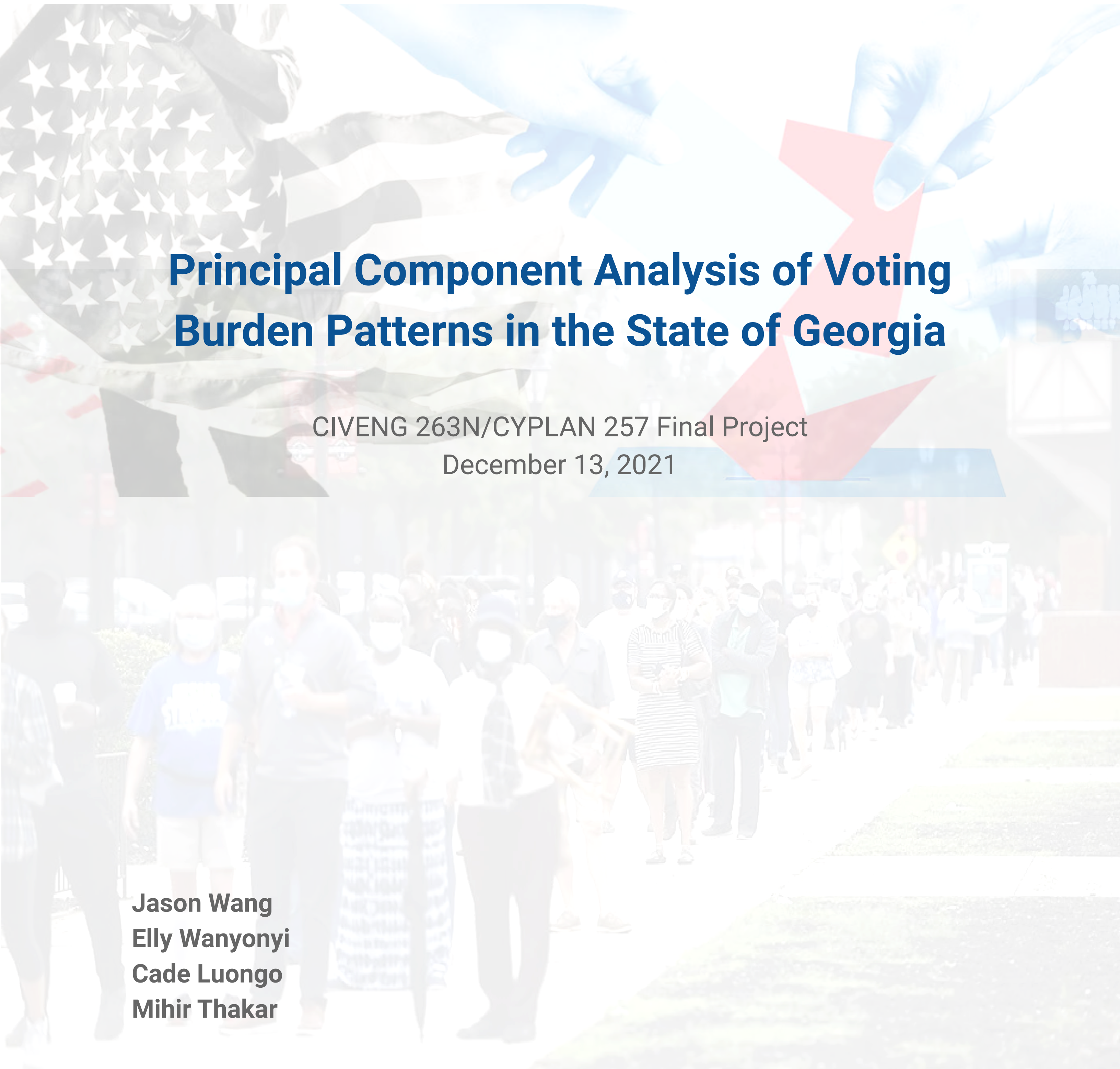

Principal Component Analysis of Voting Burden Patterns in the State of Georgia

CIVENG 263N/CYPLAN 257 Final Project
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Abstract

Equal access to voting is a core feature of a democratic government. In the recent past, however, state governments have passed legislation which has the potential to reduce access for some voters. New requirements in these states include photo identification, proof of citizenship requirements, registration restrictions, restrictions on absentee ballot voting, and reductions in early voting. These restrictions increase demand for in-person voting, particularly on election day and discourages voting using absentee ballots. There has been little analysis of whether these requirements reduce voter participation and impose a disproportionate burden on certain classes of voters. In an effort to bring empirical clarity to what has been a deeply charged, partisan, and frequently anecdotal debate regarding voter restrictions, we examined the impact of a new voting law, the “Election Integrity Act of 2021” (Georgia Senate Bill 202), on the voting burden experienced by Georgia’s electorate. To generate clusters and identify demographic groups with the highest voting burden, Principal Component Analysis (PCA) was performed on demographic data from 5533 census block groups after they were mapped to 2213 polling stations. In addition, we used Google Directions API and a deterministic queueing model to estimate waiting time, queue length and maximum distance from home. We find that deterministic queueing models are not sufficient to estimate average voter waiting times due to uncertainty in the capacity of polling stations. Round trip travel times from block groups to polling stations is shown to be correlated with income. That is, the clusters that exhibit the highest voting burden, now quantified by round trip travel time only, also exhibit the lowest income. Conversely, clusters that exhibit the lowest voting burden also exhibit the highest income. By plotting clusters with high and low voting burden onto census block groups, it is simple to propose additional or mobile voting sites to alleviate voting travel and waiting burden. We situate these findings within developments in social welfare and criminal justice policy that collectively increase electoral access among the socially marginalized populations.

1. Introduction

In recent years, several studies[1][2] have proven that strict voter ID requirements disproportionately affect African American, Hispanic, and Asian voters. The purpose of this project was to explore the impact of a voter ID law recently enacted in Georgia. This legislation shares many provisions in common with the laws previously studied, such as a reduced window for absentee ballot applications, which suggests that this law could potentially make it harder for people of color to cast a vote, and, consequently, decrease voter turnout most noticeably among minorities.

On March 25, 2021, Georgia passed the Election Integrity Act of 2021, also known as Senate Bill 202, following the first democratic victories in presidential and Senate elections in Georgia in a generation [1]. This law enacted several restrictions that curtail access to absentee ballots for voters in populous urban and suburban counties. The law made the following changes to voting logistics: (1) mail-in ballot requests will begin 11 weeks before an election, a reduction from the previous period of 180 days [2], (2) the final deadline to complete an application is moved earlier by a week, (3) ballot drop boxes will only be accessible indoors during business hours, rather than 24/7 outdoors, (4) absentee ballots will be mailed to voters roughly three weeks later than before, beginning four weeks before the election, and (5) requesting and returning a ballot will require new ID rules: either your driver's license number, state ID number or, if you don't have those, a copy of acceptable voter ID. These new provisions will reduce the ability of voters to cast their ballots early and, in turn, will shift voting demand to in-person polling stations on election day. If no measures are taken to improve capacity, this increased demand could conceivably worsen voting burden throughout the state.

The basis of our methodology for quantifying voting burden is an analysis previously conducted by Professor Daniel Chatman of UC Berkeley. Chatman evaluated the potential impact of voting reforms on the travel burdens and queueing delays experienced by voters in Travis County, Texas. On October 1, 2020, Texas “Governor Abbott issued a Proclamation limiting each county to a single in-person ballot return location prior to” the November 2020 general election, whereas in previous elections counties had multiple ballot drop off locations [5]. Professor Chatman was asked by the Texas Third District Court of Appeals to provide an expert opinion regarding the impact of this decision. His analysis focused on three broad areas:

- The travel burden for the elderly and disabled individuals who will have time-consuming and uncomfortable trips, disproportionately on public transportation or on foot due to their not having access to a personal vehicle in their household, to access a ballot drop box under the current rule.
- The queue lengths are associated with large potential demand for access to ballot drop boxes due to the circumstances of this election and based on comparisons with other locations that have implemented drop boxes as a ballot delivery option.
- Impact assessment across the major racial/ethnic groups in the state.

In Chatman’s study, a significant “travel burden” was defined as a round trip of an hour and a half or longer, which would more than double the average amount of daily household travel for a

Texas resident. The share who would have to travel for more than 90 minutes was very low for absentee-eligible citizens of voting age who live in a household with access to a personal vehicle, but very high for those without access to a car, who make up about 7.5 percent of absentee-eligible citizens of voting age in the state. About 89 percent of absentee-eligible citizens of voting age without access to a car would have to spend more than 90 minutes to deliver their ballot to a county drop box and return home. The 10 most populous counties in the state account for more than half of all burdened individuals. Several counties have a 90-minute travel burden share that is 30 to 60 percent more than the rest of the counties in the state.The presence of households with a travel burden is also highly correlated with poverty status.

The second analysis estimated how the restriction permitting only one location for drop boxes per county is likely to lead, in counties with larger populations, to long queues of vehicles and pedestrians waiting to drop off their ballots. The findings showed that lines would be particularly burdensome in the top ten counties by population in the state, with between 10,000 and 64,000 voters in each of those counties waiting for 15 hours or more to drop off their ballots.

Using Chatman's measurement of voting burden as round trip travel time combined with wait time, for polling stations rather than drop boxes in this case, our study aimed to determine the burden that Georgians would experience when voting in-person on election day. With the new legislation limiting absentee and early voting, voting demand on election day will only increase and a greater proportion of the voters will be subject to increased burden going forward.

Our analysis began with cleaning demographic data for different geographic areas within Georgia and estimating which polling station they would be likely to vote at. Then, we calculated the voting burden by determining an average travel time from each geographic area to their paired polling station as well as developing a queueing model for the average wait time at each polling station. Finally, we conducted Principal Component Analysis on the geographies and clustered them to identify which populations were subjected to the most significant voting burden.

2. Data & Methods

2.1 Data

To explore the impact of Georgia's new voter ID law, we collected statewide demographic data and identified Georgia's most recent polling locations along with a measure of their capacities.

Demographic information was obtained from the 2010 U.S. Census, since 2020 Census data was not yet available at the time of this study. For each of the 5533 block groups in Georgia, we gathered the following information:

- Population of one race - White alone
- Population of one race - Black or African American alone
- Population of one race - Asian alone
- Hispanic or Latino Origin
- Total Population
- Citizen Voting Age Population
- Income and Earnings **(by Census tract)**
- Vehicles Available **(by Census tract)**
- Disability Status **(by Census tract)**

These demographic variables were chosen since they would be informative in evaluating which groups — such as high or low-income households, voters with or without access to a car, disabled persons, or certain races — tend to experience the greatest obstacles against in-person voting. The geographic boundaries of the Census block groups were also obtained, which were necessary in evaluating travel time to and demand for voting at each polling station.

Our snapshot of Georgia's most recent voting infrastructure was provided by Stephen Fowler from Georgia Public Broadcasting (GPB), whose dataset included the (2269) polling station locations and their hourly voter check-ins during the 2020 Democratic Primary Election. These locations were used for travel time analysis from the nearest block group centroids, while their check-ins were manipulated to develop an estimate for each polling station's capacity, which formed a key input for our model of time spent in a voting queue.

Finally, voter turnout data was obtained from the Georgia Secretary of State's office for the 2020 Election. This would be used in a regression with our metric of voter burden to evaluate the strength of correlation between the two.

2.2 Methodology

2.2.1 ArcGIS

Using ArcGIS Pro, we visualized the voting infrastructure of Georgia, considering the issues of continuous gerrymandering. From the U.S. Census Bureau, we were able to obtain shapefiles of Georgia's census block groups and voting districts. Polling station addresses were used from the 2020 Democratic Primary, as provided by GPB. These datasets were key to creating the visual relationship of how the state is designed to vote. A census block group is the smallest geographic census unit that represents a contiguous area and is, "defined without regard to political and administrative boundaries, with an average population of 1,000, and to be approximately equal in area" [3]. Meanwhile, voting districts are geographical areas where voters are particularly registered and where gerrymandering gets its role in society [4]. Both the census block group and voting district data were downloaded as shape files from the census website.

The census block groups were first analyzed in order to determine the respective population density for a given polygon, and centroids were then mapped to the corresponding locale. This methodology accounted for population density, as opposed to using the geographic centers of each block group. This decision reflects an assumption that we take the centroid of a block group to be representative of its entire population; as such, only one polling station will receive all of the block group's voters. For the purpose of travel time analysis, the centroid represents the average location of its voters.

