

# Mapping changes in spatial patterns of racial diversity across the entire United States with application to a 1990–2000 period

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## Abstract

Changes in racial configuration patterns are affected by uneven population growth of different racial/ethnic groups and by modification of social attitudes. A comprehensive assessment of these changes is important for effective policy-making. Conventional assessments, which rely on tabular census data, are restricted to a handful of major metropolitan areas and do not provide spatial information. Here we propose using high resolution categorical demographic grids to assess and map spatio-temporal changes in racial configuration patterns over the entire United States. Recently published demographic grids for the years 1990 and 2000 are classified into neighborhood types based on the local level of diversity and the dominant race. Codifying the 1990-2000 transitions of neighborhood types for all grid cells yields a transition grid, which provides raw information for all subsequent assessments. The change is evaluated from three different perspectives: overall statistics, mapping, and neighborhood topology. A change diagram visualizes diversity change from statistical perspective using transitions collected from the entire U.S. Change map reveals complex spatial transitions between different neighborhood types; examples of change maps for metropolitan areas of Chicago, San Francisco, and Houston are shown and described. Topologies of spatial change for various neighborhood types are also visualized showing the specific manner of transition from one type of neighborhood to another. Presented methodology opens the door to much more comprehensive and in-depth assessment of changes of racial and diversity patterns.

**Keywords:** mapping racial diversity, high-resolution population grid, demographic change, racial classification, dasymetric modeling

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## 1. Introduction

Spatial segregation along racial and ethnic lines is a continuing reality of American social structure, but shifting social attitudes results in a gradual increase of residential racial diversity (Iceland et al., 2002). In addition, changes in the U.S. demographic makeup, in particular, significant increases of Hispanic and Asian populations (Iceland, 2004), transforms America's racial configuration from a binary paradigm (for example, a Black/White dichotomy) to a much more complex multi-racial pattern (Iceland, 2004). Thus, a thorough geospatial analysis of the U.S. racial configuration dynamics requires tracking temporal changes in a multi-class spatial pattern over the entire country at a high spatial resolution. No such analysis presently exists because the long-standing methodologies of measuring

residential segregation and diversity are not designed to address the problem in as comprehensive a fashion as stated above.

Because of a significant interest in the issue of racial configuration there exists a significant body of literature on the topic. A common thread to all previous analyzes is a demographic data model based on the U.S. Census Bureau aggregation areal units, such as census tracts or blocks. Consequently, the scope of previous investigations, analytical tools developed for these investigations, and even the nomenclature used, are heavily influenced by the character of this "tabular" data model. We submit that tabular data model impedes analysis of racial segregation and diversity as summarized in the next three paragraphs.

Residential racial segregation – the physical separation of two or more groups into different neighborhoods (Massey and Denton, 1988) – has been the major focus of previous research, with segregation indices be-

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ing the analytical tool of choice. A large number of segregation indices, later shown (Massey and Denton, 1988) to measure five independent aspects (evenness, exposure, centralization, concentration, and clustering) of two-group segregation, were proposed. These indices characterize a region (most often a metropolitan statistical area or MSA) and are calculated using demographic data assigned to the region's sub-divisions (most often census tracts or blocks). Most proposed indices are aspatial (White, 1983, 1986; Massey and Denton, 1987, 1988) although some do incorporate spatial relations between sub-divisions (Jakubs, 1981; Morgan, 1982; Reardon and Sullivan, 2004; Dawkins, 2004; Wong, 2004; Brown and Chung, 2006). The shortcomings of segregation indices include dependence on the scale of sub-divisions (for example, tracts vs. blocks) (Parisi et al., 2011) and difficulties with change assessment due to census-to-census changes in delineations of sub-divisions (Reardon et al., 2009). Also, indices-based analysis does not address the issue of diversity at a neighborhood scale, as diversity is defined only at a regional scale. Given the character of segregation indices analysis, a typical result is in a form of a table that compares the values of indices between different MSAs or between different years for the same MSA.

As the U.S. is a multi-racial rather than a bi-racial society, two-group measures of segregation were recognized as insufficient, and multigroup indices, the most prominent of these being the Theil information theory index (Theil, 1972), were developed (Reardon and Firebaugh, 2002) and applied to characterize diversity at regional scale (Iceland, 2004; Farrell, 2008). In comparison to the segregation indices the Theil index provides additional and often more relevant information on racial configuration within a region, but it still suffers from the same limitations as segregation indices due to the reliance on the tabular data model. As the Theil index and two-group segregation indices are region attributes, they are predominantly calculated for prominent regions, such as MSAs (Frey and Farley, 1996; Logan et al., 2004; Johnston et al., 2007; Farrell, 2008; Farrell and Lee, 2011) with only a few analyzes quantifying rural areas and small towns (Cromartie and Kandel, 2004; González Wahl and Gunkel, 2007; Lichter et al., 2007; Lichter, 2012).

Recent research (Holloway et al., 2012; Wright et al., 2014) breaks away from the reliance on indices as a tool to assess and quantify the U.S. racial configuration and moves toward a more cartographic approach to the problem. In such an approach, neighborhoods (census tracts) are classified into a number of types on the basis of a combination of segregation and diversity criteria.

The results are presented in the form of thematic map that explicitly shows the geography of racial diversity and segregation. Temporal change can be assessed by comparing maps constructed from data gathered at two different times. This method is a major step forward but still inherits the limitations of the tabular data model: poor spatial resolution outside MSAs and the possible incompatibility of areal units as delineated at different years.

In this paper we propose studying racial configuration in the U.S. and its temporal change using a raster data model instead of a tabular model. This is feasible due to recent availability of high resolution demographic grids for the entire U.S. (Dmowska and Stepinski, 2014). Cells in these grids have categorical values corresponding to several diversity/dominant race types (DDRTs). This allows us to think about the underlying data in terms of "human cover" in an analogy to the concept of a "land cover" in the field of remote sensing. Thus, we can analyze human cover patterns and their temporal change using robust methods already developed for the analysis of land cover. This method of analysis, intrinsically different from previous approaches, yields an in-depth assessment of racial configuration dynamics in a lucid form that could be used to inform decision makers responsible for the efficient allocation of economic, health, administrative, and law enforcement resources to a population going through changes in its racial makeup. We focus on analyzing change during the 1990–2000 period as the grids are presently available only for these two years. However, the more recent 2000–2010 change could be analyzed using the same method once 2010 grid becomes available.

