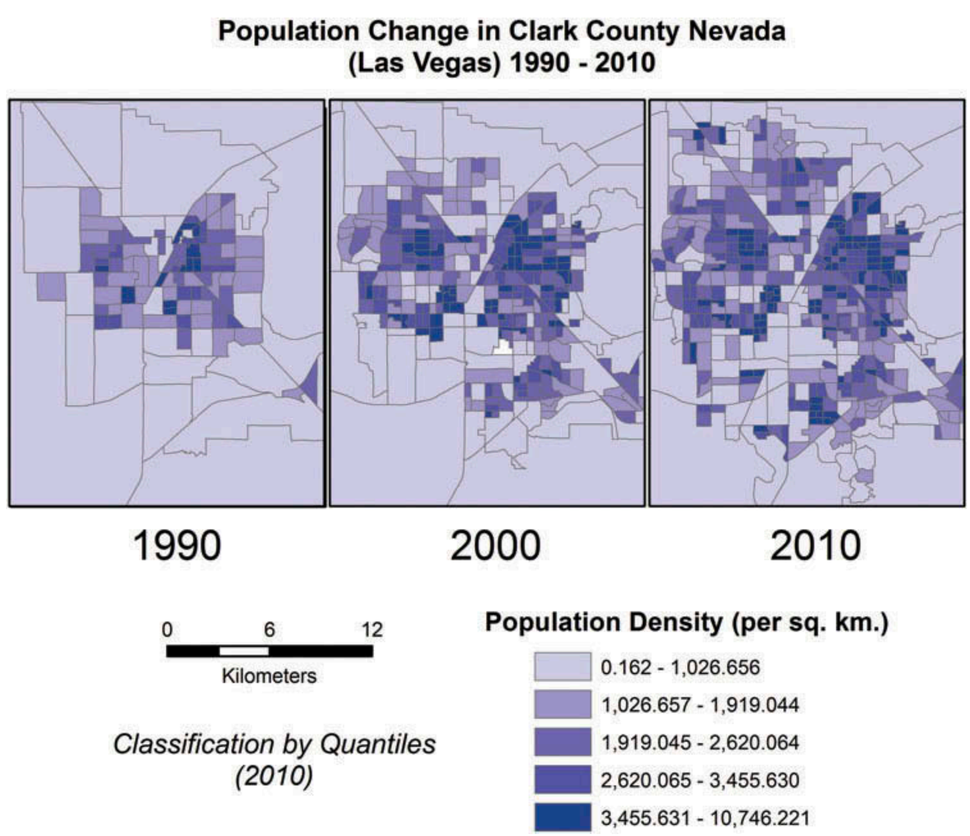

Figure 2. Three panels of central Las Vegas population density in 1990, 2000, and 2010 showing many census tract changes and dramatic increase in population density. The white tract in the middle panel had zero recorded population in 2000.