Next, these centroids were transferred and marked on the voting district shapefile. The end of the preliminary setup required the list of addresses provided by Stephen Fowler be geocoded and placed graphically on the map. In turn, the map would include a relationship between the 5543 block group centroids and the 2269 polling stations. Ultimately, the final step was to connect all these parameters together. The final map included the links between block group centroids to the nearest polling station on top of the basemap of the voting districts. Two links were created of different parameters: the first included a constraint within the confines of the voting district, while the second was solely based on shortest distance, (allowing links to cross boundaries). Although it must be pointed out that these links are not representative of feasible travel distance because they are purely the euclidean distance between the two entities, and do not consider street networks. This assumption will be folded over by the O-D analysis later in this paper that considers realistic polling station travel routing. Considering this was a statewide project, we decided to identify the most populated areas and created our visualizations for Clayton, Cobb, DeKalb, Fulton, and Gwinnett Counties. The map of block group-polling station pairings is provided below for Fulton County (Figure 2.1) with the remaining visualizations provided as Appendix A.

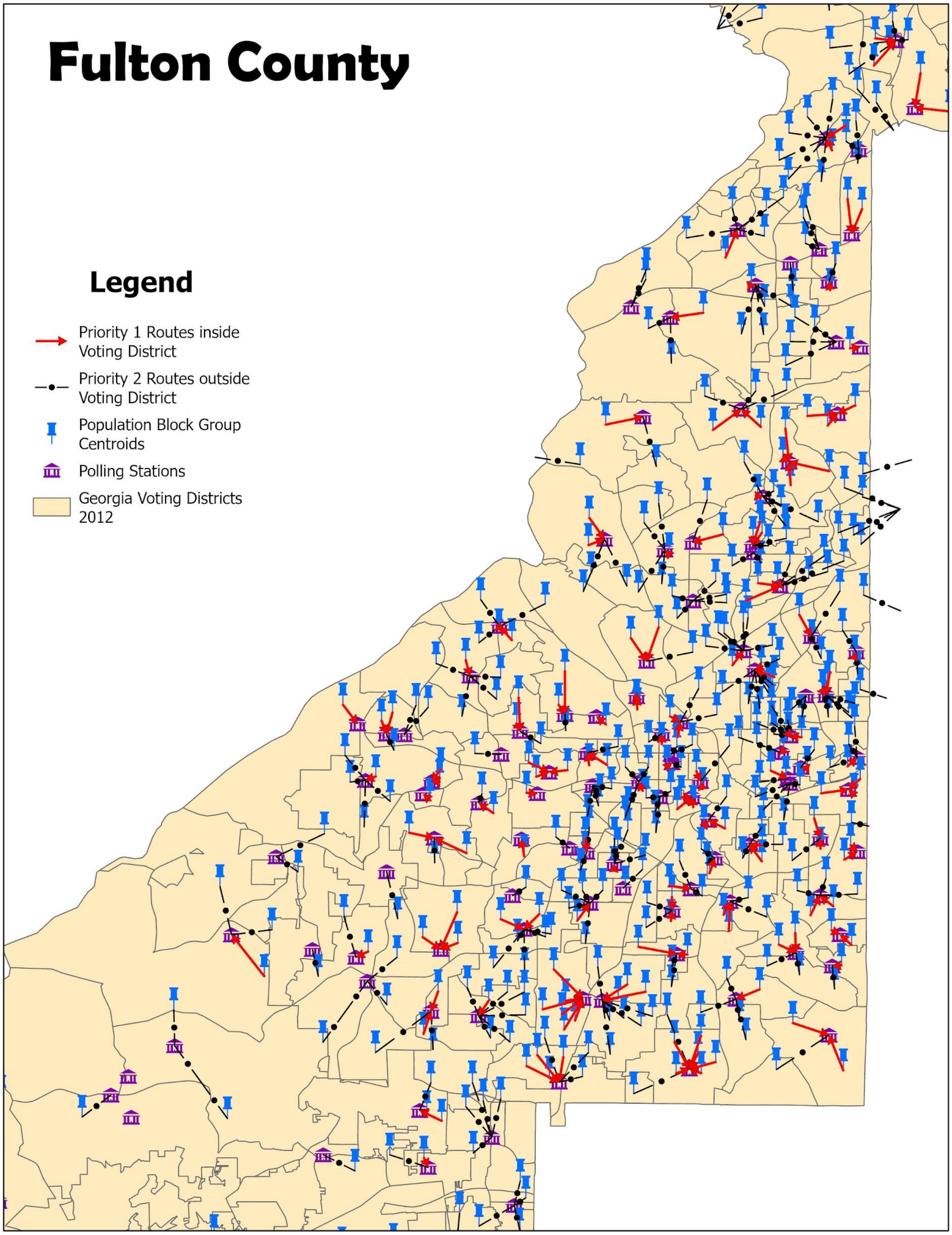

Figure 2.1: Voting District Basemap and Block Group-polling station mappings for Fulton County

The above figure displays some erroneous properties of our matching process. Since the pairings were made based on euclidean distance while neglecting voting district boundaries, some polling stations are left unused while others take on multiple block groups. This was a projected source of error for our polling station wait times, since the matched block group populations subsequently served as an input for the deterministic queueing model. Under the time limitations of this project, this potential source of inaccuracy was deemed acceptable, and is something that could be rectified in the case of a more extensive analysis.

2.2.2 Voting Burden Estimation - Travel Time

To obtain our estimate of characteristic voter burden for each block group, we treated each block group population centroid and corresponding polling station as Origin-Destination pairs. The latitude and longitude for each pair were provided as input into Google Directions API for the driving, walking, and transit trips between the O-Ds. To model a worst-case scenario and obtain a conservative estimate for the travel time, the departure time for each trip was set to be 6 p.m. on a regular weekday.

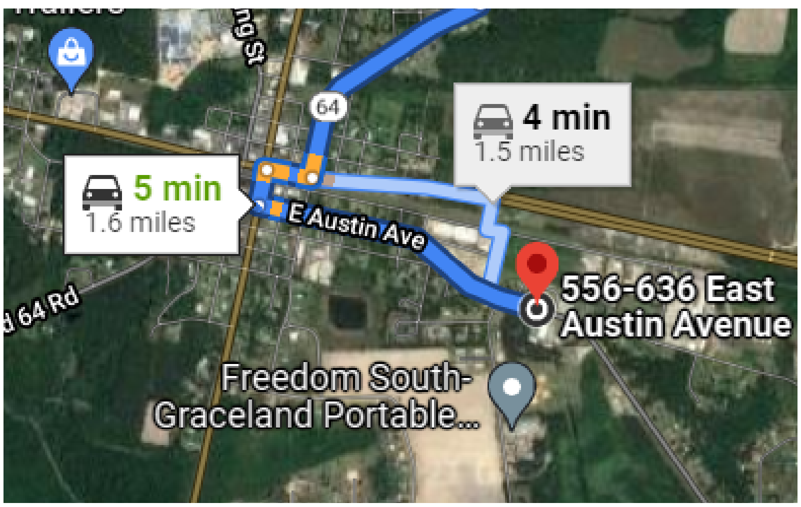

Figure 2.2: Example O-D Pair and Travel Time for Driving

Then, to condense these times into one characteristic travel time for each block group, we derived a weighted average of the trip time between voters who have access to a car and those who do not (according to the U.S. Census), where the representative time for car-less voters was taken to be the minimum of the walking and transit trips (Equation 2.1). In the relation below, *VehFrac* is the proportion of households that own a car within a given block group.

$$Travel\,Time \ = \ (Veh\,Frac)(Drive\ time) \ + \ (1 - VehFrac) \cdot min(Transit,\ Walk) \qquad 2.1$$

2.2.3 Voting Burden Estimation - Poll Wait Time

Our model to estimate the average wait time at each polling station was based on a deterministic queueing recipe such as the example shown in Figure 2.3.

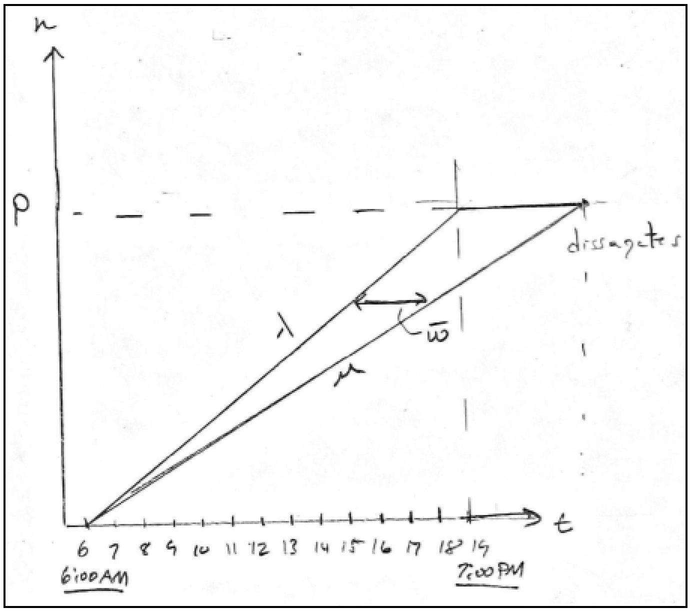

Figure 2.3: Deterministic Queueing Model with Average Wait Time

In this model, the queue's demand (λ) is derived from the number of voters expected to show up in-person on election day from the block groups matched to a given polling station. This overall number of voters was taken to be distributed uniformly across the entire time the polls remain open. Likewise, each polling station's capacity (μ) was taken to be the average of its greatest two values for check-ins per hour, as given by the GPB dataset. This capacity was also assumed to be constant over the duration of the day, neglecting any potential variation due to fluctuation in staffing or other miscellaneous effects.

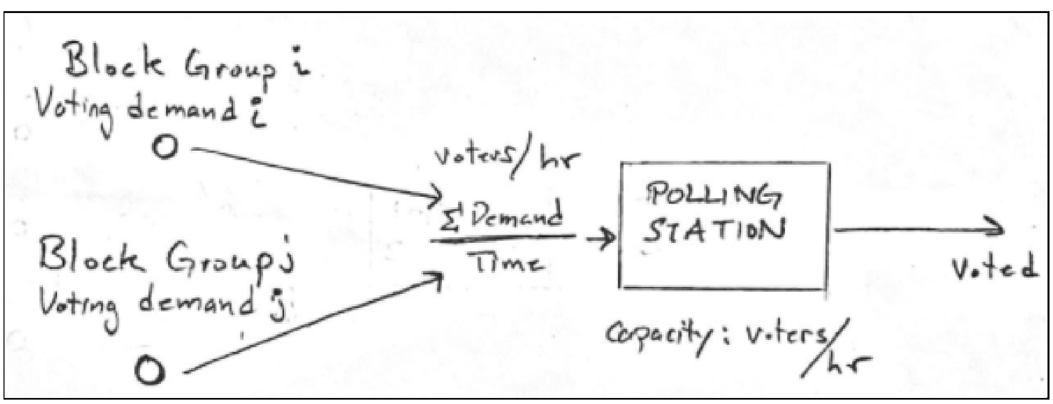

Figure 2.4: Schematic of Polling Station Inputs

The simplifying assumptions used in this model are further sources of error for our metric of wait time; however, they were deemed necessary due to the time constraints of our project and the limitations of the dataset.

2.2.4 Principal Component Analysis & Clustering

With a complete picture of voting burden in hand for Georgia's electorate, a Principal Component Analysis was performed on the dataset, with voting burden and the aforementioned block group demographics provided as variables. The loadings were plotted to determine the most influential variables. Subsequently, K-means clustering was conducted, with 5 clusters determined to be optimal from an appropriate elbow plot (Figure 2.5).

