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The determination of the relationship between friction and traffic accidents

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Erik Teekman

Promotor:

Prof. dr. Tom Brijs

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“If you examine the records of the city of Copenhagen for the ten or twelve years following World War II, you will find a strong positive correlation between (i) the annual number of storks nesting in the city, and (ii) the annual number of human babies born in the city. Jump too quickly to the assumption of a causal relationship, and you will find yourself saddled with the conclusion either that storks bring babies or that babies bring storks” (Lowry, 2008; unnumbered).

Preface

The notion that friction coefficients are a significant contributory factor in traffic crashes has been firmly entrenched in the literature since the work of Giles (1956). As a result, many highway authorities have set minimum friction requirements for road surfaces, below which the probability of a crash is considered unacceptably high. The safety benefit ascribed to friction coefficients arise from its ability to facilitate various vehicle manoeuvres, most notably braking and cornering.

In the United Kingdom minimum friction coefficient requirements for trunk roads were first prescribed in 1988 in the Design Manual for Roads and Bridges. In 2004 the minimum friction coefficient requirements as prescribed by this policy were either maintained, or increased (Viner et al., 2004). This action is alluring given that since the original 1988 policy, the vehicle fleet has improved significantly not just in terms of vehicle safety, but also in its ability to generate increased levels of skid resistance from the road surface (predominately through advances in vehicle braking systems). This study reinvestigates the relationship between friction coefficients and traffic accidents at a network level.

A total of thirteen network analysis studies were reviewed, twelve of which concluded that there was at least to some degree, an inverse relationship between friction coefficients and traffic accidents (Al-Mansour, 2006, Davies et al., 2005, Hosking, 1986, Kudrna et al., Undated, Kuttesch, 2004, Mayora and Rafael, 2008, McCullough and Hankins, 1966, Moore and Humphreys, 1973, Rizenbergs et al., 1977, Rogers and Gargett, 1991, Viner et al., 2005, Schlosser, 1976). Only Lindenmann's (2006) study found no relationship at all between the coefficient of friction and traffic accidents, a finding supported in part by the studies undertaken by Schlosser (1976), Rogers and Gargett (1991), and Viner et al., (2005).

Despite widespread agreement in the literature that a relationship between friction coefficients and traffic accidents exists, there remains a significant and unexpected level of disagreement as to the exact nature of this relationship. The lack of agreement centres not only on the fundamental elements of the relationship, that being its form (i.e. linear or non-linear), the value of the critical road surface friction coefficient beyond which accidents are considered to increase significantly, but also which road classifications are most affected by changes in friction coefficients. This disagreement is likely to reflect not only national idiosyncrasies arising as a result of research being based on data from different countries and over differing periods, but also the wide array of methodologies employed.

In addition to the conflicting conclusions reached regarding the exact nature of the relationship between friction coefficients and traffic accidents, there is also an apparent disconnect with the

advances made in the fields of both accident theory and driver psychology. Most notably, that an active human failure is required if an accident is to occur (Reason, 2000) and that driver behaviour can be considered to reflect a driver's previous driving experience and ability to assess risk.

The methodology used to investigate the relationship between friction coefficient and traffic accidents in this study rectifies a number of shortcomings found to be inherent in some of the earlier studies. While the changes in methodological approach have largely focused on the treatment of the raw data, the statistical techniques used to test the relationship and consideration of accident severity are also somewhat unique. Analysis of the relationship between friction coefficient and traffic accidents in this study has focused on A-roads with a posted speed limit of 60mph (100km/hr) in Norfolk County.

On the basis of this study, recommendations for further research have been made that would not only enhance the body of knowledge but also improve current friction coefficient management practices.

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Chapter I: Introduction

It has long been regarded that friction coefficients play a significant role in influencing both the frequency and severity of traffic accidents. This widespread acceptance arises due to the road surface's ability to facilitate the development of the skid resistance required for various vehicle manoeuvres, most notably braking and cornering. As a result, many highway authorities have set minimum friction requirements for road surfaces within their jurisdictions.

Due to the most recent changes in policy and the incremental modernisation of the vehicle fleet, this study sets out to re-investigate the relationship between friction coefficient and traffic accidents. Where prescribed minimum friction coefficients are set too low, savings associated with traffic accidents may be possible through increasing friction coefficient requirements. Conversely, where friction coefficient requirements are set too high, savings may be possible through reduced road maintenance expenditure.

This chapter is broadly divided into six sections and sets out to provide the background and context for this study. The first section highlights the scale of the accident problem in Great Britain, following which a brief synopsis of accident theory and the role of skid resistance is provided. The arrival of friction coefficient standards in policy in Great Britain is subsequently discussed, before the research topic is positioned and the research objectives clarified. The final section of this chapter provides an overview of the contents of this study.

1.1 The Accident Problem in Great Britain

Traffic accidents and their associated consequences continue to be a significant problem for transportation professionals (Noyce et al., 2005). In Great Britain in 2011 alone, a total of 1,901 people died as a result of reported traffic accidents and over 200,000 people suffered some form of injury (Department for Transport, 2012). To put these figures into context, based on an estimated population in Great Britain of 62.8 million in mid-2011 (Office for National Statistics, 2012), these figures represent one death in every 33,000 inhabitants, and almost one injury in every 310 inhabitants in Great Britain. Over the past decade there has been a continual decline in the number of reported injury and fatal accidents in Great Britain, as depicted in Figure 1.

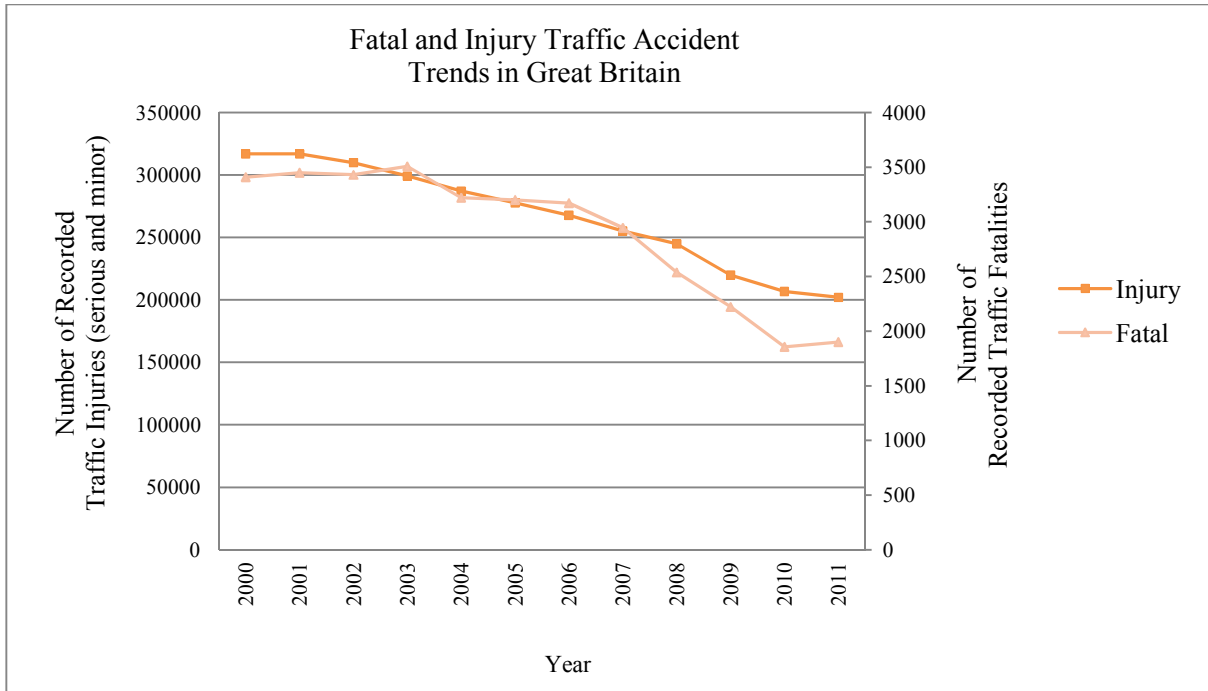


Figure 1: Traffic Accident and Injury Trends in Great Britain

The reduction rate of injury accidents as depicted in Figure 1, is however likely to be understated given that research comparing police STATS19 records with hospital accident and emergency data suggests improving reporting rates. Research undertaken by Simpson (1996) found that based on data obtained in 1993, only 50% of accident casualties seeking hospital treatment were captured on police accident records. Using a similar methodology Ward et al., (2005) using data collected in 2001, suggested that the reporting rates had improved to approximately 70%.

While the number of traffic related deaths and casualties have reduced significantly over the last decade, the impacts induced by individual traffic accidents is unlikely to have changed. The level of impact undoubtedly varies for each accident, but is likely to induce at least some level of: physical and emotional suffering, material damage, burden on emergency services and the health system, lost economic output, and insurance and legal cost (Department for Transport, 2009). Monetisation of these impacts suggests that each traffic related fatality and serious injury costs the British economy, on average, almost £1.8million, and £205,000 respectively (Department for Transport, 2009).

Considering the social and economic impacts of traffic accidents, it is undeniable even with the advances made in reducing road trauma in recent years that too many people continue to be injured or killed on roads in Great Britain.

1.2 Accident Causation

Over the last century, accident theory has progressed significantly from the concept of ‘accident proneness’ which suggested that some people were more susceptible to being involved in accidents than others. Today, accidents are generally viewed as process based events that typically involve numerous interacting elements (Benner, 2007). Perhaps one of the most dominant theories is Reason’s (2000) ‘Swiss Cheese Model’, which is now commonly cited in the literature. The Swiss Cheese Model considers that accidents occur as a result of an ‘accident trajectory’ penetrating all ‘defensive layers’ in the prevailing circumstances. While developed for organisational applications, Reason’s (2000) theory is also applicable to the field of road safety, where the driver, vehicle and environment form the basis of the defensive layers, as depicted in Figure 2.

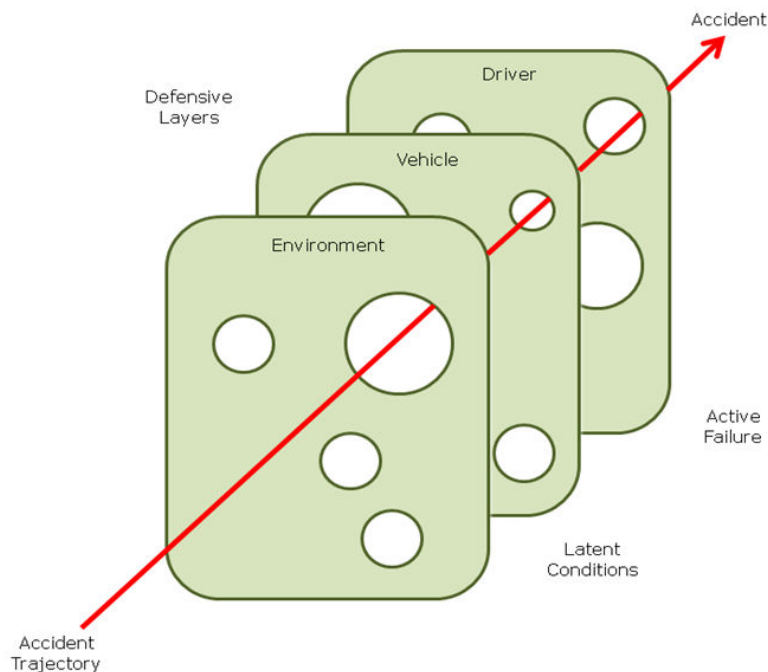


Figure 2: Adapted Depiction of Reason’s (2000) Swiss Cheese Accident Model

Reason (2000) noted that in nearly every case, there were two requirements for an accident trajectory to penetrate the required defensive layers and result in an accident. First there needed to be risk inherent in the system (a latent or dormant condition), and second there needed to be an active failure which required a person involved in the system to commit an unsafe act, whether intentionally or not (Reason, 2000).

The general requirement for an active failure in the Swiss Cheese Model is supported by the earlier work of Treat et al., (1979), who’s research investigated the causes of traffic accidents. Treat et al., (1979) found that 57% of accidents could be attributed solely to the driver, 3% to the road

environment, and 2% to the vehicle, as summarised in Figure 3 below. The remaining 37% of accidents were considered to be the result of two or more specific causal factors.

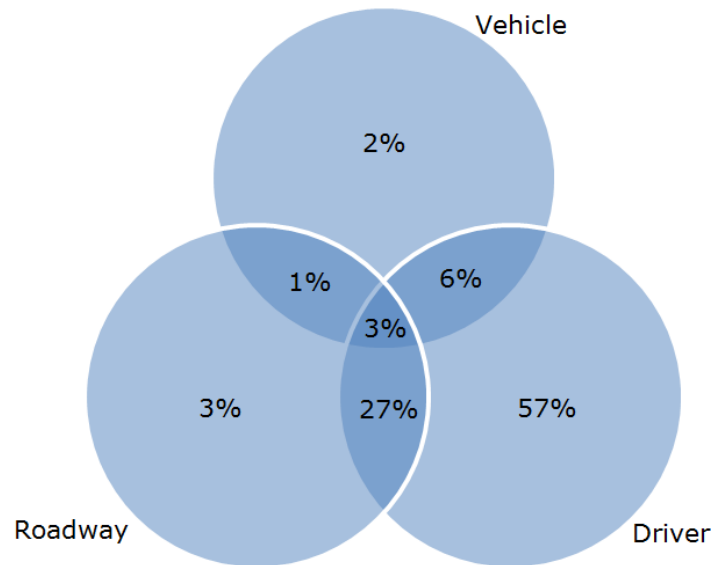


Figure 3: Adapted Depiction of Treat et al., (1979) Accident Causal Factors (PIARC, 2003).

Despite widespread acceptance amongst accident theorists that accidents occur due to the interaction between numerous elements, there continues to exist a significant body of literature suggesting that skid resistance is a significant contributory factor in accidents (Lamb, 1976, Wallman and Åström, 2001, Yaron and Nesichi, 2005). In some cases the literature even suggests skid resistance to be a primary contributory factor (Flintsch et al., 2009, Kokkalis and Panagoull, 1998), with research by Larson (2005) suggesting that approximately 30% of highway fatalities in the United States are the result of inadequate road surface friction coefficients.

Throughout the literature the terms: skid resistance, friction force, skidding resistance, braking force coefficient, pavement/road surface skid resistance, pavement/road surface friction, are all commonly used to describe both the level of friction offered by the road surface, and the overall skid resistance available between the vehicle and the road surface. In some cases, authors have even used the terms interchangeably. As the literature failed to provide clearly established terms and associated definitions, the terms 'friction coefficient' and 'skid resistance' have been used, in this study they are defined as:

Friction coefficient: The level of friction offered by the road surface, as measured by friction measuring devices. This value is considered to be static at any one point in time. It is noted that the terms friction coefficient and coefficient of friction will be used interchangeably.

Skid resistance: The total level of friction that a vehicle can derive from the road surface. This value is considered to be dynamic as it will vary depending on vehicle related factors.

The value attributed to friction coefficient arises due to its ability to enable vehicles to ‘harness’ the friction forces required by drivers if they are to successfully accelerate, decelerate and/or change direction (Wallman and Åström, 2001). Where the friction coefficient for a given road is too low for the desired manoeuvre, vehicles can lose traction and skidding of the vehicle will ensue (Viner et al., 2004). Though skidding can result in vehicles sliding along the road surface with drivers not in control, most commonly, a lack of skid resistance is experienced as an increase in braking distance (Lamb, 1976, Mayora and Rafael, 2008).

In a purely abstract sense, the laws of physics state that braking distance is not only a function of friction (f) but also one of acceleration due to gravity (g), roadway grade (G), and the initial vehicle speed (V) (Trinh, Undated). The formula for calculating braking distance is:

$$\text{Braking Distance} = \frac{V^2}{2g(f + G)}$$

While initial vehicle speed has a significant impact on the braking distance, so too does the level of friction provided by the road surface. Typically, friction coefficients are placed on a scale ranging between 0 in icy conditions, to 1.0 representing road surfaces enabling the best skid resistance (Mayora and Rafael, 2008). Using the braking distance formula above, the influence of friction coefficient on braking distance (for vehicles travelling at 100km/hr on a level surface) has been illustrated in Figure 4. It is noted that actual braking distances will vary as the level of friction generated between vehicles and the road surface may be more or less than that measured.

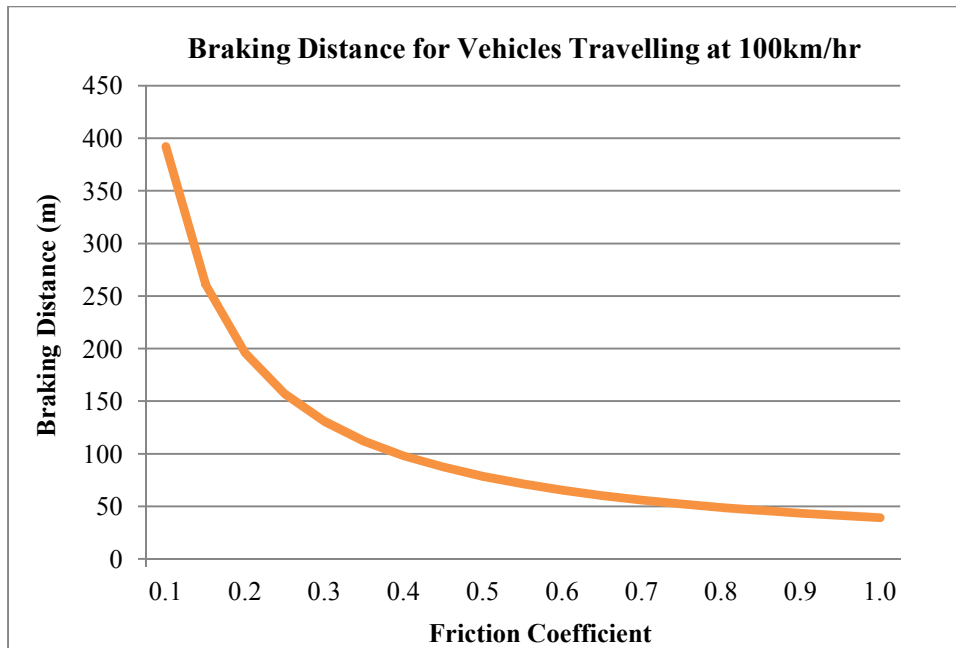


Figure 4: Influence of Friction Coefficient on Braking Distance at 100km/hr

The increase in braking distance with decreasing friction coefficient presents a problem in two ways. First, increased braking distances directly increase the chances of an accident occurring (Australian Academy of Science, 2003). Second, as the level of kinetic energy increases so too does the impact force and therefore the likely level of injury sustained by participants in the accident (Fildes and Lee, 1993).

1.3 The Arrival of Friction Coefficient Standards in Policy

Giles' (1956) paper, 'The Skidding Resistance of Roads and the Requirements of Modern Traffic' provided the first in-depth study investigating the link between friction coefficient and traffic accidents. Giles (1956) considered that vehicle skid resistance requirements varied during different parts of the journey, namely: braking, acceleration and cornering. At 'difficult' sites such as junctions, roads with a gradient, or bends, Giles (1956) found that improved skid resistance prevented further skidding accidents from occurring.

Giles (1956) found that accident risk first become measureable at sites with friction coefficients between 0.55 and 0.60, and increased dramatically as friction fell, a finding broadly supported by the majority of the literature. However, there is a small but growing body of literature that suggests friction coefficients may in fact have negligible impact on traffic accidents, or at least in some traffic situations (Breyer and Tiefenbacher, 2001, Lindenmann, 2006, Piyatrapoomi et al., 2008, Rogers and Gargett, 1991, Seiler-Scherer, 2004).

As a road surface's friction coefficient typically decreases with time (Highways Agency, 2004b), minimum friction coefficients are commonly set out in road design, and maintenance standards. This is not surprising given the value generally attributed to skid resistance in preventing traffic accidents. In the United Kingdom, policy has specified friction coefficient requirements for trunk roads since 1988 (Viner et al., 2004).

In 2004 the United Kingdom's friction coefficient policy was revised following an extensive review carried out in 1999 (Viner et al., 2004). The policy establishes investigatory levels for varying site categories and is included within the Design Manual for Roads and Bridges (Highways Agency, 2004a), as illustrated in Table 1. The level at which they are set reflects the desire to ensure that an adequate level of friction coefficient is provided over the whole trunk road network. It is noted that dark shading indicates the investigatory level for most trunk road situations, light shading is used for sites considered to have a low traffic accident risk

Site category and definition		Investigatory Level at 50km/h							
		0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65
A	Motorway								
B	Dual carriageway non-event								
C	Single carriageway non-event								
Q	Approaches to and across minor and major junctions, approaches to roundabouts								
K	Approaches to pedestrian crossings and other high risk situations								
R	Roundabout								
G1	Gradient 5-10% longer than 50m								
G2	Gradient >10% longer than 50m								
S1	Bend radius <500m – dual carriageway								
S2	Bend radius <500m – single carriageway								

Table 1: United Kingdom's Trunk Road Investigatory Levels (Highways Agency, 2004a)

Where routine measurements determine that friction coefficients are at or below the investigatory level, a more detailed site investigation is required. The investigation according to the Design Manual for Roads and Bridges should in first instance determine the suitability of the investigatory level, taking into account amongst other factors: the potential for conflict between road users, road geometry, likelihood of queuing where vehicle operating speeds are generally high, and the number and standard of adjoining accesses and junctions (Highways Agency, 2004a). The purpose of this investigation is to inform whether the road surface friction deficiency needs to be addressed to minimise accident risk, or not.

1.4 Positioning the Research Topic

The need to provide minimum friction coefficients in order to reduce traffic accidents is firmly entrenched in both the literature and in the road maintenance policies of many countries, both of which are typically backed by significant funding and industry support. As part of the United Kingdom 2004 friction coefficient policy update, the required friction coefficient provision for the various site categories were either maintained or increased (Viner et al., 2004), as tabulated in Appendix A. This change is surprising given that since the original 1988 policy, the vehicle fleet has improved significantly not just in terms of vehicle safety, but also in their ability to generate and maximise skid resistance levels from the road surface (predominately through anti-lock braking systems). The change is also interesting given that there appears to be widespread acceptance that the road environment, may only be responsible for very few traffic accidents.

This study considers that prescribed friction coefficients should represent the delicate balance between two competing objectives. The first seeking to minimise the social and economic costs associated with road trauma, while the second seeks to maximise the serviceable life of the road pavement, ensuring maximum economic return from the road asset.

Where even a marginal reduction in prescribed friction coefficients can be achieved without adversely effecting road safety, extensions to road surface life may be possible. This would enable not only an increase in the economic return from the road surface, a reduction in environmental and road user costs associated with the replacement of the road surface, but it would also enable resurfacing budgets to be used for other purposes. Conversely, where prescribed friction coefficients are set too low, accident savings may be available by revising the prescribed level upwards. Such savings would however be at the expense of decreased road surface life.

1.5 Research Objectives

If the optimum balance between maximising the serviceable life of the road surface and the provision of a safe level of friction is to be struck, there is a need to determine the level of friction coefficient that should be provided. Determining this level, requires the optimisation of the friction coefficient and monetised cost of traffic accidents relationship, with the relationship between friction coefficient deterioration and resurfacing cost.

This study seeks to investigate the relationship between friction coefficient and the monetised cost of traffic accidents, and therefore forms one half of the research required to determine the exact optimised point. The following objectives for this study are:

- Based on a review of the literature, detail the characteristics that influence friction coefficients, and the factors that affect skid resistance.
- Review the literature to identify and quantify the findings of previous research investigating the relationship between friction coefficients and traffic accidents.
- Determine whether a robust methodology exists that will enable the relationship between friction coefficients and accidents to be accurately quantified. Use, modify or develop a suitable methodology to test the relationship.
- Applying the methodology, determine how friction coefficients are related to traffic accident frequency and severity.
- If possible, monetise the relationship between friction coefficient and traffic accidents, based on both accident frequency and severity.

1.6 Overview of Study

This study has been divided into six chapters, the contents of which are summarised in the following subsections.

Chapter I: Introduction

This introductory chapter has provided an outline of the traffic accident problem in the United Kingdom, and put the problem into context. To ‘set the scene’ for the reader, a brief synopsis of accident theories, with a particular focus on Reason’s (2000) Swiss Cheese Model, and Rumar’s (1985) theory on accident causation was provided. The terms ‘friction coefficient’ and ‘skid resistance’ as used in this study were also defined. An overview friction coefficient management in the United Kingdom was outlined, from which point the research objectives were established.

Chapter II: Influencing Friction & its Measurement

Chapter II seeks to provide an understanding of the factors that influence friction coefficients and skid resistance. They have been considered individually to allow the clear separation that is required if the relationship between friction coefficients and traffic accidents is to be isolated. The remaining two sections investigate how friction coefficients are measured, and how friction measurements taken by different devices can be compared.

Chapter III: Literature Review

This chapter reviews the available studies investigating the relationship between friction coefficients and traffic accidents. As this study seeks to investigate the relationship at a network level, the review has focused heavily on the findings of such studies, however before and after studies have been acknowledged. Each of the network level studies were considered in terms of the methodology used

and also the results found, where possible results have been displayed graphically. Following the consideration of the available network level studies a summary table is provided, and the findings of the literature review are generally discussed.

Chapter IV: Methodology

Based on the findings of the literature review, Chapter IV outlines how the relationship between friction coefficients and traffic accidents is tested in this study. In fulfilling this role, this chapter details the methods with which data was collected at source, and how the data was subsequently treated and refined. The final section of this chapter is dedicated to outlining the statistical methods used in the analysis.

Chapter V: Data Analysis and Results

Chapter V provides the noteworthy results of the preliminary data analysis, and those resulting from the analysis of the relationship between friction coefficient and traffic accidents. The results are largely presented in graphical format supplemented with explanations, where appropriate. For the purposes of brevity, non-noteworthy results have been excluded from the chapter and are instead provided in the appendices.

Chapter VI: Discussion and Conclusion

The final chapter provides a discussion on the pertinent findings. The conclusions that can be drawn from the results and their implications are then subsequently discussed. The chapter then concludes with a number of recommendations that would not only enhance the body of knowledge, but also improve the current way in which friction coefficients on the road network are managed.

Chapter II: Influencing Friction & its Measurement

This chapter has been broadly divided into four sections. While friction coefficient and skid resistance are to a large part related, separating these two aspects is considered important if the relationship between friction coefficient and traffic accidents is to be isolated and accurately reported on. As such, the first section details the road characteristics that influence friction coefficient, and the environmental conditions that lead to long, medium and short term variation.

The second section focuses on skid resistance and investigates factors influencing a vehicle's ability to generate and maximise skid resistance from the road surface's available friction coefficient. To examine these factors, this section is divided into five parts, focusing on the role of tyres, braking systems, and vehicle operating speeds as well as indirect factors which relate to driver behaviour and road geometry.

The third section provides an outline of the devices available that measure friction coefficients, and provides a more detailed examination of four commonly used apparatus. The fourth section examines the complexities of comparing the measurements taken by different devices and briefly explores how the Permanent International Association of Road Congresses' (PIARC) model can be applied to provide a standardised and comparable measurement.

2.1 Factors Affecting Friction Coefficients

The level of friction offered by the road surface is chiefly determined by the inextricably linked characteristics of the pavement surface, and the prevailing environmental conditions that affect the road surface's long, medium and short term condition. These factors are discussed in the following subsections.

Pavement Surface Characteristics

A road surface's friction coefficient represents the sum of the properties relating to the pavement's macrotexture (also known as texture) and microtexture, which respectively induce hysteresis and adhesion forces on the tyre (Choubane et al., 2004, Hall et al., 2009, Noyce et al., 2005). Macrotexture and microtexture are defined in Figure 5. The influences of macrotexture and microtexture on the coefficient of friction and the environmental conditions which affect them are discussed in the following paragraphs.

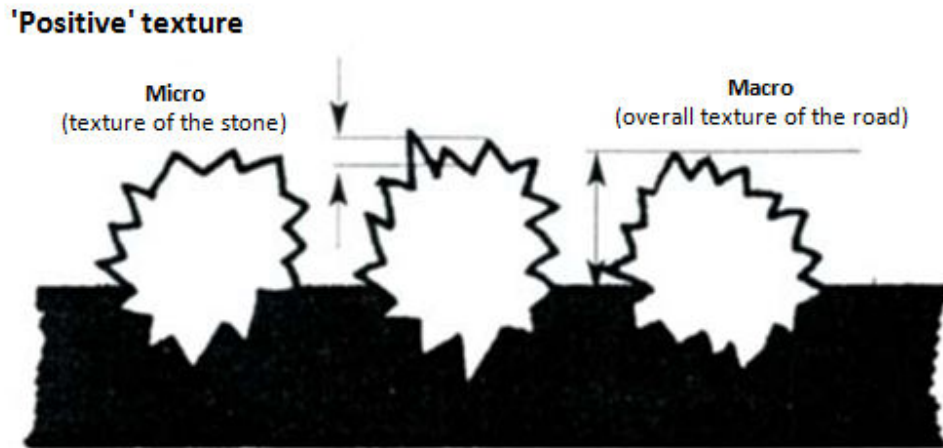


Figure 5: Illustration of Macro and Microtexture on a Positively Textured Pavement (Bullas, 2004)

Macrotexture refers to the overall texture of the road surface (0.5mm – 50mm) (Chelliah et al., 2002), that being the surface irregularities caused by the size, shape and spacing of stone chips in the pavement (Austroads, 2005). In the case of negatively textured pavements such as concrete or asphalt, macrotexture refers to the properties relating to the voids (Bullas, 2004).

Macrotexture primarily contributes to the coefficient of friction in two ways. First, it allows tyres to make ‘dry’ contact with the road surface where texture provides adequate depth to allow water to drain (Roe et al., 1991), thereby reducing the water film thickness (Ong and Fwa, 2007). This function is particularly important as it reduces the risk of aquaplaning in higher speed environments by allowing tyres to maintain contact with the road surface (Bonnot and Ray, 1976, Cenek et al., 2002, Chelliah et al., 2002, Rogers and Gargett, 1991).

The other way in which macrotexture contributes to the coefficient of friction is through the deformation of tyres as they roll over the projections of the road surface (Roe et al., 1998, Roe et al., 1991). Due to the elastic nature of tyres, such deformation induces internalised friction within the tyre (which is released as heat), a process known as hysteresis (Hall et al., 2009). As speed increases the ability of the macrotexture to contribute to skid resistance through hysteresis decreases, the rate of this decrease is more rapid where texture depth is 0.7mm, or less (Roe et al., 1998) and 2.0mm for concrete road surfaces rehabilitated through longitudinal grooving (Bonnot and Ray, 1976). However, some suggest that as speed increases so too does the hysteresis component (Cenek et al., 2002).

Research suggests that surfacing materials (Roe et al., 1998, Roe et al., 1991) and texture types (traverse or random) (Henry et al., 2000, Roe et al., 1998) do not influence the ability of macrotexture to contribute to the drainage of water or induce hysteresis. However, surfacing materials do affect macrotexture over time (Roe et al., 1991) as the low points are filled with dust and debris, and the

peaks are worn away by traffic over time, or imbedded in the case of negatively textured pavements (Ali et al., 1999, Lamb, 1976). The road surface is also slowly compacted by passing traffic (Ali et al., 1999), most significantly by heavy vehicles (Chelliah et al., 2002). On binder rich surfaces, bleeding causes the voids in the macrotexture to be filled, overtime this creates a smooth surface (Ali et al., 1999). As a result, the age of the road surface, construction methods and materials, and the amount of traffic will all impact on the rate at which compaction, bleeding and wearing occurs.

Microtexture refers to the surface properties and irregularities of individual stone chips embedded in the road pavement (<0.5mm) (Chelliah et al., 2002). Microtexture contributes to the coefficient of friction through the creation of adhesion forces, which occur as a result of the tyre interlocking with the road surface (Roe et al., 1998) and molecular bonds being sheared as the rubber of tyres pass over the road surface (Noyce et al., 2005). Microtexture contributes to skid resistance at all speeds (Cenek et al., 2002, Roe et al., 1998, Rogers and Gargett, 1991), and provides a greater contribution than macrotexture where vehicle operating speeds are low (<50km/hr) (Hall et al., 2009, Noyce et al., 2005, Roe et al., 1991).

The ability of a road surface's microtexture to contribute to the creation of adhesion forces varies over time (Roe et al., 1991). During drier periods traffic (particularly heavy vehicles) in combination with fine particles of dust and debris polish the stone chips in the road surface reducing the overall microtexture provided. In contrast, microtexture is generally improved during periods of frost due to the application of salt and grit which restores the surface through the process of abrasion (Burton, Undated, Roe et al., 1991). At some point, the contribution that microtexture makes to the coefficient of friction will reach an equilibrium level, though over the long term this will gradually decline (Burton, Undated, Chelliah et al., 2002).

For the purposes of clarity it is noted that pavement megatexture (Highways Agency, 2004a) and pavement roughness (Data Collection Ltd, 2006, Noyce et al., 2005) are considered to have a more significant impact on rolling resistance and ride quality than skid resistance. In summary megatexture is defined as any significant surface irregularity, these are often clearly visible to drivers and encompass irregularities such as pot holes, rutting, cracks and joints etc (Noyce et al., 2005), while pavement roughness is defined as longitudinal surface irregularities such as bumps and dips (Data Collection Ltd, 2006).

Long Term Variation in the Coefficient of Friction

The friction coefficient as provided by the road's macrotexture and microtexture typically diminishes as the road surface ages. The rate of this deterioration in the longer term (defined in this study as variation occurring over more than one year) relies to a large extent on three key factors: the properties

of the pavement surface (aggregate and mix characteristics), the average annual daily traffic (and the associated stress induced by the proportion of heavy goods vehicles, and respective driver behaviour), and the road's geometry.

The properties of the pavement surface can significantly affect the coefficient of friction in the long term (Ali et al., 1999). The mineral composition of the aggregate determines the polished stone values (PSV) which in turn determines the aggregate's susceptibility to resist polishing under the stresses of traffic and environmental loading (Hall et al., 2009). Historically an aggregate's PSV was considered to provide a good indication of friction coefficient (Hosking J. R. and Woodford, 1976) however more recent research by (Kennedy et al., 2005) suggests that this is incorrect. PSV also does not necessarily provide a good indication of a road surface's long term coefficient of friction equilibrium (Kennedy et al., 2005, Wilson and Kirk, 2005), but it does provide a good indication of expected long term deterioration rates of the friction coefficient (Burton, Undated, Kennedy et al., 2005).

All properties of the road surface being the same, the rate of road surface polishing is directly related to the level of traffic, in particular the number of heavy goods vehicles (Ali et al., 1999, Chelliah et al., 2002, Kennedy et al., 1990), and the levels of inter-facial stresses induced (D'Apuzzo and Nicolosi, 2007, Woodward et al., 2004). The rate of polishing due to inter-facial stress tends to increase as the size of the aggregate increases, due to the higher levels of stress induced on each chip (Chelliah et al., 2002).

The rate of a road surface's friction coefficient deterioration is also affected by road geometry. On sections with increasing gradients and/or corner/curve radii, the rate of polishing increases due to the additional demand for skid resistance, and the associated increase in inter-facial stresses induced by vehicles (Chelliah et al., 2002).

Medium Term Variation in the Coefficient of Friction

In the medium term (defined in this study as seasonal variation occurring within one year), the coefficient of friction offered by the road surface can vary significantly. Rogers and Gargett (1991) found that seasonal variation could vary by over 25%, a finding not too dissimilar from the findings of Hosking (1986) and Wilson and Kirk (2005) who suggested that variation may be up to 30% of its average value. The typical seasonal variation of road surface's friction coefficient is illustrated in Figure 6. It is noted that on newly sealed surfaces however, friction coefficients tend to increase as the binder wears off (Burton, Undated, Mercer et al., 1994).

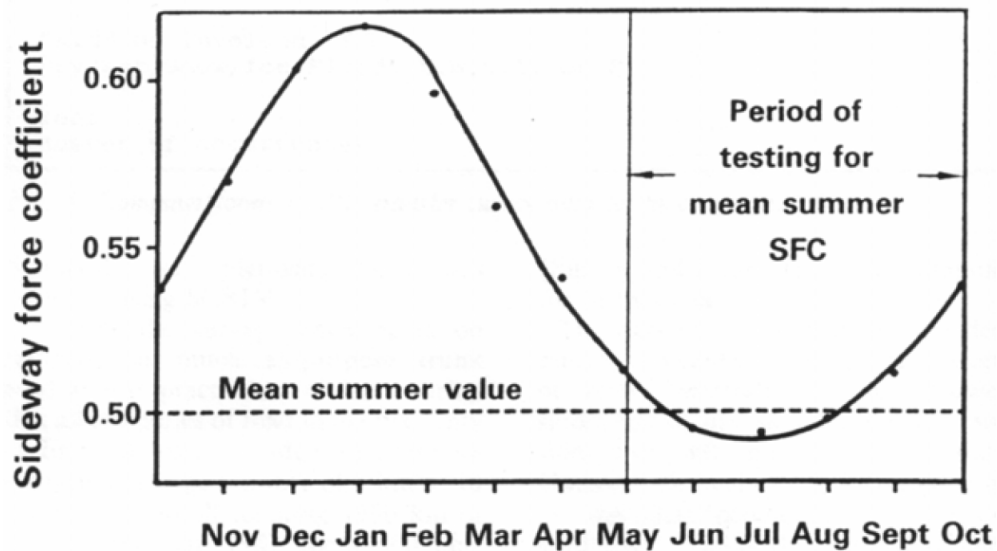


Figure 6: Seasonal Variation of Road Surface Friction (Rogers and Gargett, 1991)

Additional variation in friction coefficients can result from short-term weather patterns. For each day with no rain, skid resistance reduces by 0.01 (as measured by SCRIM), to a minimum of 0.1 below the maximum value (Kennedy et al., 2005).

Two dominant theories exist for the causes of seasonal variation, the first considers that variation is due to polishing and abrasion processes, the second theory concerns the changes in road surface temperature (McDonald et al., 2009).

Temperature has been muted as a possible cause of seasonal variation since at least 1986 with the findings of Hosking (1986). Recent literature supports the role of pavement temperature on the seasonal variation of road surface friction, though the quantified effects vary (Ahammed and Tighe, 2009, Hall et al., 2009, Lamb, 1976, McDonald et al., 2009). The role of temperature and its impact on friction coefficients was perhaps most succinctly provided by McDonald et al., (2009), who stated that:

“All three analyses provided strong evidence for the hypothesis that seasonal variations result from temperature-related causes. Thermodynamic considerations were observed to dominate the changes of the rate-based capacity for venting energy at the tire-pavement interface. This would be the case if van der Waal’s adhesion was the primary mechanism behind friction, because the exciting of individual atoms and molecules from forming junction and rupturing them would create heat. Thus, less energy could be released into hotter more excited, surface and substrata” (McDonald et al., 2009; pg.135).

The conclusions of McDonald et al., (2009) are however somewhat different to that of Ahammed and Tighe (2009) who suggested that the reduction in friction coefficient as temperature increased, was likely to be associated with a reduction in tyre hardness. While the effects of seasonal variation are perhaps not well understood, there is general consensus that friction coefficient's are at their highest in winter and lowest in summer (Chelliah et al., 2002, Hosking, 1986).

Short Term Variation in the Coefficient of Friction

In the short term (defined in this study as day to day variation), weather is the primary determinant of a road surface's friction coefficient, and its impact can be significant. Wet pavements provide a lower friction coefficient as water effectively acts as a lubricant (Andrey et al., 2001, Schlosser, 1976, Rogers and Gargett, 1991). Ali et al., (1999) suggests that friction coefficients on wet road surfaces is approximately 50% of that offered by dry roads. At low speeds (<32km/hr) water film thickness has minimal impact on the reduction on the coefficient of friction, the opposite is true where speeds increase above 64km/hr (Hall et al., 2009). The rate at which friction coefficients decline, typically increases in line with water film thickness (Hall et al., 2009).

The work of Kulakowski and Harwood (1990) found that a water film thickness as little as 0.05mm could result in a reduction in friction coefficient by between 20 and 30%. In addition, as water film thickness on the road pavement increases so too does the uplift force it exerts, which directly increases the risk of aquaplaning (Hall et al., 2009, Ong and Fwa, 2007, Pelloli, 1976). Aquaplaning results where the uplift force provided by the water film restricts the ability of the tyre to make contact with the road surface, and is therefore a function of vehicle speed, wheel load, tyre inflation and water film thickness (Ong and Fwa, 2007), and tread depth (Fwa et al., 2009). While macrotexture is noted for its importance in providing drainage routes, it is also acknowledged that adverse pavement megatexture and roughness can restrict drainage resulting in localised water ponding (Kamplade, 1990).

Like water, contaminants (including: dirt, dust, and oil) have an ability to act as a lubricant at the point of contact between the tyre and the road pavement (Hall et al., 2009). Research by Yaron and Nesichi (2005) found that due to the increased load of contaminants, rain events after long periods of dry weather decreased friction coefficients more than rain events that did not follow extensive periods of dry weather. While Yaron and Nesichi's (2005) research was based in Israel where the sub-tropical semi-arid climate where an eight month period without precipitation are not rare, the findings do concur with that found by Kennedy et al., (2005). However, it is noted that in an investigation into friction coefficient variation, Ahammed and Tighe (2009) found that the length of the dry period preceding the testing day had no statistically significant impact on the variation of friction coefficient.

Due to the conflicting nature of the literature, it is unclear whether the length of dry period preceding a rain event significantly affects friction coefficients.

Temperature of the pavement surface is known to reduce the coefficient of friction offered by a road surface (Hall et al., 2009, Hosking, 1986). The exact effect of pavement temperature on friction coefficients is difficult to quantify from the literature (Hall et al., 2009), Ahammed and Tighe (2009) described temperature to be a significant factor, while conversely Ali et al., (1999) noted its effect to be minimal (about 0.003 Sideways Force Coefficient unit per 1°C change). There is however little debate that snow and more significantly ice (Nakatsuji et al., 2005) present a profound reduction in the coefficient of friction offered by the road surface (Hall et al., 2009, Jamieson and Dravistski, 2005).

2.2 Factors Affecting Skid Resistance

In Chapter I, skid resistance was defined as the total level of friction that a vehicle can derive from the road surface. The level of skid resistance is therefore dependant not only on the friction coefficient offered by the road surface, but also on the ability of the vehicle to ‘harness’ it. The ability of the vehicle to maximise skid resistance relies chiefly on the vehicle’s tyres, braking system, and operating speed. The role of these factors, and the effect of driver behaviour and road geometry are briefly discussed in the following subsections.

The Influence of Tyres

The ability of a tyre to contribute to the development of hysteresis and adhesion forces is affected by properties relating to the tyre, including: hardness of the rubber compound, tread depth, tread pattern, tyre pressure, and contact area.

The hardness of the rubber compound in the tyre has a significant bearing on the ability of the tyre to deform and envelope around the macrotexture. Tyre hardness therefore dictates at least to some extent, the level of hysteresis forces that can be generated (Parfitt, 2004). A study by KOAC-WMD in 2000 found that even ‘standardised tyres’ from different batches could have a marked impact on the measured friction coefficient (Wallman and Åström, 2001), Figure 7 illustrates this difference for a number of ‘identical’ tyres from different batches. As the original study could not be located and therefore reviewed, it is not clear how tyres of different ages were accurately compared given that rubber degradation may have occurred, and could be responsible for some of the variation found.

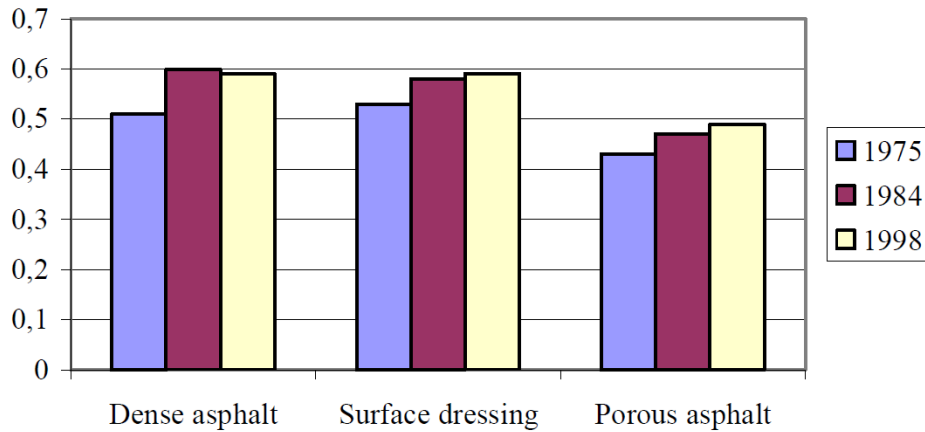


Figure 7: Measured Friction Coefficients by PIARC Test Tyre Batch (Wallman and Åström, 2001)

Where road surfaces are wet, tyre tread depth and pattern play a significant role in dispersing surface water and allowing ‘dry’ contact between the tyre and the road surface (Wallman and Åström, 2001). Where tyres are bald or where tread depth is less than the water film thickness on the road surface, skidding resistance is greatly reduced (Bullas, 2004) at both high and low speeds (Roe et al., 1998). Figure 8 depicts the relationship between tyre tread depth and road accidents involving utility poles. At high speeds, bald or low tread depth tyres may result in aquaplaning where tyres lose complete contact with the road surface (Fwa et al., 2009), further increasing the risk of a traffic accident occurring. Through the provision of additional water discharge channels, tyre tread depth and pattern influences the level of dry contact with the road surface (Fwa et al., 2009).

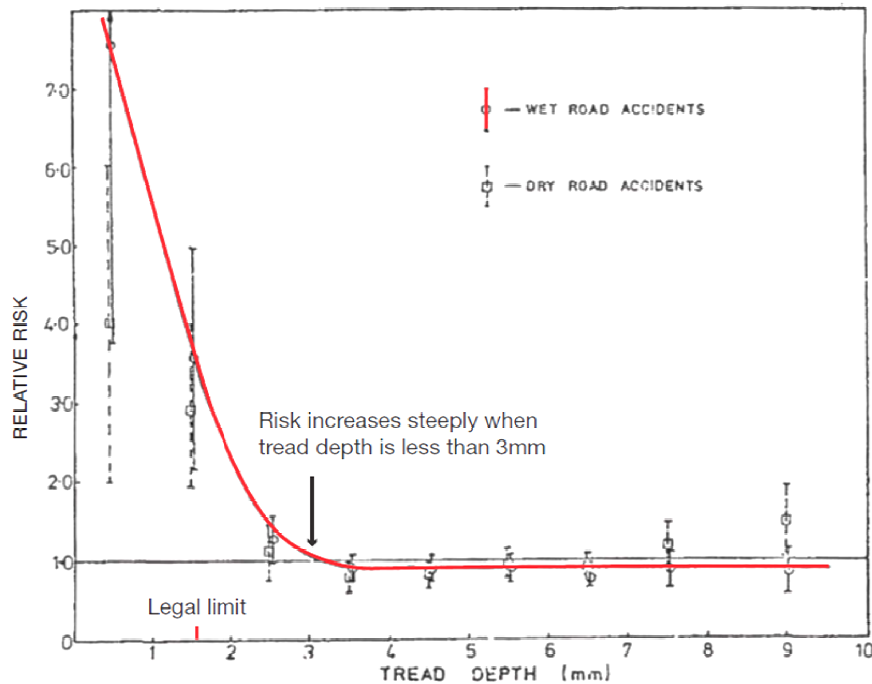


Figure 8: Relationship Between Tyre Tread Depth and Utility Pole Accidents (Bullas, 2004)

Tyre pressure is also an important factor in reducing aquaplaning risk given that aquaplaning is a direct function of: water film thickness, vehicle speed, wheel loading, and tyre pressure (Ong and Fwa, 2007). The correct tyre pressure is also important in reducing the likelihood of skid related accidents due to uneven and excessive wear and poor handling, in the case of under-inflated tyres, and reduced contact with the road surface in the case of over-inflated tyres, due to rounding of the tyre face (Bullas, 2004).

Increasing the contact area between the road surface and the tyre could also improve the ability of vehicles to generate skid resistance (Williams, 1992, Hall et al., 2009, Austroads, 2005). The extent of this increase will however be affected negatively to some extent, due to the change in the vertical load to contact patch area ratio (Nakatsuji et al., 2005, Nice, Undated, Ong and Fwa, 2007).

The Influence of Braking Systems

At present there are two main braking systems available in vehicles, locked wheel (disc and drum brakes), and anti-lock braking systems (Karr, 2004). When a wheel is locked during an emergency braking event, as illustrated in Figure 9, maximum grip is typically achieved at the beginning of the braking cycle before reducing as braking effectiveness stabilises (Roe et al., 1998).

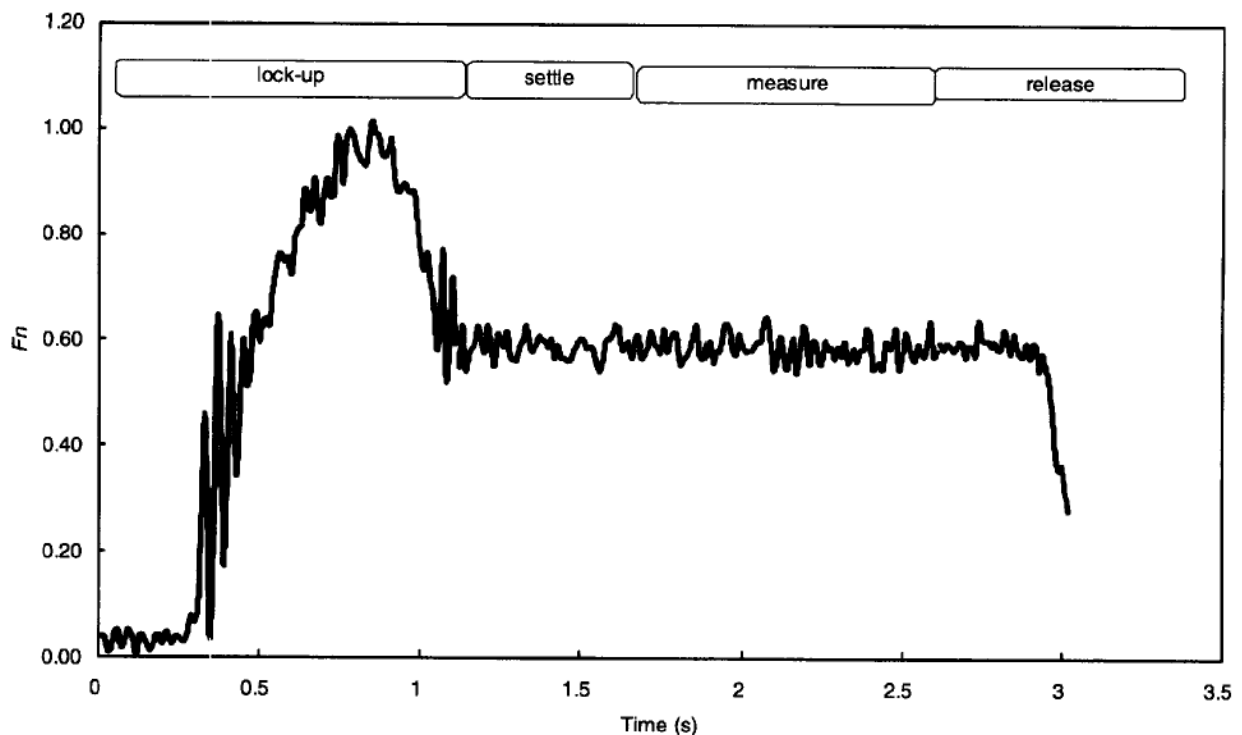


Figure 9: Representation of Locked-Wheel Skid Cycle Braking Performance (Roe et al., 1998)

Compared with locked wheel braking systems, vehicles equipped with anti-lock braking systems are able to generate higher levels of skid resistance (Roe et al., 1998). This is because rapid and

continuous removal and application of the brakes ensures that the interaction between the tyres and the road surface remain in the early stages of the 'locked-wheel skid cycle' (as illustrated in the lock-up stage in Figure 9) where maximum skid resistance can be achieved (Yeoman, 2005).

Wallman and Åström (2001) determined that maximum skid resistance could normally be attained where braking systems allowed a rate of slip of between 7 and 20%. Figure 10 illustrates how the rate of slip affects the level of skid resistance achieved, locked wheel braking systems are represented by 100% slip, to the extreme right of the graph.

