

SCHOOL PERFORMANCE AND COMMUNITY DEVELOPMENT IN NEW YORK STATE

A Spatial Statistics Perspective



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Table of Contents

| | |
|---|----|
| Introduction..... | 3 |
| Background..... | 4 |
| Data..... | 9 |
| Sources..... | 9 |
| Variable Definitions..... | 9 |
| Explanatory Variable Definition Table | 12 |
| Preparation | 12 |
| Methods..... | 13 |
| Spatial Statistics..... | 13 |
| Spatial Autocorrelation | 15 |
| Spatial Nonstationarity | 16 |
| Geographically Weighted Regression(GWR) | 18 |
| Study Design..... | 18 |
| Results..... | 19 |
| Univariate..... | 19 |
| Bivariate (Scatterplots) | 23 |
| Mapping Analyses | 28 |
| Hot Spot Analyses..... | 28 |
| Multivariate Analyses (Correlation Table) | 30 |
| OLS Regression Model..... | 31 |
| GWR Model | 35 |
| Other Spatial Regression Models..... | 37 |
| Discussion and Conclusions | 39 |
| Concluding Maps | 41 |
| References..... | 45 |
| Appendix..... | 49 |

Introduction

Education in New York State is as multifaceted as the communities its school districts represent. Over 700 districts paint a backdrop of diverse students, teachers, neighborhoods, and communities. In 2014, the average concentration of students receiving free or reduced price lunch among school districts was 44%. If viewed as a proxy variable for poverty, this implies nearly half of New York State's public school students came from families living in or near poverty. Keeping the variability of these three metrics (high school degrees, poverty, performance) and other New York school district characteristics in mind is also crucial to understanding the landscape of education in New York. In 2015, the average proportion of minority students in each school district was 20%, though some districts contained far fewer and far greater concentrations of minority students. In terms of variation in population size across NY State communities, some districts enroll over 10000 students, while others enroll fewer than 300. The average number of students defined as college and career ready was just 42%. This metric, referred to as the Aspirational Performance Measure (APM) by New York State, is a combination of a school cohort's graduation rate, math test scores, and English test scores. As a proxy for school performance, some might view this average as disheartening. Furthermore, given the variability and diversity of the educational landscape, it is difficult to consider which factors might contribute to performance more than others. Previous qualitative and empirical literature has explicated the multifaceted links between families, communities, and children with regards to schooling performance. For years, quantitative analyses of education performance have been performed through traditional means: OLS regression. Statistical studies seeking to unmask the correlates of school performance and subsequent

consequences are nothing new. Where this research attempts to bring a layer of added value to the school performance literature, including community effects, is through spatial statistics. Though some studies have begun to analyze the neighborhood effect's impact on education, including the impact of neighbors-of-neighbors—the extralocal effect—they have yet to combine this theory with certain spatial methodologies. With limited resources spread across a broad spectrum of policy needs, we must change the preordained assumptions with which we evaluate our models.

Background

Sociological theory has long posited the idea that educational attainment of parents translates fairly consistently to relative socioeconomic status and that unequal education outcomes can 'follow' individuals from parent to child (Duncan & Murnane, 2011; Carter & Welner, 2013). Thus, it is not without reason to posit that levels of educational attainment for a child can be directly impacted by the circumstances surrounding the parent; the amalgamation of natural and social circumstances as described by John Stuart Mill (Skorupski, 1989). Several decades of sociological and psychological research support the position that children benefit from parents / guardians actively participating in their educational pursuits by way of higher educational achievement (Muller & Kerbow, 1993; Simon, 2000; Dornbusch & Darling, 1992; Fehrmann et al, 1987). Research also shows that level of parental involvement can vary from household to household but that this variance can somewhat be reduced by increasing the school's interaction with families beyond that of just the student (Muller & Kerbow, 1993, Galindo & Sheldon, 2012). Flora & Flora (2013) also posit that 'life-altering assets' such as schools can be enhanced or degraded through the use of collective agency, putting forward that schools often act as

stabilizing forces within communities. It is also well accepted that parents with higher levels of education are more likely to be involved with their children's academic pursuits than those parents with less education and that certain limitations on parents in lower-income families can put students at risk of having less of said involvement (Stevenson & Baker, 1986). Variance in levels of involvement between parents in higher- and lower-income is well-recognized, so much so that in 1996 the National Network of Partnership Schools was founded in order to assist primary school educators in developing community partnership programs. These programs are designed to enhance leadership development, create action plans, and form partnership teams comprised of students, community members, teachers, administrators and parents (Carlson and Cowen, 2015). Additionally, multi-language documentation, community involvement activities, and family-to-school communication strategies attempt to strengthen the ties between home and school, underscoring the importance of schools as integral facets of communities. Partnership programs such as NNPS have been proven to increase parental involvement (Simon 2000) but there is not enough evidence to make a substantial claim on partnership programs' impact on student performance. Though years of literature supports the benefits children gain from having family involvement in their schooling, there is still a necessity for research surrounding home-school partnerships, especially those which are methodologically robust and address effects of parental education (Lawrence, 2016; Patrikakou, 2016)

The effect of the school-community relationship, or 'natural and social amalgamation,' is often challenged by the fact that school resources are not evenly distributed across locales, most famously brought to national attention by the Brown v

Board of Education case in 1954, Serrano v. Priest in 1971, and San Antonio v. Rodriguez in 1973. Following the Civil Rights Act, the somewhat successful initial move toward desegregation (Swann v. Charlotte-Mecklenberg, 1971) and the growing number of students from immigrant families going to school, the pressure on educational systems in America to provide adequate and fair resources for all students, including English Language Learners, was considerably stronger (Coleman, 1966; Fraser 2001). In his landmark 1966 report and later writing Coleman (1975) argues exploring family background enhances our explanation of the variation in achievement than school resources alone, which was in direct opposition the largest education reform act to date, the Elementary and Secondary Education Act (1965). What Coleman's report was remiss in addressing in greater detail was whether these 'family differences' were a product of neighborhood quality, family income, parent education, or other factors. More recent research suggests that the fiscal economies of communities, as a whole, play a significant part in educational opportunity for children as both the families and the schools are deeply embedded within communities (Wang and Reynolds, 1996, Giersch et al 2016).

This leads us to the supposition that *geography matters*: where a family lives and, subsequently, where a child attends school can have a profound and varied impact on her educational attainment. And, this impact is above and beyond the characteristics of individual families and local neighborhoods. Basic awareness of a community's makeup is the first step in understanding how education (opportunity and outcome) might be impacted, including how selective some families can or will be when choosing to live in a community. Selection is a result of numerous factors, one of the most important most often being income or socioeconomic status (Douglas, 1964; Ellen & Turner, 1997; Lee &

Burkam, 2002; Bast & Walberg, 2004). Research indicates that neighborhood context, including poverty rates, educational attainment, and family composition can contribute to increasing socioeconomic segregation, have direct effects on childhood intellectual development, and can be a determinant factor in where families choose to live (Bischoff & Reardon, 2013). Bischoff & Reardon illustrate the example of two children in socioeconomically disparate neighborhoods, and this relates directly to our discussions on social / cultural capital. The poor child from a poor neighborhood may see few individuals with high educational attainment and, thus, doesn't assign high value to school. The opposite effect is seen in wealthy neighborhoods, where wealthy children are surrounded by those with higher degrees of educational attainment and therefore assign a higher level of cultural capital to schooling (Bischoff & Reardon, 2013; Coleman, 1975). This variation between areas within a community or school district is not a newly researched concept. Gulson & Symes (2007) aggregate research on education, policy, and geography. One article, in specific, relates spatial theories, access, equity, and the educational differences between rural and urban districts across the United States. In a recent publication, Hogrebe and Tate (2016) speak to the importance of communities' understanding the geographical makeup of their own locale, as well as surrounding areas, in order to make informed policy decisions on neighborhood planning and educational resources.

The thought that neighborhood socioeconomic conditions can have a direct impact on children's behavior was the central point made by Jencks and Mayer (1990) in which they posit exposure to more disadvantaged neighbors impairs children's social development. Though research surrounding neighborhood effects on education is still evolving, the traditional institutional model supports the thought that schools which are

more disadvantaged socioeconomic status would tend to have fewer resources, leading to a teacher training deficit, see less support from parents, and suffer from lower overall educational expectations (Lee and Burkam, 2002). Situated cognition theory, specifically the idea of community of practice, assumes that sociocultural practices emerge when people strive toward common goals alongside other individuals with similar aims (Heidegger, 1968). More importantly, this notion that groups of people striving toward common goals often undergo processes of social learning can be analogous to many of the sociological functions of schooling. Collective socialization and epidemic theories, however, also introduce the possibility that effects beyond the insular neighborhood can impact childhood outcomes. Crowder and South (2002) posit the notion of an “extralocal” neighborhood effect – the “...areas surrounding an individual’s neighborhood of residence.” This conceptualization of a neighbors-of-neighbors effect gets at the heart of the spatial statistical assumption: it is not in the most appropriate standing for social science researchers to assume a model will predict outcomes uniformly across a geography – which is exactly what we do when we run global analyses such as traditional OLS regressions (Pasculli et al, 2014). Ordinary Least Squares regression assume a uniform goodness-of-fit for the entirety of the dataset. In straightforward terms: If someone were to run an OLS model and predicted a relationship between minority concentration and school performance across *State X*, the intrinsic assumption is that the predictability (or strength of relationship) of the model does not vary anywhere across the area of study. By running spatial regressions, I allow the model to vary in its predictive power across the area of study, thus revealing underlying structures of the dataset which would be otherwise obscured through global methods; I explain this in more detail in the methods section.

I also feel it important to note that the theorizing of the relationship between community resources, performance, and space is not complete. This study hopes to inform policymakers, administrators, and community members by providing a richer understanding of wealth, race, and educational performance in New York State through spatial relationships.

Data

Sources

Initial data for this analysis were collected through the Cornell University Program on Applied Demographics (PAD), the Community and Rural Development Institute (CaRDI), and the New York State Education Data Hub. Additional data for this study were also drawn from the United States Census Bureau, the American Community Survey (ACS), Open Data NY via the New York State Office of Information Technology Services, and the New York State Education Department. In order to represent geographic features such as state shape, county boundaries, district boundaries, and other point data relative to geospatial analyses, such files were downloaded through the US Census Bureau Tiger Line/Shape Files Program, the Cornell University Geospatial Information Repository through Mann Library, and the New York State GIS Clearinghouse.

Variable Definitions

The definitions of the dependent and explanatory variables, as well as spatial constructs, will be provided in this section.

For the purposes of this study, the dependent variable is identified as the indicator of district-level student performance labeled “PctAPM.” I use this metric instead of graduation rate, for example, because the latter only ascertains how many students actually

completed high school within four years. The aspirational performance measure (APM), however, is a metric designated by New York State to be a proxy for both performance and college & career readiness. The figure is ascertained through calculating the percentage of students who “...earned a score of 75 or greater on their English Regents examination...”, “...an 80 or better on a mathematics Regents exam”, and earned a high school diploma (NYS Board of Regents, 2012). This supersedes the value of a graduation rate because it ties the measure directly to measurable performance. Similarly, individual math or reading test scores alone were not used because of the advantage of APM being a combined metric.

The independent or explanatory variables of interest in this study include a variety of sociological, family-level, individual-level, community-level, demographic, and financial constructs which might impact student performance. In order to focus the purpose of this study, however, I will only focus on those surrounding wealth / income, race, population, and finances. To observe the relative aggregate level of families’ wealth / income within a community or district, I utilize the Free- and Reduced-Price Lunch (FRPL) metric, calculated as the percentage of those students within a district utilizing the program: “PctFRPL.” The FRPL program is a federally-sponsored initiative that provides free or inexpensive lunches to children from low-income families, providing the schools with cash subsidies to pay for the meals of those children who qualify (Shahin, United States Department of Agriculture, 2017). It is also named under the National School Lunch or Community School Lunch Program. This metric has long been used as a reliable proxy variable for poverty or similar resource deprivation. To observe the relationship of race to performance, I utilize a calculated variable of the percent of students within a district who are non-white: “PctMinority.” To determine whether the population of students has any

impact on performance, I utilize the explanatory variable “Enrollment” which is the number of currently enrolled students in the district. In keeping with the assertion that neighborhood and community effects can have an impact on student performance, I use a variable called “PctBach” to represent the aggregate level of education within the school district. This figure, generated from data U.S. Bureau of Labor Statistics American Community Survey, is the number of adults 25 years old or older within the boundaries of a school district who have earned a bachelor’s, master’s, professional, or doctoral degree. This number was then divided by the total population of adults 25 years old or older within the district to get a percentage value. Finally, I consider a financial explanatory variable and its potential impact on performance. “CWR,” or the Combined Wealth Ratio, is “...a measure of relative wealth, indexing each school district against the statewide average on a combination of...property wealth per pupil and income wealth per pupil. A school district’s wealth is measured by comparing its property value per pupil with the state average property value per pupil, and the district’s adjusted gross income per pupil with the state average adjusted gross income per pupil. The ratios derived from these comparisons are multiplied by 0.5 and added together to form the combined wealth ratio” (New York State School Boards Association, 2013). The CWR will be used to determine if the overall level of wealth within a district has any explanatory power on the district-level aggregate of student performance.

Given the conceptualization of this study as mentioned above, I introduce a set of spatial variables that allow a test of the degree that location matters, specifically how the testing for underlying spatial correlations within data is often overlooked when using global a global inference methodology. Spatial variables are not explanatory as much as

they are necessary for the proper running of spatial regression. Such non-explanatory variables independent of the a-spatial OLS regression are: “GeoID” which serves as a unique identifier per school district, “INTPTLAT” and “INTPTLON” which are the geospatially interpreted latitude and longitude measurements of each district, “ALAND” and “AWATER” which are numerical representations of the amount of land and water, respectively, in each of the districts, in square meters.

Explanatory Variable Definition Table

| Explanatory Variable Name | Description |
|----------------------------------|---|
| PctFRPL | Percent of students receiving free- and reduced-price lunch; proxy for poverty / low-income |
| PctMinority | Percent of students who are non-white |
| Enrollment | Number of students enrolled within a district |
| Combined Wealth Ratio | Measure of individual district wealth relative to all New York State districts |
| Percent Bachelor's Degree | Percentage of adults age 25 years and older, per district, who have earned a bachelor's or higher |
| ALAND (spatial) | Measurement of the amount of land area within a polygon (district) in square meters |
| AWATER (spatial) | Measurement of the amount of water area within a polygon (district) in square meters |

Preparation

In order to prepare the data for visualization and analysis, it was cleaned, manipulated and labeled through Microsoft Excel and STATA. Once data was ready for import into ArcGIS, shapefiles provided by the NYS databases were properly visualized through clipping (NYS to BOCES Districts and NYS to NYS School Districts). After the shapefile preparation was complete, the various datasets were loaded into GIS and combined using the join tool, based on the unique identifier of GeoID (code commonly

used across NYS school-based data files). Individual metrics not reported by the data source providers were quantified using the field calculator / editor tool in ArcGIS, the various variable editing tools in STATA or the variable calculation tools in GeoDa. These were crucial in eventually being able to create the maps shown here as the fields of expenditures per pupil, revenue per pupil, as well as the various percentage calculations (APM, FRPL, Minority) were not in any of the datasets originally. Through the use of the symbology tools in ArcGIS, the distinctions within variables were visualized through graduated colors and graduated symbols. The quantile classification was used for graduated symbology because the variables in question are normally distributed. There were data points that were intentionally omitted from the analysis as they skewed the results: Union-Free school districts, and those districts with five students or less in one cohort were dropped because they do not report the level of data required for the study. Furthermore, several districts were dropped due to their disproportionately high level of financial outlays (Fire Island / NYC Schools / Bridgeport / Kiryas Joel). Limitations to data gathering included the aforementioned non-reporting districts, and that the most recent data is for the 2014-2015 school year for which some school districts do not have the most up-to-date values. Statistical analyses such as OLS regression, and the GWR tool were performed in ArcGIS. Spatial lag models, and some univariate graphics were run and output through the use of GeoDa, another spatial statistics software.

Methods

Spatial Statistics

Traditional research methodologies analyzing student performance typically utilize large-scale, sampled data sets meant to introduce deductions based on universal

extrapolations. The most common of such methods is the ordinary least squares (OLS) regression. When researchers study data dealing with geographic features or datasets conceptually tied to geography, such as ozone, temperature, water usage, or contamination data, for example, the impetus for analyzing such information spatially is quite clear. What some researchers consider a-spatial—such as employment, demographic, and education—data is often analyzed without considering the possibility of a spatial component. These data, however, are inextricably bound to local geographic features: educating students requires school buildings, students live in homes with their families, and those homes are located within towns. When these factors are considered within the context of regression analyses, excluding the possibility of spatial relationships can result in a higher chance of explanatory variables returning as statistically significant when in fact they are not, also known as a Type 1 error (Lennon, 2000). If spatial autocorrelation is present and a regression is run without accounting for spatial relationships, there is a high chance of an overstated association between dependent and independent variables. The positive purpose of using spatial regression is the testing for, and subsequent reduction of, such overestimation. For example, many traditional OLS regressions return standard diagnostics which may include the Jarque-Bera test, which asserts the level of normality for the residuals. Though this is a somewhat ubiquitous diagnostic, it may not always be reported in a write-up. A diagnostic exclusive to spatial regression, however, is the Moran's I test. This tool asserts the level of spatial autocorrelation of the residuals. Any researcher using traditional regression techniques would be quite unlikely to use the Moran's I test, thereby overlooking the potential of autocorrelation and may overestimate some relationships. A

more detailed explanation of spatial autocorrelation will serve to illuminate its usefulness in this study and beyond.

