Global and Local Regression Analysis of Factors of American College Test (ACT) Score for Public High Schools in the State of Missouri

Xiaomin Qiu and Shuo-sheng Wu

Department of Geography, Geology and Planning, Missouri State University

This study aims to improve the conceptual understanding of the interrelationships among individual-level and school-level factors of academic performance by presenting a context-based conceptual framework of academic performance and articulating relationships among the factors. In addition, this study intends to advance the statistical methodology of local regression analysis through a case study analyzing predictor variables of American College Test (ACT) score for 447 public high schools in Missouri. A school-level statistical model of ACT score with nine predictor variables relevant to student, teacher, and school characteristics is tested. Ordinary least squares (OLS) global regression analysis derives a model of five predictor variables, showing that schools with higher parent income and education levels, more double-parent family background, larger class size, and more experienced teachers tend to have higher ACT scores. Geographically weighted regression (GWR) local regression analysis is conducted using the five globally verified predictor variables to minimize violations of regression assumptions, particularly multicollinearity, in local models. Geographic distributions of local regression coefficients are examined at a series of local regression neighborhoods to draw integral conclusions of variable effects for local areas. Analyses show that using globally verified predictor variables in GWR effectively avoids multicollinearity that would otherwise appear. The results highlight critical local regression neighborhoods at which certain local areas start to show opposite local variable effects from the global variable effects. *Key Words: American College Test, geographically weighted regression, global regression, local regression, ordinary least squares, weighted least squares.*

本研究旨在提高对学业表现在个体水平和学校水平上各项因素之间相互作用的概念性了解，提出了一个基于背景的概念性框架来分析学业表现，并籍此阐明各项因素之间的相互关系。此外，本研究拟通过案例分析来改进局域回归分析中的统计分析方法，个例采用了密苏里州 447 所公立高中的美国大学入学考试（ACT）的成绩汇总，对此进行了预测变量研究。本文检验了一个学校水平的 ACT 成绩的统计模型，该模型具有九个和学生，教师和办学特色相关联的预测变量。利用普通最小二乘法（OLS）的全局回归分析，我们得出了一个具有 5 个预测变量的模型，显示出具有下述特征的学校往往有较高的 ACT 成绩：家长具有更高的收入和教育水平，更多的双亲家庭背景，更大的每班学生人数，以及更多的有经验教师人数。利用上述 5 个校验过的全局变量，我们使用了地理加权回归（GWR）的局域回归分析，以减少违背回归假设的可能性，特别是局部模型的共线性。本文对局域回归系数的地理分布在一系列的局域回归近邻区进行了检验，籍此得出了对局域地区变量效果的整体结论。分析表明，在 GWR 中使用经校验的全局预测变量可以有效地避免共线性，否则共线性就会出现。研究结果突出了那些关键的局域回归近邻区，在这些邻区里，部分区域地区的局部变量显示出和全局变量效果不同的影响。*关键词：美国大学入学考试（ACT），地理加权回归，全局回归，局部回归，普通最小二乘法，加权最小二乘。*

El propósito de este estudio es mejorar el entendimiento conceptual de las interrelaciones entre los factores que obran a nivel individual y a nivel de escuela de secundaria sobre el desempeño académico, con la presentación de un marco conceptual sobre desempeño académico apoyado en contexto, articulando las relaciones entre los factores. Además, este estudio tiene la intención de mejorar la metodología estadística de análisis de regresión local por medio de un estudio de caso en el que se analizan las variables predictivas de los puntajes de la Prueba de Ingreso a la Universidad (American College Test, ACT), aplicada a 447 escuelas públicas de secundaria de Missouri. Se puso a prueba un modelo estadístico de los puntajes de la ACT a nivel de escuela, con nueve variables predictivas relevantes para caracterizar al estudiante, al maestro y la escuela. El análisis de una regresión global de mínimos cuadrados ordinarios (MCO) da lugar a un modelo de cinco variables predictivas, el cual muestra que las escuelas con padres de ingresos y niveles de educación más altos, mayores antecedentes familiares con padres en pareja, clase de tamaño más grande y maestros más experimentados, tienden a registrar puntajes ACT más

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elevados. Se corrió un análisis de regresión local de regresión geográficamente ponderada (RGP) utilizando cinco variables predictivas, verificadas globalmente para minimizar en los modelos locales la violación de supuestos de la regresión, en particular la multicolinealidad. Las distribuciones geográficas de los coeficientes de regresión local se examinan en una serie de vecindarios de regresión local para sacar conclusiones integrales de efectos variables para áreas locales. Los análisis muestran que utilizando variables predictivas globalmente verificadas en la RGP se evita efectivamente la multicolinealidad, que de otro modo aparecería. Los resultados destacan vecindarios críticos de regresión local en los que ciertas áreas locales empiezan a mostrar efectos locales variables contrarios a los efectos globales variables. *Palabras clave: Prueba de Ingreso a la Universidad, ACT, regresión geográficamente ponderada, regresión global, regresión local, mínimos cuadrados ordinarios, mínimos cuadrados ponderados.*

Student learning effectiveness is an important concern for policymakers and researchers. Policymakers look for implementable strategies to improve student learning effectiveness, whereas researchers seek to understand why some students learn better than others. The most common measure of student learning effectiveness is student performance as measured by test scores, and the common interest for the policy and research communities is factors influencing student test scores.

The American College Test (ACT) is a widely used standardized test for college admissions in the United States. Admission offices of higher education institutions use the ACT score to supplement secondary school records and, from another point of view, to put local assessments, such as coursework, grades, and class rank, in a national context. Some states even use the ACT score to assess school performance and require all high school students to take the test regardless of whether they are college bound (ACT 2007). The ACT has four subject areas: English, mathematics, reading, and science. The composite score is the arithmetic average of scores in the four subject areas.

Past studies of factors of student test scores commonly focused on individual-level variables by analyzing survey data of individual students (e.g., Schiel, Pommerich, and Noble 1996; Roberts and Noble 2004; Noble, Roberts, and Sawyer 2006). On the other hand, some studies are interested in the effects of school characteristics on test scores and use school statistics to analyze factors of school performance measured by the average student test score (e.g., Fotheringham, Charlton, and Brunsdon 2001; Fowler and Walberg 1991; Hogrebe, Kyei-Blankson, and Zou 2008). To account for factors of test score at different levels, such as school level, classroom level, and student level, a multilevel framework has been adopted to model the individual as well as combined effects of variables at different levels (e.g., Lee and Bryk 1989; Lee 2000; Rumberger and Palardy 2004). The multilevel framework provides an effective approach to model the educational processes and academic performance of students and schools. Nevertheless, the current multilevel framework has not been examined in depth regarding the interrelationships between individual-level and school-level processes and factors. This study intends to improve the conceptual understanding of this aspect. After synthesizing literature findings and theories of student and school performance factors, we formulated a context-based conceptual framework of academic performance. The interrelationships among different levels of academic performance factors were articulated.

In studying factors affecting student test scores, whether at the individual level or school level, a common approach is to build a global statistical model based on all available observations of the study area. The relationships between explanatory variables and a response variable in the model are assumed to be consistent across the geographic area, and the potential association of variable relationships with geography is ignored. One goal of this study is to investigate whether geography matters in ACT score modeling by examining whether and how effects of predictor variables vary across the geographic space of Missouri. Moreover, we aim to advance the statistical methodology of local regression analysis, specifically geographically weighted regression (GWR), one of the most common methods to study spatially varying relationships. We discuss possible misuses of GWR and potentially distorted conclusions, and propose approaches to minimize the problems.

The investigation of spatially varying effects of ACT score factors is valuable for both theoretical and practical reasons. From a theoretical perspective, educational processes and variables as well as their effects on academic performance are likely to be different at different places. Examining their geographical variations will help us understand their underlying associations with geography. From a practical standpoint, analyzing spatially varying relationships helps uncover relevant geographic variables for improving model performance. Further, finding ACT score factors that are important to local areas helps school policymakers make use of local resources and develop local strategies to improve local test scores.

In the following sections, we first provide a review of the conceptual frameworks and empirical understandings of student learning effectiveness from past literature. We then propose a context-based conceptual framework of academic performance and elaborate the interrelationships among individual-level and school-level factors. Subsequently, an ACT score statistical model corresponding to school-level academic performance in the conceptual framework is presented. Following that, we explain our statistical modeling methodology in details, focusing on the usages of GWR. Finally, we describe the analysis procedures and present the results, followed by a discussion of critical issues and implications for researchers and educators.

Conceptual Frameworks on Student Learning Effectiveness

Several conceptual frameworks explaining the mechanism of student learning effectiveness have been developed over the years. The most common one is based on the economics of schooling (Hanushek 1986; Coleman 1990; Levin 1997), as student learning is one of the most important goals of schooling. The economics of schooling describes the schooling process as an input–output model, where the inputs are students, teachers, and school resources and the outputs are student learning achievements. The efficiency and productivity of the input–output process is determined by instructional practices (Rowan, Correnti, and Miller 2002), school policies and practices (Hannaway and Carnoy 1993), as well as the academic and social climate of school (Freiberg 1999).

Another framework of student learning is based on the sociology of schooling (Tagiuri 1968; Willms 1992; Rumberger and Palardy 2004). By treating school as a social institution with organizational development, the schooling process can be studied from four dimensions: "ecology (physical and material resources), milieu (characteristics of students and staff), social system (patterns and rules of operating and interacting), and culture (norms, beliefs, values, and attitudes)" (Rumberger and Palardy 2004, 237).

The schooling process has been described as a multilevel phenomenon (Lee and Bryk 1989; Frank 1998; Rumberger and Thomas 2000). Under the multilevel framework of schooling, the educational process consists of different levels and the process at one level can be influenced by factors at the same and other levels. For example, the learning performance of individual students is influenced by variables of personal experiences and activities at the individual level as well as variables of teacher instruction at the classroom level and school climate at the school level.

Based on the input–output theory in the economics of schooling and the current multilevel schooling framework, we propose a context-based conceptual framework of academic performance to illustrate the interrelationships among individual-level and school-level factors. The conceptual framework is described after we review empirical findings on academic performance factors.

Empirical Findings on Academic Performance Factors

Most studies of academic performance factors focus on student-level variables. These variables can be put into three categories: academic preparation, personal attributes, and family background.

Student Academic Preparation

A student's academic performance is closely associated with the type and quality of his or her academic preparation. Past studies have demonstrated that the best predictor variables of a student's ACT score are those relevant to academic preparation and achievement, such as grades earned, academic honors received, and relevant courses taken in high school (ACT 2005; Noble, Roberts, and Sawyer 2006; Noble and Schnelker 2007). Education-related extracurricular activities, such as reading at the library, working on homework, or participating in school-sponsored clubs and sports are also beneficial to academic performance provided that the time spent in these activities is not too intensive (Noble et al. 1999; Noble, Roberts, and Sawyer 2006; Lipscomb 2007).