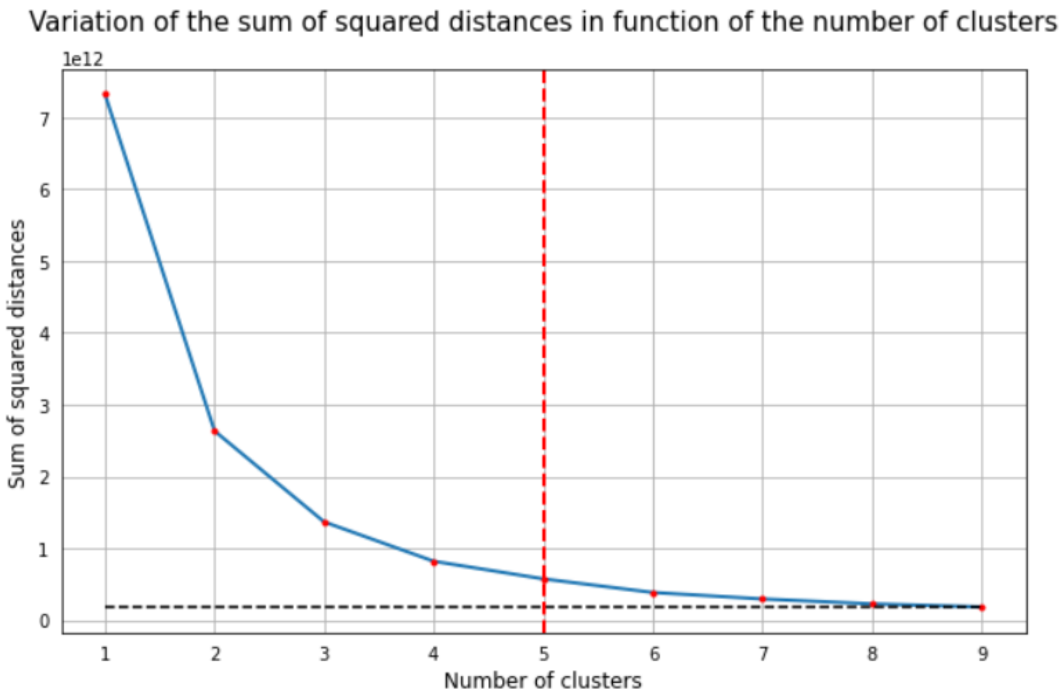

Figure 2.5: Elbow Plot for K-means Clustering

After establishing these visualizations and figuring out the spatial relationships between the population block group centroids and the nearest polling stations the links were used in python to understand proper travel times considering street networks using google maps API. The next step was to understand how different demographics are represented with respect to travel time and polling wait time. After conducting K-means clustering and principal component analysis, 5 clusters were identified using the elbow method to identify voter travel burden. Two analyses were performed, one only considering travel time (more robust trial) (Appendix B). The other one considered travel time and average poll waiting time (more erroneous with many assumptions made) (Appendix C). Continuing with the trend, the analyses were conducted for the entire state, but the visualizations were conducted on the same 5 counties as used before. The clustering results are further discussed in section 3.2.

3. Results

3.1 Voting Burden with Poll Wait Time

Our first iteration of clustering included both travel time and poll station wait time as part of voter burden. Table 3.1 displays the 75th percentile statistics to put emphasis on the higher burden members of the cluster. This produced surprising and unexpected results, such that Cluster 2, with the highest burden, was predominantly white, while Cluster 0 had the lowest burden along with the highest black population by far. Closer inspection of these results revealed that each cluster had a voting wait time of at least 300 minutes (or 5 hours).

Clusters	**Cluster 2 Highest Burden**	**Cluster 3 Higher Burden**	**Cluster 1 Middle Burden**	**Cluster 4 Lower Burden**	**Cluster 0 Lowest Burden**
% White	89.77	93.03	86.91	86.54	68.48
% Black	11.45	5.47	23.31	38.02	77.54
% Asian	9.11	5.13	5.37	2.32	1.28
% Other Race	1.59	1.00	3.03	4.06	4.87
% Hisp./Latino	5.80	4.70	8.32	9.48	9.86
% Disability	9.40	7.50	12.10	16.40	19.50
House Income	160,738	243,303	110,053	74,833	50,114
Travel Time(min)	17.24	13.15	17.66	23.13	26.12
Poll Time (min)	382.66	383.37	375.72	320.14	282.16
Voting Time(min)	399.89	396.52	393.38	343.26	308.28

Table 3.1: Clustering Results with Voting Wait Time

One explanation of the high voting times may be that we assumed that those who want to vote on election day will vote on election day when in fact, many of those voters do not vote due to the increasing wait time. These metrics can then be interpreted as the average waiting time should demand be fully met. Further investigation on average wait times reveal unrealistic results across all polling stations. As such, polling wait time will be ultimately dropped for our investigation.

The geographic distribution of these Clusters in the Clayton, Cobb, DeKalb, Fulton, and Gwinnett Counties are provided as Appendix C. These maps further suggest that the clusters are misleading because they indicate that the highest income areas have the highest burden while the lowest income areas have the lowest burden.

3.2 Voting Burden without Poll Wait Time

3.2.1 PCA & Clustering

An additional round of Principal Component Analysis was conducted without including poll station wait time. The resulting loading scores (Table 3.2) indicate that the most influential variable for grouping the block groups was, indeed, the travel time, followed by representation of asians, representation of whites, and household income.

Principal Component	**Loading Score**
Weight round trip travel time	0.8641
Percent Asian	0.0157
Percent White	0.0115
Median Income of Families	0.0107
Percent Other Race	0.0060
Percent Hispanic/Latino	0.0037
Percent Disabled	-0.0073
Percent Black/African American	-0.0148

Table 3.2: Loading Scores for Final Principal Component Analysis

Clustering the block groups with travel time alone proved to offer more sensible results (Table 3.3) than the initial groupings, with the highest burden group (Cluster 0) corresponding to the greatest minority population with the lowest representative income level by far. On the other hand, Cluster 3 had the lowest burden along with the highest proportion of whites and the highest household income.

These results tell us that low income areas with high minority populations will face the greatest obstacles to in-person voting. Especially given that low-income populations are less likely to own cars than voters in high-income areas, many will be forced to walk or take transit to polling stations on election day. While improvements to demand and capacity estimations for our queueing model will allow for a better representation of voting burden, travel time alone seems to suggest that underserved groups travel longer to polling stations.

Clusters	Cluster 0 Highest Burden	Cluster 4 Higher Burden	Cluster 1 Middle Burden	Cluster 2 Lower Burden	Cluster 3 Lowest Burden
% White	66.48	86.54	86.91	89.77	93.03
% Black	77.54	38.02	23.31	11.45	5.47
% Asian	1.28	2.32	5.37	9.11	5.13
% Other Race	4.87	4.06	3.03	1.59	1.00
% Hisp./Latino	9.86	9.48	8.32	5.80	4.70
% Disability	19.50	16.40	12.10	9.40	7.50
House Income	50,114	74,833	110,053	160,738	243,303
Travel Time (min)	26.122	23.13	17.66	17.24	13.15

Table 3.3: Clustering Results without Voting Wait Time

With these final clusters in hand, we generated maps of the clusters in ArcGIS for the 5 most populous counties in Georgia. A representative example is given below for Fulton County (Figure 3.1).

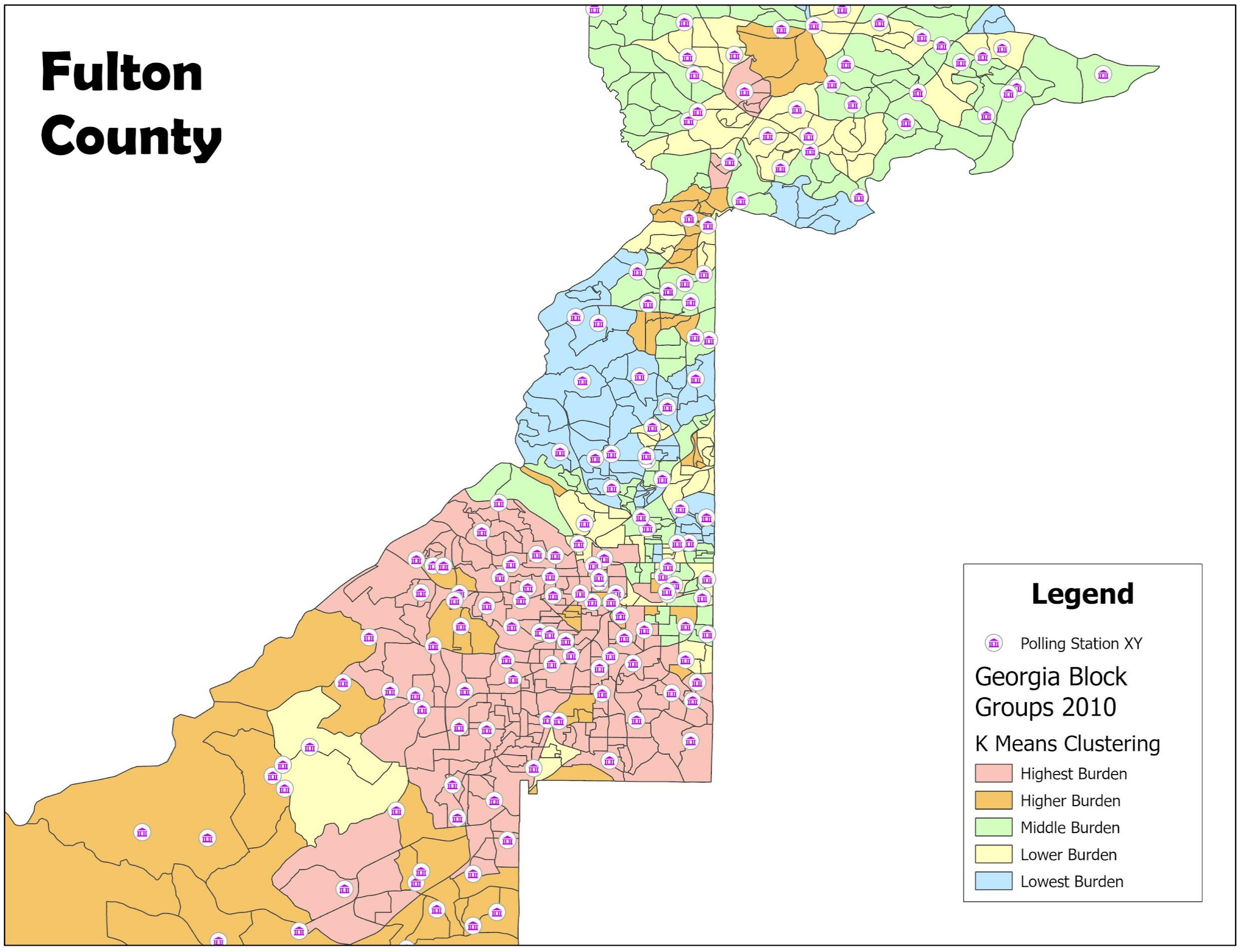

Figure 3.1: Basemap of Clustered Voting Districts in Fulton County based on Travel Time Alone

3.2.2 Regression Analysis

To tie our results back in with the overall objective - evaluating the impact of Georgia's voter ID law on voting burden and, by proxy, voter turnout - we plotted our final metric of voter burden vs. voter turnout. A single-variable ordinary least squares regression was performed on the five most populous counties' travel times and actual 2020 November turnout. The results are shown below.

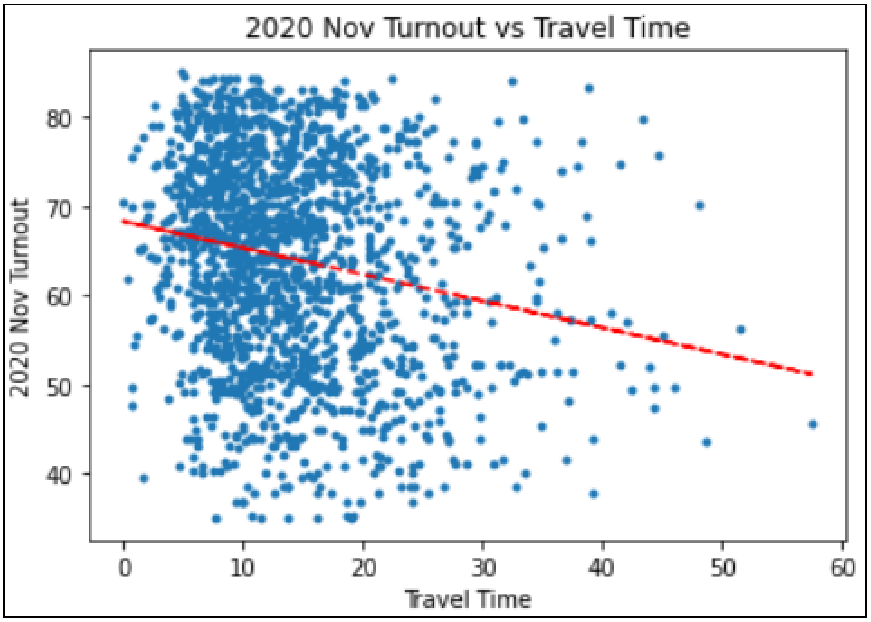

Figure 3.2: Regression Plot of Voting Burden vs. 2020 Voter Turnout

The r-squared value for this regression is 0.04 which is a very low correlation. While being inconclusive on its own, travel time can be a factor in a multivariable regression in the future.

3.3 Proposed Voting Methods

While not a long-term solution to improve voting infrastructure in Georgia, mobile voting buses have the potential to improve polling capacity and reduce voting burden in impacted regions. The new legislation bans these buses and effectively decreases capacity, even while it serves to shift a greater amount of voting demand to election day, the legislation does not provide additional voting infrastructure to meet this added demand. Instead of helping serve a shift to greater in-person demand on election day, this further limits capacity across the state. On another note, we also identified locations where polling stations should be placed considering the high travel burden that these communities often face. Symbolized by the 4 point stars in Figure 3.3, these stations are strategically placed at the intersections of multiple voting districts that experience higher voting burden, and therefore advantageous to a wide range of neighborhoods and communities who do not have the means to access the polling stations.

