A Spatial Analysis of South African Secondary School's Matric Pass Rates

Arulsivanathan Naidoo
Statistics South Africa
Pretoria
South Africa
aruln@statssa.gov.za

Abstract

The ecological theory of Urie Bronfenbrenner defined four contributing groups to school performance. At the macro level the education department's syllabus, at the Meso level the school funding and teacher's qualifications, at the Micro level the individual learners attendance and completion of homework and finally at the Exo level the socio economic factors of the community and school feeder areas.

This study evaluates the South African Matric pass rates of the secondary schools and uses Census 2011 data to validate Exo level claim that the school performance is related to the socio economic factors of the community. A spatial statistical analysis is performed on the school pass rates.

Key words: Matric pass rate, school performance, spatial analysis, socio-economic factors, spatial Relationships

1. Introduction

Urie Bronfenbrenner was an American psychologist, revered as one of the leading world authorities in the field of development psychology. He developed the ecological systems theory where he defined the four concentric systems that are the micro system, the meso system, the exo system and the macro system. At the macro level the education department's syllabus can contribute to the learner's performance. In South Africa this has changed several times, for example the Outcomes based Education (OBE) was introduced in the late 1990's. this was replaced with the CAPS in 2009 and in 2014 the first group of matric learners were produced.

At the Meso level the school funding and teacher's qualifications, contribute to the learners performance. South African has a very high spending in the education budget and unfortunately this has not improved the pass rates. At the Micro level the individual learner's attendance and completion of homework contributes to the school performance. Many students travel long distances to get to school while others are frequently absent due to alcohol and drug abuse. Finally at the Exo level the socio economic factors of the community and school feeder areas.

Schooling, the quality of education and the higher education system has been under investigation around the world and in South Africa for many years. Senior certificate examination results, commonly known as matric, provide an indicator for the functioning of the secondary school system, the schools and individual learners. An investigation into the educational system in South Africa is not only important in understanding the development of its population based on human development terms but also assist in defining the potential per capita income of the South African population (Fedderke *et al.*, 2000). Analyses of the various factors that shape schooling outcomes have been in short supply for South Africa generally, and even more so for post-apartheid South Africa: existing analyses are either dated, not based on national data or attempt to collect schooling outcomes from survey data, rather than schooling datasets (Crouch and Mabogoane, 1998)

Spaull (2013) highlights that the correlation between education and wealth still manifests in the dualistic nature of the education system in post-apartheid South Africa. New interest in

exploring geographical differences in the effect of one or more predictor variables upon a response variable have led to the application of spatial analytical techniques (Fotheringham *et al*.).
Matric pass rates attract a great deal of public interest and are seen as a major public barometer of school performance. Students from a low socio-economic background, or schools in poverty stricken areas, tend to perform much worse in their matric exam than students from affluent areas even if one statistically controls for resources (Crouch and Mabogoane, 2001; van der Berg et al.,2011; Spaull, 2013), with the mere location of a school in a township area causing a decrease in matric pass rates. By examining geographically whether the clustering of students from lower socio-economic background within a school is a predicator of average school performance would contribute to a better understanding of the distribution of low performing schools and examine if students from high socio-economic backgrounds perform better than students from low socioeconomic backgrounds. A useful definition of socio-economic status (SES) is 'relative position of a family or individual on a hierarchal social structure based on their access to, or control over wealth, prestige and power (Willms, 2003).
The use of socio-economic data from census for educational prediction is not new (Fedderke *et al*., 2000; Crouch and Mabogoane, 2001; Burger and van der Berg, 2003; Marks, 2006; van der Berg et al., 2011; Matthews and Parker, 2013; Spaull, 2013). Various estimates of the contribution of socio-economic background to examination success exist in the literature relating to school effectiveness and school effect, depending on the statistical modelling techniques employed and the choice of independent or explanatory variables. Social, economic and environmental factors account for 80% of the educational outcomes in local education authorities (Willms, 2003; Moloi and Chetty, 2010).

