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AJPP Technical Report 2020: ZIP Code-Based Jewish Population Estimates

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The Cohen Center for Modern Jewish Studies (CMJS), founded in 1980, is dedicated to providing independent, high-quality research on issues related to contemporary Jewish life.

The Cohen Center is also the home of the Steinhardt Social Research Institute (SSRI). Established in 2005, SSRI uses innovative research methods to collect and analyze sociodemographic data on the Jewish community.

Contents

Chapter 1: Introduction

The American Jewish Population Project is an innovative program of research at Brandeis University's Steinhardt Social Research Institute. It uses data from national surveys of U.S. adults to estimate the size and demographic composition of the U.S. Jewish population. This population profile serves as a point of reference for the community as a whole, and for those who conduct targeted surveys of the population and have no frame of reference for evaluating the representativeness of their surveys.

Measuring a group such as American Jewry, who are a small percentage of the total U.S. population, is inherently challenging, especially since there is no standard source of data such as the U.S. census on characteristics like religion and ethnicity. Reliable data on the size and basic demographic composition of the Jewish population is a foundation for any study of U.S. Jews. No matter how well designed, any single survey will under- or over-estimate a group (typically they under-estimate, especially rare groups). Without Census-like data, there is no way to gauge how accurate the results from a single survey might be.

Most studies, because of the lack of census data, conflate two goals: obtaining census-like population information and, at the same time, substantive data on the nature of Jewish life. When the two are estimated from the same single source of data, any errors or sources of bias in the population totals can dramatically affect understanding of Jewish life more broadly.

The American Jewish Population Project's approach – to combine data across repeated, independent samples of the population using Bayesian analysis methods – enables more precise estimates of small groups. The synthesis of data from a large number of studies addresses the first goal in Jewish survey research – providing population estimates – and, unlike a single study, has the potential to provide more reliable estimates and to incorporate new data on an ongoing basis.

The present report provides the design and methodology associated with the current 2020 population estimates. This document is organized into 6 chapters.

Chapter 2 provides a summary of the development of the project and how it has evolved over time.
Chapter 3 provides the details of the data synthesis including an overview of the Bayesian multilevel modeling with poststratification (MRP) methods that are employed, the sample of surveys that are synthesized, model specification, and details of poststratification.
Chapter 4 provides detail on estimation of groups not represented in the data synthesis: Jewish adults who do not identify their religion as Jewish and Jewish children to extrapolate the model-based estimates of Jewish adults who say their religion is Jewish to total Jewish population.
Chapters 5 provides details on the geographic clusters used in population modeling.
Chapters 6 describes models used and results for political ideology variables (forthcoming).

Chapter 2: Project History

Overview

Understanding the history of the project is important to understanding the data. Many who focus on comparison of our past estimates to the present estimates neglect to understand that current estimates represent changes in methodology and improvement in estimation methods over time as more data are incorporated, more than they represent changes in the population itself. Even with these changes in methodology, the data synthesis approach to Jewish population estimation has consistently found that 1.7%-1.9% of U.S. adults identify their religion as Judaism. Future work will focus on modeling population change over time directly.

The American Jewish Population Project originated from methodological investigations of the National Jewish Population Survey of 2000-2001 (Cohen et al., 2004). Results of the NJPS 2000-2001 indicated a significant decline in the population from the previous estimate which had been based on a national survey conducted in 1990 (Goldstein et. al, 1990). While some argued that the population decline was expected (DellaPergola, 2005), the nature of the differences, for example, declined in particular age groups, suggesting the change was likely associated with an artifact given a host of administrative and methodological problems (see Kadushin, Phillips & Saxe, 2005).

The problem of the NJPS 2000-2001 highlighted the problem of studying any religiously or ethnically defined group in the U.S. for which there is no existing systematic source of data, such as the U.S. Census, with which to evaluate the over- or under-representation in those estimates. Absent official statistics, it is difficult to provide incontrovertible evidence of bias. Although there are no census data of the U.S. Jewish population, there are many surveys that assess religious identity and are conducted with sufficient frequency that one could, at the very least, compare the achieved sample to these other sources. A data synthesis of the repeated, independent samples should provide a better estimate of the true population parameter than one based on a single sample.

The project has developed in four general phases. The first phase focused on systematic analysis of surveys conducted around the year 2000-2001 to compare to the NJPS 2000-2001 sample – in particular to the portion of the sample that identified their religion as Jewish which was the majority (80%) of the sample. The second phase of the project sought to extend the findings from this initial work to establish the method as a framework for providing the much-needed baseline population profiles for those who conduct research on this population. As the project grew and more data were added, it evolved into a third stage in which estimates for smaller geographic areas – U.S. counties and metropolitan areas – were developed. This stage also included the extension of the population profile from basic demographics to provide estimates of partisanship (Democratic/Republican) and political ideology (liberal/conservative). The current estimates represent a fourth phase of the project in which sufficient data are available for ZIP Codes of respondents, enabling improved estimation of counties by accounting for sub-county variation in the distribution of the population.

Phase I: Comparison to NJPS 2000-2001

Background

The first major national-level systematic survey of the Jewish population was in 1970, sponsored by the Council of Jewish Federations and Welfare Funds and conducted by Fred Massarik and colleagues (Chenkin, 1971; Lazerwitz, 1971; Massarik & Chenkin, 1971). Prior to this effort, the primary source of data at the national level was from a pilot study conducted by the U.S. Census Current Population Survey in 1957, which was designed primarily to examine the likelihood that U.S. citizens would answer questions about religious identification (Goldstein, 1969; Mueller & Lane, 1972). Of 35,000 households surveyed, just over 1,000 (3.2%) identified as Jewish. The data from these respondents served as the primary national-level estimate of the size and demographic composition of the population. The Census did not continue with the collection of data on religious identification. Thus, there was no way to gauge growth of Jewish households over time (Lazerwitz, 1971).

Absent such Census data, a goal of the 1970 survey was to establish a national level population profile of the U.S. Jewish population that would not be biased by the few larger communities who were better organized for local data collection.

Previous estimates were based upon the judgments of communities, in most cases without actual research. They were therefore susceptible to over-representation of a few large communities, while under-representing the population of small communities in a region. (Massarik & Chenkin, 1971, p. 2)

To better ensure a representative sample of the Jewish population that would not be biased toward the largest communities, counties in the United States were divided into 52 groups based on local community studies' estimates of the size of the Jewish community in each county (see Lazerwitz, 1971). Within each county group, much of the sample was identified through lists. It was assumed that "a sizable portion of the addresses of the nation's Jews are known to their local Jewish Federations and are available on lists from these organizations" (p.1). An exception was the New York metropolitan area where a standard probability sample was drawn.

The 1970 survey yielded an estimate of the overall size of the Jewish population as 5.4 million (Massarik & Chenkin, 1971). Re-analysis of the data adjusting for sources of bias in the estimates (Lazerwitz, 1977) indicated the true population estimate was likely 5.8 million with a lower limit of 5.6 million and upper limit of 6 million. The reanalysis yielded a result closer to the original estimate of 5.7 million that had been used to design the survey.

One lesson from the 1970 survey is the complexity associated with establishing the baseline population figure on which all of the research is based. Population estimates were based on pre-existing guesstimates of the size of the population, necessary to determine sampling ratios and survey weights. The pre-existing guesstimates were not ill informed. They were based on extensive experience of researchers devoted to the study of local Jewish communities. There was, however, no existing systematic source of data, such as the U.S. Census, with which to evaluate the over- or under-representation in those estimates. Lazerwitz (1971) was well aware of the problem, "We sought from this survey that very piece of information required to design the survey creating a sort of circular situation with the connecting link missing" (p. 2). It was, however, the best available solution to a complex problem.

The next major effort to collect national level population data was in 1990 (Goldstein, 1993). In the proposal for this study, the developers noted:

The best alternatives are surveys in which information on religious identification is collected. Three types of such surveys are relevant to our concern: 1) national and local omnibus surveys; 2) local studies of the Jewish population; and 3) a national Jewish population survey. (Goldstein, Groeneman, Mott, Mott & Waksberg, 1988, p. 3-4)

The use of national and local omnibus surveys was ruled out because of the small sample sizes in individual surveys; if analyzed individually, they yielded too few Jewish respondents for meaningful analysis.

The method proposed in the design stage of the 1990 National Jewish Population Survey of using existing national and local sources of data may have been difficult to implement three decades ago. Since 1990, however, computational methods for data aggregation that enable direct assessment and modeling of heterogeneity have become common (Carlin & Lewis, 2011; Cooper, Hedges & Valentine, 2009; Ghosh, Natarajan, Stroud, & Carlin, 1998; Jox, 2002; Kreft, 1998). What seemed infeasible in the past is feasible today; in fact, with increased interest in mining "big data," the approach is a potential model for other fields (cf. Mervis, 2012).

Ultimately population estimates derived from the 1990 survey were based on the amalgamation of a year's worth of weekly and biweekly surveys (conducted as part of an ongoing market research omnibus survey). The combined surveys were used to establish the proportion of the total U.S. population who identify as Jewish, ignoring possible heterogeneity across surveys. Respondents were then re-contacted for a longer, more in-depth survey on factors related to Jewish life.

The next major national survey was conducted in 2000. Rather than pooling multiple small samples from an omnibus survey, a single nationally representative survey was developed from which Jewish respondents could be identified (Kotler-Berkowitz, et al. 2004). Such a strategy obviated the need to adjust for possible heterogeneity across multiple samples and the potential bias associated with omnibus market research surveys. The method could not, however, remedy the challenges associated with relying on random digit dial (RDD) phone survey methods to estimate a "rare" population. The survey had a very low response rate (less than 20%), accompanied by a host of administrative and methodological issues (see Kadushin, Phillips & Saxe, 2005). Furthermore, with the lack of independent, external data about the population, there was no way to evaluate possible over- or under-representation in the sample that was achieved with this low response rate.

In the end, the same circularity described by Lazerwitz (1971), the need in survey design and evaluation for the very information that the survey sought to provide, limited the utility of the survey for purposes of population estimation. Another survey conducted during the same period

(Groeneman & Tobin, 2004) had similar problems of low response rates and lack of ability to evaluate and adjust for over- or under-representation of the samples. A third survey, employing the same design as the 1990 study (Kosmin, Mayer & Keysar, 2001), also had issues of low response rates and an increase in the rates of respondents who refused to answer the religious identification question. In addition, there was no way to gauge whether the Jewish respondents who participated were representative of the Jewish population as a whole.

The problems encountered in national Jewish population surveys reflect the broader challenges associated with general population surveys, particularly those that rely on telephone as the primary method for contacting respondents. Response rates have deteriorated as phone technology has advanced and users increasing use call-screening, call-blocking and cell phones rather than traditional landlines (Groves et al. 2004; Massey, O'Connor, and Krotski 1998; Smith 1994). Declines in response rates are especially problematic for estimation of rare populations. Such estimates are highly sensitive to disparities between responders and non-responders, especially if there are interactions with survey characteristics. For example, those for whom religion is most important might be more likely to participate in surveys that focus on issues of religion than surveys that focus on health or politics. This would lead to bias in estimates depending on how the survey is portrayed to potential respondents and who the sponsoring agency is.

Initial Data Synthesis

The goal of the initial data synthesis was based on the question of whether estimation of the Jewish population, a "rare" population in the U.S., was similar to estimation of rare events or small effects in social science research. Small effects might be difficult to detect or measure reliably in single studies. Systematic review and analysis of a large number of studies which are each designed to measure the same effect can increase statistical power and increase precision especially for estimation of small effects (cf. Cooper & Hedges, 1994; Glass, 1976). Toward that end, a review of any and all studies of U.S. adults conducted around the time period of the NJPS 2000 was done to identify those that included similar assessment of Jewish identity. Many studies included assessment of religion, the primary screener question of the NJPS 2000, but few included a broader definition of Jewish identity that would include those who identify culturally or ethnically but not by religion. The analysis, therefore, focused on the synthesis of estimates of the percentage of U.S. adults who identify their religion as Jewish.

A total of 22 independent surveys conducted between the years 2000 to 2002 were identified. These included the General Social Survey (Davis, Smith & Marsden, 2003), the American National Election Study (Burns, et al., 2002), the National Survey of Family Growth (U.S. DHHS, 2002), and a number of surveys conducted by the Pew Research Center and others (see Table 2-1). The estimates of the percentage of U.S. adults who identified their religion as Jewish ranged from a low of less than one percent in a survey of attitudes toward genetic testing to a high of three percent in a survey on civic participation. There was, however, significant variability across the surveys (with homogeneity of variance test of $Q(21)=80$, $p < .001$). Such differences suggest that surveys should not be combined to get an overall estimate without first accounting for survey variance.

Table 2-1: Percent Jewish by Surveys Containing Religion Question

	Unweighted Pct. Jewish			Weighted Pct. Jewish			
	Est.	SE	(95% CI)	Est.	SE	(95% CI)	Design Effect
Religion & Public Life 2001	1.3	.0025	(0.8, 1.9)	1.2	.0025	(0.8, 1.8)	1.04
Religion & Public Life 2002	1.6	.0028	(1.1, 2.2)	1.3	.0024	(0.9, 1.9)	0.89
Biennial Media Consumption 2000	2.2	.0027	(1.7, 2.8)	1.9	.0024	(1.5, 2.4)	0.92
Biennial Media Consumption 2002	2.0	.0026	(1.5, 2.6)	1.8	.0024	(1.4, 2.3)	0.95
Civic & Politic. Health of the Nation 2002	1.8	.0033	(1.2, 2.5)	1.4	.0024	(1.0, 2.0)	1.24
Attitudes About Genetic Testing 2000	0.6	.0022	(0.2, 1.2)	0.7	.0026	(0.3, 1.4)	1.84
Exploring Religious America 2002	1.9	.0031	(1.4, 2.7)	1.9	.0037	(1.3, 2.8)	1.35
American Perceptions of Artists 2002	1.3	.0036	(0.6, 2.2)	1.2	.0037	(0.6, 2.2)	1.11
Add Health 2002	0.9	.0013	(0.6, 1.2)	0.9	.0039	(0.4, 2.1)	8.60
Religion and Politics 2000	1.9	.0018	(1.5, 2.3)	1.6	.0016	(1.3, 1.9)	0.93
State of the First Amendment 2000	1.9	.0045	(1.1, 3.0)	1.6	.0041	(1.0, 2.7)	1.02
State of the First Amendment 2001	3.0	.0054	(2.0, 4.2)	1.9	.0036	(1.3, 2.7)	0.71
State of the First Amendment 2002	2.4	.0049	(1.5, 3.6)	1.6	.0039	(1.0, 2.6)	0.92
National Election Study 2000	2.8	.0042	(2.0, 3.8)	2.3	.0043	(1.6, 3.3)	1.25
Health And Retirement 2000	2.4	.0011	(2.1, 2.6)	2.5	.0014	(2.2, 2.8)	1.37
American Perceptions of Aging 2000	1.6	.0024	(1.2, 2.2)	1.5	.0025	(1.1, 2.1)	1.27
Amer. Pub. Opin. & U.S. Foreign Pol. 2002	2.4	.0029	(1.8, 3.0)	1.4	.0019	(1.0, 1.8)	0.88
Exercising Citizenship 2002	2.3	.0039	(1.6, 3.2)	2.9	.0050	(2.0, 4.0)	1.37
General Social Surveys 2000	2.2	.0028	(1.7, 2.9)	2.2	.0030	(1.7, 2.9)	3.72
General Social Surveys 2002	1.7	.0025	(1.3, 2.3)	1.5	.0023	(1.1, 2.0)	5.10
NSFG-CYCLE VI 2002	1.6			1.7			2.25
Social Capital Benchmark 2000				1.4			1.22

Given the significant heterogeneity, further examination was conducted using two-level multilevel models. Doing so enabled examination of the roles of both individual- and survey-level characteristics. Individual level characteristics included those typically included in sampling and poststratification (sex, age, educational attainment, and race/ethnicity). Survey level characteristics included weighting methods, administration methods, response rates, design effects, "transparency" (i.e., whether design weights or design factors were included and whether final dispositions were provided so that response rates could be calculated independently), question wording, and survey purpose.

Inclusion of demographic covariates decreased survey variance from .05 to .009 (see Table 2-2). The inclusion of response rates, administration methods, and transparency along with the demographic covariates each reduced the variance to near zero (.0001). In-person and mixed method surveys were significantly different from telephone surveys. These surveys were also the ones with higher response rates and most transparent in sharing design weights and response rate information.

Table 2-2: Multilevel Model Results for Constant-Only Model, Level 1 Covariate Model, and Level 1 Covariates Plus Individual Survey Level Variables

	Coeff.	SE	t	Level 2 Var	Chi square	p value
Constant Only						
Intercept	-3.9799	0.059		0.0500	84.02	< .001
Level 1 Covariates						
Intercept	-4.5376	0.076		0.0090	30.52	0.06
Female	-0.0203	0.059	-.35			
Black	-2.9737	0.343	-8.66			
Hispanic	-1.5764	0.217	-7.22			
Other Race	-1.2792	0.239	-5.36			
Age[a]	0.3317	0.040	8.24			
Education[b]	1.2394	0.060	20.68			
Covariates + Weight Type						
Includes prob. of selection	0.0840	0.081	1.04	0.0090	27.70	0.09
Includes post-stratification	-0.0310	0.093	-.03	0.0110	31.28	0.04
Post-stratification only	-0.0860	0.087	-.98	0.0090	28.33	0.08
Covariates + Response Rate						
Response Rate[c]	0.0040	0.001	3.16	0.0001	20.36	0.37
Covariates + Transparency						
Design weights provided[c]	0.2440	0.060	4.09	<0.0001	13.60	>.50
Final Dispositions provided	0.0260	0.080	0.32	0.0120	33.37	0.02
Covariates + Design Effect						
Design Effect	0.0350	0.021	1.70	0.0070	27.03	0.10
Trichotomized[cd]						
Low (< 1)	0.1000	0.080	1.19	0.0001	19.88	0.34
High (> 1.35)	0.2400	0.080	3.14			
Covariates + Question Text[e]						
Open-ended	-0.0600	0.126	-0.04	0.0110	30.23	0.04
Mult. choice, no rel. prompt	0.0090	0.111	0.08			
Covariates + Purpose[f]						
Politics/Civics	0.1680	0.124	1.36	0.0120	25.48	0.06
Social/Cultural Issues	0.1480	0.123	1.20			
Health & Social Behavior	0.1740	0.178	0.98			
Health & Aging	0.1660	0.141	1.18			
Covariates + Admin. Method[cg]						
In-person	0.2350	0.066	3.54	0.0001	14.43	>.50
Mixed	0.2490	0.110	2.32			

Notes:
a) Age categorized as 18-44 years, 45-64 years, and 65+ with 18-44 as the reference category.
b) Education categorized as Less than College Grad or College Grad or greater, with College Grad as the reference category.
c) Iteration criteria lowered to .001.
d) Reference category = design effects between 1 and 1.35.
e) Reference category = multiple choice w/ salient religion prompt.
f) Reference category = religion.
g) Reference category = telephone.

Estimation of the Jewish prevalence after adjusting for demographic and survey level differences yielded an estimate of 1.8% of U.S. adults (95% CI: 1.6% - 2%), which was on par with the estimate from the 1990 National Jewish Population survey (citation) which also estimated 1.8% of U.S. adults identified their religion as Jewish.

Phase 2: Beyond NJPS

The work conducted during the first phase of the project made plain the need for an independent source of baseline population data that could be used by researchers who conduct surveys of the Jewish population. The second phase of the project sought to extend the analytic framework from providing a useful resource for post-hoc comparisons to establishing a method that could be used going forward to provide baseline population data required not only for the design of a survey, but importantly, for evaluating the representativeness and potential bias in the achieved sample. Especially when the target population is a rare group and the goal of the survey is to establish prevalence estimates, small disparities in responding can yield substantial differences in estimates of prevalence.

Searches were conducted to update and increase the sample of surveys. In addition, consultation was sought with experts in multilevel modeling and Bayesian analysis. Given the challenges encountered using standard HLM software, which did not easily process large discrepancies in sample sizes of surveys (ranging from ~1,000 to as high as 80,000), the decision was made to employ Bayesian regression with poststratification (MRP) similar to that employed by Park, Gelman, and Bafumi (2004) in their cross-survey analysis of voting behavior. [See Chapter 3 for discussion of MRP.]

A sample of 50 surveys from 1998 to 2006 were analyzed (Tighe, Livert, Barnett & Saxe, 2010). In addition to demographic covariates typical in poststratification (sex, age, race/ethnicity, educational attainment), geographic clustering was also included in the model. Although most surveys included the broadly defined four categories of U.S. Census region in poststratification, some surveys included multistage sampling designs with stratification by primary sampling units defined by states or metropolitan areas (MSAs). Too few surveys provided detailed geography such as county or MSA to replicate sampling units defined by MSAs. Nearly all, however, included state and a metropolitan status variable (in metropolitan area/outside metropolitan area). This enabled comparison of estimates poststratified by census region to those poststratified by state and metropolitan status to see how inclusion of lower levels of geography affected prevalence estimates.

The inclusion of geographic variables in poststratification yielded higher estimates of the Jewish population than models that did not include these variables. With the inclusion of census region, an estimated 1.76 percent of U.S. adults were Jewish (See Table 2-3). This increased to 1.86 percent with the inclusion of State. Although there was a significant relationship between metropolitan status and likelihood of identifying as Jewish, inclusion of metropolitan status as a poststratification variable did not significantly affect estimates at the national, regional, or state levels. Overall, there were greater proportions of Jewish adults in metropolitan than nonmetropolitan areas, and this difference was most pronounced in the Northeast.

Table 2-3: Estimated Jewish Population, Poststratified by Region, State and Metropolitan Status

	Region		Region & Metropolitan Status		State		State & Metropolitan Status	
	Est.	(95% CI)	Est.	(95% CI)	Est.	(95% CI)	Est.	(95% CI)
All Regions	1.76	(1.71, 1.81)	1.78	(1.73, 1.84)	1.86	(1.80, 1.91)	1.89	(1.84, 1.96)
Northeast	4.00	(3.81, 4.18)	4.05	(3.86, 4.23)	4.20	(4.01, 4.38)	4.27	(4.09, 4.47)
Midwest	0.88	(0.80, 0.96)	0.88	(0.80, 0.95)	0.92	(0.85, 1.00)	0.93	(0.84, 1.02)
South	1.16	(1.10, 1.12)	1.15	(1.07, 1.22)	1.23	(1.16, 1.31)	1.25	(1.17, 1.33)
West	1.67	(1.57, 1.78)	1.73	(1.61, 1.84)	1.75	(1.64, 1.87)	1.75	(1.69, 1.95)
In Metro	—		2.18	(2.11, 2.25)	—		2.32	(2.25, 2.40)
Northeast			4.51	(4.31, 4.71)			4.75	(4.55, 4.97)
Midwest			1.17	(1.11, 1,27)			1.22	(1.11, 1.35)
South			1.46	(1.36, 1.55)			1.61	(1.51, 1.71)
West			1.92	(1.78, 2.04)			2.03	(1.89, 2.17)
Non-Metro	—		0.36	(0.32, 0.39)	—		0.35	(0.31, 0.40)
Northeast			0.86	(0.76, 0.95)			0.98	(0.86, 1.12)
Midwest			0.21	(0.18, 0.24)			0.25	(0.21, 0.29)
South			0.30	(0.26, 0.34)			0.25	(0.22, 0.29)
West			0.45	(0.39, 0.50)			0.39	(0.33, 0.46)

The other benefit of the MRP approach is that rather than just providing overall prevalence estimates at the national or state-level, distributions of the population across demographic characteristics included in the model can also be directly estimated (see Table 2-4). This provides a much-needed baseline population profile with which to evaluate the representativeness specifically of the Jewish samples achieved. As one would compare one's general population sample to the U.S. census distributions of sex, age, educational attainment, and race/ethnicity, the data synthesis results can be used to provide these distributions for U.S. Jewish adults.

Table 2-4: Estimated Proportion of Jewish Adults by Demographic Group

		White, non-Hispanic				Black, Hispanic & Other			
		Non-college Grad		College Grad		Non-college Grad		College Grad	
		Prop.	(95% CI)	Prop.	(95% CI)	Prop.	(95% CI)	Prop.	(95% CI)
Male	18-24 years	1.9	(1.65, 2.15)	4.28	(3.54, 5.08)	0.47	(0.40, 0.55)	1.08	(0.86, 1.34)
	25-34 years	0.78	(0.70, 0.86)	3.65	(3.34, 3.99)	0.19	(0.16, 0.23)	0.92	(0.80, 1.06)
	35-44 years	0.85	(0.77, 0.93)	3.97	(3.71, 4.29)	0.21	(0.18, 0.24)	1.00	(0.88, 1.14)
	45-54 years	1.11	(1.01, 1.22)	5.17	(4.84, 5.52)	0.27	(0.24, 0.32)	1.32	(1.15, 1.50)
	55-64 years	1.21	(1.09, 1.33)	5.61	(5.21, 6.01)	0.30	(0.25, 0.35)	1.43	(1.25, 1.65)
	65+ years	2.02	(1.83, 2.22)	6.23	(5.71, 6.75)	0.50	(0.43, 0.58)	1.60	(1.37, 1.85)
Female	18-24 years	1.81	(1.58, 2.05)	4.09	(3.40, 4.86)	0.45	(0.38, 0.53)	1.03	(0.82, 1.28)
	25-34 years	0.74	(0.66, 0.81)	3.49	(3.20, 3.79)	0.18	(0.16, 0.21)	0.88	(0.75, 1.02)
	35-44 years	0.81	(0.74, 0.88)	3.79	(3.53, 4.07)	0.20	(0.17, 0.23)	0.95	(0.83, 1.10)
	45-54 years	1.06	(0.96, 1.15)	4.94	(4.61, 5.28)	0.26	(0.22, 0.30)	1.25	(1.10, 1.43)
	55-64 years	1.16	(1.04, 1.26)	5.36	(4.98, 5.77)	0.28	(0.24, 0.33)	1.37	(1.19, 1.58)
	65+ years	1.92	(1.75, 2.11)	5.95	(5.45, 6.51)	0.48	(0.41, 0.56)	1.52	(1.30, 1.77)

Phase 3: Estimates for Counties, Politics & Validity Study

Having demonstrated the feasibility and utility of the MRP method for estimation of the Jewish population, the project evolved to focus on estimation in smaller geographic areas, particularly counties, which were the level of sampling in many local Jewish community studies. Work was done in this phase to add sufficient data for estimation of smaller geographic county areas and in many cases required establishing IRB and restricted use data agreements to include more detailed geographic data from the surveys than was available in public use files. This stage also included the extension of the population profile from basic demographics to also provide political ideology (party identification and liberal/conservative).

An additional goal in this phase was to make the data more accessible to researchers and practitioners through development of the American Jewish Population Project website that provided an online interactive map and detailed data tables.

Work in this phase also included a validation study (Magidin de Kramer, et al. 2018). Despite results to date providing convergent validity with other sources, such as consistency with the NJPS 1990, as well as the Pew Survey of American Jews (2013), the fact that there are no official statistics in the U.S. left some questioning whether an analysis based on hundreds of independent samples of U.S. adults was valid (citations e.g., DellaPergola). To address this concern, the method was replicated on a sample of surveys in Canada. The Canadian census included religion on the mandatory long form up to the year 2001. Beginning in 2011, the question was optional. Thus, the validation study targeted a sample of surveys for estimation of the population for the year 2001 so that it could be compared to the Canadian census estimate of the population.

In the validation study, the MRP method was compared to two alternative methods for combining data from complex surveys. One method employed a design-based approach in which all data were combined into a single dataset and weights from individual surveys were adjusted for their differing sampling distributions based on each survey's coefficient of variation and sample size (Robers & Binder, 2009; Korn & Graubard, 1999). The second method for comparison was more of a traditional meta-analytic approach where each survey was analyzed separately, using the original survey weights to generate an estimate of the proportion of adults who identify as Jewish. A weighted average of these surveys was then computed, weighting each estimate by a function of the variance and the design effect associated with each survey (Fox, 2011; Roberts & Binder. 2009). The MRP method out-performed the other two methods in terms of accuracy of point estimates nationally and for three major metropolitan areas in Canada (Montreal, Toronto & Vancouver) (See Figure 2-1.). During this time, the MRP method was also replicated similarly in a study with UK data, where it yielded accurate estimates of the Jewish, Muslim, and Hindu populations over a 20 year period (Claasen & Traunmüller, 2018).

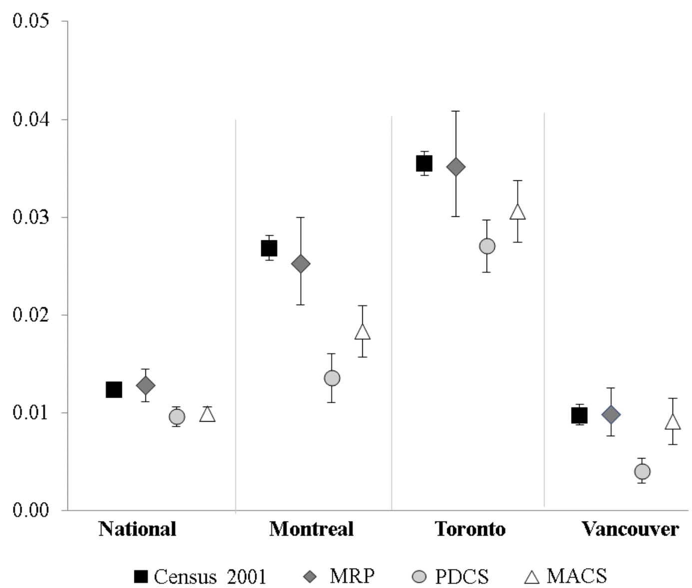

Figure 2-1: The census estimate of the proportion of Canadian adults who identify their religion as Jewish compared to the MRP and two alternative methods, nationally and for the three major metropolitan areas of Montreal, Toronto, and Vancouver.

Phase 4: ZIP Code-Based Estimation

The current estimates represent a fourth phase of the project in which sufficient data are available for ZIP Codes of respondents, enabling estimation of smaller areas. The primary benefit of this lower level of geography is the improved estimation of counties by taking into account variation within counties.

The remaining chapters provide details of the methods employed in this phase of population estimation, including an overview of MRP, a summary of the sample of surveys included in the analyses, and model specification.

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Chapter 3: Model-based Estimates of Jewish Adults by Religion

Overview

The application of hierarchical Bayesian methods to study small, religiously defined groups overcomes many of the challenges associated with single surveys. Although there is no definitive source of data on the religious composition of the total U.S. population, there is a wealth of data collected for purposes other than the estimation of religious groups that include assessment of respondents' religious identification. These include political polls, as well as surveys of health and social behavior. When combined, these data can be used to study the incidence and demographic composition of religious groups.

Combining multiple data sources to increase the reliability of estimates is the basic premise of traditional meta-analytic methods (Cooper & Hedges, 1993), as well as methods of small area estimation (SAE) (Lohr & Prasad, 2003; Pfeffermann, 2002; Rao & Yu, 1994). AJPP goes beyond the traditional meta-analytic approach by synthesizing original data rather than relying on summary statistics from each data source. Furthermore, this approach extends SAE methods by treating each survey sample as unique, and does not rely on the assumption that repeated independent samples can be combined. In this way, specific properties of each survey and the survey variances are taken into account when the data are combined. This method also affords the ability to explore other potential sources of bias in sample surveys, such as response rates, survey purpose, survey sponsorship, and question wording.

The AJPP method employs Bayesian multilevel regression with poststratification (MRP) to systematically combine data across multiple surveys (cf. Buttice and Highton 2013; Gelman and Hill 2006; Park, Gelman, and Bafumi 2004). This method is generally described as a model-based approach to estimation. Factors that are involved in the design of survey weights, that is, those that affect the probability of selection and the representativeness of the sample, are included in the model directly rather than as survey weights (cf.Little, 1993, 2004; Roberts and Binder 2009).

The MRP analysis is conducted in two steps.

- Fitting a Bayesian multilevel logistic regression model to the observed data using demographic and geographic strata.
- Model results are used to estimate each demographic-geographic combination poststratified by the percentages of each combination in the total U.S. population.

For example, in their analysis of state-level voting behavior, Park, at al. (2004) combined data from CBS/New York Times polls. First, multilevel regression was conducted with demographic covariates used in the original survey weights. These covariates were census region, along with respondent characteristics of sex, age, education, race, and ethnicity. The multilevel regression included the partial pooling of states within census regions. A sample of simulations based on the final model was used to calculate estimates poststratified to U.S. Census distributions for the demographic-geographic combinations included in the model.

AJPP 2020 Sample Description

The complete AJPP dataset consists of data from surveys of nationally representative random samples of the adult population in the U.S. conducted between 1997 and 2020. The dataset includes more than 1,200 independent samples with a total combined sample size of more than 2.9 million respondents, of whom over 69,000 identify as Jewish by religion.

As described in previous publications (Tighe et al., 2012; Tighe et al., 2013), The dataset includes surveys identified in major data repositories, such as the Inter-university Consortium for Political and Social Research (ICPSR) and the American Religion Data Archive (ARDA), as well as in poll archives at the Roper Center, Gallup, and Pew Research Center. Samples include those conducted as part of a series, such as the American National Election Studies, Pew Political surveys, and the Cooperative Congressional Election Study (CCES). In addition, the sample includes surveys conducted regularly by major news organizations (CBS, New York Times). Where a single survey may have included multiple sampling methods or frames (e.g., landline versus cellphone), each is treated as a separate independent sample, with unique identifiers to indicate series membership.[1]

As a requirement for inclusion in the data synthesis, all the surveys in the dataset must include the following baseline religious and demographic information for respondents:

- Current religious identification
- Gender
- Race
- Educational attainment
- Age
- Geographic information.

Survey Samples

The 2020 estimates are based on a subset of 266 samples from the main dataset for the most recent five-year period. This subset was for the years 2015 to 2019. Several additional surveys are included for the years 2014 and 2020 to increase the sample size, with the assumption that the size and characteristics of the Jewish population does not change substantially in this time period. This subset includes more than 1,341,600 respondents of whom 32,300 identify as Jewish by religion.

The surveys included in the AJPP 2020 dataset are the American National Election Studies, the General Social Survey, the Cooperative Congressional Election Study (CCES), Pew Political and social surveys, the Gallup Daily Tracking poll, and the Gallup Poll Social Series (See Table 3-1). Each survey includes a measure of respondent’s current religious identification, gender, race, educational attainment, and age as well as ZIP Code information.

[1] Series identification is included in the dataset to be able to examine differences across surveys that can be accounted for by survey series.

Table 3-1: Surveys in the AJPP 2020 Dataset

Survey	Date	Samples
General Social Survey (GSS)	2014, 2016, 2018	3
American National Election Studies (ANES)	2016	2
Cooperative Cong. Election Study (CCES)	2018	1
Gallup		
Poll Social Series (GPSS)	2014-2019: Jan, Feb, Mar, Apr, May, July, Aug, Sept, Oct, Nov 2020: Jan, Feb, Mar, Apr, May	130
U.S. Daily & Gallup-Sharecare Well-Being Index	2014: Jan-Apr, May-June, July-Aug, Sept-Dec 2015: Jan-Mar, Apr-May, June-Aug, Sept-Nov Dec 2015-Dec 2016 2017: Jan 2-4	40
U.S. Daily	2017: Jan 5-June, June-Dec	4
Pew Research Center		
Political Typology/Polarization Survey	Jan-Mar 2014	2
Religious Landscape Study	June-Sept 2014	2
Religion Survey	Sept 2014	2
Post-Election Survey	Nov 2014	2
Omnibus	Jan 2015	2
Survey of U.S. Catholics and Family Life	May-June 2015	2
Governance Survey	Aug-Oct 2015	2
State of American Jobs Survey	May-June 2016	2
Nonresponse Survey	Aug 2016	2
Political Typology	June-July 2017	2
Political Weekly Survey	2018: Feb 7-11, July 11-15	4
Political Survey	2014: Jan, Feb, Apr, July, Aug, Oct, Dec 2015: Jan, Feb, Mar, May, July, Sept, Dec 2016: Jan, Mar, Apr, June, Aug, Oct, Dec 2017: Jan, Feb, Apr, Oct, Dec 2018: Jan, Mar, May, June, Sept	62

The majority of surveys in the AJPP 2020 dataset were conducted with mixed random digit dialing (RDD) landline and cell phone administration methods. Across AJPP 2020, there are 130 landline samples and 130 cell phone samples. The remaining are face-to-face (4) and web surveys (2). For the RDD phone surveys, the cell phone and landline responses are included as independent samples. Additionally, Gallup conducts two parallel Daily Tracking surveys—U.S. Daily and Well-Being Index—on a daily basis. These surveys are grouped in the AJPP 2020 dataset as multi-day samples. The break points for the Gallup Daily Tracking samples are by survey type (U.S. Daily and Well-Being Index), by administration method (landline and cell phone), as well as by any difference in the sampling or weighting methodology.

Oversamples

Thirty-eight samples in the AJPP 2020 dataset contain oversamples. Oversamples typically include ethnic groups (e.g., Hispanic) or age groups (e.g., young adults aged 18 to 29 years). The current population models exclude all oversamples, and include only the nationally representative portions of the sample.

Some surveys, rather than oversampling, included disproportionate sampling of demographic groups and geographic areas. For example, the 2014 Pew Religious Landscape Study disproportionately sampled 16 states to ensure all states achieved their target of 300 completed interviews. As long as the sampling was done at the county or state level, a level of geography represented in the model, these surveys were included in the model.

Survey Purpose and Sponsor

Surveys in the AJPP 2020 dataset were conducted for a variety of purposes, ranging from polls on political issues and general social issues to targeted surveys on religious identification (see Table 3-2). Just over half of the samples were from political polls or studies (52%), followed by social life (15%) and health and aging (15%).

Table 3-2: Survey Primary Purpose

	Samples	Pct.
Religion	10	3.8
Health & Aging	39	14.7
Politics	139	52.3
Social Life	40	15.0
Miscellaneous	38	14.3
Total	266	100.0

A majority of the surveys in this sample were conducted by the Gallup Organization (65.4%). Nearly one third were conducted by Pew Research Center (32%). Of the remaining surveys, the GSS survey was conducted by NORC at the University of Chicago, the ANES by Stanford University and the University of Michigan with funding from the National Science Foundation, and the CCES by research teams across 60 universities.

Table 3-3: Survey Sponsor

	Samples	Pct.
Pew Research Centers	86	32.3
Gallup Organization	174	65.4
University of Michigan/Stanford University	2	0.8
University of Chicago/NORC	3	1.1
Multiple Sponsors (CCES)	1	0.4
Total	266	100.0

Religion question

All of the surveys included in the AJPP dataset provide data on those who identify as Jewish by religion (JBR), which is the largest proportion of the Jewish population and therefore serves as the baseline group for generating population estimates.

The source of the 'Jewish by religion' information is the religious identification question in each survey. This question is included in the demographic background section of each questionnaire along with sex, age, and education. In all of the surveys, the religion question included a general prompt such as "What is your religion?" followed by a set of discrete options (See Table 3-4). The questions vary primarily in the number of discrete options provided, ranging from a low of four options to as many as 12 options. The Gallup surveys included seven options: Protestant, Roman Catholic, Mormon, Jewish, Muslim, another religion, no religion.

Table 3-4: Religious Identification Questions

Surveys	Question	# of Options	Samples	Pct.
ANES	Do you consider yourself Protestant, Roman Catholic, Jewish, or something else?	4	2	0.8
GSS	What is your religious preference? Is it Protestant, Catholic, Jewish, some other religion, or no religion?	5	3	1.1
Gallup	What is your religious preference – are you Protestant, Roman Catholic, Mormon, Jewish, Muslim, another religion, or no religion?	7	174	65.4
Pew	What if your present religion, if any? Are you Protestant, Roman Catholic, Mormon, Orthodox such as Greek or Russian Orthodox, Jewish, Muslim, Buddhist, Hindu, atheist, agnostic, something else, or nothing in particular?	12	86	32.3
CCES	What is your religion, if any? Protestant, Roman Catholic, Mormon, Eastern or Greek Orthodox, Jewish, Muslim, Buddhist, Hindu, Atheist, Agnostic, Nothing in particular, Something else	12	1	0.4
Total			266	100.0

Survey Coding

For each survey, a targeted list of variables are recoded into standard format so that the surveys can be combined into a single large master file for analysis. For example if one survey codes Male/Female as 1/2 and another as M/F or as 0/1, all are coded as 1/2. The targeted list includes variables included in the population model:

- Religion Jewish: Not Jewish (0), Jewish (1)
- Sex: Male (1), Female (2)
- Age: 18 to 24 years (1), 25 to 34 years (2), 35 to 44 years (3), 45 to 54 years (4), 55 to 64 years (5), 65 to 74 years (6), 75 years or greater (7)
- Educational Attainment: Less than 4 year College Graduate (1), 4 year College Grad or greater (2)

- Race/Ethnicity: white non-Hispanic (1), Black non-Hispanic (2), Hispanic (3), other non-Hispanic (4)

Also included are any and all geographic identifiers such as metropolitan area, county, and ZIP Code. Survey administration variables such as date of the interview, day of the week, and interview language were also recoded. Other variables of interest are included in standardized recodes such as other religions, frequency of attending services, income, marital status, household composition, and political attitudes. Not all surveys include all of these additional variables. For a complete list variables that are recoded see AJPP 2020 Codebook Manual.

In addition to recoding data from each of the surveys into standard format, methodological characteristics of each survey that might be associated with potential sources of bias, such as survey purpose, survey sponsor, survey shop, response rates, methods of weighting are coded. (See AJPP 2020 Survey Coding Manual).

Population Model

Overview

To combine data over multiple independent samples, the multilevel regression includes the clustering of respondents within surveys in addition to sampling and weighting factors common across the surveys. All surveys included some stratification by geographic area. The lowest level of geography available for analysis was ZIP Code of the respondent. Sample sizes were too small at the ZIP Code level for reliable estimation, and were, therefore, combined into clusters. These clusters were grouped or defined by counties so that they could be used to obtain county-level population estimates.[2]

Other factors related to weighting in the surveys included sex, age, race & ethnicity, and educational attainment. Table 3-5 displays the demographic composition the AJPP 2020 sample on demographics related to poststratification in the sample surveys. Males comprised just over 50% of the sample, and were somewhat over-represented relative to their distribution in the general population (48.6%). Consistent with general population surveys, the pooled sample over-represented the older population, with 52.1% of the sample ages 55 years and older, compared to 38.2% within the general population. College graduates (42%) were also over-represented relative to the general population (38%), as were white non-Hispanic (76.6%) compared to 64.5% within the general population.

[2] See Chapter 5 for definitions of these geographic clusters.

Table 3-5: AJPP 2020 Pooled Sample Demographic Composition

	U.S. Adults[a]		AJPP Sample	
	Population	Pct.	Sample	Pct.
Total All Groups	250,324,002	100	1,341,682	100
Sex				
Male	121,775,190	48.6	677,072	50.5
Female	128,548,812	51.4	664,610	49.5
Age				
18-24 years	29,811,266	11.9	106,231	7.9
25-34 years	43,543,694	17.4	158,440	11.8
35-44 years	40,909,436	16.3	164,441	12.3
45-54 years	40,581,232	16.2	214,823	16.0
55-64 years	41,693,274	16.7	272,076	20.3
65-74 years	32,044,729	12.8	258,622	19.3
75+ years	21,740,369	8.7	167,049	12.5
Educational Attainment				
Non-College	177,624,557	71.0	778,215	58.0
College Grad	72,699,444	29.0	563,467	42.0
Race & Ethnicity				
White, non-Hisp.	161,567,880	64.5	1,028,151	76.6
Hispanic	39,096,708	15.6	129,937	9.7
Other, non-Hisp.	49,659,414	19.8	183,594	13.7
Population Density (ppl./mi^2)				
<300	67,226,928	26.9	428,820	32.0
300 to <500	18,029,727	7.2	101,228	7.5
500 to <1,000	26,687,571	10.7	144,110	10.7
1,000 to <2,000	32,415,687	12.9	170,514	12.7
2,000 to <5,000	58,897,750	23.5	296,128	22.1
5,000 to <10,000	27,591,043	11	124,269	9.3
10,000 to <45,000	16,086,618	6.4	62,245	4.6
≥45,000	3,388,679	1.4	14,368	1.1
Metropolitan Areas[b]				
Non-Top 40 Metro	121,980,697	48.7	740,739	55.2
Top 40 Metro	128,343,305	51.3	600,943	44.8

Notes:

a) U.S. adult population source: Claritas 2020 sex by age adjusted for adults in households, educational attainment, race & ethnicity using the American Community Survey 2014-2018.

b) Metropolitan areas refer to the Core-Based Statistical Areas (CBSA).

To account for these differences, the model includes not only geographic strata, but these demographics, in addition to significant interactions of age by educational attainment, geographic area by age, geographic area by educational attainment, and geographic area by race/ethnicity. These interactions were included after exploratory analyses of two- and three-way interactions. Three-way interactions were explored among the demographic covariates. There was insufficient power to be able to reliably estimate three-way interactions by geographic areas.

The model yields the proportion of U.S. adults who identify as Jewish in each of the geographic and demographic groups represented in the model. Estimates are then poststratified to distributions of the U.S. adult population across the poststratification factors included in the model. These distributions (and population counts) are based to the Claritas 2020 population by sex and age, with adjustments for educational attainment and race & ethnicity based on the ACS.

Model Specification

The model includes two categories of sex, seven categories of age, two categories of educational attainment, three categories of race and ethnicity, eight categories of population density, in addition to the 611 ZIP Code clusters. The ZIP Code clusters were nested within hyper clusters based on prior information of Jewish incidence such that clusters expected to be low or near zero Jewish population were grouped separately from areas expected to be high in Jewish incidence (see Chapter 5 for definitions of ZIP Code and hyper clusters). In addition, interactions of age and educational attainment, and ZIP Code clusters by age, educational attainment, and race-ethnicity were also included.

The basic model is displayed below, where the outcome variable, y_i, represents the Jewish identification of the respondent (yes/no), for i = 1, …, total number of respondents.

$$\Pr(y_i = 1) = logit\ \ (\beta_0 + \alpha_{j[i]}^{female} + \alpha_{k[i]}^{age} + \alpha_{l[i]}^{edu} + \alpha_{m[i]}^{race-ethn} + \alpha_{n[i]}^{pdens}$$
$$+\alpha_{k,l[i]}^{age.edu} + \alpha_{o[i]}^{zclust} + \alpha_{o,k[i]}^{zclust.age} + \alpha_{o,l[i]}^{zclust.edu} + \alpha_{o,m[i]}^{zclust.race-ethn} + \alpha_{p[i]}^{survey} + \gamma_{q[o]}^{hyclust}$$

$$\alpha_j^{female} \sim N\left(0, \sigma_{female}^2\right) \text{ for } j = 1,2\ categories\ of\ sex$$
$$\alpha_k^{age} \sim N\left(0, \sigma_{age}^2\right) \text{ for } k = 1, \dots, 7\ categories\ of\ age$$
$$\alpha_l^{edu} \sim N(0, \sigma_{edu}^2) \text{ for } l = 1,2\ categories\ of\ educational\ attainment$$
$$\alpha_m^{race-eth} \sim N(0, \sigma_{race-eth}^2) \text{ for } m = 1,2,3,4\ categories\ of\ race - eth$$
$$\alpha_n^{pdens} \sim N\left(0, \sigma_{pdens}^2\right) \text{ for } n = 1, \dots, 8\ categories\ of\ population\ density$$
$$\alpha_{k,l}^{age.edu} \sim N\left(0, \sigma_{age.edu}^2\right) \text{ for } k, l = 1, \dots 14\ categories\ of\ age.edu$$
$$\alpha_o^{zclust} \sim N(0, \sigma_{zclust}^2) \text{ for } o = 1, \dots \#\ of\ ZIP\ Code\ clusters$$
$$\alpha_{o,k}^{zclust.age} \sim N(0, \sigma_{zclust.edu}^2) \text{ for } o, k = 1, \dots \#\ of\ zclust.age$$
$$\alpha_{o,l}^{zclust.edu} \sim N(0, \sigma_{zclust.edu}^2) \text{ for } o, l = 1, \dots \#\ ofzclust.edu$$
$$\alpha_{o,m}^{zclust.race-ethn} \sim N(0, \sigma_{zclust.edu}^2) \text{ for } o, m = 1, \dots \#\ ofzclust.race - eth$$
$$\alpha_p^{survey} \sim N\left(0, \sigma_{survey}^2\right) \text{ for } p = 1, \dots \#\ of\ surveys$$
$$\gamma_q^{hclust} \sim N\left(0, \sigma_{hyclust}^2\right) \text{ for } q = 1, \dots \#\ of\ hyper\ clusters$$

The model was fit using the Bayesian software Stan (Stan Development Team, 2020) in R using the rstan package (R Core Team, 2020; Stan Development Team, 2020).[3] Preliminary multilevel logistic regressions were run using the lme4 package for R (Bates, Mächler, Bolker & Walker, 2015). These regressions, combined with results from past work, were used to provide informative priors and starting values. This was done to speed convergence since the prevalence of a Jewish adult among all U.S. adults was expected to be very small (less than 5%) and the survey variance – after accounting for sampling characteristics – was expected to be near zero.

Model Results

Results are provided on a set of 1,000 simulations, post-convergence. The estimates and 50% and 95% credible intervals for the demographic coefficients are displayed in Figure 3-1. The Bayesian credible interval represents the range of values based on variability in the observed data, which is unlike a frequentist "confidence" interval which is interpreted strictly in terms of the hypothetical of inferences that might be observed if a study were repeated. As can be seen from the graph, the demographic factors do not have strong predictive power in the likelihood of a US adult identifying as Jewish. Race and ethnicity is one of the strongest, with a greater likelihood among white non-Hispanic than other groups. Education also has a small, but significant effect, with college graduates more likely to identify as Jewish than non-college. Population density also is predictive with significantly less likelihood of an adult identifying as Jewish in low population density areas, and the highest in the most densely populated areas. Sex is not predictive, but is included in the model because all surveys included it in their weighting.

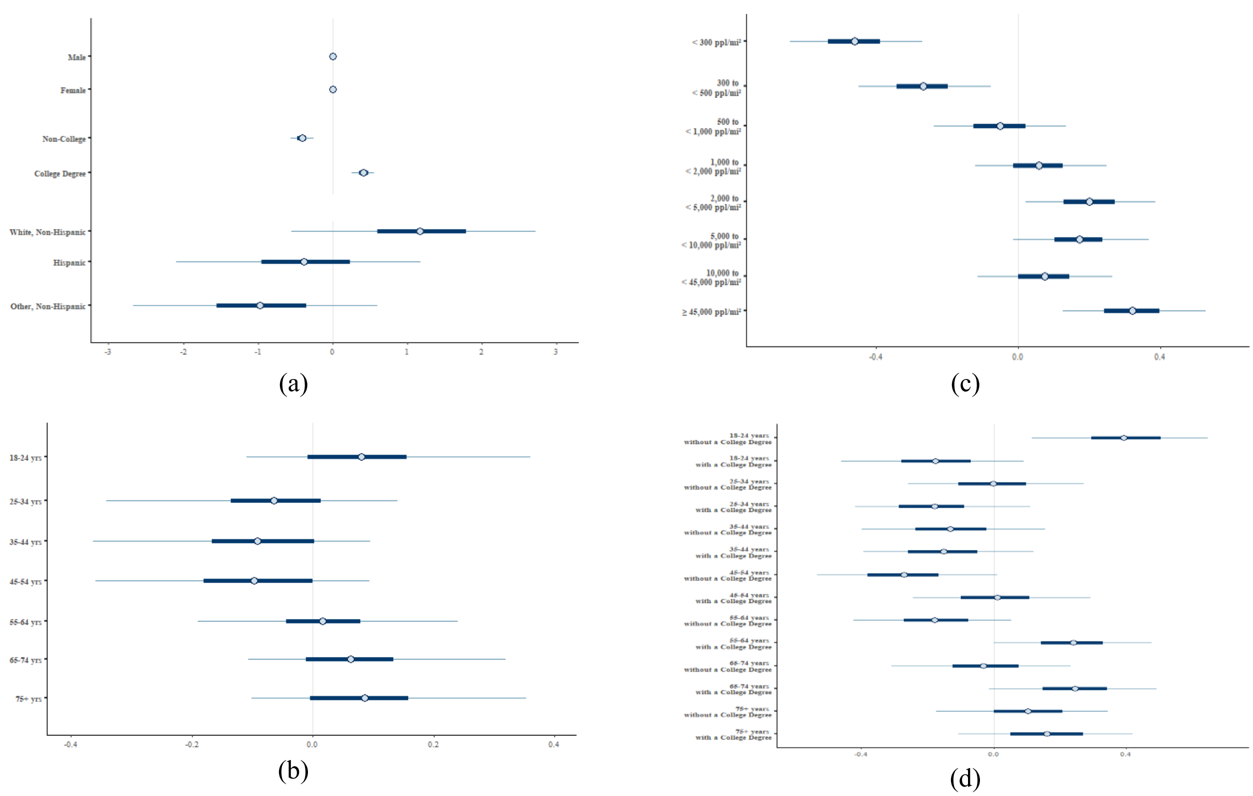

Figure 3-1: Estimates, 50% intervals, and 95% intervals for demographic variables: sex, educational attainment, race & ethnicity (a), age (b), population density (c), and the age by education interaction (d).

[3] The R base session info and rstan code are available in Appendix 3.1.

Figure 3-2 displays examples of the ZIP Code cluster by educational attainment and age interactions.[4] In areas in Brooklyn, college graduates are less likely to identify as Jewish than non-college college graduates, which is counter to the overall effect of a greater likelihood among college graduates. In Manhattan, college graduates are more likely (Figure 3-2a). Figures 3-2b and 3-2c provide examples of differences in geographic areas by age. In Palm Beach (Fig 3-2c), those ages 65 years and older are significantly more likely to identify as Jewish than those in younger age groups. In Lakewood, NJ, in contrast, younger adults, particularly those ages 25 to 34 years, were more likely to identify as Jewish than older adults (Fig. 3-2c).

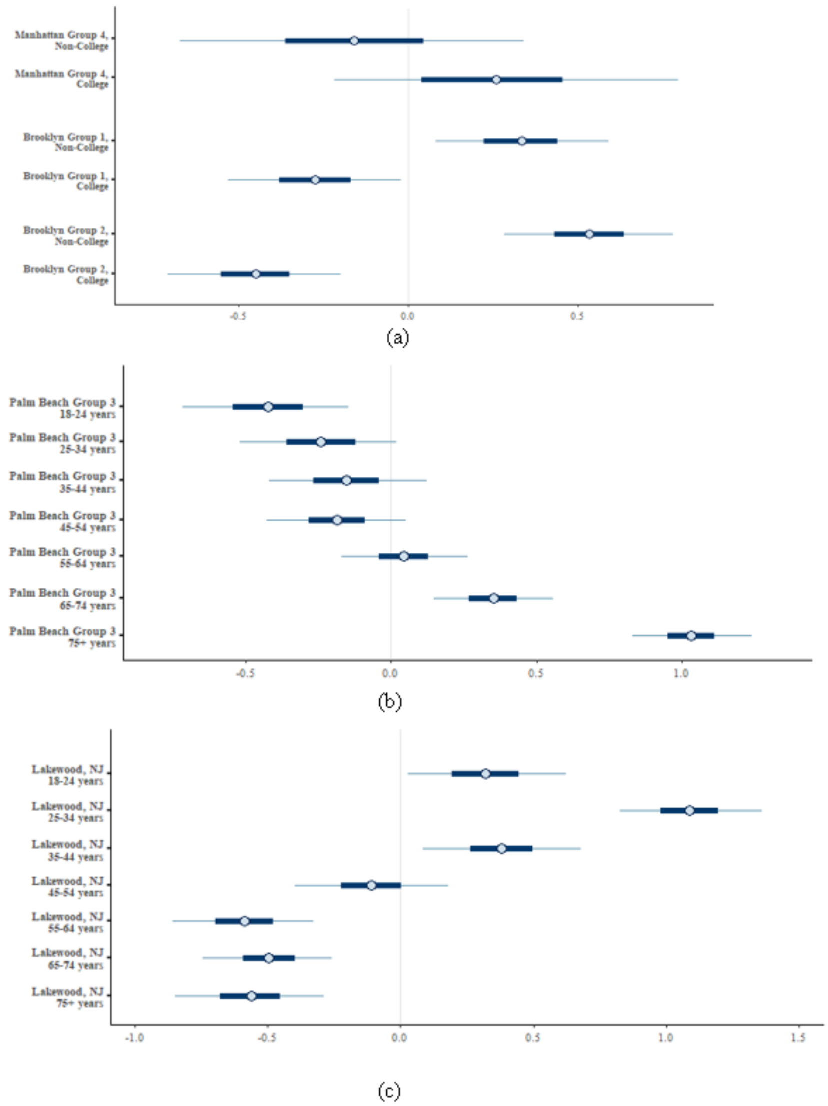

Figure 3-2: Estimates, 50% intervals, and 95% intervals for (a) ZIP Code clusters by educational attainment in Brooklyn and Manhattan; and, (b) ZIP Code clusters by age in Palm Beach, FL and Lakewood, NJ..

[4] The inclusion of the ZIP Code cluster x demographic interactions pushes the limits of the model in terms of the number of parameters estimated. They did, however, provide reliable cluster by demographic estimates for major population centers. Outlying areas with low Jewish population are less reliable. Work continues on how best to reduce these interaction terms. In the meantime, estimates are shared and should be interpreted with caution for outlying areas. See Detailed Tables for reliability indicators on estimates of age, education, and race-ethnicity distributions.

Figure 3-3 displays the variance components, where it can be seen the variance associated with surveys is near zero, reduced from 0.19, after accounting for sampling characteristics across the surveys.

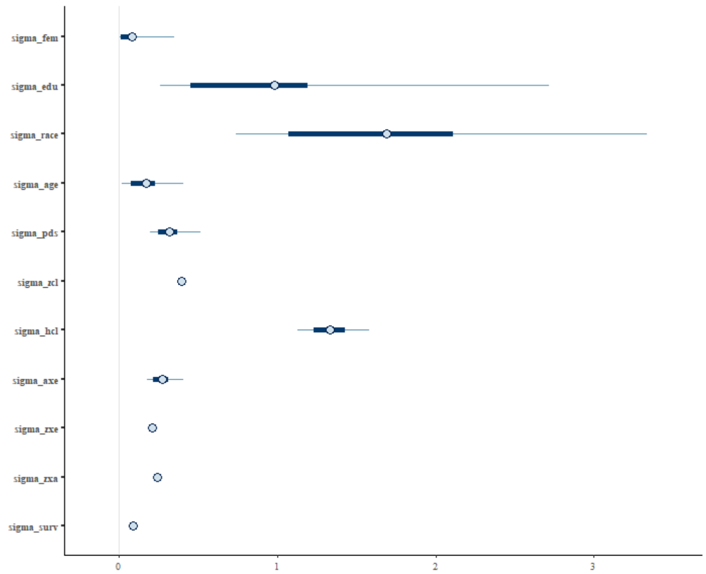

Figure 3-2: Summary of variance estimates, along with 50% and 95% uncertainty intervals.

