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Spatial targeting method for road safety education to reduce fatal and serious injury crashes

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Abstract

Road safety education is one of the cornerstones for reducing fatal and serious injuries. This research will discuss the spatial targeting method dealing with the drivers involved in road crashes. Earlier studies have used urban road vehicle kilometres travelled, road length or traffic volume data to understand the number of fatal and serious injury crashes. Few studies have also used socio-demographic data, for example, age, gender, and the level of education in the target population. However, no Australian studies have focused on geospatial analysis of drivers involved in road crashes. This research has accordingly attempted to address this gap. A traditional global ordinary least square (OLS) model was developed and compared with a Geographically Weighted Regression (GWR) model to see if a local model could be more beneficial. A geographically weighted regression analysis provided useful insights into the localisation of the effects. The spatial distribution of the strengths of explanatory variables helped in identifying the postcodes for improving road safety campaigns. The main objective of this paper is to demonstrate a practical procedure for spatial targeting of road safety policies to reduce traffic crashes by understanding the spatial variations. The research has shown that young (25 to 34 age), old drivers (65 to 74 age) and un/low educated drivers remained at high risk, but the risk rates are much higher in some postcodes when compared to other areas. Similarly, though factors influencing the risk rates for both males and females are the same, their effect varied across the metropolitan area postcodes. This research demonstrated that there is a need to focus on specific demographic factors in specific metropolitan areas regarding the formulation of traffic safety policies and managing drivers' behaviours.

1. Introduction

Road safety has been an area of focus over the past two decades throughout Australia. In Australia, a reduction in fatalities from road traffic crashes is a public policy objective (Gargett, Connelly & Nghiem 2011). Around 1,200 lives are lost each year on Australia's roads and about 40,000 people are seriously injured. Over the next 10 years, Australia is working towards significantly reducing the burden on the economy and society from road crashes in terms of deaths and life-changing injuries. The previous strategy set targets to reduce the numbers of both deaths and serious injuries by at least 30 per cent. Although there has been a downward trend, the fatality target has not been met and the number of people hospitalised after road crashes has increased (Infrastructure and transport ministers, 2022).

South Australia's Road Safety Strategy also sets out the ambitious 10-year targets of achieving a reduction of at least 50% in lives lost and 30% in serious injuries on South Australian roads by 2031 (Government of South Australia, 2022). In this strategy, one of the nine focus areas is supporting and enforcing safer road user behaviour.

Many studies around the world (Chipman et al.,1993, McCartt et al.,2009) have demonstrated the difference in crash rates among different aged groups of drivers. Earlier studies have shown that the fatal and serious injury crash rate is high for old drivers (Rakotonirainy et al. 2012) and young drivers (Bates et al. 2014, Braitman et al. 2008, Chen et al. 2010) while it is comparatively low for middle-aged persons. Other factors such as the driver's gender, driver income, speed limit weather, and time of day have also been shown to affect the crash rate for drivers of different age groups (Renski et al.1999),. One of the main objectives of this research is to focus on understanding and improving road user behaviour. This research is an attempt to predict drivers' attitudes (& how they vary spatially) from the census and other easily obtainable data sources.

Preventing crashes by educating motorists should be one of the key focuses of urban road safety efforts of transport agencies. Though the new approaches sought to reduce crash losses by focusing not only on driver behaviour and crash prevention but also on reducing injury risk during crashes, it is important to refine the targeting of appropriate groups to bring driver behaviour changes. Because most motor vehicle crashes involve driver error, improving driver behaviour must be the overriding priority.

Earlier studies (Henderson, 1991) have identified the important relationship between performance (which relates to skills) and behaviour (what the road user does on the road). In Australia and elsewhere, education and publicity have been most successful in modifying behaviour. However, they need to be coupled with strictly enforceable laws, directly linked to safety. The focus of earlier studies (Akinyemi,2019; Bíl et al., 2019; Choudhary et al.,2015) relating to spatial analysis of crashes was mainly to study the impact of various road types, employment and population densities on road crashes. However, this research has focused on finding an appropriate method to refine the targeting methods. The 'Spatial targeting' approach has accordingly been developed in this research. 'Spatial targeting' is the deliberate focus of particular actions on a particular spatial area. Spatial targeting is an instrument to help policies achieve their objectives more efficiently. Good spatial targeting is only possible when 'good' and reliable data, which is easily collectable, is available. This paper examines the gender-based spatial relationship between the socioeconomic status (SES) of the people in the Adelaide metropolitan postcodes and the number of drivers involved in the total fatal and serious injury crashes from those postcodes. The hypothesis is that different SES, age, and gender will influence the driving behaviour of the drivers from those postcodes.

While earlier researchers have focused on understanding factors associated with fatal and serious injury crashes, few studies have explored geospatial analysis of drivers involved in those crashes. This study is an attempt to fill this gap.

2. Study location and data

The study area (Figure 1), Adelaide, is located at 34.55° southern latitude and 138.35° eastern longitude. Adelaide metropolitan area postcodes were chosen as the spatial unit due to the availability of crash data. While the exact location (latitude and longitude) of crashes are recorded, the residential address of drivers, involved in the crash, is recorded at the postcode level. The study area covers 1585 km2 and includes 125 postcodes. Crash data used in this consists of recorded crashes between 2003 and 2012, provided by the South Australian Department for Infrastructure and Transport. Socio-Economic data and census data were sourced from the Australian Bureau of Statistics (ABS).

