The High-Risk Child Pedestrians: Modeling the Effects of Land Use and Temporal Factors on Child Pedestrian Casualties

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Abstract

This study investigates the suitability of land use variables in predicting the number of child pedestrian accident casualties, which remain a subject of concern in the United Kingdom, despite sustained improvements in road safety over the past decade. The relationship between land use and transport is used to establish a link between land use and child pedestrian travel; trip attractors and generators are used as variables that lead to exposure of the child to high risk environments. Accident data for Newcastle upon Tyne is used and analyzed to reveal trends and patterns of temporal variation of child pedestrian casualty numbers. Land use data is combined with the casualty data using GIS techniques to create eight spatial models, which serve as a base for associating the casualty numbers and land use types. Six regression models are developed on the basis of temporal variation of child pedestrian casualty numbers and trip attractor land use types. The results show that secondary retail and high density residential land use types are associated with all child pedestrian casualties. In addition, educational sites, junction density, primary retail, and low density residential land use types are also associated with child casualties at different time periods of the day (school time and non-school time) and week (week day and weekend). The study findings are found to concur with the current UK Child Road Safety Policies and can in fact provide some guidance for child road safety audits.

Keywords: Land use type; child pedestrian casualties; generalized linear models; road safety.
INTRODUCTION

The number of child pedestrians killed and seriously injured (KSI) in road accidents in Great Britain has continued to be a significant problem. According to the UK Department for Transport, (DfT) road traffic accidents are the leading cause of accidental injury among children and young people DfT (1). In 2001, child deaths and serious injuries due to road casualties accounted for 63% of the total child casualties (2). In 2005, a DfT report found that the number of pedestrian casualties is higher in Britain than most of the European countries as a result of exposure to specific areas of the road environment (3).

In 2000, the British Government launched its strategy for road safety improvement; one of the highlights of which was setting casualty reduction targets based on casualty numbers for the four year period starting from 1994. This was undertaken in part to restore parity with the European average in terms of the average number of child casualties. It included a target for reducing traffic related child deaths and serious injuries by 50% by 2010 (4).

A study carried out in France, Great Britain and the Netherlands found that children in Britain spent more time near or crossing wider roads or roads with high flows of traffic, were more likely to use unmarked crossings and were less likely to be accompanied by an adult (5). In comparison to the OECD member states, Britain is ranked tenth out of thirty seven countries on the subject of child pedestrian fatality rates (3). Therefore road safety improvement should be one of the key priorities in Britain for the sake of accident reduction. Safety research is a vital component of road safety initiatives as it can uncover new or modify existing methods and propose new areas for prioritization.

In terms of road safety, non-motorized users including pedestrians and cyclists, also referred to as vulnerable road users (VRUs), are at risk as they are exposed and unprotected from injury compared to motorized users. One of the most vulnerable non-motorized traffic groups are children because many of them do not know how to behave safely when they are on the road. Therefore, this study focuses mainly on child pedestrian accidents.

Land use as a principal determinant of trips is one of the main influencing factors for road-based environments and its related variables including traffic flows, speed limits and pedestrian activities (6). As reported by Ben-Akiva and Bowman (7), land use has been shown to be the major factor in generation and attraction of traffic. They have also mentioned that land use influences the level of traffic flow, speed and safety. In general, different land use patterns generate or attract different numbers of trips. A rising number of trips certainly increases the probability of accident occurrences. Therefore, it is reasonable to make an assumption that different land use patterns may generate different accident rates.

The prime objective of this study is to investigate child pedestrian accidents and its relationship with land use, which is expected to be a positive contribution to current safety research in the Britain. More explicitly, this study intends to discern the patterns of land use that are highly associated with child pedestrian casualties.

The methodology is developed by the following steps to achieve the goals of this study:

- Preliminary analysis of the child pedestrian casualty data in order to extract information, mainly on the time of the accidents, severity, and accident locations.
- Application of GIS techniques to develop spatial models that link child pedestrian casualties to urban land use types and administrative boundaries (wards).
• Investigate the suitability of existing modeling techniques, for instance Generalized Linear Models (GLM), for data modeling in this study.
• Develop and estimate a GLM model that uses urban land use types as predictor variables for all kinds of child pedestrian casualties, for example slight, serious and fatal, within defined administrative/electoral boundaries.
• Analyze a sub-model that uses urban land use types as predictor variables for only KSI within defined administrative/electoral boundaries.
• Analyze several sub-models to understand the temporal effects on child pedestrian casualties considering school time (KSI), school time (slight), non-school time (KSI), non-school time (slight), weekend (KSI) and weekend (slight) that uses urban land use types as predictor variables.
• Investigate the possible contribution of the findings into current road safety policy in the UK.

The city of Newcastle upon Tyne, the major city in the northeast of England, was chosen as the case study area. Several spatial and statistical models were developed in reference to child pedestrian accident data from Newcastle city with special consideration of urban land use patterns and their impact on child accidents, in order to ascertain and propose a possible relationship between them.