The contribution of this research to studies of school performance is the spatial component and specifically the addition of spatial analysis techniques such as point pattern analysis and geographically weighted regression (GWR). Spatial data often have special properties and need to be analysed in different ways from non-spatial data. For a long time the complexities of spatial data were ignored and spatial data were analysed with techniques derived for non-spatial data, the classic example being regression analysis. The development and maturity of Geographical Information Systems (GIS) has had an effect on quantitative geography and this ability to apply quantitative methods for spatial data within GIS leads to an increase in the potential for gaining new insight (Fotheringham *et al*., 2001, Harris *et al*., 2010; Singleton *et al*., 2012).
The poor pass rates of the matric learners at secondary schools in South Africa has been a concern for quite some time. The focus of this research is twofold, firstly to determine if there are any spatial patterns among the matric pass rates of secondary schools in the Western Cape.
Secondly to determine if there are any relationships between the matric pass rate of the school and the socio-economic attributes of the school feeder areas as captured by census data. To investigate the spatial patterns of secondary schools with similar matric pass rates in the Western Cape, spatial point pattern analysis techniques such as spatial autocorrelation and cluster and outlier analysis were used. Once the level of clustering of school performance was established, ordinary least square (OLS) regression analysis and geographically weighted regression (GWR) were used to establish which socio-economic factors influenced the matric pass rates in schools.

2. Background Research on School Performance Measures

Internationally, a number of studies have found that student attributes and socio-economic variables and learner locations are more important in influencing student learning outcomes than school attributes (Jaggia and Kelly-Hawke, 1994; Conduit *et al*., 1996; Taylor and Yu, 2009; Saifi and Mehmood, 2011). As early as 1966, Coleman *et al*. (1966) investigated equality of education opportunities by looking at the poor school performance of African American students. It was found that the learner's personal and family characteristics were major contributing influences on the students' performance rather than the characteristics of the schools they attended. The inequalities imposed on children by their home environments are carried by them into the schools, with family background and location being the main factors affecting student performance (Jaggia and Kelly-Hawke, 1994; Leventhal *et al*., 2009; Dupe're' *et al*., 2010). The problem with the concept of a school neighbourhood is that pupils are rarely drawn exclusively from the school's immediate hinterland and most parents who can exercise choice come from above average socioeconomic groups (Sammons, 2013). A strong relationship exists between socio-economic status (SES) and school performance (Conduit et al., 1996; Tschinkel, 1998; Betts et al., 2003; Holmes- Smith,2006; Smith, 2011) where a clear inverse relationship between deprivation and examination results emerged with schools located in non-deprived areas having higher pass rates. Socioeconomic based indicators such as single parent, parent's educational background, unemployment, occupation and poverty indicators of each school community influenced factors of school performance, however the association between location and achievement was much lower when schools were closely clustered, reducing the constraint of access to schools.

The poor performance by South African matriculants prompts further investigation into the factors contributing to educational outputs. Historically, South Africa has been divided along racial lines both economically and politically. Spaull (2013:437) remarks that "eighteen years after the political transition, race remains the sharpest distinguishing factor between the haves and the havenots".

According to van der Berg (2007), the poor still receive an inferior quality of education compared to their wealthier counterparts, compounded by the poor qualification of educators in the current system (Smith, 2011). Christie (2013:781) laments that "patterns of performance on tests continue to mirror former apartheid departments" and remain racially skewed. Many South African studies have considered the relationship between socio-economic indicators and school performance (Fedderke et al., 2002; Van der Berg, 2007, 2008, 2011; Christie et al., 2007; Bhorat and Oosthuizen, 2009; Smith, 2011; Spaull, 2013) with racial composition and socio-economic background as the major explanatory factors for matric pass rates (Van der Berg, 2007, 2008, 2011; Smith, 2011). Within the post-apartheid school system, school characteristics ofinfrastructure and pupil teacher ratios, teacher, child, parent and household characteristics have all been seen to play a contributing role (Christie et al., 2007; Bhorat and Oosthuizen, 2009; Smith 2011). This highlights the importance of socio-economic variables (Christie et al., 2007; Smith, 2011) as a predictor of good senior certificate results. Both Smith (2011) and Christie (2013) highlight the link between a learner within a deprived community (place) and their opportunity of attainment in education and society.

3. Spatial Analysis of School Performance

The aim of spatial data analysis is to identify relationships between pairs of variables drawn from geographical units, often using regression, in which relationships between one or more independent variables and a single dependent variable are estimated (Fotheringham et al., 1998). In regression models involving geographical locations, regression coefficients may not remain fixed over space and the model residuals may exhibit spatial dependence (Charlton and Fotheringham, 2009).