Student Personal Attributes

Past studies have examined the relationships between test score and education-related personal attributes, such as valuing education, attitude toward learning, and academic behavior (Stricker, Rock, and Burton 1992; Noble et al. 1999; Roberts and Noble 2004); self-concept and self-efficacy beliefs (Hamacheck 1995; Noble et al. 1999; Le et al. 2005);

as well as problem-solving skills and interpersonal communications (Rubin, Graham, and Mignerey 1990; Chesebro et al. 1992; Noble, Roberts, and Sawyer 2006). The research results show that positive personal attributes contribute to academic achievement due to their effects on the amount of effort and time students put into school work and studying.

Student Family Background

Past research has found that student family background is influential on student test scores. Specifically, income and education levels have positive effects (Lee and Bryk 1989; Lee and Smith 1999; Noble et al. 1999), whereas a single-parent background has a negative effect (Gamoran 1996; Fotheringham, Charlton, and Brunsdon 2001) on academic performance. Apparently, family socioeconomic status affects educational opportunities and resources to which students have access. Meanwhile, the associated family environment affects a student's aspiration in learning and interest in school.

School Demographics

A student's academic performance is influenced not only by his or her family background but by the family backgrounds of other students in the same school. In other words, a school's socioeconomic composition can influence a student's academic performance apart from his or her individual background. Past studies have found that the socioeconomic composition of schools predicts student academic performance even after the effects of individual family backgrounds are controlled (Rumberger and Thomas 2000; Lee and Burkam 2003; Rumberger and Palardy 2005a). Kahlenberg (2001) suggested that the demographic compositions of school affect student learning through three peer mechanisms: peer influence on learning process and mechanism, peer influence on learning motivation and aspiration, and peer influence on social behavior and environment. Jencks and Mayer (1990) and Wells and Crain (1997) argued that students with high levels of learning aspiration and achievement create a culture of success that has a positive effect on other students, whereas students with low levels of learning motivation and performance create a sense of despair that has a negative effect on other students.

One argument of the effect of school demographics on student learning is that the low socioeconomic status of a school will influence teachers' expectations of student performance and the type of the curriculum provided for students. Wells and Crain (1997) noted that schools with high socioeconomic status are more likely to offer challenging college-prep instructions and the teachers have high expectations for students. Rumberger and Palardy (2005a) suggested that more affluent families have more political power to demand this challenging college-prep curriculum.

In addition to the demographic statistics of schools, student learning performance is influenced by other school characteristics, which can be categorized under three headings: structural characteristics, educational resources, and policies and practices (Rumberger and Palardy 2005a).

School Structural Characteristics

Student performance is related to certain structural characteristics of schools, such as school location (urban, suburban, rural), school type (public, private), and school size. For example, urban schools usually have higher academic achievement than rural schools but lower academic achievement than suburban schools (Schiel, Pommerich, and Noble 1996; Roberts and Noble 2004). Schools from the South appear to have higher ACT mathematics score than schools from other regions (Noble and Schnelker 2007). The average student performance is lower in public schools than in private schools, in general, and Catholic schools, in particular (Chubb and Moe 1990; Morgan and Sorensen 1999; Rumberger and Thomas 2000). Large schools tend to have lower student test scores and higher dropout rates than medium-sized and small schools (Fowler and Walberg 1991; Lee and Smith 1997; Lee and Burkam 2003).

School Educational Resources

Past research has found a positive relationship between district per pupil expenditure and academic performance (Elliot 1998; Nyhan and Alkadry 1999). Schools with higher teacher salaries usually have better academic performance than schools with lower teacher salaries (Rumberger and Thomas 2000; Hogrebe, Kyei-Blankson, and Zou 2008). Schools in which students report a high quality of teachers appear to have lower dropout rates than schools in which students report an average quality of teachers (Rumberger and Thomas 2000). Hogrebe, Kyei-Blankson, and Zou (2008) reported that student test scores have a moderate positive correlation with teacher education and experience, and student percentage of good academic standing has a positive yet weak correlation with student–teacher ratio.

School Climate and Practices

Past studies have indicated that school organizational practices relevant to teacher and parent involvement in decision making affect student achievement in middle and high schools (Lee, Smith, and Croninger 1997; Morgan and Sorensen 1999; Rumberger and Palardy 2005b). Student test scores were reported to correlate with indicators of the social and academic climate of school, such as the proportion of students who feel unsafe (Rumberger and Palardy 2005b) and the level of teacher expectation for students (Lee, Smith, and Croninger 1997; Croninger and Lee 2001; Lee and Burkam 2003).

A Context-Based Conceptual Framework of Academic Performance

Past studies have established the theoretical and empirical foundations for understanding and modeling academic performance at both the individual level and the school level. On the basis of these foundations, we propose a conceptual framework that integrates individual-level and school-level frameworks to clarify the interrelationships among individual-level and school-level factors, shown in Figure 1. The individual-level process on the left side of Figure 1 describes how individual-level factors, enclosed in green boxes, affect the academic performance of individual students. The school-level process on the right side demonstrates how school-level factors, enclosed in orange boxes, affect the academic performance of school as a whole. For the individual-level process, factors of student performance are divided into three categories: family background, personal attributes, and academic preparation. Academic preparation factors directly influence student performance, whereas family background and personal attributes factors indirectly influence student performance through the academic preparation factors (Noble et al. 1999; Noble, Roberts, and Sawyer 2006). For the school-level process, based on the economics of schooling (Hanushek 1986), school performance is a function of three categories of inputs relevant to student, teacher, and school characteristics.

In the proposed conceptual framework of academic performance, some individual-level factors are related to school-level factors by aggregational relationships, represented by solid blue arrow lines in the diagram (Figure 1), whereas most individual-level factors are related to school-level factors by contextual relationships, represented by dashed blue arrow lines in the diagram. For aggregational relationship, school performance is the aggregated results of student performance, and school-level factors in the student characteristics category are aggregated variables from individual-level factors in the family background category. For contextual relationship, school-level factors in all three categories impact individual-level factors in the categories of personal attributes and academic preparation contextually, as an individual receives influences from classmates, teachers, and schools.

A Statistical Model of School Performance

A statistical model of school-level academic performance is formulated based on the school-level education process in the proposed conceptual framework (Figure 1). The nine school-level factors listed in Figure 1 are used as predictor variables. Although some potential factors of school performance mentioned in the literature are not included in the model, regression analysis of the nine predictor variables serves the purpose of studying spatially varying relationships with the aim of improving statistical methodology of local regression analysis. The nine predictor variables are discussed in detail by the three categories of schooling input as follows.

Student Characteristics

Empirical findings have shown that students from lower income, less educated, and single-parent families are less likely to succeed academically in schools (reviewed previously). To study spatially varying effects of student characteristics on school academic performance, we focus on three predictor variables that represent family income, education, and composition characteristics, including percentage of students receiving free or reduced priced lunch (LuPct), percentage of people age twenty-five or over in the school district having a college degree (BsPct), and percentage of families with children under eighteen in the school district that are married-couple families (DpPct). Based on theoretical reason and empirical evidence, we expect LuPct to have a negative relationship and BsPct and DpPct to have a positive relationship with ACT scores in regression analysis.

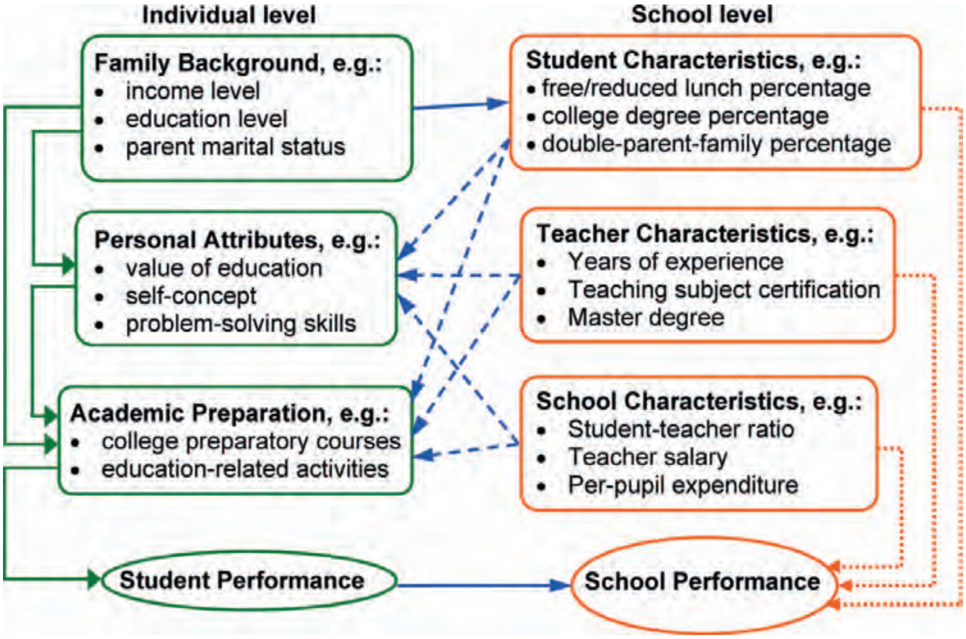

Figure 1. A conceptual model of individual-level and school-level academic performance.

Teacher Characteristics

As qualified teachers are expected to be effective in teaching and have high-achieving students, past literature has indicated the relevance of student or school performance with teacher qualification factors, such as education level, years of experience, and teaching evaluation score (reviewed previously). In this study, we focus on three predictor variables to study the spatially varying effects of teacher characteristics on school performance, including teacher average years of experience (TeEx), percentage of courses taught by teachers with appropriate certification for their teaching assignment (TeCt), and percentage of teachers with a master's degree (TeMs). Based on theoretical reason or empirical evidence, these three predictor variables are expected to have positive effects on ACT scores in regression analysis.

School Characteristics

The last dimension of factors included in a school performance model attempts to capture ACT score variations relevant to school characteristics. Past studies have indicated that improving school organization and instructional practices can substantially improve student academic performance (Borman et al. 2003; Rumberger and Palardy 2005a). Although school characteristics consist of diversified variables related to physical landscape, social and cultural amenities, policies, and school climate, we focus on three predictor variables for the purpose of studying their spatially varying effects on school performance, including students per full-time-equivalent teacher (StTe), teacher average total salary (TeSa), and per student expenditure (PsEp). As a higher student–teacher ratio usually means larger class sizes, students in a large class generally have more shared education resources and peer interaction in school work than students in a small class. These additional shared education resources and peer interactions in schoolwork could contribute to more effective learning and thus better academic performance for schools with larger class sizes. Based on theoretical reason or empirical evidence, these three school characteristics are expected to have positive relationships with ACT scores in regression analysis.