Spatial Autocorrelation

As spatial regression is not often used in areas of social science research dealing with education, an explanation of some spatial constructs is necessary. Waldo Tobler, an accomplished geographer and cartographer, and one of the pioneers of quantitative methodologies in geography, stated: “Everything is related to everything else, but near things are more related to each other” (Tobler, 1970; Goodchild, 2004). In essence, Where OLS regression returns the degree to which variables are related between or amongst each other, correlation, spatial regression shows the correlation within variables across georeferenced space (Tomlinson, 2005). Formally defined, spatial autocorrelation

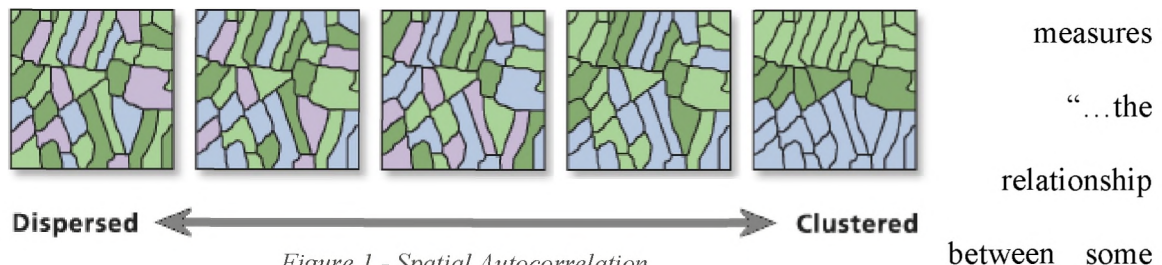


Figure 1 - Spatial Autocorrelation

variable observed in each of the n localities and a measure of geographical proximity defined for all $n(n-1)$ pairs chosen from n ” (Hubert et al, 1981). When dealing with spatial regression, the null hypothesis is known as the spatial independence hypothesis. This hypothesis is assumed to be a situation in which the observable relationships are a result of a completely random process (see Figure 1). The researcher works toward disproving this (null) hypothesis by attempting to show the process is a result of nonrandom, or systematic, processes – be they resultant in dispersion or clustering. When there are no observable spatial relationships between events, the data is considered to be spatially independent.

When evidence points to data (people, facilities, events, etc.) being clustered together, the data are considered to be positively spatially autocorrelated and, in the reverse, when data is dispersed, the data are considered to be negatively spatially autocorrelated. The Moran's I statistic, a feature of spatial regression operations, measures the level of spatial autocorrelation and returns a value as to whether the dataset is clustered, dispersed, or randomly distributed. As with many statistical techniques, attempting to determine causality is paramount. What is important to know about spatial statistics methodologies, though, is that the identification and quantification of spatial autocorrelation does not point to a causal relationship. It does alert the researcher to spatial processes which may be at work within the data.

Spatial Nonstationarity

By analyzing datasets with spatial regression, researchers can also test for indicators of nonstationarity. This is crucial to a more robust understanding of varied data, especially in instances where geographic location can play a role in what services / capabilities are offered, as is true in the case of education. When there is variability in the strength of the relationships between the dependent and independent variables, this is considered spatial nonstationarity (Brundson et al, 1996). When a regression is assumed to be stationary, this means that the effect of the model is the same across geographic locations. I.e. the factors, determined in a particular model, which effect performance in one school district uniformly effect school districts in the same manner across New York State. When stated conceptually, this seems to be somewhat of an obvious blanket statement, and we are aware that various district dichotomies (urban / rural, upstate / downstate, wealthy / under resourced) can effect resource levels, capabilities, and, in turn,

performance (Darling-Hammond, 2013). This ‘blanket method’ is how a traditional OLS regression would treat such data if a model were run on all districts at a state-level of analysis. When we observe the results of a spatial regression and they indicate spatial nonstationarity, this means the effect of that particular model has varying impact across geographies—districts, for example—the same stimulus provokes a different response in different parts of the study area (Tomlinson, 2005). Most importantly: if a dataset is analyzed by OLS regression and the researcher does not test for spatial nonstationarity, but nonstationarity is present, the OLS model will not reflect the true underlying structure of the data, thus returning a less than accurate explanation of the relationships between the variables in question. In cases where spatial nonstationarity is determined, methods can be employed to account for the fact that the model may have varying effects in different spatial regions. This assists in further specifying the model, hopefully reaching a level of prediction which exceeds that of the a-spatial OLS regression, as well as the generalized spatial model. Lersch and Hart (2014) most notably displayed the extreme case of OLS underestimation through their use of Geographic Weighted Regression (outlined in the next section). In their study, Lersch and Hart attempted to predict levels of crime based on individuals’ exposure to certain chemical toxins, in this case lead and lead-based compounds. When they ran an OLS regression on their dataset, which again does not take into account any spatial variance, the adjusted R^2 value returned as 0.08: roughly 8% of the variability in the data could be explain through their model. When they tested for spatial nonstationarity and subsequently ran a spatial statistics model using GWR, the average adjusted R^2 across census tracts was 0.44: the spatially-referenced model was close to five times as precise in its explanatory power.

Geographically Weighted Regression

The use of Geographic Weighted Regression (GWR) is a method by which researchers can narrow the field of study in an effort to increase the model's explanatory power. GWR serves as a localized methodology wherein the relationships are allowed to vary across the study area and is primarily used to detect and determine broad scale regional variation (Wheeler, 2014). By defining the local area, or neighborhood, researchers can use GWR to test where a particular model functions well, or where it may be less capable in its predictive power. Operating based on concepts outlined the literature, I intend to use spatial regression, including GWR, to more robustly define which districts, classified by resource deprivation, may be more impacted by models predicting student performance than others.

Study Design

In order to analyze the effect of the explanatory variables on student performance the study will proceed through four stages of analysis. First, univariate descriptive statistics will be observed to present a basic understanding of the dependent, explanatory, and geospatial variables. Second, multivariate statistics will be presented to observe relationships between and among all variables within the dataset. Third, a traditional a-spatial OLS regression model will be run and interpreted to ascertain various effects on student performance, and the level of predictability of the model. The residuals of the OLS model will be analyzed for spatial autocorrelation, through the use of the Moran's I statistic. Fourth, given that spatial autocorrelation is observed, weights will be calculated for the school districts and their neighborhoods, and spatial regressions will be performed. This will allow the researcher to observe potential shifts in coefficient values, statistical

significance, and the mitigation or correction of spatial autocorrelation within the model. Fifth, the implementation of a geographically weighted regression model will be tested to ascertain whether such the clustering or dispersion of data can be explained more completely by the model in certain areas than others.

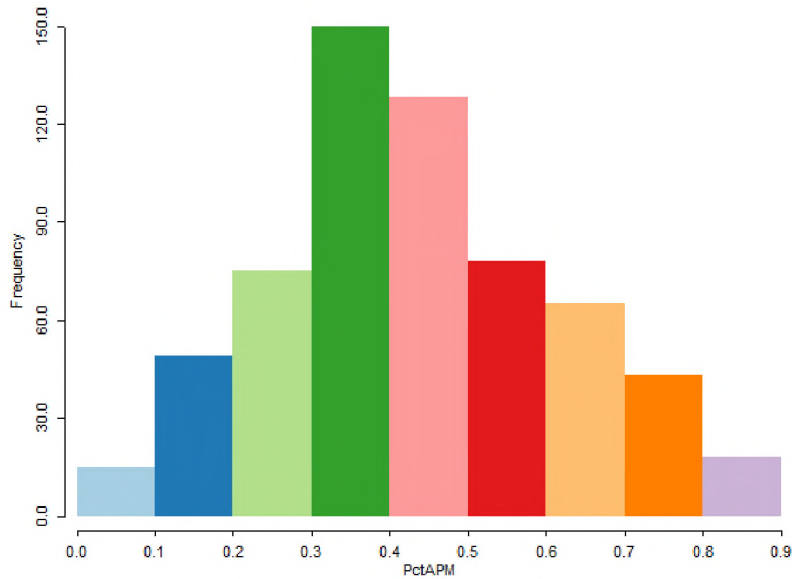
Results

Univariate

By analyzing the univariate results of the dependent variable and each explanatory variable, we can better understand the landscape of education in New York State as well as ensuring normality for statistical procedures.

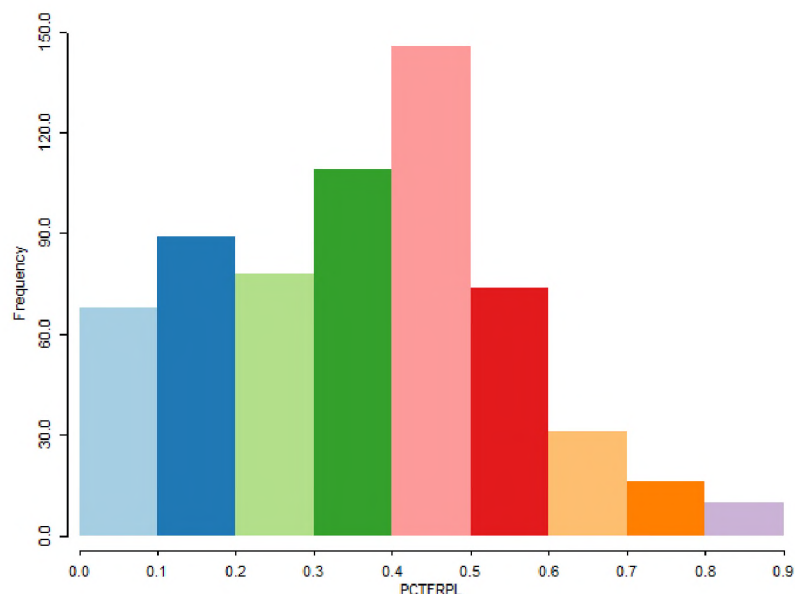
| Variable | Min | Max | Mean | S.D. | % Data |
|--------------------------|-----------|-----------|-----------|-----------|--------|
| (Dependent) PctAPM | 0.0369 | 0.8910 | 0.4472 | 0.1728 | 100 |
| (Explanatory) PctFRPL | 0.0 | 0.9310 | 0.3664 | 0.1985 | 100 |
| Enrollment | 62 | 30042 | 2427.93 | 2393.86 | 100 |
| PctMinority | 0.0032 | 0.9945 | 0.1662 | 0.2050 | 100 |
| CWR | 0.189 | 23.406 | 1.0539 | 1.3570 | 100 |
| PctBach | 0.0689 | 0.8714 | 0.2945 | 0.1509 | 100 |
| ALAND | 1.9351e+6 | 1.6565e+9 | 1.8552e+8 | 1.8591e+8 | 100 |
| AWATER | 0 | 3.5903+8 | 1.0874e+7 | 2.5704e+7 | 100 |

Review of the univariate table above provided insight into whether the variables had the appropriate, or expected, upper and lower bounds, as well as signaled the presence of potential outliers. Since I had previously cleaned the data prior to imputing it into the various shapefiles and tables, there were no unexpected results here and all of the explanatory variables are at 100% of the data available after exclusions. Observation of the primary dependent variable, PctAPM, shows a relatively normal distribution. This, a

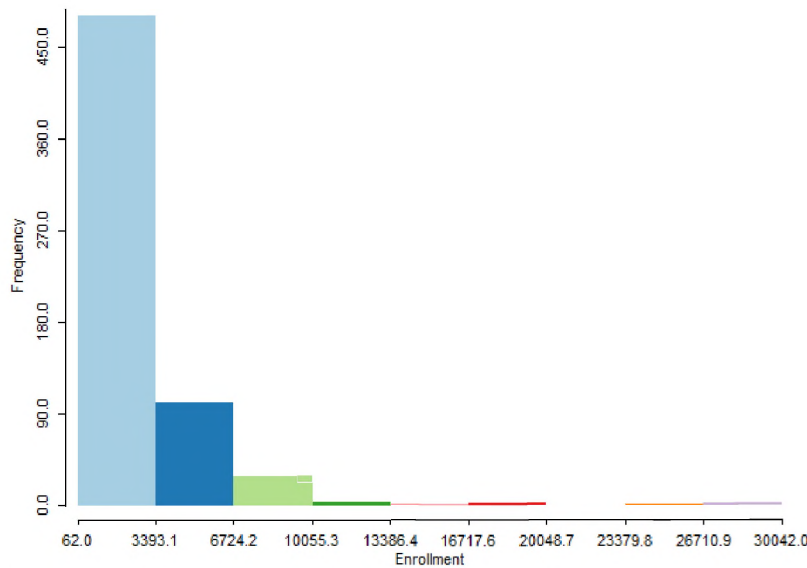


primary assumption of normality for traditional a-spatial statistics, meant that no transformation of the variable was needed. As is seen in many performance measures, the ‘bell curve’ is

prominent in the PctAPM variable as well. As expected, the mean is close to the halfway point, at approximately 44%. Notably, there are no districts where 0 students are considered college & career ready (a 0% APM) and there are no districts where all of the students are considered college & career ready (a 100% APM). Observing the explanatory variables, I begin with PctFRPL, the proxy variable for poverty. This variable, too, was fairly normally distributed, though with a larger leftward skew than PctAPM. This is to say that, on average, there are more school districts in New York that have a higher proportion of students living in poverty than those districts which have the majority of students in higher



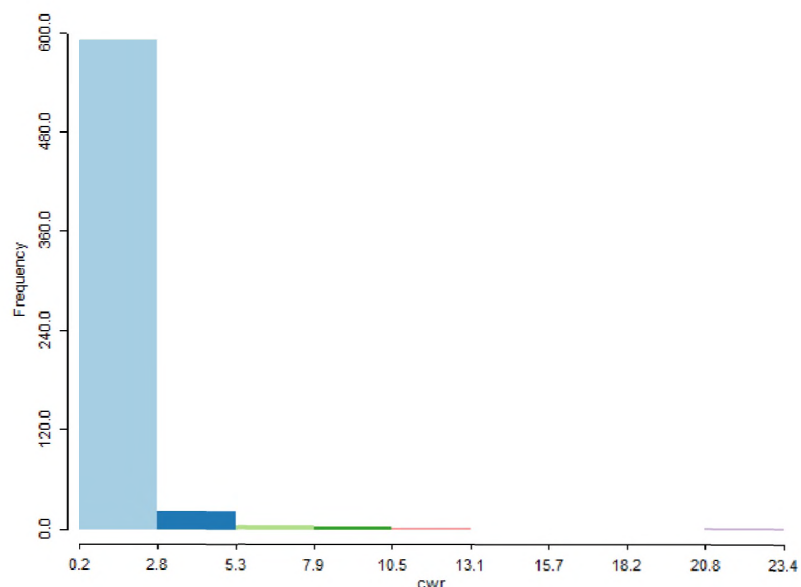
socioeconomic classes. Given what we know about the rural/urban dichotomies in New York State and that the information from New York City is excluded from this study, this

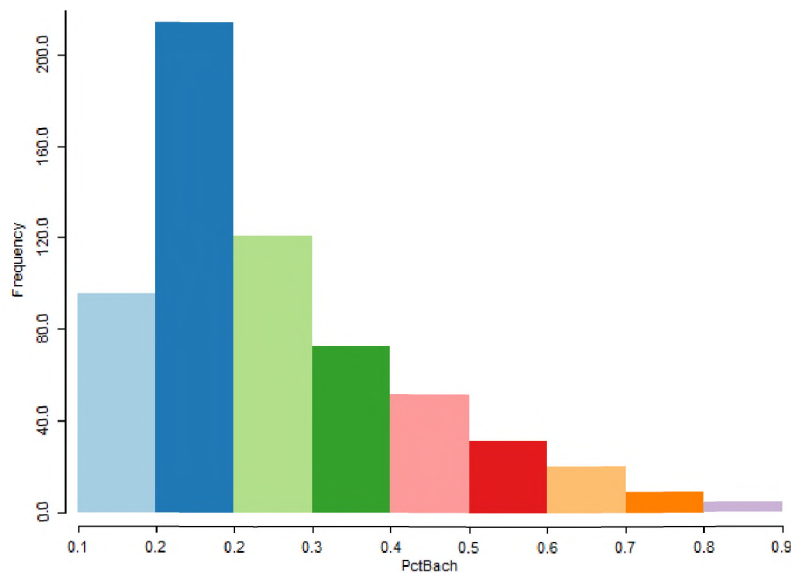


distribution is to be expected. Next, the explanatory variable of enrollment is visualized for univariate analysis. This variable is highly skewed, indicating the majority of school

districts in the study are below the 10,000 student level. Though it may be argued that the variable should be transformed in order to most effectively run an OLS regression, the resultant coefficient would be difficult to interpret and may not lend itself to further spatial analyses. I decided to leave this variable untransformed for the purpose of this study. The next explanatory variable is the Combined Wealth Ratio (CWR). Similar to the enrollment variable, the distribution

is highly skewed. Also in keeping with the thoughts concerning enrollment, this variable was left untransformed. Since this is a composite measure determined by



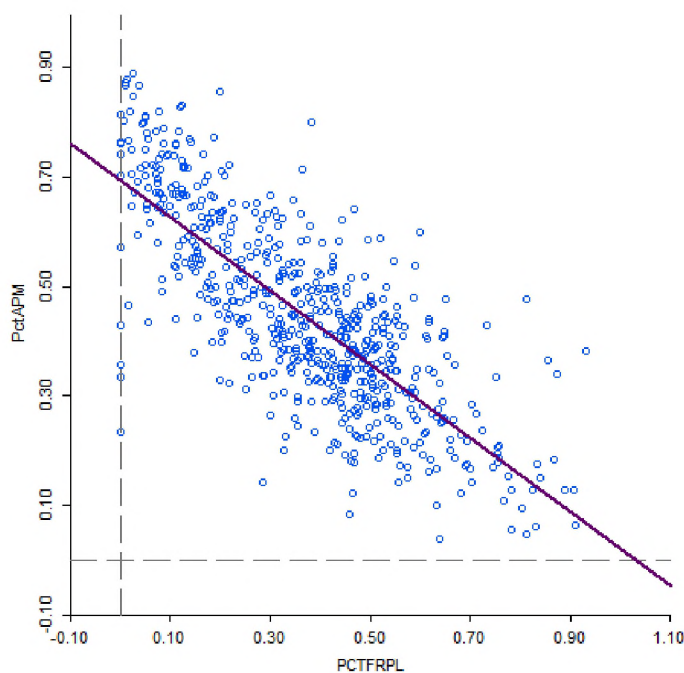


the State of New York in their own methodology (listed above), it would be inappropriate to log transform the variable. Furthermore, the unit for CWR is already difficult enough to

interpret, so logging it would only add to the difficulty of interpretability. The transformed variable can be seen in the appendix to this study, for reference. Finally, the explanatory variable PctBach is visualized. This, though not normally distributed, was not made much more normal through log transformation. I decided it, too, would be more appropriate left in its untransformed state. The univariate analyses for ALAND and AWATER, necessary variables for spatial analyses, can be seen in the appendix to this study, for reference. After univariate analyses were performed, an exploration of bivariate relationships allowed for a deeper understanding of the New York State education landscape.