The South Australia Police (SAPOL) collects the crash data using vehicle crash reports, which are entered into SAPOL's Vehicle Collision System (VCS). The reports are then electronically forwarded to the Road Crash Information Unit of the Department for Infrastructure and Transport (DIT) for further processing and geocoding.

The Australian Bureau of Statistics (ABS) collects census data once in five years and this study used the 16th Census of Population and Housing data that was collected in 2011.

The number of recorded fatal and serious injury crashes within the metropolitan Adelaide postcodes (from 2003 to 2012), broken down based on the gender of the driver, is shown in Table 1. It is worth noting that, though this study restricted its analysis to drivers residing within the metropolitan area, the crash locations could be anywhere i.e., both within the metro and outside metro areas.

Figure 1: Study Area

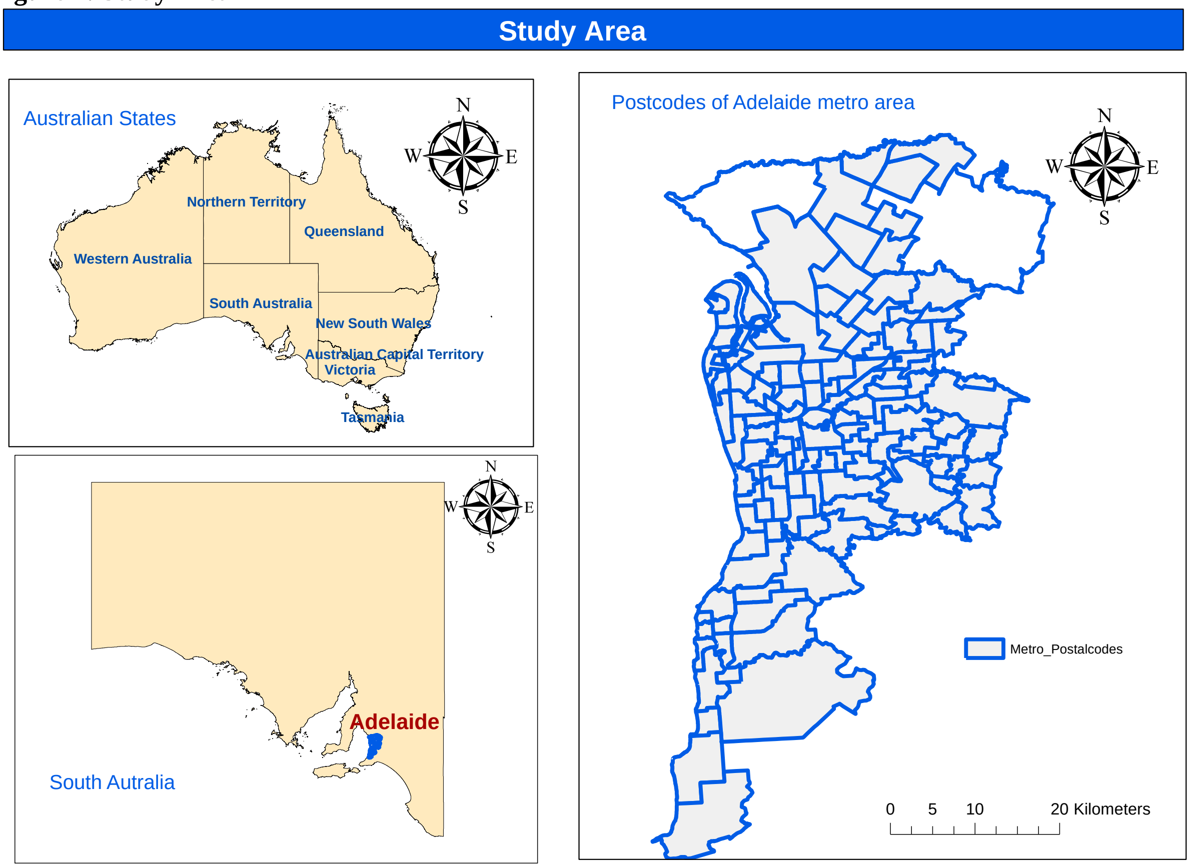


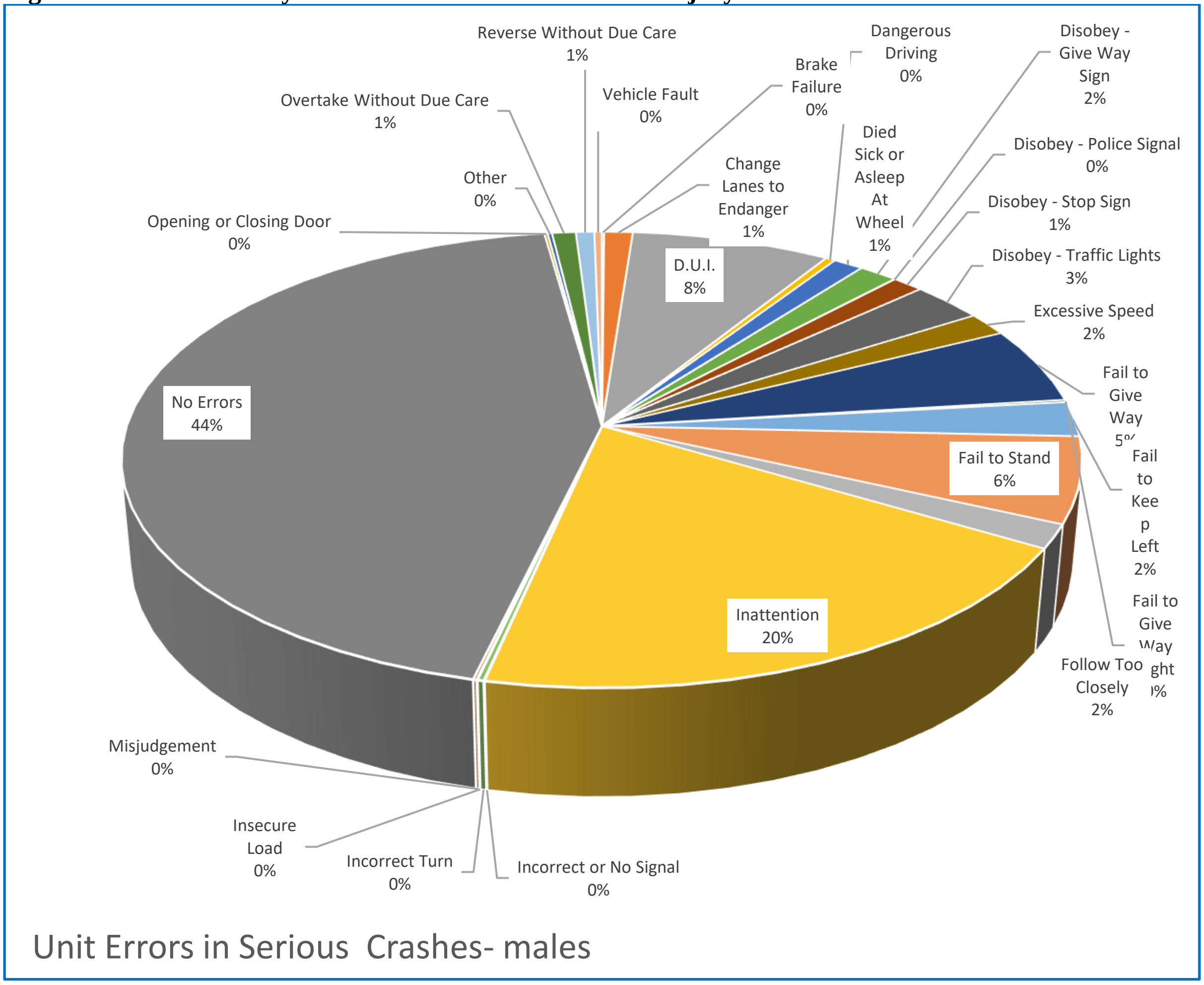
Table 1: Number of crashes recorded within Adelaide Metropolitan postcodes (2003 to 2012)

Males			Females		
Fatal Crashes	Serious Injuries	Total fatal &serious injuries	Fatal Crashes	Serious Injuries	Total fatal &serious injuries
507	5029	5536	144	2466	2610