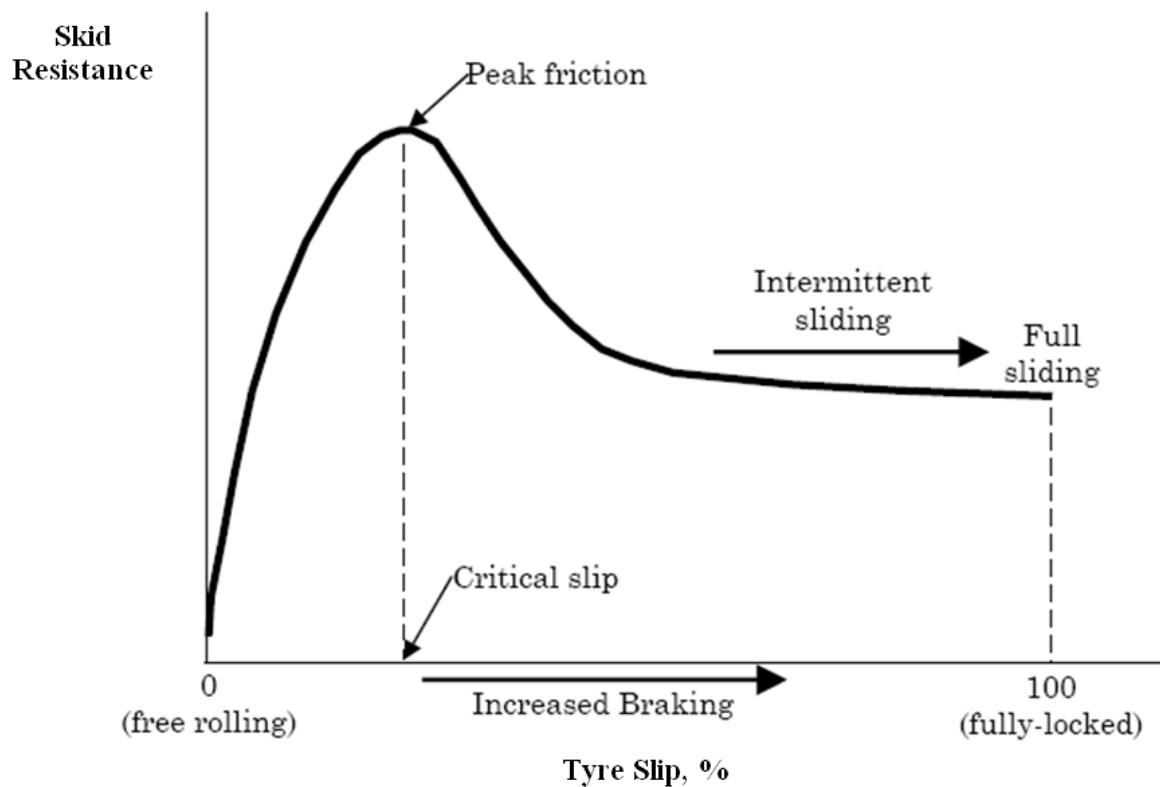


Figure 10: Relationship Between Tyre Slip and Skid Resistance (Hall et al., 2009) (Adapted)

As Wallman and Åström (2001) alluded to, and Yeoman (2005) explicitly pointed out, the use of one friction number to define a road surface's friction can be very misleading because skid resistance is not constant, it varies according to the rate of slip in braking systems.

On the basis that there continues to be an increasing proportion of vehicles equipped with anti-lock braking systems (Roe et al., 1998), it can be reasoned that on average, the level of skid resistance that the vehicle fleet can derive from the road network, all other factors unchanged, is improving incrementally with time.

The Influence of Vehicle Operating Speeds

As illustrated in Figure 11, vehicle operating speed directly affects skid resistance for the four different pavement types tested. As speeds increase from 20km/hr to 50km/hr skid resistance decreases rapidly, the rate of decline reduces as speeds increase to 80km/hr, and further still to 100km/hr (Roe et al., 1998). At around 100km/hr the point of minimum skid resistance is achieved, beyond which a slight increase in skid resistance is found (Roe et al., 1998). It is noted however that the rate of change in skid resistance will depend to a large extent on road surface texture depth (Ali et al., 1999, Cenek et al., 2002, Roe et al., 1998, Salt and Szatkowski, 1973).

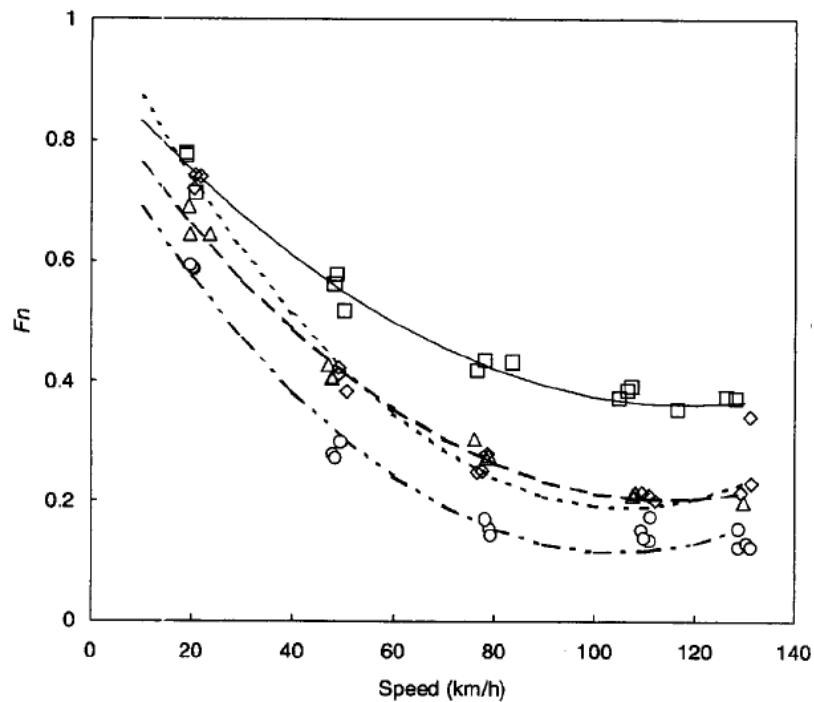


Figure 11: Effect of Speed on Skid Resistance on Four Pavement Types (Roe et al., 1998)

The exact reason for the skid resistance ‘turn-up effect’ as speeds increase is not known, though Roe et al., (1998) suggest that it may be the result of either an increase in the dominance of hysteresis over adhesion forces or due to the decrease in water film thickness applied by the testing device (as a result of consistent water application rates but increased measurement speed). Lamb (1976) established that skid resistance decreased by 14% when speeds increased from 50km/hr to 130km/hr, providing general support for the findings of Roe et al., (1998).

Where vehicle speeds exceed the aquaplaning speed, the road surface will not be able to exert its influence in the generation of skid resistance as the vehicle will not be in contact with the road surface (Ong and Fwa, 2007). Due to differences in tyre characteristics (Fwa et al., 2009) and wheel loadings (Nakatsuji et al., 2005) the actual aquaplaning speed will vary between vehicles.

The Influence of Driver Behaviour

According to Noyce et al., (2005) research undertaken by Heinijoki in 1994 sought to investigate the extent to which drivers adjusted their behaviour based on the friction coefficient provided on roads in Finland. Their conclusions found that drivers had a poor ability to evaluate the actual coefficient of friction, with just 30% of the evaluations correctly matching the measured values.

In contrast Adams (1985) noted that drivers were very sensitive to variations in the level of 'grip' they experience. In cases of special high friction surface treatments which tend to be easily identifiable, Bullas (2004) noted that drivers were observed to increase their driving speed. This was suspected to be the case on 1.9km section of road in New Zealand, which following the application of high friction surfacing resulted in an increase in the number of accidents at both the treatment site and downstream (Hudson et al., 1998).

Based on the research available it is difficult to provide a conclusive statement whether drivers can perceive changing levels of friction offered by the road surface. However, increasing macrotexture is known to increase the level of noise experienced by drivers. While Elvik and Greibe (2003) noted that the relationship between vehicle noise and vehicle operating speed was not well documented, more recent work by the HNTB Corporation (2008) suggests that drivers typically respond to increased noise by reducing vehicle operating speed.

Adams (1985) observed that safety improvements tend to be 'consumed' as performance benefits rather than as safety benefits as they were intended. This observation is supported by the 'risk homeostasis theory', which suggests that drivers have a preconceived level of risk which they are willing to accept in exchange for the benefits they derive from taking that risk (Wilde, 1988). According to this theory, drivers would then interpret the level of risk posed by the road environment and actively compare it with the benefits they wish to derive and the level of risk they are willing to accept. Risks for example may include perceived accident risk (or police detection in the case of illegal behaviour), while benefits on the other hand could include any aspect providing the driver utility such as arriving at one's destination earlier, or factors associated with thrill seeking (Wilde, 1988).

An alternative but similar theory suggests that drivers seek to maintain a specific level of task difficulty which they are happy to accept. As part of this theory however, it is acknowledged that the level of risk perceived by the driver may provide feedback into the mental calculation of task difficulty (Fuller, 2004).

While drivers may react to the road environment based on their desire to accept a certain level of risk, or task difficulty, Fuller (1991) suggests that such mental calculations change over time due to the learning process that manifests itself in two ways. First, drivers must learn appropriate responses to the road environment by knowing what presents a hazard and what does not, such learning is often referred to as a 'trial and error' process. Second, drivers learn that particular behaviour is acceptable due to past experiences that have been favourable. The former learning process is more dominant for novice drivers, while the latter becomes more dominant for the experienced driver (Fuller, 1991).

On the basis of the above, individual driver behaviour should therefore be a product of the perceived level of skid resistance, and a reflection of past experiences. On this basis roads with even slightly reduced levels of friction coefficient provision may be particularly hazardous for drivers who, based on past experiences, are unknowingly driving at the upper limits of the available skid resistance.

The Influence of Road Geometry

Road geometry does not directly affect the level of skid resistance that can be generated by the interaction between vehicles and the road. However, it does have a significant impact on the dynamics of the forces acting on the vehicle in cases of combined braking and changes in direction given that as either the lateral or longitudinal force increase, the other must decrease by a proportional amount (Hall et al., 2009).

Given that the total level of skid resistance that can be generated by a tyre is the sum of lateral and longitudinal friction forces, vehicles changing lateral position will experience a decrease in longitudinal friction forces. On bends, super-elevation (camber) of the road allow the principles of gravitational potential energy to help reduce lateral friction forces produced, ensuring improved longitudinal friction availability (Hall et al., 2009).

When travelling at grade a vehicle's gravitational potential energy will impact on the inherent level of energy, which affects the level of energy required to stop it (Boutal et al., 2008). This means that braking distances will increase and decrease for vehicles travelling downhill and uphill, respectively. The extent of the change is directly proportional to gradient.

At locations such as gradients, bends, and junctions, the high levels of skid resistance demand induces increased levels of stress resulting in increased polishing (Chelliah et al., 2002), especially in the wheel tracks (Highways Agency, 2004a). Where road surface friction coefficients are not restored and demand for skid resistance exceeds that available, accidents will ensue (Viner et al., 2005). Such risks increase where drivers are surprised by 'out of context' curves (i.e. where there is a significant difference between approach speed and curve speed) (Brodie et al., 2009). It is however noted that

while vehicles may commence skidding in a wheel track, they are likely to leave and find higher levels of skid resistance adjacent to the wheel track (Boutal et al., 2008).

2.3 Measuring the Coefficient of Friction

The rate at which a road surface's friction coefficient deteriorates generally accelerates with time (Highways Agency, 2004b), as a result many countries routinely survey roads to ensure that an acceptable coefficient of friction is provided, and that where deficiencies are noted there is timely intervention.

There is no internationally agreed method for measuring the coefficient of friction. In 2000 it was determined that there were more than 20 different machines used to measure the coefficient of friction (Henry, 2000). The devices used can be broadly categorised into four groups: side force devices, locked wheel testers, fixed slip, and variable slip devices (Noyce et al., 2005).

Based on the literature available it appears that the two most commonly used systems for measuring friction coefficient is the Sideway-force Coefficient Routine Investigation Machine (SCRIM) and the American Society for Testing and Materials developed ASTM Standard E274 (ASTM). Details of both SCRIM and ASTM have been provided in the following paragraphs. As a number of studies that are examined in Chapter III are based on Mu-Meter, and Norsemeter ROAR, a brief description of these devices have also been provided.

It is noted that a number of studies examined in Chapter III are based on data collected from undefined skid trailers (or variations of the ASTM standard). As such, no specific description has been provided, however it is noted that the principles will be similar to that of ASTM.

SCRIM

SCRIM (Sideway-force Coefficient Routine Investigation Machine) was developed by the Transport and Road Research Laboratory (TRRL) in the United Kingdom in the early 1970's, it is widely used in Europe (Mayora and Rafael, 2008) and in a number of other countries including New Zealand and three of Australian's seven states (Cenek, 2008). The machine uses a freely rotating wheel fitted with a smooth rubber tyre angled at 20 degrees from the direction of travel. A controlled flow of water wets the road in front of the test tyre and depending on the test machine, a constant or dynamic downwards pressure is applied to the test wheel to ensure that contact with the road surface is consistent and of equal force. Using the sideways force principle, the forces measured are divided by the vertical load to calculate the 'sideway-force coefficient' (SFC). For set road sample lengths

(typically 10m), SFC measurements are averaged to derive the SCRIM Reading (SR), the standard unit used to describe the friction coefficient in the United Kingdom (Highways Agency, 2004a).

The operational procedures governing friction coefficient data collection in the United Kingdom using SCRIM are set out in the DMRB HD 28/04 (Highways Agency, 2004a). This document stipulates that testing should occur (where safety permits) at a target speed of 80km/hr where legal speed limits allow, and at 50km/hr on all other roads and/or where a SCRIM is being used without dynamic vertical load measurement. However, as SCRIM operates in live traffic environments and consistent travel speeds are not always possible, the DMRB HD 28/04 (Highways Agency, 2004a) provides a conversion equation to enable friction coefficient measurements to be converted to a 50km/hr standard.

As the friction coefficient fluctuates throughout the year, the testing season is restricted to the period between 1st of May and 30th of September (Highways Agency, 2004a). Research by Wambold et al., (1995) suggests that the measurements taken by SCRIM at 50km/hr are accurate to 0.005 at a 95% confidence level, and improves to 0.003 as speed increases to 90km/hr.

The conversion equation provided in the Design Manual for Roads and Bridges is based on a linear relationship between speed and friction coefficient. This may be incorrect as research by Roe et al., (1998) found that the effects of speed on the friction coefficient are best modelled by a quadratic equation. Furthermore, the linear equation provided in the Design Manual for Roads and Bridges fails to take into consideration the effects of texture depth, which to a large extent determine the rate of friction coefficient change (Ali et al., 1999, Roe et al., 1998, Salt and Szatkowski, 1973). It is therefore noted that an additional margin of error is likely to exist where SCRIM measurements have been converted using the DMRB 28/04 conversion equation.

ASTM

The ASTM Standard E274 is commonly used in the United States and is profoundly different to SCRIM. ASTM utilises a locked wheel which replicates emergency braking conditions for a vehicle not equipped with anti-lock brakes, generally at a test speed of 40mph (~64km/hr) or 60mph (~96km/hr). Due to ASTM relying on locked wheel testing, it is not able to provide continuous coefficient of friction measurements over an entire section of road (Henry, 2000).

During testing the operator, once travelling at the required test speed, sprays a 0.5mm film of water onto the road surface in front of the test tyre (Mayora and Rafael, 2008). Due to the influence of water film thickness on skid resistance, most transportation departments in the United States prefer to use tyres with ribbed treads to reduce its affect on measurements, though smooth tyres are increasingly

being used due to research suggesting that they provide a better indication of safety (Noyce et al., 2005). The test wheel is lowered onto the road surface and a vertical load is applied. While the testing vehicle continues at a constant speed, the test wheel is locked so that the sliding friction force can be measured.

Sliding friction force measurement are recorded as Skid Number (SN), which directly reflects the standard unit used to describe the friction coefficient in the United States (Mayora and Rafael, 2008). Research by Wambold et al., (1995) suggests that the measurements taken by ASTM at 65km/hr are accurate to 0.007 at a 95% confidence level, and improves to 0.006 as speed reduces to 30km/hr. Work by Choubane et al., (2004) found that measurements taken at 40mph (67km/hr) were accurate to 0.0416 at a 95% confidence level. ASTM's level of accuracy could therefore be considered comparable to that of SCRIM.

Mu-Meter

Like SCRIM, Mu-Meter was designed in the United Kingdom and is a device that is based on side-force principles, there are however a number of differences between Mu-Meter and SCRIM worth noting. Firstly, the Mu-Meter uses patterned tyres (Wallman and Åström, 2001) and rather than having one freely rotating wheel angled at 20degrees from the direction of travel, the Mu-Meter has two test wheels angled at 7.5degrees (Wambold et al., 1995). Third, during normal testing Mu-Meter does not require water application in front of the testing wheel, the measuring apparatus is therefore much more compact and is contained in a small towable trailer unit. While Mu-Meter is most commonly used on runways it can also be used on roads (Team Eagle, Undated), however Wambold et al., (1995) consider that its use on roads is inappropriate given that the configuration of the testing wheel is such that it does not run in the 'wheel tracks'.

Norsemeter ROAR

Like the Mu-Meter, the Norsemeter ROAR can be operated in both dry and wet road conditions, and is a small towable unit. In the case of the Norsemeter ROAR the basic unit can be attached to a trailer or the underside of a larger vehicle. Although the Norsemeter ROAR is capable of operating in fixed slip mode, it is typically used in variable slip mode (Norsemeter, Undated). As a variable slip device, the Norsemeter ROAR is able to measure the friction values that range between a free rolling to locked wheel, in other words it is able to measure the complete friction slip range (Wallman and Åström, 2001). Measurements taken by the Norsemeter ROAR at 60km/hr are accurate to 0.011 at a 95% confidence level (Wambold et al., 1995).

2.4 Comparing Friction Coefficient Measurements

Typically the values measured by friction coefficient devices are placed on a scale ranging between 0 representing icy conditions, and 1 which represents road surfaces enabling the best skid resistance (Mayora and Rafael, 2008), though sometimes these figures are divided by 100 (Noyce et al., 2005). However, as each of the devices utilise different techniques to capture the coefficient of friction, the values collected by the different devices are not directly comparable (Flintsch et al., 2009, Noyce et al., 2005, Wallman and Åström, 2001).

As Wambold et al., (1995) found an average correlation of 0.799 between 37 different measuring techniques (using a total of 25 different devices), it was considered that a model could be developed to allow harmonisation between the different devices. The Permanent International Association of Road Congresses (PIARC) developed a model that provided the first real means to convert friction coefficient measurements taken from different devices into an International Friction Index (IFI), enabling direct comparison. Pereira et al., (Undated) provide perhaps the most succinct explanation of how the IFI can be calculated using the PIARC model, these steps have been outlined in Appendix B.

Henry et al., (2000), and Bustos et al., (2006) reported that the PIARC model gave fairly good results so long as texture values were above 0.7mm, though Henry et al., (2000) considered that grooved and micro-surfaced pavements may have adversely affected the correlation of their test results. In contrast, Flintsch et al., (2009) concluded that the PIARC model did not produce harmonious results following an evaluation of the PIARC model using the various devices used by the Virginia Consortium (which consisted of seven road controlling authorities). However, it is noted that in the sample used by Flintsch et al., (2009), pavements with epoxy overlays and grooved finishes were used, which the research of Henry et al., (2000) as just outlined, suggested would adversely affect results.

Since the development of the PIARC model, no less than twelve attempts have been made to harmonise varying friction devices, most notably, HERMES (Harmonisation of European Routine and Research Measurement Equipment for Skid Resistance) which was commissioned by the European Committee for Standardisation, and concluded in 2002 (Vos and Groenendijk, 2009). The HERMES experiment sought to develop, on the basis of PIARC's IFI scale, a European Friction Index (EFI) for measuring devices used within Europe. The HERMES experiment concluded that even with the new methodology, it was still not possible to harmonise varying measuring devices with sufficient precision to be useful for practical applications (Vos and Groenendijk, 2009), a finding supported by Roe and Sinhal (2005).

Due to the absence of an accepted international friction index, figures reported in the literature will not be converted onto a common scale, similarly the findings of this study will be reported in the same units as the data was collected.

2.5 Summary

In this chapter microtexture and macrotexture were identified as being primarily responsible for the level of friction offered by a road surface due to the adhesion and hysteresis forces they respectively induce on passing tyres. The literature highlighted that the coefficient of friction varied in the long, medium and short term. It was found that the fluctuation in the coefficient of friction varied by as much as 30% over the year, and generally declined gradually in the longer-term. The coefficient of friction was also found to vary significantly in the short term due to changes in the prevailing pavement condition.

The factors affecting the ability of vehicles to maximise skid resistance was also discussed in this chapter. Most poignantly, the literature emphasised that vehicles equipped with anti-lock braking system were able to generate significantly higher levels of skid resistance than vehicles using locked wheel braking systems. On this basis, and in conjunction with the fact that there continues to be an increasing proportion of vehicles equipped with anti-lock braking systems, it was reasoned that the level of skid resistance that the vehicle fleet can generate should be improving incrementally with time.

This chapter also highlighted that it was not immediately clear from the literature whether drivers could perceive the friction coefficient provided by a road surface, and if they could, how this might impact on their behaviour. It was however noted that driver behaviour was likely to be a reflection of past experiences and the ability to identify hazards. It was therefore reasoned that roads with even slightly reduced friction coefficients could be particularly hazardous for drivers who, based on past experiences, were driving to the upper limits of the available skid resistance.

Road geometry was not found to directly impact on the coefficient of friction, however due to the effects of gravitational forces (on gradients), and lateral forces (on bends) it had a significant ability to effect the level of lateral and longitudinal skid resistance that could be generated. The literature also detailed that road geometry had a significant influence on the level of vehicle induced stresses on the road surface, and therefore the rate of polishing, and thus the rate at which the coefficient of friction deteriorates.

This chapter also provided an insight into how the friction coefficient could be measured, and outlined that due to a lack of widespread acceptance of harmonisation techniques, the findings of this study will be reported in the same units as the data was collected.

In conclusion this chapter has encapsulated the necessary background for this field of study and serves as the basis for Chapter III in which the research investigating the relationship between friction coefficients and accident occurrence is examined.

Chapter III: Literature Review

This chapter has been broadly divided into four sections and seeks to provide a comprehensive review of those studies investigating the relationship between friction coefficients and traffic accidents. The first section provides an insight into the historical context, beginning with Batson's 1927 research which determined that there was a need for apparatus to test tractive forces at traffic speeds. While predominately based on theoretical and experimental assessments, an overview of Giles' (1956) work is also provided given that his work was the first in-depth study investigating the relationship between friction coefficient and traffic accidents.

The second section in this chapter provides the state of the art, summarising the identified research which has attempted to ascertain and quantify the relationship between friction coefficients and traffic accidents. This section reviews each study individually, providing a focus on the chosen methodology and the subsequent findings and conclusions. Due to the plethora of research available and the desire to utilise a network based method in this study, this section focuses solely on research that has utilised methods based on network analysis. A brief synopsis of a selected number of before and after studies has been provided in Appendix C.

The third section provides an overview table of the studies reviewed, and acts as a useful reference when reading the final section of the chapter which discusses the research reviewed.

3.1 Origins of Road Friction Coefficient Research

As motor vehicles in the United Kingdom became more prevalent in the 1920's there was a noted increase in the number of traffic accidents. Many of these accidents were attributed to a 'lack of adhesion between the tyre and the road'. In response, Batson in 1927 undertook research that found that speed influenced the tractive effort required to drag a rubber slider over a surface, and that there was a need for apparatus to test tractive forces at traffic speeds. Four years later in 1931, a number of apparatus had been developed (Salt, 1976), the principles of which remain largely unchanged today. Batson, in many ways could therefore be considered as the founder of skid resistance research.

In 1956, Giles' paper 'The Skidding Resistance of Roads and the Requirements of Modern Traffic' was published, presenting the results of the first in-depth study investigating the relationship between friction coefficient and traffic accidents. Giles' (1956) research was predominately based on theoretical and experimental assessments, and concluded that different levels of skid resistance were needed during different parts of the journey; namely at locations where increased levels of braking, acceleration and cornering occurred (Giles, 1956).

Giles (1956) found that traffic accidents tended to cluster on the busiest roads where friction coefficients were low, and at 'difficult' sites such as junctions, bends or roads with a gradient. A before and after comparison found that subsequent coefficient of friction improvements at these locations resulted in a reduction in the number of 'skidding' accidents (Giles, 1956). Though, Giles (1956) suggested that a proportion of accidents occurring within accident clusters will have occurred primarily "through no shortcoming from the road surface, but because of some sudden emergency or factor connected with characteristic of the vehicle or its driver" (Giles, 1956; pg 234).

Giles (1956) found that accident risk first become measureable at sites with road surface friction coefficients of between 0.55 and 0.60, and increased dramatically as friction coefficients fell. On this basis, Giles (1956) recommended that the level of friction coefficient prescribed to a site should depend on the level of 'difficulty', a recommendation that wasn't incorporated into policy in the United Kingdom until 1988 (Viner et al., 2004).

Since Giles' (1956) paper, a wealth of research investigating the relationship between friction coefficients and traffic accidents has emerged. A significant proportion of early work emanated from the United States, the United Kingdom and New Zealand, more recently however, research has been carried out in a number of other countries from around the world.

3.2 State of the Art - Examination of the Research

Research attempting to ascertain and quantify the relationship between friction coefficients and traffic accidents has typically been based on one of two available methods. The most commonly used method involves a comparison of before and after accident rates following road surface coefficient of friction improvement works. Of the before and after studies examined many focused on sites with an unfavourable accident history and do not appear to have taken regression to the mean into account. For this reason the results and subsequent conclusions reached in these studies are of limited use and certainly could not be extrapolated for the purposes of this study. An overview of the findings of the before and after studies reviewed have however been provided in Appendix C.

The second method used is based on a comparison of accident rates and the respective friction coefficients at a network level. A total of thirteen studies were found to utilise a network approach to ascertain and quantify the relationship between friction coefficients and traffic accidents. The studies have been based on data ranging from between 1965 and 2004 and cover a wide range of non-urban roads from a number of countries.

While the earlier studies are unlikely to provide much insight into the relationship between friction coefficients and traffic accidents today, they may help to illustrate whether the demand for friction coefficient is changing, given the improving ability of the vehicle fleet to maximise the level of skid resistance. The available network studies have been reviewed not only in terms of their key findings but also the study methodology utilised. The studies have been discussed in date order, based on the age of the data used, and where possible the findings have been displayed graphically.

1965 (estimated) - State of Texas, United States

In an effort to provide guidelines for surface improvements on highways in Texas, McCullough and Hankins (1966) undertook an analysis of the influence of friction coefficient on accident rates. Sample sections consisted predominately of rural test sections, with a smaller number of urban samples included to enable cross-checking of the results found. In total, 517 random test sections of an unknown length were used in the study. Road geometry was not considered in the study although acknowledged to be a factor by McCullough and Hankins (1966).

A pilot study saw the recorded accidents occurring on the urban samples which were categorised into three distinct groups: those caused by skidding, rain accidents and total accidents. The findings of an initial comparison between accident type and friction coefficient values indicated that the three accident classifications were very closely associated. As a result, the study progressed on the basis that all fatal and injury accidents would be included (McCullough and Hankins, 1966).

McCullough and Hankins (1966) used two methods to relate accident data and friction coefficient data. The direct comparison method found a clear inverse relationship between increasing accident rates and reducing friction coefficient values. McCullough and Hankins (1966) noted that at friction coefficient values below 0.40 and 0.35 the rate of fatal and injury accidents increased markedly for roads with posted speed limits of 20mph and 50mph respectively.

The second method used by McCullough and Hankins (1966) involved analysis by cumulative comparison. Using this method, the average accident rate for each friction coefficient range was determined with the data available for the test sections within each range. McCullough and Hankins' (1966) analysis found that roads with a friction coefficient above between 0.30 and 0.35 showed a decrease in the total number of accidents, a finding McCullough and Hankins (1966) noted as being very comparable to that found in the first test method carried out. However, for road sections with a 20mph speed limit, the critical friction coefficient was noted as being between 0.5 and 0.6, significantly higher than that determined using the first test methodology.

Figure 12 and Figure 13 respectively illustrate McCullough and Hankins' (1966) results relating to the comparison of total accident rates and friction coefficient values on roads with a posted speed limit of 20mph and 50mph roads. McCullough and Hankins (1966) concluded that while the extent to which friction coefficients related to traffic accidents wasn't exactly known, an 'inner-relation' was evident.

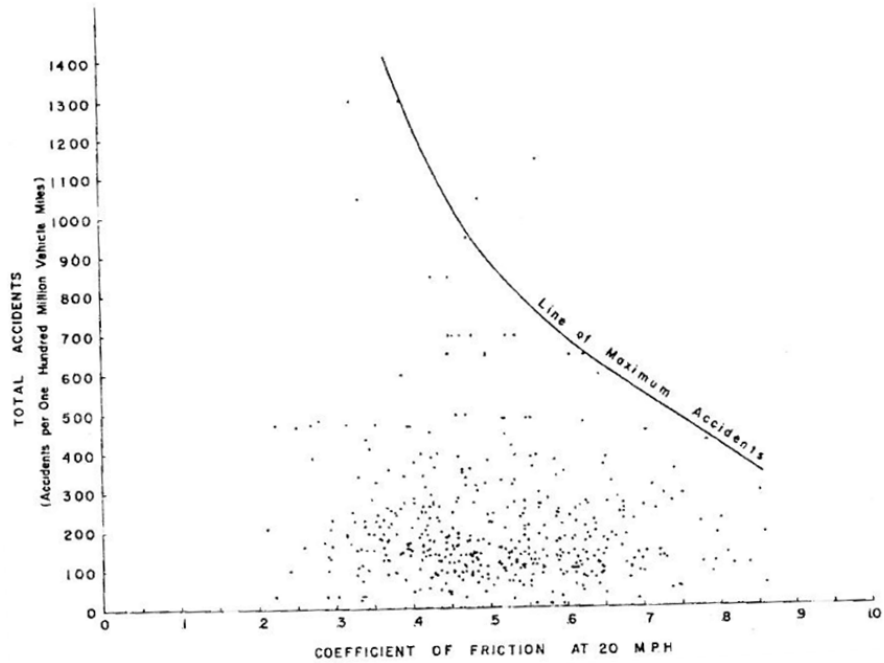


Figure 12: Accidents Rates and Friction Coefficient Values on 20mph Roads as Found by McCullough and Hankins (1966)

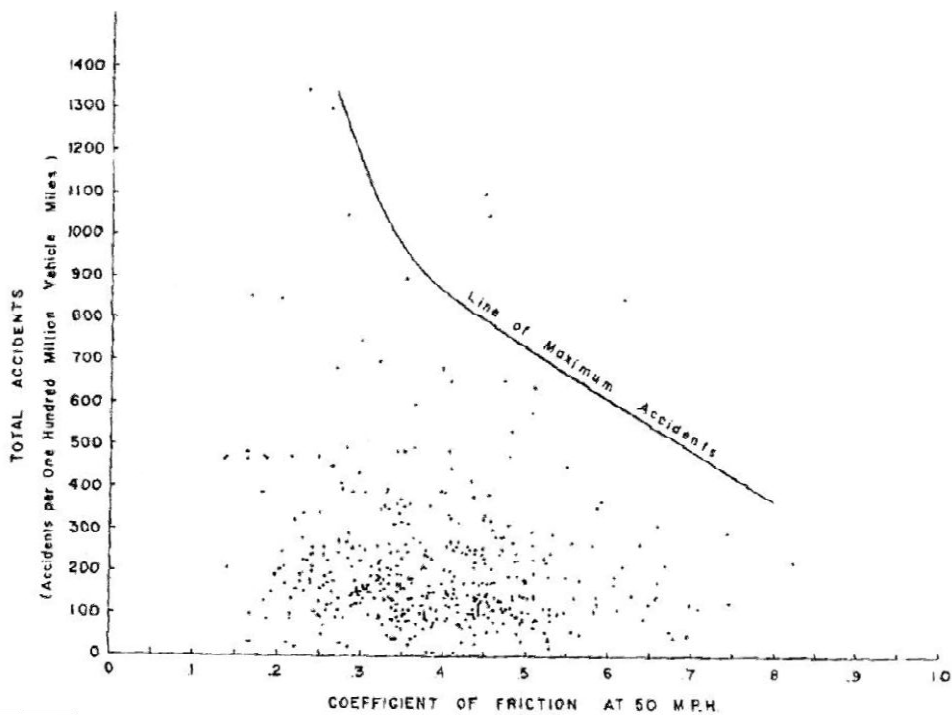


Figure 13: Accidents Rates and Friction Coefficient Values on 50mph Roads as Found by McCullough and Hankins (1966)

1966 - The Netherlands

Schlosser's (1976) study focused on determining the relationship between friction coefficients and accidents on dual carriageways and all other roads. The study took into account traffic volume (due to its impact on traffic flow characteristics), vehicle type, and weather conditions (accidents occurring due to snow/ice/dust were excluded from the sample).

Of the 36,364 traffic accidents recorded between 1965 and 1966, each was assigned to one of nine friction coefficient categories, based on the location at which the accident occurred. Accidents occurring during rainfall were assigned to the category that best matched the measured value of wet road friction coefficient. Accidents that occurred on wet roads (but not during rain) were assigned into a separate 'wet road-surface' group and assigned the respective friction coefficient category based on the measured value, and were also assigned to the 'dry-road' accident group. All accidents that were placed in the 'dry-road' accident group were assigned to the highest of the nine friction coefficient categories.

Each accident was then further categorised into the variables included in the study. Based on two-way tables Schlosser (1976) concluded that lower friction coefficients resulted in a higher propensity for traffic accidents due to a higher relative road risk. However, the relative road risk was also shown to be significantly influenced by a number of other factors particularly traffic volumes and the proportion of lower and higher vehicle classes. This finding is clearly illustrated in Figure 14, extracted from (Schlosser, 1976).

Schlosser's (1976) final recommendation was that "no causal relationship can be established. In principle, it is not possible to forecast the effect of a change in road-surface friction coefficient on the number and severity of accidents. Moreover, a change in friction coefficients can simultaneously influence other traffic circumstances, and thereby have an indirect effect on the accident pattern" (Schlosser, 1976; pg 19).

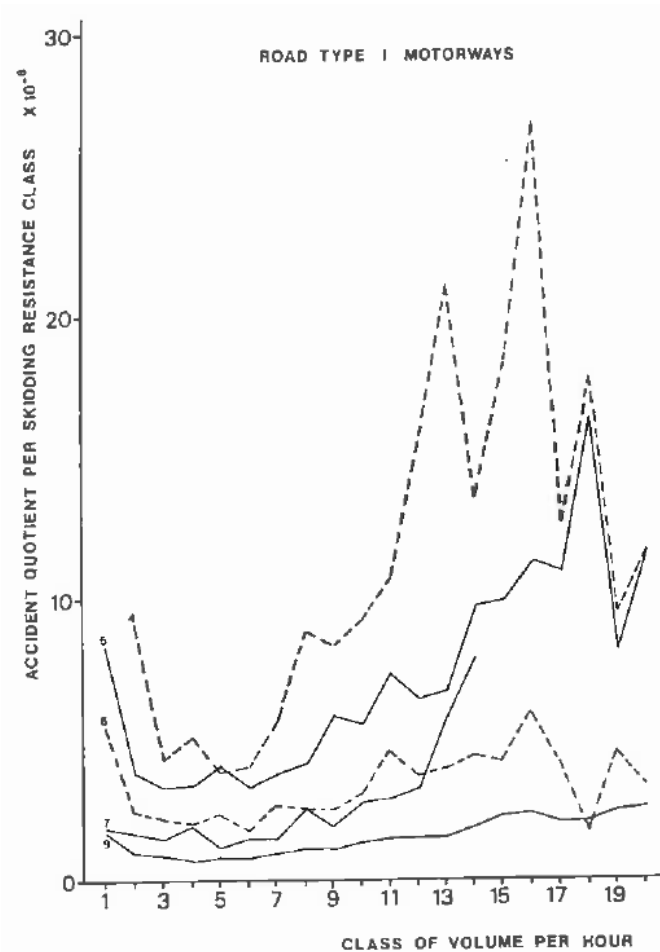


Figure 14: Motorway Accident Risk Related to Volume of Traffic per Hour, by Friction Category as Found by Schlosser (1976)

1971 - State of Kentucky, United States

Rizenbergs et al., (1977) study focused on determining the relationship between friction coefficient and accidents for principle rural two lane roads. The study included a total of 8,481 traffic accidents recorded between 1969 and 1971 on a 2,350km network surveyed with ASTM E274 in 1970. The study took into account traffic volume and density, and pavement surface condition (wet or dry). Factors relating to highway geometrics, number of accessways and traffic speeds were assumed to be 'within reasonable bounds' and were therefore not considered, Chapter II suggests such an assumption to be grossly misplaced.

Based on the ratio of wet to dry pavement accidents, Rizenbergs et al., (1977) analysed traffic accident data, and friction coefficient data. In their analysis, Rizenbergs et al., (1977) found that the ratio of wet to dry accidents did not correspond well to pavement friction coefficients, and it was noted that the relationship was masked by other causative factors. The large variance in the data found by Rizenbergs et al., (1977) is illustrated in Figure 15.

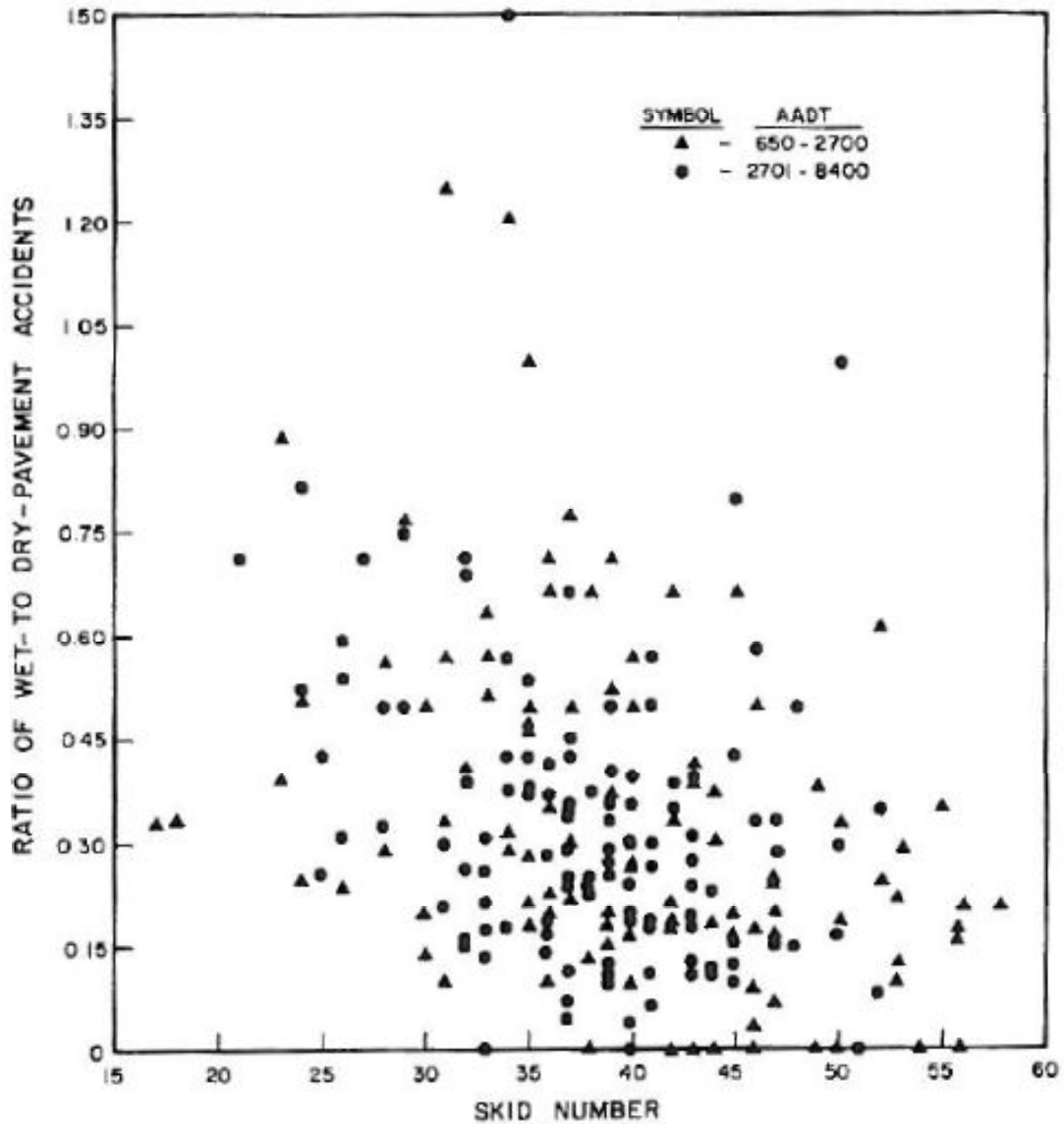


Figure 15: Ratio of Wet to Dry Pavement Accidents in Relation to Friction Coefficient Values as Found by Rizenbergs et al., (1977)

Further manipulation of the data enabled Rizenbergs et al., (1977) to conclude that where road friction coefficient values increased above 0.38 and 0.43 for high and low volume roads respectively, there was a reduction in the ratio of wet to dry traffic accidents. It was however acknowledged that the higher critical friction coefficient values attributed to roads with lower traffic volumes may be due to such roads having worse geometric standards.

1973 (estimated) - State of Tennessee, United States

Based on 75 (half mile long) road sections that had been recommended as high accident or low friction coefficient sites, Moore and Humphreys (1973) sought to determine the relationship between friction coefficient and traffic accidents. A preliminary review of the data found a reduction in the number of

accidents as road friction coefficients increased (Moore and Humphreys, 1973), as illustrated in Figure 16.

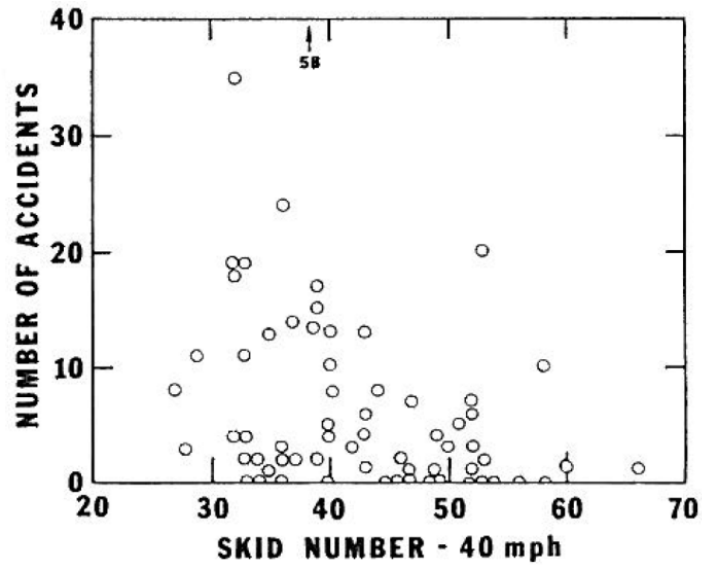


Figure 16: Relationship Between Accidents and Skid Number as Found by Moore and Humphreys (1973)

More in-depth analysis of the data was carried out on the assumption that the total number of accidents occurring at a site would provide an indication of accident potential at a site. While, the ratio of wet to dry accidents would give an indication of the impact that road friction coefficients had on the frequency of traffic accidents at each site. Based on these two assumptions it was found that for sites with friction coefficient measures less than 0.40, the ratio of wet pavement accidents increased, Figure 17 illustrates this finding.

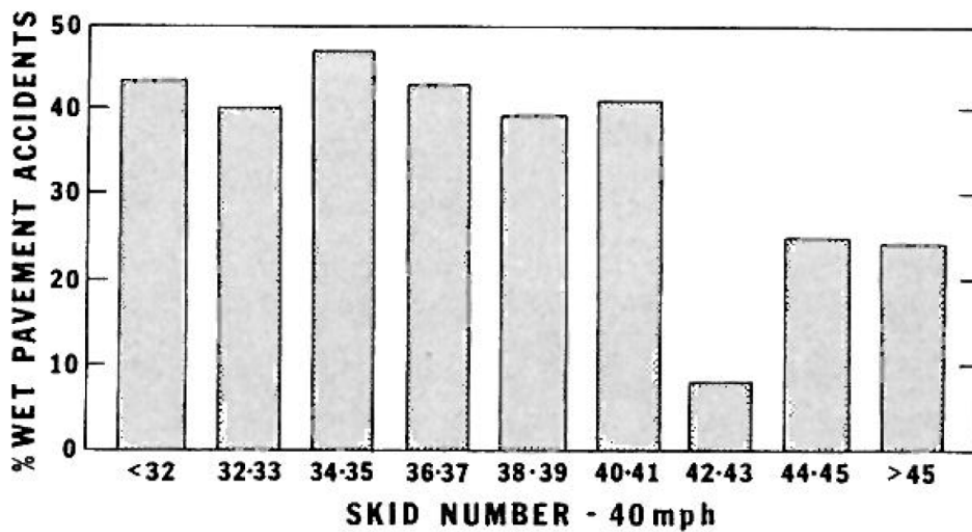


Figure 17: Proportion of Wet Road Accidents Compared to Friction Coefficient as Found by Moore and Humphreys (1973)

Another objective of the study undertaken by Moore and Humphreys (1973) was to determine the correlation between the coefficient of friction and road macrotexture. It was discovered that road macrotexture could be used to predict coefficient of friction values as measured by ASTM E274 to within ± 5 SN at the 95% confidence interval (Moore and Humphreys, 1973). This finding is not wholly surprising given that in the literature reviewed in Chapter II macrotexture was identified as a primary component of friction coefficients which dominates at higher speeds.

1982 - England

The Department for Transport used mean summer SCRIM data (based on three measurements) collected in 1981 and 1982 for over 1500km of the road network to determine the relationship between friction coefficient and traffic accidents (Rogers and Gargett, 1991). The data sample was divided into a number of site categories including: junctions (traffic lights, roundabout approaches, and pedestrian crossings), bends, gradients, and non-event sections. The study divided the data into single and dual carriageways, and took into account the posted speed limit (Rogers and Gargett, 1991).

The collected network data was then further divided into 50m sections (on approaches to 'hazards') and 200m sections for non-event segments. Friction coefficient values and accidents were then able to be assigned to their respective site categories. The analysis then focused primarily on skidding and non-skidding accidents on wet roads (Rogers and Gargett, 1991).

Numerous relationships were determined based on the analysis of several different grouping combinations. In summary, it was found that accident risk was significantly affected by the respective friction coefficient at most site categories, though no influence was found on motorways (Rogers and Gargett, 1991), as shown in Figure 18.

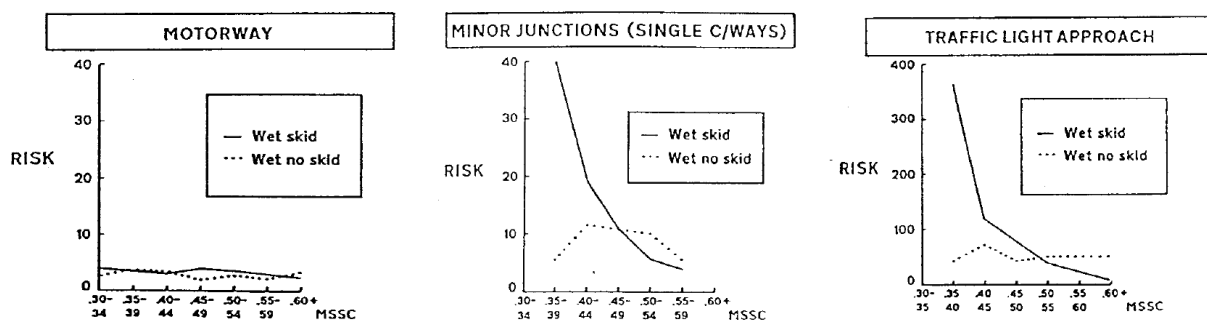


Figure 18: Accident Risk and Road Surface Friction at Three Different Site Categories as Found by Rogers and Gargett (1991)

1982 - Great Britain

Hosking's (1986) study sought to determine the effects of friction coefficient on traffic accidents using a methodology based on the principles of seasonal variation. In addition to the rate of seasonal variation that was based on three different data sources, the study also took into account road classification, vehicle type, and region. Seasonal variations in traffic volume, and light conditions were ignored as the study had investigated the influence of these factors and determined that they had negligible influence on accident rates.

Four years of accident data covering the period between 1979 and 1982 were used in the study. Due to the lack of research into seasonal variation of dry-road skidding resistance, the study focused primarily on the 'wet-road skidding rate', which was defined as the number of skidding accidents reported, as a proportion of all wet-road accidents. Using this ratio allowed issues relating to seasonal changes in the pavement wet to dry ratio to be circumvented.

Based on the correlation of wet-road skidding rates and seasonally determined coefficient of friction estimates, it was determined that friction coefficients defined by Hosking (1986) as skidding resistance ratio, significantly influenced wet-road skid accident rates. The results found are illustrated in Figure 19.

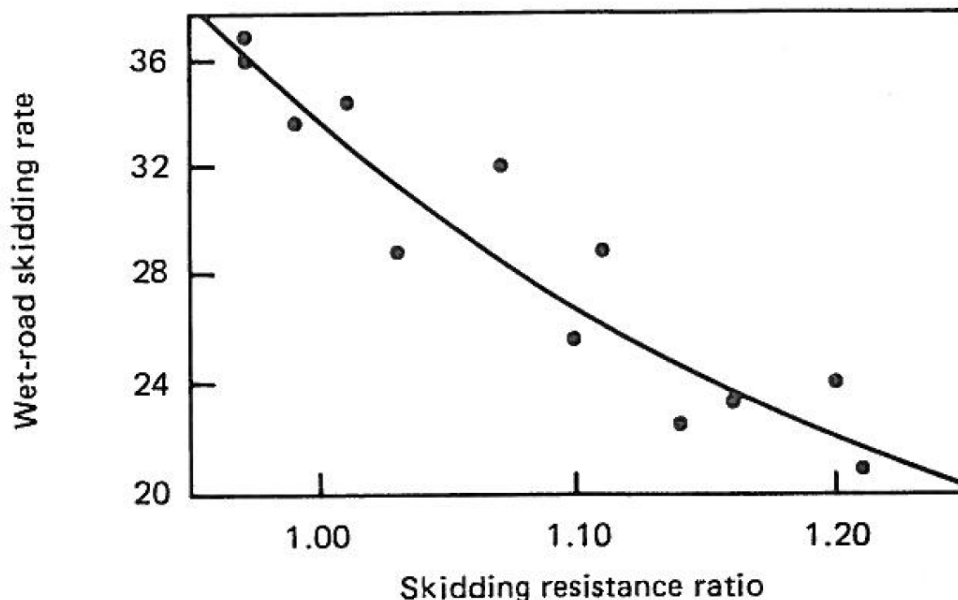


Figure 19: Wet-Road Skidding Rate and 'Skidding Resistance Ratios' as Found by Hosking (1986)

Importantly, Hosking (1986) noted that although there were only small differences in the level of friction coefficient provided amongst the regions, there were large regional differences in the reported skidding rate. The exact cause of this variation was unknown but raises questions as to the validity of the results due to the study's heavy reliance on accurate wet skidding accident rate data.

1999 - Saudi Arabia

Al-Mansour (2006) sought to determine the effect of friction coefficient on traffic accidents. Of the four road classes that were to be investigated, only three provided sufficient data to allow analysis, they were: dual carriageways, expressways (roads with more than one lane but only catering for one direction), and undivided roads.

A total of 340 traffic accidents selected from 89 high accident rate locations occurring in 1999 were assigned to the road network and matched with their respective Mu-Meter measurements. Analysis of the data found that as the friction coefficient decreased from below approximately 0.45, accidents increased, as illustrated in Figure 20. The study also found that as the class of highway rose, so too did the 'critical' skid number.

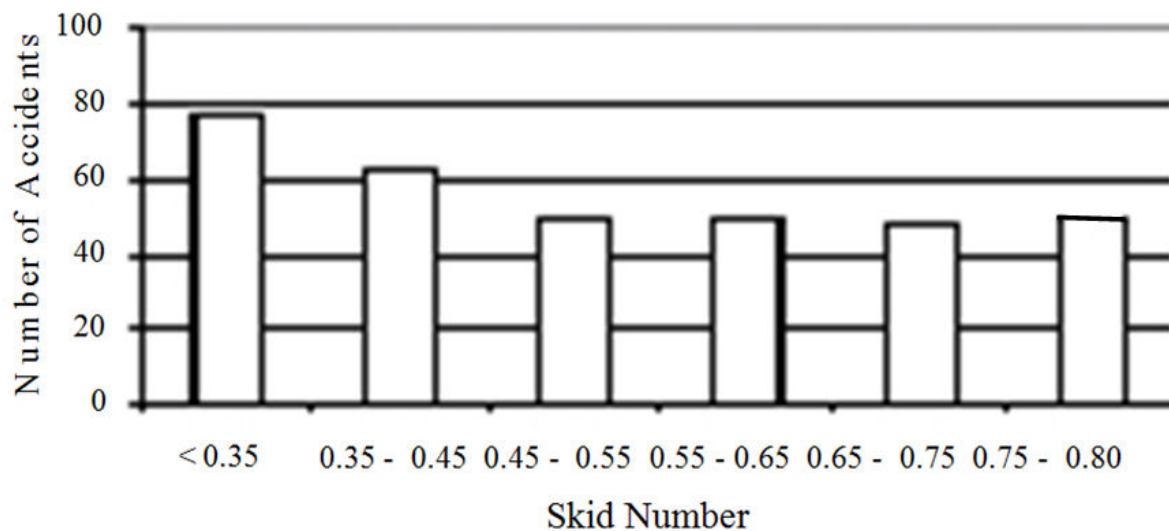


Figure 20: Effect of Friction Coefficients on Traffic Accidents as Found by Al-Mansour (2006)

1999 - Switzerland

Using almost 30,000 accident records on Switzerland's 6,000km highway network, Lindenmann (2006) sought to determine how pavements with low friction coefficients influenced accident prevalence. The methodology involved the identification of both road segments with friction coefficient values below the nationally prescribed SCRIM limit of <0.32, and those with high wet-road accident rates.