CHILD PEDESTRIAN CASUALTIES IN THE GREAT BRITAIN

Child pedestrians are generally considered a part of the non-motorized traffic group. As reported by the DfT (2), all children below the age of sixteen belong to the child pedestrian category. According to figure 1, there has been a considerable reduction in child pedestrian KSI in the UK during the past 10-12 years. However the number of casualties as recorded (2400 KSI per year) remains to be a major concern within the road safety agenda in the UK (2).

![Figure 1: Comparison of child KSI and All accident severities in UK](Produced using the data from TSGB (8))

Studies on child casualties in the UK conducted by the DfT (1) have revealed that the number of casualties increases by age and teenage children are the most at risk. As shown in figure 2, it is clear that the number of casualties increases steadily for children as they get older. For example, in 2001, the 12-15 age group has an annual KSI rate over four times that
of the 0-4 age group and over three times the casualty rate for slight injuries. Over the period of 1996-2001, there has been a decline in KSI and slight injuries for all ages. However, for the age group 8-15, the decline is slower in rate than young children.

![Figure 2: Child Accident Severity by Age in Great Britain](Produced using the data from DfT, 2002)

Recent research by the DfT (9) has found that child pedestrians who face traffic casualties are largely boys. Children from low income families, ethnic minorities, as well as children living in old terraced houses on straight roads are more vulnerable to the risk of becoming traffic casualties.

**A REVIEW: THE EFFECT OF SOCIO-ECONOMIC, ENVIRONMENTAL AND LAND USE FACTORS ON CHILD PEDESTRIAN CASUALTIES**

The child casualty studies carried out in the past primarily looked at its relationship with the physical and social environment. This review basically summarizes the work that has been conducted so far emphasizing the impacts of spatial interaction, road environment, socio-economic factors, and temporal characteristics on child pedestrian accidents.

Sideris and Liggett (10) reported that the spatial distribution of child casualties is always uneven when a city is concerned where some neighborhoods are at higher risk than others. They found that educational, residential (vacant, medium and high), and commercial land use types, as well as road and population densities can be used to predict pedestrian casualty numbers. Joly et al. (11) analyzed the effects of geographic and socio-ecologic variations on child casualties in Montreal city and found that the zones with high incidence of pedestrian and cyclist casualties have fairly similar characteristics. A recent research by Petch and Henson (12) indicates that the distribution of child pedestrian or cyclist casualties could not be simply explained by analysis at a district level. It was necessary to analyze at sub-district level focusing on specific factors, for instance trip attractors, activities and travel patterns, as there were complicated interactions between the various factor groups (12). Although this analysis did not directly relate to land use, it provides an important indication that the administrative boundary or unit for such an analysis should be smaller than the district level.
Wedagama (13) has made an attempt to investigate the relationship of pedestrian casualties with certain land use types, for example retail, offices, leisure and junction density, on weekdays and weekends. Furthermore, he was able to derive a relationship between different land use types or trip attractors and temporal variation of pedestrian and cyclist casualties. Wedagama (13) did not however disaggregate the pedestrians by age.

Over the years, there has been considerable attention to distinguishing the locations where child pedestrian casualties were likely to occur. A number of authors have identified that the areas of high child accident rates are within the immediate vicinity of residential neighborhoods and they are highly dependable on road type (5, 9, 14-17). Houses which are Victorian terraced or are located in an area with a lot of on-street parking, or have no play areas with on-street front access contribute more to pedestrian accidents (12, 17). The road environment was also found to be a cause of many pedestrian casualties. Lawson (15) mentioned that many casualties to young pedestrians occurred on minor roads in small urban areas. Researchers recognized the increased risks posed by through roads to child pedestrians (16, 18, 19). A study by the DfT (3) titled “Casualty Variation in Britain and Europe” further reinforces this notion.

Some studies found that traffic calming systems are worthwhile for areas with high incidence of child pedestrian casualties. Jones et al. (20) in a study of two cities in the UK found that traffic calming can reduce the rate of child pedestrian casualties and reduce inequalities in deprived areas. According to Agran et al. (14), there is a high risk of child pedestrian casualties in residential streets with a high proportion of parked vehicles and residences with many families with no enclosures. To reduce pedestrian casualties, they recommended traffic calming systems to reduce speed limits and reduction of parking spaces to increase the visibility.

Christie (18) found that the chance that child pedestrians in the lowest socio-economic group stand to die in an accident is four times higher than that for those in the highest socio-economic group. This was because they are more exposed to high risk traffic and less supervised by their parents. These studies mainly draw conclusions from analysis of individual casualty data resulting from exposure by travel but do not look at the generators or attractors for the travel.

Many studies on child accidents have found that casualties occur largely during morning and evening peaks corresponding to the times that they travel and leave school respectively (2, 21). They are highest on Fridays and lowest on Sundays due to different rates of traffic exposure during the week (2). Most casualties during the day occur during the period between 3 pm and 9 pm (21) and more casualties occur during the summer especially later in the day (2).