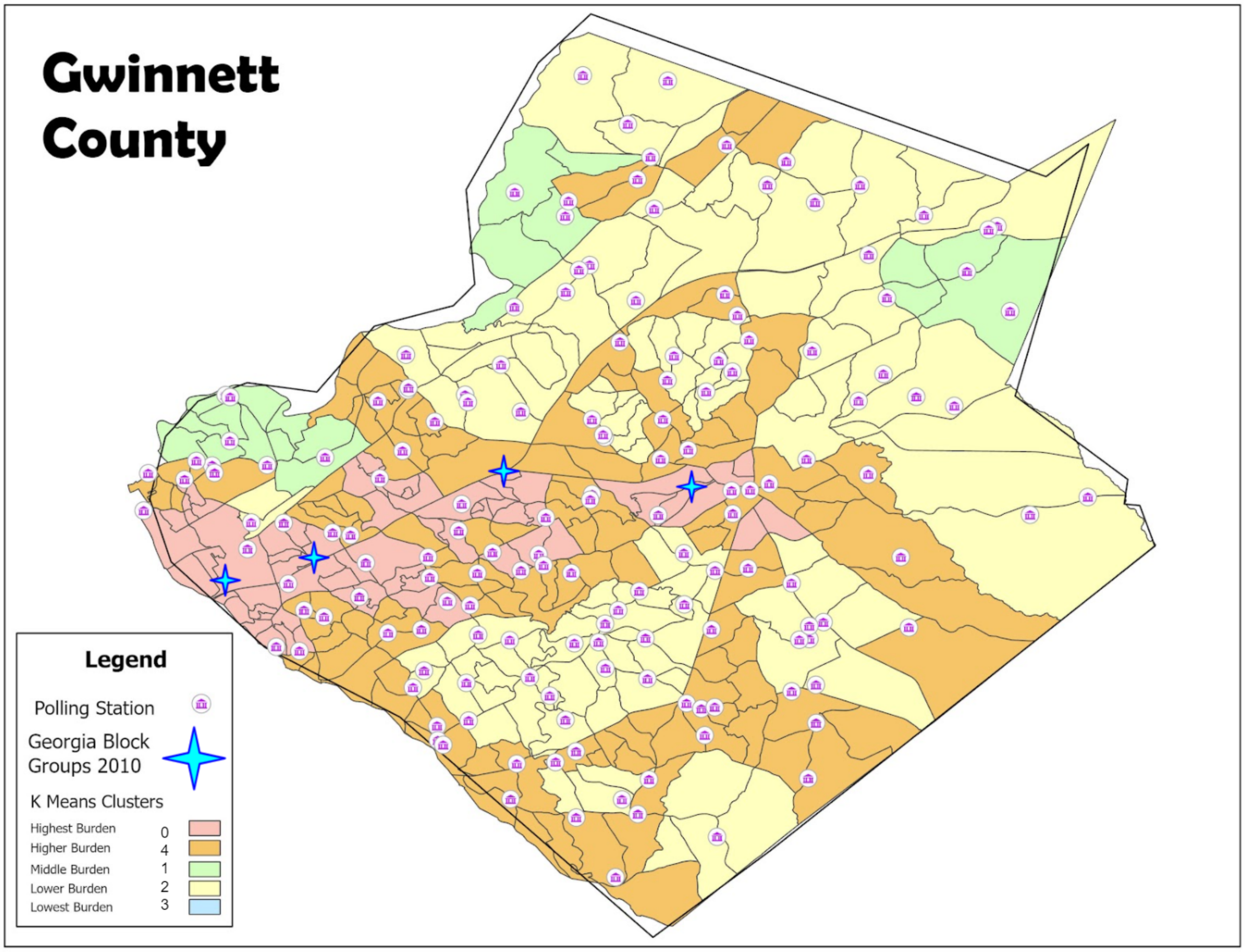

Figure 3.3 Voting District Basemap with proposed polling stations

4. Future Work & Conclusions

Five clusters of voting burden were found for the State of Georgia. Each cluster's voting burden is determined by the 75th percentile weighted round trip travel time from the block group population centroid to the polling location. The groupings suggest that income is closely related to travel time to polling stations. As a result, other parameters such as percent white, black, and disability status that are correlated with income also correlate with weighted travel time.

These clusters are plotted which allows for a preliminary determination of where mobile voting sites and new polling stations should be placed to relieve voting burden. We calculate voting burden based on weighted round trip travel time only since the deterministic queueing model yielded unrealistic results. This model requires precise estimation of demand and capacity in which our assumptions do not satisfy.

Finally, a regression model between travel time and actual voter turnout from November 2020 is created. With a low r-squared value, this regression model makes no conclusions on the dependency of voter turnout with weighted travel time, but the low correlation suggests that it can be part of a multi-variable regression model in the future.

The results of this paper do not provide a complete picture of voting burden patterns in the state of Georgia. For this procedure to be repeated in the future, we present several recommendations. Using ARCGIS Pro, block group population centroids should be joined to polling stations constrained to a voting district. This will generate more accurate polling station travel times while providing a more realistic demand for each polling station. The most recent 2020 Census decennial block group data should be used. The use of the deterministic queueing model is not recommended to estimate average wait times. An alternative source of this metric is to obtain smartphone trajectory data for an election day at the polling stations for a more accurate average wait time that is independent of ARCGIS joins.

As for proposing new voting sites, a clustering analysis should be done again with the new voting sites to see how the voting burden has changed.

Finally, we recommend creating a normalized scale for voting burden as a combination of poll waiting times and travel times. A normalized metric will allow for the comparison between cities, counties, states, regions in the country. We hope that the results of future analysis may be a useful tool to see voting disparities across the nation and help governments strategically place new polling stations to bring the most impact on voting accessibility.

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Appendix

Appendix A: ArcGIS pairing of Block Groups to Polling Stations

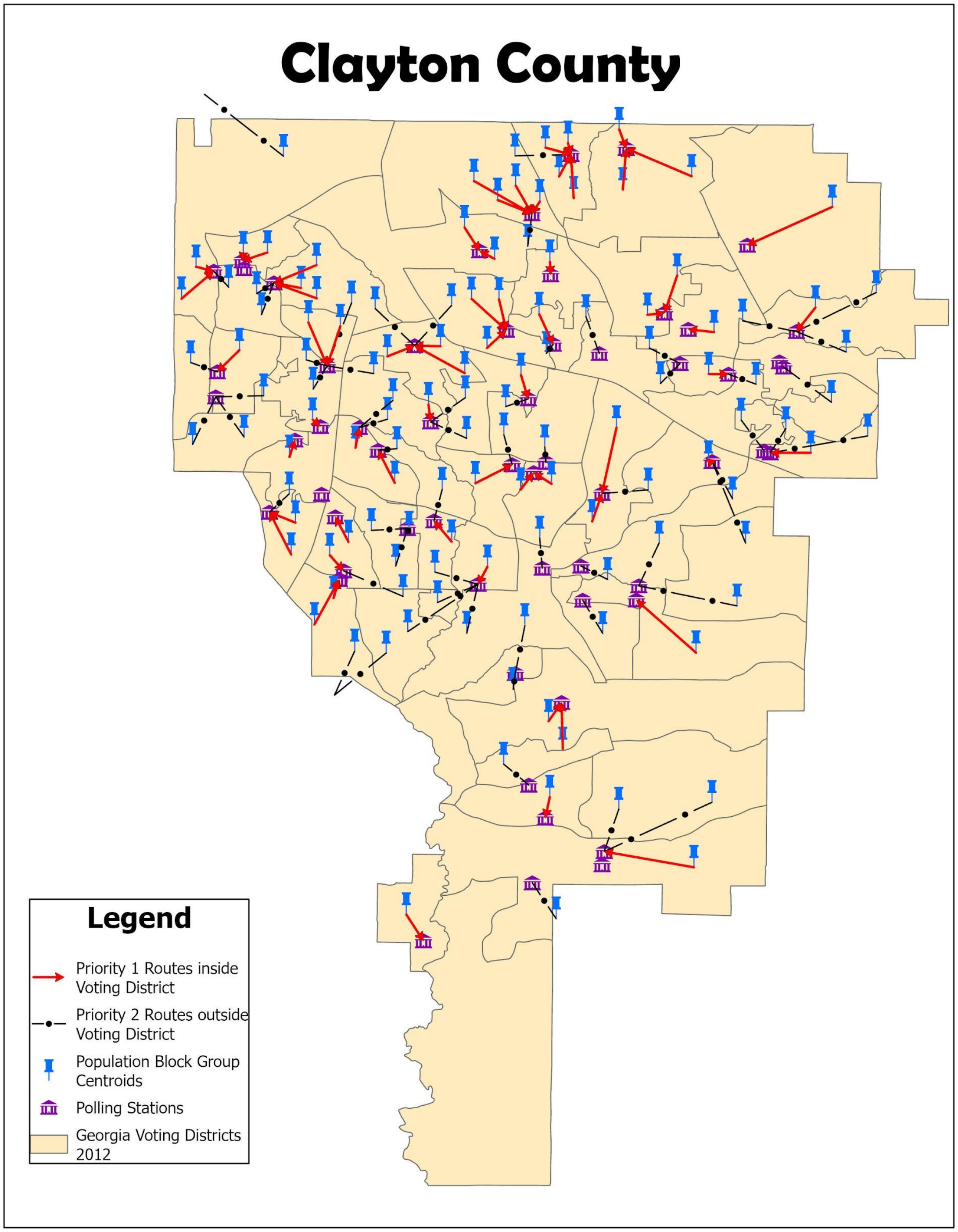

Figure A.1: U.S. Census Block Group-polling station mappings for Clayton County, GA