Four national highway road classifications were divided into 500m long route intervals to which a total of 790 accident blackspots were assigned. The accident blackspots were based on accident data recorded by police between 1995 and 1999, and took into account exposure. With the recorded friction coefficients relating to 100m long segments (and for lanes in both directions), the lowest recorded value was selected to represent each of the 500m route intervals. Using this assignment

technique, a total of 147 500m route intervals were identified on the highway network to have at least one 100m segment with a friction coefficient value below 0.32 (Lindenmann, 2006). It is not clear in what year friction coefficient data was obtained.

Based on an analysis of the whole 6,077km of national highway network, only nineteen 500m route intervals were determined to have both a low friction coefficient and an accident blackspot. On this basis it was concluded that there was no statistical evidence to suggest that there was a relationship between friction coefficient and accident frequency on the highway network in Switzerland, as shown in Figure 21. However, Lindenmann (2006) noted that further investigation should take place at the 19 intervals identified to have both low friction coefficients and an accident blackspot.

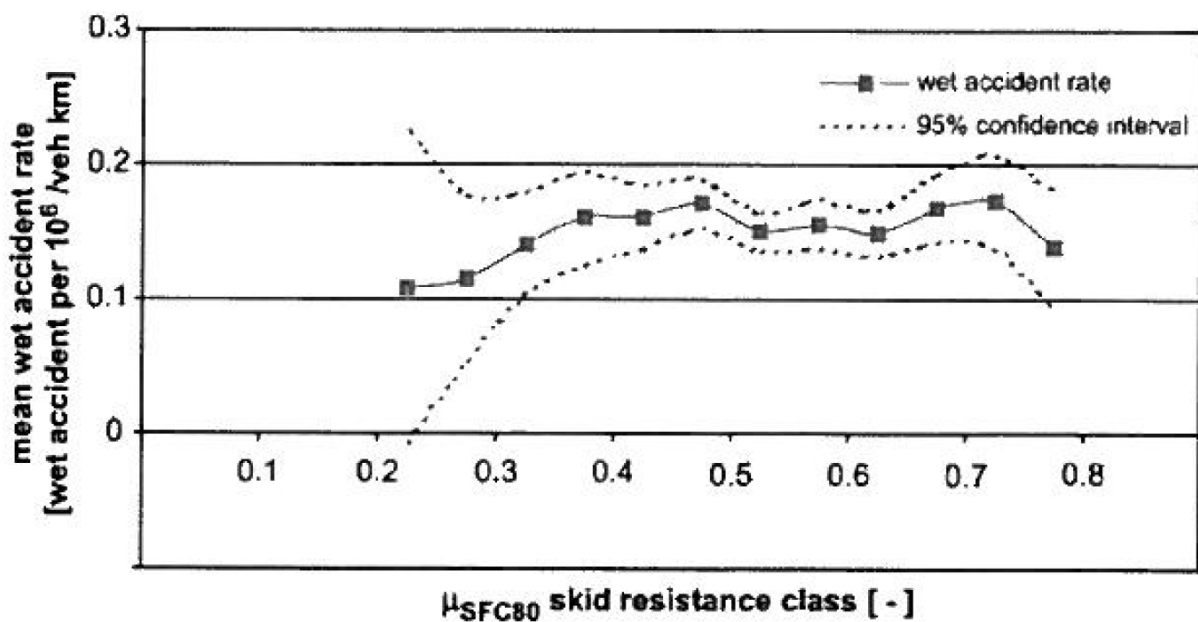


Figure 21: Relationship between Skid Resistance and Average Wet Accident Rates as Found by Lindenmann (2006)

2001 - United Kingdom

Following previous work by Hosking (1986) and Rogers and Gargett (1991), Viner et al., (2005) sought to reassess the relationship between the coefficient of friction and traffic accidents to enable a review of the policy prescribing investigatory friction coefficient values in the United Kingdom. The methodology used by Viner et al., (2005) involved the use of an accident model that took into account: traffic flow and composition, hard shoulder widths, texture and rut depth, longitudinal unevenness, and a total of thirteen site categories which took into account factors relating to road type, junction type, and road geometry (gradient, curvature, and crossfall).

Just under 6,000km of the road network was assessed in total. Motorway and non-motorway carriageways were split into 500m and 200m segments respectively. The rationale provided for this approach was that the lengths selected represented a compromise between providing more confidence that accidents would be attributed to the correct road segments on the one hand, and having more homogenous data relating to friction coefficients.

For each of the segments, recorded accident data from between 1994 and 2000, and SCRIM data collected in 2001 were assigned. Analysis using the accident model resulted in a number of findings, those of interest to this study are discussed here. First, accident risk for motorways, dual and single carriageways was found to be distinctly different, as were the thirteen site categories. This finding suggests that both road type and site category should be considered separately in future analysis. Second, the relationship between friction coefficient and traffic accidents was weak for motorways, though statistically significant for dual carriageways and more so for single carriageways. Third, a number of locations with high friction coefficients showed high accident risks, suggesting that the coefficient of friction does not always reduce accidents. The general results found by Viner et al., (2005) have been illustrated in Figure 22, Figure 23, and Figure 24.

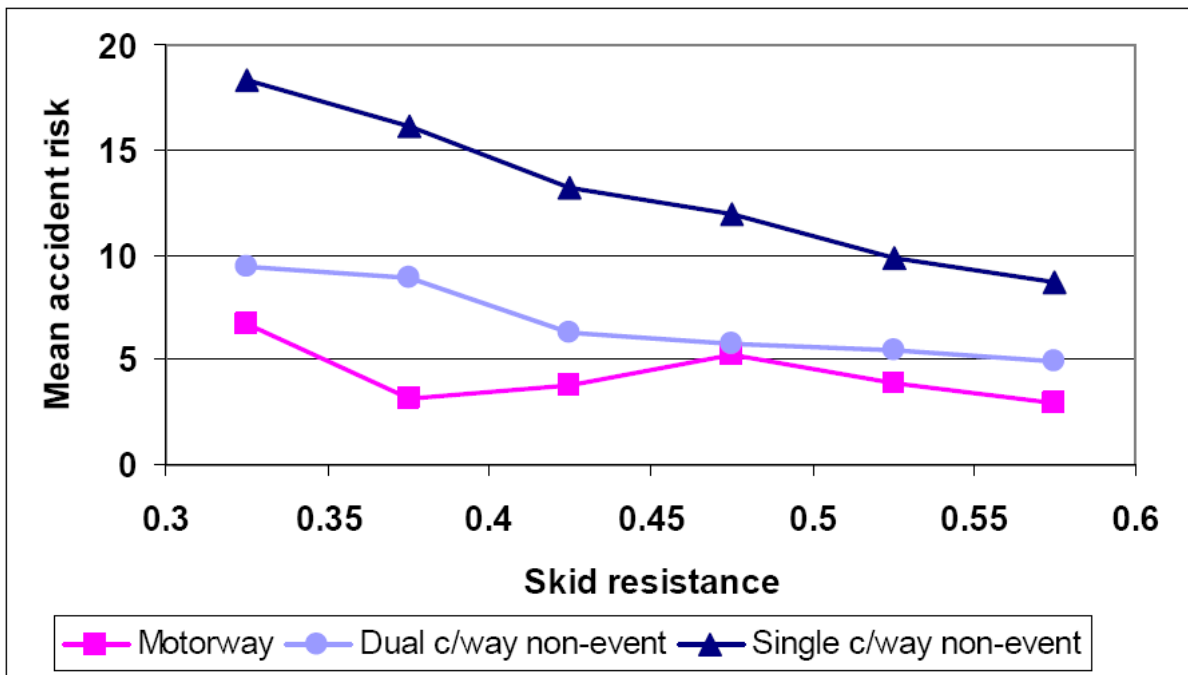


Figure 22: Relationship Between Accident Risk and Skid Resistance on Non-Event Motorway Sections as Found by Viner et al., (2005)

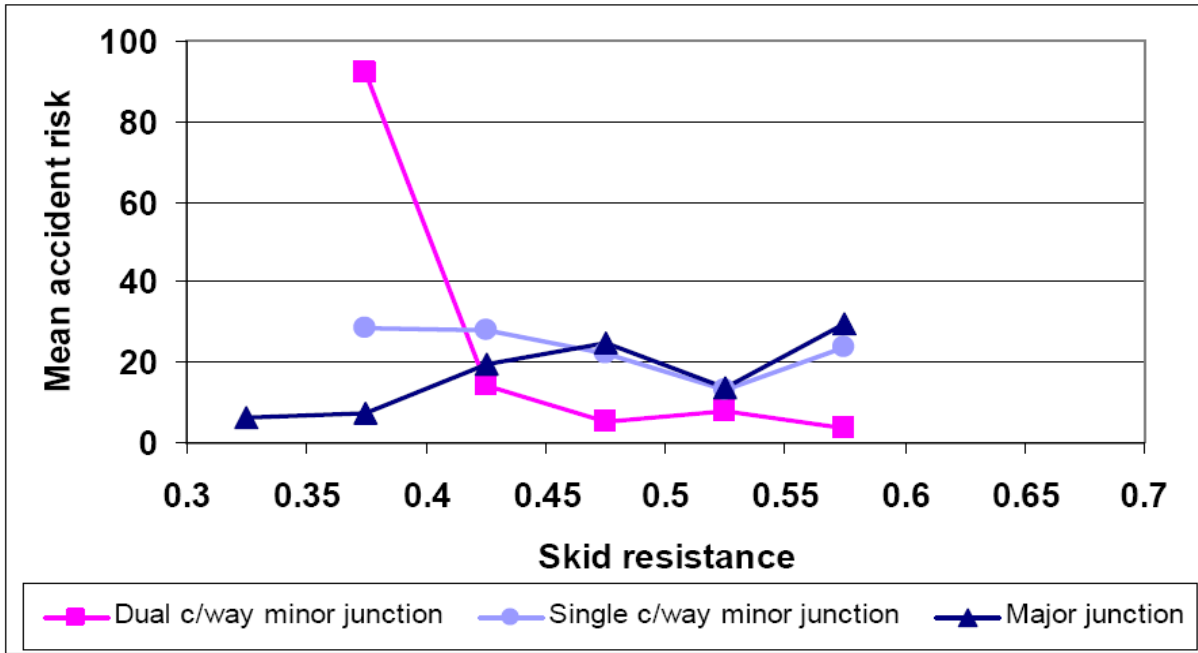


Figure 23: Relationship Between Accident Risk and Skid Resistance by Class of Junction as Found by Viner et al., (2005)

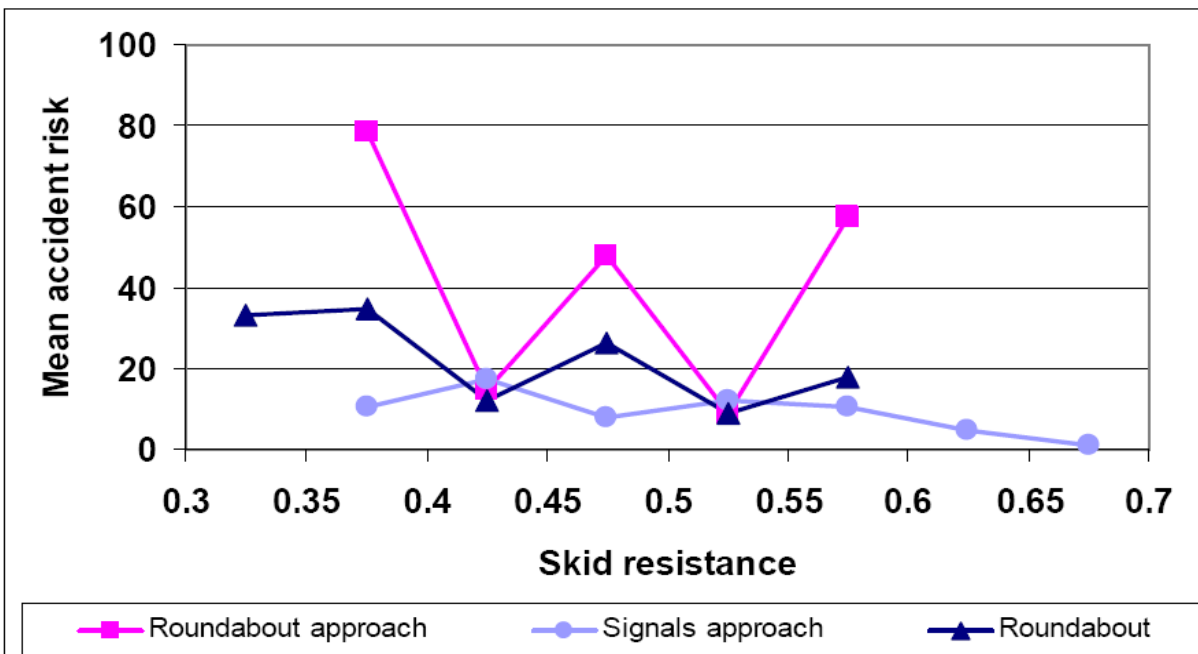


Figure 24: Relationship Between Accident Risk and Skid Resistance by Junction Type as Found by Viner et al., (2005)

It is noted that there has been up to a seven year gap between the recording of traffic accidents and collection of SCRIM data. During this time, it is highly likely that a number of sites with poor road surface friction were treated. While this is unlikely to have had a significant impact on the overall findings of the study it may explain why a number of locations displayed a high accident risk even though they had good friction coefficients.

2002 - Spain

Mayora and Rafael (2008) focused on determining the effect of friction coefficients on traffic accidents occurring on two lane rural roads in Spain. The study took into account the following variables: vertical and horizontal alignment factors; reduction in design speed from adjacent segments (out of context curves); minimum sight distances; traffic volume; and wet and dry pavement accident rates.

The data sample consisted of 3,778 traffic accidents and 1,758km of the road network which was split into 500m long segments. For each 500m long segment, highway design and traffic accident data for the years ranging 1993-1997 and 1998-2002 were assigned. With regard to the coefficient of friction, the assigned values represented the average value obtained over the 500m section and over the same five year periods.

Following the analysis, Mayora and Rafael (2008) concluded that as the friction coefficient increased, the rate of both wet and dry pavement accidents decrease. In addition Mayora and Rafael (2008) also found that wet pavement accidents were more prevalent in curves compared to tangents, though in the case of dry pavement accidents, this conclusion did not hold true. The results found by Mayora and Rafael (2008) have been illustrated in Figure 25 and Figure 26. It is interesting to note that the figures also appear to suggest that there was a general increase in crash rate for most of the friction coefficient ranges in the between year comparisons.

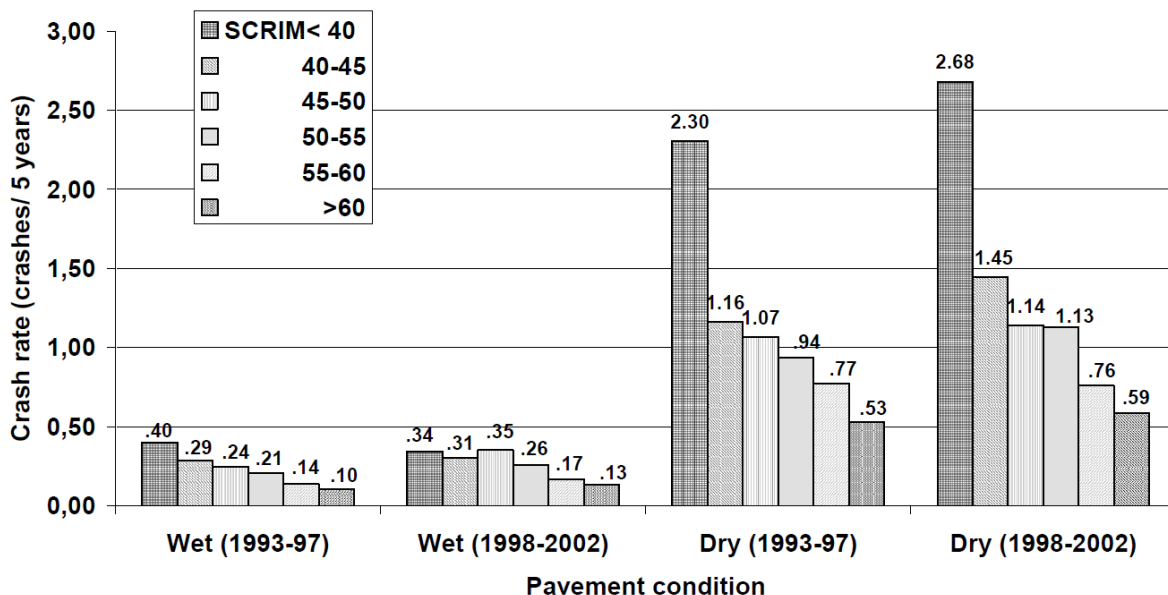


Figure 25: Dry and Wet Pavement Accident Rates by Friction Values as Found by Mayora and Rafael (2008)

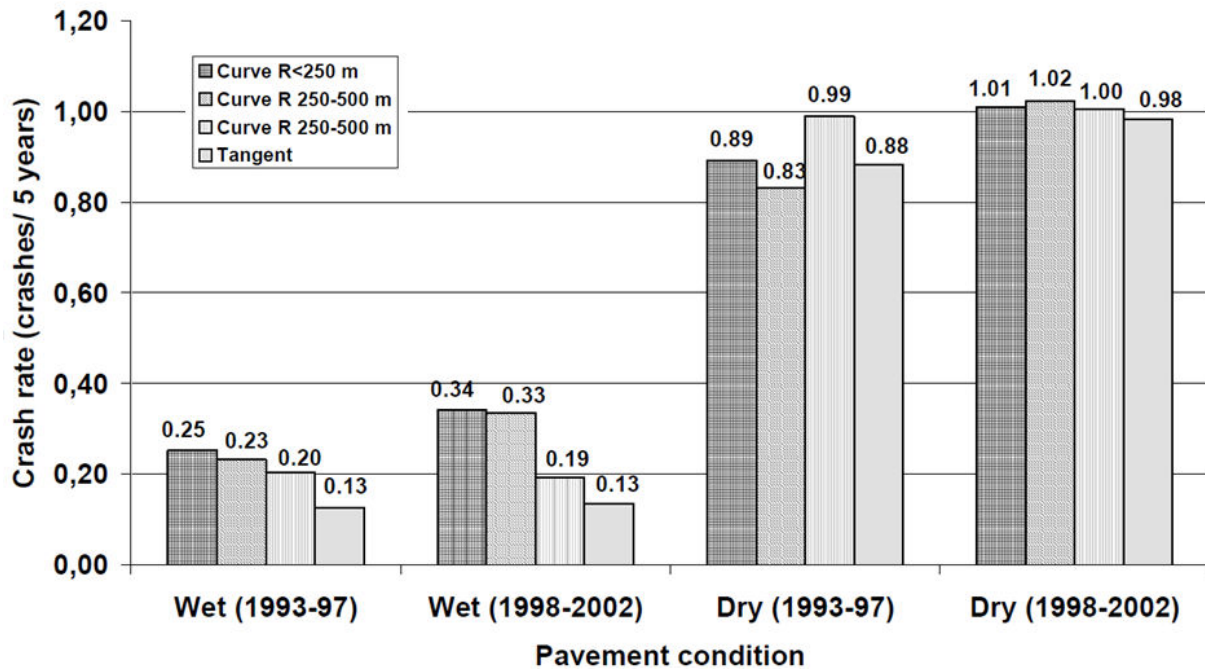


Figure 26: Dry and Wet Pavement Accident Rates by Horizontal Alignment Class as Found by Mayora and Rafael (2008)

2002 - State of Virginia, United States

Kuttesch's (2004) study focused on determining the relationship between friction coefficients and wet weather accidents, on roads in Virginia. As part of the methodology, friction coefficient data was aggregated into 3,243 one-mile long sections to which the minimum measured friction value was assigned. Traffic volume data and each of the 22,232 traffic accidents recorded in 2002 were then assigned to their respective one-mile long sections.

Following regression analysis and t-tests Kuttesch (2004) found that the number of wet accidents increased as friction coefficients decreased. However, it was acknowledged that the coefficient of friction could be attributed to only a small portion of the variation in wet accident rates when considering individual accident sites, as annual average daily traffic (AADT) also played a significant factor. It was also determined that for sites with a skid number below 0.30 as measured by ASTM E274, the wet accident rate was on average 44% higher. In conclusion Kuttesch (2004) noted that friction coefficient alone, was a poor indicator of wet road accident rates. Figure 27 illustrates the linear regression results undertaken by Kuttesch (2004).

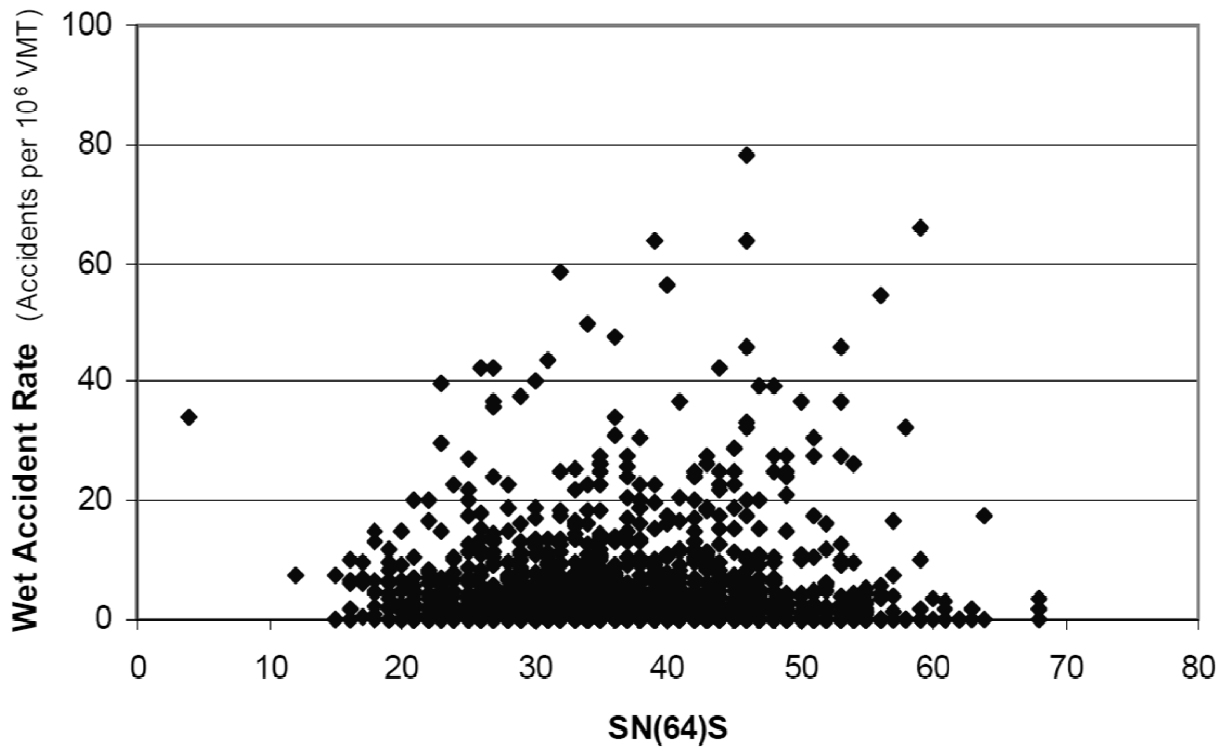


Figure 27: Relationship Between Wet Accident Rate and Skid Number as Found by Kuttesch (2004)

2002 - New Zealand

In 2005, Davies et al., set out to ascribe the effect of friction coefficients and texture on accident risk on New Zealand's 11,000km State Highway network. To do this, data relating to: friction coefficient, texture, gradient, horizontal curvature and crossfall were collected at 10m intervals and were supplemented by roughness and rut depth data recorded at 20m intervals. The whole network was surveyed annually between 1997 and 2002.

Over 14,000 recorded fatal and injury accidents reported between 1997 and 2002 were analysed and assigned the measured variables associated with the respective location at which the accident occurred. From the total pool of recorded accidents, approximately 25% were omitted due to difficulties in attributing them to a specific location on the network.

One and two-way tables were then used to compare a wide array of variables that were collected and considered to influence accident risk. For the one-way tables it was apparent that accident rates decreased as traffic volumes increased, similar results were found for both increasing curvature and friction coefficients. As the two-way tables compared two variables at a time, the volume of the data decreased which affected the level of confidence in some of the relationships considered. However, it was found that as the radius of a curve and friction coefficients increased, there was a noticeable reduction in accident rate, as illustrated in Figure 28.

Horizontal Curvature, R (m)	Crashes per 10 ⁸ vkt					
	SCRIM Coefficient Range					
	SC < 0.3	0.3 ≤ SC < 0.4	0.4 ≤ SC < 0.5	0.5 ≤ SC < 0.6	0.6 ≤ SC < 0.7	SC ≥ 0.7
10 ≤ R < 100	55	48	54	43	61	40
100 ≤ R < 1000	55	30	25	23	23	24
1000 ≤ R < 10000	13	19	16	15	15	14
10000 ≤ R < 100000	32	21	14	12	13	14
R ≥ 100000	0	26	15	11	39	0

Note: Only figures in bold should be read, unbolded figures represent samples which were too small

Figure 28: Effect of Horizontal Curvature and Friction Coefficient on Accident Rate as Found by Davies et al., (2005)

Davies et al., (2005) found that as friction coefficient decreased, the respective accident rate increased irrespective of site category. This finding is summarised in Figure 29 where: Category 4 relates to normal roads; Category 3 approaches to junctions; Category 2 curves <250m radius and/or gradients >10%; and Category 1 the highest priority (e.g. level railway crossings, traffic lights, pedestrian crossings etc.)

T/10 Skid Site Category	Crashes per 10 ⁸ vkt					
	SCRIM Coefficient Range					
	SC < 0.3	0.3 ≤ SC < 0.4	0.4 ≤ SC < 0.5	0.5 ≤ SC < 0.6	0.6 ≤ SC < 0.7	SC ≥ 0.7
4	17	16	13	13	14	12
3	44	29	27	26	23	32
2	62	39	33	31	31	33
1	0	44	52	47	47	40

Note: Only figures in bold should be read, unbolded figures represent samples which were too small

Figure 29: The Effect of Site Category Risk Rating and Friction Coefficient on Accident Rate as Found by Davies et al., (2005)

With an understanding of the variables influencing accidents, Davies et al., (2005) developed a ‘crash rate model’ that would enable accident rates to be predicted for particular sites. The model developed for final use was based on polynomial equations, which were derived from an earlier model that was based on spline curves. It was noted that there was difficulty in interpreting information pertaining to gradient as the data available did not distinguish between positive or negative gradient.

Although it was noted that some of the variables included in the model may have induced a level of intrinsic error, a comparison of actual and predicted accident rates was particularly good, as shown in Figure 30.

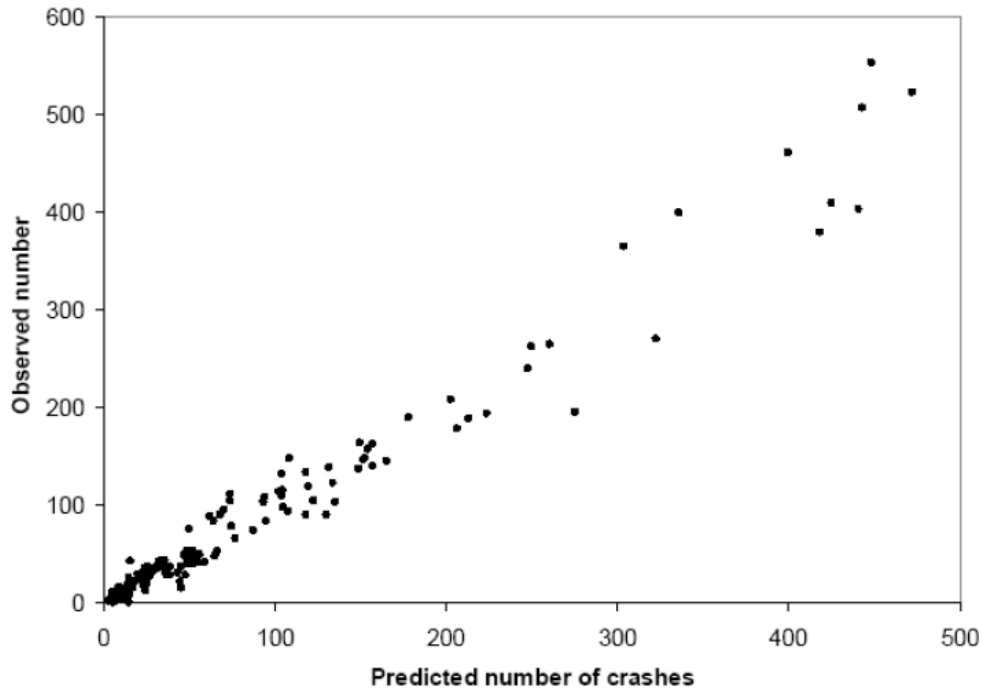


Figure 30: Relationship Between Actual and Predicted Accident Rate Based on Model Developed by Davies et al., (2005)

In conclusion Davies et al., (2005) determined that increasing friction coefficients generally resulted in a reduction in accident rate, but noted diminishing safety benefits with continued increases in friction coefficient. It was also found that improved road surface friction delivered the most significant accident savings for those occurring on wet-roads, as depicted in Figure 31.

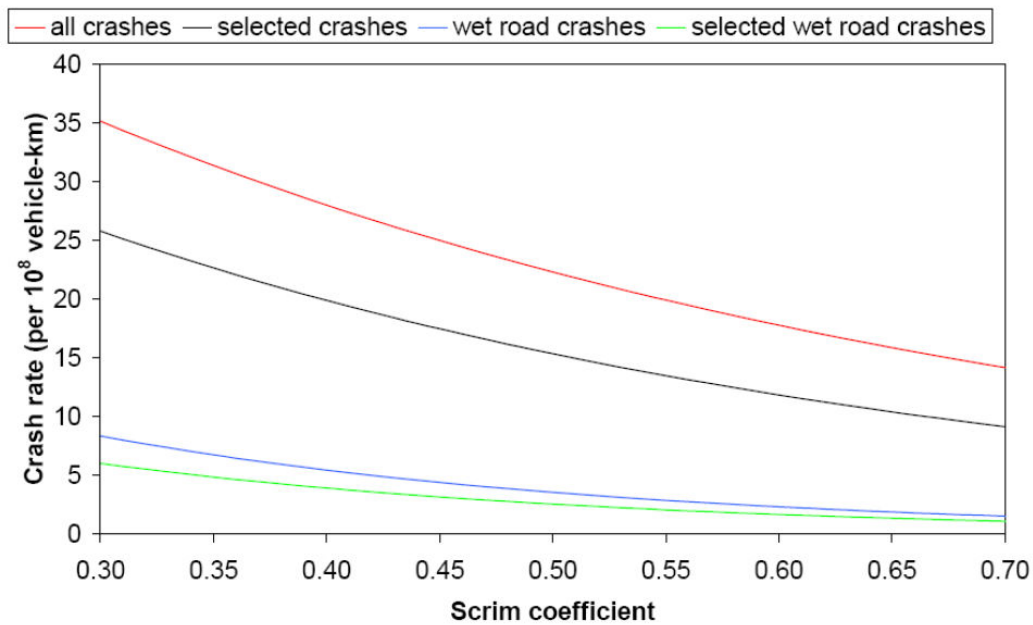


Figure 31: Friction Coefficient and Crash Rate for Four Different Accident Types as Found by Davies et al., (2005)

Davies et al., (2005) also concluded that the relationship between texture and accident rate was not strong. This is an interesting finding given that texture as outlined in Chapter II, was identified as a principle component of the coefficient of friction, and that the earlier study undertaken by Moore and Humphreys (1973) found that texture could be accurately used to predict the level of friction coefficient.

2004 - Czech Republic

To research the disparity between the rate of traffic accidents in the Czech Republic and other European Union member countries, Kudrna et al., (Undated) set out to determine the influence of friction coefficients on the number of traffic accidents. As a starting point, data was collected for 143.5km of the Class I and 351.8km of the Class II road network in 2004 using SCRIM. The collected data was represented on a GIS application which also had a total of 2,724 traffic accident records covering the period between 2003 and 2004 that had been obtained from the police. The GIS application was used to present the distribution of traffic accidents and illustrate accident 'black-spots'.

Kudrna et al., (Undated) found that 24% of traffic accidents occurring between 2003 and 2004 on Class I roads in the Czech Republic occurred on just 6% of the road network. In comparison 13% of accidents occurring on Class II roads could be linked to 8% of the road network. This difference was assumed to be the result of lower geometrical standards, narrower lanes, and different levels of traffic intensity on Class II roads. Kudrna et al., (Undated) noted that if the traffic intensity on Class II roads increased to that of Class I, the accident rate could be reasonably expected to be more than two times higher than that of Class I roads.

On this basis Kudrna et al., (Undated) focused their attention on the Class I road network and carried out further assessment using accident data from 2005. As Kudrna et al., (Undated) had found in the earlier analysis, it was again concluded that sites with lower friction coefficient classifications resulted in increased traffic accidents rates, as illustrated in Figure 32.

Skid resistance classification	I st class roads (2003-4)			II nd class roads (2003-4)			I st class roads (2005)		
	A	L	A/L	A	L	A/L	A	L	A/L
Excellent	67	39,7	0,8	508	138,4	1,8	207	87,7	2,4
Good	211	56,6	1,9	531	84,1	3,2	328	79,4	4,1
Acceptable	330	38,3	4,3	640	100,6	3,2	555	91,6	6,6
Unacceptable	150	7,6	9,9	199	24,3	4,1	278	34,5	8,6
Hazardous	42	1,3	16,2	48	4,4	5,1	130	12,3	10,6
Total	800	143,5	2,79	1924	351,8	2,73	1498	305,5	4,9

Abbreviation: A – number of accidents in specified years, L – road length,
A/L – mean year accidents number per kilometre of road

Figure 32: Mean Number of Accidents per Friction Coefficient Classification, for Class I and II roads as Found by Kudrna et al., (Undated)

3.3 Overview of Recent Research

Table 2 on the following page provides a one page overview of the results found in network level studies investigating the relationship between friction coefficient and traffic accidents. Readers may find this table useful to reference when reading the discussion in Section 3.4.

Study			Road Class Studied (or nearest equivalent classification)				Sample Details			Conclusion
Location	Author (Date Published)	Most Recent Year of Data Included	Motorway	Dual Carriageway	Single Carriageway and Minor Rural Roads	Other or Unknown	Length of Friction Coefficient Data Considered, or Number of Test Sections	No. of Accidents Considered	Length of Section to which Friction Coefficient and Accident Data were Assigned	Was a Correlation Between Friction Coefficient and Traffic Accidents Found?
State of Texas	McCullough & Hankins (1966)	1965 (est)	✓				517 random sections	Unknown	Varied	Yes
The Netherlands	Schlosser (1976)	1966		✓		✓	3,400km	36,364	Unknown (>100m likely due to accuracy of data collection)	Limited
State of Kentucky	Rizenbergs et al., (1977)	1971		✓			2,350km	8,481	Unknown	Yes
State of Tennessee	Moore & Humphreys (1973)	1973 (est)	✓				60km	450	Half Mile (805m)	Yes
England	Rogers & Gargett (1991)	1982		✓	✓		1,500km	Unknown	50-200m	Limited
Great Britain	Hosking (1986)	1982	✓	✓	✓		Unknown	Unknown	Unknown	Yes
Saudi Arabia	Al-Mansour (2006)	1999	✓	✓	✓		Unknown	340	Unknown	Yes
Switzerland	Lindenmann (2006)	1999	✓	✓			6,077km	29,994	500m	No
United Kingdom	Viner et al., (2004)	2001	✓	✓	✓		6,000km	Unknown	200-500m	Limited
Spain	Mayora & Rafael (2008)	2002			✓		1,758km	3,778	500m	Yes
State of Virginia	Kuttesch (2004)	2002				✓	5,219km	22,232	1 mile (1,609m)	Yes
New Zealand	Davies et al., (2005)	2002	✓	✓	✓		10,736km	14,094	10m	Yes
Czech Republic	Kudrna et al., (Undated)	2004	✓	✓			495km	2,724	20m	Yes

Table 2: Overview of the Network Based Studies Reviewed in Section 3.2

3.4 Discussion

Of the thirteen network analysis studies reviewed in Section 3.2, twelve concluded that there was, at least to some degree, an inverse relationship between friction coefficients and traffic accidents (Al-Mansour, 2006, Davies et al., 2005, Hosking, 1986, Kudrna et al., Undated, Kuttesch, 2004, Mayora and Rafael, 2008, McCullough and Hankins, 1966, Moore and Humphreys, 1973, Rizenbergs et al., 1977, Rogers and Gargett, 1991, Viner et al., 2005, Schlosser, 1976).

Only Lindenmann's (2006) study, which focused on Switzerland's highway network found no relationship at all between friction coefficients and traffic accidents, a finding supported in part by the studies undertaken by Schlosser (1976), Rogers and Gargett (1991), and Viner et al., (2005). Schlosser (1976) found that while a lower friction coefficient resulted in a higher propensity for traffic accidents, other factors particularly traffic volumes and the proportion of lower and higher vehicle classes also significantly influenced accident rates. In conclusion, Schlosser (1976) suggested that no causal relationship could be established and that it was not possible to determine the effect of the coefficient of friction on the number and severity of traffic accidents. More recently, Rogers and Gargett (1991) and Viner et al., (2005) concluded that there was no relationship between friction coefficients and traffic accidents on the motorways in England and the United Kingdom respectively.

The research of Rogers and Gargett (1991) and Viner et al., (2005) did however reveal a strong relationship between friction coefficients and traffic accident rates on roads other than motorways. This finding is supported by the earlier work of McCullough and Hankins (1966) who found that as speeds decrease the critical friction coefficient increased. In contrast however, Al-Mansour (2006) concluded that as the class (hierarchy) of road increased, so too did the 'critical' friction coefficient given that motorway speeds tend to be higher than that of other roads.

For those studies that found a relationship between friction coefficient and traffic accidents many sought to identify the 'critical' friction coefficient, beyond which the number of traffic accidents would increase significantly. Of those studies seeking to identify a critical friction coefficient for motorways, the critical value was reported to range from as low as 0.30 and 0.35 (McCullough and Hankins, 1966) to as high as 0.45 (Al-Mansour, 2006). Part of the reported variation in critical friction coefficients is likely to reflect national idiosyncrasies associated with the way in which friction and traffic accident data is collected and reported and also other local factors.

As discussed in Chapter II, friction coefficient data can be collected by a number of devices, each of which provides results that are not directly comparable and carry with them, differing margins of error. There are also likely to be considerable differences in both accuracy and the methods used to

report and record traffic accidents. By way of example, Hosking (1986) found only a small effect of friction coefficient change over the road network studied, but noted large regional differences in the proportion of skid related accidents. While not concluded by Hosking (1986), this finding suggests significant variation in the reporting standards between police districts, variation which is likely to be even more significant when comparing data between different countries.

Perhaps even more significantly, the different study methodologies employed are likely to have had a considerable impact on the reported range of critical friction coefficients. The methodology extends not only to the statistical methods used but also to the rationale behind the way in which data is selected and treated.

Of the studies reviewed, the two most commonly utilised methodologies involved direct comparisons between the coefficient of friction and the rate of traffic accidents as used by: Al-Mansour (2006), Kudrna et al., (Undated), Lindenmann (2006), McCullough and Hankins (1966), and Moore and Humphreys (1973); and more complex regression techniques as used by: Davies et al., (2005), Hosking (1986), Kuttesch (2004), Rizenbergs et al., (1977), and Viner et al., (2005). Given that the relationship between friction coefficient and traffic accidents has been found to be second order rather than direct, the latter method is considered to be more accurate (Owen and Donbavand, 2005).

Five of the studies reviewed considered all accident types (Al-Mansour, 2006, Davies et al., 2005, Kudrna et al., Undated, McCullough and Hankins, 1966, Viner et al., 2005); while the remaining studies investigated either the ratio of dry to wet (Mayora and Rafael, 2008, Moore and Humphreys, 1973, Rizenbergs et al., 1977, Schlosser, 1976); wet-only (Kuttesch, 2004, Lindenmann, 2006); or the ratio of skidding to non-skidding accidents (Hosking, 1986, Rogers and Gargett, 1991). The rationale provided for the inclusion or exclusion of various accident types was in many cases contradictory. This is unfortunate given that such disagreement does not assist in determining which accidents should be included or excluded in this study.

Based on the included accident types the studies took a varied approach to assigning traffic accident data with respective friction coefficient values. In most cases the assigned friction coefficient value represented the lowest reading within a set distance from the recorded accident. Accidents were typically assigned to 500m sections of the road network (Lindenmann, 2006, Mayora and Rafael, 2008, Viner et al., 2005), however the length used ranged from 10metres (Davies et al., 2005) to one mile (Kuttesch, 2004).

As assignment section length increases so too does the probability of accurately assigning a traffic accident to the correct section of road. However as assignment section length increases the ability to

take road geometry into account reduces and the probability of obtaining a low friction coefficient value increases. Conversely, shorter assignment sections increase the risk of incorrectly assigning a friction coefficient value to an accident (due to margins of error associated with referencing data location), and also fails to acknowledge that accidents tend to take place over a longer stretch of carriageway. In either case, methods where just one measured friction coefficient value is used could be potentially misleading as the reliance on only one measured value fails to recognise the overall contribution that the surrounding road surface plays in traffic accidents.

Though a total of thirteen network analysis studies have been reviewed, a clear relationship between friction coefficient and traffic accidents could not be discerned. This is not to suggest that such a relationship does or does not exist, rather it is to say that due to the diversity in the study methodologies used it is not possible to draw any such conclusion. For this reason it is also not possible to identify whether there has been a change in the demand for friction coefficient over time.

3.5 Summary

This chapter commenced by providing a brief historical background of friction coefficient and skid resistance research. The overview focused on Baston's 1927 research which identified the need for apparatus to measure road surface friction coefficients, and Giles' 1956 research which provided the first in-depth study investigating the relationship between friction coefficient and traffic accidents. Since the work of Giles (1956) there has been an abundance of research investigating this relationship.

From the pool of research available, a total of thirteen studies were identified to have used a network based methodology to investigate the relationship between friction coefficient and traffic accidents. Of the thirteen studies, twelve concluded that there was, at least to some degree, an inverse relationship between friction coefficient and traffic accidents. Only Lindenmann's (2006) study, which focused on Switzerland's highway network found no relationship at all, a conclusion supported in part by the findings of three other studies.

Despite a total of twelve studies supporting the notion that a relationship between friction coefficient and traffic accidents existed at least to some extent, there remains a significant and unexpected level of disagreement as to the exact nature of this relationship. The lack of agreement centres not only on the function of the relationship (i.e. linear or non-linear), but also the critical friction coefficient value, and which road classifications are most affected by changes in friction coefficients. The literature has however provided support for Giles' (1956) conclusion that different levels of skid resistance are needed during different parts of the journey.

With the exception that regression based techniques were widely considered the most appropriate means to test the influence of friction coefficient, there appeared little agreement with regards to methodological approach. This was evidenced primarily by the varied way in which traffic accident and friction coefficient data was treated in each of the studies. Given the lack of a widely accepted methodological approach, it was perhaps not surprising to find the range of conclusions found. Furthermore, the varied approach to testing the relationship has made it difficult to ascertain whether there has been any change in road user demand for road surface friction coefficients. It is unfortunate that agreement with regards to the methodological approach has not been found as this would have provided a useful starting point for the development of a methodology in the following chapter.

Chapter IV: Methodology

The primary objectives of this thesis as set out in Chapter I culminate in the determination and quantification of the relationship between the coefficient of friction and traffic accidents. This chapter outlines the methodology used to investigate the relationship, and has been broadly divided into three sections. The first section identifies the four categories of data that are required to enable a fair assessment of the relationship. This section also details how data was collected at source and notes the expected level of data accuracy.

The second section provides an overview of the data included in the assessment of the relationship, and how such data was refined and treated prior to inclusion in analysis.

The third section describes the statistical methods used to test the relationship between the coefficient of friction and traffic accidents and has been divided into two parts. The first part outlines the process used to explore the data, while the second details the tests used for assessing the relationship.

4.1 Data Requirements and Data Acquisition

The literature reviewed in Chapter III suggests that if the relationship between road surface friction and traffic accidents is to be fairly tested, then data relating to traffic accidents, friction coefficient, carriageway geometry, and traffic flow characteristics are required. Table 3 summarises the data items falling within each of these four broad categories, which would ideally be available for consideration in the analysis.

Road Surface Condition Data	Traffic Accident Data	Carriageway Data	Traffic Flow Data
Friction Coefficient	Accident Severity Accident Location Road User Type(s) Date Time of day Accident Classification Prevailing Road Surface Condition Prevailing Weather Prevailing Lighting	Carriageway Gradient Carriageway Superelevation Carriageway Curvature Road Hierarchy Posted Speed Limit	Annual Average Daily Traffic Flows Proportion of Heavy Goods Vehicles

Table 3: Ideal List of Data Items to be Acquired

It was originally hoped that data from the United Kingdom's Highways Agency could be used for this study. The rationale for this was twofold, not only does the Highways Agency have the largest road network in the United Kingdom from which to draw data, but road surface friction management in the United Kingdom is predominately based on findings from their road network. Following a concerted effort to obtain data relating to the Highways Agency network, it was not possible to obtain data within the required timeframe for this thesis.

Fortunately, a successful approach to Norfolk County Council enabled a dataset to be obtained which has subsequently been used for analysis in this study. Norfolk County is situated along the eastern coast of the midlands and is bordered by Lincolnshire in the north, Cambridgeshire to the west and Suffolk to the south. Norfolk County has 769.1km of A-road network which represents 3.8% of England's total A-road network.

It is acknowledged that the data obtained is not a randomly selected sample and as such will have some inherent sampling bias. The bias relates to geographic location in that the sample has been selected from the population of roads in Norfolk County, caution should therefore be applied when inferring results to other geographic locations. It is also noted that the data collected only relates to the years 2008, 2009 and 2010 at the time when the data was collected. Care should be taken when inferring results to other time periods, particularly as the time difference increases between the data period included in this study and that of any subsequent analysis.

The following four subsections provide an overview of the four datasets received from Norfolk County Council. Each subsection provides an overview of how the data items were collected at source; notes any data manipulation undertaken prior to its supply for this study; and outlines the expected levels of data accuracy (at a 95% Confidence Interval, unless otherwise noted).

Road Traffic Accident Data

All reported traffic accidents in Norfolk County are recorded by officers of the Norfolk Constabulary on a standardised traffic accident form (STATS 19) at the scene of the accident, where possible. Although a standardised form is used, it is acknowledged that there will be some variance in the way traffic accident data is classified and recorded by individual police officers.

The contents of the traffic accident forms are subsequently typed into the accident database by administrative staff, for which access is shared with selected stakeholder groups, including Norfolk County Council. Table 4 summarises the elements relating to the traffic accident data supplied by Norfolk County Council that will be considered for inclusion in the testing of the relationship between friction coefficient and traffic accidents.

Data Element	Unit of Measure	Expected Accuracy
Accident Severity	Count	99%
Accident Location	Grid Reference and Freeform Descriptive Text	20m
Road User Type(s)	Classification	99.9%
Date	Date	99.9%
Time of Day	24hr Clock	± 15min
Accident Classification	1 of 43 Descriptive Text Categories	Unknown
Prevailing Road Surface Condition	1 of 5 Descriptive Text Categories	Unknown
Prevailing Weather	1 of 9 Descriptive Text Categories	Unknown
Prevailing Lighting	1 of 7 Descriptive Text Categories	Unknown

Table 4:Details Relating to Norfolk County Council's Road Traffic Accident Data

Friction Coefficient Data

From 1999 Norfolk County Council has been collecting friction coefficient data for their A-road network on an annual basis, however only since 2007 have they routinely collected data for a significant majority of their network. The data held by the Council is provided by a third party company which utilises Sideways force Coefficient Routine Investigation Machines (SCRIM) to measure friction coefficients. In addition to the manufacturer's annual calibration requirements, the contract covering data collection stipulates that the contractor is to comply with the operating procedures outlined in the Design Manual for Roads and Bridges (Highways Agency, 2004a) ensuring both improved consistency in data collection over the network, and over time.

In accordance with the Design Manual for Roads and Bridges the timing of SCRIM data collection each year alternates between early, middle and the end of the permitted testing season (April to September). Cycling the collection of SCRIM data across the testing season enables a 'local equilibrium correction factor' to be calculated, which is used to provide information relating to seasonal as well as longer-term variation. Three benchmark sites located within the county which collectively measure 25km, are consistently used to calibrate results during the testing season.

Prior to supplying SCRIM data to Norfolk County Council, the data is processed by the contractor who reviews the data for anomalies. As SCRIM does not incorporate GPS technology there is occasionally a slight discrepancy between the length of road measured by SCRIM and the known length of the road. Where such discrepancies are encountered, the contractor adjusts data points through a process of ‘stretching’ or ‘shrinking’ the length of the total data collected. Analysis of the collected data, and discussions with the local authority suggests that no significant adjustments have been made to the acquired data.

Table 5 summarises the friction coefficient data made available by Norfolk County Council that will be considered for inclusion in the analysis. It is noted that the data provided by Norfolk County Council has been ‘corrected’ in accordance with the Design Manual for Roads and Bridges, all data can therefore be considered to have been collected at the same time of year.

Data Element	Data Reporting Intervals	Unit of Measure	Measurement Accuracy	Location Accuracy
Friction Coefficient	10m	SCRIM Co-efficient (CSC)	±0.031	±20m longitudinal ±1m lateral

Table 5: Details Relating to Norfolk County Council's Friction Coefficient Data

Carriageway Data

As a result of the annual ‘Surface Condition Assessment for the National Network of Roads’ (SCANNER) survey, Norfolk County Council holds a significant amount of information relating to carriageway geometry (curvature, superelevation and gradient) and carriageway surface condition. In accordance with United Kingdom Roads Board specifications, the entire A-road network is surveyed on a two year cycle, where data is collected using a SCANNER survey vehicle for the left most lane in one direction per year. The specifications also require operators to use survey vehicles with current accreditation certificates and to comply with agreed operating procedures.

On the basis of 48 measurements per 10m section, the data is analysed and manipulated to provide one reading for most variables (UK Roads Board and Laboratory, 2011). Collected data is referenced to National Grid Co-ordinates using GPS, which is supported by an inertial navigation system that improves accuracy and ensures that intermittent GPS signal loss does not affect the accuracy of data location referencing (UK Roads Board and Laboratory, 2011). Once collected, the carriageway condition data is provided to Norfolk County Council for upload into their pavement management system.

In addition to carriageway condition, Norfolk County Council also holds additional information pertaining to road hierarchy and posted speed limit information which are of primary interest to this study. Such information has been collated and updated by Norfolk County Council on an ad hoc basis over many years as existing posted speed limits and road hierarchy classifications have changed.

Data elements relating to carriageway data that have been made available by Norfolk County Council and will be considered for use in the analysis, along with their associated characteristics are as summarised in Table 6.

Data Element	Data Reporting Intervals	Unit of Measure	Measurement Accuracy	Location Accuracy
Carriageway Gradient	10m	%	±1.5%, or 10% of the true gradient whichever is greater	10m
Carriageway Curvature	10m	m	±50m, or 25% of the true curvature whichever is greater	10m
Carriageway Superelevation	10m	%	±1.5%, or 10% of the true superelevation whichever is greater	10m
Road Hierarchy	n/a	Classification (A, B, C, Unclassified)	100%	0m
Posted Speed Limit	n/a	Miles/Hour	100%	10m

Table 6: Details Relating to Norfolk County Council's Road Carriageway Data

Traffic Flow Data

Traffic count and vehicle classification data for the A-road network is collected by Norfolk County Council using both temporary and fixed traffic counters. Each of the 75 permanent traffic counters located on the A-road network comprise of two induction loops and a data logger. The induction loops detect passing vehicles and measure their length and axle configuration, transmitting this information to the data logger for processing and subsequent storage. Annual average daily traffic flows and the proportion of heavy goods vehicles are calculated for each year using the count data collected.