Most of the research conducted so far has identified that characteristics including socio-economic status, proximity to certain roads, and parking have a direct association with child pedestrian casualties but no effort has been made to investigate the possible relationship between child pedestrian accidents and land use.
**MODELING LAND USE AND PEDESTRIAN CASUALTIES**

Pedestrians move from one place to another in order to satisfy their requirements, and therefore the demand for transport is always considered as derived. Accordingly, land use and transport may have some interactions between them.

**Modeling Land use and Spatial Characteristics**

According to Rodrigue (22), the transport-land use system can be divided in three sub-categories of models: land use, spatial interactions and transportation network models. Accessibility and mobility both have impacts on travel where land use patterns in an urban area determine how people access services (23). Mixed land use generally improves accessibility and provides safe travel for pedestrians. This makes a positive effect on the number of casualties generated in an area.

Badruddin and Herrington (24) define a spatial model as a geographic/spatial data manipulation and analytic process that facilitates the production of information to solve complex problems. The spatial modeling process consists of several steps: problem-identification, simplification, organizing data, preparation of a logical flowchart with clear and defined operations, data analysis, and modification or correction of errors as required (24). Although the procedure suggested is suitable for the analysis of environmental or geographical data, the output of the spatial model can be used as input for accident modeling (13).

In order to carry out spatial analysis, Geographical Information Systems (GIS) techniques are found to be important. Tortosa (25) describes GIS as computer software and hardware systems that enable simulation and advanced analysis of geo-referenced data to manage information that enables decision making. Foote et al. (26) explained the manipulation abilities of GIS which involve the separation of information in layers and various combination models. A stack of map layers can be obtained using GIS methods where each map extracts a different level of information starting from the base map (26).

**Modeling Pedestrian Accidents**

Accidents are always discrete events resulting in non-negative values. This sort of data is generally analyzed using a number of methods including the Poisson, the Negative Binomial, and the Bernoulli methods. Especially for the situations when the data contains many zeros, the accident modeling has to be conducted by the Zero Inflated Poisson (ZIP) and the Zero inflated Negative Binomial methods (ZINB) (27-29).

Many accident studies have used Poisson Regression (10, 13, 30-32). The Poisson distribution has characteristics of being skewed and non-negative where the data is assumed to have a variance that increases with the mean. The Poisson Regression generally uses a log transformation to cater for the skewed and non-negative characteristics of data (33). In contrast, traditional Ordinary Least Squares Regression assumes a normal distribution of residuals, produces negative values, and assumes a constant variance (33). The assumptions of equal mean and the variance of events in the Poisson distribution sometimes make it unsuitable for real life situations as there is a possibility of under-dispersion and over-dispersion. When the variance is larger than the mean (over dispersion) or smaller (under dispersion), it indicates that Poisson distribution does not adequately fit for the analysis (33).
In such cases, the *Negative Binomial Distribution* is used as a generalization of the *Poisson distribution* as it does not assume equal chance or randomness for all elements in a distribution e.g. the chance of casualties in one ward may be higher than in another ward (33).

A number of studies have used the *GLM* (13, 30) to model casualty data. The *GLM* can be used to confront linear and non-linear effects of continuous and categorical predictor variables on a discrete or continuous dependent variable.

**CASE STUDY AREA**

This study investigates data from Newcastle upon Tyne; the regional capital of the northeast of England with a very vibrant, competitive but friendly environment. Newcastle district belongs to the Tyne and Wear conurbation, which comprises Newcastle and North Tyneside to the north of the River Tyne, Gateshead and South Tyneside south of the Tyne, and Sunderland located to the south at the mouth of the River Wear.

Newcastle upon Tyne was historically a coal mining area. Like many English cities, it is making efforts to recover from the legacy of industrial change, and compared with many, it has remained disadvantaged. These facts are recognized by Newcastle City Council, who plan to continue developing the city to be one where people have access to a more prosperous, healthier, safer and sustainable life style in an attractive environment.

Like most UK cities, Newcastle experiences significant localized congestion at key locations in its central business district. Thus one of the challenges would be to reduce the level of traffic congestion. Car ownership in Newcastle and the north-east region has remained lower than the national average. Therefore the potential for car ownership growth in Newcastle in the future is high. Indeed it is now increasing at twice the national average.

The city covers an area of 113 km². As of 2001 Census Data, it has a population of about 259,536 of whom 48,720 are children under 16 years of age representing 18.8% of the population (National Statistics, 2001). Tyne and Wear county consists of 26 wards among which 11 wards are within the Newcastle periphery (figure 3).

![Figure 3: Case Study Area – The City of Newcastle upon Tyne](image)
The most populated ward is Dene with approximately 6% of the total population, while the lowest is West City ward with 2.4%. In terms of child population the highest and lowest wards are as with the total population above, with percentages of 6% and 1.8% respectively. Newcastle Local Authority has a total of 99 schools that are attended by 37,000 pupils.