Statistical Analysis Methodology

We applied ordinary least squares (OLS) regression, weighted least aquare (WLS) regression, and GWR to study factors of ACT score. OLS has well-developed theories and diagnostic tools that allow users to apply statistical inference procedures such as test of hypothesis, confidence interval estimation, and goodness-of-fit tests. It is important to know that OLS is most effective and reliable when the data and model satisfy inherent statistical assumptions, such as model linearity, residual constant variance, residual independence, and linear independence between predictor variables (Kutner et al. 2004; Chatterjee, Hadi, and Price 2006). Also understand that conclusions of OLS analysis using aggregated spatial data are legitimate only for the current level of aggregation and the conclusions might not be applicable to other levels of spatial units. Making inferences of individuals based on aggregate statistics might commit ecological fallacy (Robinson 1950; Openshaw 1984). In our case, we used school statistics to investigate factors of ACT scores. The results are conclusive in determining significant predictor variables of school average ACT scores but not for an individual student's ACT score. To shed light on critical factors at the individual level, we used WLS to give more weight to schools with more students in modeling the regression coefficients. WLS regression analysis can highlight crucial factors at the individual level that might otherwise be ignored in OLS. The results are of particular importance to large schools in metropolitan areas.

OLS regression analysis using geographic data often violates the statistical assumption of independent residuals because geographic variables are usually spatially autocorrelated. Spatial autocorrelation is the phenomenon that near features tend to be similar, which is due to the fact that they are under the same influence associated with the located geographic area. Autocorrelated residuals lead to underestimated standard errors of regression coefficients, giving a spurious impression of accuracy (Chatterjee, Hadi, and Price 2006).

OLS regression analysis of geographic variables might also violate the statistical assumption of residual constant variance because of geographic uniqueness; different places have different characteristics and, consequently, different interactions and relationships among variables. Whereas OLS finds a single equation to represent the variable relationship for the entire study area, a global model might not be appropriate when the variable relationship is not consistent across the study area. In this situation, a global regression model is more of an average of the mix of relationships than a representative of the relationship. The local relationship can also be seriously misspecified. The phenomenon of spatially varied relationship can be termed *spatial nonstationarity* or *regional variation* (Fotheringham, Charlton, and Brunsdon 2002; Lloyd 2006).

Although spatial nonstationarity and spatial autocorrelation often come together as characteristics of geographic data, GWR, a common local regression technique, can be used to alleviate problems from both in the conventional OLS global regression. GWR fits a regression model for every observation point based on all observation points falling within a specified neighborhood. A modified WLS approach is used to calibrate local models so that observations closer to the target observation are given more weight than observations farther away in determining the regression coefficients. In addition to mitigating problems in regression analysis of geographic data, GWR is increasingly used as a geographic analysis tool in its own right for examining spatially varying relationships (e.g., Longley and Tobón 2004; Malczewski and Poetz 2005; Mennis and Jordan 2005).

It is important to know that GWR, as a least squares approach, has the same statistical assumptions as those in OLS. As GWR extends OLS functionality from constructing a global model to building multiple local models, standard OLS regression diagnostics are, nevertheless, unable to carry out in GWR due to its nature of extensive computation of a large amount of local models (same as the number of observations). Due to this limitation of GWR, we argue that GWR should be used with restrictions and the results be interpreted in a global context. Specifically, GWR should be used only with predictor variables that are statistically valid and significant from a preliminary OLS analysis. Using globally verified indicator variables in GWR is particularly helpful in minimizing multicollinearity in local models. Multicollinearity is the statistical phenomenon in which two or more predictor variables in a multiple regression model are highly correlated. With the existence of multicollinearity, the coefficient estimates will have large standard errors and can change erratically with the exclusion of a correlated variable or a few influential observations (Chatterjee, Hadi, and Price 2006). As studies applying GWR often use the entire set of predictor variables in GWR, their conclusions regarding the effects of individual predictor variables at a location are potentially distorted due to local multicollinearity. Focusing on those globally significant predictor variables also allows us to examine their local effects under the respective global context.

Another commonly ignored phenomenon of GWR is the dependence of local regression coefficients on the specified neighborhood distance parameter (Lloyd and Shuttleworth 2005). Our empirical analyses showed that local variable coefficients can change from significantly positive to significantly negative when the size of the neighborhood distance changes. Considering that GWR derives a regression equation for every location based on a defined size of neighborhood, this neighborhood size can be regarded as a spatial unit of GWR, and the phenomenon of changing regression coefficients with changing spatial unit of regression can be regarded as a modifiable areal unit problem (Openshaw 1984). To ensure that conclusions of local variable effects are legitimate, it is necessary to examine and interpret local variable effects at a range of spatial scales of local regression. From a statistical point of view, we would want to make certain that a fitted local model is reliable and not overly determined by a few influential observations and a diagnostic approach is to examine whether fitting with different neighboring observations results in substantially different model coefficients. Examining spatial patterns of variable coefficients across a series of local regression neighborhoods can be regarded as an exploratory analysis in its own right for detecting local anomalies or for discovering critical geographic extents. From a methodological point of view, we argue that conducting GWR at a series of neighborhood distances is a proper procedure to investigate spatially varying relationships, and conclusions of local variable effect should be referenced with a series of spatial units of local regression. As studies using GWR often conclude local variable effects based on a certain optimized neighborhood distance parameter,[1] the conclusions are potentially distorted and are thus deemed methodologically flawed.

Data Source and Initial Data Processing

Relevant high school statistics needed for the regression analysis were acquired from Missouri Department of Elementary and Secondary Education (DESE) for the 2006–2007 school year (DESE 2008). Spatial point data of public high schools and spatial area data of public school districts were acquired from the Center for Applied Research and Environmental Systems (CARES) at the University of Missouri at Columbia (CARES 2008), which are for the 2007–2008 school year. We also obtained relevant Census 2000 demographics at the block group level from the U.S. Census Bureau's American FactFinder (U.S. Census Bureau 2008). Spatial area data of block groups were obtained from CARES.

There are a total of 641 public high schools in Missouri (Figure 2A). Examining their spatial distribution, we see that the St. Louis and Kansas City metropolitan areas have noticeable clusters of public high schools, corresponding to their high population density (Figure 2B). Because spatial data for each individual school's attendance area are not available for calculating the associated census demographics (for modeling ACT score), we calculated the demographic variables of BsPct and DpPct based on school district covered areas. The variables were calculated from relevant census statistics of block groups that geographically intersect the local school district. There are a total of 522 public school districts in Missouri; 75 of them are elementary school districts and 447 of them have one or many high schools. We aggregated records of multiple high schools within a school district into a single record of a "virtual" school and use the centroid of the school district as the location of the virtual school. After this data processing, there are a total of 447 high school (district) records for regression analysis. A visual examination of the distribution of ACT score by high school district shows that there are small clusters of districts with similar ACT scores in some areas (Figure 2C). Also notice the considerable contrast of ACT scores in the downtown school districts versus the neighboring school districts in the St. Louis and Kansas City metropolitan areas.

Examine Spatial Patterns of Predictor Variables

We calculated the regression variables of LuPct, TeEx, TeCt, TeMs, TeSa, and StTe for 447 virtual schools from the aggregated school records. The distribution of individual variables was examined by high school district. Parent income level (indicated by LuPct) has apparent regional patterns, showing high income levels in the St. Louis, Jefferson City, Columbia, and Kansas City metropolitan areas and low income levels in numerous southeast Missouri counties (Figure 3A). Furthermore, income level has a distinctive spatial divide of downtown versus outlying areas in the St. Louis and Kansas City metropolitan areas, similar to the distribution of ACT scores. The correspondence between ACT scores and income level is also evident in the Springfield metropolitan area and a few counties in the southeast corner of Missouri, indicating that schools in high-income areas tend to have high ACT scores, and vice versa.

Parent education level has a distinctive spatial pattern showing high education level in numerous metropolitan areas (Figure 3B). Obviously, metropolitan areas provide many job opportunities for people with higher education. Notice the particularly high education level in a few suburban school districts of the St. Louis metropolitan area, where the income level (Figure 3A) and double-parent percentage (Figure 3C) are also relatively high. Although double-parent

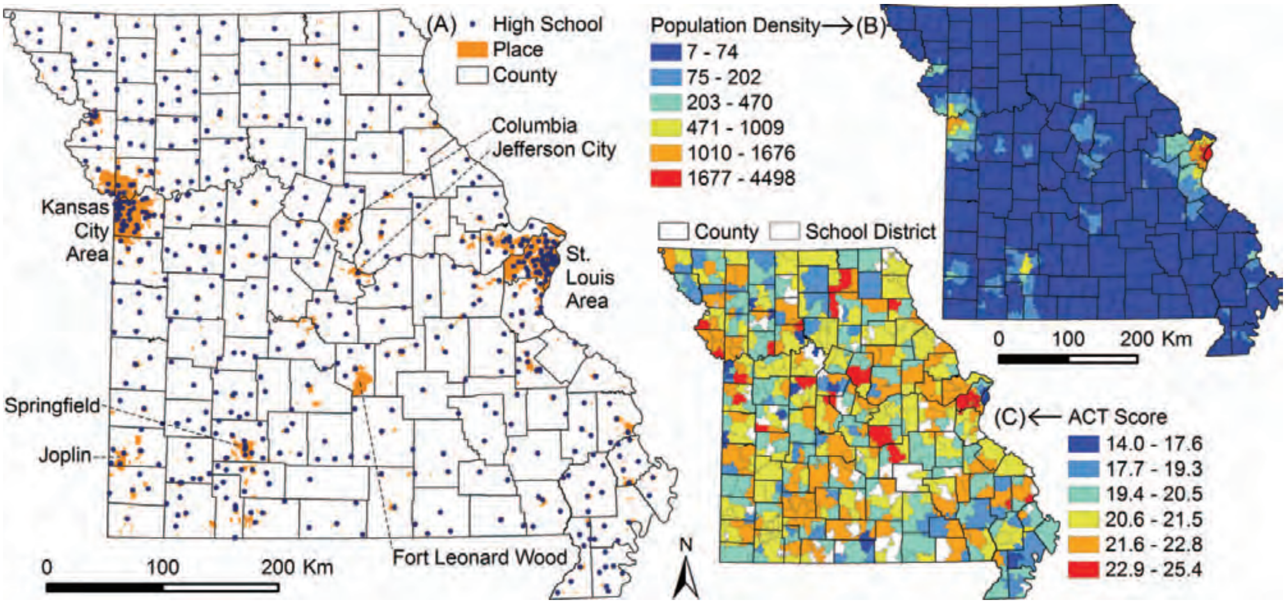

Figure 2. (A) A total of 641 public high schools in Missouri referenced with incorporated places. (B) Persons per square kilometer by school district (based on natural breaks classification). (C) American College Test (ACT) scores by high school district.

percentage does not have a distinctive regional trend as do those for income and education levels, it is particularly low (i.e., single-parent percentage is high) in downtown St. Louis and Kansas City, which corresponds to the low income levels of these areas.