In addition to the permanent count sites, Norfolk County Council also hires Metrocount count equipment to collect additional traffic flow data using temporary counters on an as needed basis. While the hardware components of the temporary and permanent traffic counters are similar (with the

exception that pneumatic rubber tubes are used in place of induction loops), the method used to calculate annual average daily traffic values is significantly different.

Samples collected by the temporary traffic counters (generally covering a two week period) are expanded into ‘full year’ values on the basis of a comparison with the data recorded at the nearest permanent counter. This method of expanding sample counts into estimated full year counts is considered by Council staff to be the most accurate manner to take into account localised seasonal variation. The estimated full year counts are then used to calculate annual average daily traffic flows and the proportion of heavy goods vehicles in the same manner as at permanent sites.

Data elements relating to traffic flow that have been made available by Norfolk County Council and will be considered for use in the analysis, along with their associated characteristics are as summarised in Table 7.

Data Element	Unit of Measure	Expected Accuracy
Annual Average Daily Traffic Flows	Count	±0.5% - permanent Unknown - temporary
Proportion of Heavy Goods Vehicles (HGV)	% of Count	±2.5% of total count attributed to HGV's (permanent) Unknown - temporary

Table 7: Details Relating to Norfolk County Council's Traffic Flow Data

4.2 Preparation of the Data

Between the 16th of February and 22nd of March 2012, Norfolk County Council provided a number of electronic database files containing data relating to friction coefficients, traffic accidents, the carriageway, and traffic flow on their road network. Upon receipt, all datasets were opened to check that the files could be opened in ARC GIS and Microsoft Excel, that the data was as expected, and that the data contained within each file could be selected, manipulated and extracted.

All datasets were loaded into ARC GIS and geographically referenced to the British National Grid. An overview of the datasets in ARC GIS found that full coverage of the data items required for analysis was only available for the A-road network, for the years 2008, 2009 and 2010. All data unrelated to the A-road network and these three years was therefore superfluous and removed. Sections of the A-road network which did not have a posted speed limit of 60mph were also removed from the sample. This helped to ensure that the analysis was as fair as possible with respect to the

function of the road sections included in analysis, and minimise the range of geometric and vehicle operating parameters.

With the remaining data in ARC GIS, the 'spatial join' command was utilised to link the data at 10m intervals and create an output table. The following subsections detail the method and rationale of how each of the datasets were treated and refined prior to the statistical analysis described in Section 4.3.

Traffic Accident Data

To ensure a robust assessment of the relationship between friction coefficient and traffic accidents, some refinement to the accident dataset was required. The first refinement involved the removal of traffic accidents involving pedestrians, cyclists and equestrians. The rationale for removing vulnerable road users was that they are particularly susceptible to serious injury or death in relatively low speed accidents, and are not reliant on road surface friction to the same extent as motorised traffic. In addition it was considered that vulnerable road users were most likely to be involved in traffic accidents near built areas and may therefore unfairly skew results towards urban locations.

The second modification to the accident dataset involved the removal of traffic accidents that occurred during the winter months (December, January and February), the rationale for which was threefold. First, it removed the risk of including accidents occurring as a result of grit, snow or ice, during which time no, or only partial contact with the road surface is made. Second, the winter months represent the period furthest from the friction coefficient testing season, meaning that the actual friction coefficient values are likely to be significantly different from that measured. Third, the effects of pavement temperature which is considered to influence skid resistance (Ahammed and Tighe, 2009, Hall et al., 2009, Lamb, 1976, McDonald et al., 2009), will be reduced. While the removal of accident data from the winter months will not wholly compensate for the variations in friction coefficients, it will to some extent moderate the effects.

The final stage in the preparation of the traffic accident dataset involved the monetisation of the remaining traffic accidents. Using 'Transport Analysis Guidance' (Department for Transport, 2009), values of £21,372, £205,056 and £1,790,203 were respectively applied to all slight, serious and fatal injury accidents.

In the literature reviewed in Chapter III it was common practice to select specific accident movement classifications, road surface conditions, and/or weather conditions for inclusion in the statistical analysis. Given that research by Hosking (1986) highlighted the potentially subjective nature of such refinements, the datasets included in this study were not refined in this manner. It is emphasised that should a relationship between friction coefficient and traffic accidents exist, it should be evident over

and above the noise created by those accidents included in the dataset for which friction coefficients bare no influence, and which would be randomly distributed on the road network.

Friction Coefficient Data

A preliminary review of the data provided by Norfolk County Council (as illustrated in Appendix D), revealed significant annual shifts in the measured values of friction. The annual shifts in friction coefficients were greater than what could be explained by annual road surface improvement works and/or surface deterioration. As the cause of the observed variation was unclear, it was considered prudent to analyse the relationship between friction coefficient and traffic accidents for each of the years separately. The review also revealed that for a number of friction coefficient values, the number of records were notably higher, or lower than expected.

As discussed in Chapter III, the use of a single measurement (from a defined length of road) did not specifically account for the fact that accidents tended to take place over a longer section of carriageway than standard measurement values referred to. It was also noted that the use of a single measured value failed to account for friction values preceding the recorded accident location, or the entire length of carriageway involved in the accident. Therefore, 'representative friction' values were calculated for every 10m interval, enabling the relative level of friction provided by the carriageway to be considered.

To calculate representative friction coefficient values, it was critical to determine how many individual 10m measurements should be included in its calculation. The number of measurements used in this study has been dictated by the expected braking distance, and the estimated displacement error for friction and accident record placement (in both cases 20m). It is acknowledged that the friction values as provided by SCIRM may not directly correlate to the level of friction that the vehicle fleet can generate. However, the expected braking distance has been calculated as follows:

- Stage 1. The average and standard deviation values for friction coefficient measurements were calculated on the basis of data collected in 2008, 2009 and 2010. The resultant calculations determined that the sample had an average friction coefficient value of 0.477, and a standard deviation of 0.0645.

- Stage 2. Using standard normal (z) tables, average (μ) and standard deviation (σ) values, the 5th percentile friction coefficient value was calculated using Equation 1, and found to equal 0.31.

Equation 1 $Z = \frac{x - \mu}{\sigma}$

$$-2.57 = \frac{x - 0.477}{0.0645}$$

$$x = (-2.57 \times 0.0645) + 0.477$$

$$x = 0.31$$

Stage 3. Using a friction value (f) of 0.31, the 95th percentile braking distance was calculated using Equation 2 below. As the effects of carriageway gradient (G) are factored in the road geometry section, a value of 0% was used. A vehicle speed (V) of 100km/hr (27.78m/s) was used in the calculation. It is noted that a value of 9.81 has been used to represent gravity (g).

Equation 2 $\text{Braking Distance} = \frac{V^2}{2g((f) \pm G)}$

$$\text{Braking Distance} = \frac{27.78^2}{2(9.81) \times ((0.31) \pm 0)}$$

$$\text{Braking Distance} = \frac{27.78^2}{2(9.81) \times 0.31}$$

$$\text{Braking Distance} = 126.88\text{m}$$

On the basis of the calculation undertaken in Equation 2, 95% of road sections within Norfolk County Council's road network could be expected to enable a vehicle travelling at 100km/hr on a level road to stop within 130m.

Given that bearing information provided as part of individual traffic accident records could not be reconciled with actual carriageway lane direction the calculation of representative friction required data from both the increasing and decreasing lanes (lanes in opposing directions). Figure 33 illustrates the location of measurements included in the calculation of representative friction. An extract from the dataset has been provided in Appendix E to demonstrate how the measurements in the dataset were used to calculate representative values.

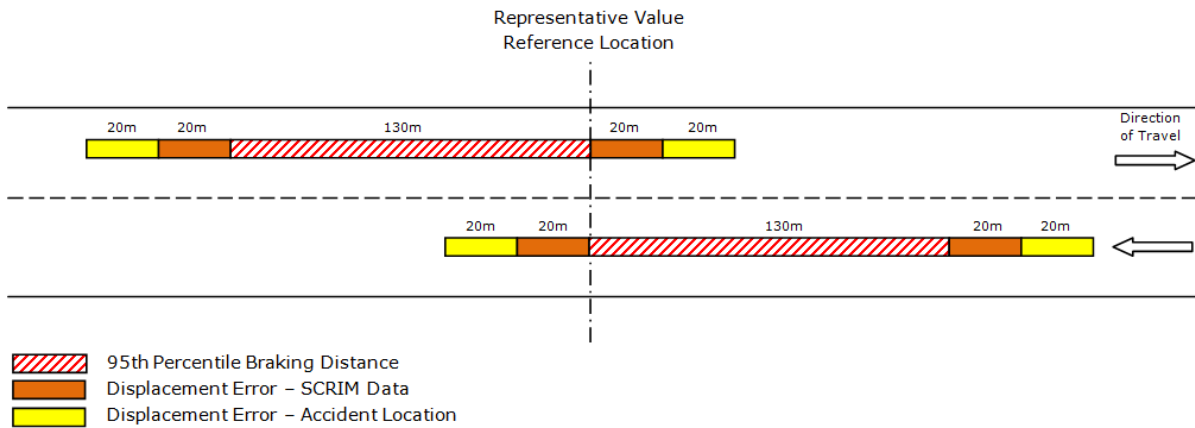


Figure 33: Measurements to be Included in the Calculation of the Representative Values

As the relationship between braking distance and friction coefficient is non-linear, the representative friction value could not be derived by simply calculating the arithmetic average of the measured values. Representative friction values were therefore calculated as follows:

Stage 1. The ‘effective’ braking distance was calculated for each of the 42 friction coefficient measurements (two carriageway lane lengths of 210m, divided by the 10m measurement interval), for reasons already outlined a value of 0% was used to represent carriageway gradient, and a value of 100km/hr used to represent vehicle operating speed. The arithmetic average was then calculated for the 42 braking distances. The process for calculating the average braking distance is summarised in Equation 3.

$$\text{Equation 3} \quad \text{Average Braking Distance} = \frac{\sum_{n(42)} \left[\frac{v^2}{2(g) \times (\text{road surface friction} \pm G)} \right]}{n(42)}$$

Stage 2. Using the average braking distance value calculated, representative friction values were determined using Equation 4. It is noted that due to the calculation method, representative values could not be calculated for the last 170m of each road section.

$$\text{Equation 4} \quad \text{Representative Friction} = \frac{v^2}{2g \times \text{Average Braking Distance}}$$

Carriageway Data

Norfolk County Council provided SCANNER data collected in 2010 and 2011 which respectively related to the decreasing and increasing lanes of the A-road network. In light of the literature reviewed in Chapters II and III, data relating to carriageway curvature, superelevation, and gradient as collected by SCANNER were of primary interest to this study. To enable data to be cross tabulated at 10m intervals, representative values were calculated for carriageway curvature, superelevation, and

gradient using the same measurement selection rationale as depicted in Figure 33. As for representative friction, values could not be calculated for the last 170m of each road section due to the calculation method utilised.

Representative curvature and superelevation were determined by calculating the arithmetic average. Initially it was hoped that carriageway curvature and superelevation could be represented by $V_{critical}$ given that together they directly affect the speed at which a vehicle can travel through a bend without utilising any friction (PhysicsLAB., Undated). This value would have provided valuable information pertaining to the road environment, and enabled comparison between varying curvature and super elevation combinations. Unfortunately however, the use of $V_{critical}$ was not possible due to the sensitivity of the SCANNER survey vehicle to carriageway camber on ‘straight’ sections of carriageway.

As illustrated in Equation 2, the relationship between braking distance and gradient is non-linear meaning that equal increments in gradient exert non-equal changes in braking distance. Gradient can therefore be considered to not only change the probability of a traffic accident occurring due to increased braking distances (Australian Academy of Science, 2003), but also the likely level of injury sustained by participants (Fildes and Lee, 1993, Richards and Cuerden, 2009) due to a reduced ability to shed kinetic energy. Representative gradient values were calculated using the following two stage process:

Stage 1. The ‘effective’ braking distance was calculated for each of the 42 gradient measurements using Equation 2. With friction accounted for elsewhere, a constant value of 0.40 was assigned and a value of 100km/hr was assigned to represent vehicle operating speed on the premise that all roads with posted speed limits other than 60mph (100km/hr) were excluded from the dataset.

Stage 2. Using the average braking distance value calculated, representative gradient values were determined using Equation 5.

$$\text{Equation 5 Representative Gradient Value} = \frac{\left[\frac{v^2 \div \sum_{n42} \text{Braking Distance}}{2g(f)} \right]}{n_{42}}$$

It is acknowledged that elements relating to road marking arrangements, carriageway and lane widths may influence driver behaviour. With the inclusion of only one road classification, and one posted speed limit environment, it is considered that geometric factors influencing driver behaviour will fall

within reasonable bounds, and that the influence of any significant variations will be moderated by the large sample size.

Traffic Flow Data

To enable traffic flow data to be considered in the assessment of the relationship between friction coefficient and traffic accidents, some refinement to the traffic flow dataset was required. The following paragraphs detail the step by step process for how the traffic flow dataset has been treated prior to its inclusion in the statistical analysis.

As the traffic count data supplied related only to specific locations on the network, the first manipulation involved the assignment of traffic flow data to each 10m section of the A-road network. Each section of carriageway was assigned traffic flow data on the basis of the nearest count on the same road, where carriageway sections were located equidistant from two count locations, traffic flow data from the highest count site was applied. Those roads that did not have traffic counters were removed from the sample.

On the basis of the assigned traffic count station, respective values for AADT and the proportion of heavy goods vehicles were assigned to each 10m carriageway section. It is noted that Norfolk County Council's classification of heavy goods vehicle was used, which includes both rigid and articulated vehicles, but excludes buses and coaches.

Although the application of traffic count data to the network in this manner is rather crude, it is considered the best approach to ensure that exposure rates were able to be included in analysis without the inherent risks associated with more complex and significant data manipulation. An additional category for motorcycles was initially considered, however following discussions with Council staff a separate category was not included due to the unreliability of count stations to accurately capture this vehicle classification.

4.3 Statistical Analysis Methodology

Following the tabulation of the spatial GIS data and refinement of each of the dataset outputs as outlined in Section 4.2, complete datasets were only available for the years 2008, 2009 and 2010. The datasets for 2008, 2009 and 2010 respectively had 26,673, 25,556, and 26,407 data points, which represented every 10m of the network included in the analysis. Each data point consisted of its respective representative friction coefficient and carriageway data values (calculated on the basis of 42 measured values as illustrated in Figure 33), traffic count information (from the nearest traffic count

site), and traffic accident records. It is noted that no one 10m data point included in this study had more than one recorded traffic accident.

Each of the three datasets were imported into 'R' Version 2.15.0 following which the data could be explored and the relationship between the coefficient of friction and traffic accidents could be tested. The following subsections respectively detail the process and methods used in both the preliminary data exploration and testing of the relationship.

Preliminary Data Exploration

To determine the most appropriate statistical methods for testing the relationship between the coefficient of friction and traffic accidents it was necessary to explore and understand the data available. This subsection details the process and methods used for this purpose.

The initial focus of the preliminary data exploration was centred on understanding the distribution of each of the variables from the 2008, 2009 and 2010 datasets, summary statistics produced by R were used for this purpose. From this the variables were classified as being either categorical (accident number), ordinal (accident severity, AADT and percentage HGV), or continuous (friction, curvature, super elevation and gradient).

Accident number, accident severity and AADT were tabularised, and bar graphs were used to provide an overview of the data and highlight any patterns of interest.

The continuous variables were displayed in histograms to provide an initial overview of the data, enabling a review of any distribution patterns, gaps in the data and outliers. Where variables appeared to display normal distribution properties, skewness and kurtosis values were calculated. To visually assess the variables closeness of fit with the normal distribution, Quantile - Quantile plots (QQ - plots) were generated. Where residual values were more significant for the larger values, the data was log transformed in an effort to achieve a better fit. Where a reasonable match with normality was found, the Lilliefors test was used to quantify the fit.

Between year comparisons were undertaken for all variables. Bar plots were used to compare categorical and ordinal data, while box and whisker plots were used for the continuous data. The Pearson's chi squared test was used to test the strength of association of the categorical and ordinal data between the datasets.

While efforts were made to compare the continuous datasets, the use of Z-tests and Mann-Whitney U tests were considered inappropriate due to the lack of normality and independence.

Testing of the Relationship

The results of the preliminary data exploration guided the selection of statistical methods to test and analyse the relationship between friction and the number and severity of traffic accidents. This subsection outlines the statistical methods utilised and provides a discussion of why these tests were selected and considered appropriate.

To enable a visual examination of any potential relationships (linear or non-linear), all variables contained within the three datasets were paired, and displayed in X, Y scatter plots. Due to the potential for relationships to be masked by the number of data points plotted, Pearson's correlation coefficients and p-values were calculated for all variables paired with the representative coefficient of friction.

To examine the predictive value of representative friction in traffic accidents, binomial logistic regression was applied to the three datasets given that no more than one accident was recorded at any one data point. Regression included representative values relating to friction, curvature, superelevation, gradient and AADT for all data points included in the datasets (those with and without recorded accidents). Each dataset was run through a total of five iterations in an attempt to improve the predictive value of the model. The variable removed in each iteration was determined on the basis of the highest p-value obtained in the preceding iteration. Zero inflated Poisson regression was considered but not used, this was due to no one data point having more than one recorded traffic accident.

Following the results of the models, the 2008, 2009 and 2010 datasets were split into two subsets. The first subset for each year contained information relating to representative friction, curvature, superelevation, gradient and AADT values at sites where accidents had been recorded. The second subset for each year contained information relating to representative friction, curvature, superelevation, gradient and AADT values at sites where no accidents had been recorded. The Anderson-Darling k-sample test was then used to examine whether variables contained in the two subsets for each year were drawn from a population which was identical. The Anderson-Darling k-sample test was determined to be suitable for this purpose on the basis that sample sizes from both subsets were greater than four, and share a common continuous distribution. It is acknowledged that some bias may be present given that our data is not an independent random sample.

To investigate the extent to which representative friction influenced accident severity, box and whisker plots were used to display representative friction coefficient data for each of the accident severity classifications and non-accident sites, for each year.

The Anderson-Darling k-sample test was then used to examine whether the variables relating to the different accident severity classifications were drawn from an identical population. These four subsets (fatal, serious, slight, no accident) were analysed in terms of representative friction, carriageway curvature, superelevation, gradient and AADT values. These tests were repeated for data derived from each of the 2008, 2009 and 2010 datasets.

Box and whisker plots were used to visually examine whether friction coefficient variation (standard deviation) along the carriageway was different for sites where accidents had been recorded, and those sites where no accidents had been recorded. The Anderson-Darling k-sample test was then used to examine whether variables contained in the two subsets for each year were drawn from a population which was identical.

4.4 Summary

The objective of this chapter was to detail the methodology used to test the relationship between friction coefficient and traffic accidents. The chapter was broadly divided into three parts, with the first part detailing how the data included in the analysis was collected, and its expected level of accuracy. Potential sources of bias were also outlined.

The second part of this chapter revealed that the assignment of the lowest friction value (within a defined distance) to a traffic accident could not be robustly justified for use in this study, even though the literature review completed in Chapter III found this to be common practice. Instead, a representative value that considered the entire length of road over which a traffic accident could be expected to occur, was calculated. The use of representative values also extended to carriageway curvature, superelevation, and gradient data. The use of representative values in this manner is a significant departure from existing methodologies described in the literature.

The final part of this chapter detailed the techniques used to provide a preliminary overview of the data, and test the relationship between friction and traffic accidents. As outlined in the statistical analysis methodology, both visual and calculated statistical techniques were used to review the data and test the relationship.

Chapter V: Results

On the basis of the methodology developed for this study, this chapter seeks to display the noteworthy results found for the Norfolk County 2008, 2009 and 2010 datasets. This chapter has been broadly divided into two sections. The first section displays the results found as a consequence of the preliminary data exploration which had the primary aim of enabling a better understanding of the available data. The results displayed relate to the outputs of a Pearson's chi squared test, histograms, box and whisker plots, normal Q-Q plots, Kurtosis calculations, skewness calculations, and Lilliefors tests.

The second section of this chapter displays the noteworthy results found as a result of relationship testing. The first part of this section focuses on the results found when relationships with the number of accidents were investigated. The results for this part relate to the model fitting process including scatter plots and correlations. The second part of this section focuses on the results found when relationships with accident severity classification were investigated, these results are displayed as box and whisker plots and quantified with Anderson-Darling k-sample tests.

The input commands for R (Version 2.15.0), and associated non-graphical R outputs have been provided in Appendix F.

5.1 Preliminary Data Exploration Results

The datasets were reviewed to establish the accident risk for each of the various accident severity types for the three datasets obtained, this review is summarised in Table 8. It is noted that the length of road included in the analysis varies to some extent, therefore care is required when comparing 'non-rate' data between years. In addition, the varying length of the network affected the number of data points available for analysis, the datasets for 2008, 2009 and 2010 respectively had 26,673, 25,556, and 26,407 data points.

A graphical representation of the accident rate, per 100million vehicle kilometres travelled (VKT), for each of the three datasets is displayed in Figure 34. A Pearson's chi squared test was carried out to calculate whether the difference between the actual number of accidents within each severity category was associated with year. The Pearson's Chi Square test found $p=0.945$, accepting the null hypothesis that there was no significant associations between the accident severity category, and the year. Therefore it can be noted that the proportions of fatal, serious and slight accidents are consistent over all three datasets.

Data Attribute		Year		
		2008	2009	2010
Road Sample Length (km)		266.73	255.56	264.07
Total VKT (million km)	All Traffic	890.91	856.53	863.81
	HGV	59.26	52.77	52.87
Average Number of VKT (million km) per sample length km	All Traffic	3.3401	3.3516	3.2711
	HGV	0.2222	0.2065	0.2002
Number of Accidents	Slight	51	45	50
	Serious	14	8	13
	Fatal	5	6	4
	All	70	59	67
Accidents per 100m vehicle kilometres travelled	Slight	5.72	5.25	5.79
	Serious	1.57	0.93	1.5
	Fatal	0.56	0.70	0.46
	All	7.86	6.89	7.76

Table 8: Preliminary Overview of the Data

An initial review of the outputs provided by 'R' Version 2.15.0 summary command, suggested that the data elements contained within the datasets were not normally distributed given that the respective means and medians were not well aligned. R outputs containing the minimum, 1st quartile, median, mean, 3rd quartile, and maximum values, for all data elements included in the three datasets have been provided in the R output file, contained in Appendix F. More specific investigation of the distribution of data elements have been outlined in the following subsections.

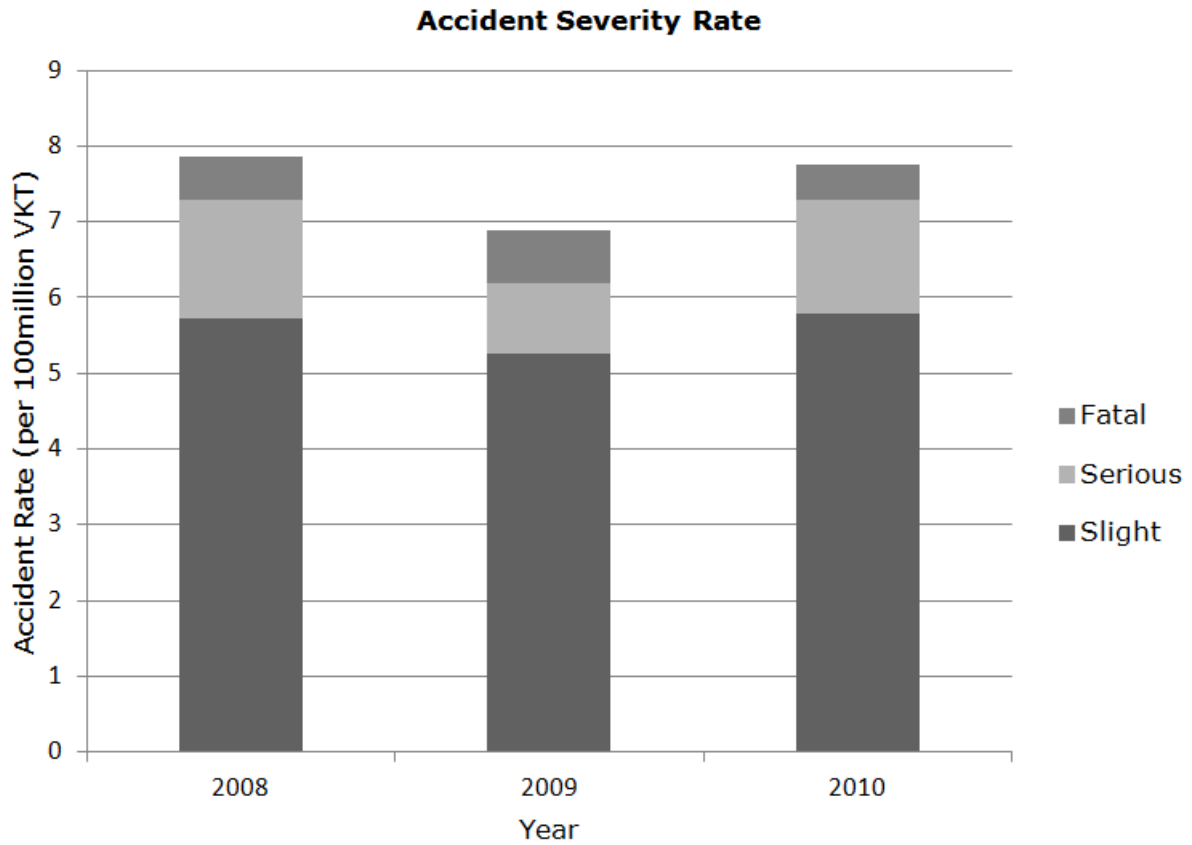


Figure 34: Accident Severity by Year in Norfolk County

Representative Coefficient of Friction

Values relating to representative coefficient of friction for the 2008, 2009 and 2010 datasets were respectively plotted in Figure 35, Figure 36, and Figure 37 to provide a visual illustration of the data's distribution. As illustrated in the figures, the distribution characteristics of the coefficient of friction changed markedly year to year. In addition, it is worth noting that the median representative coefficient of friction drops by 0.03 in 2009 (0.4656) when compared with data from 2008 (0.4953) and 2010 (0.4957).

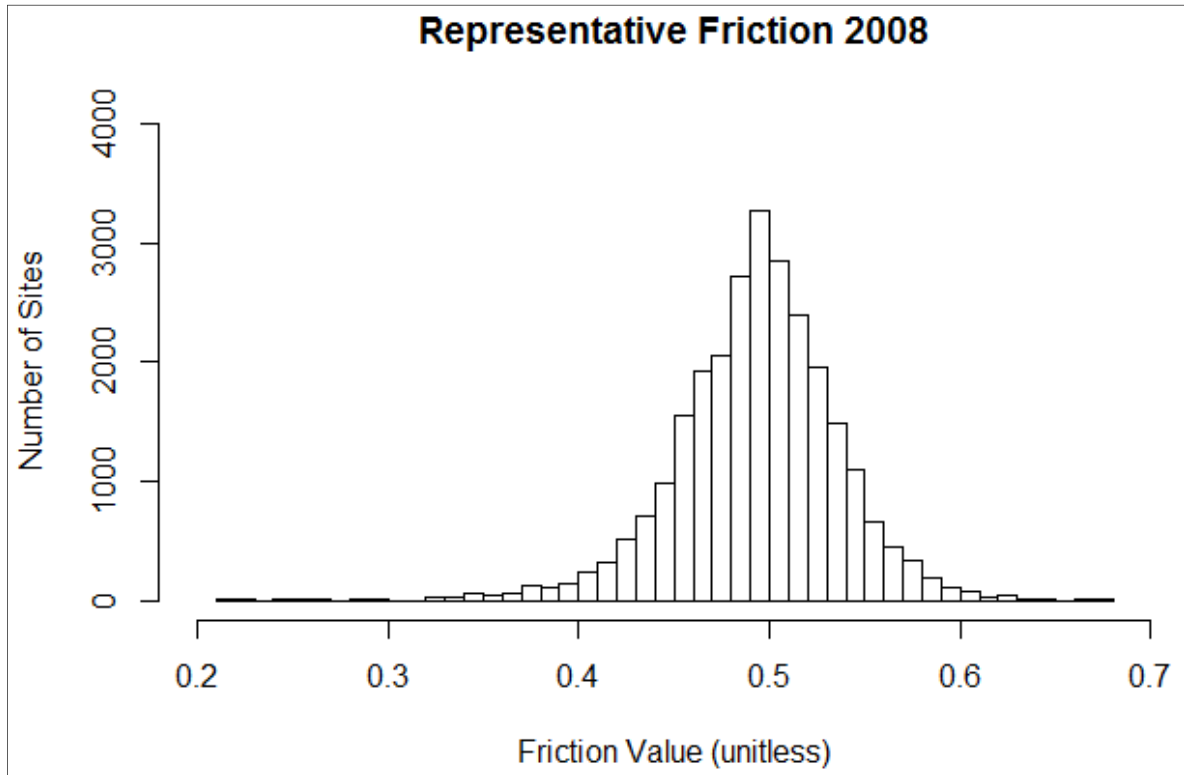


Figure 35: Spread of 2008 Representative Coefficient of Friction

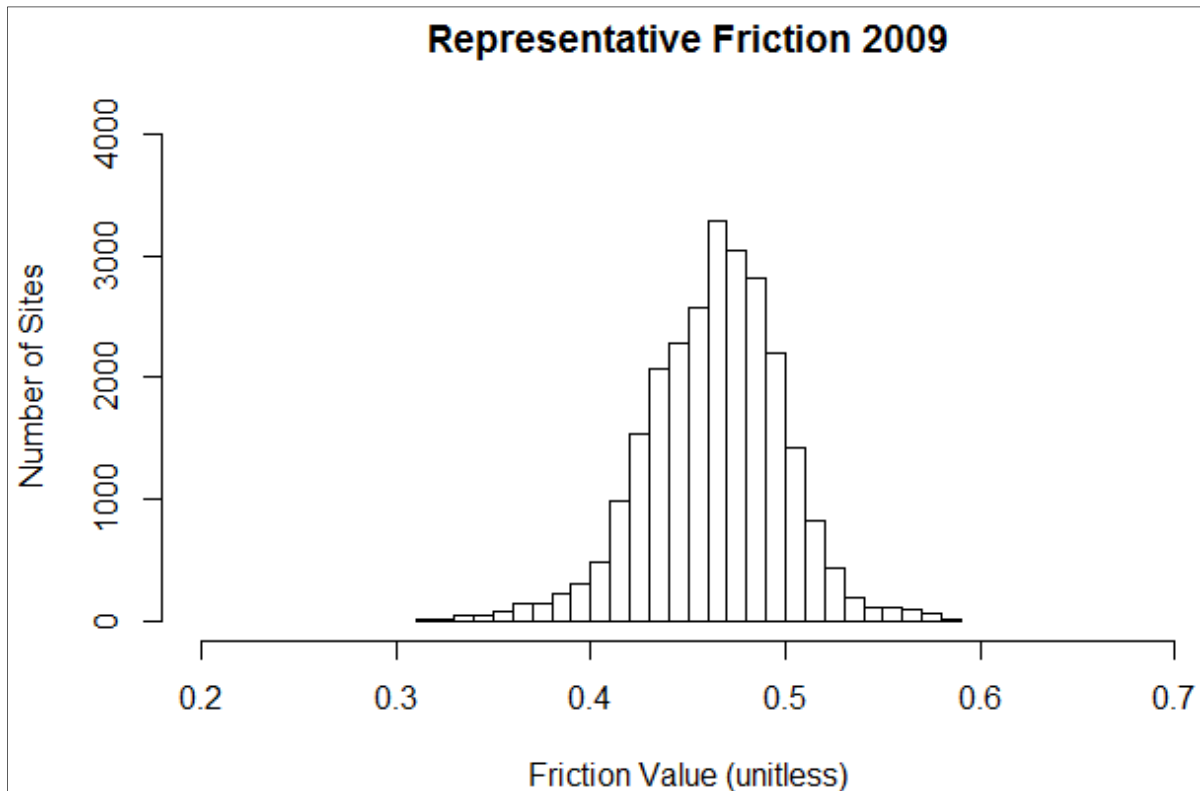


Figure 36: Spread of 2009 Representative Coefficient of Friction

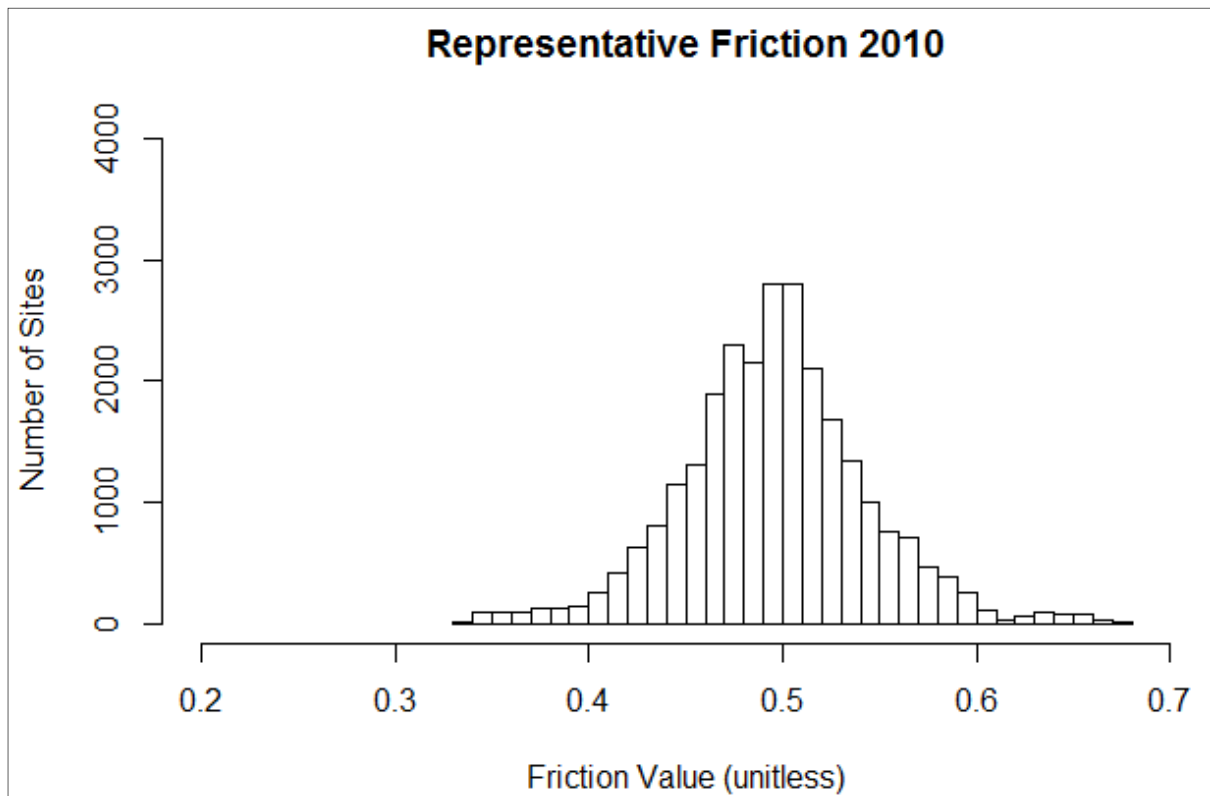


Figure 37: Spread of 2010 Representative Coefficient of Friction

The kurtosis values show all three datasets as having peaked kurtosis for the representative coefficient of friction. Notably, the kurtosis value for the 2008 (5.84) dataset, showed significant variation when compared with the 2009 (3.95) and 2010 (3.97) datasets. Skewness was quantified as being between -0.62, -0.31 and 0.07 for the 2008, 2009 and 2010 datasets respectively.

The box and whisker plots displayed in Figure 38 illustrate the difference in all of the 'five-number summary' values (minimum, quartile 1, median, quartile 3, and maximum), for the three datasets. The 2008 dataset had a group of unusually low representative friction values, these were investigated and were found to all be located on a section of the A149 (chainage 800), it is assumed that the site was treated prior to the following SCRIM survey (hence their absence in the 2009 dataset). Data relating to these sites have not been removed from the dataset on the basis that they were not considered outliers as they were found to be valid sites. Figure 38 also highlights that the five-number summary values in the 2009 dataset are lower than those contained in the 2008 and 2010 datasets, with the exception of minimum values in the 2008 dataset.

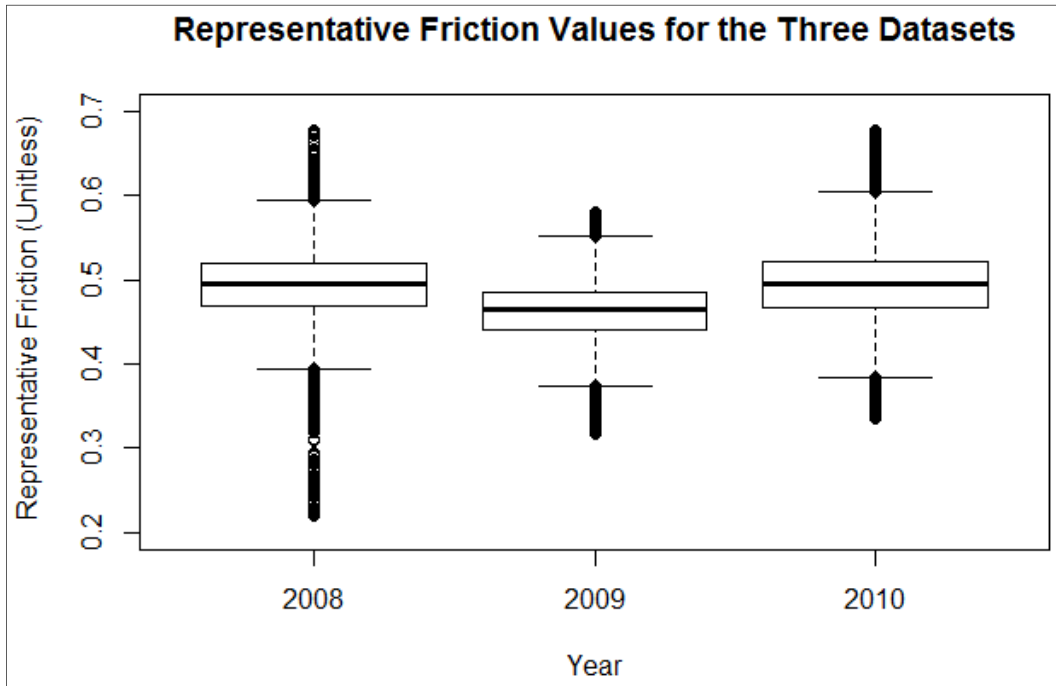


Figure 38: Representative Friction Data over the Three Datasets

The QQ plots of representative friction values for the 2008, 2009 and 2010 datasets are respectively depicted in Figure 39, Figure 40, and Figure 41. The quantile function of the standard normal distribution (straight line) illustrates where the observed data should lie if it were normally distributed. As illustrated, there were less low, and more high representative friction values than would be expected if the data was normally distributed, the middle section of data however does appear to follow a normal pattern.

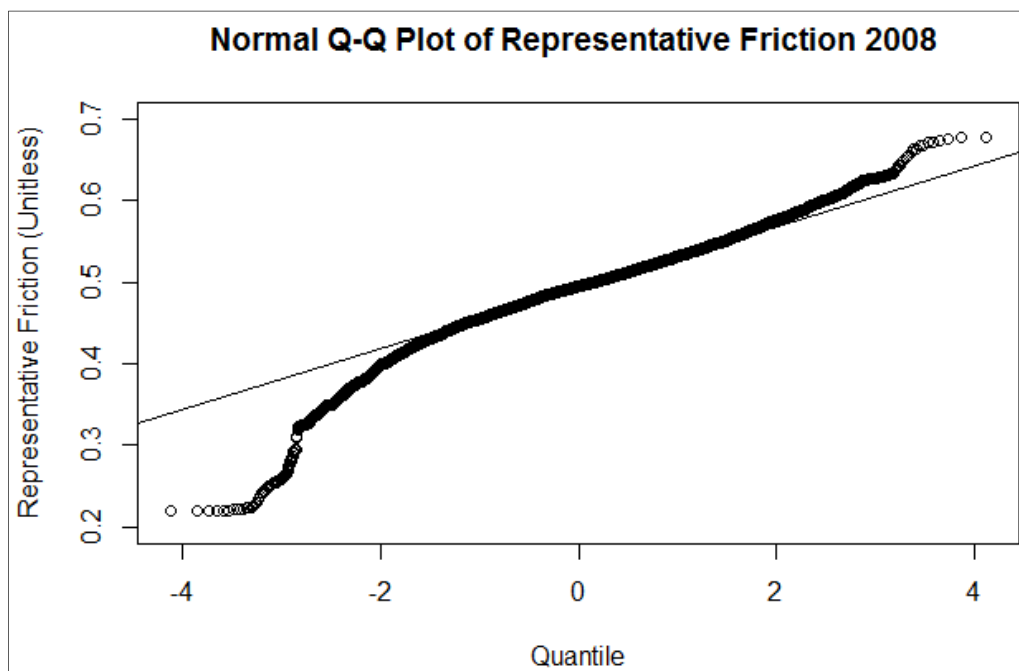


Figure 39: Normal Q-Q Plot of the 2008 Representative Coefficient of Friction

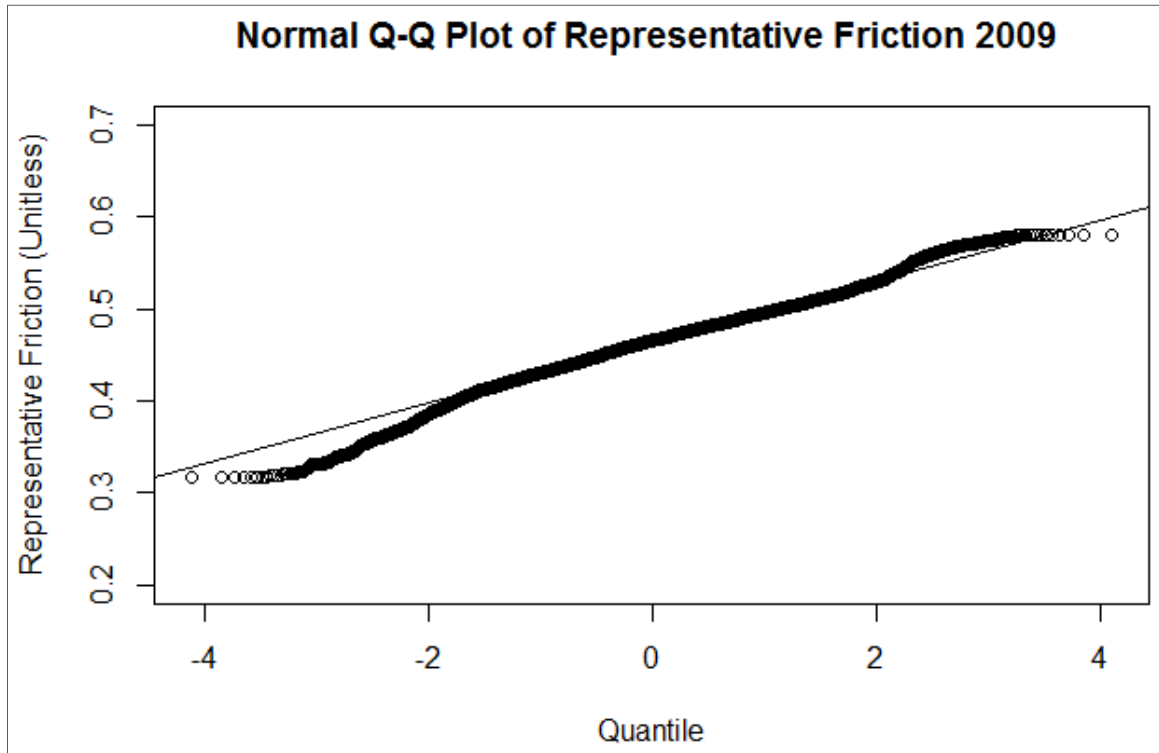


Figure 40: Normal Q-Q Plot of the 2009 Representative Coefficient of Friction

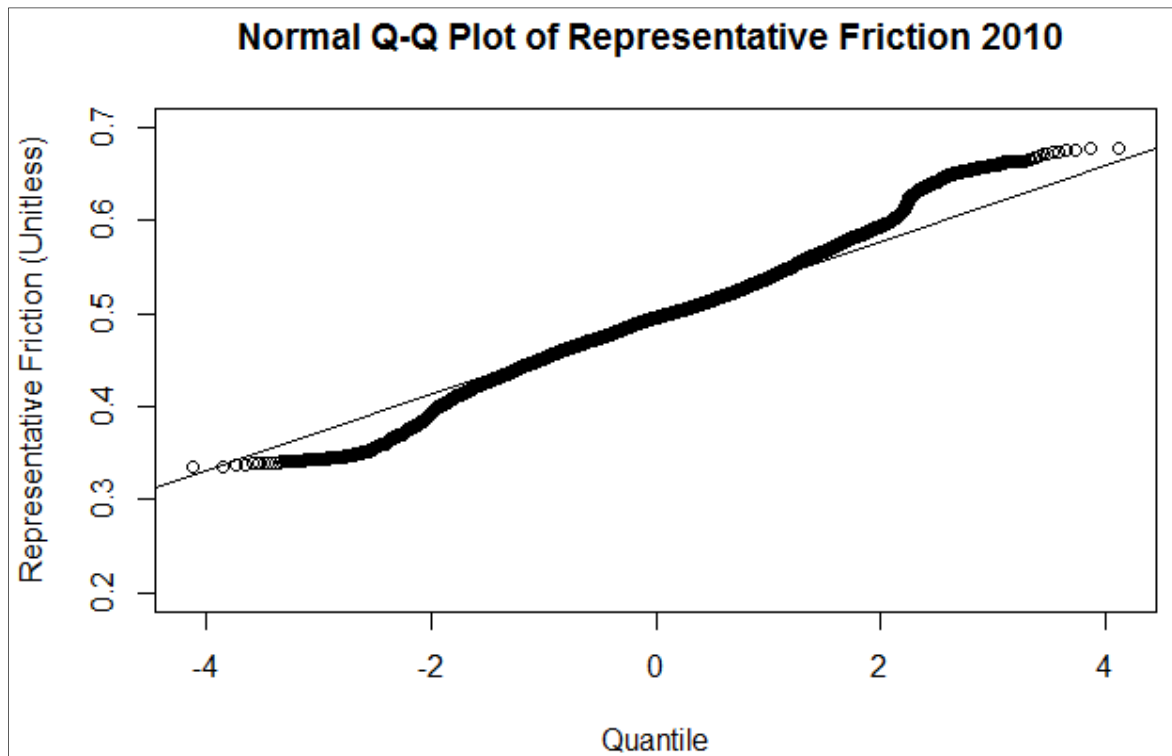


Figure 41: Normal Q-Q Plot of the 2010 Representative Coefficient of Friction

The probability that the representative coefficient of friction values were normally distributed was tested using the Lilliefors test. Table 9 illustrates the results found, proving that it is highly unlikely that the representative coefficient of friction values are normally distributed.

Year	D	p-value	n
2008	0.0468	$2.2e^{-16}$	26,673
2009	0.0332	$2.2e^{-16}$	25,556
2010	0.0379	$2.2e^{-16}$	26,407

Table 9: Lilliefors Test Results for Representative Coefficient of Friction

Representative Carriageway Curvature

Values relating to representative carriageway curvature for the 2008, 2009 and 2010 datasets were respectively plotted in Figure 42, Figure 43, and Figure 44 to provide a visual illustration of the data's distribution. As illustrated, data relating to the representative carriageway curvature is strongly left skewed, and displaying non-normal distribution. It is emphasised however, that the maximum curvature value that can be assigned to any given section of road is 2000m, as a result 'straight' roads are likely to have further contributed to the skew.

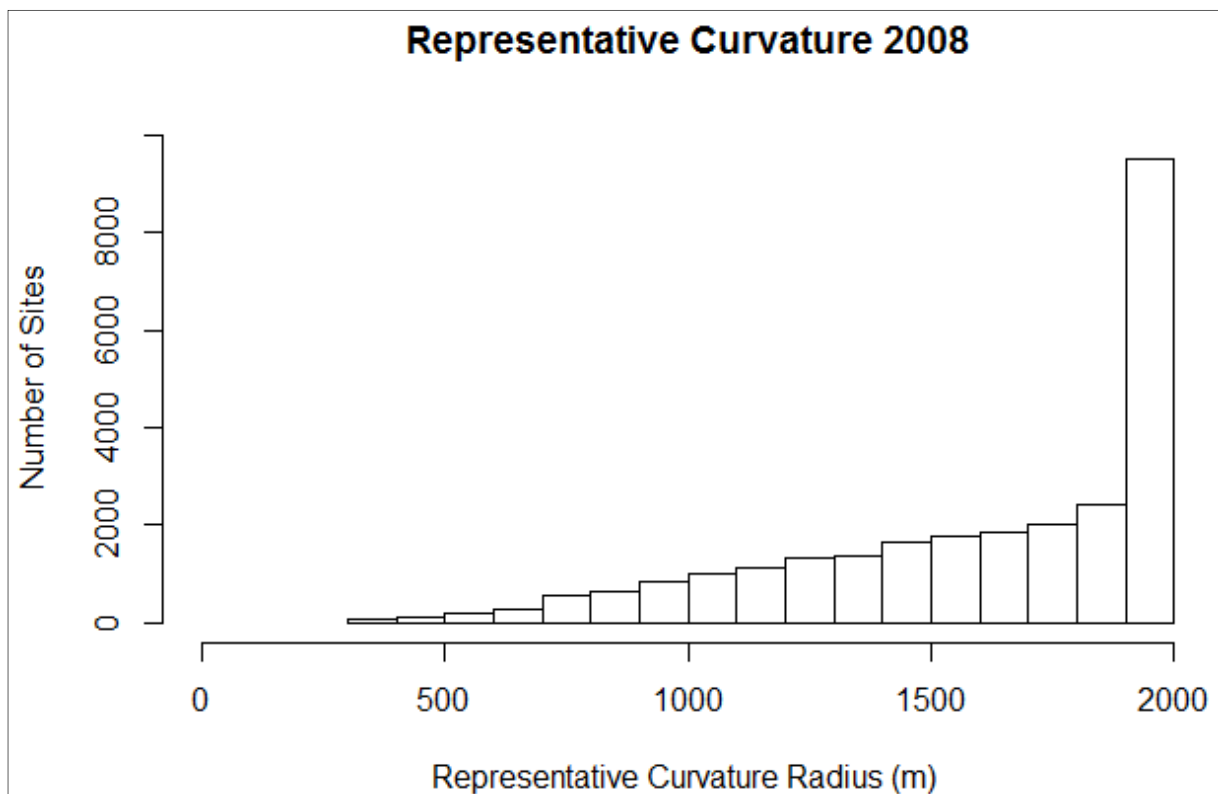


Figure 42: Spread of 2008 Representative Carriageway Curvature

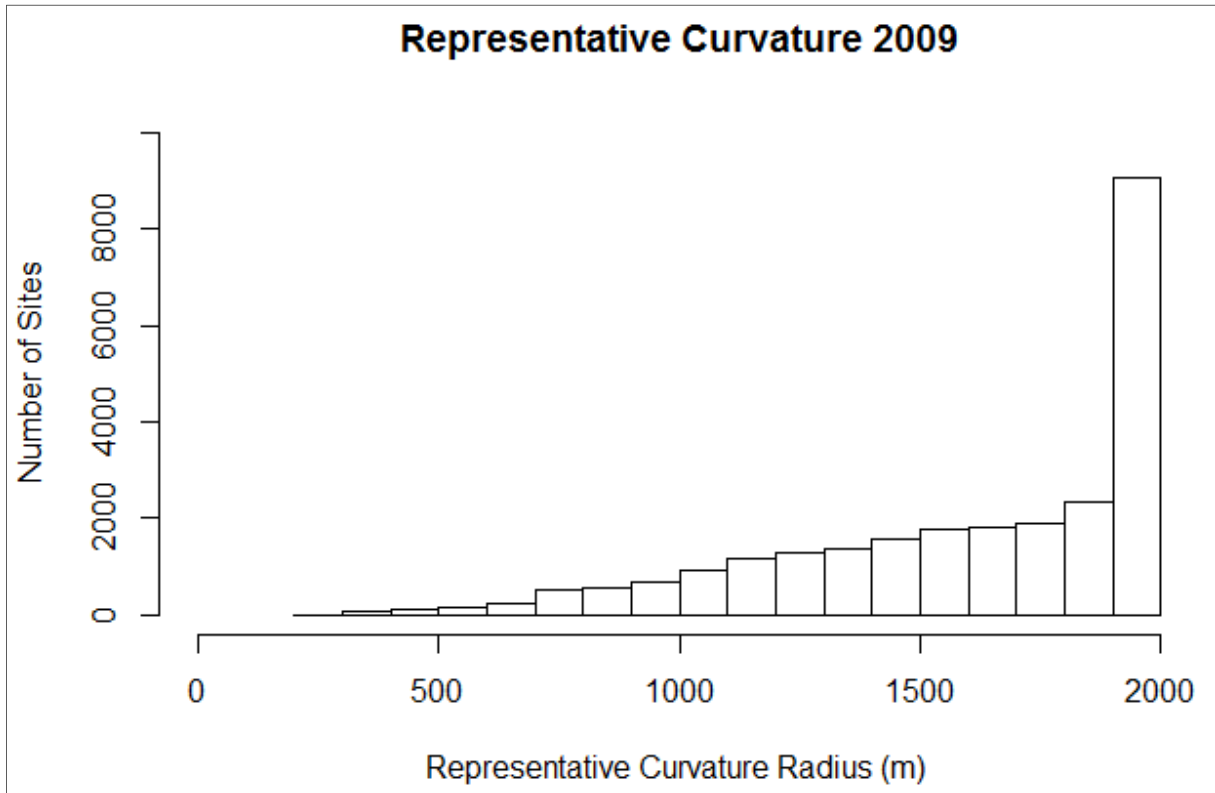


Figure 43: Spread of 2009 Representative Carriageway Curvature

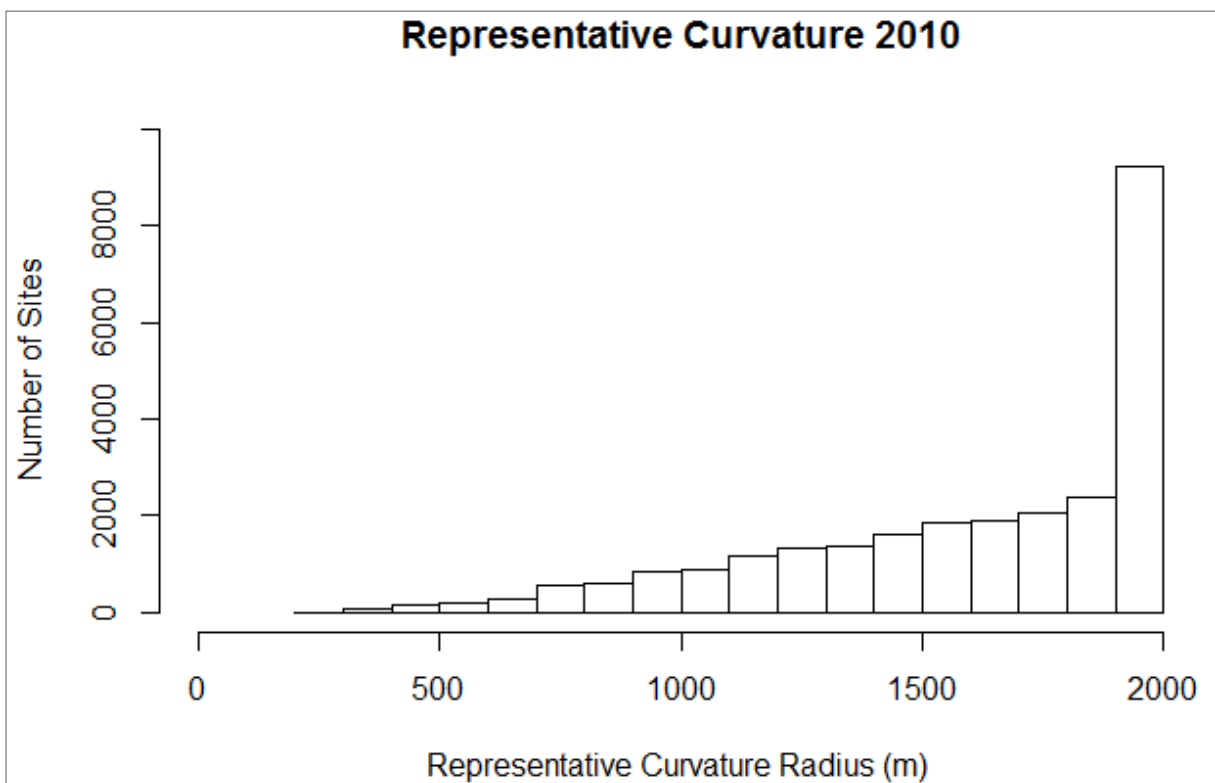


Figure 44: Spread of 2010 Representative Carriageway Curvature

Representative Carriageway Superelevation

Values relating to representative carriageway superelevation for the 2008, 2009 and 2010 datasets were respectively plotted in Figure 45, Figure 46, and Figure 47 to provide a visual illustration of the data's distribution. As illustrated, data relating to the representative carriageway superelevation is right skewed.