Poststratification: Using the Model to Obtain Prevalence Estimates

In the second step, the model results are used to estimate the prevalence of Jewish adults (based on religious identification) in the U.S. population after adjusting for the representativeness across the survey samples on the key demographics included in the population model. Stratification refers to partitioning the population into subgroups to reduce variance and improve estimation. After fitting a model to the observed data, poststratification involves adjusting non-representative survey samples for key demographic characteristics that define each strata (Little, 1993).

Each ZIP Code cluster was partitioned into 84 subgroups representing the combination of sex (male/female), the seven categories of age, two categories of educational attainment, and three categories of race and ethnicity.

The proportion of Jewish respondents in each subgroup is estimated where each respondent's religious identification (Jewish/not) is modeled as:

$$y_{\mathrm{n}} \sim \mathrm{bernoulli}(\theta_{jj[n]}),$$

where *jj[n]* represents the subgroup to which the nth respondent belongs (e.g., male, age 18 to 24 years, white non-Hispanic, college graduate in South Brooklyn, NY)

The outcome, y^{pred} – the probability of identifying as Jewish by religion for each of the categories j=1, …, J defined by the model – is first computed over the set of 1,000 simulation draws.

$$y_j^{pred} = logit^{-1}(\beta^0 + \beta_{female(j)}^{female} + \beta_{age(j)}^{age} + \beta_{edu(j)}^{edu} + \beta_{racethn(j)}^{racethn} + \beta_{popdens(j)}^{popdens} + \beta_{zclust(j)}^{zclust} + \beta_{age\cdot edu(j)}^{age\cdot edu} + \beta_{zclust\cdot edu(j)}^{zclust\cdot edu} + \beta_{zclust\cdot age(j)}^{zclust\cdot age} + \gamma_{hycl(jk)}^{hycl}$$

Note, this is the same equation as that for the population model, except rather than estimated over individual respondents, *i*, the estimates are for each population subgroup, *j*; and, the equation omits the term for survey (β_{surv}), to estimate the average over survey samples.

These sample draws of $\theta^{(l)} \sim p(\theta/y)$ from the posterior predictive distribution are combined with the population sizes (N_j from the Claritas 2020 population frame) to estimate ϕ, the proportion of Jewish adults in the population for each subgroup within each ZIP Code cluster.

$$\phi^{(l)} = \frac{\sum_{j=1}^{J} \theta_j \cdot N_j}{\sum_{j=1}^{J} N_j}$$

Estimates are obtained by summing over these categories. For the nation as a whole, 2.4% of adults in the sample surveys identified as Jewish by religion, but after poststratification this was reduced to 1.9%. While women were under-represented in the survey samples, the estimated proportion of Jewish adults who were female increased from 48% to 51%. Similarly, poststratification reduced the proportion of Jewish adults with college degrees from 74% in the samples to 57%.

Table 3-6: Demographic Comparison of U.S. Adults and Jewish Adults Before and After Poststratification

	U.S. Adults[a]		Jewish Adults[b]					
	Population	Pct.	Sample Size	Pct.	JBR Sample Size	Pct.	Post-stratified	(95% Bayesian CI)
Total All Groups	250,324,002	100	1,341,682	100	32,523	2.4*	1.9*	(1.9*, 2.0*)
Sex								
Male	121,775,190	48.6	677,072	50.5	16,846	51.9	48.6	(47.1, 50.2)
Female	128,548,812	51.4	664,610	49.5	15,677	48.1	51.4	(49.8, 53.0)
Education								
Non-College	177,624,557	71.0	778,215	58.0	8,579	26.3	42.6	(41.2, 44.2)
College Grad	72,699,444	29.0	563,467	42.0	23,944	73.7	57.4	(55.7, 59.0)
Race								
White, non-Hisp.	161,567,880	64.5	1,028,151	76.6	30,535	93.9	88.9	(87.4, 90.4)
Hispanic	39,096,708	15.6	129,937	9.7	1,057	3.3	6.3	(5.9, 6.7)
Other, non-Hisp.	49,659,414	19.8	183,594	13.7	931	2.8	4.9	(4.6, 5.2)
Age								
18-24 years	29,811,266	11.9	106,231	7.9	2,064	6.3	10.7	(10.2, 11.3)
25-34 years	43,543,694	17.4	158,440	11.8	3,220	9.8	14.6	(14.0, 15.3)
35-44 years	40,909,436	16.3	164,441	12.3	2,996	9.2	12.6	(12.0, 13.2)
45-54 years	40,581,232	16.2	214,823	16.0	4,189	12.9	13.2	(12.6, 13.7)
55-64 years	41,693,274	16.7	272,076	20.3	7,076	21.7	18.8	(18.2, 19.5)
65-74 years	32,044,729	12.8	258,622	19.3	7,646	23.6	16.2	(15.6, 16.8)
75+ years	21,740,369	8.7	167,049	12.5	5,332	16.4	13.9	(13.3, 14.4)
Pop. Density (ppl./mi^2)								
<300	67,226,928	26.9	428,820	32.0	2,518	7.7	6.4	(6.1, 6.7)
300 to <500	18,029,727	7.2	101,228	7.5	1,209	3.7	3.5	(3.2, 3.7)
500 to <1,000	26,687,571	10.7	144,110	10.7	2,640	8.1	7.8	(7.4, 8.2)
1,000 to <2,000	32,415,687	12.9	170,514	12.7	4,339	13.3	12.9	(12.4, 13.4)
2,000 to <5,000	58,897,750	23.5	296,128	22.1	10,040	30.9	30.1	(29.1, 31.2)
5,000 to <10,000	27,591,043	11.0	124,269	9.3	5,776	17.8	18.0	(17.4, 18.6)
10,000 to <45,000	16,086,618	6.4	62,245	4.6	3,965	12.2	14.4	(13.9, 15.0)
≥45,000	3,388,679	1.4	14,368	1.1	2,036	6.3	7.0	(6.7, 7.3)
Metropolitan								
Non-Top 40 Metro	121,980,697	48.7	740,739	55.2	7,471	23.0	20.0	(19.3, 20.8)
Top 40 Metro	128,343,305	51.3	600,943	44.8	25,052	77.0	80.0	(77.7, 82.4)

Notes:
a) U.S. adult population values are from Claritas, 2020.
b) Values with an asterisk (*) represent the percent of the total sample size.

To get state and county estimates, ZIP Code cluster-level estimates are summed over the subgroups within each state or county.

Table 3-7: U.S. Adults and Jewish Adults by U.S. State, Before and After Poststratification

	U.S. Adults[a]		Jewish Adults[b]					
	Population	Pct.	Sample Size	Pct.	JBR Sample Size	Pct.	Post-stratified	(95% Bayesian CI)
Total All Groups	250,324,002	100	1,341,682	100	32,523	2.4*	1.9*	(1.9, 2)
State								
Alabama	3,726,998	1.5	22,803	1.7	110	0.3	0.3	(0.2, 0.3)
Alaska	542,160	0.2	4,327	0.3	26	0.1	0.0	(0.0, 0.1)
Arizona	5,552,036	2.2	31,885	2.4	723	2.2	1.8	(1.6, 1.9)
Arkansas	2,259,424	0.9	14,857	1.1	58	0.2	0.1	(0.1, 0.2)
California	30,190,515	12.1	130,033	9.7	4,686	14.4	14.4	(13.8, 14.9)
Colorado	4,425,855	1.8	26,047	1.9	437	1.3	1.3	(1.2, 1.5)
Connecticut	2,755,466	1.1	14,915	1.1	704	2.2	2.0	(1.9, 2.2)
Delaware	755,637	0.3	4,139	0.3	101	0.3	0.3	(0.2, 0.3)
Wash D.C.	545,617	0.2	3,430	0.3	279	0.9	0.7	(0.6, 0.7)
Florida	17,111,575	6.8	80,109	6.0	3,563	11.0	12.1	(11.6, 12.7)
Georgia	7,964,360	3.2	40,090	3.0	525	1.6	1.6	(1.5, 1.7)
Hawaii	1,087,469	0.4	4,421	0.3	52	0.2	0.1	(0.1, 0.2)
Idaho	1,320,685	0.5	9,442	0.7	39	0.1	0.1	(0.1, 0.1)
Illinois	9,641,373	3.9	43,232	3.2	1,201	3.7	4.1	(3.8, 4.3)
Indiana	5,017,499	2.0	29,985	2.2	178	0.5	0.5	(0.4, 0.6)
Iowa	2,362,752	0.9	15,402	1.1	70	0.2	0.2	(0.2, 0.2)
Kansas	2,146,202	0.9	13,342	1.0	113	0.3	0.3	(0.3, 0.4)
Kentucky	3,371,770	1.3	20,673	1.5	138	0.4	0.4	(0.3, 0.5)
Louisiana	3,474,779	1.4	18,831	1.4	115	0.4	0.3	(0.3, 0.4)
Maine	1,064,495	0.4	7,787	0.6	113	0.3	0.3	(0.2, 0.3)
Maryland	4,631,263	1.9	23,811	1.8	1,178	3.6	3.2	(3.0, 3.4)
Massachusetts	5,372,607	2.1	27,839	2.1	1,409	4.3	4.2	(4.0, 4.5)
Michigan	7,683,086	3.1	38,377	2.9	478	1.5	1.6	(1.5, 1.8)
Minnesota	4,255,316	1.7	25,069	1.9	266	0.8	0.8	(0.7, 0.9)
Mississippi	2,217,949	0.9	12,691	0.9	33	0.1	0.1	(0.1, 0.1)
Missouri	4,630,813	1.8	26,961	2.0	263	0.8	0.7	(0.6, 0.8)
Montana	824,151	0.3	7,905	0.6	41	0.1	0.1	(0.1, 0.1)
Nebraska	1,421,353	0.6	10,360	0.8	50	0.2	0.1	(0.1, 0.2)
Nevada	2,378,133	1.0	11,340	0.8	311	1.0	0.9	(0.8, 1.0)
New Hampshire	1,074,318	0.4	6,212	0.5	102	0.3	0.3	(0.2, 0.3)
New Jersey	6,862,881	2.7	34,030	2.5	2,465	7.6	7.4	(7.1, 7.8)
New Mexico	1,600,129	0.6	10,845	0.8	132	0.4	0.2	(0.2, 0.3)

New York	15,018,731	6.0	75,706	5.6	6,277	19.3	21.8	(21.0, 22.6)
North Carolina	8,021,350	3.2	43,750	3.3	454	1.4	1.3	(1.1, 1.4)
North Dakota	563,478	0.2	4,018	0.3	6	0.0	0.0	(0.0,0.0)
Ohio	8,913,913	3.6	49,237	3.7	609	1.9	1.8	(1.7, 1.9)
Oklahoma	2,930,165	1.2	19,893	1.5	87	0.3	0.2	(0.2, 0.3)
Oregon	3,295,639	1.3	22,364	1.7	333	1.0	0.8	(0.8, 0.9)
Pennsylvania	9,906,757	4.0	62,093	4.6	1,640	5.0	4.6	(4.4, 4.9)
Rhode Island	817,844	0.3	4,664	0.3	111	0.3	0.3	(0.2, 0.4)
South Carolina	3,958,610	1.6	20,958	1.6	184	0.6	0.5	(0.5, 0.6)
South Dakota	647,850	0.3	4,529	0.3	6	0.0	0.0	(0.0, 0.0)
Tennessee	5,204,411	2.1	31,566	2.4	236	0.7	0.6	(0.6, 0.7)
Texas	21,318,985	8.5	99,248	7.4	996	3.1	3.0	(2.8, 3.2)
Utah	2,261,334	0.9	15,824	1.2	70	0.2	0.2	(0.1, 0.2)
Vermont	488,999	0.2	4,406	0.3	120	0.4	0.2	(0.2, 0.3)
Virginia	6,521,061	2.6	37,935	2.8	721	2.2	1.8	(1.7, 2.0)
Washington	5,895,973	2.4	33,605	2.5	428	1.3	1.3	(1.2, 1.4)
West Virginia	1,404,183	0.6	9,349	0.7	31	0.1	0.1	(0.1, 0.1)
Wisconsin	4,454,079	1.8	27,210	2.0	233	0.7	0.7	(0.6, 0.7)
Wyoming	431,975	0.2	4,137	0.3	22	0.1	0.0	(0.0, 0.1)

Notes:
a) U.S. adult population values are from Claritas, 2020.
b) Values with an asterisk (*) represent the percent of the total sample size.

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Chapter 4: Estimation of Jewish children and other Jewish adults

Overview

The model-based estimation of Jewish adults based on general population surveys that ask about religion is the most robust source of data on this segment of the population. Researchers and policy makers, however, are interested in total Jewish population estimates, which include Jewish children and Jewish adults who identify ethnically or culturally but not by religion as Jewish. These two groups are not easily estimated through general population surveys. Too few surveys ask about Jewish identity beyond religion, and, similarly, too few surveys ask about the religion in which children are being raised. There are, however, targeted surveys of the Jewish population that have been done, including a national survey conducted by Pew Research Center (2013), and a number of local community studies which are summarized yearly in the American Jewish Year Book (AJYB) (cf. Dashefsky & Sheskin, 2019). These studies are used to estimate Jewish children and other Jewish adults and are then combined with the model-based estimate of Jewish adults by religion to obtain total population estimates for each geographic area. This chapter describes the available surveys and analyses of these surveys.

The Jewish Federations of North America (JFNA) represent a total of 146 organized Jewish communities in the U.S. and Canada and a network of more than 300 smaller communities. Of these, 37 communities in the U.S. have conducted some form of community study in the past 10 years, representing just over a quarter (28%) of the main Federations and less than 10% of all communities. Seven of these studies were designed as marketing studies, needs assessment surveys, or voter polls, and do not provide population estimates. Thirty studies include some type of population survey. Some of these include "representative samples" of the general population obtained through phone surveys, supplemented with known samples identified through organization lists. Others are based on Distinctive Jewish Names samples (Aronson, et al., 2016; Sheskin, 1998).

It should be noted that surveys vary in terms of quality and questions can be raised regarding how representative these surveys are of the true underlying population. No attempt is made here to adjust results from individual surveys for possible over- or under-representation. Results from the individual surveys are taken at face value. Thus, estimates of Jewish children and ethnically or culturally Jewish adults of no religion are provided as a best estimate given available data. The estimates of Jewish children are based on how the original researchers classified children in the local study. The definition of JNR adults was standardized as described in more detail below.

For both Jewish children and JNR adults, we do not estimate the numbers of children or JBR adults form the local study, but instead we estimate the proportion of the population in each group. These proportions are then applied to our model-based estimate of the JBR population to obtain total population estimates.

Definition of JNR

In analyzing these supplemental sources to estimate the proportion of the Jewish adults who identify ethnically or culturally but not by religion (JNR), we include all adults who:

- consider themselves Jewish
- have at least one Jewish parent
- do not belong to any other religious group

This definition is consistent with common definitions of those who would be considered part of the core Jewish population (p. 484-512, Schmelz & Pergola, 1992; Pew Research Center, 2013). It is more restrictive than some community studies that include those who identify ethnically and culturally as Jewish but are currently practicing another religion (Aronson et al., 2017; Boxer, et al., 2017), which is why some of our estimates differ from those published in local studies.

Our definition also differs from the current definition used by Professor Sergio DellaPergola who restricts estimates of the core Jewish population to “the group who consider Judaism their mutually exclusive identification framework, including both those who do see or do not see religion as a major avenue for identification" (DellaPergola, 2020, p. 270), where "mutually exclusive identification framework" means that those who self-declare themselves to be Jewish cannot identify with any other religion. In addition, those who identify as Jewish but do not declare Judaism as their religion because they are atheist, agnostic, or otherwise not religiously identified, they must also identify only as Jewish.

That the core Jewish population should exclude those who currently belong to another religion is non-controversial. What it means, however, for those who are Jewish and are otherwise affiliated with no religion, to identify as “only” Jewish is unclear. It has not, in the past, been an aspect of Jewish identification that has been formally assessed. For DellaPergola, the distinction arose after the 2013 Pew Survey of American Jews. Given the difficulties of surveying the Jewish population in the U.S., both the 2000-2001 NJPS (Kotler-Berkowitz, et al., 2004, p. 200) and the Pew Survey of American Jews (Pew Research Center, 2013) included broad screening questions to screen-in as large a potential Jewish sample as possible. For those who do not identify their religion as Jewish, they were asked whether they considered themselves Jewish and why they considered themselves Jewish. To cast as wide a net as possible in screening potential Jewish respondents into the survey, responses to the consider-self-Jewish question included the option of “partially (or half)” Jewish. After screening into the survey, detailed questions about Jewish identity were assessed to describe the total U.S. Jewish population, with the main population estimate including those who declare themselves Jewish by religion or declare themselves Jewish and have no religion, and have at least one Jewish parent or were raised Jewish. DellaPergola excludes all those who responded “partially” to the screener question regardless of how they responded to the detailed questions about identity after screening into the survey.

It is difficult to know what is meant by respondents’ choosing the "partially" option in a screener question. Many who said "partially", were raised Jewish, both of their parents were Jewish, and they identify with no other religious group. There was no official assessment of the reasons why one might consider themselves to be partially Jewish and whether they should be considered part of the core or extended Jewish population. A review of open-ended responses in the Pew survey to the question about why one considered themselves to be Jewish revealed that many who answered “partially” said it was because they consider themselves culturally Jewish, or because they are not religious—the very definition of the group who do not identify by religion. We, therefore, do not exclude those who said partially, and include all those who self-declare as Jewish whether by religion or consider themselves, and had at least one Jewish parent and do not identify with another religion.

Given these definitions of JNR and Jewish children, secondary analyses were conducted on the past ten years' worth of local community studies to estimate within each community the percentage of Jewish adults who do not identify by religion but instead by ethnicity or culture, as well as the percentage of Jewish children.

Because these are only single sources of data for particular geographic areas and are not based on a systematic analysis of multiple independent samples of the population, every attempt was made to provide conservative estimates. For example, if a local community estimated that thirty percent of the population were children, rather than applying the thirty percent to all geographic areas covered by the survey, analyses were conducted to examine whether the percentage varied by regions within the larger community. If analyses indicated that there were significant differences, with some areas displaying lower percentages of children than other areas, these lower estimates were applied to the subareas.

For all geographic areas not represented in the community studies that have been done in the past ten years, estimates were based on the last national Jewish population survey (Pew Research Center, 2013).

Each of the surveys and results from the secondary analyses are described below, starting with individual community studies, and followed by the Pew national survey.

Jewish Community Studies

Local Jewish communities have used population surveys as a tool for planning and policy purposes for over half a century. Today, dozens of communities have conducted Jewish population surveys, with many repeating the study decennially. To use these local Jewish community studies for the purpose of extrapolating the proportion of JNR adults and Jewish children, we limit our analyses to studies that used a systematic survey methodology and were completed within the past 10 years. These parameters ensure that robust analysis of the data can be performed, and that the data is contemporaneous to the present estimates of JBR adults.

There are 29 local Jewish community studies that meet these criteria, shown below in Table 4-1, which includes whether the survey was used to estimate JNR adults, Jewish children, or both. Of these local studies, about half were conducted by researchers at the Cohen Center for Modern Jewish Studies/Steinhardt Social Research Institute at Brandeis University (e.g., Aronson et al., 2019; Boxer et al., 2020), seven were conducted by Professor Ira Sheskin (University of Miami), and the remaining seven were conducted by other independent researchers. Five of the seven were conducted by Jacob B. Ukeles in collaboration with Steven M. Cohen (n=4), Ron Miller (n=4), and David Dutwin (n=3) in collaboration with JPAR (Jewish Policy and Action Research). Of the other two surveys, one was conducted by David Marker & Darby Steiger (Westat), and the other was by Ron Miller, Laurence Kotler-Berkowtiz, and Stephen Percy (at the University of Wisconsin, Milwaukee).

Table 4-1: Local Jewish Community Studies Included in Analysis of JNR Adults and Jewish Children

Local Jewish Community Study	Study Date	Principal Investigators	Jews of No Religion	Jewish Children
Baltimore	2020	Boxer, Brookner, Chapman, Aaronson, Mangoubi, Feinberg, Aronson, Saxe	X	X
Boston	2015	Aronson, Boxer, Brookner, Kadushin, Saxe, Preuss	X	X
Broward County	2016	Sheskin		X
Buffalo	2013	Boxer, Aronson, Davidson, Aitan		X
Cincinnati	2019	Aronson, Chapman, Brookner, Aaronson, Feinberg, Boxer, Saxe	X	X
Cleveland	2011	Beck, Ukeles, Miller, Dutwin		X
Columbus	2013	Cohen, Ukeles, Miller, Dutwin		X
Denver	2019	Aronson, Brookner, Chapman, Mangoubi, Aaronson, Feinberg, Boxer, Saxe	X	X
Detroit	2018	Sheskin		X
Houston	2016	Sheskin		X
Howard County	2020	Boxer, Brookner, Chapman, Aaronson, Mangoubi, Aronson, Saxe	X	X
Indianapolis	2017	Sheskin		X
Miami	2014	Sheskin		X
Milwaukee	2011	Miller, Kotler-Berkowitz, Percy		X
Naples	2017	Boxer, Brookner	X	X
Nashville	2015	Boxer, Aronson, Brookner, Perry	X	X
New York Metropolitan Area	2011	Cohen, Ukeles, Miller	X	X
Omaha	2017	Sheskin		X
Palm Beach County[a]	2018	Aronson, Brookner, Boxer, Chapman, Saxe	X	X
Philadelphia	2019	Marker, Steigert	X	X
Pinellas and Pasco Counties	2017	Sheskin		X
Pioneer Valley	2020	Boxer, Chapman, Brookner, Mangoubi, Aaronson, Feinberg, Aronson, Saxe	X	X
Pittsburgh	2017	Boxer, Brookner, Aronson, Saxe	X	X
San Francisco Bay Area	2017	Cohen, Ukeles, Grosse	X	X
Sarasota	2019	Boxer, Brookner, Chapman, Aronson	X	X
Seattle	2014	Boxer, Aronson, Brown, Saxe		X
St. Louis	2015	Cohen, Ukeles, Miller, Dutwin, Sherr	X	X
Twin Cities	2019	Aronson, Brookner, Chapman, Mangoubi, Aaronson, Feinberg, Boxer, Saxe	X	X
Washington, D.C.	2017	Aronson, Brookner, Boxer, Saxe	X	X

Notes:

a) Datasets from the 2018 South Palm Beaches and Greater Palm Beach County studies were combined to analyze proportions of JNR adults and Jewish children.

Secondary analysis of each study was performed to examine the reliability of JNR adults and Jewish children and to obtain, where possible, subarea proportions specifically for the ZIP Code clusters or county areas that matched the AJPP model. In cases where these subarea estimates were not reliable, or if the differences between subarea estimates were not statistically significant, the overall study estimate of the proportion of JNR adults or Jewish children was applied to the corresponding ZIP Code areas.

Estimates of the proportions of JNR adults and Jewish children were based on secondary analyses of the publicly available datasets, which can be found at the Berman Jewish Databank. For analysis of surveys conducted by researchers at CMSJ/SSRI, restricted-use data that included ZIP Code of the respondent was made available. All analyses were conducted using the survey package (svy) in Stata 16.

Jewish Community Studies Conducted by Prof. Ira M. Sheskin

Seven of the local community studies were conducted by Professor Ira M. Sheskin at the University of Miami.[5] His surveys do not include assessment of JNR adults but can be used to estimate proportions of Jewish children within each study's geographic area. All of the data sets for these surveys were designed similarly in terms of the variable definitions needed for analysis. These included a final household weight (WF), a variable to identify geographic stratification (finalstrata),[6] and variables to identify Jewish adults (cj1 up to cj9) and children (cjc1 up to cjc9) in households. For each of these surveys, analyses were conducted using the survey package in Stata (svy) with the following design statement:

```
svyset _n [pweight=WF], strata(finalstrata) vce(linearized) singleunit(missing)
```

Analyses of each study area were conducted to examine the proportion of the total Jewish population who are children and to determine whether the estimate of children varied substantially within the study area.

Broward County

The 2016 Jewish Federation of Broward County Population Study reported 21,700 Jewish children out of a total Jewish population of 148,900 (Sheskin, 2016, p. 5-22). This corresponds to 14.6% of the total Jewish population in Broward County.

The study's sampling frame was divided into six subareas defined by cities and groups of ZIP Codes within the county. These included: Southeast Broward, Southwest Broward, West Central, Northwest, North Central, and East Broward (p. 1-4 & 1-5, Sheskin, 2016). The AJPP 2020 national model for Broward county consisted of two ZIP Code clusters, one representing the northern portion of the county and a second representing the southern portion of the county. The southern ZIP Code cluster approximated the Southeast and Southwest county regions in the

[5] Ira M. Sheskin, Professor and Chair, Department of Geography, University of Miami & Director of the Jewish Demography Project of the Sue and Leonard Miller Center for Contemporary Judaic Studies.
[6] The Omaha study did not include the strata variable.

Broward study and the northern ZIP Code cluster provided a close approximation to the rest of the sampling frame.

The six Broward study subareas were recoded into two groups representing the AJPP 2020 ZIP Code clusters. The proportion of Jewish children in these groups were then examined to determine if significant differences existed between the estimates (see Table 4-2). The southern area of the county appeared to have a somewhat greater proportion of children (16.3%) than the northern area (13.2%). This difference, however, was not statistically significant ($F_{1.0, 2696.0} = 2.0200$, $p = .1500$) and, therefore, the study's overall estimate of 14.6% was used to estimate the proportion of Jewish children in Broward county.

Table 4-2: Analysis of Jewish Children in Broward County, FL

Study Areas	Prop. Jewish Children (95% CI)		Coefficient of Variation
South Broward	.163	(.133, .2)	10.4
North Broward	.132	(.106, .163)	10.9
Total	.146	(.125, .169)	7.6

Detroit

The 2018 Detroit Jewish Population Study reported 13,098 children out of a total Jewish population of 70,800 (p. 4-22, Sheskin, 2018). This corresponds to 18.5% of the total Jewish population in metropolitan Detroit.

The study's sampling frame, which consists of Oakland, Wayne, and Macomb Counties in Michigan, was divided into two large geographic regions and six geographic subareas defined by cities and ZIP Code areas within Metropolitan Detroit. The large regions include a Core Area, which spans the cities of Berkley, Birmingham, Bloomfield Hills, Commerce Township, Farmington, Farmington Hills, Franklin, Oak Park, Southfield, Royal Oak, Huntington Woods, Walled Lake, and West Bloomfield in Oakland County, as well as a Non-Core Area, which includes the rest of Oakland County as well as all of Wayne and Macomb Counties (p. 1-4, Sheskin, 2018). The AJPP 2020 national model splits Detroit and its surrounding areas into five ZIP Code clusters, two within Oakland County, two within Wayne County, and one within Macomb County.

The study's geographic subareas were recoded into three groups to capture variation between the Core and Non-Core Areas within Oakland County, as well as between Oakland County and the outlying areas in Wayne and Macomb Counties (see Table 4-3). The first of these groups, which approximated one of the five AJPP ZIP Code clusters, corresponded to the Core Area of Oakland County. The second group, which also approximated an AJPP ZIP Code cluster, corresponded to the Non-Core Area of Oakland County. The third group, which combined the remaining three AJPP ZIP Code clusters, corresponded to the combined areas of Wayne and Macomb Counties (8.5%).

The estimates for the Core (20.8%) and Non-Core (10.1%) areas of Oakland County were shown to be reliable and have distinct confidence intervals, however, due to insufficient sample, the estimate for the combined area of Wayne and Macomb Counties (8.5%) could not be used (CV=31.7).

Table 4-3: Initial Analysis of Jewish Children in Detroit Subareas

Study Areas	Prop. Jewish Children (95% CI)		Coefficient of Variation
Core Area	.208	(.183, .235)	6.3
Non-Core, Oakland County	.101	(.062, .159)	24.1
Wayne and Macomb Counties	.085	(.045, .155)	31.7
Total	.185	(.164, .208)	6.1

Rather than applying the study's overall proportion of Jewish children in Metropolitan Detroit to the city's outlying areas in Wayne and Macomb Counties, a follow-up analysis was conducted to obtain estimates of the study's entire Non-Core Area, which included parts of Oakland County (see Table 4-4). This Non-Core estimate of Jewish children (9.3%) was shown to be both reliable and, with non-congruent confidence intervals, significantly different from the Core area.

Table 4-4: Analysis of Jewish Children in Non-Core Area

Study Areas	Prop. Jewish Children (95% CI)		Coefficient of Variation
Core Area	.208	(.183, .235)	6.3
Non-Core Area	.093	(.062, .135)	19.8
Total	.185	(.164, .208)	6.1

The more reliable Non-Core estimate of Jewish children (9.3%) was applied to the three AJPP ZIP Code clusters that span Wayne and Macomb Counties. The two remaining AJPP ZIP Code clusters were estimated using results from the initial analysis (see Table 4-3), where the study's Core Area (20.8%) was shown to have about twice the percentage of Jewish children as the Non-Core portion of Oakland County (10.1%).

Houston

The 2016 Greater Houston Jewish Community Study reported 7,808 children out of a total Jewish population of 50,700 (p. 5-22, Sheskin 2016). This corresponds to 15.5% of the total Jewish population in the greater Houston area.

The study's sampling frame includes all of Harris County, Texas, as well as select ZIP Codes in Fort Bend County, southern Montgomery County, northern Brazoria County, and Galveston County. This geographic profile was divided into the following eight subareas: Central City, which includes Houston, Houston Heights, Memorial Park, and Texas Southern University; a Core Area, which includes West University Place, Bellaire, Meyerland, and Westwood Park; Memorial, which includes Lamar Terrace, Piney Point Village, Hunters Creek Village, and Bunker Hill Village; Suburban Southwest, which includes Almeda Plaza, Missouri City, Sugar Land, Fort Bend, and Sienna Plantation; West, which includes Bellaire West, Addicks, Spring

Valley, Barker, and Melendy; North, which includes Hawthorne Place, Hudson, North Houston, Cypress, Scenic Woods, Dyersdale, Aldine, Louetta, Tomball, Bammel, Kingwood, Atascocita,

and Huffman; Southeast, which includes Magnolia Park, Pecan Park, Galena Park, South Houston, and Pearland; and East Houston, which includes Jacinto City, Cloverleaf, Channelview, and Highlands. The AJPP 2020 national model splits the greater Houston area into four ZIP Code clusters within Harris County.

The study's subareas were recoded into two groups, one that approximated an AJPP ZIP Code cluster by combining the Core area with Central and Memorial, and another that included the rest of sampling frame, which approximated the other three ZIP Code clusters. Estimates for these two groups, though reliable, were not considered significantly different ($F_{1.0, 2{,}409.0} = .0002$, $p = .9881$) and, therefore, the study's overall estimate of Jewish Children (15.5%) was applied to all four of AJPP's ZIP Code clusters in Harris County (see Table 4-5).

Table 4-5: Analysis of Jewish Children in Houston Areas

Study Areas	Prop. Jewish Children (95% CI)	Coefficient of Variation
Core Area	.155 (.129, .185)	9.2
Non-Core Areas	.155 (.120, .197)	12.6
Total	.155 (.133, .179)	7.5

Indianapolis

The 2017 Indianapolis Jewish Population Study reported 5,000 Jewish children out of a total Jewish population of 17,900 (p. 5-22, Sheskin, 2017). This corresponds to 28.2% of the total Jewish population in Marion and Hamilton Counties, IN.

The study's geographic profile includes all of Marion and Hamilton County, IN as well as a single ZIP Code (46077) in Boone County, IN. This sampling frame was divided into three areas defined by cities and groups of ZIP Codes within the counties. These included: a Core Area in northern Marion County, a North of Core area in Hamilton County, and South of Core area in southern Marion County (p. 1-4, Sheskin, 2017). The AJPP 2020 national model for Indianapolis consisted of two ZIP Code clusters in Marion, IN, one representing the northern portion of the county and a second representing the southern portion. Hamilton County was grouped with Madison and Hancock Counties, neither of which were included in the study's sampling frame.

The two AJPP Zip Code clusters in Marion County are approximated by the study's Core and South of Core areas. Estimates of Jewish children for these areas were examined to see if variation existed between the northern and southern portions of the county. Although sufficient sample existed in Marion County to estimate both areas reliably, the Core Area estimate (23.0%) and the South of Core area estimate (15.5%) shared overlapping confidence intervals (see Table 4-6) and, therefore, were not considered statistically significant.

Table 4-6: Analysis of Jewish Children in Marion County, IN

Study Areas	Prop. Jewish Children (95% CI)		Coefficient of Variation
Core Area	.230	(.178, .291)	12.5
South of Core	.155	(.084, .269)	30.0
North of Core	.356	(.300, .416)	8.4
Total	.283	(.246, .323)	6.9

Given the lack of meaningful difference between the estimates for the Core and South of Core, these areas were combined to obtain a single estimate of Jewish children in Marion County. The rest of the sampling frame, all of Hamilton County and the single Boone County ZIP Code, was estimated separately (see Table 4-7).

Table 4-7: Analysis of Jewish Children in Marion County, IN

Study Areas	Prop. Jewish Children (95% CI)		Coefficient of Variation
Marion County	.208	(.163, .261)	12.0
Hamilton County	.356	(.3, .416)	8.4
Total	.283	(.246, .323)	6.9

Absent more comprehensive data on Jewish children, higher proportions were not applied to AJPP ZIP Code clusters that included areas beyond a study's sampling frame. As Hamilton County was included in a cluster with two counties—Madison and Hancock—not within the study's geographic profile, its estimate of Jewish children (35.6%) was not generalized to the corresponding AJPP area. The estimate of Jewish children for Marion County (20.8%), which was both reliable (CV = 12.0) and statistically significant ($F_{1.0,\ 1{,}222.0} = 14.1278$, $p = .0002$), was applied to both AJPP ZIP Code clusters in Marion, IN.

Miami

The 2014 Greater Miami Jewish Federation Population Study reported 23,300 Jewish children out of a total Jewish population of 122,200 (p. 5-22, Sheskin, 2017). This corresponds to 19.1% of the total Jewish population in Miami-Dade County, FL.

The study's sampling frame is divided into three main regions defined by cities and groups of ZIP Codes within Miami-Dade County. These include: North Dade, which includes the subareas of North Dade Core East, North Dade Core West, and Other North Dade; South Dade, which includes the subareas of West Kendall, East Kendall, and Northeast South Dade; and The Beaches, which includes the subareas of North Beach, Middle Beach, and South Beach (p. 1-4, Sheskin, 2014). The AJPP 2020 national model for Miami-Dade County consisted of three ZIP Code clusters, one which captured ZIP Codes in and around North Miami, one which captured the more southern coastal areas near South Miami and Kendall, and a third which captured the rest of the county's inland ZIP Codes.

None of the AJPP ZIP Code clusters map well onto the three main regions, which required the study's subareas to be recoded into two groups. One of these groups captured the more densely populated subareas along the coast, including North Dade Core East, North Dade Core West, North Beach, Middle Beach, South Beach, Northeast South Dade, and East Kendall. The other captured the more inland subareas of Other North Dade and West Kendall, which are less densely populated. Estimates of Jewish children for these areas were examined (see Table 4-8) to see if meaningful variation existed between Miami's city center and the outlying areas in the rest of the county.

Table 4-8: Analysis of Jewish Children in Miami-Dade Areas

Study Areas	Prop. Jewish Children (95% CI)		Coefficient of Variation
Coastal Areas	.204	(.188, .222)	4.3
Inland Areas	.142	(.115, .175)	10.7
Total	.191	(.176, .206)	4.0

Estimates for these areas were both reliable and significantly different ($F_{1.0,\,4,718.0}$ = 10.4544, p = .0012). The estimate of Jewish children for the more densely populated urban core (20.4%) was applied to the two AJPP ZIP Code clusters which span the coastal areas of North Miami, South Miami, and Kendall. The estimate of Jewish children for the less densely populated group (14.2%) was assigned to the remaining cluster, which encompassed the rest of the county's outlying areas.

Omaha

The 2017 Jewish Federation of Omaha Population Study reported 1,400 Jewish children out of a total Jewish population of 8,800 (p. 5-23, Sheskin, 2017). This corresponds to 15.9% of the total Jewish population in Omaha, Nebraska.

The study's geographic profile, which includes all of Douglas and Sarpy Counties, is divided into three regions defined by groups of ZIP Codes within the sampling frame. These include: East Omaha, West Omaha, and Other Areas (p. 1-4, Sheskin, 2017). These areas are not well-approximated by the AJPP 2020 national model, which estimates Douglas County on its own and groups Sarpy with four counties outside of the study's sampling frame.

In the absence of a variable for ZIP Codes or more detailed geographic subareas, East Omaha and West Omaha were combined to approximate the AJPP ZIP Code cluster corresponding to Douglas County. The rest of the sampling frame, which captures the outlying areas of Omaha in Douglas County as well as all of Sarpy County, is estimated separately (see Table 4-9).

Table 4-9: Analysis of Jewish Children in Omaha Areas

Study Areas	Prop. Jewish Children (95% CI)		Coefficient of Variation
East-West Omaha	.168	(.130, .214)	12.6
Sarpy and Outlying Douglas	.101	(.045, .210)	39.7
Total	.159	(.125, .200)	12.1

The estimates for these areas were reliable and, despite overlapping confidence intervals, both were applied to their corresponding AJPP ZIP Code clusters in order to capture variation between Omaha's urban center and the city's outlying areas. The estimate of Jewish children for the combined areas of East and West Omaha (16.8%) was used to approximate all of Douglas County. Although Sarpy County was part of an AJPP ZIP Code cluster that included other counties outside of the study's sampling frame, the conservative nature of the estimate for the outlying areas in Douglas and Sarpy Counties (10.1%) made it a better fit for this cluster than the study's overall estimate of Jewish children (15.9%).

Pinellas/Pasco

The 2017 Pinellas/Pasco Jewish Population Study reported 2,200 Jewish children out of a total Jewish population of 27,900 (p. 5-23, Sheskin, 2017). This corresponds to 7.9% of the total Jewish population in Pinellas and Pasco Counties, FL.

The study's geographic profile, which includes all of Pinellas and Pasco Counties, is divided into four regions defined by groups of ZIP Codes within the sampling frame. These include: North Pinellas, which includes ZIP Codes in Clearwater, Ozona, Oldsmar, Crystal Beach, Palm Harbor, and Tarpon Springs; Central Pinellas, which includes ZIP Codes in Belleair, Clearwater, and Largo; South Pinellas, which includes ZIP Codes in St. Petersburg, Gulfport, Largo, and Pinellas Park; and Pasco County, which includes all areas within Pasco County (p. 1-4, Sheskin, 2017). The AJPP 2020 model divides these areas into three ZIP Code clusters, one spanning the southern portion of Pinellas County, another spanning the northern portion, and a third encompassing all of Pasco County.

The study's subareas were recoded to approximate the three AJPP ZIP Code clusters by combining North and Central Pinellas. This split Pinellas along a north-south border that well-approximated the county's two clusters and left Pasco County to be estimated on its own (see Table 4-10).

Table 4-10: Analysis of Jewish Children in Pinellas and Pasco Counties, FL

Study Areas	Prop. Jewish Children (95% CI)		Coefficient of Variation
North Pinellas	.040	(.028, .057)	18.1
South Pinellas	.089	(.059, .130)	20.1
Pasco County	.163	(.086, .288)	31.2
Total	.079	(.059, .105)	14.8

The analysis demonstrated that variation existed between the proportion of Jewish children in northern Pinellas County (4.0%) and that of southern Pinellas County (8.9%), however, overlapping confidence intervals on these estimates suggested that the difference was not statistically significant. Additionally, the estimate of Jewish children in Pasco County (16.3%) was unreliable (CV = 31.2) due to insufficient sample. For these reasons, the study's overall estimate of Jewish children (7.9%) was applied to all three of the AJPP ZIP Code clusters in Pinellas and Pasco Counties, FL.

Summary

Out of the seven studies conducted by Ira M. Sheskin, four were shown to have meaningful variability in the proportion of Jewish children within their respective sampling frames. The proportions of Jewish children applied to the studies' corresponding AJPP ZIP Code clusters ranged from less than 10% in Florida's Pinellas and Pasco Counties as well as in Michigan's Wayne and Macomb Counties to greater than 20% in the Bloomfield Area of Oakland County, MI, all of Marion County, IN, and the more densely populated areas of Miami-Dade County, FL.

Table 4-11: Estimates of Jewish Children from AJPP Analysis of Studies Conducted by Ira M. Sheskin

Study Area and Subareas	Study Date	Pct. of Total Population (95% CI)	
Broward	2016		
Broward County, FL		14.6	(12.5, 16.9)
Detroit	2018		
Bloomfield Area (Oakland County), MI[1]		20.8	(18.3, 23.5)
Rest of Oakland County, MI		10.1	(6.2, 15.9)
Wayne and Macomb Counties, MI		9.3	(6.2, 13.5)
Houston	2016		
Harris County, TX[2]		15.5	(13.3, 17.9)
Indianapolis	2017		
Marion County, IN		20.8	(16.3, 26.1)
Miami	2014		
West Kendall and Other North Miami-Dade, FL		14.2	(11.5, 17.5)
Rest of Miami-Dade, FL[3]		20.4	(18.8, 22.2)
Omaha	2017	15.9	(12.5, 20.0)
Douglas County, NE		16.8	(13.0, 21.4)
Sarpy County, NE		10.1	(4.5, 21.0)
Pinellas and Pasco Counties	2017		
Pinellas and Pasco Counties, FL		7.9	(5.9, 10.5)

Notes:
1) "Core Area" of Detroit in Oakland County, spanning Bloomfield, Southfield, Farmington, & Oak Park. These areas include ZIP Codes: 48009, 48025, 48034, 48067, 48070, 48072, 48073, 48075, 48076, 48237, 48301, 48302, 48304, 48322, 48323, 48324, 48331, 48334, 48335, 48336, 48382, and 48390.
2) The 2016 Houston Community Study includes all of Harris County as well as 16 ZIP Codes in Brazoria, Fort Bend, Galveston, and Montgomery Counties.
3) Includes the following ZIP Codes in definitions of Miami-Dade subareas (excluding West Kendall and Other North Miami-Dade): 33160, 33180, 33162, 33179, 33143, 33156, 33157, 33158, 33189, 33190, 33114, 33128, 33129, 33130, 33131, 33133, 33134, 33135, 33144, 33145, 33146, 33149, 33155, 33159, 33165, 33174, 33154, 33140, 33141, 33109, 33139, 33127, 33128, 33129, 33130, 33131, 33132, 33136, 33137, & 33149.

Jewish Community Studies Conducted by CMJS/SSRI

About half of the 28 local community studies were conducted by the Cohen Center for Modern Jewish Studies/Steinhardt Social Research Institute at Brandeis University. These surveys include identifier variables to estimate proportions of JNR adults and Jewish children within each study's geographic profile. Nearly all of the data sets for these surveys were designed similarly in terms of the variable definitions needed for analysis, with small variations in older studies such as the 2013 Nashville and the 2014 Seattle Jewish community studies compared with more recent studies. Specific details for each study are described in the summaries that follow, however, common study characteristics are described here.

Each study includes a roster of household members that was used to identify children and adults. Variables identifying whether each child in the household was being raised Jewish were used to estimate proportions of Jewish children. The Jewish identity of adults was determined using variables that indicated if the adult was not Jewish, Jewish by religion (JBR), Jewish not by religion (JNR), or a Jew of multiple religions (JMR). Adults considered Jewish by religion and Jewish not by religion comprised the total Jewish adult population, which was used as the denominator for estimating the proportion of JNR adults. CMJS studies included a final household weight identified in the study documentation and dataset (e.g. *wthh*), a variable to identify geographic stratification (e.g. *strata*), and variables to identify Jewish children (e.g. *hhchjew1* thru *hhchjew10*) and adults (e.g. *respjewtype* and *hhadjewtype2* thru *hhadjewtype10*) in households. For each of these surveys, analyses were conducted using the survey package in Stata (svy) with the following design statement:

svyset hhid [pweight= wthh], strata(strata) vce(linearized) singleunit(missing)

Analyses of each study area were conducted to examine the proportion of Jewish adults who identify as Jews of no religion and the proportion of the total Jewish population who are children. The data were analyzed to determine whether the estimate of JNR adults or Jewish children varied significantly in geographic subareas within the overall study area.

Analyses of each study area were conducted to examine the proportion of Jewish adults who identify as Jews of no religion and the proportion of the total Jewish population who are children. The data were analyzed to determine whether the estimate of JNR adults or Jewish children varied significantly across geographic subareas within each study's overall sampling frame. Unlike the available datasets of studies conducted by Ira M. Sheskin, those conducted by CMJS and SSRI contained variables for each sampling area's ZIP Codes. This allowed AJPP ZIP Code-based areas to be matched into each study's dataset and estimated precisely. Wherever these areas could not be estimated reliably, multiple AJPP ZIP Code-based areas were pooled to ensure robust sample sizes.

Proportions of Jewish children could be estimated for each of the CMJS studies. Proportions of JNR adults could be estimated for all CMJS studies with the exceptions of the 2013 Greater Buffalo Jewish Community Study, which did not include any variable that could be used to identify JNR adults, and the 2014 Greater Seattle Jewish Community Study, which included adults who were, in fact, not Jewish among those who identified as Jews of no religion. A summary of these estimates can be found in Table 4-12. For areas that were pooled to improve the reliability of an estimate, table notes are included to describe how counties and AJPP ZIP Code-based areas were combined. Estimated percentage of JNR adults range from 2.7% in Collier County, FL, a known retirement community, to 30% in Cincinnati, OH. Estimated proportions of Jewish children range from 6.9%, also in Collier County, to 26.7% in the southern suburbs of Nashville TN.

Table 4-12: Estimates of Jews of No Religion and Jewish Children from AJPP Analysis of CMJS Studies

Study Area and Subareas	Study Date	Jews of No Religion: Pct. of Total Jewish Adults (95% CI)		Jewish Children: Pct. of Total Jewish Population (95% CI)	
Baltimore	2020				
Baltimore Northern Suburbs, MD		15.2	(10.8, 20.9)	23.4	(18.6, 28.9)
Baltimore, MD		23.1	(16.1, 32)	19.3	(14.1, 25.8)
Baltimore Western Suburbs, MD		16.4	(11.8, 22.3)	21.8	(17.5, 26.7)
Baltimore Eastern Suburbs, MD		17.7	(13.9, 22.2)	22.4	(18.7, 26.5)
Buffalo	2013				
Western New York[1]		-	-	18.7	(15.1, 22.9)
Cincinnati	2019				
Cincinnati, OH		30.0	(19.5, 43.1)	19.1	(14.9, 23.9)
Rest of Cincinnati, OH-KY[2]		25.8	(15.4, 40.1)	19.1	(14.9, 23.9)
Denver	2019				
Greater Denver, CO[3]		26.2	(21.7, 31.2)	21.5	(18.1, 25.3)
Greater Boston	2015				
Boston Western Suburbs, MA		27.8	(20.9, 36)	23.8	(21.2, 26.6)
Rest of Greater Boston, MA[4]		13.0	(8.1, 20.1)	23.8	(21.2, 26.6)
Greater Naples	2017				
Collier County, FL[5]		2.7	(0.7, 10.5)	6.9	(5.4, 8.8)
Nashville	2015				
Nashville, TN		3.7	(2.3, 5.9)	17.5	(14.9, 20.3)
Nashville Southern Suburbs, TN[6]		3.7	(2.3, 5.9)	26.7	(20.4, 34.2)
Nashville Outlying Western Counties, TN		3.7	(2.3, 5.9)	16.9	(9.3, 28.9)
Palm Beach	2018				
Palm Beach County, FL[7]		11.6	(8.2, 16.1)	13.5	(10.6, 17.0)
Pioneer Valley	2020				
Western Massachusetts[8]		24.2	(17.8, 32.1)	17.6	(12.2, 24.6)
Pittsburgh	2017				
Pittsburgh, PA		12.6	(8.1, 19.0)	15.7	(13.2, 18.6)
Other Pittsburgh Counties, PA[9]		10.9	(7.0, 16.5)	14.0	(11.7, 16.6)
Sarasota	2019				
Sarasota and Manatee Counties, FL		7.8	(5.1, 11.7)	12.1	(9.6, 15.2)
Seattle	2014				

Seattle, WA		-	-	22.0	(20.2, 24.0)
Rest of Seattle and Outlying Areas, WA[10]		-	-	15.5	(12.7, 18.8)
Twin Cities	2019				
Minneapolis-St. Paul and Outlying Areas, MN[11]		14.9	(10.4, 20.9)	26.4	(21.2, 32.4)
Washington, DC	2017				
Washington, DC		24.5	(15.5, 36.5)	15.6	(11.8, 20.2)
Frederick-Gaithersburg-Rockville, MD		9.8	(6.6, 14.5)	19.1	(16.5, 21.9)
Rest of DC and Outlying Areas, MD-VA[12]		21.9	(17, 27.7)	18.5	(16.2, 21)

Notes:
1) CMJS estimates that 97% of Jewish-connected Households in Western New York are located in Erie County, with the remainder distributed throughout Niagara, Wyoming, Genesee, and Chautauqua Counties. The estimate of Jewish children was only applied to Erie County, NY.
2) The rest of Cincinnati includes Butler, Brown, Clermont, and Warren Counties, OH, as well as Boone Bracken, Campbell, Gallatin, Grant, Kenton, and Pendleton Counties, KY.
3) The Greater Denver areas include Adams, Arapahoe, Boulder, Broomfield, Denver, Douglas, and Jefferson Counties, CO.
4) The rest of Boston includes Essex, Suffolk, Norfolk, and Plymouth Counties, MA.
5) CMJS estimates that 86% of Jewish individuals reside in Collier County, with the remainder distributed throughout Lee County and Marco Island. The estimates of Jewish children and JNR adults were applied to the AJPP ZIP Code-based area comprised of Collier and Monroe Counties.
6) Estimates of Jewish children and JNR adults for the southern suburbs of Nashville were applied to the AJPP ZIP Code cluster comprised of Rutherford and Williamson Counties, TN.
7) Estimates for Palm Beach County are derived from the combined datasets of the Greater Palm Beaches and South Palm Beach County 2018 Community Studies.
8) Estimates of Jewish children and JNR adults were applied to AJPP ZIP Code clusters that included the following counties in Western Massachusetts: Hampden, Hampshire, Berkshire, and Franklin Counties, MA.
9) Other Pittsburgh Counties include Armstrong, Westmoreland, Beaver, Butler, Fayette, Greene, and Washington, PA.
10) The rest of Seattle and its outlying areas include Pierce, Snohomish, Island, Kitsap, Skagit, and Whatcom Counties, WA.
11) Minneapolis-St. Paul and Outlying Areas, MN include Carver, Chisago, Isanti, Le Sueur, Mille Lacs, Scott, Sherburne, and Wright Counties.
12) The rest of DC and its outlying areas include Calvert, Charles, and Prince Georges Counties in Maryland, Arlington, Fairfax, Prince William and Loudoun Counties in Virginia, as well as the Cities of Fairfax, Alexandria, Falls Church, Manassas, and Manassas Park.

Other Jewish Community Studies:

Cleveland

The 2011 Greater Cleveland Jewish Population study (CJP2011) found that 23% of the Jewish population in Cleveland were children aged 17 years and younger (p. 7, Ukeles, et., al. 2011).

The study area included six counties, primarily Cuyahoga County but also including Geauga, Lake, Lorain, Portage, and Summit Counties. The AJPP 2020 study areas corresponding to these counties included:

- Cuyahoga, estimated singly,
- Geauga, Lake, Lorain & Medina (the remaining counties in the Cleveland CBSA), estimated in a combined area,
- Summit County (Akron) estimated singly; and,
- Portage (outside of the Cleveland CBSA) combined with other remaining counties east of Cleveland (Mahoning, Trumbull & Ashtabula).

Children as the proportion of the total Jewish population was based on the categorization by the original researchers of children as Jewish/not. This was represented in the variables c1JewCount to c8JewCount (and corresponding variables for adults in the household), and was analyzed using the household weight, HHWTFinalDec. Table 4-13 displays the proportion by the groups of counties that correspond to the AJPP2020 areas. The greatest proportion was in Cuyahoga County (24%) and the lowest was in Portage and Summit counties (12%). The estimates for areas outside of Cuyahoga, however, were unreliable, with wide 95% confidence intervals that overlap the estimate for Cuyahoga County. These two areas were combined to yield an estimate of 17.4% children. This estimate still had a wide confidence interval (10% - 29%), but was used to be conservative in the estimate of children in these areas given the lack of strong data, or repeated measurements of the population in this area.

Table 4-13: Proportion of Jewish Children by Cleveland County Groups

	Prop. Jewish Children (95% CI)		Coefficient of Variation
Cuyahoga County	0.244	(0.208, 0.285)	8.1
Geauga, Lake, Lorain Counties	0.194	(0.096, 0.352)	33.4
Portage & Summit Counties	0.123	(0.049, 0.274)	44.5
Total	0.234	(0.199, 0.272)	8.0

Columbus

The 2013 Portrait of Jewish Columbus study found that of the total Jewish population of 25,500 in Columbus, 18% (4,650) were children under the age of 18 years (p. 5, Cohen, et al., 2013). The study area, defined by ZIP Code areas, included much of Franklin county, and parts of Delaware, Licking, and Pickaway counties. These ZIP Codes were grouped into four areas of interest: (1) Downtown/University area (pop. 9,000), (2) Bexley (pop. 5,400), (3) East (pop. 4,700), and (4) Perimeter North (pop. 3,500).

The AJPP 2020 model included all of these counties. Franklin County included three ZIP Code clusters. One of these areas corresponded to the Downtown/University area as defined in the Columbus study. Another represented the portion of Franklin County in Perimeter North. The third included Bexley and the portion of Franklin County in the study's East area.

The proportion of Jewish children was based on the categorization by the original researchers of children as Jewish/not. This was represented in the variables c1jewish to j5jewish, along with corresponding variables for adults (respjewish_revised, spjewish, a1jewish to a10jewish) and was analyzed using the household weight, HHWt. Table 4-14 displays the proportion children by Columbus study area. There was not much variability across the sampling frame, with estimates ranging from 20% in the Perimeter North area to 17% in Downtown/University. Estimates for two of the areas, in particular, Downtown/University, which matched the AJPP 2020 ZIP Code-based area, were highly unreliable with coefficients of variation of 35 and 40.

Table 4-14: Proportion of Jewish Children in Columbus Areas

	Prop. Jewish Children (95% CI)	Coefficient of Variation
Perimeter North	0.199 (0.140, 0.275)	17.3
Bexley	0.176 (0.131, 0.233)	14.8
East	0.188 (0.090, 0.351)	35.1
Downtown/University	0.174 (0.075, 0.353)	40.0
Total	0.183 (0.130, 0.250)	16.6

As an alternative, analyses were run by county to determine whether the main county, Franklin, differed significantly from the portions of the sample that were in other counties. Although the outer counties appears to have a higher proportion of children (32%) than Franklin (16%), the estimate was highly unreliable (CV=33) due to the small sample sizes. The estimate of 16% was used for Franklin County, and the area-wide average of 18% was used for the remaining counties (see Table 4-15).

Table 4-15: Proportion of Jewish Children by Columbus County Groups

	Prop. Jewish Children (95% CI)	Coefficient of Variation
Franklin	0.163 (0.111, 0.233)	18.9
Delaware, Licking & Pickaway Counties	0.316 (0.153, 0.541)	32.7
Total	0.183 (0.130, 0.250)	16.6

Milwaukee

The Jewish Community Study of Greater Milwaukee was conducted in 2011, with revised estimates released in 2015 (Percy, Miller, and Berkowitz, 2015). Results of the study indicated that of the 25,800 total Jewish population, just 10% were children under the age of 18 years (pp.6-7).

The study area covered all of Milwaukee and Waukesha counties, and the southern portion of Ozaukee County. The study results indicated that over half of the Jewish population (52%) were in the North Shore area of Milwaukee and Waukesha counties, stretching from the northeastern portion of the City of Milwaukee up to Cedarburg. The high-density Jewish population areas of the North Shore are located within Milwaukee County, so the sample for the region was assigned to Milwaukee County for analysis.

Children as the proportion of the total Jewish population was based on the categorization of children as Jewish/not by the original researchers. This was represented in the variables kid1 to kid9, along with corresponding variables for adults (adult1 to adult6), and was analyzed using the household weight, HHWt_BJDB_v2. Table 4-16 displays the proportion children by Milwaukee study area. There was very low sample size in Waukesha County (n=28), including no Jewish children. Estimates of Jewish children for Milwaukee County (12.2%) is very similar to the overall study's estimate (10.8%). Therefore, the overall estimate of 10.8% is applied to the two AJPP county groups, Milwaukee and Milwaukee Suburbs, which map onto the study area.

Table 4-16: Proportion of Jewish Children by Milwaukee Areas

	Prop. Jewish Children (95% CI)		Coefficient of Variation
Milwaukee County	.122	(0.092, 0.159)	13.8
Waukesha County	0	-	-
Total	0.108	(0.081, 0.143)	14.3

New York

Results from the Jewish Community Study of New York 2011 (Cohen, Ukeles & Miller, 2012) indicated that in the eight-county UJA-Federation of New York area there were an estimated 338,000 Jewish children out of a total population of 1,538,000 (p. 57), that is, 22% of the population are children. In addition, the study found that 16% of Jewish adults were JNR adults (p. 36).

The study area covered the counties of Bronx, Kings (Brooklyn), Queens, New York (Manhattan), Richmond (Staten Island), Nassau, Suffolk, and Westchester. Variability within each of these counties was described based on a total of 44 ZIP Code-based subareas (Beck, Cohen, Ukeles & Miller, 2013). The AJPP 2020 ZIP Code clusters also provided for subarea estimation within these counties, with the exception of Bronx and Richmond Counties.

Jewish Children. Children as the proportion of the total Jewish population was based on the categorization by the original researchers of children as Jewish/not. This was represented in the variables jchild1 to jchild10, along with corresponding variables for adults (howJewr, jspouse, jothadult1 to jothadult11). respjewish_revised, spjewish, a1jewish to a10jewish) and was analyzed using the household weight, HHWt. Table 4-17 displays the results in each of the eight counties in the study area. These estimates ranged from a high of 0.34 in Kings County (Brooklyn) to a low of 0.11 in New York County (Manhattan).

Table 4-17: Proportion of Jewish Children by Counties in the New York Metro Area

	Prop. Jewish Children (95% CI)		Coefficient of Variation
Kings County	0.337	(0.307, 0.368)	7.7
Queens County	0.177	(0.137, 0.226)	16.0
New York County	0.108	(0.086, 0.136)	14.1
Suffolk County	0.138	(0.108, 0.175)	14.8
Bronx County	0.110	(0.061, 0.189)	35.3
Nassau County	0.199	(0.175, 0.227)	9.2
Westchester County	0.214	(0.179, 0.254)	13.1
Richmond County	0.128	(0.094, 0.173)	19.5
Total	0.227	(0.211, 0.243)	4.8

Analysis by subareas was conducted to examine whether the proportion of children varied substantially within counties, and whether the high of one third of the Jewish population in Kings County (Brooklyn) would apply to the entire county. Estimates for subareas in Bronx County were highly unreliable with CVs of 68 and 70. In Kings County (Brooklyn), as expected, there was substantial variability with a high of just over half of the population (0.52) in Williamsburg to a low of less than 10% (0.09) in the Coney Island/Brighton Beach/Sheepshead Bay area, though some of these areas are less reliable than others with CVs greater than 25 (see Table 4-18).