## 2. Data and Methods

### 2.1. Population and diversity/dominant race grids

The U.S.–wide high resolution demographic grids by Dmowska and Stepinski (2014) constitute an input to our analysis. We refer a reader to that paper regarding detailed information on the method used to construct those grids. In the rest of this sub-section we briefly recount the computational process leading to obtaining DDRT grids.

Dmowska and Stepinski (2014) start by applying dasymetric modeling (Wright, 1936) to coarse, 1 km grids previously developed by the Socioeconomic Data and Application Center (SEDAC) (Seirup et al., 2012). SEDAC grids are products of a simple areal weighting interpolation from census blocks. They are disaggregated from 1 km to 90m resolution using dasymetric

137 model with the National Land Cover Dataset (NLCD) 187  
138 land cover 1992 and 2001 data as an auxiliary variable. 188  
139 Because 1992 and 2001 editions of NLCD have differ- 189  
140 ent legends, a dasymetric model does not use the main 190  
141 land cover categories of each NLCD edition. Instead, 191  
142 it uses the NLCD 1992/2001 retrofit product (Fry et al., 192  
143 2009) which classifies land cover into a smaller number 193  
144 of more generalized classes which, however, are com- 194  
145 mon to 1992 and 2001. 195

146 Dasymetric modeling works for disaggregating total 196  
147 population because of the correlation between the type 197  
148 of land cover and the total population density. How- 198  
149 ever, there is no robust correlation between land cover 199  
150 type and the density of population belonging to a given 200  
151 race/ethnicity group. Thus, members of race/ethnicity 201  
152 groups located within a coarse 1km SEDAC grid cell 202  
153 are disaggregated using weights established for the en-  
154 tire population. This means that in each populated 90m  
155 cell the relative percentages of different race/ethnicity  
156 groups is the same as in the entire coarse 1km cell,  
157 but the disaggregation improves information on the spa-  
158 tial distribution of different groups inasmuch as it shifts  
159 people away from uninhabited or sparsely inhabited ar-  
160 eas.

161 Using population and race grids all inhabited grid 209  
162 cells are classified into 11 diversity/dominant race types 210  
163 (DDRTs) taking into consideration the level of diver- 211  
164 sity and the dominant race. Demographic information 212  
165 in a cell is encapsulated by a normalized histogram 213  
166 whose bins represent the proportions of a cell's popu- 214  
167 lation belonging to different racial/ethnic groups. Five 215  
168 race/ethnicity groups: white, black, Hispanic, Asian, 216  
169 and other are considered. Following (Holloway et al., 217  
170 2012) the racial diversity of a cell is classified on the 218  
171 basis of the standardized informational entropy  $E$  of 219  
172 its histogram with modifications made to ensure agree- 220  
173 ment between obtained classes and customary notions 221  
174 of group dominance (Farrell and Lee, 2011). 222

175 All inhabited cells are classified into three diversity 223  
176 types: 224

- 177 • **Low diversity** type if the histogram fulfills two con- 225  
178 ditions: (1)  $E < 0.41$ , and (2) the dominant race 226  
179 constitutes more than 80% of a cell's population. 227
- 180 • **High diversity** type if the histogram fulfills three 228  
181 conditions: (1)  $E > 0.79$ , (2) the dominant race 229  
182 constitutes less than 50% of a cell's population, 230  
183 and (3) the sum of the two most dominant races 231  
184 constitutes less than 80% of a cell's population. 232
- 185 • **Moderate diversity** type if the cell does not belong 233  
186 to either high or low diversity types. 234  
235

Two of the three diversity types (low and moderate di-  
versity) are further sub-divided with respect to five possi-  
ble dominant races resulting in 11 DDRTs. Note that,  
by definition, the high diversity type does not have a  
dominant race and does not need further division. Using  
this classification scheme categorical grids of DDRTs  
for 1990 and 2000 are constructed. These grids form  
the basis for our analysis of spatio-temporal change in  
racial configuration during the 1990s. Each grid has 12  
categories, 11 DDRTs and an "uninhabited area." They  
can be viewed using the SocScape (Social Explorer) – a  
GeoWeb application designed for fast and intuitive ex-  
ploration of population and diversity patterns starting at  
the scale of the entire U.S. and progressing down to the  
scale of an individual street. SocScape is accessible at  
<http://sil.uc.edu/>.

## 2.2. Transition matrices

The first aspect of racial diversity dynamics is an  
overall change in the membership of individual DDRTs  
between 1990 and 2000. The term "DDRT member-  
ship" denotes the entire population living in a region  
consisting of grid cells having a given DDRT label. Pre-  
vious research (Wright et al., 2014) quantified national  
change in diversity using a transition matrix which enu-  
merated how many census tracts of a given DDRT in  
an earlier year transitioned to various DDRTs in a later  
year. We can construct an analogous matrix by enumer-  
ating cell instead of tracts transitions. As the cells are  
spatial units, such a transition matrix will account for  
changes in areal occupancy of different DDRTs, but, we  
are more interested in changes to membership of var-  
ious DDRTs. Because we keep the full demographic  
information about each cell we can convert a cell-based  
transition matrix into a membership transition matrix.  
A membership transition matrix enumerates how many  
people living in a given DDRT in 1990 found them-  
selves living in various DDRTs in 2000. The member-  
ship transition matrix has a size of  $11 \times 11$  correspond-  
ing to 11 DDRTs in each of the two years. The matrix is vi-  
sualized using a change diagram (Fig. 1).