Bivariate Analyses (Scatterplots)

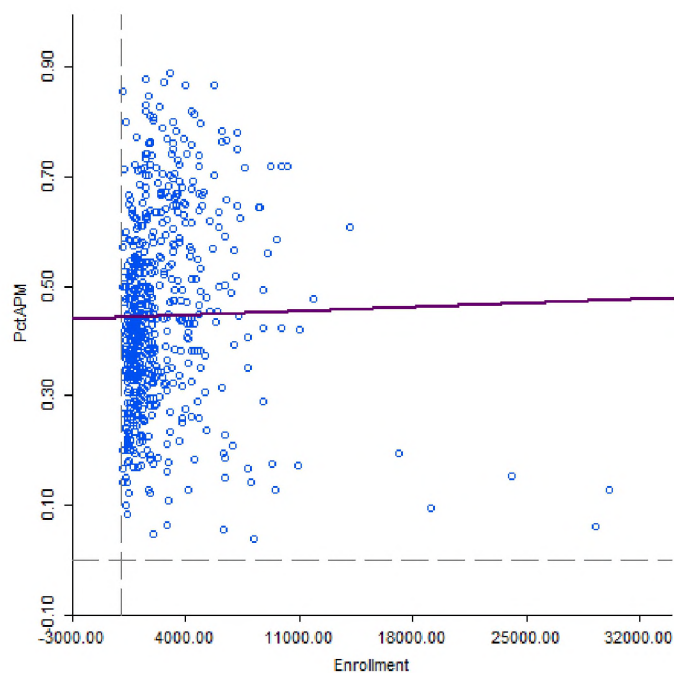
Through the use of scatterplots, both through STATA and the geospatial statistical software GeoDA, bivariate analyses are performed between the dependent variable and each of the explanatory variables. *Note:* for the sake of visual consistency, I present the scatterplots from GeoDA here, as the histograms were also produced using GeoDA. The scatterplots created in STATA are presented in the appendix, for reference. I then produced

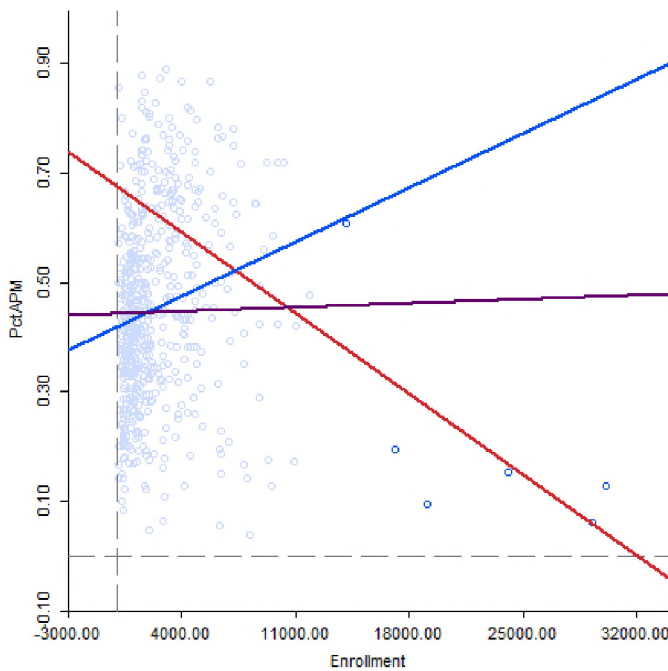


a correlation table between all variables. The first bivariate relationship I examined was that between PctAPM and PctFRPL, or the relationship between proxy variables for performance and poverty. The first figure in this section depicts the

relationship between these two variables. From the plot, we can observe a clear negative relationship between performance and increasing levels of impoverished students; as the percentage of students within a district receiving free or reduced price lunch increases, the performance of that district decreases. Observing the relationship between performance

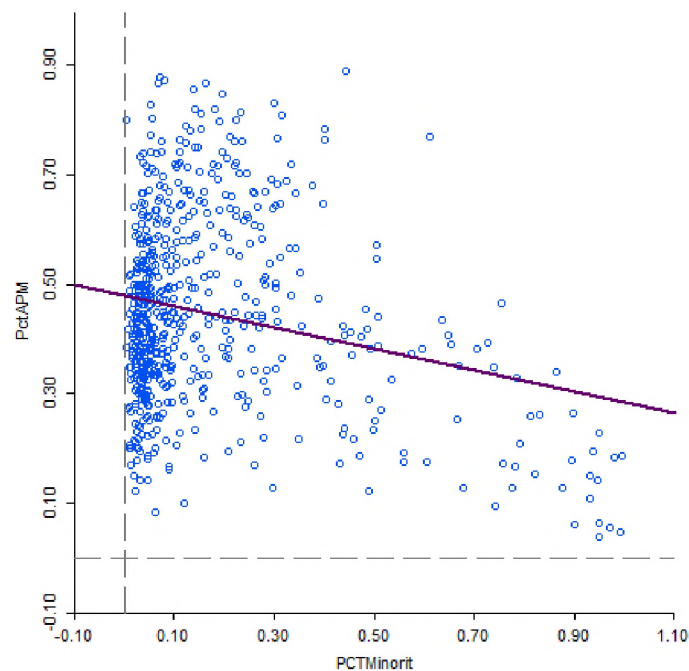
and enrollment, we see very little evidence of a positive or negative correlation. This is to say that the size of the school district, or number of individual students attending, does not seem to have an effect on the level

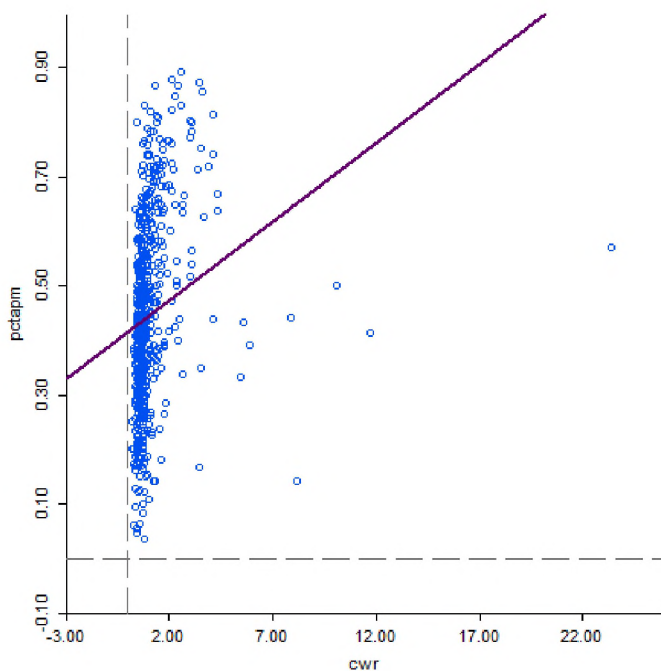




of performance of the district. It is clear, however, that there are some profound outliers in the enrollment variable. When we control for these outliers and remove them from the bivariate relationship, shown on the left, we can see that there

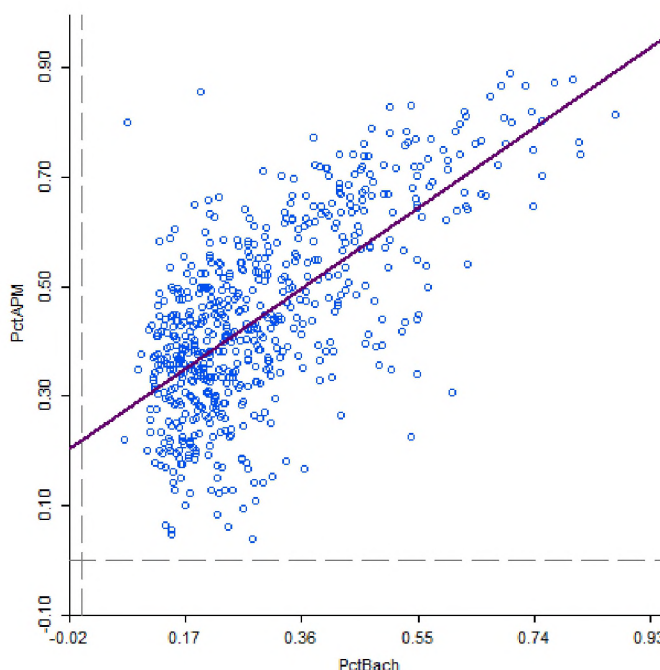
appears to be a positive relationship (blue line) between enrollment and performance; the red line displays the estimated relationship between performance and the enrollment of the largest schools (not statistically significant). Next, I analyze the relationship between performance and concentration of minority students. The scatterplot appears to show a negative correlation, though it is not particularly strong. This indicates that as the proportion of minority students within a district increases, there is an associated drop in the aggregate performance of the district. Observing the



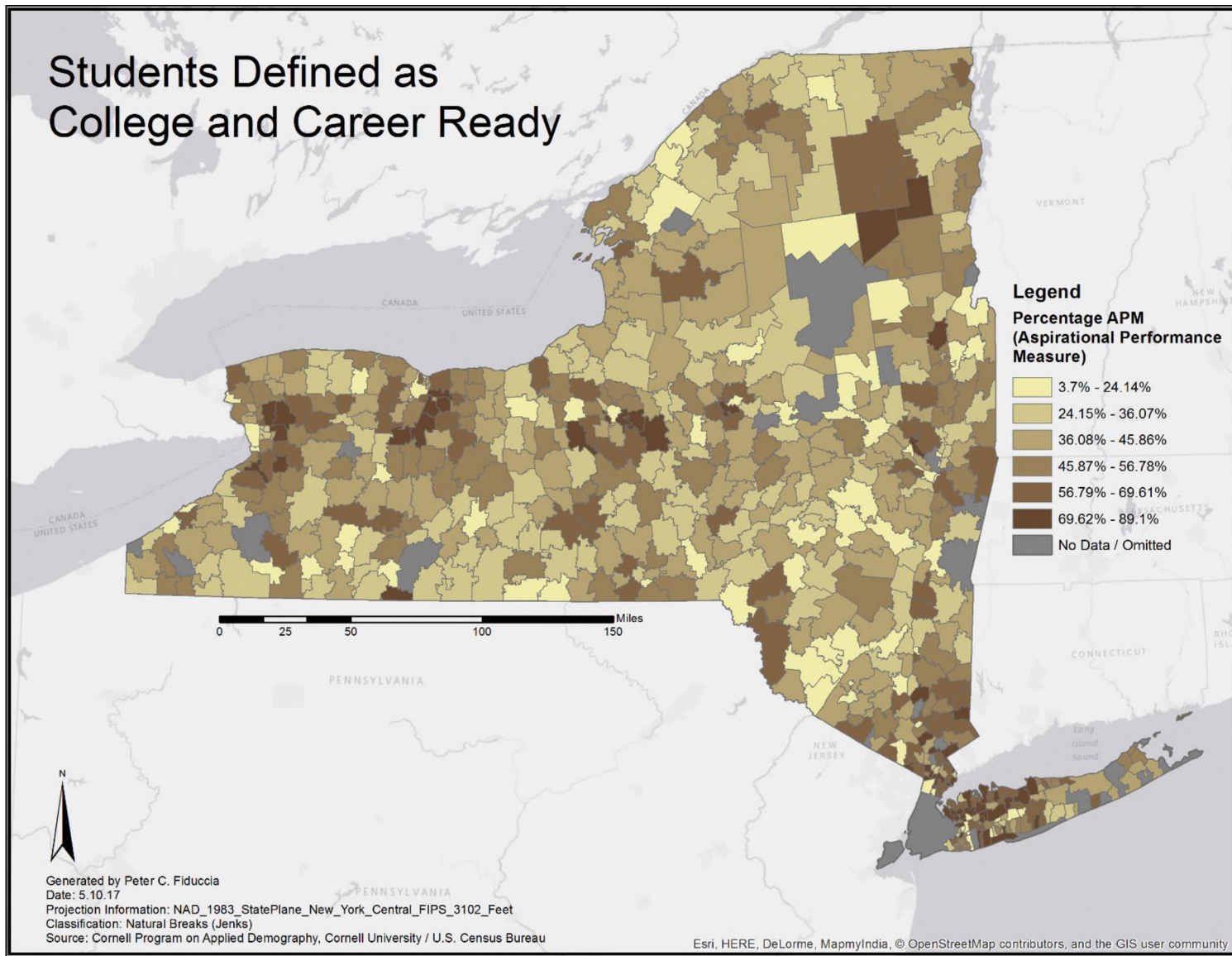


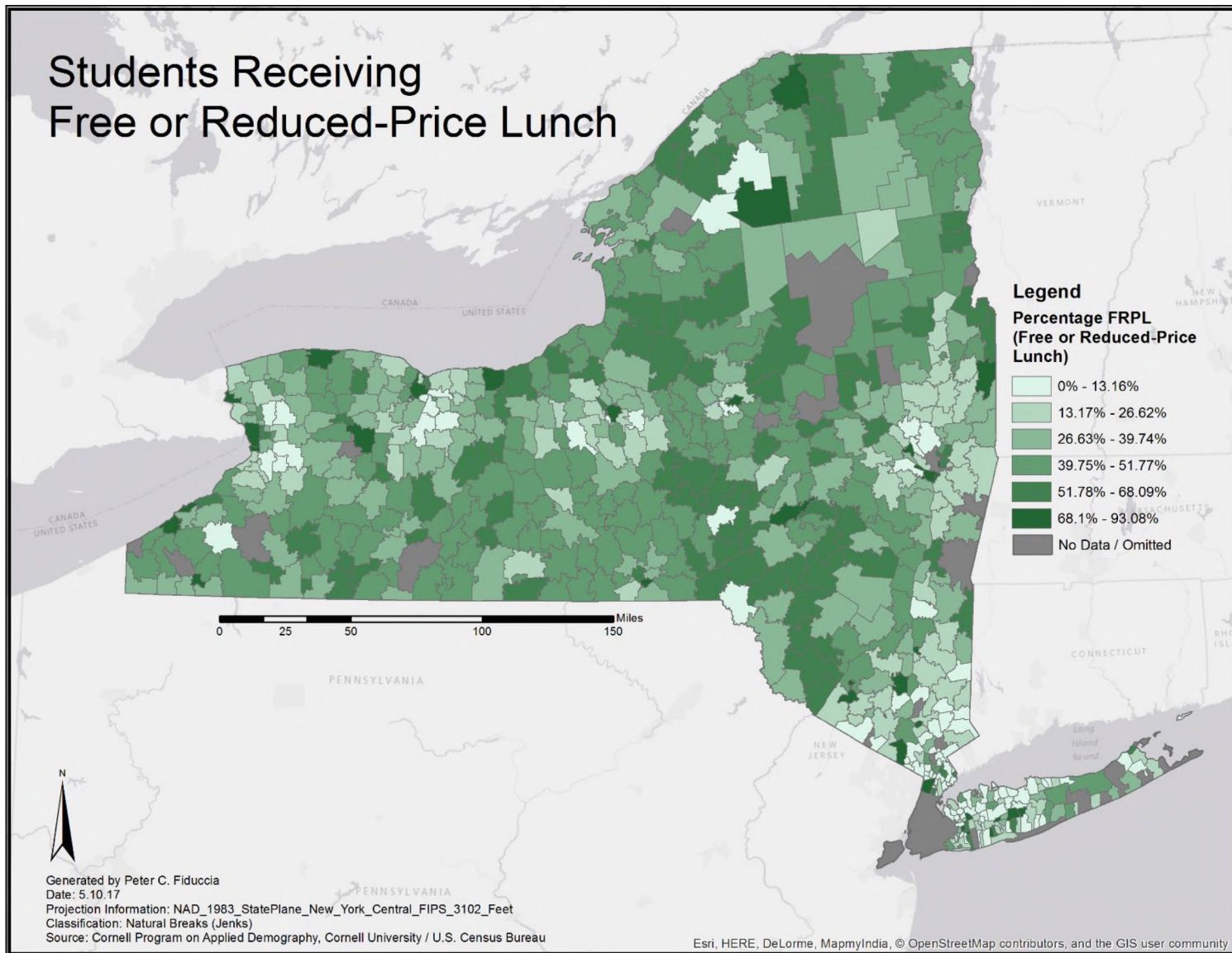
relationship between performance and the derived Combined Wealth Ratio measure, we appear to see a positive relationship. Though difficult to decipher due to the unique calculation of this metric, it would appear to tell us that as the relative

wealth of a district increases, so too does the average performance. Given the distribution of the data, however, this would be an inappropriate inference to make. Lastly, we observe the relationship between performance and the level of education within the district, represented by the PctBach variable. This seems to be a clear trend, indicating that the more adults in the community with a bachelor's degree or above, the higher the average performance of the students in that district.