Table 4-18: Proportion of Jewish Children by Subareas within New York Metro Counties

		Prop. Jewish Children (95% CI)		Coefficient of Variation
Bronx County	Riverdale/Kingsbridge	0.121	(0.079, 0.180)	20.9
	Northeast Bronx	0.075	(0.019, 0.255)	68.0
	Bronx Residual	0.136	(0.031, 0.438)	70.4
Kings County	Bensonhurst/Gravesend/Bay Ridge	0.156	(0.086, 0.268)	29.4
	Kingsbay/Madison	0.278	(0.156, 0.446)	27.0
	Borough Park	0.498	(0.443, 0.552)	5.6
	Coney Island/Brighton Beach/Sheepshead Bay	0.089	(0.056, 0.139)	23.4
	Flatbush/Midwood/Kensington	0.345	(0.277, 0.419)	10.6
	Williamsburg	0.515	(0.458, 0.572)	5.7
	Brownstone Brooklyn	0.201	(0.134, 0.290)	19.9
	Crown Heights	0.361	(0.244, 0.497)	18.3
	Canarsie/Mill Basin	0.115	(0.071, 0.181)	23.9
	Brooklyn Residual	0.236	(0.137, 0.376)	26.0
New York County	Lower Manhattan East	0.041	(0.019, 0.085)	38.7
	Lower Manhattan West	0.042	(0.020, 0.087)	38.0
	Upper East Side	0.182	(0.133, 0.242)	15.3
	Upper West Side	0.120	(0.076, 0.183)	22.4
	Washington Heights/Inwood	0.095	(0.048, 0.179)	33.8
	Manhattan Residual	0.107	(0.040, 0.255)	47.9
Queens County	Kew Gardens Hills/Jamaica/Fresh Meadows	0.253	(0.174, 0.352)	18.0
	Forest Hills/Rego Park/Kew Gardens Area	0.154	(0.095, 0.240)	23.7
	Flushing/Bay Terrace/Little Neck Area	0.054	(0.028, 0.103)	33.2
	The Rockaways	0.407	(0.276, 0.553)	17.8
	Long Island City/Astoria/Elmhurst Area	0.061	(0.020, 0.166)	54.2
	Queens Residual	0.089	(0.045, 0.170)	34.4
Richmond County	Mid Staten Island	0.122	(0.080, 0.180)	20.7
	Southern Staten Island	0.117	(0.068, 0.194)	27.0
	Staten Island Residual	0.164	(0.075, 0.320)	37.4
Nassau County	Great Neck	0.211	(0.145, 0.296)	18.3
	Roslyn/Port Washington/Glen Cove/Old Westbury/Oyster Bay	0.254	(0.196, 0.323)	12.7

	Plainview/Syosset/Jericho	0.215	(0.151, 0.297)	17.2
	Merrick/Bellmore/East Meadow/Massapequa	0.162	(0.118, 0.218)	15.6
	Oceanside/Long Beach/West Hempstead/Valley Storm	0.144	(0.099, 0.206)	18.8
	Five Towns	0.289	(0.211, 0.381)	15.1
	Nassau Residual	0.146	(0.083, 0.243)	27.7
Suffolk County	Commack/East Northport/Huntington	0.195	(0.136, 0.273)	17.9
	Dix Hills/Huntington Station/Melville	0.127	(0.077, 0.201)	24.6
	Smithtown/Port Jefferson/Stony Brook	0.166	(0.099, 0.263)	24.9
	Suffolk Residual	0.096	(0.052, 0.170)	30.4
Westchester	South Central Westchester	0.262	(0.198, 0.338)	13.6
	Sound Shore Communities	0.227	(0.158, 0.314)	17.6
	River Towns	0.179	(0.116, 0.266)	21.2
	North-Central and Northwestern Westchester	0.231	(0.166, 0.313)	16.2
	Westchester Residual	0.089	(0.034, 0.215)	47.5

Given the variability within counties such as Kings (Brooklyn), and New York (Manhattan), the New York subareas were matched to the AJPP 2020 ZIP Code areas to examine whether sub-county estimates of Jewish children should be applied to the AJPP 2020 estimates.

The ten subareas in Kings County could be grouped to provide a close approximation to the AJPP 2020 subareas. In particular, the Williamsburg, Brownstone, and Crown Heights areas closely approximated the first AJPP 2020 subarea within Kings County. The residual and Canarsie and Mill Basin areas approximated another AJPP 2020 subarea. And the remaining areas provided close approximation to the third AJPP 2020 subarea.

In New York County, one AJPP 2020 area closely approximated the New York study subareas of Lower Manhattan East and West. The second subarea matched the New York study areas of Upper East and West sides. The third closely matched the remaining areas of Washington Heights, Inwood and residual.

In the other counties, there were either too few cases for reliable subarea estimation, or the matching of the New York study subareas to the AJPP 2020 subareas would result in combining areas of high and low proportions of Jewish children and would not improve estimation. For example, in Queens, one AJPP 2020 subarea would include the New York study areas of Kew Gardens, Forest Hills, and Flushing with estimated proportions of Jewish children ranging from 0.25 to 0.05. And another would require combining the Rockaways with a high of 0.42 proportion Jewish children with most of the New York study area of Queens residual which had a low of 0.09 proportion Jewish children.

Estimates of the proportion of Jewish children in subareas of Kings and New York counties that best match the AJPP 2020 subareas are displayed in Table 4-19. In Kings county, the three subareas yielded significantly different estimates of the proportion of children (indicated by the non-overlapping 95% Cis). Thus, rather than applying the county level 34% of Jewish children to the entire county, the estimates for the subareas are used. This includes the higher estimate of

0.43 for the AJPP 2020 area that includes the Williamsburg, Brownstone, and Crown Heights areas, as well as the lower proportion of 0.19 for the large portion of the county represented in the NY study as Brooklyn residual. Similarly, in New York county, there was a higher proportion of children in the Upper East and West sides (0.19) than in Lower Manhattan (0.04).

Table 4-19: Proportion of Jewish Children in Combined New York Study Areas within Kings and New York Counties to Match AJPP 2020 ZIP Code-Based Areas

		Prop. Jewish Children (95% CI)		Coefficient of Variation
Kings County	AJPP 2020 subarea 1: Williamsburg, Brownstone & Crown Heights areas	0.433	(0.383, 0.485)	6.1
	AJPP 2020 subarea 2: Bensonhurst, Kingsbay, Borough Park, Coney Island, & Flatbush areas	0.332	(0.294, 0.372)	5.9
	AJPP 2020 subarea 3: Canarsie, Mill Basin & Residual Areas	0.193	(0.122, 0.290)	22.2
New York County	AJPP 2020 subarea 1: Upper East and West Sides	0.147	(0.113, 0.190)	13.2
	AJPP 2020 subarea 2: Lower Manhattan	0.041	(0.024, 0.070)	27.2
	AJPP 2020 subarea 3: Washington Heights & residual areas	0.100	(0.056, 0.171)	28.5

JNR Adults. All Jewish respondents in the survey were asked if they considered Judaism to be their religion, if they had no religion, or if they had some other religion. This question was used to categorize Jews of no religion, and to exclude from the estimate those who are in another religion. Because the religion question was asked only of the respondent, and not of all other adults in the household, the estimate is based on analysis of the respondent level file, using the final weight for Jewish adults (wtJadults) and stratification variable (finalstrata). The following design statement was used:

svyset caseid [pweight=wtJadults], strata(finalstrata) vce(linearized) singleunit(missing)

Results by county are displayed in Table 4-20. Overall, 11% of Jewish adults in the eight-county area were JNR adults, with a low of 6% in Nassau County to a high of 17% in New York County.

Table 4-20: Proportion of JNR Adults by County in New York Metro Counties

	Prop. JNR Adults (95% CI)		Coefficient of Variation
Kings County	0.111	(0.090, 0.137)	10.6
Queens County	0.067	(0.046, 0.097)	29.0
New York County	0.173	(0.144, 0.206)	9.1
Suffolk County	0.161	(0.104, 0.243)	21.9
Bronx County	0.142	(0.085, 0.228)	25.2
Nassau County	0.056	(0.041, 0.076)	15.7
Westchester County	0.110	(0.076, 0.157)	18.6
Richmond County	0.159	(0.100, 0.243)	22.9
Total	0.112	(0.101, 0.125)	5.5

Analysis by subareas was conducted to examine whether these JNR rates varied substantially within counties, especially within the largest counties such as Kings (Brooklyn) and New York (Manhattan). Estimates varied from a low of less than 1% in Five Towns (Nassau County) and the Rockaways (Queens County) to a high of 29% in Brownstone Brooklyn (Kings County). Many of the estimates, however, were highly unreliable with CVs over 50 (see Table 4-21).

Table 4-21: Proportion of JNR Adults by Subareas within New York Area Counties

		Prop. JNR Adults (95% CI)		Coefficient of Variation
Bronx County	Riverdale/Kingsbridge	0.082	(0.051, 0.130)	24.2
	Northeast Bronx	0.185	(0.076, 0.385)	42.3
	Bronx Residual	0.249	(0.076, 0.571)	53.2
Kings County	Bensonhurst/Gravesend/Bay Ridge	0.128	(0.072, 0.217)	28.4
	Kingsbay/Madison	0.115	(0.055, 0.226)	36.3
	Borough Park	0.019	(0.010, 0.039)	35.8
	Coney Island/Brighton Beach/Sheepshead Bay	0.224	(0.150, 0.321)	19.5
	Flatbush/Midwood/Kensington	0.050	(0.027, 0.089)	30.3
	Williamsburg	0.051	(0.025, 0.102)	36.3
	Brownstone Brooklyn	0.291	(0.169, 0.453)	25.4
	Crown Heights	0.158	(0.038, 0.475)	67.4
	Canarsie/Mill Basin	0.153	(0.064, 0.321)	41.7
	Brooklyn Residual	0.197	(0.111, 0.325)	27.6
New York County	Lower Manhattan East	0.137	(0.082, 0.220)	25.1
	Lower Manhattan West	0.241	(0.163, 0.341)	18.9
	Upper East Side	0.158	(0.100, 0.240)	22.4
	Upper West Side	0.168	(0.122, 0.226)	15.7
	Washington Heights/Inwood	0.118	(0.058, 0.225)	34.8
	Manhattan Residual	0.277	(0.143, 0.468)	30.5
Queens County	Kew Gardens Hills/Jamaica/Fresh Meadows	0.062	(0.024, 0.151)	47.6
	Forest Hills/Rego Park/Kew Gardens Area	0.077	(0.039, 0.147)	34.1
	Flushing/Bay Terrace/Little Neck Area	0.039	(0.016, 0.093)	45.9
	The Rockaways	0.007	(0.001, 0.049)	101.8
	Long Island City/Astoria/Elmhurst Area	0.148	(0.068, 0.293)	37.8
	Queens Residual	0.094	(0.040, 0.202)	41.6
Richmond County	Mid Staten Island	0.165	(0.083, 0.304)	33.5
	Southern Staten Island	0.153	(0.072, 0.297)	36.8
	Staten Island Residual	0.145	(0.058, 0.317)	43.9
Nassau County	Great Neck	0.035	(0.011, 0.112)	60.5
	Roslyn/Port Washington/Glen Cove/Old Westbury/Oyster Bay	0.089	(0.044, 0.171)	34.8
	Plainview/Syosset/Jericho	0.042	(0.017, 0.097)	44.4
	Merrick/Bellmore/East Meadow/Massapequa	0.057	(0.029, 0.106)	32.8

	Oceanside/Long Beach/West Hempstead/Valley Storm	0.082	(0.046, 0.143)	29.1
	Five Towns	0.006	(0.001, 0.024)	73.5
	Nassau Residual	0.048	(0.018, 0.124)	49.9
Suffolk County	Commack/East Northport/Huntington	0.132	(0.074, 0.227)	28.9
	Dix Hills/Huntington Station/Melville	0.196	(0.045, 0.555)	67.0
	Smithtown/Port Jefferson/Stony Brook	0.046	(0.017, 0.115)	49.0
	Suffolk Residual	0.213	(0.135, 0.320)	22.2
Westchester	South Central Westchester	0.060	(0.029, 0.120)	36.3
	Sound Shore Communities	0.131	(0.067, 0.238)	32.5
	River Towns	0.113	(0.060, 0.204)	31.5
	North-Central and Northwestern Westchester	0.107	(0.045, 0.232)	42.1
	Westchester Residual	0.217	(0.078, 0.475)	47.2

Analyses were conducted of the same subareas within Kings and New York counties as those used for estimates of Jewish children. There was some variability in Kings county with a lower proportion of JNR adults (.095) in the Bensonhurst, Kingsbay, Borough Park, and Flat Bush areas, than in the residual areas (0.178) and Williamsburg, Brownstone, and Crown Heights areas (0.126) (See Table 4-22). In New York county, there was less variability.

Table 4-22: Proportion of JNR Adults in Combined New York Metro Areas within Kings and New York Counties to Match AJPP 2020 ZIP Code-Based Areas

		Prop. JNR Adults (95% CI)		Coefficient of Variation
Kings County	AJPP 2020 subarea 1: Williamsburg, Brownstone & Crown Heights areas	0.126	(0.074, 0.206)	26.4
	AJPP 2020 subarea 2: Bensonhurst, Kingsbay, Borough Park, Coney Island, & Flatbush areas	0.095	(0.073, 0.122)	13.1
	AJPP 2020 subarea 3: Canarsie, Mill Basin & Residual Areas	0.178	(0.110, 0.274)	23.4
New York County	AJPP 2020 subarea 1: Upper East and West Sides	0.163	(0.126, 0.210)	13.0
	AJPP 2020 subarea 2: Lower Manhattan	0.183	(0.135, 0.244)	15.1
	AJPP 2020 subarea 3: Washington Heights & residual areas	0.188	(0.116, 0.289)	23.4

Philadelphia

The 2019 Greater Philadelphia Community Study found that of the total Jewish population of 351,200 Jewish, 42,500 (12%) were children 17 years old and younger (p. iii, Marker & Steiger, 2020). The study did not report the proportion of JNR adults. The data from the study was not available for secondary analysis. The Jewish Federation of Greater Philadelphia who commissioned the study did make the data available through an online analysis tool (https://communityportrait.org/, accessed November 2, 2020).

The study's sampling frame was divided into five areas based on counties – Philadelphia, Montgomery, Bucks, Delaware, and Chester. These corresponded directly to the AJPP 2020 county-level estimates. Estimates of both JNR adults and Jewish children are displayed in Table 4-23. Estimates of JNR adults ranged from 29.7% in Philadelphia County to 43% in Delaware County. The proportion of Jewish children was also lowest in Philadelphia County (9.6%) and highest in Delaware County (21.2%).

Table 4-23: Proportion of JNR Adults and Jewish Children by Philadelphia Counties

	Prop. JNR adults	Prop. Jewish children
Philadelphia County	0.297	0.096
Montgomery County	0.253	0.141
Bucks County	0.326	0.123
Delaware County	0.430	0.212
Chester County	0.424	0.129
Total	0.311	0.122

Within the two largest counties, Philadelphia and Montgomery, the AJPP 2020 model included ZIP Code clusters which approximated the Philadelphia study's subareas. In Philadelphia County, the community study area of Center City split across two of the AJPP 2020 clusters. The area of Northeast closely approximated a third AJPP 2020 cluster. Within Montgomery County, AJPP 2020 had two ZIP Code clusters. The Bux-Mont area in the community study closely approximated one of these, and the Old York Road area was used to estimate the other.

Estimates of JNR adults and Jewish children by these subareas is displayed in Table 4-24. In both counties, there were substantial differences in estimates of JNR adults. In Philadelphia County, the Center City area had about 20% JNR adults compared to 36% in the Northeast. In Montgomery, Old York Road area had 16% JNR compared to 35% in the Bux-Mont area. There was very little difference in the proportion of Jewish children in these areas.

Table 4-24: Proportion of JNR Adults in Combined Philadelphia Areas within Philadelphia and Montgomery Counties to Match AJPP 2020 ZIP Code-Based Areas

		Prop. JNR adults	Prop. Jewish children
Philadelphia County	AJPP 2020 subarea 1 & 2: Center City	0.198	0.100
	AJPP 2020 subarea 3: Northeast	0.361	0.087
Montgomery County	AJPP 2020 subarea 1: Old York Road	0.156	0.118
	AJPP 2020 subarea 2: Bux-Mont	0.354	0.109

San Francisco Bay Area

The 2017 Portrait of Bay Area Jewish Life and Communities found that out of a total Jewish population of 350,000, 20% (68,000) were children 17 years and younger (p. 16, Cohen &

Ukeles, 2018). The study did not report the proportion of JNR adults, but it could be estimated through secondary analysis.

The study area covered 11 counties. These included: the East Bay area of Alameda, Contra Costa, and Solano counties; San Francisco County; the North Bay area of Marin, Sonoma, and Napa counties; and, the Peninsula and South Bay counties of San Mateo, Santa Clara, and Santa Cruz. The AJPP 2020 study areas corresponding to these counties included:

- Alameda County, with two ZIP Code-based subareas
- San Francisco County
- Contra Cost and Marin Counties, with two ZIP Code-based subareas
- San Mateo County
- Santa Clara County, with three ZIP Code-based subareas
- Solano County,
- Napa and Sonoma Counties
- Santa Cruz county grouped with Tulare County

The community study did not include any sub-county areas. Therefore, all analyses are at the county-level, or for groups of counties.

Children as the proportion of the total Jewish population was based on assessment of how each child in the household was being raised (Jewish, Partially Jewish, Not Jewish, undecided). The 68,000 children reported in the study included all those who were being raised Jewish or partially Jewish. Data were analyzed using the household weight, HHWeight. Table 4-25 displays the proportion by the groups of counties that correspond to the AJPP2020 areas. The greatest proportion was in Contra Costa and Marin Counties (25.3%) and the lowest was in Solano County (9%). The estimates in the outer counties of Solano, Napa, Sonoma, Santa Cruz, and Tulare were less reliable with CVs ranging from 30 to 67. These counties were combined to yield a pooled estimate of 17.9 (95% CI: 0.101 – 0.226).

Table 4-25: Proportion of Jewish Children by San Francisco Counties

	Prop. Jewish Children (95% CI)		Coefficient of Variation
Alameda County	0.137	(0.092, 0.200)	19.9
Contra Costa & Marin Counties	0.253	(0.203, 0.312)	11.0
San Francisco County	0.187	(0.142, 0.241)	13.5
San Mateo County	0.220	(0.159, 0.297)	16.0
Santa Clara County	0.202	(0.148, 0.270)	15.3
Napa & Sonoma Counties	0.130	(0.040, 0.349)	56.8
Solano County	0.090	(0.023, 0.296)	67.1
Santa Cruz & Tulare Counties	0.243	(0.130, 0.409)	29.6
Total	0.198	(0.173, 0.226)	6.85

All respondents in the survey were asked their present religion. If their religion was not Jewish, they were asked if they considered themselves Jewish aside from religion. Responses to these questions, in addition to questions about parents and upbringing, were used by the original researchers to categorize respondents as Jewish by religion, Jewish no religion, Partly Jewish, Jewish other religion, or not Jewish at all. For these analyses, Jewish adults were those who were categorized as either Jewish by religion or Jewish no religion, with JNR adults represented by the latter category. The proportion of JNR adults relative to total adults was analyzed using the weight JewishAdults_WT.

Results by county are displayed in Table 4-26. Overall, 24% of Jewish adults in the Bay Area were JNR adults, with a low of nearly 10% in Santa Cruz and Tulare counties to a high of 32% in Alameda County. Given the overlapping 95% confidence intervals and the low reliability indicated by the CVs greater than 25 for several of the areas, the overall estimate of 24.2% was applied to these counties.

Table 4-26: Proportion of JNR Adults by San Francisco Counties

	Prop. JNR Adults (95% CI)		Coefficient of Variation
Alameda County	0.320	(0.228, 0.428)	15.1
Contra Costa & Marin Counties	0.252	(0.171, 0.355)	18.7
San Francisco County	0.215	(0.151, 0.296)	17.2
San Mateo County	0.132	(0.069, 0.238)	31.9
Santa Clara County	0.239	(0.126, 0.407)	30.3
Napa & Sonoma Counties	0.319	(0.152, 0.551)	33.4
Solano County	0.454	(0.140, 0.810)	45.4
Santa Cruz & Tulare Counties	0.099	(0.025, 0.315)	65.9
Total	0.242	(0.198, 0.293)	10.0

St. Louis

The 2014 St. Louis Jewish Community Study Area Jewish Life and Communities found that 19% of the total Jewish population were children 17 years and younger (p. 6, 16, Cohen, Ukeles, Miller, Dutwin, & Sherr, 2014). The study did not report the proportion of JNR adults, but it could be estimated through secondary analysis.

The study area covered St. Louis City, St. Louis County, and St. Charles County. St. Louis County was divided into subareas consisting of University City/Clayton (which accounted for 15% of the total Jewish population in the St. Louis study area), Olivette/Ladue (10%), Creve Coeur (22%), Des Peres (4%), and residual areas North (7%) and South (9%). The AJPP 2020 model combined St. Louis city and St. Louis County, and divided the area into two ZIP Code-based subareas. The first consisted of St. Louis city and the University City/Clayton and Olivette/Ladue areas in the community study. The second area was the rest of the county. St. Charles County was not estimated on its own, but was included in a five-county area consisting of the rest of the counties in the Missouri area of the CBSA (Franklin, Jefferson, Lincoln, St. Charles & Warren Counties).

Children as the proportion of the total Jewish population was based on categorization by the original researchers of how each child in the household was being raised (Jewish/Not) represented in the variables c1jewcount to c7jewcount. Data were analyzed using the household weight, HHWtFinal. Table 4-27 displays the proportion of children by county. St. Louis city was best estimated at about 20% children with a CV of 12.8. St. Louis County had a similar proportion of children (20.6%) but was much less reliable (CV=34.6). Given the small sample sizes for subarea estimation, the overall estimate of 18.8% children for the study area was used.

Table 4-27: Proportion of Jewish Children by St. Louis Counties

	Prop. Jewish Children (95% CI)		Coefficient of Variation
St. Louis City	0.201	(0.155, 0.256)	12.8
St. Louis County	0.206	(0.099, 0.379)	34.6
St. Charles County	0.040	(0.015, 0.102)	49.5
Total	0.188	(0.147, 0.238)	12.4

All respondents in the survey were asked their present religion. If their religion was not Jewish, they were asked if they considered themselves Jewish aside from religion. Responses to these questions, in addition to questions about parents and upbringing, were used by the original researchers to categorize respondents as Jewish by religion, Jewish no religion, Jewish other religion, Jewish by religion converted, or not Jewish. For these analyses, Jewish adults were those who were categorized as either Jewish by religion (including converts) or Jewish no religion, with JNR adults represented by the latter category. The proportion of JNR adults relative to total adults was analyzed using the weight WtJews.

Results indicated that just 2.6% of Jewish adults in the St. Louis study area were JNR adults. There were far too few in the sample for subarea analysis.

Summary of JNR and Jewish Children Estimates Other Community Studies

Table 4-28 displays a summary of the JNR and Jewish children estimates that were used for the areas and subareas within the Cleveland, Columbus, Milwaukee, New York, Philadelphia, San Francisco, and St. Louis Jewish community studies.

Table 4-28: Estimates of Jews of No Religion and Jewish Children from Other Community Studies

Study Area and Subareas	Study Date	Jews of No Religion: Pct. of Total Jewish Adults (95% CI)		Jewish Children: Pct. of Total Jewish Population (95% CI)	
Cleveland	2011				
Cleveland, OH		-	-	24.4	(20.8, 28.5)
Cleveland Outlying Counties, OH		-	-	17.4	(9.5, 29.6)
Columbus	2013				
Franklin County, OH		-	-	16.3	(11.1, 23.3)
Delaware, Licking, and Fairfield Counties, OH		-	-	18.3	(13.0, 25.0)
Milwaukee	2011				
Milwaukee and Waukesha Counties, WI		-	-	10.9	(8.2, 14.3)
New York Metropolitan Area	2011				
Kings County: Bensonhurst, Kingsbay, Borough Park, Coney Island, & Flatbush areas, NY		9.5	(7.3, 12.2)	33.2	(29.4, 37.2)
Kings County: Williamsburg, Brownstone & Crown Heights areas, NY		12.6	(7.4, 20.6)	43.3	(38.3, 48.5)
Kings County: Canarsie, Mill Basin & residual areas, NY		17.8	(11, 27.4)	19.3	(12.2, 29.0)
Queens County, NY		6.7	(4.6, 9.7)	17.7	(13.7, 22.6)
New York County: Upper East and West Sides, NY		16.3	(12.6, 21.0)	14.7	(11.3, 19.0)
New York County: Lower Manhattan, NY		18.3	(13.5, 24.4)	4.1	(2.4, 7.0)
New York County: Washington Heights & residual areas, NY		18.8	(11.6, 28.9)	10.0	(5.6, 17.1)
Suffolk County, NY		12.8	(5.7, 26.3)	16.4	(12.7, 21.0)
Bronx County, NY		14.2	(8.5, 22.8)	11.0	(6.1, 18.9)
Nassau County, NY		5.6	(4.1, 7.6)	19.9	(17.5, 22.7)
Westchester, NY		11.0	(7.6, 15.7)	21.4	(17.9, 25.4)
Staten Island, NY		15.9	(10.0, 24.3)	12.8	(9.4, 17.3)
Philadelphia	2019				
Bucks County		32.6	-	12.3	-
Delaware County		43.0	-	21.2	-
Chester County		42.4	-	12.9	-
Philadelphia County: Center City		19.8	-	10.0	-
Philadelphia County: Northeast		36.1	-	8.7	-
Montgomery County: Old York Road		15.6	-	11.8	-
Montgomery County: BuxMont		35.4	-	10.9	-
San Francisco Bay Area	2017				
Alameda County, CA		24.2	(19.8, 29.3)	13.7	(9.2, 20.0)
Contra Costa and Marin Counties, CA		24.2	(19.8, 29.3)	25.4	(20.3, 31.2)
San Francisco County, CA		24.2	(19.8, 29.3)	18.7	(14.2, 24.1)
San Mateo County, CA		24.2	(19.8, 29.3)	22.0	(15.9, 29.7)
Santa Rosa-Vallejo-Santa Cruz Areas, CA		24.2	(19.8, 29.3)	17.9	(10.1, 29.7)
St. Louis	2015				
St. Louis City and County, MO		2.6	(1.3, 5.1)	18.8	(14.7, 23.8)

Florida areas not covered by Local Jewish Community Studies

A substantial portion of the State of Florida has had a Jewish community study conducted over the past ten years, comprising Broward, Collier, Miami, Palm Beach, Pinellas and Pasco, and Sarasota and Manatee Counties (Table 4-29). Consistent across each of the studies is a low proportion of JNR adults (where available) and Jewish children compared to the Pew national averages of 25% and 21%, respectively (2013).

Given the consistently lower proportions and wide coverage of the state, Pew national averages are not used for areas of Florida that are not covered by local Jewish community studies. Instead, a weighted average of JNR adults and a weighted average of Jewish children from the Florida community studies were calculated. These weighted averages are applied to the AJPP model-based estimates of the non-local study areas of Florida. Each study's contribution to the average is determined by the study's estimated population count of JBR adults, JNR adults, and Jewish children. Florida studies conducted by Sheskin—Broward, Miami, and Pinellas and Pasco—do not include estimates of JNR adults, and are thus only included in the overall estimate of Jewish children. The JNR proportion of the Greater Naples study would have a low contribution to the average and is not reliable (CV=72), so it is excluded from the JNR weighted average. The combined weighted averages of 11% JNR and 14% Jewish children are applied to all Florida areas not covered by local Jewish community studies.

Table 4-29: Estimates and Weighted Averages of Jews of No Religion and Jewish Children from AJPP Analysis of Florida Community Studies

Study Area	Study Date	Jews of No Religion: Pct. of Total Jewish Adults (CI)		Jewish Children: Pct. of Total Jewish Population (CI)	
Broward	2016				
Broward County, FL		-	-	14.6	(12.5, 16.9)
Greater Naples	2017				
Collier County, FL[1]		2.7	(0.7, 10.5)	6.9	(5.4, 8.8)
Miami	2014				
Miami-Dade County, FL		-	-	19.1	(17.6, 20.6)
Palm Beach	2018				
Palm Beach County, FL[2]		11.6	(8.2, 16.1)	13.5	(10.6, 17.0)
Pinellas/Pasco	2017				
Pinellas and Pasco Counties, FL		-	-	7.9	(5.9, 10.5)
Sarasota	2019				
Sarasota and Manatee Counties, FL		7.8	(5.1, 11.7)	12.1	(9.6, 15.2)
Overall (Weighted Average)		11.2		14.5	

Notes:
1) The JNR estimate of Collier County is not included in the JNR overall weighted average. CMJS estimates that 86% of Jewish individuals reside in Collier County, with the remainder distributed throughout Lee County and Marco Island. The estimates of Jewish children and JNR adults were applied to the AJPP ZIP Code-based area comprised of Collier and Monroe Counties.
2) Estimates for Palm Beach County are derived from the combined datasets of the Greater Palm Beaches and South Palm Beach County 2018 Community Studies.

Survey of American Jews, Pew Research Center 2013

For all areas not covered by a local Jewish community study, data from the Pew Survey of American Jews (2013) was used to estimate the proportion of JNR adults and Jewish children. The Pew survey is one of the largest studies of U.S. Jewry in the past decade. They estimated a total Jewish population of 6.7 million (2.2% of the U.S. population), with 1.8% of U.S. adults identifying their religion as Jewish. This estimate of JBR adults was identical to the previous AJPP estimate (Tighe et al., 2019), which had a 95% Bayesian credible interval from 1.7% to 1.9%. This survey included assessment of the Jewish identity of all adults and children in the household. Jewish adults included both those who identify their religion as Jewish as well as those who identify ethnically or culturally as Jewish. The latter group was included in the estimate of the core Jewish population only if the person did not identify with any other religious group. Pew estimated that 23% of Jewish adults were JNR (Pew Research Center, 2013). Jewish children were any children in households with at least one Jewish adult and who were being raised as Jewish in any way, and were estimated to be about 19% of the total Jewish population.

Secondary analysis of the Pew survey indicated that there were additional Jewish adults who had not been included in the original population estimate because their religion was coded as "Other, Specify", rather than as no religion ("Atheist", "Agnostic", or "Nothing in particular"). Review of open-ended responses of those who said Other indicated many statements of no affiliation with any religion such as "I'm secular," or general statements of belief in God. Independent coders rated the open-ended responses to categorize them as affiliated with a religion, or unaffiliated with any religion (Tighe, et al., 2014 [link to online report]). This yielded an estimate of nearly 25% (24.9%) of Jewish adults were JNR. Including these adults, consequently increased the estimated percentage of Jewish children (including the children of the additional JNR adults) to 21%.

Rather than applying the estimated 25% JNR and 21% children to all areas, secondary analysis was conducted to examine whether there were differences by census region. Although the survey was designed to provide estimates nationally, and not for small area estimation, census region, was included in the weighting, and results were reported by region (p. 16).

Estimates by census region are displayed in Table 4-30 and ranged from 18% in the Northeast to 35% in the Midwest.

Table 4-30: Proportion of JNR adults by Census Region

	Prop. JNR Adults (95% CI)		Coefficient of Variation
Northeast	0.181	(0.158, 0.208)	7.0
Midwest	0.352	(0.283, 0.429)	10.7
South	0.233	(0.188, 0.285)	10.6
West	0.341	(0.290, 0.396)	7.9
Total	0.249	(0.223, 0.268)	4.0

Another consideration of the Pew survey was that to increase the efficiency of the design, the sampling frame excluded nearly half of the counties in the U.S. where it was expected there would be near zero Jewish population. These 1,430 counties account for just 10% of the total U.S. population. They were, however, distributed disproportionately by census region (See Table 4-31). The Northeast had the greatest coverage with less than 10% of counties excluded from the sampling frame, corresponding to less than 1% of the total population of the Northeast excluded from the sampling frame. The Midwest had the least coverage with 60% of all counties excluded and 16% of the population, followed by the South with 43% of counties excluded and 13% of the population.

Table 4-31: Distribution of the Excluded Counties from the Pew Sampling Frame

	All Counties		Excluded Counties			
	Count	Population[1]	Count	Population	Proportion of Counties in Region	Proportion of Population in Region
Northeast	217	55,604,223	19	677,006	0.088	0.012
Midwest	1,055	67,157,800	631	11,113,500	0.598	0.165
South	1,422	116,006,522	616	15,209,317	0.433	0.131
West	448	72,788,329	164	3,273,229	0.366	0.045
Total	3,142	311,556,874	1,430	30,273,052	0.455	0.097

Notes:

1) Population for 2011, the year the survey was conducted, from the Census Population Estimates 2011.

Given the disparities in coverage, and that the estimate of 18% JNR for the Northeast was on par with that observed in community studies of the largest Jewish population areas in the Northeast, this census region estimate was used for areas of the Northeast where there was no community study. For other areas where there was no community study information, the national rates of JNR and kids from the Pew survey were used. This was done to provide a conservative estimate given the lack of convergent evidence of the high rates of JNR for the Midwest and West.

Summary

For each geographic area, the estimates of the proportion of adults who are JNR and the proportion of the population that are children are combined with the model-based population estimate JBR adults to obtain estimates of total Jewish adults and total Jewish population. For example, in the San Francisco Bay area where it was estimated from the local study that in Alameda county 24.2% of Jewish adults were Jews of no religion, this was combined with the AJPP 2020 model-based estimate of JBR adults for the county (32,240 [95% CI: 28,120 – 36,560] to obtain an estimated total Jewish adult population of 32,240/(1 - .242), or 42,550 (95% CI: 37,100 – 48,240). Similarly, the estimate that 13.7% of the total Jewish population in Alameda county are children, is combined with the estimate of Jewish adults to obtain a total population estimate for the area of 42,500/(1-.137) or 49,300 (95% CI: 43,000 – 55,900).

These estimates are summed over geographic areas to obtain estimates for the nation, states, metropolitan areas and counties.

Table 4-32: National Population Estimates, including JBR adults, JNR adults, and Jewish children (in thousands)

	Pop.	95% CI
Adults		
Jewish by religion	4.873	(4.769, 4.977)
Jews of no religion	1.174	(1.047, 1.550)
Total Jewish Adults	6.047	(5.918, 6.176)
Children		
Total Jewish children	1.583	(1.309, 1.919)
Total Jewish Population	7.631	(7.230, 8.341)

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Chapter 5: Definition of Geographic Clusters & Claritas 2020 Population Counts

The large AJPP 2020 sample size enabled estimation of smaller geographic areas. It was expected that past models, which were based on county-level data, could be improved by taking into account variability in the distribution of the population within counties. ZIP Codes of respondents were used to create ZIP Code clusters within counties. In many of the surveys ZIP Code was based on the self-reported location at the time of the interview, often a more accurate reflection of the respondent's location, rather than county, based on the sampling frame. Counties were estimated singly. When sample size was insufficient for reliable estimation of a county, counties were grouped.

The use of ZIP Codes for analysis also required ZIP Code level population data for evaluation of the representativeness of survey samples and for postratification. For the most recent ZIP Code level population counts, data from Claritas (Claritas, 2019) in combination with the American Community Survey (citation) were used.

This chapter provides definitions of the county and ZIP Code clusters used for analysis along with detailed description of the Claritas population data.

Definition of Geographic Clusters

County Groups

The 3,143 counties in the U.S. were grouped into 498 unique areas. With the exception of Loving County, Texas, there were respondents in all of the 3,143 counties in the U.S. Sample sizes by county ranged from a high of over 28,000 in Los Angeles County, California to a low of just one or two observations in small counties in Idaho, Nebraska, and Texas (e.g., Clark County, ID, Loup County, NE, & Kenedy County, TX). The median sample size by county was 130.

For the top 50 Combined Statistical Areas (CBSAs) in the U.S., counties were estimated singly where there was sufficient sample size to do so. Where there was insufficient sample size to estimate a county singly, counties within the metropolitan area were grouped to achieve a minimum target sample size of 1,000 observations (see Figure 5-1).

For example, in the New York CBSA area, all of the counties in New York City – Kings, Queens, New York, Bronx, Richmond – were estimated singly with sample sizes ranging from 7,798 in Kings to 3,957 in the Bronx. Nassau, Westchester and Richmond also were estimated singly. Putnam had a much smaller sample size and was combined with Rockland. In the New Jersey portion of the New York CBSA, all counties with the exception of Hunterdon, Sussex and Warren had sufficient sample size to be estimated singly.

In all 50 of the top metropolitan areas, there was sufficient sample size to estimate, singly, the main county containing the central city. Other counties in the CBSA were combined if there was insufficient sample size. Sample sizes for single or combined counties ranged from 1,300 (counties outside of Austin, TX) to 28,107 (Los Angeles County, CA). The majority of counties (64%) had sample sizes between 1,500 and 3,500.

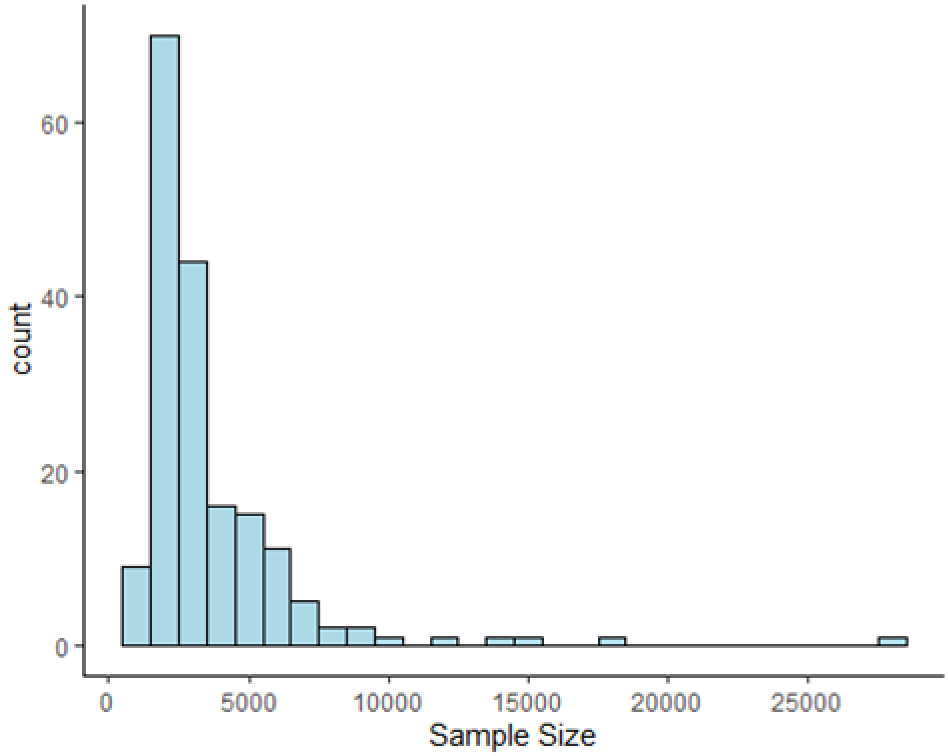

Figure 5-1: Histogram of county and county group sample sizes within the top 50 metropolitan areas.

Outside of the top 50 metropolitan areas, counties were grouped within each of the 50 states. First, counties were grouped within metropolitan areas within each state where there was sufficient sample size. Second, particular attention was given to areas where:

- there were local UJA Federations (e.g., Nashville, TN),
- past work with organizations who provide services to the Jewish community (e.g., Harold Grinspoon Foundation) indicated known Jewish community (e.g., Knoxville, TN), or
- Birthright registration data indicated likely Jewish population.

Third, attempts were made to create cohesive geographic areas, with minimal discontinuity. In some instances, micropolitan areas outside of a main metropolitan area were combined in ways that were discontinuous (e.g., North and South suburbs, or East and West of the metropolitan area).

Sample sizes for these counties and groups of counties ranged from 1,250 to 5,000, with just over half (53%) between 1,275 and 2,475 (See Figure 5-2).

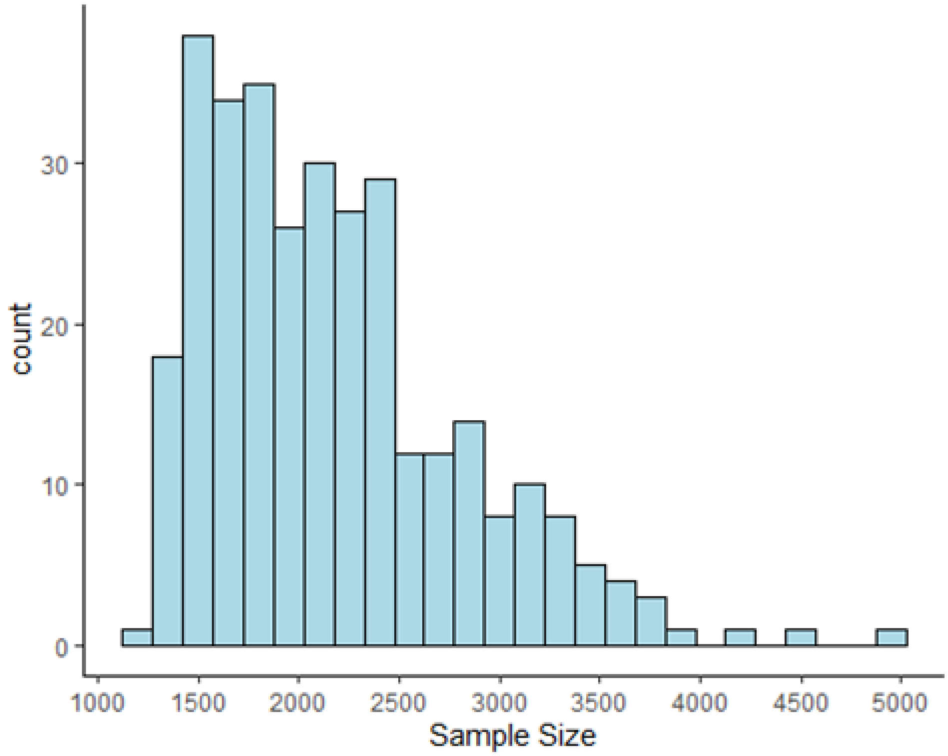

Figure 5-2: Histogram of county and county group sample sizes outside the top 50 metropolitan areas.

ZIP Code Clusters

For the purpose of analysis, postal codes on the original files were converted to ZIP Code Tabulation Areas (ZCTAs)[7]. A total of 611 ZCTA groups were created across the 498 counties/county groups. ZCTAs were matched to county groups based on the proportion of the population of the ZCTA in the county. The ZCTA was assigned to the county in which the largest proportion of the ZCTA population resided.[8] For counties and county groups with sufficient sample size, sub-areas defined by groups of ZCTAs were created. For example, in Los Angeles County, CA with a sample size of over 28,000, eleven separate groups of ZCTAs were created (see Figure 5-3).

[7] UDS Mapper. *ZIP Code to ZCTA Crosswalk*. https://udsmapper.org/zip-code-to-zcta-crosswalk/ Accessed on October 2019.

[8] ZCTA to county proportions were based on the Missouri Census Data Center Geocorr 2018: Geographic Correspondence Engine, https://mcdc.missouri.edu/applications/geocorr2018.html, *accessed, March 6, 2020.*

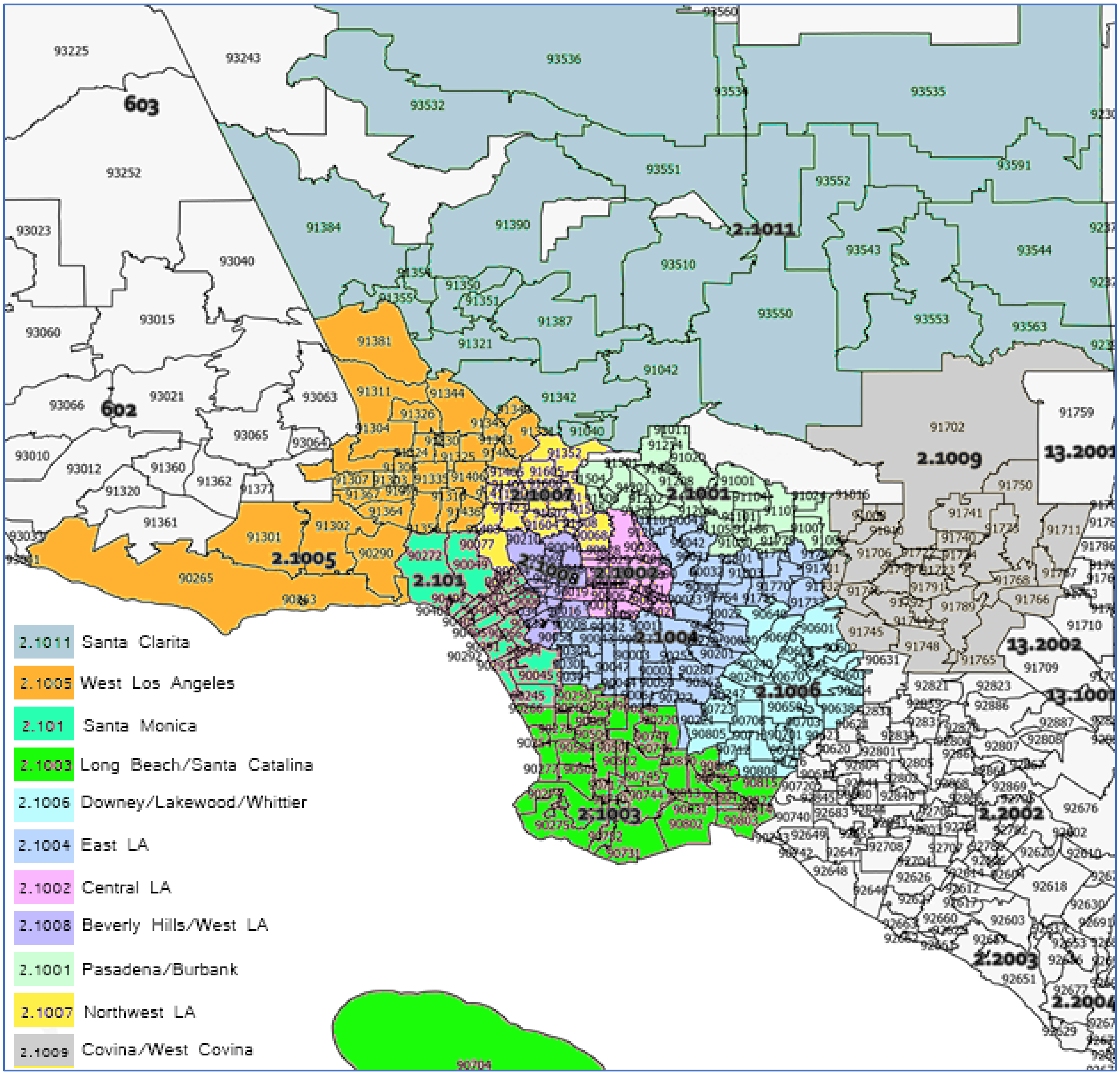

Figure 5-3: The ZCTA Cluster map of Los Angeles County, CA. The eleven ZCTA Clusters in the county are shaded and labelled with numbers 2.1001 to 2.1011.

K-Means clustering was used for *initial* clustering of counties and zip codes within counties (wherever possible). To generate these initial clusters, the following constraints were imposed, in order:

1. All county groupings must be confined *within* the state the county is in. That is, county groupings are taken on a state-by-state basis.

2. Counties that are in one of the top 50 most populated metropolitan areas are flagged and grouped separately from the rest of the counties in that state. The definition of what counties belong to which metropolitan area is taken from the Census[9].
3. If a county has a sample size of at least 3,200, it is flagged and automatically grouped as its own county group. It will then be considered for further grouping at the ZCTA level to create ZCTA groups akin to the example given above in Figure 5-3.
4. The distance from the geocenters of each of the counties to all other counties in a state is calculated using latitude-longitude data. The latitude-longitude data is from the TIGER line files from the Census[10]. The reciprocal of this distance is then calculated to reduce the likelihood that geographically far apart counties end up in the same group. The reciprocal distance of a county to itself is set to 0 in this step. This reciprocal distance matrix is then weighted to take into consideration the contribution of the 2-pair combinations that the counties involved have: whether it be by sample size, by Jewish incidence rates, or by population density.
5. The minimum number of clusters that can be made of counties within a state is set to 1. The maximum number of clusters that can be made of counties within a state (that aren't part of a top-50 metro area or already flagged to be their own county group as discussed in steps 2 and 3) is defined to be the integer part of the total sample size within the state divided by 2000, minus 1. (For example, in our data Iowa has a total sample size of 15,506. That means that the maximum allowable number of clusters that can be made in Iowa will be 6 (15506 / 2000 = 7.753; 7 - 1 = 6.)) This step is taken to maximize the chance that there will be sufficient sample size of at least 1000 within all the county groups that are generated.
6. K-Means Clustering is then used in conjunction with the reciprocal distance matrix calculated in step 4 and the sample size, Jewish incidence rates and population density data to determine the optimal number of clusters between the bounds defined in step 5.
7. A check is run to see that the sample size of the smallest cluster made is over 1000. If not, K-Means Clustering is run again with the maximum amount of clusters allowed lowered by one. This process repeats until the sample size of the smallest cluster exceeds 1000. The groupings are then labelled with a number similar to the county group numbering AJPP has for its county groups currently.
8. All counties that were separated in step 2 (but not separated in step 3) are then run through steps 4 through 7.
9. Counties that were separated in step 3 go through steps 4 through 7, but with the ZCTAs inside that county.

The results from the K-means grouping were reviewed on a county-by-county basis and manual modifications were made as needed primarily to ensure geographical contiguity, to better consider known federation areas, and to ensure that high Jewish population areas were not combined with non-Jewish population areas unless no other feasible alternative were possible.

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[9] U.S. Census Bureau (2020). *Delineation Files - Core based statistical areas (CBSAs), metropolitan divisions, and combined statistical areas (CSAs), March 2020.* Retrieved from https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/delineation-files.html

[10] U.S. Census Bureau (2019). *2019 TIGER/Line® Shapefiles: ZIP Code Tabulation Areas*. Retrieved from https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2019&layergroup=ZIP+Code+Tabulation+Areas

For example, if there were a county bordering a high Jewish population county group that had a low Jewish population but also a low sample size, it would be grouped into the high Jewish population county group if it could not be reasonably grouped elsewhere.

Finally, concerning county groupings, there were a few exceptions when creating groups based on the counties that are part of a top-50 most populated metro area. For example, because we were strict in not having county groupings cross state lines, Kenosha County in Wisconsin is not included in how we defined the Chicago-Naperville-Elgin, IL-IN-WI metropolitan area because it by itself did not have at a sample size of at least 1000. Kenosha ended up being grouped with Racine County in Wisconsin (county group 5505). The full list of the exceptions can be found in the footnote of the Metro Area Definitions file on the AJPP website.

Ninety percent of the sub-county areas were counties in the top 50 CBSAs. Other ZCTA sub-areas were created in Tucson, Fresno, Connecticut, Sarasota, Worcester MA, Rochester, Tulsa, Eugene OR, and Harrisburg PA.

Sample sizes for the ZCTA groups ranged from 6,100 in Maricopa County, AZ to 1,400 in Tulsa County, TX with a median sample size of 2,000.

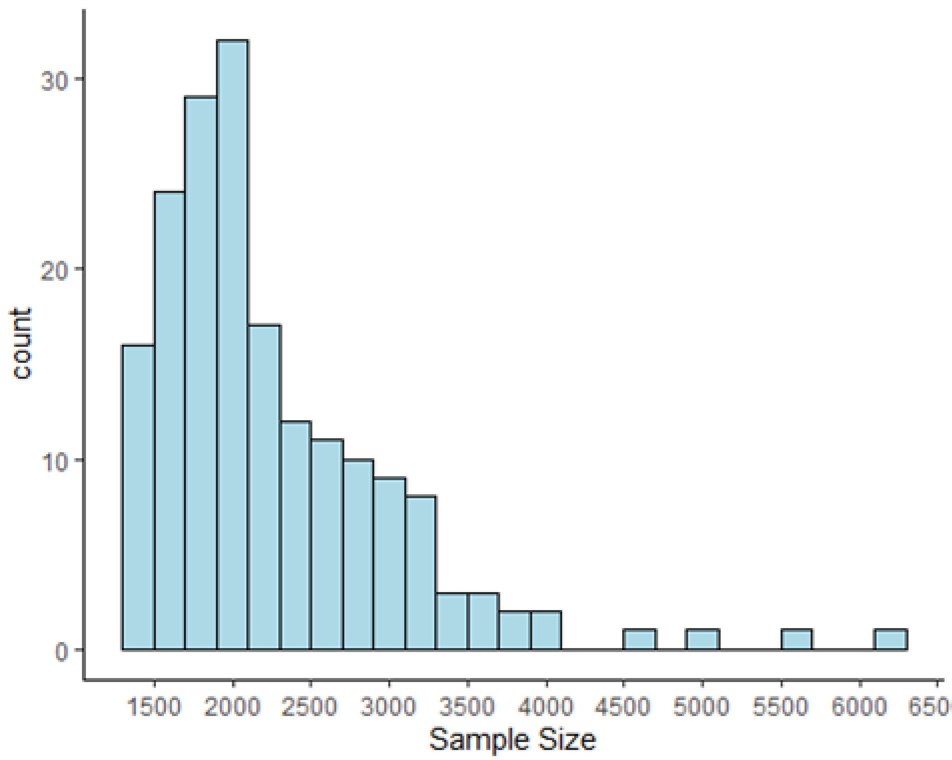


Figure 5-4: Histogram of sample sizes of ZCTA groups.

Hyper clusters

The 611 ZCTA clusters were further grouped into 52 hyperclusters based on preliminary estimates of the proportion Jewish in each cluster. The average number of ZCTA clusters per group was 10. Six ZCTA clusters with the highest proportion Jewish were grouped singly. These were clusters in Manhattan, Brooklyn, Palm Beach, and Los Angeles where preliminary models yielded estimates greater than 20%.

Claritas 2020 Population Data for Poststratification

Unlike county level census data which is available for the current year through the Census Population Estimates Program, ZIP code level census data is available only through the 5 years American Community Study program, which at the time of the release, was available for years 2014-2018. Therefore, in order to allow poststratification to the 2020 population, AJPP purchased 2020 ZIP Code level distributions by age and sex from Claritas, LLC (2019).

The Claritas data frame consisted of estimates of the resident population by sex and 13 categories of age.

Table 5-1: Claritas 2020 Demographic Update, Sex by Age

	Population	Pct.
Males	162,698,834	
0 to 4 yrs	10,267,180	6.3
5 to 9 yrs	10,331,370	6.3
10 to 14 yrs	10,566,689	6.5
15 to 17 yrs	6,533,729	4
18 to 20 yrs	7,010,832	4.3
21 to 24 yrs	9,059,256	5.6
25 to 34 yrs	22,690,417	13.9
35 to 44 yrs	20,854,289	12.8
45 to 54 yrs	20,406,723	12.5
55 to 64 yrs	20,511,873	12.6
65 to 74 yrs	15,273,874	9.4
75 to 84 yrs	6,856,932	4.2
85+ yrs	2,335,670	1.4
Females	167,643,459	
0 to 4 yrs	9,820,725	5.9
5 to 9 yrs	9,889,023	5.9
10 to 14 yrs	10,129,286	6
15 to 17 yrs	6,279,403	3.7
18 to 20 yrs	6,660,399	4
21 to 24 yrs	8,497,843	5.1
25 to 34 yrs	21,943,634	13.1
35 to 44 yrs	20,974,116	12.5
45 to 54 yrs	20,978,769	12.5
55 to 64 yrs	21,971,997	13.1
65 to 74 yrs	17,400,584	10.4
75 to 84 yrs	8,849,064	5.3
85+ yrs	4,248,616	2.5

These base population counts were adjusted to the population in households by race & ethnicity and educational attainment using the American Community Survey (ACS) 2014-2018.[11]

Race & Ethnicity

ACS Tables B01001(H)(I) provide ZCTA level distributions of sex and 14 categories of age for the total population, Hispanic, and white alone non-Hispanic. The 14 categories in the ACS and the 13 categories of age Claritas were reduced to 12 categories to match the distributions. Also for the ACS, the population counts in tables B01001H & B01001I were subtracted from the total population table B01001 to obtain counts for other non-Hispanic, creating three categories of race and ethnicity on the Claritas frame.

Educational Attainment

ACS Table B15001 provides distributions at the ZCTA level for the adult population ages 18 years and over by sex, five categories of age, and seven categories of educational attainment. The age categories were 18 to 24 years, 25 to 34 years, 35 to 44 years, 45 to 64 years, and 65 years and over. The education categories were: Less than 9th grade, 9th to 12th grade with no diploma, High school graduate, Some college with no degree, Associate's degree, Bachelor's degree, and Graduate or professional degree. The estimated proportion of the population in each sex by age by education category within each ZCTA was distributed over the base population counts for the corresponding sex by age group to obtain distributions by educational attainment.

Household Population

ACS Tables B01003 (Total population) and B25008 (Total population in occupied housing units) were used to obtain the percent of the population in housing units for each ZCTA.

The final population frame provides 2020 population estimates for ZCTAs by sex, age, educational attainment and three categories of race and ethnicity.

[11] ZIP codes were converted to ZIP Code Tabulation Areas (ZCTAs) using the U.S.D Mapper ZIP Code to ZCTA Crosswalk, https://udsmapper.org/zip-code-to-zcta-crosswalk/, accessed 2/28/2020.