Geographically weighted regression (GWR), a method of spatial statistical analysis, allows

modelled relationships between the response variable and a set of covariates to vary geographically across a study area (Harris *et al*., 2010), thereby allowing characterization of spatial heterogeneity and accommodating spatial non-stationarity. GWR is a local refinement of global linear regression methodologies such as the ordinary least squares (OLS) model (Charlton and Fotheringham, 2009).
The equation for a typical GWR version of the OLS regression model describing a relationship around location **u**, would be:

$y_i(\mathbf{u})=$ •

$_{0i}(\mathbf{u})$ + [1]
Where: is the independent variable,

- is the coefficient for each of the predictor variable (x) and is the residual.

In this equation **u** represents the two-dimensional geographical space defined as the local neighbourhood.With GWR, local rather than global parameters are estimated allowing the generation of a continuous surface of parameter values and measurements to denote the spatial variability of the variable (Charlton and Fotheringham, 2009). The choice of a spatial weighting function or kernel, defining the extent of “local” (proximity of data points to location u) is crucial (Brunsdon *et al*., 1996; Páez *et al*., 2002; Charlton and Fotheringham, 2009). A number of kernels are possible: GWR supports fixed, Gaussian-shaped and adaptive kernels, based on a fixed distance (bandwidth) or a number of adjacent points (neighbours) (Charlton and Fotheringham, 2009). The distance-based weighting rests on the assumption that observations that are closer together share a common but spatially localised context that differs across the study area. Spatial autocorrelation (SA) arises when the measures of a variable in multiple sample units are not independent of each other and this describes the spatial structure of the data (Harris *et al*., 2013). Pattern analysis can be used to reveal spatial distribution patterns (random, dispersed or clustered) of school performance as well as identify local clusters of high or low values (Chang, 2010).
Several studies have applied spatial statistical analysis to examine educational performance. These studies model the relationship between school performance and socio-economic variables of the community surrounding the school (Conduit *et al*., 1996, Pitts and Reeves, 1999, Gibson and Asthana, 1998, Fotheringham et al., 2001, Gordon and Monastiriotis, 2007; Xiaomin and Shuosheng, 2011) using spatial statistical techniques: namely OLS regression (Conduit *et al*., 1996, Pitts and Reeves, 1999, Gibson and Asthana, 1998), GWR (Fotheringham *et al*., 2001, Gordon and Monastiriotis, 2007; Xiaomin and Shuo-sheng, 2011) and a grid-based variation of GWR (Harris *et al.*, 2010).
There are, however, limited studies using spatial statistical analysis techniques on South African schools data (Bhorat and Oosthuizen, 2009). The purpose of this paper is therefore to focus on the spatial analysis of South African schools data, modelling the relationship between school performance (expressed by matric pass rates) and socio-economic variables of the community surrounding the school in particular characteristics of parents (Xiaomin and Shuo-sheng, 2011) and households (Fotheringham *et al*., 2001; Bhorat and Oosthuizen, 2009).

4. Methodology

In this study quantitative geographical techniques were used to analyse the 2010 matric results of 261 secondary schools in Cape Town. The school data was obtained from the Western Cape Department of Basic Education extracted from their Education Management Information System (EMIS) and Final Matric Register. Coordinates were verified using GIS.

Firstly, using spatial point pattern analysis, the spatial distribution of schools was characterised and secondly, spatial relationships between school matric pass rates and socio-economic variables of the school feeder communities were identified and mapped. The socio-economic variables were extracted from Statistics South Africa's 2011 Population Census for Cape Town, a city with an estimated population of 3.7 million (City of Cape Town, 2012), was chosen as the study area. Ninety two percent of Cape Town schools fall in the higher quintiles of socio-economic strata as defined by the then National department of education (Christie *et al*., 2007), making it a homogeneous community to study. Sub-place areas were selected as the spatial analysis unit, since it is the smallest unit of analysis at which StatsSA release the majority of their socio-economic information, and spatial delineation data is available at sub-place level. Cape Town consists of 684 sub-places with most suburbs divided into a number of sub-places.

Point pattern analysis, using ESRI's ArcMap version 10.1, was used to determine if the physical location of schools are random, dispersed or clustered, after which clusters of schools with high matric pass rates and clusters with low pass rates were identified. Finally high performing schools surrounded by low performing schools and low performing schools amongst a cluster of high performing schools were detected. To identify the most relevant explanatory variables for spatial analysis the correlation between selected socio-economic attributes and school performance was determined. The four attributes with the strongest correlation, reflecting the parent and household characteristics (Fotheringham *et al*., 2001; Bhorat and Oosthuizen, 2009; Xiaomin Shuo-sheng, 2011) were percentage of persons who are employed, percentage of households that have a computer, percentage of households that have a telephone and percentage of persons who acquired a tertiary qualification.