## 2.3. Mapping change

The second aspect of racial diversity dynamics is a  
change in spatial coverage of DDRTs. Mapping the  
change in areal coverage of various DDRTs is necessary  
for understanding the local details of diversity spatial  
dynamics. The usual way to illustrate change in areal  
coverage, both in remote sensing and in diversity studies  
(Wright et al., 2011; Holloway et al., 2012; Dmowska  
and Stepinski, 2014; Wright et al., 2014), is to show two

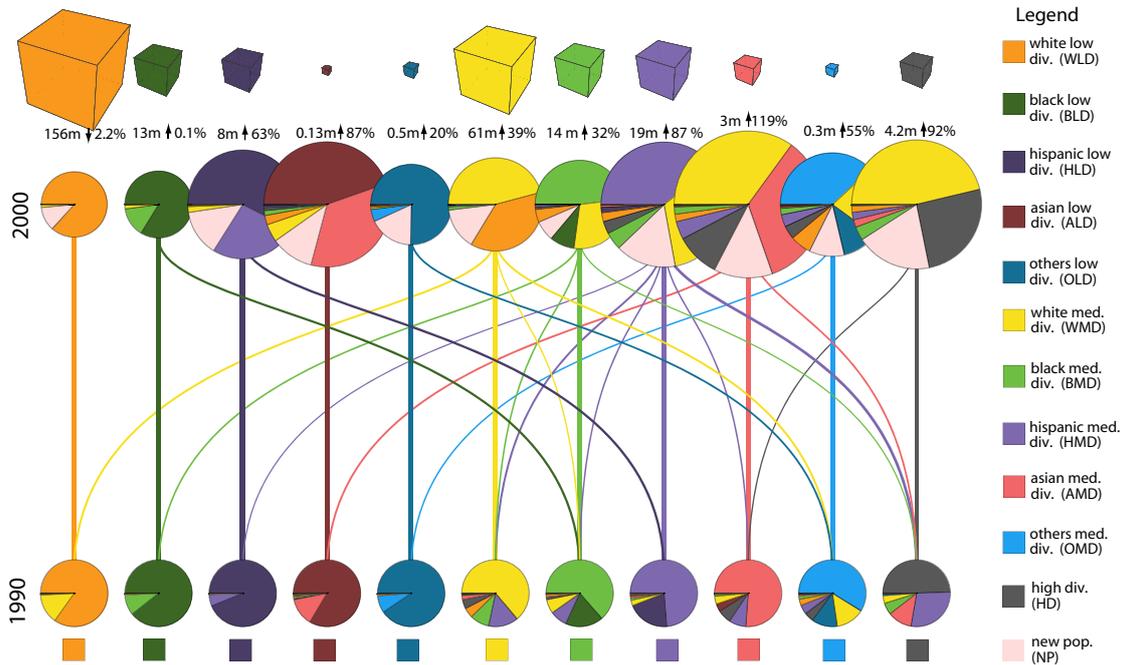


Figure 1: Change diagram summarizing 1990-2000 transitions of population between different diversity/dominant race neighborhood types. Diagram pertains to the population of the entire conterminous U.S. See the main text for a detailed description of the diagram.

236 maps (corresponding to two different years) for a side-  
 237 by-side comparison. We have found this method to be  
 238 adequate for an overall impression of the change but in-  
 239 sufficient for an in-depth description. To best convey the  
 240 complex dynamics of areal change we have developed a  
 241 visualization method that explicitly shows all transitions  
 242 in a single map. The raster map with all  $12 \times 12 = 144$   
 243 possible transitions between cell labels is converted to  
 244 a vector (shapefile) format and generalized to eliminate  
 245 very small regions. Unchanged areas are shown in the  
 246 original colors as assigned to the DDRTs, while the areas  
 247 which experienced transitions are shown in stripes –  
 248 with the color of the broader strip indicating the DDRT  
 249 in 2000 and the color of the narrower stripe indicating  
 250 the DDRT in 1990.

#### 251 2.4. Landscape metrics

252 The third aspect of racial diversity dynamics is the  
 253 change in the extent and topology of an area occupied  
 254 by each DDRT. Although it is possible to characterize  
 255 such change on the scale of the entire U.S. it is more  
 256 telling to characterize it for a collection of MSAs. We  
 257 perform our spatial analysis on a collection of 37 MSAs  
 258 distributed across all geographical regions of the U.S.  
 259 Like any other categorical (thematic) map, the map of

260 DDRTs constitutes a spatial pattern or, in ecological  
 261 terms, a “landscape.” Landscape metrics (Haines-Young  
 262 and Chopping, 1996), originally developed for applica-  
 263 tion in ecology, are algorithms that quantify the specific  
 264 spatial characteristics of a landscape pattern. For the  
 265 purpose of characterizing the extent and topology of an  
 266 area occupied by a given DDRT we use two metrics,  
 267 PLAND (percentage of landscape) which gives the per-  
 268 centage of an MSA area occupied by a DDRT, and the  
 269 aggregation index (AI).

270 An aggregation index (He et al., 2000) is a class  
 271 (DDRT)–specific landscape metric designed to work  
 272 with raster data and independent of PLAND. Let  $e_i$  rep-  
 273 resent the total number of edges that an  $i$ -th DDRT  
 274 shares with itself (as opposed to edges shared with other  
 275 DDRTs in the region under consideration). The value of  
 276 AI is the value of  $e_i$  divided by the maximum possible  
 277 number of like adjacencies involving the given DDRT  
 278 multiplied by 100 (to convert to a percentage). Thus,  
 279 the theoretical range of values for both PLAND and AI  
 280 is between 0 and 100. The maximum aggregation level  
 281 (AI=100) is reached when raster cells making up a given  
 282 DDRT areal clump into one compact patch. The mini-  
 283 mum aggregation level (AI=0) is reached when the en-

284 tire DDRT area consists of individual disjointed cells. 334  
285 The actual ranges of PLAND and AI, as calculated for 335  
286 our selection of MSAs, are narrower and vary from one 336  
287 DDRT to another. 337

288 To analyze tendencies in the spatial evolution of areas 338  
289 occupied by a given DDRT we construct a PLAND-AI 339  
290 diagram on which each MSA is represented by an arrow 340  
291 starting at the point (PLAND, AI)<sub>1990</sub> and ending at the 341  
292 point (PLAND, AI)<sub>2000</sub>. 342