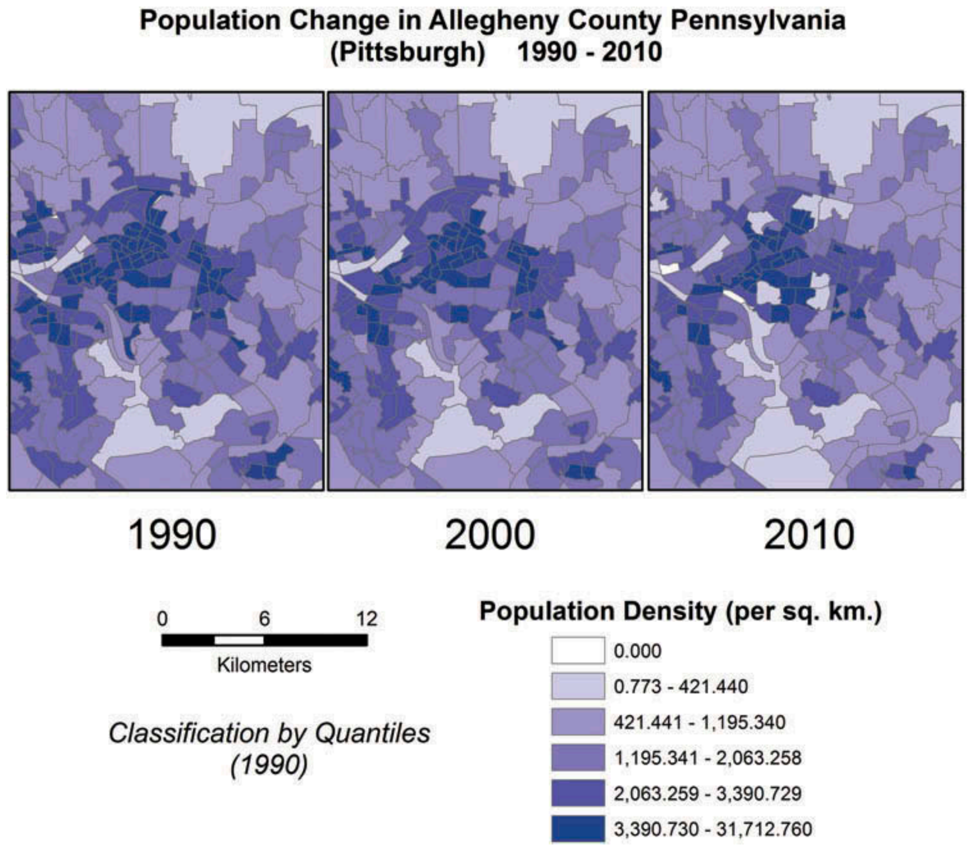

Figure 3. Three panels of Pittsburgh population density in 1990, 2000, and 2010, showing few tract boundary changes and relatively stable population. White tracts in the left and right panels had zero recorded population in 1990 and 2010, respectively.

time periods, dropping quickly as the edge of the city core is reached. In Pittsburgh, in contrast, concentrated population extends beyond the confines of the city core (the confluence of the three rivers sits at the central west edge of the panels). Overall, population densities are dropping in Pittsburgh between 1990 and 2010, and increasing as well as expanding in Las Vegas.

Results

Table 1 displays error measures for each interpolation method, with and without dasymetric refinements, for tracts whose boundary change between 2000 (or 1990) and 2010 was substantial. For the source year 2000, all metrics indicate that for Clark County, where population growth has been dramatic, the dasymetrically refined TDW interpolation has highest accuracy. For Allegheny County, TDW-DR shows highest accuracy on all metrics except for the median error metric, for which the dasymetrically refined AW shows highest accuracy. Recall that Allegheny County exhibits population stability or slight decline in the time

Table 1. Interpolation errors for tracts with substantial boundary change, by study area and decade.

		AW	AW-DR	TDW	TDW-DR	EM
2000 (Source)/2010 (Target)						
Allegheny	Mean	326	249	127	**101**	199
(N = 151)	Median	59	**36**	73	57	49
	90%	1088	974	317	**227**	627
	RMSE	775	627	205	**186**	453
Clark	Mean	741	546	457	**356**	428
(N = 241)	Median	448	309	313	**213**	274
	90%	1808	1240	1148	**880**	1010
	RMSE	1173	903	673	**535**	684
1990 (Source)/2010 (Target)						
Allegheny	Mean	271	181	163	**149**	155
(N = 206)	Median	74	70	110	96	**66**
	90%	672	435	370	336	**316**
	RMSE	631	378	233	**221**	**326**
Clark	Mean	667	380	516	363	**335**
(N = 475)	Median	349	168	305	216	**157**
	90%	1732	1079	1250	918	**896**
	RMSE	1069	659	760	**560**	592

Note: N refers to the number of substantially changed tract boundaries. Lowest errors are highlighted in boldface.

period. This suggests that within the contexts of stable population and stable extents of developed land, the dasymetrically refined AW method may perform adequately, despite its inherent assumption of uniform density within populated areas. For the 1990 source year, results are more mixed, with the highest accuracy metrics split evenly between TDW-DR and EM for Allegheny County, and three of four EM metrics performing best for Clark County.