Table 5-2: Claritas 2020 Demographic Update, Sex by Age with ACS Adjustments for Population in Households by Race, Ethnicity, and Educational Attainment

	U.S. Adults	
	Population	Pct.
Total All Groups	250,324,002	100
Sex		
Male	121,775,190	48.6
Female	128,548,812	51.4
Education		
Non-College	177,624,557	71
College Grad	72,699,444	29
Race		
White, non-Hisp.	161,567,880	64.5
Hispanic	39,096,708	15.6
Other, non-Hisp.	49,659,414	19.8
Age		
18-24 years	29,811,266	11.9
25-34 years	43,543,694	17.4
35-44 years	40,909,436	16.3
45-54 years	40,581,232	16.2
55-64 years	41,693,274	16.7
65-74 years	32,044,729	12.8
75+ years	21,740,369	8.7

Appendices

Appendix 3.1: R session info and stan code

R Session Info

```
> sessionInfo()
R version 4.0.2 (2020-06-22)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 18.04.5 LTS

Matrix products: default
BLAS:   /usr/lib/x86_64-linux-gnu/blas/libblas.so.3.7.1
LAPACK: /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.7.1

locale:
 [1] LC_CTYPE=en_U.S..UTF-8       LC_NUMERIC=C               LC_TIME=en_U.S..UTF-8
LC_COLLATE=en_U.S..UTF-8
 [5] LC_MONETARY=en_U.S..UTF-8    LC_MESSAGES=en_U.S..UTF-8    LC_PAPER=en_U.S..UTF-8
LC_NAME=C
 [9] LC_ADDRESS=C               LC_TELEPHONE=C             LC_MEASUREMENT=en_U.S..UTF-8
LC_IDENTIFICATION=C

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

loaded via a namespace (and not attached):
[1] compiler_4.0.2
```

rstan code

```
data {
  int<lower=1> N;
  int<lower=1> n_fem;
  int<lower=1> n_edu;
  int<lower=1> n_race;
  int<lower=1> n_age;
  int<lower=1> n_pds;
  int<lower=1> n_axe;
  int<lower=1> n_surv;
  int<lower=1> n_zcl;
  int<lower=1> n_hcl;
  int<lower=1> n_zxe;
  int<lower=1> n_zxa;

  int<lower=0, upper=1> curreljw[N];

  int<lower=1, upper=n_fem> fem[N];
  int<lower=1, upper=n_edu> edu[N];
  int<lower=1, upper=n_race> race[N];
  int<lower=1, upper=n_age> age[N];
  int<lower=1, upper=n_pds> pds[N];
  int<lower=1, upper=n_surv> survs[N];
  int<lower=1, upper=n_zcl> zcls[N];
  int<lower=1, upper=n_hcl> hcls[n_zcl];
```

```
  int<lower=1, upper=n_axe> axes[N];
  int<lower=1, upper=n_zxe> zxes[N];
  int<lower=1, upper=n_zxa> zxas[N];
}
parameters {
  real b_cons;

  real<lower=0> sigma_fem;
  real<lower=0> sigma_edu;
  real<lower=0> sigma_race;
  real<lower=0> sigma_age;
  real<lower=0> sigma_pds;
  real<lower=0> sigma_surv;
  real<lower=0> sigma_zcl;
  real<lower=0> sigma_hcl;
  real<lower=0> sigma_axe;
  real<lower=0> sigma_zxe;
  real<lower=0> sigma_zxa;

  vector<multiplier=sigma_fem>[n_fem] b_fem;
  vector<multiplier=sigma_edu>[n_edu] b_edu;
  vector<multiplier=sigma_race>[n_race] b_race;
  vector<multiplier=sigma_age>[n_age] b_age;
  vector<multiplier=sigma_pds>[n_pds] b_pds;
  vector<multiplier=sigma_axe>[n_axe] b_axe;
  vector<multiplier=sigma_surv>[n_surv] b_surv;
  vector<multiplier=sigma_zcl>[n_zcl] b_zcl;
  vector<multiplier=sigma_hcl>[n_hcl] g_hcl;
  vector<multiplier=sigma_zxe>[n_zxe] b_zxe;
  vector<multiplier=sigma_zxa>[n_zxa] b_zxa;
}
model {
  curreljw ~ bernoulli_logit(b_cons + b_fem[fem] + b_edu[edu] + b_race[race] +
                              b_age[age] + b_pds[pds] + b_axe[axes] +
                             b_surv[survs] +
                             b_zcl[zcls] + g_hcl[hcls[zcls]] +
                             b_zxe[zxes] + b_zxa[zxas]);

  b_cons ~ normal(-4.75, 10);

  b_fem ~ normal(0, sigma_fem);
  sum(b_fem) ~ normal(0, 0.1);
  b_edu ~ normal(0, sigma_edu);
  sum(b_edu) ~ normal(0, 0.1);

  b_race ~ normal(0, sigma_race);
  b_age ~ normal(0, sigma_age);
  b_pds ~ normal(0, sigma_pds);
  b_axe ~ normal(0, sigma_axe);
  b_surv ~ normal(0, sigma_surv);

  g_hcl ~ normal(0, sigma_hcl);
  b_zcl ~ normal(0, sigma_zcl);

  b_zxe ~ normal(0, sigma_zxe);
  b_zxa ~ normal(0, sigma_zxa);

  sigma_fem ~ normal(0, 2);
  sigma_edu ~ normal(0, 3);
  sigma_race ~ normal(0, 3);
```

```
  sigma_age ~ std_normal();
  sigma_pds ~ std_normal();
  sigma_axe ~ std_normal();
  sigma_surv ~ std_normal();

  sigma_zcl ~ std_normal();
  sigma_hcl ~ normal(0, 2);

  sigma_zxe ~ std_normal();
  sigma_zxa ~ std_normal();
}
```

Appendix 5.1: Counties in the top 50 Metro Areas (CBSA)

County Group	Counties/Parishes/Boroughs
1.11	Kings County, NY
1.12	Queens County, NY
1.13	New York County, NY
1.14	Suffolk County, NY
1.15	Bronx County, NY
1.16	Nassau County, NY
1.17	Westchester County, NY
1.18	Richmond County, NY
1.19	Putnam and Rockland Counties, NY
1.2	Bergen County, NJ
1.21	Middlesex County, NJ
1.22	Essex County, NJ
1.23	Hudson County, NJ
1.24	Monmouth County, NJ
1.25	Ocean County, NJ
1.26	Union County, NJ
1.27	Passaic County, NJ
1.28	Morris County, NJ
1.29	Somerset County, NJ
1.291	Hunterdon, Sussex, and Warren Counties, NJ
2.1	Los Angeles County, CA
2.2	Orange County, CA
3.11	Cook County, IL
3.12	DuPage County, IL
3.13	Lake County, IL
3.14	Will County, IL
3.15	Kane County, IL
3.16	DeKalb, Grundy, Kendall, and McHenry Counties, IL
3.2	Jasper, Lake, Newton, and Porter Counties, IN
4.1	Dallas County, TX
4.2	Tarrant County, TX
4.3	Collin County, TX
4.4	Denton County, TX
4.5	Ellis, Hunt, Johnson, Kaufman, Parker, Rockwall, and Wise Counties, TX
5.1	Harris County, TX
5.2	Fort Bend County, TX
5.3	Austin, Montgomery, and Waller Counties, TX
5.4	Brazoria, Chambers, Galveston, and Liberty Counties, TX
6.1	District Of Columbia

6.11	Frederick and Montgomery Counties, MD
6.12	Calvert, Charles, and Prince Georges Counties, MD
6.21	Fairfax City and Fairfax County, VA
6.22	Alexandria City, Arlington County, and Falls Church City, VA
6.23	Manassas City, Manassas Park City, and Prince William County, VA
6.24	Loudoun County, VA
6.25	Clarke, Culpeper, Fauquier, Fredericksburg City, Madison, Rappahannock, Spotsylvania, Stafford, and Warren Counties, VA
7.1	Miami-Dade County, FL
7.2	Broward County, FL
7.3	Palm Beach County, FL
8.11	Philadelphia County, PA
8.12	Montgomery County, PA
8.13	Bucks County, PA
8.14	Delaware County, PA
8.15	Chester County, PA
8.21	Camden County, NJ
8.22	Burlington County, NJ
8.23	Gloucester and Salem Counties, NJ
8.3	New Castle County, DE
9.1	DeKalb County, GA
9.2	Fulton County, GA
9.3	Gwinnett County, GA
9.4	Cobb County, GA
9.5	Bartow, Carroll, Coweta, Dawson, Douglas, Haralson, Heard, Paulding, and Pickens Counties, GA
9.6	Barrow, Butts, Jasper, Lamar, Meriwether, Morgan, Newton, Pike, Spalding, and Walton Counties, GA
9.7	Clayton, Fayette, Henry, and Rockdale Counties, GA
9.8	Cherokee and Forsyth Counties, GA
10.1	Maricopa County, AZ
10.2	Pinal County, AZ
11.1	Middlesex County, MA
11.2	Essex County, MA
11.3	Suffolk County, MA
11.4	Norfolk County, MA
11.5	Plymouth County, MA
11.6	Rockingham and Strafford Counties, NH
12.1	Alameda County, CA
12.2	Contra Costa and Marin Counties, CA
12.3	San Francisco County, CA
12.4	San Mateo County, CA
13.1	Riverside County, CA
13.2	San Bernardino County, CA

14.1	Wayne County, MI
14.2	Oakland County, MI
14.3	Macomb County, MI
14.4	Lapeer, Livingston, and St. Clair Counties, MI
15.1	King County, WA
15.2	Pierce County, WA
15.3	Snohomish County, WA
16.1	Hennepin County, MN
16.2	Ramsey County, MN
16.3	Dakota County, MN
16.4	Anoka and Washington Counties, MN
16.5	Carver, Chisago, Isanti, Le Sueur, Mille Lacs, Scott, Sherburne, and Wright Counties, MN
17.1	San Diego County, CA
18.1	Hillsborough County, FL
18.2	Pinellas County, FL
18.3	Hernando and Pasco Counties, FL
19.1	Jefferson County, CO
19.2	Denver County, CO
19.3	Arapahoe County, CO
19.4	Adams County, CO
19.5	Broomfield and Douglas Counties, CO
20.11	St. Louis City and St. Louis County, MO
20.12	Franklin, Jefferson, Lincoln, St. Charles, and Warren Counties, MO
20.21	Bond, Calhoun, Clinton, Jersey, Macoupin, Madison, Monroe, and St. Clair Counties, IL
21.1	Baltimore County, MD
21.2	Baltimore City, MD
21.3	Anne Arundel County, MD
21.4	Carroll and Howard Counties, MD
21.5	Harford and Queen Annes Counties, MD
22.11	Mecklenburg County, NC
22.12	Anson, Cabarrus, Rowan, and Union Counties, NC
22.13	Gaston, Iredell, and Lincoln Counties, NC
22.21	Chester, Lancaster, and York Counties, SC
23.1	Orange County, FL
23.2	Seminole County, FL
23.3	Lake and Osceola Counties, FL
24.1	Bexar County, TX
24.2	Atascosa, Bandera, Comal, Guadalupe, Kendall, Medina, and Wilson Counties, TX
25.1	Multnomah County, OR
25.2	Columbia and Washington Counties, OR
25.3	Clark and Skamania Counties, WA
25.4	Clackamas and Yamhill Counties, OR
26.1	Sacramento County, CA

26.2	Placer County, CA
26.3	El Dorado and Yolo Counties, CA
27.1	Allegheny County, PA
27.2	Armstrong and Westmoreland Counties, PA
27.3	Beaver and Butler Counties, PA
27.4	Fayette, Greene, and Washington Counties, PA
28.1	Clark County, NV
29.1	Travis County, TX
29.2	Williamson County, TX
29.3	Bastrop, Caldwell, and Hays Counties, TX
30.11	Hamilton County, OH
30.12	Butler County, OH
30.13	Brown, Clermont, and Warren Counties, OH
30.21	Boone, Bracken, Campbell, Gallatin, Grant, Kenton, and Pendleton Counties, KY
31.11	Jackson County, MO
31.12	Bates, Caldwell, Cass, Clay, Clinton, Lafayette, Platte, and Ray Counties, MO
31.21	Johnson County, KS
32.1	Franklin County, OH
32.2	Delaware, Licking, and Morrow Counties, OH
32.3	Fairfield, Hocking, Madison, Perry, Pickaway, and Union Counties, OH
33.1	Marion County, IN
33.2	Hamilton, Hancock, and Madison Counties, IN
33.3	Boone, Brown, Hendricks, Johnson, Morgan, Putnam, and Shelby Counties, IN
34.1	Cuyahoga County, OH
34.2	Geauga, Lake, Lorain, and Medina Counties, OH
35.1	Santa Clara County, CA
36.1	Davidson County, TN
36.2	Rutherford and Williamson Counties, TN
36.3	Cannon, Cheatham, Dickson, Macon, Maury, Robertson, Smith, Sumner, Trousdale, and Wilson Counties, TN
37.1	Virginia Beach City, VA
37.2	Hampton City, Newport News City, and Norfolk City, VA
37.3	Accomack, Gloucester, James City, Mathews, Northampton, Poquoson City, Williamsburg City, and York Counties, VA
37.4	Chesapeake City, Franklin City, Isle of Wight, Portsmouth City, Southampton, Suffolk City, and Surry Counties, VA
38.1	Providence County, RI
38.2	Bristol County, MA
38.3	Bristol, Kent, Newport, and Washington Counties, RI
39.1	Milwaukee County, WI
39.2	Ozaukee, Washington, and Waukesha Counties, WI
40.1	Duval County, FL
40.2	Baker, Clay, Nassau, and St. Johns Counties, FL
41.1	Oklahoma County, OK

41.2	Canadian, Cleveland, Grady, Lincoln, Logan, and McClain Counties, OK
42.1	Wake County, NC
43.11	Fayette, Shelby, and Tipton Counties, TN
44.1	Henrico County, VA
44.2	Chesterfield County and Richmond City, VA
44.3	Amelia, Charles City, Colonial Heights City, Dinwiddie, Goochland, Hanover, Hopewell City, King and Queen, King William, New Kent, Petersburg City, Powhatan, Prince George, and Sussex Counties, VA
45.1	Jefferson Parish, LA
45.2	Orleans Parish, LA
45.3	Plaquemines, St. Bernard, St. Charles, St. James, St. John the Baptist, and St. Tammany Parishes, LA
46.11	Jefferson County, KY
47.1	Salt Lake County, UT
48.1	Hartford County, CT
48.2	Middlesex and New London Counties, CT
49.1	Erie County, NY
50.1	Jefferson County, AL
50.2	Bibb, Blount, Chilton, Shelby, and St. Clair Counties, AL

Appendix 5.2: Counties in the County Groups by State Outside the top 50 Metro Areas

County Group	Counties/Parishes/Boroughs
101	Madison County, AL
102	DeKalb, Etowah, Jackson, and Marshall Counties, AL
103	Colbert, Franklin, Lauderdale, Lawrence, Limestone, and Morgan Counties, AL
104	Baldwin and Mobile Counties, AL
105	Autauga, Coosa, Dallas, Elmore, Lowndes, Montgomery, and Tallapoosa Counties, AL
106	Cullman, Fayette, Greene, Hale, Lamar, Marion, Perry, Pickens, Tuscaloosa, Walker, and Winston Counties, AL
107	Bullock, Butler, Choctaw, Clarke, Conecuh, Covington, Crenshaw, Escambia, Marengo, Monroe, Pike, Sumter, Washington, and Wilcox Counties, AL
108	Barbour, Coffee, Dale, Geneva, Henry, Houston, Lee, Macon, and Russell Counties, AL
109	Calhoun, Chambers, Cherokee, Clay, Cleburne, Randolph, and Talladega Counties, AL
201	Anchorage Borough, AK
202	Aleutians East Borough, Aleutians West Census Area, Bethel Census Area, Bristol Bay Borough, Denali Borough, Dillingham Census Area, Fairbanks North Star Borough, Haines Borough, Hoonah-Angoon Census Area, Juneau Borough, Kenai Peninsula Borough, Ketchikan Gateway Borough, Kodiak Island Borough, Kusilvak Census Area, Lake and Peninsula Borough, Matanuska-Susitna Borough, Nome Census Area, North Slope Borough, Northwest Arctic Borough, Petersburg Census Area, Prince of Wales-Hyder Census Area, Sitka Borough, Skagway Municipality, Southeast Fairbanks Census Area, Valdez-Cordova Census Area, Wade Hampton Census Area, Wrangell City and Borough, Yakutat Borough, and Yukon-Koyukuk Census Area, AK
401	Pima County, AZ
402	Coconino and Yavapai Counties, AZ
403	La Paz, Mohave, and Yuma Counties, AZ
404	Apache, Cochise, Gila, Graham, Greenlee, Navajo, and Santa Cruz Counties, AZ
501	Conway, Faulkner, Grant, Lonoke, Perry, Pulaski, and Saline Counties, AR
502	Benton and Washington Counties, AR
503	Baxter, Boone, Carroll, Cleburne, Fulton, Independence, Izard, Lawrence, Madison, Marion, Newton, Randolph, Searcy, Sharp, Stone, and Van Buren Counties, AR
504	Arkansas, Clay, Cleveland, Craighead, Crittenden, Cross, Greene, Jackson, Jefferson, Lee, Lincoln, Mississippi, Monroe, Phillips, Poinsett, Prairie, St. Francis, White, and Woodruff Counties, AR
505	Ashley, Bradley, Calhoun, Chicot, Columbia, Dallas, Desha, Drew, Hempstead, Howard, Lafayette, Little River, Miller, Nevada, Ouachita, Sevier, and Union Counties, AR
506	Clark, Crawford, Franklin, Garland, Hot Spring, Johnson, Logan, Montgomery, Pike, Polk, Pope, Scott, Sebastian, and Yell Counties, AR
601	Fresno, Kings, and Madera Counties, CA
602	Ventura County, CA
603	Kern County, CA
604	Napa and Sonoma Counties, CA
605	San Joaquin County, CA
606	Mariposa, Merced, San Benito, and Stanislaus Counties, CA
607	Santa Barbara County, CA
608	Solano County, CA

609	Santa Cruz and Tulare Counties, CA
610	Butte, Colusa, Glenn, Sutter, and Yuba Counties, CA
611	Lassen, Modoc, Nevada, Plumas, Shasta, Sierra, Siskiyou, and Tehama Counties, CA
612	Del Norte, Humboldt, Lake, Mendocino, and Trinity Counties, CA
613	Monterey and San Luis Obispo Counties, CA
614	Alpine, Amador, Calaveras, Imperial, Inyo, Mono, and Tuolumne Counties, CA
801	El Paso County, CO
802	Larimer and Weld Counties, CO
803	Boulder County, CO
804	Delta, Mesa, Montrose, and Ouray Counties, CO
805	Alamosa, Archuleta, Chaffee, Clear Creek, Conejos, Costilla, Dolores, Eagle, Garfield, Gilpin, Grand, Gunnison, Hinsdale, Jackson, La Plata, Lake, Mineral, Moffat, Montezuma, Park, Pitkin, Rio Blanco, Rio Grande, Routt, Saguache, San Juan, San Miguel, Summit, and Yuma Counties, CO
806	Baca, Bent, Cheyenne, Crowley, Custer, Elbert, Fremont, Huerfano, Kiowa, Kit Carson, Las Animas, Lincoln, Logan, Morgan, Otero, Phillips, Prowers, Pueblo, Sedgwick, Teller, and Washington Counties, CO
901	Fairfield County, CT
902	New Haven County, CT
903	Litchfield, Tolland, and Windham Counties, CT
1001	Kent and Sussex Counties, DE
1201	Charlotte and Lee Counties, FL
1202	Brevard County, FL
1203	DeSoto, Glades, Hardee, Hendry, Highlands, Okeechobee, and Polk Counties, FL
1204	Flagler, Putnam, and Volusia Counties, FL
1205	Sarasota County, FL
1206	Marion County, FL
1207	Manatee County, FL
1208	Escambia and Santa Rosa Counties, FL
1209	Collier and Monroe Counties, FL
1210	Alachua, Bradford, Columbia, Dixie, Gilchrist, Lafayette, Levy, Suwannee, and Union Counties, FL
1211	Okaloosa and Walton Counties, FL
1212	Indian River, Martin, and St. Lucie Counties, FL
1213	Franklin, Gadsden, Hamilton, Jefferson, Leon, Liberty, Madison, Taylor, and Wakulla Counties, FL
1214	Citrus and Sumter Counties, FL
1215	Bay, Calhoun, Gulf, Holmes, Jackson, and Washington Counties, FL
1301	Columbia and Richmond Counties, GA
1302	Chattahoochee, Harris, Marion, Muscogee, Stewart, Talbot, Troup, Upson, and Webster Counties, GA
1303	Clarke, Hall, Jackson, Madison, Oconee, and Oglethorpe Counties, GA
1304	Appling, Baldwin, Bibb, Bleckley, Crawford, Dodge, Hancock, Houston, Jeff Davis, Johnson, Jones, Laurens, Macon, Monroe, Peach, Pulaski, Taylor, Telfair, Twiggs, Washington, Wheeler, and Wilkinson Counties, GA
1305	Bryan, Bulloch, Burke, Candler, Chatham, Effingham, Emanuel, Evans, Glascock, Jefferson, Jenkins, Liberty, Long, Montgomery, Screven, Tattnall, Toombs, and Treutlen Counties, GA

1306	Catoosa, Chattooga, Dade, Floyd, Gordon, Murray, Polk, Walker, and Whitfield Counties, GA
1307	Banks, Elbert, Fannin, Franklin, Gilmer, Greene, Habersham, Hart, Lincoln, Lumpkin, McDuffie, Putnam, Rabun, Stephens, Taliaferro, Towns, Union, Warren, White, and Wilkes Counties, GA
1308	Baker, Ben Hill, Berrien, Brooks, Calhoun, Clay, Colquitt, Cook, Crisp, Decatur, Dooly, Dougherty, Early, Echols, Grady, Irwin, Lanier, Lee, Lowndes, Miller, Mitchell, Quitman, Randolph, Schley, Seminole, Sumter, Terrell, Thomas, Tift, Turner, Wilcox, and Worth Counties, GA
1309	Atkinson, Bacon, Brantley, Camden, Charlton, Clinch, Coffee, Glynn, McIntosh, Pierce, Ware, and Wayne Counties, GA
1501	Honolulu County, HI
1502	Hawaii, Kalawao, Kauai, and Maui Counties, HI
1601	Ada County, ID
1602	Benewah, Bonner, Boundary, Clearwater, Idaho, Kootenai, Latah, Lemhi, Lewis, Nez Perce, and Shoshone Counties, ID
1603	Adams, Boise, Canyon, Elmore, Gem, Owyhee, Payette, Valley, and Washington Counties, ID
1604	Bannock, Bear Lake, Bingham, Blaine, Bonneville, Butte, Camas, Caribou, Cassia, Clark, Custer, Franklin, Fremont, Gooding, Jefferson, Jerome, Lincoln, Madison, Minidoka, Oneida, Power, Teton, and Twin Falls Counties, ID
1701	Fulton, Hancock, Henderson, Knox, Marshall, Mason, McDonough, Peoria, Stark, Tazewell, Warren, and Woodford Counties, IL
1702	Boone, Carroll, Jo Daviess, Ogle, Stephenson, and Winnebago Counties, IL
1703	De Witt, Logan, Macon, McLean, and Sangamon Counties, IL
1704	Christian, Clark, Clay, Coles, Crawford, Cumberland, Edwards, Effingham, Fayette, Gallatin, Jasper, Lawrence, Montgomery, Richland, Shelby, Wabash, Wayne, and White Counties, IL
1705	Bureau, Iroquois, Kankakee, La Salle, Lee, Livingston, and Putnam Counties, IL
1706	Adams, Brown, Cass, Greene, Henry, Menard, Mercer, Morgan, Pike, Rock Island, Schuyler, Scott, and Whiteside Counties, IL
1707	Alexander, Franklin, Hamilton, Hardin, Jackson, Jefferson, Johnson, Marion, Massac, Perry, Pope, Pulaski, Randolph, Saline, Union, Washington, and Williamson Counties, IL
1708	Champaign, Douglas, Edgar, Ford, Moultrie, Piatt, and Vermilion Counties, IL
1801	Allen and Whitley Counties, IN
1802	Benton, Carroll, Cass, Clay, Clinton, Fountain, Howard, Miami, Montgomery, Parke, Sullivan, Tippecanoe, Tipton, Vermillion, Vigo, Warren, and White Counties, IN
1803	Decatur, Delaware, Fayette, Henry, Randolph, Rush, Union, and Wayne Counties, IN
1804	Elkhart and St. Joseph Counties, IN
1805	Fulton, Kosciusko, La Porte, Marshall, Pulaski, and Starke Counties, IN
1806	Daviess, Dubois, Gibson, Knox, Martin, Perry, Pike, Posey, Spencer, Vanderburgh, and Warrick Counties, IN
1807	Adams, Blackford, De Kalb, Grant, Huntington, Jay, Lagrange, Noble, Steuben, Wabash, and Wells Counties, IN
1808	Bartholomew, Greene, Jackson, Jennings, Lawrence, Monroe, and Owen Counties, IN
1809	Clark, Crawford, Dearborn, Floyd, Franklin, Harrison, Jefferson, Ohio, Orange, Ripley, Scott, Switzerland, and Washington Counties, IN
1901	Boone, Dallas, Guthrie, Jasper, Madison, Mahaska, Marion, Polk, Story, and Warren Counties, IA
1902	Benton, Johnson, Jones, Linn, and Washington Counties, IA
1903	Appanoose, Cedar, Clayton, Clinton, Davis, Delaware, Des Moines, Dubuque, Henry, Iowa, Jackson, Jefferson, Keokuk, Lee, Louisa, Monroe, Muscatine, Poweshiek, Scott, Van Buren, and Wapello Counties, IA

1904	Adair, Adams, Audubon, Cass, Clarke, Decatur, Fremont, Lucas, Mills, Montgomery, Page, Pottawattamie, Ringgold, Shelby, Taylor, Union, and Wayne Counties, IA
1905	Allamakee, Black Hawk, Bremer, Buchanan, Butler, Cerro Gordo, Chickasaw, Fayette, Floyd, Franklin, Grundy, Hamilton, Hancock, Hardin, Howard, Marshall, Mitchell, Tama, Winnebago, Winneshiek, Worth, and Wright Counties, IA
1906	Buena Vista, Calhoun, Carroll, Cherokee, Clay, Crawford, Dickinson, Emmet, Greene, Harrison, Humboldt, Ida, Kossuth, Lyon, Monona, OBrien, Osceola, Palo Alto, Plymouth, Pocahontas, Sac, Sioux, Webster, and Woodbury Counties, IA
2001	Sedgwick County, KS
2002	Barber, Butler, Chautauqua, Clark, Comanche, Cowley, Edwards, Elk, Finney, Ford, Grant, Gray, Greenwood, Hamilton, Harper, Harvey, Haskell, Hodgeman, Kearny, Kingman, Kiowa, Marion, McPherson, Meade, Morton, Ness, Pawnee, Pratt, Reno, Seward, Stafford, Stanton, Stevens, and Sumner Counties, KS
2003	Barton, Cheyenne, Clay, Cloud, Decatur, Dickinson, Ellis, Ellsworth, Gove, Graham, Greeley, Jewell, Lane, Lincoln, Logan, Mitchell, Norton, Osborne, Ottawa, Phillips, Rawlins, Republic, Rice, Rooks, Rush, Russell, Saline, Scott, Sheridan, Sherman, Smith, Thomas, Trego, Wallace, and Wichita Counties, KS
2004	Atchison, Brown, Chase, Coffey, Doniphan, Geary, Jackson, Jefferson, Leavenworth, Lyon, Marshall, Morris, Nemaha, Osage, Pottawatomie, Riley, Shawnee, Wabaunsee, Washington, and Wyandotte Counties, KS
2005	Allen, Anderson, Bourbon, Cherokee, Crawford, Douglas, Franklin, Labette, Linn, Miami, Montgomery, Neosho, Wilson, and Woodson Counties, KS
2101	Fayette and Scott Counties, KY
2102	Anderson, Bath, Bourbon, Clark, Estill, Franklin, Jessamine, Madison, Menifee, Montgomery, and Woodford Counties, KY
2103	Bell, Boyle, Casey, Clay, Clinton, Cumberland, Garrard, Harlan, Jackson, Knox, Laurel, Leslie, Lincoln, McCreary, Mercer, Pulaski, Rockcastle, Russell, Washington, Wayne, and Whitley Counties, KY
2104	Boyd, Breathitt, Carter, Elliott, Fleming, Floyd, Greenup, Harrison, Johnson, Knott, Lawrence, Lee, Letcher, Lewis, Magoffin, Martin, Mason, Morgan, Nicholas, Owsley, Perry, Pike, Powell, Robertson, Rowan, and Wolfe Counties, KY
2105	Allen, Barren, Butler, Edmonson, Hart, Logan, Metcalfe, Monroe, Simpson, Todd, and Warren Counties, KY
2106	Adair, Breckinridge, Bullitt, Carroll, Grayson, Green, Hardin, Henry, Larue, Marion, Meade, Nelson, Oldham, Owen, Shelby, Spencer, Taylor, and Trimble Counties, KY
2107	Ballard, Caldwell, Calloway, Carlisle, Christian, Crittenden, Fulton, Graves, Hickman, Livingston, Lyon, Marshall, McCracken, and Trigg Counties, KY
2108	Daviess, Hancock, Henderson, Hopkins, McLean, Muhlenberg, Ohio, Union, and Webster Counties, KY
2201	East Baton Rouge Parish, LA
2202	Ascension, Assumption, East Feliciana, Iberville, Livingston, Pointe Coupee, St. Helena, West Baton Rouge, and West Feliciana Parishes, LA
2203	Acadia, Avoyelles, Catahoula, Concordia, Evangeline, Grant, Iberia, La Salle, Lafayette, Madison, Rapides, St. Landry, St. Martin, St. Mary, Tensas, and Vermilion Parishes, LA
2204	Bienville, Bossier, Caddo, Claiborne, De Soto, Natchitoches, Red River, Sabine, Webster, and Winn Parishes, LA
2205	Caldwell, East Carroll, Franklin, Jackson, Lincoln, Morehouse, Ouachita, Richland, Union, and West Carroll Parishes, LA
2206	Lafourche, Tangipahoa, Terrebonne, and Washington Parishes, LA
2207	Allen, Beauregard, Calcasieu, Cameron, Jefferson Davis, and Vernon Parishes, LA
2301	Cumberland County, ME
2302	Androscoggin, Sagadahoc, and York Counties, ME
2303	Franklin, Kennebec, Knox, Lincoln, Oxford, Somerset, and Waldo Counties, ME

2304	Aroostook, Hancock, Penobscot, Piscataquis, and Washington Counties, ME
2401	Allegany, Caroline, Cecil, Dorchester, Garrett, Kent, Somerset, St. Marys, Talbot, Washington, Wicomico, and Worcester Counties, MD
2501	Worcester County, MA
2502	Hampden County, MA
2503	Barnstable, Dukes, and Nantucket Counties, MA
2504	Berkshire, Franklin, and Hampshire Counties, MA
2601	Kent County, MI
2602	Genesee County, MI
2603	Washtenaw County, MI
2604	Clinton, Eaton, Ingham, Jackson, and Shiawassee Counties, MI
2605	Allegan, Barry, Ionia, Mecosta, Montcalm, Muskegon, Newaygo, Oceana, Ottawa, and Van Buren Counties, MI
2606	Berrien, Branch, Cass, Hillsdale, Lenawee, Monroe, and St. Joseph Counties, MI
2607	Arenac, Bay, Clare, Gladwin, Gratiot, Huron, Isabella, Midland, Ogemaw, Saginaw, Sanilac, and Tuscola Counties, MI
2608	Alcona, Alpena, Antrim, Benzie, Charlevoix, Cheboygan, Crawford, Emmet, Grand Traverse, Iosco, Kalkaska, Lake, Leelanau, Manistee, Mason, Missaukee, Montmorency, Osceola, Oscoda, Otsego, Presque Isle, Roscommon, and Wexford Counties, MI
2609	Calhoun and Kalamazoo Counties, MI
2610	Alger, Baraga, Chippewa, Delta, Dickinson, Gogebic, Houghton, Iron, Keweenaw, Luce, Mackinac, Marquette, Menominee, Ontonagon, and Schoolcraft Counties, MI
2701	Blue Earth, Dodge, Faribault, Fillmore, Freeborn, Goodhue, Houston, Mower, Olmsted, Rice, Steele, Wabasha, Waseca, and Winona Counties, MN
2702	Brown, Chippewa, Cottonwood, Jackson, Kandiyohi, Lac qui Parle, Lincoln, Lyon, Martin, McLeod, Meeker, Murray, Nicollet, Nobles, Pipestone, Redwood, Renville, Rock, Sibley, Swift, Watonwan, and Yellow Medicine Counties, MN
2703	Aitkin, Benton, Big Stone, Cass, Crow Wing, Douglas, Grant, Hubbard, Kanabec, Morrison, Pine, Pope, Stearns, Stevens, Todd, Traverse, and Wadena Counties, MN
2704	Carlton, Cook, Itasca, Koochiching, Lake, and St. Louis Counties, MN
2705	Becker, Beltrami, Clay, Clearwater, Kittson, Lake of the Woods, Mahnomen, Marshall, Norman, Otter Tail, Pennington, Polk, Red Lake, Roseau, and Wilkin Counties, MN
2801	Copiah, Hinds, Holmes, Madison, Rankin, Simpson, and Yazoo Counties, MS
2802	George, Hancock, Harrison, Jackson, Pearl River, and Stone Counties, MS
2803	Benton, Bolivar, Carroll, Coahoma, DeSoto, Grenada, Humphreys, Issaquena, Lafayette, Leflore, Marshall, Montgomery, Panola, Quitman, Sharkey, Sunflower, Tallahatchie, Tate, Tunica, Warren, Washington, and Yalobusha Counties, MS
2804	Adams, Amite, Claiborne, Clarke, Covington, Forrest, Franklin, Greene, Jasper, Jefferson Davis, Jefferson, Jones, Kemper, Lamar, Lauderdale, Lawrence, Leake, Lincoln, Marion, Neshoba, Newton, Perry, Pike, Scott, Smith, Walthall, Wayne, and Wilkinson Counties, MS
2805	Alcorn, Attala, Calhoun, Chickasaw, Choctaw, Clay, Itawamba, Lee, Lowndes, Monroe, Noxubee, Oktibbeha, Pontotoc, Prentiss, Tippah, Tishomingo, Union, Webster, and Winston Counties, MS
2901	Christian, Dallas, Greene, Polk, and Webster Counties, MO
2902	Audrain, Boone, Callaway, Camden, Cole, Cooper, Howard, Maries, Miller, Moniteau, Monroe, Morgan, Osage, Randolph, and Shelby Counties, MO
2903	Adair, Andrew, Atchison, Benton, Buchanan, Carroll, Chariton, Clark, Daviess, DeKalb, Gentry, Grundy, Harrison, Henry, Hickory, Holt, Johnson, Knox, Lewis, Linn, Livingston, Macon, Marion, Mercer, Nodaway, Pettis, Putnam, Ralls, Saline, Schuyler, Scotland, St. Clair, Sullivan, and Worth Counties, MO

2904	Barry, Barton, Cedar, Dade, Dent, Douglas, Howell, Jasper, Laclede, Lawrence, McDonald, Newton, Oregon, Ozark, Phelps, Pulaski, Shannon, Stone, Taney, Texas, Vernon, and Wright Counties, MO
2905	Bollinger, Butler, Cape Girardeau, Carter, Crawford, Dunklin, Gasconade, Iron, Madison, Mississippi, Montgomery, New Madrid, Pemiscot, Perry, Pike, Reynolds, Ripley, Scott, St. Francois, Ste. Genevieve, Stoddard, Washington, and Wayne Counties, MO
3001	Big Horn, Carbon, Carter, Custer, Daniels, Dawson, Fallon, Fergus, Garfield, Golden Valley, Judith Basin, McCone, Musselshell, Petroleum, Powder River, Prairie, Richland, Roosevelt, Rosebud, Sheridan, Stillwater, Sweet Grass, Treasure, Valley, Wibaux, and Yellowstone Counties, MT
3002	Blaine, Cascade, Chouteau, Flathead, Glacier, Hill, Lake, Liberty, Lincoln, Mineral, Missoula, Phillips, Pondera, Ravalli, Sanders, Teton, and Toole Counties, MT
3003	Beaverhead, Broadwater, Deer Lodge, Gallatin, Granite, Jefferson, Lewis and Clark, Madison, Meagher, Park, Powell, Silver Bow, and Wheatland Counties, MT
3101	Douglas County, NE
3102	Lancaster County, NE
3103	Cass, Dodge, Sarpy, Saunders, and Washington Counties, NE
3104	Adams, Arthur, Banner, Blaine, Box Butte, Brown, Buffalo, Chase, Cherry, Cheyenne, Clay, Custer, Dawes, Dawson, Deuel, Dundy, Franklin, Frontier, Furnas, Garden, Garfield, Gosper, Grant, Greeley, Hall, Hamilton, Harlan, Hayes, Hitchcock, Hooker, Howard, Kearney, Keith, Keya Paha, Kimball, Lincoln, Logan, Loup, McPherson, Merrick, Morrill, Nuckolls, Perkins, Phelps, Red Willow, Rock, Scotts Bluff, Sheridan, Sherman, Sioux, Thomas, Valley, and Webster Counties, NE
3105	Antelope, Boone, Boyd, Burt, Butler, Cedar, Colfax, Cuming, Dakota, Dixon, Fillmore, Gage, Holt, Jefferson, Johnson, Knox, Madison, Nance, Nemaha, Otoe, Pawnee, Pierce, Platte, Polk, Richardson, Saline, Seward, Stanton, Thayer, Thurston, Wayne, Wheeler, and York Counties, NE
3201	Washoe County, NV
3202	Carson City, Churchill, Douglas, Elko, Esmeralda, Eureka, Humboldt, Lander, Lincoln, Lyon, Mineral, Nye, Pershing, Storey, and White Pine Counties, NV
3301	Hillsborough County, NH
3302	Belknap, Carroll, Cheshire, Coos, Grafton, Merrimack, and Sullivan Counties, NH
3401	Mercer County, NJ
3402	Atlantic, Cape May, and Cumberland Counties, NJ
3501	Bernalillo, Los Alamos, and Santa Fe Counties, NM
3502	Catron, Cibola, Guadalupe, McKinley, Mora, Rio Arriba, San Juan, San Miguel, Sandoval, Socorro, Taos, Torrance, and Valencia Counties, NM
3503	Dona Ana, Grant, Hidalgo, Lincoln, Luna, Otero, and Sierra Counties, NM
3504	Chaves, Colfax, Curry, DeBaca, Eddy, Harding, Lea, Quay, Roosevelt, and Union Counties, NM
3601	Monroe County, NY
3602	Onondaga County, NY
3603	Albany, Schenectady, and Schoharie Counties, NY
3604	Rensselaer and Saratoga Counties, NY
3605	Broome, Tioga, and Tompkins Counties, NY
3606	Orange and Sullivan Counties, NY
3607	Chemung, Livingston, Ontario, Schuyler, Seneca, Steuben, Wayne, and Yates Counties, NY
3608	Clinton, Essex, Franklin, Fulton, Hamilton, Jefferson, Lewis, Montgomery, St. Lawrence, Warren, and Washington Counties, NY
3609	Allegany, Cattaraugus, and Chautauqua Counties, NY

3610	Columbia, Dutchess, Greene, and Ulster Counties, NY
3611	Madison, Oneida, and Oswego Counties, NY
3612	Cayuga, Chenango, Cortland, Delaware, Herkimer, and Otsego Counties, NY
3613	Genesee, Niagara, Orleans, and Wyoming Counties, NY
3701	Guilford County, NC
3702	Buncombe and Henderson Counties, NC
3703	Durham and Orange Counties, NC
3704	Cumberland, Harnett, and Hoke Counties, NC
3705	Alexander, Burke, Caldwell, Catawba, Cleveland, Polk, and Rutherford Counties, NC
3706	Alamance, Caswell, Chatham, Davidson, Montgomery, Randolph, Rockingham, and Stanly Counties, NC
3707	Alleghany, Davie, Stokes, Surry, Wilkes, and Yadkin Counties, NC
3708	Ashe, Avery, Cherokee, Clay, Graham, Haywood, Jackson, Macon, Madison, McDowell, Mitchell, Swain, Transylvania, Watauga, and Yancey Counties, NC
3709	Forsyth County, NC
3710	Beaufort, Bertie, Camden, Chowan, Currituck, Dare, Gates, Hertford, Hyde, Martin, Pasquotank, Perquimans, Pitt, Tyrrell, and Washington Counties, NC
3711	Carteret, Craven, Greene, Jones, Lenoir, Onslow, and Pamlico Counties, NC
3712	Brunswick, Columbus, New Hanover, and Pender Counties, NC
3713	Bladen, Duplin, Lee, Moore, Richmond, Robeson, Sampson, and Scotland Counties, NC
3714	Edgecombe, Franklin, Granville, Halifax, Johnston, Nash, Northampton, Person, Vance, Warren, Wayne, and Wilson Counties, NC
3801	Adams, Billings, Bottineau, Bowman, Burke, Burleigh, Divide, Dunn, Emmons, Golden Valley, Grant, Hettinger, McHenry, McKenzie, McLean, Mercer, Morton, Mountrail, Oliver, Renville, Sioux, Slope, Stark, Ward, and Williams Counties, ND
3802	Barnes, Benson, Cass, Cavalier, Dickey, Eddy, Foster, Grand Forks, Griggs, Kidder, LaMoure, Logan, McIntosh, Nelson, Pembina, Pierce, Ramsey, Ransom, Richland, Rolette, Sargent, Sheridan, Steele, Stutsman, Towner, Traill, Walsh, and Wells Counties, ND
3901	Montgomery County, OH
3902	Allen, Auglaize, Hardin, Logan, Mercer, Putnam, Shelby, and Van Wert Counties, OH
3903	Champaign, Clark, Darke, Greene, Miami, and Preble Counties, OH
3904	Summit County, OH
3905	Lucas County, OH
3906	Stark County, OH
3907	Ashtabula, Mahoning, Portage, and Trumbull Counties, OH
3908	Ashland, Crawford, Erie, Holmes, Huron, Knox, Marion, Richland, and Wayne Counties, OH
3909	Carroll, Columbiana, Harrison, Jefferson, and Tuscarawas Counties, OH
3910	Athens, Belmont, Coshocton, Guernsey, Monroe, Morgan, Muskingum, Noble, and Washington Counties, OH
3911	Adams, Clinton, Fayette, Gallia, Highland, Jackson, Lawrence, Meigs, Pike, Ross, Scioto, and Vinton Counties, OH
3912	Defiance, Fulton, Hancock, Henry, Ottawa, Paulding, Sandusky, Seneca, Williams, Wood, and Wyandot Counties, OH
4001	Tulsa County, OK
4002	Creek, Okmulgee, Osage, Pawnee, Payne, Rogers, and Wagoner Counties, OK
4003	Cherokee, Craig, Haskell, Mayes, McIntosh, Muskogee, Nowata, Okfuskee, Pittsburg, and Washington Counties, OK

4004	Atoka, Bryan, Carter, Coal, Garvin, Hughes, Jefferson, Johnston, Love, Marshall, Murray, Pontotoc, Pottawatomie, Seminole, and Stephens Counties, OK
4005	Beckham, Caddo, Comanche, Cotton, Custer, Greer, Harmon, Jackson, Kiowa, Roger Mills, Tillman, and Washita Counties, OK
4006	Alfalfa, Beaver, Blaine, Cimarron, Dewey, Ellis, Garfield, Grant, Harper, Kay, Kingfisher, Major, Noble, Texas, Woods, and Woodward Counties, OK
4007	Adair, Choctaw, Delaware, Latimer, Le Flore, McCurtain, Ottawa, Pushmataha, and Sequoyah Counties, OK
4101	Lane County, OR
4102	Marion and Polk Counties, OR
4103	Crook, Deschutes, Hood River, Jefferson, Sherman, and Wasco Counties, OR
4104	Coos, Curry, Douglas, Jackson, and Josephine Counties, OR
4105	Benton, Clatsop, Lincoln, Linn, and Tillamook Counties, OR
4106	Baker, Gilliam, Grant, Harney, Klamath, Lake, Malheur, Morrow, Umatilla, Union, Wallowa, and Wheeler Counties, OR
4201	Lancaster County, PA
4202	York County, PA
4203	Berks County, PA
4204	Lehigh County, PA
4205	Crawford and Erie Counties, PA
4206	Lackawanna and Luzerne Counties, PA
4207	Northampton County, PA
4208	Cumberland, Dauphin, and Lebanon Counties, PA
4209	Adams, Franklin, Juniata, and Perry Counties, PA
4210	Clinton, Columbia, Lycoming, Montour, Northumberland, Snyder, and Union Counties, PA
4211	Cambria, Cameron, Clearfield, Elk, and Somerset Counties, PA
4212	Bedford, Blair, Centre, Fulton, Huntingdon, and Mifflin Counties, PA
4213	Bradford, Mc Kean, Potter, Sullivan, Susquehanna, Tioga, Warren, and Wyoming Counties, PA
4214	Carbon, Monroe, Pike, Schuylkill, and Wayne Counties, PA
4215	Clarion, Forest, Indiana, Jefferson, Lawrence, Mercer, and Venango Counties, PA
4501	Greenville County, SC
4502	Horry County, SC
4503	Charleston County, SC
4504	Richland County, SC
4505	Beaufort, Berkeley, Colleton, Dorchester, Hampton, and Jasper Counties, SC
4506	Calhoun, Clarendon, Fairfield, Kershaw, Lee, Orangeburg, and Sumter Counties, SC
4507	Aiken, Allendale, Bamberg, Barnwell, Edgefield, Lexington, Newberry, and Saluda Counties, SC
4508	Abbeville, Anderson, Greenwood, McCormick, Oconee, and Pickens Counties, SC
4509	Cherokee, Laurens, Spartanburg, and Union Counties, SC
4510	Chesterfield, Darlington, Dillon, Florence, Georgetown, Marion, Marlboro, and Williamsburg Counties, SC
4601	Clay, Lake, Lincoln, McCook, Minnehaha, Moody, Turner, and Union Counties, SD
4602	Aurora, Beadle, Bon Homme, Brookings, Brown, Brule, Buffalo, Charles Mix, Clark, Codington, Davison, Day, Deuel, Douglas, Edmunds, Faulk, Grant, Hamlin, Hand, Hanson,

	Hutchinson, Hyde, Jerauld, Kingsbury, Marshall, McPherson, Miner, Roberts, Sanborn, Spink, and Yankton Counties, SD
4603	Bennett, Butte, Campbell, Corson, Custer, Dewey, Fall River, Gregory, Haakon, Harding, Hughes, Jackson, Jones, Lawrence, Lyman, Meade, Mellette, Oglala Lakota, Pennington, Perkins, Potter, Stanley, Sully, Todd, Tripp, Walworth, and Ziebach Counties, SD
4701	Knox County, TN
4702	Hamilton County, TN
4703	Anderson, Blount, Campbell, Loudon, Monroe, Morgan, Roane, Scott, and Union Counties, TN
4704	Claiborne, Cocke, Grainger, Hamblen, Hancock, Jefferson, and Sevier Counties, TN
4705	Bledsoe, Bradley, Marion, McMinn, Meigs, Polk, Rhea, and Sequatchie Counties, TN
4706	Carter, Greene, Hawkins, Johnson, Sullivan, Unicoi, and Washington Counties, TN
4707	Benton, Carroll, Chester, Crockett, Decatur, Dyer, Gibson, Hardeman, Hardin, Haywood, Henderson, Henry, Lake, Lauderdale, Madison, McNairy, Obion, and Weakley Counties, TN
4708	Clay, Cumberland, DeKalb, Fentress, Jackson, Overton, Pickett, Putnam, Van Buren, Warren, and White Counties, TN
4709	Bedford, Coffee, Franklin, Giles, Grundy, Hickman, Houston, Humphreys, Lawrence, Lewis, Lincoln, Marshall, Montgomery, Moore, Perry, Stewart, and Wayne Counties, TN
4801	El Paso County, TX
4802	Hidalgo County, TX
4803	Bell, Coryell, Falls, Freestone, Lampasas, Limestone, and McLennan Counties, TX
4804	Hardin, Jasper, Jefferson, Newton, Orange, and Tyler Counties, TX
4805	Brooks, Cameron, Dimmit, Duval, Frio, Jim Hogg, Jim Wells, Kenedy, Kleberg, La Salle, Live Oak, Maverick, McMullen, Starr, Webb, Willacy, Zapata, and Zavala Counties, TX
4806	Aransas, Nueces, Refugio, and San Patricio Counties, TX
4807	Cooke, Fannin, Grayson, Henderson, Hood, Navarro, and Palo Pinto Counties, TX
4808	Armstrong, Bailey, Carson, Castro, Dallam, Deaf Smith, Donley, Gray, Hansford, Hartley, Hemphill, Hutchinson, Lipscomb, Moore, Ochiltree, Oldham, Parmer, Potter, Randall, Roberts, Sherman, and Wheeler Counties, TX
4809	Anderson, Cherokee, Smith, Van Zandt, and Wood Counties, TX
4810	Camp, Delta, Franklin, Gregg, Harrison, Hopkins, Marion, Morris, Panola, Rains, Rusk, Titus, and Upshur Counties, TX
4811	Bosque, Brown, Coleman, Comanche, Eastland, Erath, Hamilton, Hill, Jack, McCulloch, Mills, San Saba, Somervell, Stephens, Throckmorton, and Young Counties, TX
4812	Brazos, Burleson, Grimes, Lee, Madison, Milam, Robertson, Walker, and Washington Counties, TX
4813	Angelina, Houston, Leon, Nacogdoches, Polk, Sabine, San Augustine, San Jacinto, Shelby, and Trinity Counties, TX
4814	Bee, Calhoun, Colorado, DeWitt, Fayette, Goliad, Gonzales, Jackson, Karnes, Lavaca, Matagorda, Victoria, and Wharton Counties, TX
4815	Borden, Briscoe, Cochran, Crosby, Dawson, Dickens, Floyd, Gaines, Garza, Hale, Hockley, Lamb, Lubbock, Lynn, Motley, Swisher, Terry, and Yoakum Counties, TX
4816	Archer, Baylor, Bowie, Callahan, Cass, Childress, Clay, Collingsworth, Cottle, Fisher, Foard, Hall, Hardeman, Haskell, Jones, Kent, King, Knox, Lamar, Mitchell, Montague, Nolan, Red River, Scurry, Shackelford, Stonewall, Taylor, Wichita, and Wilbarger Counties, TX
4817	Andrews, Brewster, Crane, Culberson, Ector, Glasscock, Howard, Hudspeth, Jeff Davis, Loving, Martin, Midland, Pecos, Presidio, Reagan, Reeves, Terrell, Upton, Ward, and Winkler Counties, TX
4818	Blanco, Burnet, Coke, Concho, Crockett, Edwards, Gillespie, Irion, Kerr, Kimble, Kinney, Llano, Mason, Menard, Real, Runnels, Schleicher, Sterling, Sutton, Tom Green, Uvalde, and Val Verde Counties, TX
4901	Utah County, UT

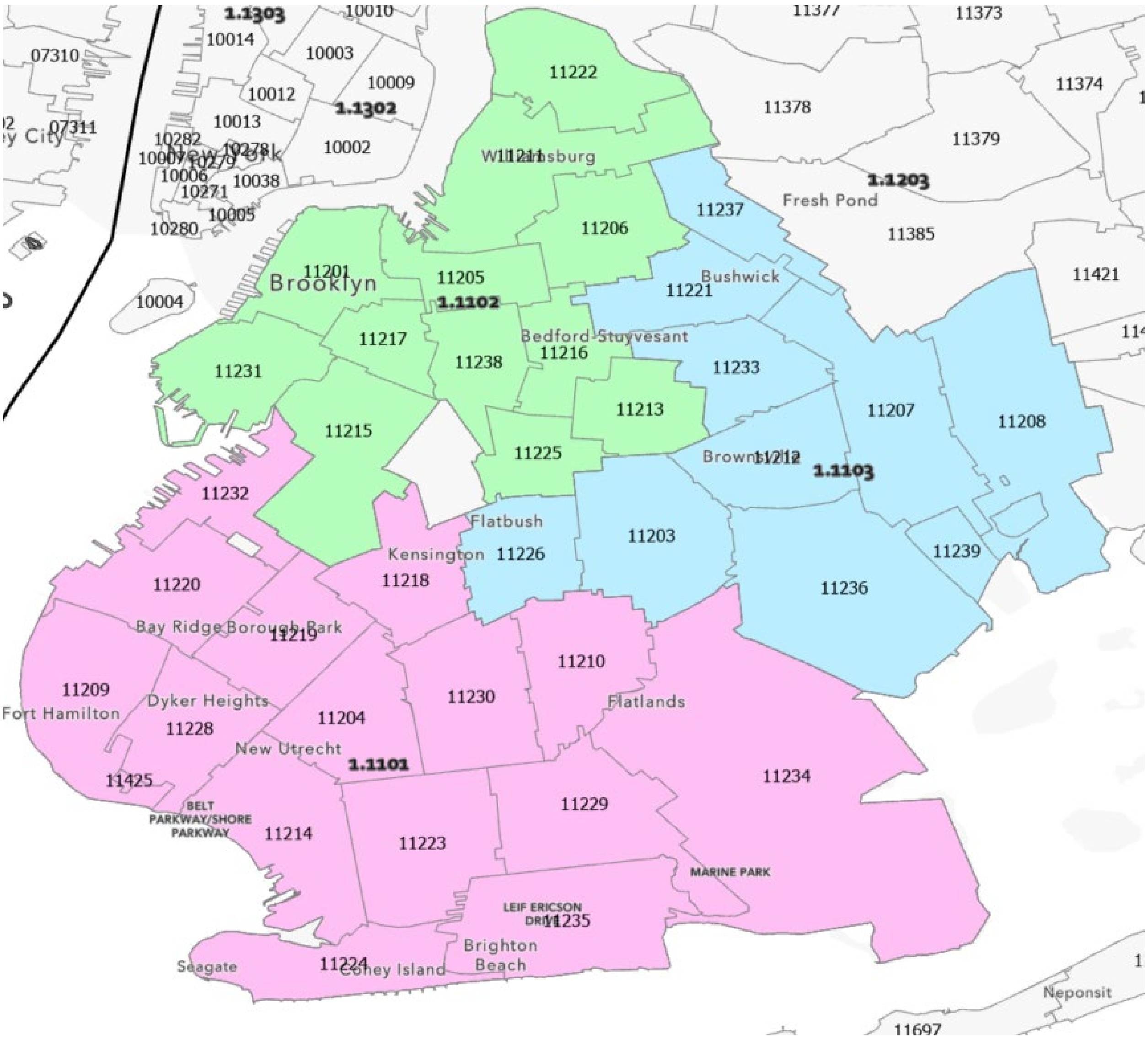
4902	Davis County, UT
4903	Box Elder, Morgan, and Weber Counties, UT
4904	Cache, Carbon, Daggett, Duchesne, Emery, Grand, Juab, Millard, Rich, San Juan, Sanpete, Summit, Tooele, Uintah, and Wasatch Counties, UT
4905	Beaver, Garfield, Iron, Kane, Piute, Sevier, Washington, and Wayne Counties, UT
5001	Chittenden, Lamoille, and Washington Counties, VT
5002	Bennington, Rutland, Windham, and Windsor Counties, VT
5003	Addison, Caledonia, Essex, Franklin, Grand Isle, Orange, and Orleans Counties, VT
5101	Alleghany, Botetourt, Covington City, Craig, Franklin, Roanoke City, Roanoke, and Salem City Counties, VA
5102	Augusta County, Bath County, Buena Vista City, Frederick County, Harrisonburg City, Highland County, Lexington City, Page County, Rockbridge County, Rockingham County, Shenandoah County, Staunton City, Waynesboro City, and Winchester City, VA
5103	Bristol City, Buchanan, Dickenson, Lee, Norton City, Russell, Scott, Smyth, Tazewell, Washington, and Wise Counties, VA
5104	Albemarle, Buckingham, Charlottesville City, Fluvanna, Greene, Louisa, Nelson, and Orange Counties, VA
5105	Brunswick, Caroline, Charlotte, Cumberland, Emporia City, Essex, Greensville, King George, Lancaster, Lunenburg, Mecklenburg, Middlesex, Northumberland, Nottoway, Prince Edward, Richmond, and Westmoreland Counties, VA
5106	Amherst, Appomattox, Bedford, Campbell, Danville City, Halifax, Henry, Lynchburg City, Martinsville City, and Pittsylvania Counties, VA
5107	Bland, Carroll, Floyd, Galax City, Giles, Grayson, Montgomery, Patrick, Pulaski, Radford City, and Wythe Counties, VA
5301	Spokane County, WA
5302	Lewis, Mason, and Thurston Counties, WA
5303	Island and Kitsap Counties, WA
5304	Benton, Columbia, Franklin, and Walla Walla Counties, WA
5305	Skagit and Whatcom Counties, WA
5306	Clallam, Cowlitz, Grays Harbor, Jefferson, Pacific, San Juan, and Wahkiakum Counties, WA
5307	Chelan, Kittitas, Klickitat, and Yakima Counties, WA
5308	Adams, Asotin, Douglas, Ferry, Garfield, Grant, Lincoln, Okanogan, Pend Oreille, Stevens, and Whitman Counties, WA
5401	Boone, Cabell, Clay, Jackson, Kanawha, Lincoln, Mason, Putnam, and Wayne Counties, WV
5402	Braxton, Calhoun, Fayette, Gilmer, Greenbrier, Logan, McDowell, Mercer, Mingo, Monroe, Nicholas, Pleasants, Pocahontas, Raleigh, Ritchie, Roane, Summers, Webster, Wirt, Wood, and Wyoming Counties, WV
5403	Brooke, Doddridge, Hancock, Harrison, Lewis, Marion, Marshall, Ohio, Taylor, Tyler, Upshur, and Wetzel Counties, WV
5404	Barbour, Berkeley, Grant, Hampshire, Hardy, Jefferson, Mineral, Monongalia, Morgan, Pendleton, Preston, Randolph, and Tucker Counties, WV
5501	Dane County, WI
5502	Brown, Door, and Kewaunee Counties, WI
5503	Calumet, Menominee, Oconto, Outagamie, Shawano, Waupaca, Waushara, and Winnebago Counties, WI
5504	Adams, Columbia, Crawford, Grant, Green, Iowa, Juneau, Lafayette, Marquette, Richland, Rock, and Sauk Counties, WI
5505	Kenosha and Racine Counties, WI
5506	Dodge, Fond du Lac, Green Lake, Jefferson, Manitowoc, Sheboygan, and Walworth Counties, WI

5507	Ashland, Bayfield, Clark, Florence, Forest, Iron, Langlade, Marinette, Oneida, Price, Taylor, and Vilas Counties, WI
5508	Buffalo, Eau Claire, Jackson, La Crosse, Monroe, Pepin, Trempealeau, and Vernon Counties, WI
5509	Barron, Burnett, Chippewa, Douglas, Dunn, Pierce, Polk, Rusk, Sawyer, St. Croix, and Washburn Counties, WI
5510	Lincoln, Marathon, Portage, and Wood Counties, WI
5601	Big Horn, Campbell, Crook, Fremont, Hot Springs, Johnson, Park, Sheridan, Sublette, Teton, Washakie, and Weston Counties, WY
5602	Albany, Carbon, Converse, Goshen, Laramie, Lincoln, Natrona, Niobrara, Platte, Sweetwater, and Uinta Counties, WY

