

DETERIORATION MODELS AND MARKET
LINKED MAINTENANCE TRIGGERS BASED
ON BIG DATA FOR UNPAVED ROADS

DEFINITIONS

BIG DATA

“Big Data is a phrase used to mean a massive volume of both structured and unstructured data that is so large it is difficult to process using traditional database and software techniques” (Beal, 2018).

CORRECTIVE MAINTENANCE

Corrective maintenance is performed to repair damage and/or to restore infrastructure facilities to satisfactory operation or function, after failure. This type of maintenance is classified as reactive maintenance” (Uddin et al., 2013).

SPECIAL MAINTENANCE

Special maintenance is a form of corrective maintenance that is scheduled due to unplanned circumstances resulting from natural phenomena” (SANRAL, 2018).

PERIODIC MAINTENANCE

“Periodic maintenance comprises works that are scheduled to be undertaken at intervals of several years prior to manifestation of distresses” (SANRAL, 2018).

PREVENTIVE (PREDICTIVE) MAINTENANCE

“Preventive maintenance is performed to retard or prevent deterioration or failure of a component or system. This type of maintenance is classified as proactive or preservation maintenance” (Uddin et al., 2013).

ARTIFICIAL INTELLIGENCE

“Artificial intelligence is an entity (or collective set of cooperative entities), able to receive inputs from the environment, interpret and learn from such inputs, and exhibit related and flexible behaviours and actions that help the entity achieve a particular goal or objective over a period of time” (Faggella, 2018).

DEEP LEARNING

Deep learning is a collection of algorithms, used to model high-level abstractions in data through the use of model architectures, which are composed of multiple nonlinear transformations (Techopedia, 2018).

**DETERIORATION MODELS AND MARKET LINKED
MAINTENANCE TRIGGERS BASED ON BIG DATA FOR
UNPAVED ROADS**

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DISSERTATION SUMMARY

DETERIORATION MODELS AND MARKET LINKED MAINTENANCE TRIGGERS BASED ON BIG DATA FOR UNPAVED ROADS

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The consumer perception is a growing concern for the fresh farm produce market as external damage reduces the likelihood of purchase and thus reduces the economic value to the retailer and grower. One of the major causes of mechanical damage to the surface of the fruit results from the vertical vibrations generated by the movement of haulage trucks on roads with high surface roughness. Although careful handling and well-designed packaging reduce the loss of fruits due to bruising, this can only be altered to a certain extent beyond which it becomes economically unfeasible and environmentally harmful to increase the number of protective packaging layers (Steyn et al., 2015).

Experiments conducted by Pretorius and Steyn (2012) have shown that although the length of an unpaved road section forming part of the transportation route from the grower to the marketplace may be 40 times shorter than the length of the paved road section, the transported freight accumulates more damage over the short unpaved section than over the significantly longer, smoother paved section. Thus the quality of unpaved roads has a significant effect on the profitability of commercial farming.

The deterioration of roads is governed by the behaviour of the material and the capacity of the drainage system under the combined actions of traffic and the environment (Paterson, 1987). Effective pavement management is a challenging task due to increased pavement deterioration and performance demands along with limited budget and human resources. Effective maintenance can take place when decision making is informed by knowledge of the current condition and expected future condition of the road which can be derived by analysing the historical performance of similar road segment types.

Extensive historical road roughness data has been collected using a response type road roughness measuring system over a period of 16 months for various unpaved roads in Limpopo, South Africa. This project used the historical road roughness data, supplemented by maintenance history and rainfall data, to generate roughness deterioration models for unpaved road sections with varying characteristics by fitting various mathematical functions to the collected field data. Simple annual maintenance cost models were derived from the roughness deterioration models and used in conjunction with previously developed tomato shelf-life models to obtain optimum roughness thresholds for road sections with varying characteristics and tomatoes with varying degrees of ripeness. The classification of ripening tomatoes has been formally standardised by the United States Department of Agriculture into green, pink and red stages of ripeness

In general, greater deterioration occurred over the dry season with the most rapidly deteriorating road section type having a slope of greater than 6 per cent as well as relatively heavy traffic. Exponential models were found to be the most appropriate to model deterioration of the road condition over the dry season while linear models were best suited for modelling deterioration over the wet season using the road roughness as a condition indicator.

The optimum roughness thresholds were highest for pink tomatoes and lowest for red tomatoes thus indicating that the lowest optimal maintenance expenditure is achieved when transporting red tomatoes while foregoing an extended shelf-life. The highest optimal shelf-life is reached when transporting pink tomatoes while incurring a greater maintenance cost. Thus, the results indicate that the optimum scheduling of maintenance activities on unpaved roads is dependent upon the demand of the product at the market.

Greater demand for tomatoes will require a lower optimal shelf-life, thus the maintenance cost is minimised by transporting red tomatoes and scheduling maintenance activities using roughness triggers ranging between 4.4 m/km and 5.6 m/km (which is dependent upon the slope and traffic on the road section). Lower market demand will require a higher optimal shelf-life, thus the maintenance cost is minimised by transporting pink tomatoes while scheduling maintenance activities using roughness triggers ranging between 3.9 m/km and 4.4 m/km. The difference between these two scenarios results in an average shelf-life increase of 48 per cent while increasing the maintenance cost by an average of 82 per cent.

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LIST OF SYMBOLS AND ABBREVIATIONS

ADT	Annual Daily Traffic
ANN	Artificial Neural Network
ARRB	Australian Road Research Board
ARS	Average Rectified Slope
ARV	Average Rectified Velocity
CMMS	Computerised Maintenance Management System
COTO	Committee of Transport Officials
CSIR	Council for Scientific and Industrial Research
CVS	Computer Vision System
GDP	Gross Domestic Product
GHG	Green House Gases
GM	Grading Modulus
GPS	Global Positioning System
HCS	Half-Car Simulation
HRI	Half-Car Roughness Index
Hz	Hertz
IRI	International Roughness Index
IRRE	International Roughness Experiment
LOS	Level of Serviceability
LSTM	Long Short-term Memory
PMS	Pavement Management System
PSD	Power Spectral Density
RIMS	Road Infrastructure Management Support
RMS	Root-mean-square
RTRRMS	Response-type road roughness measurement system
SAE	Society of Automotive Engineers
SANRAL	South African National Roads Agency SOC Ltd
TRB	Transportation Research Board
TRH	Technical Recommendations for Highways
VOC's	Vehicle Operating Costs
V-PI	Vehicle- Pavement Interaction

1 INTRODUCTION

The consumer perception is a growing concern for fresh farm produce market as external damage reduces the likelihood of purchase and thus reduces the economic value to the retailer and grower. Pre-shelf damage incurred through handling, distribution and transportation should be minimized where possible. When using road transport, damage occurs to both the transportation vehicles and produce when vertical vibrations, resulting from high road roughness, are significant. In order to reduce the mechanical damage incurred during transportation and extend the shelf-life of fresh produce, a maintenance management strategy must be developed for use by the road management authority to maintain an optimal road roughness.

Infrastructure asset management refers to a decision support system that aids authorities in choosing alternatives for further development, maintenance or improvement of infrastructure (FHWA, 1999). A pavement management system (PMS's) is a subdivision of transportation infrastructure asset management that includes all of the planning and activities involved in providing and maintaining pavements at an adequate level of service. Pavement management is a challenging task due to increased pavement deterioration and performance demands along with limited budget and human resources. Two of the most critical analysis tools in a PMS include the condition evaluation and performance prediction of the roads which require extensive data collection and analysis.

A database of historical road roughness over a period of 16 months has been developed by an external telematics company for the roads belonging to an agricultural company in Limpopo, South Africa. This project uses the historical road roughness data to create models that forecast the deterioration of the unpaved roads to aid in the decision-making process so that the road authority can adopt a predictive maintenance strategy. The triggering of maintenance activities can be optimised by analysing the effect of the road surface condition on the quality of the fruit arriving at the market.

1.1 BACKGROUND

ZZ2 is an organisation specialising in agricultural engineering and technical services with the aim of providing high-quality agricultural produce. This project focuses on the transportation of their tomatoes.

Once the acceptable produce has been hand-picked from the field, the tomatoes are transported by trolley to the tractor, by tractor to the packing platform, by truck to the packing house and by truck to the marketplace. During these trips, the tomatoes are exposed to various vibrations depending on how they are contained during transportation, the suspension system of the vehicle and the quality of the road surface on which the vehicles are travelling. These vibrations affect the tomatoes to various extents depending on the position of the individual tomatoes on the truck and the degree of ripeness of the harvest.

Taking this into consideration, there are many aspects of the transportation value chain that can be investigated to minimise the deterioration of the fruit once it has been picked in order to maintain the quality of the tomatoes throughout the journey to the marketplace. The quality of the unpaved roads between the farms and the packing houses is the direct responsibility of the farming organisation and has a significant influence on the deterioration of the fruit during transportation. Thus, it is essential to optimise the surface roughness of the unpaved road network used for the transportation of fruits from the packing platforms to the packing house and, for a small portion, from the packing house to the marketplace. A smoother ride will reduce the mechanical damage to the fruits caused by vertical vibrations during transportation.

A study has been conducted investigating the influence of the road condition on the shelf-life of tomatoes (Pretorius, 2017). The study measured the vertical vibrations experienced by the trucks and the transported produce as a result of the road roughness using a laser profilometer, accelerometer and Global Positioning System (GPS). The contact stresses between tomatoes in various packaging crate sizes and degrees of ripeness were also measured. The road roughness was linked to the frequency and amplitude of the vibrations experienced by the tomatoes in order to simulate the effect of the vibrations in a laboratory. The damage to the produce was measured using colour change measurements and a consumer perception survey. The deterioration of the produce was quantified by plotting the relationship between the shelf-life and the roughness of the road for various transportation periods ranging between 60, 600 and 6000 seconds. These relationships can be used by the farming organisation to optimise its road maintenance management program.

In 2016, Tracker, a telematics and vehicle tracking company, installed an accelerometer into the centre compartment of a Toyota Hilux vehicle used by the farming organisation for the purpose of recording the vertical and horizontal accelerations experienced by the vehicle while driving on their unpaved roads. An algorithm was developed to process and analyse the sensor-based data to calculate the road roughness along the transport route in real-time while the vehicle travels at a velocity greater than 20 m.s⁻¹. The data has been recorded for 16 months providing a significant roughness condition history record for the roads frequently travelled.

Individual road deterioration models for selected road types can be developed using the historical roughness data. These models can form part of a pavement management system with the ability to forecast the road condition which will assist with the efficient allocation of resources. The roughness of the roads forming part of the transportation network needs to be maintained at an optimum level in order to reduce the mechanical damage to trucks and extend the shelf-life of the produce.

There are many factors affecting the rate of deterioration of unpaved roads. The primary factors contributing to rapid deterioration are rain, traffic, grading action and wind. In Limpopo, wear of the road surface due to wind-action is relatively small compared to the effects of rain, traffic and grading. The quality of road deterioration models that can be derived for selected road types is dependent upon the quantity of the available historical road condition data, rainfall data, traffic data and maintenance history data as well as the quality and integrity of the datasets. It is vital to apply appropriate methods and mathematical models to describe deterioration trends and quantify optimal maintenance triggers.

At the current time, very few tools are available to the farming community to assist with describing and quantifying the deterioration trends of their roads which are necessary for the development of an optimal maintenance management strategy. Currently, road maintenance is scheduled by allocating grading vehicles and associated plant and equipment one week after a maintenance action is triggered in response to complaints from farmers and staff, while some preventive maintenance activities are planned strategically in anticipation of harvesting periods. No quantitative data is used in the decision-making process with most of the grading activities being scheduled based on the intuitive interpretation of the road condition. The effectiveness of the individual maintenance actions taken and the general maintenance management strategy employed are unknown to the organisation which does not currently have a method of processing the roughness data measured by the telematics company.

There is a need for a tool to be developed to enable the farming organisation to effectively manage the maintenance of their roads to ensure that resources are used effectively and efficiently, profits are maximised and the usability of their roads is continuously sustained. Tomato shelf-life deterioration models, together with historical road roughness, rainfall and maintenance history data, can be used as inputs to conduct a simple cost-benefit analysis of various road maintenance management strategies to provide an indication of the comparative opportunity cost associated with their implementation.

1.2 PROBLEM STATEMENT

Road quality has a significant influence on the profitability of commercial farming. Fresh farm produce such as tomatoes have a limited shelf-life, thus factors leading to early deterioration must be minimised as much as possible. If there is no forecast of the condition of the road network, it is challenging to efficiently allocate resources and make effective decisions regarding road network planning and maintenance. If gravel roads, which are commonly found in farming communities, are not adequately maintained, the road roughness tends to increase over time leading to increased vertical vibrations experienced by both the transport vehicles and the transported tomatoes. These vibrations are likely to cause an increase in the maintenance costs of the vehicles and a decrease in the profitability of the tomatoes at the market due to the mechanical damage on the surface of the fruit. Furthermore, the longer the road is left without adequate maintenance, the costlier the repair of the road is likely to be in the long run.

If the fresh farm produce is transported on high-quality, well-maintained roads, the road roughness is likely to be relatively low, thus minimising the damage to the vehicles and produce at the cost of maintaining the road. To maintain an optimal balance between maintenance expenditure and commercial benefit, a cost-benefit analysis tool can be made available to farmers to quantify the opportunity cost of various maintenance strategies and recommend a suitable maintenance trigger. Due to tomato yields being seasonal, it is preferable that maintenance management strategies be dynamic to allow maintenance strategies to be reassessed in response to crop size and market demand.

1.3 OBJECTIVES

The objectives of this study are to:

- Investigate the most appropriate mathematical tool for the analysis of large amounts of road roughness condition data for unpaved roads;
- Develop road deterioration models for selected road categories using the most appropriate model form; and
- Apply tomato-shelf life models to identify and optimise road roughness grading triggers.

1.4 SCOPE & LIMITATIONS

This study aims to establish deterioration models and optimum grading triggers using the appropriate application of mathematical models to historical road roughness data collected in the field.

The scope of this research includes the following:

- Discuss current knowledge, methods and techniques used for modelling road deterioration in a literature survey;
- Develop deterioration models that can be automatically generated for selected roads of significance to the organisation; and
- Use the deterioration models and available data to identify and recommend optimum road roughness grading triggers that can easily be applied in practice.

It falls outside of the scope of this study to:

- Generate models for flexible and rigid pavements; and
- Extrapolate the deterioration models for periods greater than one year.

1.5 RESEARCH METHODOLOGY

An outline of the steps followed to reach the objectives of the study are described below:

- i) Unpaved roads of critical value to the transportation of tomatoes were identified and selected for analysis.
- ii) Information relevant to the development of road deterioration models was sourced;
- iii) Physical features and geometric attributes of the roads of interest were identified through the collection of geotagged GoPro image footage of the roads of interest.
- iv) A script was written using the Python programming language to sort the collected GoPro images according to location, date and time; and
- v) Road roughness data collected by Tracker and rainfall data collected by ZZ2 were processed and analysed using the following steps:
 - a. A Python script was written to extract the roughness time series data corresponding to each road of interest before calculating the weighted daily averages of the road roughness for each road segment forming the lengths of the roads, concatenating the rainfall time-series data to the averaged roughness data interpolating the road condition data between rainfall events and outputting the information in CSV format;
 - b. The applicability of a Long Short-term Memory (LSTM) deep learning model to predict future road roughness was investigated by inputting the CSV files into a Python programmed LSTM model, tuning the model parameters and analysing the output;
 - c. The time series road condition dataset was separated into individual periods of deterioration according to the dates that maintenance activities were carried out on the selected roads;
 - d. The datasets for the individual deterioration periods were further separated according to the various segments forming the length of the roads;
 - e. The datasets were grouped for road segments with similar characteristics;
 - f. Linear and non-linear regression models were fitted to the datasets containing road deterioration data for roads with similar characteristics;
 - g. The regression models were compared and analysed using statistical parameters;
 - h. Final road roughness deterioration models for unpaved roads with various characteristics were chosen based on the analysis of the statistical parameters;
 - i. Tomato shelf-life models were used to determine optimum grading trigger values for road segments with various characteristics;
 - j. Conclusions were made on the suitability of various mathematical models in predicting road roughness deterioration, the trends displayed by the final road roughness deterioration models and the optimum market-related maintenance triggers for the transportation of tomatoes; and
 - k. Recommendations were made for improving the accuracy of the models developed in this study and the application of the optimum maintenance triggers in practice.

A detailed description of the methodology followed to reach the objectives of this study is provided in Chapter 3 with the corresponding results obtained presented in Chapter 4.

1.6 ORGANISATION OF THE REPORT

This dissertation documents the work conducted to meet the study objectives. The report is organised into six chapters as outlined below:

- i) **Chapter 1** details what the project aims to achieve by introducing the project, providing a background to describe how the project relates to previous research studies and the context in which it is most useful, outlining the objectives that the project aims to achieve, clearly defining the scope and limitations of the project and briefly outlining the methodology followed to meet the study objectives.
- ii) **Chapter 2** presents literature published relevant to the advancement of road maintenance management practices and specifically the development of road deterioration models using historical data. It presents the function of a pavement, the importance of maintenance, vehicle-pavement interaction, road condition indices, road roughness measurement methods and classes, factors influencing the deterioration of unpaved roads and the formulation of deterioration models using artificial intelligence and traditional regression methods from big data.
- iii) **Chapter 3** details the research methodology followed to reach the objectives of the project. It provides a step-by-step procedure on the analysis of the data and how the results presented in Chapter 4 were achieved.
- iv) **Chapter 4** presents the results obtained from the processing of the available data and the application of various mathematical models.
- v) **Chapter 5** provides an analysis of the results presented in Chapter 4. It assesses the appropriateness of the various mathematical models fitted to the datasets and discusses the effectiveness and limitations of the resulting deterioration curves before evaluating the models for their usefulness in practice and suitability for inclusion into a maintenance management tool.
- vi) **Chapter 6** discusses the conclusions reached after analysing the results obtained from the study and whether the objectives of the project were reached.
- vii) **Chapter 7** makes recommendations to improve the road deterioration models from big data for inclusion into a maintenance management tool and makes suggestions for further research to be conducted that would make way for potential future developments.
- viii) **Chapter 8** supplies a list of references that were used in the development of the project and have been referenced in the compilation of this document.

2 LITERATURE REVIEW

This chapter presents information sourced from literature and published sources that address aspects related to the research conducted in this dissertation. This chapter discusses seven key concepts including: the significance of pavements, unpaved roads, vehicle-pavement interaction, pavement management and maintenance, pavement condition monitoring, pavement deterioration modelling and artificial neural networks.

2.1 THE SIGNIFICANCE OF PAVEMENTS

Pavements can be defined as constructed, obstruction-free surfaces, which transmit loads to the sub-base and underlying soil. Pavements can be divided into paved roads (flexible and rigid pavements) and unpaved roads (earth and gravel pavements). South Africa has an extensive road network with an estimated total length of 750 000 km, 79 per cent of which is unpaved (Kannemeyer, 2016). In many African countries, unpaved roads constitute upwards of 80-90 per cent of the overall network length.

Pavements play a significant role in economic and social development as they link farms and homes to markets, enable mobility and provide access to essential services such as health, education, civic and recreational facilities. Freight transport is an essential component for economic development making a high-quality road network essential to all industries and the national economy as a whole. Rural roads should not be neglected as they provide a critical link between raw materials and markets.

It is important for a transportation network to develop in tandem with the development of the economy as a whole to avoid inequality by granting local communities the opportunity to take part in economic development and avoid goods being sourced from other economically developed regions (Nistor & Popa, 2014). Transportation networks are vitally important for the sustainable and balanced development of economic and social systems in a country (Nistor & Popa, 2014).

Studies have shown that poverty is more prevalent in unconnected areas with unreliable access. Evidence of this is shown in Bhutan where the number of girls attending primary school is three times higher in connected villages when compared to unconnected ones and in Andhra Pradesh, India where the female literacy rate is 60 per cent higher in villages with road access during all seasons of the year compared to those with unreliable access (Lebo & Shelling, 2002).

Road authorities have an obligation to plan, design, construct and maintain the road network, to protect the public investment in the existing road infrastructure and provide access to essential services and opportunities to enable the economic participation for all communities.

2.1.1 Functions of a pavement

The primary function of a pavement as stated by SANRAL (2018) include:

- To provide an acceptable smooth riding surface essential for the ride comfort of the road user. This is achieved by maintaining the roughness of the road below a threshold value;
- To ensure that the surface friction of the pavement is sufficient to prevent accidents and skidding in wet conditions as far as possible;
- To protect the underlying soil beneath the pavement (subgrade) by ensuring that the pavement layer is sufficiently strong and thick to maintain a sufficient structural capacity.

The improper design of pavements may reduce the life-span leading to early failure of the pavement, inadequate riding quality and diminished usability of the transportation network.

2.1.2 Pavements in transportation logistics

Logistics is part of the supply chain that plans, implements and controls the efficient and effective movement and storage of goods, services and information from the point of origin to the point of consumption in order to meet customer requirements (King & Botha, 2008). The management of logistics is vital in the business environment today because it provides an opportunity for cost reduction and enables an organisation to gain an advantage on its competitors (Mashoko, 2013).

Trucks are often selected as the most suitable means of transport for perishable products as they can move goods directly from the origin to the destination resulting in shorter transport times and they have the flexibility to reach the most inland destinations compared to other means of transport (Jarimopas et al., 2005). South Africa's rail system is aged and has a narrow-gauge making it uncompetitive in general freight, increasing the burden placed on road freight (Havenga, 2007). In South Africa, 90 per cent of freight is transported via roads (Havenga, 2015). Almost half of the freight transport in Europe is conducted via road networks (Khavassefat, 2014).

Logistics costs in South Africa for 2013 amounted to R423 billion or 12.5 per cent of the Gross Domestic Product (GDP) and are highly dependent on the magnitude of fuel inflation (Havenga et al. 2014). Logistics costs are sensitive to changes in the exchange rate and crude oil price. Instead of trying to control economic drivers, efforts should be made to reduce the overall demand for fuel. This can be achieved by improving the road surface condition as poor surface quality decreases fuel efficiency. Some vehicle operating cost (VOC) models provide an indication of the effect of road condition on fuel consumption, vehicle damage and tyre wear (Steyn et al., 2015). In the agricultural industry, these models should include the effect of the road condition on the potential damage to transported cargo.

Figure 2-1 shows how transport costs have dominated the logistics costs distribution in South Africa for the last few years contributing between 52.5 and 61.6 per cent between 2006 and 2014. This cost is far greater than the world average 39 per cent and is partially caused by the fact that South Africa is a spatially challenged economy (Havenga et al., 2014). Logistic costs have remained fairly constant as improvements in vehicle fuel efficiency have been offset by rising fuel inflation.

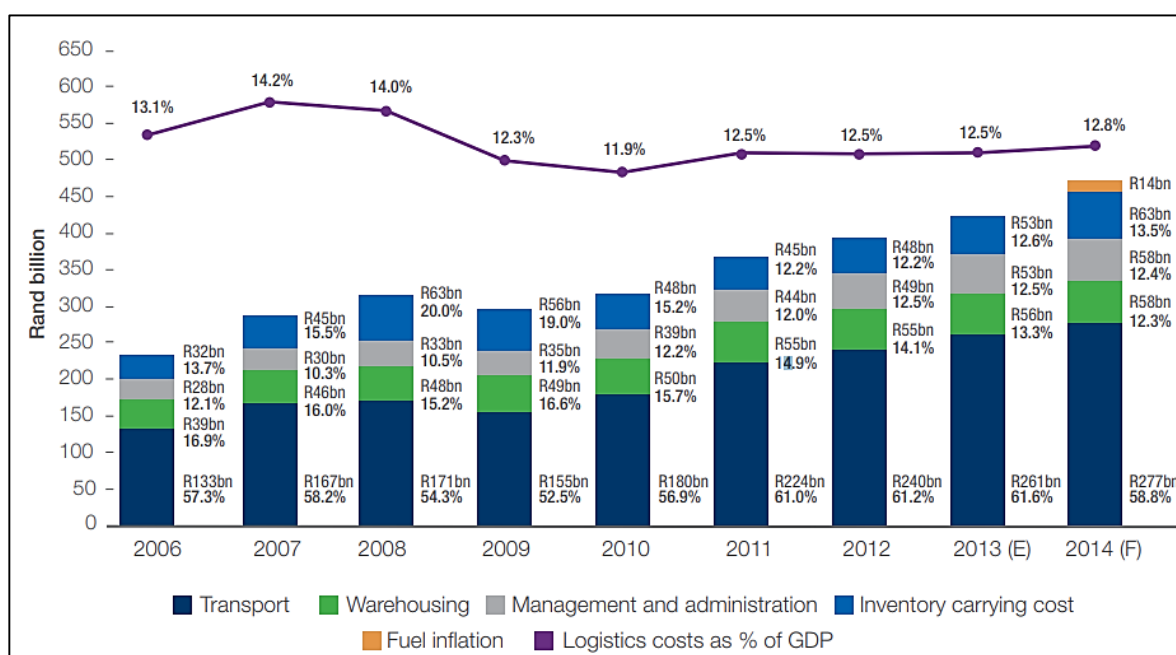


Figure 2-1: Total logistics costs for South Africa from 2006 – 2014 (Havenga et al., 2014)

Figure 2-2 shows the trends of the logistic cost components over the past decade. Warehousing, management and administration and inventory carrying costs have remained fairly constant over the time period. Transport costs have increased since 2003 with a slight decrease over the last three years.

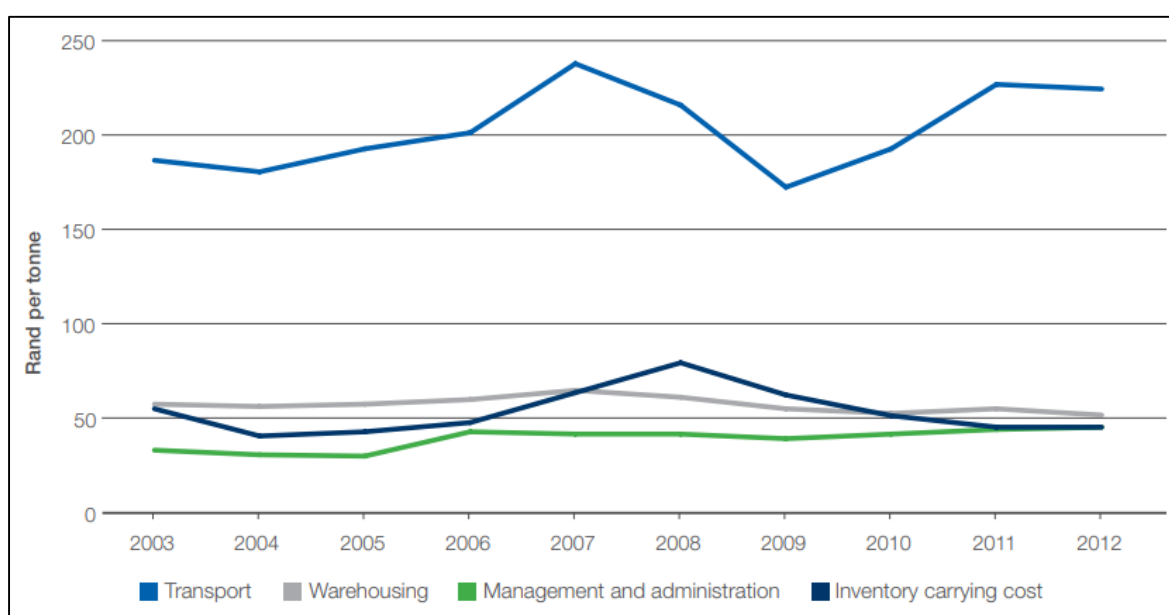


Figure 2-2: Logistic cost components per tonne of freight (Havenga et al., 2014)

2.1.3 Pavements in agriculture

Agriculture plays a prominent role in the South African economy due to the backwards linkages to the manufacturing sector such as the purchase of fertilisers and chemicals and established forward linkages by supplying raw materials to the manufacturing industry (Matsei, 2017). It has long been established that a relationship exists between a country's agricultural development and its investment in infrastructure capital such as transportation and communication facilities (Antle, 1983). Better roads increase the opportunities for profitable trade which encourages farm investments and a rise in agricultural production (Binswanger et al., 1993). Thus, it has been noted that transportation infrastructure is critical in the maintenance of food prices and reducing the dependence of a country on food imports (Ulimwengu et al., 2009).

Roads linking farms to packing houses are typically unpaved low-volume roads that need to be built to withstand occasional but significant stresses to be able to bear the load of heavy agricultural equipment and freight trucks (Khazanovich, 2012). A low-volume road typically carries less than 300 vehicles per day and less than 1.0 million equivalent standard axles over its design life. Economic constraints often result in inadequate maintenance and rehabilitation of the unpaved roads leading to early deterioration and low surface quality.

It is of economic importance to note that many tropical fruits are rejected for purchase due to the presence of bruising incurred during the transportation and handling of the fruit (Chonhenchob & Singh, 2003). Physical damage to the fruit accelerates the loss in fruit quality resulting in a financial loss for the farmer (Chonhenchob & Singh, 2003). In most cases, damage to transported products is caused by vibrations originating from the transportation method (Jarimopas et al., 2005). The deterioration of fruits and vegetables resulting from transportation vibrations and handling can constitute up to 65 per cent of their total market losses (Jarimopas et al., 2005).

Vibrations during truck haulage are generated by the movement of the vehicle on an uneven surface of the road. Thus, the quality of the road surface has a direct influence on the deterioration of the freight condition, the deterioration of the haulage fleet and the transportation logistic component. A decrease in the quality of the road surface may decrease the value of the products, increase truck maintenance and operating costs and increase the logistics costs (Pretorius & Steyn, 2012).

Pretorius and Steyn (2012) investigated the vibrations experienced by a haulage truck resulting from the transportation journey from the packing house to the market. Accelerometers were placed above the axles and at the point furthest from the centre of gravity of the truck. Accelerometers were also placed within the palletised containers carried by the truck to measure the damping effect of the packaging. The energy absorbed by the truck was evaluated for three different road sections classified as gravel, provincial and national roads. The result of the comparison is given in Figure 2-3.

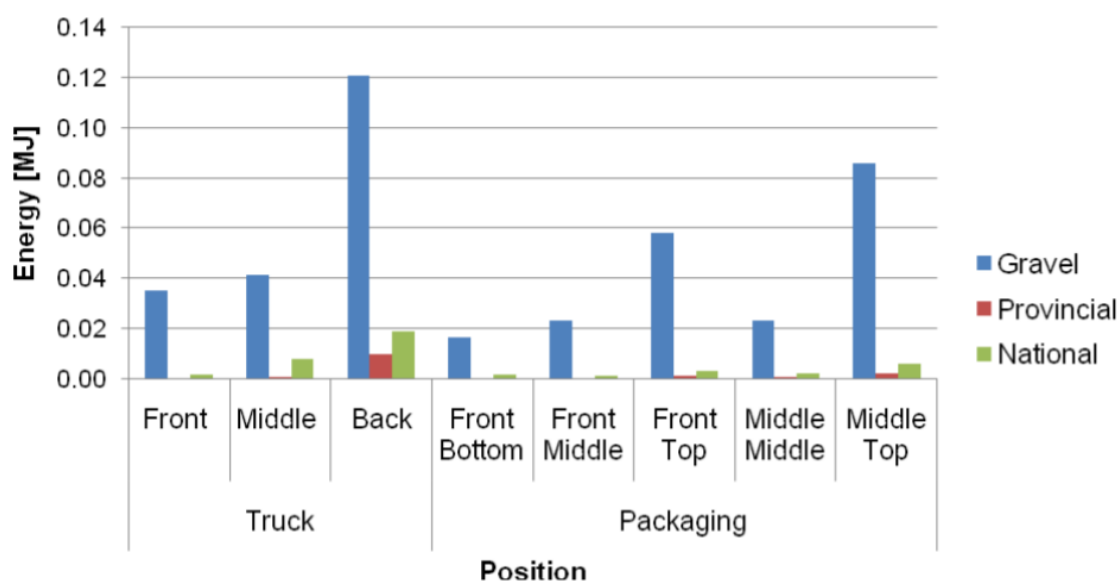


Figure 2-3: Energy absorbed a truck and cargo on various roads (Pretorius & Steyn, 2012)

It was found that the boxes at the top of the stack experienced higher accelerations than the truck. The produce at the bottom and middle positions were better protected against vibration damage. The pallets carried at the front of the truck experienced fewer vibrations than those in the middle. It is significant to note that although the gravel road section that the truck travelled was 40 times shorter than the national road section, the freight accumulated more damage over this short section than over the significantly longer well-maintained national road section which had a smoother, high-quality surface. Thus, the condition of the unpaved roads forming the initial sections of most transport routes between farms, packing houses and markets are vital to the quality of the delivered product and in turn, the profitability of the agricultural industry.

Although careful handling and well-designed packaging will reduce the loss of fruits due to bruising, this can only be altered to a certain extent beyond which it becomes economically unfeasible and environmentally harmful to increase the number of protective packaging layers. Steyn et al. (2015) state that packaging is not often a solution in mitigating potential damages to freight because the main contributor to the problem is the use of aged vehicle technology on rural roads with low riding quality. Thus it is important to consider the road surface itself and find solutions to minimize the vibrations caused by the interaction between the transportation vehicle and the road surface.

2.1.4 Unpaved roads

Unpaved roads remain a considerable part of the road network in most countries (Alzubaidi & Magnusson, 2002). Most farming communities have extensive networks of unpaved roads. It is highly unlikely that the overall percentage of unpaved roads will decrease significantly in the foreseeable future and, therefore, techniques for improving the condition of unpaved road networks are becoming increasingly important (TRH 20, 1990).

Many unpaved roads are designed with little scientific input and are constructed from the nearest available material. Minimal resources are directed towards providing an adequate structure, effective drainage and suitable material selection for the prevailing environmental conditions. Minimal maintenance is common in most developing areas (TRH 20, 1990). It has been acknowledged, however, that applying appropriate engineering methods can yield significant benefits (Ferry, 1986).

Unpaved roads are classified into three categories, namely; earth tracks, earth roads and gravel roads. Earth tracks are the simplest low-volume roads often used as local access roads and are normally not constructed or maintained by a recognised road authority. Earth roads made of in situ material that is cleared of vegetation and lightly compacted and are usually maintained by a road authority. Gravel roads have a designed layer of imported material which is typically constructed to a specified standard and are systematically maintained by a road authority (TRH 20, 1990).

Gravel road research was intensive from the 1930s to the 1970s however, attention has since been directed towards paved roads. Greater competence in unpaved road management is necessary to obtain a transport network that is sustainable in the long-term (Alzubaidi & Magnusson, 2002).

2.1.5 Factors contributing to the deterioration of unpaved roads

The deterioration of a road can be defined as the gradual worsening of conditions that is governed by the behaviour of the material (surfacing and roadbed) and the capacity of the drainage system under the combined actions of traffic and the environment (Paterson, 1987).

In the 1960s and 1970s, road networks expanded faster than corresponding institutional capacities and maintenance budgets (Harral & Faiz, 1988). Traffic became heavier than expected and changes in vehicle design resulted in increased axle loadings exceeding the design capacity of the pavements resulting in extensive road network damage. Although the design standards of paved roads have been updated to incorporate these changing conditions, the necessity of improved strength for unpaved roads is often neglected (Skorseth & Selim, 2000).

The factors influencing road deterioration are the material properties (material type, particle size distribution, percentage of crushed material and thickness), rainfall and surface drainage (improper camber, inadequate ditches, high shoulders, failed culverts and overgrowth of vegetation) which influence the behaviour of the surfacing under traffic (number of vehicles, types of vehicles and vehicle speed). Surface water runoff and side drainage usually affect the moisture penetration to the roadbed and, thus, its bearing capacity (Paterson, 1987). An understanding of the mechanism of surface deterioration is necessary to preserve the life of the pavement (Khavassefat, 2014).

2.1.6 Deterioration mechanisms of unpaved roads

The deterioration of unpaved roads can be described by three underlying mechanisms, namely; wear and abrasion of the road surface under the action of traffic, deformation of the road surface and roadbed under the stresses induced by traffic loading and the prevailing moisture condition, and, lastly, erosion of the surface by water, traffic and wind. Consequently, the modes of deterioration are different in dry and wet weather conditions (Paterson, 1987).

Dry weather deterioration mechanisms

The dry weather deterioration mechanisms as described by Paterson (1987) are:

- Wear and abrasion on the surface, which generates loose material and develops ruts;
- Loss of the surfacing material by whip-off and dust;
- The movement of loose material into corrugations under traffic action; and
- Ravelling of the surface, in cases where the surface material has insufficient cohesion. This could be caused by the abrasive action of tyres, or by ill-informed blading of the surface. At locations where ravelling occurs, tyre action continues the abrasion process, and loose material is removed from the abraded areas. This results in depressions and increased roughness.

These mechanisms result in an increase in surface roughness and material loss.

Wet weather deterioration mechanisms

Under wet weather conditions, the pattern of deterioration is determined by the shear strengths of the materials (Paterson, 1987). When the shear strengths of the surfacing and roadbed materials are sufficient for the stresses induced by traffic, deterioration occurs only at the surface. This occurs in regions where either road drainage is effective, or good quality materials have been used. An example of wet weather deterioration on a road with poor drainage is shown in Figure 2-4. The wet weather deterioration mechanisms as described by Paterson (1987) are:

- Environmental and traffic influences on surface erosion;
- Wear and abrasion of the surface by traffic causing rutting and loss of the surface material; and
- The formation of potholes under the action of traffic. Standing water on the surface accumulates in the depressions, and the passage of a vehicle stirs up the water causing fine material to pass into suspension. Water, with the suspended fine material, is also forced out of the depression. Under the action of traffic and sufficient water, this is a rapidly accelerating phenomenon causing distress and failure.



Figure 2-4: Deterioration of an unpaved road in wet conditions (Rnews.co.za, 2018)

2.1.7 Modes of distress of unpaved roads

Based on the general classification of deterioration mechanisms, specific modes of distress can be identified. For unpaved roads with generally adequate material specifications and pavement thickness, the principal modes of distress are:

- **Roughness:** which increases over time under the actions of traffic and environment, and is defined in units of a standard roughness scale such as the IRI, and
- **Material loss:** from the surfacing, which occurs under the actions of traffic (through whip-off of stones and dust loss) and of erosion by water and wind, and is defined by the change in average thickness of the surfacing material over time.

These modes of distress are the ones which need to be addressed by regular maintenance activities, comprising blading by motorized or towed grader, spot gravelling, dust palliatives, and full width-gravelling (although this last action is sometimes also classified as a rehabilitation activity).

The other modes of distress are ones which need to be addressed at the “design” or material selection stage of the construction or rehabilitation of unpaved roads, namely:

- **Rutting:** which develops under traffic when the surface or roadbed materials have inadequate shear strength under the traffic loading and moisture conditions prevailing.
- **Surface looseness:** which affects the tracking, skidding and safety of vehicles;
- **Impassability:** which occurs when the surfacing material has inadequate strength (usually through saturation or inundation) to allow a vehicle to pass over the surface.

These modes of distress are controlled through the material strength and thickness design criteria.

2.1.8 The significance of road dust

Many unpaved roads in South Africa generate high levels of dust (Jones, 2000). Dust generated by vehicles on unpaved roads has significant environmental and social impacts in terms of health, safety and visual pollution and substantial economic impacts resulting from the loss of road construction material, higher vehicle operating costs, vehicle wear and reduced agricultural yields (Jones, 2000). Despite the potentially damaging impacts of the cumulative effects of dust on health, safety, agriculture and the environment, quantitative data on the impacts of dust generated from unpaved roads is extremely scarce (Greening, 2011).

Dust is predominantly comprised of silt-sized particles (2–75 μm) and the quantity generated by a vehicle is a function of its aerodynamic shape and speed of travel (TRH 20, 1990). The loss of soil fines results in an increase in the rate of loss of coarser particles due to ravelling of the material under traffic. Other problems associated with the loss of soil fines include potholing and corrugations which will become more severe with time, thus contributing to increased road roughness.

Dust can have both a physical and chemical impact on vegetation (Farmer, 1991). The deposition of dust onto plants may physically smother the leaves and lower photosynthesis. Trace elements in the dust may be toxic to the plant biological processes and large quantities of dust on the soil’s surface may draw subsoil moisture leaving less water available for growth and plant health. High dust can cause an outbreak of mites which damage plant foliage by piercing the cells and sucking the contents, causing collapse and death of the cells (Agriculture Victoria, 2010). The impact of dust from the estimated 13 million kilometres of unpaved roads worldwide is estimated to affect the volume and value of 26 million hectares of productive land worldwide and result in a reduced agricultural revenue of \$260 million (Greening, 2011).

2.2 VEHICLE PAVEMENT INTERACTION (V-PI)

Vehicle-Pavement Interaction (V-PI) is the relationship between the vehicle components and the pavement and explores how these components influence each other. This interaction mechanism is complex and the study of this relationship allows us to understand how the pavement roughness may influence the vehicle and in turn the potential damage to freight carried by the vehicle.

One of the main causes of vertical excitation is the pavement roughness, therefore, the roughness is a critical parameter in the development of V-PI relationships. Steyn and Visser (2002) studied the effect of moving dynamic tyre loads on tyre-pavement contact stresses and found that various vehicular components; vehicle tyres, suspension, dimensions, configuration, load and speed as well as pavement roughness have the most significant effect on the V-PI. The dynamic response of the pavement caused by the changing vehicle parameters is highly nonlinear (Xia et al., 2015).

2.2.1 Vehicle dynamics

Vehicle dynamics studies the motion of motor vehicles (acceleration, braking, ride and turning) on a pavement surface. The dynamic behaviour is determined by the forces imposed on the vehicle from the tyres, gravity and aerodynamics. The most dominant force influencing the performance of the vehicle is generated by the tyres against the road. Vehicle motion due to pavement roughness can be categorised as broad-band random vibrations (Gillespie & Sayers, 1981).

A motor vehicle is made up of many components yet for most analyses applied to it, the components move together. For acceleration, braking and most turning analyses, it is sufficient to model the vehicle as a single unit, with its mass concentrated at its centre of gravity. When conducting a ride analysis, it is often necessary to model the wheels as separate mass units where the body is represented as a sprung mass and the wheels as unsprung masses (Gillespie, 1992).

The point mass at the centre of gravity is dynamically equivalent to the vehicle itself when appropriate rotational moments of inertia are applied. Vehicle motions are defined with reference to a right-hand orthogonal coordinate system which originates at the centre of gravity and travels with the vehicle. By the convention used by the Society of Automotive Engineers (SAE), the coordinates are:

x	Forward and on the longitudinal plane of symmetry
y	Lateral out and right side of the vehicle
z	Downward with respect to the vehicle
p	Roll velocity about the x-axis
q	Pitch velocity about the y-axis
r	Yaw velocity about the z-axis

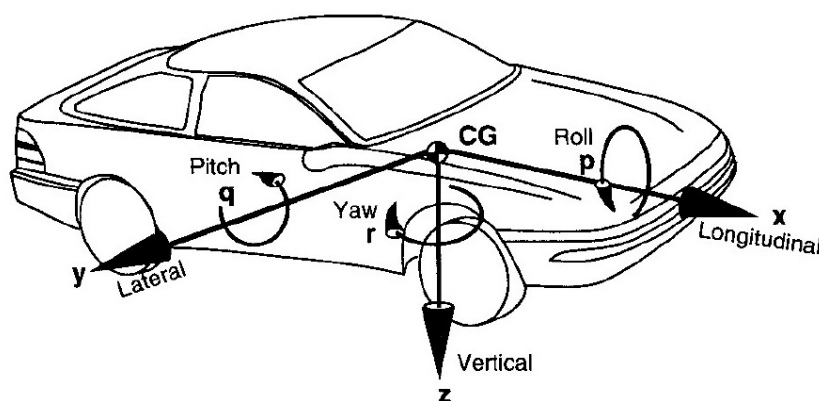


Figure 2-5: SAE coordinate system of a vehicle as a single mass representation

The roll of a vehicle can be calculated using Equation 2-1 (STMicroelectronics, 2010):

$$Roll (Degrees) = \tan^{-1} \left(\frac{a_{x(i)}}{\sqrt{(a_{y(i)})^2 + (a_{z(i)})^2}} \right) \times \left(\frac{180}{\pi} \right) \quad (2-1)$$

Where:

$a_{x(i)}$ = x-acceleration value at the current (i) position

$a_{y(i)}$ = y-acceleration value at the current (i) position

$a_{z(i)}$ = z-acceleration value at the current (i) position

The pitch of the vehicle can be calculated using Equation 2-2 (STMicroelectronics, 2010):

$$Pitch (Degrees) = \tan^{-1} \left(\frac{a_{y(i)}}{\sqrt{(a_{x(i)})^2 + (a_{z(i)})^2}} \right) \times \left(\frac{180}{\pi} \right) \quad (2-2)$$

Where:

$a_{x(i)}$ = x-acceleration value at the current (i) position

$a_{y(i)}$ = y-acceleration value at the current (i) position

$a_{z(i)}$ = z-acceleration value at the current (i) position

2.2.2 Vehicle tyres

The rolling of a wheel on a road initiates a force between the tyre and pavement surface known as rolling resistance. The tractive and lateral forces are developed by a shear mechanism. During this process, mechanical energy is converted into heat which results in a decrease in the energy efficiency of a vehicle. Minimising the effect of rolling resistance will decrease the fuel consumption of a vehicle and, on a larger scale, reduce a country's national fuel cost and carbon footprint (Steyn et al, 2016).

Vehicular loads are transferred from the vehicle to the pavement through the tyres. The contact stresses on the pavement surface and the geometry of the loaded area are affected by the tyre load, tyre type, tyre dimensions and inflation pressure (Khavassefat, 2014). The axles may be single, tandem or tridem and the load distribution and magnitude is not always ideal (Huhtala, 1995).

Due to the increase in legal axle weight limits, bias-ply tyres have been replaced by heavy-duty radial-ply tyres, and truck tyre inflation pressures have increased steadily (Wang, 2005). An increase in tyre-inflation pressure results in a reduction in the stress contact area. A decrease in tyre-inflation pressure increases the stress contact area due to the deformation of the tyre when it comes into contact with the road. Thus a rolling wheel does not truly reflect the irregularities of the road surface due to the smoothing caused by tyre deformation (Rutka & Sapragnas, 2002).

2.2.3 Vehicle suspension and loading

Vehicular loads are transmitted from the vehicle body through the suspension systems and tyres to the pavement surface. The interaction of the vehicle with the pavement surface roughness results in vehicle vibrations and generates random dynamic loads on the pavement (Khavassefat, 2014). Traditionally these loads have been modelled as constant stresses applied through circular uniform contact areas to a pavement surface. However, developments in technology allow these loads to be modelled as dynamic, non-uniform contact stresses with non-circular contact stress areas (Steyn & Visser, 2002). The response properties of the vehicle determine the magnitude and direction of the vibrations imposed on the passenger compartment (Gillespie, 1992).