3. Methods and preliminary analysis

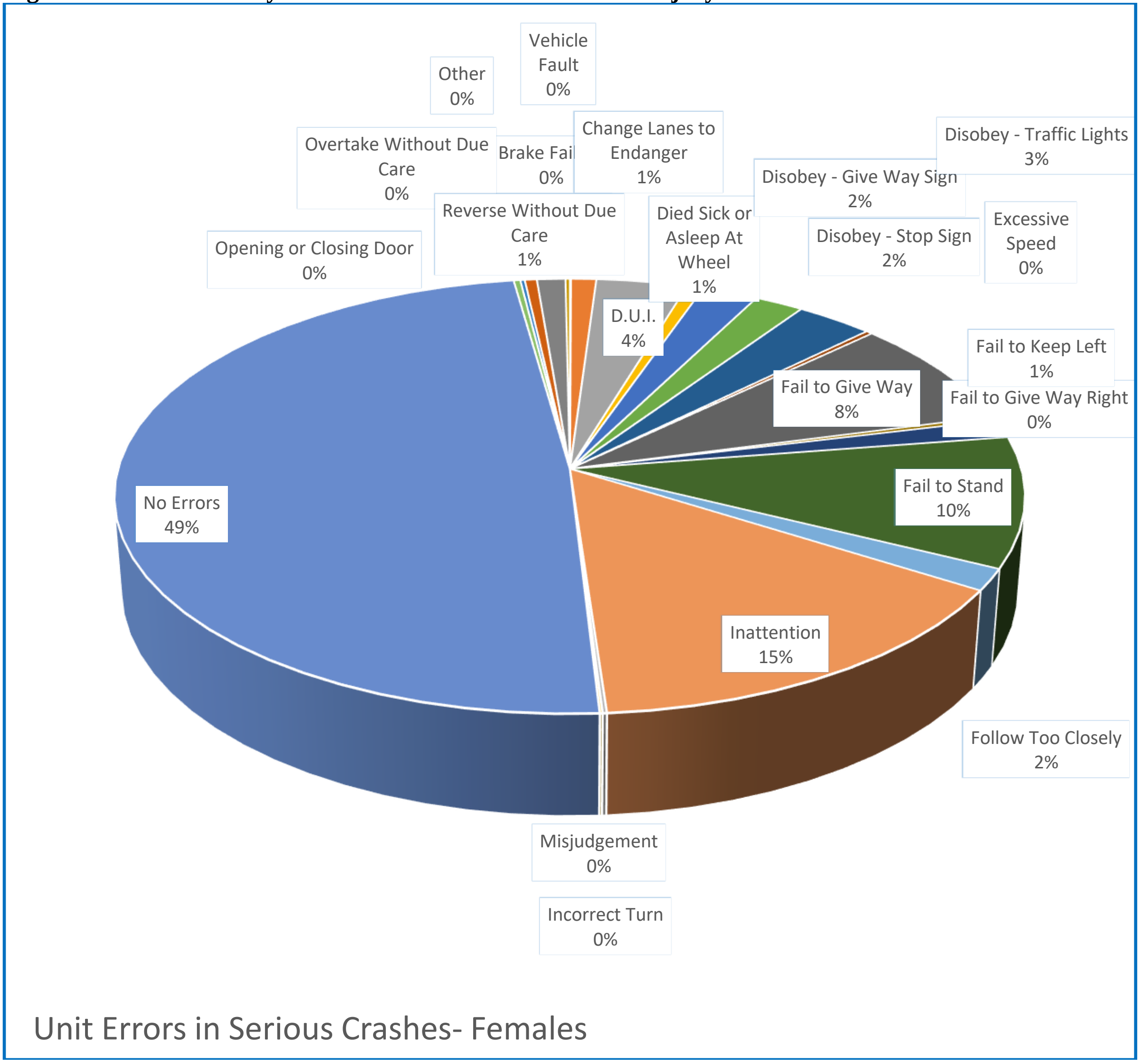
After geocoding all the fatal and serious injury crashes, the first step was to analyse the gender-specific errors. The errors made by male and female drivers are summarised for both fatal and serious injury crashes. The next stage was to aggregate the gender-wise crash data at the postcode level and relate it with the easily available census data. The crash database had driver postcode details for each driver involved in the crash, all the male and female drivers involved in serious and injury crashes are aggregated for all the postcodes in metropolitan Adelaide. Figure 2 shows the errors made by male drivers involved in serious injury crashes. Among the errors made by male drivers, (i) 'inattention'(20%), Drivers Under the Influence (D.U.I) (8%) and 'fail to stand'(6%) stand out. Earlier studies (Alonso et al., 2015) showed that many drivers habitually drive after consuming alcohol and there is a need to eradicate this type of traffic infraction.

Figure 2: Errors made by male drivers involved in serious injury crashes



In the case of female drivers (Figure 3), the three main errors that dominate are (i)inattention (15%), (ii) 'fail to stand' (10%) and (iii) 'fail to give way (6%). So when compared to males, it is not surprising to note that the influence of alcohol or drugs is a less prevalent issue for female drivers. It is even more striking in the case of fatal crashes in males, where drivers under the influence take the top spot (17%). Earlier studies (Zhao et al., 2014, Alonso et al. 2015) have also demonstrated that the average speed, inattention and lane position standard deviation were significantly higher under the influence of alcohol.

Figure 3: Errors made by female drivers involved in serious injury crashes



4. Regression Analysis

4.1 Selection of Variables

Before OLS regression analysis, all the logical and easily available explanatory variables are shortlisted and an exploratory regression analysis was carried out to select the best performing variables. The shortlisted variables are listed below.

4.1.1 Education level

An earlier study (Sami et al. 2013) found that uneducated adults have a high mortality rate. Those studies have also shown that crash mortality among low-education levels was higher. In this study, fatal and serious injury crash data related to drivers with no education or below year 8 qualification are aggregated. The aggregated data is divided based on the driver's gender.

4.1.2 Average income

The 2011 Census collected personal income for all persons aged 15 years and over. People were asked to report their usual weekly income by selecting one of the given income ranges. By assuming the middle of that range as their personal income, the average income for each postcode was calculated for both males and females.

4.1.3 Age

Age is often used as a predictor of fatal and serious injury crashes in motor vehicle crashes. More often younger age adults and older age adults are involved in such crashes. However, the significance of the exact younger and older age groups involved in such crashes is not very clear. So this study has attempted to address this issue for both male and female age groups.

4.1.4 Martial status

The marital status was divided into three groups (married, never married, and separated & divorced) while the gender was divided into female and male.

The shortlisted variables for explanatory regression include for both male and female driver crash models include (i) uneducated (ii) low educated (year 8 and below) (iii) un/low educated (iv) average income (v) all adults over age 15 (vi) adult belonging to various age groups and (vii) their marriage status. Table 2 shows the details of all the variables for male driver crashes tested in the exploratory regression tool. We have used the same variables for female driver crashes.