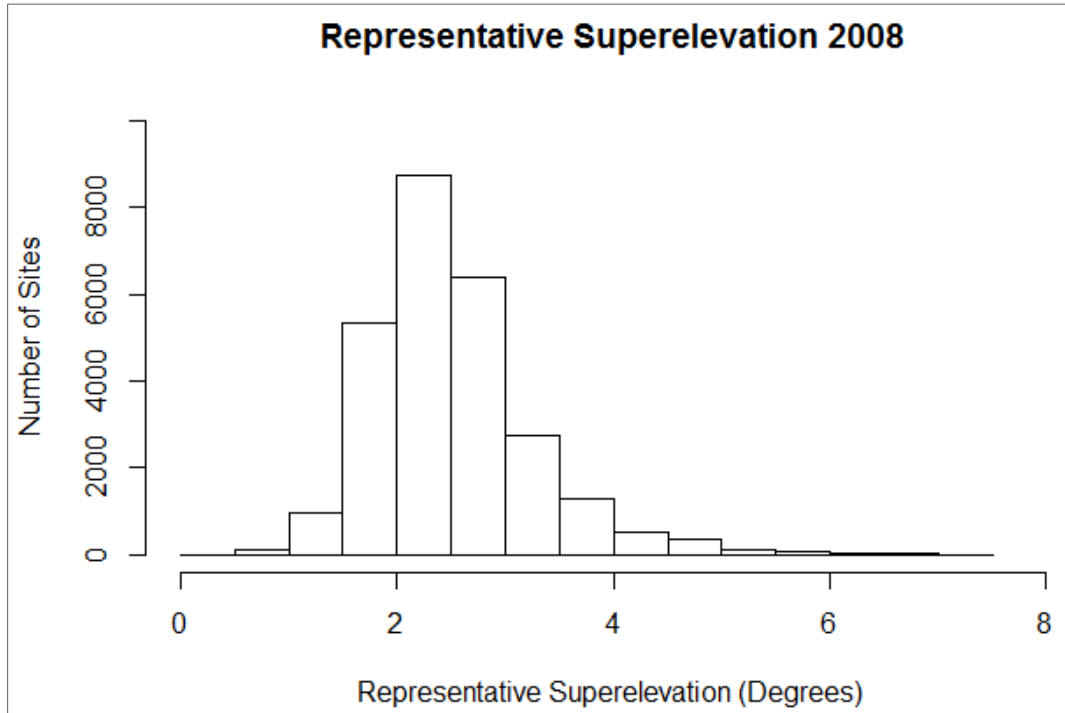


Figure 45: Spread of 2008 Representative Carriageway Superelevation

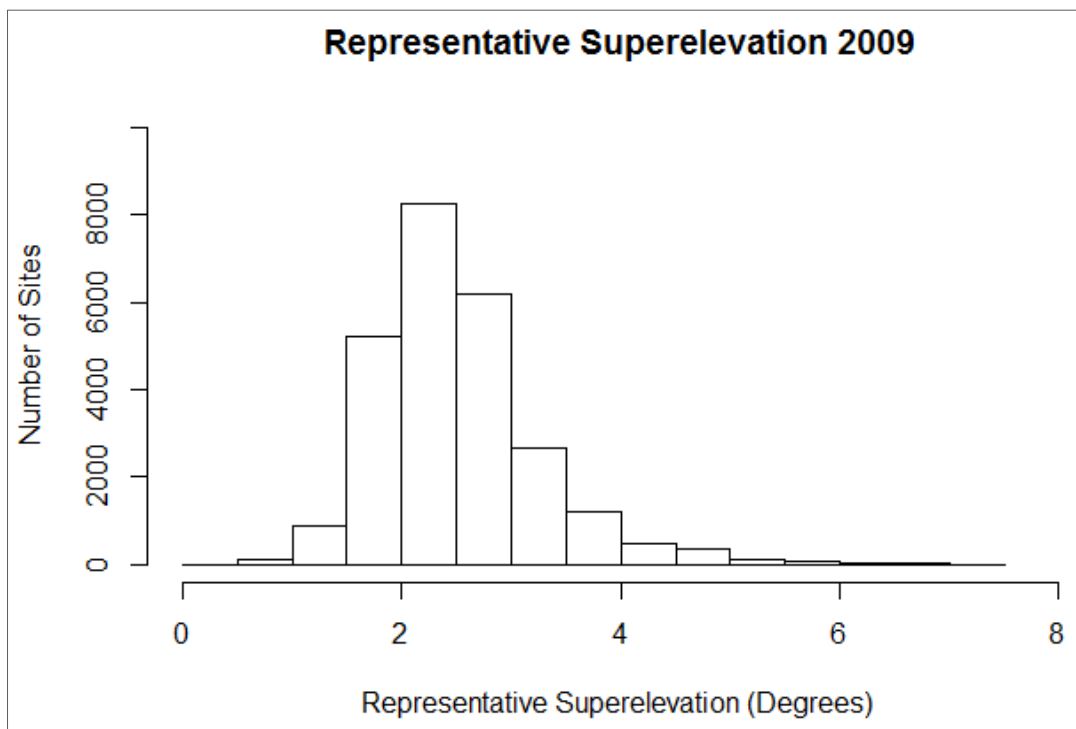


Figure 46: Spread of 2009 Representative Carriageway Superelevation

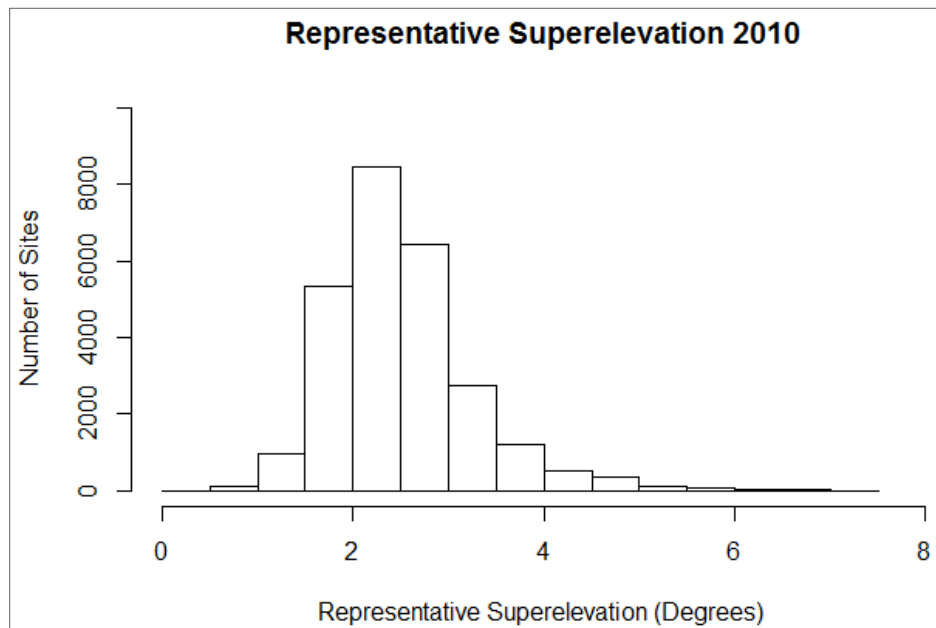


Figure 47: Spread of 2010 Representative Carriageway Superelevation

The kurtosis values show all three datasets as having peaked kurtosis (values ranging between 6.05 and 6.18) for the representative superelevation. Right skew was quantified as being between 1.26 and 1.27.

The QQ plots of representative carriageway superelevation values for the 2008, 2009 and 2010 datasets are respectively depicted in Figure 48, Figure 49, and Figure 50. The right skew was again evident in the plots given that there was an overrepresentation of high representative carriageway superelevation values.

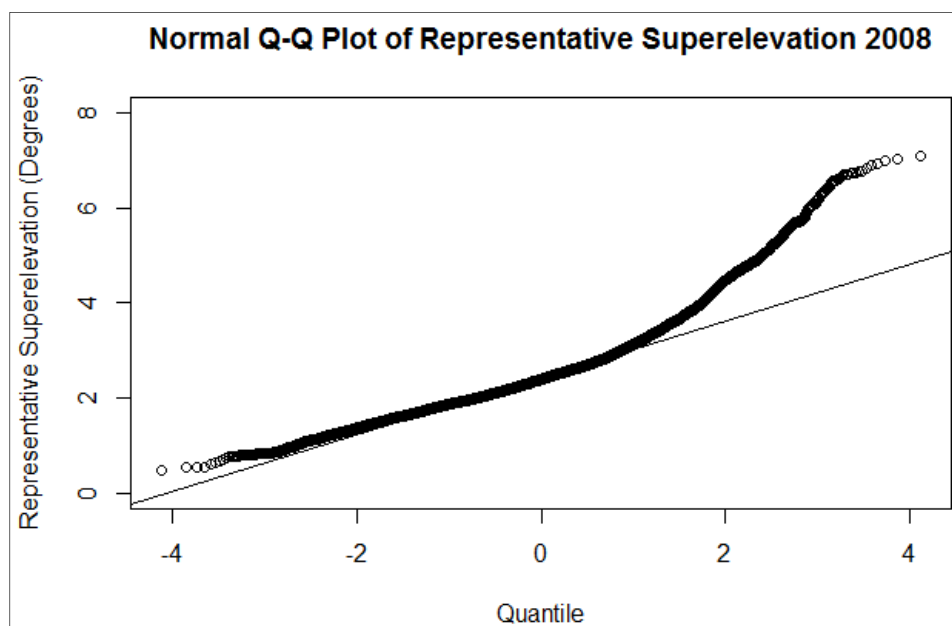


Figure 48: Q-Q Plot of the 2008 Representative Superelevation

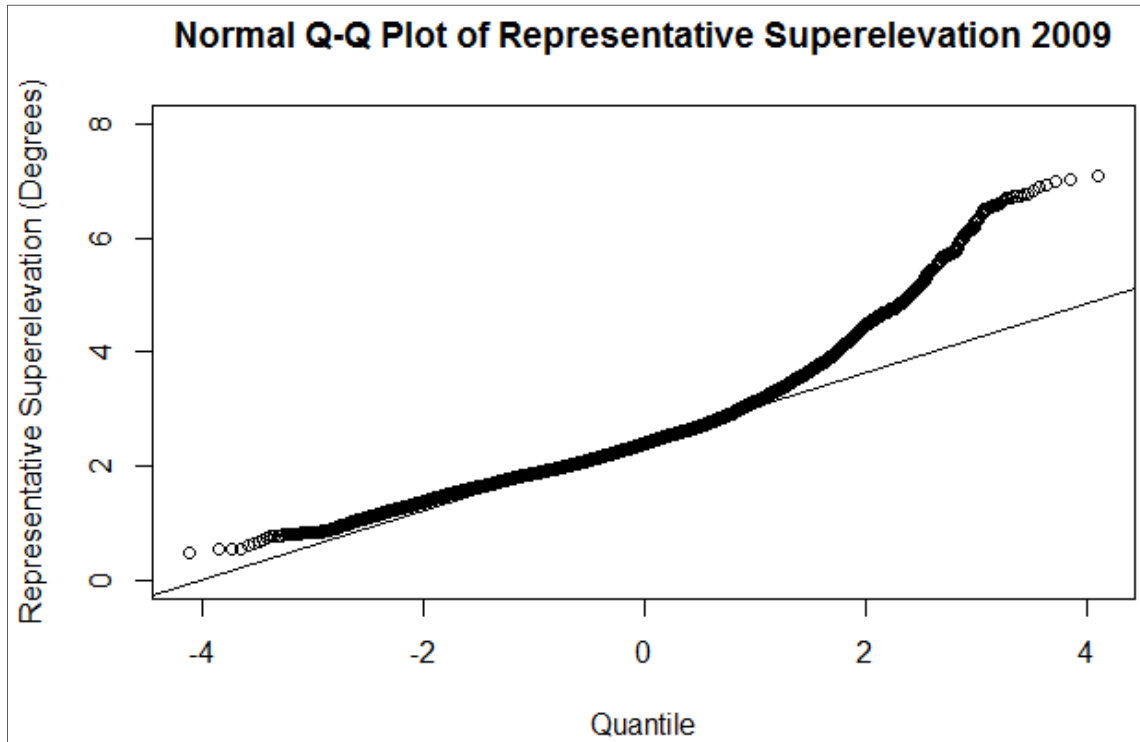


Figure 49: Normal Q-Q Plot of the 2009 Representative Carriageway Superelevation

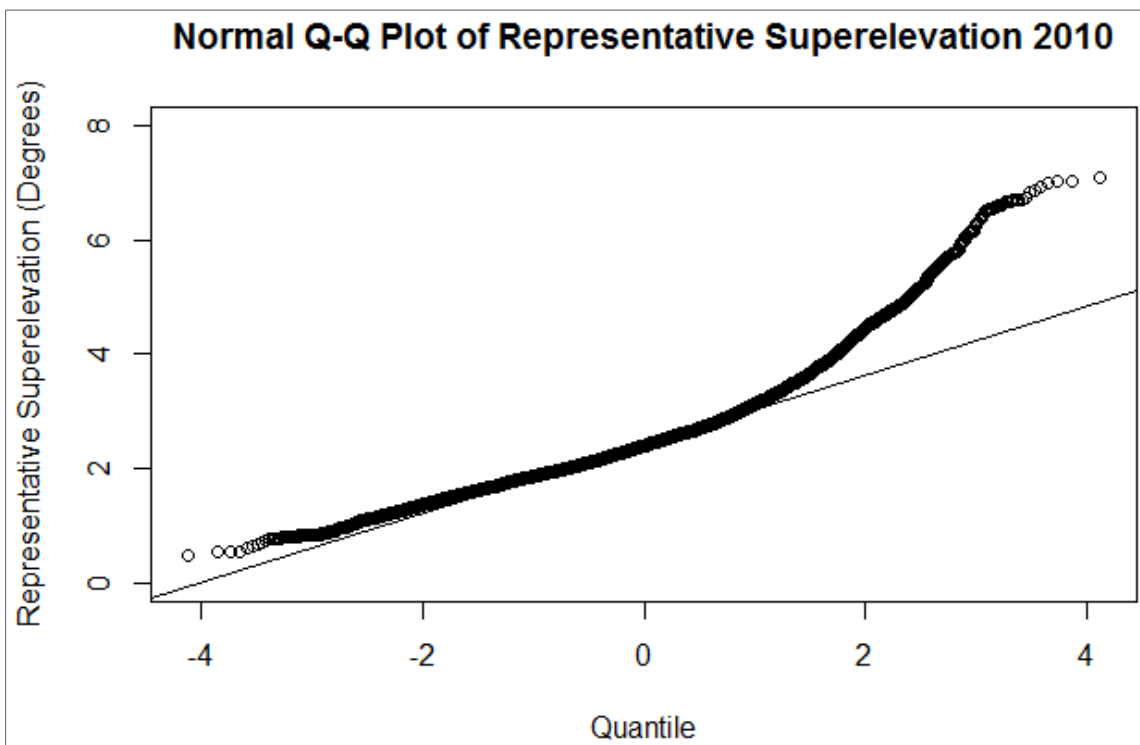


Figure 50: Normal Q-Q Plot of the 2010 Representative Carriageway Superelevation

A log transform was applied to representative superelevation as the residuals were observed to deviate at high values. The QQ plots of the log transformed representative superelevation values for the 2008, 2009 and 2010 datasets are respectively depicted in Figure 51, Figure 52, and Figure 53.

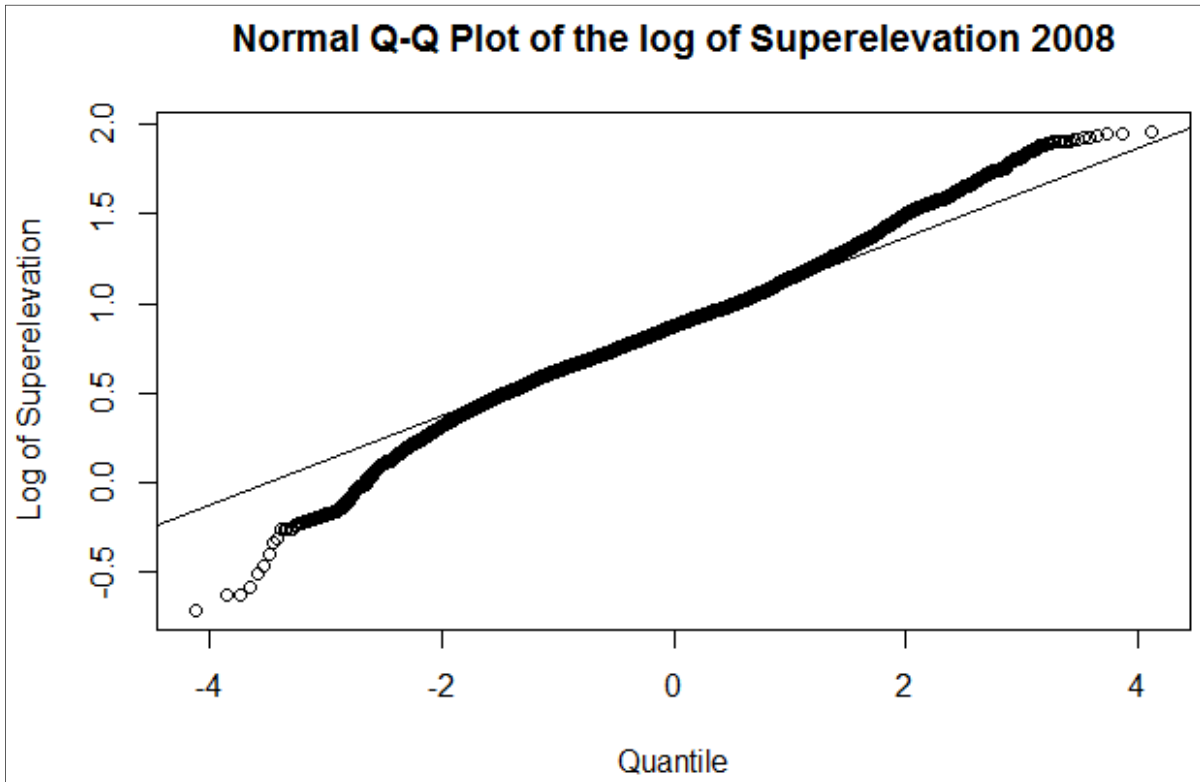


Figure 51: Normal Q-Q Plot of the 2008 Log Transformed Representative Superelevation

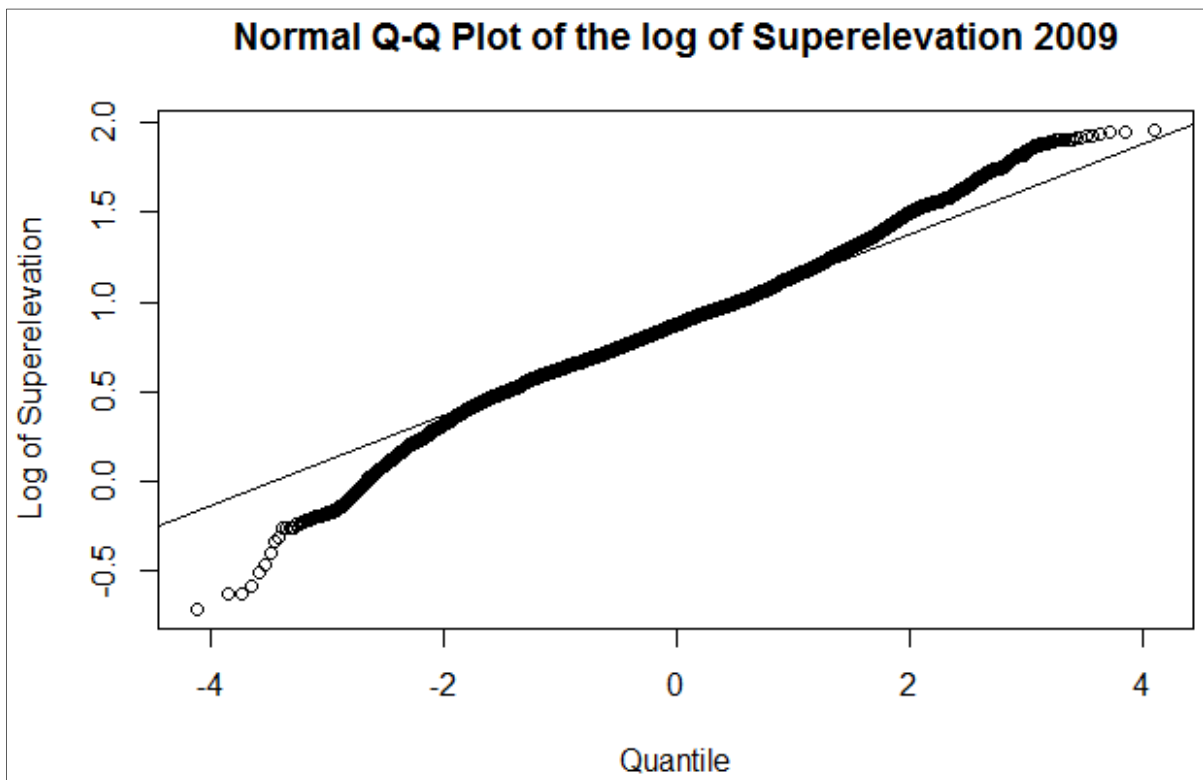


Figure 52: Normal Q-Q Plot of the 2009 Log Transformed Representative Superelevation

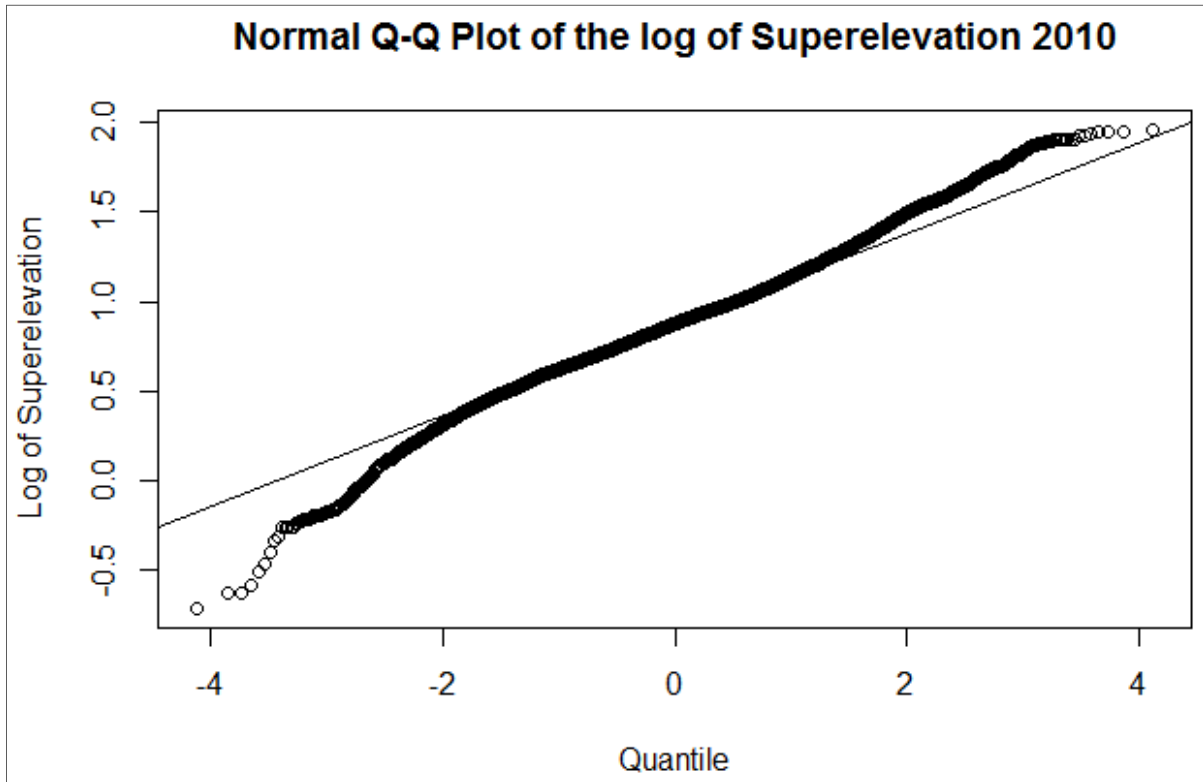


Figure 53: Normal Q-Q Plot of the 2010 Log Transformed Representative Superelevation

The probability that the log transformed representative superelevation values were normally distributed was tested using the Lilliefors test. Table 10 illustrates the results, proving that it is highly unlikely that the log transformed representative superelevation values are normally distributed. While an improved fit was gained, the log transform of the representative superelevation values continued to display sufficient variation from normality and has therefore not been used in further analysis.

Year	D	p-value	n
2008	0.0359	$2.2e^{-16}$	26,673
2009	0.0340	$2.2e^{-16}$	25,556
2010	0.0333	$2.2e^{-16}$	26,407

Table 10: Lilliefors Test Results for Log Transformed Representative Superelevation Values

Representative Carriageway Gradient

Values relating to representative carriageway gradient for the 2008, 2009 and 2010 datasets were respectively plotted in Figure 54, Figure 55, and Figure 56 to provide a visual illustration of the data's distribution. The figures suggest a left skew.

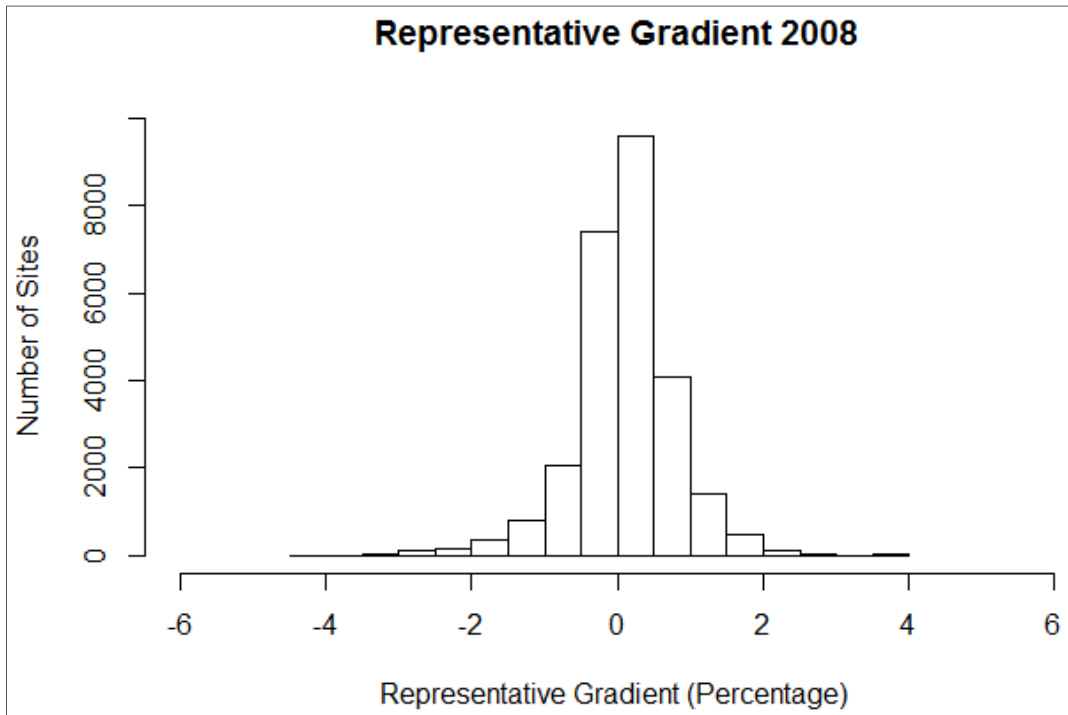


Figure 54: Spread of 2008 Representative Carriageway Gradient

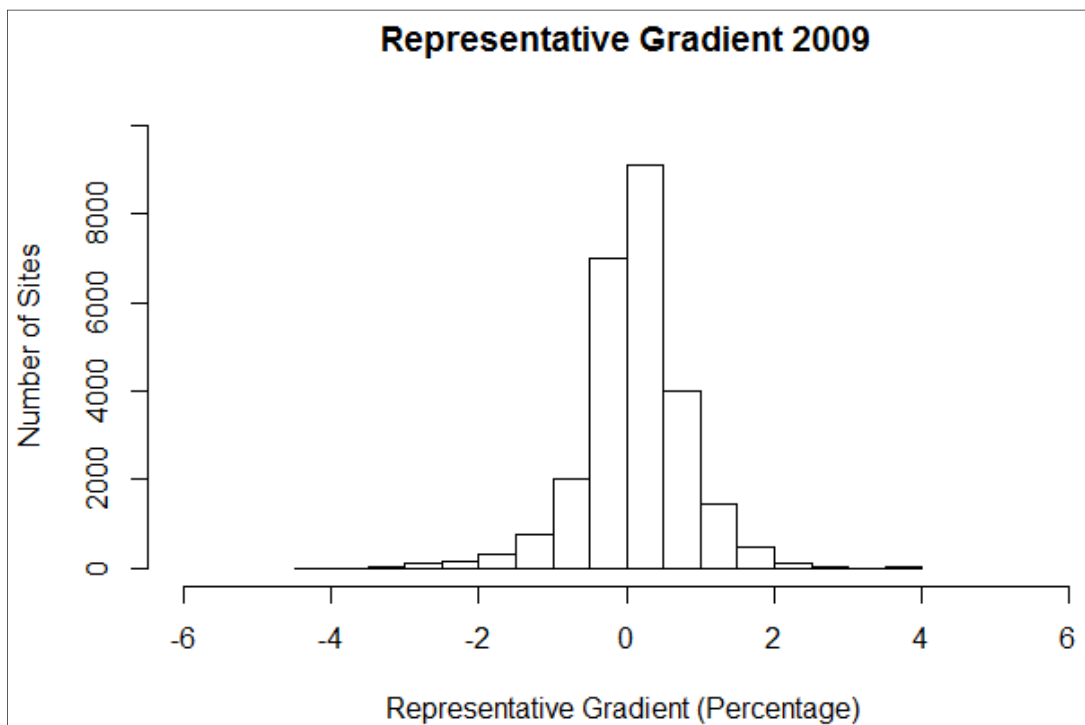


Figure 55: Spread of 2009 Representative Carriageway Gradient

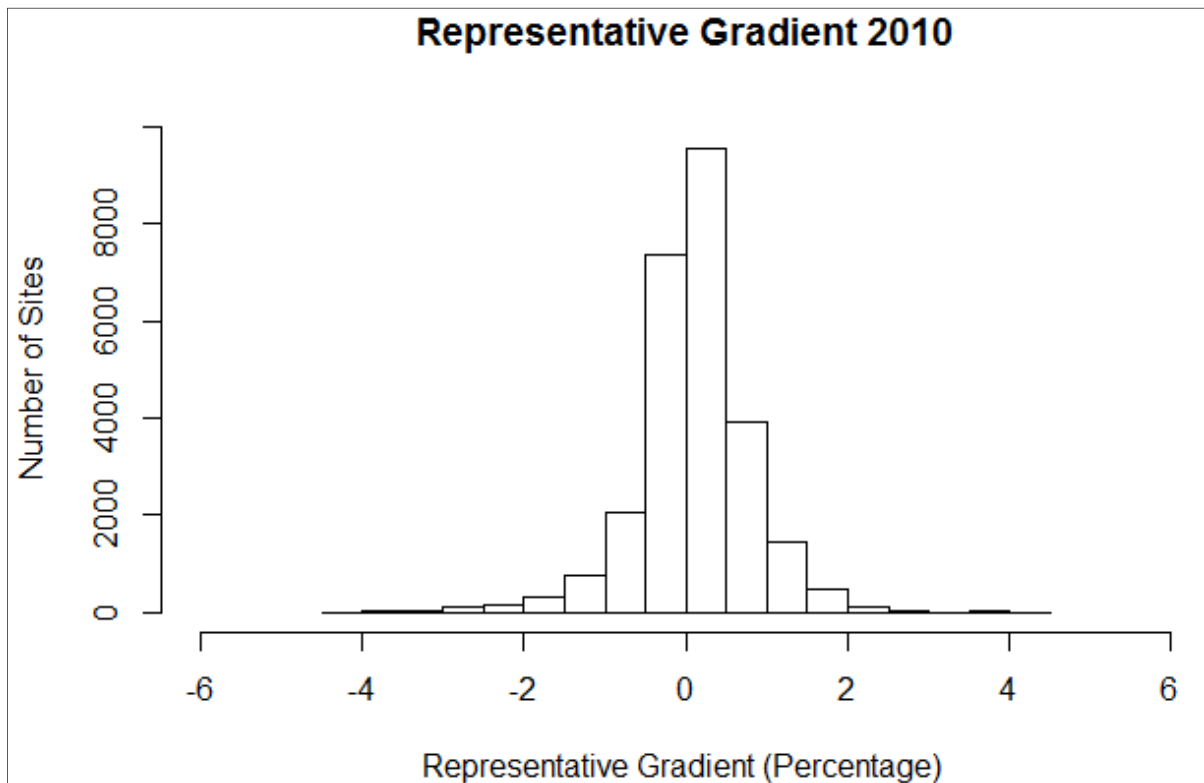


Figure 56: Spread of 2010 Representative Carriageway Gradient

The kurtosis values show all three datasets as having peaked kurtosis (values ranging between 6.49 and 6.65) for the representative carriageway gradient, while left skew was quantified as being between -0.49 and -0.48.

QQ plots were used to display representative gradient values. As a result of the poor normal fit, data underwent a log transformation which was subsequently not found to improve the fit.

5.2 Relationship Testing Results

To assist with the appropriate selection of statistical methods for testing the relationship between the representative coefficient of friction and traffic accidents the data from the three datasets were displayed in X, Y Scatter Plots. The plots for the 2008, 2009 and 2010 datasets have been illustrated in Figure 57, Figure 58, and Figure 59 respectively. From the plots no patterns of linearity or association were discernible.

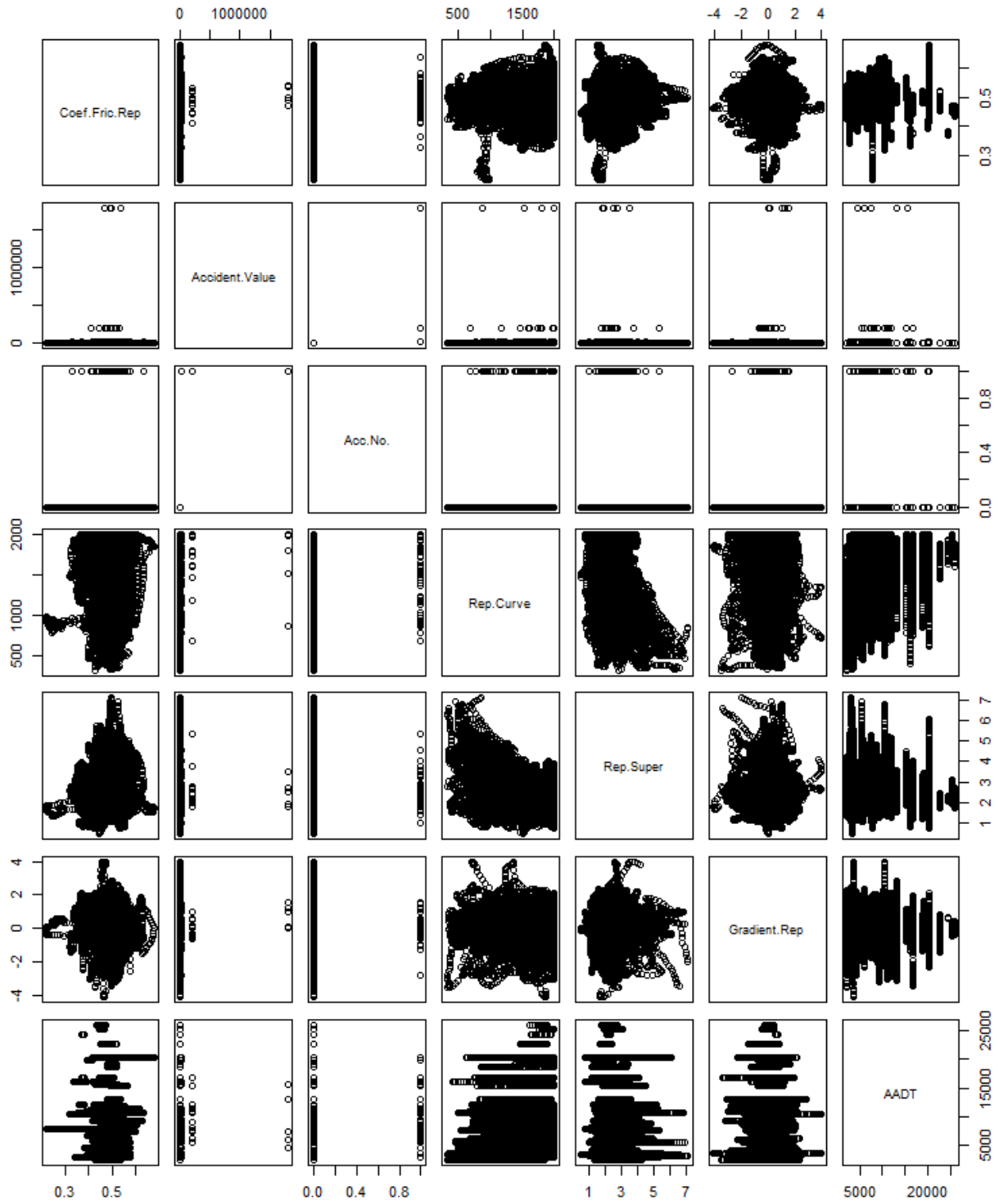


Figure 57: Summary X, Y Scatter Plots for the 2008 dataset

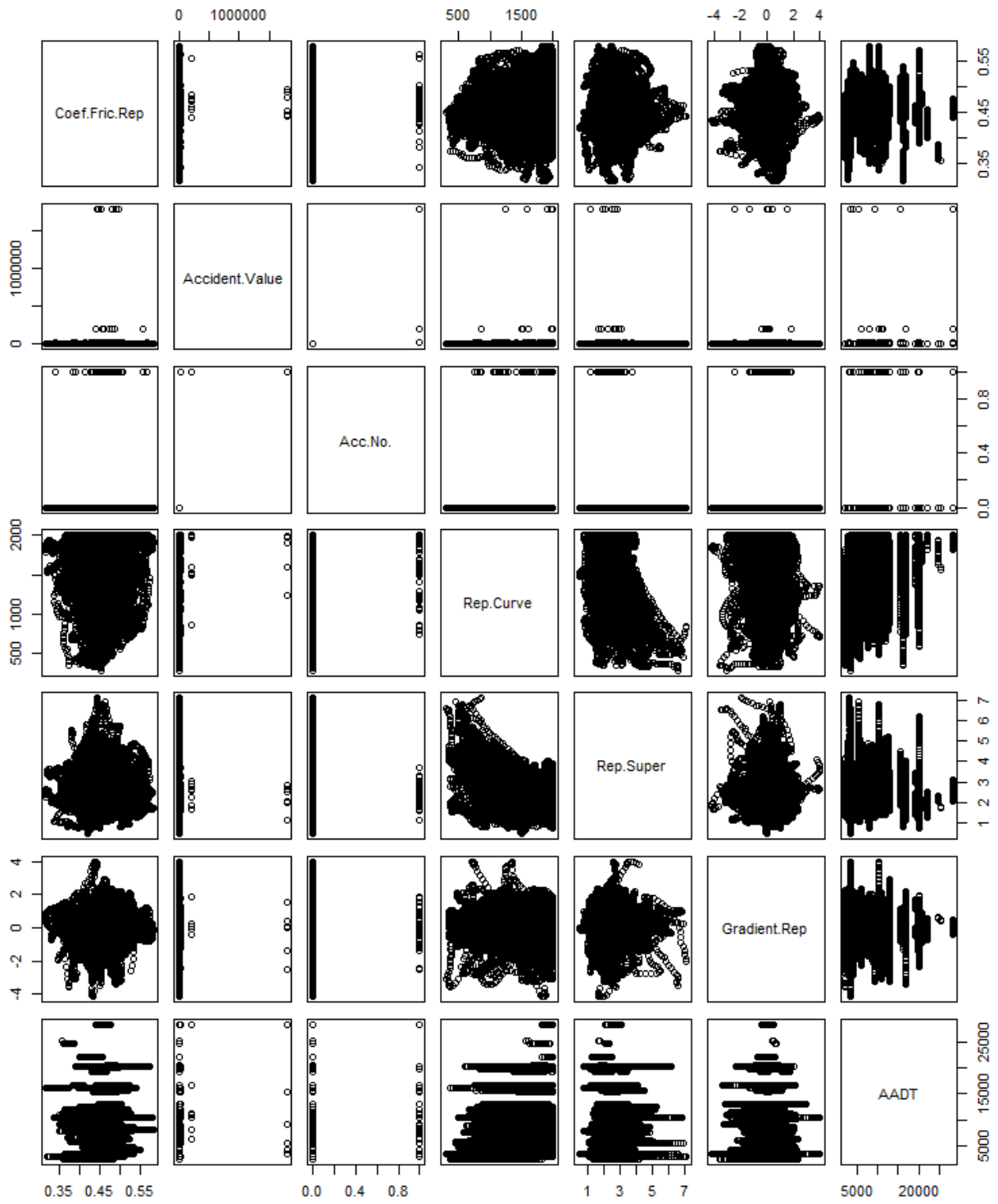


Figure 58: Summary X, Y Scatter Plots for the 2009 dataset

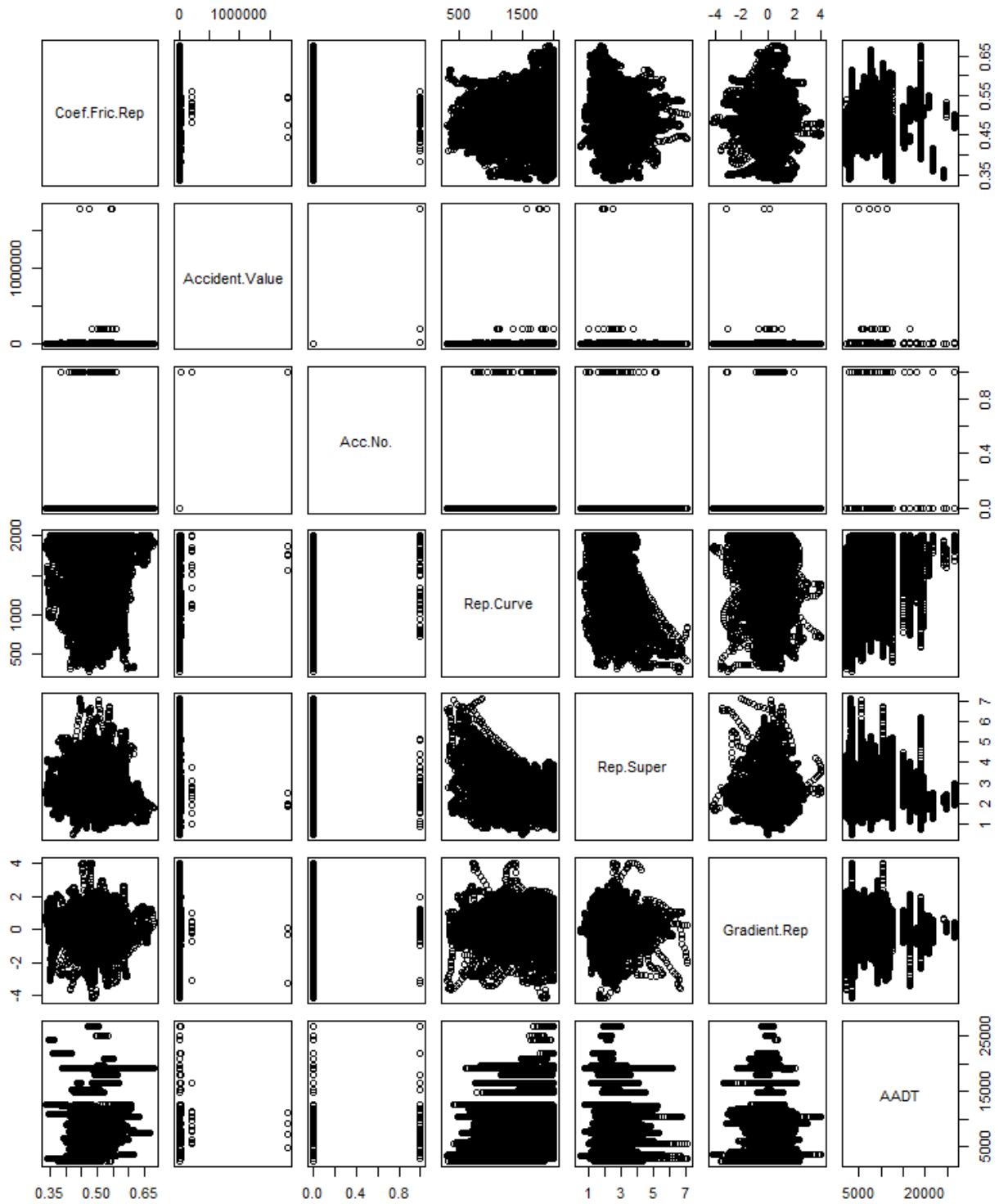


Figure 59: Summary X, Y Scatter Plots for the 2010 dataset

To ensure no relationships were obscured in the X, Y Scatter Plots due to the volume of data, Pearson's correlation coefficient values were calculated to test whether any linear relationships with the representative coefficient of friction existed. The Pearson's correlation coefficient results for representative friction have been displayed in Table 11, full results of the correlation are included in Appendix F. The results show weak correlation between the representative coefficient of friction and

representative AADT (-0.1398) for the 2008 dataset, representative curvature values for both the 2009 and 2010 datasets (0.1013 and 0.1487 respectively), and representative superelevation (-0.0972) in the 2010 dataset. No significant correlation was evident over all three datasets.

Variables Paired	Representative Coefficient of Friction					
	2008		2009		2010	
	r	p	r	p	r	p
Number of Accidents	-0.0088	0.1527	-0.0056	0.3674	-0.0055	0.3696
Accident Value	0.0027	0.6554	0.0026	0.6804	0.0034	0.5834
Representative Curvature (m)	0.0049	0.4223	0.1013	2.2e⁻¹⁶	0.1487	2.2e⁻¹⁶
Representative Superelevation (%)	0.0431	1.87e⁻¹²	-0.0114	0.0685	-0.0972	2.2e⁻¹⁶
Representative Gradient (%)	0.0210	0.0006	-0.0073	0.2459	0.0140	0.0234
Representative AADT	-0.1398	2.2e⁻¹⁶	-0.0088	0.1578	-0.0128	0.0372

Note: Bold figures indicate that statistical significance at the 5% level has been achieved

Table 11: Pearson's Correlation Coefficient and Significance Values

To explore whether an accident was more or less likely to occur as a result of a relationship between the representative friction and another variable(s), binomial logistic regression was applied. The estimated coefficient (β) and p-values (p) derived from the regression analysis for the 2008, 2009 and 2010 datasets have been displayed in Table 12, Table 13 and Table 14 respectively.

Representative Variables Modelled	Iteration									
	1		2		3		4		5	
	β	p	β	p	β	p	β	p	β	p
Coefficient of Friction	-3.31	0.212	-3.31	0.212	-3.20	0.223	-3.39	0.199	-3.73	0.151
Curvature (m)	-2.4e ⁻⁴	0.515	-2.4e ⁻⁴	0.512	-3.1e ⁻⁴	0.313				
Superelevation (%)	6.9e ⁻²	0.708	6.8e ⁻²	0.709						
Gradient (%)	-1.9e ⁻²	0.913								
AADT	2.9 ⁻⁵	0.269	2.9e ⁻⁵	0.264	3.0e ⁻⁵	0.250	2.1e ⁻⁵	0.392		

Table 12: Binomial Logistic Regression Results for the 2008 Dataset

Representative Variables Modelled	Iteration									
	1		2		3		4		5	
	β	p	β	p	β	p	β	p	β	p
Coefficient of Friction	-1.96	0.598	-1.92	0.605						
Curvature (m)	-5.6e ⁻⁴	0.176	-5.6e ⁻⁴	0.173	-5.9e ⁻⁴	0.151				
Superelevation (%)	3.4e ⁻¹	0.120	-3.4e ⁻¹	0.118	-3.5e ⁻¹	0.107	-2.1e ⁻¹	0.305		
Gradient (%)	-7.8e ⁻²	0.680								
AADT	9.7e ⁻⁵	3.3e ⁻⁵	9.8e ⁻⁵	6.7e ⁻⁵	9.9e ⁻⁵	1.8e ⁻⁵	8.9e ⁻⁵	5.2e ⁻⁵	9.1e ⁻⁵	2.9e ⁻⁵

Table 13: Binomial Logistic Regression Results for the 2009 Dataset

Representative Variables Modelled	Iteration									
	1		2		3		4		5	
	β	P	β	p	β	p	β	p	β	p
Coefficient of Friction	-1.31	0.604	-1.34	0.597						
Curvature (m)	-7.0e ⁻⁴	0.058	-6.1e ⁻⁴	0.052	-6.3e ⁻⁴	0.044	-6.3e ⁻⁴	0.041		
Superelevation (%)	-8.8e ⁻²	0.638								
Gradient (%)	-1.3e ⁻¹	0.438	-1.3e ⁻¹	0.434	-1.3e ⁻¹	0.436				
AADT	8.0e ⁻⁵	0.001	7.9e ⁻⁵	0.001	8.0e ⁻⁵	0.001	8.2e ⁻⁵	0.001	6.6e ⁻⁵	0.005

Table 14: Binomial Logistic Regression Results for the 2010 Dataset

Representative AADT was found to be statistically significant in predicting the likelihood of traffic accidents at the 5% level, however this was only the case for the 2009 and 2010 datasets. For these two datasets, the odds of an accident occurring was found to increase with increasing representative AADT. In 2010 representative curvature was found to be statistically significant in predicting the likelihood of an accident occurring. The odds of an accident occurring was found to decrease as representative curvature increased (increasing carriageway ‘straightness’). The remaining variables, including the representative coefficient of friction were found to be poor predictors in all three models for whether an accident was likely to occur.