In vehicle dynamics, the suspension component is modelled as a spring and damper (Yang et al., 2013). Vibrations cause springs to oscillate, storing energy within. The release of the energy is controlled by a damper which releases the energy slowly to reduce the body bounce of a vehicle resulting in a more comfortable ride. Tests have investigated the human tolerance to vibration while seated and have shown that people are sensitive to the amplitude, frequency and direction of the excitation (Gillespie & Sayers, 1981). The maximum sensitivity is found at 5 Hz due to resonance of the abdominal cavity and maximum tolerance occurs at 1 Hz (Sayers & Karamihas, 1998). A vehicle designer should keep the body bounce resonant frequency as low as possible, however, 1 Hz is roughly the lowest that can be achieved by the range of available suspension travel (Gillespie & Sayers, 1981).

Designers try to isolate the rider from the roughness excitations on the road surface. The isolation is obtained by supporting the passenger compartment on a soft suspension system. A representation of the isolation of a vehicle from a simple suspended mass system is shown in Figure 2-6. The ratio of the amplitude of the sprung-mass motion (acceleration, velocity or displacement) to the input at the pavement-wheel interaction surface is dependent on the frequency. At low frequencies, the mass will move with the tyre. At the natural frequency, the mass will resonate amplifying the amplitude of the vertical motion. The amplification factor depends on the damping in the vehicle suspension system and typically ranges from 1.5 to 3 for typical cars (Gillespie et al., 1980). At high frequencies above resonance, the amplitude is not directly linked to the input at the pavement-tyre interface as attenuation (or isolation) is obtained and the displacement is absorbed by the deflection of the tyre (Gillespie & Sayers, 1981).

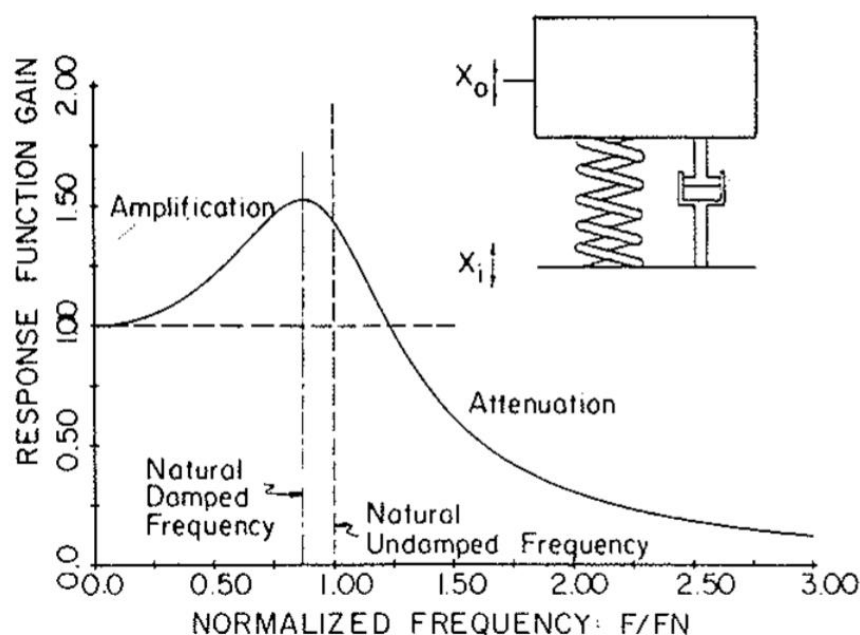


Figure 2-6: Suspended mass system (Gillespie & Sayers, 1981).

The dynamic loads occur at two distinct frequencies known as the body bounce and axle hop frequencies at which resonance occurs leading to significant increases in the dynamic load. The body bounce frequency is associated with the sprung mass of the vehicle (approximately 90 per cent of the total mass of a loaded vehicle) while the axle hop is associated with the unsprung mass of the vehicle (Steyn & Visser, 2001). The peak acceleration values are obtained at typical body bounce frequencies between 1.5 and 3 Hz, while typical axle hop frequencies are between 13 and 18 Hz (Steyn & Visser, 2001; Xu et al., 2017). Friction in the suspension system will increase the resonant axle hop frequency (Gillespie, 1992). The body bounce frequency is usually dominant and has been shown to coincide with the ruts observed on the road (Huhtala, 1995; Steyn & Visser, 2001). The sprung mass remains stationary during axle hop as the axle hop frequencies are much higher than the sprung mass resonance frequencies (Gillespie, 1992).

The effect of the magnitude of the unsprung mass (consisting of the wheels, axle, brakes and suspension components) on the transmission of road inputs to the sprung mass is shown in Figure 2-7. The body bounce remains constant regardless of a mass change. Increasing the mass reduces the axle hop frequency, increasing the transmissibility in the lower range. Lowering the mass increases the axle hop frequency, providing better isolation in the mid-frequency range. It is easier to isolate high-frequency vibrations, therefore, a lighter mass will improve ride performance (Gillespie, 1992).

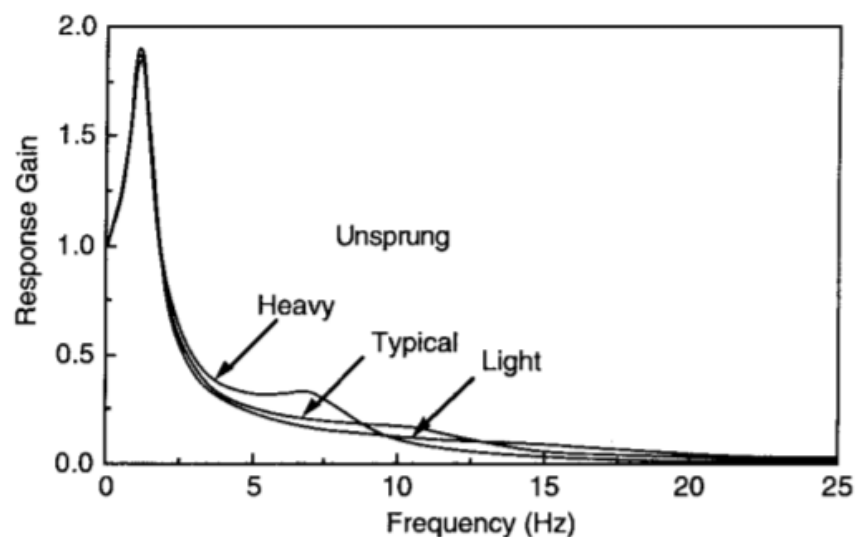


Figure 2-7: Effect of unsprung mass on suspension isolation behaviour (Gillespie, 1992)

The dynamic stresses induced on a pavement increase with an increase in suspension stiffness (Xia, et al., 2015). Compared with the tyre stiffness, the effect of suspension stiffness on the pavement dynamic stress response is significant. The dynamic stress decreases with increases in the suspension damping coefficient. Compared with the suspension stiffness, the effect of suspension damping on the pavement dynamic stress response is relatively small, almost differing by ten orders of magnitude (Xia et al., 2015).

Heavy trucks and tractor-trailers achieve different results due to factors related to the suspension system, structural differences and rider location. Irrespective of the bounce, pitch and roll motions, the trailer is also allowed to move freely, which adds other resonances to the system. The suspensions commonly used on trucks are much stiffer than on passenger vehicles. This is necessary to limit height changes related to loading. The longer wheelbases allow the chassis bending resonance to occur at lower frequencies. The ride motions are more severe in all directions and richer in resonances in the mid-frequency range (Gillespie & Sayers, 1981).

2.2.4 Vehicle velocity

Aerodynamic drag and rolling resistance have been investigated due to their significant effect on fuel consumption. The dynamic load component is dependent on the vehicle speed and is shown in Figure 2-8. As the speed increases to approximately 57 mi/h (92 km/h), the aerodynamic drag becomes the dominant component of the road load force. Below the speed of 57 mi/h, the rolling resistance is the dominant component. The influence of speed on rolling resistance becomes more pronounced when the speed is combined with low tyre-inflation pressure (Gillespie, 1992). As speed increases, the amplitude of the vehicle resonance increases due to (1) the greater amplitude associated with longer wavelengths and (2) for a given road slope, the excitation velocity increases proportionately with speed (Gillespie et al., 1980).

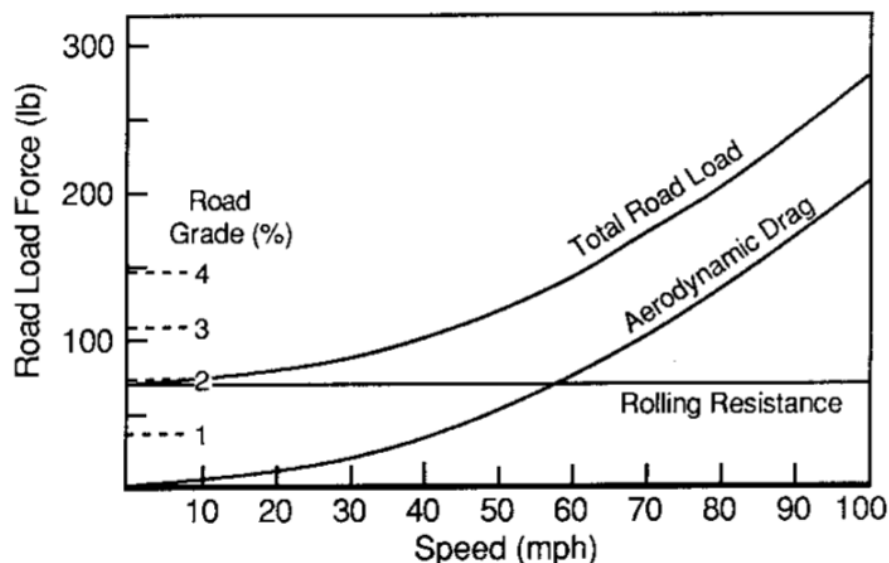


Figure 2-8: Dynamic load components vs speed (Gillespie, 1992)

2.2.5 Pavement roughness

Pavement roughness can be defined as the deviations of a pavement surface from a true planar surface that adversely affect the ride quality of a vehicle. The pavement surface roughness can be regarded as a random process and thus the response of a vehicle traversing a road can be analysed using the theory of random vibration (Dodds & Robson, 1973). Road roughness is often described by a power spectral density (PSD) in the frequency or wavenumber domain (Khavassefat, 2014). The roughness of a pavement is controlled through construction and maintenance actions (Steyn & Visser, 2001).

Road roughness is an important road condition indicator as a measure of pavement performance as it directly relates to the experience of road users and collectively measures several aspects of road condition, including rutting, cracking, potholes, local failures and undulations (COTO, 2007). A rough pavement surface increases the tyre wear rate and is the primary source of vibrations and noise (Gent & Walter, 1985). Roughness is a significant determinant of road user costs including fuel consumption, vehicle maintenance costs and travel time and is, therefore, a primary factor in the analyses of trade-off decisions involving road quality vs. user cost (Gillespie et al., 1986).

The objective nature of road roughness makes it a valuable road condition indicator which has initiated the development of many measurement instruments. One of the most critical elements in the collection of roughness data is the selection of a measurement method that is practical yet suitably accurate for the purposes of the project. In order to explore the details of roughness measurement collection, it is necessary to define the roughness scale and the models used to develop it.

2.2.6 Quarter-Car model

A quarter-car model is a mathematical model of a vehicle that represents a body and a single wheel (Sayers, 1989). It consists of a sprung mass supported on a primary suspension, which is connected to the unsprung mass of the axle. The suspension system has specific stiffness and damping properties. The tyre is represented as a simple spring, although a damper is often included to represent the small amount of damping inherent to the visco-elastic nature of the tyre. A representation of the quarter-car model is given in Figure 2-9.

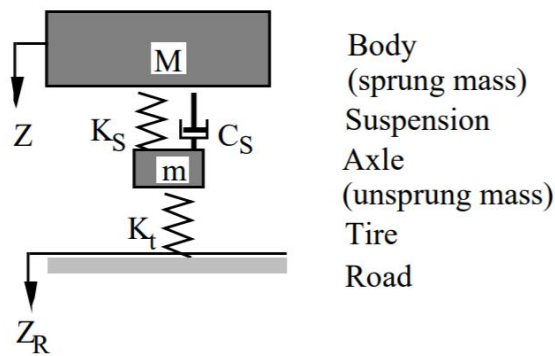


Figure 2-9: Quarter-Car model (Sayers & Karamihas, 1998)

2.2.7 Half-Car model

A half-car model is a mathematical model of a vehicle that represents a body and a single axle with two wheels (Sayers, 1989). The half-car model describes both the left and right-hand wheel track profile conditions as seen by a vehicle. A representation of the half-car model is given in Figure 2-10.

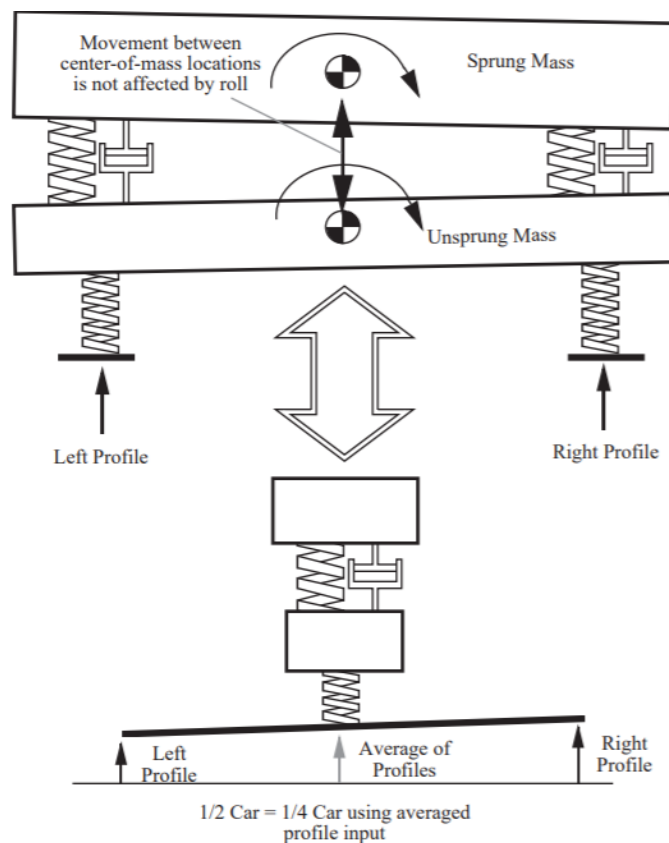


Figure 2-10: Half-car model (Sayers & Karamihas, 1998)

2.2.8 Golden Car

The Golden Car parameters is a set of four values that can be used with either the quarter-car model or the half-car model to simulate the behaviour of most vehicles although with a higher damping coefficient (Sayers & Karamihas, 1998). Extensive computer simulations were conducted to select the Golden Car set of values which maximise the correlation between the car models and a variety of response-type systems based on a spectrum of vehicles (Sayers, 1989). The Golden Car parameters are reported by Sayers & Karamihas (1998) as:

$$\frac{m_u}{m_s} = 0.15 \qquad \frac{K_s}{m_s} = 63.3 \qquad \frac{C_s}{m_s} = 6.0 \qquad \frac{K_t}{m_s} = 653$$

Where

m_u = unsprung mass

m_s = sprung mass

K_s = spring rate

C_s = damper rate

K_t = tyre spring rate

2.2.9 Average Rectified Slope (ARS)

The amplitude reached by the excitation of a moving vehicle due to road roughness is quantified by the average rectified velocity (ARV) statistic. The average rectified slope (ARS) statistic is the cumulative displacement of an axle in relation to the body which can be measured at any speed (Gillespie et al., 1980). The relationship between the two statistics is given by Equation 2-3.

$$ARV_v = V \times ARS_v \qquad (2-3)$$

Where

ARV_v = average rectified velocity of axle-body motion at the vehicle speed, V, in mm/s

ARS_v = average rectified slope of axle-body motion at the vehicle speed, V in m/km

V = vehicle speed in m/s

The ARS is the numeric measure obtained from a response-type road roughness measuring system and changes with the vehicle, the condition of the vehicle and the speed. The quarter-car model determines the ARS roughness level separately for the left and right-hand profiles (Sayers, 1989).

2.2.10 International Roughness Index

The International Roughness Index (IRI) is a standardized pavement roughness measurement that provides a summary of the characteristics of the longitudinal profile of a single travelled wheel-track with units of m/km and is used to evaluate the smoothness of the road surface (Gillespie et al., 1986). The IRI was developed in 1982 as part of the international roughness experiment conducted in Brazil. It is an indirect statistical measure of surface roughness that describes the suspension motion of a moving vehicle and is widely used in the pavement community. It was originally developed as a scale for calibrating Response Type Road Roughness Measuring Systems (RTRRMS) and was the first widely used profile index that was intended to work with different types of profilers (Khavassefat, 2014). The IRI is obtained using a quarter-car simulation with the Golden Car vehicle parameters.

The reference RTRRMS used for the IRI is a mathematical model and exists as a computation procedure applied to a measured profile. The IRI is computed independently for each wheel track. The measurement varies with the speed of the vehicle, and therefore, a standard speed of 80 km/h is specified in the definition of the IRI.

The direct measurement of the IRI requires that the profile of the wheel-track be obtained which is directly measurable by most profilometric methods. The IRI is also strongly related to the subjective opinions of road roughness that can be obtained from the public. Because IRI is (1) measurable by many profilometric methods, (2) highly correlated with the measures from RTRRMSs, and (3) highly correlated with subjective opinion, it is considered to be a highly transportable scale.

The IRI ranges from 0 to 20 m/km with the approximate range of IRI values on different classes of roads given in Figure 2-11. The IRI scale of roughness is 0 for a perfectly smooth surface and ranges from 8 to 20 m/km for rough unpaved roads and 3.25 to 10 m/km for maintained unpaved roads.

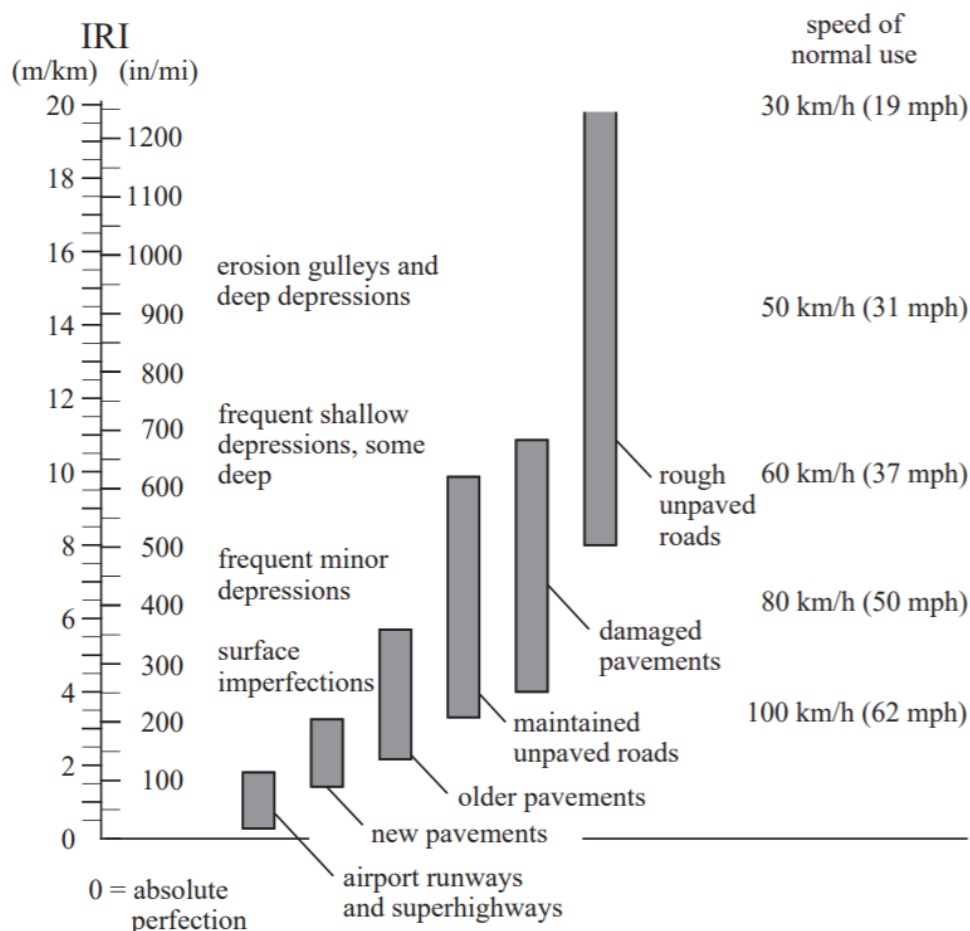


Figure 2-11: IRI roughness scale (Sayers & Karamihas, 1998)

The IRI index summarizes the roughness qualities impacting on vehicle response and is appropriate in applications when a roughness measure is desired that relates to; overall vehicle operating cost, overall ride quality, dynamic wheel loads (damage to the road from heavy trucks and braking) and overall surface condition. High IRI values are indicative of surface distress, uneven pavements and low riding quality. The IRI as a single number indicator has limitations as it cannot represent the statistical properties of the pavement surface fully. The dynamic loads induced at different profiles with identical IRI can be significantly different (Khavassefat, 2014). These limitations can be overcome using the Power Spectral Density (PSD) as a statistical measure of the road surface roughness (Khavassefat, 2014).

2.2.11 Half-Car Roughness Index (HRI)

The Half-Car Roughness Index (HRI) is related to the IRI as it uses the same computer algorithm although both longitudinal wheel track profiles are used as input rather than the single wheel track used in IRI measurement. In the Half-Car Simulation (HCS) the longitudinal profiles are averaged and then filtered. The HRI was developed using a half-car model and the Golden Car parameter values and a simulation speed of 80 km/h (Sayers, 1989).

2.2.12 IRI vs HRI

The slight difference between IRI and HRI is partly derived from experiencing roughness at different points in a vehicle. The IRI is a closer indication of the vehicle response at the wheels, whereas the HRI is a closer indication of the vehicle response at its centre. It is not clear which is the better indicator of cargo damage and ride quality, as this depends on how the roll dynamics contribute to the vibrations of the sprung mass away from the centreline of the vehicle (Sayers, 1989).

The HRI from two wheel-track profiles is always lower than the average of the IRIs from the two wheel-tracks because some of the roughness is cancelled in the HRI analysis. There are subtle differences in how the two are interpreted. The distinctions are so slight, however, that the choice of which to measure should be largely determined from practical considerations.

IRI might be viewed as a potentially more useful roughness index simply because it can provide roughness levels separately for left and right-hand wheel-tracks, to show how one side of the road has deteriorated more than the other. The HRI cannot be used for this purpose; neither, however, can most response-type systems now in use.

The major practical consideration is simply which is more convenient to measure and to relate to other data. Some profiling systems can measure IRI and not HRI and others can measure HRI and IRI. There is no compelling reason to switch the current method in use.

2.2.13 Measurement of roughness

Many approaches have been developed to quantify the degree of discomfort a road user will experience. The instruments available to measure road roughness range from simple devices to complicated systems and are known as profilers. A substantial body of knowledge exists for the field of profiler design and technology. There are also many methods of processing data similar to the measures obtained from profilers. Obtaining data representing road profiles is useful to monitor the condition of the road network, evaluate the quality of newly constructed sections and to diagnose the condition of specific sites (Sayers & Karamihas, 1998).

The International Road Roughness Experiment (IRRE) was conducted in Brazil in 1982 to find a way to correlate and calibrate measurements from various measurement instruments to a common scale which led to the development of the Road Roughness Index (Gillespie et al., 1986). It was important for the measurements to be consistent with time and to create a scale that would allow the characterization of road roughness using different methods to be equivalent.

The road profile is measured along a fixed line in the direction of travel. A profiler works by combining three components; the reference elevation, the height relative to the reference and the longitudinal distance. Profiles taken along a lateral line show the super-elevation and crown of the road design and pavement distresses. Longitudinal profiles show the design grade, roughness and texture. Roughness is primarily concerned with the longitudinal profile while transverse profiles are mainly used to assess rutting (COTO, 2007).

To obtain information from any measured profile the profiler must be capable of sensing the relevant information present in the true profile and computer software must exist to process the measured values to extract the summary index. It is neither economical nor useful to measure the true profile with enough detail to extract texture information and view large-scale landscape features such as hills and valleys (Sayers & Karamihas, 1998). This would require vast amounts of data which would fill computer storage capabilities rapidly and make the management of the database unnecessarily complex, thus, only a part of the information in a true profile is measured.

Key concepts related to the measurement of a road profile include the following (COTO, 2007):

- Along any line on the road, there exists a “true profile”. The true profile is approximated by the measured profile, which is a profile measured at a predetermined sampling interval.
- The sampling interval is the spacing between measurement points along the line of measurement and must be standardized for the root-mean-square (RMS) measurement to be meaningful. The RMS value has been shown to decrease with increasing sampling interval (Sayers & Karamihas, 1998). A profile can be divided into a number of sinusoidal curves (including both sine and cosine waves), each with different wavelengths amplitudes and phases.
- Not all of the sinusoid curves that make up a profile are important for road roughness measurements. The wavelengths that have the greatest influence on road user comfort are those between 0.4 and 30 m. It is necessary to set the sample interval to be no larger than half of the wavelength of the information we wish to capture in the true profile. The power spectral density function is used to create a statistical representation of the importance of various wavenumbers.
- When a road profile is processed to compute roughness, the wavelengths outside of the critical range are typically filtered out (using linear filters) to isolate and sum the amplitudes of the most important wavelengths in the profile that correspond to critical profile features.
- The processing of the road profile results in a number which indicates the roughness of the road.

The accuracy of a calculated roughness index is limited by errors in the measured profile (Sayers & Karamihas, 1998). Therefore, the technical requirements for measuring the profile have been defined for four categories of profiler applications on the basis of how directly their measurements pertain to the IRI, which in turn affects the calibration requirements and the accuracy associated with their use (Sayers et al., 1989).

Table 2-1: Road roughness measurement classes, devices and definitions (Sayers et al., 1989)

Class	Definition	Instruments
Class 1: Profiles of high precision.	Highest standard of accuracy and precision for IRI measurement with a frequency response covering a wavelength of between 0.5 and 20 m.	• Rod and level • Dipstick • TRRL Beam
Class 2: Other profilometric methods.	Profiles measured for direct computation of IRI but accuracy below class 1.	• High speed profilometers • Static methods not meeting the precision or measurement interval requirements for class 1.
Class 3: IRI estimates from correlation equations.	All roughness measuring instruments capable of generating a roughness index which can be reasonably correlated to the IRI.	• RTRRMS. The profile of the road is never actually measured, instead, the vehicle's response to the profile is measured and quantified.

Class 4: Subjective ratings and uncalibrated measures.	Uncalibrated or subjective measures that are visually linked to the IRI scale but not scientifically verified.	• Subjective evaluation after ride experience • Visual inspection • Measurements from uncalibrated instruments.
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2.2.14 Class 1 and 2 profiling methods

The rod and level is a static method as the instruments remain stationary when measures are taken. Although the equipment is accurate and familiar to most engineers, the intervals required to obtain a representation of the road roughness makes this an expensive and costly system. The dipstick is a device developed by the Face Company and is faster than the rod and level for measuring profiles suited for roughness analysis as it includes an on-board computer to automatically record data and perform the arithmetic needed to produce a profile.

2.2.15 Class 3 Response Type Road Roughness Measuring Systems (RTRRMS)

From the early 1920s, engineers installed devices into various vehicles to record the suspension stroke as an indication of the road roughness. These devices are known as road meters or Response Type Road Roughness Measuring Systems (RTRRMS). These devices are installed into vehicles to measure the accumulated suspension motions. The parameter measured by response type devices is the average rectified slope (ARS) which is usually reported in units of m/km or in/mi.

The RTRRMS measure depends on the dynamics of a vehicle to scale the measurements to yield roughness properties comparable to the IRI. The dynamic properties are unique for each vehicle and change with time, thus, the “raw” measurements obtained from the RTRRMS must be corrected to the IRI scale using a calibration equation that is obtained experimentally for that specific RTRRMS. Because the dynamics of a vehicle change easily, very rigorous maintenance and operating procedures must be employed for the vehicle used, and control testing must be made a routine part of normal operations. When changes occur, the entire roadmeter-vehicle system must be recalibrated.

The key difference between response-type measurements and profilometric measurements is that Response type devices apply a physical filter to the actual road profile while profilometric methods apply a mathematical filter to a measured profile (COTO, 2007). The response-type systems are beneficial as they are inexpensive and easy to use. Near identical correlations with response-type systems have been obtained with both the quarter-car model and the half-car models, consequently, the two perform equally well as a calibration reference for response-type systems (Sayers, 1989).

2.2.16 Vehicle characteristics affecting RTRRMS measurements

Variations in the inertial and mechanical properties of the measurement vehicle will affect how the axle body responds to deviations in the road surface. The parameters affecting the measurement obtained from the RTRRMS include:

- The load carried by the vehicle;
- Tyre inflation pressure;
- Suspension spring rate;
- Friction, and
- Shock absorbers.

If any of these parameters are altered, the RTRRMS needs to be recalibrated for the vehicle recording the measurement.

2.3 THE SIGNIFICANCE OF ROAD SURFACE CONDITION

The efficient operation of a country's economy depends on an effective transport network to enable the efficient transport of goods between producers and users (Steyn et al., 2011). As freight transportation in South Africa is mostly conducted via road networks, it is important to ensure that the road network is in good condition to enable regional integration and global competitiveness (Steyn & Bean, 2013). The degree of development of a region is related to the condition of the road infrastructure (Mashoko, 2013). Good quality roads can enhance poverty reduction by improving access between regional and rural communities, ultimately enhancing socio-economic growth and development. The importance of having good quality road infrastructure becomes apparent when the effect that deteriorating road conditions have on communities, economies and logistics operations are understood.

The World Bank sponsored several large-scale research programs in the 1970s and 1980s to investigate whether developing countries would benefit from borrowing money to invest in a good quality road network or by saving the money by neglecting to invest in their road infrastructure, allowing it to deteriorate. It was discovered that road deterioration can worsen an economic crisis and stunt the development of an economy as important road sections become almost impassable and access to internal areas becomes limited (Harral & Faiz, 1988). The loss of physical infrastructure is only part of the picture. Bad roads seldom deter users or curb the volume of traffic. Instead, poor quality roads result in road users bearing the cost burden in the form of damage to vehicles and freight and increased fuel consumption as accelerations are imposed on the body of the vehicle through the tyres and suspension system and frictional forces are generated between the tyre and the pavement surface. Harral and Faiz (1988) estimated that transport costs have increased in real terms by approximately 100 per cent on rural roads due to the deterioration of the pavement condition.

The roughness of a road (often represented by the IRI or HRI) is used as the primary indication of the condition of a road and is often used in the analyses of trade-offs involving road quality vs user costs (Steyn & Bean, 2013). This is attributed to the fact that most functional and structural pavement defects translate to an increase in road roughness (Steyn et al., 2011). The initial roughness of a newly constructed road is dependent on the construction method and quality and ranges between 1 m/km and 4 m/km for asphalt surfaces and 4 m/km to 8 m/km for standard gravel and earth roads (Paterson, 1987).

As a road deteriorates, the roughness or IRI value increases. The higher roughness of a deteriorated pavement increases the magnitude of the dynamic loads induced on the pavement which further accelerates the deterioration. Therefore, the magnitude of the traffic load increases during pavement service life and results in accelerated damage as the pavement ages and no maintenance action is taken (Khavassefat, 2014). The accelerated deterioration translates into an increase in road maintenance and reconstruction costs increasing the life-cycle cost of the project. This may have detrimental effects on the health of the economy.

Many of the problems associated with the failure to maintain road networks at adequate levels of service are rooted in economic and institutional aspects such as inadequate incentives and weak accountability derived from the separation of interests between road authorities and road users (Harral & Faiz, 1988). The poor condition of the municipal roads in South Africa is a result of a lack of funding and expertise which are generating a backlog of maintenance actions (Pretorius & Steyn, 2012). Consequently, progressively higher funding is required in order to restore a deteriorating road system to an acceptable condition thus it is of vital importance that the significance of road condition be made transparent to those with the authority to preserve it.

2.3.1 The effect of road roughness on vehicle operating cost

Pavement roughness affects the vibrations and responses in vehicles (Steyn & Visser, 2001). The cost of operating vehicles rises as road roughness increases (Paterson, 1987). The total operating costs of all vehicles on a road are typically 10 to 20 times greater than the agency costs of maintaining the road, thus small improvements may yield significant economic benefits (Paterson, 1987).

The road user incurs significant costs that are related to fuel and oil consumption, tyre wear, repair, maintenance and depreciation which are collectively termed Vehicle Operating Costs (VOCs) (Steyn & Bean, 2013). The rise in operating costs of unpaved roads is typically between 40 to 60 per cent between the extremes of good condition (4 m/km) and very poor condition (16 m/km). This is far greater than the rise in costs of paved roads which is typically 15 per cent between the extremes of excellent condition (2 m/km) and poor condition (8m/km) (Paterson, 1987). Nordengen (2004) found that heavy vehicle operating costs are on an average 12.8 per cent higher on a deteriorated road network when compared to the operating costs on an ideal, high-quality network.

Relationships developed by Chesher and Harrison (1987) to quantify the impact of road roughness on VOCs for Tunisia 1983 are shown in Figure 2-12. The relationships show that operating costs rise as roughness increases, with slightly different rates applying for different vehicle classes.

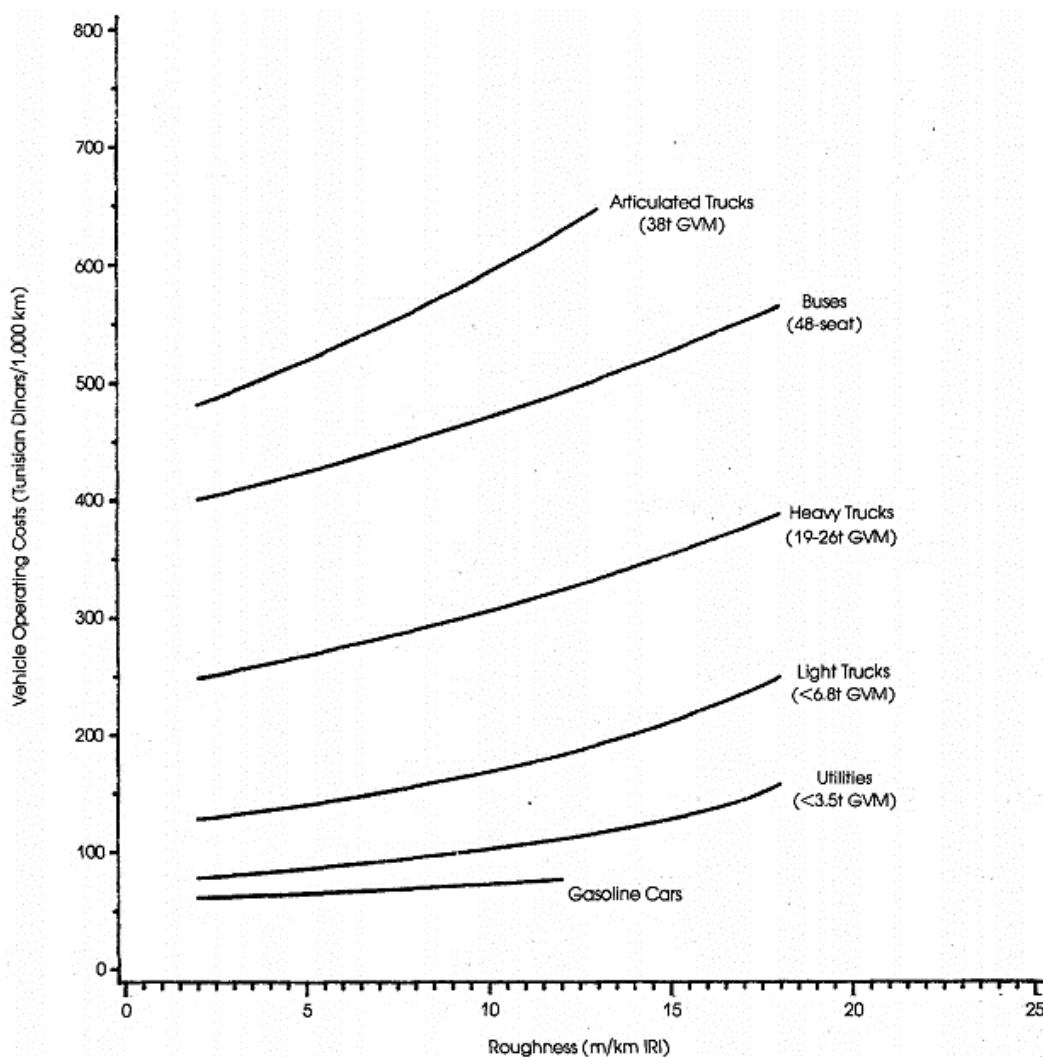


Figure 2-12: Influence of road roughness on vehicle operating costs (Paterson, 1987)

Tyre wear

When a tyre rolls on a road surface, tractive and lateral forces develop through shear mechanisms. A friction coupling develops between the tyre and the road surface. The two mechanisms responsible for this friction coupling are surface adhesion between the rubber and the road surfacing and hysteresis through the deformation of the rubber as it interacts with the unevenness on the road surface. The interaction causes the tyre to flex, dampening the forces transmitted to the vehicle. The deformation of the tyre causes heat build-up in the tyre, reducing the tyre life. The extent of the deformation is affected by the tyre load, tyre inflation pressure, tyre construction and road surface profile. For smaller tyres, the tyre has to roll more often to cover the same distance of travel and therefore the heat build-up gets exaggerated (Steyn & Haw, 2005).

De Weille (1966) reported that tyre wear on unpaved roads is higher than on paved roads and that tyre wear is more significant than fuel consumption when determining the operating costs of heavy vehicles.

Chatti and Zaabar (2012) reported that an increase of 1 m/km in IRI would increase tyre wear for passenger cars and heavy trucks by 1 per cent at 88 km/h. It was also found that tyre wear increases at increasing speed thus the effect of roughness is greater at higher speeds.

Fuel consumption

Studies have shown increased fuel consumption of rough pavements, resulting in increased operating costs. De Weille (1966) conducted one of the earliest studies revealing that operating costs were 20 per cent higher for gravel roads and 40 per cent higher on earth roads when compared to smooth paved roads.

A South African study by Bester (1984) reported that for a truck travelling at 80 km/h, fuel consumption will be 18 per cent higher on a gravel road when compared to a paved road in good condition.

Chatti and Zaabar (2012) reported that road roughness is the most important pavement condition factor relating to fuel consumption with an increase of 1 m/km in IRI typically increasing the fuel consumption of heavy trucks by around 1 per cent at 96 km/h and around 2 per cent at 56 km/h. It was estimated that a 10 per cent reduction in tyre rolling resistance will lead to a 2 to 3 per cent decrease in fuel consumption.

Vehicle repair and maintenance

Increased road roughness is a major cause of increased vibrations and subsequent structural damage to vehicles (Steyn et al., 2012). Correlations between pavement roughness and vehicle maintenance and repair costs including labour costs have received the least attention of all VOC components (Robbins & Tran, 2015).

Chatti and Zaabar (2012) reported that maintenance and repair costs were only significant when the IRI is greater than 3 m/km. Beyond 3 m/km in IRI, the rate of the increase in the maintenance and repair costs varies by the IRI level. An IRI increase from 3 to 4 m/km would increase maintenance and repair costs by 10 per cent for heavy trucks. An increase from 4 to 5 m/km would result in a 40 per cent increase in maintenance and repair costs for heavy trucks.

A South African study using a database of VOCs for an operational fleet of 577 trucks indicated that trucks travelling on roads with poor riding conditions experienced increased suspension replacement costs of between 685 per cent and 1 560 per cent (Steyn et al., 2012).

2.3.2 The effect of road roughness on freight damage

The cost of transporting goods rises as road roughness increases (Paterson, 1987). An increase in road roughness increases the vibrations experienced by a vehicle and thus the freight that a vehicle is carrying is also affected. Studies on the effects of freight vibration of fruit caused by low riding quality found that differences between the levels of vibration-induced damage during transport may be attributed to mechanical differences between trailers, as well as road condition (Steyn et al., 2012). Fruit damage was found to be greatest when placed in the location experiencing the highest vibration levels. Rougher roads even cause an increased loss/spillage of fine product (e.g. maize) through the vibrations.

The adverse effect on freight caused by road roughness is not expected to be restricted to the agricultural sector and could have wide-ranging cost impacts, e.g. vibration effects on sensitive electronic components in freight (Steyn et al., 2012). It is important to prioritize good quality roads in order to avoid the additional costs associated with transporting freight on roads in poor condition (Steyn & Bean, 2013).

2.3.3 Environmental costs of deteriorating road conditions

Road transport's dependence on fossil fuels makes it an important energy consumer. A study by Bartholomeu and Filho (2008) found that a lower road roughness resulted in lower fuel consumption due to increased energy efficiency. Lower energy demands lead to lower adverse environmental impacts (Steyn et al., 2012). Significant adverse environmental effects linked to road condition include increased energy consumption corresponding to an increase in Greenhouse gas (GHG) emissions. GHG emissions result in global warming and climate change (Mashoko et al., 2014).

Havenga (2015) highlights that it is currently estimated that transport contributes 23 per cent of GHG emissions globally and that freight transport specifically contributes approximately 10 per cent. Steyn et al. (2012) reported that the US freight transportation network is the second-highest source of GHG emissions in the US after electricity generation.

Bartholomeu and Filho (2008) found that a lower road roughness resulted in lower CO₂ emissions. This was confirmed by Mashoko et al., (2014) who showed that there is an increase in GHG emissions when road roughness increases. The increases are not very significant for small increases in road roughness, however, there is a significant increase in the emissions produced when the road condition is very poor. These results are shown in Figure 2-13.

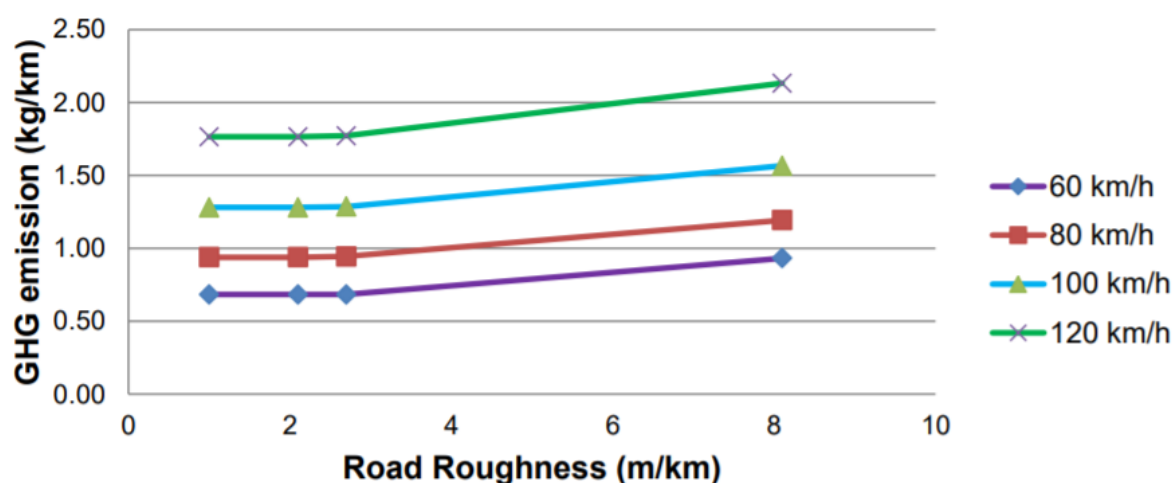


Figure 2-13: Effect of road roughness on GHG emissions at different speeds (Mashoko et al., 2014)

2.4 MAINTENANCE PLANNING AND MANAGEMENT

To explore current developments in pavement maintenance management systems, it is logical to define the concepts and inspect methods developed for consolidating information in an efficient manner to facilitate strategic decision making. This section presents important concepts in maintenance management, the application of these in practice and the integration of information and systems to form effective and efficient decision-making tools.

2.4.1 The importance of maintenance

Maintenance can be defined as the act or process of preserving or restoring an operational condition of a system or asset so as to extend its useful life. The development of the maintenance definition has shifted from a solely technical responsibility to an emphasis on the balance of both a technical and managerial responsibility (Lee & Scott, 2009). The target operational condition is one of the key components in maintenance planning and can now be measured objectively using modern technology. Maintenance is essential to sustain the reliability of an asset, provide safe operational conditions and manage risk.

The high capital and maintenance costs of assets have attributed increasing importance to maintenance management (Coetzee, 1999). Although maintenance is exceptionally important its value is not always recognized at high decision-making levels and history continues to show neglect of maintenance leading to disasters worldwide (McNulty, 2004). Sirvio (2015) noted that this is particularly noticeable in public expenditure as politicians tend to allocate funds to new construction allowing the condition of existing infrastructure to deteriorate. An example of this happened in New Zealand where the historical promotion of sealed pavements resulted in the upgrading of unpaved roads to paved roads. The capacity of the councils to maintain the roads did not correspond to the investment in the new road infrastructure thus the ownership of the roads was returned to local communities and some paved roads were reverted back to unpaved roads (RIMS, 2015).

Sharaf and Abdul-Hai (1992) reported that many developing countries, and more specifically, Egypt, suffer a low maintenance budget with inefficient maintenance management systems leading to the random application of limited funds to fill the most extreme needs for repair. The remaining budget is often inadequate to conduct routine maintenance thus in most cases, maintenance is completely omitted leading the pavements to deteriorate more rapidly than expected. This, in turn, causes the already limited budget to be allocated to heavy remedial work rather than routine maintenance activities continuing the downward cycle of deterioration. This problem is not unique to certain countries or industries.

It is necessary to stimulate a more positive and proactive awareness of maintenance planning which is being partially achieved through the increasing awareness of the scarcity of natural resources and the promotion of sustainable construction (Sirvio, 2015). An ideal pavement preservation program would extend the pavement's service life, and more importantly improve the users' safety and satisfaction while saving money for the road authority that could be better spent elsewhere. Rapid advancements in technology have opened new opportunities for organizations to find solutions to effectively manage their assets while meeting financial goals and organisational objectives.

The complexity and optimization of a problem are affected by the project needs and availability of resources. It is worth developing a maintenance management system that can be easily implemented to progress the effective use of scarce resources to reduce waste, eliminate confusion and increase flexibility in any project or system (McNulty, 2004). In times of world recession, a reliable and well-operated asset management system of adequate quality offers a short and long-term view of potential cost reductions, optimization of resources, and survival (McNulty, 2004).