MODELING APPROACH

This study proposes an integrated modelling approach to deal with spatial interaction as well as child pedestrian casualties in order to accomplish the task of investigating land use impacts on child pedestrian accidents. At first, spatial land use/accident interaction models were analysed to generate necessary land use outputs. Next, the land use outputs from the spatial models were used as inputs in the child pedestrian casualty modelling in order to identify the relationship between land use and casualties.

Spatial Model

A spatial model is developed to assign child casualties to specific land use types in specific wards of Newcastle district. The model should fit the following criteria:

- Child pedestrian casualties geographically referenced
- Newcastle district area with defined ward boundaries
- Land use classification of Newcastle district (referenced to ward boundaries)
- Child pedestrian casualties in specific land use and ward

The expected outputs of the model represent the proportion of independent variables (land use types) and casualties per spatial unit. The required data sets for this model are the baseline map for Newcastle upon Tyne, geo-referenced child pedestrian casualties and land use data for the area. Figure 4(a) shows the flow chart of the spatial model development process.

Accident Model

The GLM technique is selected in this study due to its applicability over the normalization facility of non-linear data. The response or the dependent variable can be non-normal, and does not necessarily have to be continuous.

In linear regression models, a dependent variable $Y$ is linearly associated with a series of independent explanatory variables ($X$).

$$Y = \beta_0 + \sum_{j=1}^{p} \beta_j X_j + \varepsilon$$

(1)

Where

$Y$: dependent variable (Child pedestrian casualty)
$X$: explanatory variables (road length, junction density, land use type)
$\beta$: unknown parameters
$\varepsilon$: error term

The expected value of $Y$ can be calculated by,

$$E[Y] = \mu = \beta_0 + \sum_{j=1}^{p} \beta_j X_j$$

(2)

Where, $\mu$ is the expected value of $Y$. 
In the GLM, the relationship between $E(Y)$ and $\mu$ is specified by a non-linear link function called $g(\mu)$, and it can be in any form of Poisson, Normal, Gamma, Inverse Normal, Binomial, multinomial distributions.

$$E[Y] = g(\mu) = \beta_0 + \sum_{j=1}^{p} \beta_j X_j$$  \hspace{1cm} (3)

The link function for Generalised Linear Poisson Regression is specified as:

$$\ln(\mu) = \beta_0 + \sum_{j=1}^{p} \beta_j X_j$$  \hspace{1cm} (4)

In order to estimate the GLM, the values of the parameters ($\beta_0$ through $\beta_j$ and the scale parameter) are obtained by maximum likelihood estimation (MLE).

Basically, the GLMs are developed in order to predict child pedestrian casualties that can be expected to occur for a given proportion of land use type. In order to obtain a valid model, a number of criteria have to be met such that it can be relied upon for real world application. The following criteria shall be pursued in development of the model:

- Logical output results
- Consistency and robustness

In order to estimate the Generalized Linear Poisson Regression (Poisson GLM) models using MLE methods, the models should meet the following criteria:

- The ratio of the Poisson deviance to degrees of freedom or Pearson chi square to degrees of freedom should be approximated to 1.
- The predicted coefficients should have significant z-score probabilities at a confidence level of $p=0.05$.

Figure 4(b) represents the development of accident modeling process.

Negative Binomial Regression models are used when the result for the Poisson GLM shows over dispersion. Use of the Maximum Quasi Likelihood (MQL) estimation to optimize the deviance has been found to solve this as well when using S-Plus (28). In the case of Negative Binomial (NB) Regression, the Likelihood Ratio (LR) test is used to determine the suitability of the regression to model the data. For this test the value if the $\alpha=0$, the NB Regression equates the Poisson Regression otherwise its probability should be significant at a $p=0.05$ confidence level.

Data Description

The child casualty data was obtained as secondary geo-referenced data from the Traffic Accident and Data Unit (TADU) of Gateshead Metropolitan Borough Council (MBC). It consists of details of child casualties that took place between the years of 2000 and 2005 inclusive. It was collected for the area between the ordnance survey coordinates of 421,500, 563000 (Easting, Northing) and 428000, 569000 (Easting Northing) for the top left and bottom right hand corners respectively.

UK regional accident data is collected from Transport Statistics Great Britain (TSGB), while other school data for the accident period is obtained from Newcastle City Council Education Department.
Land use data was obtained in secondary form from the School of Civil Engineering and Geosciences at the University of Newcastle, Newcastle City Council, and EDINA Digimap of Edinburgh University. It consists of details of land use classification of Newcastle city as defined by the Office of the Deputy Prime Minister (ODPM) now the Department for Communities and Local governments (DCLG). A map from UKBORDERS on the EDINA portal is also available with the smallest electoral unit of division, a ward, for the Newcastle area.