Appendix 5.3: Maps of ZCTA Clusters within County Groups

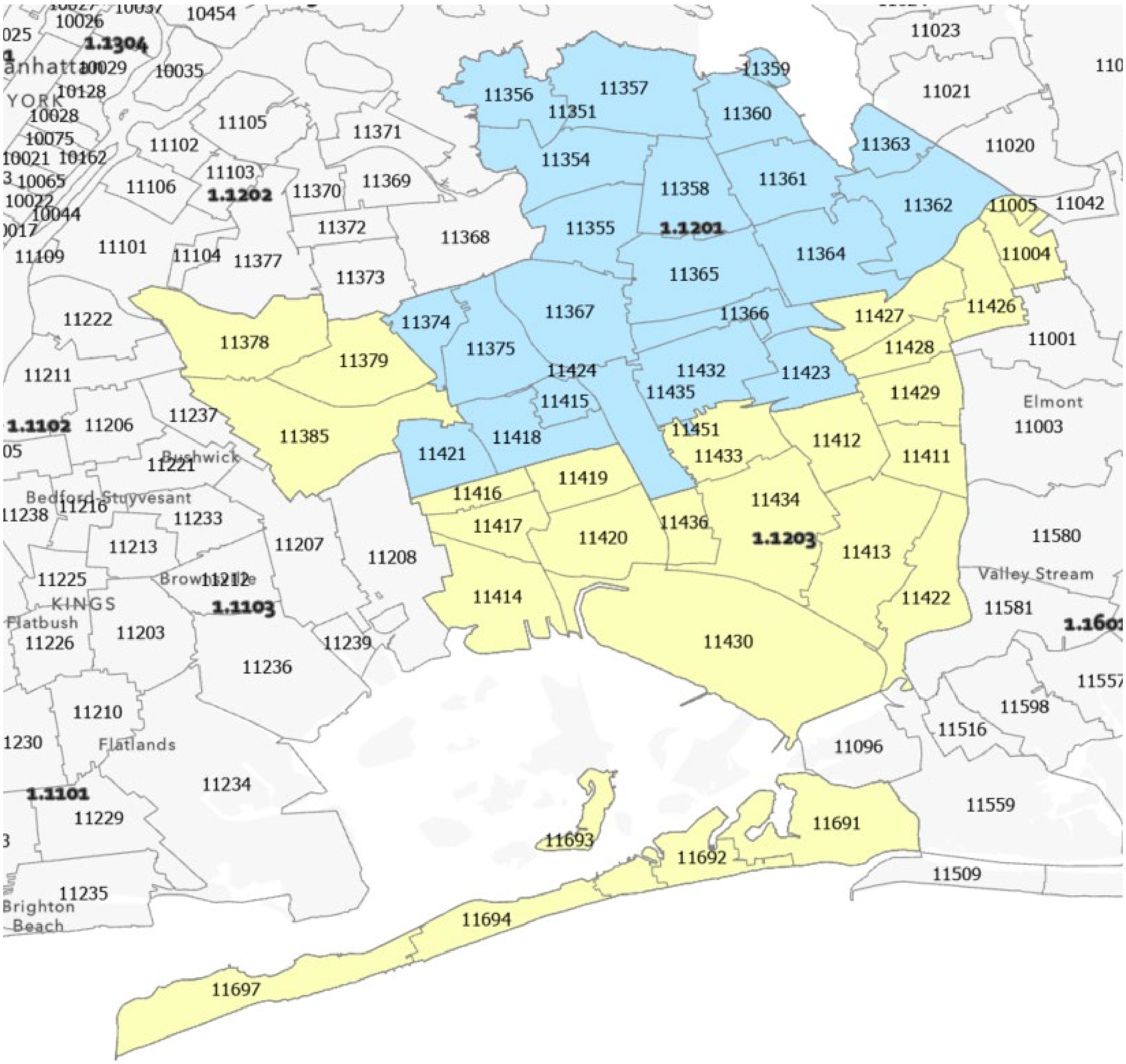
CntyGrp 1.11 – Kings County, NY
ZCTA Clusters (Zclusts):

1. 1.1101
2. 1.1102
3. 1.1103



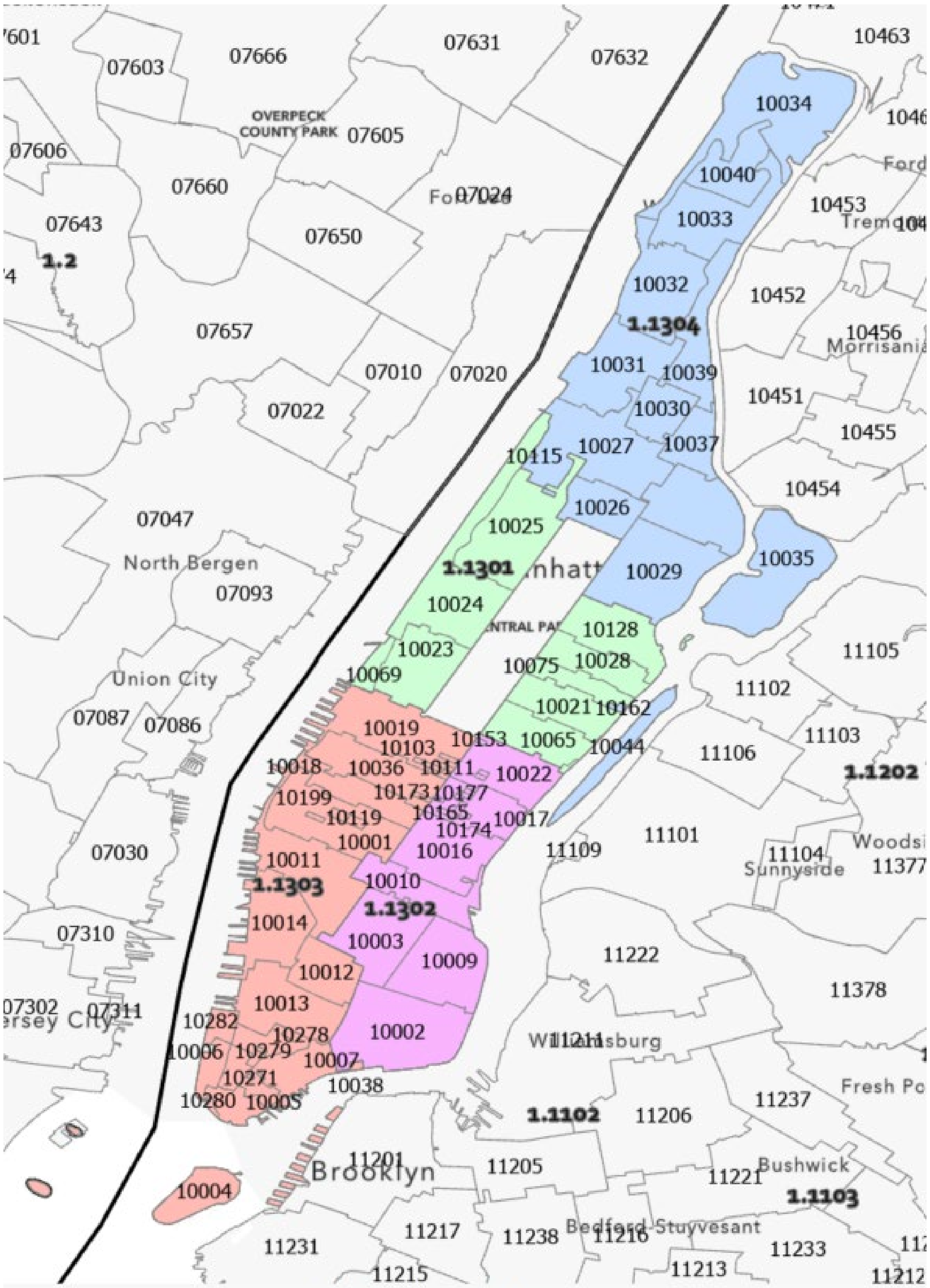
CntyGrp 1.12 – Queens County, NY
Zclusts:

1. 1.1201
2. 1.1203
3. 1.1202

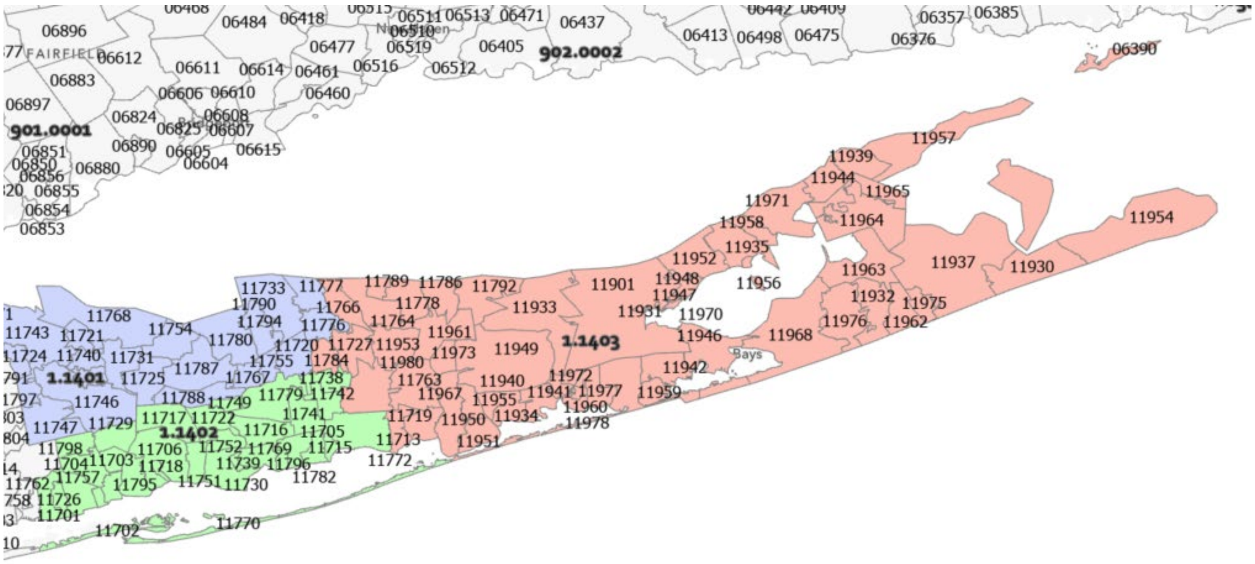


CntyGrp 1.13 – New York County, NY
Zclusts:

1. 1.1301
2. 1.1302
3. 1.1303
4. 1.1304

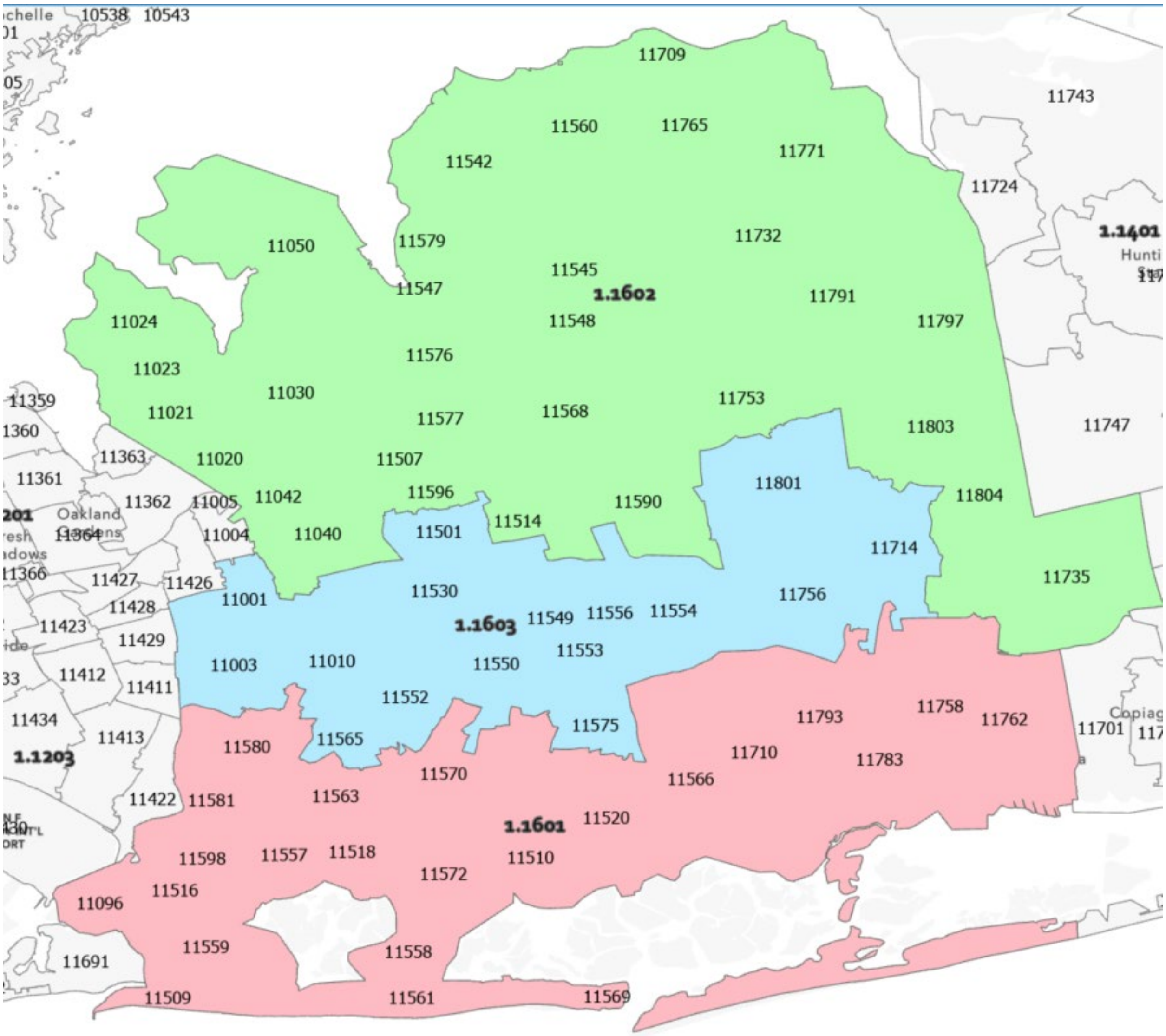


CntyGrp 1.14 – Suffolk County, NY
ZClusts:
1. 1.1401
2. 1.1402
3. 1.1403



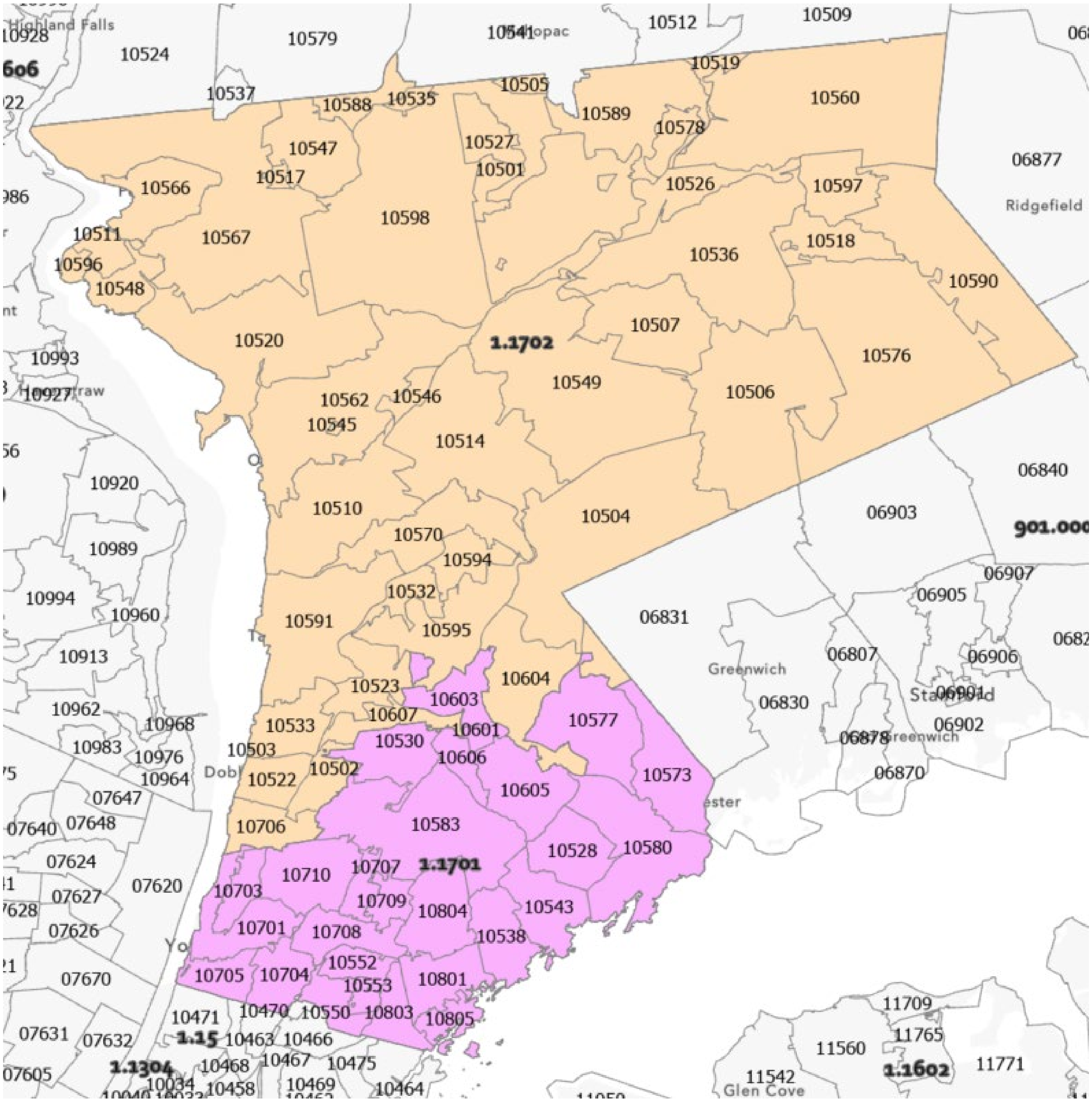
CntyGrp 1.16 – Nassau County, NY
Zclusts:

1. 1.1601
2. 1.1602
3. 1.1603



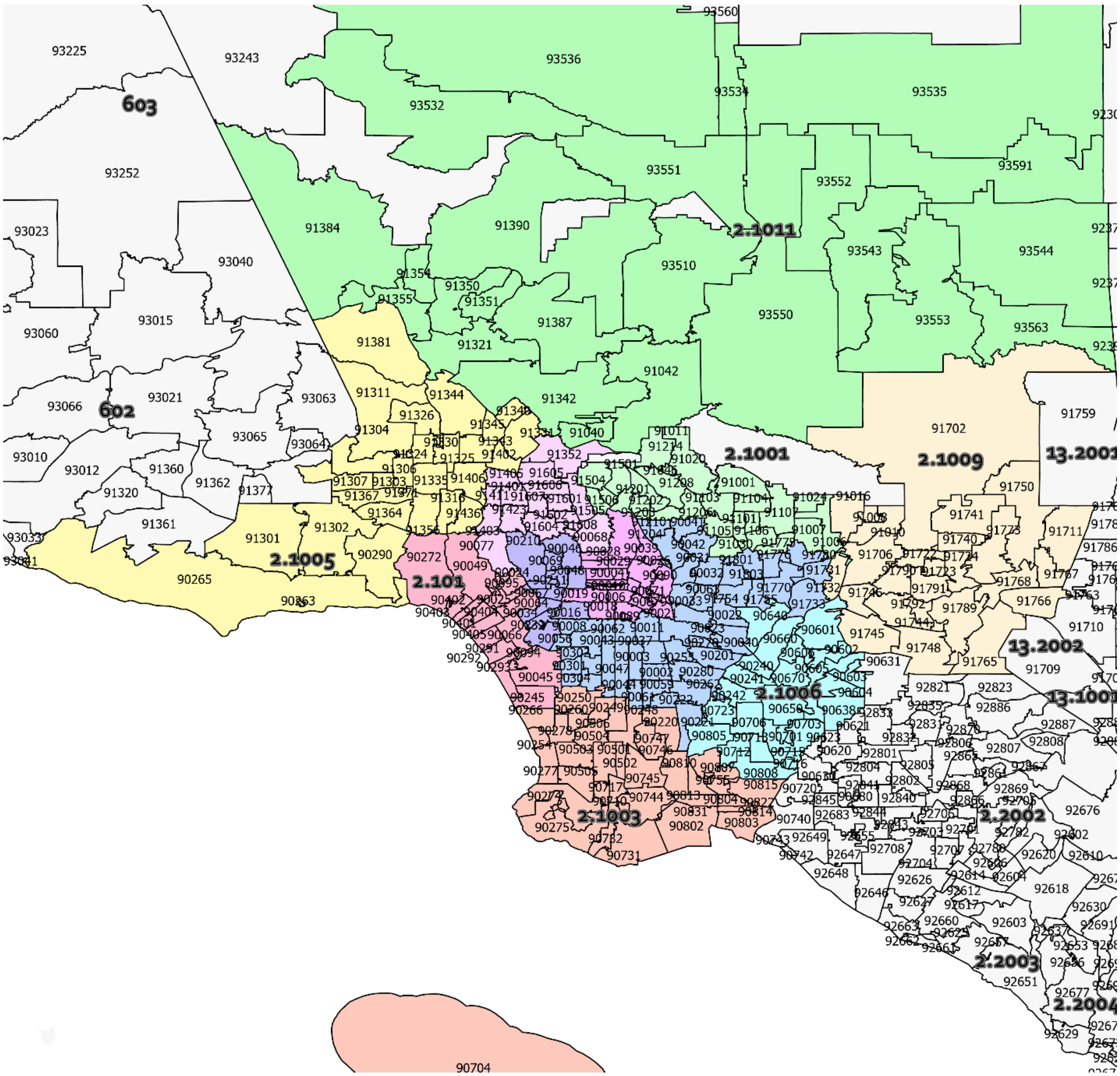
CntyGrp 1.17 – Westchester County, NY
ZClusts:

1. 1.1701
2. 1.1702

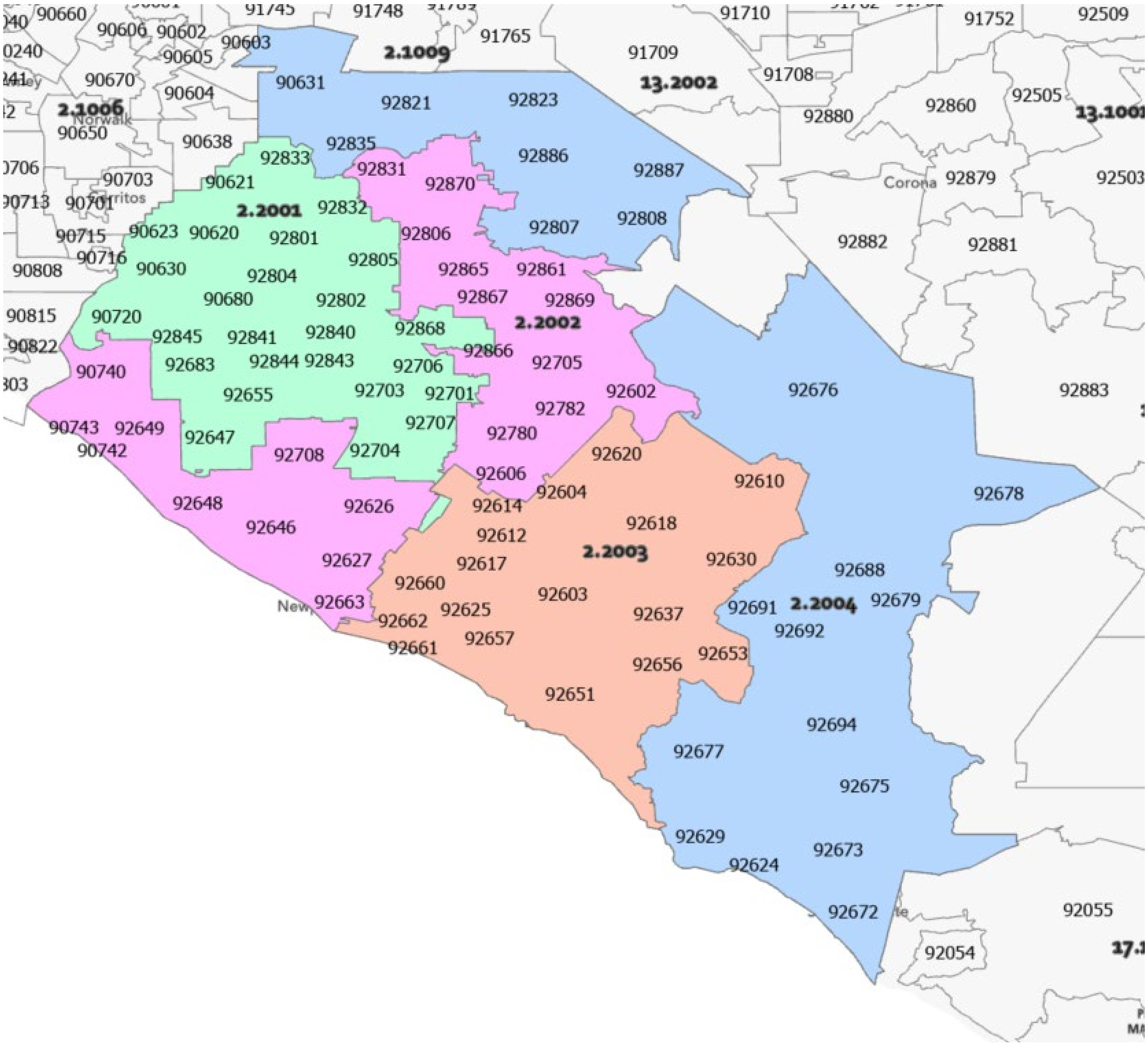


CntyGrp 2.1 – Los Angeles County, CA
Zclusts:

1. 2.1001
2. 2.1002
3. 2.1003
4. 2.1004
5. 2.1005
6. 2.1006
7. 2.1007
8. 2.1008
9. 2.1009
10. 2.101
11. 2.1011

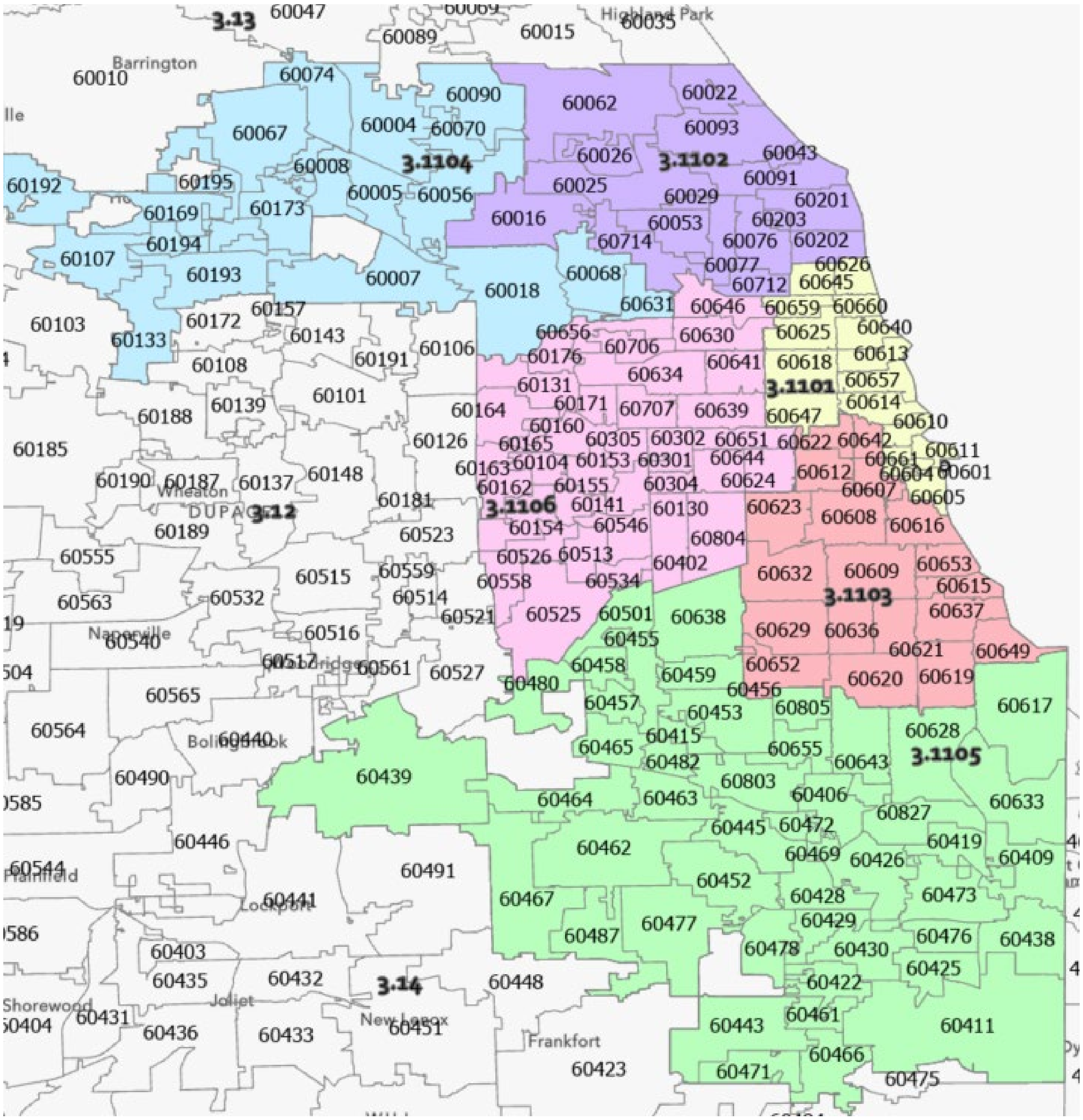


CntyGrp 2.2 – Orange County, CA
Zclusts:
1. 2.2001
2. 2.2002
3. 2.2003
4. 2.2004



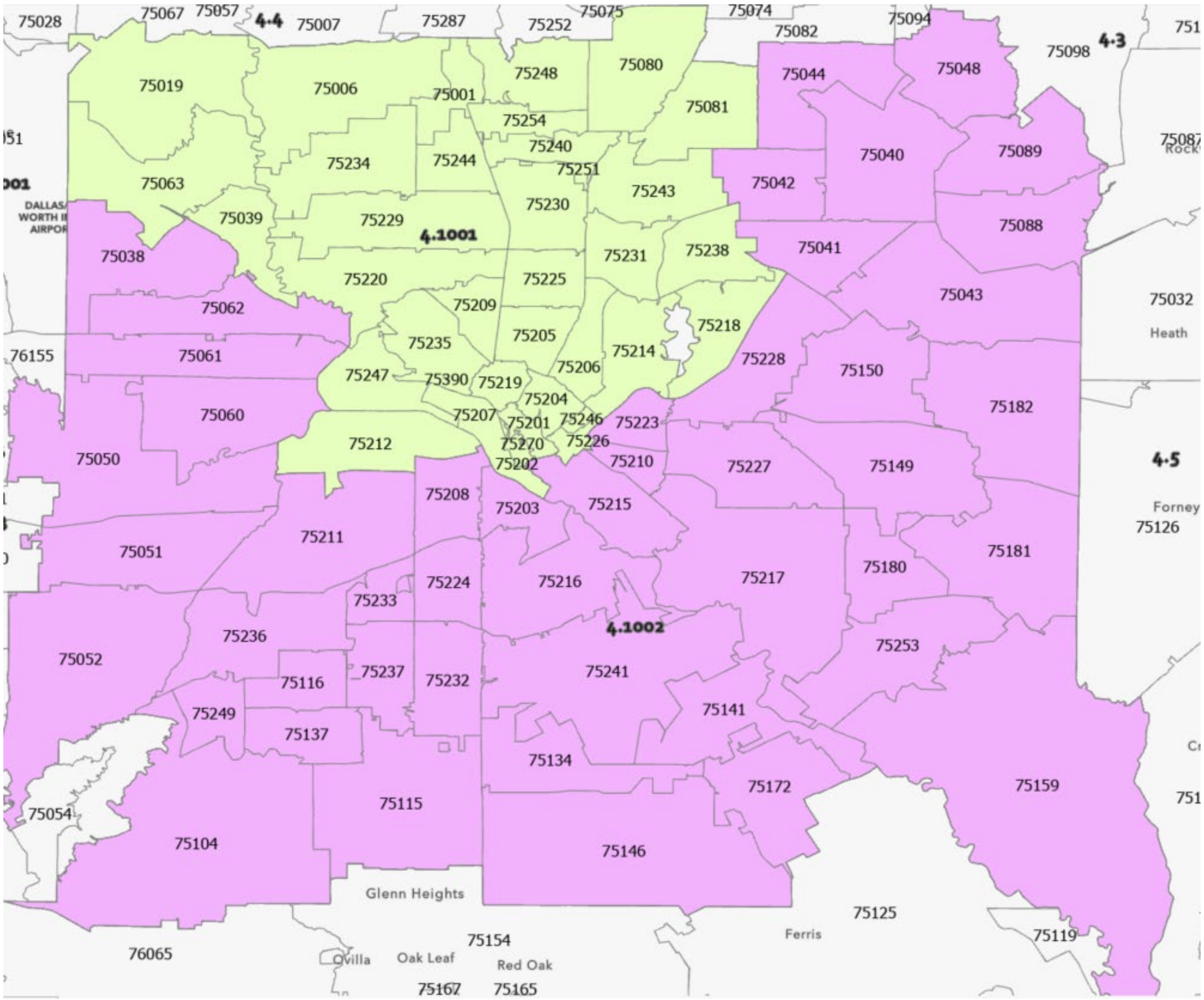
CntyGrp 3.11 – Cook, IL
Zclusts:

1. 3.1101
2. 3.1102
3. 3.1103
4. 3.1104
5. 3.1105
6. 3.1106



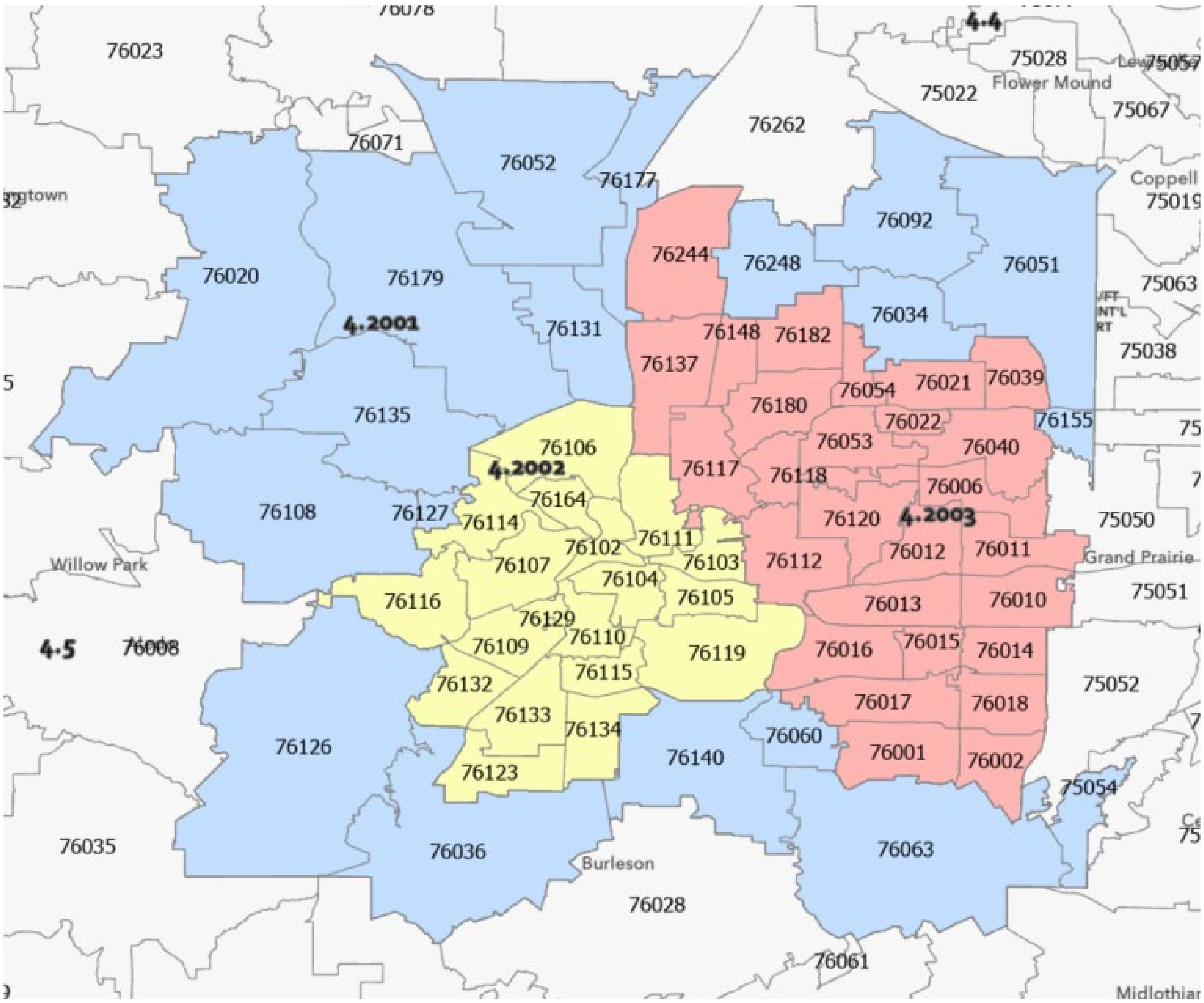
CntyGrp 4.1 – Dallas County, TX
Zclusts:

1. 4.1001
2. 4.1002



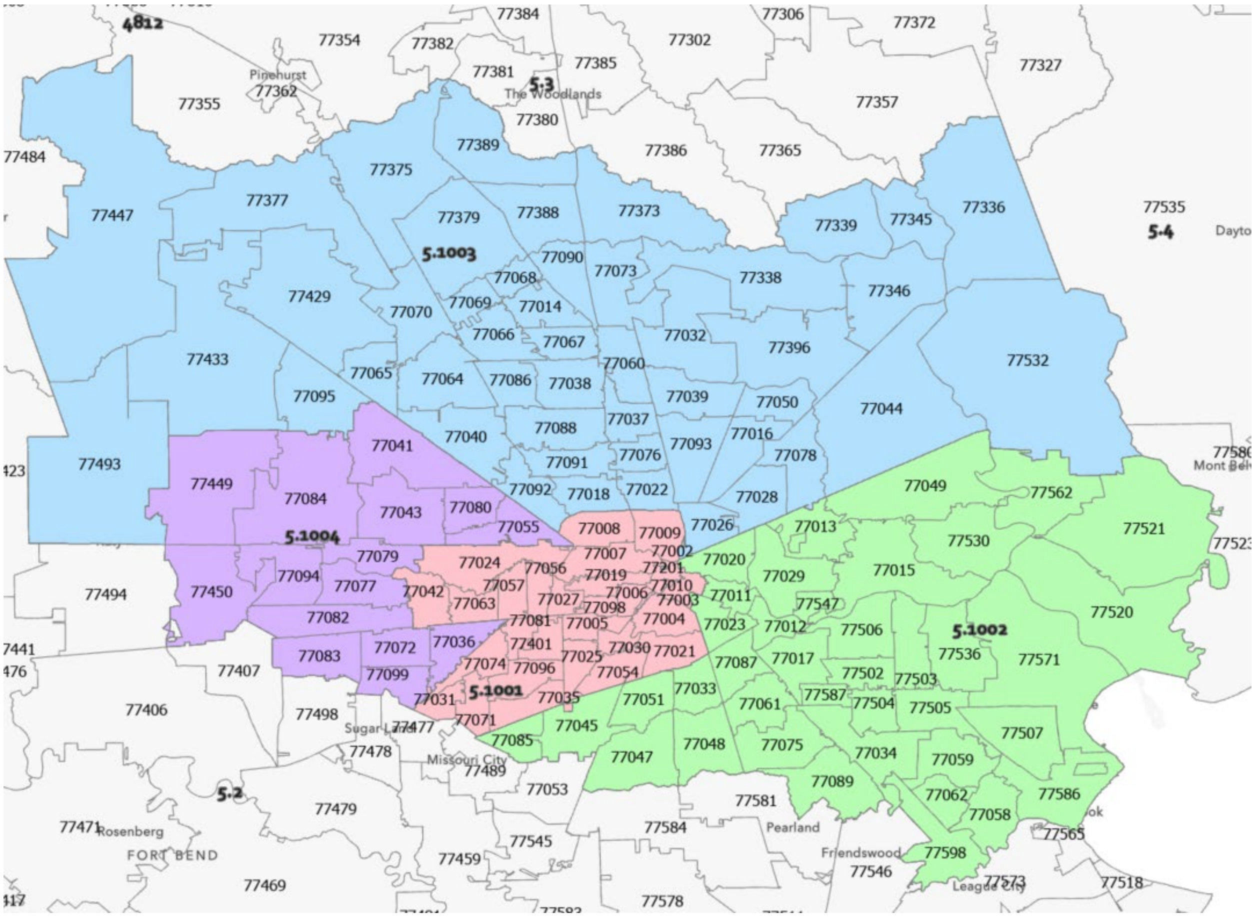
CntyGrp 4.2 – Tarrant County, TX
Zclusts:

1. 4.2001
2. 4.2002
3. 4.2003



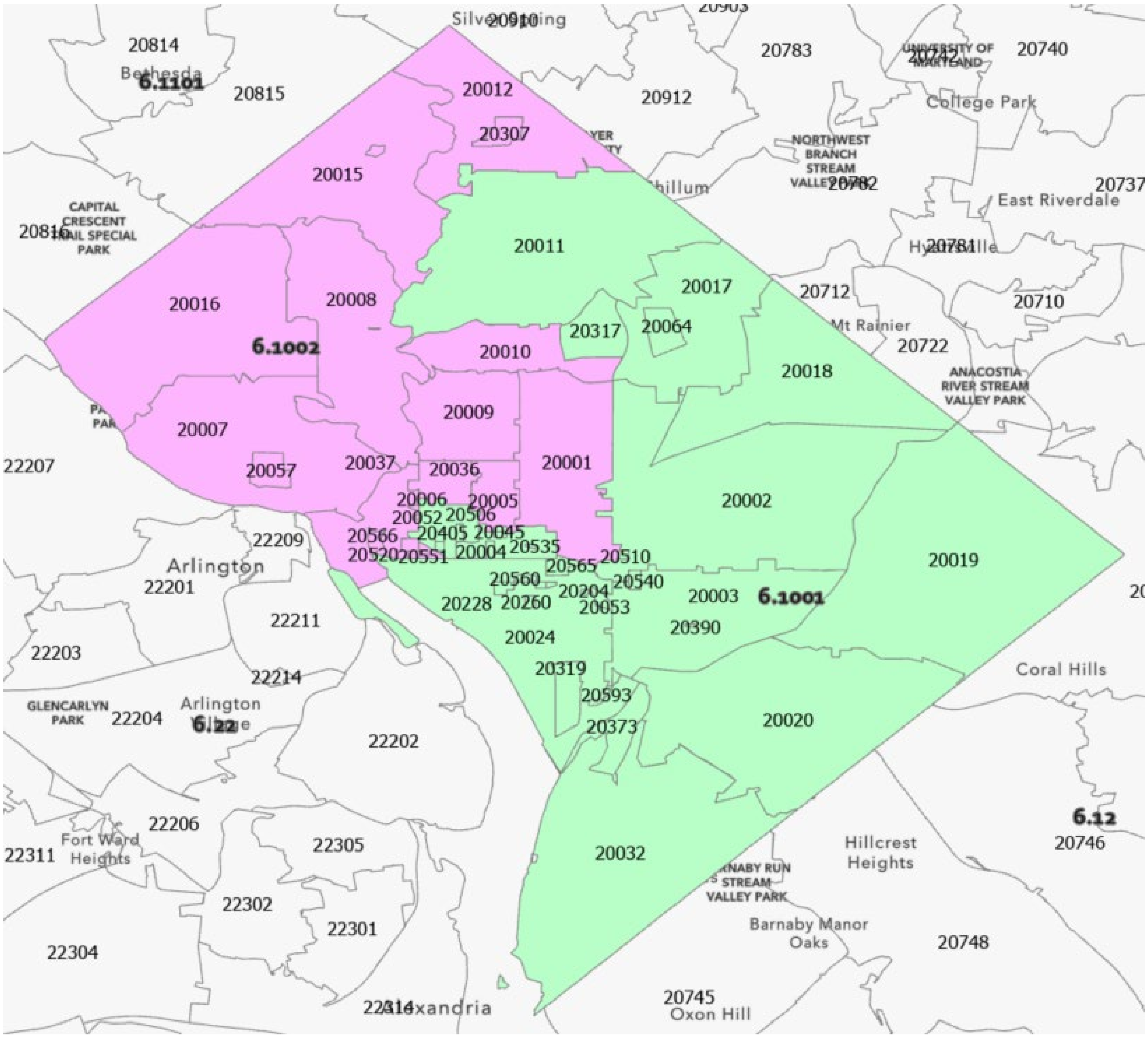
CntyGrp 5.1 – Harris County, TX
Zclusts:

1. 5.1001
2. 5.1002
3. 5.1003
4. 5.1004



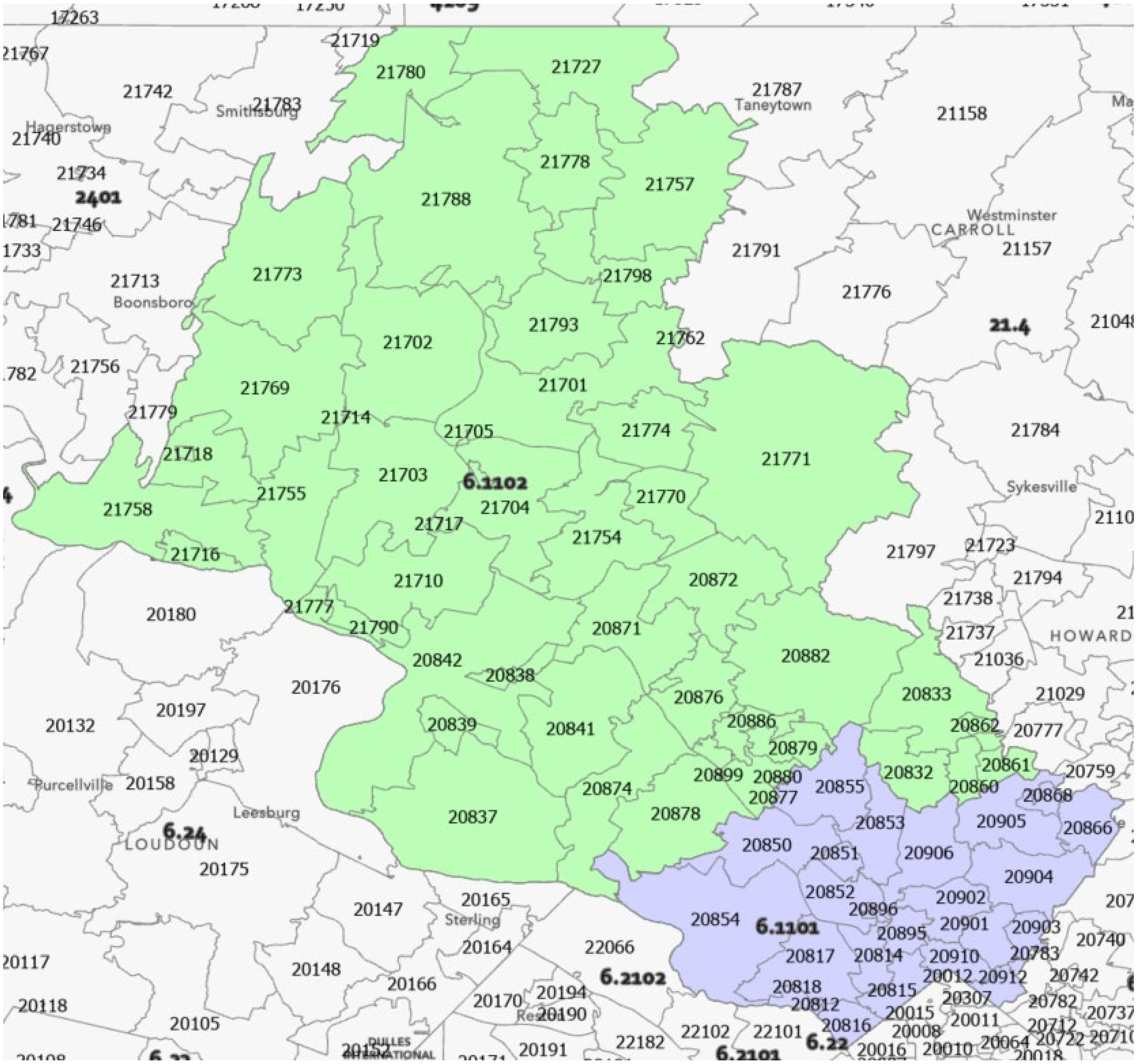
CntyGrp 6.1 – District of Columbia
Zclusts:

1. 6.1001
2. 6.1002

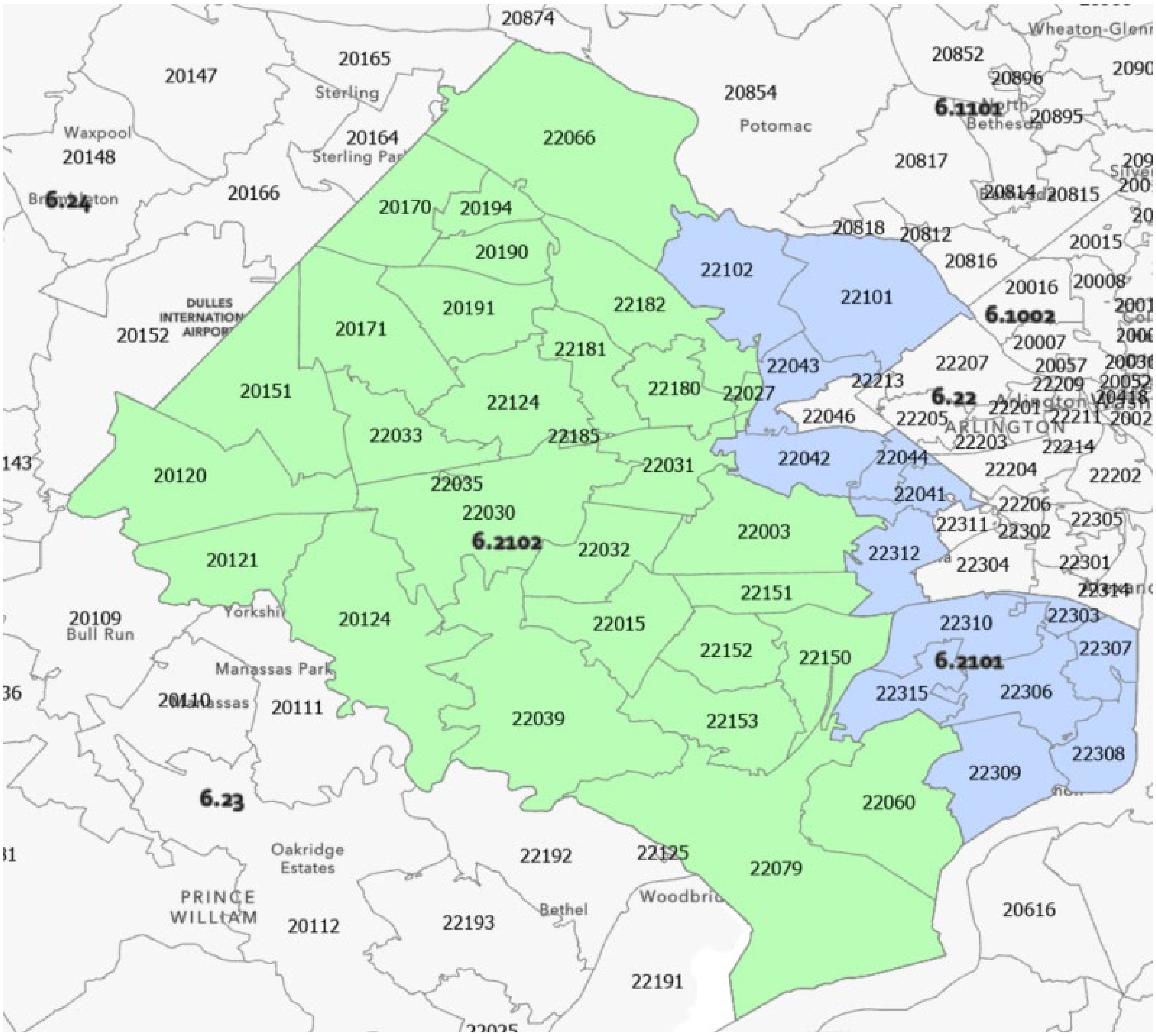


CntyGrp 6.11 – Frederick County, MD
Zclusts:

1. 6.1101
2. 6.1102

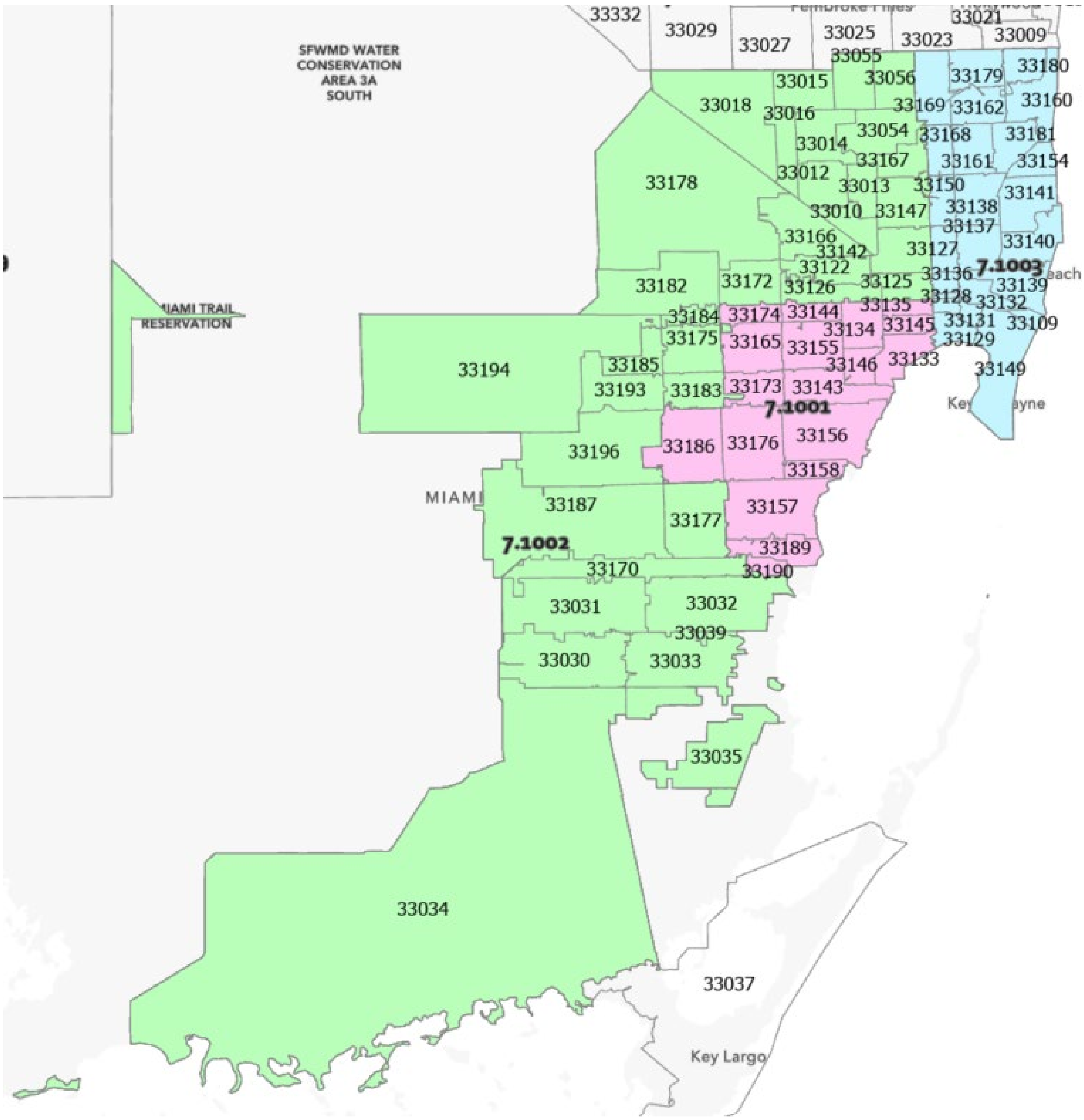


CntyGrp 6.21 – Fairfax County, VA
Zclusts:
1. 6.2101
2. 6.2102



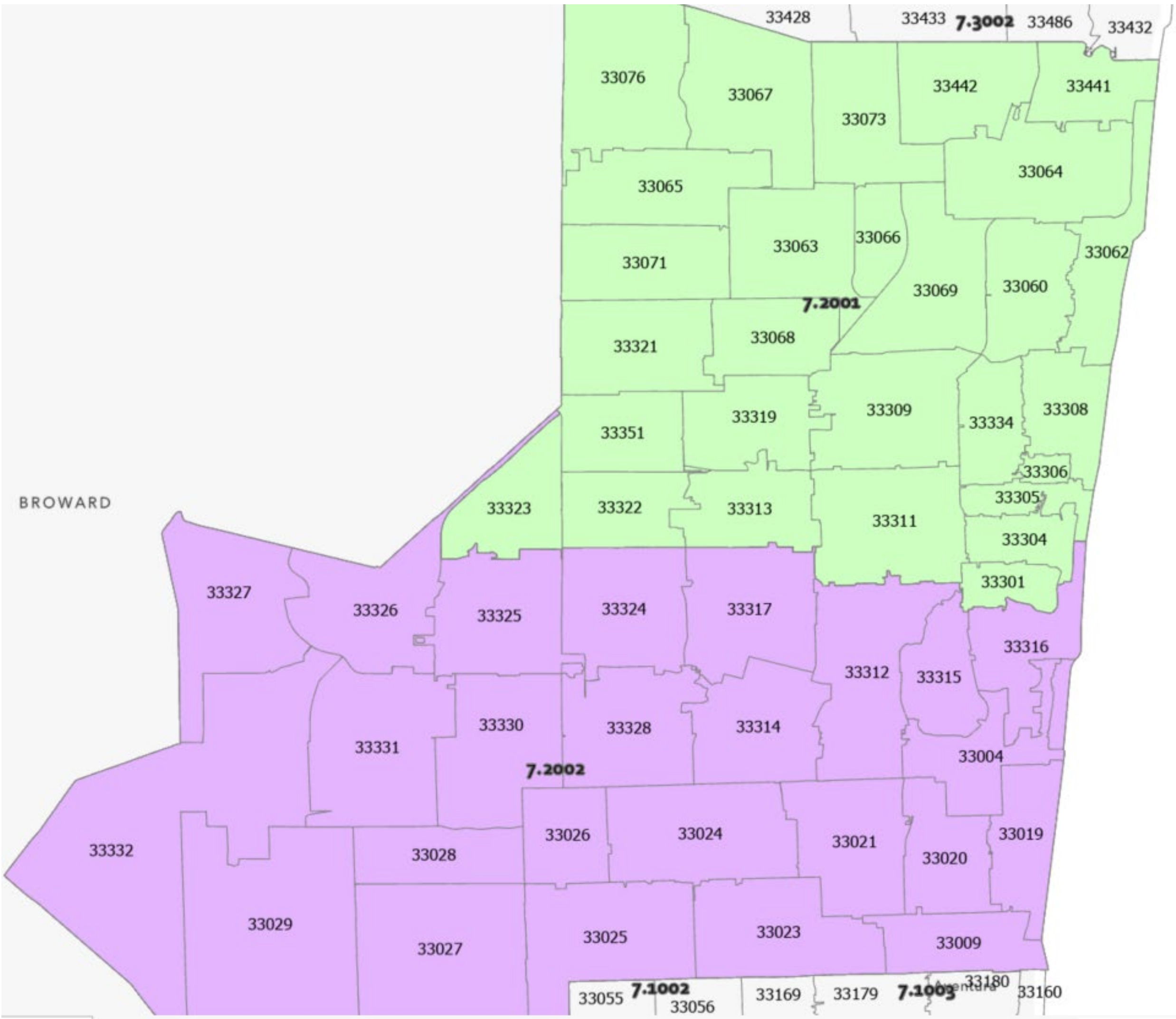
CntyGrp 7.1 – Miami-Dade County, FL
Zclusts:

1. 7.1001
2. 7.1002
3. 7.1003



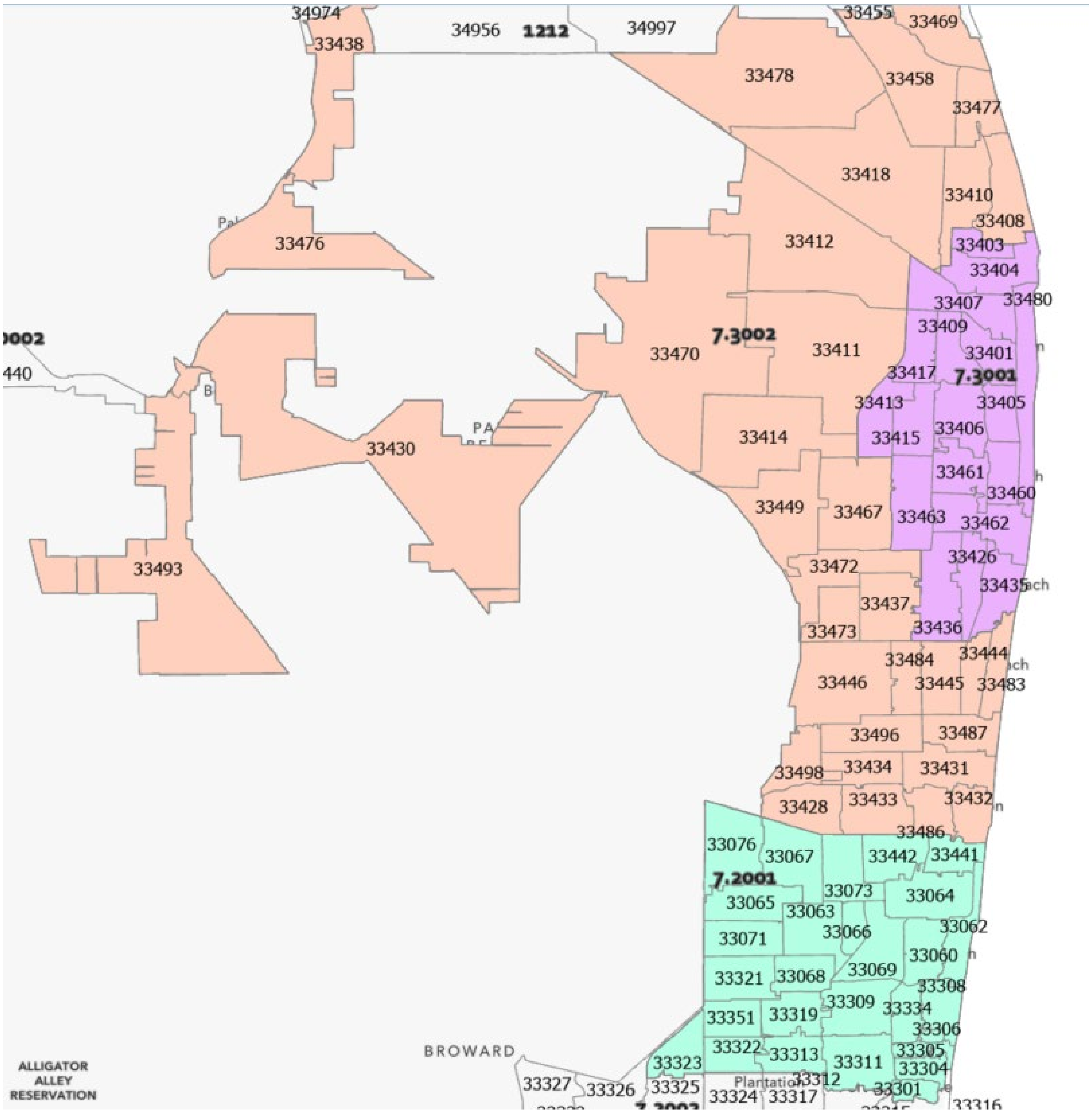
CntyGrp 7.2 – Broward County, FL
Zclusts:

1. 7.2001
2. 7.2002

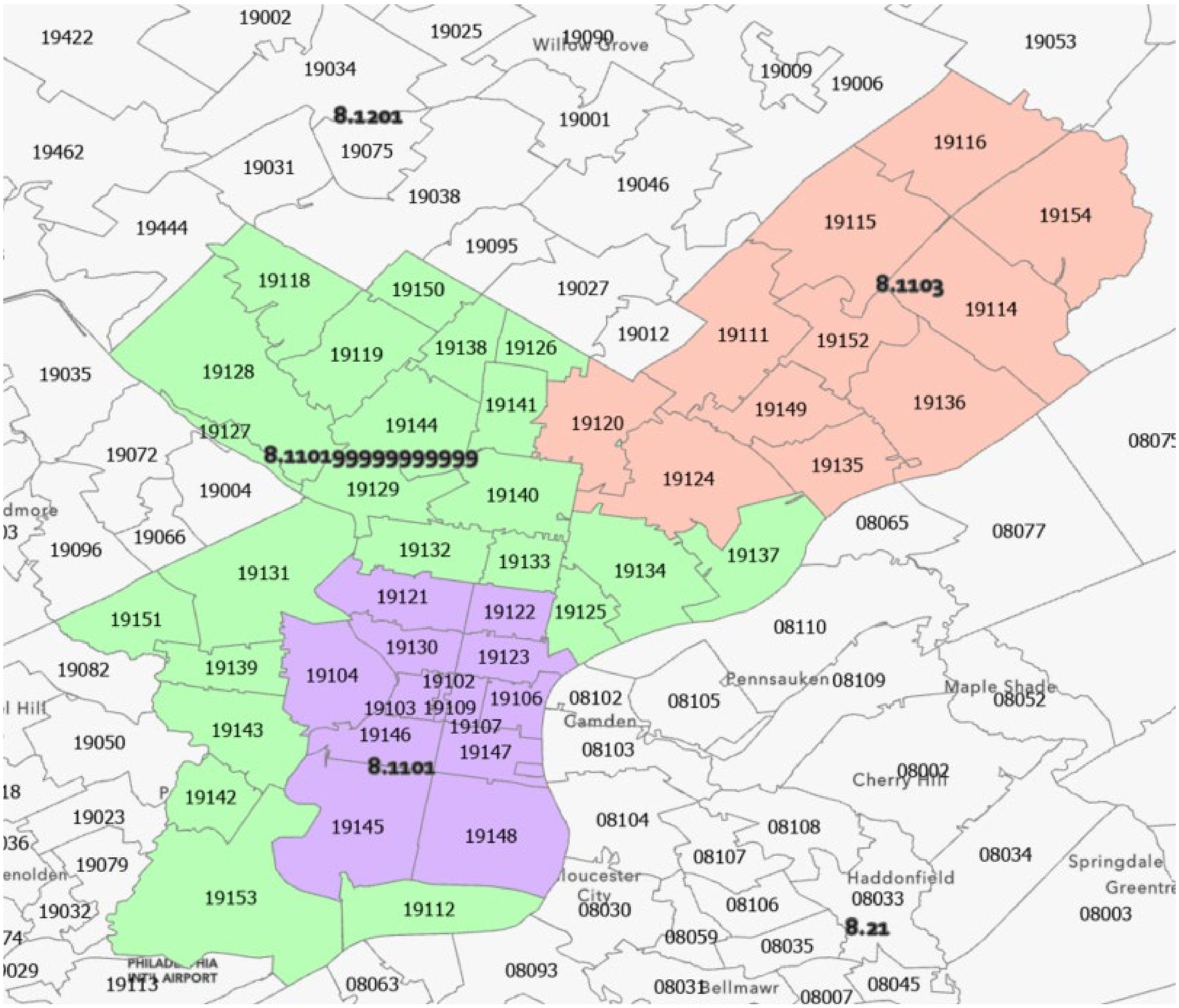


CntyGrp 7.3 – Palm Beach County, FL
Zclusts:

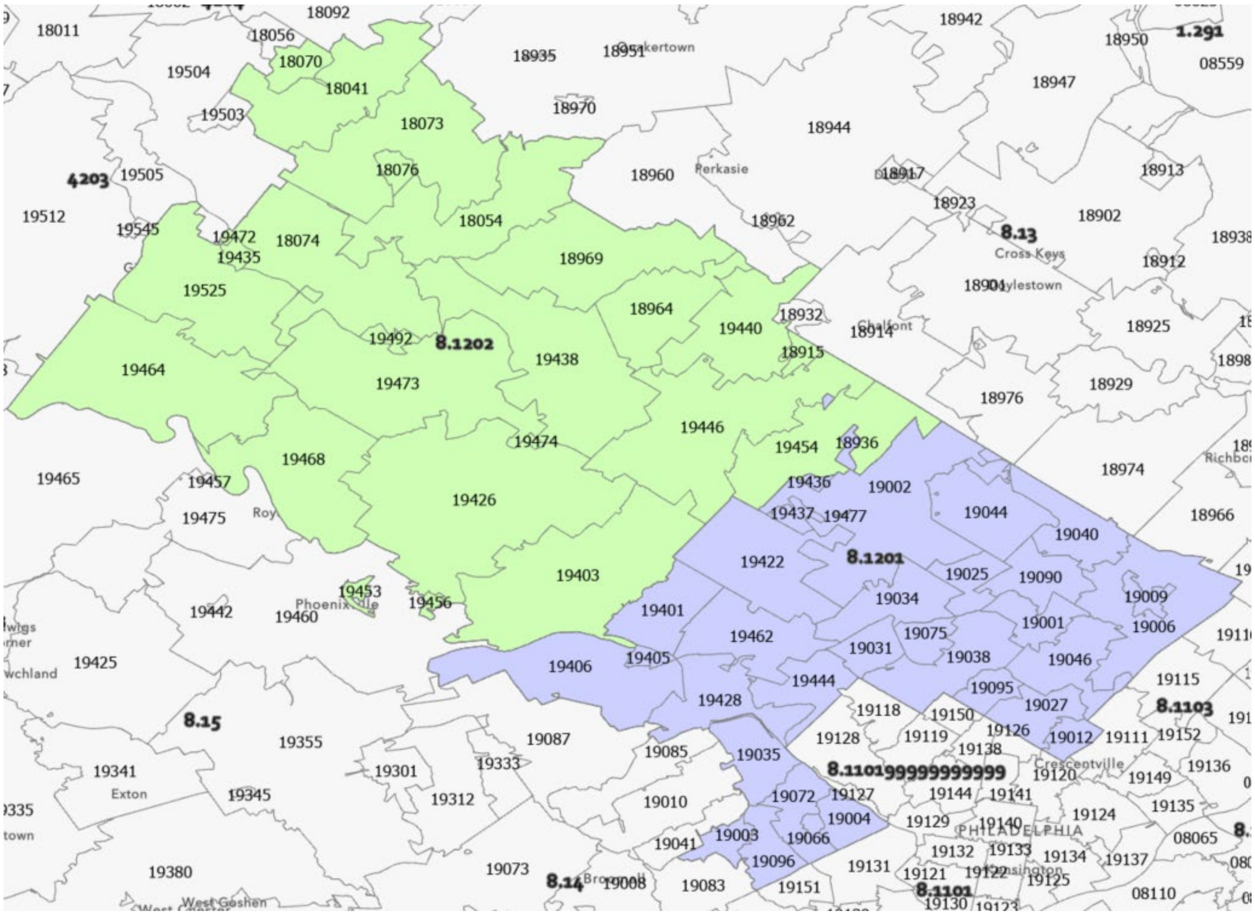
1. 7.3001
2. 7.3002



CntyGrp 8.11 – Philadelphia County, PA
Zclusts:
1. 8.1101
2. 8.1102
3. 8.1103

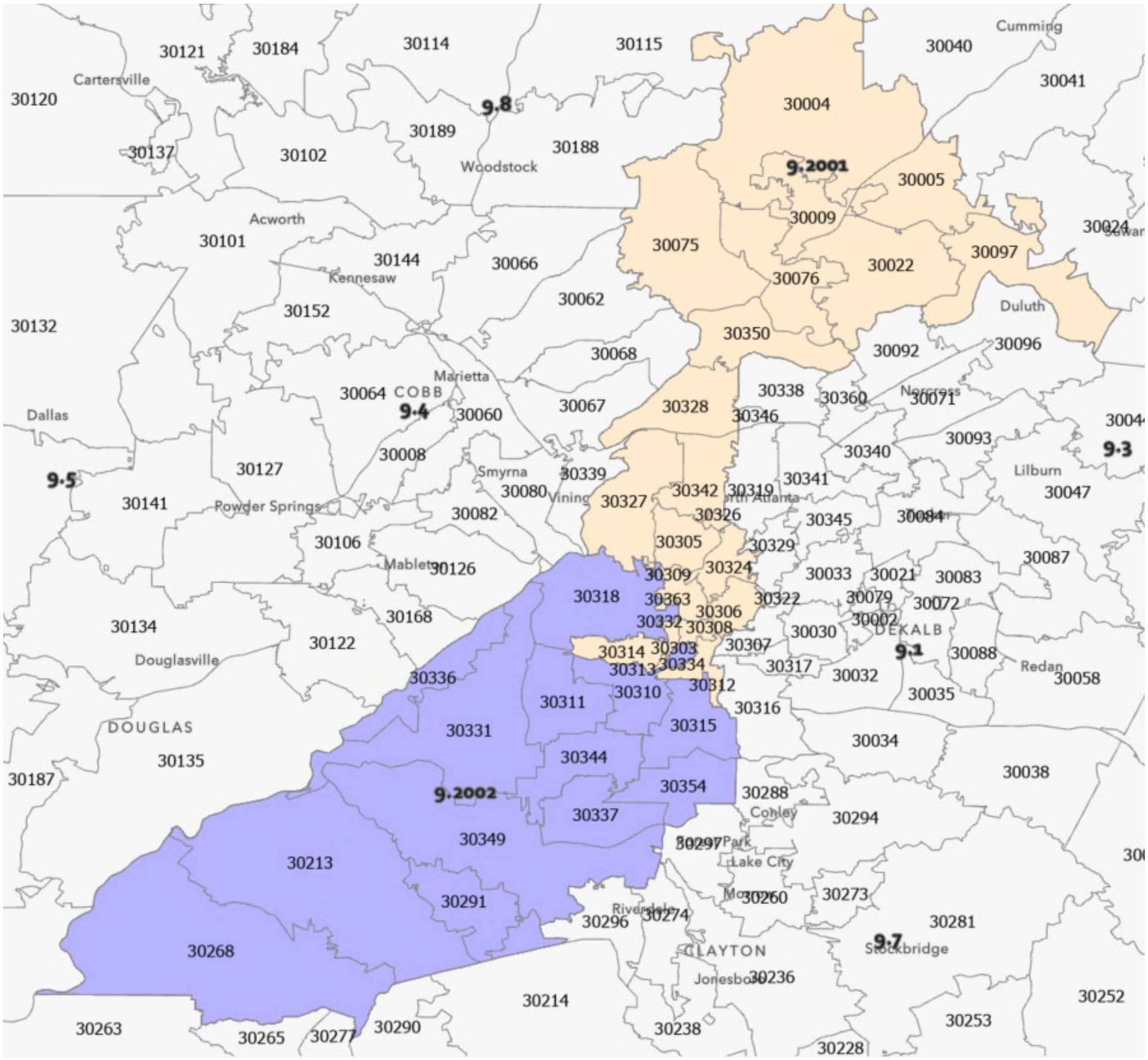


CntyGrp 8.12 – Montgomery County, PA
Zclusts:
1. 8.1201
2. 8.1202



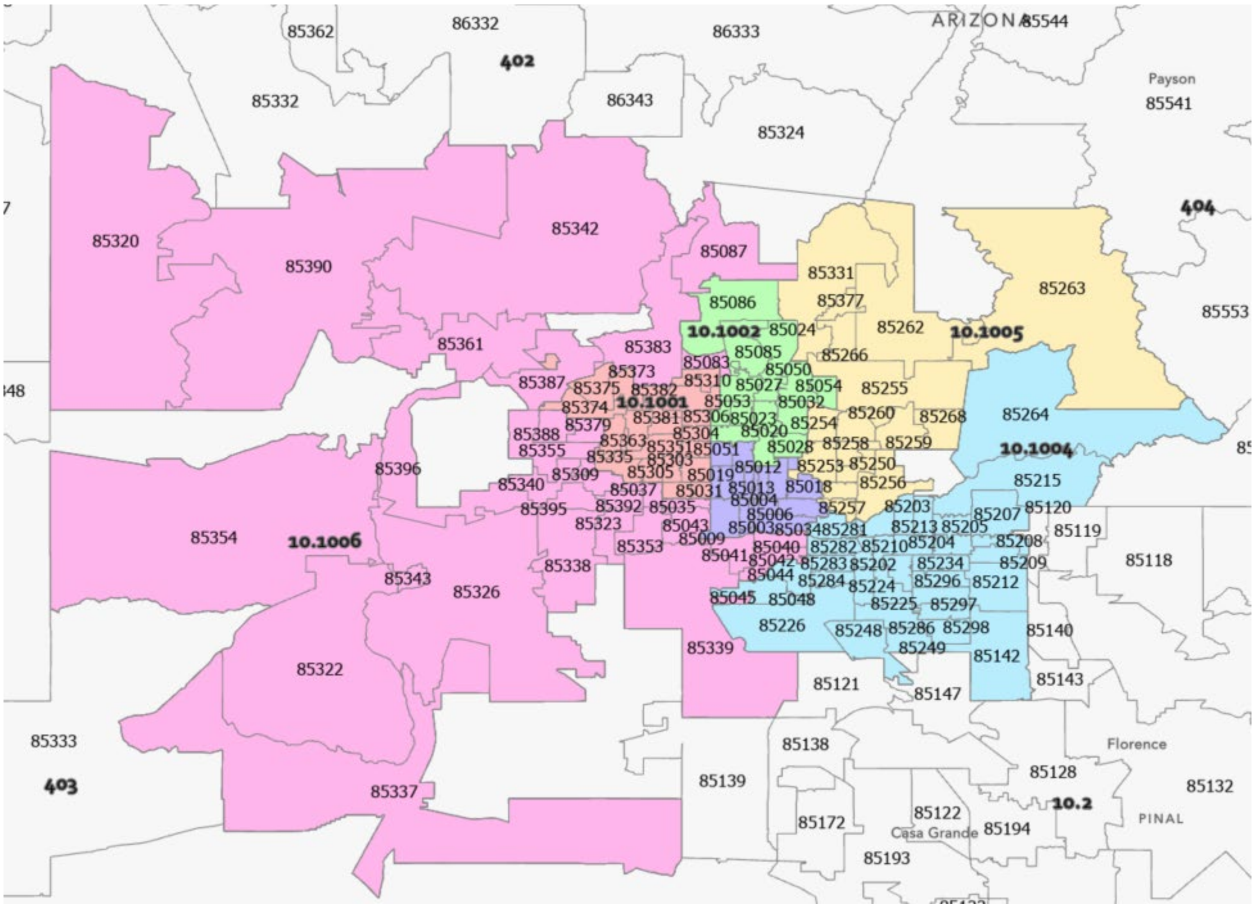
CntyGrp 9.2 – Fulton County, GA
Zclusts:

1. 9.2001
2. 9.2002



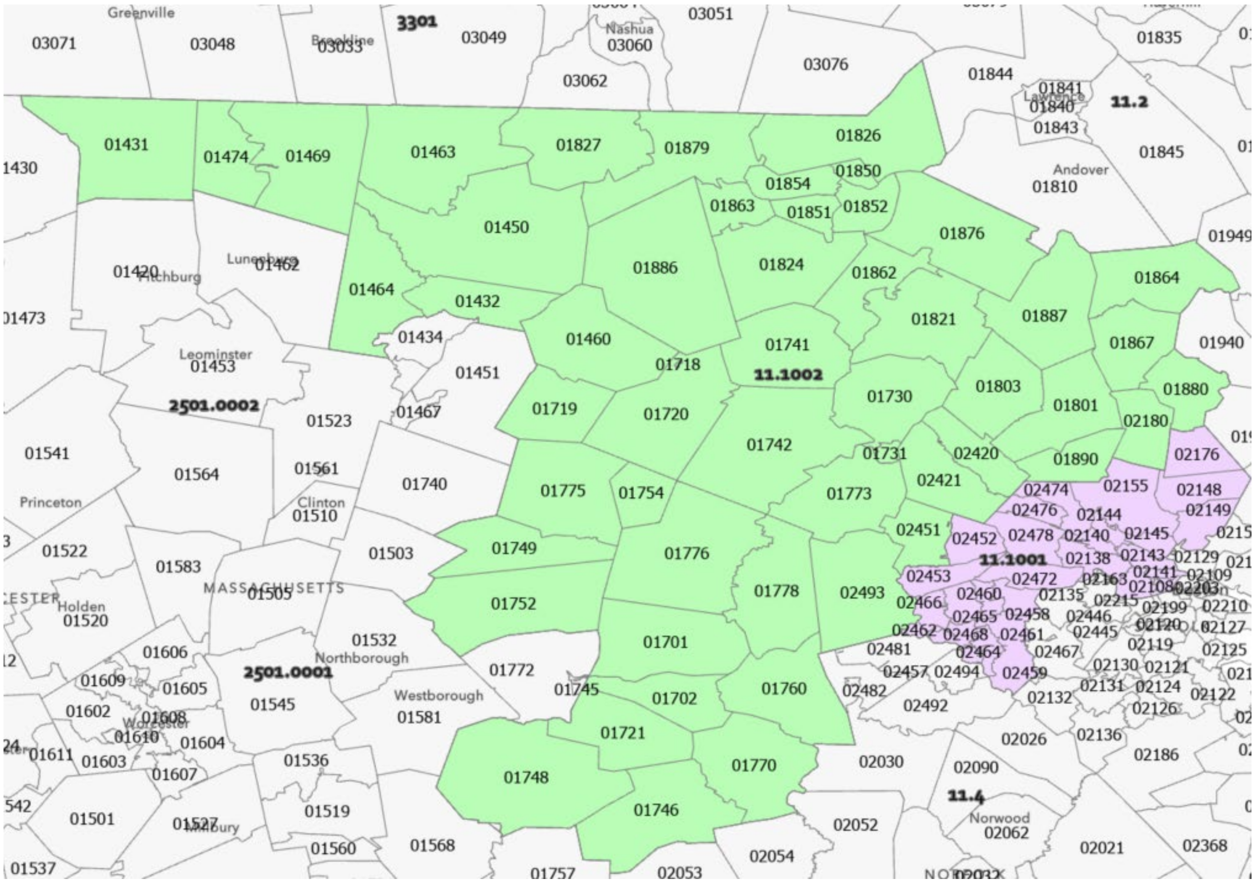
CntyGrp 10.1 – Maricopa County, AZ
Zclusts:

1. 10.1001
2. 10.1002
3. 10.1003
4. 10.1004
5. 10.1005
6. 10.1006



CntyGrp 11.1 – Middlesex County, MA
Zclusts:

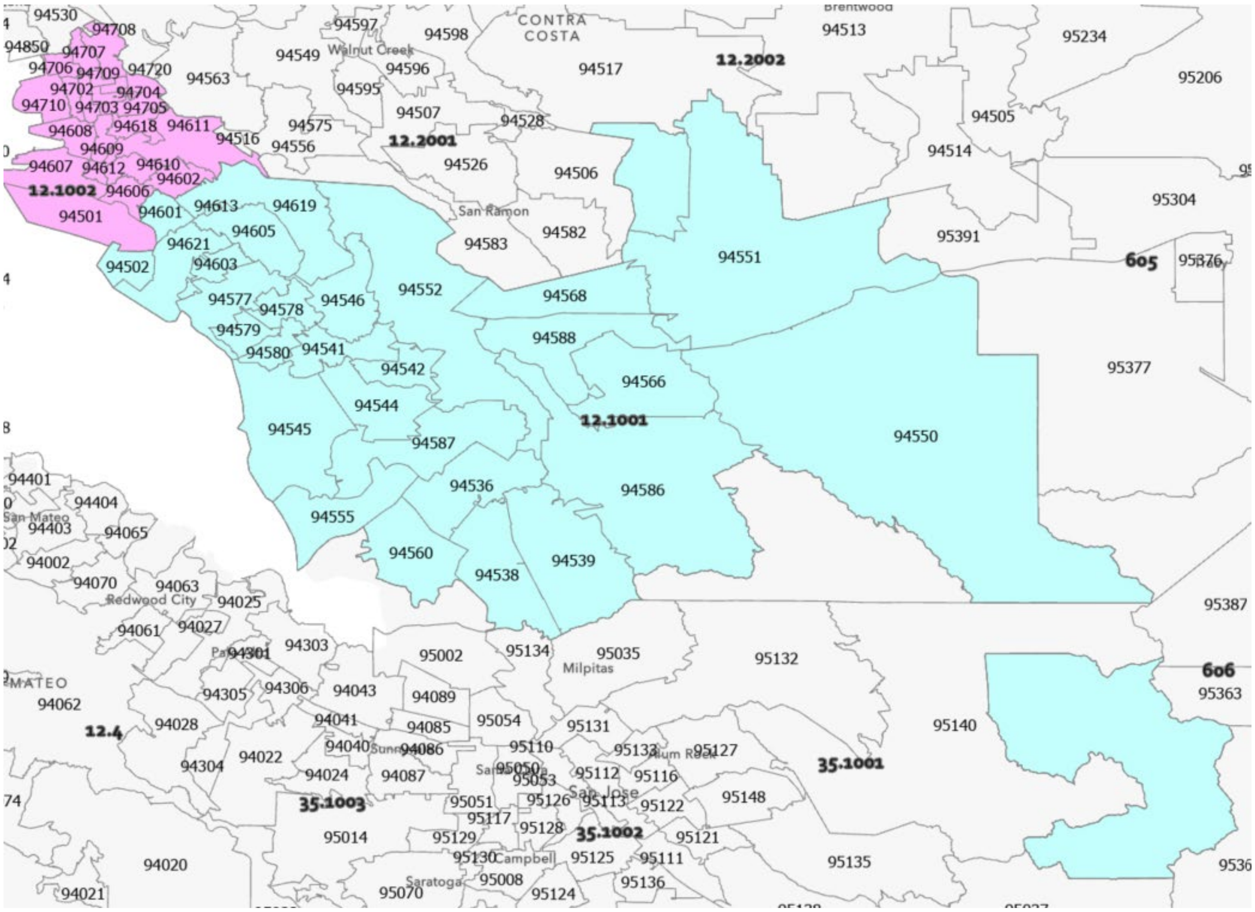
1. 11.1001
2. 11.1002



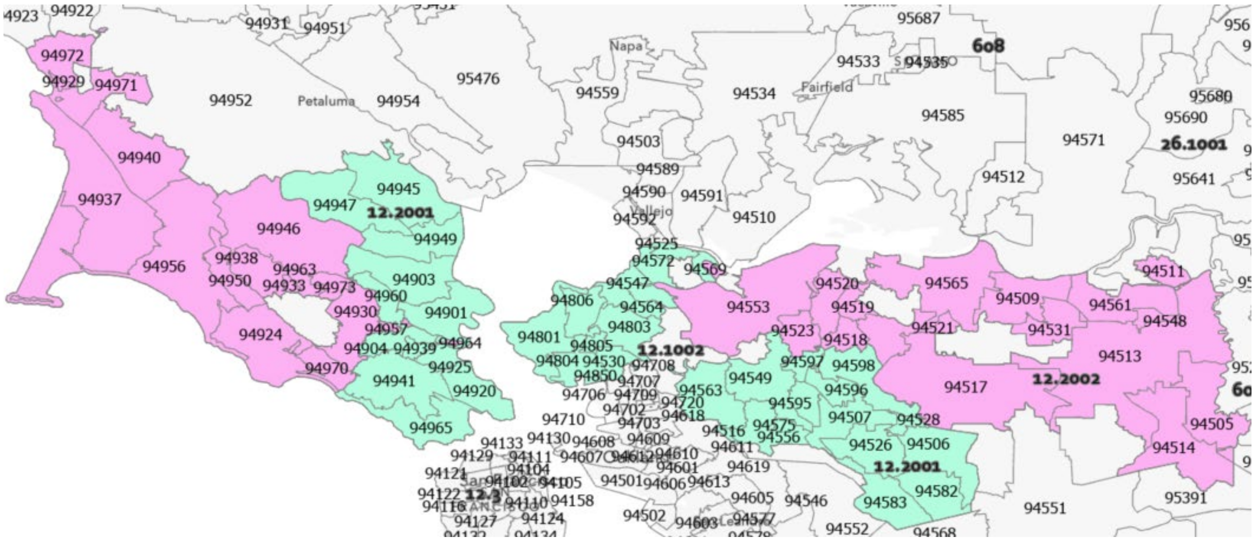
CntyGrp 12.1 – Alameda County, CA

Zclusts:

1. 12.1001
2. 12.1002

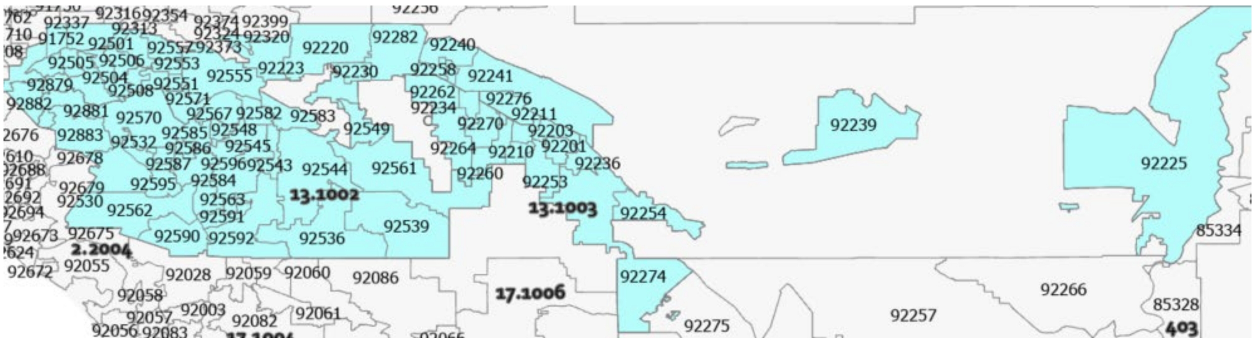


CntyGrp 12.2 – Contra Costa County, CA
Zclusts:
1. 12.2001
2. 12.2002



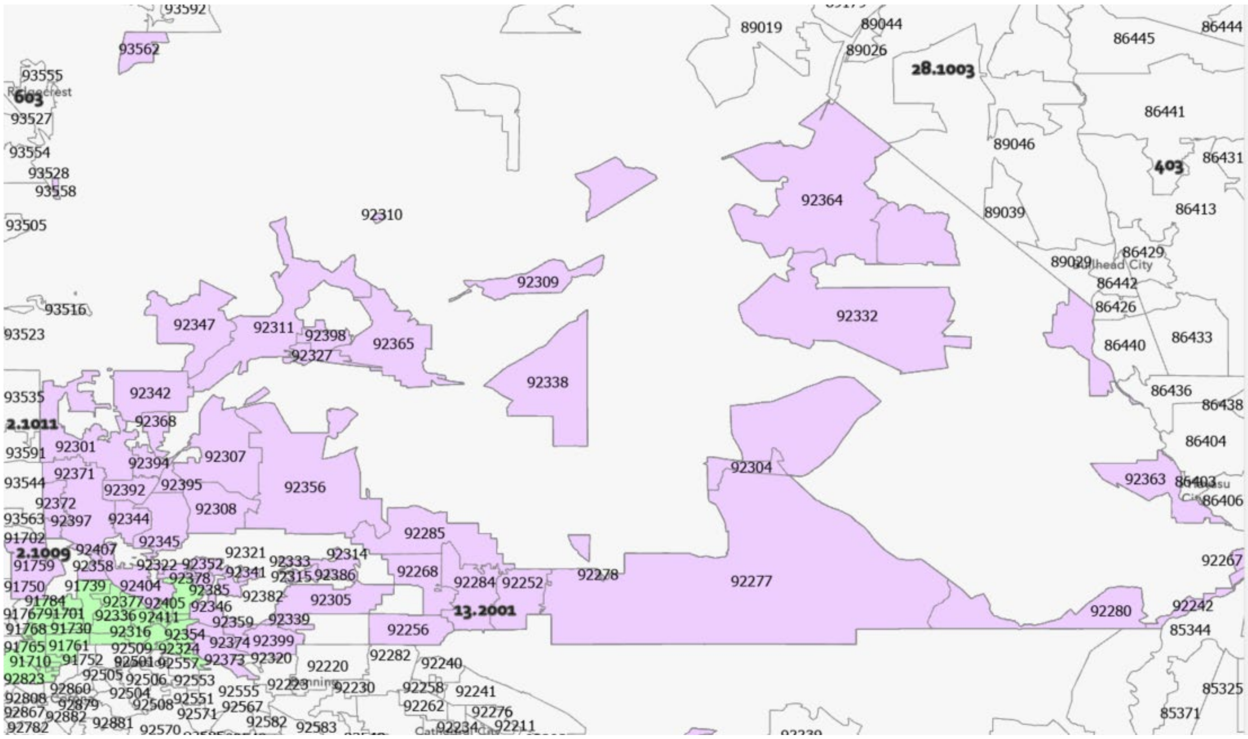
CntyGrp 13.1 – Riverside County, CA
Zclusts:

1. 13.1001
2. 13.1002
3. 13.1003



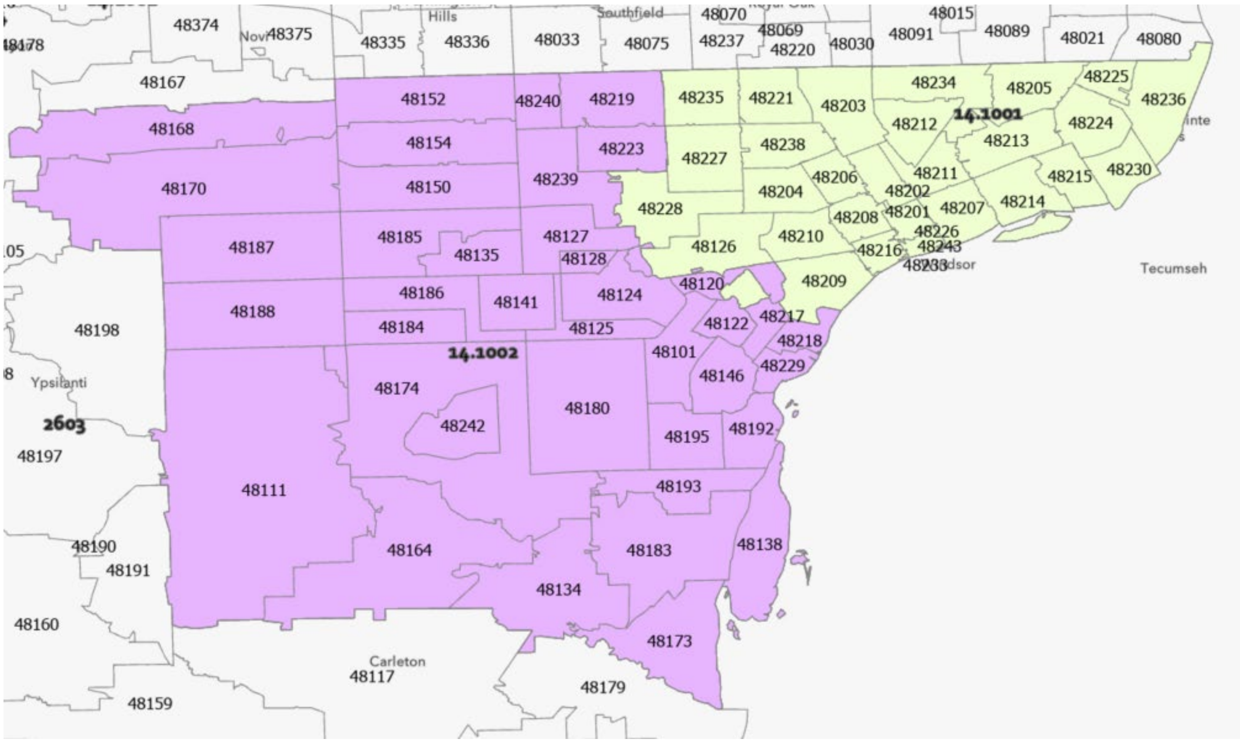
CntyGrp 13.2 – San Bernadino County, CA
Zclusts:

1. 13.2001
2. 13.2002



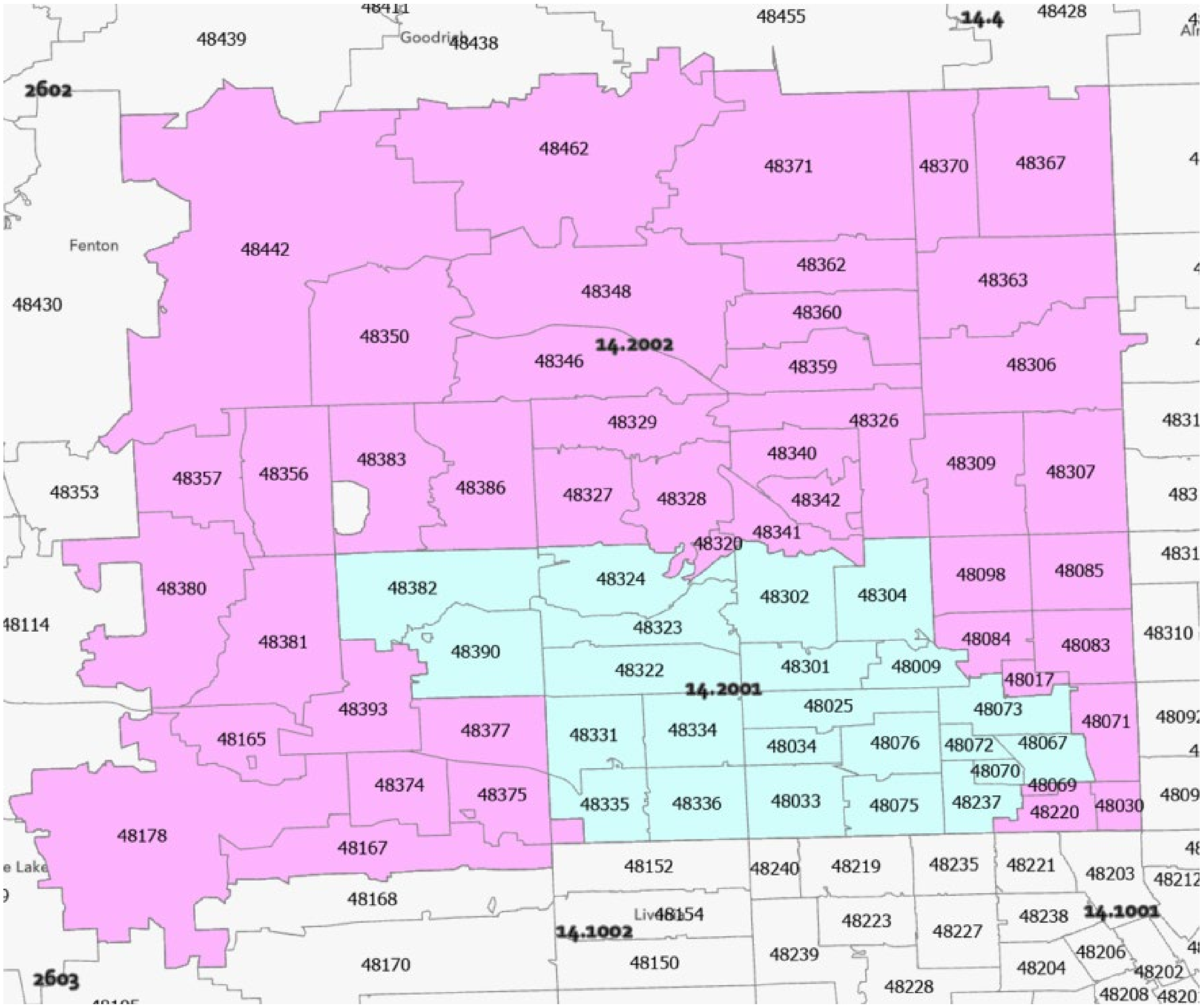
CntyGrp 14.1 – Wayne County, MI
Zclusts:

1. 14.1001
2. 14.1002



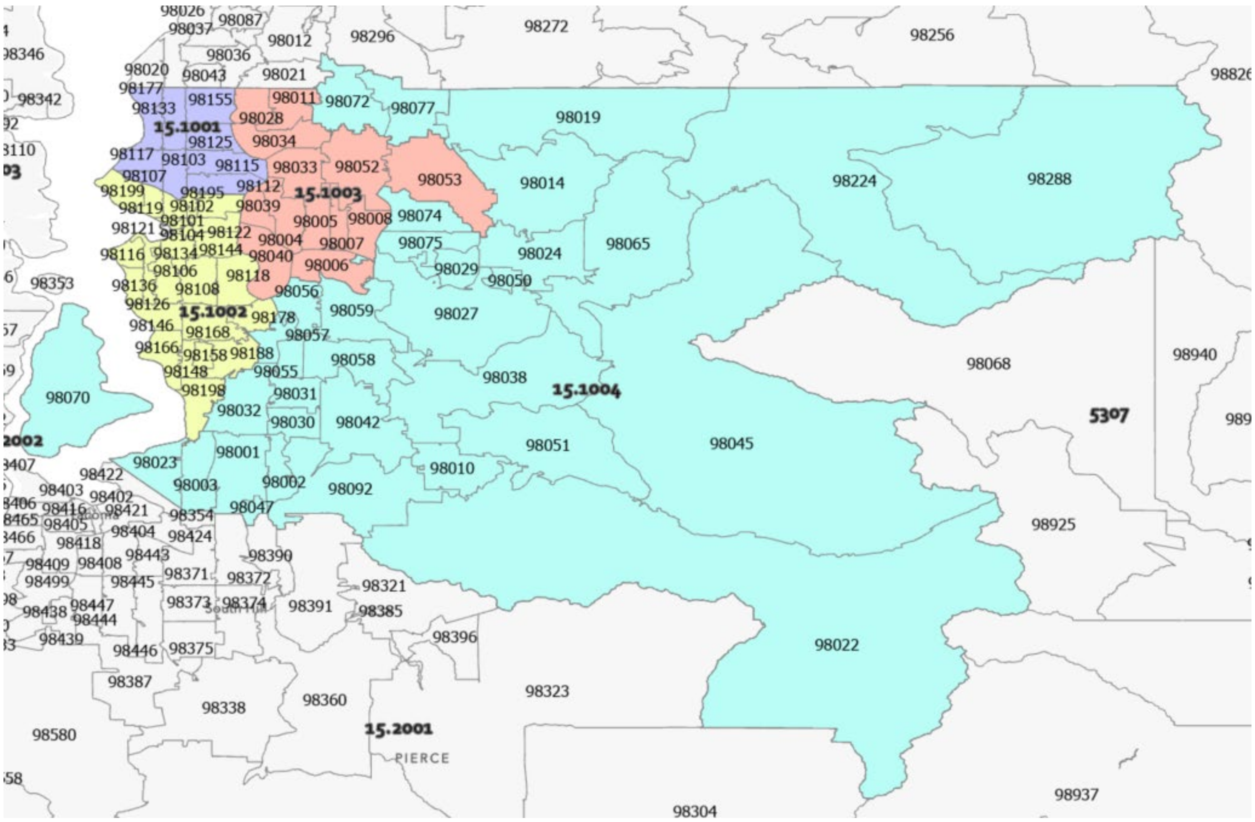
CntyGrp 14.2 – Oakland County, MI
Zclusts:

1. 14.2001
2. 14.2002

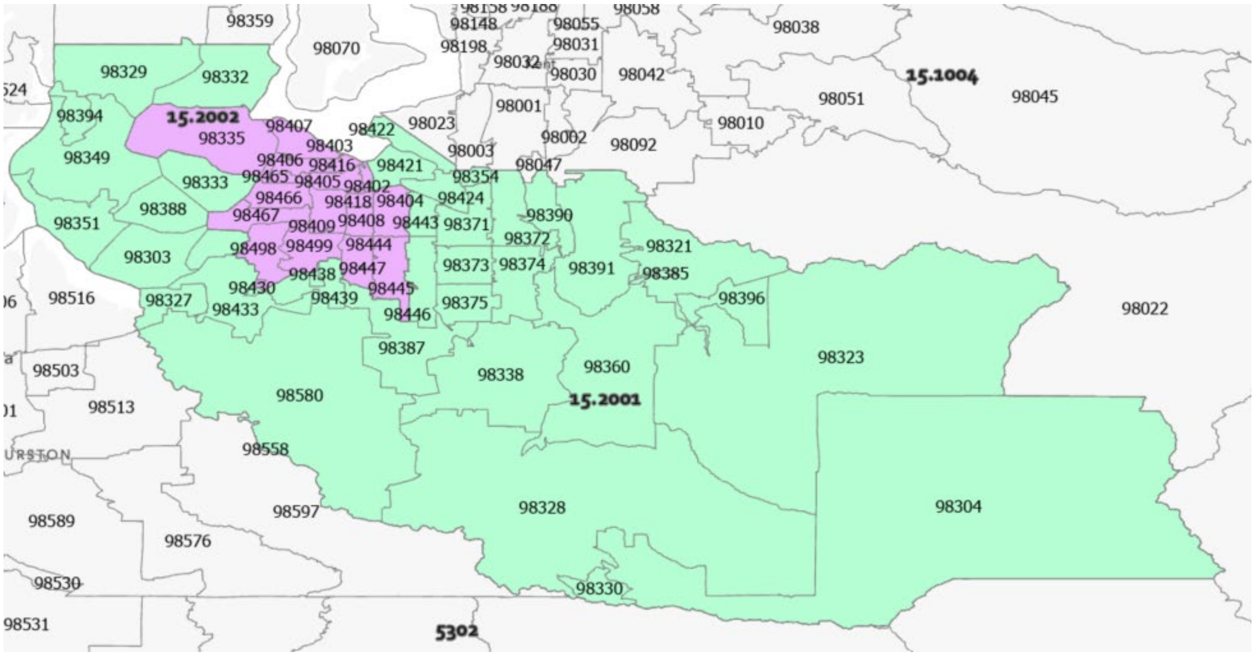


CntyGrp 15.1 – King County, WA
Zclusts:

1. 15.1001
2. 15.1002
3. 15.1003
4. 15.1004

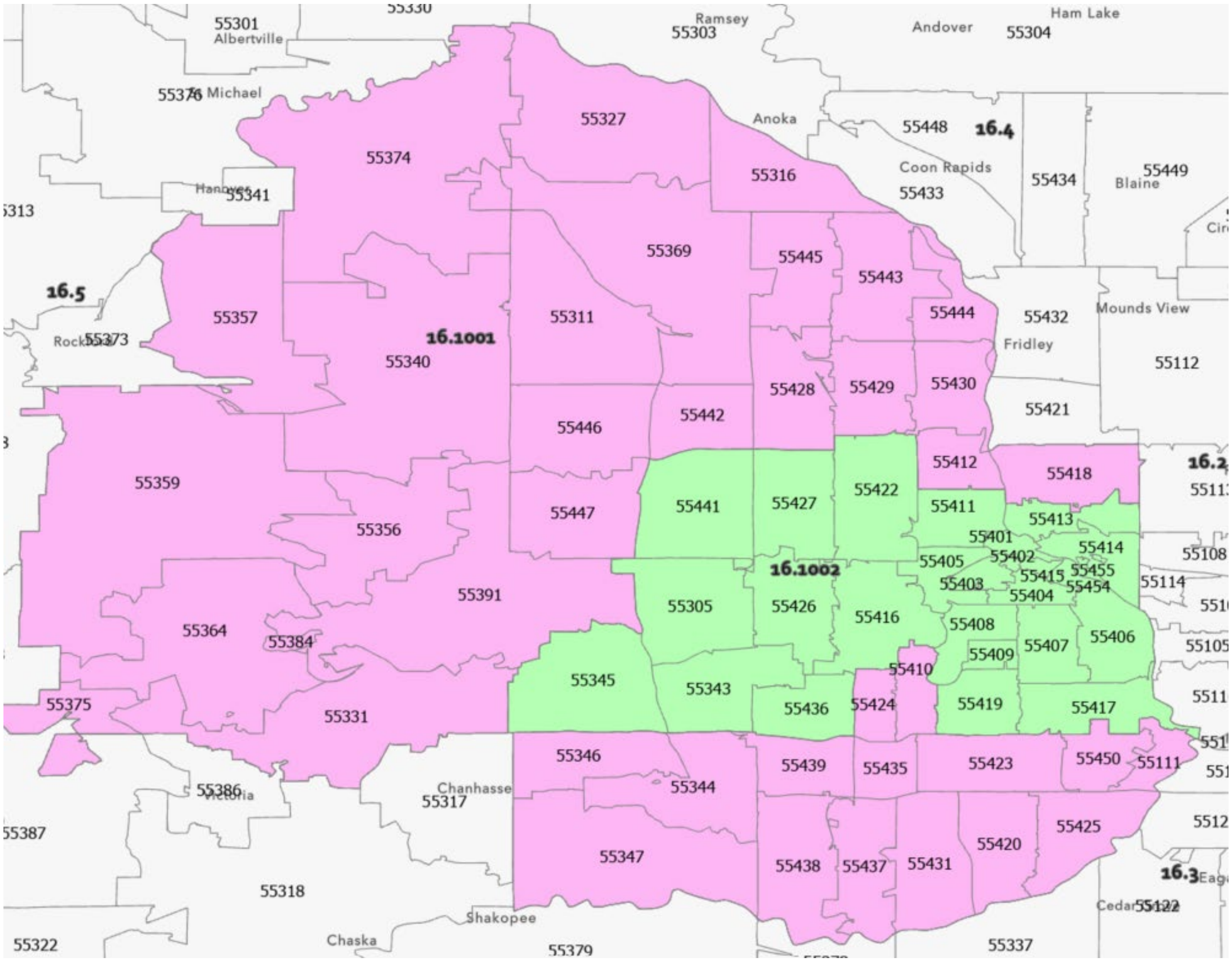


CntyGrp 15.2 – Pierce County, WA
Zclusts:
1. 15.2001
2. 15.2002



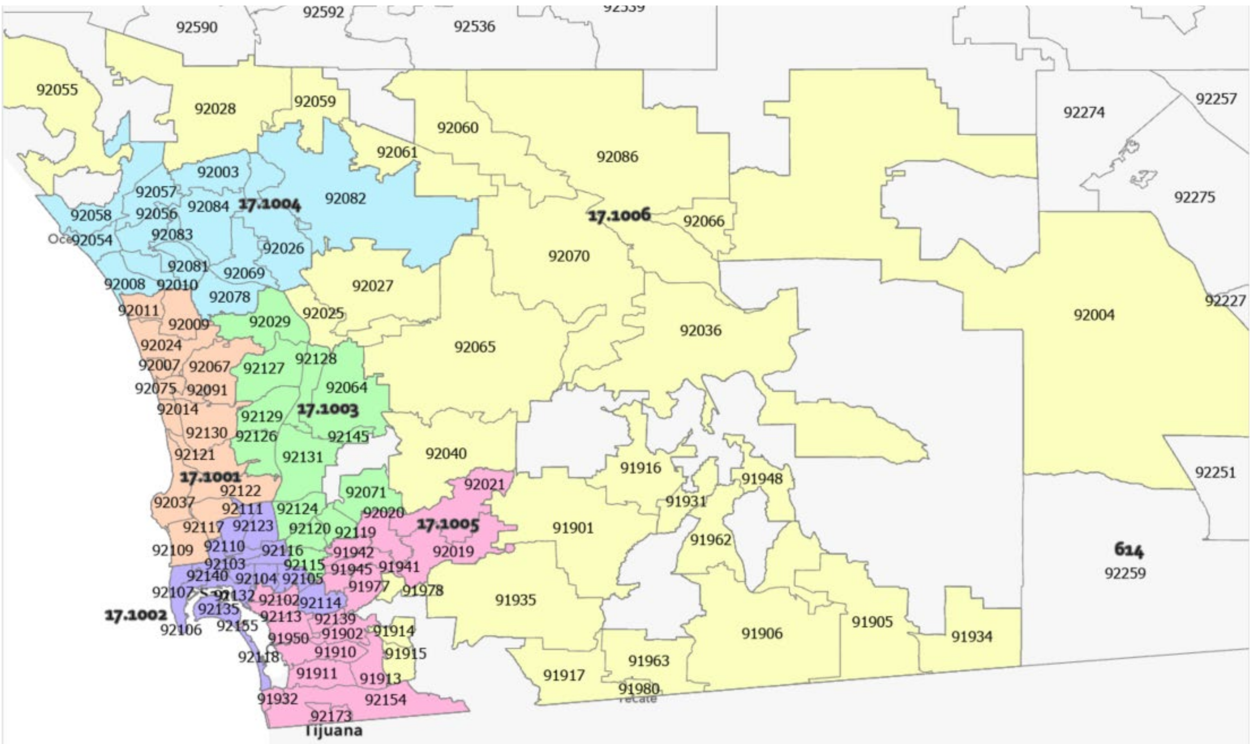
CntyGrp 16.1 – Hennepin County, MN
Zclusts:

1. 16.1001
2. 16.1002



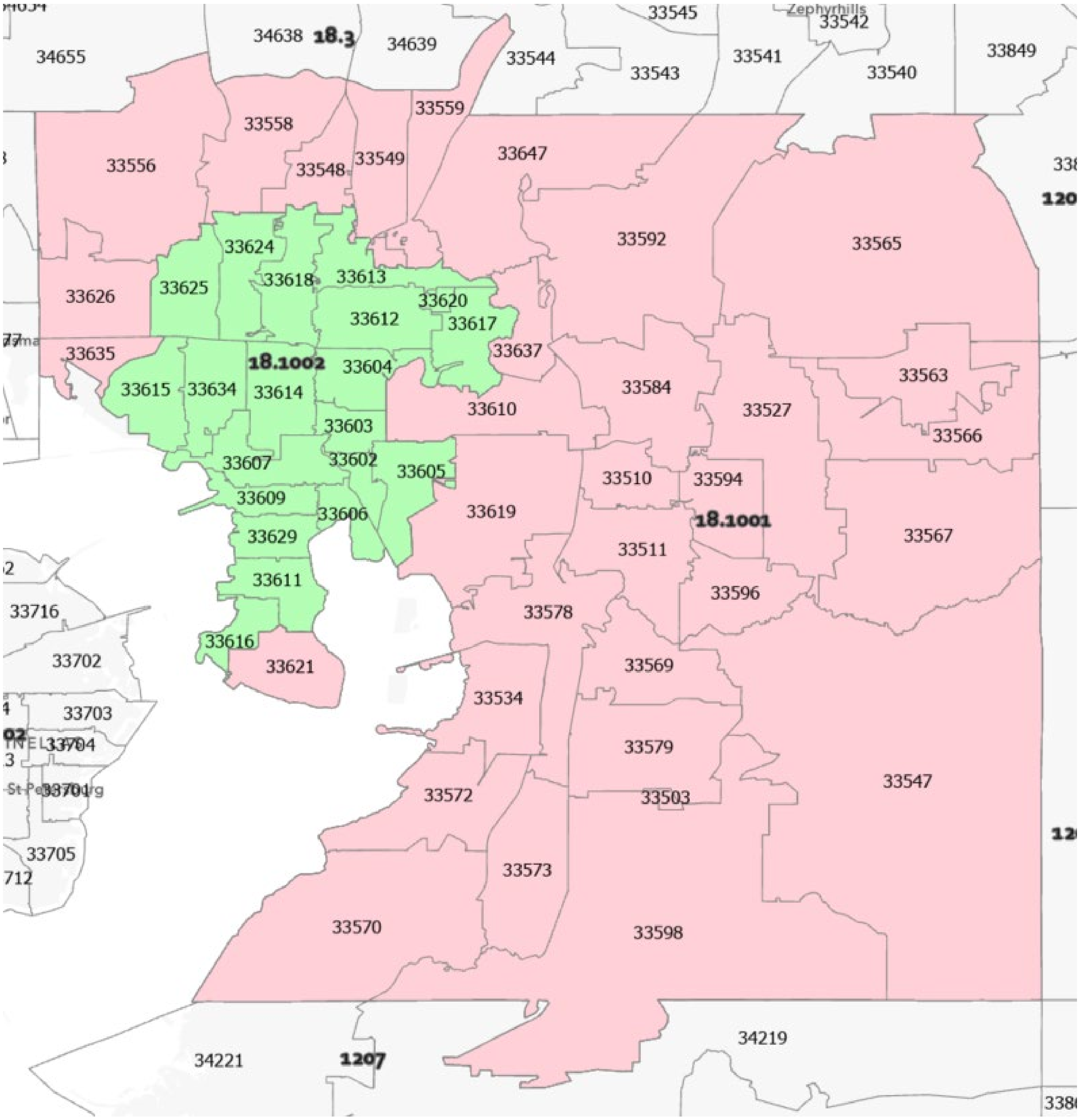
CntyGrp 17.1 – San Diego, CA
Zclusts:

1. 17.1001
2. 17.1002
3. 17.1003
4. 17.1004
5. 17.1005
6. 17.1006



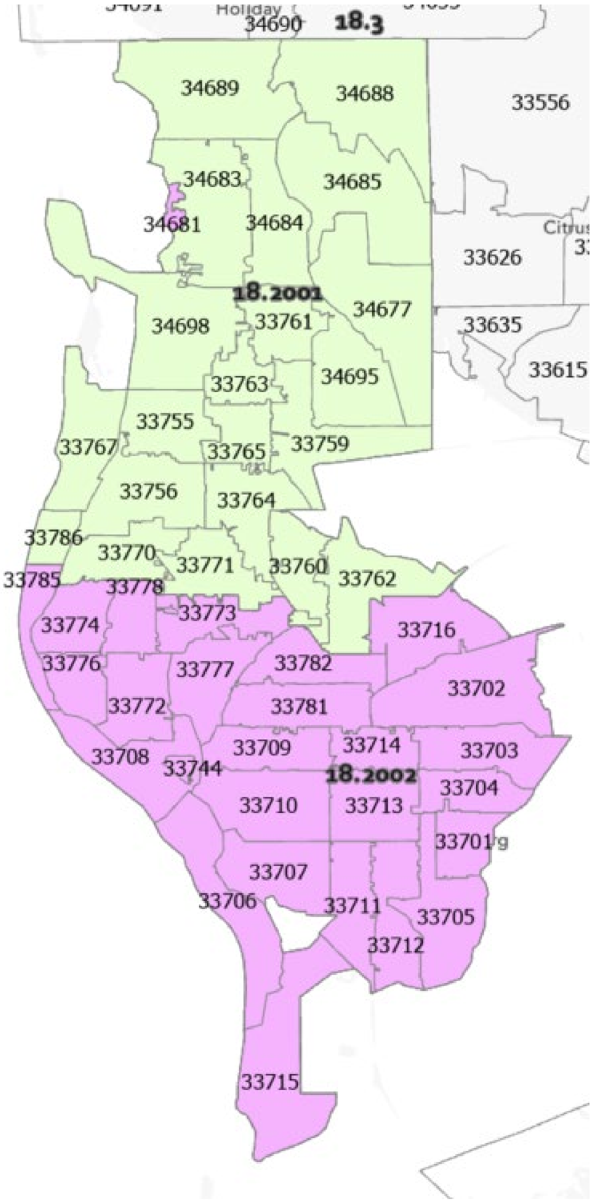
CntyGrp 18.1 – Hillsborough County, FL
Zclusts:

1. 18.1001
2. 18.1002



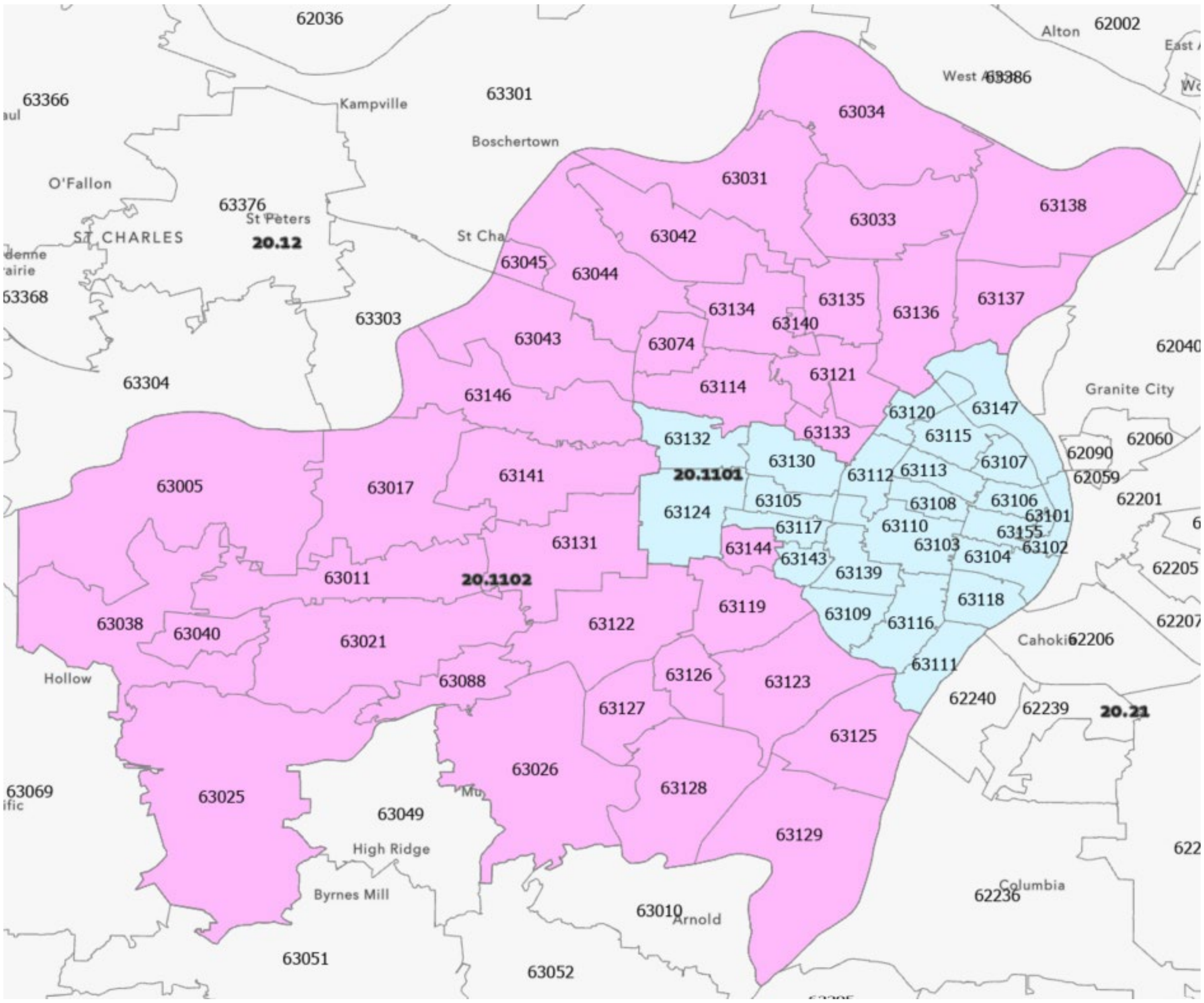
CntyGrp 18.2 – Pinellas County, FL
Zclusts:

1. 18.2001
2. 18.2002



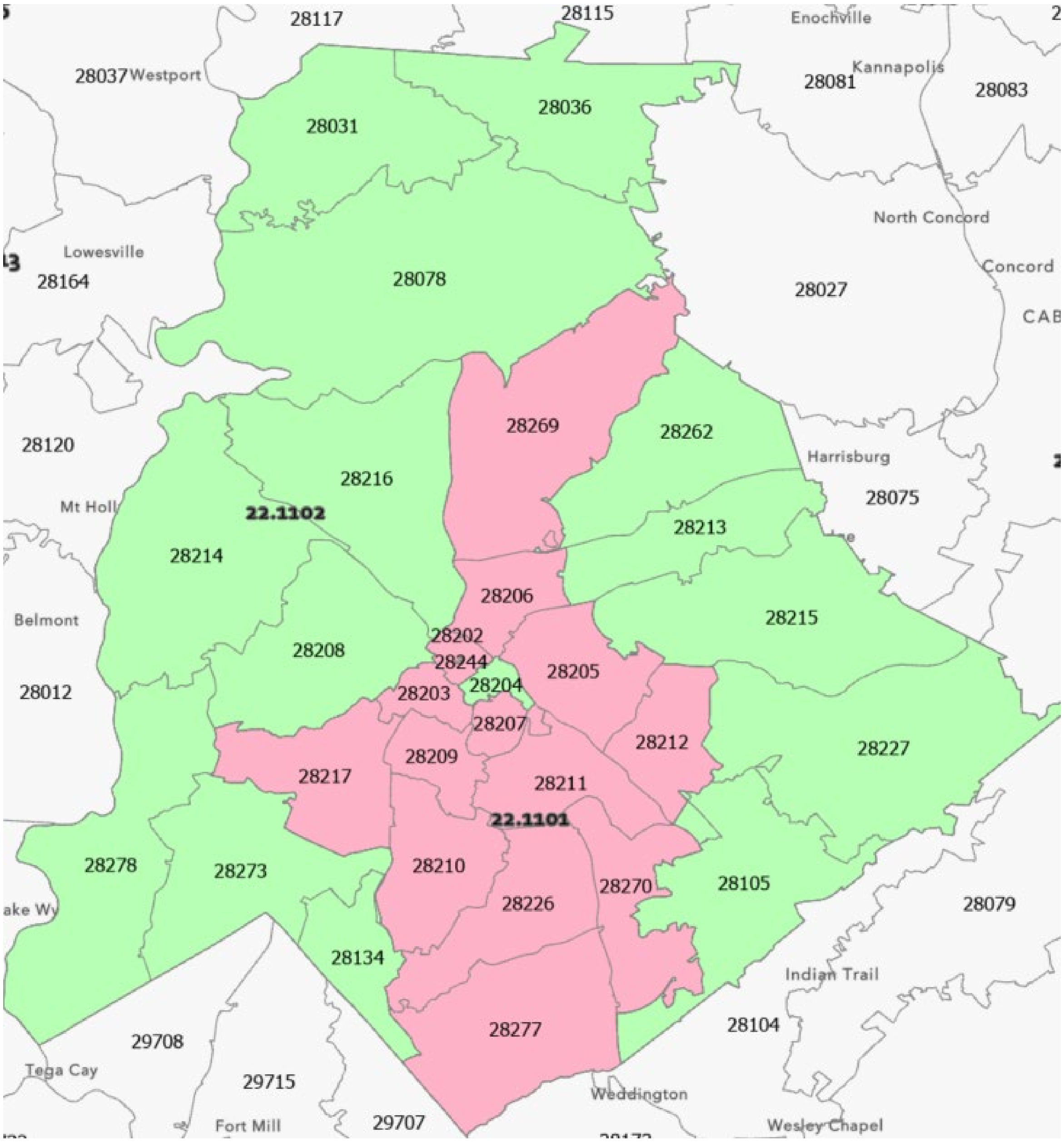
CntyGrp 20.11 – Saint Louis County, MO
Zclusts:

1. 20.1101
2. 20.1102



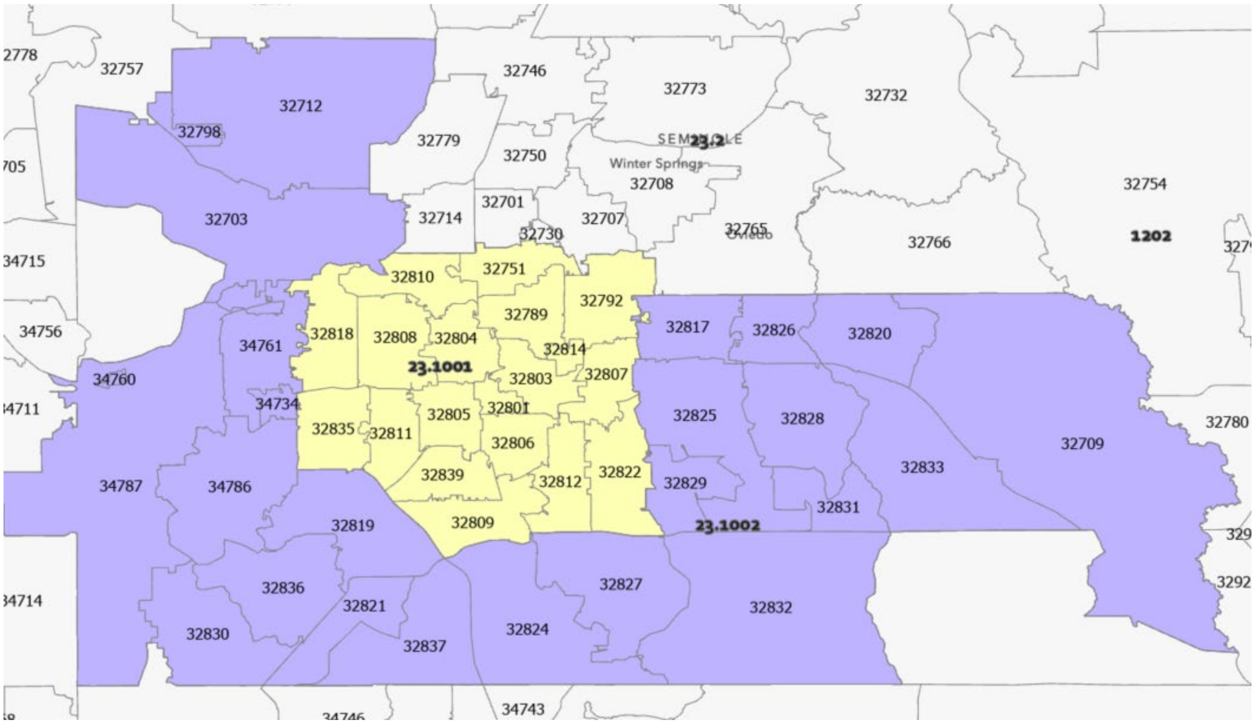
CntyGrp 22.11 – Mecklenburg County, NC
Zclusts:

1. 22.1101
2. 22.1102



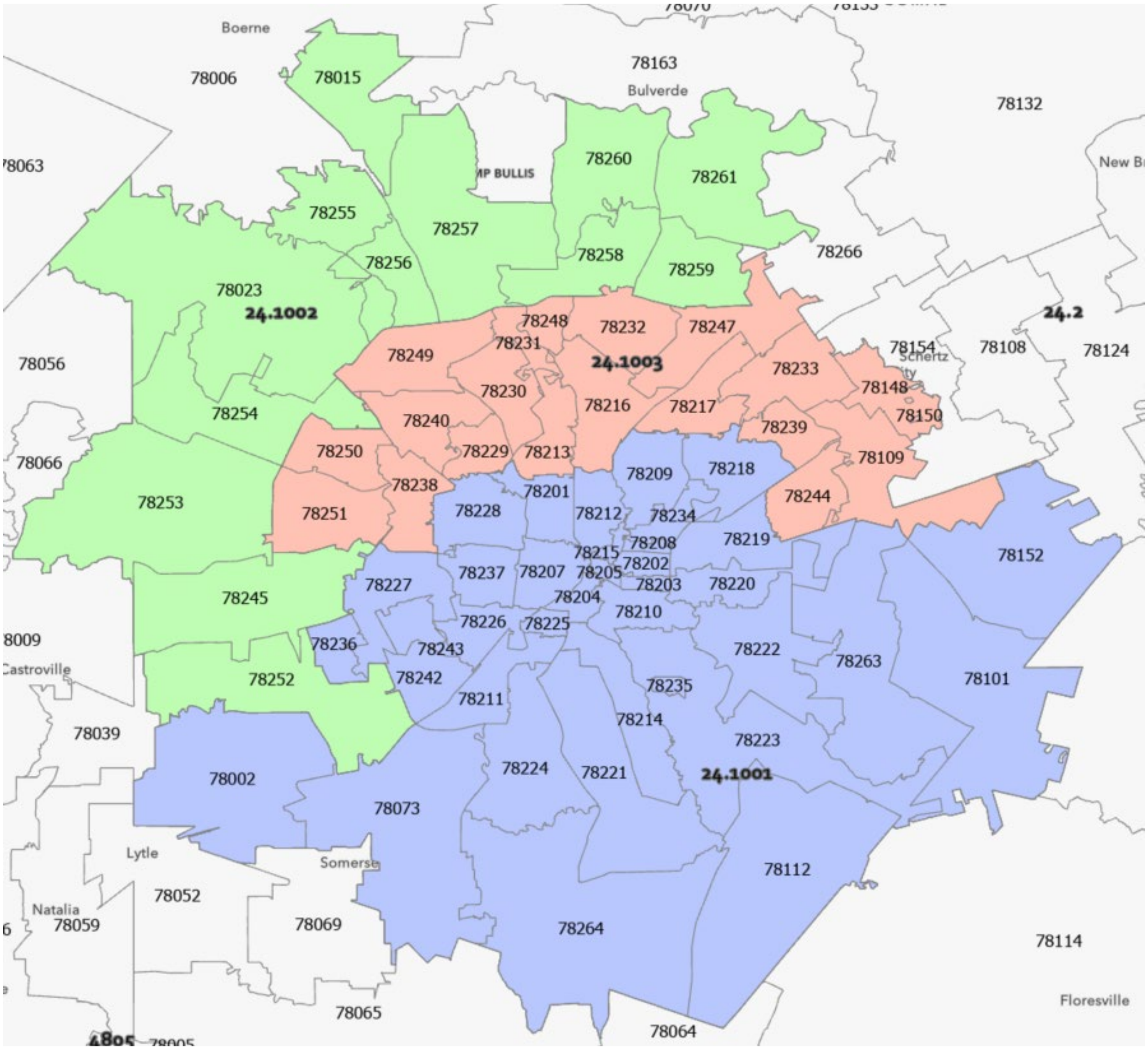
CntyGrp 23.1 – Orange County, FL
Zclusts:

1. 23.1001
2. 23.1002



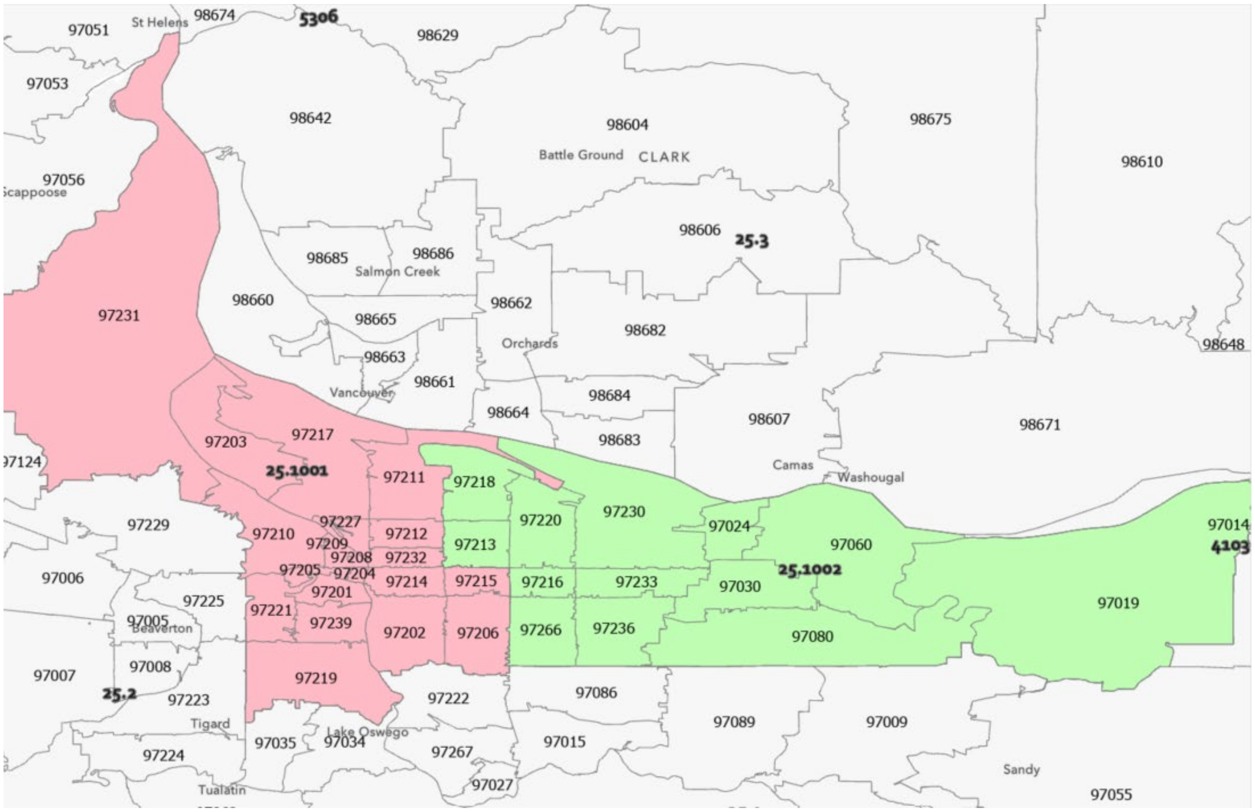
CntyGrp 24.1 – Bexar County, TX
Zclusts:

1. 24.1001
2. 24.1002
3. 24.1003



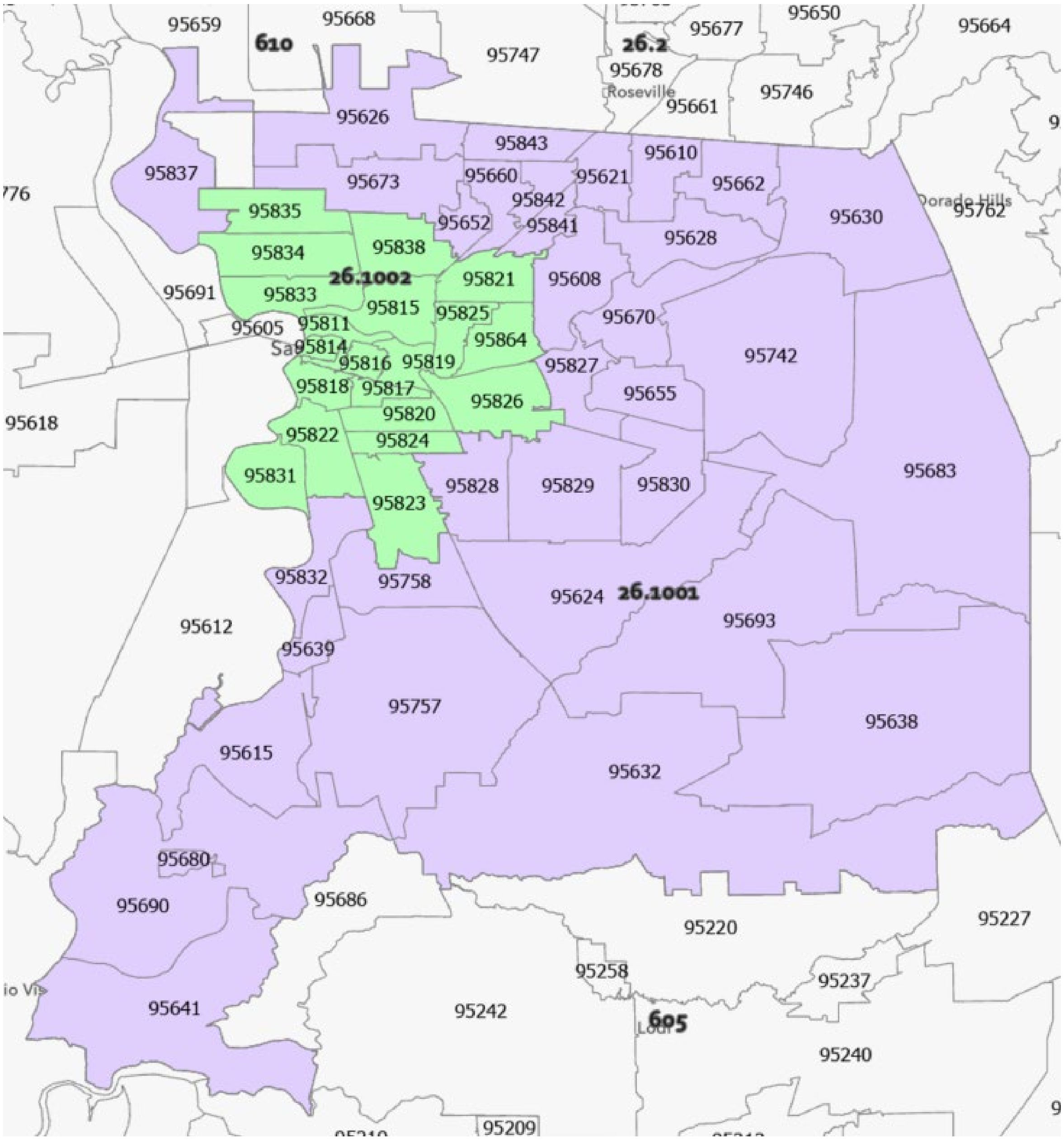
CntyGrp 25.1 – Multnomah County, OR
Zclusts:

1. 25.1001
2. 25.1002



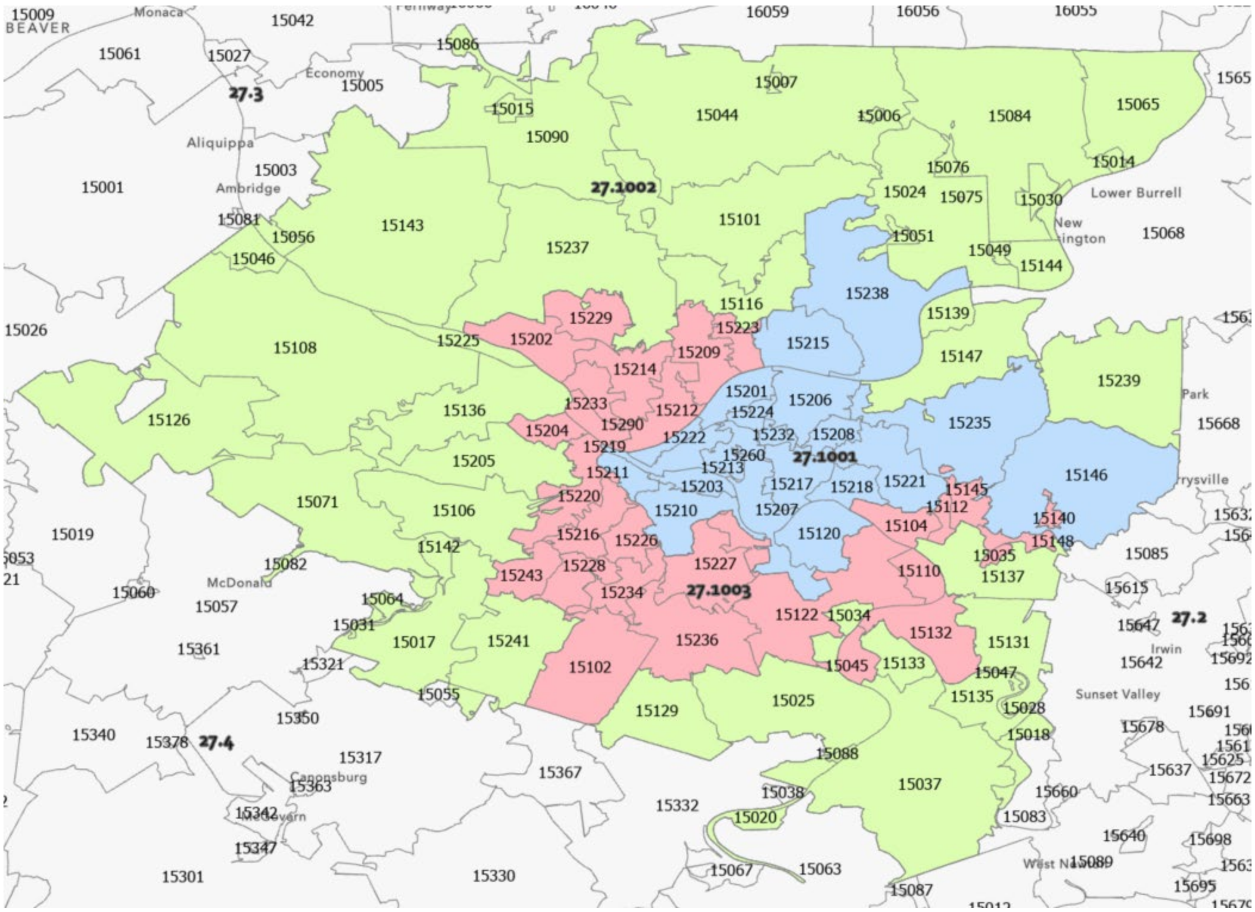
CntyGrp 26.1 – Sacramento County, CA
Zclusts:

1. 26.1001
2. 26.1002



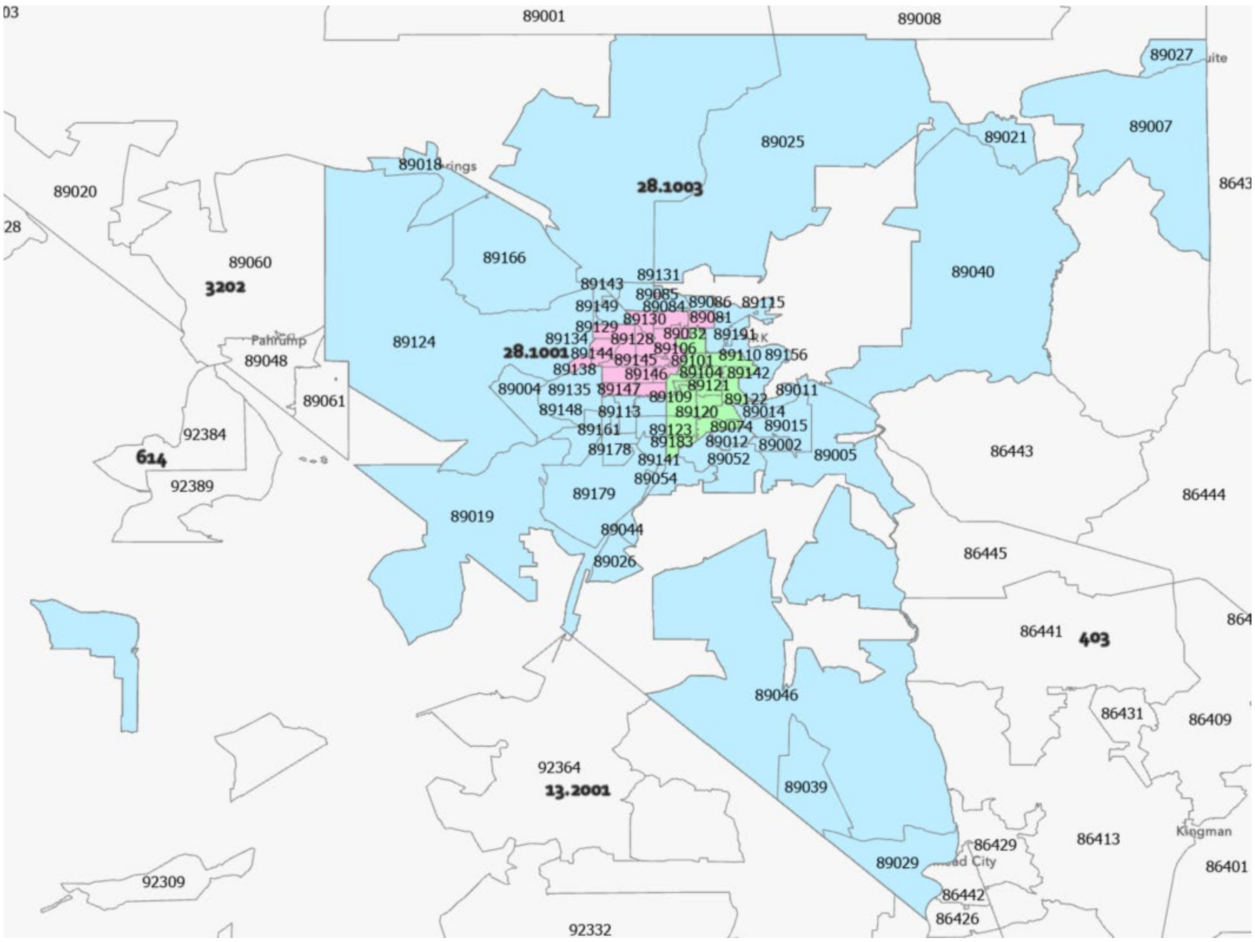
CntyGrp 27.1 – Allegheny County, PA
Zclusts:

1. 27.1001
2. 27.1002
3. 27.1003



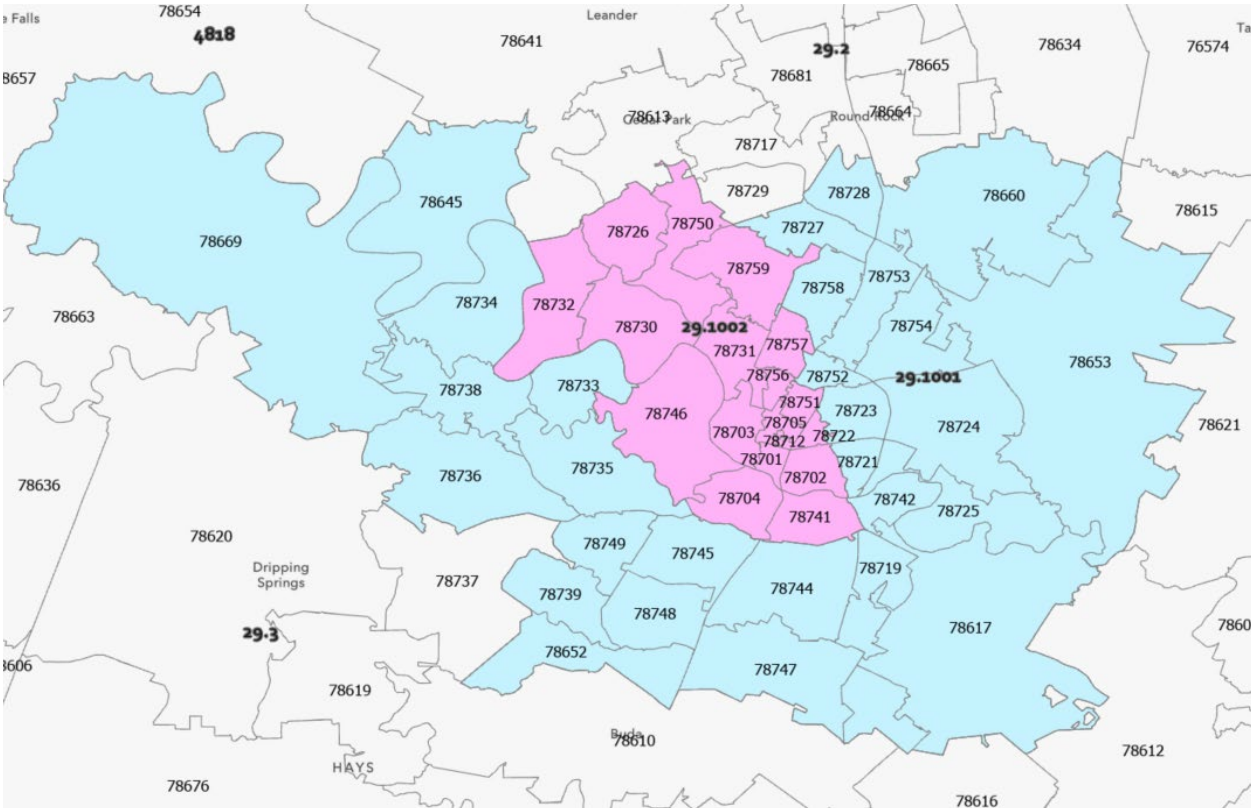
CntyGrp 28.1 – Clark County, NV
Zclusts:

1. 28.1001
2. 28.1002
3. 28.1003



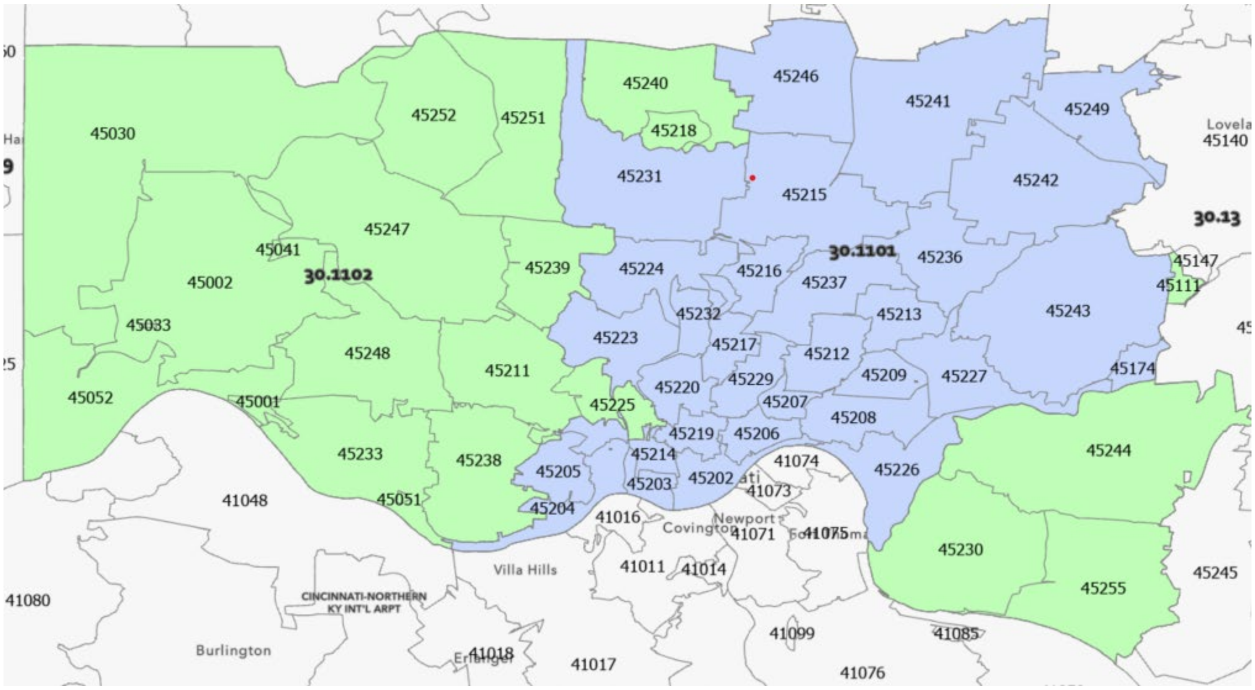
CntyGrp 29.1 – Travis County, TX
Zclusts:

1. 29.1001
2. 29.1002



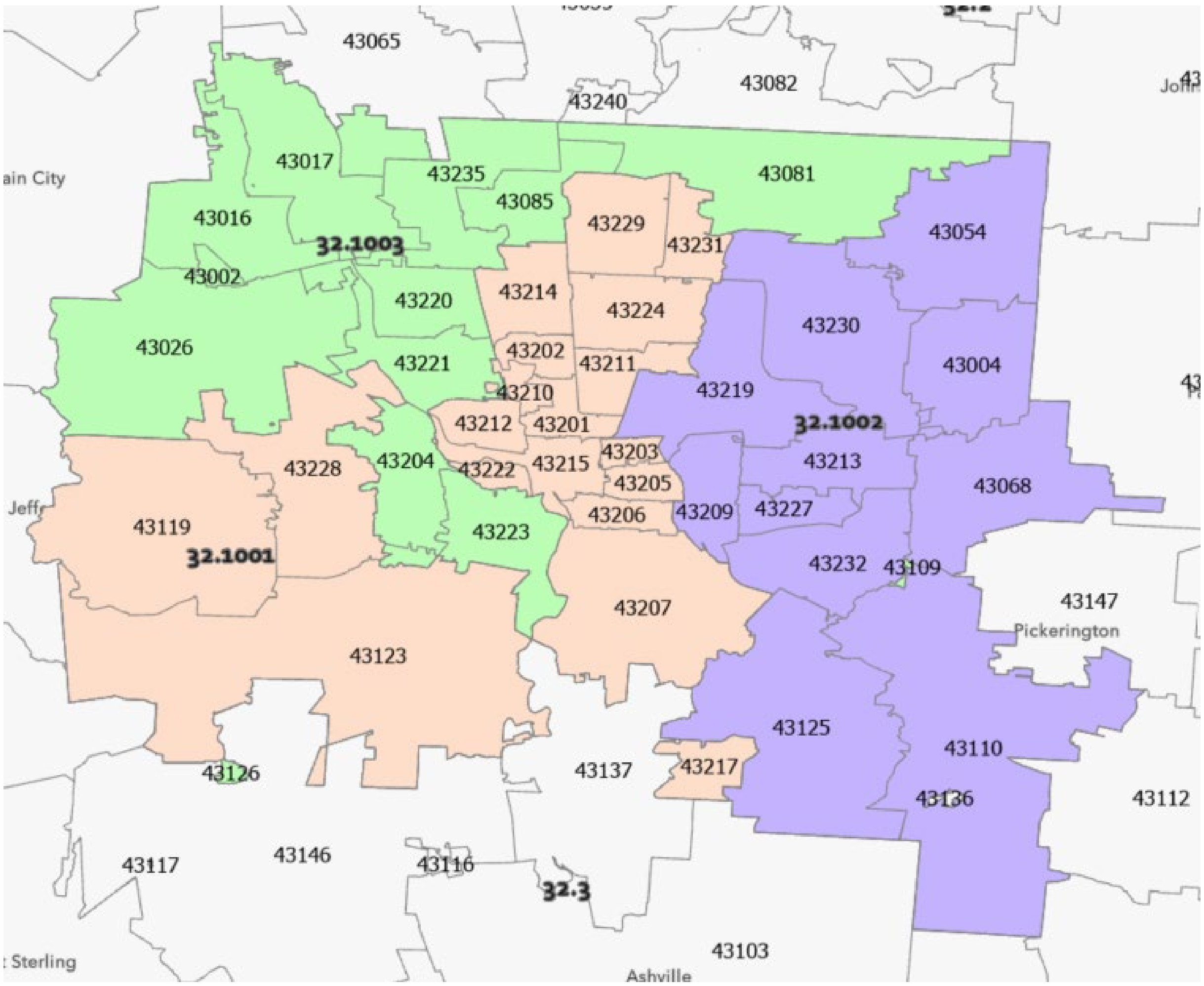
CntyGrp 30.11 – Hamilton County, OH
Zclusts:

1. 30.1101
2. 30.1102

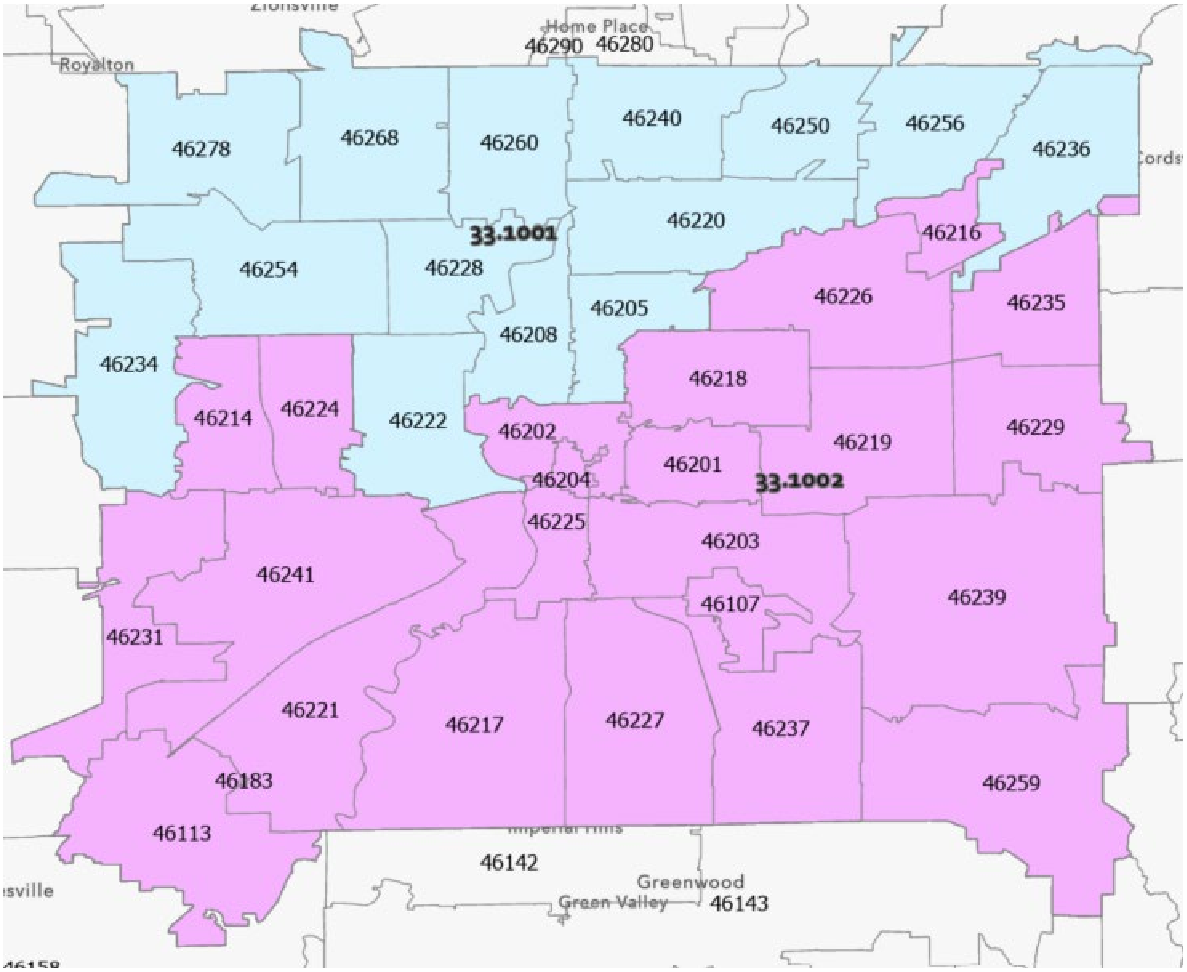


CntyGrp 32.1 – Franklin County, OH
Zclusts:

1. 32.1001
2. 32.1002
3. 32.1003

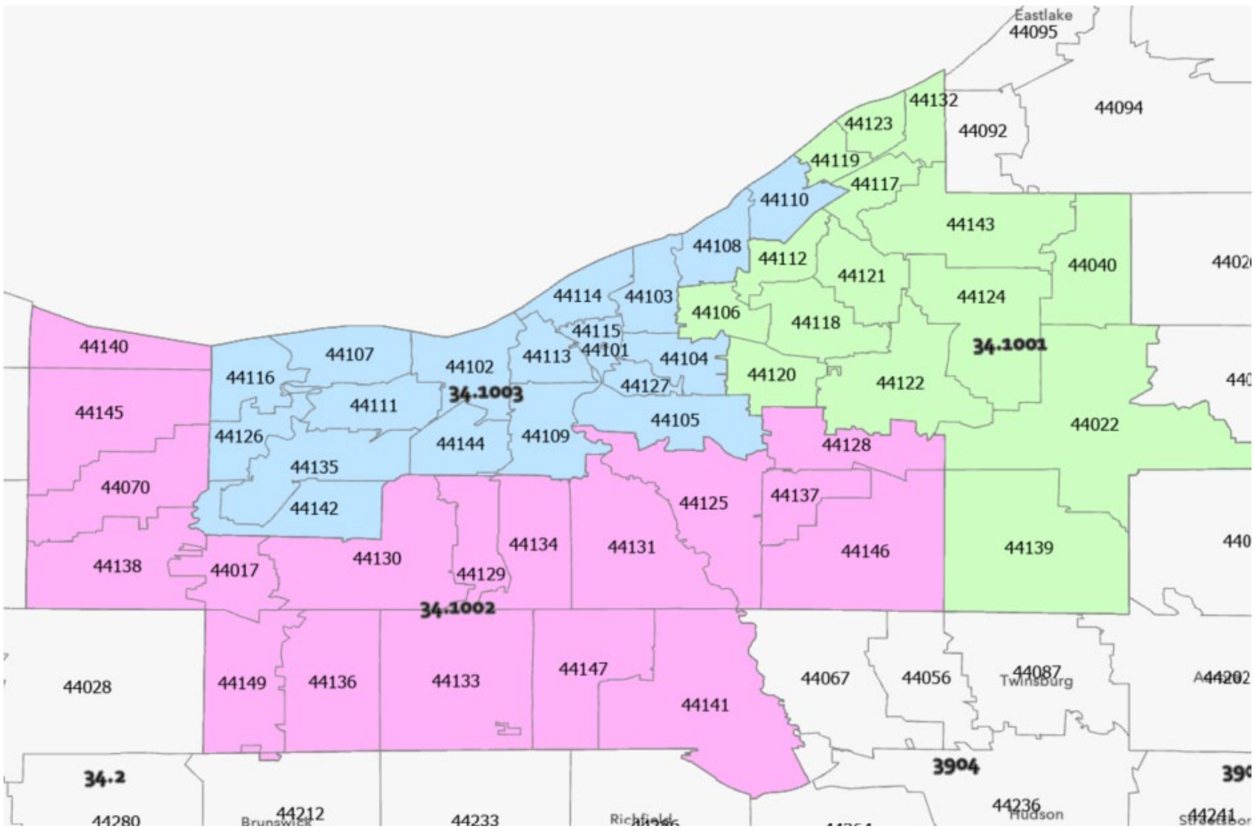


CntyGrp 33.1 – Marion County, IN
Zclusts:
1. 33.1001
2. 33.1002



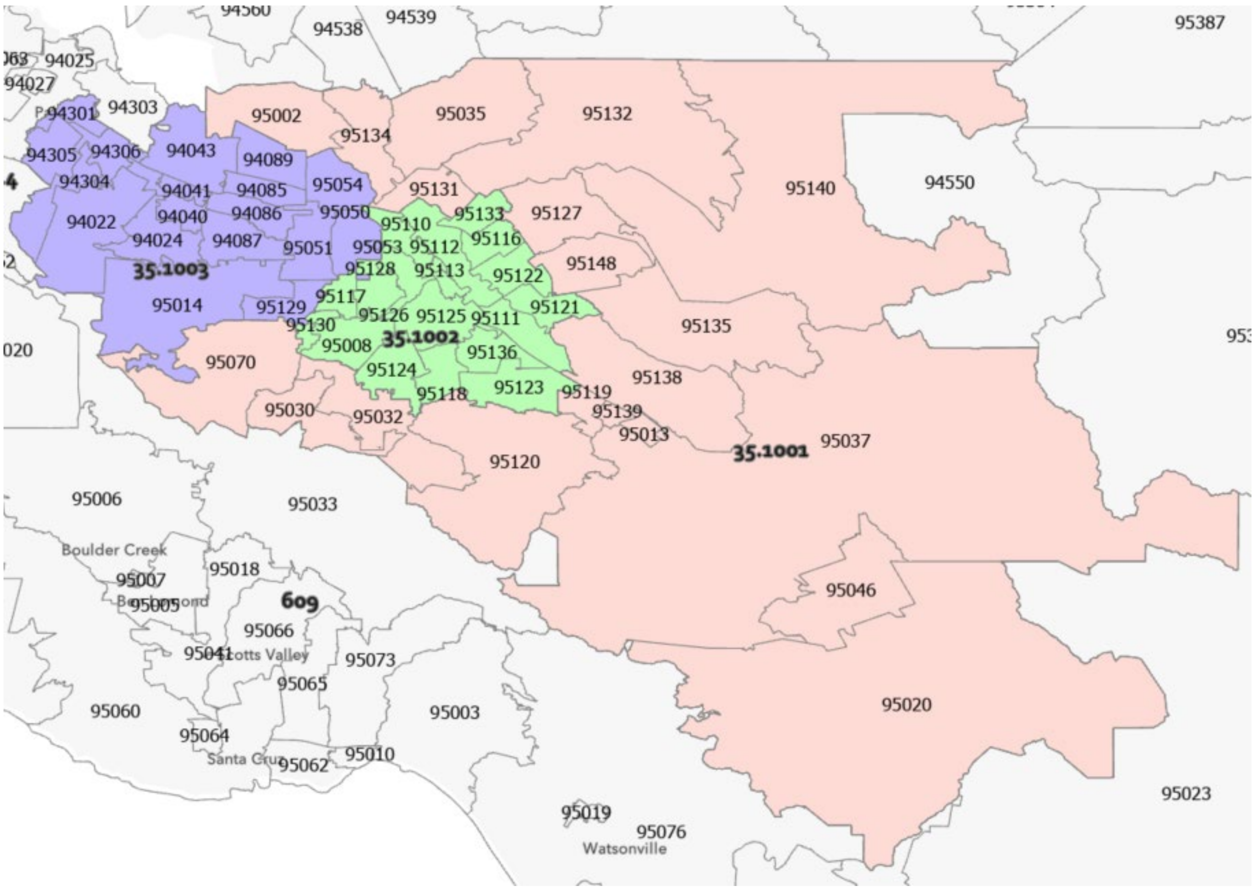
CntyGrp 34.1 – Cuyahoga County, OH
Zclusts:

1. 34.1001
2. 34.1002
3. 34.1003



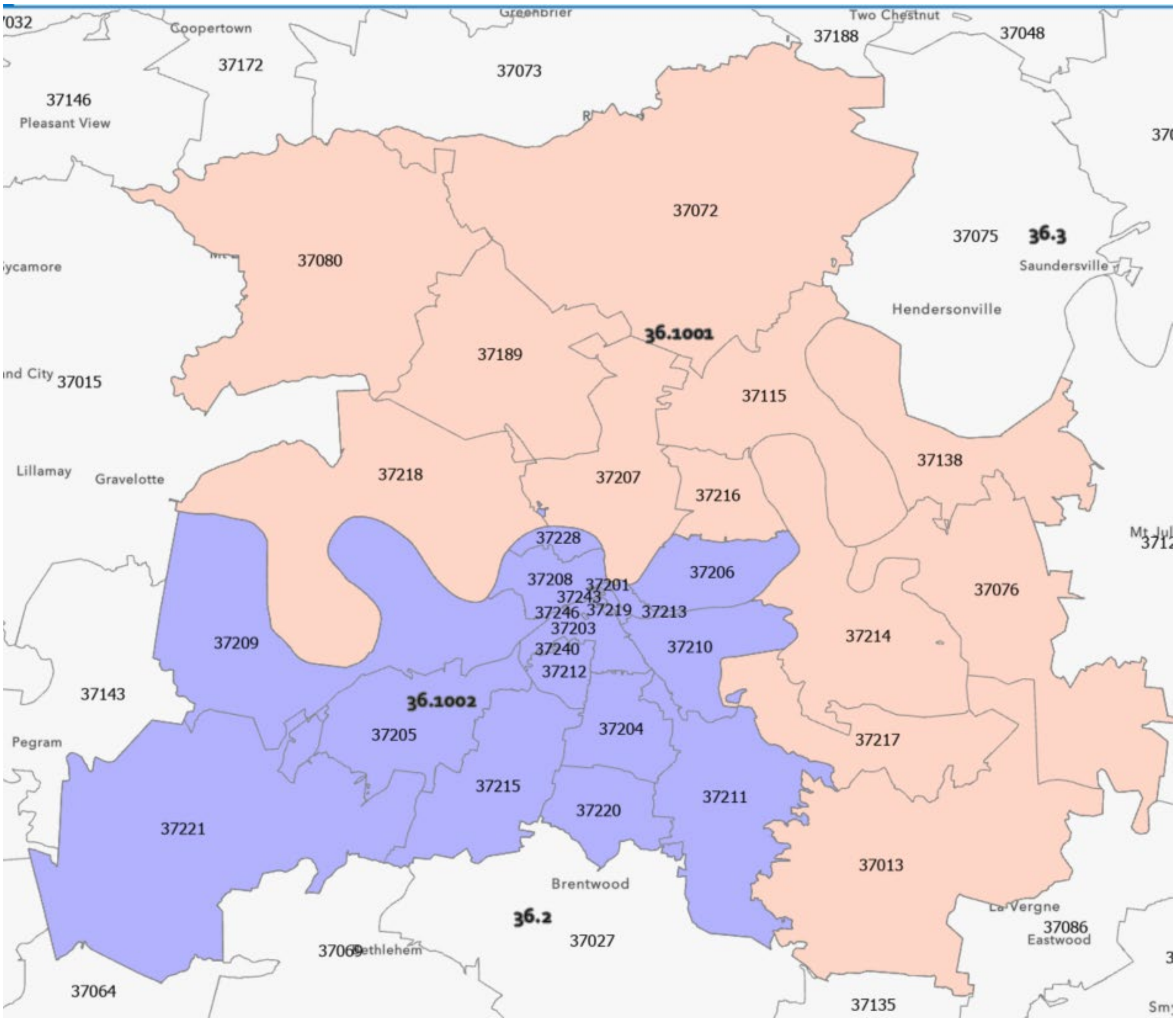
CntyGrp 35.1 – Santa Clara, CA
Zclusts:

1. 35.1001
2. 35.1002
3. 35.1003



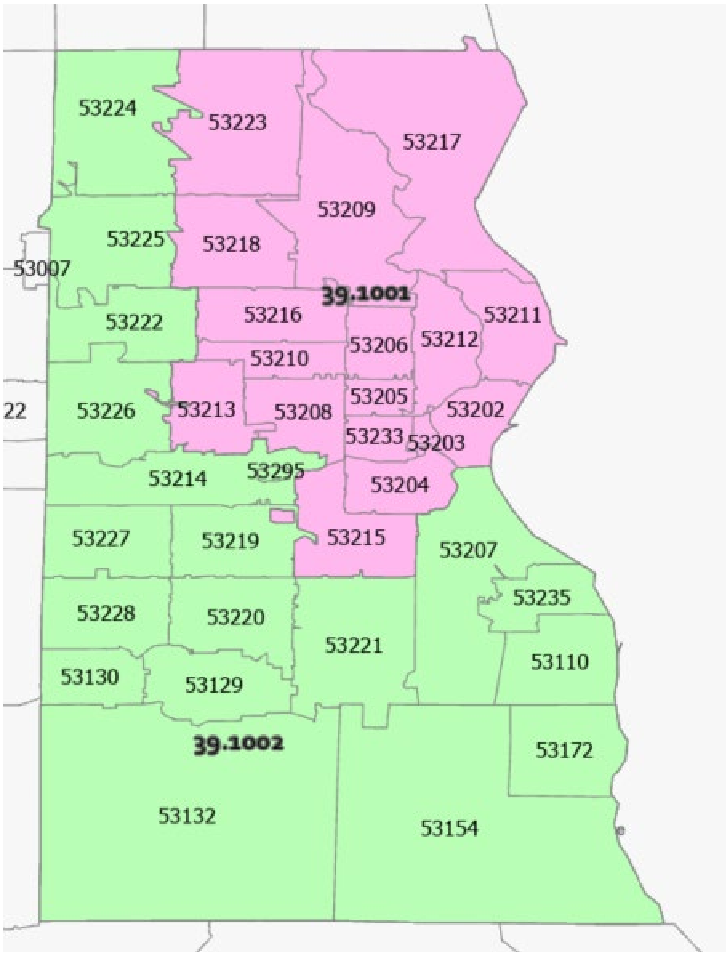
CntyGrp 36.1 – Davidson County, TN
Zclusts:

1. 36.1001
2. 36.1002



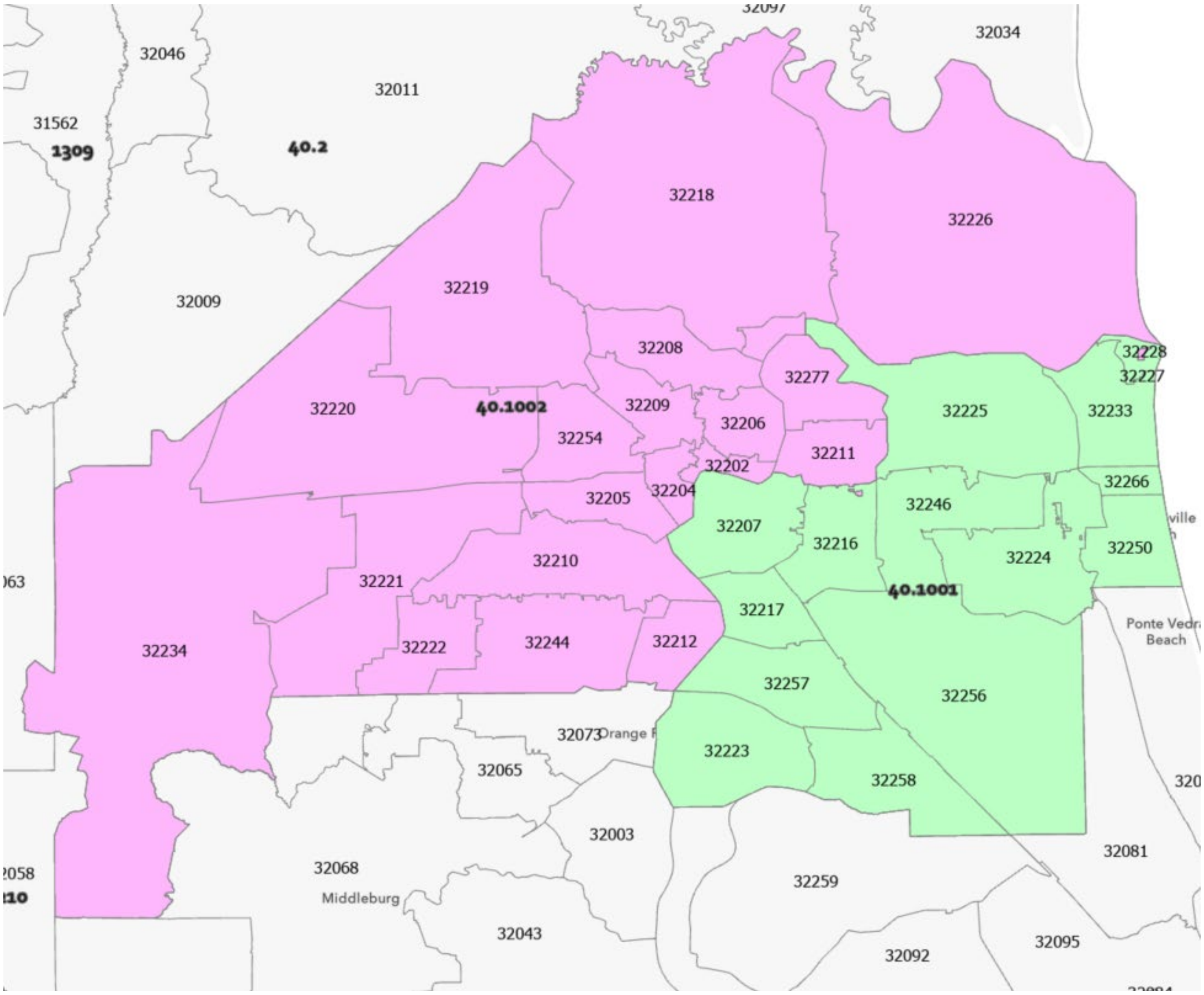
CntyGrp 39.1 – Milwaukee County, WI
Zclusts:

1. 39.1001
2. 39.1002



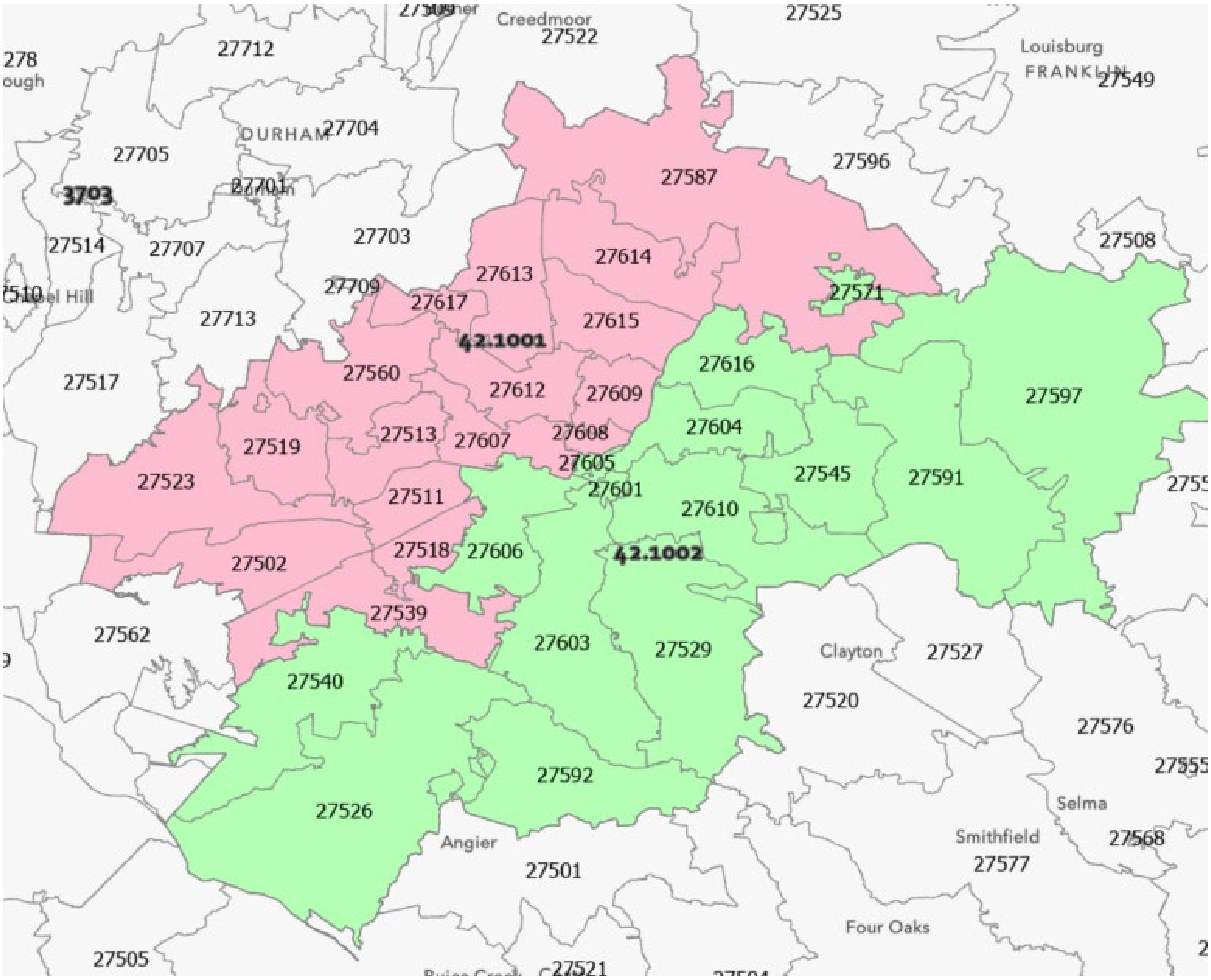
CntyGrp 40.1 – Duval County, FL
Zclusts:

1. 40.1001
2. 40.1002



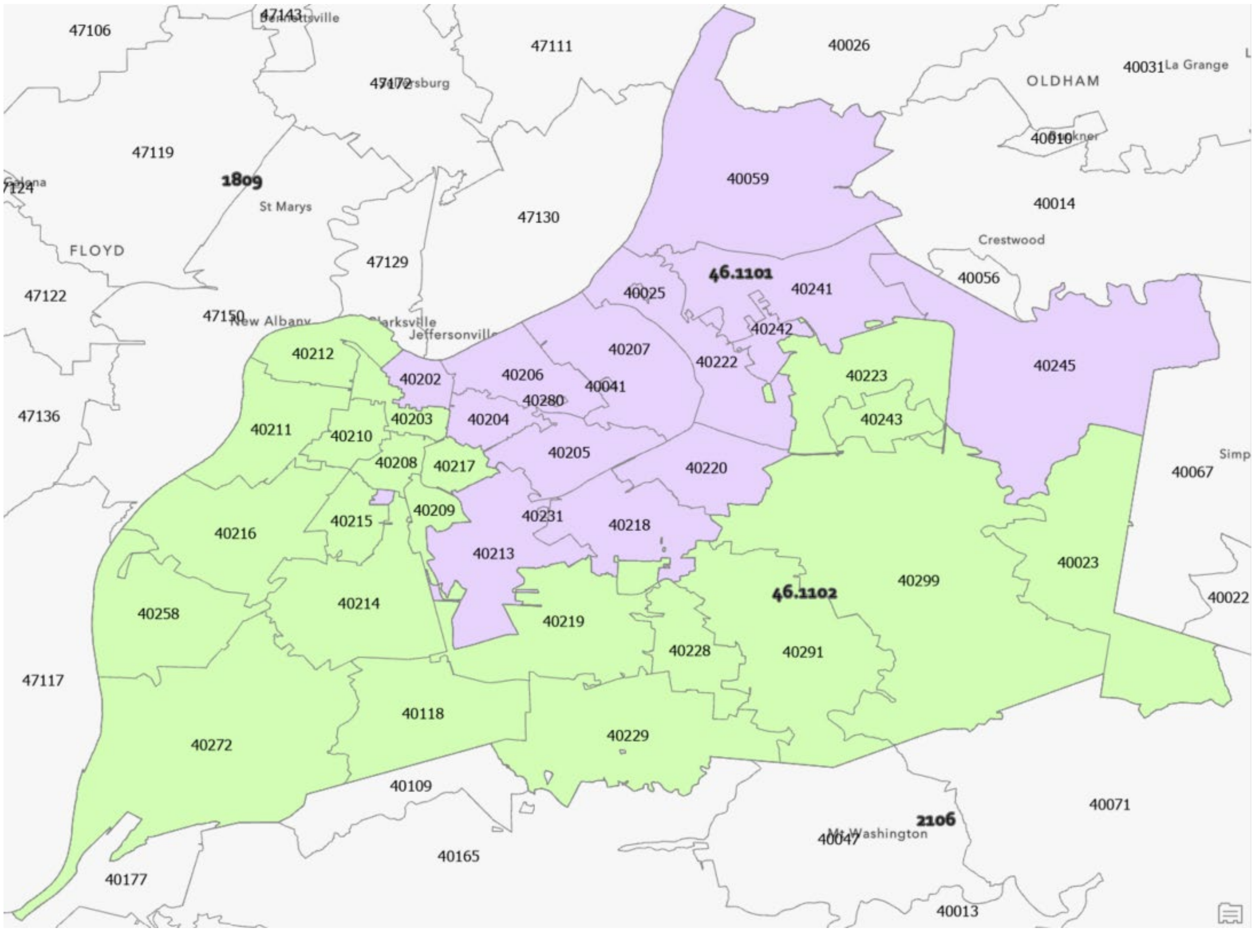
CntyGrp 42.1 – Wake County, NC
Zclusts:

1. 42.1001
2. 42.1002



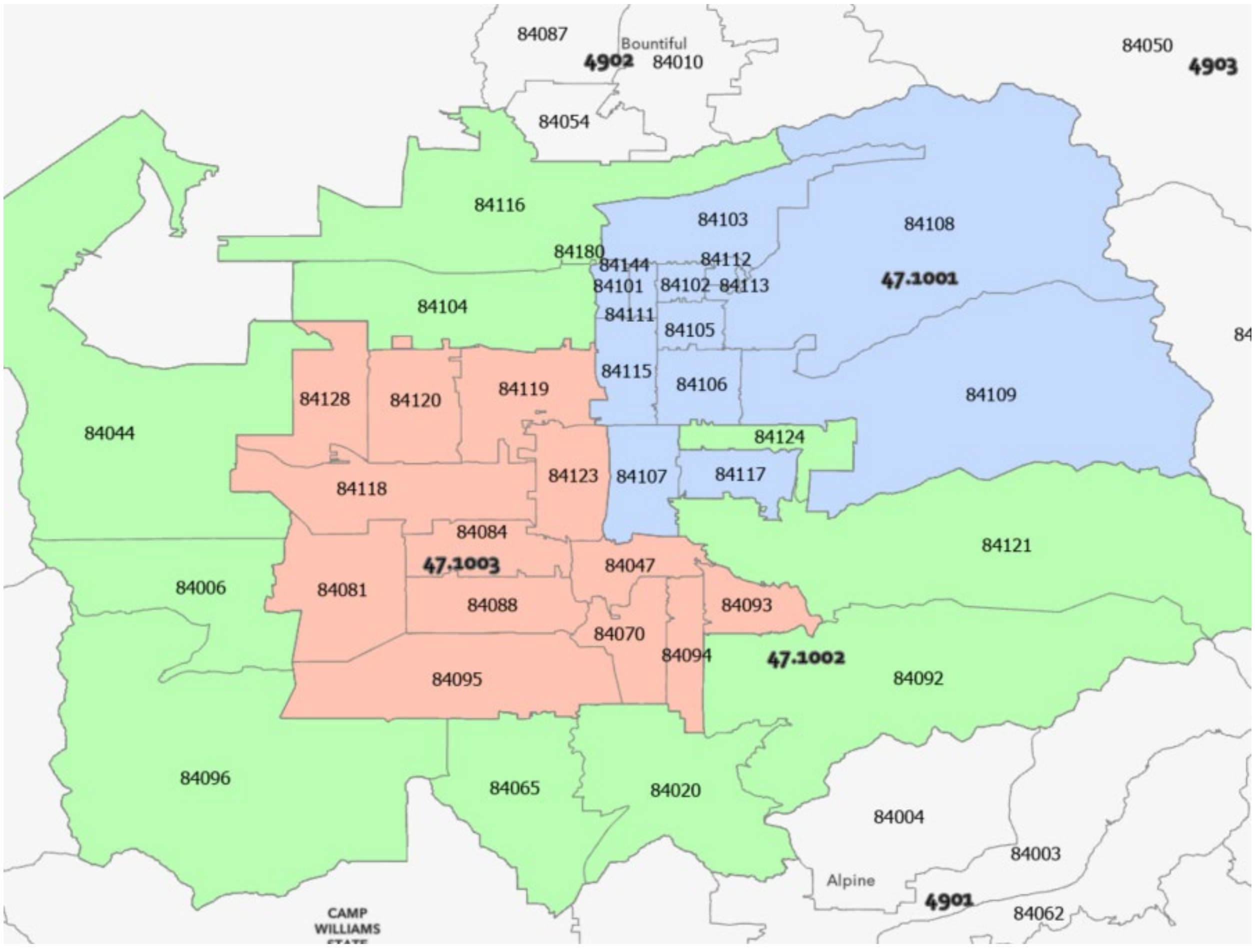
CntyGrp 46.11 – Jefferson County, KY
Zclusts:

1. 46.1101
2. 46.1102



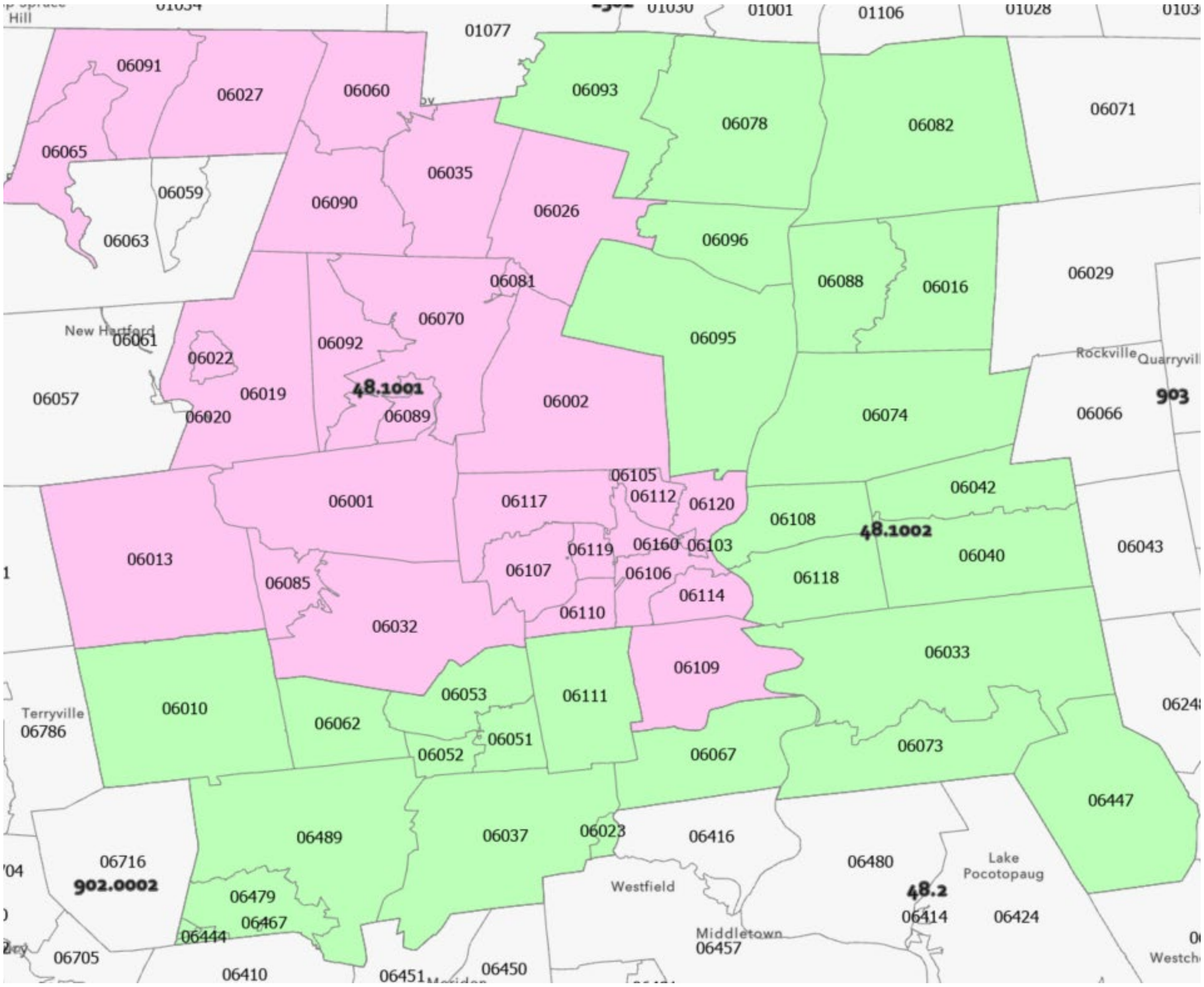
CntyGrp 47.1 – Salt Lake County, UT
Zclusts:

1. 47.1001
2. 47.1002
3. 47.1003



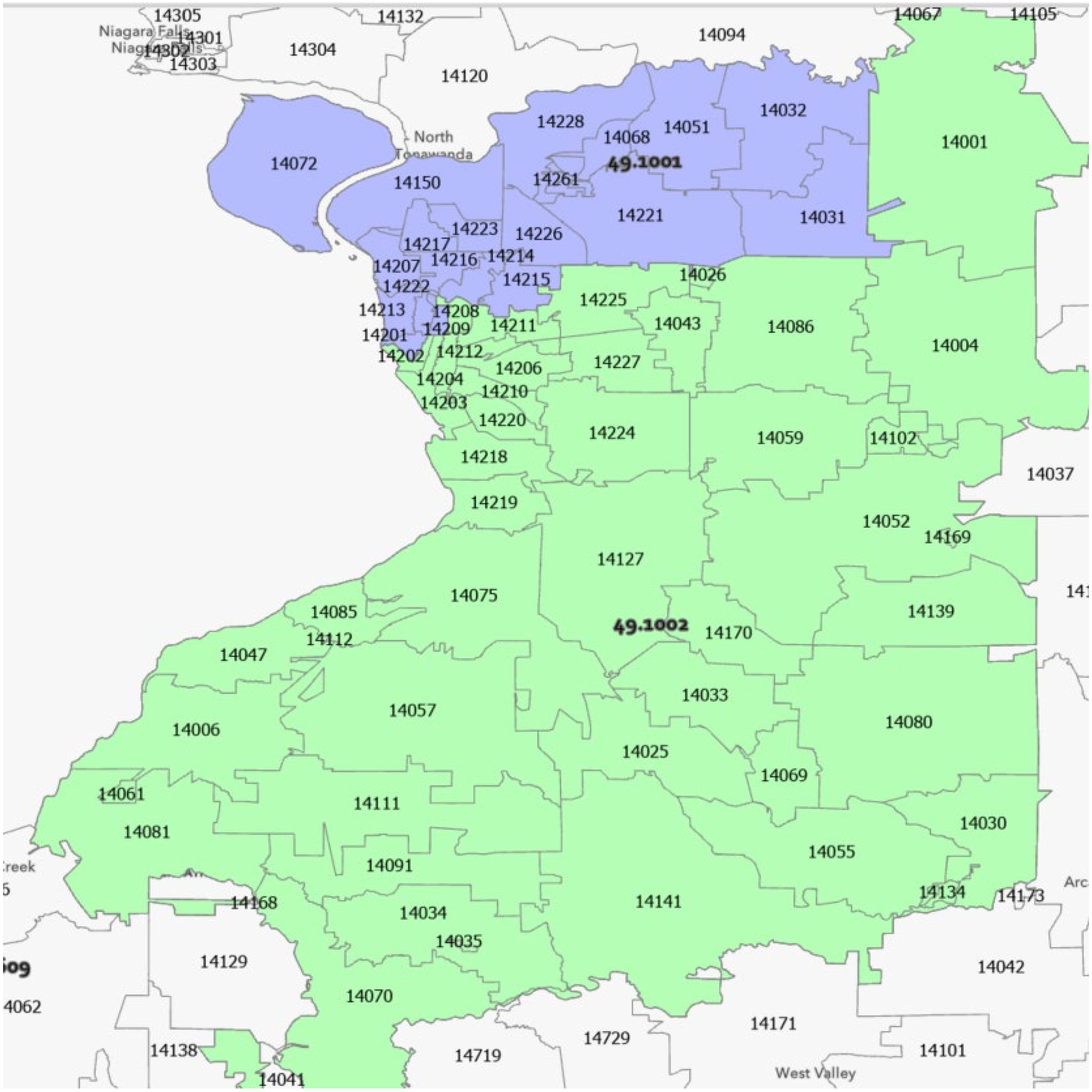
CntyGrp 48.1 – Hartford County, CT
Zclusts:

1. 48.1001
2. 48.1002



CntyGrp 49.1 – Erie County, NY
Zclusts:

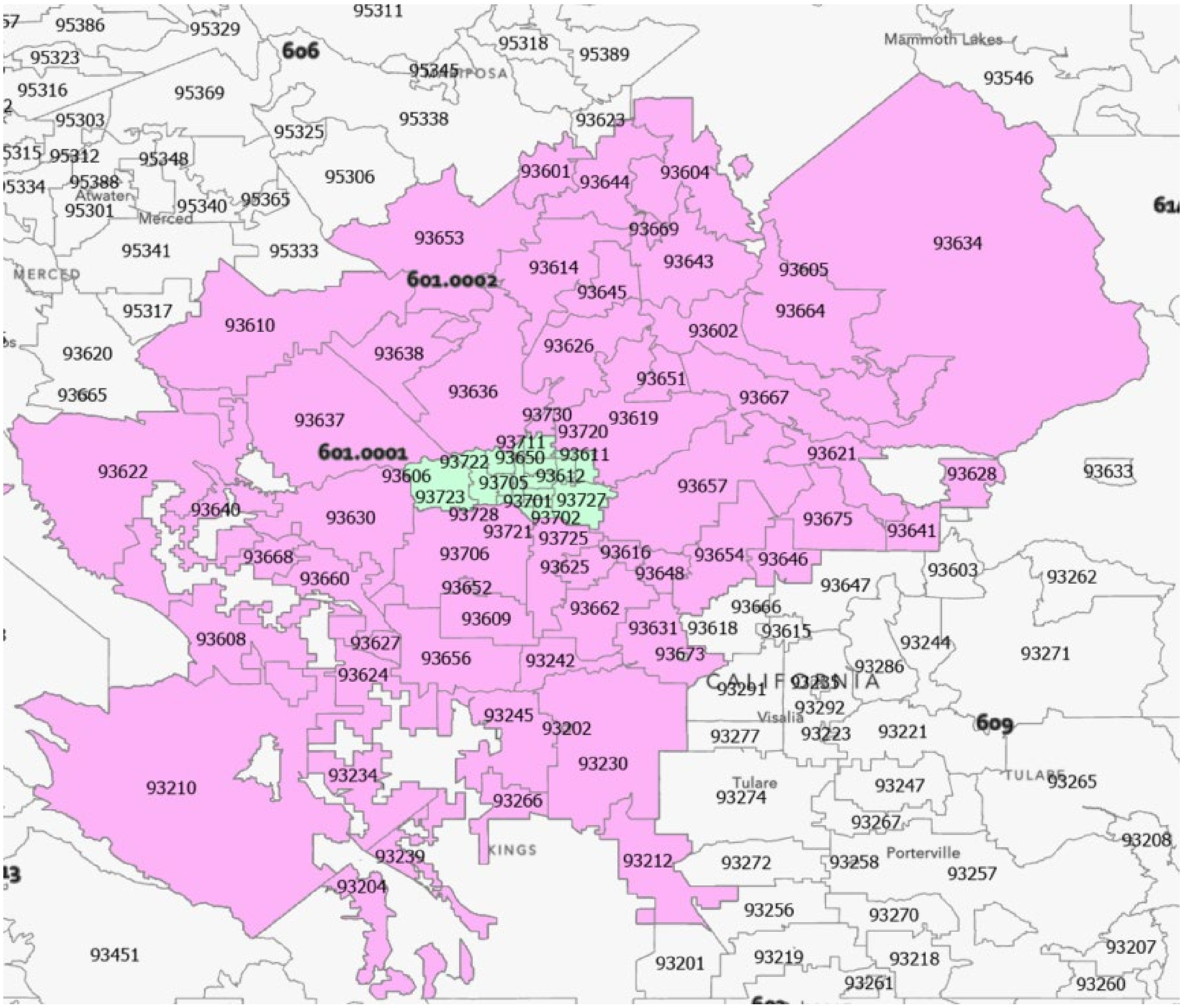
1. 49.1001
2. 49.1002



CntyGrp 401 – Pima County, AZ
Zclusts:

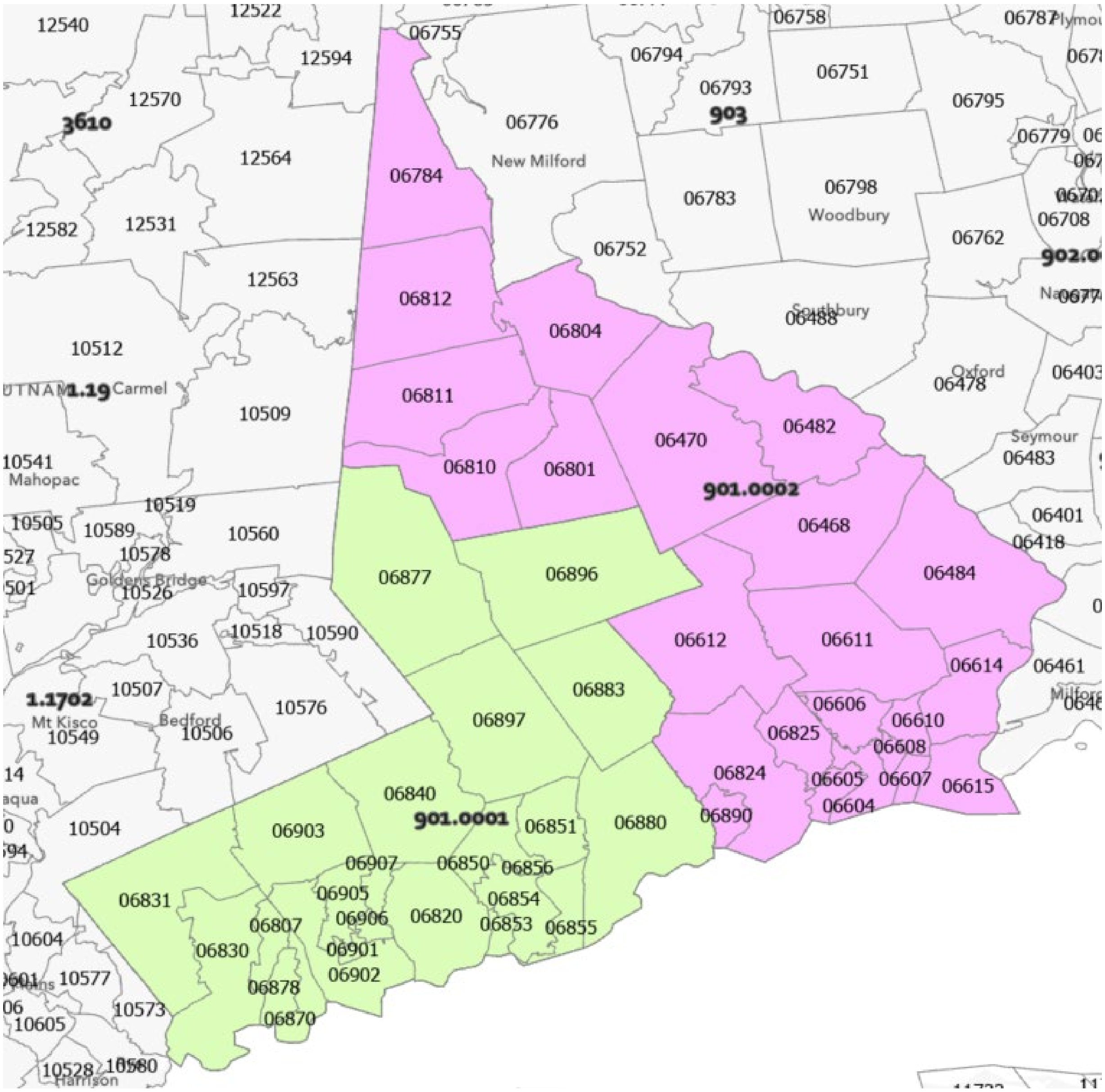
1. 401.0002
2. 401.0001

CntyGrp 601 – Fresno/Kings/Madera Counties, CA
Zclusts:
1. 601.0001
2. 601.0002



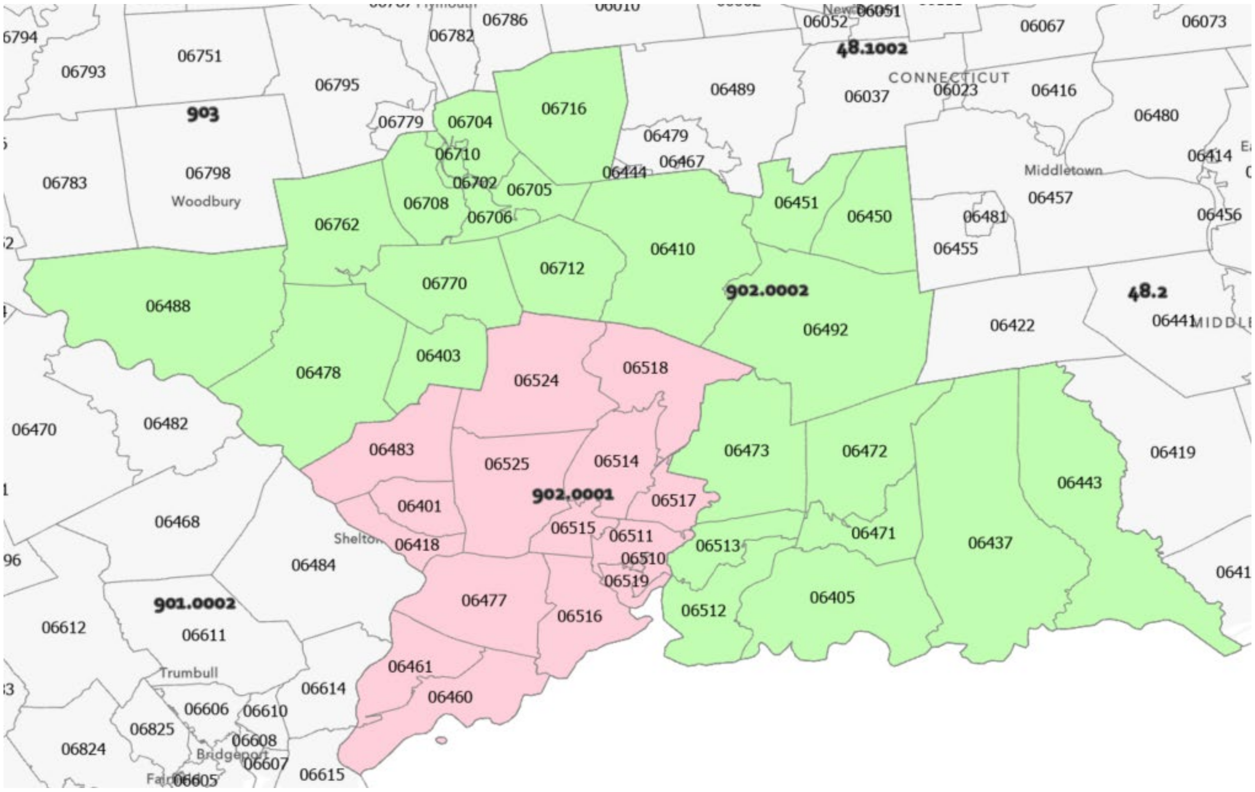
CntyGrp 901 – Fairfield County, CT
Zclusts:

1. 901.0001
2. 901.0002



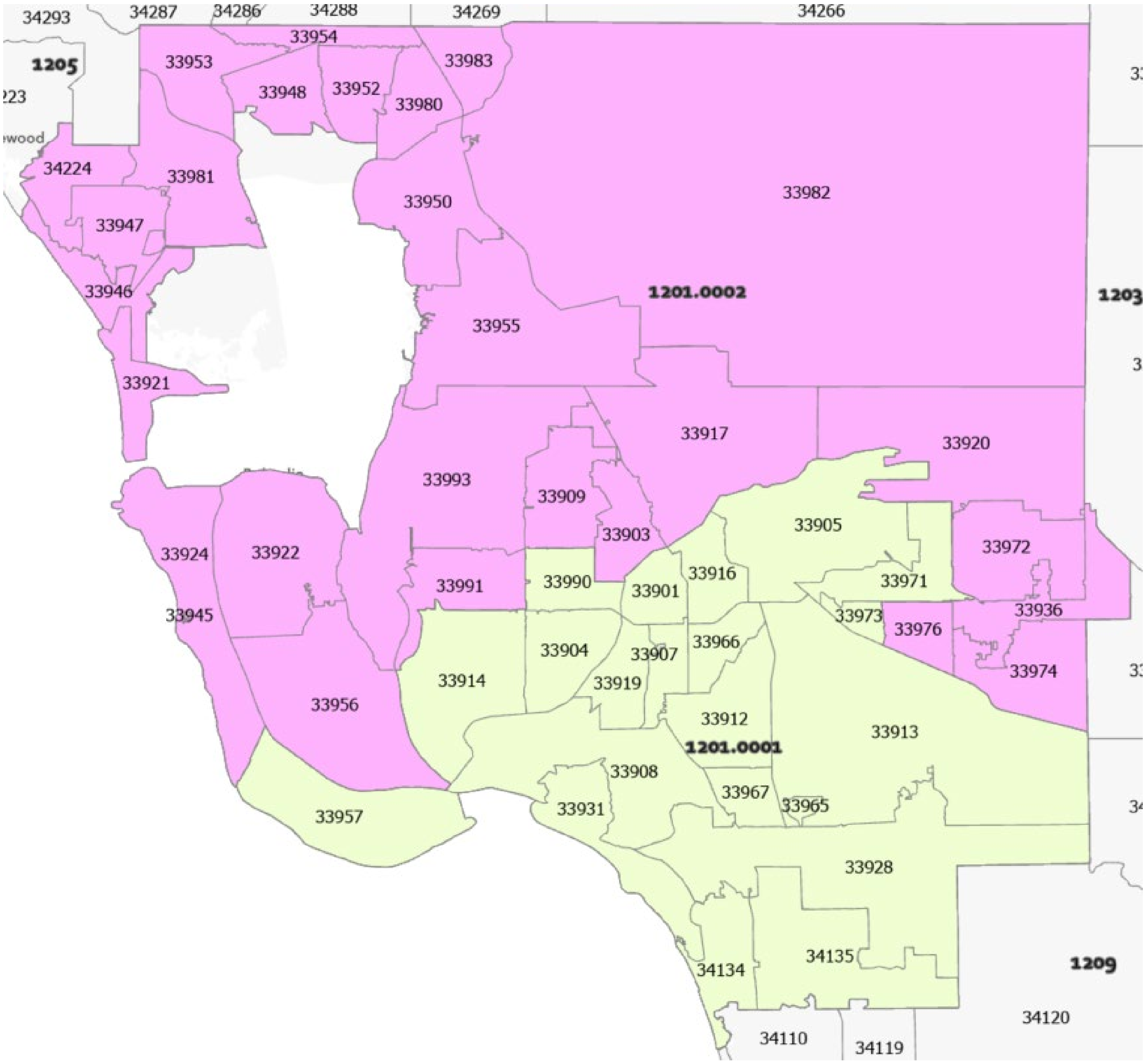
CntyGrp 902 – New Haven County, CT
Zclusts:

1. 902.0001
2. 902.0002



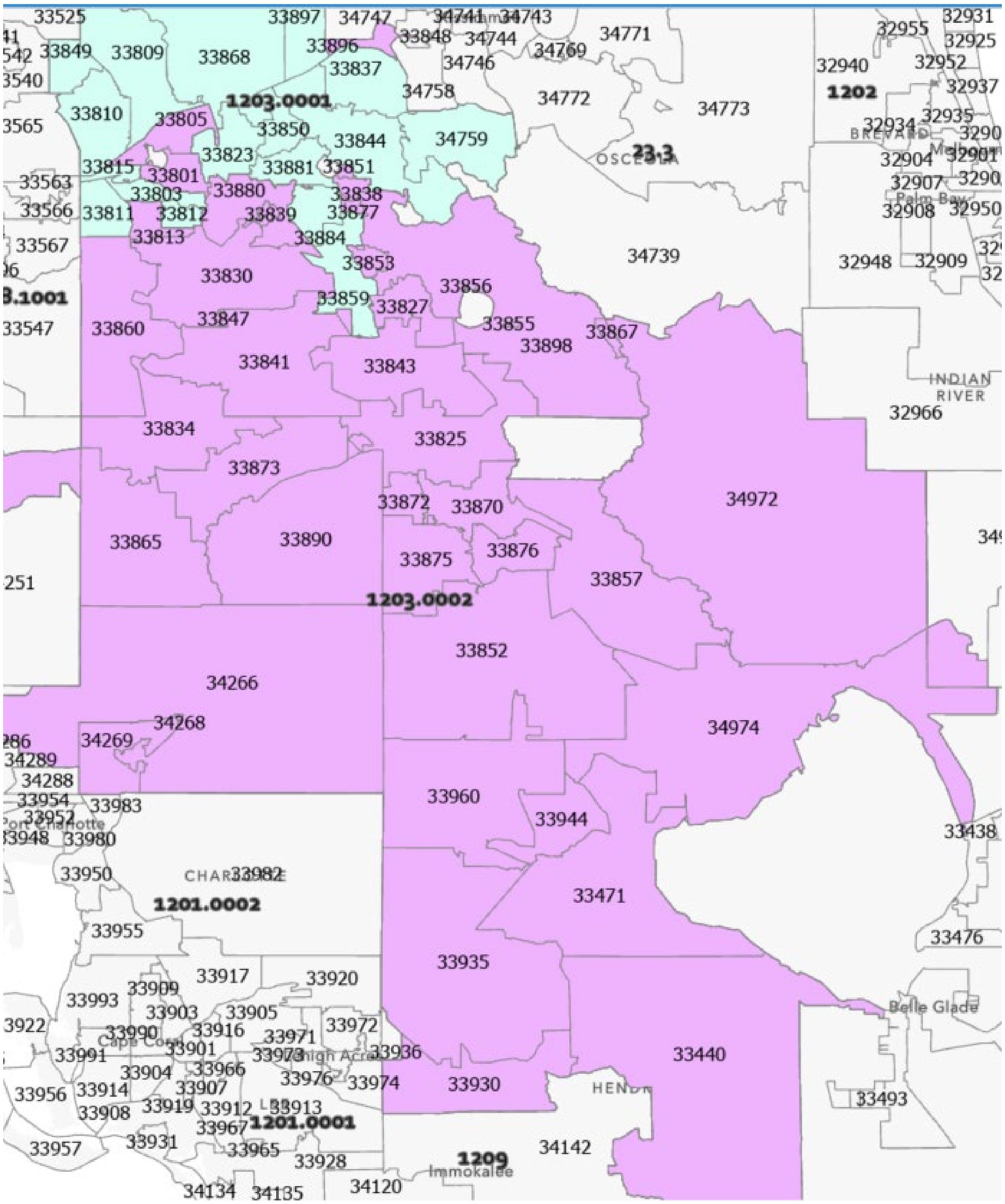
CntyGrp 1201 – Charlotte/Lee Counties, FL
Zclusts:

1. 1201.0001
2. 1201.0002



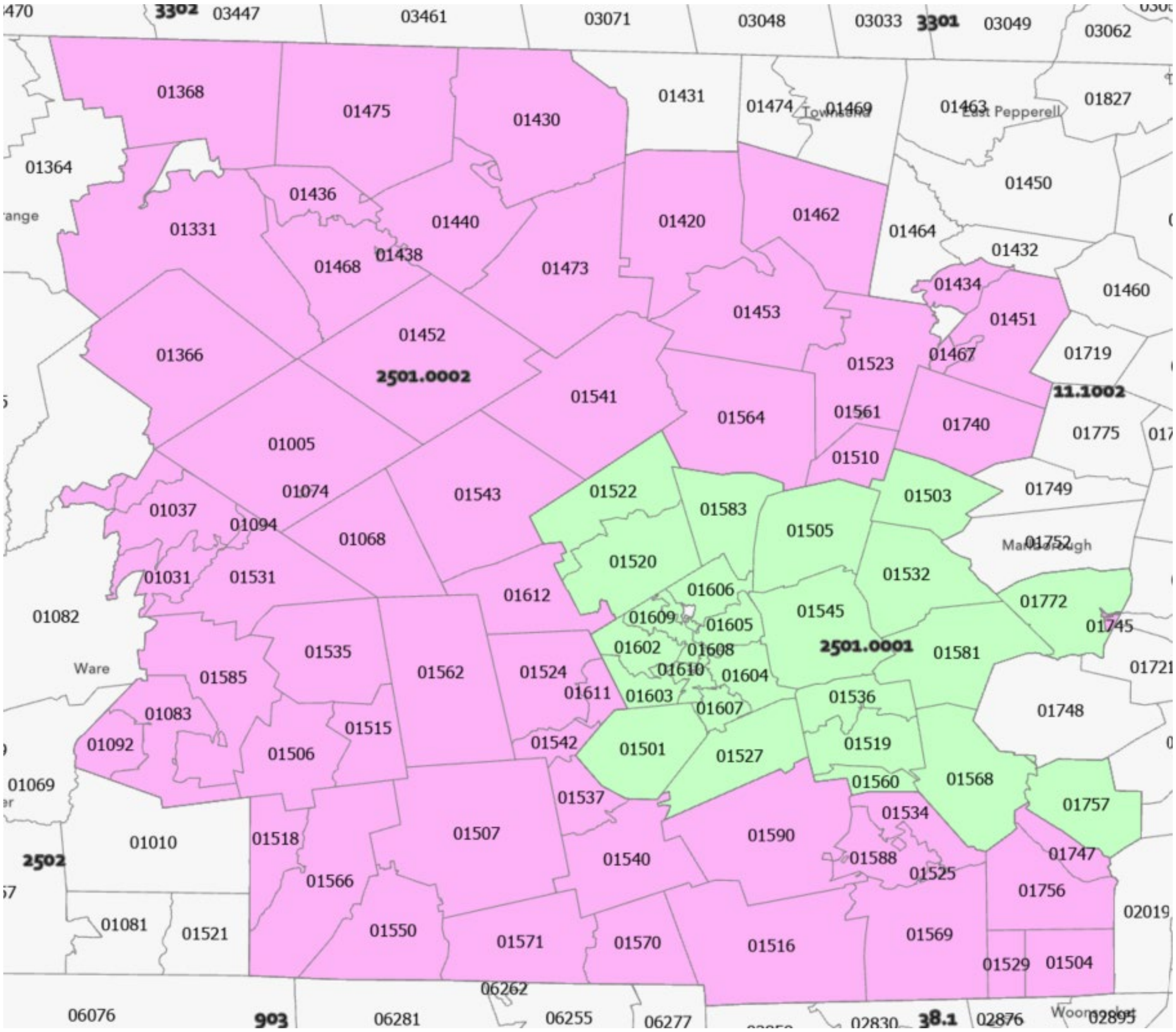
CntyGrp 1203 – Highlands and Surrounding Counties, FL
Zclusts:

1. 1203.0001
2. 1203.0002



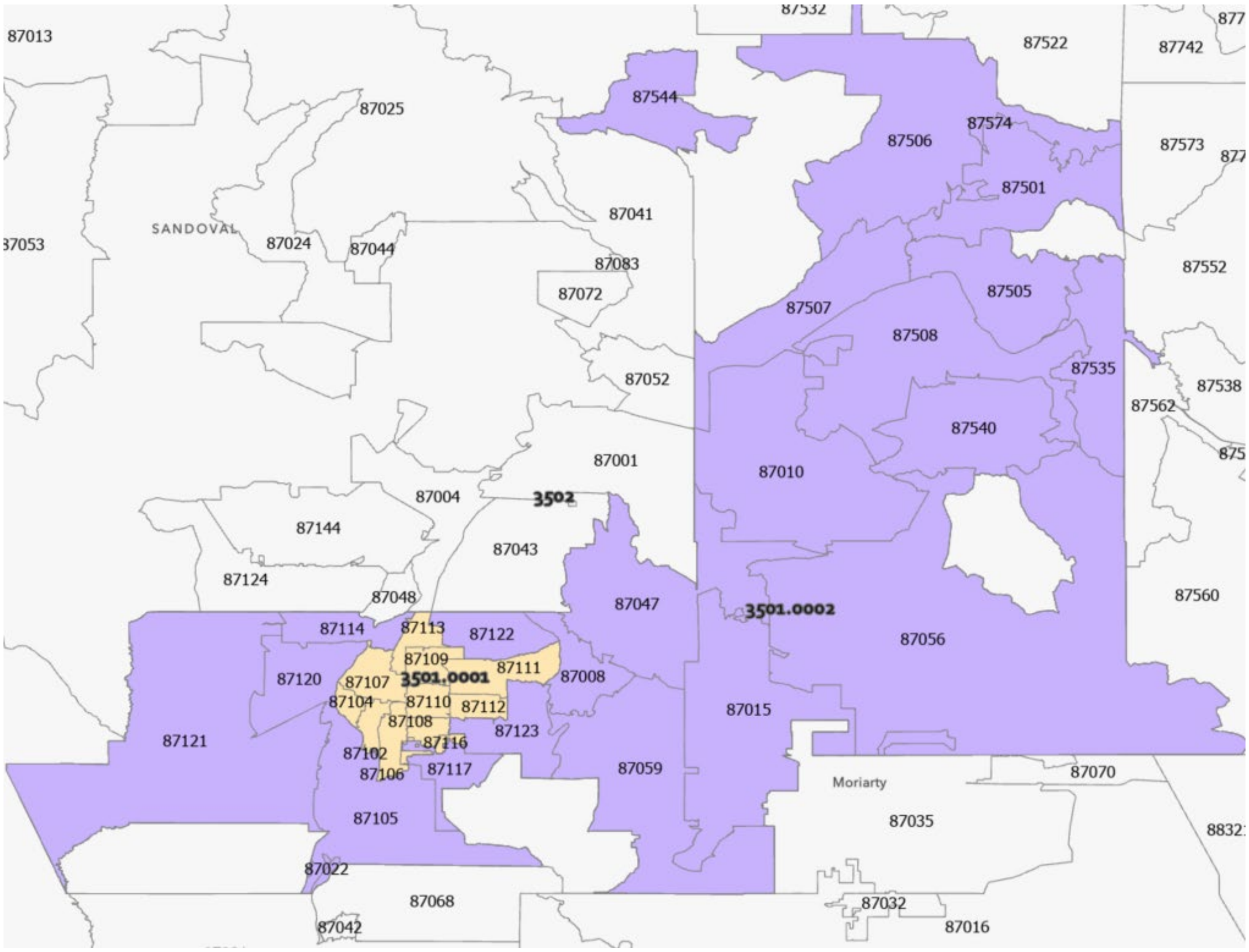
CntyGrp 2501 – Worcester County, MA
Zclusts:

1. 2501.0001
2. 2501.0002

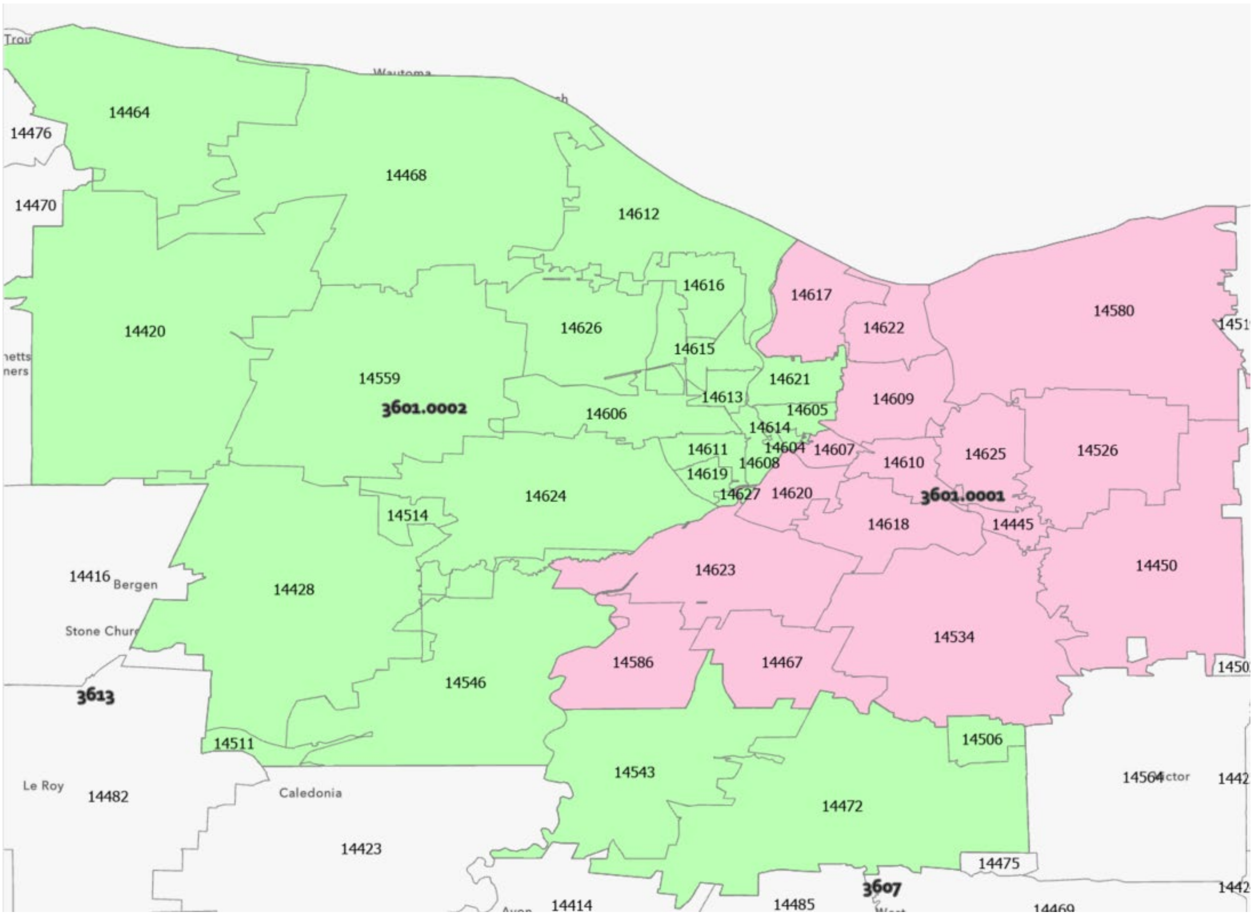


CntyGrp 3501 – Albuquerque-Santa Fe Area, NM
Zclusts:

1. 3501.0001
2. 3501.0002

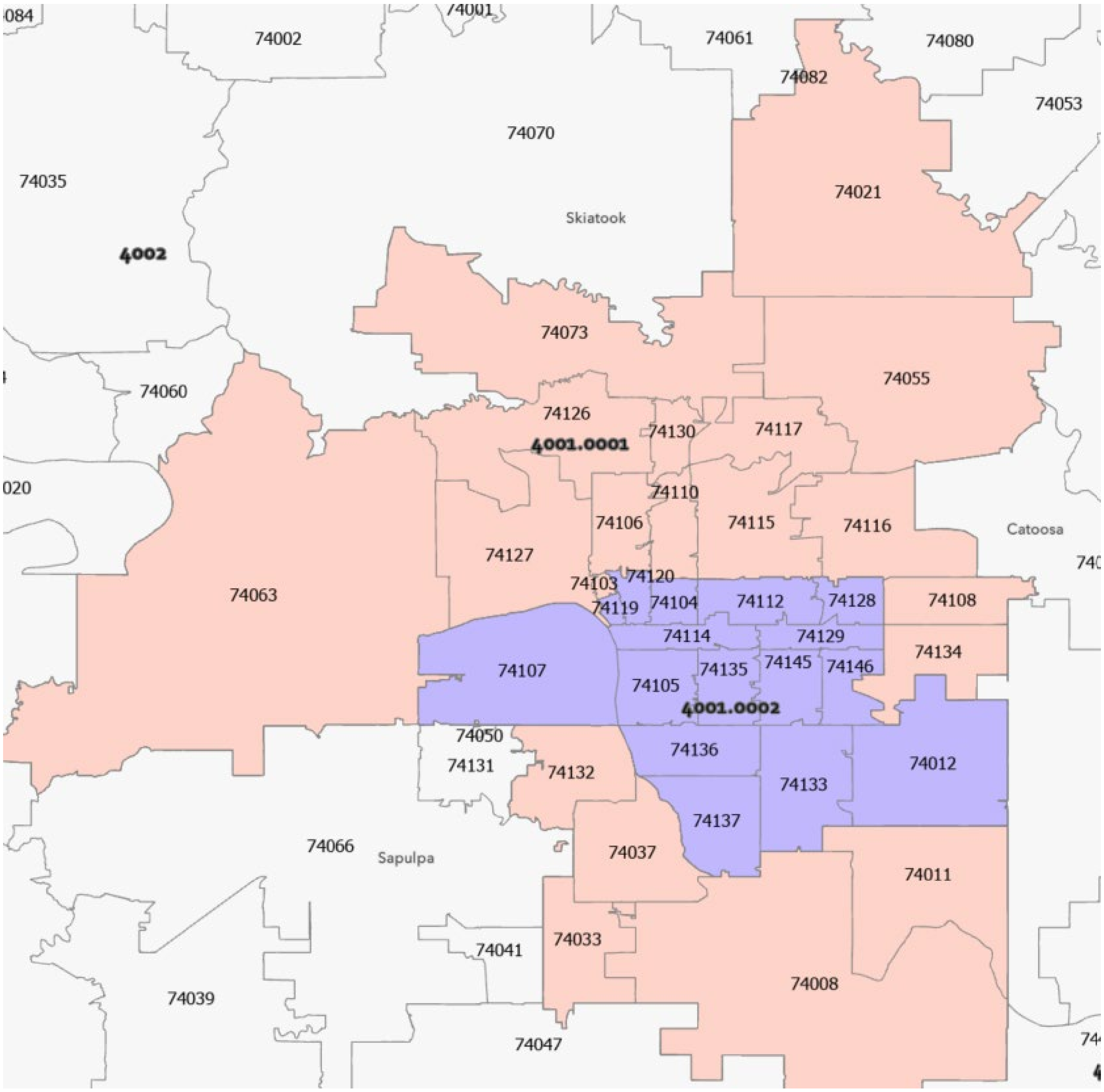


CntyGrp 3601 – Monroe County, NY
Zclusts:
1. 3601.0001
2. 3601.0002



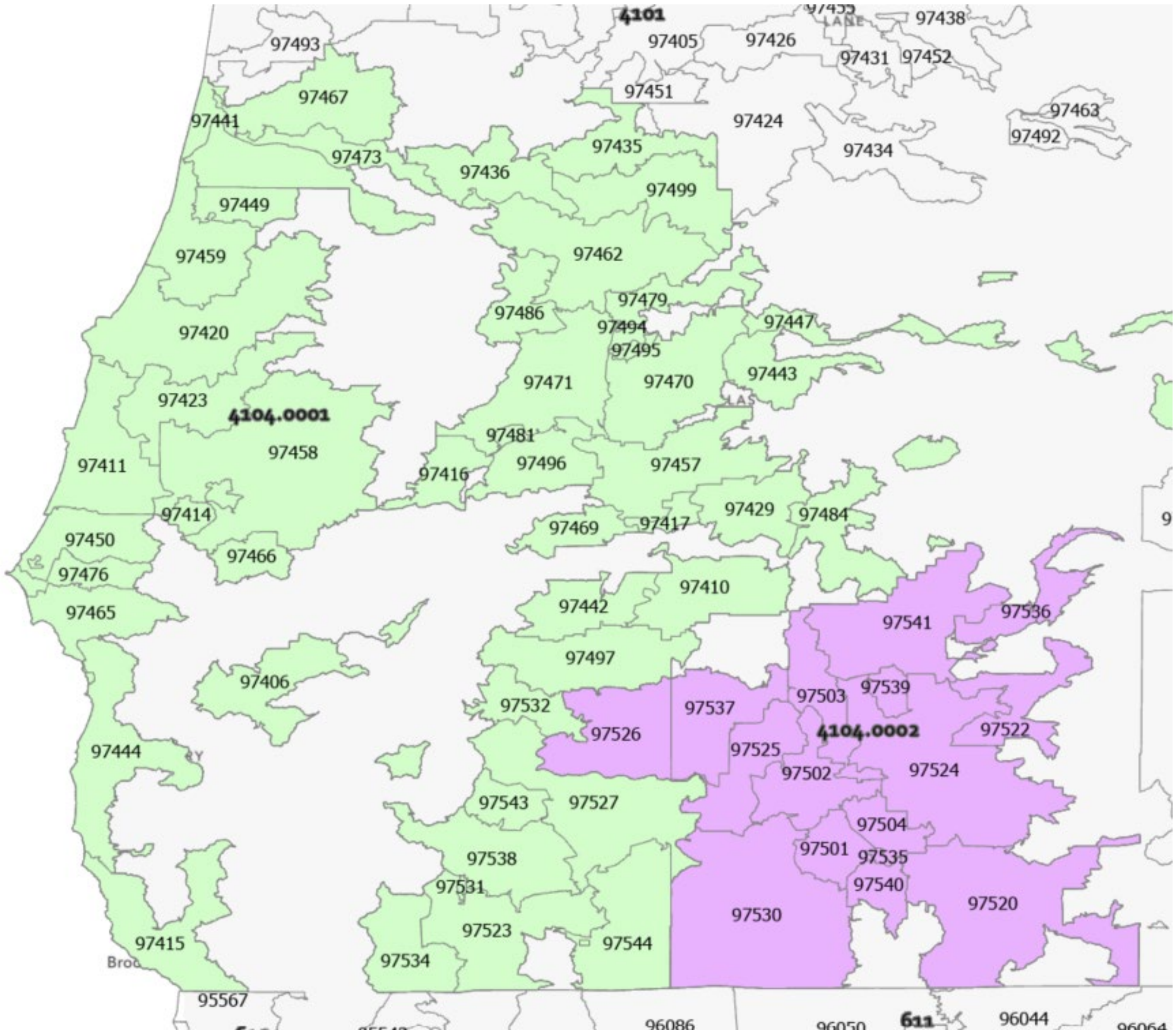
CntyGrp 4001 – Tulsa County, OK
Zclusts:

1. 4001.0001
2. 4001.0002



CntyGrp 4104 – Southwestern Counties, OR
Zclusts:

1. 4104.0001
2. 4104.0002



CntyGrp 4208 – Harrisburg and Outlying Area, PA
Zclusts:

1. 4208.0001
2. 4208.0002