### 293 3. Results 343

#### 294 3.1. Statistics of change 344

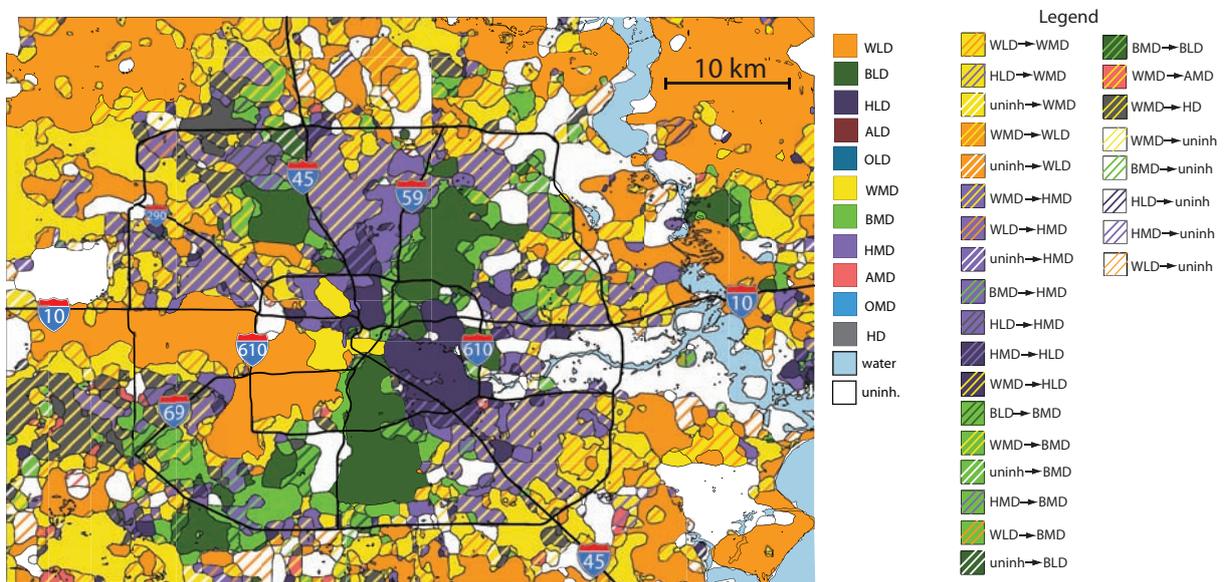
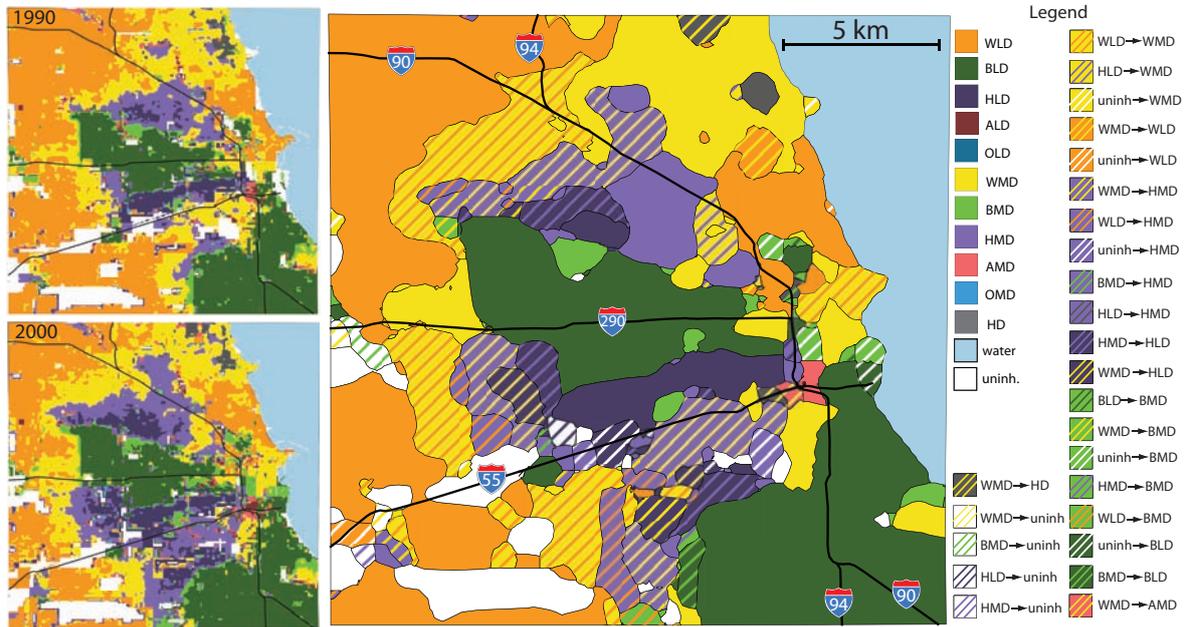
295 Fig. 1 visualizes all the information from the 1990– 347  
296 2000 DDRT membership transition matrix. DDRTs are 348  
297 color-coded as shown in the legend. The names of 349  
298 DDRTs in the legend indicate the dominant race and 350  
299 the level of diversity. Hereafter we refer to different 351  
300 DDRTs by abbreviations of their names as indicated 352  
301 in the legend. The lower row of pie-diagrams pertains 353  
302 to DDRTs membership in 1990. Sizes of the 1990 354  
303 pie-diagrams are normalized to the same size. Sectors 355  
304 of a 1990 pie-diagram correspond to percentages 356  
305 of a given DDRT’s 1990 membership transitioning to 357  
306 2000 DDRTs. Thus, for example, 85% (orange sector) 358  
307 of the 1990 WLD membership transitioned to the 359  
308 2000 WLD while 14% (yellow sector) transitioned to 360  
309 the 2000 WMD. Note that the term “transitioned” does 361  
310 not refer to direct spatial movement of people but rather 362  
311 to a reclassification of their neighborhood as a result 363  
312 of multiple factors including, but not limited to, spatial 364  
313 movement. The upper row of pie-diagrams pertains 365  
314 to DDRTs membership in 2000. Sizes of the 2000 pie- 366  
315 diagrams are in proportion to 1990–2000 membership 367  
316 increases/decrease of corresponding DDRTs. Sectors of 368  
317 a 2000 pie-diagram correspond to percentages of a given 369  
318 DDRT’s 2000 membership coming from 1990 DDRTs. 370  
319 Again, the term “coming from” refers to reclassification 371  
320 of neighborhood rather than physical movement. 2000 372  
321 pie-diagrams have also an additional sector accounting 373  
322 for population growth between 1990 and 2000. Thus, 374  
323 for example, 45% (maroon sector) of the 2000 ALD 375  
324 membership came from the 1990 ALD, 35% (red sector) 376  
325 came from the 1990 AMD, while 11% (pink sector) 377  
326 is due to population growth. Transfers larger than 5% 378  
327 of membership are illustrated by lines connecting the 379  
328 1990 DDRTs with the 2000 DDRTs; the widths of the 380  
329 lines are proportional to the percentage of the transfer. 381  
330 The row of cubes illustrates the absolute size of DDRTs 382  
331 membership in 2000; actual numbers (in millions), as 383  
332 well as the percentage of change from 1990, are also 384  
333 given.