2.4.2 Asset Management

Asset management is the systematic process of specifying, designing, constructing, operating, maintaining, modifying, and disposing of an asset cost-effectively throughout its life. Asset management involves assessing and balancing costs, opportunities and risks against the desired performance of assets to achieve organisational objectives. A common objective is to minimise the life cycle cost of assets while maximising their value to the organisation.

The increasing demands for better services under constrained budgets are creating growing challenges. Today, more roads authorities are acknowledging the potential that continuously developing technology and growing historical data records have to transform their approach to effectively managing their assets. It is in the interest of all economies to maximise the value provided by their transportation network.

2.4.3 Maintenance Approaches

Maintenance requires the availability of materials, personnel, and equipment, thus a well-planned maintenance management schedule can vastly improve business productivity by allowing convenient scheduling and preventing unexpected failures. Two maintenance approaches are in use; namely reactive and preventive maintenance. The effect of these approaches on asset condition is given in Figure 2-14.

In reactive maintenance, an asset is operated until failure is identified after which repairs are made to return the asset to operational condition. There is a delay related to the transmittal of information regarding the failure identified as well as a delay in the maintenance reaction (Sirvio, 2015). This approach results in inconsistent breakdowns, resulting in unplanned expenses associated with lost productivity due to reduced asset availability and challenging management of resources.

A major breakthrough for managing maintenance is preventive maintenance (Nakajima, 1988). Preventive maintenance (PM) is a time-based or interval-based planned service to detect and prevent potential failures. It is triggered by time, events or condition readings of the asset under consideration and is useful in reducing asset operation losses, optimising maintenance costs and inventory stock handling, and increasing user safety and asset lifespan. Preventive maintenance can be divided into time-based maintenance and predictive maintenance approaches.

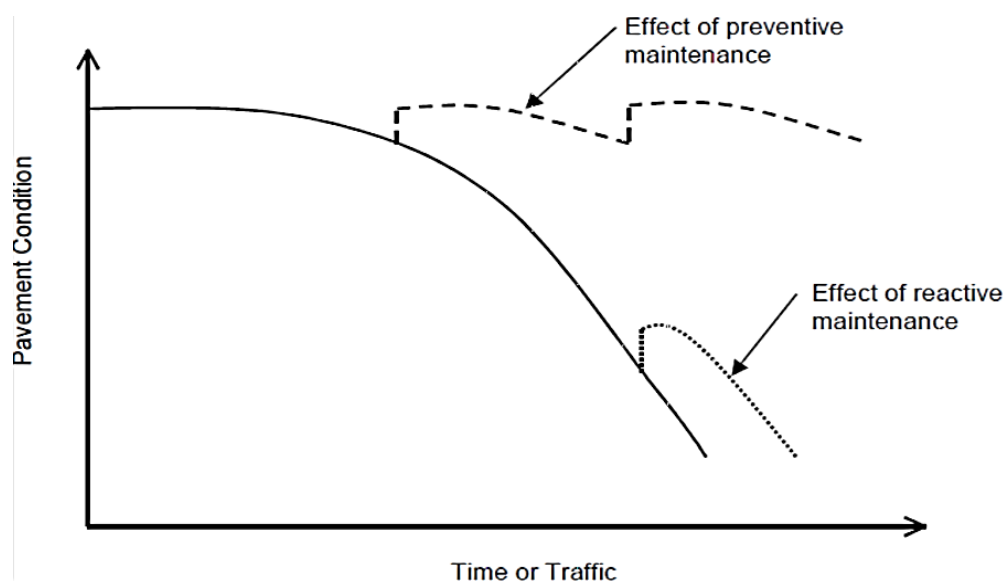


Figure 2-14: Effect of reactive and preventive maintenance approaches on asset condition (Sarsam, 2016).

Time-based preventive maintenance

The preventive maintenance of an asset scheduled following a time-based approach (also called periodic maintenance) is based on an expected rate of failure and may not accurately reflect the usage of an asset. Time-based preventive maintenance triggers a maintenance action after a time interval has been exceeded. It relies on an assumption that the deterioration of the system follows a deterministic path and, therefore, the threshold time remains constant (Sirvio, 2015). A representation of the simplified assumption of deterministic deterioration and constant threshold time is given in Figure 2-15.

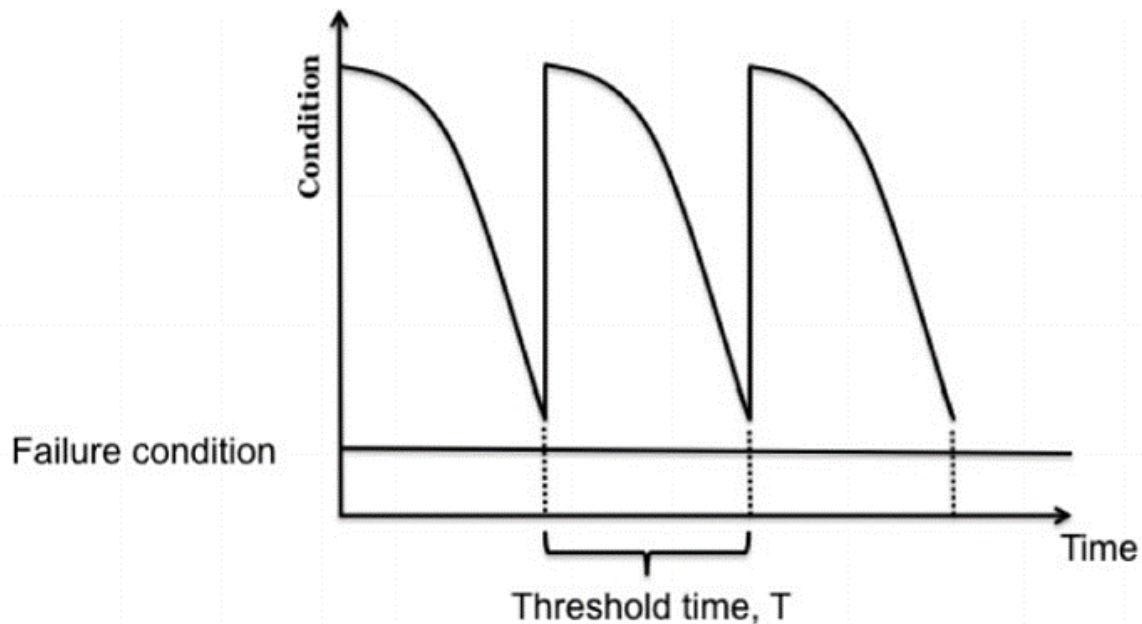


Figure 2-15: Time-based preventive maintenance (Sirvio, 2015)

Most organizations utilize their assets differently during daily operations, thus the time-based maintenance management strategy can result in performing unnecessary maintenance fixes. This may be an expensive maintenance option, especially if accidental damage occurs during repair or replacement. Statistical methods can improve the optimization of a periodic maintenance management schedule by improving the scheduling of inspections, repairs and reconstruction.

Preventive predictive maintenance

Preventive predictive maintenance (PPM) directly evaluates the condition of an asset by performing periodic or continuous condition monitoring and applies analytical techniques to forecast future deterioration and failure times, thus also allowing maintenance to be conveniently scheduled in advance. The loss of asset performance is minimized within a specified threshold. This approach, however, is accompanied by a more complex maintenance system as regular condition monitoring and systematic examination is required. The result is a proactive environment preventing sudden failure, optimizing the asset performance and service life by reducing the rate of asset deterioration. Secondary benefits include trend tracking, managing of manpower and minimization of inventory stock.

It is beneficial to implement this maintenance approach as early as possible to prevent a maintenance team from being preoccupied to responding to a reactive maintenance program making it more challenging to effectively adopt a new maintenance system.

Optimum maintenance approach

The optimum maintenance approach is shown in Figure 2-16. The optimum trade-off between the cost and number of failures is obtained using a predictive maintenance strategy.

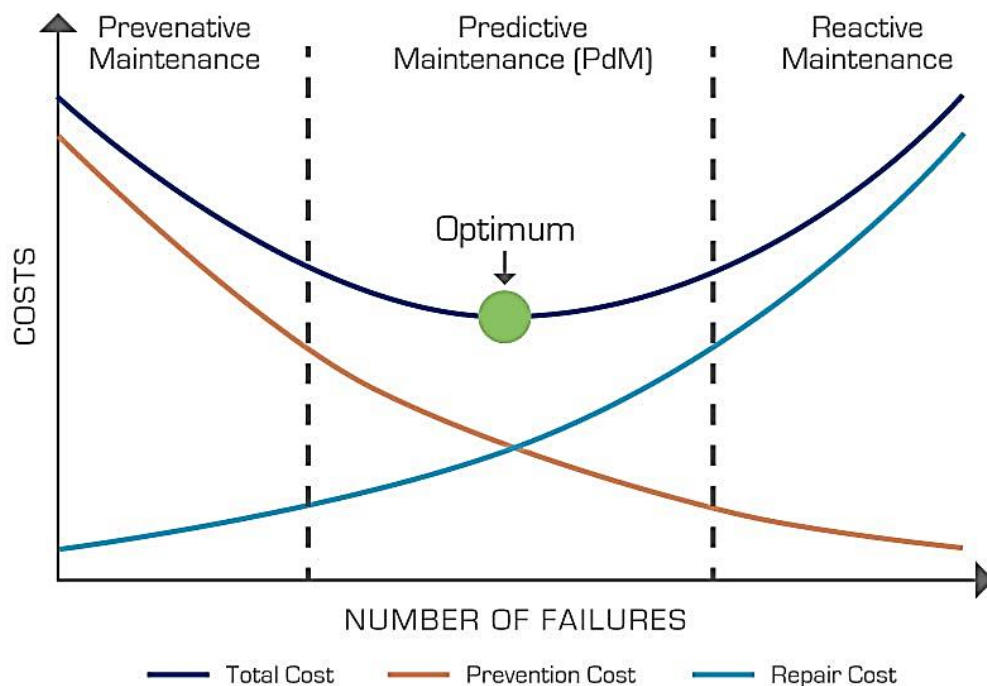


Figure 2-16: Optimum maintenance approach (Sanger, 2018)

2.4.4 Maintenance Management

Maintenance management is the process of overseeing maintenance resources which leads to better control of maintenance organization. The primary objectives of maintenance management are to facilitate consistency in the planning and implementation of maintenance, control costs and ensure regulatory compliance. Modern maintenance management aims to keep assets operating at a high condition with the lowest cost possible. To achieve this objective, data is collected from the asset and processed to present critical information for maintenance authorities to make effective decisions. The overall framework of a maintenance management system is provided in Figure 2-17.

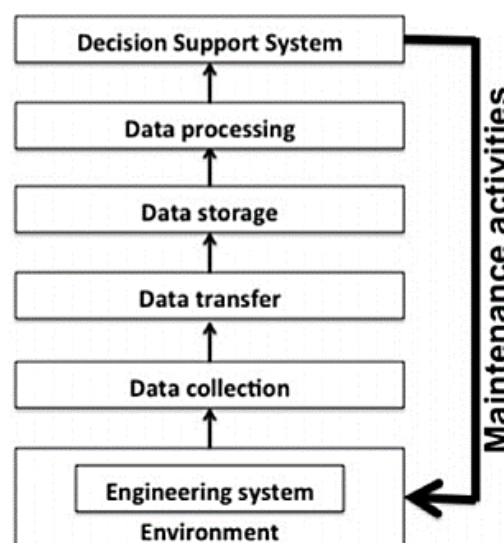


Figure 2-17: Maintenance management framework (Sirvio, 2015).

2.4.5 Challenges in maintenance management

During times of recession, organisations come under pressure to reduce operational costs while maintaining the operational condition of their assets. Often, maintenance resources do not meet maintenance needs (Lee & Scott, 2009). When maintenance is not well planned, the allocation of resources is often chaotic resulting in a waste of scarce resources which further leads to scepticism regarding maintenance effectiveness.

Although the simplest way to reduce maintenance costs is to do nothing, this approach may turn out to be the most expensive option in the long run. It is recommended to find an optimal maintenance management strategy that will reduce financial expenditure and total life cycle costs (Horner et al., 1997).

2.4.6 Pavement management systems

The primary goal of a pavement management system (PMS) is to maintain or improve a road network by optimally allocating the available budget in order to achieve the maximum benefits over a given period of time. The two basic elements of a PMS are an information system and a decision support system. The information system should comprise a database of network inventory, current and historical pavement condition, traffic volume and loadings, maintenance works, and regular monitoring to update the data. The decision support system should analyse the data, identify current and future requirements according to prescribed criteria, prioritize maintenance activities and process feedback information (Paterson, 1987).

There is a significant benefit to adopting a preventive maintenance approach as minor maintenance treatments on pavements still in good condition are more cost-effective than major rehabilitation work required on severely deteriorated pavements. A predictive PMS aids road authorities with the assessment of the current and projected condition of the roads, the determination of the budget requirements to maintain the pavement condition above an acceptable level, the identification of work requirements, the prioritization of projects and optimization of resource allocation.

These systems usually require advanced tools and techniques to carry out data collection and analysis and to provide a user-friendly visual display of output which helps achieve the maximum benefits of such systems (Velaga & Dhingra, 2011). Condition monitoring equipment is used to gauge the true condition of the asset rather than scheduling maintenance and rehabilitation activities from educated guesses and can be used to quantify the impacts of maintenance. Equipment monitoring devices can be integrated with PMS's to drive maintenance schedules, graph asset condition and automatically trigger a work order when acceptable condition limits are exceeded.

2.4.7 Maintenance strategy

Asset intensive industries require sustainable, long-term maintenance strategies in order to remain competitive (Stenström et al. 2015). The strategies are developed through strategic planning and involve the collection of information, setting of goals, translation of goals to specific objectives and development of activities to achieve the objectives (Stenström et al. 2015). The maintenance manager must understand how the company works and know the relative priority of different pieces of plant and equipment to achieve the goal of efficient scheduling.

A maintenance strategy should compare the advantages and disadvantages of using a centralized warehouse for plant and materials versus a decentralised warehouse, using internal maintenance staff or external contracting maintenance, the maintenance approach be followed for each asset and the type, level and timing of maintenance interventions.

2.4.8 Maintenance and rehabilitation of low-volume roads

Typically, the lighter the traffic on a road, the smaller the budget available for maintenance and rehabilitation. Consequently, many low-volume roads around the world are in need of rehabilitation and improvement although this can be prevented if regular road maintenance activities are undertaken to maintain the condition of the road as close to the original condition as possible. Examples of these maintenance activities for unpaved roads are presented in Table 2-2.

Table 2-2: Maintenance activities for unpaved roads (Paterson, 1987)

Mode	Activity	Effect
Routine maintenance	Spot re-gravelling using selected material or crushed aggregate.	Fill potholes and small depressions; reduce roughness and prevent surface water pooling.
	Drainage and verge reshaping, compaction and maintenance.	Control runoff of surface water, reduce erosion and material loss and improve surfacing and subgrade strengths by lowering moisture contents.
	Dragging	Redistribute surface gravel, fill minor depressions and improve safety.
	Shallow blading	Redistribute surface material, fill minor depressions and reduce roughness.
	Dust control	Controls depth of loose fine material and dust loss.
	Grass cutting	Prevents vegetation from forming a barrier for surface water runoff, improves the driver's line of sight.
	Deep blading with re-profiling and/or re-compaction	Reshape road profile, reduce roughness and rate of deterioration, improve crown and drainage.
Resurfacing	Full re-gravelling	Restore the required thickness of surfacing.
Rehabilitation	Major re-gravelling after ripping re-compaction and drainage rehabilitation.	Improve strength, shape, drainage and performance.
Improvement	Rehabilitation and geometric improvement, drainage rehabilitation.	Improve geometric and structural standards.
	Upgrading earth road to gravel road.	Improve structural standards, performance and all-weather possibility.

Gravel roads are generally maintained by routine blading and re-gravelling. However, almost any gravel road will gradually begin to deteriorate and show distress that requires more intensive maintenance activities to correct. The effectiveness of the maintenance or rehabilitation activities is dependent on the correct use of the grading device and the selection of surface gravels of suitable quality (Skorseth & Selim, 2000).

Shallow blading refers to blading conducted with a motor grader that does not disturb the existing hard crust of the road surface and may include removing loose material from the road surface and distributing the fine material over the width of the road to fill minor depressions (Van Zyl, 2011).

When maintenance material is not available or when the roughness exceeds 25 mm, deep blading is required to generate material from the road shoulder which can be evenly distributed across the width of the road and is normally conducted under wet conditions (Van Zyl, 2011). Deep blading is conducted by creating a deep cut to loosen an appropriate volume of material, evenly distributing the material, re-shaping the road cross-section and compacting the road.

To maintain an unpaved road effectively, it is important to understand the necessity of a crowned cross-section, a shoulder that slopes away from the driving surface and a ditch. The incorrect shape of the cross-section will contribute to the rapid deterioration of the road, even under very low traffic (Skorseth & Selim, 2000). The crown should form a straight line from the shoulder to the centre with a slope between 4 and 6 per cent (TR 514, 2006). If the shape becomes rounded and forms a parabolic crown, standing water will occur in the centre of the road, softening the surface and causing severe potholes and rutting under traffic (FWHA, 2015). An A-shaped and parabolic crown are shown in Figure 2-18. If the slope of the crown is too high, road users will drive in the centre of the road to prevent their vehicles from slipping off the road (TR 514, 2006).

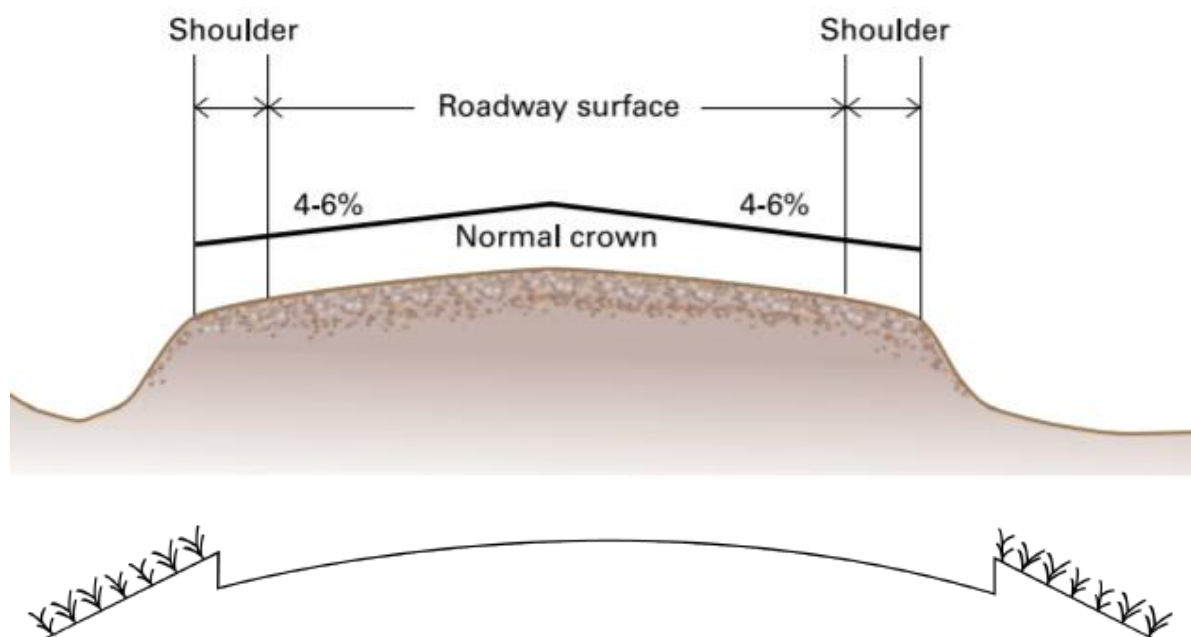


Figure 2-18: Recommended A-shaped crown and parabolic crown (TR 514, 2006)

Reshaping is normally conducted when the surface profile contains irregularities exceeding 50 mm in amplitude and only when the road has surfacing material that is a sufficient thickness and quality and when the road level is sufficiently high relative to the adjacent ground level and side drainage (Van Zyl, 2011). A high road shoulder formed from incorrect shaping, windrows, heavy loads on roads with insufficient strength or material deposited during whip-off under traffic will prevent water from draining into the drainage ditch. This results in water pooling in the shoulder line which seeps into the subgrade causing the whole roadway to soften. If the road has a steep slope, the water will flow downhill along the shoulder eroding away a significant amount of surface material and sometimes even the subgrade (FWHA, 2015). The high road shoulder is corrected by dragging the shoulder material into the roadbed and distributing the material using a grader. It is beneficial to remove vegetation prior to commencing grading operations.

Unfortunately, most gravel roads exhibit failure when exposed to heavy loads even when shaped properly, due to weak subgrade strength and shallow gravel depths (FWHA, 2015). The strength of the surface can, however, be significantly improved by using a roller for compaction. A compacted surface is denser, stronger and smoother and will be easier to maintain. Pneumatic (rubber tyres) rollers are recommended for compaction of gravel however, smooth steel drum rollers are sometimes used but should be restricted to gravels of low cohesion and low moisture content to avoid material building up on the roller (TR 514, 2006).

Locating and transporting wearing course gravels is one of the most expensive operations associated with the development and maintenance of unpaved roads. It is therefore recommended that the optimum material be located within a short distance from the site to be used to maximum advantage (TRH 20, 1990). Gravel materials are needed for spot re-gravelling, which refers to the re-gravelling of short sections of road where extensive gravel loss has occurred and for full re-gravelling which refers to the addition of a wearing course layer with a thickness of 100 to 150 mm (Van Zyl, 2011).

Due to the relatively high cost associated with full re-gravelling, it is normally accompanied by secondary rehabilitation activities such as an improvement in the drainage or installation of culverts, minor changes in the alignment and camber and improvements in the pavement strength achieved by proper roadbed preparation and the use of suitable materials with sufficient thickness (Van Zyl, 2011). A maintenance strategy employed by some agencies in South Africa after re-gravelling consists of regular cycles of light blading, hard blading and reshaping.

2.4.9 Optimisation of gravel road blading

Regular blading maintenance of gravel roads is important to ensure that the functional performance of the road is optimal and that vehicle operating costs are minimized (Steyn, 2018). The effect of blading maintenance on road roughness is illustrated in Figure 2-19.

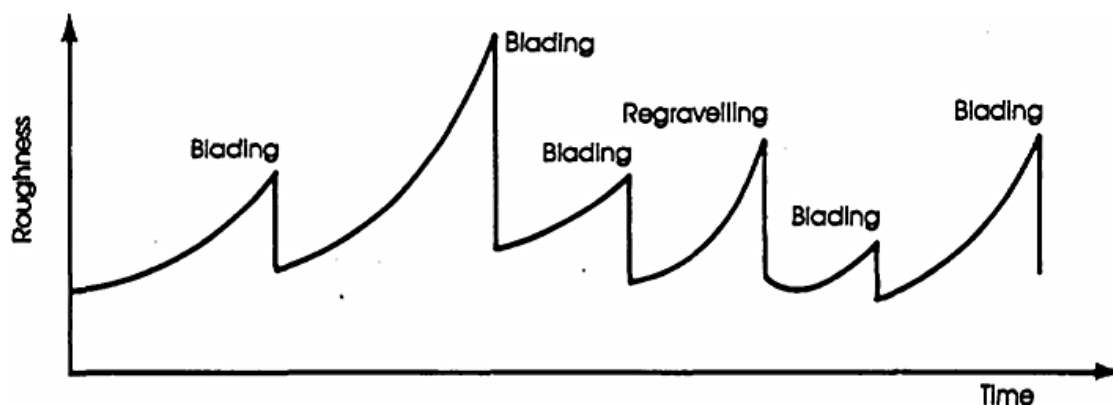


Figure 2-19: The effect of blading on road roughness (Paterson, 1987)

The cost of blading is the second largest expense, after re-gravelling, in the maintenance cycle of unpaved roads (Van Zyl, 2011). The blading cycle can be optimised by conducting regular condition monitoring of the road surface to determine when blading is required. The frequency of the condition monitoring must be adequately high to capture the relatively fast deterioration of the unpaved roads (Steyn, 2018).

Steyn (2018) used a Response Type Road Roughness Measurement System (RTRRMS) to inform the blading maintenance decisions on a small gravel road network. The optimization resulted in a reduced blading requirement as only the pavement sections with an inadequate roughness were maintained. The long-term condition of the road was improved through the use of optimised appropriate blading.

2.4.10 The need to predict unpaved road deterioration

The deterioration of ageing road infrastructure needs to be controlled taking into account the best interests and constraints of the economy and resources (Paterson, 1987). Unpaved roads are known to deteriorate from excellent to failed condition in less than a year (Saha & Ksaibati, 2017). The IRI can rise from 5 m/km on a newly graded gravel road to approximately 20 m/km within a few weeks under high traffic loading (Liautaud & Faiz, 1994). The primary factor affecting the deterioration of unpaved roads is the permeability as significant damage is caused by moisture ingress (Saha & Ksaibati, 2017). Pavement deterioration manifests in many ways and is corrected by maintenance activities that vary with the type and extent of deterioration (Alfelor & McNeil, 1989).

A study conducted by Harral and Faiz (1988) used data from 85 countries and found that a third of unpaved roads are in need of reconstruction and the total costs of these roads could have been reduced to approximately 15 per cent of the total cost if earlier preventive maintenance actions were taken. When the condition of an unpaved road falls from poor to failed condition, the rehabilitation cost can increase 4 to 8 times (Saha & Ksaibati, 2015). The management of unpaved roads remains unscientific as a study found that fewer than 15 per cent of Australian Local Councils with at least 50 km of unsealed roads used any form of a pavement management system (Linard, 2008).

The collection of data for the measurement and documentation of the deterioration process is essential in the analysis of condition changes (Alzubaidi & Magnusson, 2002). Roads tend to deteriorate slowly at first with accelerated damage experienced later in the service life unless maintenance action is taken. The fast deterioration rate necessitates the development of a novel system for managing the maintenance of unpaved roads. It has been established that a prerequisite for the optimization of a maintenance management system is a function that can accurately predict the road condition in the future (Kobayashi et al., 2010; Sirvio & Hollmen, 2008; Thube et al., 2006; Heidari et al., 2018). Such a function is known as a performance prediction model (Oladele, 2013).

Pavement performance prediction models are an important driver to establish optimised maintenance policies and improve the performance over time based on a range of maintenance interventions rather than relying solely on experience to schedule maintenance which is often the case in municipalities (Rashedi et al., 2018). A versatile maintenance management system should incorporate performance prediction models to facilitate reliable economic evaluations so that road authorities can appreciate the long-term impact of implemented policies and compare budgeting strategies to produce a cost-effective maintenance management system (Rashedi et al., 2018).

2.4.11 Traditional methods used to model the deterioration of unpaved roads

A performance prediction model is a mathematical description of the expected values that a pavement attribute will take during a specified analysis period (Hudson et al., 1979). An attribute is a property of a pavement that provides a significant measure of the performance, quality or value of the pavement (Muhammad, 2010). A performance prediction model is a mathematical function that can be used to predict the future pavement deteriorated condition based on the present condition, deterioration factors and the effects of maintenance (OCED, 1987).

Many international studies have attempted to forecast the deterioration of unsealed roads (Van Zyl et al., 2007; ARRB, 2000; Henning et al., 2008). A common difficulty in the development of these models is the complex interaction between the factors influencing deterioration (RIMS, 2015). The deterioration can be categorized into different modes of distress. Prediction models can be used to predict a single pavement distress mechanism, or an overall condition index combining the effects of all distresses and ride quality such as the IRI as all other measures of condition contribute to surface roughness (Alfelor & McNeil, 1989).

The condition of specified pavement sections is usually collected at regular intervals to establish a record of the current and historical pavement condition over time. Curves are fitted through the historical pavement condition database to show the trend of past performance (Muhammad, 2010). These curves are used to forecast changes in condition over time and are known as prediction models. Successful PMS is highly dependent on the accuracy of pavement performance prediction models as they allow the type of maintenance treatment, prioritization of network sections requiring treatment and the timing of maintenance actions to be optimized by analysing the consequences of deferring maintenance actions. These models only become reliable once a considerable history of data has been established (Muhammad, 2010). Predictive models are applied based on the assumption that the identified correlations will persist into the future (Linard, 2000).

Predictive models which have been derived from a broad empirical base, and which use the current condition and physical parameters to estimate deterioration, are extremely valuable because they are versatile and relatively little effort is required to adapt them to local conditions (Muhammad, 2010). Darter (1980) outlined the basic requirements for reliable prediction models as follows:

- An adequate database based on in-service sections;
- Consideration of all factors that affect prediction or performance;
- Selection of an appropriate functional form of the model; and
- A method to assess the precision and accuracy of the model.

It is important to meet these requirements for the development of accurate performance prediction models which can be developed using the following methods outlined by FHWA (1990):

- Empirical: The empirical method is constructed on the basis of statistical methods and is generally used to develop performance prediction models for road surface condition when a large amount of road surface condition data is available;
- Mechanistic: The mechanistic method is constructed on the basis of mechanics theory which is generally used to model the entire road structure and is not appropriate for modelling only the road surface condition;
- Mechanistic-empirical: The mechanistic-empirical method has been widely applied in flexible pavement design and consists of calculating the response of the pavement to applied loading and predicting the pavement performance from these responses;
- Probabilistic: The probabilistic method treats the pavement condition as a random variable with probabilities associated with its values described by a probability distribution; and
- Bayesian methods: The Bayesian method combines observed data and expert experience using Bayesian regression techniques. This method is applied when there is a lack of measured data.

To date, many prediction approaches have been used to forecast the pavement condition, however, deterministic regression is the most popular prediction model for pavement condition (Luo, 2014; Yu, 2005; Kaur & Pulugurta, 2008). Regression can be either linear or non-linear. One of the most important aspects of constructing an empirical model using regression is the selection of an appropriate curve such as linear, power, logarithmic and sigmoid and polynomial curves which are shown in Figure 2-20. When developing performance prediction models, it is important to choose a function that obeys the boundary conditions of the variable being predicted (Muhammad, 2010).

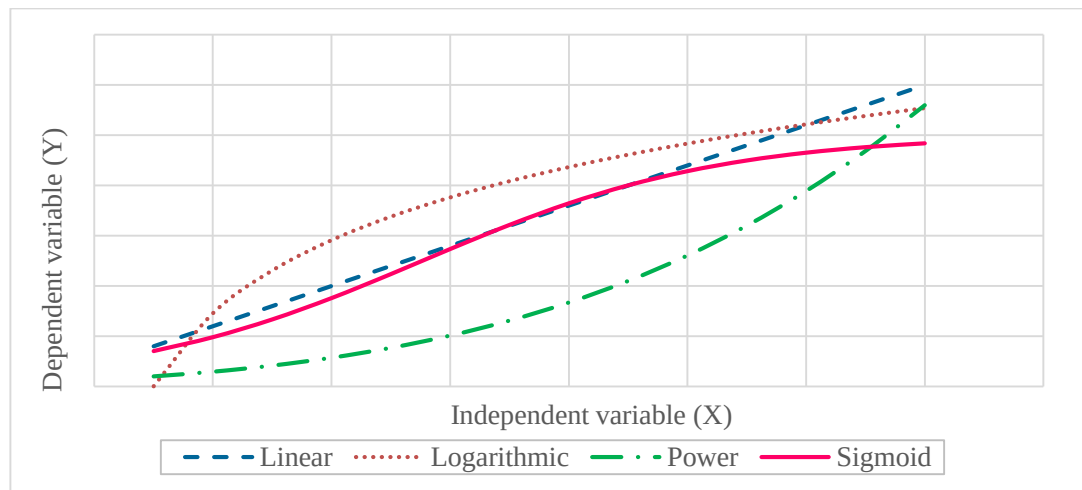


Figure 2-20: Typical regression curves

Regression models are used to establish a deterministic empirical relationship between two or more variables which is expressed as a regression equation with the dependent variable being the condition index and independent variables being the factors that influence pavement deterioration (Yu, 2005). Linear models have been used (Gu & Madanat, 2012) however the more complex power curve (Chan et al., 1997) and sigmoidal curve (Sadek et al., 1996; Sahin et al., 2014) are the most popular non-linear regression formats used to forecast pavement condition (Yu, 2005). The fit of the model is described by the coefficient of determination, R^2 which is based on sample correlation coefficients that indicate the strength of the relationship between the independent variables and the dependent variable when compared to the observed data (Muhammad, 2010). However, R^2 is not always the right indication especially when non-linear regression is performed (Muhammad, 2010). Some studies do not claim a specific mathematical form of function for deterioration, but multivariate regression models (Sirvio & Hollmen, 2014).

Roughness is the most important condition parameter affecting the vehicle operating costs of a particular road (Paige-Green, 1990). Intensive research conducted on the measurement of roughness since the 1970s resulted in simple, durable, response-type measurement devices that have made the measurement of roughness simple and repeatable allowing regular measurements of pavement condition to be collected (Paige-Green, 1990). Factors influencing the deterioration of unpaved roads (such as material properties, drainage, surface erosion, loading, geometric characteristics, subgrade conditions, environmental factors, the effectiveness of maintenance and quality of construction) are highly variable, thus the roughness tends to be variable over time with irregular progression (Paterson, 1991). For the purpose of analysis, it is considered reasonable to associate surface deterioration with a progressive increase in roughness and/or by a loss of surface material (Paterson, 1991).

Roughness progression affects the ride quality and operational safety of unpaved roads. As the road roughness increases, the crown decreases which leads to an increase in ponding and water infiltration which accelerates the rate of deterioration (Rashedi et al., 2018). Various models of roughness progression with time have been developed based on extensive studies on the performance of large samples of gravel roads (Watanatada et al., 1987; Henning et al., 2008; TRH 20, 1990). Roughness progression models can become complex since they require a range of inputs and are not universally applicable or are subject to large prediction errors and in many cases, the input data is not readily available (Rashedi et al., 2018).

Gravel loss is a mode of deterioration caused by a combination of dynamic traffic loading, rainfall and maintenance activities over time. The loss of material results in a reduction in the structural

strength and crown of a road, contributes to rutting, leads to the clogging of culverts and ditches and has negative environmental impacts such as sedimentation and dust generation (Rashedi et al., 2018). A gravel loss function can be used to determine the average change in gravel thickness over time, predicting the time for the next re-gravelling operation. Gravel loss functions are typically less complex and require relatively small amounts of input data when compared to roughness progression prediction models although they are highly significant when considering the high cost of re-gravelling operations (Rashedi et al., 2018).

Empirical models

Empirical prediction models of deterioration for the management of unpaved roads were developed by Paterson (1991). The models quantify the effective rates of deterioration as a function of traffic, road geometry (gradient and curvature), material properties, rainfall and maintenance interventions using successive cycles of roughness progression and maintenance bladings, which were represented as a cyclic process reaching a steady-state pattern. One model predicts the roughness progression and a second model predicts the rate of gravel loss. These models have been incorporated in the HDM-III and HDM-IV model for highway strategy evaluation and economic analysis (Paterson, 1991).

The first model was a simple bivariate cubic polynomial relating the roughness at any point in time to the cumulative number of vehicle passes since the last major reshaping or blading. The model was developed from data collected in Kenya from 1971 to 1974. Different coefficients for each material type were determined by statistical regression of the data. A later study using a similar model reported different coefficients for each material. The prediction curves from both studies are shown in Figure 2-21. The relationships were generally concave in shape (exponential) with an increasing rate of roughness progression although some displayed linear or slightly convex shapes.

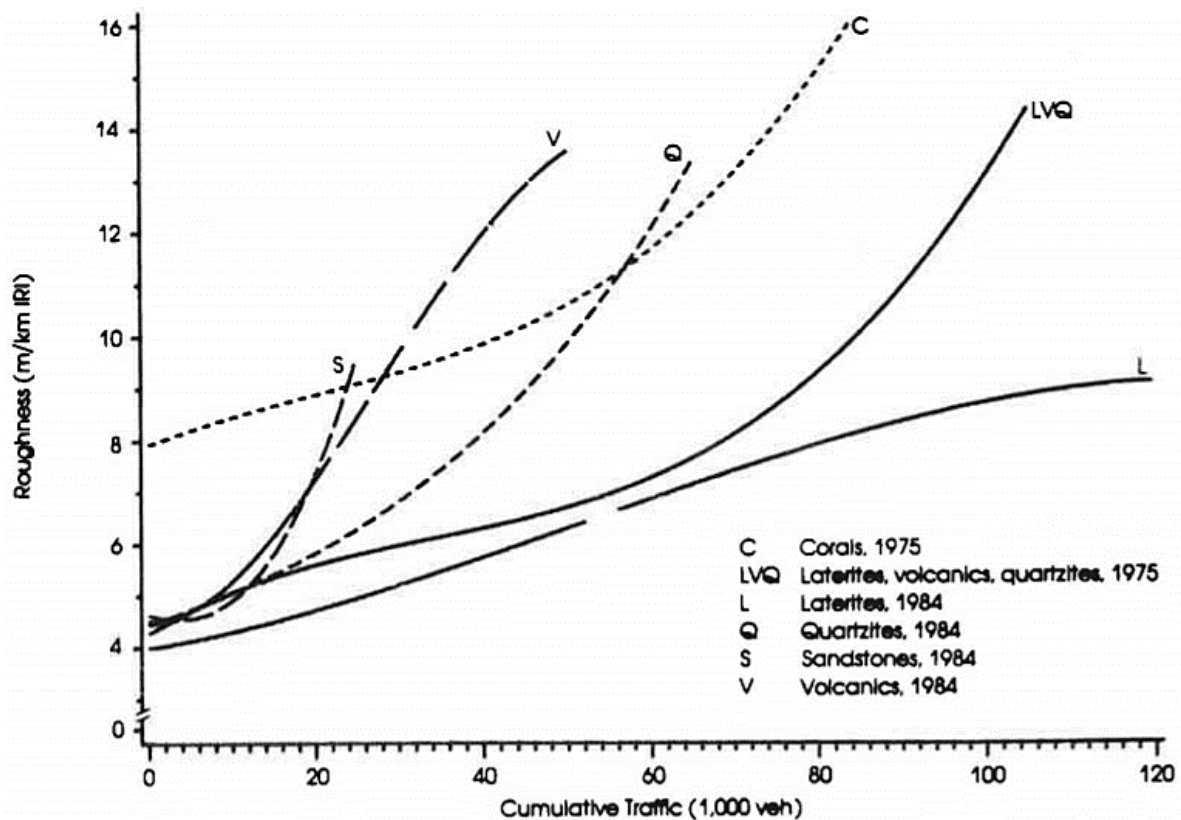


Figure 2-21: Roughness progression for various materials from Kenya study (Paterson, 1991)

The effectiveness of blading is dependent on the material, its moisture content, the type of motor grader, the skill of the operator, and the roughness before maintenance (Paterson, 1991). The result of blading was modelled as achieving a constant level of roughness, regardless of the previous conditions. This level was 4.3 m/km on the IRI for lateritic, quartzitic and volcanic gravels or 7.9 m/km for coral gravels.

A study exploring a wider range of traffic volumes, material types and road geometries for unpaved roads was sponsored by Brazil, UNDP and the World Bank which advanced towards models with greater transferability. Visser (1987) developed exponential models from the data using an imposed maximum roughness as the upper bound. A logistic model was also fitted satisfactorily, however, the exponential model was preferred for its computational simplicity. An exponential form was used for modelling the effect of blading on roughness. A limitation of the models was that the roughness progression was significantly overestimated on roads with low blading frequency due to the exponential form. Low blading frequencies are common in developing countries thus improvements to the models were sought through different model forms (Paterson, 1991).

Typical observations extracted from the Brazil-UNDP study showed irregular patterns of both roughness progression and the effect of blading which is depicted in Figure 2-22.

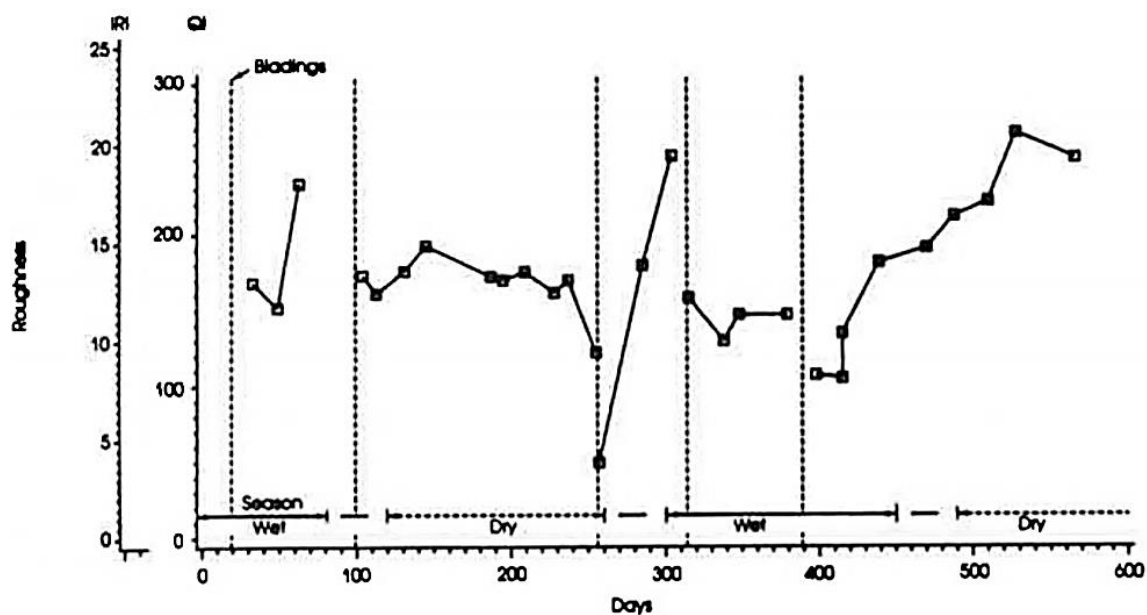


Figure 2-22: Roughness progression from Brazil-UNDP study (Paterson, 1991)

A tendency toward a convex shape is evident, although during some roughness progression intervals, an initial reduction in roughness is distinct which may be a result of the bedding-down effect under traffic. Major differences were noted in the roughness progression trend for any road section between different cycles which may be caused by differences in the weather. Another factor contributing to the irregularity is the high level of measurement errors (10 to 18 per cent) found with response-type roughness instruments. It is recommended that large datasets be used for model development to minimize the effects of errors in the data. The Brazil-UNDP data consisted of 8095 observations on 48 sections over 24 months (Paterson, 1991).

Paterson (1991) recommends that a roughness prediction model should be responsive to the main factors that will influence the frequency of maintenance and that it should rather predict average trends than an individual cycle using a steady-state approach.

The constraints used to solve the set of equations are as follows:

- The maximum roughness was determined by a function of the material, road geometry and weather. This is due to the fact that roughness is often less severe on positive slopes than on level sections where depressions and potholes form if the drainage and crown are inadequate;
- The roughness was assumed to eventually become asymptotic to the maximum roughness because of the combined effects of vehicles finding alternative wheel paths and slowing down;
- The major part of the progression phase is linear by all intents, and the assumed trend is essentially linear within the central part, which is the phase of interest; and
- The roughness after blading was modelled as a linear function of how close it was to a minimum roughness. This minimum roughness was considered to be the best condition that can be achieved by a motor grader on that particular surface material.

At a steady-state with regular blading maintenance at a given interval, where the roughness before and after blading remains essentially constant, the roughness progression and roughness after blading are given by Equation 2-4 and Equation 2-5.

Roughness progression:

$$RG_b = RG_{max} - \rho(RG_{max} - RG_a) \quad (2-4)$$

Roughness after blading:

$$RG_a = RG_{max} - q(RG_b - RG_{min}) \quad (2-5)$$

The long-term average roughness can be expressed as a unique function of the limits and the vector functions ρ and q :

$$RG_{ave} = RG_{max} + (RG_{max} - RG_{min}) \times \frac{(1 - \rho)(1 - q)}{(1 - \rho q) \ln \rho} \quad (2-6)$$

Where:

- ρ = $\exp(XT)$, such that $0 < \rho < 1$;
- X = vector of explanatory variables that is to be estimated;
- T = time between maintenance bladings, and $T > 0$;
- q = vector of explanatory variables to be estimated, such that $0 < q < 1$;
- RG_b = Roughness before blading;
- RG_a = Roughness after blading;
- RG_{min} = Minimum roughness limit;
- RG_{max} = Maximum roughness limit.

The analysis of the models yielded the following conclusions:

- The rate of roughness progression, represented by the parameter ρ , was found to be a function of traffic and rainfall, with no significant effects of material properties found;
- The maximum roughness, RG_{max} was found to be a function of the material properties, road geometry and rainfall. RG_{max} represents the potential roughness that the road could reach under no maintenance;
- The roughness progression is essentially linear in most cases and only becomes noticeably convex at blading frequencies as low as once per year;
- The progression model explained well most of the wide range of rates observed under different conditions through the material, traffic, and environment parameters, but it clearly applied primarily to roads under regular blading maintenance, even if at very low frequencies;
- The effectiveness of blading maintenance on roughness depends on the roughness before blading, the material properties and the minimum roughness, RG_{min} . This minimum roughness was itself found to be a function of material properties being relatively low for fine materials and higher for coarse materials;
- The convex shape of the progression is a concern, but the shape is virtually linear over the range of interest. The concave exponential model of Visser (1987) also has problems of overestimation under low traffic volumes. The most practical solution may be a linear progression model;
- The rate of roughness progression tends to be highest in dry conditions and is usually slower or sometimes negative (i.e., improving) under light to moderate rainfall; and
- There is an apparent tendency to overestimate the progression rate and the average roughness in the initial phase, when there has been compaction or other special treatment of the gravel surface. This tendency would result in a slight overestimation of the amount of maintenance input.

From the results of the Brazil study, the World Bank developed a comprehensive model to be used as a decision support tool for the economic evaluation of road projects in developing countries. The system is called Highway Design and Maintenance Standards Model, HDM-III. The tool performs an economic analysis of user-defined alternatives for both paved and unpaved roads which are analysed by calculating their life-cycle costs. For unpaved roads, maintenance options are entered as number of bladings per year. A steady-state roughness progression cycle based on the mechanistic-empirical prediction methodology and relationships developed by Paterson (1991) is used to represent an equilibrium condition given a specific blading frequency.

Some limitations of the model include the restrictive assumptions regarding the constant roughness after blading and constant maintenance cost as the interaction among maintenance, deterioration and performance can be modelled more realistically using a dynamic optimization framework as both pavement condition and performance change over time (Alfelor & McNeil, 1989). The software was updated in 1993 to version HDM-IV to provide a more refined and flexible programme based on the same underlying principles. The additional capabilities include models for traffic congestion, climate effects, safety and environmental effects that did not form part of HDM-III. The technical relationships were improved by incorporating the results of additional research that had been undertaken around the world, including South Africa and Namibia, since the development of HDM-III.