Comparing each method against its dasymetrically refined counterpart, one can see that for these two counties, spatial refinement prior to interpolation improves accuracy somewhat in every case, and the accuracy improvement can be substantial. Generally, spatial refinement appears to improve the accuracy of interpolated estimates more for the AW method, relative to the TDW method. This can be computed directly from Table 1, by computing a ratio of the proportions for each measure in any single year. For example, the AW-DR for 2000 method improves mean error of AW for 2000 by 30.92% (326/249 = 1.3092), and median error by 44.44%. The 90th percentile error and RMSE improvements are more modest, at 11.70% and 23.60%, respectively. As an exception, the 90th percentile metric for TDW-DR improves accuracy by 39.65%, three times more than for AW-DR in 2000. This indicates that spatial refinement of TDW eliminates gross errors more effectively and it is logically given that refinement for this method involves both source and target time periods.

It is difficult to compare absolute errors (raw population counts) between source years, because the number of tracts undergoing significant change in 1990 and 2000 differs, as does the average population of those tracts. For a more objective comparison of performance among interpolation methods, the absolute error was standardized by actual tract population, using the block data for the respective census year. The median absolute standardized error was then computed for each study area (Table 2). While the proportion values compress the contrast between methods, the values are comparable.

Table 2. Median absolute standardized error for tracts with substantially changed boundaries, by study area and decade.

	AW	AW-DR	TDW	TDW-DR	EM
2000 (Source)/2010 (Target)					
Allegheny	0.02	0.01	0.03	0.02	0.01
Clark	0.42	0.30	0.24	0.22	0.26
1990 (Source)/2010 (Target)					
Allegheny	0.02	0.02	0.04	0.03	0.02
Clark	0.64	0.39	0.50	0.37	0.37
Drop in Accuracy when interpolating 2000 (source) versus 1990 (source)					
Allegheny	–	−0.01	−0.01	−0.01	−0.01
Clark	−0.22	−0.09	−0.26	−0.15	−0.11

Little difference in error metrics can be noted for Allegheny County for 1990 and 2000 source years; and once again it should be remembered that this metropolitan area exhibited mostly stable populations over the two decades studied. For Clark County however, accuracies in Table 2 drop substantially in 1990 relative to 2000. Looking at the third panel of Table 2, the differences between median errors for nonrefined and refined interpolation methods indicate that refinement dampens this effect somewhat. For example, the accuracy differences for Clark County when interpolating 1990 to 2010 versus 2000 to 2010 show a drop of 15% or less in standardized median accuracy when spatial refinement preceded interpolation, versus dropping accuracies of 22–26% when refinement was not utilized. Table 2 also shows that the EM method performs similarly well in comparison with the TDW-DR method in both study areas and years, and better than the AW-DR and the unrefined methods. Relative to other methods, the interpolation performance of the EM method decreases less when using the 1990 source data versus the 2000 source data.

It is helpful to evaluate the spatial pattern of error for the interpolation methods, focusing upon the changing accuracy patterns that manifest when dasymetric refinement is introduced. Figure 4 shows maps for a central portion of Las Vegas County highlighting changes in absolute standardized error that refinement may cause for each interpolation using 1990 as source year and 2010 as target year. Tracts shown in shades of light or dark blue have larger errors following spatial refinement; and tracts in light and dark brown have smaller errors. Because refinement is inherent in the EM method, there is no unrefined estimate against which to compare. In the figure, all EM standardized errors are reported as positive. The unrefined spatial error is essentially unknown for this interpolation method. Tract boundaries are shown in red, with tracts outlined in black indicating places where population did not change from 1990 to 2010. Interpolated estimates for unchanged tracts have zero error. White tracts were interpolated but cannot be evaluated because no population was reported for blocks within these tracts. The legend has been standardized so that the patterns in all three panels are visually comparable. The extreme values for AW error are −114.000 and 395.667; the extrema for TDW are −496.000 and 387.000; and the maximum positive error for EM is 46.000.