The Fig. 1 diagram contains rich information about 334  
dynamics of various DDRTs. In general, only the WLD 335  
lost membership (mostly to the WMD) but remained by 336  
far the largest DDRT in the U.S. The membership of 337  
the BLD remained stable while undergoing some back 338  
and forth exchange with the BMD. The memberships 339  
of AMD, HD, ALD, HMD, and HLD experienced large 340  
relative gains. The 92% growth of the HD membership 341  
came mostly from converting the WMD neighborhoods 342  
to higher diversity neighborhoods. The growth of AMD 343  
and HMD memberships also came from converting the 344  
WMD neighborhoods. However, the WMD member- 345  
ship experienced 32% gains itself at the expense of the 346  
WLD neighborhoods and remained the second largest 347  
DDRT. The growth of ALD and HLD memberships 348  
came mostly from the incorporation of AMD and HMD 349  
neighborhoods, respectively. The neighborhoods domi- 350  
nated by Asians (ALD and AMD) were the fastest grow- 351  
ing but remained small in absolute terms. The neigh- 352  
borhoods dominated by Hispanic population (HLD and 353  
HMD) were also fast growing and much larger in abso- 354  
lute terms than those dominated by the Asian popula- 355  
tion. 356

#### 357 3.2. Spatio-temporal change 358

U.S.-wide statistics succinctly reveal the changes in 359  
racial configuration during the 1990s at the scale of the 360  
entire country but do not reveal any information about 361  
the spatial aspects of those changes. To analyze changes 362  
in areal cover of various DDRTs we constructed a U.S.- 363  
wide change map as described in section 2.3. Fig. 2 364  
shows a fragment of this map covering the Chicago, Illi- 365  
nois region. The two smaller maps in Fig. 2 show the 366  
spatial extents of various DDRTs in 1990 and 2000, re- 367  
spectively. A comparison of the two maps reveals the 368  
expansion of areas dominated by the Hispanic popula- 369  
tion and contraction of areas dominated by the white 370  
population. However, a more detailed analysis of the 371  
spatial dynamics is difficult-to-impossible using a side- 372  
by-side comparison of the two maps. The main map 373  
in Fig. 2 shows spatial change in a way that permits a 374  
detailed analysis. There are 24 different DDRT transi- 375  
tions within the mapped region but most of them involve 376  
small areas. 377

The major racial configuration dynamic in the 378  
Chicago region involves the transition of white- 379  
dominated neighborhoods into Hispanic-dominated 380  
neighborhoods. There are two main locations where 381  
such transitions occur. The first location is along I-55 382  
and the second is along the northern stretch of I-90,94. 383  
In the first location the Hispanic-dominated areas ex- 384  
panded to the west and to the south from the centrally-



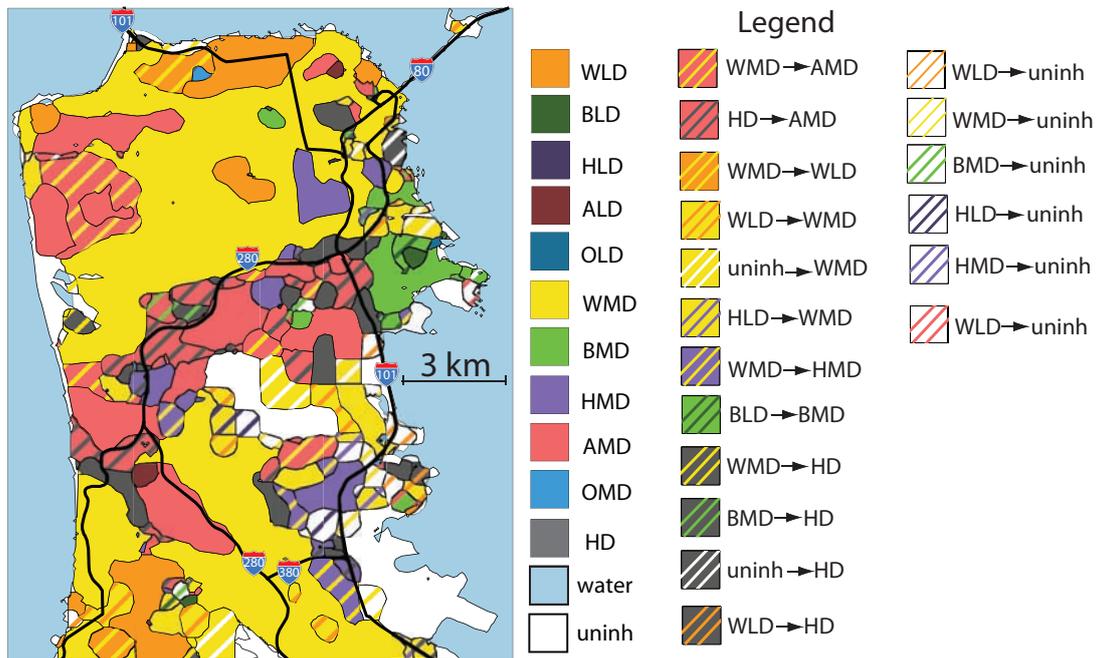


Figure 4: Map of areal change of different diversity/dominant race neighborhood types in San Francisco, California during the period of 1990-2000. Major highways are mapped for spatial reference.