The road deterioration models that form part of HDM-IV are deterministic in nature developed using the structured empirical methodology and consist of separate distress models which can be divided into three categories: surface distress models (potholing), deformation distress models (rutting and roughness) and surface texture distress models (texture depth and skid resistance) (Muhammad, 2010). These models predict the change in distress over time or traffic.

The roughness progression relationship used in HDM-IV constrains the roughness to a maximum roughness using a convex function in which the rate of progression decreases linearly until it reaches zero at the maximum roughness as illustrated in Figure 2-23.

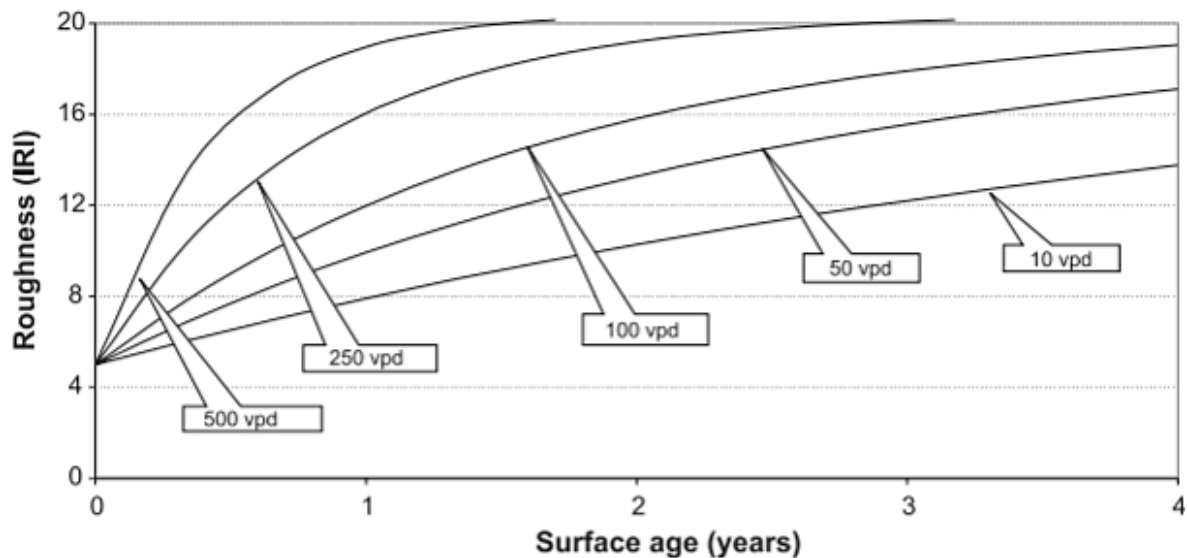


Figure 2-23: Roughness progression on unpaved roads with no maintenance (DFID, 2006)

The rate of roughness progression is a function of the current roughness, maximum roughness, time, light and heavy vehicle passes and material properties. The relationship for predicting the effect of maintenance (in the form of grading) on the roughness is a function of the roughness before the grading, the material properties and the minimum roughness. The minimum roughness increases as the maximum particle size increases and the gradation of the surfacing material worsens (DFID, 2006).

It was found after comparing the results of the HDM-IV model with observed data from roads in Uganda that the observed rate of roughness progression was lower than that predicted by the HDM-IV and the effect of increased traffic levels was far greater in the HDM-IV model (DFID, 2006). Another evaluation of the HDM-IV model using data from 144 monitored road sections in the Western Cape province of South Africa found that the initial rate of deterioration as measured on the road sections was much slower than that predicted using the HDM-IV. However, once blading was done at high roughness levels, the actual measurements followed the rate of deterioration predicted by the HDM-IV models (Van Zyl et al., 2007).

Other models that have been used successfully are power and sigmoid models developed by the Virginia Department of Transportation (Adel et al., 1996). The power prediction model represented a more realistic model than a simple linear model. The model was fitted using nonlinear regression techniques and was capable of satisfying the initial boundary condition of no distress at zero. The sigmoid model was appropriate for predicting pavement indices as by having an inflection point, the model is capable of reflecting different deterioration rates throughout the pavement life (Muhammad, 2010).

Cardosa and Marcon (1998) studied three model types and concluded that curve fitting of actual performance data using regression was more accurate when compared to the models developed by HDM models. Regression analyses were carried out relating pavement condition, represented by five dependent variables to the predictor independent variables (age or traffic loading). Five types of models (linear, logarithmic, polynomial, power and exponential) were considered in the analysis.

A project conducted on collected samples of 10 000 roughness measurements over the province of Gauteng, South Africa and 1 500 samples in Namibia showed that factors, such as seasonal rainfall effects, variability of roughness measurement, blading effectiveness, and stoniness are the most important contributors to roughness. The variable subgrade conditions had no noticeable influence on the performance of these road sections (Paige-Green, 1990). Regression was performed on the data and the best-fit model for the prediction of the rate of change of roughness was:

$$\ln R = D[-8.3 + 0.0003PF + 0.07S_1 + 0.081 P26 + 0.0003N ADT + GM(3.63 - 0.035P26)]$$

Where:

$\ln R$ = natural logarithm of roughness, counts per km

D = time since the last grader blading, days/100

PF = plastic factor (product of per cent finer than 0.075 mm and plastic limit),

S_1 = season dummy variable ($S_1 = 0$, if season = wet; $S_1 = 1$ if season = dry).

$P26$ = per cent finer than 26.5 mm.

N = climatic N-value

ADT = annual daily traffic

GM = grading modulus (sum of per centages retained on 2.0, 0.425 and 0.075 mm sieves /100)

A review of the implementation of an optimized maintenance management programme for unpaved roads in the Western Cape, South Africa by Van Zyl (2011) concluded that the generalization of gravel road deterioration can hinder maintenance strategy decision making. Van Zyl (2011) recommended that the optimization of grader maintenance should use a reiterative process which should incorporate local knowledge, all variables and constraints and make use of computer technology. It has been proposed that internationally accepted prediction models are no longer applicable due to the performance trends exhibited by newly designed and constructed unpaved roads (Henderson et al., 2008). A comparison of these trends is shown in Figure 2-24.

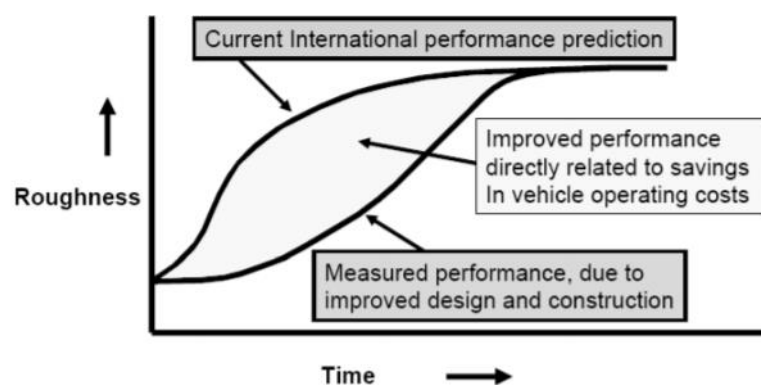


Figure 2-24: Predicted performance vs measured performance (Henderson et al., 2008).

2.4.12 Pavement condition monitoring

Pavement condition describes the ability of a pavement to sustain a certain level of serviceability under given traffic loadings and is usually represented by a condition index such as the IRI or HRI. The assessment of the condition of unpaved roads is an important part of establishing predictive PMS.

To successfully manage the maintenance of any asset, information is required to analyse what is occurring. The practice of condition-based monitoring aims to ensure better monitoring of the degradation process. Manually, this requires a tremendous amount of effort and time. In recognition of this, many companies are developing and using computerized maintenance management systems (CMMS).

Continuous, real-time monitoring of the road network with predictive maintenance allows a CMMS to assist workers in prioritising when roads should be maintained or rehabilitated by indicating a potential failure. Timely maintenance or rehabilitation activities improve road safety and comfort, preserve the asset and can be used to assist with allocating available funds and resources more intelligently (Wessels & Steyn, 2016).

2.4.13 Use of sensor technology for continuous, real-time road condition monitoring

Telematics technology is continuously evolving in terms of reduced size and cost and is currently used to monitor and manage vehicle fleets. Most telematics units incorporate Global Positioning Systems (GPS), accelerometers and gyroscopes. Global Positioning Systems are global navigation satellite systems that are used for outdoors positioning. The accuracy of the GPS for civil use is some metres, but with differential correction, it can be improved to 10 cm (Sirvio, 2015). Leading telematics companies generally have large databases to store extensive acceleration information thus it is becoming increasingly feasible to use sensor technology in maintenance management systems.

Wessels and Steyn (2016) showed that telematics technology can potentially be used to monitor the condition of the extended road network and on a continuous, real-time basis. Effective calibration and statistical analysis techniques (such as the Root Mean Square and Coefficient of Variation) were applied to vertical acceleration data harvested from telematics units to produce a class 3 RTRRMS to generate continuous data of the road condition with relatively low cost.

Obaidat and Al-Kheder (2006) investigated the potential of integrating geographic information systems, Global Positioning Systems (GPS) and computer vision systems (CVS) for the purpose of flexible pavement distress classifications. It is envisaged that the integration of GPS, GIS and CVS systems is a powerful tool for collecting road condition data economically, accurately and safely.

2.4.14 Big data

Big data is a term that is used to describe vast amounts of stored information and data that can be structured or unstructured and is typically analysed to inform strategic decisions. Data generation is occurring at a record rate which is attributed to the exponential increase in devices such as sensors, smartphones and computers. The growing availability of data creates opportunities to extract meaningful information in various fields and is becoming an increasingly feasible option due to the developments in computational power at decreasing cost.

The effective management of roads is only possible on the basis of relevant information about the current and future road surface and weather conditions on specific road sections. Such real-time information can generate a vast quantity of data and form the basis for support of maintenance decision process and efficient fleet management if relevant information can be effectively extracted.

2.4.15 Optimisation of maintenance

Gravel roads are primarily maintained by blading which involves the redistribution of surface material over the road surface using a motor grader with the aim of reducing the surface roughness (Burger & van Rooyen, 2004). Blading maintenance is important to ensure the optimal functional performance of the road is maintained (Steyn, 2018a). The optimisation is achieved by maintaining the highest surface quality at the lowest cost, minimizing the vehicle operating costs. To facilitate the optimised maintenance management of a road network, it is essential that the road network be well defined and characterised, thereafter, a number or description must be allocated to each road link which is made up of maintenance sections defined by uniform functional purpose, materials, traffic, drainage and condition. This ensures that a uniform blading activity will be appropriate for the entire length of the maintenance section which typically varies in length between 1 km and 5 km (Van Zyl, 2011). Sirvio and Hollmen (2011) recommend using road segment lengths of 100 m for network-level planning.

In order to optimise blading cycles, the functional performance of a road needs to be monitored at regular intervals to inform the blading need (Steyn, 2018a). A prediction model can be constructed from the functional performance history which should ideally consider all the variables that affect pavement deterioration although in practice the choice of variables included in the model is limited by data availability (Yu, 2005). An optimal maintenance action threshold such as a target roughness value should be allocated to each road section forming the network based on the future prediction of the road performance (Yang et al., 2006). This value can be obtained by calculating the roughness value and corresponding blading frequency that would minimize the total transportation cost of the network within a fixed budget. Alternatively, a level of serviceability (LOS) could be assigned to each road section, based on traffic volumes and function of the road. The importance of the road e.g. in terms of accessibility to medical facilities or sensitivity of agricultural produce would result in a higher required LOS (Van Zyl, 2011). Experience in southern Africa and previous studies in Namibia indicate a drastic increase in road user complaints due to IRI values exceeding 8 (Van Zyl et al., 2003). This relates to a comfortable speed of approximately 70 km/h (Van Zyl, 2011).

2.4.16 Artificial Intelligence

Artificial intelligence (AI) techniques have already been applied to pavement engineering and management (Salim et al., 2002; Salini et al., 2015). AI techniques such as fuzzy sets, neural networks, genetic algorithms, and simulated annealing can be combined with mathematical optimization methods, including linear programming or integer programming to yield powerful algorithms. However, these algorithms and methods can be difficult to program and slow to converge to a solution, and sometimes convergence is never obtained (Salim et al., 2002).

The so-called intelligence implied in “artificial intelligence” is the idea of machines being able to carry out tasks in a way humans would consider intelligent. The current application of AI is the application of Machine Learning (ML) algorithms. Machine Learning can be defined as the science of programming computers to learn as humans do and improve their learning in an autonomous fashion by feeding them continuous data and information from real-world observations to find relationships between variables without being explicitly programmed. Machine learning is a method used to construct complex algorithms that can make predictions from data.

The application of machine learning algorithms in forecasting and optimization can improve existing methods as an increasing quantity of collected data can be used by the model to improve predictions. Due to the complexity and scale of pavement management activities, traditional analytical methods used to formulate prediction models may not be able to provide accurate results (Salini et al., 2015).

2.4.17 Computational problem solving

According to Moore's law, the number of transistors in an integrated circuit doubles approximately every 24 months causing exponential growth in computational power. The use of artificial intelligence in the maintenance management of pavements has become increasingly feasible as the techniques rely heavily on computational problem solving having forecasting and optimisation algorithms in the core of the problem. In cases where a vast amount of reliable data is collected at high frequency, efficient data pre-processing and computing power is required to extract meaningful information to inform decisions (Sirvio, 2015). These new developments in data processing and high-performance computing can be applied to improve gravel road deterioration models.

2.5 INTELLIGENT MAINTENANCE

Maintenance planning is intelligent when maintenance needs are predicted and optimised. Intelligent maintenance systems require data collection, data transfer, data storage, data processing and decision support systems to be in place (Sirvio, 2015). Recent developments in information and communication technology are perhaps the main driver of intelligent maintenance systems (Sirvio, 2015). Data can be collected using intelligent asset monitoring equipment that can transmit data to a database to be processed using algorithms. The algorithms can be applied to current and historical road condition data to generate deterioration curves for each road segment allowing maintenance needs to be predicted (Sarsam, 2016). Automatic maintenance scheduling can take place to enhance maintenance quality and efficiency (Lee & Scott, 2009).

Several studies have formulated intelligent road maintenance planning approaches although these optimised maintenance approaches in the form of software solutions do not yet exist in the market and the development of customised solutions is slow and costly (Sirvio, 2015). Most of the software tools available for pavement management are essentially black-box solutions that require a large number of inputs to calculate a maintenance strategy. Although some tools allow more calibration than others, they often require inputs that are not readily available or are too expensive to collect, especially for small transportation agencies. Another limitation of the available software packages is that the output maintenance strategies are not always suitable or viable (Salini et al., 2015).

Developments in the predictability and manageability of autonomous vehicles have the potential to disrupt traditional pavement management systems (Steyn, 2018b). Construction and maintenance vehicles may soon be able to conduct autonomous maintenance based on numerous inputs from a host of sensors. Pavement management data systems need to be developed with the focus of collecting, storing, analysing and extracting relevant data in an automated fashion to allow these systems to integrate with autonomous vehicles when they become available. Although the technical knowledge and the system components required for intelligent pavement management systems already exist, they have not yet been effectively combined. The research is being slowly implemented into practice due to obstacles such as the availability of vast quantities of data which is required to form performance models using forecasting algorithms (Sirvio, 2015).

Intelligent planning relies primarily on the ability to implement accurate prediction and optimisation algorithms. Recent developments in artificial intelligence and the improved implementation of neural networks can result in prediction models of higher accuracy that can be produced in dynamic situations. Examples from real-world applications in different fields such as road and factory maintenance show that even if novel algorithms exist there are still problem areas in practical applications concerning cost modelling and data collection among other issues (Sirvio, 2015).

2.6 ARTIFICIAL NEURAL NETWORKS

A particular group of machine learning algorithms that are gaining an increasingly important role in solving prediction problems are called artificial neural networks (ANN) (Yu, 2005). ANN are valuable computational tools that are used to solve resource-intensive complex problems as an alternative to using more traditional techniques (Oladele, 2013). The concept behind ANN stems from the understanding of the functioning of the brain with the abilities of learning, pattern recognition and generalisation (Oladele, 2013). ANN simulate a collection of parallel interconnected information processing units, called neurons, which receive inputs and transfer outputs through their connections. Each connection has an associated weight that determines the strength of the connection between the neurons, an illustration is provided in Figure 2-25. Each neuron determines its output signals by applying a function to the sum of the weighted inputs received from neurons in the previous layer.

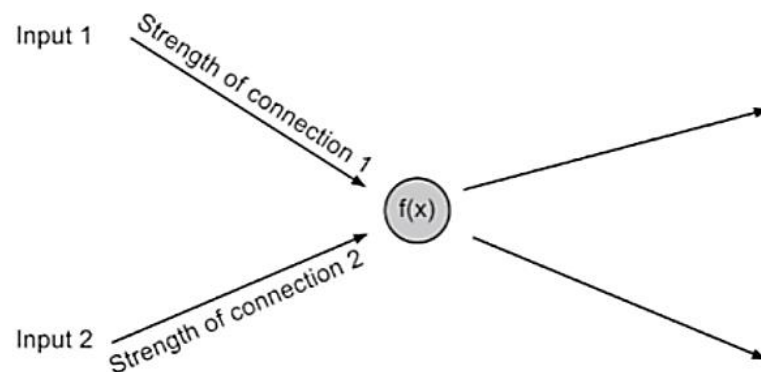


Figure 2-25: Schematic representation of an individual neuron

There are three important components which need to be considered when building ANN. They are the pattern of connection between neurons, which is referred to as the model architecture, the method of determining the weight of the connections, which is referred to as the learning algorithm and the function applied at each neuron, which is referred to as the activation function (Yang et al., 2003). The weights of the connections are adjusted using a learning algorithm. When learning takes place, the network is trained to map inputs to target outputs using a matrix of training data. At first, random weights are assumed which are adjusted after the inputs are processed by the network to produce predicted outputs which are compared to the target outputs. The error is calculated as the difference between the target output and the predicted output. This error is propagated backwards through the network by multiplying the connection weights with the error to produce new adjusted weights. This process continues until the network is sufficiently trained by minimizing the error function. This process is powerful as almost anything can be learned using sufficient quantities of data.

Programmed computational models of different types of ANN are being continuously developed. Two ANN types used for prediction models are the relatively simple feed-forward neural networks (FFNN) and more complex recurrent neural networks (RNN). The models are differentiated based on the overall architecture of the network and the way in which the networks are trained. In FFNN, the input travels in one direction and the model performs classification or regression. RNN feed information forward and backwards to train the networks and use time-series inputs and therefore produce outputs that predict a sequence of events using regression. These quantitative methods are mainly based on historical values, which means that existing historical data should be available to train the prediction models. Fitting the model on a training data set can lead to overfitting which leads to the model producing poor predictions. Therefore, a resampling method called cross-validation is used whereby the historical data is divided into training and testing sets and the testing set (which is an out-of-sample dataset) is used to validate the model to see if it generalises well on different data.

2.6.1 Advantages of using artificial neural networks

Some of the advantages of using artificial neural networks are listed below:

- It exploits non-linearity. If there is a system in which the relationship between the input and output is best described with a simple linear equation the model will behave linearly. If the relationship is best described using higher-order terms, the system becomes non-linear. Most real-world problems tend to be non-linear in nature. In artificial neural networks we have an interconnection of non-linear neurons thus the non-linearity is distributed throughout;
- ANNs learn patterns themselves through input-output mapping, which does not need to be explicitly programmed. The inputs and expected outputs are simply fed into the system in order to train it to provide the correct output from the given input;
- The adaptivity of neural networks through the tuning of the connection weights allows the robust system to solve complex problems;
- The output of the ANN not only gives us the response but it can also provide the confidence level of the response;
- The parallel nature allows the model to continue even if one element of the network fails because the neurons perform independent computation. Thus ANN has a high fault tolerance. If more neurons are affected there may be some evidence of malfunction but catastrophic failure will not occur;
- The parallel processing capability provides computational strength and efficiency as more than one computation can be performed at the same time;
- ANN can be easily implemented in almost any application if sufficient data is available; and
- If more data becomes available, the ANN can be easily improved by retraining the model using the growing database of information.

2.6.2 Disadvantages of using artificial neural networks

Some of the disadvantages of using ANN are listed below:

- The way in which the network solves the problem to produce is the output is unknown. Thus it is impossible to explain how the output was obtained reducing trust in the network;
- ANN can only work with numerical information, thus problems have to be translated into numerical values before being introduced to the ANN;
- The duration of the network training is unknown and large networks require high processing time;
- There is no specific rule for determining the optimal network structure for ANN, thus the appropriate network structure is achieved through experience and trial and error. There are many design decisions that have to be made such as the number of layers and the number of nodes in each layer, thus it may take a long time to achieve an optimal network structure if the ANN requires high processing time;
- ANN may require vast amounts of data which may be a challenge to obtain and any information that is inherent in the training data will form part of the model output.

2.6.3 Road performance prediction models using ANN

In order to understand the deterioration mechanism and predict the future condition of a pavement, it is important to study the complex interaction of the various factors that affect pavement deterioration. The effectiveness of maintenance planning is dependent on the accuracy of the predicted performance therefore if the deterioration models do not sufficiently represent the actual deterioration process, the planned maintenance strategies may be far from optimal (Lin et al., 2014). However, the pavement deterioration process is so complex that is sometimes impossible to find an appropriate functional form using traditional modelling (Lee et al., 2013). Hence, in recent years ANNs are becoming more widely used for pavement deterioration prediction modelling as ANN can represent any arbitrary non-linear function, while in regression analysis non-linearity needs to be pre-specified (Xu et al., 2014). ANN models discover implicit functions independently without having to be explicitly programmed (Luo, 2014). ANN abstract the underlying relationship between the dependent and independent variables from the training data pairs and express this relationship in the form of a matrix of the connection weights (Yang et al., 2003). They are increasingly applied in transportation in the areas of performance prediction, project prioritization and treatment selection. To illustrate the applicability of ANN models to forecast pavement condition, seven papers are introduced.

Terzi (2007) used ANN to estimate the pavement serviceability of flexible pavements using the slope variance, rut depth, patches, cracking and longitudinal cracking variables as the model input to return the present serviceability index (PSI) as the output variable. The data used in the training and test set were normalised between 0 and 1. The Levenberg-Marquardt backpropagation training algorithm was used as well as the logarithmic sigmoid activation function in the hidden and output layers. Various combinations of the network architecture were examined and the network with four neurons in the hidden layer produced the optimal model architecture. The ANN produced an R^2 of 0.99 for the training set and 0.87 for the testing set showing that ANN models can produce highly accurate models for deterioration forecasting.

Gupta et al. (2011) developed pavement performance models for low volume bituminous pavements in India using statistical analysis tools and ANN. The input parameters included the current IRI, pavement age, traffic, CBR of the soil subgrade and the pavement thickness. The pavement deflection and IRI were considered in the model output as pavement condition indicators. The backpropagation learning algorithm was used as well as the hyperbolic tangent sigmoid (Tansig) activation function. The ANN model achieved a Mean Square Error (MSE) of 0.05 per cent and an R^2 of 0.997 which was more accurate than the statistical models which achieved a maximum R^2 of 0.83 using the polynomial function.

Thube (2012) studied the implementation of ANN to forecast cracking, ravelling, rutting and roughness for low volume flexible pavements in India and compared the results to those obtained from calibrated HDM-4 models. Data including pavement distresses, subgrade characterization and traffic data were collected from in-service pavement sections over a three year period which formed 31 inputs used in the roughness progression model. Different model architectures as well as activation functions were tested on the data to determine the optimum model which would correspond to the minimum mean square error (MSE). The back-propagation learning algorithm was used for all the models. The best-fit model was found to have an architecture consisting of three hidden layers with seven neurons in each layer. The best-fit model was obtained using the hyperbolic tangent activation function. This model produced an R^2 value of 0.969 and an RMSE of 0.094 for the roughness progression model which was significantly more accurate than HDM-4 models calibrated using the same data which produced an R^2 of 0.852 and an RMSE of 0.183. The study concluded that the ANN models were more useful than the HDM-4 models for pavement condition prediction and can accurately predict cracking, ravelling, rut depth and roughness of pavements.

Suman and Sinha (2012) used a three-layer ANN trained using the backpropagation algorithm and sigmoid activation function to produce pavement surface condition forecasting models for bituminous pavements. The two input variables used in the model were the present pavement condition index (PCI) and age of the pavement, the hidden layer consisted of 10 neurons and the output neuron produced the PCI at a time in the future. The ANN was used to forecast the next PCI value of the pavement section. This forecasted PCI value was then used as the preceding PCI value to forecast the next consecutive PCI value. This process was repeated until the desired forecasting period was reached. The model reached a performance value of 7.321E-006 after 100 epochs. The performance error was quantified with a mean absolute error (MAE) of 0.184, a root mean squared error (RMSE) of 0.271 and a mean absolute relative error of 0.233 per cent. An R^2 of 0.999 was reached when comparing the predicted and observed values. It was concluded that the ANN model is capable of forecasting pavement condition when only the present condition and pavement age is known.

Oladele (2013) used feed-forward neural networks (FFNN) to model gravel road performance by producing gravel loss prediction functions. The FFNN outperformed the multiple regression model by producing a coefficient of determination, R^2 , of 0.94 in comparison to 0.74 obtained using multiple regression. The FFNN model used the Levenberg - Marquardt (L-M) method for training and input variables relating to the gravel material quality, traffic volume, gravel thickness and gravel road conditions such as potholes, loose material and stoniness.

Taddesse (2013) developed rutting prediction models for stone mastic asphalt pavements from in-service road data using multiple linear regression (NLR) and a three-layer ANN. The factors influencing rutting progression used as input into the models were the pavement age, pavement layer thickness, traffic levels and precipitation. The ANN model was designed using the backpropagation learning algorithm. Different combinations of activation functions were tested in the hidden and output layers. The combination of hyperbolic tangent function for the hidden layer neurons and the sigmoid function for the output layer neurons produced the model with the best fit and smallest error. The optimum number of neurons in the hidden layer was determined based on a trial-and-error procedure which produced an optimum number of 13 neurons in the hidden layer. The MLR model produced a maximum R^2 of 0.595 whereas the ANN model produced a maximum R^2 of 0.761 thus the ANN models predicted the rut depth with greater accuracy than the MLR models.

Georgiou et al. (2018) developed models for the prediction of pavement roughness for high volume flexible pavements in terms of the IRI using ANN and another form of artificial intelligence called support vector machines (SVM). The historical roughness IRI gathered over 6 years using a laser profiler system was used as the model input. The ANN was designed with three layers, using the backpropagation learning algorithm and the hyperbolic tangent and sigmoid activation functions. The comparative study concluded that the ANN model performed slightly better at predicting the pavement roughness achieving a mean absolute error (MAE) of 6.9 per cent for the ANN model and 7.7 per cent for the SVM model although both models are suitable for accurate pavement roughness predictions.

As listed above, many neural network studies have been conducted to predict pavement condition although relatively few have focused on unpaved roads. This may be due to the fact that relatively little data is available for unpaved roads due to the lower traffic volumes and maintenance budgets typical of unpaved roads. Although artificial intelligence-based methodologies have demonstrated favourable results for pavement condition prediction, so far the number of successful applications transforming those possibilities into real results is by no means substantial, suggesting that the practical AI tools are underutilized in this specific field (Salini et al., 2015).

3 METHODOLOGY

As unpaved roads are used extensively in agricultural production, deteriorate relatively quickly and generally have a higher roughness than paved roads, this project focused on the deterioration and maintenance management of unpaved roads. This chapter presents the process followed to generate deterioration models for unpaved roads based on historical roughness data as well as the formation of a maintenance management strategy cost-benefit analysis tool that can be used to enable tomato farmers to optimise their road maintenance expenditure according to their desired output. This chapter is organised into three sections, namely; data collection, data preparation and data analyses and presents these topics in great detail to allow the processes to be easily replicated for use on other roads with similar data availability.

3.1 DATA COLLECTION

Data was collected on roads in various parts of Limpopo, mostly concentrated around the areas of Mooketsi and Malale, with the assistance of the agricultural organisation, ZZ2 and the vehicle tracking company, Tracker. The collected data included time-lapse images of the roads of interest, road condition data, daily rainfall captured manually on the surrounding farms and road maintenance history data for the selected roads of interest. Models relating the deterioration of tomato quality as a function of road roughness were developed by Pretorius (2017) and used in the analysis. The methods used to collect the data are explained in the following sections.

3.1.1 Road network data collection

The unpaved road network linking the farms and packing houses of the agricultural organisation was constructed using minimal designed input. Thus the geographical location and geometric details of the road network were unknown and had to be captured in a short period of time. The geographical location of the roads was captured in the field using a GeoTrace and some network details, such as the location of intersections, gates and booms were captured using GoPro footage of the roads of interest. The data was uploaded to an online database. A visual representation of the extensive unpaved road network managed by the agricultural organisation is given in Figure 3-1.

The unpaved roads form clustered networks that are situated as far as 200 km apart. It is a challenge for the organisation to optimise their maintenance planning and the use of their maintenance vehicles due to the time involved in transporting the maintenance vehicles from one road to another. It is desired that the maintenance of each road should coincide with the harvesting season of the surrounding farms so that the produce from each farm will be transported on roads with high surface quality from the farms to the packing houses and from the packing houses onto the paved secondary and primary road networks to the marketplace.

Although the agricultural organisation farms a variety of crops, tomatoes form the largest percentage of their output and they currently provide 40 per cent of South Africa's tomatoes. Tomatoes are soft-skinned fruits and are therefore sensitive to the vibrations experienced when transported over roads with high surface roughness. The tomato farms managed by the organisation are concentrated around the Mooketsi area and therefore this area was chosen as the focus for this study.

Details of the road structure, materials, slope, geometry and drainage capacity were unknown. Staff were unavailable to capture these details thus it was decided to use a GoPro Hero 6 to capture visual imagery and geographical information of the roads of interest relatively quickly and at a relatively low cost so that areas of consistently high roughness could be superficially examined from a desktop for possible structural, geometric or drainage flaws.

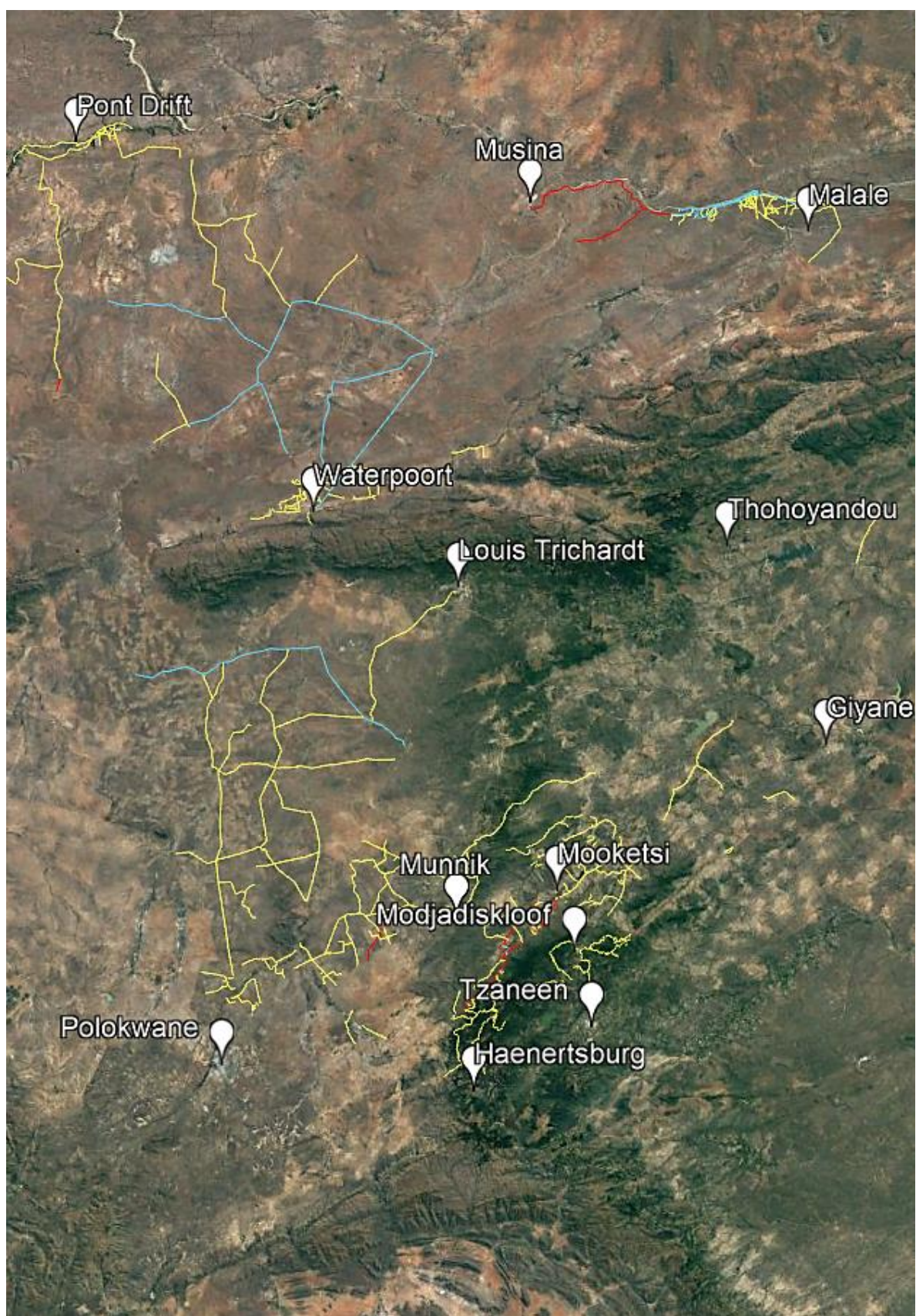


Figure 3-1: Unpaved road network managed by the agricultural organisation

GoPro Hero 6 capabilities in road network data capturing

A GoPro is a compact action camera that is capable of capturing photos, videos and time-lapses in extreme weather conditions with high-quality. The GoPro Hero 6, shown in Figure 3-2, was the latest GoPro available at the time of the study with the ability to capture and embed GPS data (such as the location, speed and altitude of the camera) into an image. The ability to embed the GPS details with the visual imagery made the GoPro Hero 6 a useful choice for capturing details of the road network.



Figure 3-2: GoPro Hero 6

Setup of GoPro Hero 6 for road network data capturing

The GoPro was inserted into a protective weatherproof case and attached to the roof of a Toyota Hilux vehicle using a mechanical arm and a suction cup. The placement of the GoPro on the roof of the vehicle prevented glare from being captured in the images. The angle of the GoPro was measured and fixed at 45 degrees to the normal which allowed a clear view of the road as well as of two black identification points on the bonnet of the vehicle to be captured in each frame. The identification points provided a frame of reference for the image pixels to be scaled. A visual representation of the setup is shown in Figure 3-3.



Figure 3-3: Setup of GoPro Hero 6 on Toyota Hilux construction vehicle

The GoPro settings that were used to capture the visual imagery of the roads is provided in Table 3-1.

Table 3-1: Recommended GoPro settings

Setting	Recommendation
Mode	Time-lapse photo
Frame rate	1 second
Field of view (FOV)	Linear
Quality	1080p

It is recommended to operate the GoPro from inside the vehicle using the GoPro Quik software downloaded onto a mobile device and to mount the GoPro externally to the vehicle in order to reach the desired angle and avoid glare. Operating the GoPro from a mobile device has the added benefit of preventing the setup angle from being incrementally moved by the pressure required to be applied to the buttons of the GoPro in order to operate it. An example of the images captured using the described GoPro setup is provided in Figure 3-4.



Figure 3-4: Road image captured using GoPro

The images allow details such as the surface type of the road and the existence and location of large drainage structures, shoulders, fences, gates, booms, speed bumps and large defects in the road surface to be identified and recorded. Capturing images at regular intervals allows changes in the road geometry to be identified and may assist with identifying causes of rapid road deterioration. The images can be downloaded and the data extracted from an office environment much faster than the current practice used at the agricultural organisation whereby a data capturer is sent into the field to create a record of the feature of interest by stopping at every feature, completing a predefined digital form and capturing an image of the feature before uploading the data for review. The GoPro can capture data for approximately 4 hours before needing to be recharged. It is recommended that the images be removed from the memory card after each day of use before capturing new images of the road network.

Extraction of geometric features from imagery

An attempt was made to extract the width of the road from the visual imagery using an automated method. The algorithm approach consisted of counting the number of pixels contained in a horizontal band across the width of the road feature. The extent of the road surface was identified using a range of explicitly programmed colours unique to the road surface, however, using an explicitly programmed colour range was found to be an ineffective approach as the road surface colour varied rapidly from frame to frame. Currently, road lane detection is used successfully on paved roads as the white paint markings are easily detected against the dark asphalt. For unpaved roads, there is no singular feature that can be simply detected to extract the edge of the road.

There are various factors affecting the uniformity of the images that made the explicit programming of the road edge detection impractical. These factors included shadows cast by trees, passing vehicles and gatehouses which affect the colour range of the road surface, excess road material located adjacent to the road surface, changes in lighting conditions due to the variability of sun exposure, the presence of roadside furniture and vehicles and lastly, changes in the material surface colour due to variances in the saturation of the soil and variances in the materials used for the construction of the road. The variances in the images occurred at a considerably high frequency. Examples of the variances captured in the imagery are provided in Figure 3-5 to Figure 3-14.



Figure 3-5: Example of excess road material



Figure 3-6: Example of the effect of shadows



Figure 3-7: Example of change in exposure 1



Figure 3-8: Example of change in exposure 2



Figure 3-9: Example of roadside furniture 1



Figure 3-10 Example of roadside furniture 2



Figure 3-11 Example of non-homogenous soil texture



Figure 3-12 Example of non-homogenous soil saturation



Figure 3-13: Example of variance in road surface colour 1



Figure 3-14: Example of variance in road surface colour 2

An attempt was made to extract a measurement of the road segment width in defined ranges using a convolutional neural network typically used in the extraction of categorical information from imagery. However, this approach was not feasible as the quantity of visual data available was not sufficient to train a neural network. However, it must be noted that extracting measurements from visual imagery is currently used for paved road management systems and the extension to unpaved roads will be extremely beneficial for the efficient and effective management of unpaved roads.

3.1.2 Road condition data collection

Data of the road condition was provided by vehicle telematics company, Tracker. Vehicle dynamic motion data was captured using the SkyTrax telematics device shown in Figure 3-15 which was installed into the centre compartment of the Toyota Hilux construction vehicle used by the agricultural organisation, henceforth referred to as the Data Capturing Vehicle. The device is constituted of a GPS, accelerometer and gyroscope. The device is low cost and is suitable to quantify vehicle dynamic motions (Wessels, 2017).



Figure 3-15: SkyTrax telematics device (Tracker Connect Pty Ltd, 2017)

An algorithm was developed by Wessels (2017) to accurately estimate the road roughness in the form of the HRI in m/km for the dynamic response exhibited by the Data Capturing Vehicle. This algorithm was applied by Tracker to the data generated by the telematics device to provide a reasonable estimate of the road roughness. The road roughness data was provided in the form of a spreadsheet with data points captured for every second that the Data Capturing Vehicle was operated at a speed of 20 km/h or more. Road condition data was captured for every road driven by the Data Capturing Vehicle for the 16 months spanning from 3 April 2017 until 31 July 2018. The road condition data points were mapped to road segments defined by Tracker. The segments were assigned ID numbers and delineated based on the location of intersections and changes in road surface material. The road segment lengths varied between 3 m and 13 570 m. A single road condition data point was constituted of the date, time, longitude, latitude, segment ID and estimated road roughness.

The segment ID numbers for the roads of interest managed by the agricultural organization were extracted by plotting all of the road condition data points provided by Tracker in the Microsoft analytics software Power BI and manually identifying the segment ID numbers that corresponded with the roads of interest. The segment IDs were verified by reversing the process, plotting only the identified IDs and ensuring that the data points fell on top of the roads of interest and that the identified segments met end to end. The separation and extraction of the relevant data points for each road of interest were automated using the general-purpose programming language, Python. The entire dataset was loaded as a database which was subdivided into smaller databases corresponding to each road using the relevant segment IDs identified in Power BI. The smaller datasets were easier for the computer to manage and increased the data processing speed.

3.1.3 Rainfall data collection

Rainfall data is vital to the accurate modelling of unpaved road deterioration due to the detrimental effects of water ingress and pooling. Fortunately, this data was captured manually at the rain gauge stations managed by the farming organisation, the locations of which are shown in Figure 3-16.



Figure 3-16: Location of rain gauge stations managed by the agricultural organisation

The density of the rain gauge stations corresponds to the density of the farms managed by the agricultural organisation thus it can be noted that most of the farms are located in the area northeast of Polokwane known as Mooketsi. The Doddington rain gauge station ceased operation in February 2017 thus there was no data available from this rain gauge station for the analysis period which fell between April 2017 and July 2018.

3.1.4 Road materials

Although material properties play an important role in road deterioration, the road material properties were not measured or recorded by the road authority and could not be obtained at the time of the study. However, it can be noted that similar materials were present on all roads in the study area.

3.1.5 Road maintenance data record

The agricultural organisation provided details of the maintenance conducted on their unpaved roads in the form of a spreadsheet consisting of the date, construction vehicle employed, total hours and hourly cost of the construction vehicle. Graders are used to improve the surface condition of the roads and are generally followed by single drum vibratory rollers to compact the surface, further decreasing the roughness and improving the strength of the surface. Water trucks are employed daily on all of the main unpaved roads to minimise dust and maintain the quality of the road surface. No re-gravelling activities were conducted on the roads. The gravel depth of the roads is unknown and is not measured by the agricultural organisation. From observation, it was noted that the gravel on the surface of the highest priority roads was hardly visible and thus some of the most highly trafficked road sections may be classified as earth roads.

3.1.6 Models of the deterioration of tomato condition vs road roughness

Pretorius (2017) investigated the influence of road condition on the shelf-life of tomatoes. Relationships were developed between road roughness, measured as IRI in m/km and shelf-life, measured in days, for tomatoes of varying degrees of ripeness indicated by the colour of the tomato skin. The tomatoes were exposed to vibrations with a frequency of 13 Hz (corresponding to the axle hop of the transportation vehicle) and an amplitude of 5 mm in a laboratory setting for time periods of 60, 600 and 6000 seconds. The relationships developed by Pretorius (2017) are summarized in Table 3-2.

Table 3-2: Relationships between shelf-life of tomatoes in days vs road roughness IRI m/km

Ripeness	Roughness interval	60 second exposure	600 second exposure	6000 second exposure
Red	$x \leq 3.5$	SL = 10.0	SL = $-1.14x + 10.0$	SL = $-1.11x + 9.95$
	$x > 3.5$	SL = $-0.22x + 10.76$	SL = $-0.43x + 7.52$	SL = $-1.11x + 9.95$
Pink	$x \leq 3.5$	SL = 10	SL = $-0.29x + 10$	SL = $-0.29x + 10$
	$3.5 > x \leq 5.49$	SL = 10	SL = $-1.51x + 14.28$	SL = $-1.73x + 15.06$
	$x > 5.49$	SL = $-0.38x + 12.09$	SL = 6	SL = $-1.73x + 15.06$
Green	$x \leq 3.5$	SL = 10	SL = $-0.62x + 10.06$	SL = $-0.57x + 10.0$
	$x > 3.5$	SL = $-0.22x + 11.73$	SL = $-0.62x + 10.06$	SL = $-1.52x + 13.3$

Note: x represents the road roughness in m/km.

3.1.7 Data availability

It must be appreciated that real historical data often do not have perfectly complete data sets with consistent measurement intervals and flexible scheduling that allow for simple modelling and relationship extraction that is possible from carefully planned experimental outputs. However, analysing the performance of real road segments that have been exposed to natural deterioration mechanisms and maintenance measures has the unique benefit of showing how these types of roads behave in reality. Details of the pavement structure, age and material construction technique were unknown and could not be obtained. However, it is assumed that these parameters are similar for the roads analysed as they are closely situated priority roads constructed and maintained by the same authority.

3.2 DATA PREPARATION

The road network images, road condition data, rainfall data and maintenance history data collected during the project were pre-processed into a form that was suitable for analyses. The data preparation process was automated as far as possible using the general programming language, Python, to allow the process to be easily extended to any roads that may become of interest and for which the necessary data is available.

3.2.1 Selection of roads for analysis

The gravel roads used in the analyses were selected based on their priority to the farming organisation, proximity to tomato farms and packing houses and the quantity of road condition data available for the road sections forming the length of the road. The selected roads, namely the Vreedsaam, Houtbosdorp and Jachtpad roads, had the longest HRI record lengths of all the roads captured using the Data Capturing Vehicle with data captured on 146 days, 98 days and 304 days respectively over the 16 month analysis period from April 2017 until July 2018. The roads are all frequently used for the transportation of tomatoes from the farms situated along the Vreedsaam and Houtbosdorp roads to the packing house situated along the Jachtpad Road. The roads are situated in and around Mooketsi, Limpopo and are shown in Figure 3-17.