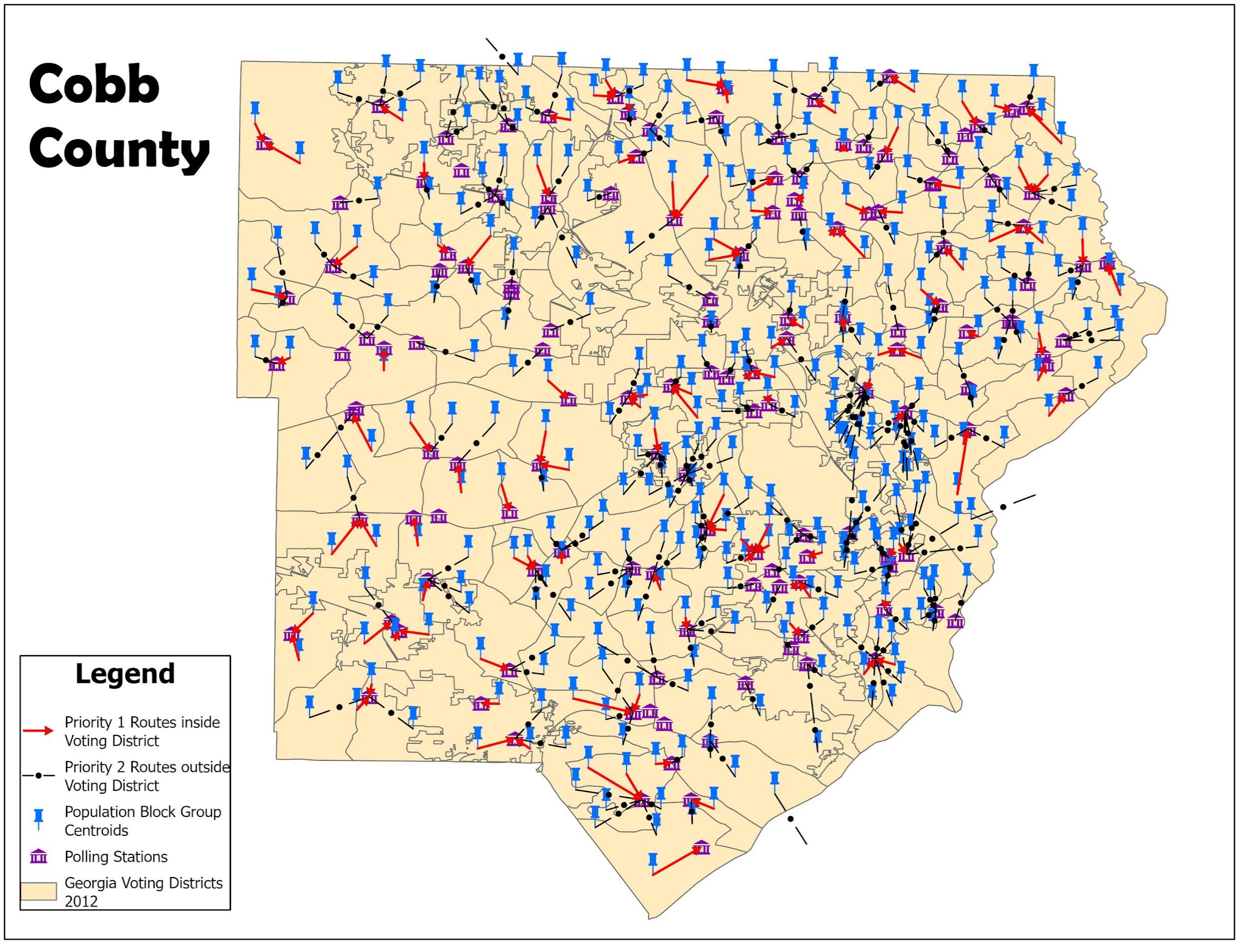

Figure A.2: U.S. Census Block Group-polling station mappings for Cobb County, GA

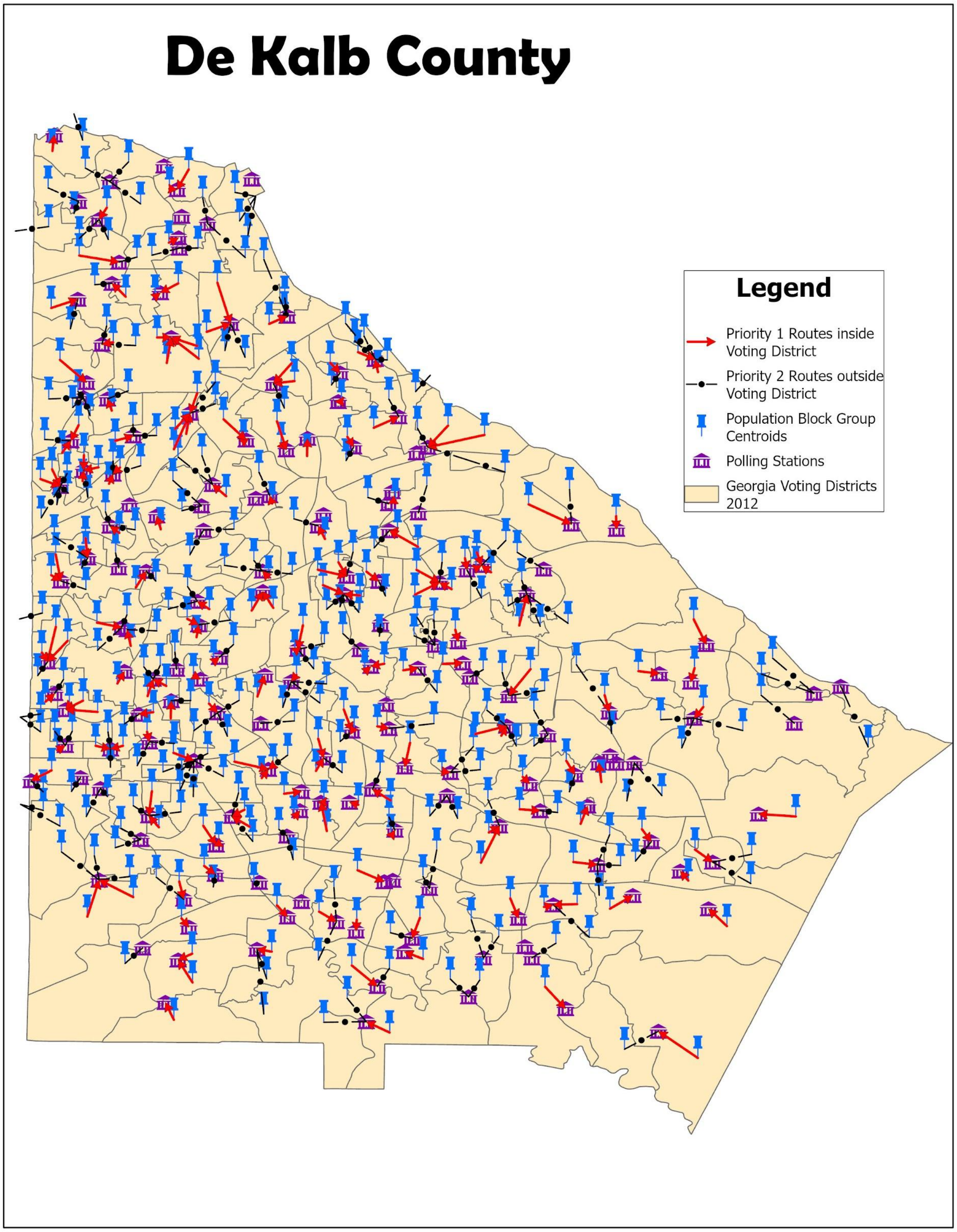

Figure A.3: U.S. Census Block Group-polling station mappings for DeKalb County, GA

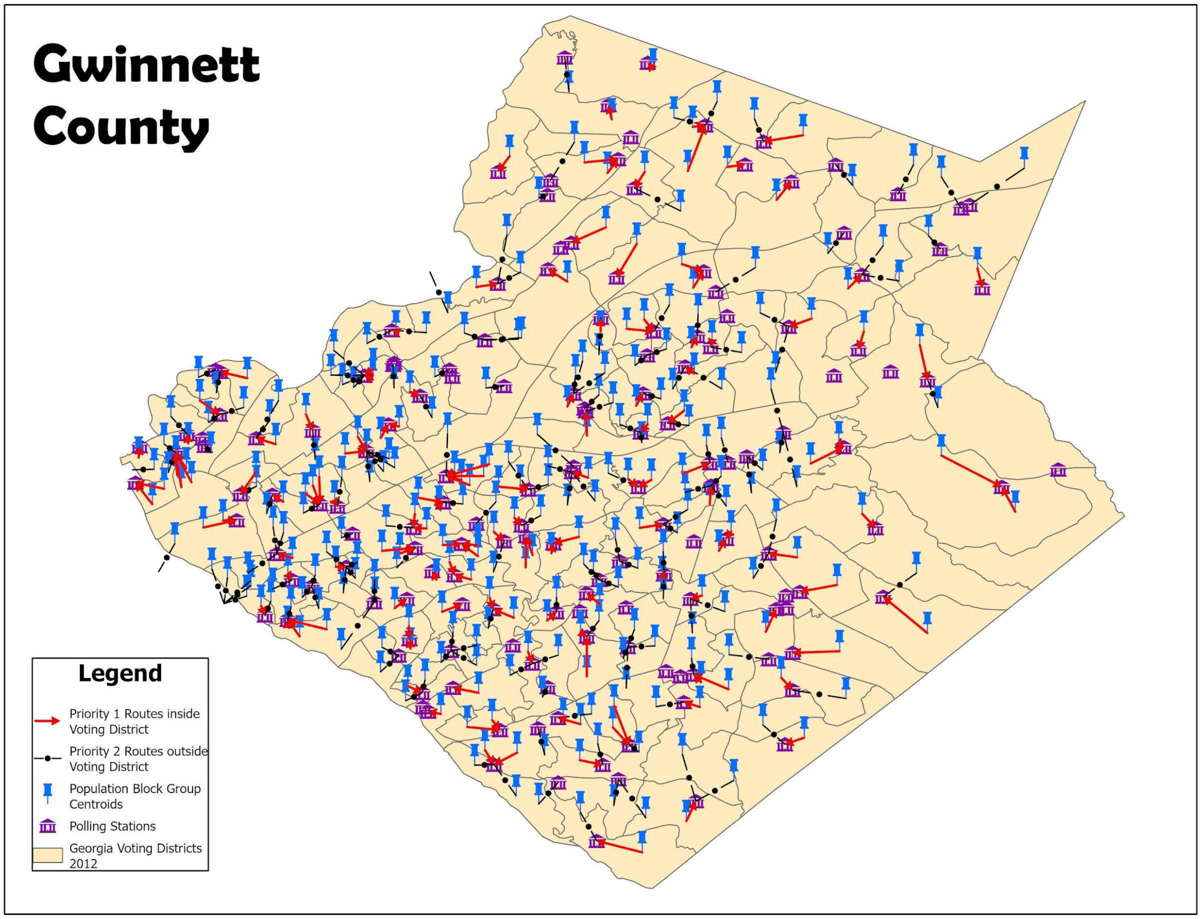

Figure A.4: U.S. Census Block Group-polling station mappings for Gwinnett County, GA

Appendix B: ArcGIS - Final Clusters (Travel Time only)

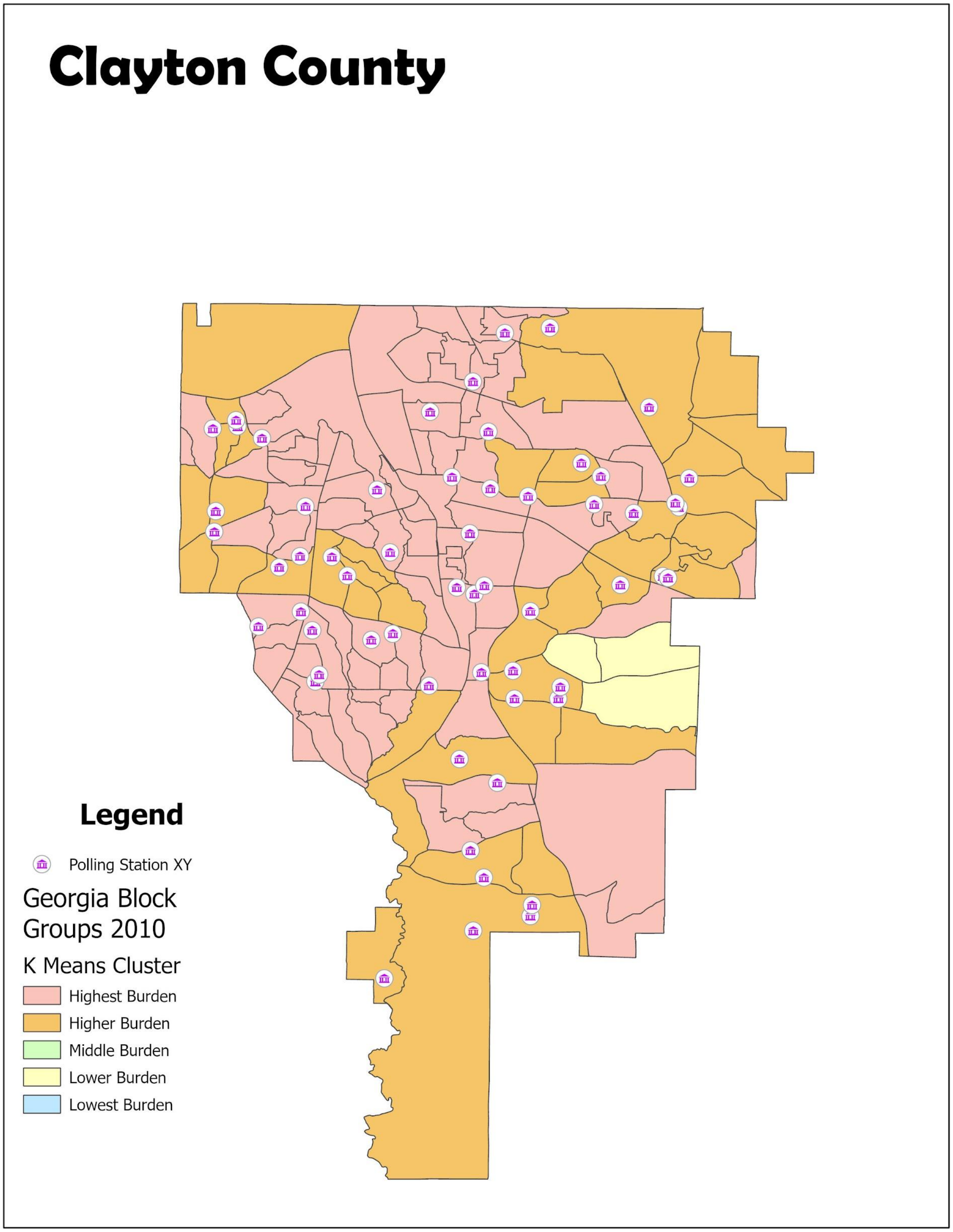

Figure B.1: Basemap of Clustered Voting Districts in Clayton Cty based on Travel Time Alone