Students Defined as College and Career Ready





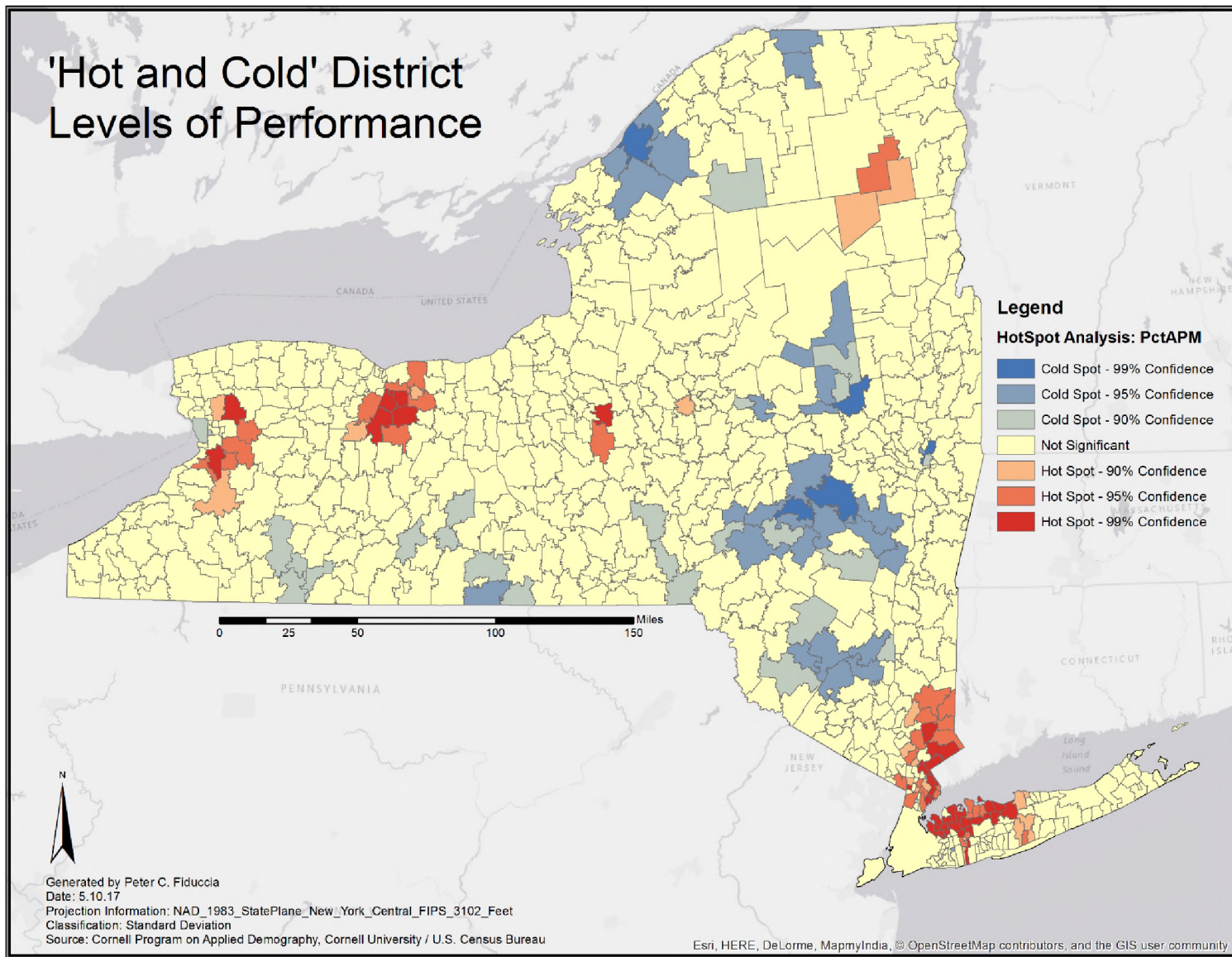
Mapping Analysis

Before delving into the multivariate results, it is important to take a moment to assign a visual to this ‘education landscape’ I have been mentioning throughout the analysis thus far. The map on the previous page depicts the average performance (PctAPM) of school districts in New York visualized through choropleth breaks. Even in this basic univariate map I can observe grouping of high performance districts around urban areas, including notable regions such as Buffalo, Rochester, Syracuse, Albany, as well as Westchester and some districts on Long Island. The map on the following page shows a similar visualization, but plotting the average percentage FRPL (proxy for poverty) across New York. In this case, the darker choropleths represent higher levels of impoverished students. Interestingly, though I don’t see the same kind of obvious grouping that we see in the APM map, there seems to be a preponderance of high poverty districts surrounding the city center areas seen in the previous map. It can be clearly seen, however, that the urban areas do tend to have a much lower level of average FRPL, noted by the tendency of the aforementioned regions to be lighter in coloration (note the mainly light depiction of Long Island).

Hot Spot Analysis

In order to determine where local clusters of districts with high or low performance, considering the PctAPM dependent variable, exist I utilize a spatial technique known as hot spot analysis through ArcGIS which also returns the confidence of these spots. Though somewhat counter-intuitive, the blue and red colorations do not simply indicate areas of high and low performance. In order to be labeled as a ‘hot’ or ‘cold’ spot, and be statistically significant, the district would need to be:

'Hot and Cold' District Levels of Performance



Above or below the average of the distribution **and** in a neighborhood of counties with correspondingly high or low performance. The choropleths are meant to signify a hot-neutral-cold conceptualization which indicates that with increasing red coloration that depicts districts increasingly above the statewide average for PctAPM. Conversely, with increasing blue coloration the districts increasingly below the statewide average for PctAPM are shown. What does this mean? This underscores the importance of ascertaining underlying spatial dependence. If researchers were to run an OLS regression with a set of explanatory variables on New York state and state the predictive outcomes, they would do so without accounting for spatial dependency, running the risk of incorrectly assuming there is no spatial variability. I would be remiss if I didn't note that I am not attempting to 'dethrone' OLS regression. It is important to remember, however, that when there is spatial variance within the data OLS can either mask localized effects, or underestimate extralocal effects within a sample data set if such variance is not accounted for.

Multivariate Analyses (Correlation Table)

| | PctAPM | PctFRPL | enroll~t | pctmin~t | CWR | PctBach |
|--------------------|---------------|----------------|-----------------|-----------------|------------|----------------|
| | | | | | | |
| PctAPM | 1 | | | | | |
| PctFRPL | -0.7759 | 1 | | | | |
| enrollment | 0.0174 | -0.0079 | 1 | | | |
| PctMinority | -0.2318 | 0.2437 | 0.5227 | 1 | | |
| CWR | 0.2271 | -0.2952 | -0.0463 | 0.0755 | 1 | |
| PctBach | 0.6772 | -0.6849 | 0.2161 | 0.1846 | 0.4226 | 1 |

In the first of the multivariate analyses, the correlation table above, I observe the relationships explicated in the scatterplots in the previous section, as well as the

relationships between explanatory variables. Notably, I see a strong negative relationship between PctFRPL and PctBach, which is expected: as the number of adults in a school district with a bachelor's degree or higher increase, the relative level of disadvantaged students (free or reduced price lunch) decreases. This further supports the family / neighborhood effect previously posited in the paper. I also observe two other expected relationships: that between Enrollment and PctMinority—as enrollment increases, so does the number of individuals in the school including minorities—, as well as the interaction between CWR and PctBach—as the relative wealth of a community increases, there is increased likelihood that more adults will have at least a bachelor's degree.

OLS Regression Model

After completing univariate and bivariate analyses, I constructed an empirical model to determine the predictors of performance in New York which will first be run through a standard OLS regression. Before I discuss the final model's results, the below model iteration table depicts the previous forms of the model which tested for increasing explanatory power, significance, and potential specification errors.

| | Dependent Variable: PctAPM with Independent(s): | Significant Exp. Var | Adjusted R ² |
|---------|---|----------------------|-------------------------|
| Model 1 | Enrollment | 0 | -0.10% |
| Model 2 | Enrollment + PctFRPL | 1 | 60.09% |
| Model 3 | Enrollment + PctFRPL + PctMinority | 2 | 60.38% |
| Model 4 | Enrollment + PctFRPL + PctMinority + CWR | 2 | 60.33% |
| Model 5 | Enrollment + PctFRPL + PctMinority + CWR + PctBach | 4 | 67.20% |
| Model X | PctFRPL + PctMinority + CWR + PctBach | 4 | 66.12% |
| | <i>(Red indicates a non-significant independent variable)</i> | | |

As the table shows, the most predictive model is Model 5, which results in a ~67% adjusted R2 value. Enrollment returns as statistically insignificant in each model, though when removed from analysis in Model X, it results in a decrease of explanatory power. Noting this, I decided to leave Enrollment in as an explanatory variable in the primary model, even though it returns insignificant in the OLS. Using the OLS function in ArcGIS, I ran Model 5 and returned the following results:

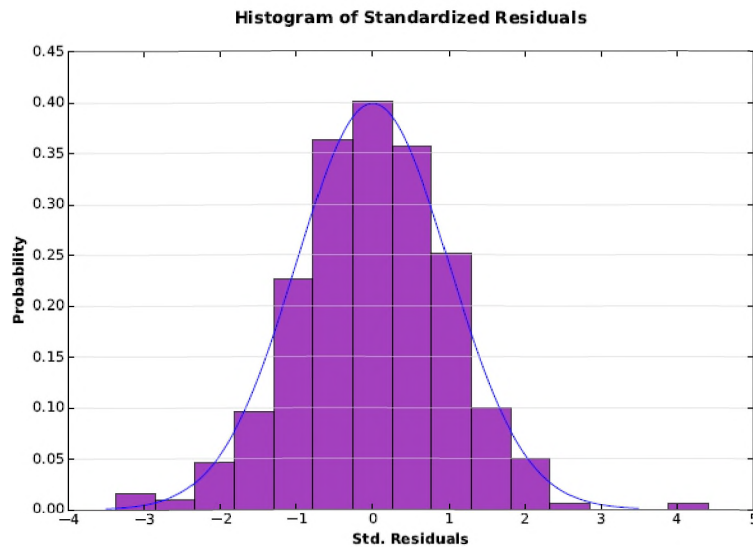
Summary of OLS Results - Model Variables

| Variable | Coefficient [a] | StdError | t-Statistic | Probability [b] | Robust_SE | Robust_t | Robust_Pr [b] | VIF [c] |
|------------|-----------------|----------|-------------|-----------------|-----------|-----------|---------------|----------|
| Intercept | 0.479324 | 0.021296 | 22.507967 | 0.000000* | 0.029190 | 16.420889 | 0.000000* | ----- |
| ENROLLMENT | 0.000002 | 0.000002 | 0.990375 | 0.322368 | 0.000001 | 1.276276 | 0.202346 | 1.461976 |
| PCTFRPL | -0.390391 | 0.032224 | -12.114894 | 0.000000* | 0.043752 | -8.922773 | 0.000000* | 2.590571 |
| PCTMINORIT | -0.178222 | 0.026336 | -6.767107 | 0.000000* | 0.025253 | -7.057336 | 0.000000* | 1.845771 |
| CWR | -0.009054 | 0.003285 | -2.755813 | 0.006028* | 0.003713 | -2.438484 | 0.015018* | 1.258222 |
| PCTBACH | 0.495941 | 0.043504 | 11.400001 | 0.000000* | 0.058631 | 8.458708 | 0.000000* | 2.727925 |

OLS Diagnostics

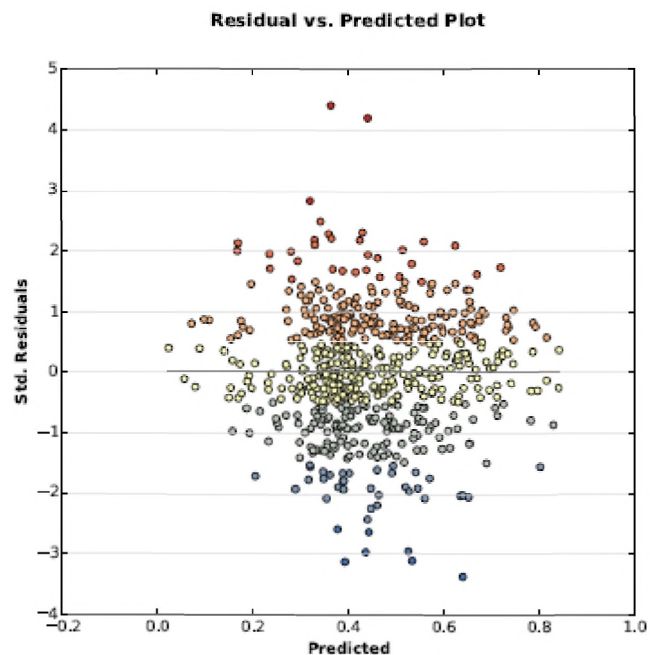
| | | | |
|-----------------------------|-------------|---|--------------|
| Input Features: | NewThesis | Dependent Variable: | PCTAPM |
| Number of Observations: | 621 | Akaike's Information Criterion (AICc) [d]: | -1102.326510 |
| Multiple R-Squared [d]: | 0.674624 | Adjusted R-Squared [d]: | 0.671978 |
| Joint F-Statistic [e]: | 255.023709 | Prob(>F), (5,615) degrees of freedom: | 0.000000* |
| Joint Wald Statistic [e]: | 1751.304144 | Prob(>chi-squared), (5) degrees of freedom: | 0.000000* |
| Koenker (BP) Statistic [f]: | 26.757240 | Prob(>chi-squared), (5) degrees of freedom: | 0.000064* |
| Jarque-Bera Statistic [g]: | 30.797340 | Prob(>chi-squared), (2) degrees of freedom: | 0.000000* |

The model, as shown in the table, predicts performance across New York fairly well at 67.20%. The coefficients of the statistically significant explanatory variables return with the expected sign: PctFRPL and PctAPM are both negatively associated with PctAPM, and PctBach is positively associated with PctAPM. Though a weak relationship and not as significant as other variables, CWR returns as having a slight negative association with PctAPM, which is opposite to what our bivariate analysis suggested. All of the VIF scores on the explanatory variables are below 10, indicating that we have little to no