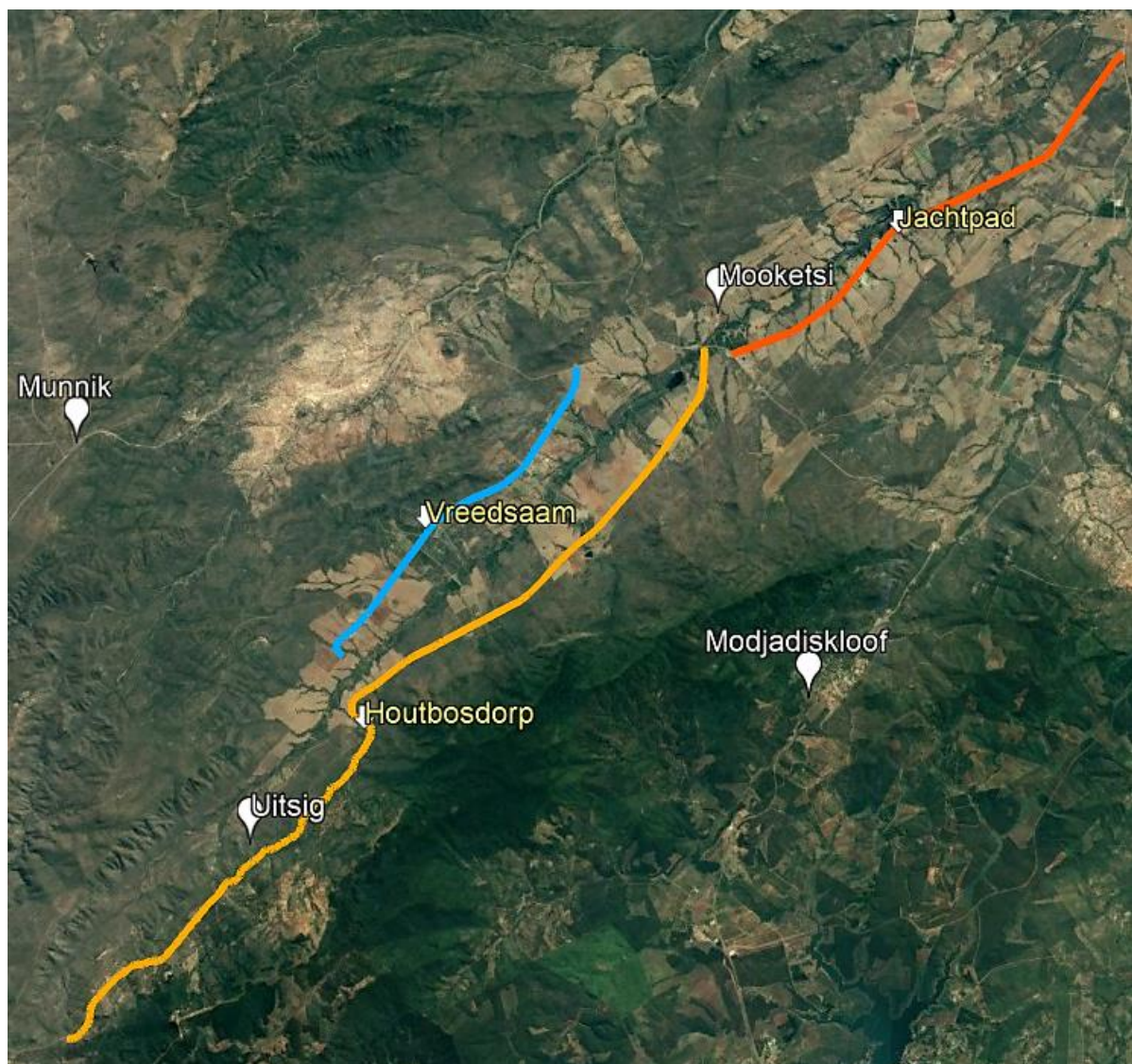


Figure 3-17: Location of the gravel roads used in the study

3.2.2 Segmentation of the roads of interest

The road condition data provided by Tracker was associated with specific road segments delineated by Tracker based on the intersection of the roads with other priority roads and changes in the pavement surface material. The segments forming the length of the selected roads were manually identified using the Microsoft analytics software Power BI. The road condition data points were plotted in the Power BI software and the segment numbers of the points falling along the selected roads were identified. The segment numbers were verified by plotting the identified section numbers individually to confirm that the sections did indeed form part of the selected roads and that the section boundaries met end to end.

The delineation of the road segments was not altered so that an automated process could be developed and used to prepare the data for analysis simply and seamlessly from the data provided from Tracker and to allow the process to be extended to any road with road condition data captured by the Data Capturing Vehicle. An automated data preparation process may be a useful tool to the agricultural organisation. It should be noted, however, that the segmentation of the roads could be improved for maintenance purposes by determining an optimal minimum segment length that would be economically feasible for grading and maintenance activities taking the cost of transporting the maintenance vehicles to the site into consideration.

The details of the road segments such as the longitude and latitude of the starting and endpoints and the lengths of the segments were obtained from the road condition data provided by Tracker. The data for the elevation profiles of the segments were obtained from plotting the segment coordinate boundaries in Google Earth, joining the coordinates using a polyline and extracting the KML data representing the road segment.

3.2.3 Preparation of road network images

Once the time-lapse images of the roads had been captured and downloaded from the GoPro, it was difficult to establish which of the images corresponded to each road as the images were placed into automatically generated folders on the SD card of the GoPro such that each subsequent folder was filled until a maximum capacity of 999 images was reached regardless of the time-lapse sequence that the image formed part of. In instances where more than one road had been captured in a single field trip without first removing the images from the SD card it became difficult to distinguish which roads the images represented thus an algorithm to sort the images into a user-friendly file system was programmed in Python.

The Python script requires the folders on the SD card to be copied to a storage device before running the algorithm on the specified folder. The algorithm sorts the images into separate folders for each road using the geotags (and specifically the longitude and latitude of the images) embedded into each image by the GoPro, then by date and lastly by time to distinguish between different time-lapse sequences. The algorithm starts by moving all of the images into a single folder before moving the images again based on the pre-defined criteria previously described. The script can also be used to sort the images by road segment if adequate boundary coordinates are established for the road segment of interest and can similarly be extended to any road that may become of interest to the agricultural organisation. A rectangular-shaped boundary sorted the images with 100 per cent accuracy.

The images allow the engineer to visually compare changes in the road sections over time and superficially identify possible factors contributing to rapid road deterioration. The image database may become more useful over time as more data is collected and the images can be compared over the years. It is recommended that image data be collected biannually in the late morning or early afternoon on a clear day. The script used to sort the images is provided in Appendix A.

3.2.4 Rainfall data

Due to the proximity of the roads chosen for analyses and the respective locations of the rain gauge stations, the data from the PD, ES and WP rain stations were discarded as they fell far beyond the catchment area of the selected roads. The locations of the selected rain gauge stations and roads used in the analyses are provided in Figure 3-18.

The spreadsheets containing the datasets from the relevant rain gauge stations provided from the farming organisation were loaded and merged into a single data frame in Python. No significant outliers were identified in the datasets. The daily rainfall landing on a given road segment was calculated by weighting the rainfall data.

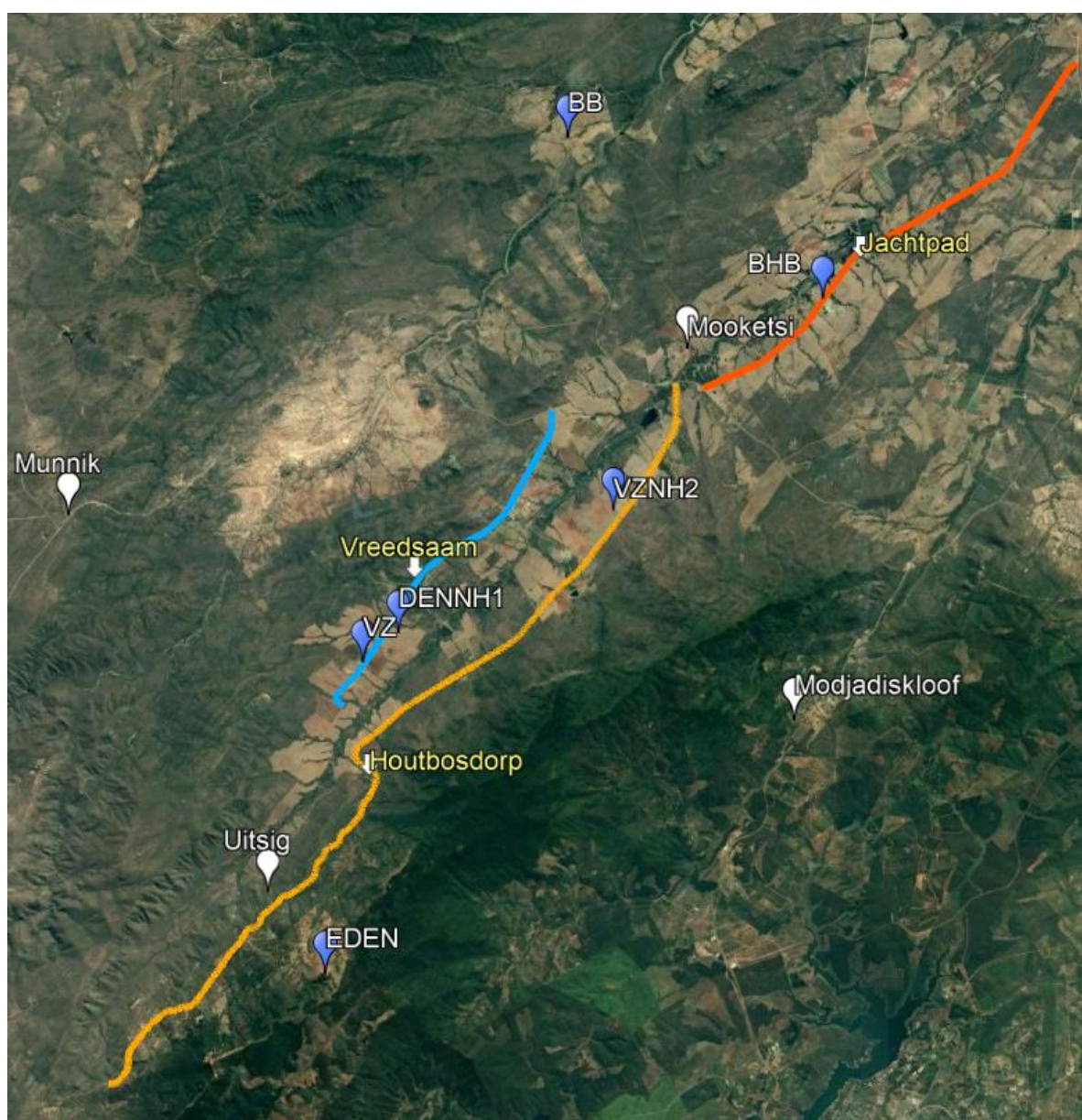


Figure 3-18: Location of selected roads and rain gauge stations

Weighting the rainfall data

A representative daily rainfall falling on each road segment was estimated by weighting the rainfall from each rain gauge station on a linear probability scale defined by the relative distances of the stations from the centre of the road segment.

3.2.5 Road condition data

A great emphasis was put into the data preparation process because it was a vital step for the development of robust deterioration models from big data. Therefore, the approach for preparing the road condition data for use in the development of pavement deterioration and condition forecasting models is demonstrated. It involves data cleaning, filtering and alignment, the establishment of boundary limits and compiling and splitting datasets (Alaswadko, 2016).

Splitting the datasets

The spreadsheets obtained from Tracker containing the road condition data were large enough to cause tremendous difficulty filtering the datasets using Microsoft Excel due to memory and processor limitations of the desktop computer, therefore, the datasets were prepared using Python. The road condition spreadsheets for 2017 and 2018 were merged into a single data frame before the datasets were split into smaller datasets representing each road of interest and the segments for the roads by using the road segment identification numbers forming the length of the three roads of interest. The automated script can be expanded to include other roads if the identification numbers of the segments forming the length of the road are known or have been identified using the Power BI software.

Weighting the road roughness data

The estimated HRI values provided by Tracker for every second that the Data Capturing Vehicle travelled at a speed of 20 km/h or greater were not useful in this specific form thus the HRI values were averaged to provide a representation of the average condition of the road segment per day of data collection. The daily average estimated HRI for each road segment was calculated using Equation 3-7.

$$\text{Daily average estimated HRI} = \frac{\sum \text{estimated HRI} \times d}{\sum d} \quad (3-7)$$

Where d represents the distance traversed by the Data Capturing Vehicle in the 1 second period over which the HRI was calculated. The distance, d was calculated using the haversine formula which gives the shortest distance over the earth's surface between two points. The haversine formula is represented by Equation 3-8 to Equation 3-10.

$$a = \sin^2(\Delta\varphi/2) + \cos \varphi_1 \times \cos \varphi_2 \times \sin^2(\Delta\lambda/2) \quad (3-8)$$

$$c = 2 \times \text{atan2} \left(\sqrt{a}, \sqrt{(1-a)} \right) \quad (3-9)$$

$$d = R \times c \quad (3-10)$$

Where:

φ	=	Latitude in radians
λ	=	Longitude in radians
R	=	Radius of the earth (6371 000 m)
d	=	Distance (m)

3.2.6 Concatenating the roughness and rainfall data

The dates on which rainfall events occurred and the dates on which road condition data was collected did not always correspond hence when the road condition and rainfall datasets were concatenated into a single time series, the road condition had to be interpolated. In order to determine the most appropriate form of the road roughness interpolation function, samples from the road roughness condition data collected over one-day intervals were plotted for all of the roads. Examples of the change in road condition over one-day intervals are provided in Figure 3-19.

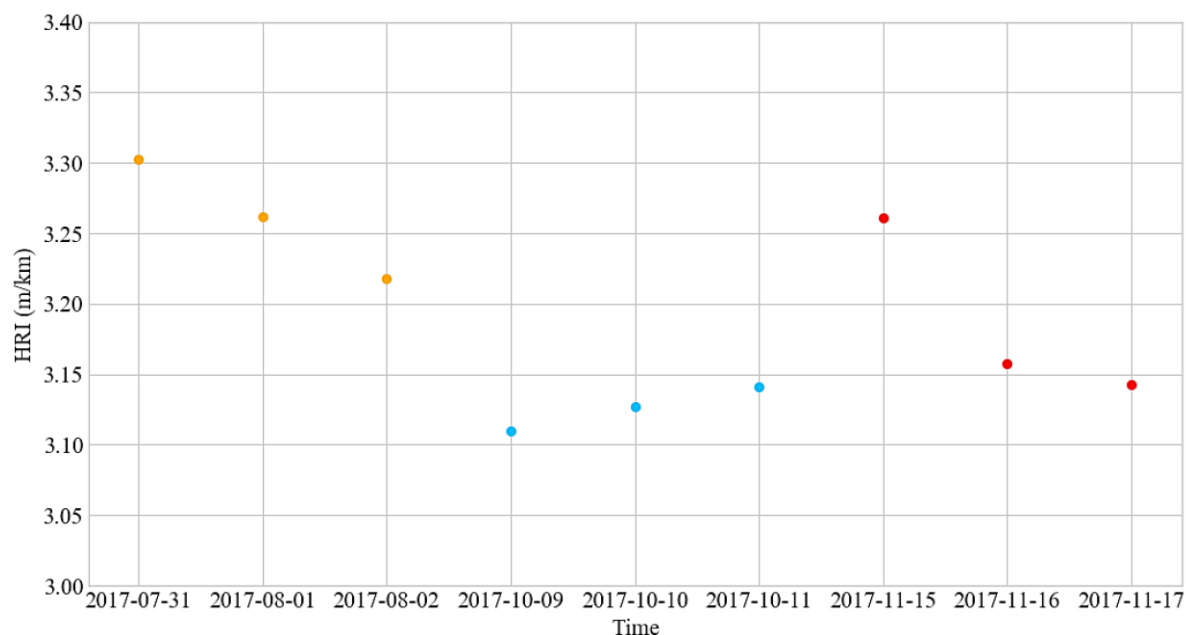


Figure 3-19: Samples of road condition change over single day intervals

In the majority of cases, a linear function was the most suitable to represent the change in road condition over one day intervals, thus it was assumed that a linear interpolation function would be suitable to predict the road condition for days on which data was not collected due to the relatively short time intervals between the days on which the road condition was measured.

3.2.7 Road maintenance history data

The road maintenance history data obtained from the agricultural organisation was filtered in Microsoft Excel, isolating the days on which water trucks, graders and rollers were employed on the Houtbosdorp, Vreedsaam and Jachtpad roads over the 16-month analysis period. The filtered dates imported as a Python data frame. The Jachtpad road received the most frequent maintenance although the grader was employed for a similar number of days on the Houtbosdorp road. This is due to the fact that the length of the Houtbosdorp road is over twice the length of the Jachtpad road thus more days were needed to grade the Houtbosdorp road in a single grading activity.

3.2.8 Segregation of time-series datasets into isolated periods of deterioration

Data frames were created in Python containing pairs of dates corresponding to the intervals between gradings for each road over the analysis period. These date pairs were used to extract sections from the road condition data frames to remove the influence of maintenance on the measured road condition data and isolate the periods of deterioration for each road. These segregated datasets containing road condition and rainfall data between grading events for each road were filtered to remove datasets containing less than 4 data points before the datasets were plotted from the origin to represent the observed deterioration of the roads without the influence of maintenance.

3.3 DATA ANALYSIS

This section describes the processes applied to the data in order to generate road roughness deterioration models that can be used to predict the future condition of the road. Thereafter the processes of applying the models to generate optimal grading trigger values are described.

3.3.1 Application of deep learning in the form of LSTM Models

A robust long short-term memory (LSTM) ANN model was scripted in Python using the Keras library to determine whether the ANN was suitable to predict the future trend of the road condition using the historical road condition data. The model structure had four layers and included dropout regularization in order to prevent the model from overfitting to the data. The data was prepared by splitting the dataset according to an 80/20 ratio to be used separately for model training and model validation. The datasets were pre-processed by normalising the data to a smaller range in order to reduce the time required to fit the model to the data and reduce the computational intensity. The following equation was applied for the normalisation process:

$$X_{norm} = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (3-11)$$

The rectifier function was used as the activation function in the hidden layers and the sigmoid activation function was selected for the final output layer as recommended in the literature study. The model parameters included the time-steps, epochs, number of neurons and batch size. The model was run on the pre-processed data and the output obtained for the Jachtpad Road using various time-steps is provided in Figure 3-20 to Figure 3-22.

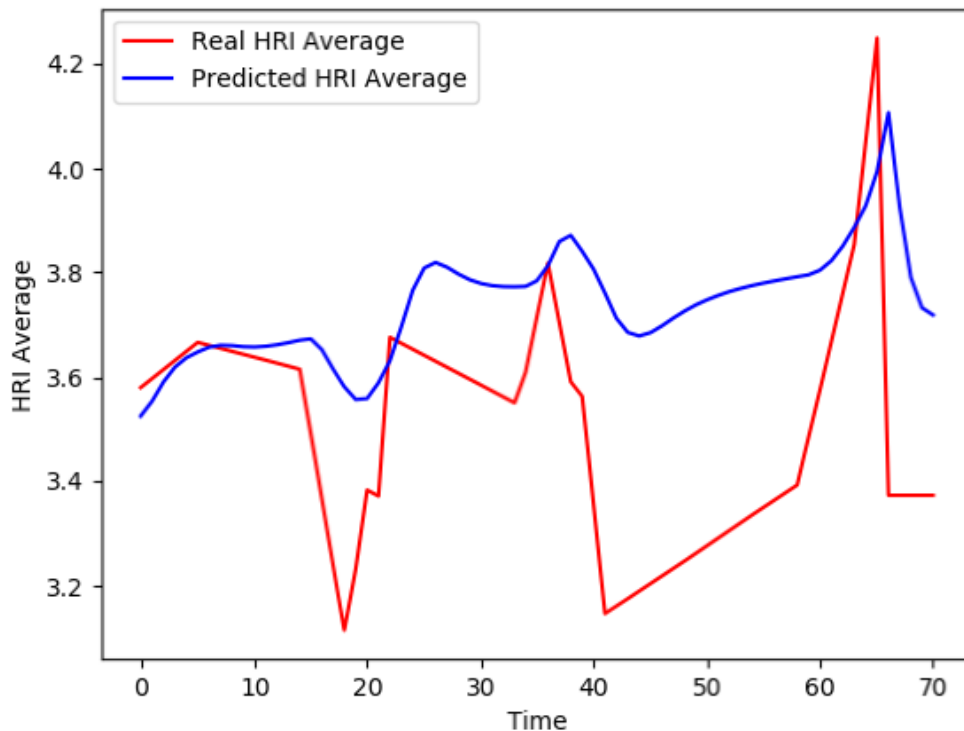


Figure 3-20: Predicted and Real HRI vs time for ts = 60, epochs = 100, neurons = 50 and batch size = 5

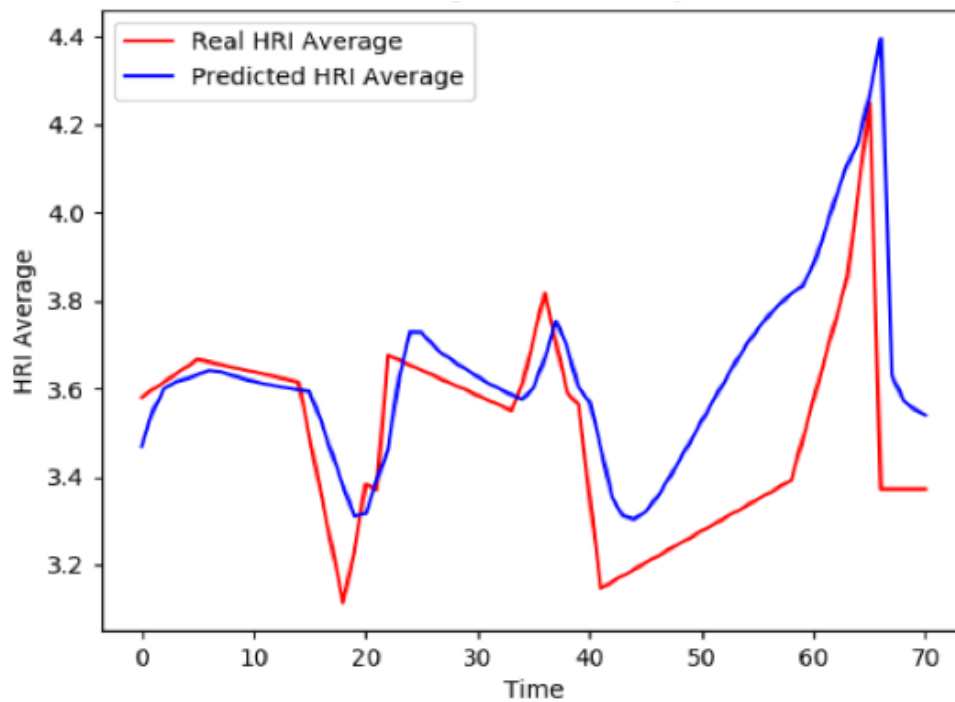


Figure 3-21: Predicted and Real HRI vs time for $ts = 30$, epochs = 100, neurons = 50 and batch size = 5



Figure 3-22: Predicted and Real HRI vs time for $ts = 70$, epochs = 100, neurons = 50 and batch size = 5

The models took up to 24 hours to compute and produced a prediction of the change in road condition over time. The model is successful in predicting the trend of the road condition progression, however, owing to the fact that the maintenance data is embedded in the datasets, the resulting output yielded from the LSTM model is not a prediction of the road condition deterioration but rather a prediction of the state of the road condition if the current maintenance strategy continues to be employed into the future without alteration. Furthermore, the form of the model solution is not easily implementable into a cost-benefit analysis tool as the LSTM model does not yield a closed-form solution that can easily be applied by road maintenance staff who are not familiar with Artificial Neural Networks.

3.3.1 Isolating the effect of maintenance on the road roughness deterioration

In order for predictive road deterioration models to be generated from the real road condition data collected for the study, the effect of the maintenance activities performed on the roads had to be removed from the datasets. This was achieved by isolating the data points between the dates on which grading activities were performed. Due to the relatively high frequency of the maintenance activities in comparison to the relatively low frequency of road roughness data collection, the isolation of the deterioration trends resulted in a vast quantity of small datasets rather than a small number of large datasets previously input into the LSTM model. These datasets were too small to be used to train and validate any form of ANN model, thus the LSTM model could not be applied to generate predictive deterioration models from the available data.

The isolation of the road condition deterioration between maintenance activities placed a further limitation on the usefulness of the rainfall time series data due to most of the isolated datasets considered large enough for modelling purposes containing only a singular rainfall event. This limitation can be attributed to the relatively high frequency of maintenance activities in comparison to the relatively low frequency of rainfall events.

In order to model the general road deterioration trend of each road segment, the road roughness deterioration datasets were aggregated by plotting the start of each deterioration period from the origin, which represented the end of maintenance activity, for the datasets belonging to the same road segment. Thus the unit of the deterioration period was plotted in days. No trends were visible from the aggregated data for each road segment as the roads were frequently maintained. Further pre-processing was conducted on the datasets, starting with the normalisation of the deterioration period.

3.3.2 Normalising the deterioration period

The datasets representing the deterioration of the roads were normalised by converting the time period over which the deterioration occurred from the time given in days to time given as a percentage of the deterioration period. Thus all the deterioration periods were assumed to reflect the same degree of deterioration which was considered valid as the scheduling of the grading activities conducted on the roads was based on similar perceived deterioration. Although this assumption limits the applicability of the models generated from the data, it was necessary for the development of the road roughness progression models from real data which was not obtained under fully controlled circumstances or generated at ideal specified frequencies. It must be noted that changing the scale of the deterioration period had the added effect of removing the sequencing of the rainfall events, thus the rainfall data could no longer be utilised as a time series parallel to the road condition data, however, the effect of rainfall on the road deterioration was retained by categorising the datasets for the wet and dry seasons.

3.3.3 Splitting the deterioration datasets

The datasets containing the normalised deterioration data for each road were segregated according to the major factors known to affect road deterioration such as rainfall, slope and traffic thus the datasets were split according to dry and wet seasons, flat and mountainous segments as well as low trafficked segments and relatively high trafficked segments. This segregation was conducted to identify whether the deterioration trends would become more uniform as the datasets were controlled for various factors known to affect roughness progression. The segregation of the data generated a large number of small datasets, where most datasets contained fewer than 4 data points, which were not considered sufficient for the generation of reliable road roughness progression models. Thus larger datasets were created from the segregated data by aggregating the data points for road segments (belonging to various roads) with data belonging to road segments with similar characteristics which were possible due to the normalisation of the deterioration period conducted previously.

3.3.4 Grouping the datasets according to similar road segment characteristics

The roughness progression trends exhibited by the normalised datasets were aggregated for datasets belonging to road sections with similar traffic and slope characteristics over the wet and dry seasons to form larger datasets. This allowed mathematical curves to be fitted to the data to enable road deterioration to be predicted for various types of unpaved road segments over both the wet and the dry season.

3.3.5 Development of roughness deterioration models

Linear and non-linear regression analyses were performed on the grouped datasets using logarithmic, exponential and linear model functions. The linear regression models were evaluated by comparing the goodness-of-fit of the regression indicated by the coefficient of determination R^2 . The linear and non-linear models were compared by analysing the residuals and predicted values of the models. The final road deterioration models were selected based on both the goodness-of-fit parameter and the ability of the model to predict the variability in the data.

3.3.1 Multivariate Analysis

Although at this stage in the data analysis process it would be beneficial to perform a multivariate analysis in order to quantify the effect of each road deterioration factor on the exhibited deterioration, the available data was found to be unsuited to a multivariate analysis due to the datasets between maintenance activities containing few data points caused by the relatively high frequency of maintenance actions compared to the relatively low frequency of road roughness measurement events. Additionally, the isolation of the roughness progression between maintenance activities transformed the rainfall time-series into a non-numeric, categorical variable, similar to the traffic and slope variables, which made the application of a multivariate analysis even more impractical.

3.3.2 Defining maintenance cost models

The final road deterioration models were analysed to determine the number of maintenance interventions that would be required to maintain the respective road types below specific roughness thresholds over an annual period. The cost of the annual maintenance interventions for various road section types was calculated per hour required to complete a maintenance activity on the road based on the required number of annual grading activities and the hourly cost of vehicle hire. Thus, the length and distance of the road segment to be maintained remain a variable that can be incorporated into the cost model by multiplying the sum of the number of hours required to transport the grader and grade the road in a single grading activity by the annual maintenance cost given in the model.

3.3.3 Application of shelf-life models to road condition data

Models of the expected shelf-life of tomatoes with varying degrees of ripeness transported over roads with constant roughness for a period of 10 minutes simulated in laboratory conditions were developed by Pretorius (2017). These models were plotted to visually compare the relationship between the maintenance cost and the shelf-life deterioration as a function of various roughness values which can be used to trigger grading activities.

3.3.4 Optimisation of maintenance cost and shelf-life

The optimum HRI values for the triggering of grading activities were obtained by finding the HRI that simultaneously gave a minimum of the annual grading cost and a maximum of the tomato shelf-life. The optimum HRI trigger values were calculated by finding the point at which the difference between the annual grading cost curve and shelf-life curve was at a maximum. The optimum HRI trigger values, as well as the corresponding maintenance cost and expected shelf-life, were tabulated.

4 RESULTS

This chapter presents the results produced following the data preparation procedures and analysis of the data discussed in the previous chapter. The accuracy of the results achieved from the data analysis could be improved by expanding the database used in the analysis.

4.1 ROAD NETWORK CHARACTERISTICS

The three gravel roads analysed in the study are managed by a single agricultural organisation and are all situated within a 25 km radius. The roads differ by length, slope and traffic volume. The Houtbosdorp Road is the longest with a length of 31.5 km followed by the Jachtpad Road with a length of 16.4 km and lastly the Vreedsaam Road with a length of 12.5 km. The Houtbosdorp Road is constituted of a flat and mountainous section whereas the Vreedsaam and Jachtpad roads are both relatively flat. The Jachtpad Road carries the highest traffic volume particularly on the southern sections as they provide access from the paved road network to the main packing house, truck fuelling station and head office. The Houtbosdorp Road carries the second-highest traffic volume on the northern sections leading to the tomato net-houses, fertiliser suppliers and seedling distributors. The Vreedsaam Road has the lowest traffic volume. The locations and relative lengths of the segments forming the length of the roads as well as the elevation profile plots of the roads are presented in the following sections. The details of the road segments are provided in Table 4-1.

Table 4-1: Road segment details

Road	Segment ID	No. in sequence from northern end of road	Length (km)	Average slope (per cent)
Houtbosdorp	1710002206466	1	0.333	2.5
	17100022050121	2	0.584	2.9
	17100022165429	3	0.889	2.8
	17100022275362	4	0.104	0
	17100022176107	5	5.64	1.7
	17100023349369	6	3.52	1.5
	17100024083528	7	5.97	2
	17100024776586	8	2.46	6.9
	17100023399786	9	0.327	9
	17100023838534	10	1.21	9.9
	17100024063171	11	4.09	8
	17100023733686	12	1.29	4
	17100024272752	13	3.17	4.8
	17100024418609	14	0.141	0
	17100024809472	15	1.13	5
	17100023031026	16	0.136	0
	17100024741876	17	0.275	2.9
	17100024809479	18	0.197	2.3
Vreedsaam	17100023044624	1	3.68	2.6
	17100024072076	2	6.83	1.5
	17100024046817	3	0.105	0
	17100022758644	4	1.92	1.7
Jachtpad	17100023199273	1	9.47	1.7
	17100024819125	2	1.70	1.2
	17100022256372	3	0.454	2.2
	17100023438190	4	0.292	1.9
	17100023402227	5	4.49	1.7

D617 Houtbosdorp Road

The Houtbosdorp Road is comprised of 18 segments of varying lengths as shown in Figure 4-1.

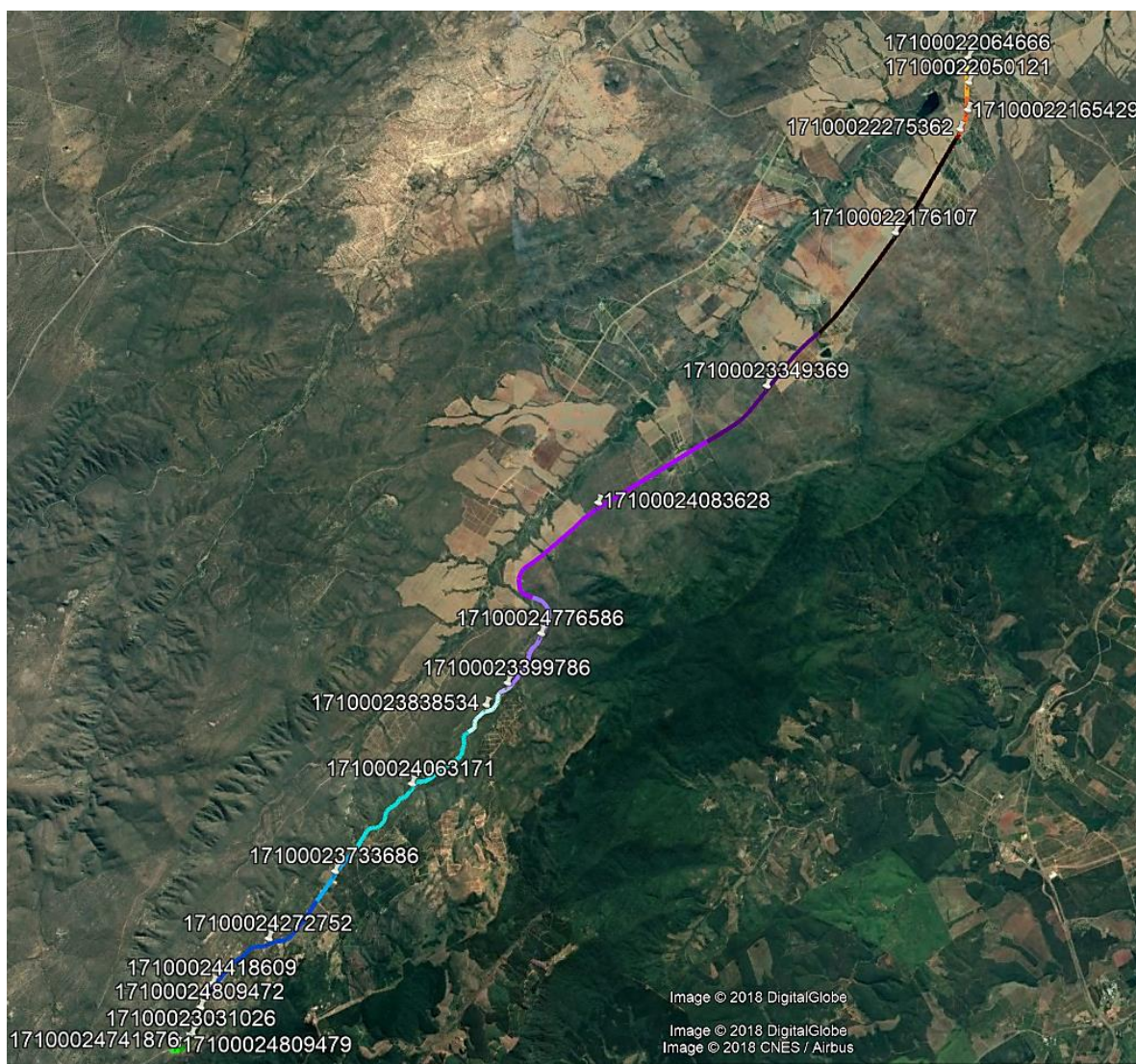


Figure 4-1: Road segments forming the length of the Houtbosdorp road

The elevation plot of the Houtbosdorp Road starting from the south end is shown in Figure 4-2.

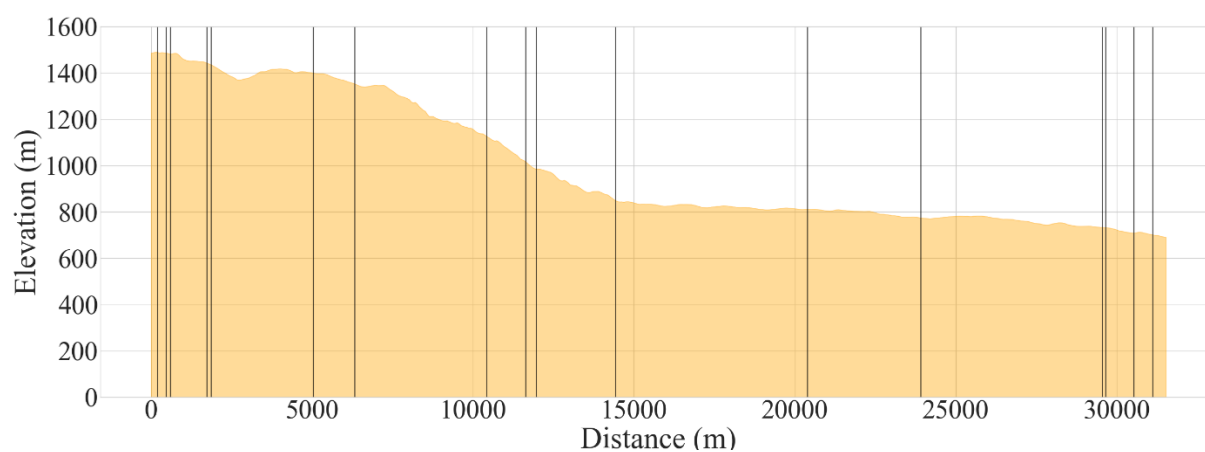


Figure 4-2: Elevation plot of Houtbosdorp road

D839 Vreedsaam Road

The Vreedsaam Road is comprised of 4 segments of varying lengths as shown in Figure 4-3.

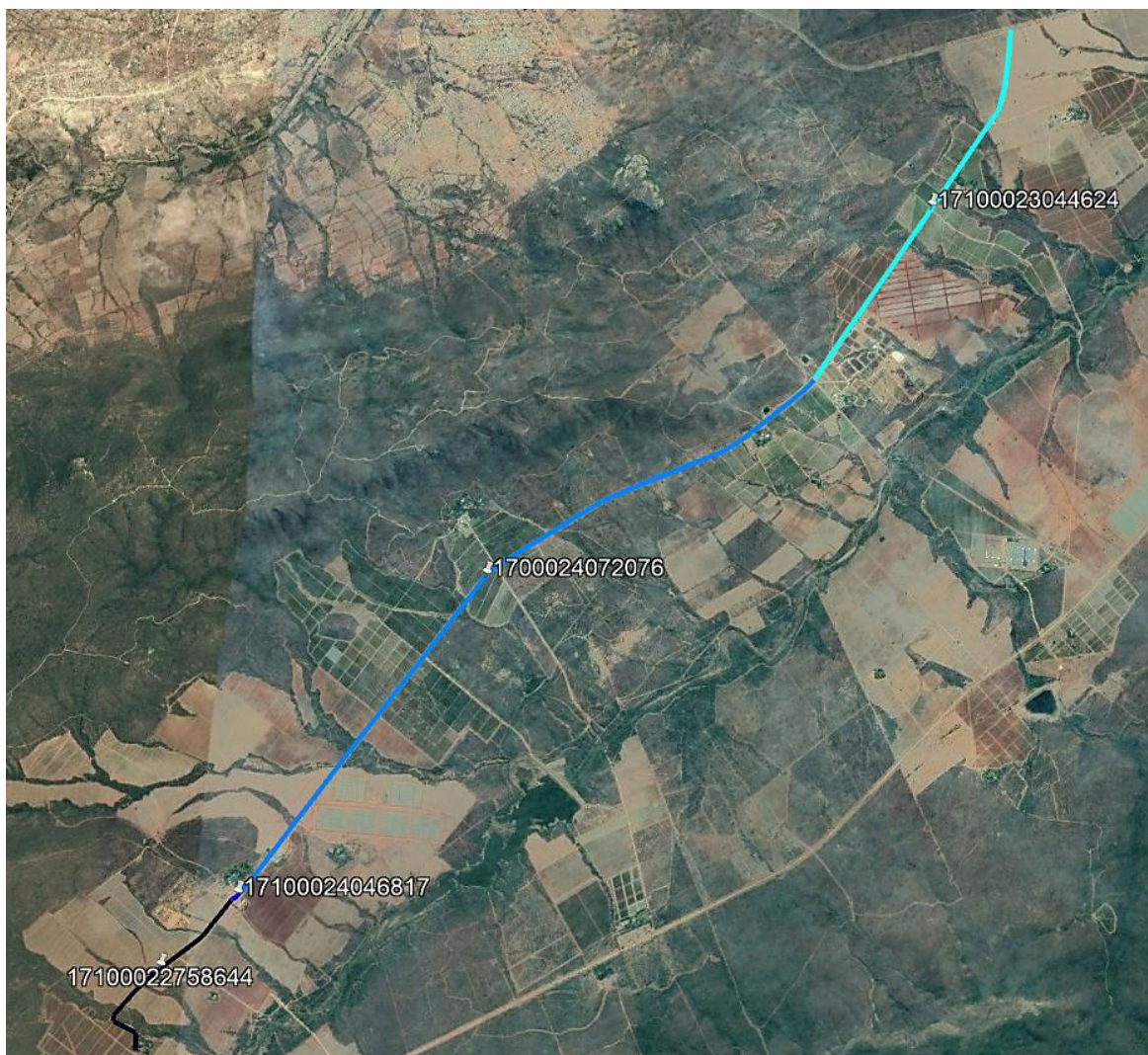


Figure 4-3: Road segments forming the length of the Vreedsaam road

The elevation profile plot of the Vreedsaam Road starting from the south end is shown in Figure 4-4.

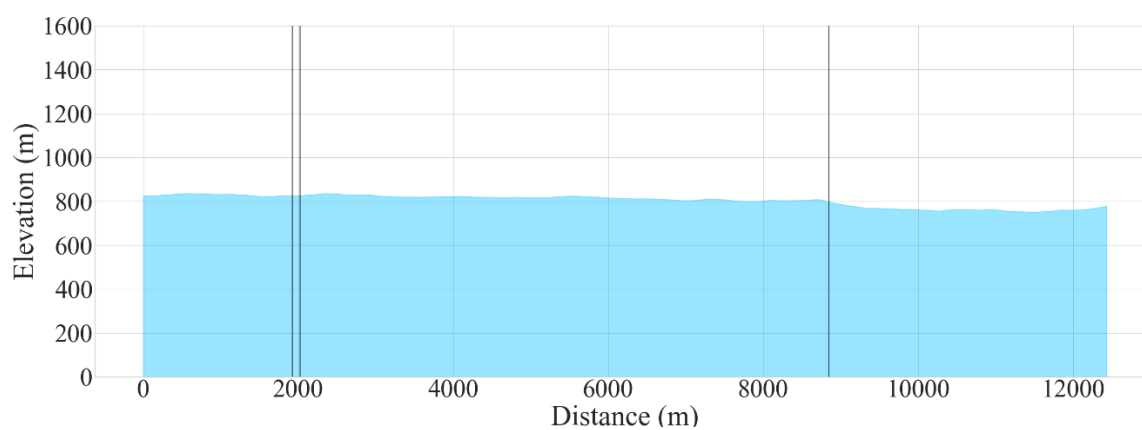


Figure 4-4: Elevation profile plot of Vreedsaam road

D678 Jachtpad Road

The Jachtpad Road is comprised of 5 segments of varying lengths as shown in Figure 4-5.

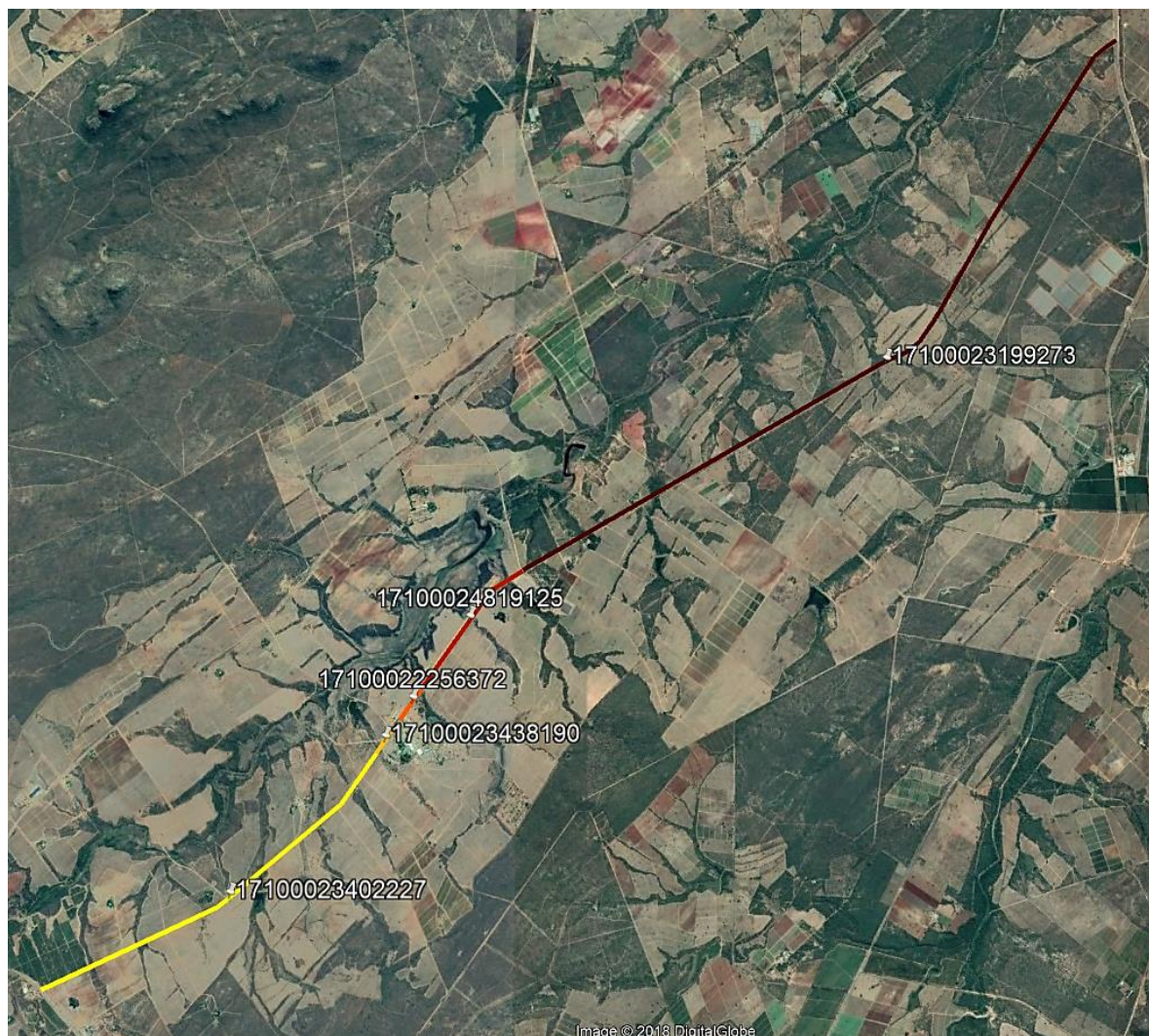


Figure 4-5: Road segments forming the length of the Jachtpad road

The elevation profile plot of the Jachtpad Road starting from the south end is shown in Figure 4-6.

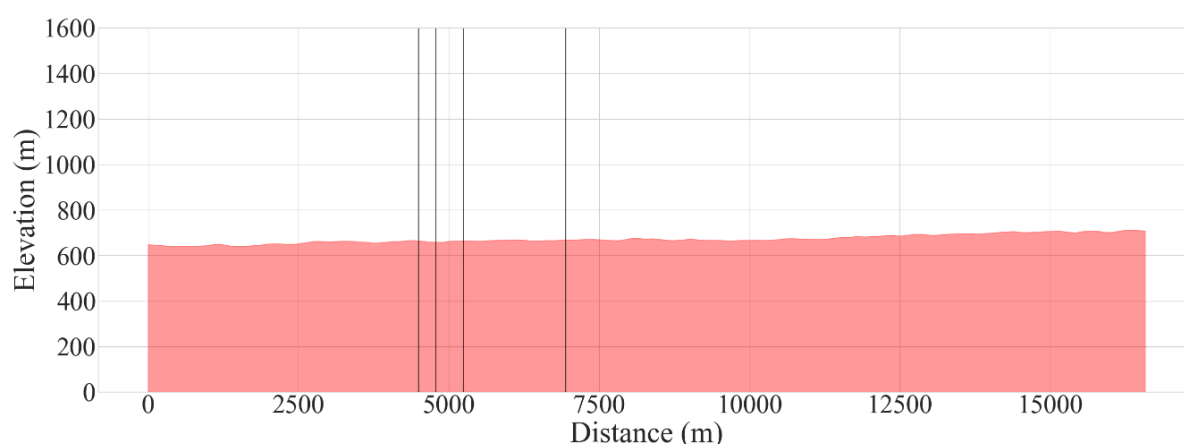


Figure 4-6: Elevation profile plot of Jachtpad road

4.2 ROAD CONDITION

The road roughness progression given in HRI averaged over the segments forming the length of the selected roads for the analysis period is shown in Figure 4-7.