Effects of spatial refinement in Clark County are distinct, showing larger positive errors that are somewhat concentrated in the larger tracts at the edge of the metropolitan area, where population growth is most marked in the 1990–2010 period. With many changes to tract boundaries in peripheral tracts, the spatial refinement can provide small area estimates that are much closer to the block population counts. In the center of Las Vegas,

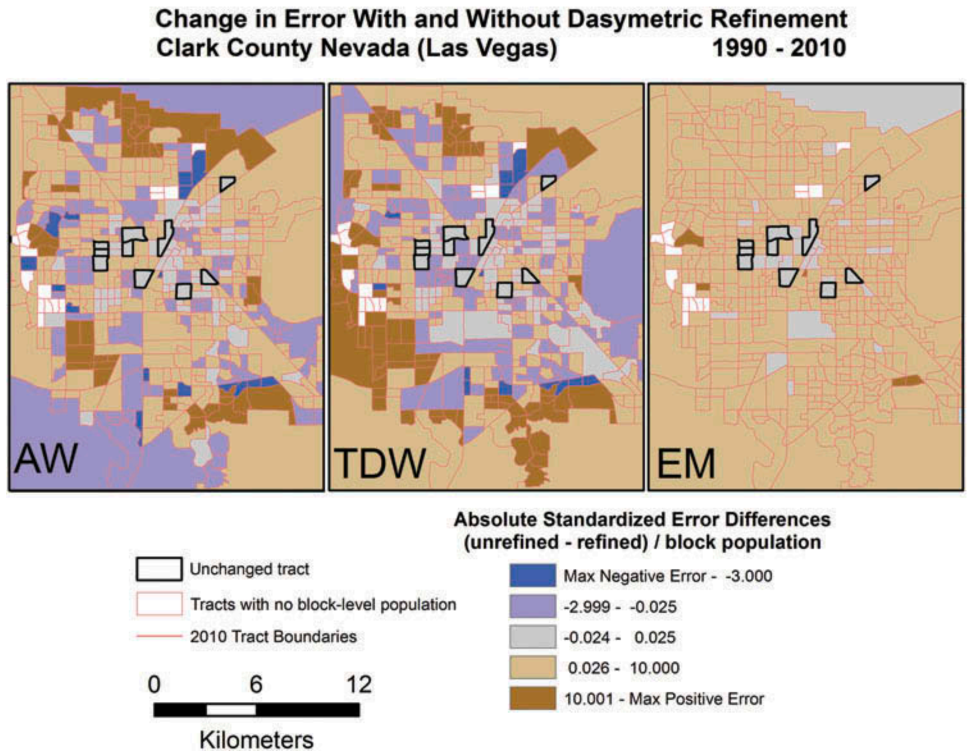

Figure 4. A comparison of standardized interpolation errors for three interpolation methods (AW, TDW, EM) for Las Vegas, with and without prior spatial refinement. Negative values (blue) indicate higher error without spatial refinement; and positive values (brown) indicate higher error with prior refinement. Tracts outlined in black identify populations that did not change from 1990 to 2010.

where neighborhoods are older and hold more stable populations, estimates of tract population appear to be less affected by refinement and interpolation errors are less extreme.

In comparing TDW with AW, the effect of spatial refinement appears to generate high positive errors in more outlying tracts, and at the same time reduces lower positive errors in the central city core. This assessment is based on the increased number of light brown tracts in the AW panel that are gray in the TDW panel. The darkest blue tracts (highest negative errors, indicating more error in the unrefined estimates) are nearly identical for the two interpolation methods. The EM error pattern differs dramatically from the other two in some part because there is no unrefined interpolation against which to compare results. Error differences between the two time periods are lower overall, implying that for a fast-growing population over a 20-year period, the EM method may be preferable to either AW or TDW.