Table 2: Details of the explanatory variables considered for the Male driver crash model

	Variable	Abbreviation	Min	Max	Mean	SD
Male crash model-dependent variable	Total number of fatal and Serious Injury crashes	MaleFat_SI	0	228	44.29	37.56
Male crash model - explanatory variable(s)	Education-Year 8 &below males	Year8_below_M	0	1141	203.8	177.94
	Not attended any school males	NoSchool_M	0	275	28.16	38.06
	Uneducated/low educated (year 8 or below) males	Y8_NoSholM	0	1416	231.96	210.81
	Male population over 15	Mal_Over15	3	14806	3671.63	2720.14
	Male Average Weekly Income	Mal_Av_inc	$433	$1057	$747.71	$181.32
	Divorced males	Male_Divor	3	1424	283.92	223.51
	Separated males	Male_Separ	3	559	99.03	84.26
	Males aged 16 to 24	Male_16_24	14	2418	583.07	463.89
	Males aged 25 to 34	Male_25_34	12	2838	626.84	512.51
	Males aged 65 to 74	Male_65_74	3	1867	448.14	330.58
	Males aged 75 and over	Male_75Plus	6	1389	492.45	326.31

An exploratory regression analysis was done to identify independent variables for the two models, i.e. male driver crashes and female driver crashes. It tests all possible combinations of explanatory variables. Some variables such as separated males and females, and younger aged drivers (aged 16-24) showed significance initially; however, when multicollinearity was taken into account, those variables were discarded. The average income was not a significant variable in these models. After running the exploratory regression, the three best performing exploratory variables, selected for each gender model are (i) un/low educated, (ii) young drivers (aged 25 to 34), and (iii) old drivers (aged 65 to 74).

4.2 Ordinary Least Squares (OLS) Regression

The OLS regression represents a global regression technique used to model the linear relationship between a dependent variable and one or more explanatory variable(s). The OLS regression model assumes the relationship between the dependent and explanatory variable(s) to be consistent across space and hence it represents a nonspatial regression model. Since spatial data usually possess regional variations and spatial autocorrelation, it is difficult to model spatial data and meet the assumptions of an OLS model. (Gao and Li, 2011). The dependent variable in this example is the number of male drivers involved in the fatal and serious injury crashes from each postcode (MaleFat_SI). The independent variables that we shall use are the number of un/low educated males in each postcode (Y8_NoSholM), the number of young drivers (25 to 34 years male drivers) in each postcode (Male_24_34), and the number of old drivers (65 to 74 years male drivers) in each postcode (Males_65_74).

4.2.1 OLS Results

The Adjusted R^2 value for the OLS model is 0.92, indicating that 92% of the male driver crashes can be explained by the explanatory variables included in the model (Table 3). The OLS diagnostic results showed (Table 4) that poor education level is one of the most dominant variables which was positively associated with fatal and injury crashes of both male and female drivers. BP statistic is significant, i.e. a p-value (probability) smaller than 0.05, which indicates the statistically significant heteroscedasticity and/or nonstationarity. Regression models with statistically significant nonstationarity are often good candidates for Geographically Weighted Regression (GWR) analysis, i.e. the model results will improve by performing GWR models.

As the Jarque-Bera Statistic test is statistically significant ($p < 0.01$), the model residuals are not normally distributed. OLS does not require variables to be normally distributed. If we had trouble finding a properly-specified model, we could have tried transforming strongly skewed variables to improve the results. However, as we could derive a properly specified model, we did not test transformed variables.

In the case of the female driver crash OLS model, the R^2 was 0.86; which shows a strong relationship. The OLS diagnostics results also showed the same pattern as the male driver model but their strength was different. In the case of both the models, the Variable Inflation Factor (VIF) was below 7.5; meaning that there was no multicollinearity among the explanatory variables, i.e. they are truly independent of each other. Jarque Bera's statistic results for female models showed that the residuals are normally distributed and thus passed all the tests and proved that it is a robust model.

Table 3: Summary of OLS model results

Gender	**Number of Observations**	**Adjusted R^2**	**Akaike's Information Criterion (AICc)**	**Koenker (BP) statistics**	**Jarque-Bera Statistic**
Males	125	0.92	952.956703	37.737075 Prob(chi-squared) 0.000000*	6.887700 Prob(chi-squared) 0.031941*
Females	125	0.86	814.557225	15.934501 Prob(chi-squared) 0.001170*	4.000366 Prob(chi-squared) 0.135310

Table 4: OLS model diagnostics

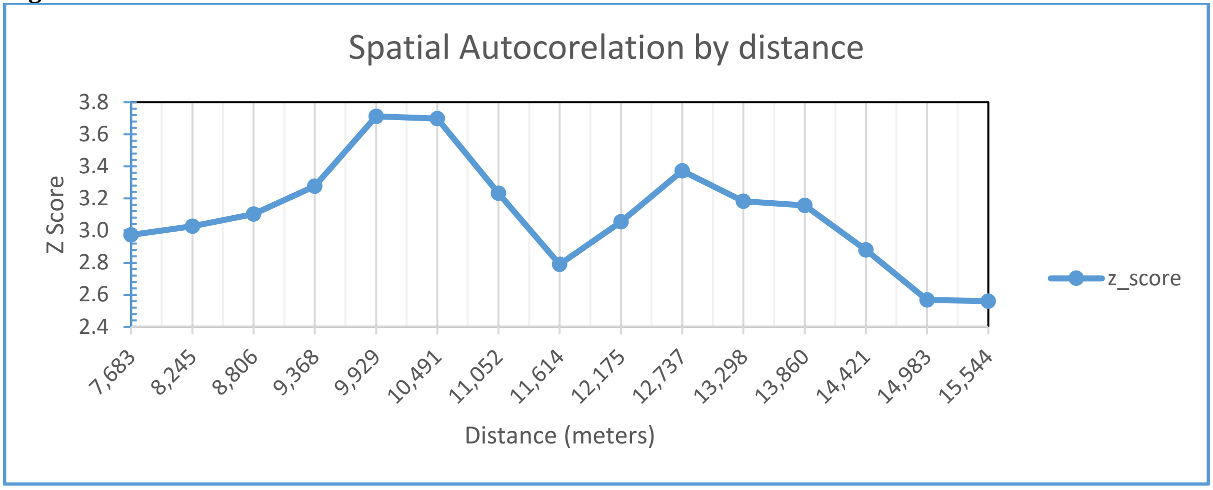
Gender	Variable	Details	Coefficient	t-statistic	Robust Probability	VIF
Males	Intercept	--------	-3.687455	-2.266967	0.025664*	-------
	Y8_NOSHOLM	Un/lowly educated males	0.072010	9.281057	0.000000*	2.939420
	MALE_25_34	Males belonging to 25 to 34 age group	0.021785	5.322914	0.002582*	4.83347
	MALE_65_74	Males belonging to 65 to 74 age group	0.039304	7.869144	0.000000*	2.995169
Females	Intercept	--------	-0.082505	-0.087429	0.917028	--------
	Y8_NOSHOLF	Un/lowly educated Females	0.009317	2.705213	0.022512*	2.772346
	FEM_25_34	Females belonging to 25 to 34 age group	0.012305	5.056738	0.000002*	5.061766
	FEM_65_74	Females belonging to 65 to 74 age group	0.021762	7.549118	0.000000*	3.409024