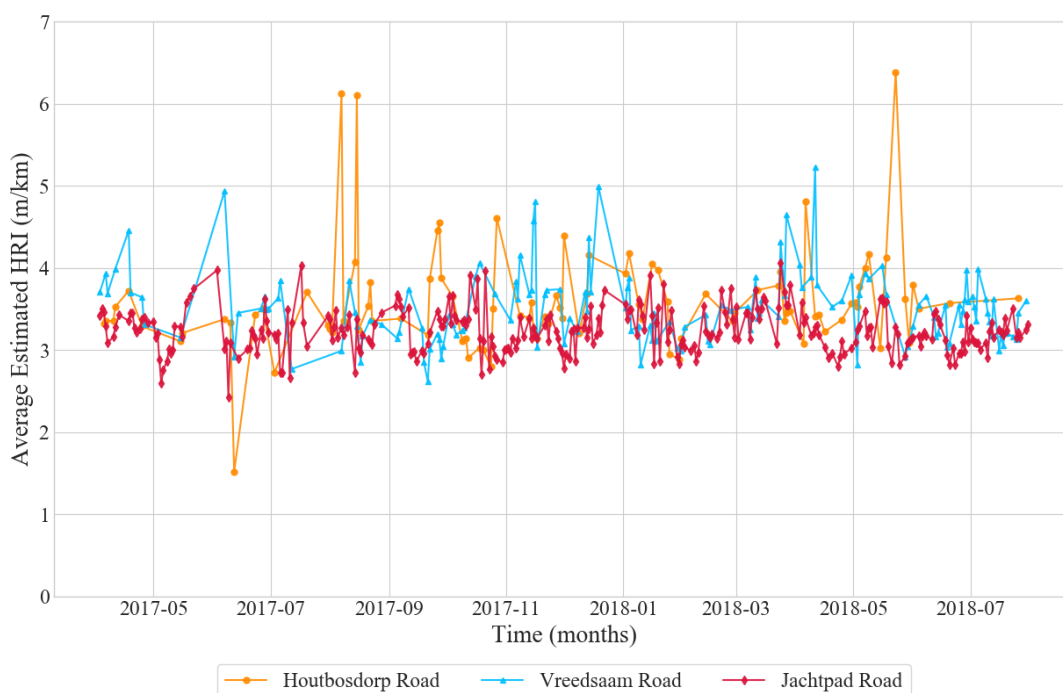


Figure 4-7: Road roughness progression over time

The road roughness progression given in HRI for each segment forming the length of the Houtbosdorp Road is shown in Figure 4-8.

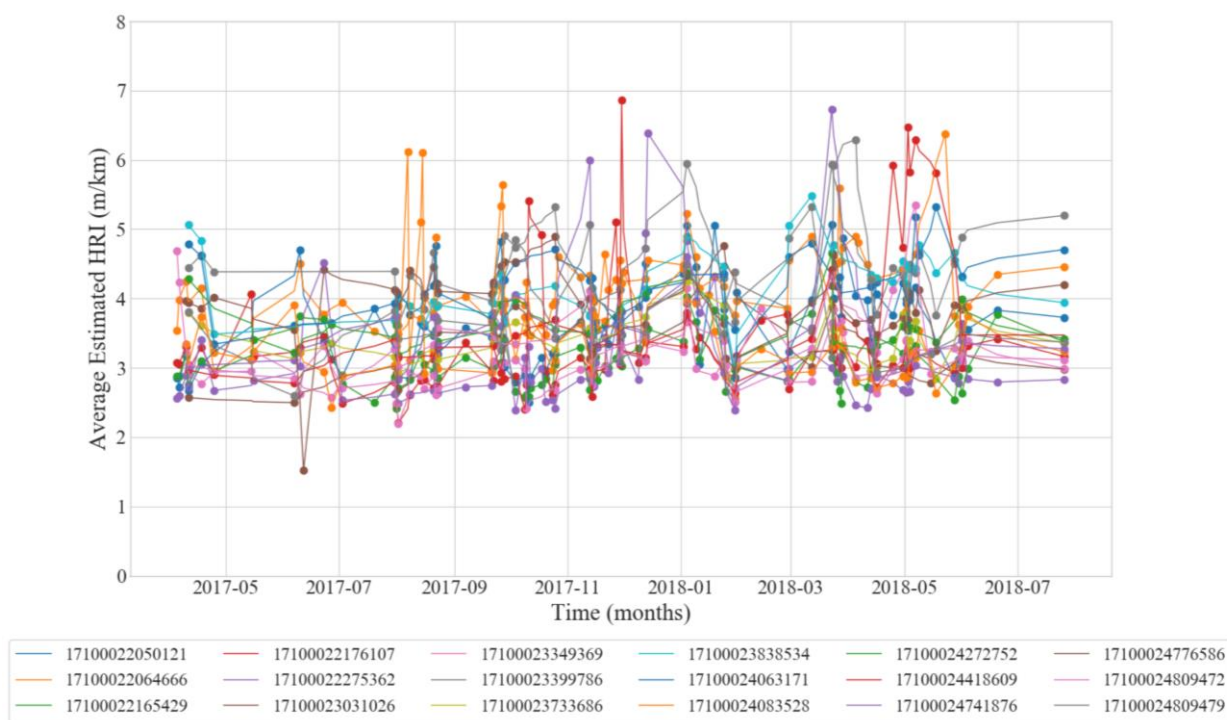


Figure 4-8: Road roughness progression over time for Houtbosdorp Road

The road roughness progression given in HRI for each segment forming the length of the Vreedsaam Road is shown in Figure 4-9.

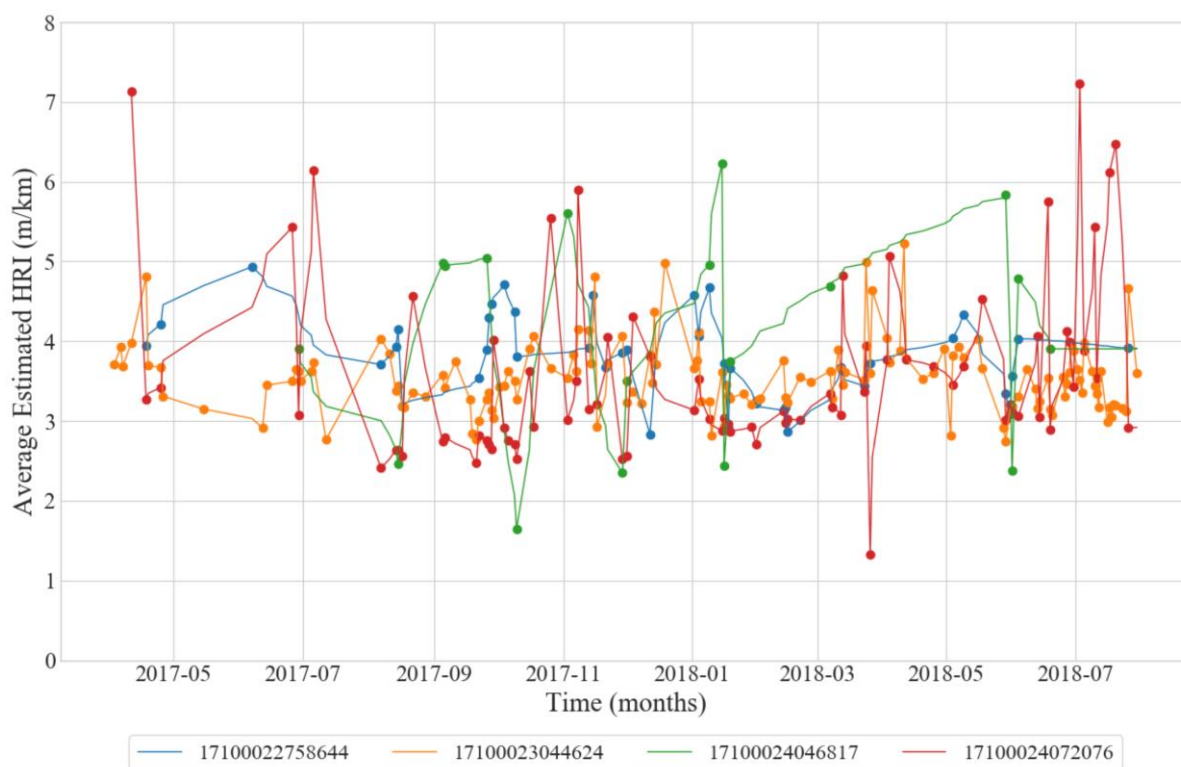


Figure 4-9: Road roughness progression over time for Vreedsaam Road

The road roughness progression given in HRI for each segment forming the length of the Jachtpad Road is shown in Figure 4-10.

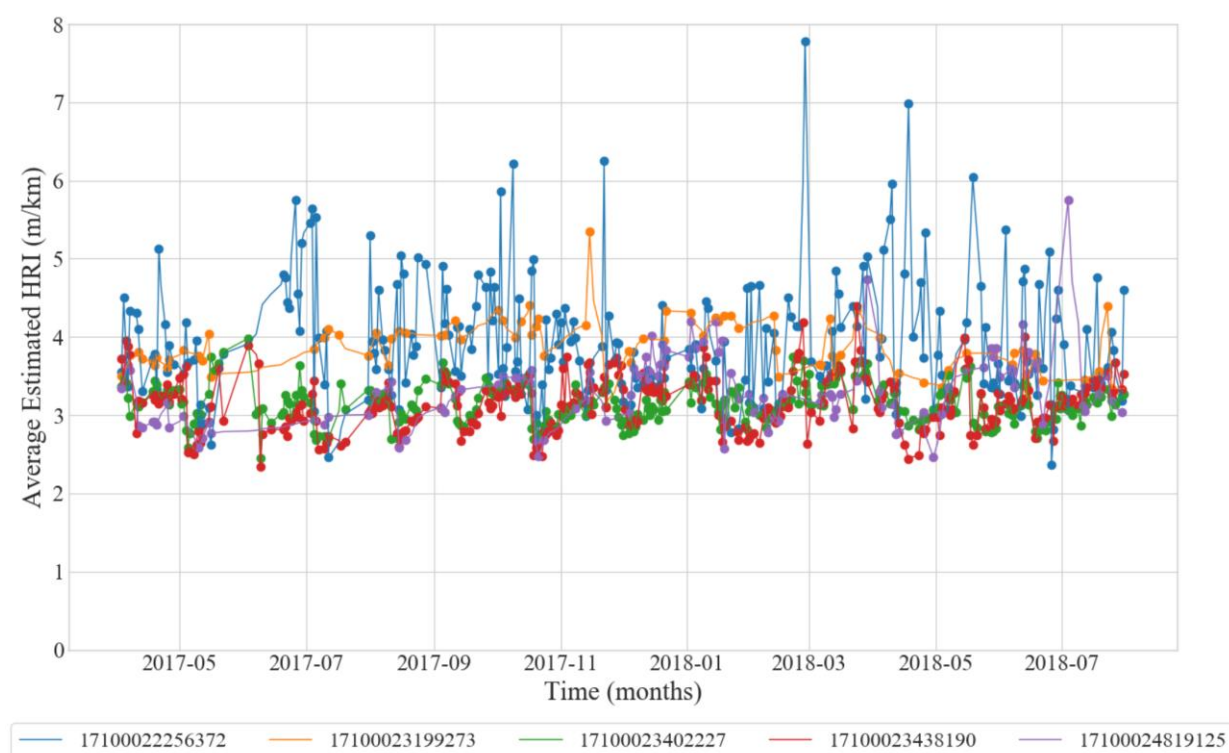


Figure 4-10: Road roughness progression over time for Jachtpad Road

4.3 RAINFALL

The estimated daily rainfall for each road was calculated from rainfall data measured at selected rain gauge stations. The datasets were weighted according to the distances of each rain gauge station from the centre of each road segment forming the length of the road of interest. The daily rainfall for each road was then calculated by weighting the datasets further according to the length of the individual segments. The results are shown in Figure 4-11 to Figure 4-13. The data measured at each rain gauge station is shown in Figure 4-14.

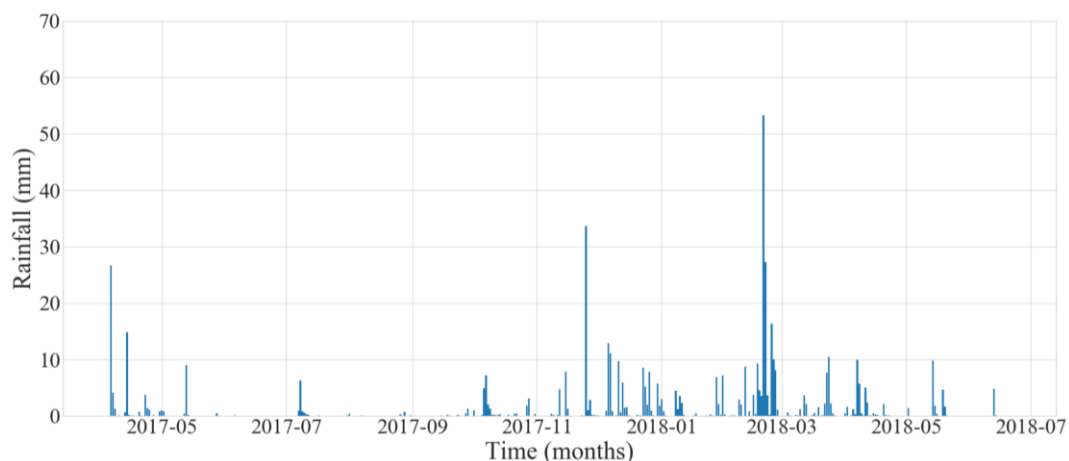


Figure 4-11: Daily rainfall for the Houtbosdorp Road over the analysis period

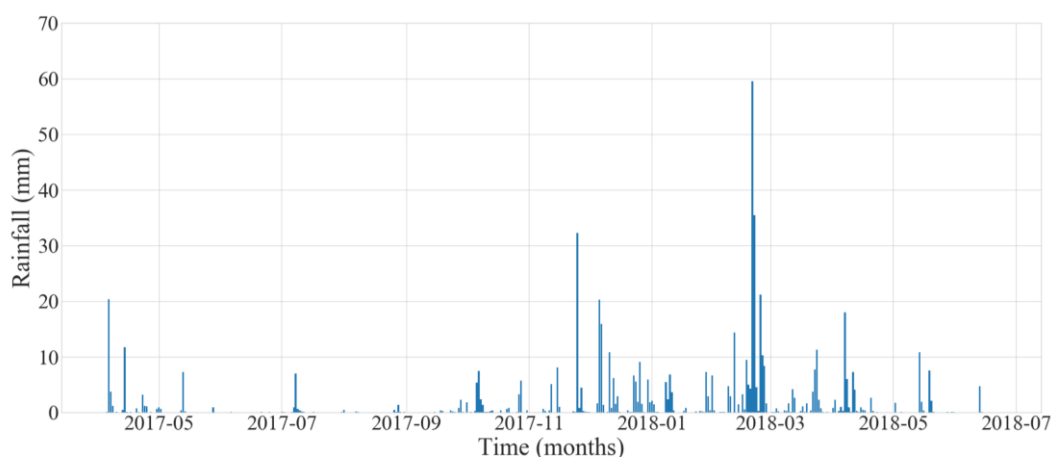


Figure 4-12: Daily rainfall for the Vreedsaam Road over the analysis period

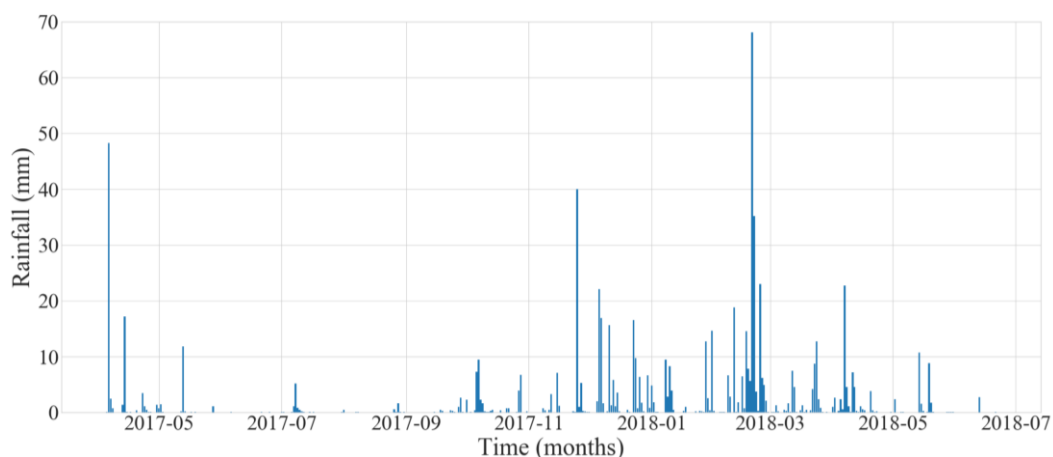


Figure 4-13: Daily rainfall for the Jachtpad Road over the analysis period

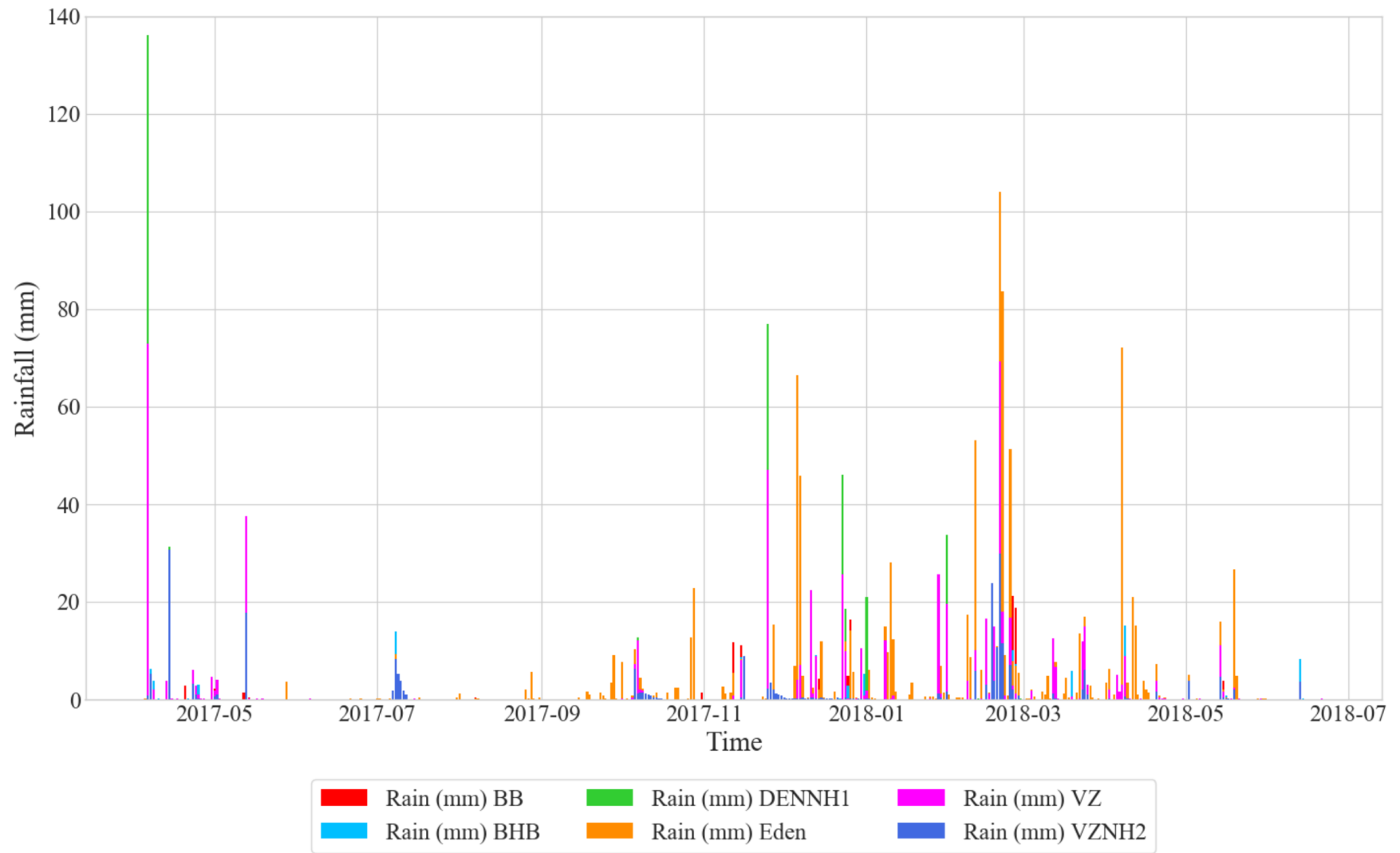


Figure 4-14: Daily rainfall recorded at selected rain gauge stations from April 2017 to July 2018

4.4 ROAD MAINTENANCE HISTORY

The road maintenance history data provided by the agricultural organisation revealed that water trucks were employed on weekdays on the Houtbosdorp Road for the entire analysis period, from July 2017 on the Vreedsaam Road and from 16 October 2017 on the Jachtpad Road. The water trucks typically drive a circuit of the road at a fixed speed distributing enough water to wet the surface but not enough to cause ponding. This typically results in less dust generation and material loss from the road surface and a slight increase in the compactibility of the road surface. No re-gravelling activities were conducted on the roads during the analysis period.

Road graders were employed intermittently on the selected roads to redistribute the surface material and redefine the crown of the roads. Grading activities were followed by compaction using a single drum vibratory roller to increase the surface density, thereby strengthening the road surface and minimizing material loss. A summary of the costs spent on vehicle hire for the maintenance of the selected roads and details of the grading activities over the 16 month analysis period is provided in Table 4-2.

Table 4-2: Summary of road maintenance costs over the analysis period

Road	Cost of maintenance vehicle hire	Cost of grading	No. of days on which grader employed	No. of grading activities
Houtbosdorp	R 2 313 947	R 562 120	109	16
Vreedsaam	R 800 667	R 340 637	66	12
Jachtpad	R 1 367 465	R 466 161	107	19

The effect of the maintenance activities on the road surface condition was investigated by segregating the roughness progression history by the dates on which grading was conducted for each road. The results are shown in Figure 4-15 to Figure 4-17. The grading activities are indicated by vertical black lines.

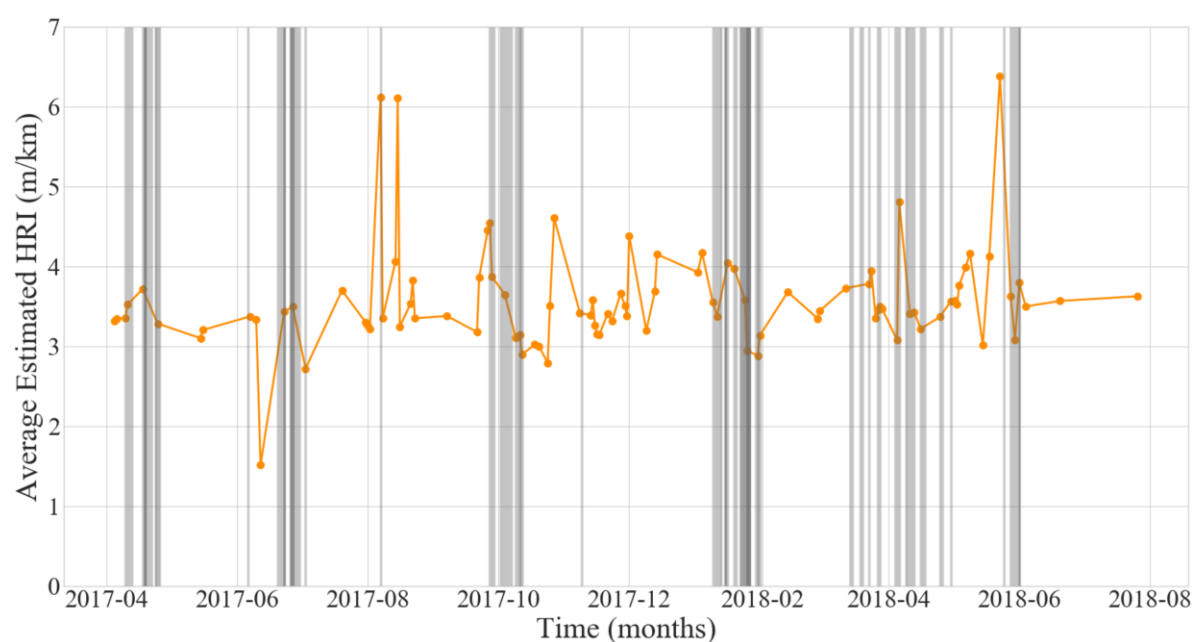


Figure 4-15: Road roughness progression of the Houtbosdorp Road segregated by grading activities

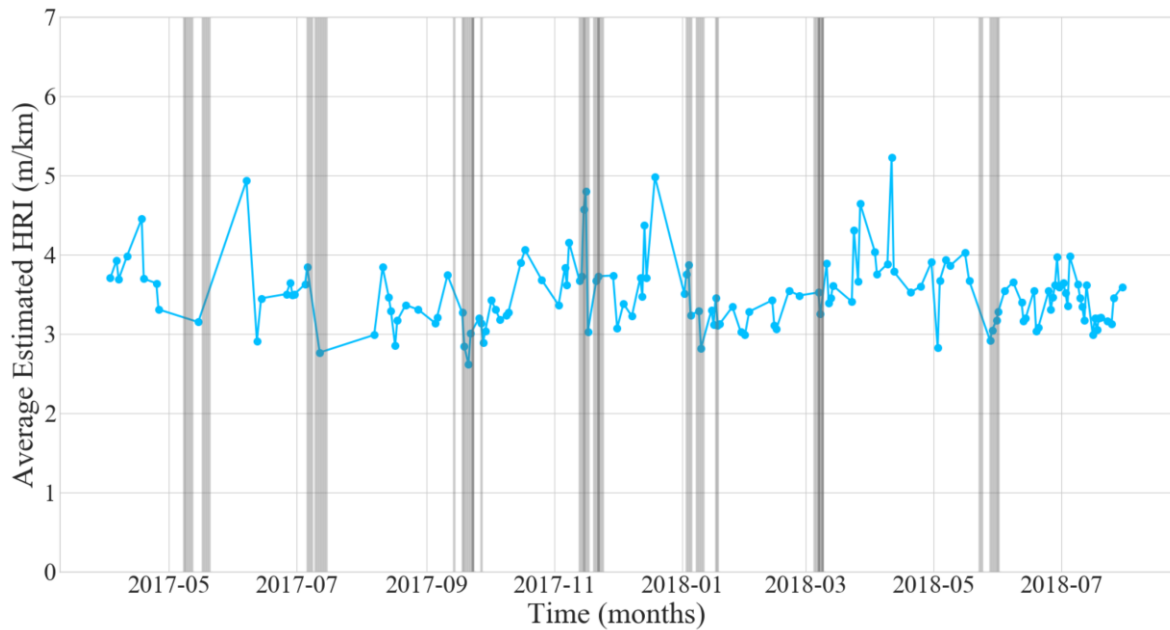


Figure 4-16: Road roughness progression of the Vreedsaam Road segregated by grading activities

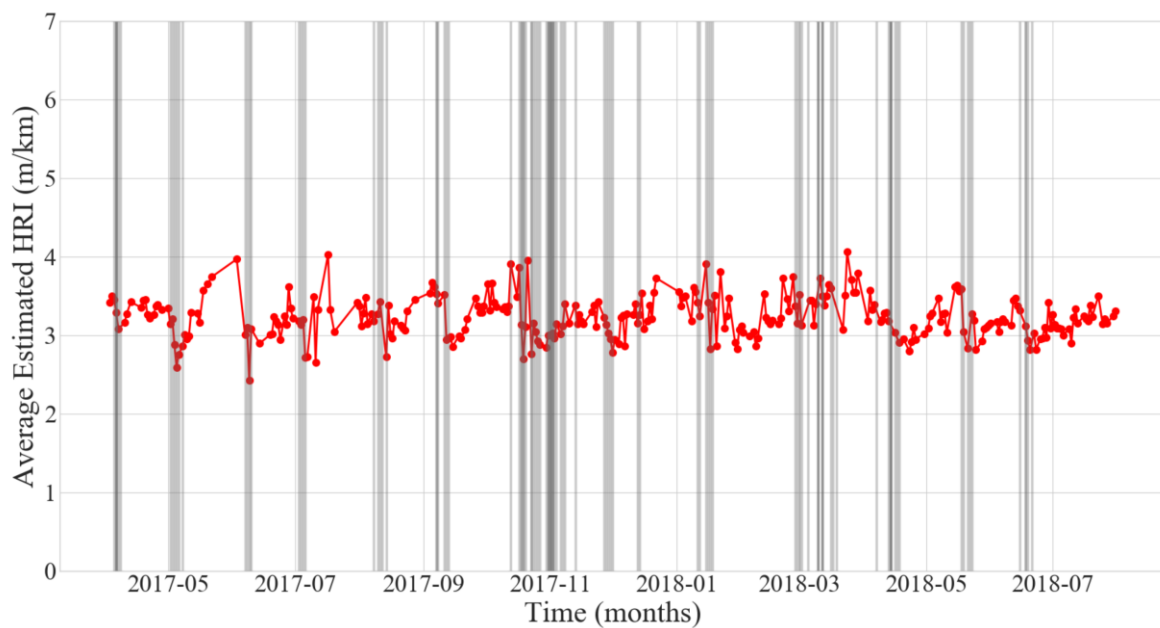


Figure 4-17: Road roughness progression of the Jachtpad Road segregated by grading activities

4.5 ROAD ROUGHNESS PROGRESSION TRENDS

The road roughness progression of each road was isolated into periods of deterioration using the dates of the grading activities. This removed the effect of grading on the captured road roughness data by isolating the periods of deterioration. The isolated periods of deterioration for which the roughness of the roads was captured using the Data Capturing Vehicle for four days or more were plotted from the origin to illustrate the roughness deterioration trends for the selected roads. The results of the analysis are shown in Figures 4-18 to 4-21. The road roughness progression trends were normalised along the x-axis by presenting the time of the measured roughness as a percentage of the deterioration period. The results are shown in Figures 4-21 to 4-23.

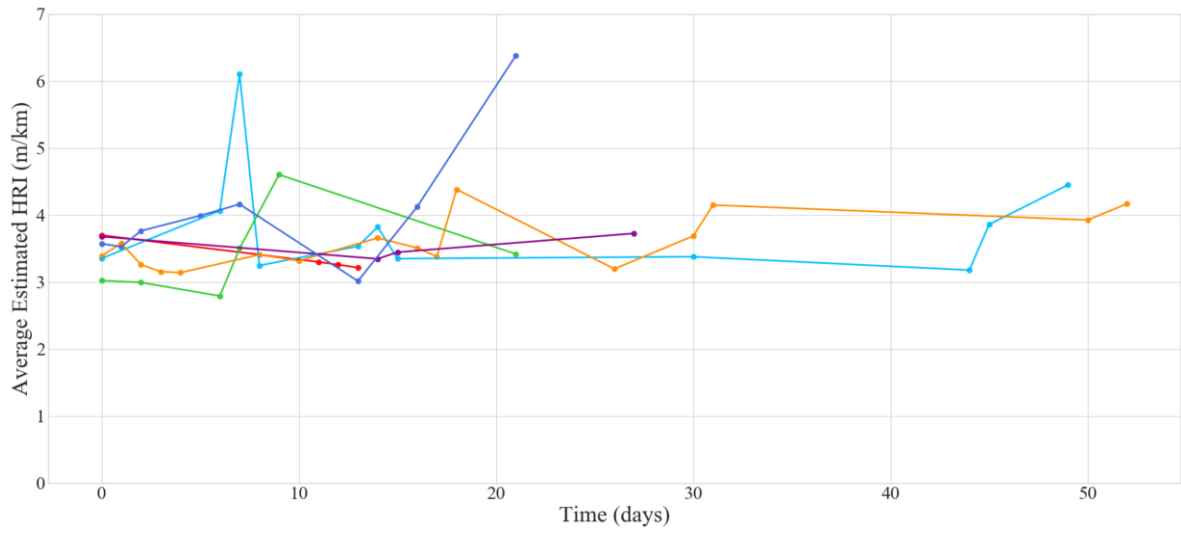


Figure 4-18: Road roughness deterioration trends for the Houtbosdorp Road

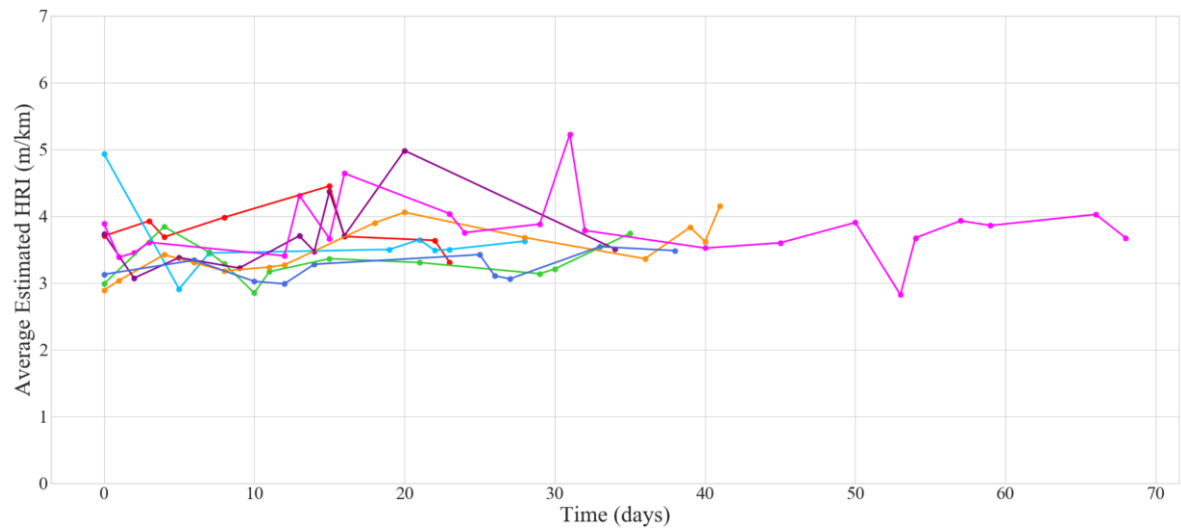


Figure 4-19: Road roughness deterioration trends for the Vreedsaam Road

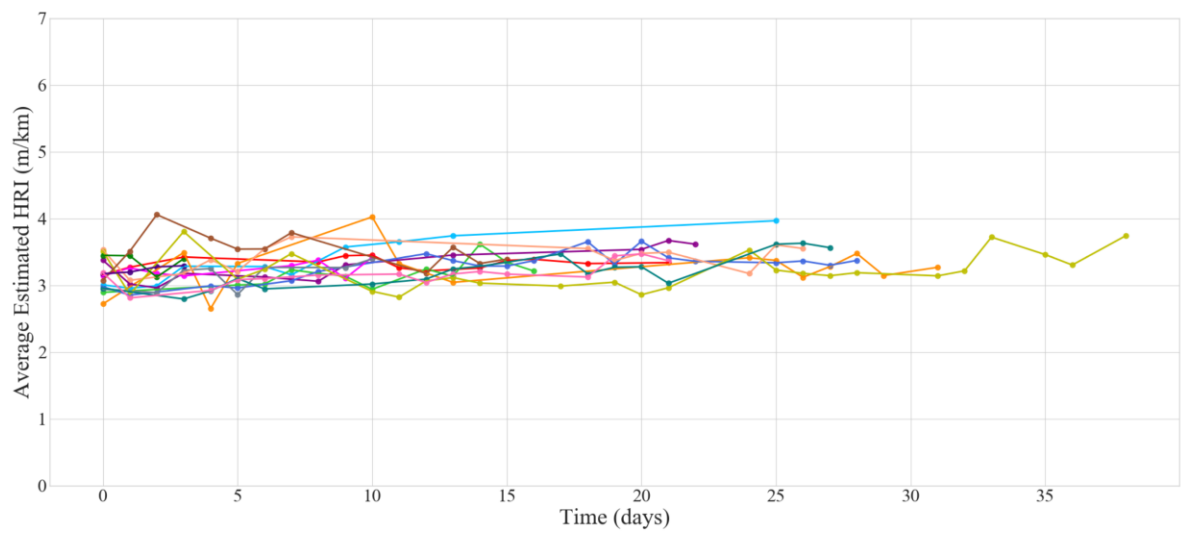


Figure 4-20: Road roughness deterioration trends for the Jachtpad Road

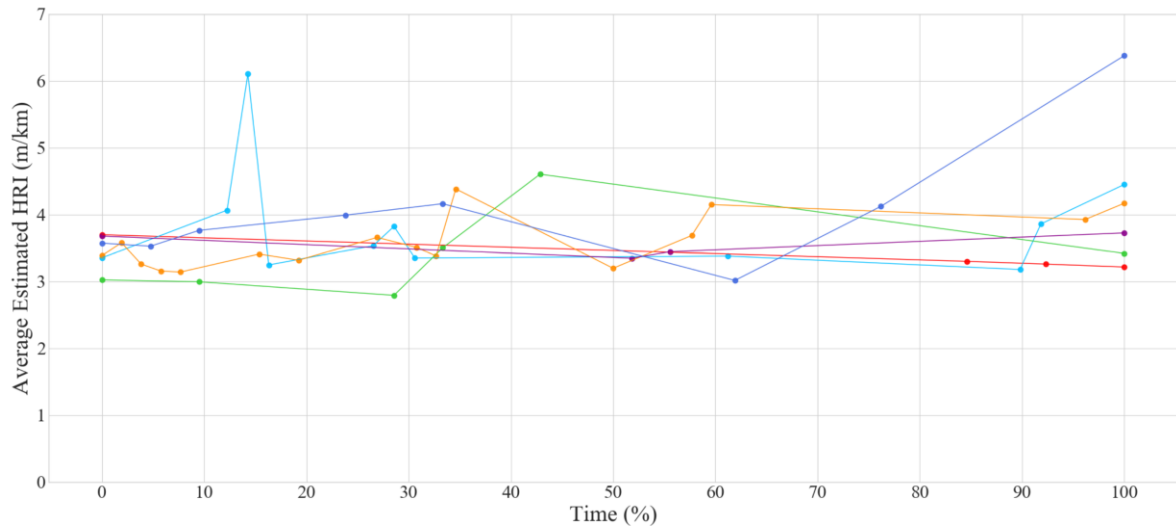


Figure 4-21: Normalised road roughness deterioration trends for the Houtbosdorp Road

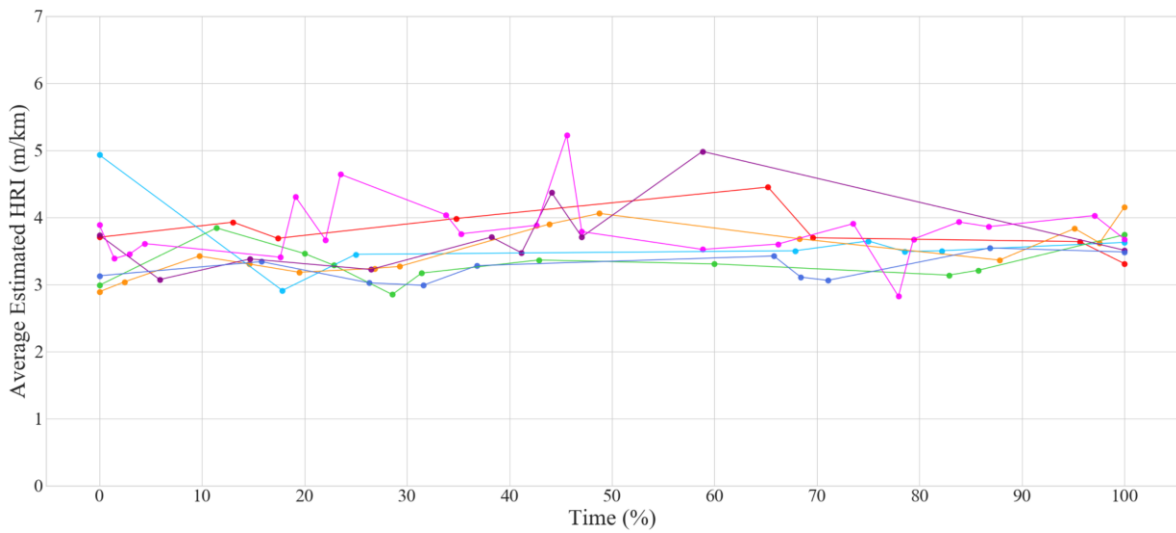


Figure 4-22: Normalised road roughness deterioration trends for the Vreedsaam Road

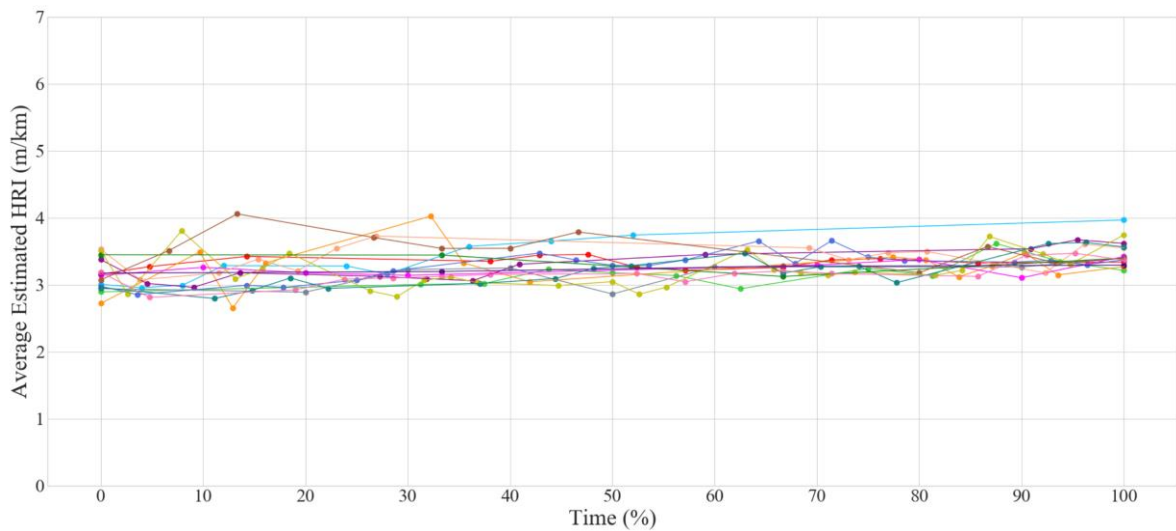


Figure 4-23: Normalised road roughness deterioration trends for the Jachtpad Road

4.5.1 Normalised road roughness progression isolated by rainfall season

The normalised road roughness deterioration was isolated by rainfall season for the selected roads. The results are given in Figures 4-24 to 4-26.

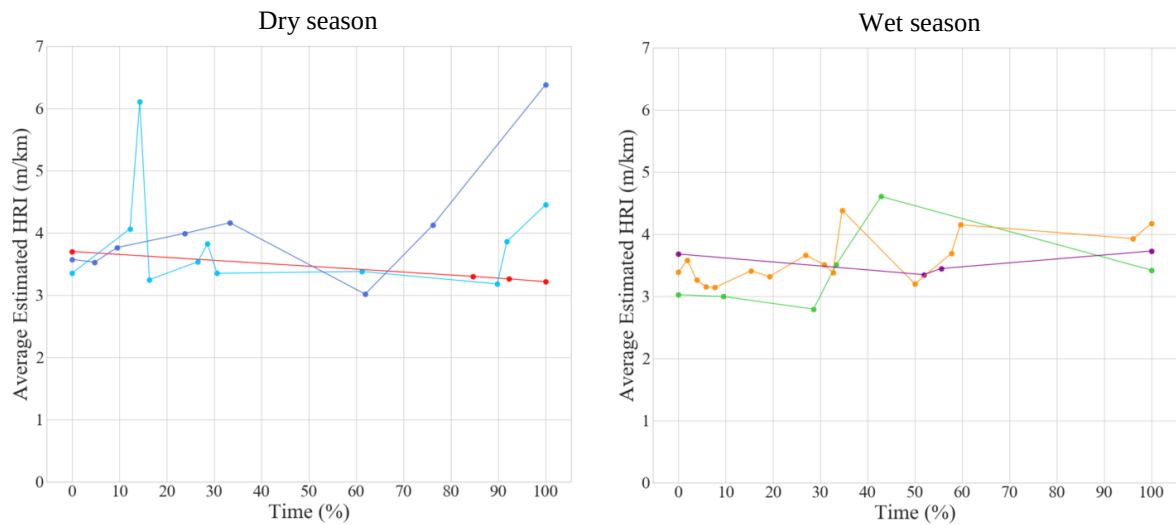


Figure 4-24: Roughness progression isolated by rainfall season for the Houtbosdorp Road

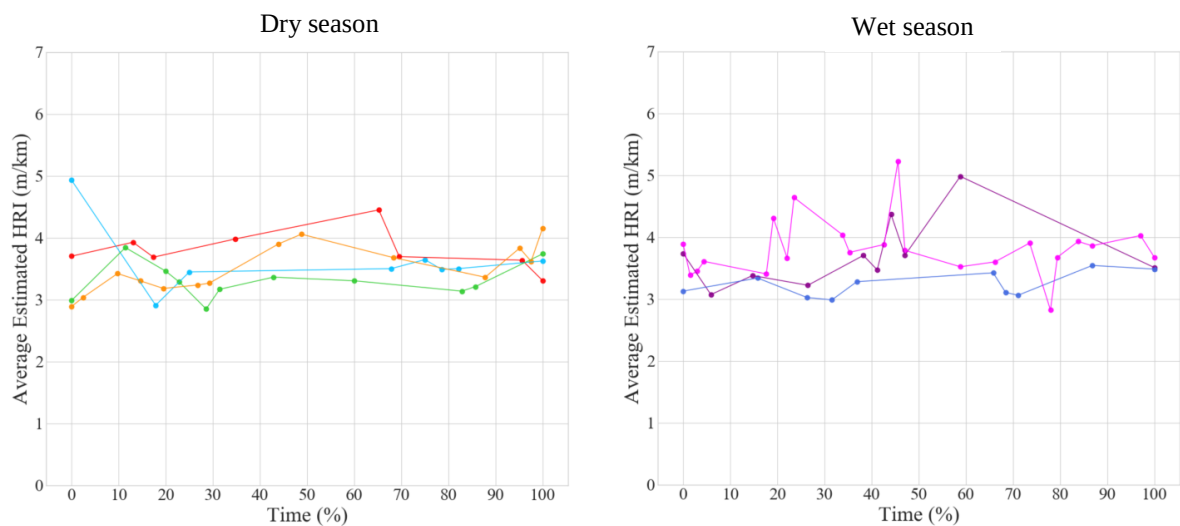


Figure 4-25: Roughness progression isolated by rainfall season for the Vreedsaam Road

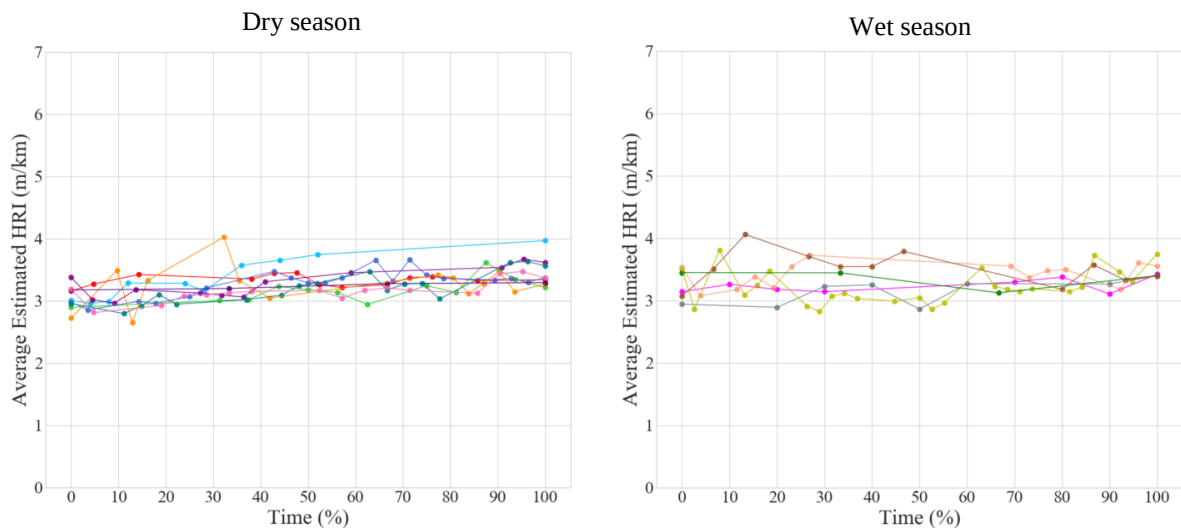


Figure 4-26: Roughness progression isolated by rainfall season for the Jachtpad Road

4.5.2 Normalised road roughness progression isolated by road slope

The normalised road roughness deterioration was isolated by steepness where a slope greater than 6 per cent represented a mountainous section. The results are provided in Figures 4-27 to 4-29.