Figure 5 shows the same type of error difference maps for the three types of interpolation for a central portion of Pittsburgh, in Allegheny County. One can easily see the confluence of the Monongahela, Allegheny, and Ohio Rivers marking the central (downtown) area at the far west side of the map panels. The legend makes clear that the range of error values is compressed, relative to Figure 4, and this reflects a smaller error difference with and without spatial refinement that marks a region of stable population counts. Extreme values for AW are −23.2 and 243.00; for TDW the values are −13.850 and 0.259; and for EM (with no negative error values again) the maximum positive error value is 91.000.

The Pittsburgh data show many more tracts with (essentially) zero error difference. The AW map indicates a number of tracts showing high positive error differences; here, unrefined interpolation errors are high. The area highlighted in the center of the AW panel is called Polish Hill, one of the older blue collar ethnic neighborhoods in the city that was losing population in 1990. The unrefined AW method seriously over-estimated this population, whereas the TDW method slightly underestimated it, and EM underestimated it to a greater degree. Tracts immediately north of the Allegheny River (in the North Hills neighborhoods) are underestimated by all three methods. Estimation errors appear to be most widespread with the EM method. It would appear that overall none of these methods does a particularly good job of small area estimation in regions where populations are stable.

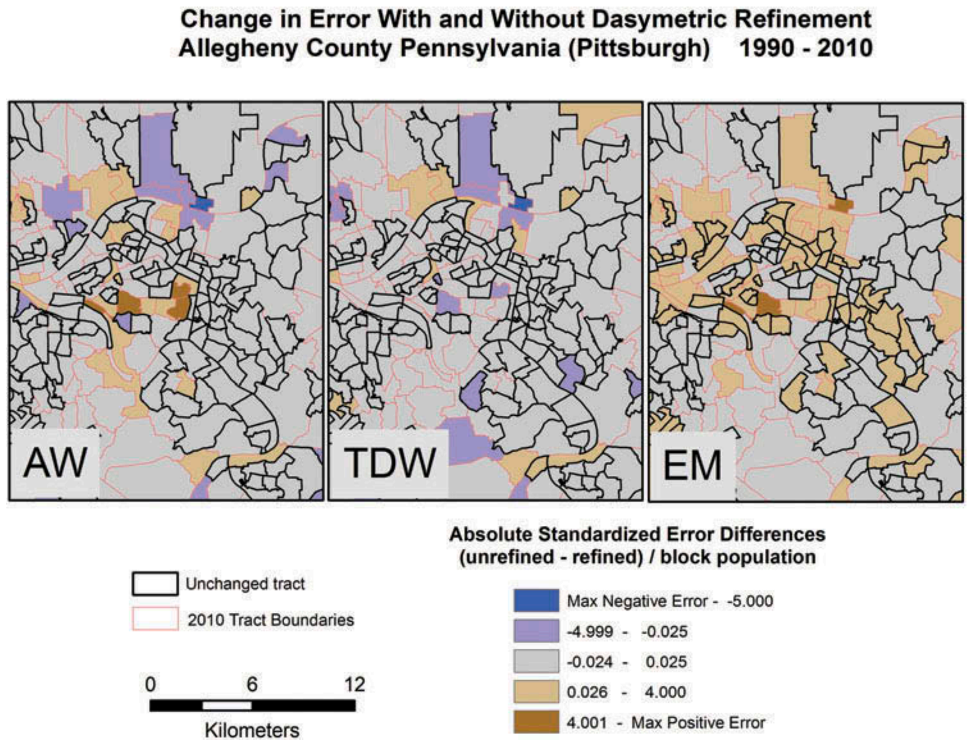

Figure 5. A comparison of standardized interpolation errors for three interpolation methods (AW, TDW, EM) for Pittsburgh, with and without prior spatial refinement. Negative values (blue) indicate higher error without spatial refinement; and positive values (brown) indicate higher error with prior refinement. Tracts outlined in black identify populations that did not change from 1990 to 2010.