Teacher experience level has a relatively random spatial distribution that does not show any regional trends or downtown versus suburban patterns in Missouri. Teaching certificate percentage has a negatively skewed distribution, with 58 percent of the high school districts having over 96 percent of teachers with the certification for their teaching assignment. School districts with low teaching certificate percentage are mainly in rural areas. Teacher master's degree percentage does not show a regional trend, although clusters of school districts with high master's degree percentage are evident in the suburban St. Louis and Kansas City metropolitan areas. It appears that teachers in these areas have more access to graduate programs than teachers in other areas.

Numerous counties in north and northwest Missouri have small average class sizes in high school, whereas clusters of counties with large average class size for high school appear in the St. Louis metropolitan area and to the south (Figure 4A). Relatively large class sizes can also be observed in other metropolitan areas, such as Kansas City, Springfield, Jefferson City, and Columbia. Evidently, average class size tends to be large in metropolitan school districts. Clusters of low teacher salaries for high schools in north and northwest Missouri correspond to clusters of small class size in those

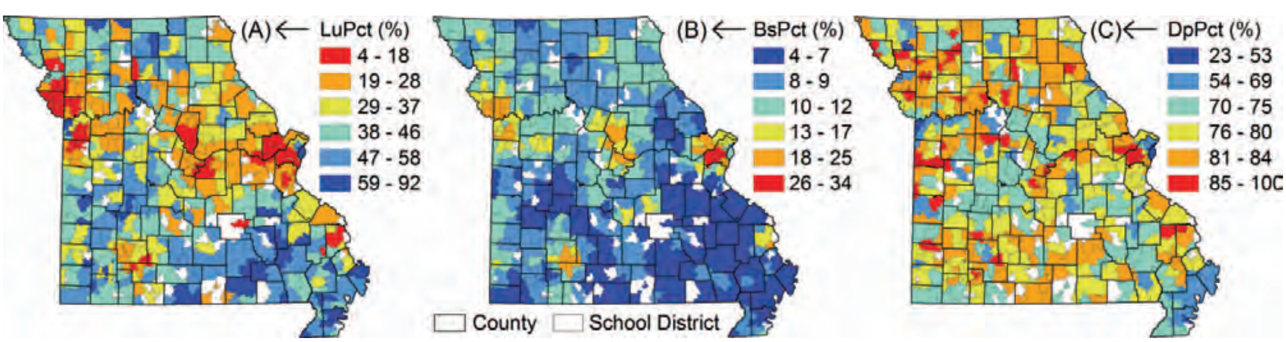

Figure 3. (A) Percentage of students receiving free or reduced priced lunch (LuPct), (B) college degree percentage (BsPct), and (C) double-parent family percentage (DpPct), by high school district (based on natural breaks classification).

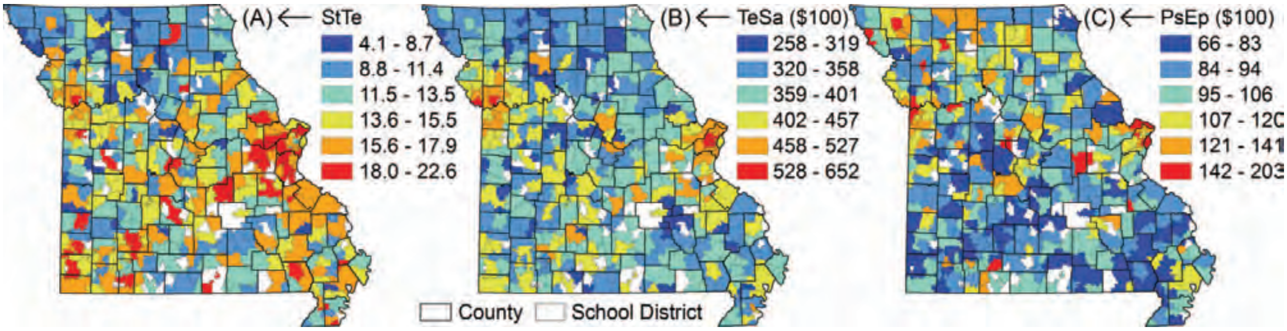

Figure 4. (A) Student–teacher ratio (StTe), (B) average teacher salary (TeSa), and (C) per student expenditure (PsEp), by high school district (based on natural breaks classification).

areas (Figure 4B). Clusters of school districts with high teacher salaries are evident in the St. Louis and Kansas City metropolitan areas, although not present for other smaller metropolitan areas. Per student expenditure is also relatively high for numerous St. Louis and Kansas City metropolitan school districts (Figure 4C). Interestingly, the third largest metropolitan area of Missouri, Springfield, has considerably lower per student expenditure in its local county areas. This dramatic difference among metropolitan areas despite their common urban context can be explained by the uniqueness of geography.

Exploring Pairwise Relationships between Regression Variables

We examined pairwise scatterplots and Pearson correlation coefficients (r) between regression variables to explore their relationships and potential multicollinearity. The degrees of correlation between TeSa and TeMs, between TeSa and StTe, and between TeSa and BsPct are relatively high with coefficients of 0.68, 0.62, and 0.61, respectively (Table 1), although their pairwise scatterplots (Figure 5) do not show strong linear relationships. Even with a potential multicollinearity problem, we did not drop any of these predictor variables from regression analysis because these variables are all chosen based on respective theoretical reasons, understanding that multicollinearity is not a problem of model misspecification and its formal investigation should begin after the model has been satisfactorily specified; that is, model calibrated and residual diagnostics conducted and verified (Chatterjee, Hadi, and Price 2006). From another perspective, because we cannot justify the removal of any of the correlated predictor variables, it is appropriate to screen variables by the common variable selection statistical procedures (discussed later) before verifying multicollinearity through formal diagnostics.

We postulated a linear regression model for the ease of interpretation of variable relationships and for the purpose of examining geographic variations of variable

Table 1. Pearson correlation coefficients for all paired variables

	ACT	LuPct	BsPct	DpPct	TeEx	TeCt	TeMs	StTe	TeSa	PsEp
ACT	1	−0.50	0.38	0.25	0.16	0.25	0.29	0.30	0.31	−0.06
LuPct	−0.50	1	−0.51	−0.29	−0.10	−0.32	−0.34	−0.37	−0.39	0.01
BsPct	0.38	−0.51	1	0.04	0.12	0.20	0.48	0.23	0.61	0.39
DpPct	0.25	−0.29	0.04	1	−0.12	−0.06	−0.18	−0.32	−0.35	−0.17
TeEx	0.16	−0.10	0.12	−0.12	1	0.21	0.41	0.11	0.34	0.03
TeCt	0.25	−0.32	0.20	−0.06	0.21	1	0.36	0.42	0.44	−0.07
TeMs	0.29	−0.34	0.48	−0.18	0.41	0.36	1	0.37	0.68	0.21
StTe	0.30	−0.37	0.23	−0.32	0.11	0.42	0.37	1	0.62	−0.22
TeSa	0.31	−0.39	0.61	−0.35	0.34	0.44	0.68	0.62	1	0.25
PsEp	−0.06	0.01	0.39	−0.17	0.03	−0.07	0.21	−0.22	0.25	1

Note: ACT = American College Test score; LuPct = lunch plan percentage; BsPct = college degree percentage; DpPct = double-parent family percentage; TeEx = teacher years of experience; TeCt = teacher certification percentage; TeMs = teacher master's degree percentage; StTe = student–teacher ratio; TeSa = teacher salary; PsEp = per student expenditure.

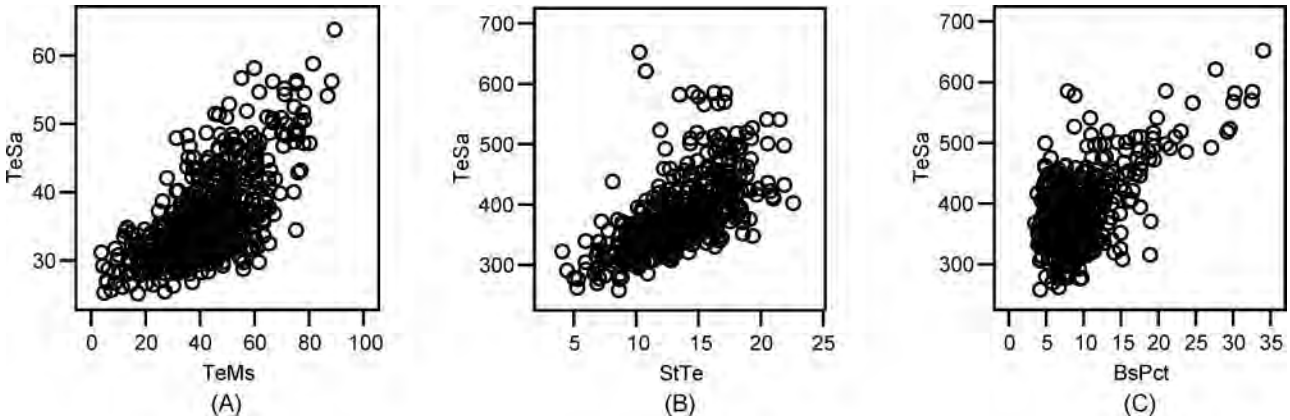

Figure 5. Scatterplots of average teacher salary (TeSa) versus (A) percentage of teachers with a master's degree (TeMs), (B) student–teacher ratio (StTe), and (C) college degree percentage (BsPct).

relationships. Even though pairwise scatterplots do not show a strong linear relationship between ACT score and any of the predictor variables, the response variable could still depend on the predictor variables in a linear way collectively but not individually (Chatterjee, Hadi, and Price 2006). We will confirm that the linearity assumption is not seriously violated through residual diagnostics.

OLS Regression Analysis

We used a backward elimination (BE) procedure (SPSS 2008) that removes less significant predictor variables in turn to find the best combinations of predictor variables. Compared with a forward selection (FS) procedure and a stepwise method, a BE procedure is preferred because it allows us to inspect the results from the initial full-set variables. In addition, a BE procedure is able to handle multicollinearity better than an FS procedure, although the use of variable selection procedures in a collinear situation might be problematic (Chatterjee, Hadi, and Price 2006). Collinearity diagnostics for the initial full-set variables based on condition index and variance-decomposition proportion (Callaghan and Chen 2008; SPSS 2008) show the presence of multicollinearity, indicating likely problems of local multicollinearity if the full-set variables, instead of the globally verified predictor variables, are used in local regression analysis.