(a) Flow Chart for the Spatial Modeling Process

(b) Flow Chart for the Accident Modeling Process (GLM Model)

Figure 4: Spatial and Accident Modeling Framework

Preliminary Data Analysis

The average annual number of casualties for the six-year period is 87 and average KSI is 15 (figure 5).
The majority of the casualties (83%) resulted in slight injuries and there was only one fatal accident. Of the 522 casualties in the data, 320 of them are male, while 222 are female. This trend was also observed by other literature (9).

Figure 6 shows the distribution of casualties in all Newcastle wards. They are highest in the West City ward (9%) and least in the Jesmond ward (1%). By carrying out preliminary spatial analysis with ESRI’s Arc Toolbox, calculating the kernel density of the accident points reveals spatial clusters in the area in and around the city centre that has a relatively higher concentration of retail, leisure and residential land use as well as road length. It is also noted that two thirds (66%) of the casualties occurred whilst the children crossed at points more than 50 meters away from the designated pedestrian crossing. A significantly high number (10%) also occurred on the pedestrian crossing itself.

**Variable Selection**

Pearson’s coefficient of correlation is calculated for all the land use types as shown in table 1 below to check for multicolinearity. Land use variables including industrial and storage (IS), offices (J), vacant land (V), footpaths (W), and Transport (T) were left out of the
modeling process while others including road length (rl), community buildings (c), primary and secondary retail (pk, sk), both high and low density residential (hd, ld), open spaces (o) and educational sites (es) were selected as trip attractors for child pedestrian travel hence predictor variables. The variables for community buildings (c) and open spaces (o) were then not considered for the modeling process because the number of predictor variables would in that case be 9 for the 10 wards being observed in the study. This is avoided because the models obtained might ‘over-fit’ because of only one degree of freedom (34).

Table 1 Correlation of Essential Land Use Variables

<table>
<thead>
<tr>
<th>cpoD</th>
<th>c</th>
<th>es</th>
<th>hd</th>
<th>ld</th>
<th>o</th>
<th>pk</th>
<th>sk</th>
<th>jd</th>
<th>ln(rl)</th>
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<td></td>
<td></td>
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<tr>
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Model Estimation, Results and Discussion

The GLM models were developed considering the casualty types and temporal variations in Newcastle city for the period of 2000-2005. Ten out of eleven wards in the Newcastle district were incorporated in the analysis. The Heaton ward, in particular, wasn’t included in the analysis due to land use data limitations.

To remove the appearance of ‘at risk’ wards due to road length, it was offset such that the road length variable enters on the right-hand side of the equation, but with a parameter estimate constrained to 1.

$$\ln(\mu) = \ln(rl) + \beta_0 + \sum_{j=1}^{p} \beta_j X_j$$  \hspace{1cm} (5)

It implies,

$$\ln\left(\frac{\mu}{rl}\right) = \beta_0 + \sum_{j=1}^{p} \beta_j X_j$$  \hspace{1cm} (6)

Therefore, the GLM equation can be written as:

$$\ln(\mu) = \ln(rl) + \beta_0 + \beta_{jd} + \beta_{es} + \beta_{hd} + \beta_{ld} + \beta_{pk} + \beta_{sk}$$  \hspace{1cm} (7)

Table 2 represents the number of child pedestrian accidents and the proportions of the land use types for each ward. Table 3 explains the models developed in this study.

Stata 7.0 is used to estimate the land use –accident models. All the models except the overall child casualties’ model are to be fit with the Poisson regression as the Negative Binomial regression does not properly fit the models that do not perfectly fit the Poisson regression (table 3). MQL estimation is also carried out but the resulting standard errors are the same. The Poisson regression is thus used. Estimation results of the above models are tabulated in the table 4.
### Table 2: Spatial Model Output for Selected Ward and Land use Types

<table>
<thead>
<tr>
<th>Ward</th>
<th>AL</th>
<th>KSI</th>
<th>ST-SLT</th>
<th>ST-KSI</th>
<th>N-ST-SLT</th>
<th>N-ST-KSI</th>
<th>WE-SLT</th>
<th>WE-KSI</th>
<th>Land Use Proportions (%)</th>
<th>Jd /km</th>
<th>Ln(rl)</th>
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</thead>
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<td></td>
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<td>es</td>
<td>hd</td>
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<td>0</td>
<td>7</td>
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<td>3</td>
<td>2</td>
<td>0</td>
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<td>0</td>
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<td>4</td>
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<td>1.525</td>
<td>3.206</td>
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<td>Sandyford</td>
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<td>3</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>1</td>
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<td>0.033</td>
<td>1.973</td>
<td>12.270</td>
</tr>
<tr>
<td>South Gosforth</td>
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<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>10</td>
<td>1</td>
<td>0</td>
<td>0.000</td>
<td>0.525</td>
<td>9.711</td>
</tr>
<tr>
<td>West City</td>
<td>47</td>
<td>7</td>
<td>2</td>
<td>3</td>
<td>25</td>
<td>3</td>
<td>13</td>
<td>1</td>
<td>0.000</td>
<td>2.172</td>
<td>2.240</td>
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<tr>
<td>Wingrove</td>
<td>28</td>
<td>4</td>
<td>6</td>
<td>1</td>
<td>11</td>
<td>3</td>
<td>7</td>
<td>0</td>
<td>0.082</td>
<td>4.342</td>
<td>9.464</td>
</tr>
</tbody>
</table>