Discussion

This paper reports a systematic comparison of multi-temporal areal interpolation methods for two American metropolitan areas and examines the impact of dasymetric refinement on estimation accuracy. The interpolations span a 20-year period extending from 1990 to 2010. One area (Clark County, Nevada) contains Las Vegas, a region exhibiting dramatic population growth, and the other (Allegheny County, Pennsylvania) contains Pittsburgh, whose population has been relatively stable. Two interpolation methods (AW and TDW) are run twice for each method in each metropolitan area, incorporating dasymetric refinement in one instance and leaving it out in the other. The purpose of comparison is first, to assess the effects of prior dasymetric refinement on interpolation accuracy, and second, to examine these effects in two very different demographic contexts.

Both the error metrics and the error maps indicate the benefits of prior spatial refinement on interpolation accuracy in the three interpolation methods. This finding is especially important since each interpolation method integrates spatial refinement in a slightly different manner, incorporated respectively from the source period (AW), the source and target periods (TDW), and used implicitly in a maximization fitting process (EM). Spatial refinement is shown in all metrics for each city and each method to improve interpolation accuracy and the implication is that the processing stage at which it is incorporated matters less than the fact that refinement happens somewhere along the line.

The question of demographic contexts for which refinement improves accuracy most markedly cannot be definitively answered without studying additional cities with different temporal demographic structures. Examples of other demographic contexts might include a region experiencing dramatic population decline, or one characterized by sudden within-region migration, as for example, the various forms of "white flight" in Detroit, Michigan, Cleveland, Ohio, or Atlanta, Georgia, in the mid-1960s (Kruse 2007), or an urban area experiencing modest growth, as for example, Cincinnati, Ohio. Exploration of a variety of demographic contexts forms an area for ongoing research.

Among the three methods compared, the dasymetrically refined TDW provides the overall best performance for the 2000 source data and the EM method gives the overall best performance for the 1990 source data. The TDW method uses NLCD land cover data for both source and target years to guide interpolation of population estimates in the source years within 2010 census target units.

As the length of time increases between the source census and the target census, target population density and land cover become less accurate predictors of source year population density. This may be especially salient in fast-growing regions, and may explain at least partially the very large errors observed in the TDW method in Las Vegas. In contrast, the EM algorithm uses only the distribution of the ancillary land cover variable in the source year, and may be the preferred approach over TDW as temporal spans increase.

Few prior studies comparing various areal interpolation methods have compared differences in errors that emerge over differing time periods. One objective of this paper has been to assess disparities in performance by duration of interpolation interval. The errors calculated from the 1990 source zone estimates are similar to the errors from the 2000 source zone estimates and smaller according to some metrics, although statistical significance is not assessed. It is possible that longer time spans might negate this similarity, but additional time periods were not examined here. This sensitivity to the length of the time period represents another avenue that needs to be explored in greater detail, differentiated for various demographic settings and extended periods of time.

As data and ancillary data for longer time periods (e.g., 1940 census data, land cover pre-dating 1992) become digitally available, one might reasonably argue for an examination of incremental interpolation, meaning to use 1990 population to estimate 2000, and then use 2000 to estimate 2010. The disadvantage of additional incremental computations may be offset by the advantage of introducing periodic adjustments to avoid possible interpolation drifts, or choosing increments that provide more reliable ancillary data sources. Here lies another area of research that may be insightful.

One limitation of this study is related to the previous point. The temporal mismatch between the compilation dates of the NLCD and the census tract data is quite small (only 2 years for the 1990 source year and 1 year for the 2000 source year) and yet it is difficult to know in a fast-changing metropolitan area whether such time lags introduce a source of error that cannot be taken into account directly. In particular, rapid shifts in undeveloped land and residential land might not be captured which could lead to unreliable estimations. The NLCD data are also based on imagery collected over some duration of time prior to the compilation date, complicating its use in dasymetric refinement within fast-growing areas like Las Vegas. An additional area for further investigation involves the use of multiple sources of ancillary data, for example, to intermix land cover with parcel data, road density measurements, or orthophotography to establish more reliable determinations of residential areas and their spatiotemporal patterns.

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