Note:* An asterisk next to a number indicates a statistically significant p-value ($p < 0.01$).

4.2.2 Spatial autocorrelation analysis of residuals (Global Moran's I)

Spatial autocorrelation is the phenomenon where the value of a spatial variable of nearby locations may be similar (Li et al., 2016). Spatial autocorrelation occurs when events such as vehicle crashes occurring at different but nearby locations are correlated (Rhee et al. 2016). One of the inputs for spatial autocorrelation is the distance band, which can be obtained by using incremental autocorrelation. This tool was first run to allow multiple morans I test runs for 15 bandwidths. The first peak of the z value is recommended as the optimal distance to pick. The analysis showed (Figure 4) that the z value peaked at 9929 meters and hence was used as input bandwidth for the spatial autocorrelation analysis.

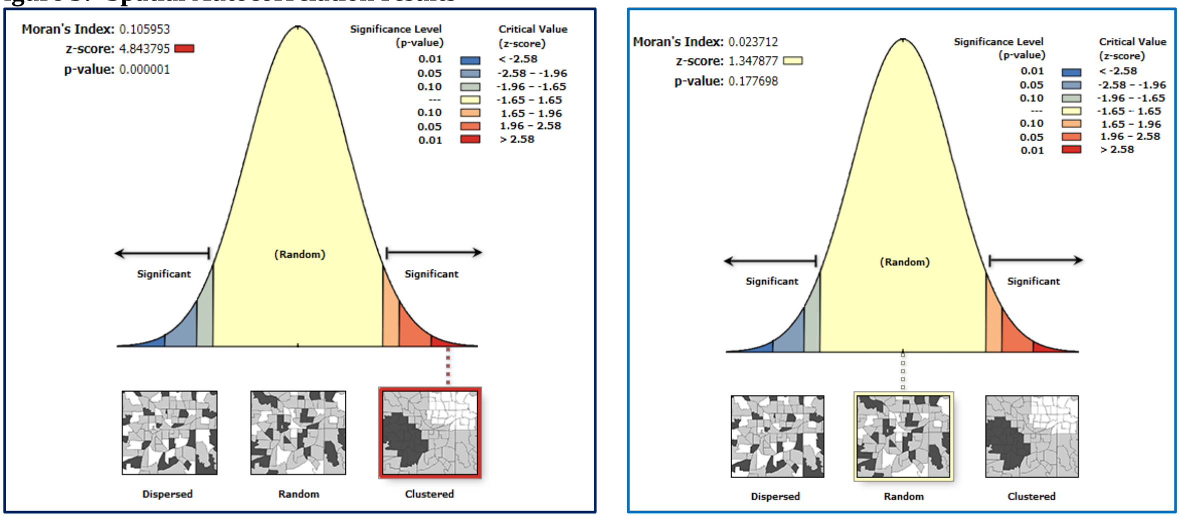
Figure 4: Incremental autocorrelation results



The OLS method is not the best way to analyse the spatially autocorrelated data as the correlation violates the basic assumption of ordinary least squares (OLS) regression. OLS assumes the regression coefficients of the explanatory variables are the same in all locations of the analysed area. Also, the OLS results showed the need for running Moran's I tool to check for spatial autocorrelation. This analysis measures spatial autocorrelation based on feature locations and attributes values using the Global Moran's I statistic. If the values in the dataset tend to cluster spatially Moran's Index will be positive. When high values repel other high values and tend to be near low values, the Index will be negative. If positive cross-product values balance negative cross-product values, the Index will be near zero. The results of the analysis are interpreted within the context of its null hypothesis. The null hypothesis for this analysis is that the attribute being analysed is randomly distributed among the features in the study area. This z-score and p-values will indicate whether the null hypotheses can be rejected. When the p-value returned by this tool is statistically significant and the z score is positive or negative, the null hypothesis is rejected.

As the p-value returned by this tool is statistically significant and the z score is positive, the null hypothesis is rejected. Given that Z value of 4.843 (Figure 5), there is less than a 1% likelihood that the clustered pattern shown in the Figure above could be the result of random choice. So the residuals are clustered. The results indicate the necessity of considering spatial correlation when developing regression-based crash models. This analysis has also shown that global regression models fail to predict the dependent variable effectively. There will be significant spatial variations in the strength of the model. Hence it is important to run the Geographically Weighted Regression (GWR) analysis to improve the model.