The final model from the BE variable selection procedure retains all three student characteristic variables (LuPct, BsPct, DpPct), one teacher characteristic variable (TeEx), and one school characteristic variable (StTe), which are statistically significant from zero at the 99 percent level (Table 2). ACT score is negatively affected by LuPct and positively affected by BsPct, DpPct, TeEx, and StTe, indicating that schools with higher parent income and education levels, more double-parent families, larger class sizes, and more experienced teachers tend to have high ACT scores. Their relationships with ACT score are consistent with empirical findings and theoretical expectations. Examination of the standardized coefficients shows that double-parent family and class size are more influential variables regarding ACT scores than other predictor variables.

We verified that the regression assumptions of model linearity and normality, zero mean, constant variance, and independence of residuals are not seriously violated, and multicollinearity is not a problem using standard regression diagnostics (Chatterjee, Hadi, and Price 2006). The goodness-of-fit index, R^2, for the model is 0.35. The analysis of variance (ANOVA) test further indicates that the variation explained by the model is statistically significant at the 99 percent level. We

Table 2. Regression coefficients statistics from ordinary least squares

	Coefficient	Standardized coefficient	*t* value	*p* value
Constant	14.16		12.74	0.00
LuPct	−0.02	−0.21	−4.02	0.00
BsPct	0.06	0.18	3.94	0.00
DpPct	0.06	0.28	6.06	0.00
TeEx	0.08	0.12	3.16	0.00
StTe	0.12	0.26	5.50	0.00

Note: LuPct = lunch plan percentage; BsPct = college degree percentage; DpPct = double-parent family percentage; TeEx = teacher years of experience; StTe = student–teacher ratio.

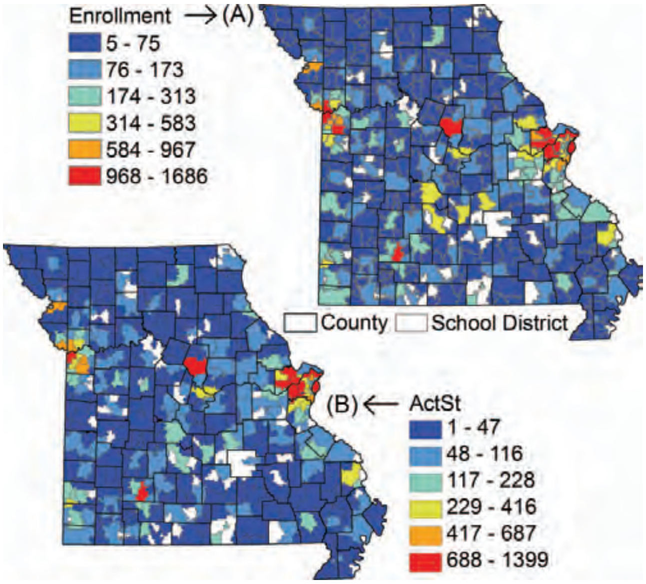

Figure 6. (A) Enrollments in twelfth grade and (B) number of students taking the American College Test (ActSt), by high school districts.

conclude that the model consisting of the five predictor variables is able to explain 35 percent of the variation in ACT score.

WLS Regression Analysis

We used WLS that gives greater weight to larger schools in regression analysis to shed light on whether important predictor variables for school performance are also important for student performance. From an individual point of view, this approach implicitly recognizes that data from schools with a large number of students taking the ACT are more reliable and should have more weight in determining the regression coefficients than data from schools where only a few students took the ACT. A map of twelfth-grade enrollment shows that schools in metropolitan areas have relatively large enrollments (Figure 6A). Both the twelfth-grade enrollments and the numbers of students taking the ACT vary substantially between urban and nonurban schools (Figure 6B).

WLS using a BS procedure retains predictor variables of LuPct, BsPct, DpPct, TeEx, TeCt, TeMs, and PsEp. Multicollinearity diagnosis indicates the problem of multicollinearity. To find a model without multicollinearity, we interactively removed one of the less significant predictor variables and used the other variables for regression analysis. A model that contains predictor variables of LuPct, BsPct, DpPct, TeEx, TeMs, and PsEp satisfies the requirement (Table 3). We further confirmed that other regression assumptions are not seriously violated. The R^2 for the WLS model is 0.74, which is much higher than the R^2 of the OLS model. The higher R^2 is reasonable considering that WLS weights large metropolitan schools that have similar urban context and likely more consistent variable relationships than other schools. Compared with OLS, WLS has additional predictor variables of TeMs and PsEp but without the StTe variable, indicating that teacher master's degree and per student expenditures are influential factors of ACT score for large, metropolitan schools but not for small, rural schools. Similarly, class size appears to be an important factor of ACT score for small, rural schools but not for large, metropolitan schools. This difference between large, metropolitan schools and small, rural schools indicates the potential advantage of local regression analysis. Notice that WLS analysis shows a negative effect of PsEp on ACT score, indicating that schools with high per student expenditure tend to have low ACT scores, which is contrary to findings in the literature and theoretical expectation. Examining individual maps of ACT and PsEp variables (Figure 2 and Figure 4, respectively), we found that their negative relationship is evident in the core of the three major metropolitan areas where WLS includes many weights. Because these key areas have relatively low ACT scores and high PsEp, we can hypothesize that school officials purposefully allocate a large percentage of financial resources to schools that most need to improve their student test scores.

Table 3. Regression coefficients statistics

	Coefficient	Standardized coefficient	t value	p value
Constant	16.03		17.58	0.00
LuPct	−0.04	−0.34	−7.74	0.00
BsPct	0.06	0.24	5.89	0.00
DpPct	0.07	0.35	8.42	0.00
TeEx	0.10	0.10	3.76	0.00
TeMs	0.01	0.09	2.50	0.01
PsEp	−0.01	−0.12	−3.62	0.00

Note: LuPct = lunch plan percentage; BsPct = college degree percentage; DpPct = double-parent family percentage; TeEx = teacher years of experience; TeMs = teacher master's degree percentage; PsEp = per-student expenditure.

Although OLS and WLS find different predictor variables, their spatial patterns of residuals look considerably similar, with observable differences only in

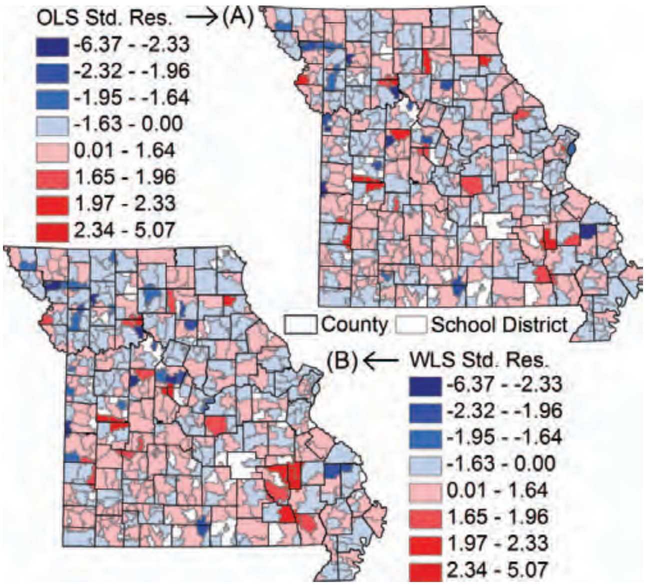

Figure 7. Standardized residuals from (A) ordinary least squares (OLS) and (B) weighted least squares (WLS), based on natural breaks classification.

the St. Louis and Kansas City metropolitan areas (Figure 7). The similarity is because the four common predictor variables (LuPct, BsPct, DpPct, TeEx) of OLS and WLS together have the major influence on ACT scores. Furthermore, although high residuals (underestimation) and low residuals (overestimation) are distributed rather evenly across the geographic space of Missouri, there are still small aggregations of districts of similar residuals, indicating the potential improvement of using local regression instead of global regression.

GWR Regression Analysis

We performed GWR regression analysis to investigate spatially varied effects of factors of ACT scores. The five predictor variables that are significant and valid in a global regression model were used in GWR to minimize potential violations of regression assumptions in local models, particularly multicollinearity. For the GWR neighborhood distance (or bandwidth [BW]) parameter, we used an adaptive bandwidth defined by a specified number of observations to accommodate sparse high schools in some geographic regions. GWR analyses were compared for nine different bandwidths to examine how local estimates of regression coefficients, R^2, and residuals change with the spatial unit of GWR. The nine bandwidths range from the maximum number of 447 observations (schools) to the minimum reasonable number of 50 observations (ten times the number of predictor variables), with 400, 350, 300, 250, 200, 150, and 100 observations in between.

The overall goodness-of-fit index, R^2, is calculated for GWR in the same manner as for OLS that measures the agreement between observed and predicted values from individual local models. We compared adjusted R^2 instead of raw R^2 for different GWR bandwidths, understanding that an R^2 weakly decreases with increasing sample size in least squares regressions, whereas an adjusted R^2 is a notionally unbiased index in the sense that it accounts for the respective degrees of freedom, denoting the extent to which the modeling improves prediction over what would be expected by chance.

The adjusted R^2 shows an increasing trend with decreasing GWR bandwidth (Figure 8A). Nevertheless, the overall modeling reliability indicated by the F value[2] has a decreasing trend. Evidently, a smaller sample size has a smaller variance and results in a better fit, but the fitted model is less reliable in applying to the overall population. We further conducted an ANOVA test to investigate the statistical significance of the improvement of GWR over OLS (Figure 8B). The significance levels for all bandwidths are over 90 percent but under 97.5 percent. The improvement is particularly significant at the 95 percent level for bandwidths from 250 to 100. A bandwidth of 100 is determined to be optimal for GWR modeling in our case considering both the prediction and reliability of modeling. The improvement of GWR over OLS indicates the existence of spatial nonstationarity or similar variable relationships for close observations, understanding that GWR gives weights to nearby observations.

We mapped the local adjusted R^2 (Figure 9) and F values (Figure 10) at different bandwidths to examine their geographic relevance. As the local variable relationships become more prominent with decreasing bandwidth, local models tend to have a better fit but become more unreliable, corresponding to the opposite trends of the overall R^2 and F value. Importantly, local models with high R^2 also tend to have high F values, indicating that the two statistics of local models are positively correlated, although their trends with bandwidth are negatively correlated. Local models in the three major metropolitan areas—St. Louis, Kansas City, and Springfield—predict ACT score relatively well and are also relatively reliable with high F values, likely due to their common metropolitan geographical context and the consequent consistent variable relationships.