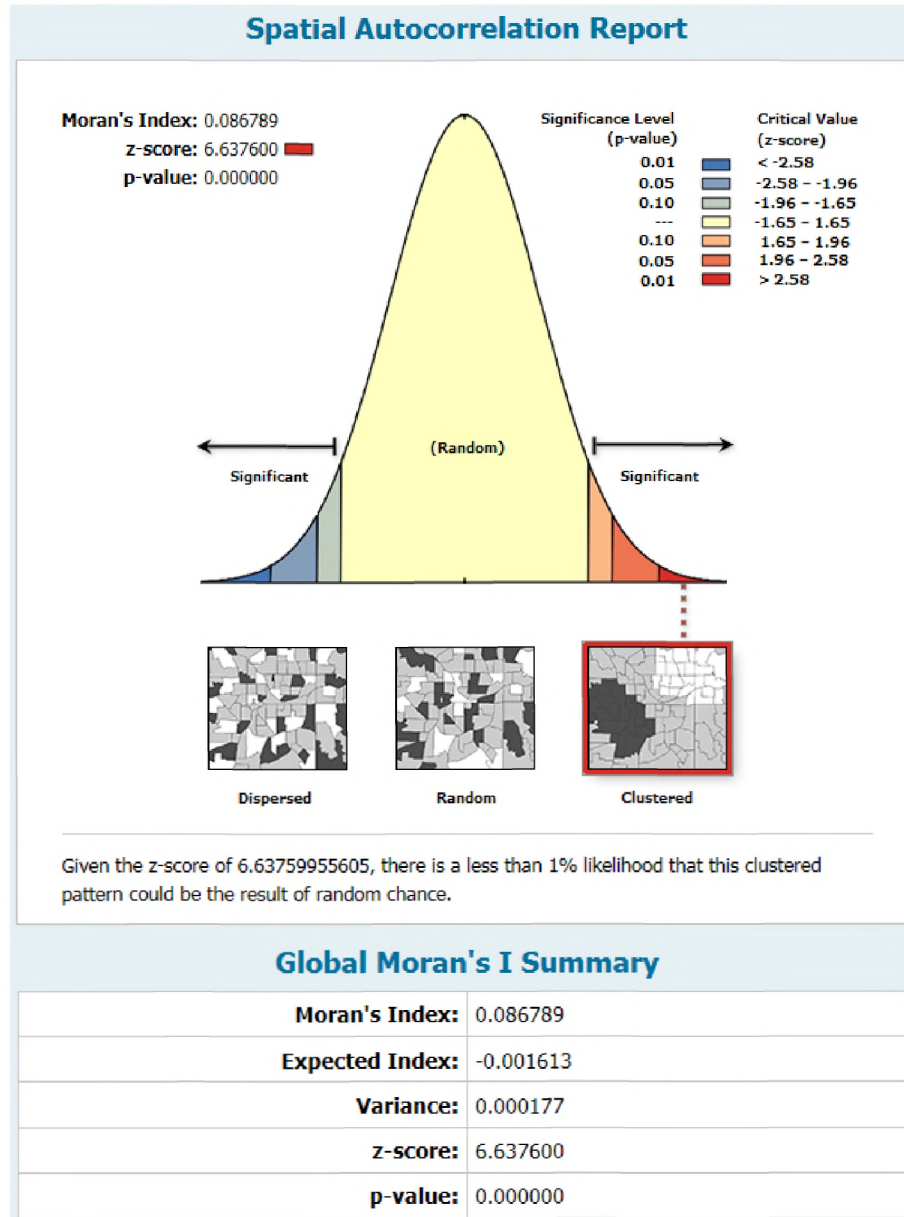
multicollinearity present in the model. These are all good signs and, without thinking of spatial variance, one might assume this model to be an excellent fit for use in a social science experiment, or to enact

policy changes relating to school performance. Further supporting this model's applicability is yet another 'check mark' that statisticians look for after running an OLS regression: normally and randomly distributed residuals. As shown from the two visualizations on this page – my OLS model has both of those positive attributes. Where we begin to see indications of incomplete conceptualization of the model is through the remaining statistics provided in the ArcGIS OLS output.



Both the Koenker and Jarque-Bera statistics return as statistically significant; this indicates that there is some kind of spatial variance present and it must be determined what kind of variance this is. By running a Moran's I statistic on the residuals of the OLS model, I can determine whether the residuals are spatially autocorrelated, indicating the presence of

some form of nonstationarity. Below is the Moran's I report for the residuals of the OLS model. Here is where we begin to see what traditional OLS can't account for: spatial autocorrelation. In observing the residual analysis, it appears that there is significant (p-



value)

autocorrelation and that the data is clustered. The

Koenker statistic's significance also indicates that there is some form of nonstationarity

in the data, implying the use of the

Geographically Weighted Regression:

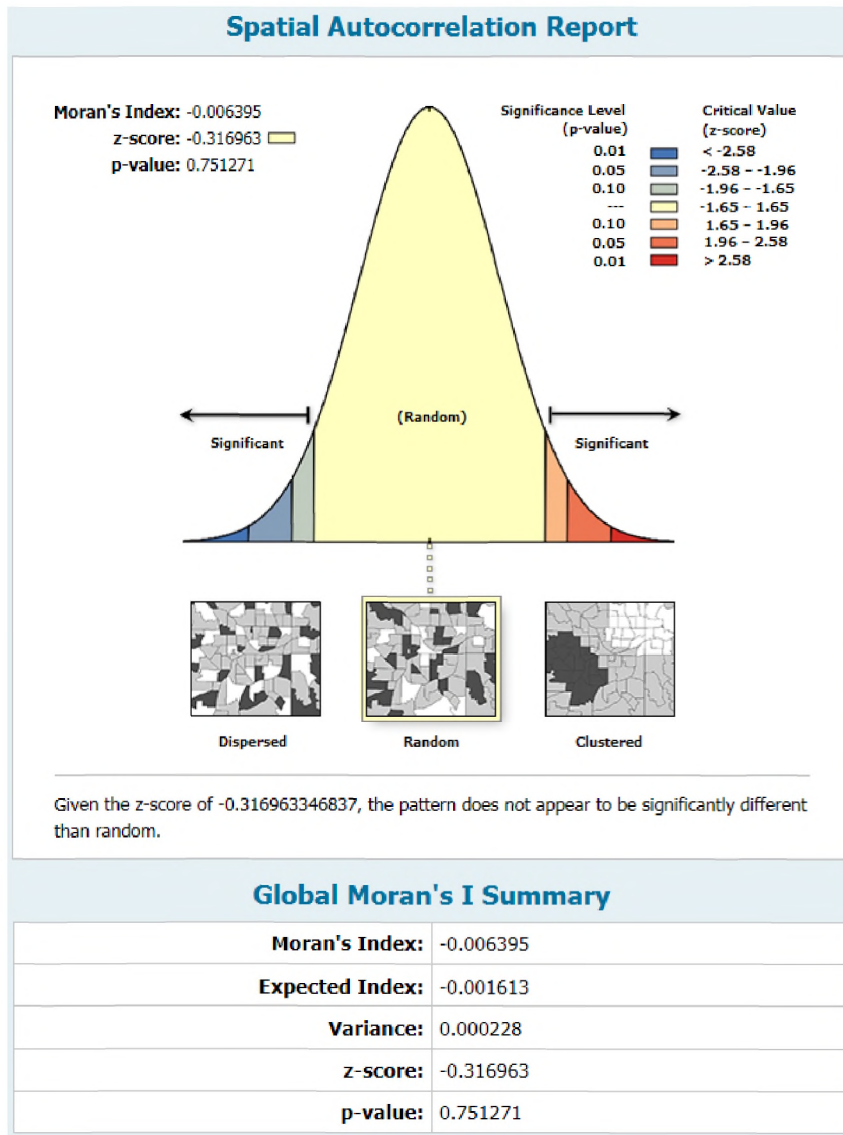
allowing the model to vary in its predictive power over space (in this case, districts). The determination of spatial autocorrelation in the residuals of the OLS model, combined with other statistics in the output, indicate that I should attempt using a GWR to better

understand the variance within the dataset. As mentioned in the methods section, the importance of GWR is inextricably linked to the potential variance in a model's predictability; public policy decisions such as the allocation of limited resources can be directed with more efficient effect than without the use of such a method.

Geographically Weighted Regression Model

Tabular output diagnostics provided by ArcGIS for the GWR are limited. There is no long report with various graphical representations, only a brief table summarizing the predictability results. Where the GWR does allow for enhanced visualization, however, is the resultant plottable choropleth maps capable of being output by ArcGIS, which will be shown in a following section. After running the GWR and 'allowing' the model to vary across geographic space, I observed a nearly 4% improvement in the predictive power of the model. This may not seem like a vast improvement but for a social science dataset this is indeed noteworthy. The Aikake's Information Criterion (AICc) metric improved, indicating that this model is indeed a better fit than the traditional OLS. Similar to the OLS model, we need to also evaluate the residuals of the GWR model in order to determine whether or not we have accounted for the spatial autocorrelation present in the

| Table | | | |
|--------------|-----|-------------------|--------------|
| APM_GWR_supp | | | |
| | OID | VARNAME | VARIABLE |
| | 0 | Neighbors | 158 |
| | 1 | ResidualSquares | 4.964312 |
| | 2 | EffectiveNumber | 62.907872 |
| | 3 | Sigma | 0.094314 |
| | 4 | AICc | -1126.570144 |
| | 5 | R2 | 0.731802 |
| | 6 | R2Adjusted | 0.702052 |
| | 7 | Dependent Field | 0 pctapm |
| | 8 | Explanatory Field | 1 pctfrpl |
| | 9 | Explanatory Field | 2 enrollment |
| | 10 | Explanatory Field | 3 pctminorit |
| | 11 | Explanatory Field | 4 cwr |
| | 12 | Explanatory Field | 5 pctbach |



previous model.

Shown here is the Moran's I report from the residuals of the GWR model. This output confirms that I have accounted for the spatial autocorrelation by showing spatially-random residuals. As noted in the output:

"...the pattern does not appear to be significantly different than random." What

we have yet to completely account for, however, is some of the nonstationarity within the original OLS model, indicated by the significant Koenker statistic. This can be achieved by running either a spatial lag or spatial error model, as determined by output from a spatially weighted OLS regression run in the GeoDA program. By running this slightly nuance form of OLS, the output returns an estimation as to which enhanced spatial regression is most appropriate for use in reducing nonstationarity / autocorrelation. These diagnostics will be shown in the next section.

Additional Spatial Regression Models

As the Koenker statistic has indicated additional nonstationarity within the original OLS model, I use the GeoDA program to run a spatially-weighted OLS model which returns an additional section of regression diagnostics. This section indicates whether or not a spatial lag or spatial error regression will further enhance the predictability of my model, and which is more likely to be significant. The below image shows the spatial

dependence
output from
GeoDA,
including the

| DIAGNOSTICS FOR SPATIAL DEPENDENCE | | | | |
|---|--------|---------|---------|--|
| FOR WEIGHT MATRIX : NYSFinalThesisWeights (row-standardized weights) | | | | |
| TEST | MI/DF | VALUE | PROB | |
| Moran's I (error) | 0.0920 | 3.7735 | 0.00016 | |
| Lagrange Multiplier (lag) | 1 | 10.6063 | 0.00113 | |
| Robust LM (lag) | 1 | 1.3054 | 0.25323 | |
| Lagrange Multiplier (error) | 1 | 12.8342 | 0.00034 | |
| Robust LM (error) | 1 | 3.5333 | 0.06015 | |
| Lagrange Multiplier (SARMA) | 2 | 14.1396 | 0.00085 | |

highest significance (Lagrange Multiplier) value being attributed to the spatial error model at 0.00034. When a spatial error model is run, the results are promising.

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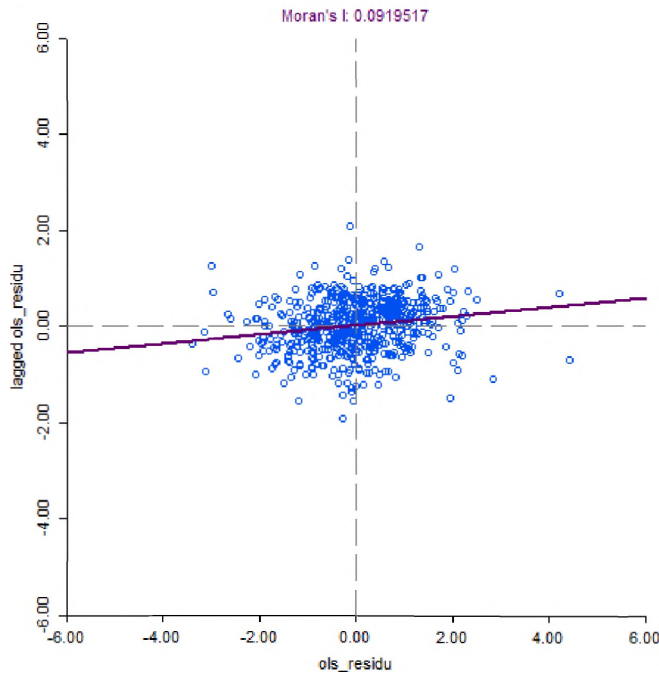
-----
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set          : NYSFinalThesis
Spatial Weight    : NYSFinalThesisWeights
Dependent Variable : pctapm   Number of Observations: 621
Mean dependent var : 0.447163 Number of Variables : 6
S.D. dependent var : 0.172646 Degrees of Freedom : 615
Lag coeff. (Lambda) : 0.194627