Spatial relationships between the dependant variable, school matric pass rate and these selected independent socio-economic variables were investigated with sub-place as geographical unit. The pass rate of the school was assigned to the attributes of the sub-place in which it resides, which is simple for cases where there is only one school per sub-place (n=135). For sub-places without schools, the pass rate of the nearest school (Euclidian distance) was allocated to the attributes of the sub-place (n=481), the assumption being that learners attend the school closest to their home. In the cases where there are two or more schools within the sub-place (n=53) the mean pass rate of the schools was assigned to the sub-place attributes. The number of schools within these 53 sub-places varied between two (n=33) and eight (n=1). Sub-places identified as nature reserves and sub-places with a total population of zero were assigned a pass rate of zero (n=15).

Multivariate linear regression was performed on the data using the OLS model after which the GWR model was applied to deal with spatial non-stationarity. For both global and local regression, the response variable (*Pass*) is the proportion of learners who passed the matric examination in year 2010 in each secondary school (*Pass*). The four independent variables used are percentage of persons who completed high school (*High*), percentage of persons who are employed (*Employed*), percentage of households that have a computer (*Computer*) and percentage of homes that are occupied by the owners (*Owned*). Different methods of determining the local neighbourhood (kernel) for the GWR model were selected (Fixed kernel with variable bandwidth; Adaptive kernel with varying neighbourhood size). In addition, the spatial relationships of the coefficients (beta (β) values) of the significant exploratory variables for the GWR model were investigated.

5. Visualisation of the Schools Spatial Point Data

Results from the nearest neighbour analysis lead to the conclusion that the physical locations of secondary schools in Cape Town municipality are clustered and not randomly distributed within the study area. The next step in the analysis was to calculate the distance band. Results will differ depending on the distance at which the Moran’s I statistic (for SA) is calculated. To find the optimim distance the incremental spatial autocorrelation tool was used and the appropriate scale of analysis (distance band) was determined as 11.5km, which was used for further analysis. Moran’s I spatial autocorrelation tool was used to measure if schools with higher pass rates are situated closer to each other or if schools with higher pass rates are next to schools with lower pass rates. The results indicated that schools with higher matric pass rates are clustered with a Moran’s I index of 0.11 (p-value < 0.0001). Since results indicated that schools with higher pass rates are clustered, Anselin local Moran’s I was used to identify outlier schools. An outlier would be a school with a high pass rate surrounded by schools with low pass rates, indicated in Figure 1 as orange dots (HL) and vice versa (LH) as green dots. Schools with high pass rates enclosed by other schools with high pass rates (HH) (red) and schools with low pass rates bordered by other low scores (LL) (blue) are also shown in Figure 1.

There are 12 schools identified as part of statistically significant clusters of high values (HH) at the 5% level of significance, all these schools had pass rates over 90%. These schools are situated in suburbs towards both the north and south of the city haveing a majority of white (Tableview, Plumstead, Constantia and Simons’s Town) and coloured (Wynberg) residents, mostly employed with some level of secondary and even tertiary education. The statistically significant clusters of low values included 41 schools with pass rates mostly below 40%. These schools can be found in areas of poor socio-economic conditions, traditionally known to have a majority of black African residents. The unemployment is high and the education level generally below matric. These suburbs towards the south-east of the city include Khayelitsha, Langa and Gugulethu.

Figure 1: Cluster and outlier analysis of matric pass rates.

The results from the outlier analysis also identified 13 schools that are outliers, eight of which represent LH-clustering and five with HL-clustering. The eight outlier schools that have a pass rate
lower than their surrounding schools are listed in Table 1.

The schools in Table 1 highlighted by the analysis are located in areas ranging from affluent (Cape Town central and the southern suburbs) through middle to low income areas, down right to areas with real socio-economic challenges. Further investigations are required to determine why these particular schools (even in affluent areas) have such low pass rates compared to neighbouring schools. One possible explanation may be a boarding school, not populated from the surrounding geographic area. The outlier schools with high performance within a cluster of low performing schools (HL) are listed in Table 2.

Table 2: Schools with a high pass rate surrounded by schools with a low pass rate (HL).