385 located HLD area. The expansion to the west clearly  
 386 shows a westerly progression of transitions. The HMD  
 387 area immediately adjacent to the central HLD area  
 388 transitioned into HLD. Next, the previously WMD area  
 389 (which already included a minority of Hispanics)  
 390 transitioned to the HMD area, and finally, the WLD area  
 391 transitioned into the WMD area due to an increasing number  
 392 of Hispanics. The expansion of Hispanics from the  
 393 centrally-located HLD area to the south resulted in the  
 394 transition of the WMD area into the HMD area. In the  
 395 north a similar series of transitions took place in a north-  
 396 western direction. There has been no expansion of  
 397 the Hispanic population into black-dominated neighbor-  
 398 hoods. The boundaries of black-dominated neighbor-  
 399 hoods (overwhelmingly consisting of BLD) remained  
 400 stable during the 1990s. The small AMD area almost  
 401 doubled in size by changing the makeup of the adjacent  
 402 WMD neighborhood. A small HD neighborhood  
 403 appeared in the northernmost extent of the mapped region  
 404 where the WMD neighborhood existed in 1990.

405 Fig. 3 shows the changes in racial configuration dur-  
 406 ing the 1990s in the Houston, Texas region. The racial  
 407 dynamic in the Houston region resembles the dynamic  
 408 in the Chicago region inasmuch as its major feature is  
 409 the expansion of Hispanic-dominated areas at the ex-

410 pense of the white-dominated areas. As in Chicago,  
 411 the progression of transitions from HLD to WLD took  
 412 place along preferred directions of this expansion. The  
 413 boundaries of black-dominated neighborhoods in Hous-  
 414 ton were less stable than in Chicago as some transi-  
 415 tions from BLD to BMD or even to HMD did occur.  
 416 Thus, unlike in Chicago, mixed, black-Hispanic neigh-  
 417 borhoods emerged in the 1990s. Houston also devel-  
 418 oped more HD areas than Chicago, they all transitioned  
 419 from the WMD areas.

420 Fig. 4 shows the changes in racial configuration dur-  
 421 ing the 1990s in the San Francisco, California region.  
 422 The racial dynamic in the San Francisco region is dif-  
 423 ferent from what we observed in Chicago and Houston  
 424 as the major feature is an expansion of Asian-dominated  
 425 areas. They have expanded into what in 1990 were  
 426 white-dominated and HD areas. Hispanic-dominated  
 427 areas, small in 1990, expanded slightly into WMD ar-  
 428 eas, and WLD areas expanded into the WMD areas.  
 429 Thus, the second major feature of racial dynamics in  
 430 the San Francisco area is a change toward a less di-  
 431 verse areal configuration as the higher diversity areas  
 432 contracted and the lower diversity areas expanded.

Table 1: Selected metro areas

Metro area	Abbr.	Region	Metro	Abbr.	Region		
1	Atlanta	ATL	Southeast	20	New York	NY	Northeast
2	Baltimore	BAL	Southeast	21	Orlando	ORL	Southeast
3	Boston	BOS	Nottheast	22	Philadelphia	PHL	Northeast
4	Chicago	CHIC	Midwest	23	Phoenix	PHX	Southwest
5	Cincinnati	CIN	Midwest	24	Pittsburgh	PIT	Northeast
6	Cleveland	CLE	Midwest	25	Portland	PPR	Pacific
7	Columbus	COL	Midwest	26	Providence	PRV	Northeast
8	Dallas	DAL	Southwest	27	Riverside	RIV	Pacific
9	Denver	DEN	Rocky Mtn.	28	Sacramento	SAC	Pacific
10	Detroit	DET	Midwest	29	San Antonio	SA	Southwest
11	Houston	HOU	Southwest	30	San Diego	SD	Pacific
12	Indianapolis	IND	Midwest	31	San Francisco	SF	Pacific
13	Kansas City	KC	Midwest	32	San Jose	SJ	Pacific
15	Las Vegas	LV	Rocky Mtn.	33	Seattle	SEA	Pacific
16	Los Angeles	LA	Pacific	34	St. Louis	SL	Midwest
17	Miami	MIA	Southeast	35	Tampa	TP	Southeast
18	Milwaukee	MIN	Midwest	36	Virginia Beach	VB	Southeast
19	Minneapolis	BAL	Southeast	37	Washington DC	DC	Southeast
19	New Orleans	NO	Southeast				