R-squared         : 0.682951   R-squared (BUSE) : -
Sq. Correlation   : -         Log likelihood : 563.923472
Sigma-square      : 0.00945016 Akaike info criterion : -1115.85
S.E of regression : 0.0972119 Schwarz criterion : -1089.26

```

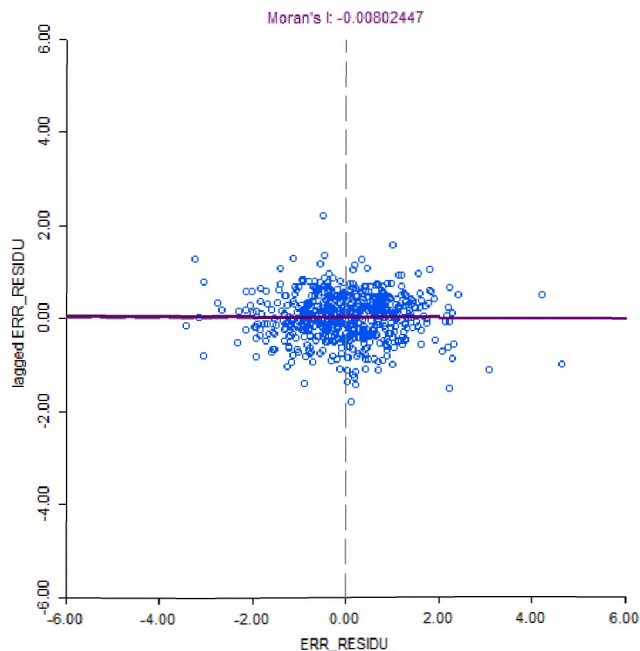
| Variable | Coefficient | Std.Error | z-value | Probability |
|------------|--------------|--------------|----------|-------------|
| CONSTANT | 0.468187 | 0.0217192 | 21.5564 | 0.00000 |
| enrollment | 1.49555e-006 | 1.64263e-006 | 0.910462 | 0.36258 |
| pctfrpl | -0.371763 | 0.0326424 | -11.389 | 0.00000 |
| pctminorit | -0.18329 | 0.027661 | -6.62631 | 0.00000 |
| cwr | -0.00937888 | 0.00334923 | -2.80031 | 0.00511 |
| pctbach | 0.5146 | 0.0446438 | 11.5268 | 0.00000 |
| LAMBDA | 0.194627 | 0.0578897 | 3.36203 | 0.00077 |

All of the originally significant explanatory variables not only remain significant, but gain significance through the error model. Notably, as compared with the OLS results, several of the explanatory variables' coefficients have changed. PctBach has gone from an predicted positive relationship of 0.49 to 0.51, PctFRPL has moved from a predicted



negative relationship of -0.39 to -0.37, and PctMinority has moved from a predicted negative relationship of -0.17 to -0.18. Finally, by observing the spatial autocorrelation report (from GeoDA) of the OLS model's residuals at 0.092 (note: this is just a

simpler representation of the larger report shown earlier) and now the residuals of the spatial error model at -0.008, I have nearly completely accounted for all spatial autocorrelation within the dataset (no correlation is a score of 0). Implications of these results will be addressed in the discussion section.



Discussion and Conclusions

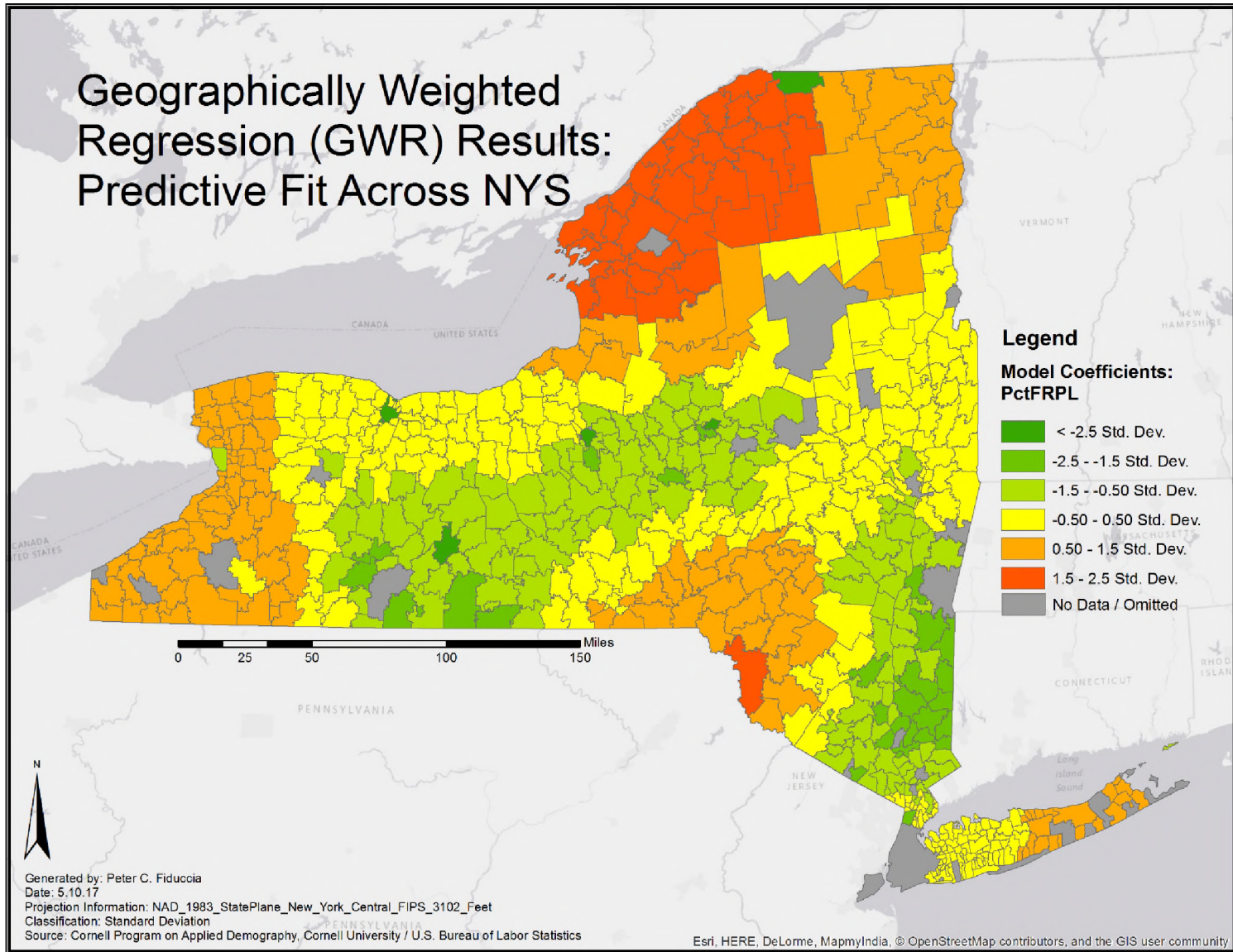
What can we take away from this iterative process of testing for, identifying, and accounting for underlying spatial variance within the data? After running the first OLS regression, though it returned a fair R^2 , I was alerted to the possible presence of spatial autocorrelation through the OLS diagnostics and the Moran's I report of the residuals. The GWR model was the run, allowing the predictive capability of the model to vary across the study area. This improved my