**ALL**
- All casualties
- WE-SLT: Weekend Slight
- WE-KSI: Weekend Killed & Seriously Injured
- ST-SLT: School Time Slight
- ST-KSI: School Time Killed & Seriously Injured
- N-ST-SLT: Non School Time Slight
- N-ST-KSI: Non-School Time Killed & Seriously Injured

**KSI**
- Killed and Seriously Injured
- WE-KSI: Weekend Killed & Seriously Injured
- Community Buildings
- Educational Sites
- High Density

**Jd**
- Junction Density

**Ln(rl)**
- Natural log of Road Length
Table 3 Determination of Model Fit

<table>
<thead>
<tr>
<th>No</th>
<th>Casualty Model</th>
<th>Model Description</th>
<th>Data Type</th>
<th>Time Period</th>
<th>Explanatory variables</th>
<th>Deviance/Deg of Freedom</th>
<th>Test statistic</th>
<th>Best Model</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>ALL</td>
<td>All casualties</td>
<td>ALL</td>
<td>All year</td>
<td>es, hd, ld, pk, sk, jd</td>
<td>14.59276</td>
<td>LR test for NB: $\chi^2 = 20.54, p=0.000$. Significant at $p=0.05$</td>
<td>Negative Binomial</td>
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<tr>
<td>2</td>
<td>KSI</td>
<td>KSI</td>
<td>KSI</td>
<td>All year</td>
<td>es, hd, ld, pk, sk, jd</td>
<td>3.650512</td>
<td>LR test for NB: $\chi^2 = 0.00, p=0.5$. Not significant at $p=0.05$</td>
<td>Poisson</td>
</tr>
<tr>
<td>3</td>
<td>ST-SLT</td>
<td>School Time casualties (ST)</td>
<td>Slight</td>
<td>0830 – 1530 Weekdays</td>
<td>es, hd, ld, pk, sk, jd</td>
<td>4.920896</td>
<td>LR test for NB: $\chi^2 = 1.2, p=0.136$. Not significant at $p=0.05$</td>
<td>Poisson</td>
</tr>
<tr>
<td>4</td>
<td>ST-KSI</td>
<td>KSI</td>
<td>KSI</td>
<td>Holidays &amp; 1530 - 0830 Weekdays</td>
<td>es, hd, ld, pk, sk, jd</td>
<td>1.15 *10^-7</td>
<td></td>
<td>Poisson</td>
</tr>
<tr>
<td>5</td>
<td>N-ST-SLT</td>
<td>Non-School Time casualties (N-ST)</td>
<td>Slight</td>
<td>Holidays &amp; Weekdays</td>
<td>hd, ld, pk, sk, jd</td>
<td>4.086733</td>
<td>LR test for NB: $\chi^2 = 0.19 p=0.33$. Not significant at $p=0.05$</td>
<td>Poisson</td>
</tr>
<tr>
<td>6</td>
<td>N-ST-KSI</td>
<td>KSI</td>
<td>KSI</td>
<td>All School Time</td>
<td>hd, ld, pk, sk, jd</td>
<td>4.511074</td>
<td>LR test for NB: $\chi^2 = 0.37, p=0.273$. Not significant at $p=0.05$</td>
<td>Poisson</td>
</tr>
<tr>
<td>7</td>
<td>WE-SLT</td>
<td>Weekend (WE)</td>
<td>Slight</td>
<td>All weekends of the year</td>
<td>hd, ld, pk, sk, jd</td>
<td>4.466034</td>
<td>LR test for NB: $\chi^2 = 2.18, p=0.070$. Just not significant at $p=0.05$</td>
<td>Poisson</td>
</tr>
<tr>
<td>8</td>
<td>WE-KSI</td>
<td>KSI</td>
<td>KSI</td>
<td>All School Time</td>
<td>hd, ld, pk, sk, jd</td>
<td>1.86753</td>
<td>LR test for NB: $\chi^2 = 0.00, p=1.00$. Not significant at $p=0.05$</td>
<td>Poisson</td>
</tr>
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</table>
Table 4 Accident Model Output