The findings from this HL analysis differ from the previous LH findings in that all the schools are situated in areas with challenging socio-economic conditions. Despite these challenging socioeconomic conditions, learners from these schools were able to perform and an explanation for the differing performance needs to be investigated, possibly looking at school characteristics. From these results, it is clear that school performance cannot necessary be linked to location only, but has to be investigated with other factors in mind.

6. Measuring the Spatial Relationships Between the Matric Pass Rates and the Socio-economic Attributes

The fit of the OLS regression model was not good as only 32% of the variation is accounted for by the explanatory variables (*High, Employed, Computer, Owned*). The proportion of residents who have completed high school (*High*) accounts for the largest part of the variation, with high employment rates (*Employed*), percentage of households that have a computer (*Computer*) and percentage of homes that are occupied by the owners (*Owned*) measuring the unaccounted variation. Variables such as occupation, female head of household, tertiary education and ownership of telephone were dropped during regression model specification since they were not statistically significant, however this does not mean that these variables have no relationship with the school performance and matric pass rate. Many of the variables measuring the socio-economic status of the community are highly correlated indicating multi-colinearity among the variables. The evaluation statistics for the OLS model are shown in Table 3.

Table 3: OLS regression statistics.

Description	**Value**	**p-value**
R squared	0.32	
Adjusted R squared	0.32	
Akaike Informaton Criterion (AIC)	5763	
Koenker Statistic	83.76	<0.0000 *
Jarque-Bera Statistic	146.40	<0.0000 *

When running the GWR regression model it is important to determine the optimum bandwidth at which the model can perform best. In this study several different local neighbourhood sizes based on bandwidth were investigated. Using a fixed kernel and varying the bandwidth (ranges between 30km to 1km) caused the model to improve. However, as the bandwidth decreased the model bias increased. The best model was a compromise between bandwidth and bias and the effective number helped in determining the best model. Even though the R-squared and Akaike Information Criterion (AIC) showed improvement with bandwidths less than 5km, not all sub-places could be modelled at that level, therefore a fixed kernel with bandwidth of 5km was chosen as best model.

This GWR model was able to explain about 50% of the variation (R-squared = 0.57; Adjusted Rsquared = 0.49; AIC = 5397) and all the socio-economic variables displayed non-stationarity, indicating spatial variation in the relationship between the pass rates and the socio-economic predictor variables.

The GWR output intercept term, determines the matric pass rate should the coefficients for all explanatory variables be negligible (zero). Figure 2 shows the spatial distribution of the intercept of the GWR model. Local estimates of the intercept coefficients range from a minimum of -83.75 (associated with nature reserves) to a maximum of 124.05 (with predicted pass rate of 95.5%) with a mean of 31.89. These GWR results show the apparent spatial variations in the constant parameters. High parameter estimates mean that the effect of the variables is higher in that particular region as compared to other regions and is indicated in Figure 2as the red shaded area.

The low parameter estimates are shown in blue.

Figure 2: Spatial variations for the intercept in GWR.

Figure 3 shows the coefficients for the explanatory variables per sub-place in Cape Town obtained from the GWR model: higher education (*High*) (Map 1), employment (*Employed*) (Map 2), access to computers (*Computers*) (Map 3) and home ownership (*Owned*) (Map 4). Red and darker and lighter shades of orange in Figure 3 indicate high coefficient estimates that mean the effect of the variable is high in that particular sub-place. When considering each of the explanatory variables, where there is a positive relationship (value has a positive sign), an increase in that variable (*High, Employed, Computer, Owned*) will induce an increase in the dependent variable (matric pass rate). If the sign is negative, it will cause a decrease. In Figure 3, areas indicated in blue represent a negative value, thus the effect of the particular explanatory variable on the matric pass rate is negative. For example, in Khayelitsha (see Figure 3), ownership of a computer and employment have a strong positive relationship with the matric pass rate, while higher education of the head of household (*High*) and home ownership (*Owned*) have a negative relationship.

Figure 3: Spatial variation of the explanatory variables in GWR.

The GWR model accounts for spatial autocorrelation, the Moran index for the residuals of the GWR model is 0.0345 with z-score of 4.58 ($p<0.00001$) as shown in Figure 4. The Moran index shows that the residuals are clustered. This could indicate that there are missing variables in the regression analysis. By considering spatial variation as being a surrogate for missing variables (Harris *et al*., 2013), GWR can reveal that in some places there are other factors that need to be considered to account for the local school performance – these however, may not be of a spatial nature and may be associated with individual learner or educator characteristics (Spaull, 2013).