model's predictive power overall, and returned spatially random residuals, but some diagnostics continued to alert me to the presence of nonstationarity and autocorrelation – indicating that there may yet be a better fitting model given the underlying clustering of the data. Finally, through the GeoDA application's OLS testing, I determined a spatial error regression model to be the most appropriate for the dataset. Though the spatial error model's predictive power was only a slight ($\sim 1\%$ in R^2 value) improvement, the resulting coefficient changes revealed a story about what may have been happening in my original OLS model. In the spatial error model, the PctBach and PctMinority explanatory variables both increased in their respective relationships to the dependent variable – i.e. PctBach became more strongly positively associated and PctMinority became more strongly negatively associated with PctAPM. This is a clear indication that the original OLS regression, not accounting for any spatial variance, underpredicted these two variables' effect on performance across the study area. Conversely, PctFRPL's negative relationship to PctAPM weakened according to the spatial error model. This indicates that the OLS regression overpredicted the impact of minority concentration on performance across the study area. When allowed to vary with space, these three explanatory variables' coefficient effects are more appropriately stated. As

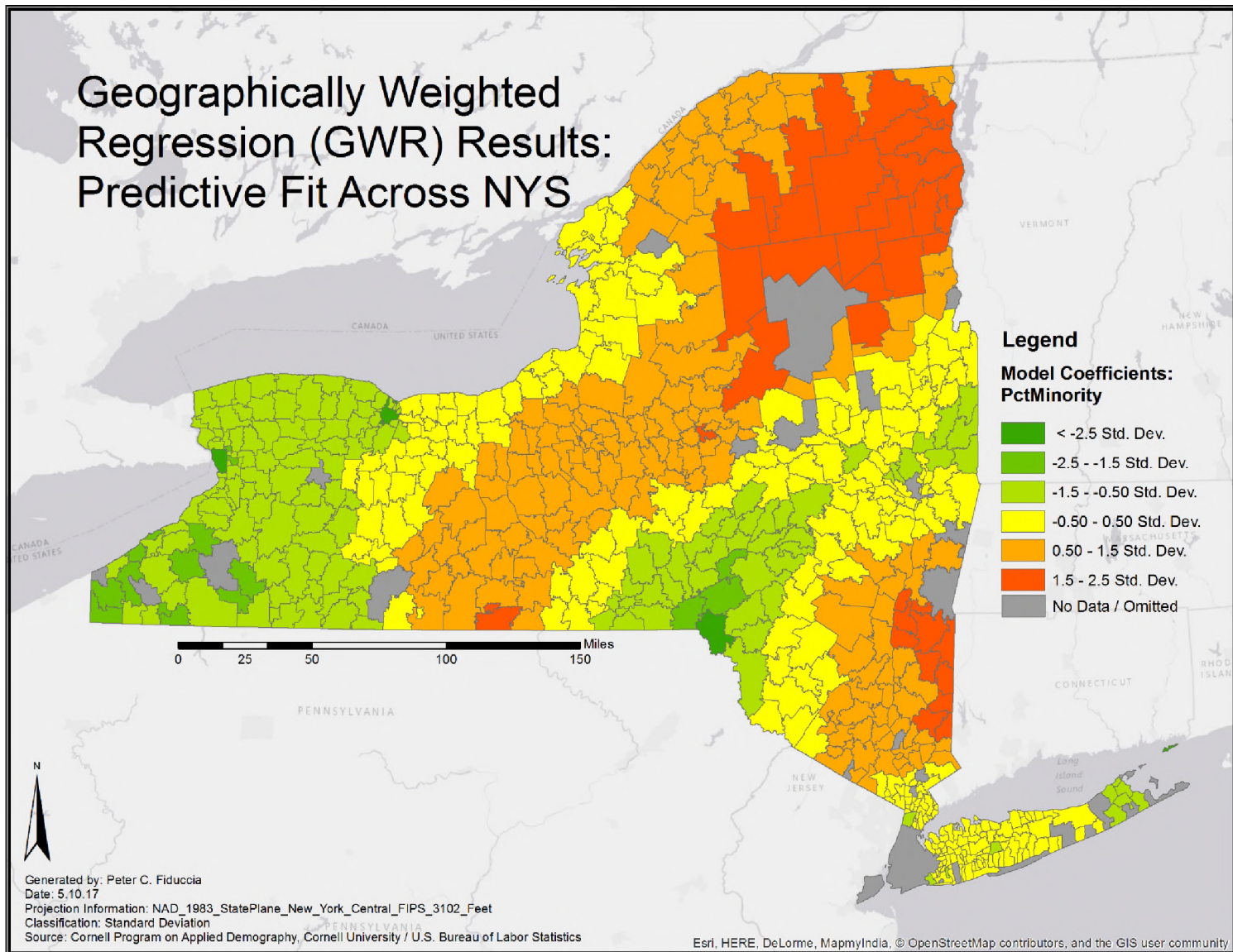
mentioned at the beginning of this study, the conceptualization of the interrelationships between the explanatory variables and the dependent variable of performance is not complete. Models predicting performance will continue to be refined, as will the understanding of more robust spatial methodologies with which to test those predictions. For now, however, there is still an actionable purpose behind the results garnered in this analysis. The final several pages show choropleth maps of the Geographically Weighted Regression model's predictive power for the primary explanatory variables in the study; this shows where across New York State the GWR does a better, or worse, job of predicting that particular explanatory variable's impact on performance. The final map shows the *local* R² values for the GWR model; where the regression model, taken with all five explanatory variables, holds the most predictive power. Non-significant explanatory variable coefficient maps can be found in the appendix, for reference.