The Anderson-Darling k-sample (ADK) test was used to compare the representative coefficient of friction, geometric and traffic characteristic variables for sites where accidents had been recorded with those sites where no accidents had been recorded. This test was undertaken for data originating from the 2008, 2009 and 2010 datasets, the results, which have been adjusted for ties due to the large number of identical pairs, are summarised in Table 15. As the AADT data displays categorical properties due to the method used to assign traffic count data to each data point, and as the Anderson-Darling k-sample test assumes continuous data, the results should be treated with caution as the test is very sensitive to ties due to poor precision.

The results show that the population of the representative friction coefficient, curvature, superelevation and gradient values where accidents had been recorded were not significantly different from the population of sites where no accidents had been recorded. This was true for all three years tested. As highlighted in Table 15 however, it was found that representative AADT at accident sites in both the 2009 and 2010 datasets were statistically different from the representative AADT at non-

accident sites. As the relationship between AADT and traffic accidents is not the focus of this study, no further analysis was undertaken.

Representative Variables	Year					
	2008		2009		2010	
	ADK test-value	p-value	ADK Test-value	p-value	ADK Test-value	p-value
Coefficient of Friction	0.9728	0.1325	0.1788	0.2851	-0.1270	0.3669
Curvature (m)	-0.4437	0.4605	-0.7998	0.5688	0.0085	0.3294
Superelevation (%)	-0.6518	0.5240	0.4245	0.2256	-0.6512	0.5238
Gradient (%)	-0.2187	0.3933	-0.4201	0.4535	0.1018	0.3047
AADT	0.7769	0.1608	8.6301	0.0002	2.5604	0.0282
HGV	-0.4549	0.4919	-0.9191	0.6042	0.1000	0.3051

Note: Bold figures indicate that statistical significance at the 5% level has been achieved

Table 15: Anderson-Darling k-sample Test Results

To determine whether the representative coefficient of friction influenced accident severity, the representative coefficient of friction values for each accident severity classification (including non-accident sites) were plotted. The box and whisker plots displayed in Figure 60, Figure 61, and Figure 62 respectively illustrate the 2008, 2009 and 2010 datasets. Due to the low number of accidents included in each accident severity classification, it is difficult to conclude with any certainty whether accident severity is influenced by the representative coefficient of friction value from the box and whisker plots.

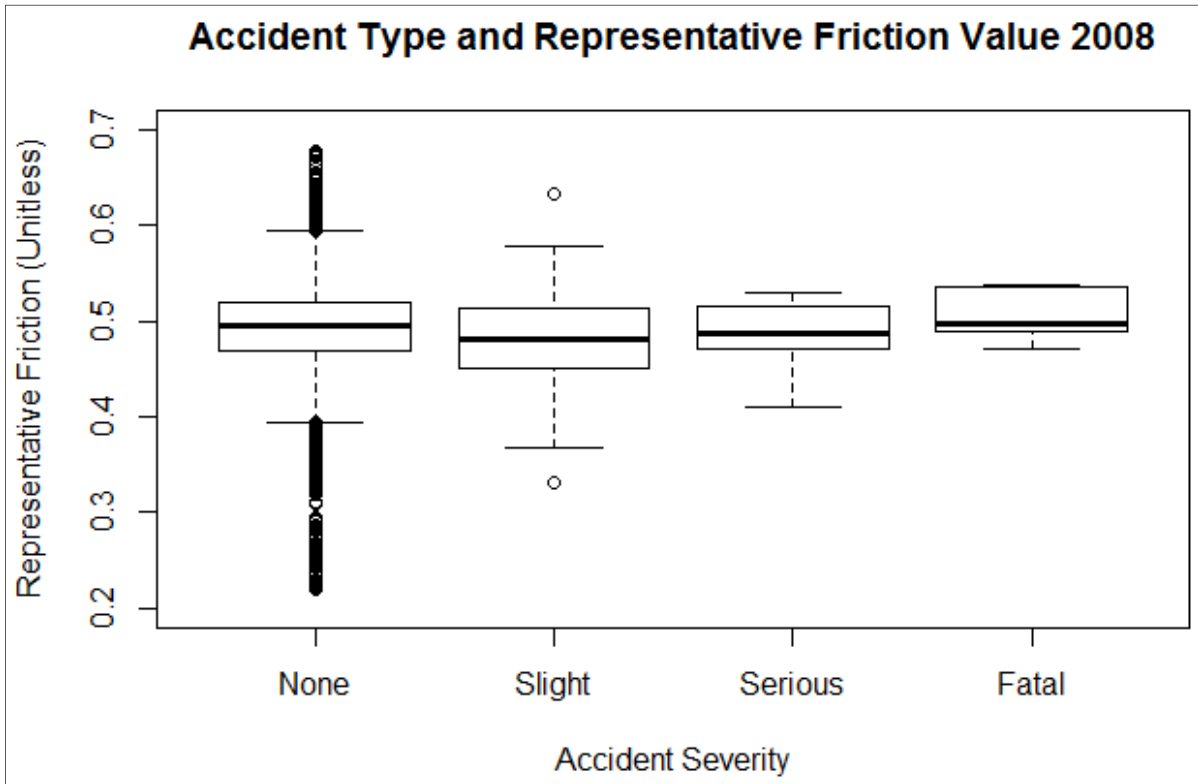


Figure 60: Representative Friction Values for Recorded Accident Sites in 2008

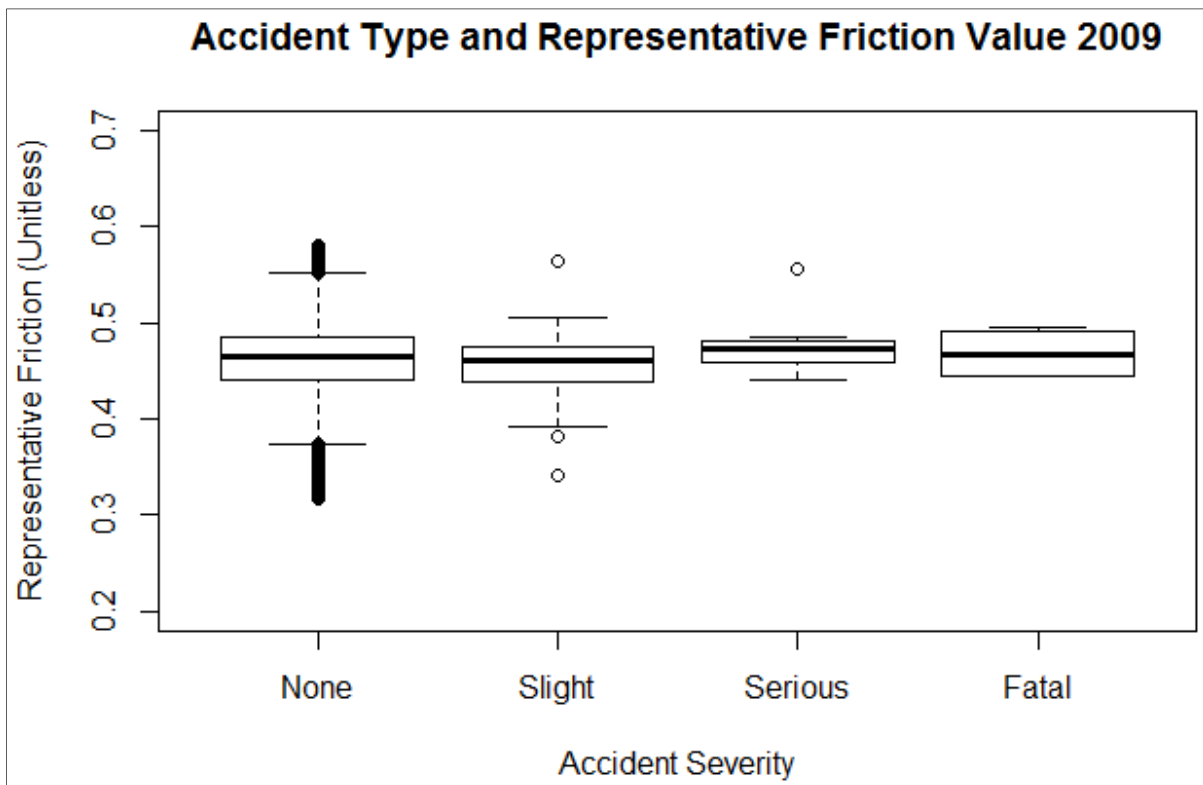


Figure 61: Representative Friction Values for Recorded Accident Sites in 2009

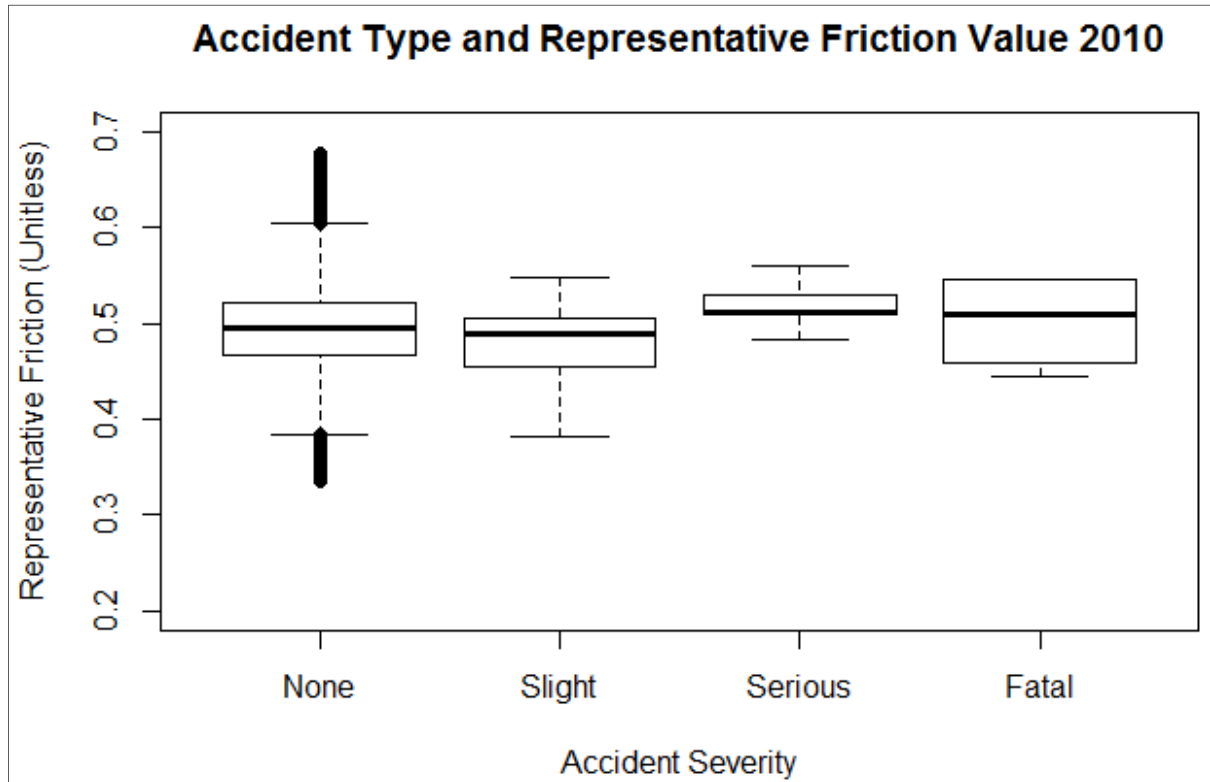


Figure 62: Representative Friction Values for Recorded Accident Sites in 2010

The ADK test was used to compare the representative coefficient of friction, geometric and traffic characteristic variables for sites where fatal, serious and slight accidents had been recorded with those sites where no accidents had been recorded. The results of the ADK test for fatal, serious and slight accidents for data originating from the 2008, 2009 and 2010 datasets, have been respectively summarised in Table 16, Table 17 and Table 18. The results have been adjusted for ties. As highlighted in Table 16 the null hypothesis is accepted for the representative coefficient of friction, curvature and superelevation for fatal traffic accidents in all three years. In other words, there is no evidence to suggest that representative coefficient of friction, curvature and superelevation values are significantly different between fatal accident and non-accident sites. As highlighted, representative gradient was found to be statistically different between fatal accident and non-accident sites in both 2008 and 2010, however the sample size for 2010 was not sufficiently large to be statistically conclusive. The statistical difference between representative gradient values was not investigated further as this is not the focus of this study.

Representative Variables	Year					
	2008		2009		2010*	
	ADK test-value	p-value	ADK test-value	p-value	ADK test-value	p-value
Coefficient of Friction	-0.5812	0.5024	-0.6823	0.5333	-0.6117	0.5117
Curvature (m)	-1.0365	0.6379	-0.2955	0.4159	-0.0640	0.3492
Superelevation (%)	-0.9738	0.6200	-0.4613	0.4659	0.4581	0.2186
Gradient (%)	2.4925	0.0300	0.2027	0.2792	2.1560	0.0413
AADT	-0.8155	0.5735	0.2101	0.2774	-0.9904	0.6248
HGV	-0.4847	0.4730	1.1014	0.1166	-0.7568	0.5559

Note: Bold figures indicate that statistical significance at the 5% level has been achieved

* Sample less than four for fatal accident dataset

Table 16: ADK Results for Fatal Accidents

As highlighted in Table 17 the null hypothesis is accepted for the representative curvature, superelevation and gradient for serious traffic accidents in all three years. In other words, there is no evidence to suggest that representative curvature, superelevation and gradient values are significantly different between fatal accident and non-accident sites. However as highlighted, representative coefficient of friction was found to be statistically different between serious accident and non-accident sites in 2010, though this was not found to be true in 2008 or 2009. When the 2010 dataset was interrogated, the average representative friction value was found to be higher at serious accident sites (0.52) than at non-accident sites (0.50).

Representative Variables	Year					
	2008		2009		2010	
	ADK test-value	p-value	ADK test-value	p-value	ADK test-value	p-value
Coefficient of Friction	-0.4083	0.4498	-0.1852	0.3836	3.1812	0.0162
Curvature (m)	-0.3139	0.4214	-0.8887	0.5952	-0.8736	0.5908
Superelevation (%)	-0.6013	0.5086	-0.7204	0.5448	-0.2081	0.3902
Gradient (%)	0.1175	0.3006	-0.0551	0.3467	-0.1380	0.3700
AADT	0.0647	0.3144	1.0708	0.1202	-0.7099	0.5417
HGV	-0.7619	0.5574	-1.0214	0.6336	-0.2875	0.4136

Note: Bold figures indicate that statistical significance at the 5% level has been achieved

Table 17: ADK Results for Serious Accidents

As highlighted in Table 18 the null hypothesis is accepted for the representative coefficient of friction, curvature, superelevation and gradient for slight traffic accidents in all three years. In other words, there is no evidence to suggest that representative coefficient of friction, curvature, superelevation and gradient values are significantly different between slight accident and non-accident sites. However as highlighted, representative AADT was found to be statistically different between slight accident and non-accident sites in 2009 and 2010, though this was not found to be true in 2008. The statistical difference between representative AADT values was not investigated further as this is not the focus of this study.

Representative Variables	Year					
	2008		2009		2010	
	ADK test-value	p-value	ADK test-value	p-value	ADK test-value	p-value
Coefficient of Friction	1.4773	0.0802	0.9608	0.1341	1.5600	0.0739
Curvature (m)	0.8992	0.1426	-0.8786	0.5923	0.7254	0.1691
Superelevation (%)	-0.7598	0.5568	0.2730	0.2622	-0.5396	0.4897
Gradient (%)	-0.2995	0.4171	-0.8592	0.5865	-0.1405	0.3707
AADT	-0.0435	0.3435	7.8773	0.0004	4.2213	0.0069
HGV	-0.6419	0.5210	-0.6712	0.5300	-0.4673	0.4677

Note: Bold figures indicate that statistical significance at the 5% level has been achieved

Table 18: ADK Results for Slight Accidents

To determine whether coefficient of friction variation along the carriageway influenced accident occurrence, coefficient of friction standard deviation values were compared between those sites with and without accidents. The box and whisker plots displayed in Figure 63, Figure 64, and Figure 65 respectively illustrate the 2008, 2009 and 2010 datasets coefficient of friction standard deviation for accident and non-accident sites. The results of the ADK test revealed that the coefficient of friction standard deviation values were not significantly different between accident and non-accident sites for the 2008, 2009 and 2010 datasets.

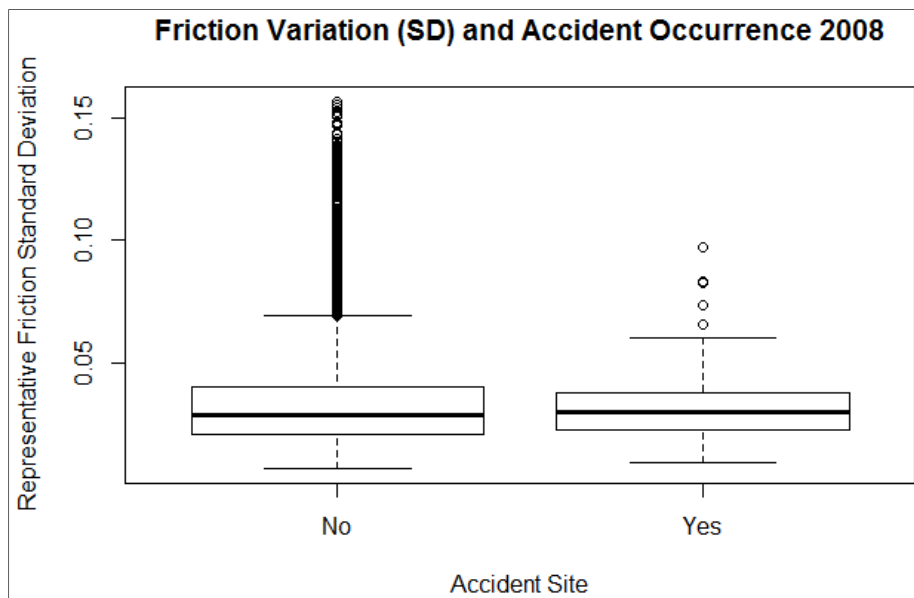


Figure 63: Friction Variation and Accident Occurrence for 2008

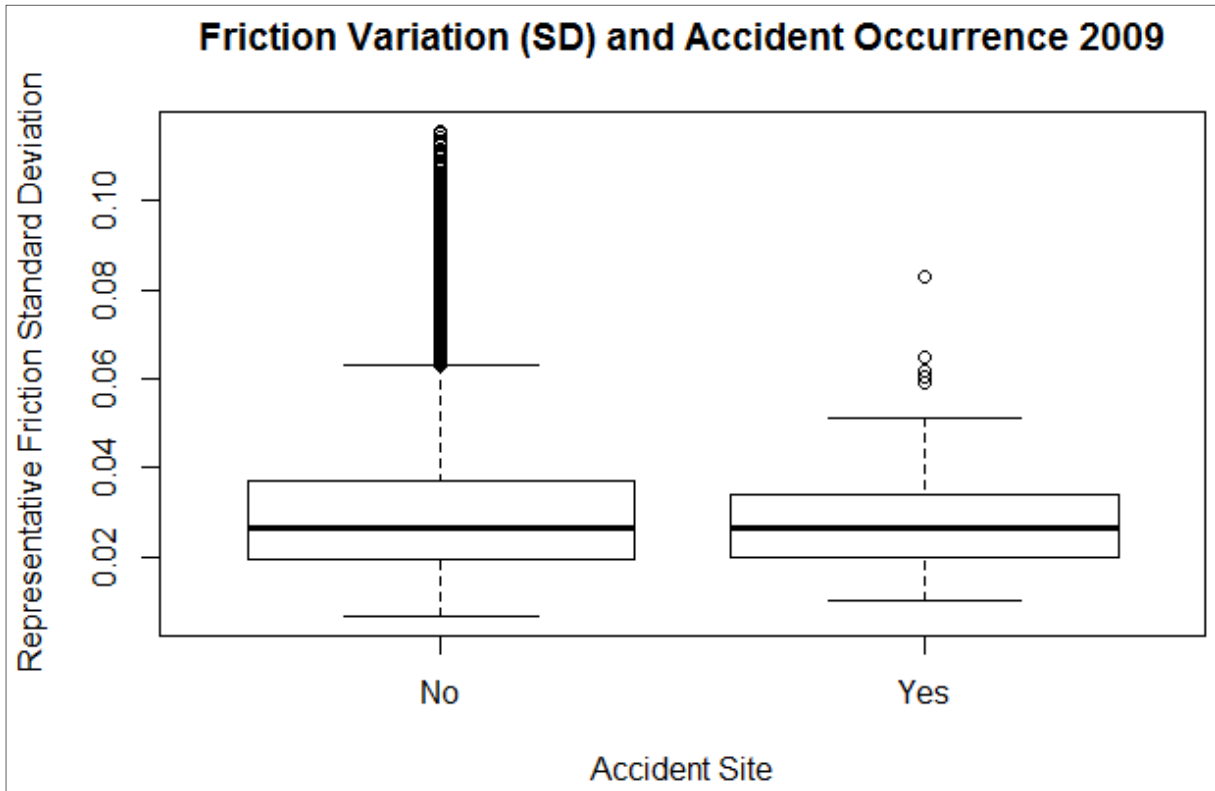


Figure 64: Friction Variation and Accident Occurrence for 2009

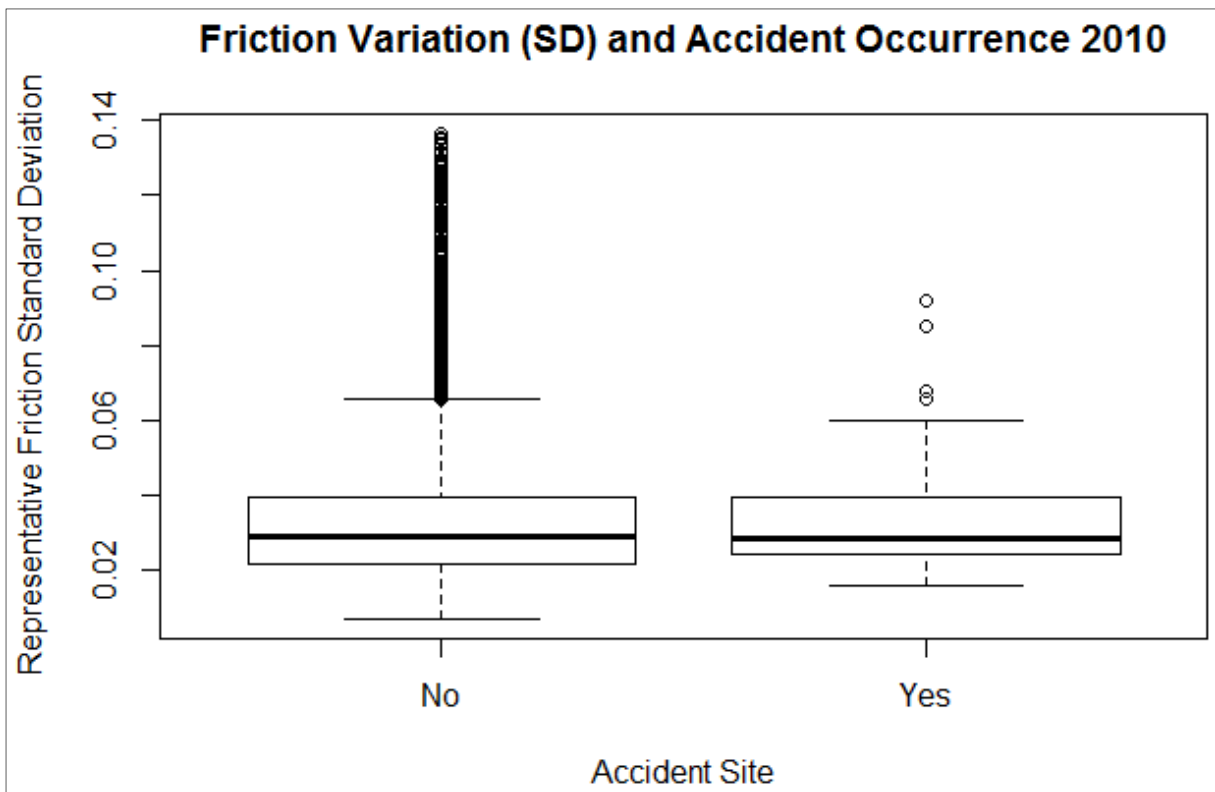


Figure 65: Friction Variation and Accident Occurrence for 2010

5.3 Summary

The results of the preliminary data exploration found that both the number of accidents and the severity classifications within each dataset were not significantly different from one another. The preliminary review of the data also found that representative values for the coefficient of friction, curvature, superelevation and gradient were not normally distributed.

Representative coefficient of friction distributions were found to have peaked kurtosis, with 2008 demonstrating a significantly higher level of kurtosis than that found in the 2009 and 2010 datasets. Skewness was quantified as being relatively varied amongst the datasets.

Low variability between the datasets was found with relation to representative curvature, superelevation and gradient values. This result was expected given that geometric elements could be expected to remain static and that the majority of the geometric data contained in the three datasets relate to the same roads and were derived from one data collection exercise. However, the data did reveal that the median representative gradient value was positive, not zero as expected suggesting that there are more uphill sections of road in the sample than downhill.

Pearson's correlation coefficients were calculated to test whether any linear relationships with representative coefficient of friction existed in the datasets. A weak relationship was found with representative AADT in the 2008 dataset, but not in either 2009 or 2010. A weak relationship was also found between representative coefficient of friction and representative curvature in the 2009 and 2010 datasets, however this relationship was not found in 2008. No relationship was found between representative friction coefficients and the number of accidents, or accident severity.

The binomial logistic regression model revealed that no significant relationship existed between representative coefficient of friction and the number of traffic accidents. Representative AADT was found to be the only variable to be statistically significant in predicting the likelihood of traffic accidents at the 5% level, however this was only found to be true for the 2009 and 2010 datasets.

The Anderson-Darling k-sample test was used to compare the representative coefficient of friction, friction variation, geometric and traffic flow data between sites where accidents had been recorded, with those sites where no accidents had been recorded. The results suggested that the null hypothesis be accepted for representative coefficient of friction, friction variation, curvature, superelevation and gradient on the basis that no statistically significant difference was found.

The Anderson-Darling k-sample test was rerun on datasets, which included data relating specifically to each accident severity classification, for each year. The results suggested that the null hypothesis be accepted for the representative coefficient of friction on the basis that no statistically significant difference was found, with the exception of that for serious traffic accidents in the 2010 dataset only. A review of the data tested found the average representative friction coefficient to be higher at serious accident sites (0.52) than at non-accident sites (0.50).

On the basis of the tests utilised, no robust statistical evidence was found to suggest a relationship between the representative coefficient of friction (or its variation along the carriageway) and recorded traffic accidents.

Chapter VI: Discussion, Conclusions & Recommendations

This chapter has been broadly divided into five parts. The first two sections focus on the results found in the previous chapter, respectively providing a discussion on the preliminary data review, and the analysis of the relationship between friction coefficient and traffic accidents.

The third section presents the conclusions that can be drawn from the study, not only in terms of the results found, but also on the basis of the literature review. The focus of the conclusions are centred on the central research question posed by this thesis. The fourth section of this chapter outlines the 'real world' implications posed by the conclusions reached in this study.

The final section of the chapter focuses on providing recommendations for further research which may not only enhance the body of knowledge but could also improve current practices with regards to the way in which friction is managed.

6.1 Discussion of Preliminary Results

The primary objectives of the preliminary data exploration exercise were to gain a better understanding of the data, and determine the most appropriate statistical techniques for testing the relationship between friction coefficient and traffic accidents. The significant results of this exercise are discussed in the following paragraphs.

While the number of road traffic accidents included in the study was found to vary between the years, the proportion of accidents within each accident severity category was found to be consistent. This was an expected finding, and suggests that the sample of traffic accidents were sufficiently large.

The values used to calculate the representative friction coefficient values for each of the three datasets were predominantly collected from the same sections of carriageway. It was therefore surprising to discover stark differences in their distribution characteristics. The calculated kurtosis values showed significant variation for the 2008 dataset, returning a value of 5.84, compared to the 3.95 and 3.97 values respectively calculated for the 2009 and 2010 datasets. The representative friction coefficient values contained within the 2008 dataset were also found to be more left skewed providing a value of -0.62, compared to the -0.31 and 0.07 values calculated for the 2009 and 2010 datasets. As the number of values contained within each of the datasets was large (at least 25,556) the differences in both skewness and kurtosis were larger than what had been initially expected.

In addition to the difference in distribution shape, it was also found that the median representative friction coefficient value in the 2009 dataset was 0.03 units lower than the median values of both the 2008 and 2010 datasets. This was unexpected given that it exceeds the 0.003 - 0.005 measurement accuracy of SCRIM (at the 95% confidence interval) identified by Wambold et al., (1995), and furthermore because:

- The data in all three datasets were predominantly collected from the same sections of carriageway in Norfolk County, using the same prescribed technique and quality control procedures.
- As sample size increases, the effects of random error should decrease, given that individual measurements both over and under cancel one another out in the calculation of the representative values.
- All three datasets displayed high kurtosis values around the median value, meaning that for any shift to occur in the median value, a significant number of samples had to be affected.

In light of what was considered a real and significant difference in median representative friction values, possible causes for the variation in the 2009 dataset were considered, avenues explored are discussed in the following paragraphs.

Long-term variation (>1year) in the coefficient of friction was initially considered a possible cause for the anomaly, however this was discounted given that a road's macrotexture and microtexture typically diminishes as the road surface ages. Had long-term variation been responsible, it could be reasonably expected that a similar deterioration rate to that found between 2008 and 2009 datasets, should have been evident between the 2009 and 2010 datasets.

As highlighted in Chapter II, friction can vary by between 25% (Rogers and Gargett, 1991) and 30% (Hosking, 1986, Wilson and Kirk, 2005) over a year. Though the data has been 'corrected' in accordance with the Design Manual for Roads and Bridges which theoretically compensates for such seasonal variation, the literature suggests that seasonal variation is poorly understood. As a result it is not possible to discount the effects of seasonal variation (and subsequent treatment thereof), for the variation found in friction coefficient values between the datasets.

As the collection of data by SCRIM does not compensate for the factors influencing day to day changes in friction, the cumulative effects of short-term variation could also explain the differences found in three dataset's median representative friction values.

While each SCRIM device is calibrated regularly, the actual operating environment encountered during the testing season could have been distinctly different between years, affecting the measurements derived. The operation of the SCRIM device could be influenced by the driver's choice of both driving line (within the white lines if they are to comply with the standard) and the device's operating speed (though measurements are considered to be corrected for this). As suggested by Roe et al., (1998) SCRIM's constant water application rate, will affect water film thickness when SCRIM's operating speed changes, in light of the findings of Kulakowski and Harwood (1990), this could have a significant effect on the measured friction coefficients.

As increasing traffic volumes typically correspond to decreased vehicle operating speeds, on roads with high traffic flows SCRIM would be expected to return lower friction coefficient values. A comparison of the vehicle kilometres travelled on the surveyed network, found that the highest total average traffic flows (and second highest with regard to heavy goods traffic) correspond to the 2009 dataset, where friction coefficients were found to be at their lowest. Despite this crude comparison, it is considered inconclusive as to whether traffic volumes affected SCRIM operating speeds given that it would be impossible to ascertain whether the recorded traffic volumes were reflective of that on the date of data collection.

As the rate of road surface polishing is directly related to the level of traffic particularly the number of heavy goods vehicles (Ali et al., 1999, Chelliah et al., 2002, Kennedy et al., 1990), this was also examined as a potential cause of the reduction in median representative friction coefficients. Following examination, the possibility that heavy vehicle traffic flows were responsible for the changes in median representative friction coefficients was dismissed. The rationale for this was that a decrease in friction coefficients similar to that between the 2008 and 2009 datasets would be expected, and between the 2009 and 2010 datasets, albeit more muted.

Resurfacing budgets for all roads within Norfolk County for the 2007/08, 2008/09, 2009/10 and 2010/11 financial years were obtained from Council and were found to respectively equate to £4.1m, £4.5m, £1.6m, and £3.6m per annum. An examination of the resurfacing budgets revealed that the budget for the 2009/10 financial year was notably smaller than that for both 2008/09 and 2010/11, mirroring the drop in median representative friction values between the datasets. While the total annual resurfacing budgets for all roads within the county could explain some changes in the 'tails' of the friction coefficient data; the budgets are not large enough to explain wholesale shifts in representative friction coefficients in the datasets.

The variation found in the median representative friction coefficient values was mirrored by that found in the review of the raw data, as discussed in Chapter IV (Methodology). In addition to the variability

of the three datasets, plots of the raw data also revealed that for a number of friction coefficient values, the number of records were notably more, or fewer than what would have been expected. The exact cause for this anomaly is unknown. The only hypothesis conceived to explain this anomaly was that the SCRIM computers may have errors associated with rounding individual readings, however such an error could be expected to be uniformly spread over the dataset, this hypothesis was therefore rejected.

As SCRIM data has been used to formulate national skid resistance policy, it was considered that despite the observed irregularities, analysis continue. Despite the unexpected number of values for some friction coefficient values, there was no evidence to suggest, and it was considered unlikely, that SCRIM had returned low friction values for high friction sites, and conversely high friction values for low friction sites. As such, sufficient confidence was held with regard to the ability to pursue the objectives of this study, both in terms of the data review and testing of the relationship between friction coefficients and traffic accidents. To err on the side of caution, the datasets were not combined and no examination of trends over time was undertaken.

The results of the Lilliefors test found that it was highly unlikely that the representative friction coefficients in all three datasets were normally distributed. As shown in the QQ plots there were fewer 'low' friction sites, and more 'high' friction sites than normal distribution would predict. This was not a surprising finding given that sites gain greater chances of resurfacing as they deteriorate. Conversely, the relatively large number of 'high' friction sites was expected given the way in which some accident sites are treated with high friction and high polished stone value surfacing, such as calcined bauxite.

Representative carriageway curvature was found to be strongly left skewed, given the high level of service provided on the A-road network, this finding was anticipated. The consistency found between the three datasets was also expected as the data had predominantly been collected from the same sections of carriageway in Norfolk County, and were derived from the same data collection exercise.

No surprising results were found as part of the preliminary review of the representative superelevation values. Both skew and kurtosis values were found to be very similar which was again expected as the data was derived from the same collection exercise and predominantly from the same sections of carriageway. Unfortunately, the effects of carriageway camber appear to have masked carriageway superelevation to some extent, given that almost no roads had a 'superelevation' of less than 1°, and very few below 1.5°. Representative values were found to be non-normal both naturally, and when log transformed.

A high level of consistency was also found between the three datasets with regard to the representative carriageway gradient values, which was again expected due to data coming predominantly from the same sections of carriageway. However, the finding that the data was left skewed, and had positive median and mean values was very surprising, as it infers that there were more uphill sections of carriageway in the dataset than downhill. This was an unexpected finding as the method of calculating representative gradient values took into account both sides of the carriageway, therefore where one lane was uphill, the corresponding value should have been the inverse. It is however acknowledged that the method of calculation does exclude two 170m sections of carriageway from opposing lanes for each link included in the study.

6.2 Discussion of the Relationship Testing Results

The investigation of the relationship between friction coefficient and traffic accidents commenced with a simplistic X, Y scatter plot, for all data variables, for each year. An overview of the scatter plots did not reveal any immediately obvious relationships between any of the variables. Given that each of the datasets had at least 25,556 samples, there was a possibility that any relationships could be masked, as such further investigation was carried out.

To examine whether any linear relationships existed, Pearson's correlation coefficients were calculated. No relationship was found in any of the three datasets between the representative friction coefficient values with either the number of traffic accidents, or the value of traffic accidents (a numerical surrogate for accident severity). Weak relationships were found between representative friction coefficient and both representative AADT and curvature, however these were not consistent for all years and are only of limited interest in this study.

The model results were not wholly surprising given that the work of Giles (1956), McCullough and Hankins (1966), Moore and Humphreys (1973), Rogers and Gargett (1991), Hosking (1986), Al-Mansour (2006), Mayora and Rafael (2008), and Davies et al., (2005) collectively suggested that if a relationship between friction and traffic accidents did exist, it was likely to be non-linear.

In the absence of a direct linear relationship a binomial logistic regression model was built for each of the three datasets. The models found that representative friction coefficients were poor predictors of traffic accidents. Only representative AADT in 2009 and 2010, and representative curvature in 2010 were found to have a relationship with traffic accidents.

With no relationship found between representative friction coefficients (either in isolation, or in association with other variables) and traffic accidents, the Anderson-Darling k-sample test was used to

further examine the three datasets. When the representative friction coefficients were compared between those at recorded accident sites and sites where no accidents had been recorded, no statistically significant difference was found between the samples. This was true for each of the three datasets. This finding was on one hand unexpected on the basis that twelve of the thirteen studies reviewed in Chapter III had concluded at least to some degree that an inverse relationship between friction coefficient and traffic accidents existed.

The findings were also somewhat unexpected because from a purely abstract perspective, it doesn't make sense. The laws of physics state that friction coefficient directly affects skid resistance, which provides drivers' the opportunity to reduce speed and manoeuvre. In other words, increased friction provision should improve the probability of both avoiding a crash, and decrease the likely accident severity where an accident does occur.

On the other hand, the finding that no difference in representative road surface friction existed between accident and non-accident sites was not a complete surprise for a number of reasons, these are discussed here. First, Lindenmann's (2006) research had concluded that no relationship existed between friction coefficients and traffic accidents. This finding was supported in part by that undertaken by Schlosser (1976), Rogers and Gargett (1991) and Viner et al., (2004), who found no relationship on roads classified as motorways.

Second, the work of Treat et al., (1979), which was discussed in Chapter I suggested that the road environment alone, was responsible for just 3% of all traffic accidents. In consideration that friction coefficients form only one small part of the road environment, it's contribution to the overall number of accidents could be expected to be notably smaller. In consideration of Reason's (2000) research, even where low friction coefficients had the potential to cause a traffic accident, there would still be a need for an active failure on the part of the driver, whether intentional or not.

The likelihood of an active failure as defined by Reason (2000) will to a large extent be determined by driver behaviour. Based on the research reviewed, it is unclear whether drivers are aware of the level of friction provided and therefore whether they adjust their driving style to compensate for changing levels of 'risk'. In either case, it was found in Chapter II that driver behaviour was also a reflection on past driving experiences. As such, while drivers may not be able to perceive a section of road with a low friction coefficient the first time they travel over it, they may after having driven over it a number of times, acquire this knowledge through experience and subsequently change their future behaviour. Such drivers may also affect the collective behaviour when travelling in platoons.

Finally, the results were to some extent expected due to Norfolk County Council's use of 'Slippery Road' warning signs on sites with low friction values, and likely provision of higher friction surfacing on 'dangerous' sections of carriageway. The effect of Norfolk County Council's management of the A-road network on the results found in this study, have not been investigated.

The results also found that there was no discernible difference between the representative friction coefficient at the sites of any of the three accident severity classifications, and that at non-accident sites. However a statistically significant difference was found for serious accidents in 2010. A review of the data revealed that representative friction coefficients were in fact higher at the serious accident sites than at the non-accident sites.

The results of the analysis also found that friction coefficient variation along the section of carriageway included in the calculation of the representative carriageway friction coefficient, was not significantly different between accident and non-accident sites. This test therefore precludes sudden changes in friction as being a causative factor in traffic accidents in Norfolk County between 2008 and 2010.

6.3 Conclusion

Based on a review of the literature the friction coefficient offered by a road surface was found to be the sum of properties relating to the pavement's macrotexture and microtexture (Choubane et al., 2004, Hall et al., 2009, Noyce et al., 2005). While the literature was frequently found to use the terms friction coefficient and skid resistance interchangeably this was determined to be inappropriate. While closely related, the term 'friction coefficient' refers to a measured value, while the term skid resistance refers to the level of friction generated between vehicles and the road surface. Distinguishing between the two terms is essential if one is to consider the effects of friction coefficients on traffic accidents, given that it is the skid resistance that is of practical importance.

The ability of vehicles to maximise skid resistance from the provided road surface friction coefficient was found to rely chiefly on the vehicle's tyres, braking systems, and operating speed. Of particular note it was reasoned that as a result of improvements in vehicle braking technology (through the advent of ABS braking systems) that on average, the level of skid resistance that the vehicle fleet can collectively derive from the road surface (all other factors remaining unchanged) is improving incrementally with time. As a review of the friction coefficient data between years revealed significant and unexplained variation, this hypothesis could unfortunately not be tested.

Road geometry was found to be a relevant consideration in the generation of skid resistance due to the dynamics between lateral and longitudinal friction (Hall et al., 2009), and gradient (Boutal et al., 2008). The specification of varying friction coefficient levels for different site categories (of varying gradient and curvature) in the United Kingdom's skid resistance policy suggests that the effects of carriageway geometry have been adequately provided for.

Though not directly affecting skid resistance, driver behaviour was also found to be of particular importance in the consideration of the relationship between friction coefficient and traffic accidents. While it was not clear from the literature whether drivers' could perceive the level of skid resistance available, driver behaviour was found to be influenced by a driver's perceived level of skid resistance available (whether possible or not), and a reflection of their past experiences. On this basis it can be concluded, that drivers exert a 'demand' for skid resistance in a utilitarian sense.

A review of the literature found an abundance of studies investigating the relationship between friction coefficient and traffic accidents. Of the literature available, a total of thirteen studies were found to assess the relationship at a network level. Analysis of the methodologies used in the network studies were found to vary considerably, and in a number of cases the way in which data was assigned and linked was very questionable. The way in which data was prepared for use in this study has been based on first principles and rectifies a number of shortcomings found in the literature. Most significantly, the length of carriageway assigned to each accident was based on expected braking distances for 95% of the road network, and second, representative friction coefficient values were used in place of a single measured reading, or value determined by directly averaging friction coefficient values.

It was originally hoped that the United Kingdom's motorway network could be used as the basis for assessing the relationship between the coefficient of friction and traffic accidents given that the United Kingdom's 'Skid Resistance' policy is based on data obtained from their road network. As this was not possible, data pertaining to the A-road network in Norfolk County was used.

The preliminary review of the data revealed what was considered a real and significant difference in median representative friction values between the data representing each of the three years; comparison between years was therefore not possible. It is not entirely clear whether the cause of the variation was due to the way in which friction coefficients were measured by SCRIM; the way in which the collected data was corrected to compensate for testing conditions (such as speed) and seasonal variation; or a combination of both factors.

The accuracy of individual measurements collected by SCRIM was also found to be questionable. This assertion is made on the basis the data obtained from Norfolk County Council revealed that while the coefficient of friction values were to some extent normally distributed, a number of friction coefficient values had an unexpectedly high or low number of readings. This irregularity suggests that the SCRIM machines used were not capable of providing accurate friction coefficient readings for the roads included in this study's analysis. On the basis of the irregularities it is noted that SCRIM is likely to have a larger margin of error than that identified by Wambold et al., (1995). The assertion is also supported by the failed attempts to harmonise measurements between friction measuring devices (Vos and Groenendijk, 2009). While it is not possible to isolate SCRIM in particular as the cause for the inability to harmonise friction measurements, it does support the notion that difficulty exists in providing consistent friction coefficient measurements.

The analysis of the relationship between friction coefficients and traffic accidents (and accident severity), revealed that for A-roads with a posted speed limit of 60mph (100km/hr) in Norfolk County, no relationship existed. This finding was found to be consistent for all three years assessed, and directly supports the work of Lindenmann (2006), which concluded that no relationship existed between friction coefficients and traffic accidents on Switzerland's highway network. The findings in this study are also supported in part by the work of Schlosser (1976) who noted that while lower friction coefficients resulted in a higher propensity for traffic accidents, accident were significantly influenced by a number of other factors. It is however noted that this study failed to identify a variable that consistently influenced the number of accidents in all three datasets.

The results are further supported in part by the work of Rogers and Gargett (1991), and Viner et al., (2005) who both concluded that there was no relationship between friction coefficient and traffic accidents on the motorways in England and the United Kingdom respectively. It is however acknowledged that when road classification is taken into account the findings of this study are not supported by the work of Rogers and Gargett (1991), and Viner et al., (2005). Nor are the findings of this study supported by the work of Al-Mansour, (2006), Davies et al., (2005), Hosking, (1986), Kudrna et al., (Undated), Kuttesch, (2004), Mayora and Rafael, (2008), McCullough and Hankins, (1966), Moore and Humphreys, (1973), and Rizenbergs et al., (1977).

The comparison of results found in this study with those found in the literature is perhaps however, a fallacious act. This is asserted as the results of the different studies have unique temporal and geographical boundaries, affecting the contexts in which the data was collected. With changes in temporal and geographical boundaries, it would be problematical to reconcile differences in vehicle fleet technology (namely that associated with tyres, braking systems, and other vehicle safety

features), mean vehicle operating speeds, carriageway design standards, climatic conditions, and road user behaviour and expectations (with regard to both safety and performance).

Due to the inability to identify and quantify a relationship between friction coefficient and traffic accidents, it has not been possible to monetise the accident costs associated with the provision of varying levels of friction coefficient on the road network. While the study was unable to discover a relationship between friction coefficients and traffic accidents, this is not to say one does not exist for contexts outside of those analysed in this study.

6.4 Implications of the Study

Ultimately this study has revealed that no relationship between friction coefficients and traffic accidents existed on A-roads with a posted speed limit of 60mph (100km/hr) in County Norfolk between 2008 and 2010. The implication of this finding is that it would appear unnecessary for Norfolk County Council to have a friction coefficient policy for roads that fall within this classification. The budgets currently spent on monitoring and maintaining carriageway friction coefficients on this classification of road in the County could therefore be diverted to other priority areas.

On the basis that significant variation was found in friction coefficient data supplied by Norfolk County Council, there is significant reason to believe that the margins of error surrounding friction coefficient data collected by SCRIM are considerably larger than previously thought. While the exact cause of the variation was unclear, it does suggest that either: accuracy in collecting friction coefficient data by SCRIM needs to improve; the methods of moderating data to compensate for seasonal variation need to be revised; and/or the policies dictating friction coefficient levels should be revised to reflect the potential limitations of the data.

As discussed there is strong evidence to suggest that due to improvements in vehicle braking technology, the level of skid resistance that the vehicle fleet can collectively derive from the road surface has been increasing over time. Therefore as illustrated in Figure 66, prescribed friction coefficient requirements could be gradually reduced in the longer term, with no adverse effect on the level of skid resistance that can be generated by the vehicle fleet. This action could result in extensions to road surface life, enabling not only an increase in the economic return from the road surface, but also a reduction in environmental and road-user costs associated with the replacement of the road surface.

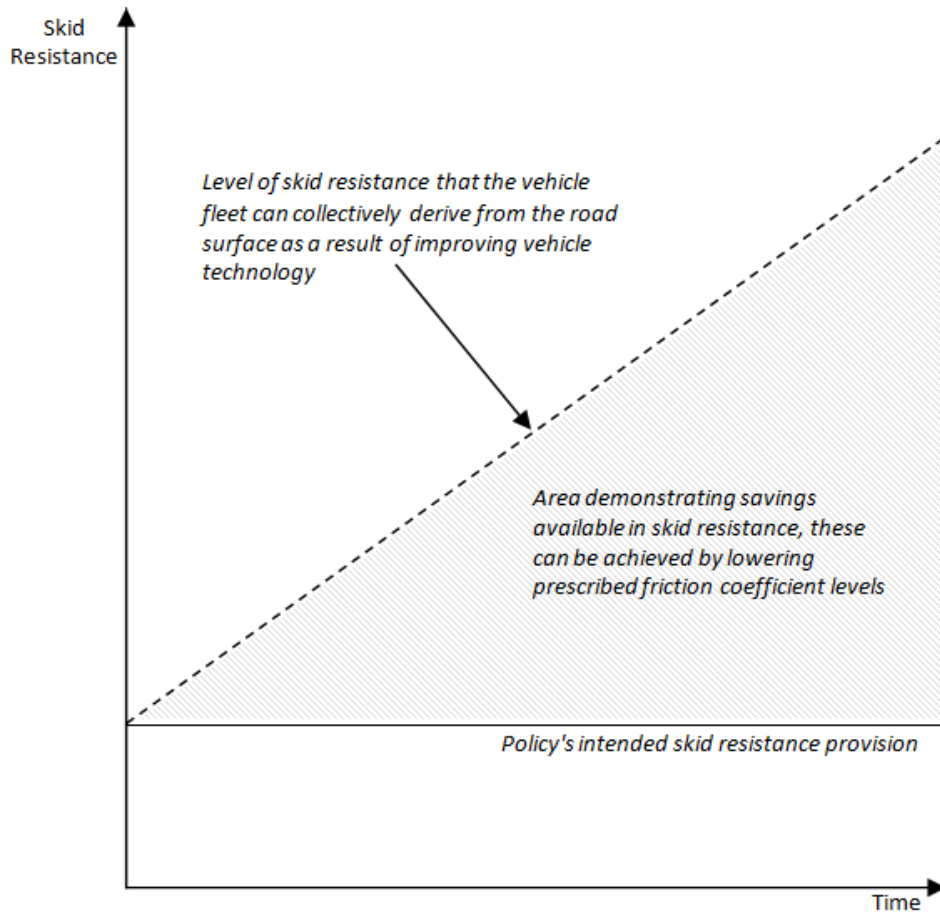


Figure 66: Depiction of Improved Braking Performance

When one considers the findings in the literature relating to driver behaviour, the failure to compensate for the improving levels of skid resistance that the vehicle fleet can derive from the road surface, in policy, may be problematic. Collective increases in skid resistance levels, could lead to changes in driver expectations and subsequent behaviour, where the intended safety benefits are instead (or in part) consumed as performance benefits. Therefore, the most recent revision of the United Kingdom's 1988 'Pavement Design and Maintenance - Skid Resistance' policy (for trunk roads), in which the prescribed friction coefficient values were either maintained or increased, may have unintentionally changed driver expectations and behaviour.

Though this study has concluded that no relationship between friction coefficient and traffic accidents exists (within the confines of that examined), it is acknowledged that the majority of the literature has suggested that an inverse relationship does exist. In cognisance that the literature reviewed also suggested that driver behaviour was a reflection of a driver's perceived level of skid resistance and past experiences, it stands to reason that an inverse relationship between friction coefficient and traffic accidents would exist regardless of a network's average friction coefficient value. This is because the distribution characteristics of friction coefficient necessitates that a proportion of carriageway sections will provide a lower level of friction than the majority of the network.

6.5 Recommendations for Further Research

This study has suggested that the measurement of road surface friction coefficient is not as accurate as one might have been expected. An analysis of the converted SCRIM data from other road networks could be useful in determining whether the anomalies found in this study, are similar to those in other networks. Confidence in the accuracy of friction coefficient data could enable two significant advances in skid resistance research. First, for those roads where a relationship between friction coefficients and traffic accidents exists, trends can be assessed over time. This information would be essential if considering a long-term reduction in the prescribed levels of friction coefficient.

The second benefit of being able to obtain accurate friction coefficient data would enable the rate of friction coefficient deterioration (year on year) to be accurately quantified. This could serve as a useful indicator of driver demand for skid resistance given that deterioration is partly due to the stresses induced by passing vehicles. This would enable asset engineers to not only consider the level of friction provided on a given section of carriageway, but also consider this with respect to the demand for skid resistance at this site. Such an approach would enable spending on resurfacing projects at sites with low friction coefficient values and low demand for skid resistance to be deferred. Furthermore, identification of high skid resistance demand sites may be helpful in determining those sections of carriageway subjected to undesirable driver behaviour, such as heavy braking, or fast cornering. Where such behaviour is identified, the provided friction coefficient can be more closely monitored or perhaps more appropriately, the road environment could be improved to remove the root cause, rather than relying on the unsustainable practice of using higher levels of friction coefficient as a 'band-aid'.