Figure 4: Residuals for GWR

When the socio-economic characteristics are modelled using the GWR model, the explanatory power is increased. The results replicate closely, those obtained by Gibson and Asthana (1998) and Fotheringham *et al*. (2001), namely socio-economic indicators, in particular household and parent characteristics, are predictors of school average performance. In the local, urban setting of Cape Town, these translated to schooling (*High*) and employment (*Employed*) of parents, home (*Owned*) and computer ownership. According to Christie (2013) the practice of representing information in terms of aggregated spatial units such as provinces masks deeper patterns in the production of spatial inequalities in education. The difference between urban and rural location on the provision of education and achievement of school performance is concealed. The use of a local spatial analysis technique such as GWR can be used to tease out important factors influencing this. Therefore the analysis should be expanded to other area in South Africa, in particular the comparison between rural school setting and urban environments should need a very different set of independent variables to define parent and household characteristics for success (Spaull, 2013). In addition school characteristics need to be investigated as van der Berg (2007) reported that school functioning and education management also contribute towards school performance. In addition the use of non-standardised assessment methods, especially in low-functioning schools, leading up to matric, exacerbate poor pass rates (van der Berg *et al*., 2011).

The results of this study indicate strongly that additional work using these spatial analysis techniques is called for. Despite some of the limitations in using GWR, such as the fact that boundaries of the neighbourhoods representing the spatial analysis units for contextual data, may not reflect real-world boundaries between communities and in fact dissect areas of social homogeneity, i.e. the classical modifiable unit problem, local analysis can be performed to address the problem of reporting averages within South African education, thereby “overestimating the educational achievement of students” (Spaull, 2013:436). In addition, the method of assigning pass rates to sub-places as well as the measurement of proximity not only in regard to physical distance but using contextual similarity should be investigated. The use of a grid-based GWR model, especially for use with larger data sets (Harris *et a*l. 2010) is recommended. In addition, spatial autoregressive models and spatial filtering can be investigated to characterise the spatial autocorrelation and spatial heterogeneity inherent in spatial data. Given that educational processes and variables and their effect on school performance are likely to vary according to geographical location and place (Xiaomin and Shuo-sheng, 2011), examining geographical variations will help create better understanding not only of the associations with geography, but help uncover relevant variables for improving model performance.

7. Conclusion

Pattern analysis was performed on the Cape Town municipality’s 261 secondary school’s locations and matric pass rates. The average nearest neighbour index suggested the physical location of the secondary schools are clustered with the Moran’s I autocorrelation showing that pass rates of schools are also clustered: there were clusters of schools that performed well, achieved high pass rates but there were also clusters of schools that were producing low pass rates. The local Moran's I identified schools that could be termed outliers. These were schools that were part of a cluster but were performing differently from other schools within the cluster for example, in a cluster of high performing schools, despite poor socio-economic conditions there was one school with a very low pass rate. On the other hand a few schools were also identified that were performing very well amongst neighbouring poorly performing schools. five high performing schools were surrounded by low performing schools, while eight low performing schools were surrounded by high performing schools. The regression models used to measure the spatial relationships between the school performance and the socio-economic attributes of the areas surrounding the school, found a relationship between several attributes and school performance. The attribute that accounted for most of the variation was employment. It was clearly shown that schools that were situated in suburbs and sub-places in Cape Town municipality that had a large proportion of people employed produced better matric pass rates than schools that were situated in areas of low employment. In order to improve our understanding of the matric pass rates, in this present study we examined the relationship between matric pass rates and the socio-economic factors of the surrounding areas of the school. This relationship was tested using a spatial regression modelling approach, by taking Cape Town, a relatively homogeneous, urban area, as a target study area. The OLS and GWR models were used to study the relationship between matric pass rates and socio-economic factors, The GWR model explained about 50% of the variance in school performance. Since GWR has the advantage of providing local parameter estimates, interesting patterns of spatial variation or nonstationary of parameters were revealed. Even within this relatively homogeneous study area, the spatial distribution of all parameters showed significant spatial variation.Even though this study found that there is a strong relationship between school performance and the socio-economic variables of the community where the school is situated, in particular parent and household characteristics, there is evidence that school characteristics need to be considered within the South African context. This leads to two further areas of research: the first is to replicate this study for the RSA Census 2011 results in order to obtain a time-series of performance and second, to extend the study to other parts of South Africa.

8. References

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