Similar to standardized residuals in OLS, local standardized residuals from GWR distribute evenly across Missouri (Figure 11). Comparing different GWR

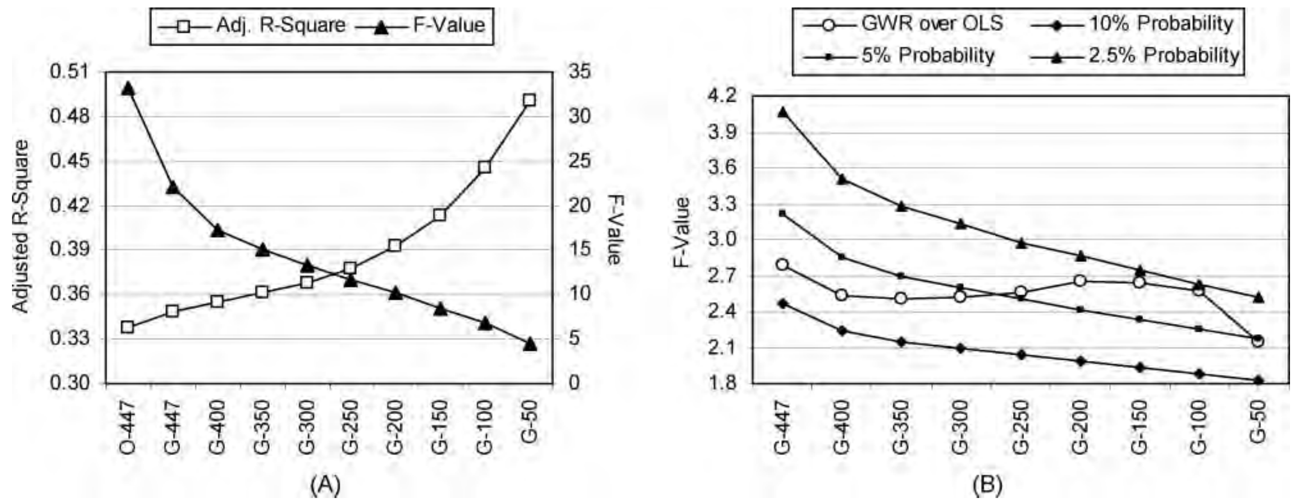

Figure 8. (A) Adjusted R^2 and F values for ordinary least squares (OLS) and for geographically weighted regression (GWR) at different bandwidths. (B) F values testing the improvements of GWR over OLS at different bandwidths, referenced with the corresponding F values at different error probabilities. *Note:* O-447 is OLS based on 447 observations, W-447 is GWR based on 447 observations, W-400 is GWR based on 400 observations, etc.

bandwidths, we see that there are more outliers of high local standardized residuals at a smaller bandwidth, indicating less reliability of local models. Nevertheless, the even distribution of these outliers indicates their validity as input data. Corresponding to trends of outliers, local regression at a shorter bandwidth has more influential observations indicated by high Cook's distance.[3] The influential observations are also evenly distributed, indicating that they are valid samples but simply influential to local models.

We mapped local coefficient t values[4] at different bandwidths to examine how variable effects change with local regression scale and across geographic space. As local influences become more prominent with decreasing bandwidth, the local variable effect might become different or even opposite from the global effect. For example, although family income level shows a globally significant and positive effect (i.e., negative LuPct regression coefficient) on ACT scores for 447 schools or school districts, the positive effect becomes relatively weak for seven school districts in southern Missouri (shaded in light blue with t value ≥ -1.67 in Figure 12, BW $= 350$) based on GWR analysis in a neighborhood of 350 observations. Moreover, at a regression neighborhood of 150 observations, one school district in northeast Missouri (shaded in light red in

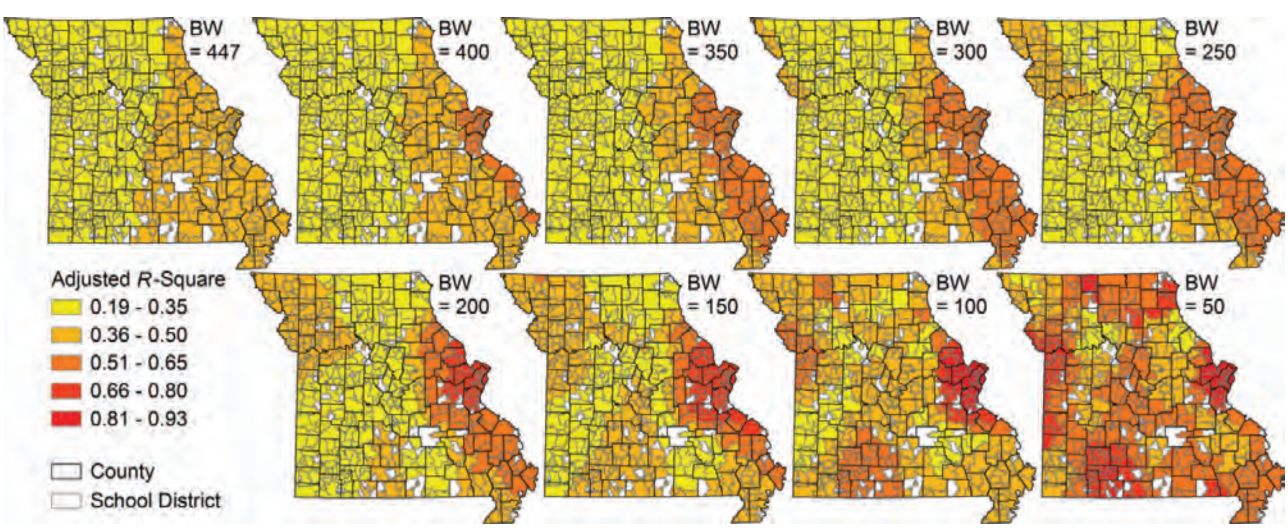

Figure 9. Local adjusted R^2 values from geographically weighted regression (GWR) at different bandwidths (BW).

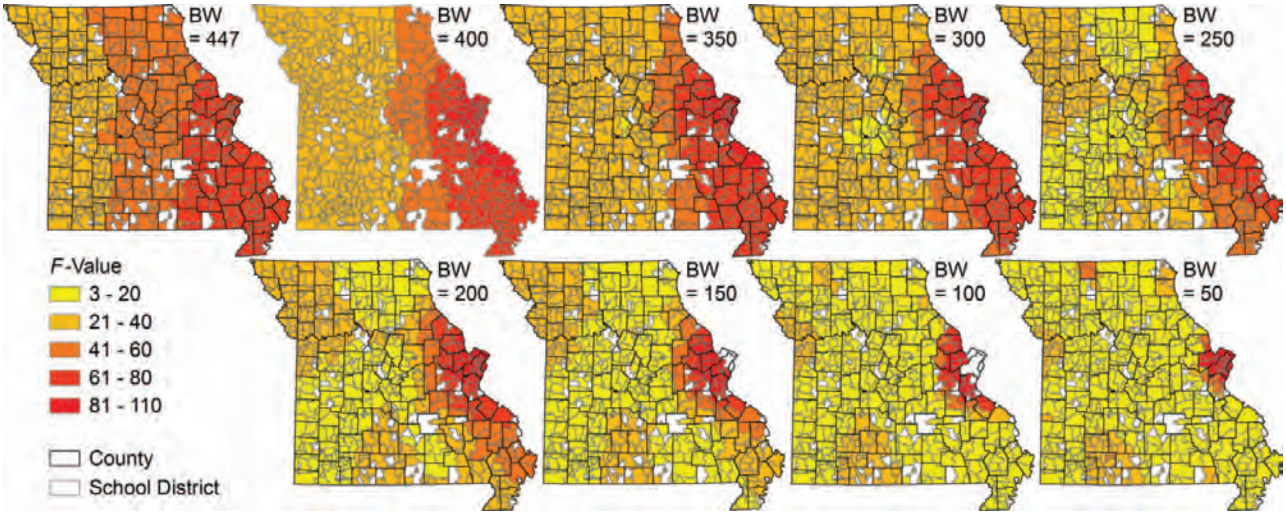

Figure 10. Local F values from geographically weighted regression (GWR) at different bandwidths (BW).

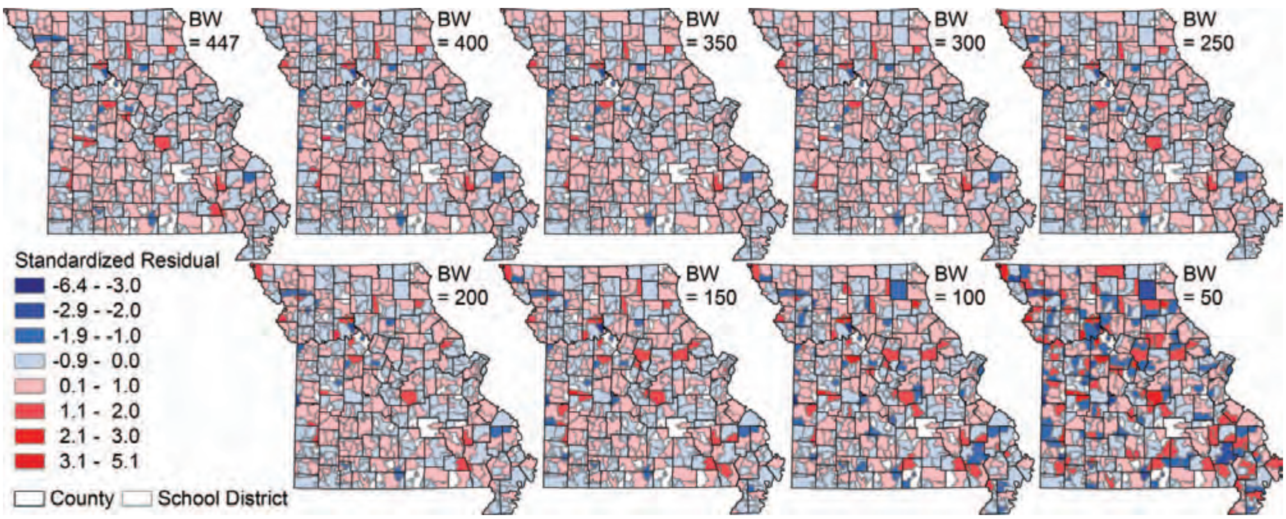

Figure 11. Local standardized residuals from geographically weighted regression (GWR) at different bandwidths (BW).