Figure 5: Spatial Autocorrelation results



Male driver Crashes | Female driver Crashes

4.3 GWR analysis

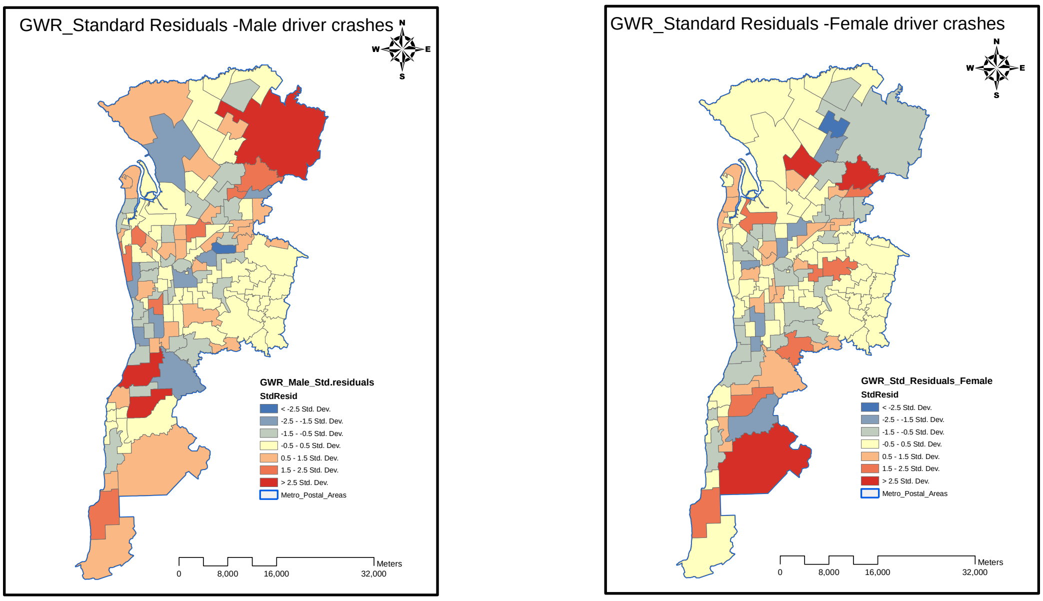
As spatial autocorrelation has shown the need for running the Geographically Weighted Regression (GWR) model to improve the model performance, GWR analysis was carried out with the same selected variables used in the OLS model. Geographically weighted regression (GWR) is a spatial analysis technique that takes non-stationary variables into consideration and models the local relationships between these predictors and an outcome of interest (Charlton and Fotheringham 2022, Pirdavani et al. 2014). GWR is an outgrowth of ordinary least squares regression (OLS) and improves the model by allowing the relationships between the explanatory variable(s)and dependent variables to vary by locality. GWR constructs a separate OLS equation for every postcode; which incorporates the dependent and explanatory variables of locations falling within the bandwidth of each target location. The variables used in this model are the same as that which was specified in the OLS model. The output feature class will contain the coefficient estimates and their associated standard errors as well as a range of observation-specific diagnostics. AICc bandwidth parameter was chosen as this is an automatic method for finding the bandwidth which gives the best predictions. The AICc method finds the bandwidth which minimises the AICc value – the AICc is the corrected Akaike Information Criterion. Table 5 shows the results of the GWR analysis. GWR models improved the R^2 value for the male driver crash model from 0.92 to 0.94 and the female driver crash model from 0.86 to 0.87. As there is no significant spatial variation in the case of female driver residuals (as can be seen from the Jarque-Bera Statistic), the GWR model strength only improved marginally.

Table 5: GWR analysis results

Gender	Number of Observations	Adjusted R^2	Akaike's Information Criterion (AICc)
Male drivers model	125	0.94	924.342963
Female drivers model	125	0.87	813.011498

Results (Figure 6) show that over and underpredictions are randomly distributed indicating that it is a well-specified regression model. The GWR model residuals were further examined to see if they provide clues about what those missing variables might be. So the Spatial Autocorrelation (Moran's I) tool on the regression residuals was run to ensure that they are spatially random. The results clearly showed that the residuals are randomly distributed and there is no evidence to show that statistically significant clustering of high and/or low residuals (model under- and over predictions), which indicates that the GWR model is not misspecified.