<table>
<thead>
<tr>
<th>Variables</th>
<th>ALL</th>
<th>KSI</th>
<th>ST-SLT</th>
<th>ST-KSI</th>
<th>N-ST-SLT</th>
<th>N-ST-KSI</th>
<th>WE-SLT</th>
<th>WE-KSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1.50</td>
<td>-1.13</td>
<td>-7.09</td>
<td>-2.92</td>
<td>-3.19</td>
<td>-1.91</td>
<td>-65.62</td>
<td>-0.01</td>
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<tr>
<td>es</td>
<td>-0.11</td>
<td>-1.38</td>
<td>0.28</td>
<td>2.06</td>
<td>0.18</td>
<td>1.82</td>
<td>8.58</td>
<td>0.01</td>
</tr>
<tr>
<td>hd</td>
<td>-0.10</td>
<td>-2.79</td>
<td>-0.24</td>
<td>-2.51</td>
<td>-0.01</td>
<td>-0.37</td>
<td>-0.54</td>
<td>-0.00</td>
</tr>
<tr>
<td>ld</td>
<td>0.02</td>
<td>0.87</td>
<td>-0.06</td>
<td>-1.56</td>
<td>0.01</td>
<td>0.37</td>
<td>-0.82</td>
<td>0.00</td>
</tr>
<tr>
<td>pk</td>
<td>0.08</td>
<td>1.39</td>
<td>-0.01</td>
<td>-0.19</td>
<td>0.01</td>
<td>0.20</td>
<td>3.53</td>
<td>0.01</td>
</tr>
<tr>
<td>sk</td>
<td>1.72</td>
<td>3.34</td>
<td>3.98</td>
<td>3.32</td>
<td>1.37</td>
<td>2.50</td>
<td>41.03</td>
<td>0.01</td>
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<tr>
<td>jd</td>
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<td>-0.71</td>
<td>0.30</td>
<td>1.17</td>
<td>-0.19</td>
<td>-1.03</td>
<td>-3.96</td>
<td>-0.08</td>
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</table>

Summary Statistics

<table>
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<tr>
<th></th>
<th>n</th>
<th>N</th>
<th>dv/df</th>
<th>Model Type</th>
<th>Neg. Binomial</th>
<th>Poisson</th>
<th>Poisson</th>
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<tbody>
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<td>235</td>
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<td>14.59</td>
<td>Poisson</td>
<td>Poisson</td>
<td>Poisson</td>
<td></td>
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</tbody>
</table>

Notes:
- Bold figures are significant at: *95% and **90%.
- -- in Coef. and t-stat. indicates parameter not estimated and t-stat. not calculated respectively.
Results and Discussion

Table 5 shows that secondary retail (sk), low density residential land use (ld) and educational sites (es) are positively associated with child pedestrian casualties of different severities, while high density residential (hd) and junction density (jd) land use are noted to have a negative association. A negative association implies that as the land use increases, the occurrence of child pedestrian casualty decreases, while for a positive association, the reverse is true. It is also observed that some of the models, for example school time KSI (ST-KSI) and weekend KSI (WE-KSI), did not produce significant estimates in order to prove the relationship between land use variables and child casualties. This is probably due to the lower number of KSI accidents, which have occurred during these times, and are insufficient to generate a meaningful statistical relationship.

Table 5 Results obtained from the models

<table>
<thead>
<tr>
<th>Accident Model</th>
<th>Land use Predictor</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALL</td>
<td>High density (-), Secondary Retail (+)</td>
</tr>
<tr>
<td>KSI</td>
<td>Educational sites (+), High density (-), Secondary retail (+)</td>
</tr>
<tr>
<td>ST-KSI</td>
<td>Nil</td>
</tr>
<tr>
<td>ST-SLT</td>
<td>Educational sites (+), Secondary retail (+)</td>
</tr>
<tr>
<td>N-ST-KSI</td>
<td>High density (-), Secondary retail (+)</td>
</tr>
<tr>
<td>N-ST-SLT</td>
<td>High density (-), Secondary retail (+)</td>
</tr>
<tr>
<td>WE-KSI</td>
<td>Nil</td>
</tr>
<tr>
<td>WE-SLT</td>
<td>High density (-), Low density (+), Primary retail (+), Secondary retail (+), Junction density (-)</td>
</tr>
</tbody>
</table>

Note: Land use shown in bold format is significant at 95% level of confidence, while the one significant at 90% confidence level has been included as other entries.

Effect of Secondary Retail

All the models except ST-KSI and WE-KSI predicted that secondary retail (sk) is positively associated with child casualties. The secondary retail shops and stores in the UK are usually located along through roads and therefore road safety issues could be a concern. Because some of such retail streets only provide on street parking, these could be a problem for child pedestrians as they have to cross crowded streets. The positive association therefore does make sense. It was expected that primary retail (pk) would also have a significant positive association with child casualties, but the model explains this differently. The insignificance of primary retail may be a result of few observations; only 3 of the 10 wards have a primary retail land use type. On the other hand, most of the primary retail land uses in Newcastle have been pedestrianised for over 10 years so that the chances of facing accidents in primary retail areas are low.