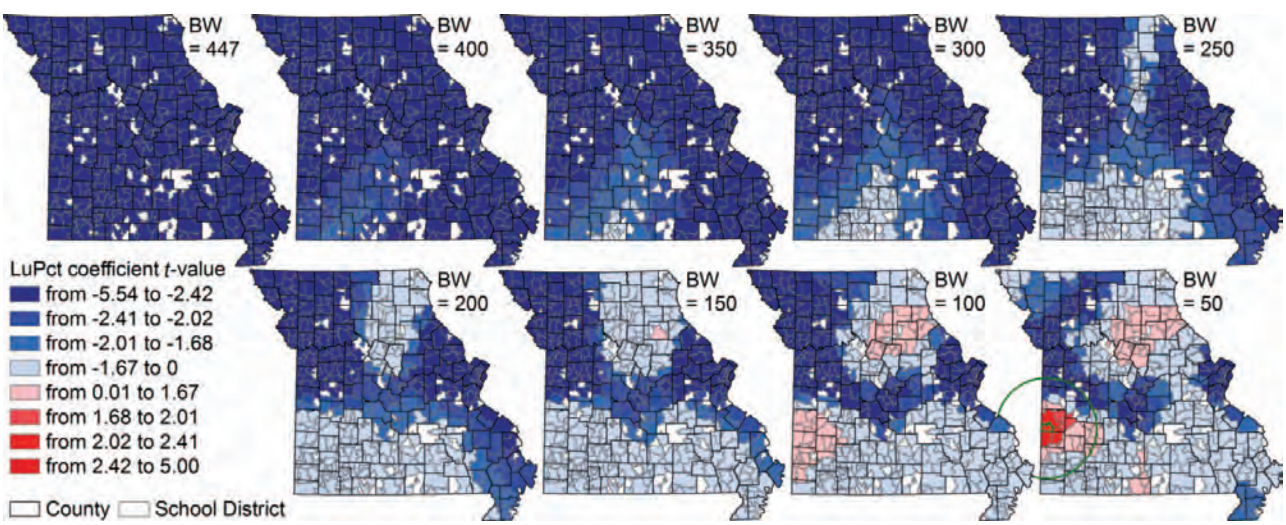

Figure 12. Local coefficient t values of percentage of students receiving free or reduced priced lunch (LuPct) from geographically weighted regression (GWR) at different bandwidths (BW).

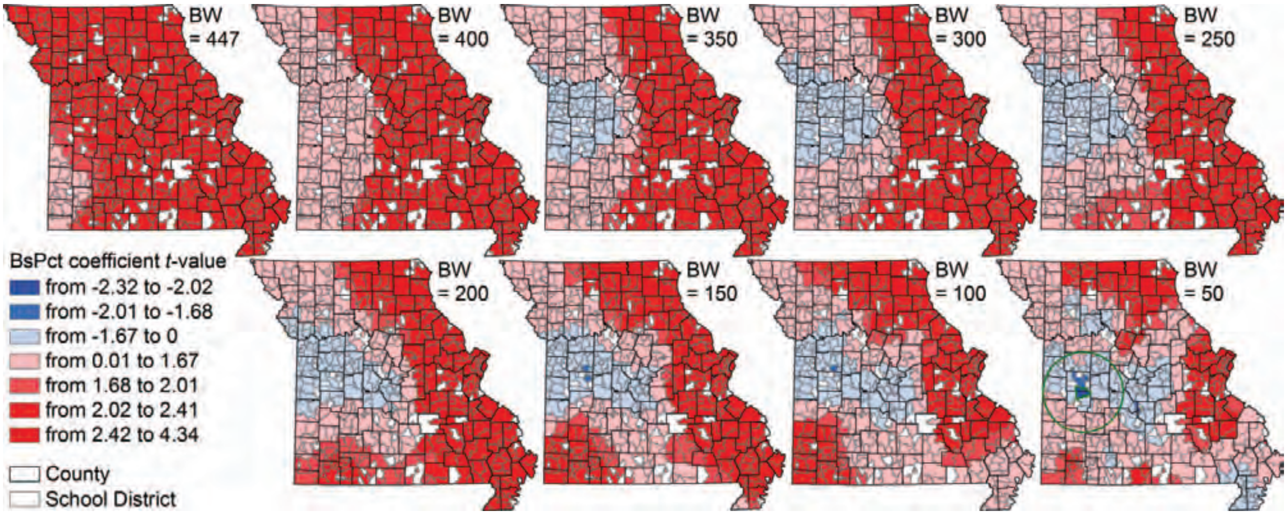

Figure 13. Local coefficient t values of college degree percentage (BsPct) from geographically weighted regression (GWR) at different bandwidths (BW).

Figure 12, BW = 150) started to show a negative, although weak, regression relationship between the two variables. When local regression is based on a fifty-school neighborhood, seven school districts in southwest Missouri (shaded in dark red with t value $\geq$ 1.68 in Figure 12, BW = 50) have a negative effect of income level on ACT scores that is statistically significant at the 90 percent level (one of the school districts and its corresponding regression neighborhood are outlined in green). We examined individual maps of ACT and LuPct variables in the local areas of the seven school districts (Figure 2 and Figure 3, respectively) and found evidence that some local school districts have relatively low family income level (i.e., high LuPct) but achieve well in ACT.

Although parent education level has a strong positive relationship with ACT scores in OLS, GWR based on a 447-school neighborhood shows that twenty-six schools in southwest Missouri (shaded in light red in Figure 13, BW = 447) have a weak positive relationship between BsPct and ACT score. At a local regression neighborhood of 350 schools, parent education level shows a weak negative relationship with ACT score for sixty-seven schools in Kansas City and the surrounding thirteen-county area (shaded in light blue in Figure 13, BW = 350). When local regression is based on a fifty-school neighborhood, four school districts in middle and midwest Missouri (shaded in dark blue with t value $\leq$ –1.68 in Figure 13, BW = 50) have a negative effect of BsPct on ACT variable that is statistically significant at the 90 percent level (one of the school districts and its corresponding regression neighborhood are outlined in green). Observe the individual maps of ACT and BsPct variables (Figure 2 and Figure 3, respectively); it is apparent that some local school districts in the regression neighborhoods of the four school districts have relatively high ACT scores but low parent education levels.

Even though global regression analysis shows that double-parent family background is the most influential factor on ACT score with a positive effect, local regression analysis indicates that schools with high percentage of double-parent family background might not necessarily perform well on the ACT (Figure 14). Specifically, the negative regression relationship between double-parent family background and ACT score becomes evident for nine local school districts in the Jefferson City area (shaded in dark blue with t value $\leq$ –1.68 in Figure 14, BW = 150) in a 150-school local regression neighborhood. Moreover, local regression in a fifty-school neighborhood highlights a total of thirty-two school districts (shaded in dark blue with t value $\leq$ –1.68 in Figure 14, BW = 50) that are likely (at the 90 percent statistical significance level) not performing well on the ACT even with a high percentage of double-parent family background, or vice versa, performing well on the ACT even a with high percentage of single-parent family backgrounds.

Whereas OLS shows that experienced teachers usually have students achieving well on the ACT, local regression analysis indicates that schools with junior faculty could potentially have students with high ACT scores. Specifically, local regression at a 100-school neighborhood shows two school districts in southeast

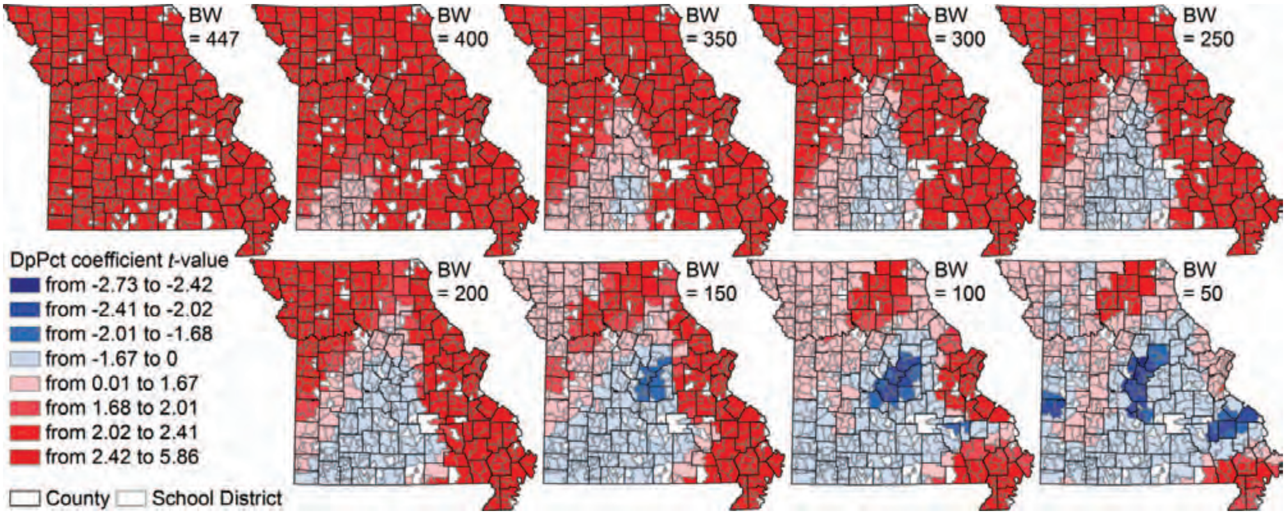

Figure 14. Local coefficient t values of double-parent family percentage (DpPct) from geographically weighted regression (GWR) at different bandwidths (BW).

Missouri (shaded in dark blue with t value ≤ -1.68 in Figure 15, BW $= 100$) having a strong negative regression relationship between ACT score and teacher experience. Local regression in a fifty-school neighborhood further highlights a total of thirteen school districts (shaded in dark blue with t value ≤ -1.68 in Figure 15, BW $= 50$) that have a significantly negative effect of teacher experience on ACT scores. Examining individual maps of ACT and TeEx variables, we found that many local school districts in the neighborhoods of those thirteen school districts have either high ACT scores but low TeEx or low ACT scores but high TeEx. TeEx has a relatively heterogeneous t value patterns in a fifty-school regression neighborhood compared to other predictor variables, which indicates a less consistent global variable effect and explains its lesser significance in a global model.