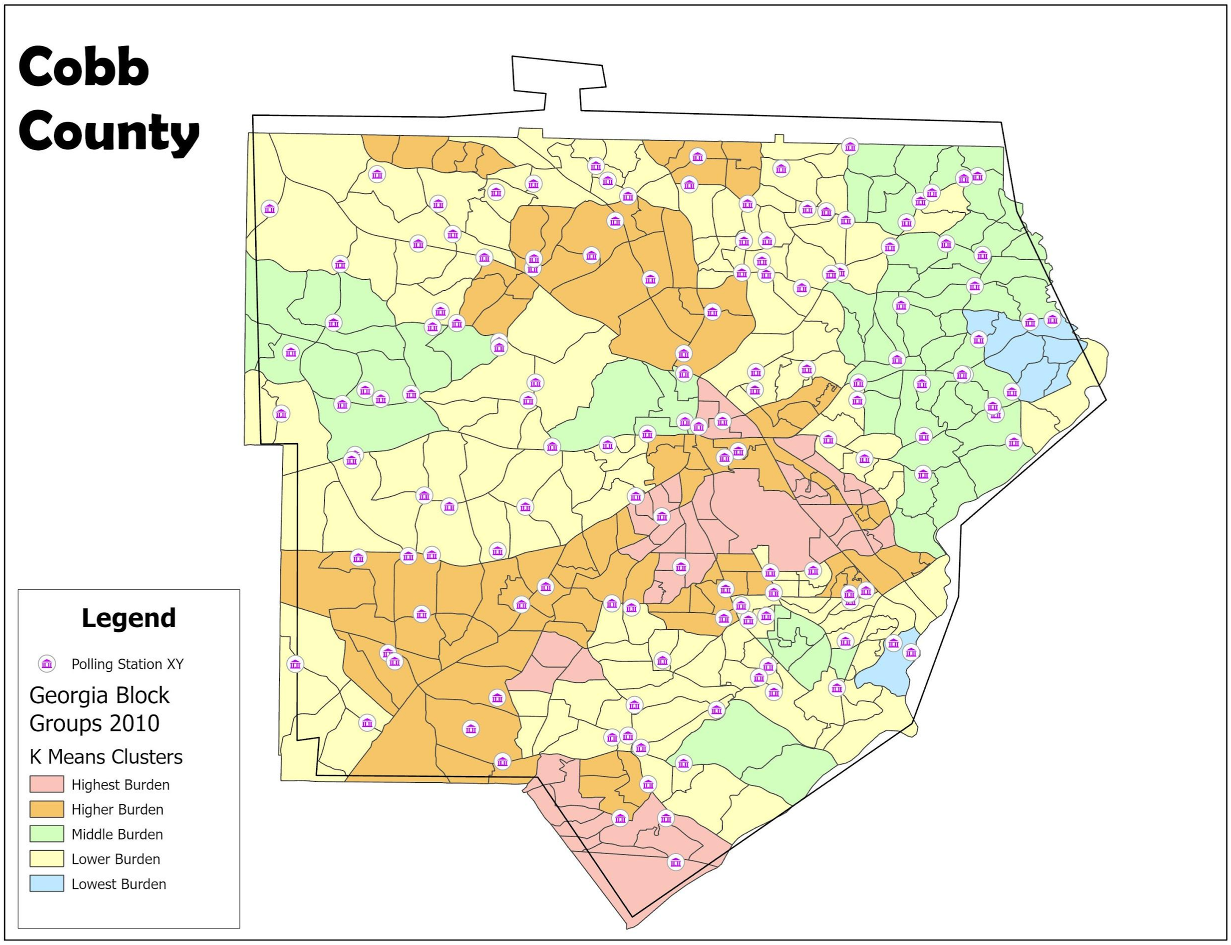

Figure B.2: Basemap of Clustered Voting Districts in Cobb County based on Travel Time Alone

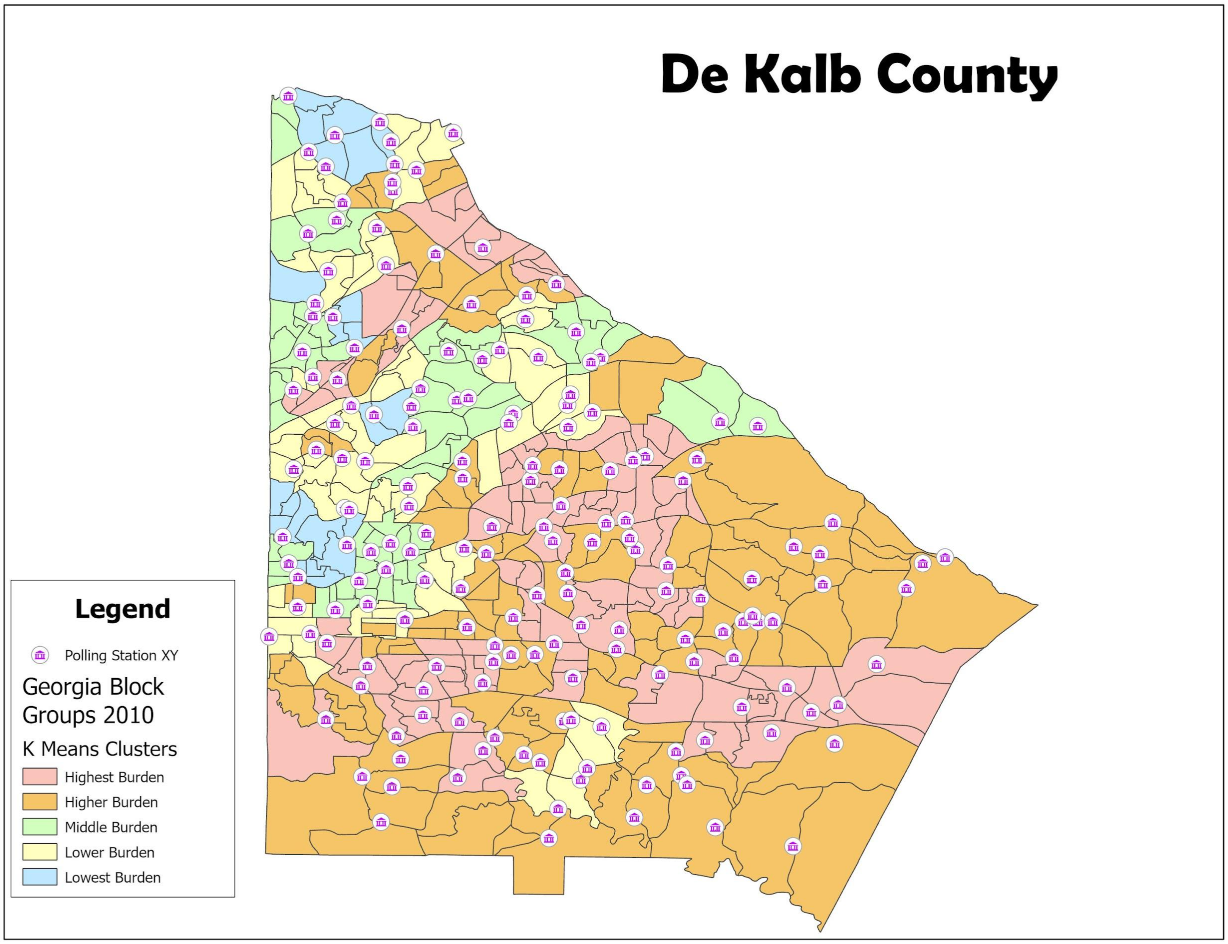

Figure B.3: Basemap of Clustered Voting Districts in DeKalb Cty based on Travel Time Alone

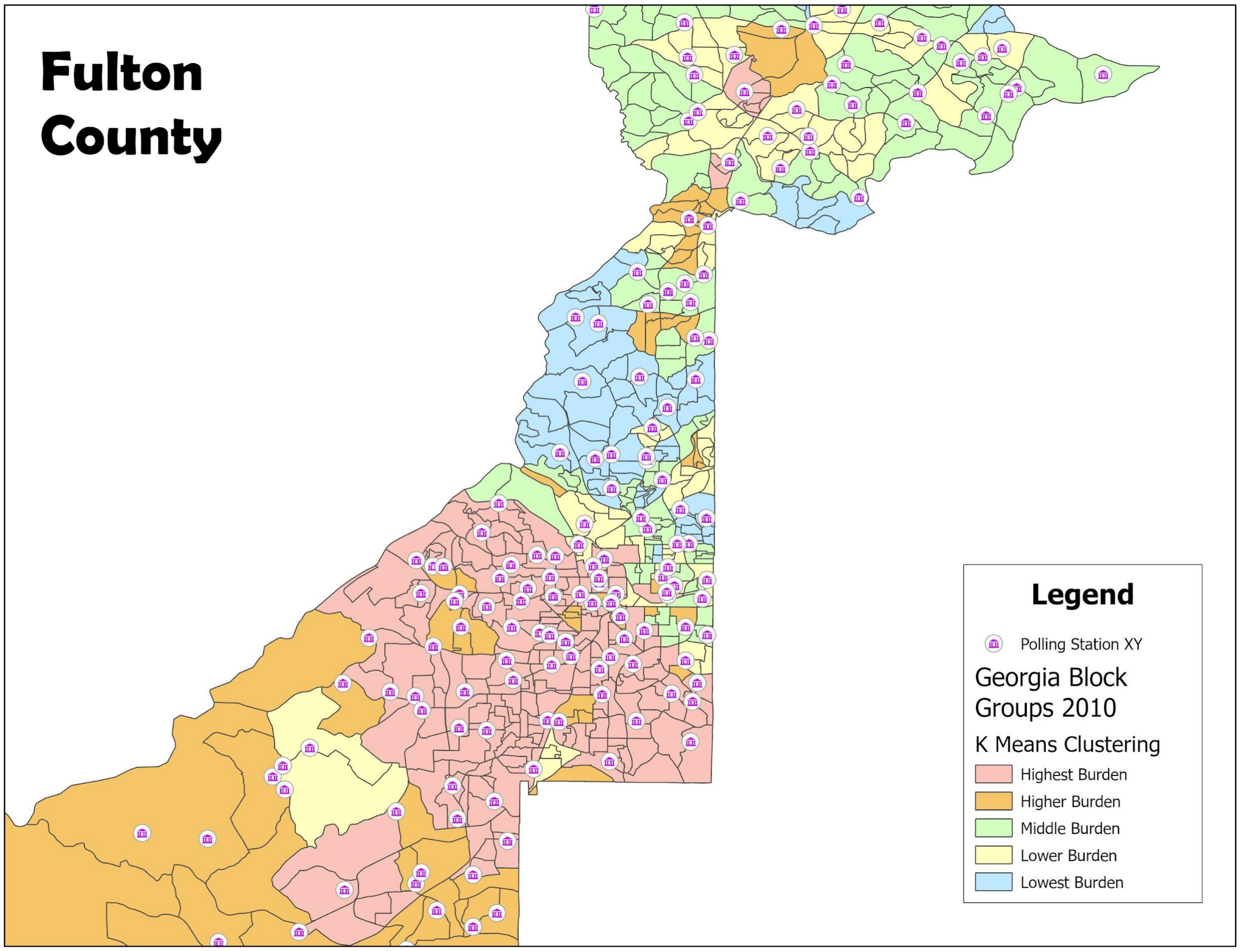

Figure B.4: Basemap of Clustered Voting Districts in Fulton County based on Travel Time Alone