As part of this study, a more robust methodology for treating data was established which has rectified a number of shortcomings that were identified from the literature reviewed. For this reason the relationship between friction coefficient and traffic accidents for those roads governed by a friction coefficient management policy should be retested using the methodological approach used in this study. From a practical position, the importance of undertaking a review of the trunk road network cannot be overstated given it would appear that by far the majority of local authorities are using it as the basis for their own policies, with what would appear little, or no analysis of their own.

The work of Owen et al., (Undated) found that the New Zealand's State Highway friction management policy (T/10) resulted in a decrease in traffic accidents while on all other roads which are typically not governed by any friction management policy the accident rate increased. While this study found that there is no relationship between the level of friction coefficient provided and traffic accidents, it would

be prudent to investigate the potential migration of traffic accidents given the number of alternative policies and practices governing friction provision within the United Kingdom.

To enable an incremental reduction in prescribed friction provision, there is an urgent need to develop a method for measuring the level of skid resistance that the vehicle fleet can generate. The creation of a vehicle and tyre index which considers the changing nature of the vehicle fleet may be one method. This index should also consider changes in traffic accident survivability, as this has a significant impact on the monetised cost of traffic accidents, and therefore the cost benefit ratio of friction management policies.

As the average level of skid resistance that the vehicle fleet can collectively derive from the road surface is improving incrementally with time, there may be justification for a review of prescribed stopping sight distances. A reduction in required stopping sight distance may help to change the feasibility of roading projects or land development in constrained environments.

6.6 Summary

The primary objective of this thesis as set out in Chapter I was to examine the relationship between friction coefficient and traffic accidents. This chapter has combined the findings of the literature and the results of the analysis included in this study and provided a frank discussion on the conclusions that can be reached. On the basis of these conclusions, it was found that no relationship between friction coefficient and traffic accidents existed on A-roads with a posted speed limit of 60mph (100km/hr) in County Norfolk between 2008 and 2010.

While this conclusion cannot be assumed to be true of all road classifications it does suggest the need for further research into the relationship. This study has provided a new approach for undertaking this assessment which rectifies a number of shortcomings found in the methodologies used by previous studies.

A significant number of recommendations have been provided which have been based on the assumption that while a relationship was not found in this study, one may exist on other road classifications. Fulfilment of these recommendations would enable the body of knowledge in relation to the effects of friction coefficients on traffic accidents to be greatly enhanced. This in turn would enable a more proactive approach in the management of carriageway friction and traffic safety.

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Appendix A – Prescribed Investigatory Levels in the United Kingdom

Comparison of the prescribed friction coefficient investigatory levels contained within the Design Manual for Roads and Bridges between 1988 and 2004 as extracted from Viner et al., (2005).

Table 2 Old and new recommended site categories and Investigatory Levels from HD28/88 (and subsequently HD28/94) and HD28/04 for trunk roads in Great Britain			
Site category and definition		Investigatory level (at 50km/h)	
		HD28/88 (preceding)	HD28/04 (current)
A	Motorway	0.35	0.35
B	Dual carriageway non-event	0.35	0.35-0.40
C	Single carriageway non-event	0.40	0.40-0.45
Q	Dual Carriageway (all purpose) - minor junctions	0.40	0.45-0.55
	Single Carriageway minor junctions & approaches to and across major junctions (all limbs)	0.45	
	Approach to roundabout	0.55	
K	Approaches to pedestrian crossings and other high risk situations	0.45	0.50-0.55
R	Roundabout	0.45	0.45-0.50
G1	Gradient 5-10% longer than 50m	0.45	0.45-0.50
G2	Gradient $\geq 10\%$ longer than 50m	0.50	0.50-0.55
S1	Bend radius <500m – dual carriageway	0.45-0.50	0.45-0.50
S2	Bend radius <500m – single carriageway		0.50-0.55

Table notes: 1. Category R and some sites in new categories S1 and S2 were previously tested at 20km/h. 2. A reduction in Investigatory Level of 0.05 is permitted for categories A, B, C, G2 and S2 in low risk situations, such as low traffic levels or where the risks present are well mitigated and a low incidence of accidents has been observed. Exceptionally, a higher or lower Investigatory Level than indicated in the Table may be assigned if justified by the observed accident record and local risk assessment.

Appendix B – Calculation of International Friction Index

The PIARC model provides the means to convert measurements taken from different devices into an international friction index (IFI), enabling direct comparison. Pereira et al., (Undated) provide perhaps the most succinct explanation of how the IFI can be calculated using the PIARC model, they outline the following four steps:

Step 1. The first step requires the measurement of road surface friction $FR(S)$ using a selected friction device at a known slip speed S (in km/hr). For the same section of road, select a texture measuring device to collect pavement macrotexture information and determine the mean texture depth (in mm).

Step 2. Using the calculated mean texture depth, calculate the estimated the IFI Speed Number Sp (in km/hr) using Equation 6:

$$\text{Equation 6} \quad Sp = a + b * Tx$$

Where:

a, b = are specific constants developed for specific texture measuring devices

Tx = the mean texture depth

Step 3. Adjust the measured friction values $FR(S)$ and known slip speed S to the equivalent friction value at 60km/hr using Equation 7:

$$\text{Equation 7} \quad FR(60) = FR(S) * e^{\left(\frac{S-60}{Sp}\right)}$$

Where:

$FR(60)$ = measured friction value $FR(S)$ at a slip speed of S converted to a slip speed of 60km/hr

$FR(S)$ = friction value measured using selected friction device

S = slip speed (speed at which test tyre travels)

Step 4. In the final step the IFI $F(60)$ can be calculated using the speed adjusted friction values determined in Equation 7. Equation 8 should be used to determine $F(60)$:

$$\text{Equation 8} \quad F(60) = A + B * FR(60) + C * Tx$$

Where:

- F(60) = friction value on the international friction index
FR(60) = measured friction value FR(S) at a slip speed of S converted to a slip speed of 60km/hr
A, B, C = specific constants developed for specific texture measuring devices, where C relates to tyre tread
Tx = the mean texture depth
S = slip speed (speed at which test tyre travels)

Based on the work of PIARC, Bustos et al., (2006) determined that to enable direct comparison of friction values measured by a specific friction device to another, Equation 9 could be used:

Equation 9

$$FR(S)_j = \frac{\left[A_i + B_i * FR(S)_i * e^{\left(\frac{(Se_j - 60)}{(a + b * Tx)} \right)} \right]}{\left[A_j + B_j * e^{\left(\frac{(Se_j - 60)}{(a + b * Tx)} \right)} \right]}$$

Where:

- FR(S)_j = friction value at a slip speed of S of one device j based on that measured by another specific friction (device i)
FR(S)_i = friction value at a slip speed of S as measured by a specific friction device i
Se_x = survey speed for each of the friction devices
A_x, B_x = specific constants developed for each of the friction devices
a, b = specific constants developed for specific texture measuring devices
Tx = the mean texture depth

Appendix C – Sample of Before and After Study Results

Of the before and after studies reviewed, most analysed the effects of road surface friction coefficient improvement on sites with a known traffic accident history. While plethora of before and after studies exist, a sample of those reviewed are summarised in the table on the following page, it noted that most studies do not appear to have taken regression to the mean into account. Some of the results may therefore misrepresent the actual contribution made for friction coefficient improvement.

It is also noted that many of the studies reflect the application of anti-skid surfacing on existing roads, unfortunately data pertaining to the before and after road surface friction measurements have not always been provided.

Location (Reference)	Treatment Year	Road Surface Friction Measurement		Details	Accident Saving
		Before	After		
Texas, US (McCullough and Hankins, 1966)	1964	0.275	0.462	Unknown	42.5%
		0.275	0.359		36.0%
		0.275	0.467		33.4%
		0.275	untreated		19.8%
London, UK (Lamb, 1976)	1967-1969	Unknown	Unknown	23 known blackspots	31%
London, UK (MacKenzie, 1971)	1968	Unknown	Unknown	41 Urban Junctions	31%
Surrey, UK (Bennett, 2000)	1992	Unknown	Unknown	18 known blackspots	26%
	1993				42%
New York, US (Lyon and Persaud, 2008)	1994 - 2003	Below 32 (ASTM E501)	Unknown	256 junctions	20%
				118 segments	24%
Wellington, NZ (Hudson, 2003)	1997	Unknown	Unknown	1.6km of step gradient and curved road	80%
Victoria, Aus (VicRoads, 2006)	1999 & 2005 ¹	Unknown	Unknown	Unknown	-% ²
Auckland, NZ (Wilson and Kirk, 2005)	1999-2001	Unknown	Unknown	2 motorway on ramps	-% ³
	2002			2 motorway off ramps	0%
Toronto, Canada (Erwin and Tighe, 2008)	2001-2004	Unknown	Unknown	11 sites with AADT of <3,000	0%
				15 sites with AADT of 3,000 – 6,999	26%
				14 sites with AADT of >7,000	37%
Tasmania, Aus (Dumitru et al., Undated)	2005	Unknown	Unknown	Unknown	-% ⁴
Florida, US (Abdel-Aty et al., 2008)	2003-2006	Unknown	Unknown	136 sites on multilane highways	-0.63%
Florida, US (HNTB Corporation, 2008)	2006	35 (ASTM E274)	104 (ASTM E274)	1 motorway on-ramp	-% ⁵
California, US (Mi Oh et al., 2010)	2008	Unknown	Unknown	13 sites with open grade AC	46-96%
				4 sites with groove pavement and 4 sites with rubberised open grade AC	0-100% ⁶

Table 19: Summary of Before and After Findings Examined

¹ Estimated treatment year.

² Data revealed that of the treated sites, only 46% provided a reduction in traffic accidents, the review concluded that the effectiveness was inconclusive.

³ Reduction in on ramps accidents following treatment was inconclusive, at one site no accidents occurred for three years following treatment (from a previous rate of 2.1 accidents per year), at the second site accidents increased but this was assumed to be due to the location at which the seal was stopped.

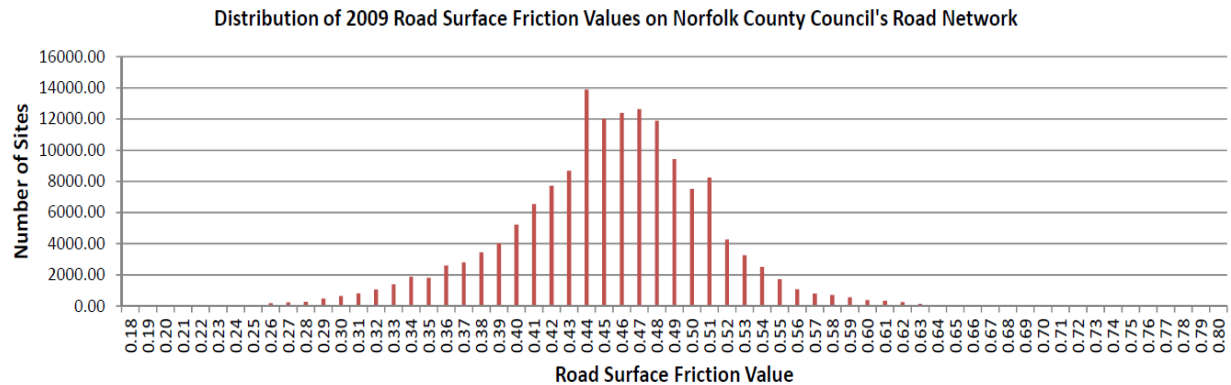
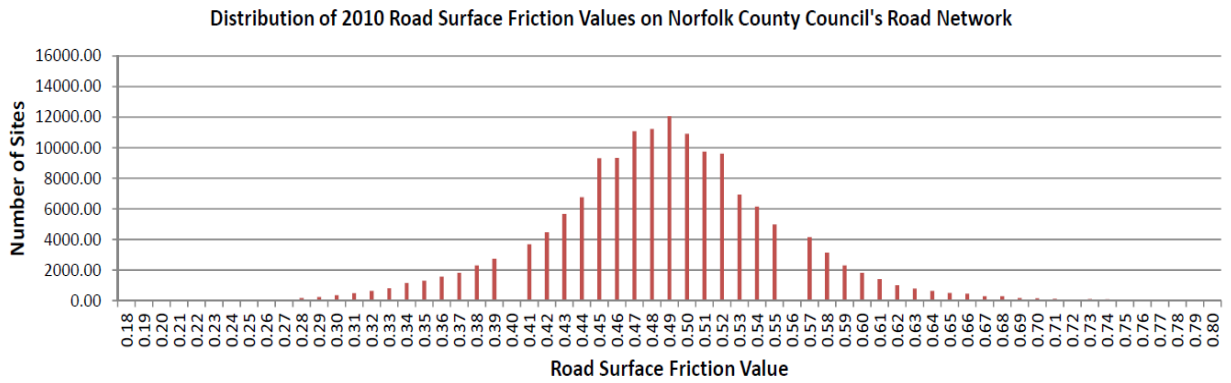
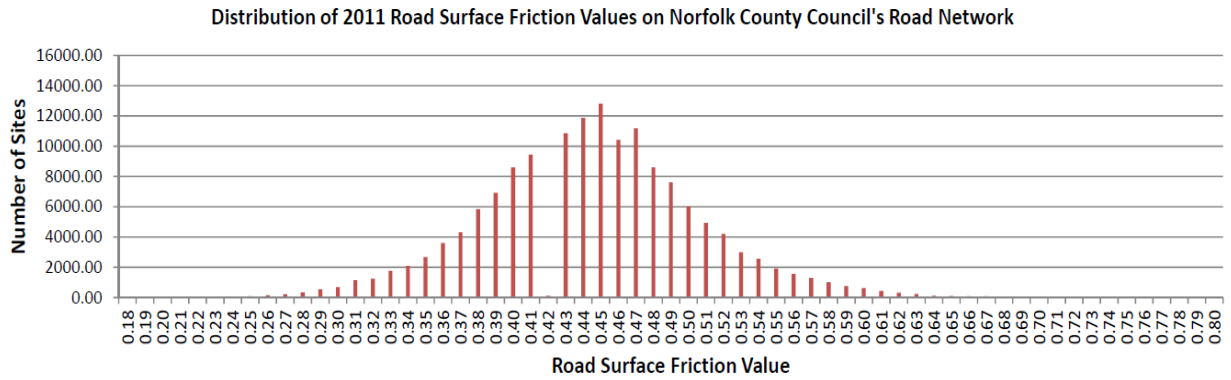
⁴ Two years after resurfacing analysis it was not possible to determine a relationship between road surface friction and traffic accidents.

⁵ Over a four year and four month period prior to improvement works accident rate was 2.54 per year, one year after treatment there had been two accidents. It was concluded that there was not enough data to quantify safety benefit, however it was claimed that the new surface resulted in improved driver behaviour with regard to speed and staying in lane.

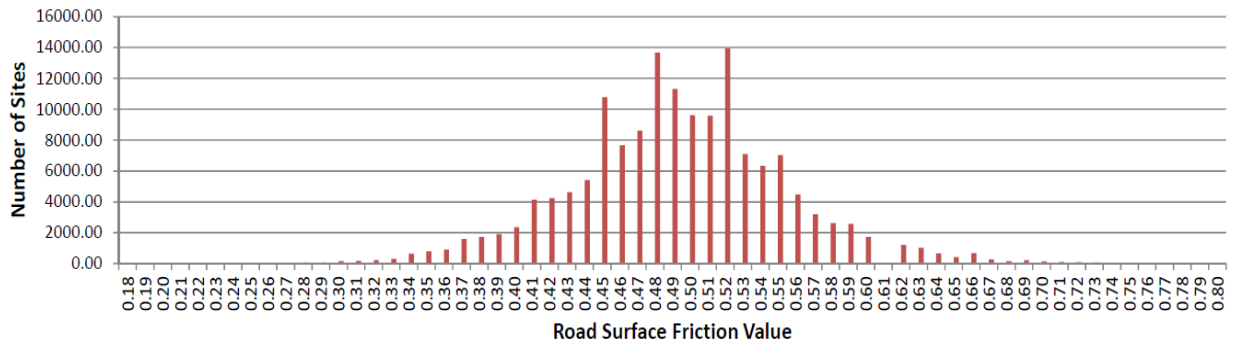
⁶ Range in results due to the small sample size.

Appendix D – Raw SCRIM Friction Coefficient Distribution

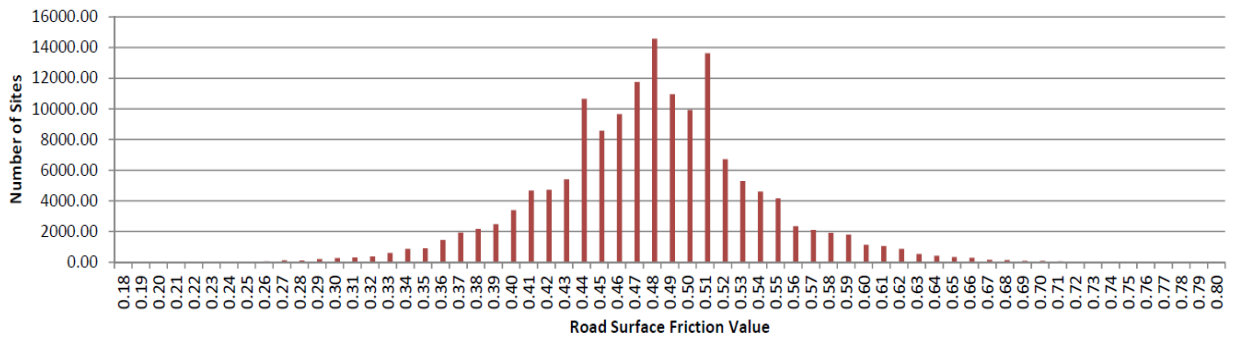
The following plots present the distribution of raw friction coefficient data (seasonally adjusted) as measured by SCRIM on the Norfolk County A-road network.



Distribution of 2008 Road Surface Friction Values on Norfolk County Council's Road Network



Distribution of 2007 Road Surface Friction Values on Norfolk County Council's Road Network



Appendix E – Example of Representative Value Calculation

An extract from the dataset used in this study has been included to illustrate how representative surface friction values were calculated (other representative values follow a similar process).

- Step 1: Friction coefficient values for the left and right lanes (columns B and C respectively) were converted into expected braking distances (columns D and E respectively)
- Step 2: Average braking distances were then calculated for each respective site. For example: the average braking distance calculated for road section A17/80 210 (cell A24) was calculated using the braking distance values highlighted in red (cells D4:D24 + E24:E44). The resultant is displayed in cell F24.
- Step 3: Representative friction coefficients (column G) were then calculated on the basis of the average braking distance value recorded in column F.

F24 f_x =AVERAGE(D4:D24,E24:E44)

	A	B	C	D	E	F	G	H
1								
2	ID	Road Surface Friction Coefficient (RFC)						
3	Unique ID	RFC L	RFC R	BD Left Lane	BD Right Lane	BD Average	RFC Rep	RFC SD Rep
4	A17/80 9	0.44	0.45	89	87			
5	A17/80 19	0.45	0.45	87	87			
6	A17/80 29	0.44	0.45	89	87			
7	A17/80 39	0.45	0.45	87	87			
8	A17/80 49	0.44	0.46	89	86			
9	A17/80 59	0.44	0.45	89	87			
10	A17/80 69	0.45	0.44	87	89			
11	A17/80 80	0.45	0.44	87	89			
12	A17/80 90	0.45	0.45	87	87			
13	A17/80 100	0.45	0.44	87	89			
14	A17/80 110	0.46	0.43	86	91			
15	A17/80 120	0.45	0.42	87	94			
16	A17/80 130	0.45	0.43	87	91			
17	A17/80 140	0.45	0.45	87	87			
18	A17/80 150	0.44	0.45	89	87			
19	A17/80 160	0.45	0.46	87	86			
20	A17/80 170	0.44	0.46	89	86			
21	A17/80 180	0.45	0.44	87	89			
22	A17/80 190	0.45	0.44	87	89			
23	A17/80 200	0.46	0.45	86	87			
24	A17/80 210	0.47	0.45	84	87	88	0.45	0.0078
25	A17/80 221	0.45	0.44	87	89	87	0.45	0.0083
26	A17/80 231	0.45	0.44	87	89	87	0.45	0.0093
27	A17/80 241	0.46	0.46	86	86	87	0.45	0.0092
28	A17/80 251	0.45	0.46	87	86	87	0.45	0.0091
29	A17/80 261	0.45	0.46	87	86	87	0.45	0.0088
30	A17/80 271	0.45	0.45	87	87	87	0.45	0.0090
31	A17/80 281	0.45	0.44	87	89	87	0.45	0.0094
32	A17/80 291	0.46	0.43	86	91	87	0.45	0.0101
33	A17/80 301	0.46	0.45	86	87	86	0.46	0.0102
34	A17/80 311	0.45	0.44	87	89	86	0.46	0.0104
35	A17/80 321	0.46	0.45	86	87	86	0.46	0.0101
36	A17/80 331	0.45	0.45	87	87	86	0.46	0.0101
37	A17/80 341	0.45	0.46	87	86	86	0.46	0.0102
38	A17/80 351	0.45	0.45	87	87	86	0.46	0.0104
39	A17/80 361	0.45	0.45	87	87	86	0.46	0.0101
40	A17/80 372	0.45	0.45	87	87	86	0.46	0.0102
41	A17/80 382	0.45	0.45	87	87	86	0.46	0.0099
42	A17/80 392	0.45	0.45	87	87	86	0.46	0.0098
43	A17/80 402	0.44	0.46	89	86	86	0.46	0.0102
44	A17/80 412	0.44	0.45	89	87	86	0.46	0.0106
45	A17/80 422	0.44	0.47	89	84	86	0.46	0.0108

Appendix F – 'R' Commands and Console Outputs

R Console

R version 2.15.0 (2012-03-30)
Copyright (C) 2012 The R Foundation for Statistical Computing
ISBN 3-900051-07-0
Platform: x86_64-pc-mingw32/x64 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

[Previously saved workspace restored]

```
> # Loading new file full data set for each year
> data08<-read.csv(file.choose(),header=TRUE)
> data09<-read.csv(file.choose(),header=TRUE)
> data10<-read.csv(file.choose(),header=TRUE)
>
> #Loading new file accident only data set for each year
> acc08<-read.csv(file.choose(),header=TRUE)
> acc09<-read.csv(file.choose(),header=TRUE)
> acc10<-read.csv(file.choose(),header=TRUE)
>
> # Loading new file non-accident only data set for each year
> nacc08<-read.csv(file.choose(),header=TRUE)
> nacc09<-read.csv(file.choose(),header=TRUE)
> nacc10<-read.csv(file.choose(),header=TRUE)
>
> # Loading new file accident yes, accident no for each year
> AccYN08<-read.csv(file.choose(),header=TRUE)
> AccYN09<-read.csv(file.choose(),header=TRUE)
> AccYN10<-read.csv(file.choose(),header=TRUE)
>
> # Loading new file accident type slight for each year
> slight08<-read.csv(file.choose(),header=TRUE)
> slight09<-read.csv(file.choose(),header=TRUE)
> slight10<-read.csv(file.choose(),header=TRUE)
>
> # Loading new file accident type serious for each year
> serious08<-read.csv(file.choose(),header=TRUE)
> serious09<-read.csv(file.choose(),header=TRUE)
> serious10<-read.csv(file.choose(),header=TRUE)
>
> # Loading new file accident type fatal for each year
> fatal08<-read.csv(file.choose(),header=TRUE)
> fatal09<-read.csv(file.choose(),header=TRUE)
> fatal10<-read.csv(file.choose(),header=TRUE)
>
> # Loading new file representative friction values for 3 datasets
> databoxfriction<-read.csv(file.choose(), header=TRUE)
> # Print summary data for all the datasets
> summary(data08)
  Unique.ID      Coef.Fric.Rep      Coef.Fric.SD.Rep      Accident.Value
A1042/230 219:      1      Min.      :0.2192      Min.      :0.006713      Min.      : 0.0
A1042/230 229:      1      1st Qu.:0.4689      1st Qu.:0.020546      1st Qu.: 0.0
A1042/230 239:      1      Median :0.4953      Median :0.028289      Median : 0.0
A1042/230 250:      1      Mean    :0.4931      Mean    :0.032778      Mean    : 484.1
A1042/230 260:      1      3rd Qu.:0.5192      3rd Qu.:0.039892      3rd Qu.: 0.0
A1042/230 270:      1      Max.    :0.6777      Max.    :0.156703      Max.    :1790203.0
(Other)      :26667
  Acc.No.      Rep.Curve      Rep.Curve.SD      Rep.Super
Min.      :0.000000      Min.      : 311.8      Min.      : 0.0      Min.      :0.4905
1st Qu.:0.000000      1st Qu.:1344.1      1st Qu.:121.1      1st Qu.:2.0143
Median :0.000000      Median :1735.4      Median :397.2      Median :2.3952
Mean    :0.002624      Mean    :1613.0      Mean    :367.1      Mean    :2.5018
```

R Console

3rd Qu.:0.000000	3rd Qu.:1972.8	3rd Qu.:592.7	3rd Qu.:2.8214
Max. :1.000000	Max. :2000.0	Max. :888.1	Max. :7.0810

Rep.Super.SD	Gradient.Rep	Gradient.SD.Rep	X.HGV
Min. :0.1147	Min. :-4.09956	Min. :0.0005809	Min. :0.005082
1st Qu.:0.5412	1st Qu.: -0.19797	1st Qu.:0.0053255	1st Qu.:0.035626
Median :0.7906	Median : 0.07610	Median :0.0094000	Median :0.053394
Mean :0.9274	Mean : 0.09403	Mean :0.0117466	Mean :0.067042
3rd Qu.:1.1685	3rd Qu.: 0.45273	3rd Qu.:0.0163466	3rd Qu.:0.086681
Max. :4.3371	Max. : 3.99668	Max. :0.0706324	Max. :0.194311

AADT

Min. : 2242
1st Qu.: 6047
Median : 8084
Mean : 9151
3rd Qu.:10963
Max. :26019

> summary(data09)

Unique.ID	Coef.Fric.Rep	Coef.Fric.SD.Rep	Accident.Value
A1042/230 220:	1 Min. :0.3164	Min. :0.006803	Min. : 0.0
A1042/230 230:	1 1st Qu.:0.4412	1st Qu.:0.019555	1st Qu.: 0.0
A1042/230 240:	1 Median :0.4656	Median :0.026499	Median : 0.0
A1042/230 250:	1 Mean :0.4634	Mean :0.030350	Mean : 522.1
A1042/230 260:	1 3rd Qu.:0.4859	3rd Qu.:0.037056	3rd Qu.: 0.0
A1042/230 270:	1 Max. :0.5808	Max. :0.115574	Max. :1790203.0

(Other) :25550

Acc.No.	Rep.Curve	Rep.Curve.SD	Rep.Super
Min. :0.000000	Min. : 287.5	Min. : 0.0	Min. :0.4905
1st Qu.:0.000000	1st Qu.:1348.9	1st Qu.:123.2	1st Qu.:2.0119
Median :0.000000	Median :1728.1	Median :396.8	Median :2.3952
Mean :0.002309	Mean :1613.5	Mean :367.9	Mean :2.5018
3rd Qu.:0.000000	3rd Qu.:1972.8	3rd Qu.:593.1	3rd Qu.:2.8262
Max. :1.000000	Max. :2000.0	Max. :866.8	Max. :7.0810

Rep.Super.SD	Gradient.Rep	Gradient.SD.Rep	X.HGV
Min. :0.1147	Min. :-4.1424	Min. :0.0005809	Min. :0.005019
1st Qu.:0.5401	1st Qu.: -0.1921	1st Qu.:0.0053715	1st Qu.:0.033672
Median :0.7979	Median : 0.0803	Median :0.0095311	Median :0.050323
Mean :0.9309	Mean : 0.1037	Mean :0.0118581	Mean :0.062659
3rd Qu.:1.1836	3rd Qu.: 0.4677	3rd Qu.:0.0165125	3rd Qu.:0.082492
Max. :4.3371	Max. : 3.9967	Max. :0.0667327	Max. :0.186507

AADT

Min. : 2277
1st Qu.: 6043
Median : 8109
Mean : 9182
3rd Qu.:10923
Max. :28336

> summary(data10)

Unique.ID	Coef.Fric.Rep	Coef.Fric.SD.Rep	Accident.Value
A1042/230 219:	1 Min. :0.3359	Min. :0.00712	Min. : 0.0
A1042/230 229:	1 1st Qu.:0.4671	1st Qu.:0.02159	1st Qu.: 0.0
A1042/230 239:	1 Median :0.4957	Median :0.02877	Median : 0.0
A1042/230 250:	1 Mean :0.4955	Mean :0.03265	Mean : 412.6
A1042/230 260:	1 3rd Qu.:0.5224	3rd Qu.:0.03921	3rd Qu.: 0.0
A1042/230 270:	1 Max. :0.6775	Max. :0.13639	Max. :1790203.0

(Other) :26401

Acc.No.	Rep.Curve	Rep.Curve.SD	Rep.Super
Min. :0.000000	Min. : 287.5	Min. : 0.0	Min. :0.4905
1st Qu.:0.000000	1st Qu.:1342.9	1st Qu.:125.5	1st Qu.:2.0119
Median :0.000000	Median :1724.9	Median :405.1	Median :2.4000
Mean :0.002537	Mean :1609.1	Mean :371.7	Mean :2.5030
3rd Qu.:0.000000	3rd Qu.:1970.9	3rd Qu.:596.6	3rd Qu.:2.8310
Max. :1.000000	Max. :2000.0	Max. :876.5	Max. :7.0810

Rep.Super.SD	Gradient.Rep	Gradient.SD.Rep	X.HGV
Min. :0.1147	Min. :-4.14239	Min. :0.0005809	Min. :0.005175
1st Qu.:0.5446	1st Qu.: -0.19972	1st Qu.:0.0053883	1st Qu.:0.033873
Median :0.7978	Median : 0.07364	Median :0.0095088	Median :0.050988
Mean :0.9331	Mean : 0.09306	Mean :0.0118664	Mean :0.062083

R Console

```
3rd Qu.:1.1774    3rd Qu.: 0.44234    3rd Qu.:0.0164911    3rd Qu.:0.083681
Max.      :4.3371    Max.      : 4.02103    Max.      :0.0706324    Max.      :0.189507
```

```
      AADT
Min.   : 2219
1st Qu.: 6042
Median : 8042
Mean   : 8962
3rd Qu.:10844
Max.   :26721
```

```
> # plot to view the distribution of representative coefficient of friction values
> hist(data08$Coef.Fric.Rep,main="Representative Friction 2008",xlab="Friction Value (unitless)",ylab="Number of Sites",breaks=46, xlim= c(0.2, 0.7), ylim = c(0.0, 4000))
> hist(data09$ Coef.Fric.Rep,main="Representative Friction 2009",xlab="Friction Value (unitless)",ylab="Number of Sites",breaks=27, xlim= c(0.2, 0.7), ylim = c(0.0, 4000))
> hist(data10$ Coef.Fric.Rep,main="Representative Friction 2010",xlab="Friction Value (unitless)",ylab="Number of Sites",breaks=35, xlim= c(0.2, 0.7), ylim = c(0.0, 4000))
> databoxfriction$Year <- ordered(databoxfriction$Year, levels=c("2008", "2009", "2010"))
> boxplot(Friction~Year,main="Representative Friction Values for the Three Datasets", xlab="Year",ylab=" Representative Friction (Unitless)" ,ylim=c(0.2,0.7),data=databoxfriction)
> #call the set of functions in the moments file,calculate the skewness and kurtosis for each friction dataset
> library(moments)
> skewness(data08$ Coef.Fric.Rep)
[1] -0.6196688
> skewness(data09$ Coef.Fric.Rep)
[1] -0.308281
> skewness(data10$ Coef.Fric.Rep)
[1] 0.07261089
> kurtosis(data08$ Coef.Fric.Rep)
[1] 5.844363
> kurtosis(data09$ Coef.Fric.Rep)
[1] 3.948483
> kurtosis(data10$ Coef.Fric.Rep)
[1] 3.969368
> # plot to view the distribution of representative standard deviation values for the coefficient of friction data
> hist(data08$Coef.Fric.SD.Rep,main="Representative Friction Standard Deviation 2008",xlab="Standard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 0.20), ylim = c(0.0, 10000))
> hist(data09$Coef.Fric.SD,main="Representative Friction Standard Deviation 2009",xlab="Standard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 0.20), ylim = c(0.0, 10000))
> hist(data10$Coef.Fric.SD,main=" Representative Friction Standard Deviation 2010",xlab="Standard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 0.20), ylim = c(0.0, 10000))
> # plot to view the distribution of representative curve radius values
> hist(data08$Rep.Curve,main="Representative Curvature 2008",xlab="Representative Curvature Radius (m) ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 2000), ylim = c(0.0, 10000))
>
> hist(data09$Rep.Curve,main="Representative Curvature 2009",xlab="Representative Curvature Radius (m) ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 2000), ylim = c(0.0, 10000))
>
> hist(data10$Rep.Curve,main="Representative Curvature 2010",xlab="Representative Curvature Radius (m) ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 2000), ylim = c(0.0, 10000))
>
>
> #calculates skewness and kurtosis values for RSF values
> skewness(data08$Rep.Curve)
[1] -0.8962829
> skewness(data09$Rep.Curve)
[1] -0.9028858
> skewness(data10$Rep.Curve)
[1] -0.896083
> kurtosis(data08$Rep.Curve)
[1] 2.836742
> kurtosis(data09$Rep.Curve)
[1] 2.891963
> kurtosis(data10$Rep.Curve)
[1] 2.864195
>
> # plot to view the distribution of standard deviation for representative curvature data
> hist(data08$Rep.Curve.SD,main="Representative Curvature standard deviation 2008 ",xlab="Standard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 900), ylim = c(0.0, 5000))
> hist(data09$ Rep.Curve.SD,main="Representative Curvature standard deviation 2009 ",xlab="Sta
```

R Console

```
ndard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 900), ylim = c(0.0, 5000))
>
> hist(data10$ Rep.Curve.SD,main="Representative Curvature standard deviation 2010",xlab="Stan
dard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 900), ylim = c(0.0, 5000))
>
>
> #plot to view the distribution of superelevation values for each year
> hist(data08$ Rep.Super,main="Representative Superelevation 2008",xlab="Representative Supere
levation (Degrees) ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 8), ylim = c(0.0, 10000))
>
> hist(data09$ Rep.Super,main="Representative Superelevation 2009",xlab="Representative Supere
levation (Degrees) ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 8), ylim = c(0.0, 10000))
>
> hist(data10$ Rep.Super,main="Representative Superelevation 2010",xlab="Representative Supere
levation (Degrees) ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 8), ylim = c(0.0, 10000))
>
>
> # calculate the skewness and kurtosis for each representative superelevation dataset
> skewness(data08$ Rep.Super)
[1] 1.258376
> skewness(data09$ Rep.Super)
[1] 1.270717
> skewness(data10$ Rep.Super)
[1] 1.258126
> kurtosis(data08$ Rep.Super)
[1] 6.058286
> kurtosis(data09$ Rep.Super)
[1] 6.183531
> kurtosis(data10$ Rep.Super)
[1] 6.138953
>
>
> #plot to view the distribution of the Representative Superelevation standard deviations
> hist(data08$ Rep.Super.SD,main="Representative Superelevation Standard Deviation 2008",xlab=
"Standard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 5), ylim = c(0.0, 12000))
>
> hist(data09$ Rep.Super.SD,main="Representative Superelevation Standard Deviation 2009",xlab=
"Standard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 5), ylim = c(0.0, 12000))
>
> hist(data10$ Rep.Super.SD,main="Representative Superelevation Standard Deviation 2010",xlab
="Standard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 5), ylim = c(0.0, 12000)
)
>
> # plot to view the distribution of the Representative Gradient Values
> hist(data08$Gradient.Rep,main="Representative Gradient 2008",xlab="Representative Gradient (
Percentage) ",ylab="Number of Sites",breaks=15, xlim= c(-6, 6), ylim = c(0.0, 10000))
>
> hist(data09$ Gradient.Rep,main="Representative Gradient 2009",xlab="Representative Gradient
(Percentage) ",ylab="Number of Sites",breaks=15, xlim= c(-6, 6), ylim = c(0.0, 10000))
>
> hist(data10$ Gradient.Rep,main="Representative Gradient 2010",xlab="Representative Gradient
(Percentage) ",ylab="Number of Sites",breaks=15, xlim= c(-6, 6), ylim = c(0.0, 10000))
> # calculate the skewness and kurtosis for each representative gradient dataset
> skewness(data08$ Gradient.Rep)
[1] -0.4933774
> skewness(data09$ Gradient.Rep)
[1] -0.4836966
> skewness(data10$ Gradient.Rep)
[1] -0.4850433
> kurtosis(data08$ Gradient.Rep)
[1] 6.488067
> kurtosis(data09$ Gradient.Rep)
[1] 6.495751
> kurtosis(data10$ Gradient.Rep)
[1] 6.653844
>
> #plot to view the distribution of representative gradient standard deviation
> hist(data08$ Gradient.SD.Rep,main="Representative Gradient Standard Deviation 2008",xlab="St
andard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 0.08), ylim = c(0.0, 10000))
>
>
> hist(data09$ Gradient.SD.Rep,main="Representative Gradient Standard Deviation 2009",xlab="St
andard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 0.08), ylim = c(0.0, 10000))
>
```

R Console

```
> hist(data10$ Gradient.SD.Rep,main="Representative Gradient Standard Deviation 2010",xlab="Standard Deviation ",ylab="Number of Sites",breaks=15, xlim= c(0.0, 0.08), ylim = c(0.0, 10000))
>
> #As AADT and %HGV values have been assigned on the basis of the nearest most applicable count, these have not been plotted or analysed in detail
>
> #normal test plots package
> library(nortest)
> #qqnorm = normal quantile plot to view whether data appears normal,
> #qqline = adds a reference line to display where data should lie if data is normal
>
> qqnorm(data08$Coef.Fric.Rep, main="Normal Q-Q Plot of Representative Friction 2008 ",xlab="Quantile",ylab="Representative Friction (Unitless)", ylim = c(0.2, 0.7)); qqline(data08$Coef.Fric.Rep)
>
> qqnorm(data09$Coef.Fric.Rep, main="Normal Q-Q Plot of Representative Friction 2009 ",xlab="Quantile",ylab="Representative Friction (Unitless)", ylim = c(0.2, 0.7)); qqline(data09$Coef.Fric.Rep)
>
> qqnorm(data10$Coef.Fric.Rep, main="Normal Q-Q Plot of Representative Friction 2010 ",xlab="Quantile",ylab="Representative Friction (Unitless)", ylim = c(0.2, 0.7)); qqline(data10$Coef.Fric.Rep)
>
> #provides p-value to determine probability of normality
> lillie.test (data08$Coef.Fric.Rep)

      Lilliefors (Kolmogorov-Smirnov) normality test

data:  data08$Coef.Fric.Rep
D = 0.0468, p-value < 2.2e-16

> lillie.test (data09$Coef.Fric.Rep)

      Lilliefors (Kolmogorov-Smirnov) normality test

data:  data09$Coef.Fric.Rep
D = 0.0332, p-value < 2.2e-16

> lillie.test (data10$Coef.Fric.Rep)

      Lilliefors (Kolmogorov-Smirnov) normality test

data:  data10$Coef.Fric.Rep
D = 0.0379, p-value < 2.2e-16

>
> qqnorm(data08$Rep.Curve, main="Normal Q-Q Plot of Representative Curvature 2008 ",xlab="Quantile",ylab="Representative Curvature Radius (m)", ylim = c(0, 2000)); qqline(data08$ Rep.Curve)
>
> qqnorm(data09$ Rep.Curve, main="Normal Q-Q Plot of Representative Curvature 2009",xlab="Quantile",ylab="Representative Curvature Radius (m)", ylim = c(0, 2000)); qqline(data09$Rep.Curve)
>
> qqnorm(data10$ Rep.Curve, main="Normal Q-Q Plot of Representative Curvature 2010",xlab="Quantile",ylab="Representative Curvature Radius (m)", ylim = c(0, 2000)); qqline(data10$Rep.Curve)
>
> #provides p-value to determine probability of normality
> lillie.test (data08$Rep.Curve)

      Lilliefors (Kolmogorov-Smirnov) normality test

data:  data08$Rep.Curve
D = 0.1633, p-value < 2.2e-16

> lillie.test (data09$Rep.Curve)

      Lilliefors (Kolmogorov-Smirnov) normality test

data:  data09$Rep.Curve
D = 0.1622, p-value < 2.2e-16

> lillie.test (data10$Rep.Curve)

      Lilliefors (Kolmogorov-Smirnov) normality test
```

R Console

```
data: data10$Rep.Curve
D = 0.161, p-value < 2.2e-16
```

```
>
> qqnorm(data08$Rep.Super, main="Normal Q-Q Plot of Representative Superelevation 2008",xlab="
Quantile",ylab="Representative Superelevation (Degrees)", ylim = c(0, 8)); qqline(data08$ Rep.
Super)
>
> qqnorm(data09$ Rep.Super, main="Normal Q-Q Plot of Representative Superelevation 2009",xlab=
"Quantile",ylab="Representative Superelevation (Degrees)", ylim = c(0, 8)); qqline(data09$ Rep
.Super)
>
> qqnorm(data10$ Rep.Super, main="Normal Q-Q Plot of Representative Superelevation 2010",xlab=
"Quantile",ylab="Representative Superelevation (Degrees)", ylim = c(0, 8)); qqline(data10$ Rep
.Super)
>
> lillie.test (data08$Rep.Super)
```

Lilliefors (Kolmogorov-Smirnov) normality test

```
data: data08$Rep.Super
D = 0.0897, p-value < 2.2e-16
```

```
> lillie.test (data09$Rep.Super)
```

Lilliefors (Kolmogorov-Smirnov) normality test

```
data: data09$Rep.Super
D = 0.0864, p-value < 2.2e-16
```

```
> lillie.test (data10$Rep.Super)
```

Lilliefors (Kolmogorov-Smirnov) normality test

```
data: data10$Rep.Super
D = 0.0858, p-value < 2.2e-16
```

```
>
> qqnorm(data08$Gradient.Rep, main="Normal Q-Q Plot of Representative Gradient 2008 ",xlab="Qu
antile",ylab="Representative Gradient (Percentage)", ylim = c(-6, 6)); qqline(data08$ Gradient
.Rep)
>
> qqnorm(data09$ Gradient.Rep, main="Normal Q-Q Plot of Representative Gradient 2009",xlab="Qu
antile",ylab="Representative Gradient (Percentage)", ylim = c(-6, 6)); qqline(data09$ Gradient
.Rep)
>
> qqnorm(data10$ Gradient.Rep, main="Normal Q-Q Plot of Representative Gradient 2010",xlab="Qu
antile",ylab="Representative Gradient (Percentage)", ylim = c(-6, 6)); qqline(data10$ Gradient
.Rep)
> #log transform applied to superelevation data
> logsuper08<-log(data08$Rep.Super)
> logsuper09<-log(data09$ Rep.Super)
> logsuper10<-log(data10$ Rep.Super)
>
> qqnorm(logsuper08,main="Normal Q-Q Plot of the log of Superelevation 2008",xlab="Quantile",y
lab="Log of Superelevation");qqline(logsuper08)
>
> qqnorm(logsuper09,main="Normal Q-Q Plot of the log of Superelevation 2009",xlab="Quantile",y
lab="Log of Superelevation");qqline(logsuper09)
>
> qqnorm(logsuper10,main="Normal Q-Q Plot of the log of Superelevation 2010",xlab="Quantile",y
lab="Log of Superelevation");qqline(logsuper10)
>
> lillie.test(logsuper08)
```

Lilliefors (Kolmogorov-Smirnov) normality test

```
data: logsuper08
D = 0.0359, p-value < 2.2e-16
```

```
> lillie.test(logsuper09)
```

Lilliefors (Kolmogorov-Smirnov) normality test

R Console

```
data: logsuper09
D = 0.034, p-value < 2.2e-16
```

```
> lillie.test(logsuper10)
```

Lilliefors (Kolmogorov-Smirnov) normality test

```
data: logsuper10
D = 0.0333, p-value < 2.2e-16
```

```
>
> #log gradient test not considered as gradients have negative values
> #compute correlation matrix
> cor08<-data08[,c(2,4,5,6,8,10,13)]
> cor(cor08)
```

	Coef.Fric.Rep	Accident.Value	Acc.No.	Rep.Curve
Coef.Fric.Rep	1.000000000	0.002732591	-0.008755626	0.0049132461
Accident.Value	0.002732591	1.000000000	0.377939256	0.0013402386
Acc.No.	-0.008755626	0.377939256	1.000000000	-0.0042168244
Rep.Curve	0.004913246	0.001340239	-0.004216824	1.0000000000
Rep.Super	0.043108791	0.001136675	0.004085615	-0.5147189025
Gradient.Rep	0.021021118	0.012308069	-0.001352218	0.0002911459
AADT	-0.139841248	0.001734909	0.006541506	0.3195001384

	Rep.Super	Gradient.Rep	AADT
Coef.Fric.Rep	0.043108791	0.0210211177	-0.139841248
Accident.Value	0.001136675	0.0123080688	0.001734909
Acc.No.	0.004085615	-0.0013522178	0.006541506
Rep.Curve	-0.514718903	0.0002911459	0.319500138
Rep.Super	1.000000000	0.0112331003	-0.116294436
Gradient.Rep	0.011233100	1.0000000000	-0.067631585
AADT	-0.116294436	-0.0676315846	1.000000000

```
> cor09<-data09[,c(2,4,5,6,8,10,13)]
```

```
> cor(cor09)
```

	Coef.Fric.Rep	Accident.Value	Acc.No.	Rep.Curve
Coef.Fric.Rep	1.000000000	0.002576541	-0.005638684	0.101313452
Accident.Value	0.002576541	1.000000000	0.392142850	0.006471810
Acc.No.	-0.005638684	0.392142850	1.000000000	0.003028556
Rep.Curve	0.101313452	0.006471810	0.003028556	1.000000000
Rep.Super	-0.011394633	-0.006649447	-0.008507412	-0.525359389
Gradient.Rep	-0.007259373	-0.008404572	-0.004398906	-0.006748911
AADT	-0.008836664	0.008365008	0.026549837	0.298797789

	Rep.Super	Gradient.Rep	AADT
Coef.Fric.Rep	-0.011394633	-0.007259373	-0.008836664
Accident.Value	-0.006649447	-0.008404572	0.008365008
Acc.No.	-0.008507412	-0.004398906	0.026549837
Rep.Curve	-0.525359389	-0.006748911	0.298797789
Rep.Super	1.000000000	0.012807658	-0.107101666
Gradient.Rep	0.012807658	1.000000000	-0.062152305
AADT	-0.107101666	-0.062152305	1.000000000

```
> cor10<-data10[,c(2,4,5,6,8,10,13)]
```

```
> cor(cor10)
```

	Coef.Fric.Rep	Accident.Value	Acc.No.	Rep.Curve
Coef.Fric.Rep	1.000000000	0.003375385	-0.005522059	0.148741892
Accident.Value	0.003375385	1.000000000	0.363367737	0.003493300
Acc.No.	-0.005522059	0.363367737	1.000000000	-0.006698994
Rep.Curve	0.148741892	0.003493300	-0.006698994	1.000000000
Rep.Super	-0.097248133	-0.006705485	0.002387110	-0.519297899
Gradient.Rep	0.013952984	-0.019481210	-0.006084610	-0.003710482
AADT	-0.012821537	-0.001785655	0.017249640	0.312284288

	Rep.Super	Gradient.Rep	AADT
Coef.Fric.Rep	-0.097248133	0.013952984	-0.012821537
Accident.Value	-0.006705485	-0.019481210	-0.001785655
Acc.No.	0.002387110	-0.006084610	0.017249640
Rep.Curve	-0.519297899	-0.003710482	0.312284288
Rep.Super	1.000000000	0.012850621	-0.107773227
Gradient.Rep	0.012850621	1.000000000	-0.058298640
AADT	-0.107773227	-0.058298640	1.000000000

```
> library(Hmisc)
Loading required package: survival
Loading required package: splines
Hmisc library by Frank E Harrell Jr
```

```
Type library(help='Hmisc'), ?Overview, or ?Hmisc.Overview'
```

R Console

to see overall documentation.

NOTE:Hmisc no longer redefines [.factor to drop unused levels when subsetting. To get the old behavior of Hmisc type dropUnusedLevels().

Attaching package: 'Hmisc'

The following object(s) are masked from 'package:survival':

untangle.specials

The following object(s) are masked from 'package:base':

format.pval, round.POSIXt, trunc.POSIXt, units

```
> #compute p values for Pearson's correlation coefficient
>
> cor.test(cor08$Coef.Fric.Rep,cor08$ Acc.No)
```

Pearson's product-moment correlation

```
data: cor08$Coef.Fric.Rep and cor08$Acc.No
t = -1.43, df = 26671, p-value = 0.1527
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.020754399 0.003245668
sample estimates:
      cor
-0.008755626
```

```
> cor.test(cor08$Coef.Fric.Rep,cor08$Accident.Value)
```

Pearson's product-moment correlation

```
data: cor08$Coef.Fric.Rep and cor08$Accident.Value
t = 0.4463, df = 26671, p-value = 0.6554
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.009268666 0.014733060
sample estimates:
      cor
0.002732591
```

```
> cor.test(cor08$Coef.Fric.Rep,cor08$ Rep.Curve)
```

Pearson's product-moment correlation

```
data: cor08$Coef.Fric.Rep and cor08$Rep.Curve
t = 0.8024, df = 26671, p-value = 0.4223
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.007088125 0.016913202
sample estimates:
      cor
0.004913246
```

```
> cor.test(cor08$Coef.Fric.Rep,cor08$ Rep.Super)
```

Pearson's product-moment correlation

```
data: cor08$Coef.Fric.Rep and cor08$Rep.Super
t = 7.0468, df = 26671, p-value = 1.876e-12
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.03112394 0.05508125
sample estimates:
      cor
0.04310879
```

```
> cor.test(cor08$Coef.Fric.Rep,cor08$ Gradient.Rep)
```

Pearson's product-moment correlatio

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```
data: cor08$Coef.Fric.Rep and cor08$Gradient.Rep
t = 3.4338, df = 26671, p-value = 0.0005961
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.009022441 0.033013742
sample estimates:
      cor
0.02102112
```

```
> cor.test(cor08$Coef.Fric.Rep, cor08$ AADT)
```

Pearson's product-moment correlation

```
data: cor08$Coef.Fric.Rep and cor08$AADT
t = -23.0645, df = 26671, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.1515878 -0.1280552
sample estimates:
      cor
-0.1398412
```

```
>
> cor.test(cor09$Coef.Fric.Rep, cor09$ Acc.No)
```

Pearson's product-moment correlation

```
data: cor09$Coef.Fric.Rep and cor09$Acc.No
t = -0.9014, df = 25554, p-value = 0.3674
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.017897868 0.006622195
sample estimates:
      cor
-0.005638684
```

```
> cor.test(cor09$Coef.Fric.Rep, cor09$Accident.Value)
```

Pearson's product-moment correlation

```
data: cor09$Coef.Fric.Rep and cor09$Accident.Value
t = 0.4119, df = 25554, p-value = 0.6804
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.009684186 0.014836493
sample estimates:
      cor
0.002576541
```

```
> cor.test(cor09$Coef.Fric.Rep, cor09$ Rep.Curve)
```

Pearson's product-moment correlation

```
data: cor09$Coef.Fric.Rep and cor09$Rep.Curve
t = 16.2793, df = 25554, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.08916379 0.11343297
sample estimates:
      cor
0.1013135
```

```
> cor.test(cor09$Coef.Fric.Rep, cor09$ Rep.Super)
```

Pearson's product-moment correlation

```
data: cor09$Coef.Fric.Rep and cor09$Rep.Super
t = -1.8216, df = 25554, p-value = 0.06852
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.0236517502 0.0008659085
sample estimates:
      cor
-0.01139463
```

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```
> cor.test(cor09$Coef.Fric.Rep, cor09$ Gradient.Rep)

Pearson's product-moment correlation

data: cor09$Coef.Fric.Rep and cor09$Gradient.Rep
t = -1.1605, df = 25554, p-value = 0.2459
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.019518057  0.005001493
sample estimates:
      cor
-0.007259373

> cor.test(cor09$Coef.Fric.Rep, cor09$ AADT)

Pearson's product-moment correlation

data: cor09$Coef.Fric.Rep and cor09$AADT
t = -1.4127, df = 25554, p-value = 0.1578
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.021094800  0.003424128
sample estimates:
      cor
-0.008836664

>
> cor.test(cor10$Coef.Fric.Rep, cor10$ Acc.No)

Pearson's product-moment correlation

data: cor10$Coef.Fric.Rep and cor10$Acc.No
t = -0.8973, df = 26405, p-value = 0.3696
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.017582133  0.006539623
sample estimates:
      cor
-0.005522059

> cor.test(cor10$Coef.Fric.Rep, cor10$Accident.Value)

Pearson's product-moment correlation

data: cor10$Coef.Fric.Rep and cor10$Accident.Value
t = 0.5485, df = 26405, p-value = 0.5834
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.008686214  0.015436003
sample estimates:
      cor
0.003375385

> cor.test(cor10$Coef.Fric.Rep, cor10$ Rep.Curve)

Pearson's product-moment correlation

data: cor10$Coef.Fric.Rep and cor10$Rep.Curve
t = 24.4419, df = 26405, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.1369263 0.1605152
sample estimates:
      cor
0.1487419

> cor.test(cor10$Coef.Fric.Rep, cor10$ Rep.Super)

Pearson's product-moment correlation

data: cor10$Coef.Fric.Rep and cor10$Rep.Super
t = -15.8777, df = 26405, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
```

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95 percent confidence interval:

-0.10918132 -0.08528692

sample estimates:

cor

-0.09724813

> cor.test(cor10\$Coef.Fric.Rep, cor10\$ Gradient.Rep)

Pearson's product-moment correlation

data: cor10\$Coef.Fric.Rep and cor10\$Gradient.Rep

t = 2.2675, df = 26405, p-value = 0.02337

alternative hypothesis: true correlation is not equal to 0

95 percent confidence interval:

0.001892057 0.026009853

sample estimates:

cor

0.01395298

> cor.test(cor10\$Coef.Fric.Rep, cor10\$ AADT)

Pearson's product-moment correlation

data: cor10\$Coef.Fric.Rep and cor10\$AADT

t = -2.0836, df = 26405, p-value = 0.0372

alternative hypothesis: true correlation is not equal to 0

95 percent confidence interval:

-0.0248789351 -0.0007604085

sample estimates:

cor

-0.01282154

>

> #Plots to view whether any obvious linear associations exist.