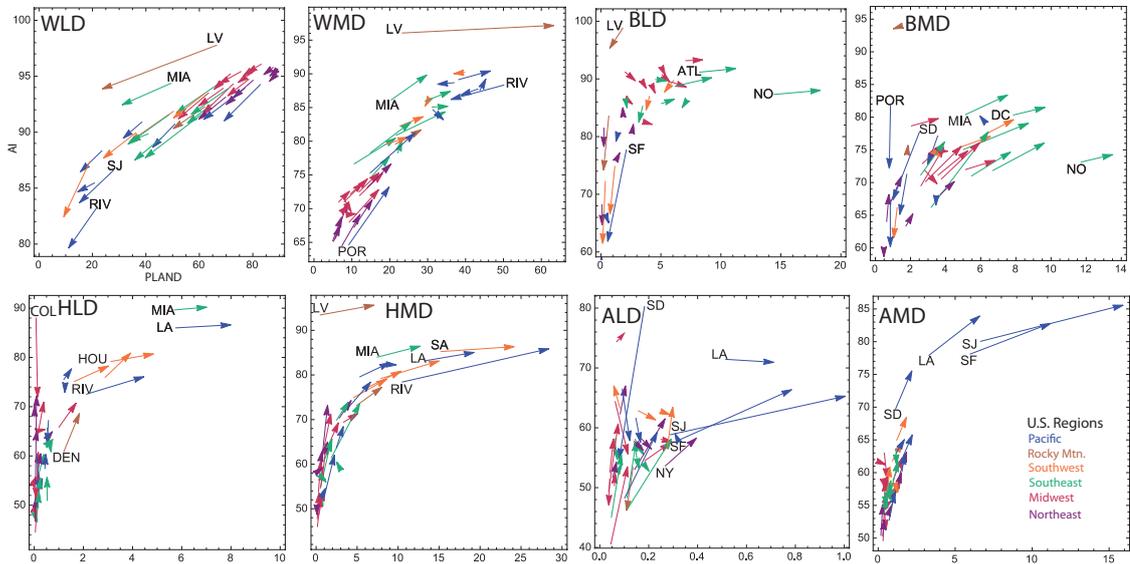


Figure 5: PLAND – AI diagrams for different diversity/dominant race neighborhood types. DDRTs in metropolitan areas are represented by arrows indicating changes in values of PLAND and AI from 1990 to 2000. See Table 1 for the list of included metropolitan areas.

434 Table 1 lists the 37 metro areas used in our study  
 435 of topology of change (section 2.4). The panels in  
 436 Fig. 5 show the PLAND-AI diagrams for eight different  
 437 DDRT areas, as indicated on the panels. PLAND and  
 438 AI values are calculated for areas occupied by a given  
 439 DDRT in 37 MSAs. The purpose of the PLAND-AI dia-  
 440 gram is twofold, first to observe a correlation (if any) be-  
 441 tween the degree of aggregation and percentage of area  
 442 occupied by a DDRT, and second, to observe tempo-  
 443 ral change of area percentage/aggregation between 1990  
 444 and 2000.

445 There exists a clear correlation between the values  
 446 of PLAND and AI for all DDRT areas; the bigger  
 447 the relative area of a DDRT the more aggregated it  
 448 is. Moreover, this correlation is non-linear, for rela-  
 449 tively small DDRT areas the degree of agglomeration  
 450 increases steeply with an increase of the area, whereas  
 451 for larger areas the dependence is flatter. That means  
 452 that DDRTs which occupy a relatively small area of a  
 453 MSA most likely consist of small disjointed enclaves  
 454 but as they grow the enclaves aggregate to form an in-  
 455 creasingly more compact clump.

456 The 1990-2000 changes in topological properties of  
 457 DDRT areas are shown by arrows. The collection of  
 458 37 arrows illustrates the trends of these changes over  
 459 the geographically diverse set of MSAs. The arrows  
 460 on the WLD panel of Fig. 3 show that all WLD areas  
 461 decreased in size and underwent disaggregation. Thus,  
 462 the transition of WLD neighborhoods to other neigh-  
 463 borhoods (mostly WMD) occurred by their fragmenta-  
 464 tion. The WLD areas in MSAs located in the North-  
 465 east region, which relatively had the largest sizes, de-  
 466 creased the least, while the WLD areas in MSAs located  
 467 in the Pacific and Southwest regions, which relatively  
 468 had the smallest sizes, decreased the most. A differ-  
 469 ent type of dynamic can be observed for BLD areas. In  
 470 MSAs where the BLD areas were relatively large (in the  
 471 Southeast region) they further increased their size, but  
 472 in MSAs where BLD areas were relatively small, their  
 473 sizes sharply decreased or they vanished altogether. For  
 474 MSAs where the BLD areas have an intermediate size  
 475 (5-7%) the black-dominated neighborhoods were stable.  
 476 For DDRTs with small memberships, like HLD and  
 477 ALD, there is no clear pattern to their dynamic, the cor-  
 478 responding diagrams show the existence of outliers –  
 479 MSAs experiencing fast growth of those neighborhoods  
 480 – while the remaining MSAs show mixed trends.

482 Census Bureau population projections (Colby and  
 483 Ortman, 2014) indicate that the racial dynamic in the  
 484 U.S. is steering the country toward a society with no  
 485 absolute racial majority by 2044. How this overall pre-  
 486 diction translates to a change in racial makeup of local  
 487 neighborhoods is of great interest to academics, as well  
 488 as to policy makers, due to their impact on economics,  
 489 politics, social services, and urban planning. We started  
 490 with the thesis (see section 1) that assessing change in  
 491 racial makeup of neighborhoods by using census ag-  
 492 gregation unit-based data yields inadequate information  
 493 and can be significantly improved by using input data in  
 494 the form of high resolution demographic grids.

495 Grids-based demographic data have a number of ad-  
 496 vantages over the aggregation units-based data (say,  
 497 census tracts). First, it is easy to use. Aggregation units-  
 498 based data, which is given at spatially irregular and size-  
 499 variable sections, presents difficulties even for spatial  
 500 analysis alone due to the modifiable areal unit problem.  
 501 For spatio-temporal analysis these difficulties are ampli-  
 502 fied by the fact that units boundaries change from one  
 503 census to another. Thus, assessing demographic change  
 504 while using units-based data requires interpolation (Holt  
 505 et al., 2004; Schroeder, 2007; Ruther et al., 2015). On  
 506 the other hand, demographic grids for different years are  
 507 spatially co-registered and are ready for a cell-by-cell  
 508 comparison without any data preprocessing. Second,  
 509 high resolution grids provide consistent spatial resolu-  
 510 tion throughout the entire country, which, even in the ur-  
 511 ban areas, is higher than that offered by the tract-based  
 512 data. Finally, gridded data offer analytic possibilities,  
 513 such as, for example, calculation of landscape metrics,  
 514 which has not been utilized before because they cannot  
 515 be calculated from census units.