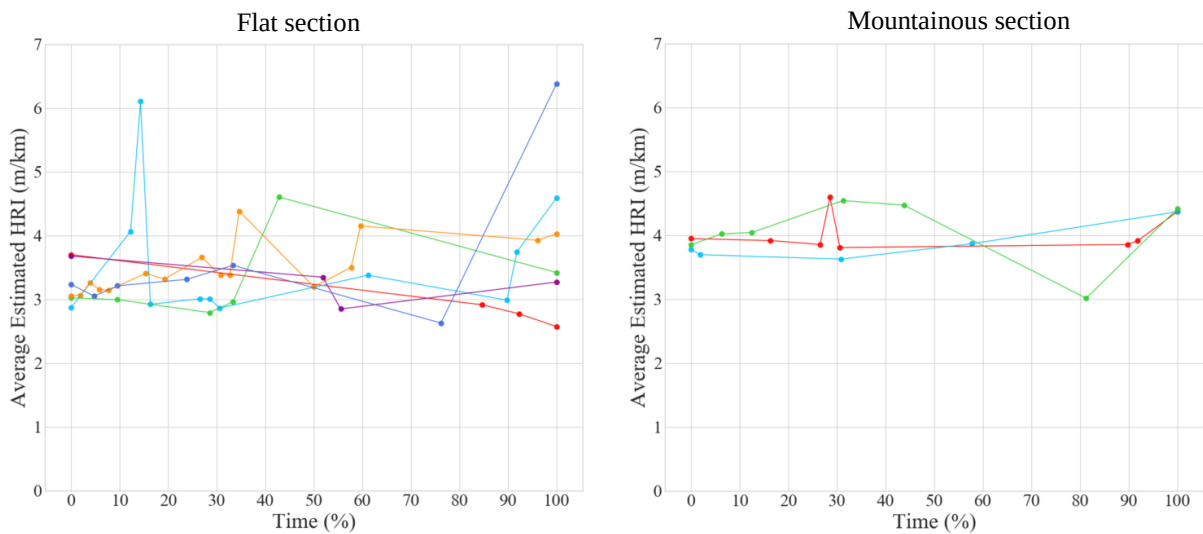


Figure 4-27: Roughness progression isolated by slope for the Houtbosdorp Road

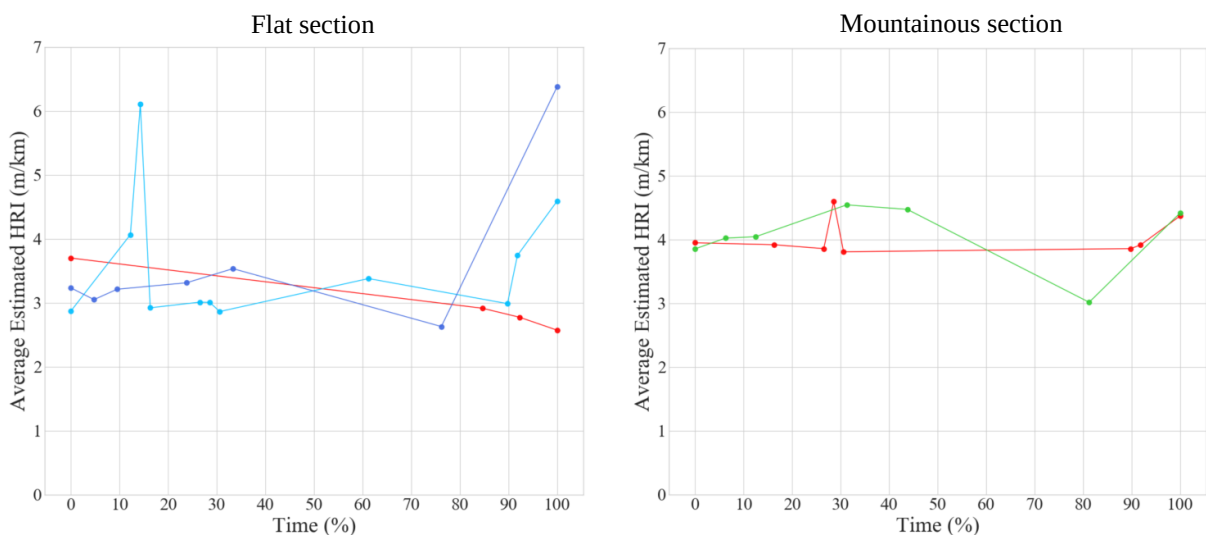


Figure 4-28: Roughness progression isolated by slope over the dry season for the Houtbosdorp Road

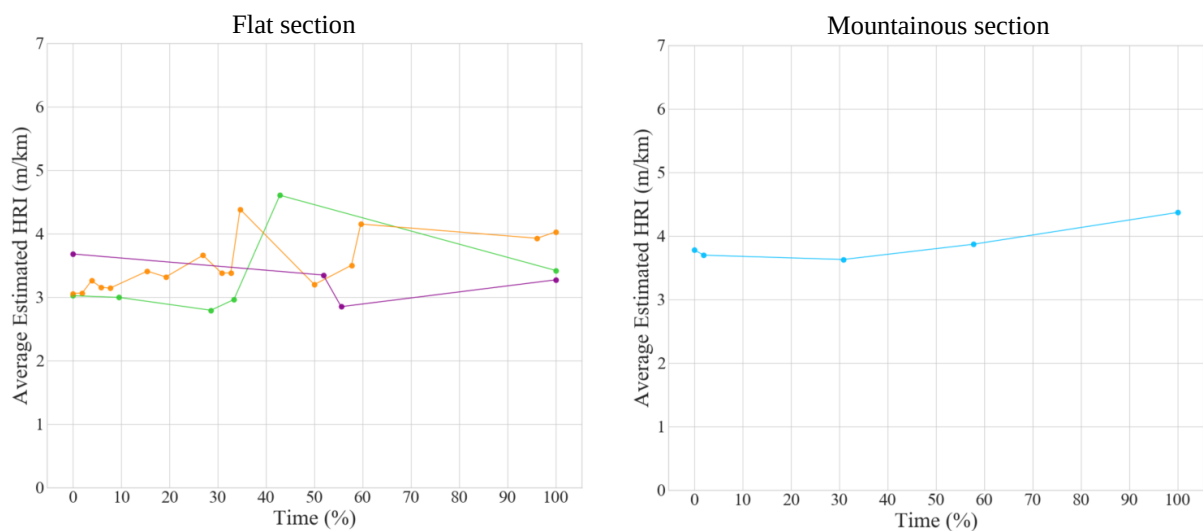


Figure 4-29: Roughness progression isolated by slope over the wet season for the Houtbosdorp Road

4.5.3 Normalised road roughness progression isolated for high trafficked sections

The normalised road roughness deterioration isolated by traffic for high trafficked sections are provided in Figures 4-30 to 4-32.

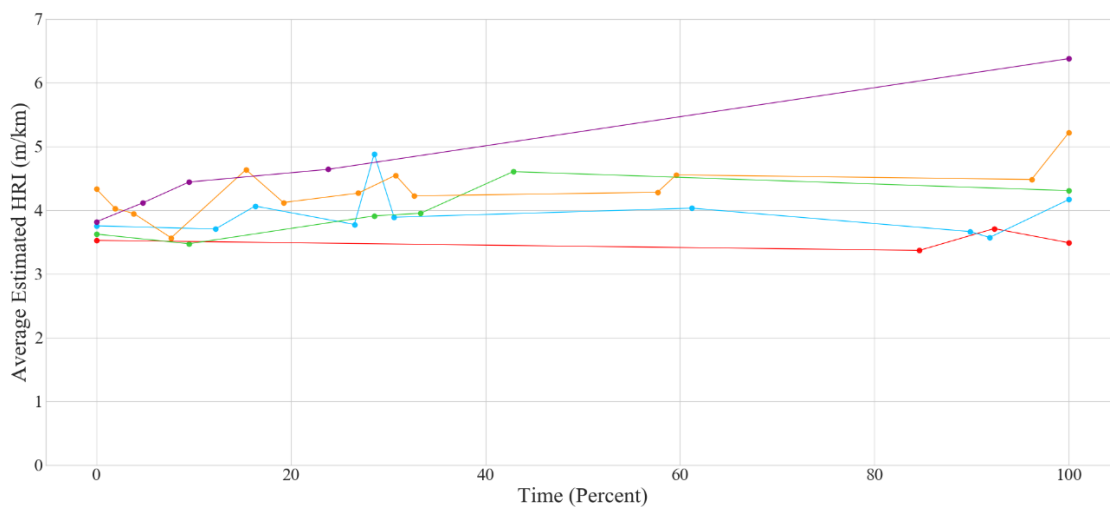


Figure 4-30: Roughness progression for segment 1710002206466 of the Houtbosdorp Road

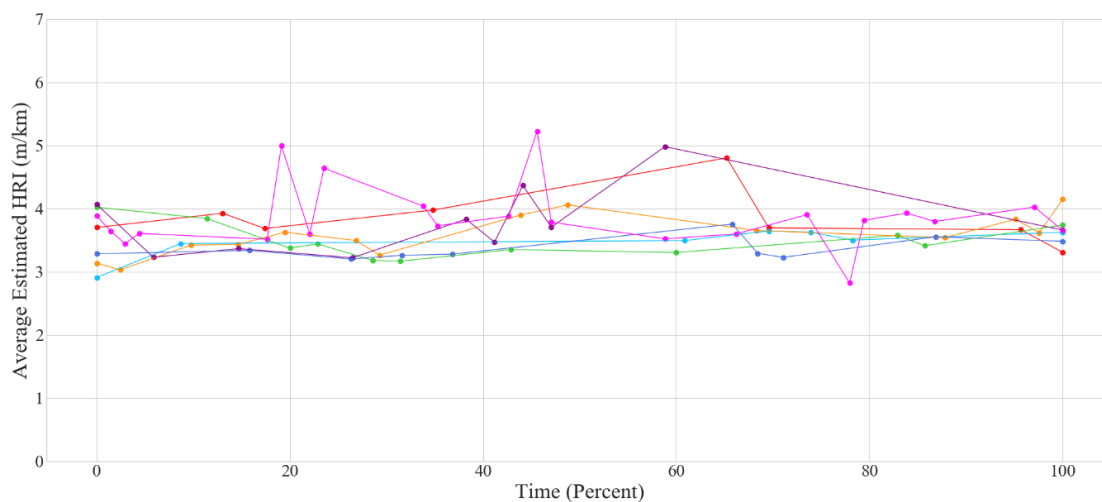


Figure 4-31: Roughness progression for segment 17100023044624 of the Vreedsaam Road

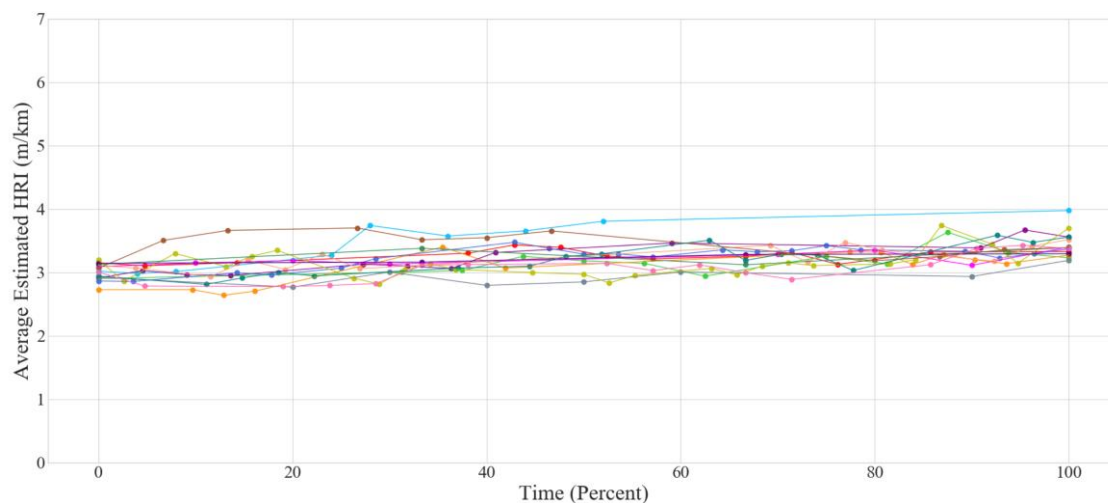


Figure 4-32: Roughness progression for segment 17100023402227 of the Jachtpad Road

4.5.4 Normalised road roughness progression isolated by rainfall season for high trafficked sections

The normalised road roughness deterioration for high trafficked sections isolated by rainfall season are provided in Figures 4-33 to 4-35.

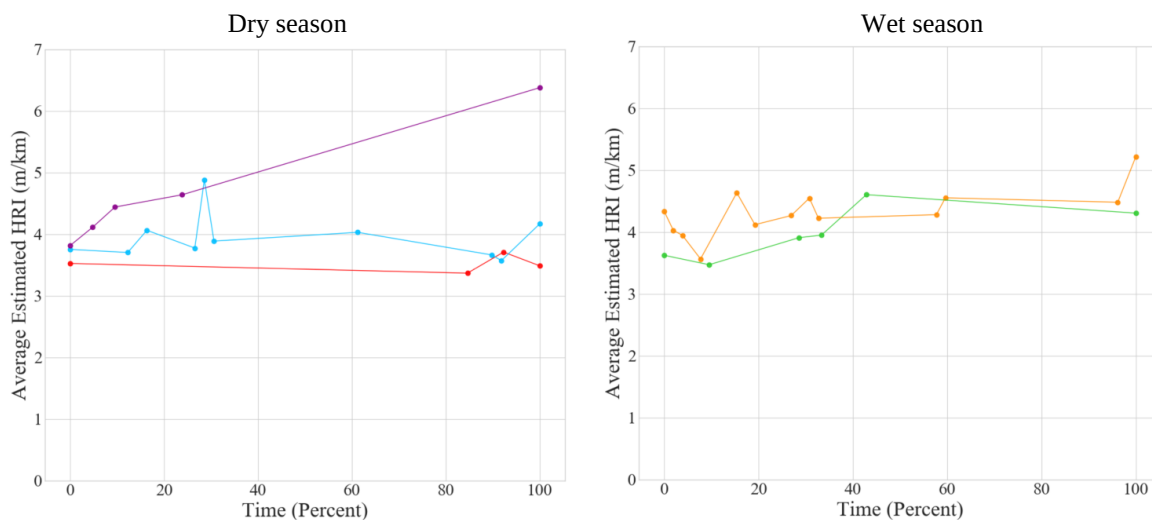


Figure 4-33: Roughness progression isolated by rainfall season for segment 1710002206466

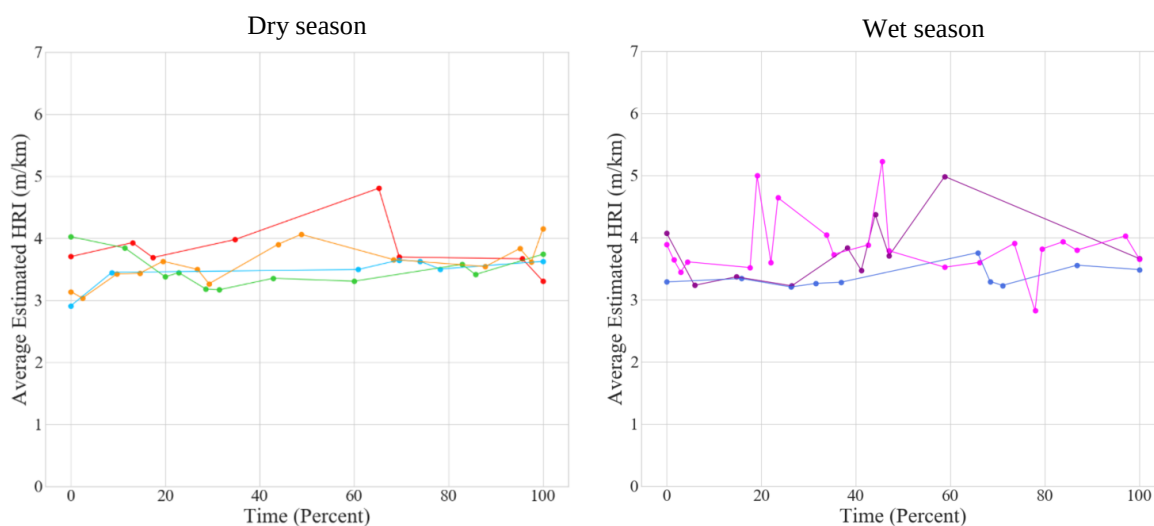


Figure 4-34: Roughness progression isolated by rainfall for segment 17100023044624

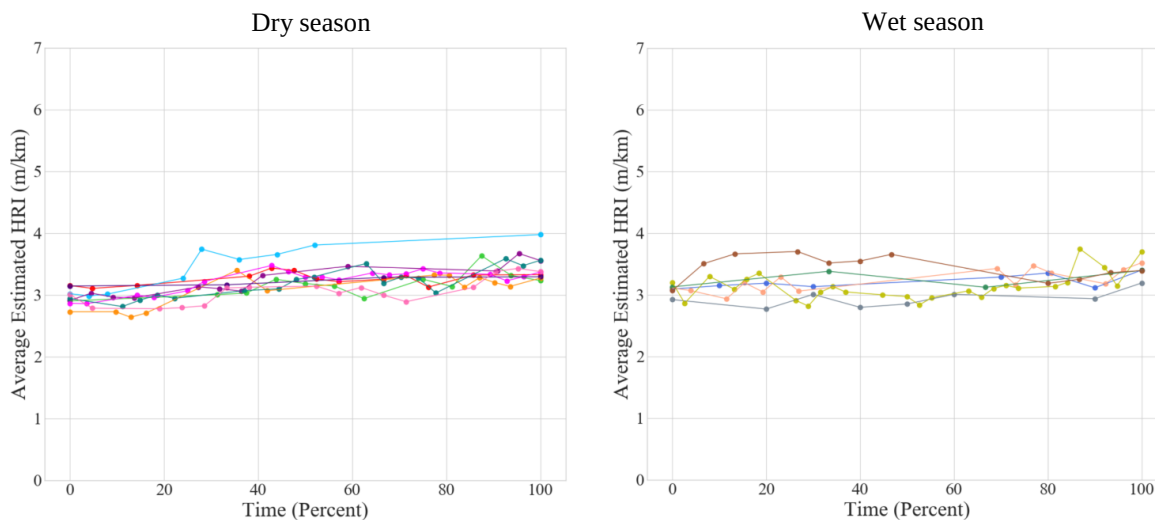


Figure 4-35: Roughness progression isolated rainfall for segment 17100023402227

4.5.5 Normalised road roughness progression isolated for low trafficked sections

The normalised road roughness deterioration isolated by traffic for low trafficked sections are provided in Figures 4-36 to 4-38.

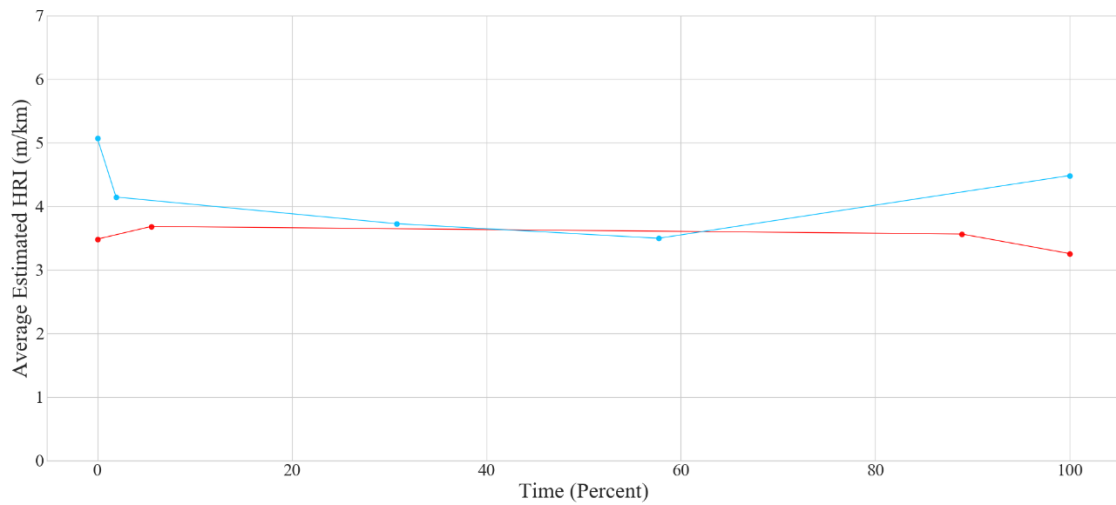


Figure 4-36: Roughness progression for segment 17100024809479 of the Houtbosdorp Road

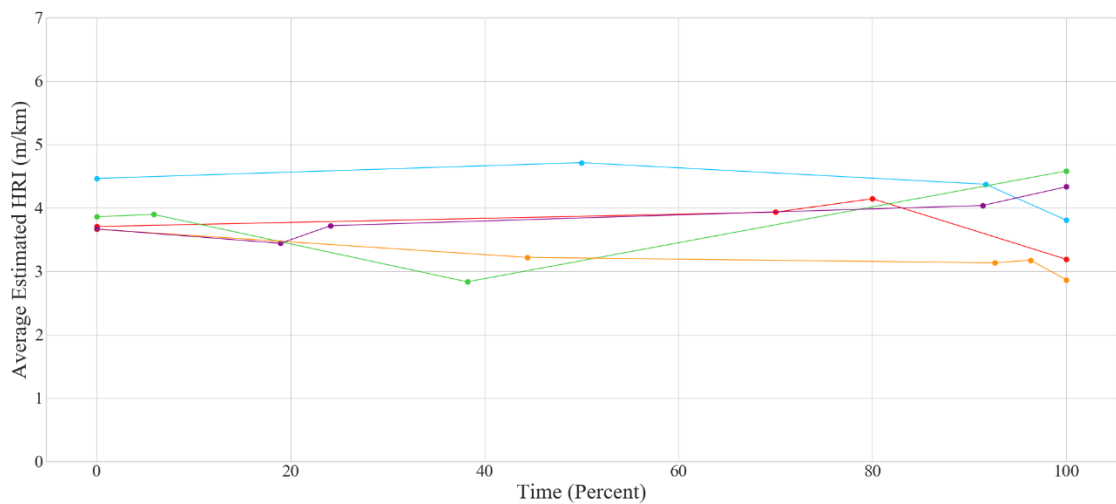


Figure 4-37: Roughness progression for segment 17100022758644 of the Vreedsaam Road

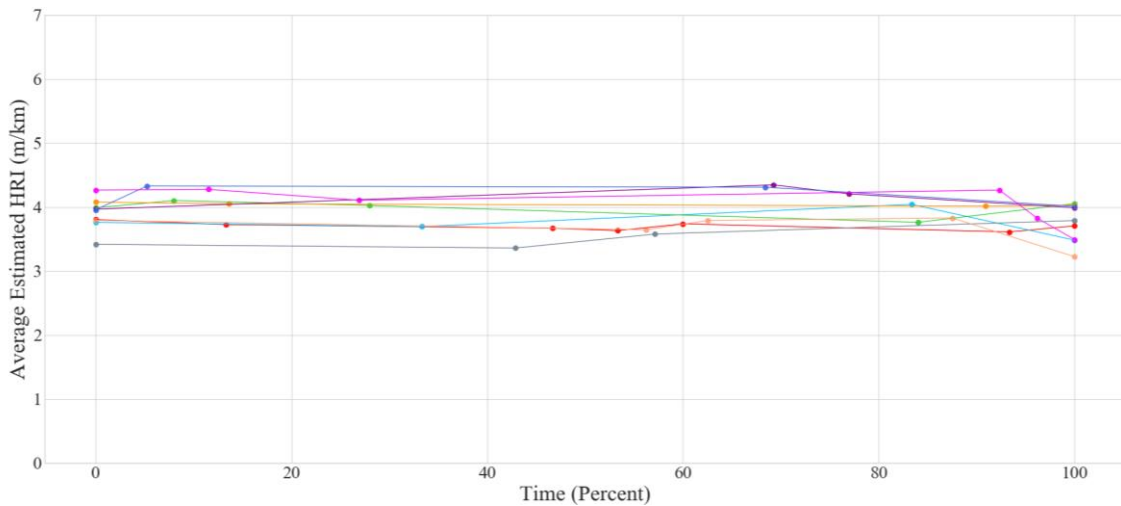


Figure 4-38: Roughness progression for segment 17100023199273 of the Jachtpad Road

4.5.6 Normalised road roughness progression isolated by rainfall season for low trafficked sections

The normalised road roughness deterioration for low trafficked sections isolated by rainfall season are provided in Figures 4-39 to 4-41.

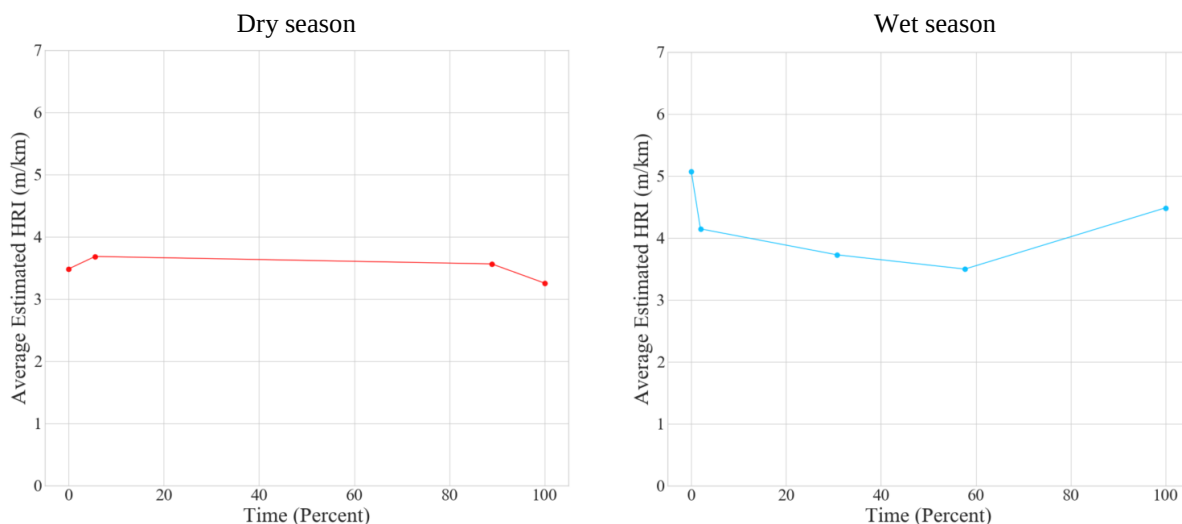


Figure 4-39: Roughness progression isolated by rainfall season for segment 17100024809479

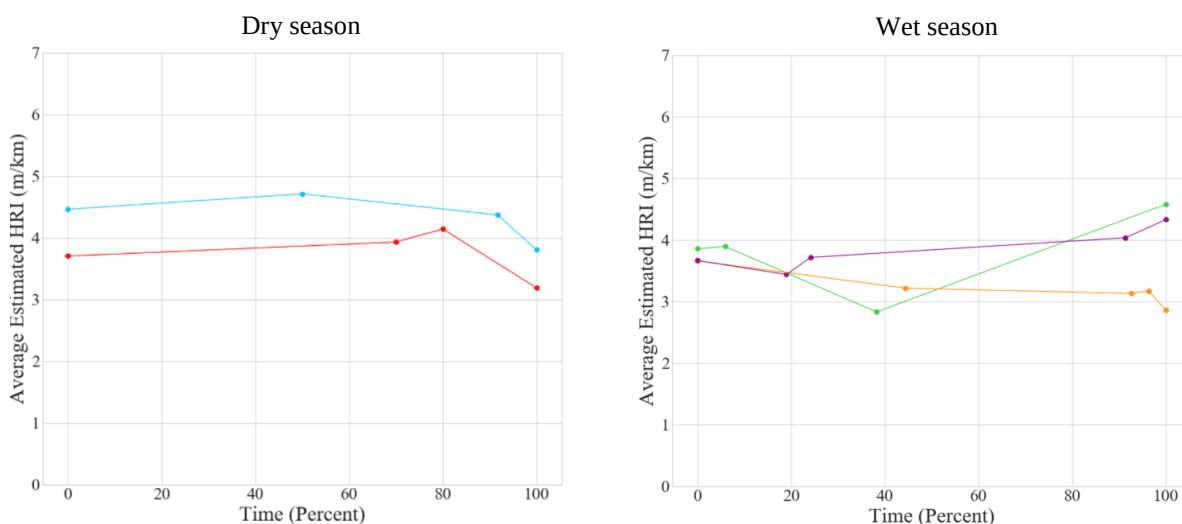


Figure 4-40: Roughness progression isolated by rainfall season for segment 17100022758644

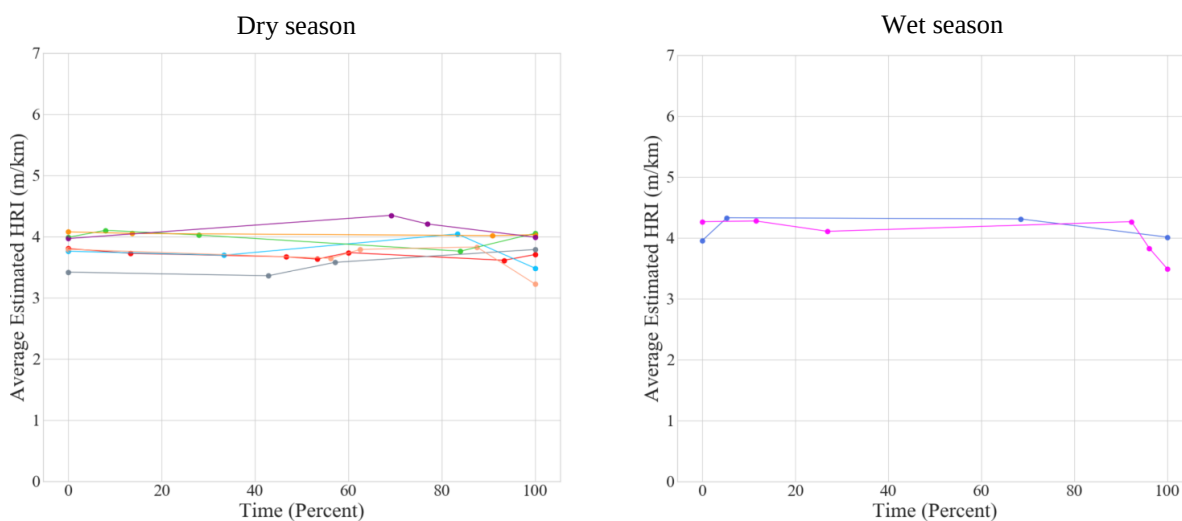


Figure 4-41: Roughness progression isolated by rainfall season for segment 17100023199273

4.6 DETERIORATION MODELS

The isolated roughness progression data per segment was grouped into datasets according to the traffic and slope of the segment. The results over the wet season are given in Figure 4-42 to 4-44.

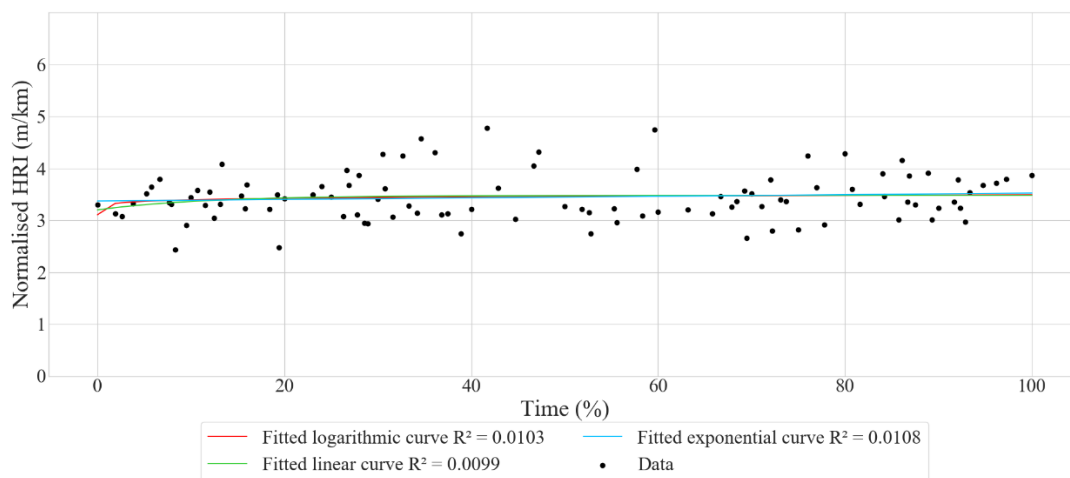


Figure 4-42: Linear deterioration models of high traffic, low slope segments over the wet season

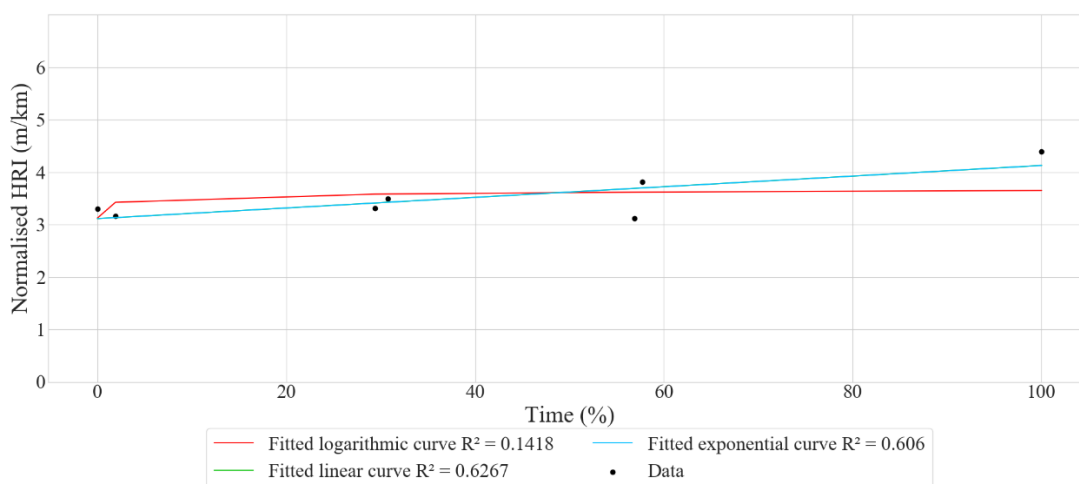


Figure 4-43: Linear deterioration models of low traffic, high slope segments over the wet season

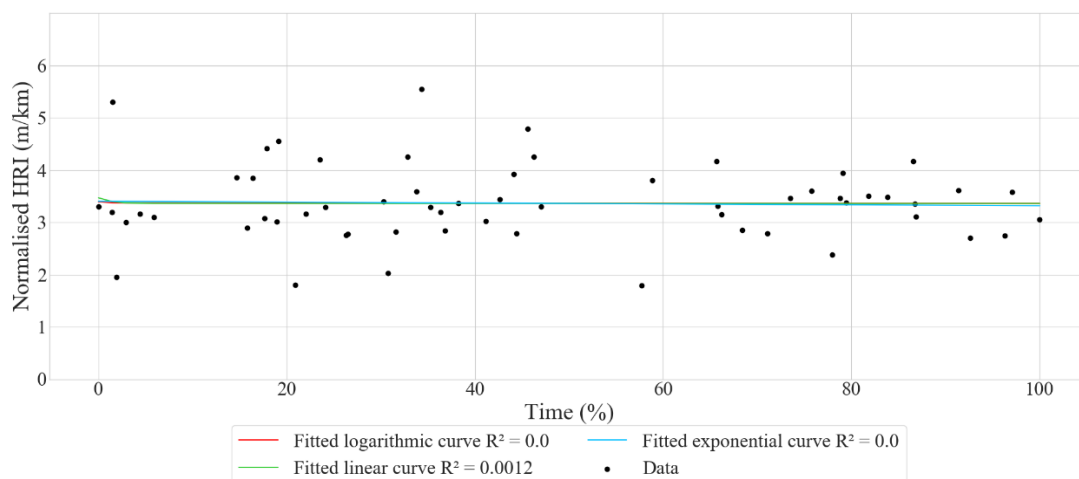


Figure 4-44: Linear deterioration model of low traffic, low slope segments over the wet season

The grouped roughness progression data over the dry season is provided in Figures 4-45 to 4-47.

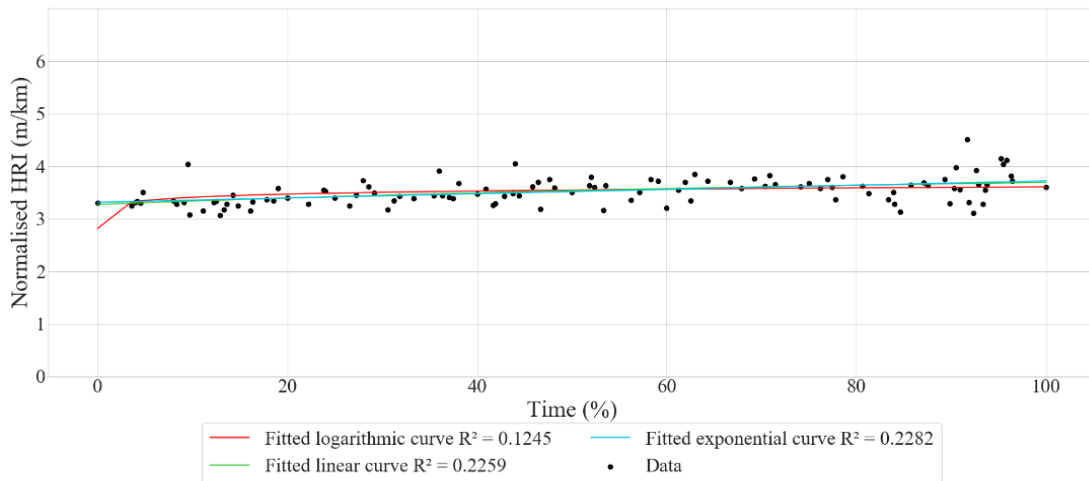


Figure 4-45: Linear deterioration models of high traffic, low slope segments over the dry season

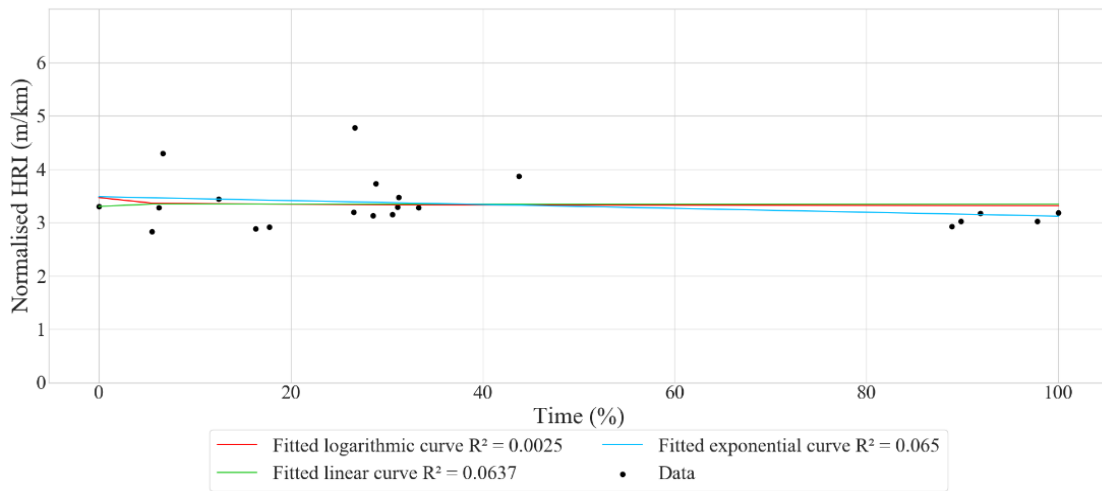


Figure 4-46: Linear deterioration models of low traffic, high slope segments over the dry season

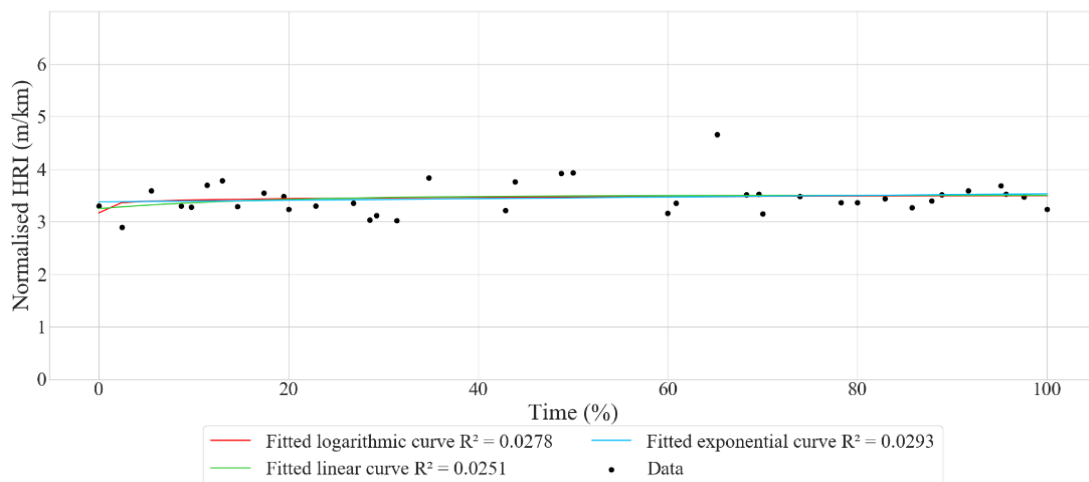


Figure 4-47: Linear deterioration models of low traffic, low slope segments over the dry season

4.6.1 Evaluation of deterioration models for the wet season

The following figures show the residual versus predicted value plots using linear and non-linear regression for grouped segments over the wet rainfall season.