With a globally positive effect on ACT score, student–teacher ratio (indicating average class size) has the most consistent local effect compared to other predictor variables. No school districts have a statistically significant (at the 90 percent level) negative local coefficient of StTe at varying local regression neighborhoods (Figure 16). In a 150-school regression neighborhood, forty school districts in the St. Louis area (shaded in light blue in Figure 16, BW $= 150$) start

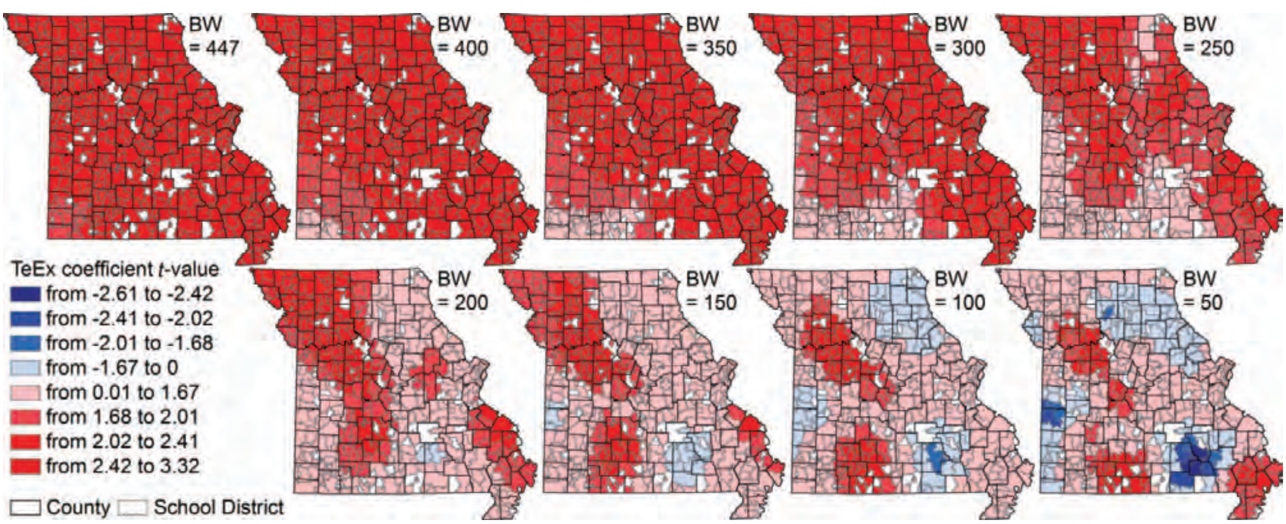

Figure 15. Local coefficient t values of teacher average years of experience (TeEx) from geographically weighted regression (GWR) at different bandwidths (BW).

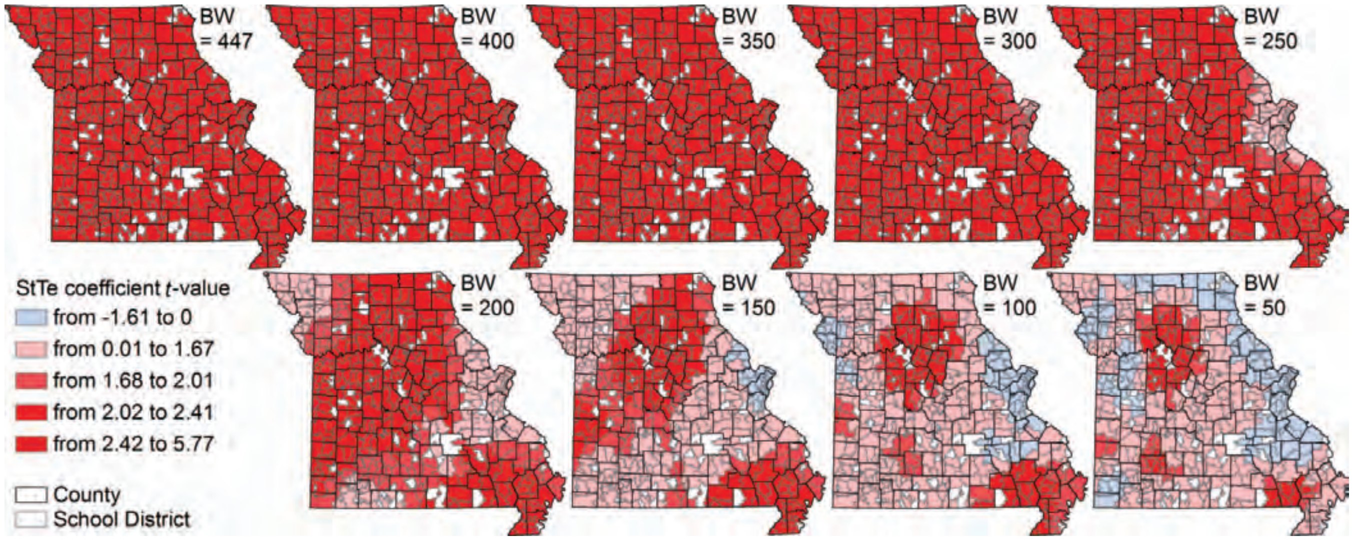

Figure 16. Local coefficient *t* values of student–teacher ratio (StTe) from geographically weighted regression (GWR) at different bandwidths (BW).

to show a negative, although weak, effect of class size on ACT score. Examining individual maps of ACT and StTe variables (Figure 2 and Figure 4, respectively), we observe that many school districts in downtown St. Louis have relatively low ACT scores but large average class size. This phenomenon also explains our previous finding that average class size is a significant predictor variable in OLS but not in WLS, as WLS weights large downtown St. Louis school districts that have a different local variable relationship from the global relationship.

Discussion

OLS provides overall summary statistics of variable relationships for a group of observations, whereas GWR provides localized regression statistics at each location based on its neighborhood observations. The different outputs from OLS and GWR are of interest for different purposes. For example, if the researcher intends to understand ACT score factors to aid planning for statewide education policies, conducting global regression to build a single, statewide model would be appropriate. If the researcher intends to understand local factors of ACT scores to provide guidance in allocating local resources for improving school performance, conducting local regression to build local models would be preferred.

This study analyzed a school-level statistical model for studying geographic variations of school-level factors of ACT score. The best modeling result from GWR based on a fifty-school neighborhood has an R^2 of 0.63. The unexplained variation is mainly due to the individual nature of ACT score. Specifically, the ACT is taken by individuals and the score is only directly related to an individual's academic abilities, influenced by factors relevant to individual personality, family background, and school quality. Clearly, school demographic variables are simplified and deficient surrogates of individual and family variables for explaining ACT score variations. From another point of view, the imperfection of a school-level model is due to uncertainty of data aggregation. As individual characteristics are assumed to be homogeneous within schools, the internal variations within school would contribute to unexplained variations of a school-level model. That being said, this study treated schools as single entities and necessarily disregarded the complex processes within schools in statistical analysis for the purposes of investigating geographic variations of ACT score factors and examining commonalities and dissimilarities across public high schools in Missouri.

Our analyses showed that a neighborhood of 100 school districts is optimal (within the nine tested GWR bandwidths) for local regression analysis of the entire Missouri area. This optimal local regression neighborhood is approximately one fifth of the state area, consisting of tens of counties. We could understand that local variable relationships are relatively consistent at this geographic scale.

From a certain point of view, GWR analysis serves as an exploratory geographic analysis tool to detect local anomalies. Further detailed analyses can be conducted for interested local areas. For example, as

GWR based on a fifty-school neighborhood highlights thirteen school districts having a significantly negative effect of teacher experience on ACT score, we can conduct an in-depth OLS analysis using local samples of the thirteen school districts with a full set of nine predictor variables for closely examining the underlying mechanism of the effect of teacher experience in the area.

GWR analysis is useful in supporting local education decision making. For example, as GWR based on a 150-school neighborhood shows that schools with large class size in the St. Louis area tend to have low ACT score, educators might test whether certain education policies are useful in improving ACT scores for local schools by conducting local regression analysis again after the implementation of the policies.

Conclusions

This study examined geographic variations of effects of ACT score factors for 447 American public high schools by testing nine predictor variables related to student characteristics, teacher characteristics, and school characteristics. OLS analysis concludes with five significant and valid predictor variables, including parent income and education levels, double-parent family rate, student–teacher ratio, and teacher experience, of which double-parent family rate is the most influential variable. The roles of teacher and school variables in explaining portions of ACT score variations indicate the responsibility of providing a quality education from administrators, teachers, and counselors in improving student learning outcome.

Although GWR is able to provide localized regression statistics, it is unable to carry out numerous standard regression diagnostics of OLS to ensure the satisfaction of certain least-squares assumptions. Therefore, GWR analysis should be based on the results of a preliminary OLS analysis to minimize violation of regression assumptions in local models, particularly local multicollinearity. In addition, results of GWR should be examined at a series of local regression scales to draw integral conclusions of local variable effects.

GWR analysis based on the five globally verified predictor variables shows that some local areas have weak variable relationships or even opposite variable effects from their corresponding global effects at certain local regression neighborhoods. Furthermore, GWR analyses at incremental regression scales highlight critical neighborhood sizes at which variable effects vary across local areas. The results provide insights of the geographic relevance of ACT score factors.

The results of this study allow us to understand critical school-level factors of ACT score and their geographic variations. For state educational officials, the results help them allocate state education resources to local areas based on what needs appear to be for local schools. For local school administrators, the results help pinpoint critical academic performance factors for local schools in a defined neighborhood and determine appropriate local resources for improving local academic competitiveness.

Notes

1. Common GWR software provides two default methods to determine an optimized neighborhood distance, either by minimizing a cross-validation (CV) function or by minimizing the corrected Akaike Information Criterion (AICc; Fotheringham, Charlton, and Brunsdon 2002).
2. An F value of a model is used in an ANOVA to test the statistical significance of a model improving prediction over what would be expected by chance, by comparing the variation due to regression with the variation due to error while accounting for the respective degrees of freedom. Here we do not calculate the statistical significance level from an F value but use the F value to indicate model reliability for the comparison of GWR modeling at different bandwidths. Although F values at different bandwidths are not directly comparable due to the different degrees of freedom involved, in our case the F values are substantially different and, therefore, the comparison is still valid. It is worth noting that the F value for GWR modeling is based on the effective number of parameters and the corresponding effective number of degrees of freedom in local regression (Fotheringham, Charlton, and Brunsdon 2002).
3. An observation is influential if its deletion causes substantial changes in the fitted model. The Cook's distance, measuring the difference between the fitted values obtained from the full data and the fitted values obtained by deleting a target observation, is used here to determine whether an observation is influential.
4. The t values instead of raw coefficient estimates are of interest because the local t value, calculated from dividing the local coefficient estimate by the corresponding local standard error of the estimate, accounts for uncertainty in the local estimate. The t value is, therefore, a normalized statistic that is appropriate for the comparison of different locations and variables.

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Correspondence: Department of Geography, Geology and Planning, Missouri State University, Springfield, MO 65897, e-mail: qiu@missouristate.edu (Qiu); swu@missouristate.edu (Wu).