516 Using newly available demographic grids by  
 517 Dmowska and Stepinski (2014) we demonstrated three  
 518 novel types of spatio-temporal analysis of change in  
 519 racial diversity. These analyzes (U.S.-wide statistics of  
 520 1990–2000 transitions between membership of differ-  
 521 ent DDRTs, mapping the change in spatial extents of  
 522 DDRTs, and depicting changes in topology of DDRTs)  
 523 provide comprehensive insight into the dynamics of  
 524 DDRTs during the decade of 1990s. Such analyzes  
 525 would be difficult-to-impossible to carry out using  
 526 methods based on census aggregation units.

527 The DDRTs membership transition diagram (Fig.1)  
 528 not only shows the magnitude of membership transfers  
 529 between different types of neighborhoods but also il-  
 530 lustrates all the components of every transfer – incom-  
 531 ing sources of membership (1990 DDRTs) which to-

532 gether constituted each 2000 DDRT and outgoing des- 584  
533 tinations of membership (2000 DDRTs) which together 585  
534 constituted each 1990 DDRT. This is valuable informa- 586  
535 tion that has not been previously available as the only 587  
536 published data on neighborhood transitions (Farrell and 588  
537 Lee, 2011; Holloway et al., 2012; Wright et al., 2014) 589  
538 referred to a number of census tracts that transitioned 590  
539 from one DDRT to another. Furthermore, with an ex- 591  
540 ception of the study by Wright et al. (2014), previous 592  
541 studies were restricted to a handful of metropolitan ar- 593  
542 eas rather than covering the entire U.S. For studying 594  
543 socio-economic change membership transitions offer a 595  
544 directly relevant information whereas tract transitions 596  
545 can only serve as an imperfect proxy for such infor- 597  
546 mation. Admittingly, DDRTs membership transitions 598  
547 could be calculated from census tracts, but this would 599  
548 yield a different and less accurate results due to the mod- 600  
549 ifiable areal unit problem inherent to census aggregation 601  
550 units.

551 Our change maps (Figs.2, 3, and 4) show how bound- 602  
552 aries between different types of neighborhoods changed 603  
553 in a fashion that allows further qualitative and quanti- 604  
554 tative analysis. For example, they show that in Chicago 605  
555 (Fig. 2) and Houston (Fig. 3) the expansion of Hispanic- 606  
556 dominated neighborhoods from HLD cores occurs in 607  
557 preferred directions, forming a progression of neigh- 608  
558 borhoods with a decreasing degree of Hispanic pop- 609  
559 ulation. They also show that expansion of Hispanic- 610  
560 dominated neighborhoods is at the expense of adjacent 611  
561 white-dominated neighborhoods but not at the expense 612  
562 of adjacent black dominated neighborhoods. To fully 613  
563 appreciate the informational content of our change maps 614  
564 they need to be compared to previous cartographic de- 615  
565 pictions of change in neighborhood types (Wright et al., 616  
566 2011; Holloway et al., 2012; Wright et al., 2014). As the 617  
567 change map (in the form of a grid of cell transition val- 618  
568 ues) is calculated for the entire U.S. it can be used, in 619  
569 conjunction with other gridded demographic variables 620  
570 (for example, income and age) to explore questions of 621  
571 connection between neighborhood transitions and the 622  
572 socio-economic environment. 623

573 The topology of neighborhood transitions (Fig. 5) is 624  
574 an analysis made possible by using the grid – this in- 625  
575 formation cannot be obtained from tract-based data. It 626  
576 has revealed that expanding neighborhoods first disag- 627  
577 gregate the adjacent regions of a contracting neighbor- 628  
578 hood then aggregates their own extent in a fashion that 629  
579 resembles the results of geographical models of residen- 630  
580 tial mobility (Torrens, 2007). It also shows that in the 631  
581 1990s the spatial size and shape of different neighbor- 632  
582 hood types evolved differently, with a particularly sharp 633  
583 difference between WLD and BLD.

One disadvantage of using high resolution demo-  
graphic grids by Dmowska and Stepinski (2014) is that,  
at present, no grids for 2010 are available. This is be-  
cause Dmowska and Stepinski method of calculating  
high resolution grids is to disaggregate coarser SEDAC  
grids which are only available for 1990 and 2000. There  
are two feasible solution to this problem. First, to wait  
until SEDAC will make available 2010 grids, and sec-  
ond, to change the procedure for obtaining high resolu-  
tion grids so they can be calculated directly from census  
blocks without using SEDAC grids. Calculating high  
resolution grid for the entire conterminous U.S. is com-  
putationally challenging. Dasymetric modeling from  
coarser to finer grid is the simplest and least compu-  
tationally demanding procedure to obtain it, but disag-  
gregation directly from census blocks is also computa-  
tionally feasible and will need to be done if SEDAC will  
not publish their grids for 2010.

In addition, when working with the grids it is im-  
portant to remember that they are models of popula-  
tion distribution rather than pure data. Uncertainties  
associated with accuracy of auxiliary data and with  
the dasymetric model itself are discussed in Dmowska  
and Stepinski (2014). Here we would like to focus  
on an additional assumption made when modeling spa-  
tial disaggregation of sub-population associated with  
a given race/ethnicity. We simply assumed that each  
sub-population is disaggregated the same way as the  
entire population. Thus, our model does not provide  
any additional insight into differential disaggregation  
of various race/ethnicity groups beyond the insight al-  
ready provided by the land cover model. We are not  
aware of any potential auxiliary data that could pro-  
vide information on differential distribution of different  
race/ethnicity sub-populations. Note that this assump-  
tion is only a concern on the smallest scale because:  
(a) populations are still kept away from uninhabited or  
sparsely populated areas, and (b) all segments of popu-  
lations add up to the total population at the level of 1 km  
SEDAC cell (250 m cell in major metropolitan areas).

Finally, a new interesting analysis will become pos-  
sible once 2010 demographic grid becomes available.  
With gridded data available for 1990, 2000, and 2010  
there will be enough information to attempt the calcula-  
tion of predictions for future neighborhood transitions  
at high spatial resolution using techniques originally  
developed to predict land use/over change (Mas et al.,  
2014). Such model could be used to predict spatial con-  
figuration of neighborhoods in 2020 and later checked  
for accuracy of prediction with the data from 2020 cen-

634 SUS.

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