Effect of High Density Vs Low Density Residential Land Use

The model showed that low density residential (ld) areas are not significantly associated with child pedestrian casualties. Therefore the road layout and road environment features in high density residential (hd) areas could be a possible cause for this association. Whereas the scope of this study did not involve assessment of the road network structure for each land use type used in the analysis, this could be a further component for further study to see what contribution it makes to the casualties observed.
**Effect of Educational Sites**

In this study, educational sites (es) include all schools, colleges and universities, and libraries in a ward. The GIS data used in this study was not at a detailed enough level to identify the educational sites that are most attractive to children below the age of 16. This therefore might have an effect on the sensitivity of the model to the schools' land use proportion as it was expected to return a positive association. On the other hand it is likely that some of the casualties which occurred in wards with a small number of educational land use proportion were due to other factors. Wards such as Byker, Moorside and Westcity whose proportion of educational land use is comparatively low in the 10 wards had high accident counts, while Jesmond whose proportion of similar land use is high had the lowest number of casualties.

The KSI model predicted that child KSI casualties are associated with educational sites, high density and low density residential land use types. In comparison to the ALL model, it is noted that educational sites were found significant in the KSI model.

**Implications from N-ST and ST models and WE models**

Non school time (N-ST) models found high density (hd) and secondary retail (sk) land use types as significant in relation to occurrence of child casualties. This is expected as children as likely to visit retail stores after school hours, therefore have more exposure to risk while they cross roads. It would be wrong to conclude that they should therefore be prevented from visiting these shops, but rather the traffic environment in such areas could be modified to suit the children’s needs.

School time accident models (ST) clearly explain that educational sites (es) and secondary retail (sk) have a positive relationship with child accidents. This was also expected and therefore, some measures to safeguard child pedestrians as they travel to and from school are needed.

Weekend accident models (WE-SLT) found low and high density residential, primary and secondary retail as well as junction density to be significant land use factors for child casualties. It is important to note that junction density is negatively significant for weekend accidents. In preliminary analysis of the accident data, it was found that most accidents occurred away from the pedestrian crossing. Increased Junction density therefore appears to reduce the number of casualties as it is assumed that the more junctions are provided, the more pedestrian crossings will be available hence permitting safe crossing for the pedestrians.

**Contributions from this Research to the Current Road Safety Policy in the UK**

Current road safety policy, namely the DfT’s Road Safety Strategy (1) and the Action Plan Report of the Road Safety Advisory Panel (RSAP) (2), requires local authorities to perform child road safety audits in order to collect information on child casualties, devise means of addressing their causes and monitor the progress of the schemes with regard to a reduction in the severity and number of casualties. It also empowers them to create more speed limit zones, introduce more traffic calming measures and pedestrian crossings and to develop and implement school travel plans (1). Unfortunately local authorities are finding such needs hard to implement. It was found that the models could assist in carrying out child
road safety audits as their methodology provides a starting point by identifying areas that are likely to be associated with high incidences of child pedestrian casualties. The local authorities can then focus on these areas and carry out detailed investigations.

CONCLUSIONS

The UK road safety strategy of 2000 recognizes the contribution that child road safety research makes to the development of accident reduction initiatives. The objective of the study is to obtain a relationship between urban land use and child pedestrian casualties in Newcastle District, located in the northeast region of England. The study also set out to characterize the spatial variation of land use and child casualties as well as investigate their temporal characteristics. GIS techniques and Generalized Linear Modeling (GLM) methods were used to derive and analyze the occurrence of child pedestrian casualties at the ward administrative (and geographical) level.

Eight spatial models were developed that associated child pedestrian casualties to the land use classification types that constitute their typical trip attractors and generators. Using these spatial modes, two main models (ALL, KSI) and six sub-models (ST-KSI, ST-SLT, N-ST-KSI, N-ST-SLT, WE-KSI, WE-SLT) were developed. The sub-models predict the temporal occurrence of the casualties depending on the proportion of land use types and junction density, whilst offsetting the effect of road length. The results show that secondary retail and high density residential were the main land use types associated with child pedestrian casualties, in such a way that the former was positively associated while the latter was negatively associated. A positive association implied that increase in the proportion of this land use type would appear to result in more casualties, whilst for negative association, the reverse is true. It also found that low density residential, educational sites, and primary retail were also positively associated while junction density was negatively associated with child pedestrian casualties.

This study is also comparable to the findings of the current UK road safety policy contained in the Road Safety Strategy 2000 (1), and the Road Safety Advisory Panel (RSAP) Action Plan on Child Road Safety (2). It was also found that the study methodology could be useful in performing Child Road Safety Audits at county level as the Road Safety Strategy requires Local Authorities to perform periodical measures to identify the key areas to focus the audits. Limitations of the study included the small number of wards with available land use data which restricted the number of variables used as well as the models’ sensitivity, and the level of disaggregation of the data, which limited the application of further regression techniques and post modeling tests.

Nevertheless the study finds that association of land use to child pedestrian casualties can reveal important linkages where underlying characteristics are likely to be causative factors of such casualties. It performs a mesoscopic level accident analysis that looks for associative factors in larger areas that constitute trip attractors and generators for child pedestrian travel, as opposed to a microscopic analysis that would look at individual accident sites for direct causative factors. It can therefore be helpful as an indicative tool but not as a deterministic one.
References


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