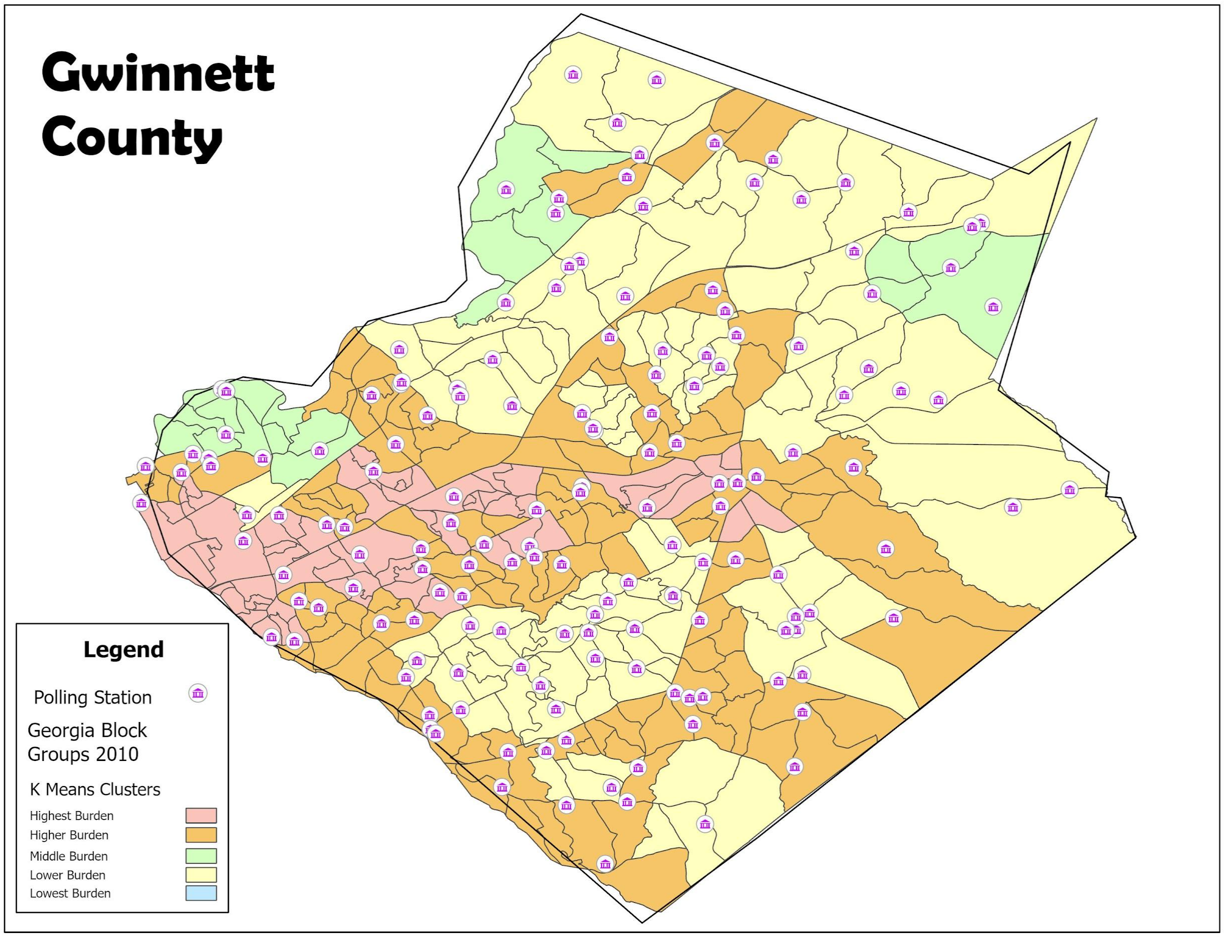

Figure B.5: Basemap of Clustered Voting Districts in Gwinnett Cty based on Travel Time Alone

Appendix C: ArcGIS - Initial Clusters (Travel Time & Wait Time)