> plot(cor08)

>

> plot(cor09)

>

> plot(cor10)

>

> # noted one road has low friction values (<0.30) when compared with AADT, Curve, Super, Gradient compared to the sample. There were no recorded accidents on this road, these values were not considered outliers as they were considered to be a normal characteristic of the expected dataset. Conversely at the higher end of the scale, there two roads that had very high friction values, it was noted that there was one accidents. Again this is considered to be a normal characteristic of the expected dataset. The high values may represent known accident 'black spots' and therefore high friction surfacing has been provided to reduce the risk of accident

.

> #Binomial Logistic Regression

>

> BLR08<-glm(Acc.No.~Coef.Fric.Rep+Rep.Curve+Rep.Super+Gradient.Rep+AADT, data=data08, family=binomial(link="logit"))

> summary(BLR08)

Call:

glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super + Gradient.Rep + AADT, family = binomial(link = "logit"), data = data08)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.1170	-0.0766	-0.0705	-0.0662	3.5716

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.381e+00	1.507e+00	-2.908	0.00364 **
Coef.Fric.Rep	-3.310e+00	2.655e+00	-1.247	0.21247
Rep.Curve	-2.400e-04	3.685e-04	-0.651	0.51481
Rep.Super	6.870e-02	1.837e-01	0.374	0.70841
Gradient.Rep	-1.874e-02	1.708e-01	-0.110	0.91266
AADT	2.880e-05	2.608e-05	1.104	0.26949

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

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```
Null deviance: 971.82 on 26672 degrees of freedom
Residual deviance: 968.01 on 26667 degrees of freedom
AIC: 980.01
```

Number of Fisher Scoring iterations: 9

```
> BLR08<-glm(Acc.No.~Coef.Fric.Rep+Rep.Curve+Rep.Super+ AADT, data=data08, family=binomial(link="logit"))
> summary(BLR08)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super +
     AADT, family = binomial(link = "logit"), data = data08)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1167 -0.0766 -0.0705 -0.0662  3.5717
```

```
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.380e+00  1.507e+00  -2.907  0.00365 **
Coef.Fric.Rep -3.313e+00  2.654e+00  -1.248  0.21196
Rep.Curve     -2.412e-04  3.682e-04  -0.655  0.51242
Rep.Super      6.845e-02  1.837e-01   0.373  0.70941
AADT           2.903e-05  2.601e-05   1.116  0.26444
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 971.82 on 26672 degrees of freedom
Residual deviance: 968.02 on 26668 degrees of freedom
AIC: 978.02
```

Number of Fisher Scoring iterations: 9

```
> BLR08<-glm(Acc.No.~Coef.Fric.Rep+Rep.Curve+ AADT, data=data08, family=binomial(link="logit"))
> summary(BLR08)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + AADT, family = binomial(link = "logit"),
     data = data08)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1207 -0.0767 -0.0704 -0.0664  3.5782
```

```
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.157e+00  1.367e+00  -3.040  0.00237 **
Coef.Fric.Rep -3.195e+00  2.620e+00  -1.219  0.22266
Rep.Curve     -3.138e-04  3.112e-04  -1.008  0.31325
AADT           2.986e-05  2.597e-05   1.150  0.25026
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 971.82 on 26672 degrees of freedom
Residual deviance: 968.16 on 26669 degrees of freedom
AIC: 976.16
```

Number of Fisher Scoring iterations: 9

```
> BLR08<-glm(Acc.No.~Coef.Fric.Rep+ AADT, data=data08, family=binomial(link="logit"))
> summary(BLR08)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + AADT, family = binomial(link = "logit"),
     data = data08)
```

```
Deviance Residuals:
```

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```
      Min      1Q   Median      3Q      Max
-0.1125 -0.0755 -0.0711 -0.0676  3.5342
```

Coefficients:

```
      Estimate Std. Error z value Pr(>|z|)
(Intercept)  -4.479e+00  1.348e+00  -3.322 0.000893 ***
Coef.Fric.Rep -3.393e+00  2.641e+00  -1.285 0.198801
AADT          2.114e-05  2.468e-05   0.857 0.391689
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 971.82 on 26672 degrees of freedom
Residual deviance: 969.15 on 26670 degrees of freedom
AIC: 975.15
```

Number of Fisher Scoring iterations: 9

```
> BLR08<-glm(Acc.No.~Coef.Fric.Rep, data=data08, family=binomial(link="logit"))
> summary(BLR08)
```

Call:

```
glm(formula = Acc.No. ~ Coef.Fric.Rep, family = binomial(link = "logit"),
    data = data08)
```

Deviance Residuals:

```
      Min      1Q   Median      3Q      Max
-0.1199 -0.0753 -0.0717 -0.0686  3.5989
```

Coefficients:

```
      Estimate Std. Error z value Pr(>|z|)
(Intercept)  -4.112      1.268  -3.244 0.00118 **
Coef.Fric.Rep -3.734      2.598  -1.437 0.15058
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 971.82 on 26672 degrees of freedom
Residual deviance: 969.86 on 26671 degrees of freedom
AIC: 973.86
```

Number of Fisher Scoring iterations: 8

```
>
>
```

```
> BLR09<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve + Rep.Super + Gradient.Rep +AADT, data=data09,
  family=binomial(link="logit"))
> summary(BLR09)
```

Call:

```
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super +
  Gradient.Rep + AADT, family = binomial(link = "logit"), data = data09)
```

Deviance Residuals:

```
      Min      1Q   Median      3Q      Max
-0.1747 -0.0714 -0.0613 -0.0544  3.6935
```

Coefficients:

```
      Estimate Std. Error z value Pr(>|z|)
(Intercept)  -4.418e+00  1.899e+00  -2.327  0.020 *
Coef.Fric.Rep -1.962e+00  3.722e+00  -0.527  0.598
Rep.Curve     -5.598e-04  4.139e-04  -1.353  0.176
Rep.Super     -3.423e-01  2.202e-01  -1.554  0.120
Gradient.Rep  -7.812e-02  1.891e-01  -0.413  0.680
AADT          9.707e-05  2.339e-05   4.151 3.32e-05 ***
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 834.25 on 25555 degrees of freedom
Residual deviance: 815.83 on 25550 degrees of freedom
```

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AIC: 827.83

Number of Fisher Scoring iterations: 9

```
> BLR09<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve + Rep.Super +AADT, data=data09, family=binomial(link="logit"))
> summary(BLR09)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super +
    AADT, family = binomial(link = "logit"), data = data09)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1782 -0.0712 -0.0613 -0.0544  3.6875
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.442e+00  1.899e+00  -2.339   0.0193 *
Coef.Fric.Rep -1.924e+00  3.720e+00  -0.517   0.6051
Rep.Curve    -5.636e-04  4.138e-04  -1.362   0.1732
Rep.Super    -3.434e-01  2.200e-01  -1.561   0.1184
AADT         9.794e-05  2.332e-05   4.200  2.67e-05 ***
---

```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 834.25 on 25555 degrees of freedom
Residual deviance: 816.00 on 25551 degrees of freedom
AIC: 826
```

Number of Fisher Scoring iterations: 9

```
> BLR09<-glm(Acc.No.~ Rep.Curve + Rep.Super +AADT, data=data09, family=binomial(link="logit"))
> summary(BLR09)
```

```
Call:
glm(formula = Acc.No. ~ Rep.Curve + Rep.Super + AADT, family = binomial(link = "logit"),
    data = data09)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1638 -0.0709 -0.0615 -0.0548  3.6757
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.281e+00  9.938e-01  -5.314 1.07e-07 ***
Rep.Curve    -5.886e-04  4.103e-04  -1.434   0.151
Rep.Super    -3.534e-01  2.193e-01  -1.611   0.107
AADT         9.944e-05  2.318e-05   4.289 1.79e-05 ***
---

```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 834.25 on 25555 degrees of freedom
Residual deviance: 816.27 on 25552 degrees of freedom
AIC: 824.27
```

Number of Fisher Scoring iterations: 9

```
> BLR09<-glm(Acc.No.~ Rep.Super +AADT, data=data09, family=binomial(link="logit"))
> summary(BLR09)
```

```
Call:
glm(formula = Acc.No. ~ Rep.Super + AADT, family = binomial(link = "logit"),
    data = data09)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1566 -0.0714 -0.0623 -0.0553  3.6797
```

```
Coefficients:
```


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```
      Estimate Std. Error z value Pr(>|z|)
(Intercept) -6.488e+00  5.755e-01 -11.274 < 2e-16 ***
Rep.Super   -2.058e-01  2.005e-01  -1.026   0.305
AADT        8.891e-05  2.198e-05   4.045 5.24e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 834.25  on 25555  degrees of freedom
Residual deviance: 818.23  on 25553  degrees of freedom
AIC: 824.23

Number of Fisher Scoring iterations: 9

> BLR09<-glm(Acc.No.~AADT, data=data09, family=binomial(link="logit"))
> summary(BLR09)
```

```
Call:
glm(formula = Acc.No. ~ AADT, family = binomial(link = "logit"),
    data = data09)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1538 -0.0698 -0.0614 -0.0559  3.6713
```

```
Coefficients:
      Estimate Std. Error z value Pr(>|z|)
(Intercept) -7.011e+00  2.866e-01 -24.462 < 2e-16 ***
AADT        9.104e-05  2.176e-05   4.183 2.87e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 834.25  on 25555  degrees of freedom
Residual deviance: 819.34  on 25554  degrees of freedom
AIC: 823.34

Number of Fisher Scoring iterations: 9
```

```
>
>
> BLR10<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve + Rep.Super + Gradient.Rep +AADT, data=data10,
  family=binomial(link="logit"))
> summary(BLR10)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super +
  Gradient.Rep + AADT, family = binomial(link = "logit"), data = data10)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1458 -0.0770 -0.0670 -0.0597  3.6685
```

```
Coefficients:
      Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.761e+00  1.492e+00  -3.191  0.00142 **
Coef.Fric.Rep -1.310e+00  2.529e+00  -0.518  0.60438
Rep.Curve     -7.047e-04  3.729e-04  -1.890  0.05882 .
Rep.Super     -8.810e-02  1.875e-01  -0.470  0.63839
Gradient.Rep -1.327e-01  1.711e-01  -0.776  0.43795
AADT         8.042e-05  2.490e-05   3.230  0.00124 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 934.71  on 26406  degrees of freedom
Residual deviance: 922.70  on 26401  degrees of freedom
AIC: 934.7

Number of Fisher Scoring iterations: 9
```

R Console

```
> BLR10<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve + Gradient.Rep +AADT, data=data10, family=binomial(link="logit"))
> summary(BLR10)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Gradient.Rep + AADT, family = binomial(link = "logit"), data = data10)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1443 -0.0771 -0.0669 -0.0597  3.6623
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.110e+00  1.306e+00  -3.913  9.1e-05 ***
Coef.Fric.Rep -1.339e+00  2.531e+00  -0.529  0.59658
Rep.Curve     -6.077e-04  3.126e-04  -1.944  0.05190 .
Gradient.Rep  -1.341e-01  1.713e-01  -0.783  0.43369
AADT          7.918e-05  2.473e-05   3.202  0.00136 **
---

```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 934.71 on 26406 degrees of freedom
Residual deviance: 922.92 on 26402 degrees of freedom
AIC: 932.92
```

Number of Fisher Scoring iterations: 9

```
> BLR10<-glm(Acc.No.~ Rep.Curve + Gradient.Rep +AADT, data=data10, family=binomial(link="logit"))
> summary(BLR10)
```

```
Call:
glm(formula = Acc.No. ~ Rep.Curve + Gradient.Rep + AADT, family = binomial(link = "logit"), data = data10)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1466 -0.0770 -0.0671 -0.0597  3.6627
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.754e+00  4.774e-01 -12.052 < 2e-16 ***
Rep.Curve   -6.252e-04  3.098e-04  -2.018  0.04360 *
Gradient.Rep -1.337e-01  1.715e-01  -0.779  0.43571
AADT         8.039e-05  2.467e-05   3.259  0.00112 **
---

```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 934.71 on 26406 degrees of freedom
Residual deviance: 923.20 on 26403 degrees of freedom
AIC: 931.2
```

Number of Fisher Scoring iterations: 9

```
> BLR10<-glm(Acc.No.~ Rep.Curve +AADT, data=data10, family=binomial(link="logit"))
> summary(BLR10)
```

```
Call:
glm(formula = Acc.No. ~ Rep.Curve + AADT, family = binomial(link = "logit"), data = data10)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1432 -0.0767 -0.0667 -0.0601  3.6295
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.765e+00  4.783e-01 -12.053 < 2e-16 ***
Rep.Curve   -6.326e-04  3.101e-04  -2.040  0.041370 *

```

R Console

```
AADT      8.198e-05  2.467e-05  3.324 0.000889 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 934.71 on 26406 degrees of freedom
Residual deviance: 923.80 on 26404 degrees of freedom
AIC: 929.8
```

Number of Fisher Scoring iterations: 9

```
> BLR10<-glm(Acc.No.~AADT, data=data10, family=binomial(link="logit"))
> summary(BLR10)
```

```
Call:
glm(formula = Acc.No. ~ AADT, family = binomial(link = "logit"),
    data = data10)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1250  -0.0741  -0.0676  -0.0631   3.5860
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -6.612e+00  2.755e-01 -23.999 < 2e-16 ***
AADT         6.597e-05  2.363e-05   2.792  0.00524 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 934.71 on 26406 degrees of freedom
Residual deviance: 927.74 on 26405 degrees of freedom
AIC: 931.74
```

Number of Fisher Scoring iterations: 9

```
>
> #Poisson Regression
>
> Poisson5v08<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve+ Rep.Super+ Gradient.Rep +AADT,family="poisson", data=data08)
> summary(Poisson5v08)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super + Gradient.Rep + AADT, family = "poisson", data = data08)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1169  -0.0765  -0.0705  -0.0661   3.2801
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.388e+00  1.504e+00  -2.918  0.00352 **
Coef.Fric.Rep -3.300e+00  2.650e+00  -1.245  0.21305
Rep.Curve     -2.393e-04  3.679e-04  -0.650  0.51547
Rep.Super      6.851e-02  1.834e-01   0.374  0.70874
Gradient.Rep  -1.868e-02  1.706e-01  -0.110  0.91280
AADT           2.872e-05  2.604e-05   1.103  0.27013
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for poisson family taken to be 1)

```
Null deviance: 832.01 on 26672 degrees of freedom
Residual deviance: 828.20 on 26667 degrees of freedom
AIC: 980.2
```

Number of Fisher Scoring iterations: 8

```
> Poisson4v08<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve+ Rep.Super+AADT,family="poisson", data=ata08)
```

R Console

```
> summary(Poisson4v08)
```

Call:

```
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super +  
  AADT, family = "poisson", data = data08)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.1166	-0.0766	-0.0705	-0.0662	3.2802

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.388e+00	1.504e+00	-2.918	0.00353 **
Coef.Fric.Rep	-3.303e+00	2.650e+00	-1.247	0.21254
Rep.Curve	-2.405e-04	3.677e-04	-0.654	0.51307
Rep.Super	6.826e-02	1.834e-01	0.372	0.70974
AADT	2.894e-05	2.597e-05	1.114	0.26508

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 832.01 on 26672 degrees of freedom
Residual deviance: 828.21 on 26668 degrees of freedom
AIC: 978.21

Number of Fisher Scoring iterations: 8

```
> Poisson3v08<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve+AADT,family="poisson", data=data08)  
> summary(Poisson3v08)
```

Call:

```
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + AADT, family = "poisson",  
  data = data08)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.1205	-0.0767	-0.0703	-0.0663	3.2873

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.165e+00	1.365e+00	-3.051	0.00228 **
Coef.Fric.Rep	-3.185e+00	2.615e+00	-1.218	0.22324
Rep.Curve	-3.129e-04	3.107e-04	-1.007	0.31393
AADT	2.977e-05	2.593e-05	1.148	0.25087

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 832.01 on 26672 degrees of freedom
Residual deviance: 828.35 on 26669 degrees of freedom
AIC: 976.35

Number of Fisher Scoring iterations: 8

```
> Poisson2v08<-glm(Acc.No.~ Coef.Fric.Rep +AADT,family="poisson", data=data08)  
> summary(Poisson2v08)
```

Call:

```
glm(formula = Acc.No. ~ Coef.Fric.Rep + AADT, family = "poisson",  
  data = data08)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.1124	-0.0754	-0.0711	-0.0675	3.2394

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.486e+00	1.346e+00	-3.333	0.000858 ***
Coef.Fric.Rep	-3.383e+00	2.636e+00	-1.283	0.199357
AADT	2.108e-05	2.465e-05	0.855	0.392327

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R Console

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 832.01 on 26672 degrees of freedom
Residual deviance: 829.34 on 26670 degrees of freedom
AIC: 975.34

Number of Fisher Scoring iterations: 8

```
> Poissonlv08<-glm(Acc.No.~ Coef.Fric.Rep,family="poisson", data=data08)
> summary(Poissonlv08)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep, family = "poisson", data = data08)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.1198	-0.0753	-0.0717	-0.0685	3.3097

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.120	1.265	-3.257	0.00113 **
Coef.Fric.Rep	-3.723	2.593	-1.436	0.15108

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 832.01 on 26672 degrees of freedom
Residual deviance: 830.05 on 26671 degrees of freedom
AIC: 974.05

Number of Fisher Scoring iterations: 8

```
>
> Poisson5v09<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve+ Rep.Super+ Gradient.Rep +AADT,family="p
oisson", data=data09)
> summary(Poisson5v09)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super +
Gradient.Rep + AADT, family = "poisson", data = data09)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.1745	-0.0713	-0.0612	-0.0544	3.4120

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.426e+00	1.896e+00	-2.334	0.0196 *
Coef.Fric.Rep	-1.955e+00	3.717e+00	-0.526	0.5989
Rep.Curve	-5.582e-04	4.132e-04	-1.351	0.1768
Rep.Super	-3.413e-01	2.199e-01	-1.552	0.1205
Gradient.Rep	-7.789e-02	1.888e-01	-0.413	0.6799
AADT	9.670e-05	2.332e-05	4.147	3.36e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 716.39 on 25555 degrees of freedom
Residual deviance: 698.03 on 25550 degrees of freedom
AIC: 828.03

Number of Fisher Scoring iterations: 8

```
> Poisson4v09<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve+ Rep.Super+AADT,family="poisson", data=d
ata09)
> summary(Poisson4v09)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super +
AADT, family = "poisson", data = data09)
```

R Console

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.1781	-0.0711	-0.0613	-0.0544	3.4055

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.449e+00	1.896e+00	-2.347	0.0189 *
Coef.Fric.Rep	-1.917e+00	3.715e+00	-0.516	0.6059
Rep.Curve	-5.620e-04	4.132e-04	-1.360	0.1738
Rep.Super	-3.425e-01	2.196e-01	-1.560	0.1189
AADT	9.757e-05	2.325e-05	4.197	2.71e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 716.39 on 25555 degrees of freedom
Residual deviance: 698.20 on 25551 degrees of freedom
AIC: 826.2

Number of Fisher Scoring iterations: 8

```
> Poisson3v09<-glm(Acc.No.~ Rep.Curve+ Rep.Super+AADT,family="poisson", data=data09)  
> summary(Poisson3v09)
```

Call:

```
glm(formula = Acc.No. ~ Rep.Curve + Rep.Super + AADT, family = "poisson",  
     data = data09)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.1636	-0.0708	-0.0615	-0.0548	3.3928

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-5.285e+00	9.921e-01	-5.327	1.00e-07 ***
Rep.Curve	-5.868e-04	4.097e-04	-1.432	0.152
Rep.Super	-3.524e-01	2.189e-01	-1.610	0.107
AADT	9.906e-05	2.311e-05	4.286	1.82e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 716.39 on 25555 degrees of freedom
Residual deviance: 698.46 on 25552 degrees of freedom
AIC: 824.46

Number of Fisher Scoring iterations: 8

```
> Poisson2v09<-glm(Acc.No.~ Rep.Super+AADT,family="poisson", data=data09)  
> summary(Poisson2v09)
```

Call:

```
glm(formula = Acc.No. ~ Rep.Super + AADT, family = "poisson",  
     data = data09)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.1564	-0.0713	-0.0623	-0.0553	3.3972

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-6.488e+00	5.746e-01	-11.293	< 2e-16 ***
Rep.Super	-2.053e-01	2.002e-01	-1.026	0.305
AADT	8.857e-05	2.191e-05	4.042	5.3e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 716.39 on 25555 degrees of freedom
Residual deviance: 700.41 on 25553 degrees of freedom
AIC: 824.41

R Console

Number of Fisher Scoring iterations: 8

```
> Poissonlv09<-glm(Acc.No.~ AADT,family="poisson", data=data09)
> summary(Poissonlv09)
```

```
Call:
glm(formula = Acc.No. ~ AADT, family = "poisson", data = data09)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1536 -0.0697 -0.0614 -0.0559  3.3880
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -7.010e+00  2.860e-01 -24.511 < 2e-16 ***
AADT         9.069e-05  2.169e-05  4.181  2.9e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for poisson family taken to be 1)

```
Null deviance: 716.39  on 25555  degrees of freedom
Residual deviance: 701.52  on 25554  degrees of freedom
AIC: 823.52
```

Number of Fisher Scoring iterations: 8

```
>
> Poisson5v10<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve+ Rep.Super+ Gradient.Rep +AADT,family="poisson", data=data10)
> summary(Poisson5v10)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Rep.Super + Gradient.Rep + AADT, family = "poisson", data = data10)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1457 -0.0769 -0.0670 -0.0597  3.3850
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.767e+00  1.489e+00 -3.200  0.00137 **
Coef.Fric.Rep -1.306e+00  2.525e+00 -0.517  0.60485
Rep.Curve     -7.025e-04  3.723e-04 -1.887  0.05916 .
Rep.Super     -8.785e-02  1.872e-01 -0.469  0.63880
Gradient.Rep -1.322e-01  1.708e-01 -0.774  0.43871
AADT          8.013e-05  2.483e-05  3.227  0.00125 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for poisson family taken to be 1)

```
Null deviance: 800.88  on 26406  degrees of freedom
Residual deviance: 788.91  on 26401  degrees of freedom
AIC: 934.91
```

Number of Fisher Scoring iterations: 8

```
> Poisson4v10<-glm(Acc.No.~ Coef.Fric.Rep + Rep.Curve+ Gradient.Rep +AADT,family="poisson", data=data10)
> summary(Poisson4v10)
```

```
Call:
glm(formula = Acc.No. ~ Coef.Fric.Rep + Rep.Curve + Gradient.Rep + AADT, family = "poisson", data = data10)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.1441 -0.0770 -0.0669 -0.0597  3.3783
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
```

R Console

```
(Intercept) -5.115e+00 1.304e+00 -3.924 8.73e-05 ***
Coef.Fric.Rep -1.336e+00 2.526e+00 -0.529 0.59702
Rep.Curve -6.058e-04 3.121e-04 -1.941 0.05220 .
Gradient.Rep -1.337e-01 1.711e-01 -0.782 0.43443
AADT 7.890e-05 2.467e-05 3.199 0.00138 **
---
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

```
Null deviance: 800.88 on 26406 degrees of freedom
Residual deviance: 789.13 on 26402 degrees of freedom
AIC: 933.13
```

Number of Fisher Scoring iterations: 8

```
> Poisson3v10<-glm(Acc.No.~ Rep.Curve+ Gradient.Rep +AADT,family="poisson", data=data10)
> summary(Poisson3v10)
```

Call:

```
glm(formula = Acc.No. ~ Rep.Curve + Gradient.Rep + AADT, family = "poisson",
     data = data10)
```

Deviance Residuals:

```
Min 1Q Median 3Q Max
-0.1464 -0.0769 -0.0670 -0.0597 3.3787
```

Coefficients:

```
Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.757e+00 4.766e-01 -12.080 < 2e-16 ***
Rep.Curve -6.232e-04 3.093e-04 -2.015 0.04389 *
Gradient.Rep -1.332e-01 1.712e-01 -0.778 0.43648
AADT 8.011e-05 2.460e-05 3.256 0.00113 **
---
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

```
Null deviance: 800.88 on 26406 degrees of freedom
Residual deviance: 789.41 on 26403 degrees of freedom
AIC: 931.41
```

Number of Fisher Scoring iterations: 8

```
> Poisson2v10<-glm(Acc.No.~ Rep.Curve+AADT,family="poisson", data=data10)
> summary(Poisson2v10)
```

Call:

```
glm(formula = Acc.No. ~ Rep.Curve + AADT, family = "poisson",
     data = data10)
```

Deviance Residuals:

```
Min 1Q Median 3Q Max
-0.1430 -0.0766 -0.0667 -0.0601 3.3429
```

Coefficients:

```
Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.768e+00 4.774e-01 -12.081 < 2e-16 ***
Rep.Curve -6.306e-04 3.096e-04 -2.037 0.041640 *
AADT 8.169e-05 2.460e-05 3.321 0.000898 ***
---
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

```
Null deviance: 800.88 on 26406 degrees of freedom
Residual deviance: 790.00 on 26404 degrees of freedom
AIC: 930
```

Number of Fisher Scoring iterations: 8

```
> Poisson1v10<-glm(Acc.No.~ AADT,family="poisson", data=data10)
> summary(Poisson1v10)
```


R Console

Call:
glm(formula = Acc.No. ~ AADT, family = "poisson", data = data10)

Deviance Residuals:
Min 1Q Median 3Q Max
-0.1248 -0.0741 -0.0675 -0.0631 3.2957

Coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept) -6.612e+00 2.750e-01 -24.043 < 2e-16 ***
AADT 6.575e-05 2.357e-05 2.789 0.00528 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 800.88 on 26406 degrees of freedom
Residual deviance: 793.93 on 26405 degrees of freedom
AIC: 931.93

Number of Fisher Scoring iterations: 8

> library(adc) #Calling Anderson-Darling K-sample Test computation
> adc.test(nacc08\$ Coef.Fric.Rep,acc08\$ Coef.Fric.Rep)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26603 70
Total number of values: 26673
Number of unique values: 25963

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76256

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

t.obs P-value extrapolation
not adj. for ties 0.97288 0.13253 0
adj. for ties 0.97275 0.13254 0
> adc.test(nacc09\$ Coef.Fric.Rep,acc09\$ Coef.Fric.Rep)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 25497 59
Total number of values: 25556
Number of unique values: 24936

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76278

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

t.obs P-value extrapolation
not adj. for ties 0.17902 0.28503 1
adj. for ties 0.17879 0.28509 1
> adc.test(nacc10\$ Coef.Fric.Rep,acc10\$ Coef.Fric.Rep)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26340 67
Total number of values: 26407
Number of unique values: 25840

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76261

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

R Console

```
          t.obs P-value extrapolation
not adj. for ties -0.12702 0.36690      1
adj. for ties    -0.12698 0.36689      1
>
> adk.test(nacc08$Rep.Curve,acc08$ Rep.Curve)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26603 70
Total number of values: 26673
Number of unique values: 15497
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76256
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties -0.59637 0.50706      1
adj. for ties    -0.44365 0.46047      1
> adk.test(nacc09$Rep.Curve,acc09$ Rep.Curve)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 25497 59
Total number of values: 25556
Number of unique values: 14885
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76278
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties -0.93137 0.60773      1
adj. for ties    -0.79984 0.56880      1
> adk.test(nacc10$Rep.Curve,acc10$ Rep.Curve)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26340 67
Total number of values: 26407
Number of unique values: 15476
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76261
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties 0.00431 0.33047      1
adj. for ties    0.00845 0.32935      1
>
> adk.test(nacc08$ Rep.Super,acc08$ Rep.Super)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26603 70
Total number of values: 26673
Number of unique values: 1850
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76256
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

R Console

```
          t.obs P-value extrapolation
not adj. for ties -0.65141 0.52386      1
adj. for ties    -0.65181 0.52399      1
> adk.test(nacc09$ Rep.Super,acc09$ Rep.Super)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 25497 59
Total number of values: 25556
Number of unique values: 1844
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76278
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties 0.42485 0.22551      0
adj. for ties    0.42451 0.22558      0
> adk.test(nacc10$ Rep.Super,acc10$ Rep.Super)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26340 67
Total number of values: 26407
Number of unique values: 1855
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76261
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties -0.64899 0.52313      1
adj. for ties    -0.65118 0.52379      1
>
> adk.test(nacc08$ Gradient.Rep,acc08$ Gradient.Rep)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26603 70
Total number of values: 26673
Number of unique values: 26479
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76256
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties -0.21863 0.39328      1
adj. for ties    -0.21871 0.39331      1
> adk.test(nacc09$ Gradient.Rep,acc09$ Gradient.Rep)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 25497 59
Total number of values: 25556
Number of unique values: 25373
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76278
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
```

R Console

```
not adj. for ties -0.42052 0.45345      1
adj. for ties    -0.42062 0.45348      1
> adk.test(nacc10$ Gradient.Rep,acc10$ Gradient.Rep)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26340 67
Total number of values: 26407
Number of unique values: 26218
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76261
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties 0.10176 0.30466      1
adj. for ties    0.10178 0.30466      1
```

```
>
> adk.test(nacc08$AADT,acc08$AADT)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26603 70
Total number of values: 26673
Number of unique values: 66
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76256
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties 0.69463 0.17423      0
adj. for ties    0.77687 0.16079      0
```

```
> adk.test(nacc09$AADT,acc09$AADT)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 25497 59
Total number of values: 25556
Number of unique values: 65
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76278
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties 8.25150 0.00027      1
adj. for ties    8.63007 0.00020      1
```

```
> adk.test(nacc10$AADT,acc10$AADT)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26340 67
Total number of values: 26407
Number of unique values: 66
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76261
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties 2.45958 0.03096      0
```

R Console

```
adj. for ties      2.56042 0.02819      0
>
```

```
> adk.test(nacc08$X.HGV,acc08$X.HGV)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26603 70
Total number of values: 26673
Number of unique values: 66
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76256
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
      t.obs P-value extrapolation
not adj. for ties -0.54669 0.49188      1
adj. for ties      -0.45486 0.46388      1
```

```
> adk.test(nacc09$X.HGV,acc09$X.HGV)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 25497 59
Total number of values: 25556
Number of unique values: 66
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76278
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
      t.obs P-value extrapolation
not adj. for ties -0.90602 0.60032      1
adj. for ties      -0.91913 0.60416      1
```

```
> adk.test(nacc10$X.HGV,acc10$X.HGV)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26340 67
Total number of values: 26407
Number of unique values: 66
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76261
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
      t.obs P-value extrapolation
not adj. for ties 0.03937 0.32105      1
adj. for ties      0.10003 0.30511      1
```

```
>
> chi08<-matrix(c( 10,23,23,2,7,5194,7958,7362,909,2039),ncol=5,byrow=T)
> chi09<-matrix(c( 4,19,18,1,9,4724,8573,6826,440,2030),ncol=5,byrow=T)
> chi10<-matrix(c( 10,23,20,1,5,5215,8634,7284,1174,1251),ncol=5,byrow=T)
> chiall<-matrix(c( 24,65,61,4,21,7,15133,25165,21472,2523,5320,3474),ncol=6,byrow=T)
> chisq.test(chi08)
```

```
Pearson's Chi-squared test
```

```
data: chi08
X-squared = 2.1375, df = 4, p-value = 0.7105
```

```
Warning message:
In chisq.test(chi08) : Chi-squared approximation may be incorrect
> chisq.test(chi09)
```

```
Pearson's Chi-squared test
```

R Console

```
data: chi09
X-squared = 8.8416, df = 4, p-value = 0.06518
```

```
Warning message:
In chisq.test(chi09) : Chi-squared approximation may be incorrect
> chisq.test(chi10)
```

Pearson's Chi-squared test

```
data: chi10
X-squared = 3.3594, df = 4, p-value = 0.4996
```

```
Warning message:
In chisq.test(chi10) : Chi-squared approximation may be incorrect
> chisq.test(chiall)
```

Pearson's Chi-squared test

```
data: chiall
X-squared = 11.7666, df = 5, p-value = 0.03813
```

```
>
> databox<-read.csv(file.choose(), header=TRUE) #imports data for box and whisker plots of acc
ident severity and representative friction values
> databox$Acc08 <- ordered(databox$Acc08, levels=c("None", "Slight", "Serious","Fatal"))
> boxplot(RFric08~Acc08,main="Accident Severity and Representative Friction Value 2008", xlab=
"Accident Severity",ylab="Representative Friction (Unitless)" ,ylim=c(0.2,0.7),data=databox)
>
> databox$Acc09 <- ordered(databox$Acc09, levels=c("None", "Slight", "Serious","Fatal"))
> boxplot(RFric09~Acc09,main="Accident Severity and Representative Friction Value 2009", xlab=
"Accident Severity",ylab="Representative Friction (Unitless)",ylim=c(0.2,0.7),data=databox)
>
> databox$Acc10 <- ordered(databox$Acc10, levels=c("None", "Slight", "Serious","Fatal"))
> boxplot(RFric10~Acc10,main="Accident Severity and Representative Friction Value 2010", xlab=
"Accident Severity",ylab="Representative Friction (Unitless)",ylim=c(0.2,0.7),data=databox)
>
> adk.test(nacc08$Coef.Fric.Rep, fatal08$ Coef.Fric.Rep)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26603 5
Total number of values: 26608
Number of unique values: 25900
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7782
```

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.58119 0.50242      1
adj. for ties    -0.58124 0.50244      1
> adk.test(nacc09$ Coef.Fric.Rep, fatal09$ Coef.Fric.Rep)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 25497 6
Total number of values: 25503
Number of unique values: 24885
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77541
```

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.68222 0.53325      1
adj. for ties    -0.68226 0.53326      1
> adk.test(nacc10$ Coef.Fric.Rep, fatal10$ Coef.Fric.Rep)
Anderson-Darling k-sample test.
```

R Console

Number of samples: 2
Sample sizes: 26340 4
Total number of values: 26344
Number of unique values: 25778

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.78236

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.61162	0.51172	1
adj. for ties	-0.61170	0.51174	1

Warning: At least one sample size is less than 5.
p-values may not be very accurate.

>
> adk.test(nacc08\$ Rep.Curve, fatal08 \$ Rep.Curve)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26603 5
Total number of values: 26608
Number of unique values: 15460

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7782

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-1.05771	0.64387	1
adj. for ties	-1.03646	0.63789	1

> adk.test(nacc09\$ Rep.Curve, fatal09 \$ Rep.Curve)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 25497 6
Total number of values: 25503
Number of unique values: 14854

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77541

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.41194	0.45086	1
adj. for ties	-0.29545	0.41590	1

> adk.test(nacc10\$ Rep.Curve, fatal10 \$ Rep.Curve)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26340 4
Total number of values: 26344
Number of unique values: 15438

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.78236

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.19529	0.3865	1

R Console

```
adj. for ties      -0.06399  0.3492          1
```

Warning: At least one sample size is less than 5.
p-values may not be very accurate.

```
>  
> adk.test(nacc08$ Rep.Super, fatal08 $ Rep.Super)  
Anderson-Darling k-sample test.
```

```
Number of samples: 2  
Sample sizes: 26603 5  
Total number of values: 26608  
Number of unique values: 1848
```

```
Mean of Anderson-Darling Criterion: 1  
Standard deviation of Anderson-Darling Criterion: 0.7782
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation  
not adj. for ties -0.97202 0.61951          1  
adj. for ties    -0.97381 0.62002          1  
> adk.test(nacc09$ Rep.Super, fatal09 $ Rep.Super)  
Anderson-Darling k-sample test.
```

```
Number of samples: 2  
Sample sizes: 25497 6  
Total number of values: 25503  
Number of unique values: 1844
```

```
Mean of Anderson-Darling Criterion: 1  
Standard deviation of Anderson-Darling Criterion: 0.77541
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation  
not adj. for ties -0.46103 0.46575          1  
adj. for ties    -0.46134 0.46585          1  
> adk.test(nacc10$ Rep.Super, fatal10 $ Rep.Super)  
Anderson-Darling k-sample test.
```

```
Number of samples: 2  
Sample sizes: 26340 4  
Total number of values: 26344  
Number of unique values: 1853
```

```
Mean of Anderson-Darling Criterion: 1  
Standard deviation of Anderson-Darling Criterion: 0.78236
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation  
not adj. for ties 0.45963 0.21825          0  
adj. for ties    0.45812 0.21856          0
```

Warning: At least one sample size is less than 5.
p-values may not be very accurate.

```
>  
> adk.test(nacc08$ Gradient.Rep, fatal08 $ Gradient.Rep)  
Anderson-Darling k-sample test.
```

```
Number of samples: 2  
Sample sizes: 26603 5  
Total number of values: 26608  
Number of unique values: 26414
```

```
Mean of Anderson-Darling Criterion: 1
```


R Console

Standard deviation of Anderson-Darling Criterion: 0.7782

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
      t.obs P-value extrapolation
not adj. for ties 2.49254 0.03002      0
adj. for ties    2.49250 0.03002      0
> adk.test(nacc09$ Gradient.Rep, fatal09 $ Gradient.Rep)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 25497 6
Total number of values: 25503
Number of unique values: 25320

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77541

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
      t.obs P-value extrapolation
not adj. for ties 0.20285 0.27913      1
adj. for ties    0.20271 0.27916      1
> adk.test(nacc10$ Gradient.Rep, fatal10 $ Gradient.Rep)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26340 4
Total number of values: 26344
Number of unique values: 26156

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.78236

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
      t.obs P-value extrapolation
not adj. for ties 2.15614 0.04124      0
adj. for ties    2.15599 0.04125      0
```

Warning: At least one sample size is less than 5.
p-values may not be very accurate.

```
>
> adk.test(nacc08$ AADT, fatal08 $ AADT)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26603 5
Total number of values: 26608
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7782

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
      t.obs P-value extrapolation
not adj. for ties -0.77599 0.56164      1
adj. for ties    -0.81548 0.57349      1
> adk.test(nacc09$ AADT, fatal09 $ AADT)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 25497 6
Total number of values: 25503

R Console

Number of unique values: 65

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77541

$T.AD = (\text{Anderson-Darling Criterion} - \text{mean})/\text{sigma}$

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	0.22624	0.27341	1
adj. for ties	0.21010	0.27735	1

> adk.test(nacc10\$ AADT, fatal10 \$ AADT)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26340 4
Total number of values: 26344
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.78236

$T.AD = (\text{Anderson-Darling Criterion} - \text{mean})/\text{sigma}$

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.97091	0.61919	1
adj. for ties	-0.99043	0.62480	1

Warning: At least one sample size is less than 5.
p-values may not be very accurate.

>
> adk.test(nacc08\$X.HGV, fatal08\$X.HGV)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26603 5
Total number of values: 26608
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7782

$T.AD = (\text{Anderson-Darling Criterion} - \text{mean})/\text{sigma}$

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.46737	0.46768	1
adj. for ties	-0.48472	0.47296	1

> adk.test(nacc09\$X.HGV, fatal09\$X.HGV)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 25497 6
Total number of values: 25503
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77541

$T.AD = (\text{Anderson-Darling Criterion} - \text{mean})/\text{sigma}$

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	0.97891	0.13174	0
adj. for ties	1.10138	0.11663	0

> adk.test(nacc10\$X.HGV, fatal10\$X.HGV)
Anderson-Darling k-sample test.

R Console

Number of samples: 2
Sample sizes: 26340 4
Total number of values: 26344
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.78236

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.75660	0.55580	1
adj. for ties	-0.75682	0.55586	1

Warning: At least one sample size is less than 5.
p-values may not be very accurate.

>
> adk.test(nacc08\$ Coef.Fric.Rep,serious08\$ Coef.Fric.Rep)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26603 14
Total number of values: 26617
Number of unique values: 25909

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7674

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.40828	0.44975	1
adj. for ties	-0.40832	0.44976	1

> adk.test(nacc09\$ Coef.Fric.Rep,serious09\$ Coef.Fric.Rep)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 25497 8
Total number of values: 25505
Number of unique values: 24887

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77192

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.18505	0.38353	1
adj. for ties	-0.18516	0.38357	1

> adk.test(nacc10\$ Coef.Fric.Rep,serious10\$ Coef.Fric.Rep)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26340 13
Total number of values: 26353
Number of unique values: 25787

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76787

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	3.18120	0.01621	0
adj. for ties	3.18116	0.01621	0

R Console

```
>
> adk.test(nacc08$ Rep.Curve, serious08$ Rep.Curve)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26603 14
Total number of values: 26617
Number of unique values: 15465

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7674

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

      t.obs P-value extrapolation
not adj. for ties -0.45918 0.46519      1
adj. for ties    -0.31392 0.42140      1
> adk.test(nacc09$ Rep.Curve, serious09$ Rep.Curve)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 25497 8
Total number of values: 25505
Number of unique values: 14856

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77192

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

      t.obs P-value extrapolation
not adj. for ties -0.89270 0.59640      1
adj. for ties    -0.88873 0.59523      1
> adk.test(nacc10$ Rep.Curve, serious10$ Rep.Curve)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26340 13
Total number of values: 26353
Number of unique values: 15445

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76787

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

      t.obs P-value extrapolation
not adj. for ties -0.92333 0.60538      1
adj. for ties    -0.87356 0.59076      1
>
> adk.test(nacc08$ Rep.Super, serious08$ Rep.Super)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26603 14
Total number of values: 26617
Number of unique values: 1849

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7674

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

      t.obs P-value extrapolation
not adj. for ties -0.60111 0.50851      1
adj. for ties    -0.60129 0.50857      1
```

R Console

```
> adk.test(nacc09$ Rep.Super, serious09$ Rep.Super)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 25497 8
Total number of values: 25505
Number of unique values: 1844
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77192
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties -0.71828 0.54420      1
adj. for ties    -0.72037 0.54484      1
> adk.test(nacc10$ Rep.Super, serious10$ Rep.Super)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26340 13
Total number of values: 26353
Number of unique values: 1854
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76787
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties -0.20912 0.39051      1
adj. for ties    -0.20814 0.39023      1
>
> adk.test(nacc08$ Gradient.Rep, serious08$ Gradient.Rep)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 26603 14
Total number of values: 26617
Number of unique values: 26423
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7674
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties 0.11749 0.30060      1
adj. for ties    0.11745 0.30061      1
> adk.test(nacc09$ Gradient.Rep, serious09$ Gradient.Rep)
Anderson-Darling k-sample test.
```

```
Number of samples: 2
Sample sizes: 25497 8
Total number of values: 25505
Number of unique values: 25322
```

```
Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77192
```

```
T.AD = (Anderson-Darling Criterion - mean)/sigma
```

```
Null Hypothesis: All samples come from a common population.
```

```
          t.obs P-value extrapolation
not adj. for ties -0.05497 0.34669      1
adj. for ties    -0.05507 0.34672      1
> adk.test(nacc10$ Gradient.Rep, serious10$ Gradient.Rep)
```

R Console

Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26340 13
Total number of values: 26353
Number of unique values: 26165

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76787

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.13786	0.36999	1
adj. for ties	-0.13800	0.37003	1

>
> adk.test(nacc08\$ AADT, serious08\$ AADT)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26603 14
Total number of values: 26617
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7674

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	0.01216	0.32835	1
adj. for ties	0.06468	0.31435	1

> adk.test(nacc09\$ AADT, serious09\$ AADT)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 25497 8
Total number of values: 25505
Number of unique values: 65

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77192

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	0.97617	0.13210	0
adj. for ties	1.07081	0.12024	0

> adk.test(nacc10\$ AADT, serious10\$ AADT)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26340 13
Total number of values: 26353
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76787

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.72354	0.54580	1
adj. for ties	-0.70987	0.54165	1

>
> adk.test(nacc08\$X.HGV, serious08\$X.HGV)

R Console

Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26603 14
Total number of values: 26617
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.7674

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.79327 0.56684      1
adj. for ties    -0.76190 0.55739      1
> adk.test(nacc09$X.HGV,serious09$X.HGV)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 25497 8
Total number of values: 25505
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.77192

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.99963 0.62743      1
adj. for ties    -1.02144 0.63364      1
> adk.test(nacc10$X.HGV,serious10$X.HGV)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26340 13
Total number of values: 26353
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76787

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.30059 0.41743      1
adj. for ties    -0.28753 0.41355      1
>
> adk.test(nacc08$ Coef.Fric.Rep,slight08$ Coef.Fric.Rep)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26603 51
Total number of values: 26654
Number of unique values: 25944

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76301

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties 1.47747 0.08016      0
adj. for ties    1.47734 0.08017      0
> adk.test(nacc09$ Coef.Fric.Rep,slight09$ Coef.Fric.Rep)
Anderson-Darling k-sample test.
```

R Console

Number of samples: 2
Sample sizes: 25497 45
Total number of values: 25542
Number of unique values: 24922

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76323

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
      t.obs P-value extrapolation
not adj. for ties 0.96110 0.13408      0
adj. for ties    0.96081 0.13412      0
> adk.test(nacc10$ Coef.Fric.Rep,slight10$ Coef.Fric.Rep)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26340 50
Total number of values: 26390
Number of unique values: 25823

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76304

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
      t.obs P-value extrapolation
not adj. for ties 1.55993 0.07385      0
adj. for ties    1.55998 0.07385      0
>
> adk.test(nacc08$ Rep.Curve, slight08$ Rep.Curve)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26603 51
Total number of values: 26654
Number of unique values: 15486

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76301

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
      t.obs P-value extrapolation
not adj. for ties 0.42154 0.22621      0
adj. for ties    0.89923 0.14255      0
> adk.test(nacc09$ Rep.Curve, slight09$ Rep.Curve)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 25497 45
Total number of values: 25542
Number of unique values: 14877

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76323

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
      t.obs P-value extrapolation
not adj. for ties -0.96345 0.61704      1
adj. for ties    -0.87862 0.59225      1
> adk.test(nacc10$ Rep.Curve, slight10$ Rep.Curve)
Anderson-Darling k-sample test.
```


R Console

Number of samples: 2
Sample sizes: 26340 50
Total number of values: 26390
Number of unique values: 15465

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76304

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties 0.70185 0.17301      0
adj. for ties    0.72535 0.16910      0
>
> adk.test(nacc08$ Rep.Super, slight08$ Rep.Super)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26603 51
Total number of values: 26654
Number of unique values: 1849

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76301

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.75783 0.55617      1
adj. for ties     -0.75975 0.55675      1
> adk.test(nacc09$ Rep.Super, slight09$ Rep.Super)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 25497 45
Total number of values: 25542
Number of unique values: 1844

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76323

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties 0.27143 0.26258      1
adj. for ties     0.27297 0.26221      1
> adk.test(nacc10$ Rep.Super, slight10$ Rep.Super)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26340 50
Total number of values: 26390
Number of unique values: 1854

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76304

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.53659 0.48879      1
adj. for ties     -0.53962 0.48972      1
>
> adk.test(nacc08$ Gradient.Rep, slight08$ Gradient.Rep)
Anderson-Darling k-sample test.
```

R Console

Number of samples: 2
Sample sizes: 26603 51
Total number of values: 26654
Number of unique values: 26460

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76301

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.29941 0.41708      1
adj. for ties    -0.29951 0.41711      1
> adk.test(nacc09$ Gradient.Rep, slight09$ Gradient.Rep)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 25497 45
Total number of values: 25542
Number of unique values: 25359

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76323

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.85908 0.58647      1
adj. for ties    -0.85921 0.58651      1
> adk.test(nacc10$ Gradient.Rep, slight10$ Gradient.Rep)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26340 50
Total number of values: 26390
Number of unique values: 26201

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76304

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.14049 0.37074      1
adj. for ties    -0.14052 0.37074      1
>
> adk.test(nacc08$ AADT, slight08$ AADT)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26603 51
Total number of values: 26654
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76301

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.06219 0.34870      1
adj. for ties    -0.04346 0.34351      1
> adk.test(nacc09$ AADT, slight09$ AADT)
Anderson-Darling k-sample test.
```

Number of samples: 2

R Console

Sample sizes: 25497 45
Total number of values: 25542
Number of unique values: 65

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76323

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties 7.56001 0.00047      1
adj. for ties    7.87725 0.00037      1
> adk.test(nacc10$ AADT, slight10$ AADT)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26340 50
Total number of values: 26390
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76304

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties 4.05492 0.00785      1
adj. for ties    4.22132 0.00688      1
>
> adk.test(nacc08$X.HGV, slight08$X.HGV)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26603 51
Total number of values: 26654
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76301

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.67648 0.53150      1
adj. for ties    -0.64188 0.52096      1
> adk.test(nacc09$X.HGV, slight09$X.HGV)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 25497 45
Total number of values: 25542
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76323

T.AD = (Anderson-Darling Criterion - mean)/sigma

Null Hypothesis: All samples come from a common population.

```
          t.obs P-value extrapolation
not adj. for ties -0.69732 0.53784      1
adj. for ties    -0.67116 0.52988      1
> adk.test(nacc10$X.HGV, slight10$X.HGV)
Anderson-Darling k-sample test.
```

Number of samples: 2
Sample sizes: 26340 50

R Console

Total number of values: 26390
Number of unique values: 66

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76304

$T.AD = (Anderson-Darling\ Criterion - mean) / \sigma$

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.46355	0.46652	1
adj. for ties	-0.46729	0.46766	1

> plot(AccYN08\$Coef.Fric.SD.Rep~AccYN08\$AccYN, main="Friction Variation (SD) and Accident Occurrence 2008",xlab="Accident Site",ylab="Representative Friction Standard Deviation")

> plot(AccYN09\$Coef.Fric.SD.Rep~AccYN09\$AccYN, main="Friction Variation (SD) and Accident Occurrence 2009",xlab="Accident Site",ylab="Representative Friction Standard Deviation")

> plot(AccYN10\$Coef.Fric.SD.Rep~AccYN10\$AccYN, main="Friction Variation (SD) and Accident Occurrence 2010",xlab="Accident Site",ylab="Representative Friction Standard Deviation")

> adk.test(nacc08\$ Coef.Fric.SD.Rep,acc08\$ Coef.Fric.SD.Rep)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26603 70
Total number of values: 26673
Number of unique values: 9380

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76256

$T.AD = (Anderson-Darling\ Criterion - mean) / \sigma$

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.60426	0.50947	1
adj. for ties	-0.60478	0.50963	1

> adk.test(nacc09\$ Coef.Fric.SD.Rep,acc09\$ Coef.Fric.SD.Rep)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 25497 59
Total number of values: 25556
Number of unique values: 8468

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76278

$T.AD = (Anderson-Darling\ Criterion - mean) / \sigma$

Null Hypothesis: All samples come from a common population.

	t.obs	P-value	extrapolation
not adj. for ties	-0.59794	0.50754	1
adj. for ties	-0.59771	0.50747	1

> adk.test(nacc10\$ Coef.Fric.SD.Rep,acc10\$ Coef.Fric.SD.Rep)
Anderson-Darling k-sample test.

Number of samples: 2
Sample sizes: 26340 67
Total number of values: 26407
Number of unique values: 9188

Mean of Anderson-Darling Criterion: 1
Standard deviation of Anderson-Darling Criterion: 0.76261

$T.AD = (Anderson-Darling\ Criterion - mean) / \sigma$

Null Hypothesis: All samples come from a common population.

R Console

```
          t.obs P-value extrapolation
not adj. for ties 0.37725 0.23575      0
adj. for ties    0.37765 0.23567      0
>
> #End of Final Statistical Analysis
>
```