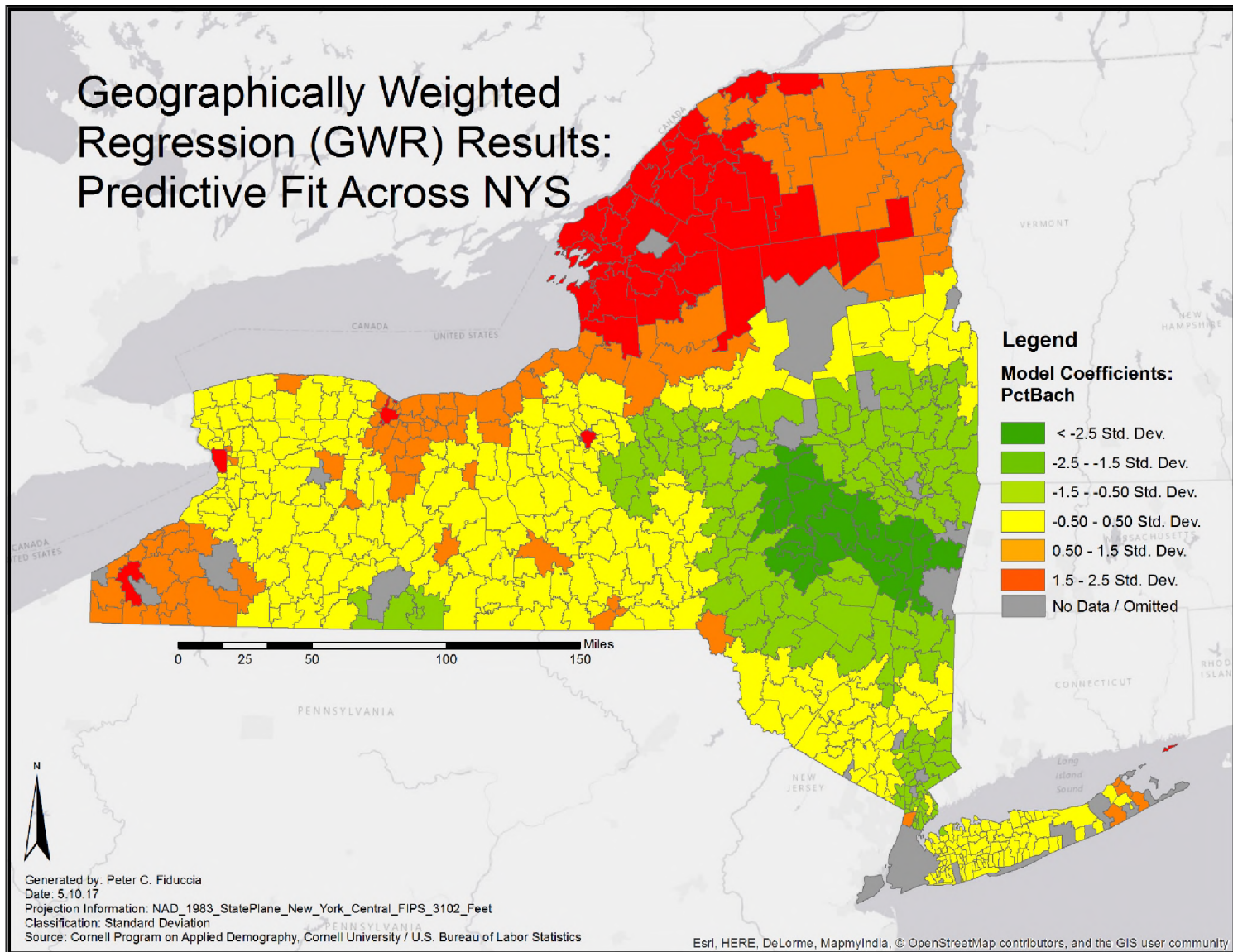
In designing future studies, it will be important to gather more detailed community-level data from school districts, as well as run many more iterations of spatial regression models in order to determine precise areas in which models may have the best predictive capability. This, in turn, will be able to most efficiently and directly inform local actors, governments, foundations, and communities themselves where to direct their limited resources. As resources continue to become more dispersed, technological advances impact both the classroom and the home, and neighborhoods continue to become more diverse, it is crucial to ascertain the most appropriate and powerful methodologies to better the educational experience for all students.

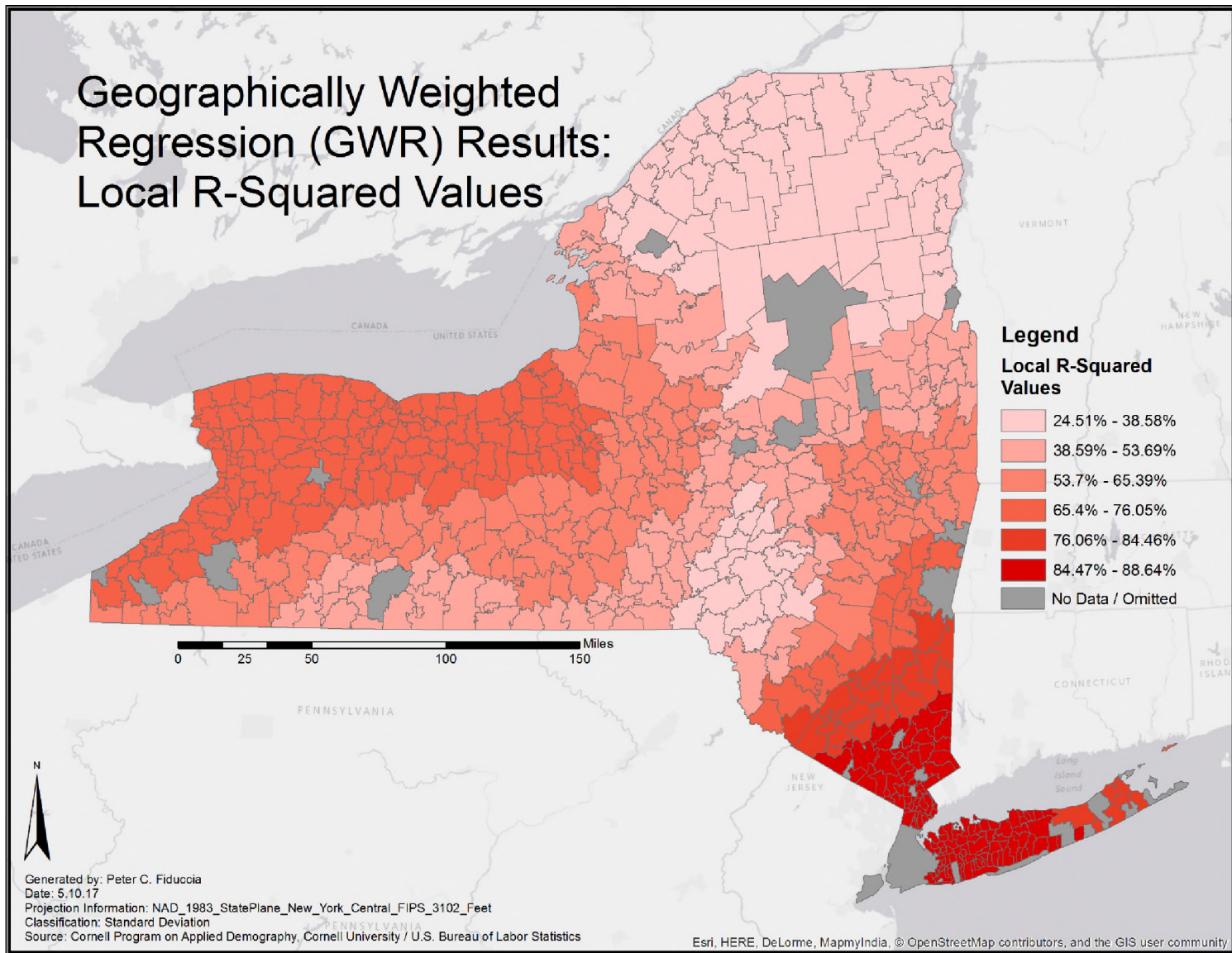
“If we teach today as we taught yesterday, we rob our children of tomorrow.” – Dewey

Geographically Weighted Regression (GWR) Results: Predictive Fit Across NYS









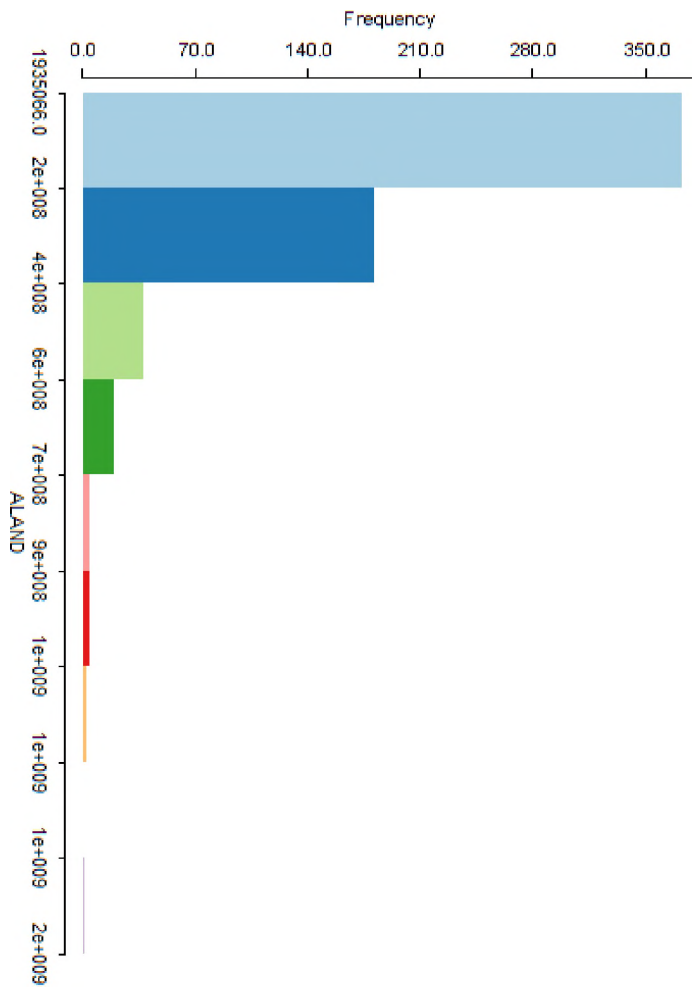
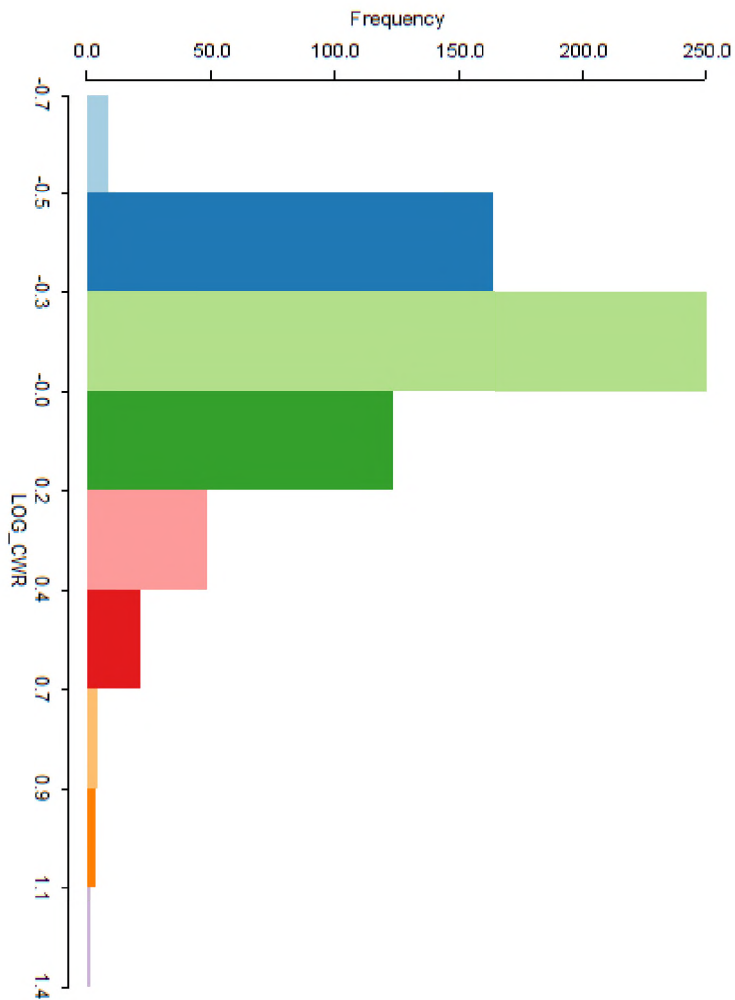
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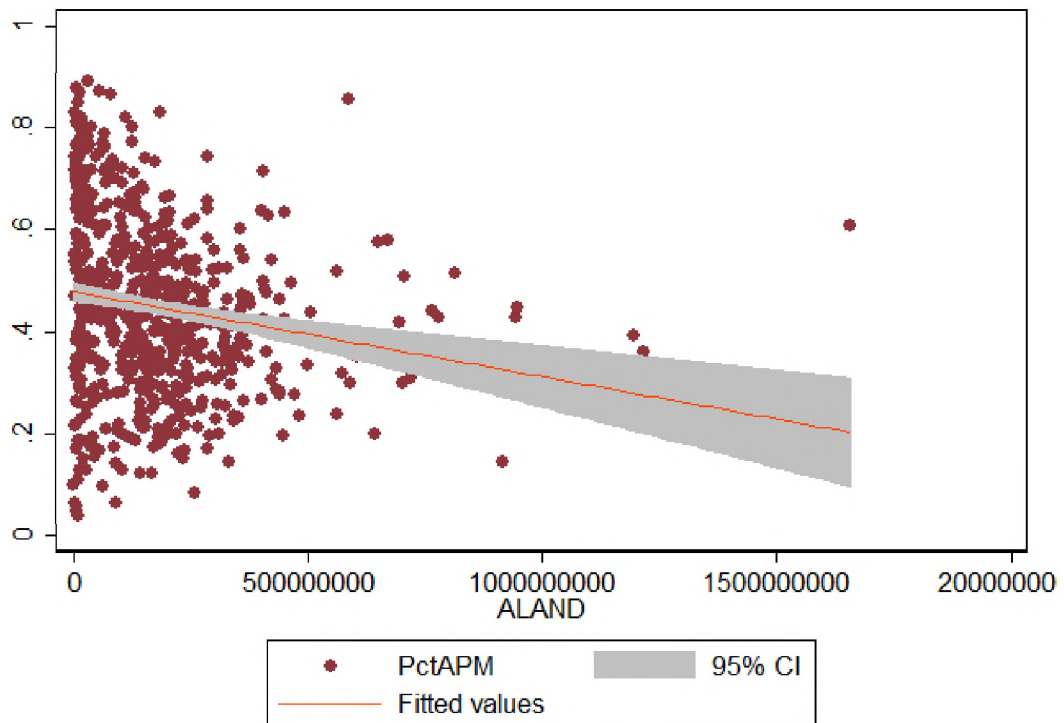
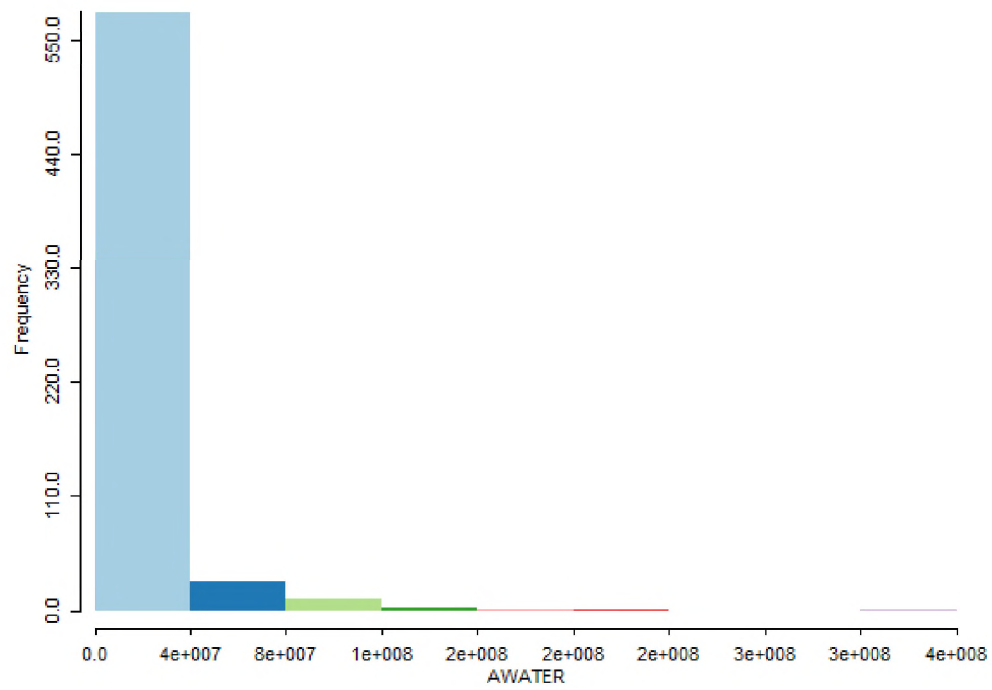
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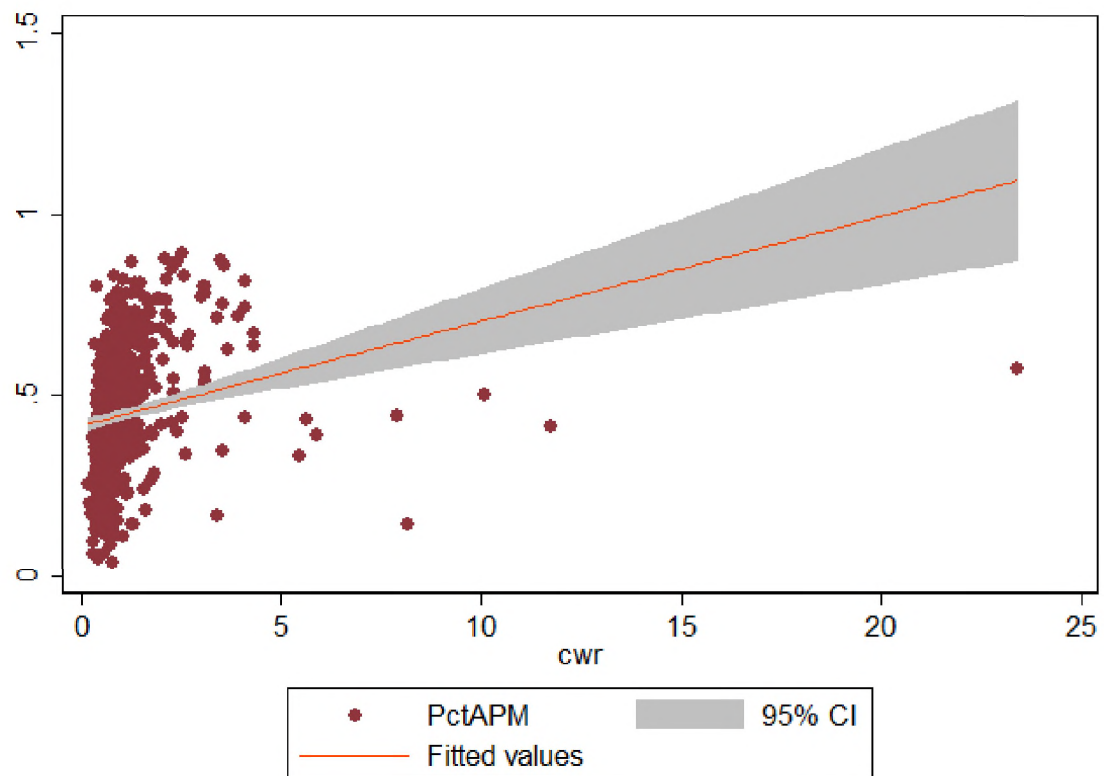
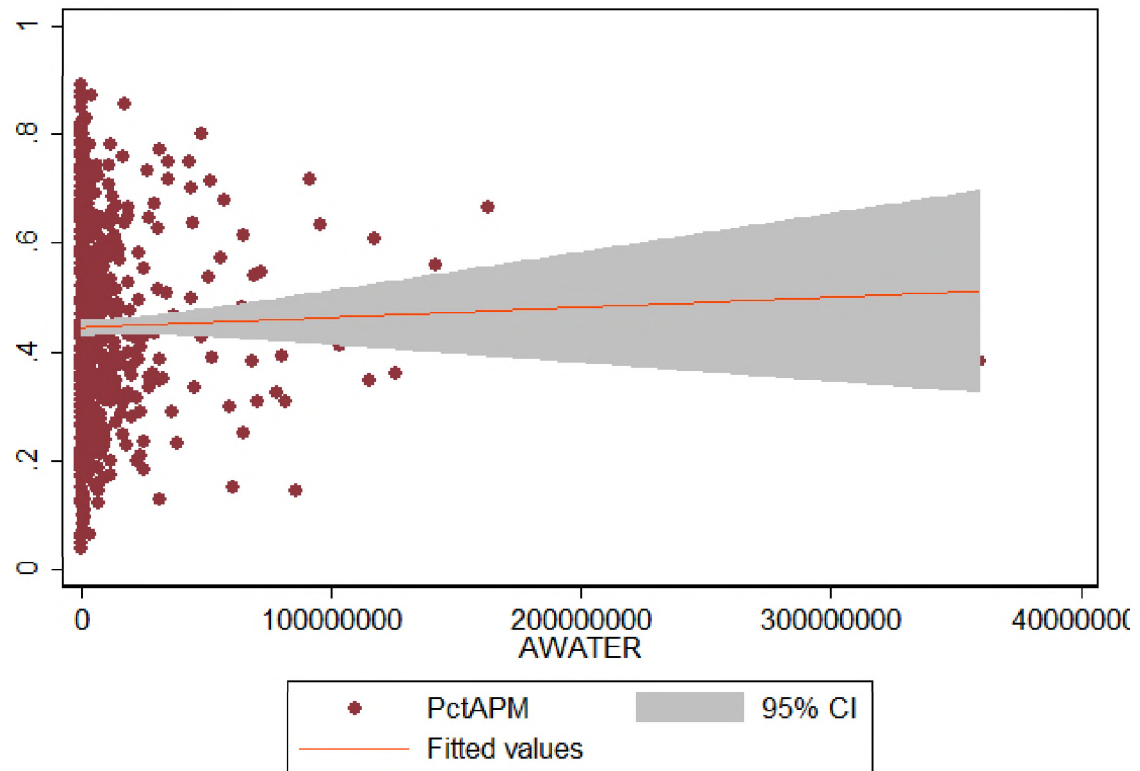
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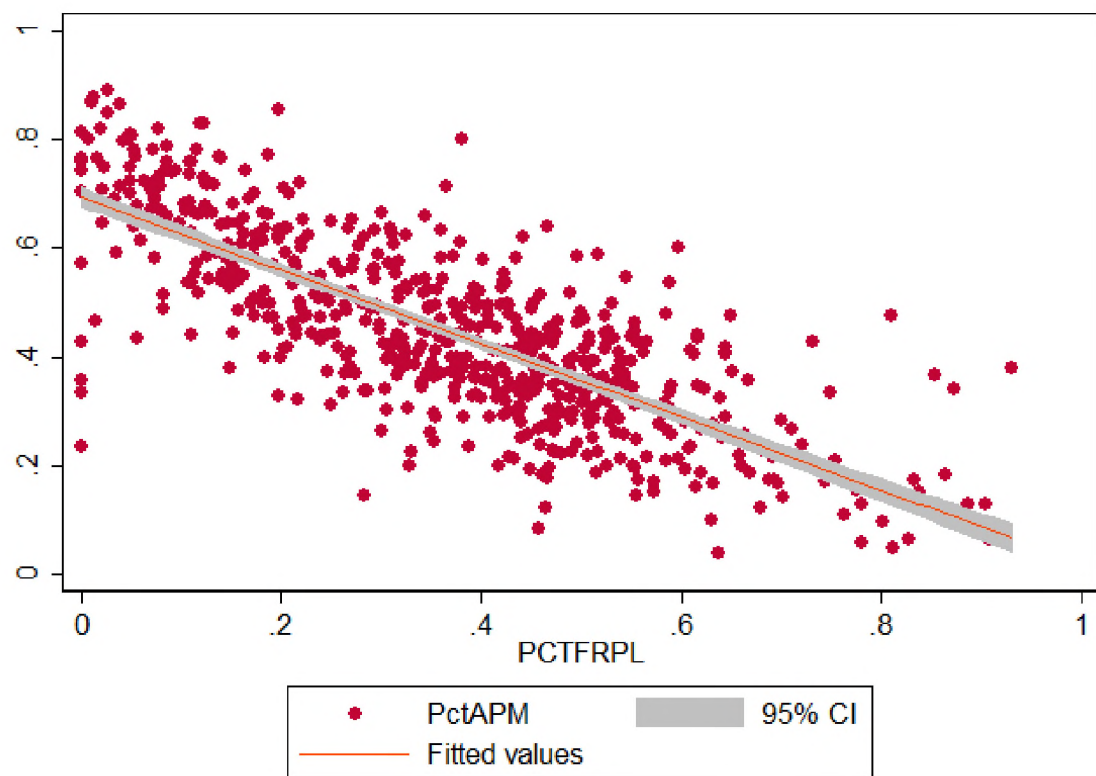
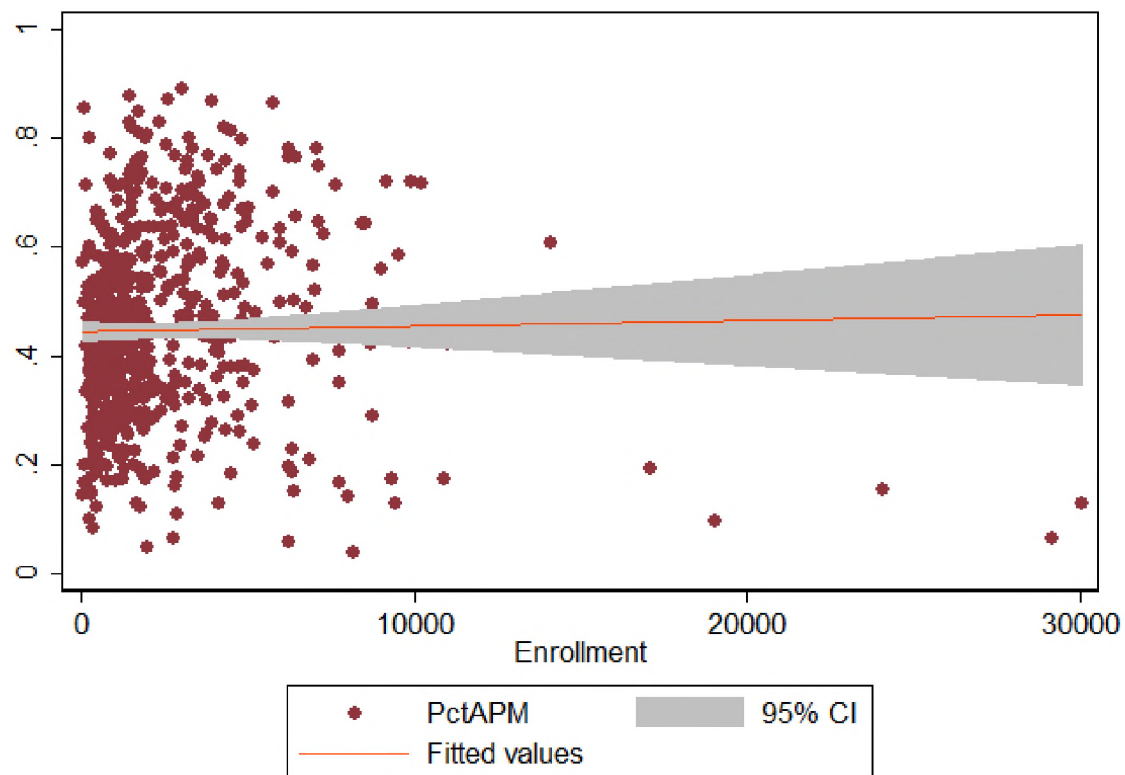
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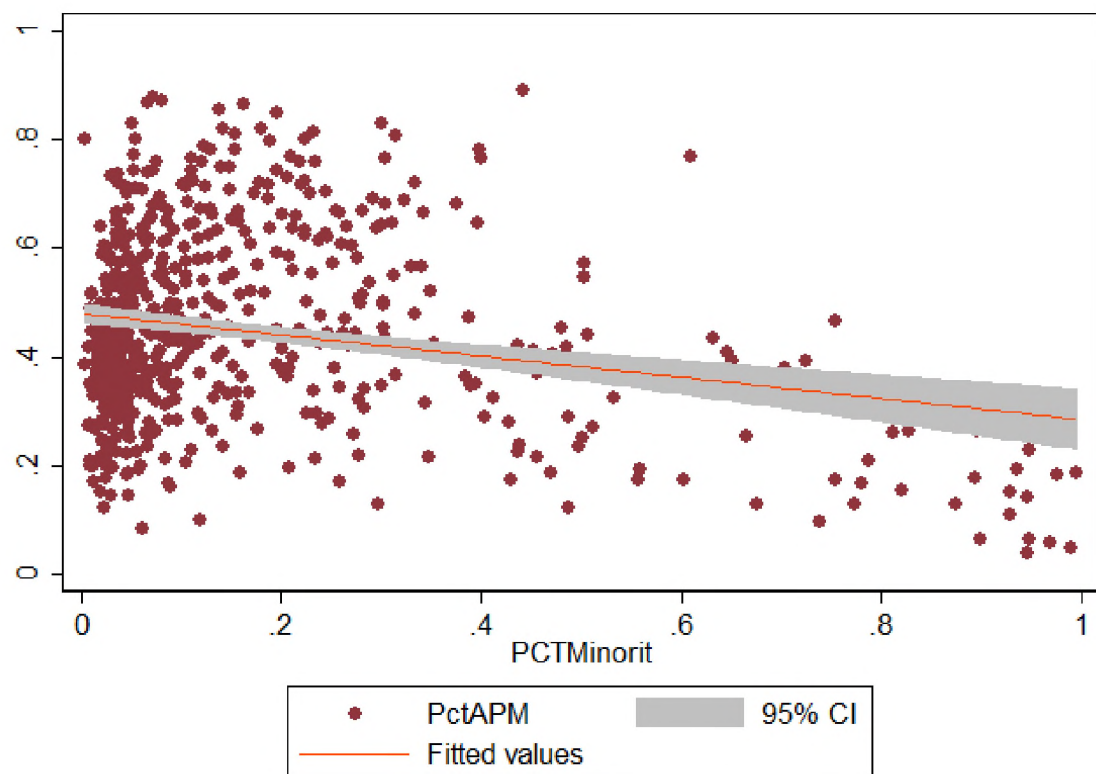
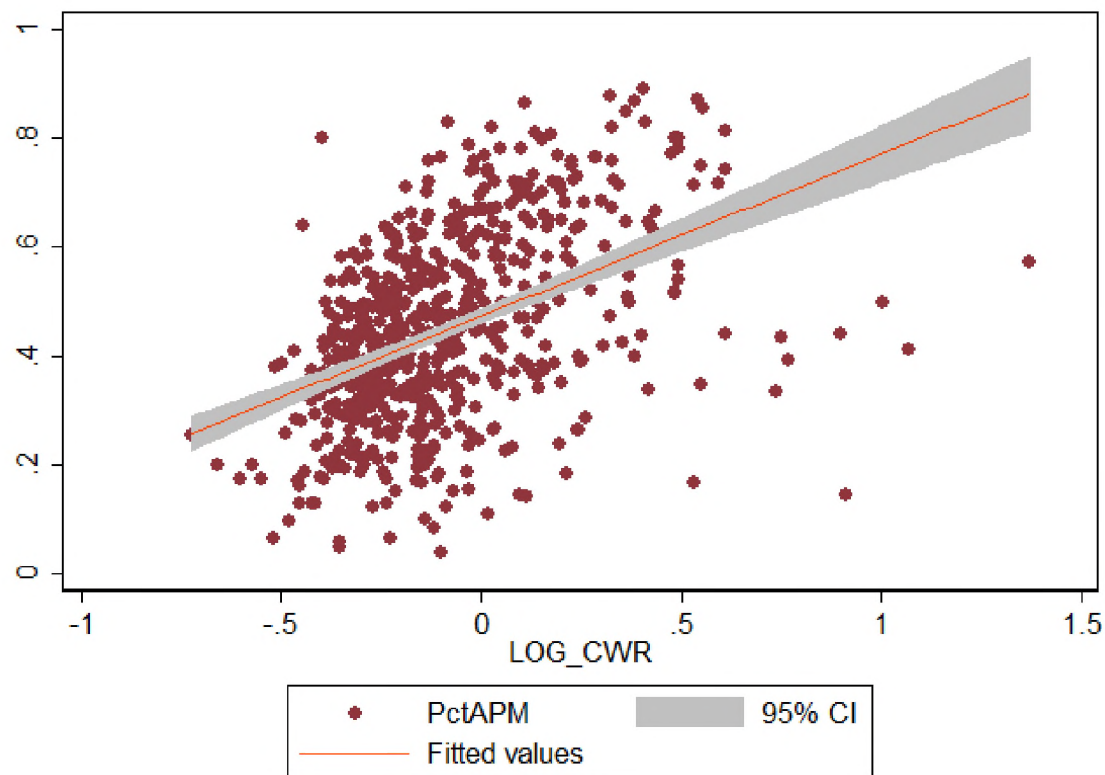
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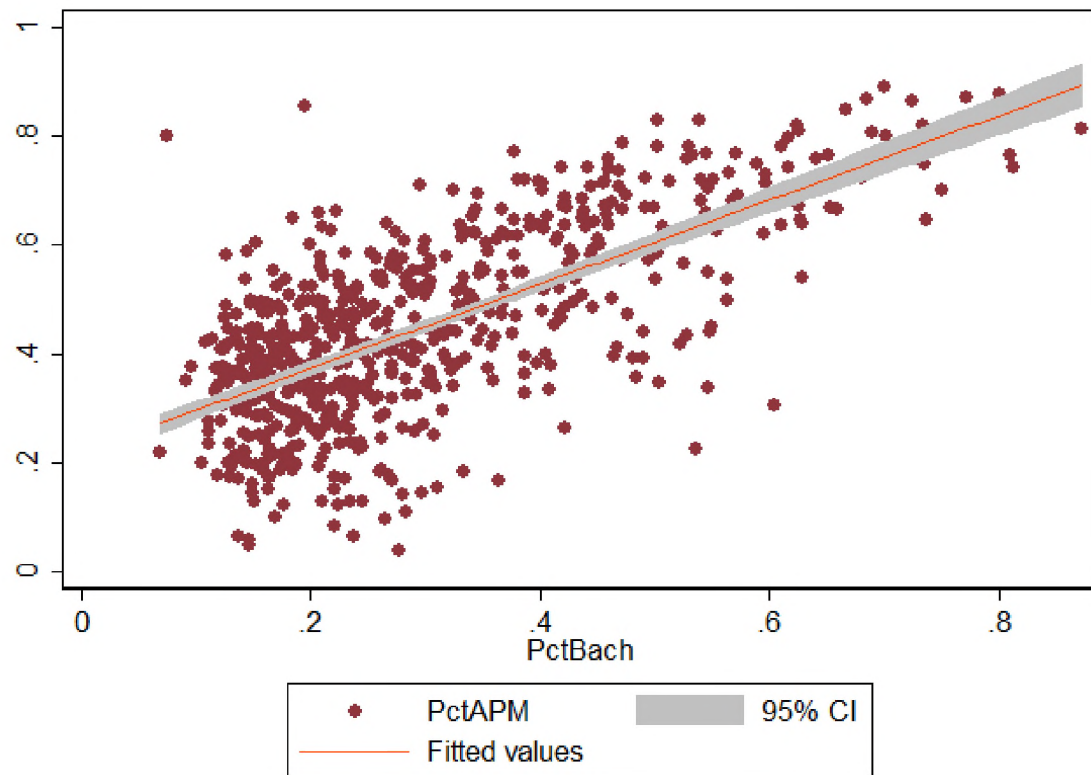




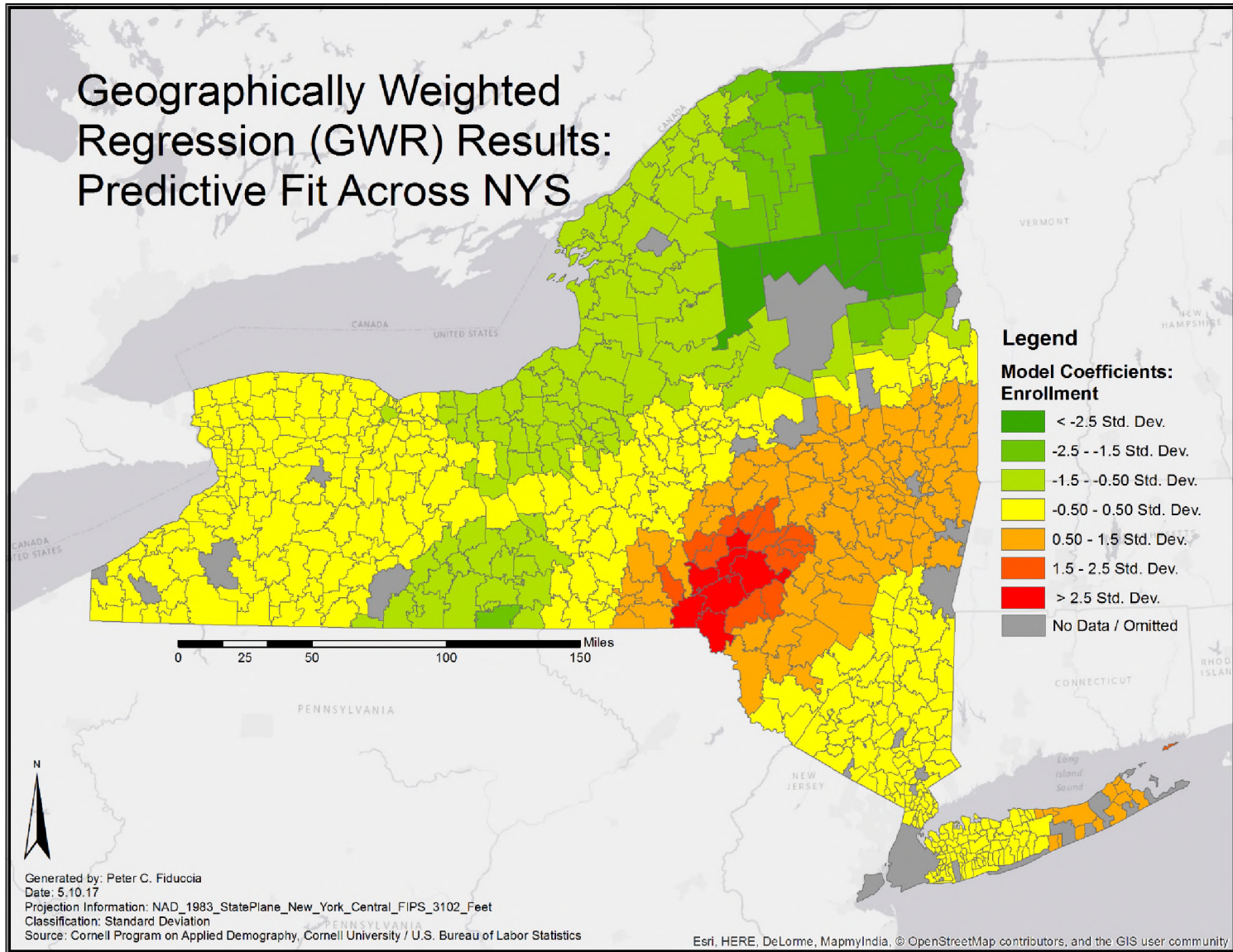




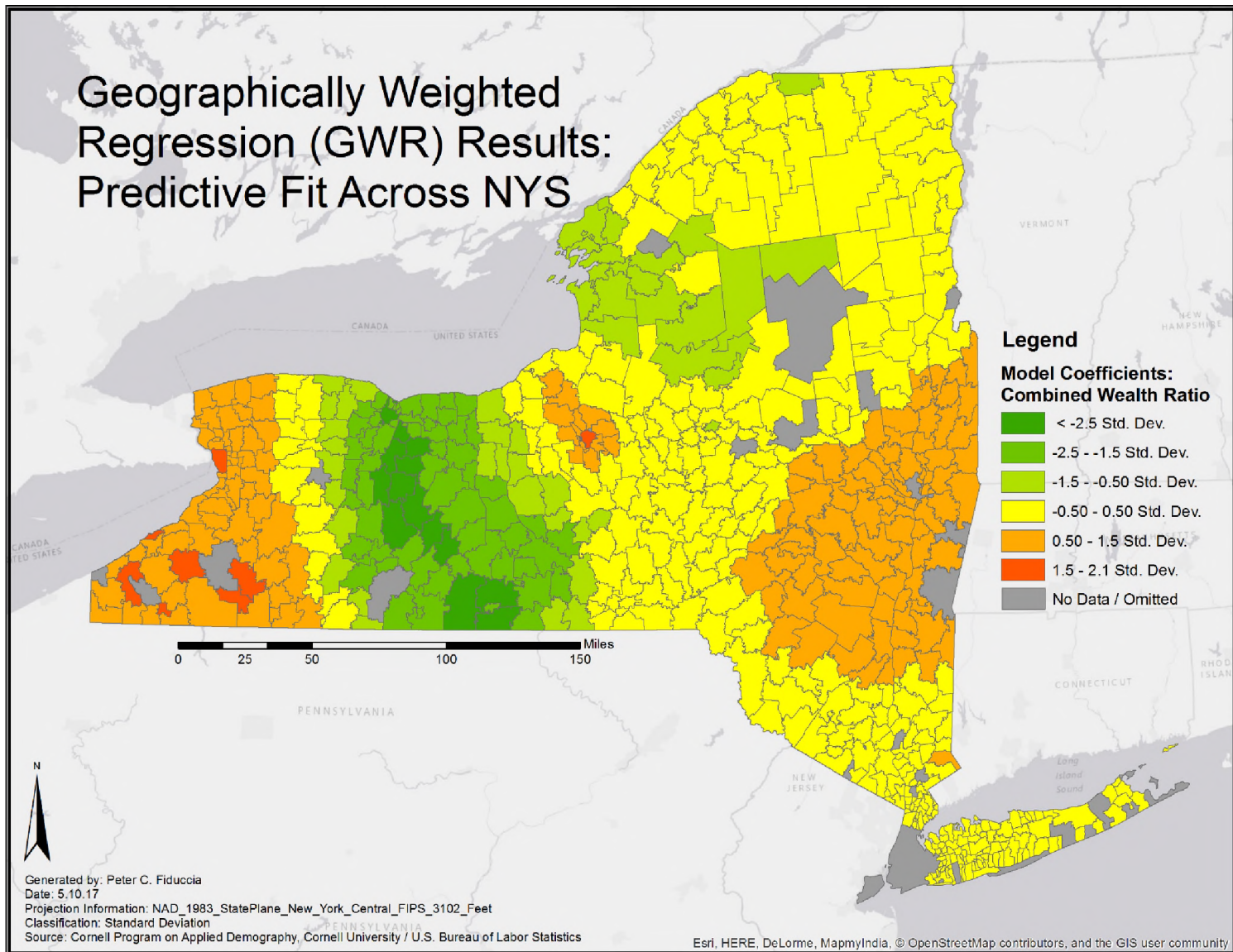




Geographically Weighted Regression (GWR) Results: Predictive Fit Across NYS



Geographically Weighted Regression (GWR) Results: Predictive Fit Across NYS



Geographically Weighted Regression (GWR) Results: Standardized Residuals