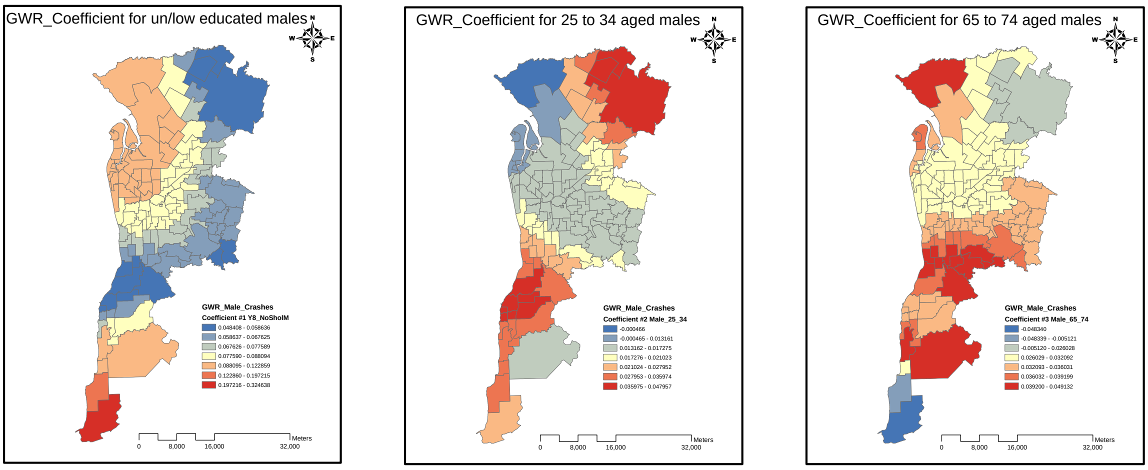
Figure 6: GWR results – Standard Residuals



5. Gender-based spatial variations of explanatory variables

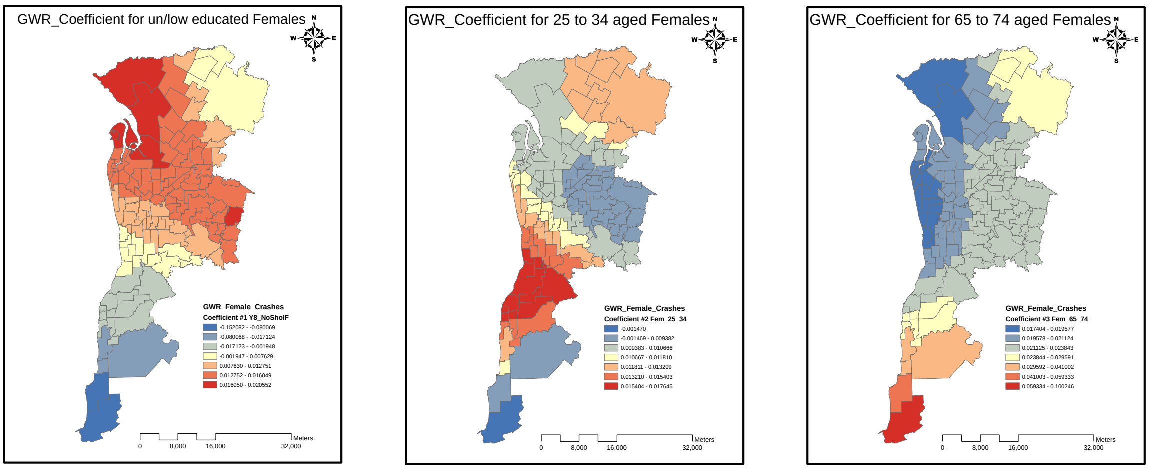
This analysis will also help us to understand the spatial variations of each independent variable with regard to its strengths. By plotting the coefficient variations, we will be able to identify suburbs and postcodes that we need to target education, publicity and training programs in Road Safety. Figures 7 and 8 show the strengths of coefficients of explanatory variables for male and female drivers respectively. These figures show that there are significant spatial variations and they are summarised in Table 6.

Figure 7: GWR results- Strengths of coefficients of explanatory variables- Male drivers



Coefficient Un/low educated Coefficient 25 to 35 age Coefficient 65 to 74 age

Figure 8 GWR results- Strengths of coefficients of explanatory variables- Female drivers



Coefficient Un/low educated Coefficient 25 to 35 age Coefficient 65 to 74 age

Table 6 Gender-based spatial targeting- low-educated, young and older age groups

Gender	Un/low educated	25 to 34 age	65 to 74 age
Males	Northwestern postcodes	South and far Northeastern postcodes	Southern postcodes
Females	North and North-western postcodes	Mostly southern postcodes	Spread all over

6. Limitations

Due to data availability issues, this study is based on older crash data (2003 to 2012 crash records). Also, the limitation of the crash data is that only one error is associated with a crash comprising multiple units and some of the important factors such as fatigue are not recorded. As the main focus of this study was on the drivers involved in road crashes the impact of other factors, such as traffic exposure, infrastructure, and the built environment was not considered.

7. Conclusions

The present study has shown that apart from the age of the drivers, their level of education plays an important role in reducing crash rates. In addition to identifying key demographic factors influencing driver crashes, this study has also identified the geographic locations where these factors have strongly influenced the models. This will help authorities focus on education and training programs, targeting those areas as earlier studies (Mayhew and Simpson 2002, McCartt et al. 2008) have shown that education and training programs, focusing on young drivers proved to be effective in reducing collisions. Among the various age groups, this study has shown that younger adults who are 25 to 34 years of age and older adults who are in the 65 to 74 years age groups are more likely to be involved in serious injury and fatal crashes. It is interesting to note that, unlike earlier studies where drivers aged 16-25 of either sex were a significant variable, in this study drivers aged 25-34 showed higher significance among the young drivers. So young drivers aged 25-34, old drivers aged 65-74 and those with low education levels (year 8 and below) or who have never been to school are the possible important target groups in the promotion of behavioural change. However, as the impact of these variables varies spatially, it is important to identify target postcodes as shown in this research for any road safety campaigns. The important contribution of this study is that it has shown how these variations differ spatially for each gender and quantified these variations.

8. Acknowledgments

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