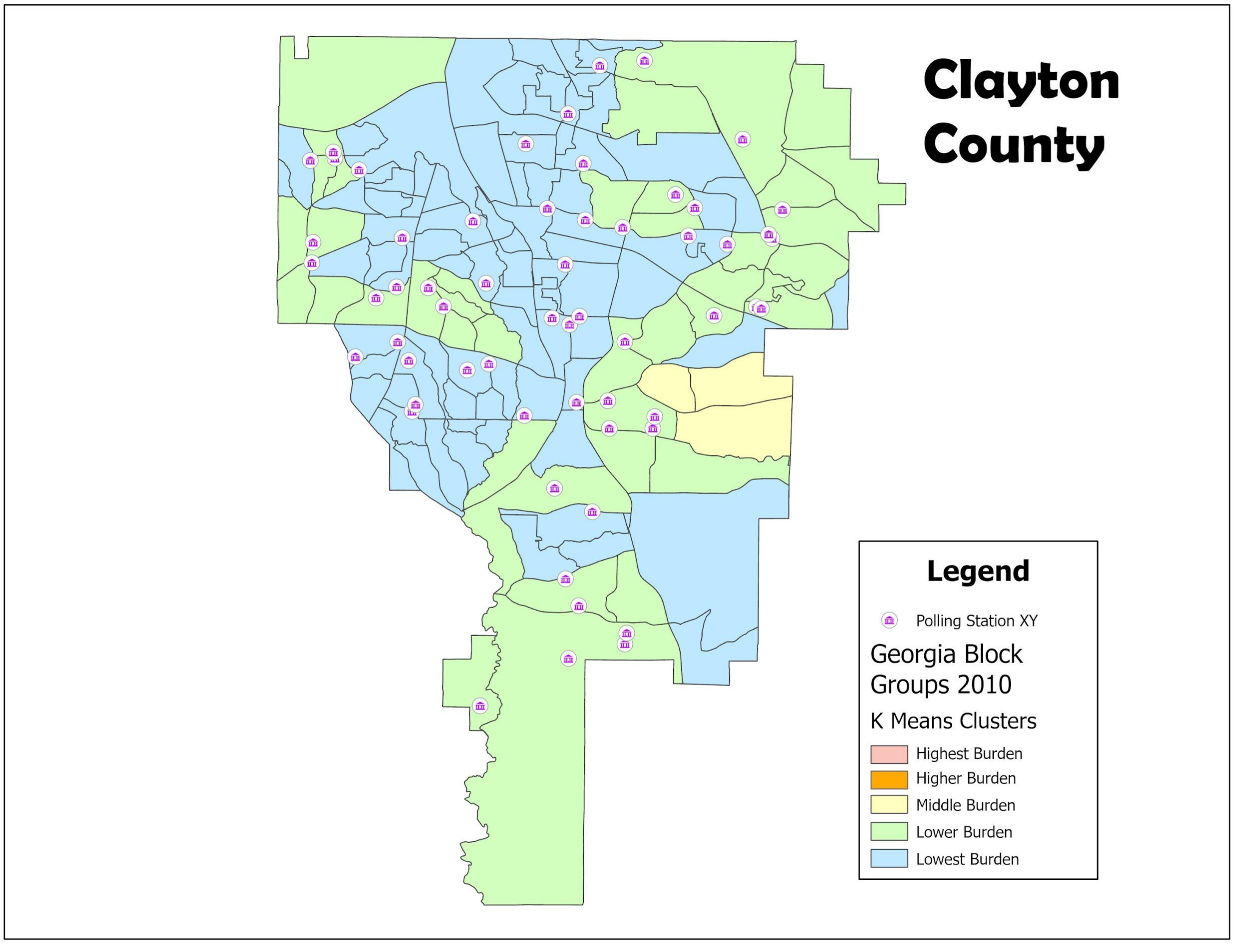

Figure C.1: Initial Basemap of Clustered Voting Districts in Clayton County

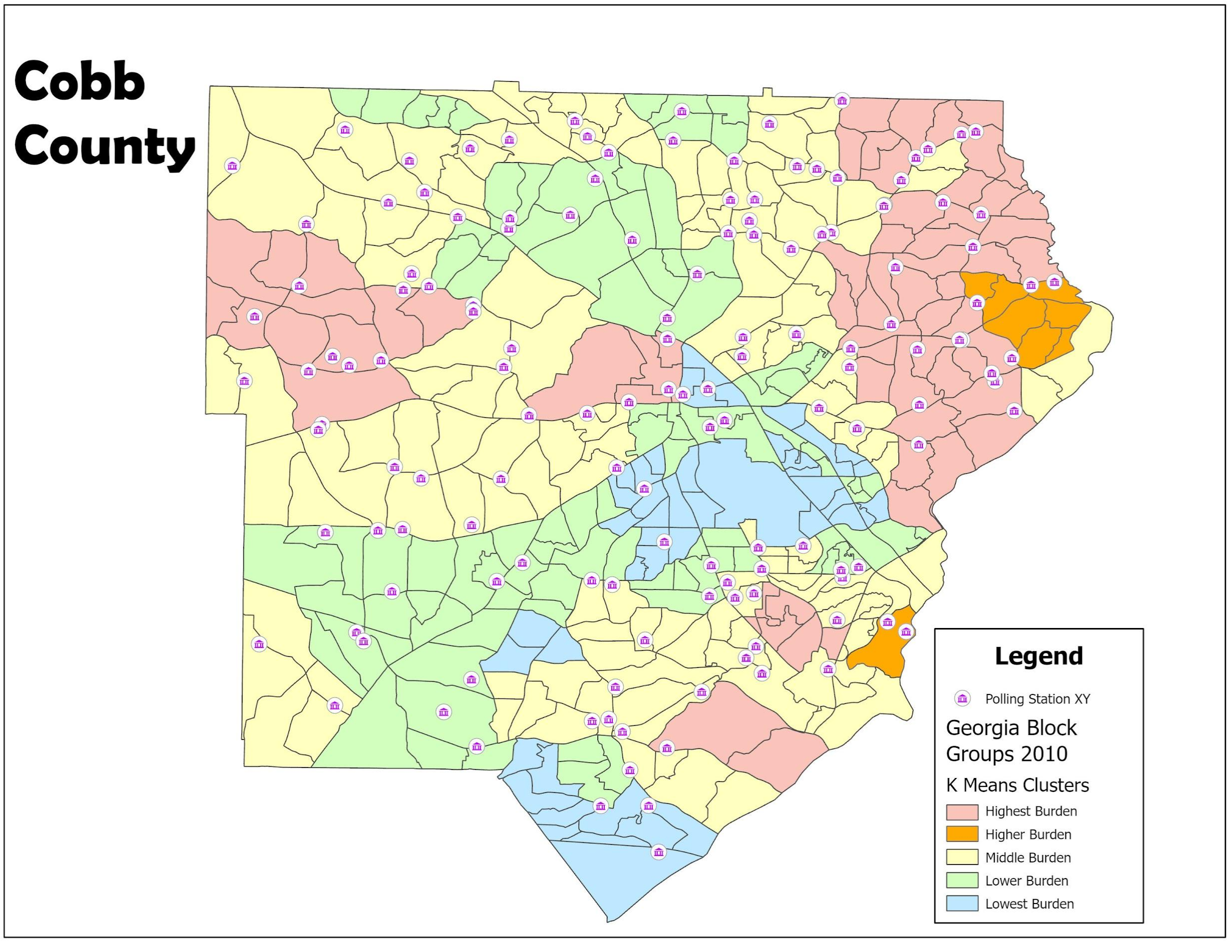

Figure C.2: Initial Basemap of Clustered Voting Districts in Cobb County

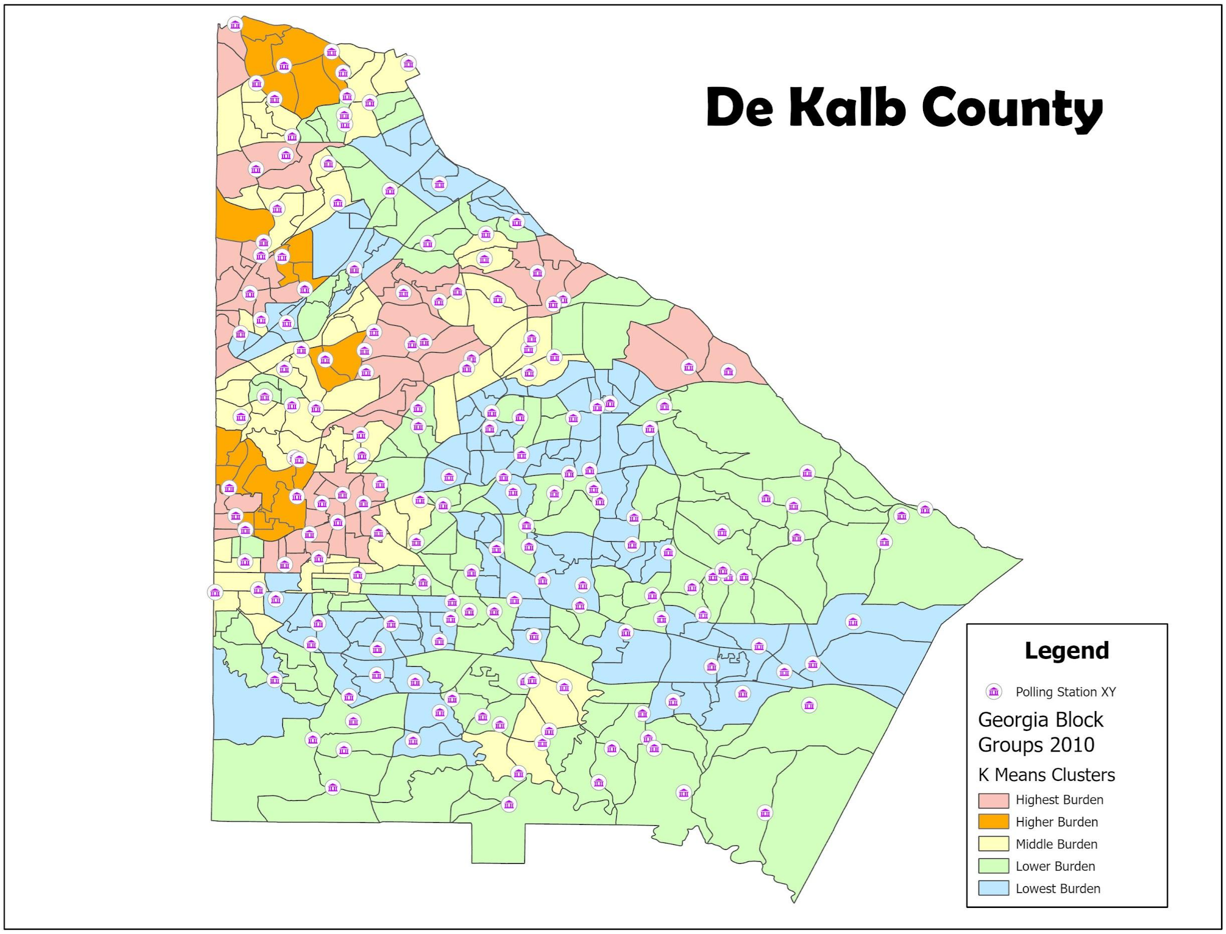

Figure C.3: Initial Basemap of Clustered Voting Districts in DeKalb County

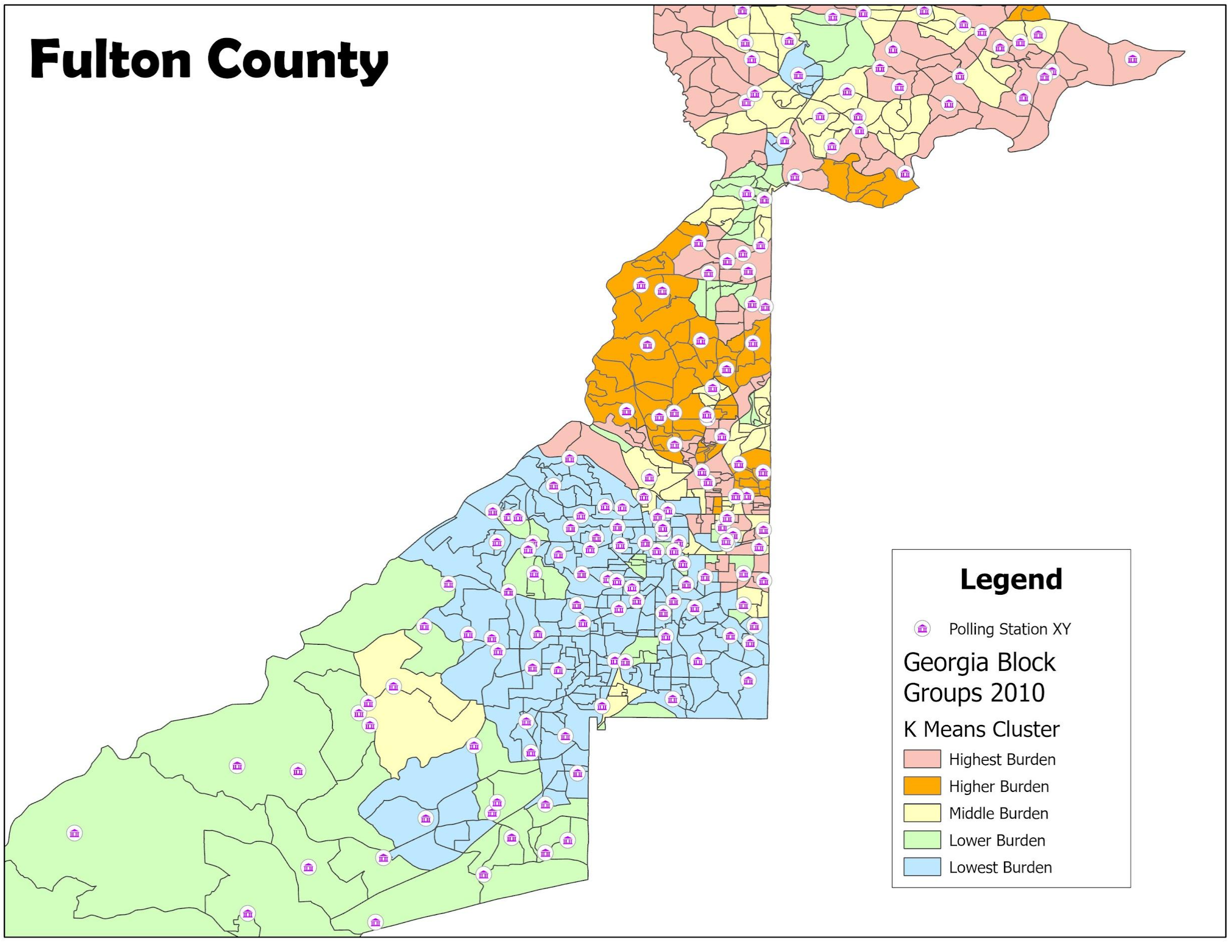

Figure C.4: Initial Basemap of Clustered Voting Districts in Fulton County

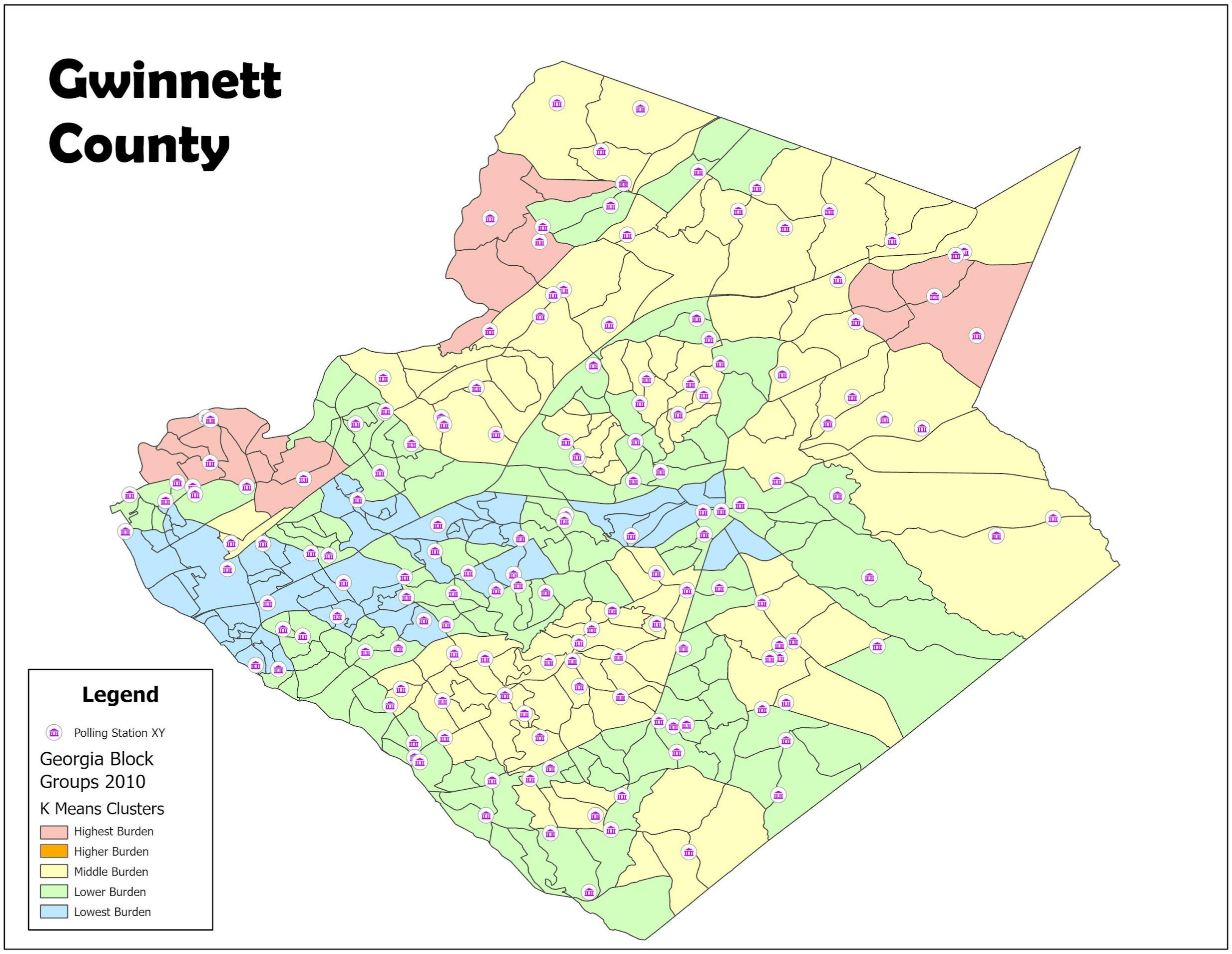

Figure C.5: Initial Basemap of Clustered Voting Districts in Gwinnett County

Appendix D: ArcGIS - State Wide Travel Time K-Means Clustering

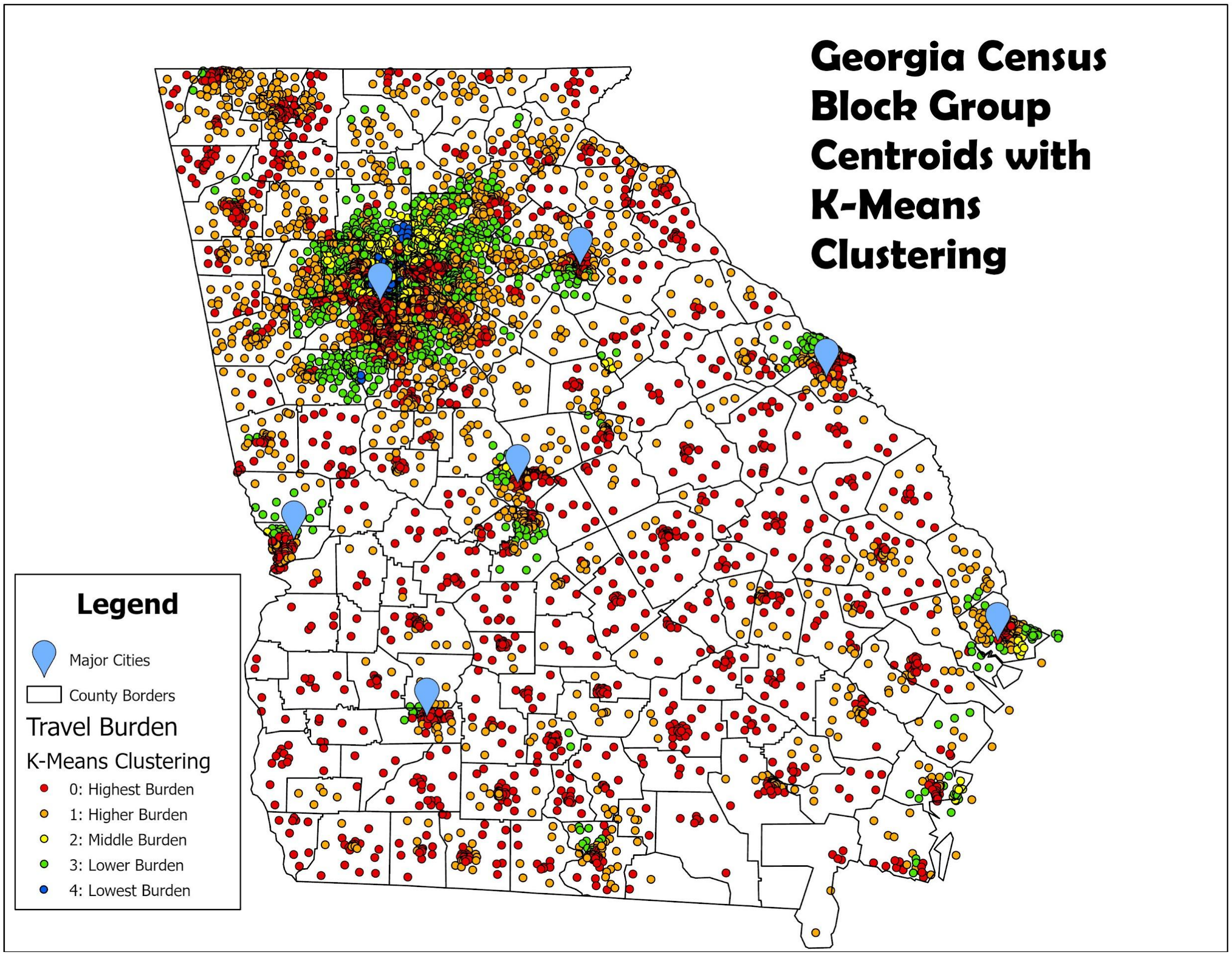

Figure D.1: State Map of Georgia with Travel Time Clusters