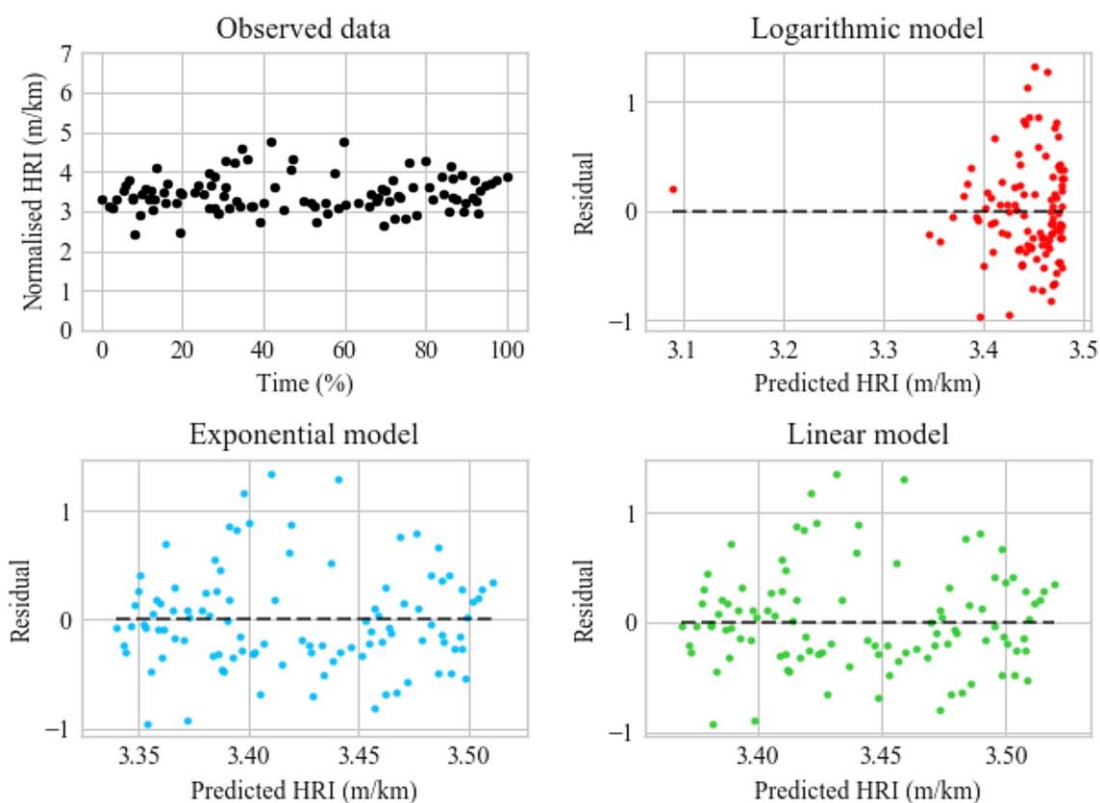


Figure 4-48: Residual vs prediction plots for high traffic, low slope segments using linear regression

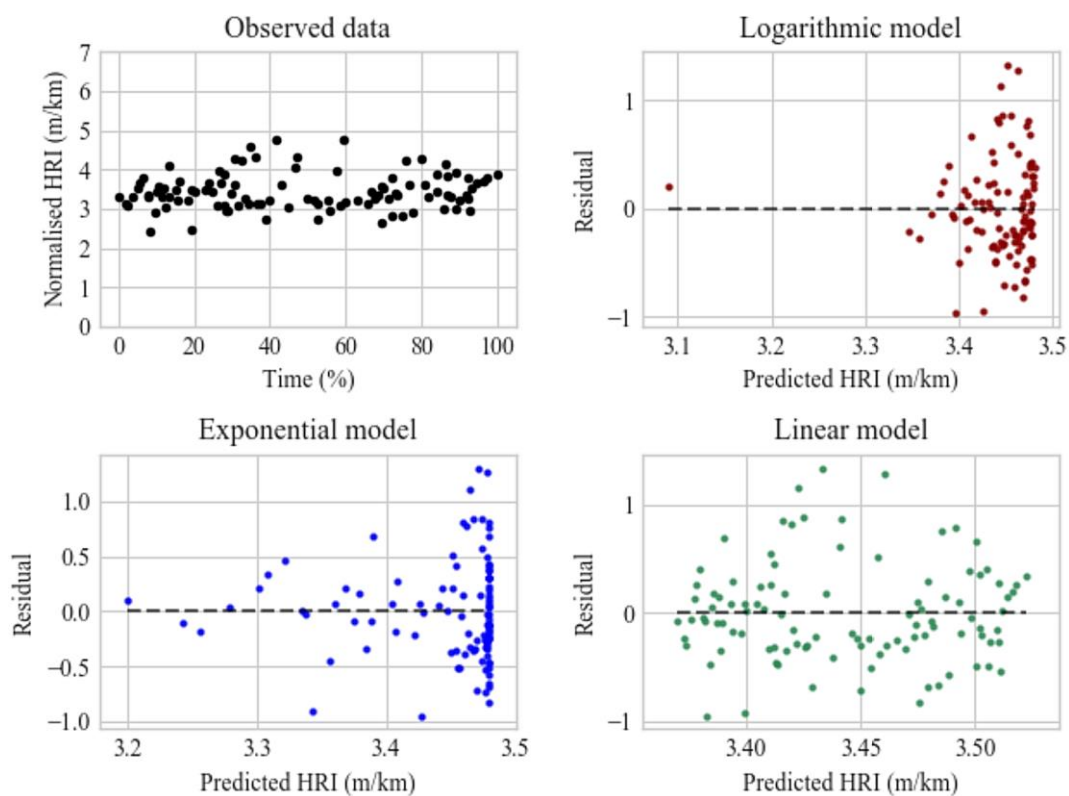


Figure 4-49: Residual vs prediction plots for high traffic, low slope segments using non-linear regression

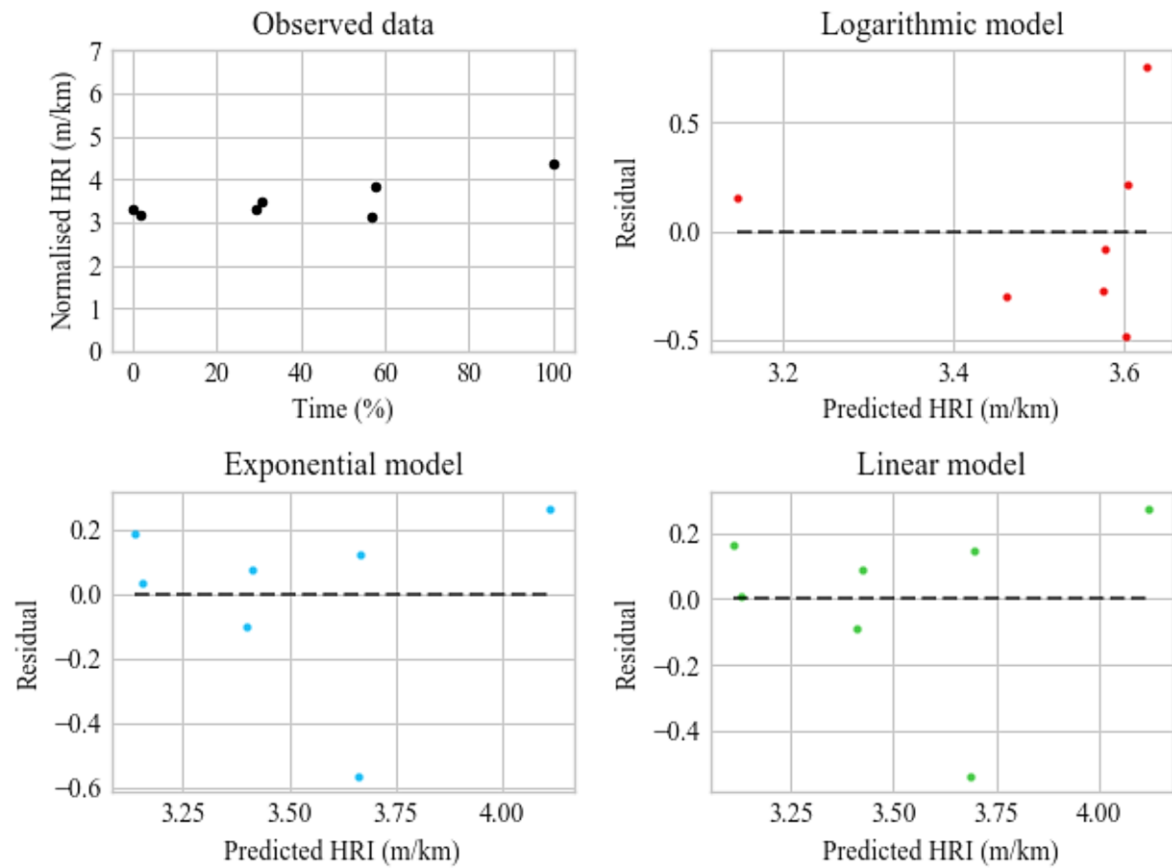


Figure 4-50: Residual vs prediction plots for low traffic, high slope segments using linear regression

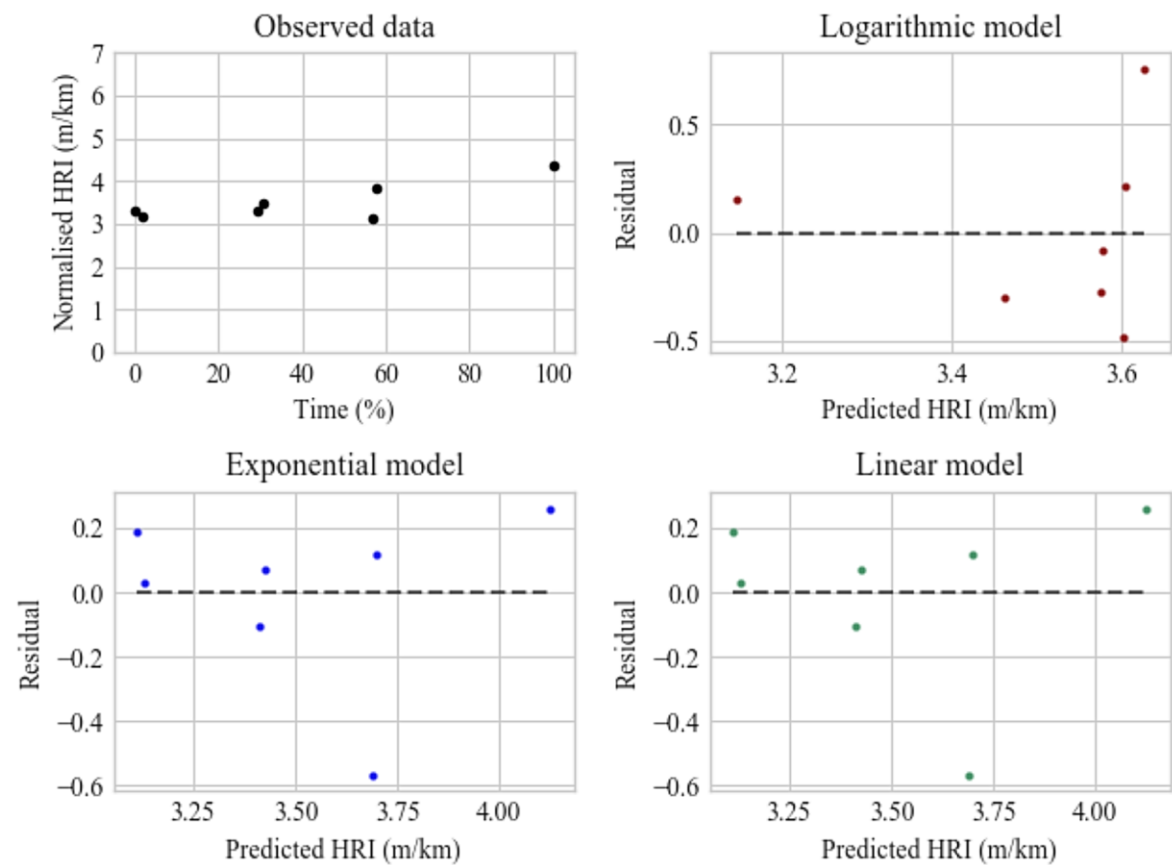


Figure 4-51: Residual vs prediction plots for low traffic, high slope segments using non-linear regression

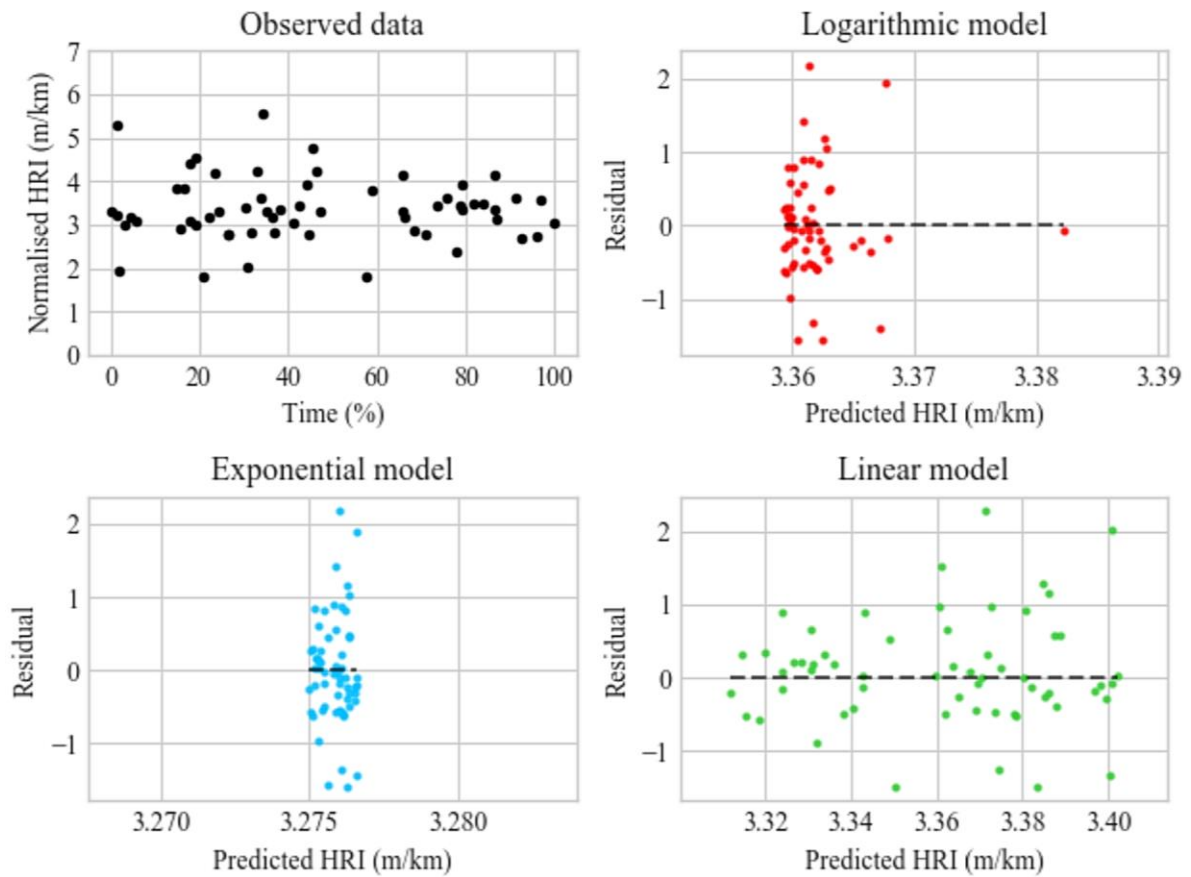


Figure 4-52: Residual vs prediction plots for low traffic, low slope segments using linear regression

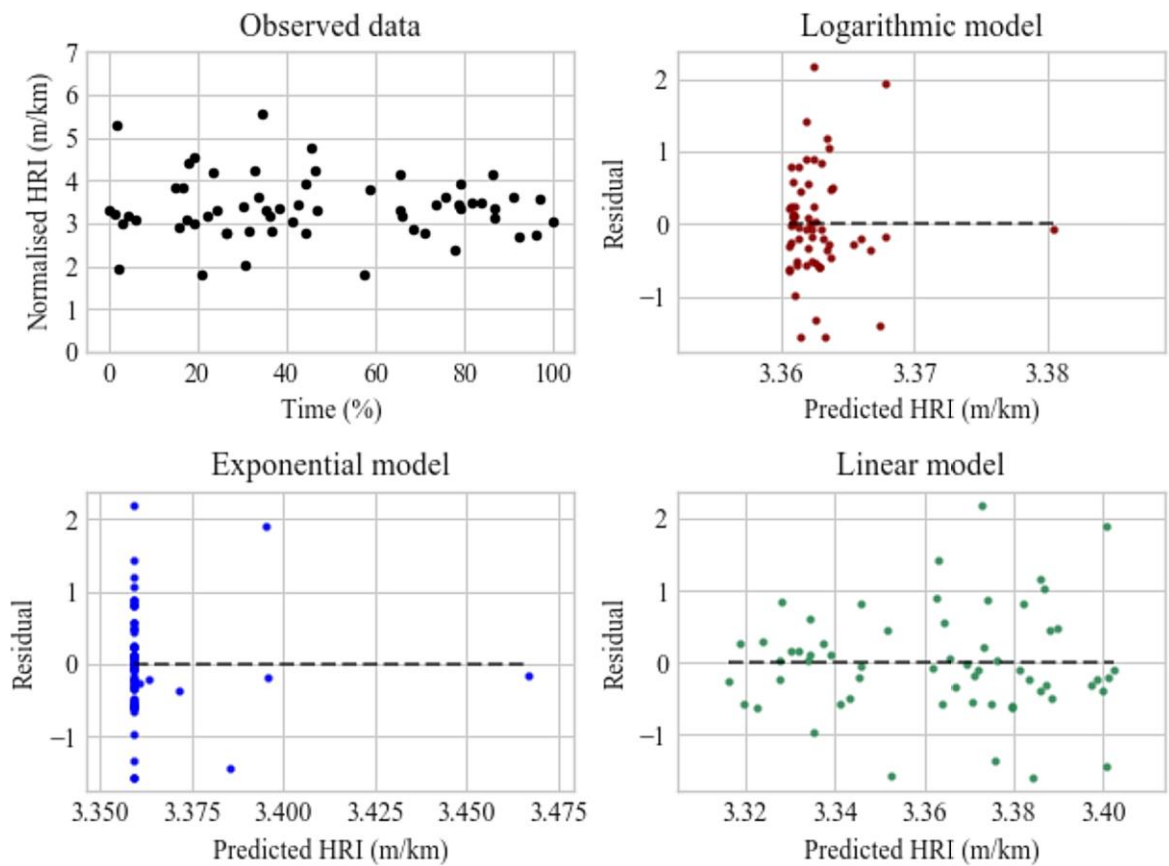


Figure 4-53: Residual vs prediction plots for low traffic, low slope segments using non-linear regression

4.6.2 Evaluation of deterioration models for dry season

The following figures show the residual vs predicted value plots using linear and non-linear regression for grouped segments over the dry rainfall season.

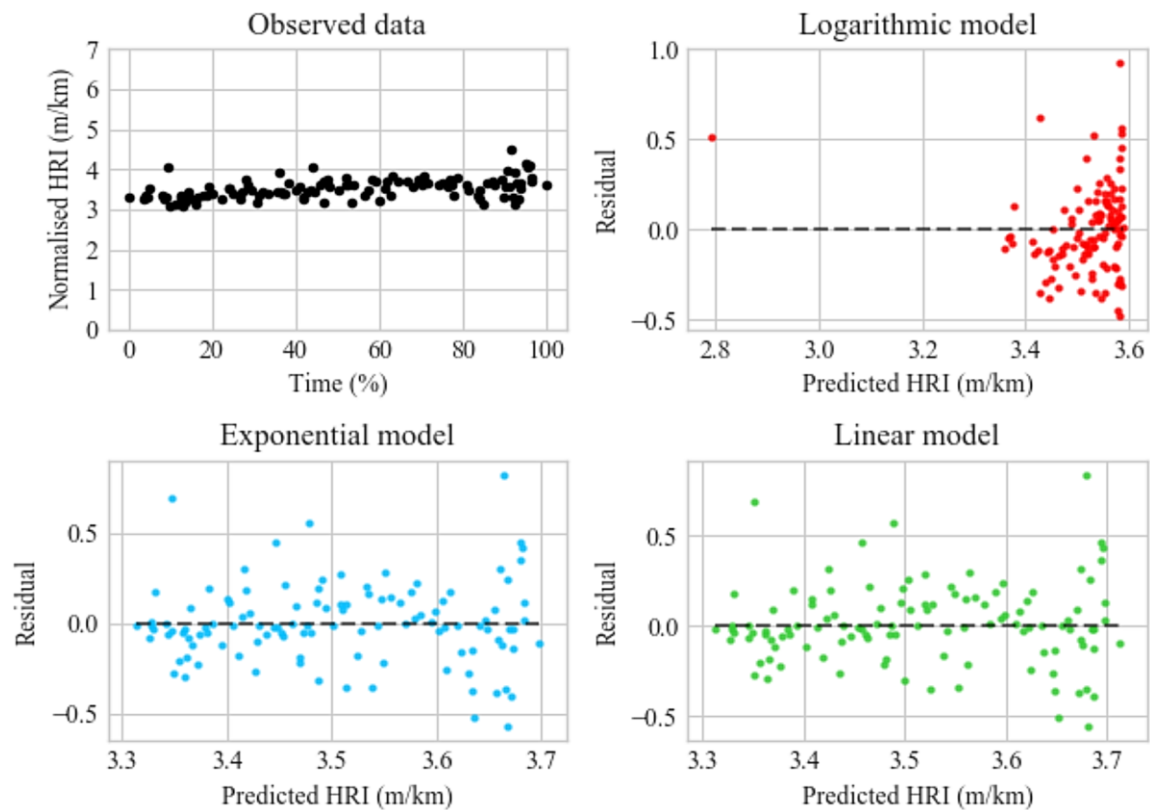


Figure 4-54: Residual vs prediction plots for high traffic, low slope segments using linear regression

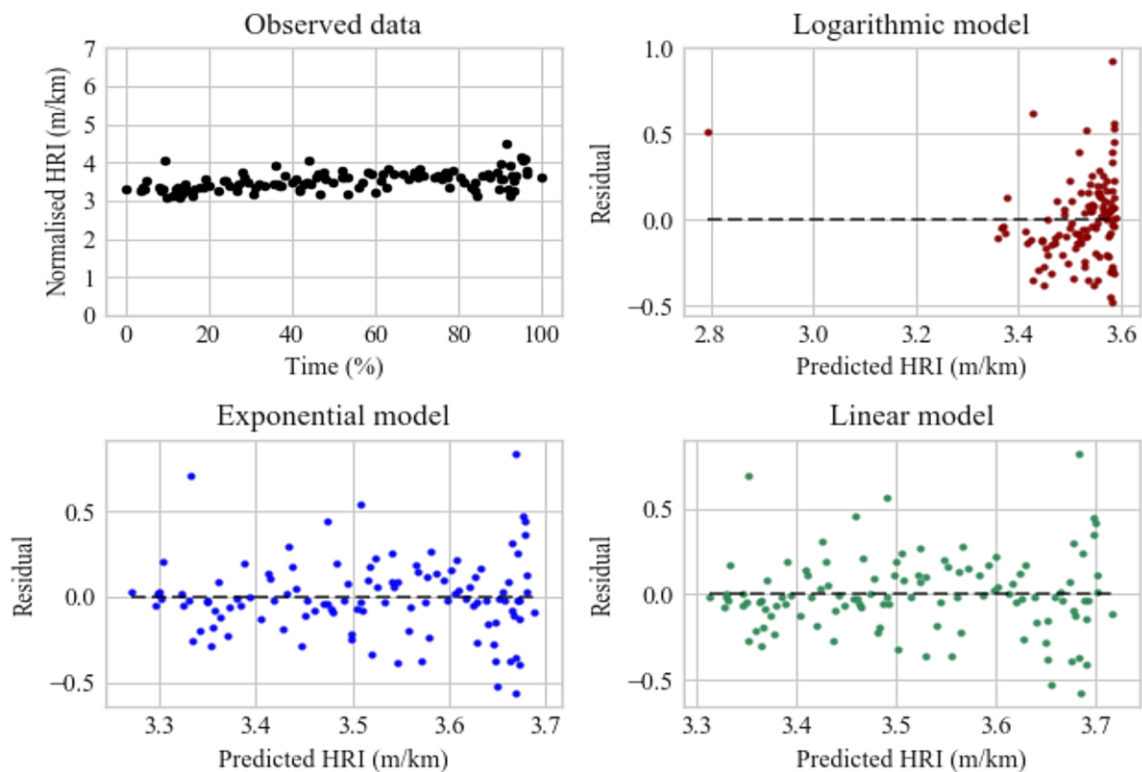


Figure 4-55: Residual vs prediction plots for high traffic, low slope segments using non-linear regression

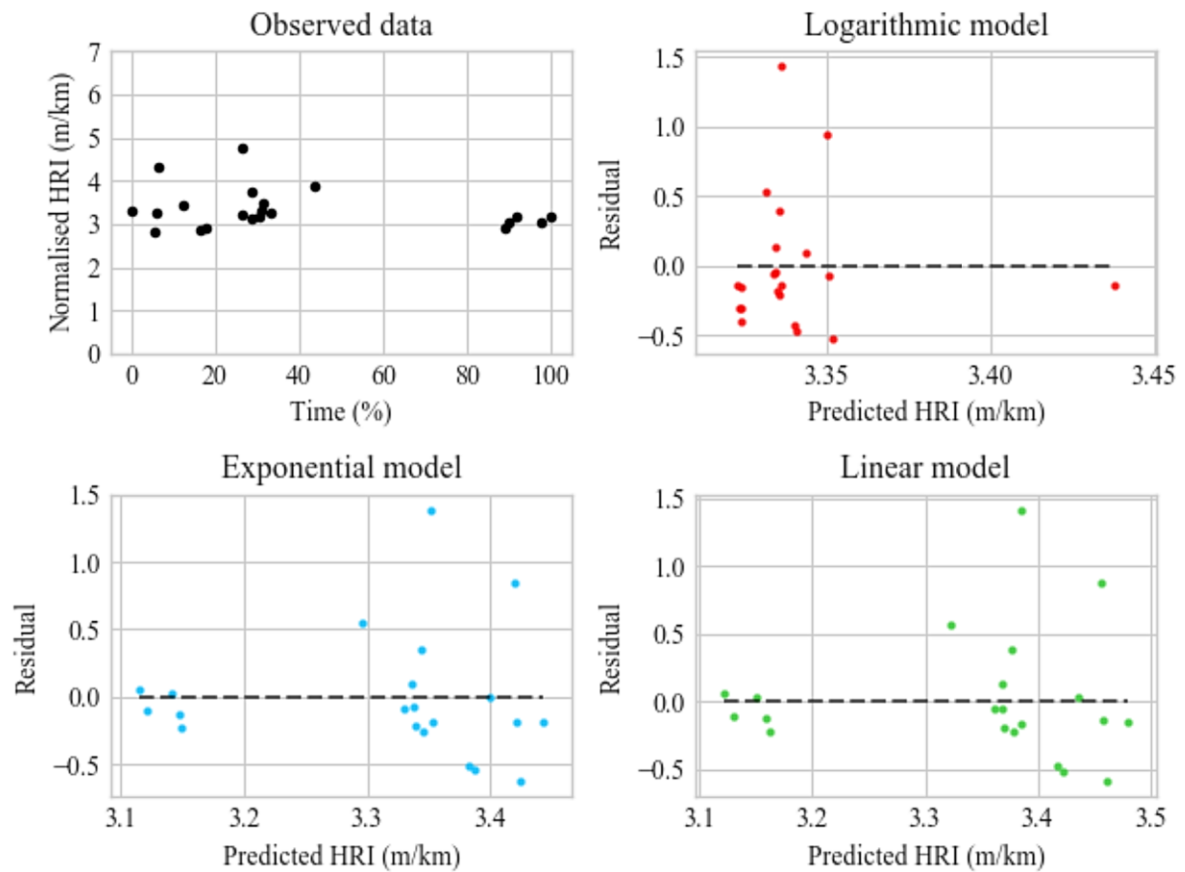


Figure 4-56: Residual vs prediction plots for low traffic, high slope segments using linear regression

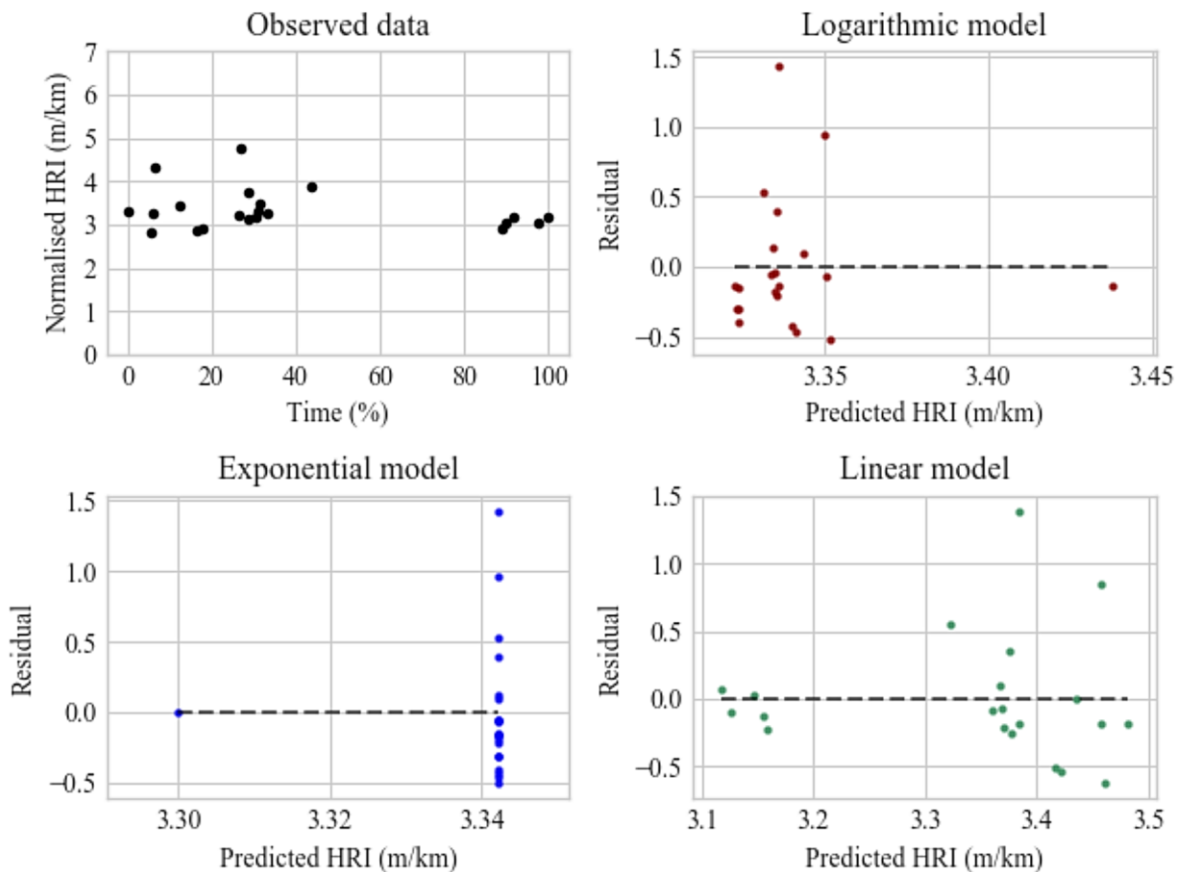


Figure 4-57: Residual vs prediction plots for low traffic, high slope segments using non-linear regression

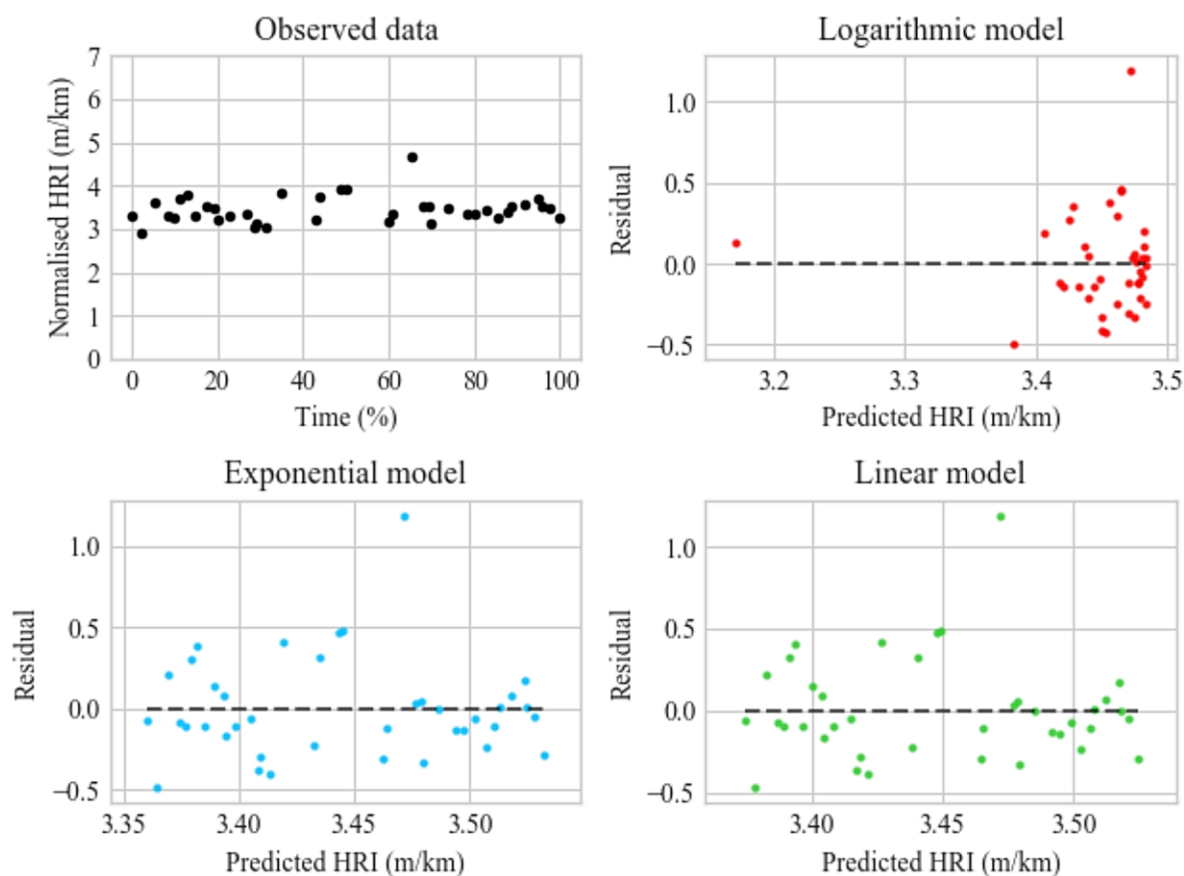


Figure 4-58: Residual vs prediction plots for low traffic, low slope segments using linear regression

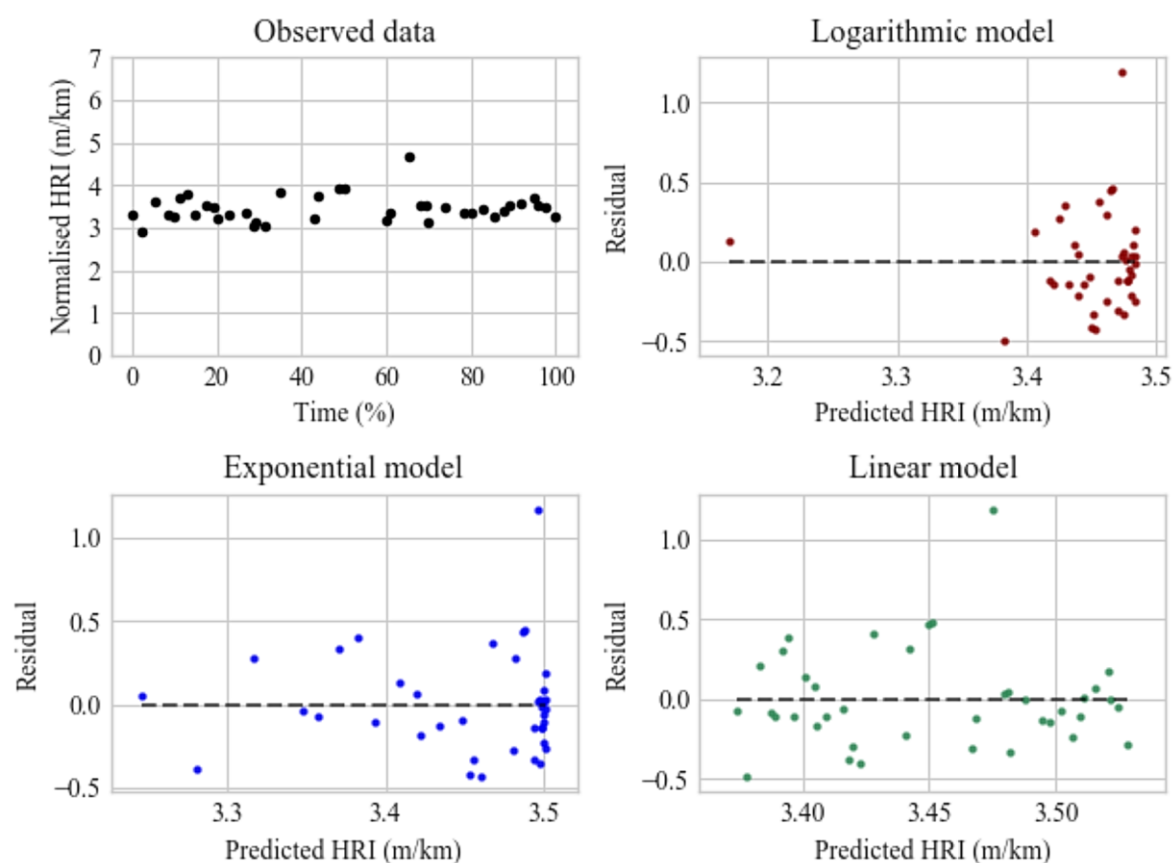


Figure 4-59: Residual vs prediction plots for low traffic, low slope segments using non-linear regression

4.7 FINAL DETERIORATION MODELS

The final deterioration models were selected from the linear regression curves as the more computationally complex non-linear regression curves did not provide a significantly improved fit. The models expressed as a percentage of time over a 30.5 day period are graphed in Figure 4-60.

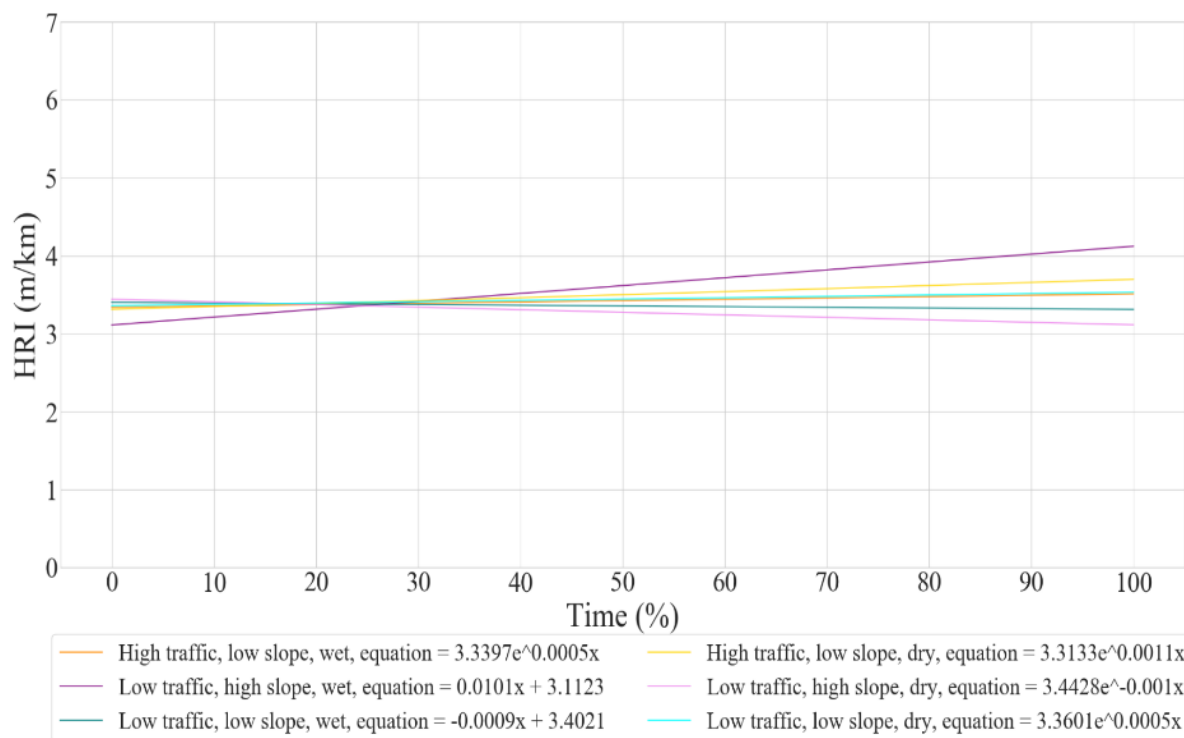


Figure 4-60: Final deterioration models expressed as a percentage of time over a 30.5 day period

The deterioration models extrapolated over an annual period and expressed as a percentage of the 30.5 day period are shown in Figure 4-61.

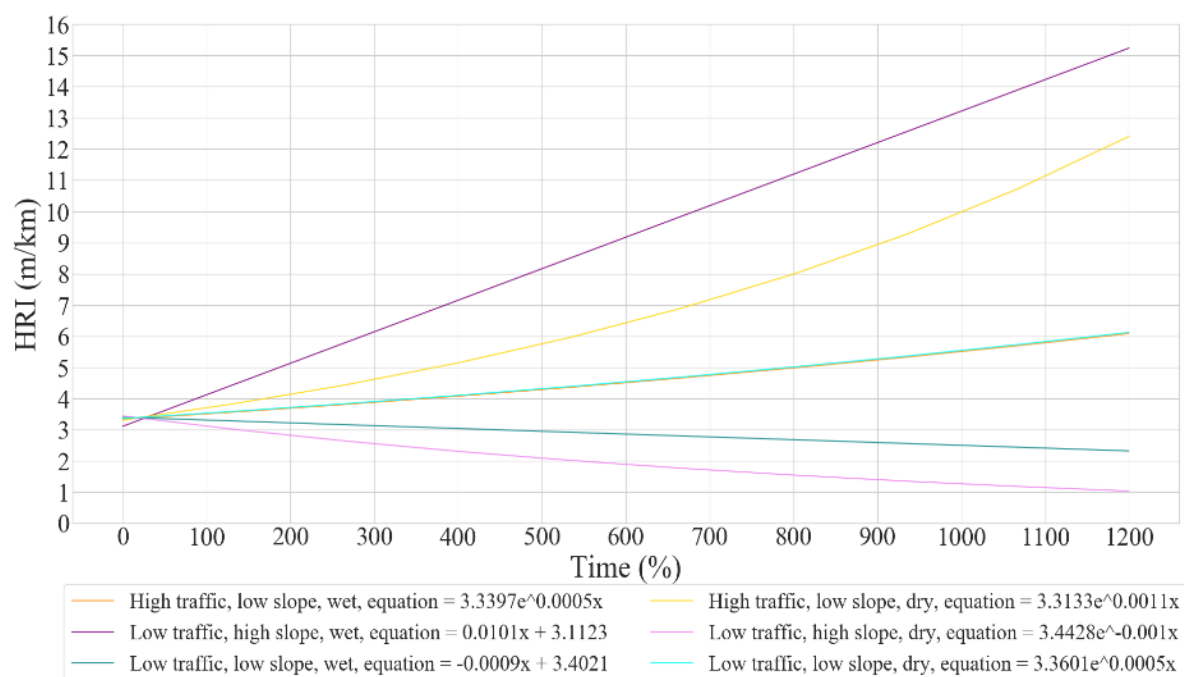


Figure 4-61: Extrapolated deterioration models expressed as a percentage of time over a 30.5 day period

The parameters of the final deterioration models are provided in Table 4-3. The models are deemed to be invalid for extrapolation where the fitted functions show a decrease in HRI over an annual period. This phenomenon is attributed to the effect of regular watering and the compaction of the road surface under vehicular loading. Further modelling should be carried out to determine the form of these functions.

Table 4-3: Final deterioration model parameters

Section type	Function curve	Equation	Coefficient of determination R ²	Valid over annual period
High traffic, low slope, wet	Exponential	$y = 3.3397e^{0.0005x}$	0.011	Yes
High traffic, low slope, dry	Exponential	$y = 3.3133e^{0.0011x}$	0.23	Yes
Low traffic, high slope, wet	Linear	$y = 0.0101x + 3.1123$	0.63	Yes
Low traffic, high slope, dry	Exponential	$y = 3.4428e^{-0.001x}$	0.065	No
Low traffic, low slope, wet	Linear	$y = -0.0009x + 3.4021$	0.0012	No
Low traffic, low slope, dry	Exponential	$y = 3.3601e^{0.0005x}$	0.03	Yes

4.7.1 Annual maintenance requirements

A maximum target surface roughness to be used as a grading trigger for the agricultural organisation was estimated to be an HRI of 5 m/km. A sensitivity analysis was performed by comparing the results obtained using target grading triggers for HRI values of 4 m/km, 4.4 m/km, 5 m/km, 5.5 m/km and 6 m/km. The estimated number of days required to reach the selected grading trigger based on the extrapolated deterioration models deemed to be valid over an annual period can be calculated using Equations 4-1 to 4-4.

$$\text{High traffic, low slope, wet:} \quad \text{No. of days} = 0.0005^{-1} \ln\left(\frac{y}{3.3397}\right) \times \frac{30.5}{100} \quad (4-1)$$

$$\text{High traffic, low slope, dry:} \quad \text{No. of days} = 0.0011^{-1} \ln\left(\frac{y}{3.3133}\right) \times \frac{30.5}{100} \quad (4-2)$$

$$\text{Low traffic, high slope, wet:} \quad \text{No. of days} = (99y - 308.15) \times \frac{30.5}{100} \quad (4-3)$$

$$\text{Low traffic, low slope, dry:} \quad \text{No. of days} = 0.0005^{-1} \ln\left(\frac{y}{3.3601}\right) \times \frac{30.5}{100} \quad (4-4)$$

Where:

y = Selected grading trigger (HRI m/km)

The estimated number of days required to activate the selected grading triggers on the various classes of road sections for the dry and wet seasons are provided in Table 4-4.

Table 4-4: Number of days required to activate various grading triggers for various road section types

Section type	No. of days to reach grading trigger				
	4 (m/km)	4.5 (m/km)	5 (m/km)	5.5 (m/km)	6 (m/km)
High traffic, low slope, wet	110	180	247	305	357
High traffic, low slope, dry	52	85	113	140	165
Low traffic, high slope, wet	27	42	57	72	87
Low traffic, low slope, dry	107	177	244	302	354

The number of annual grading activities that would be required to maintain the various classifications of road sections based on the selected maintenance triggers were calculated for the deterioration models that were deemed valid for extrapolation over an annual period, thus the models representing consistently decreasing surface roughness were not included in the maintenance cost analysis and optimisation. The annual number of required grading activities were calculated by dividing the number of days in a year by the number of days required to activate the grading triggers. The results are provided in Table 4-5.

Table 4-5: No. of annual grading activities for various grading triggers, road section types and seasons

Section type	No. of annual grading activities				
	4 (m/km)	4.5 (m/km)	5 (m/km)	5.5 (m/km)	6 (m/km)
High traffic, low slope, wet	3.3	2	1.5	1.2	1
High traffic, low slope, dry	7	4.3	3.2	2.6	2.2
Low traffic, high slope, wet	13.5	8.7	6.4	5.0	4.1
Low traffic, low slope, dry	3.4	2.1	1.5	1.2	1

The number of seasonal grading activities required to maintain various classifications of road sections below selected maintenance triggers for the derived deterioration models are provided in Table 4-6. These values are calculated by dividing the number of annual grading activities by two, as the wet and dry periods used in the analyses were both 6 months in length.

Table 4-6: No. of seasonal grading activities for various grading triggers, road section types and seasons

Section type	No. of seasonal grading activities				
	4 (m/km)	4.5 (m/km)	5 (m/km)	5.5 (m/km)	6 (m/km)
High traffic, low slope, wet	1.7	1	0.8	0.6	0.5
High traffic, low slope, dry	3.5	2.2	1.6	1.3	1.1
Low traffic, high slope, wet	6.8	4.4	3.2	2.5	2.1
Low traffic, low slope, dry	1.7	1.1	0.8	0.6	0.5

The results from Table 4-6 can be applied in practice in the following manner:

Where both seasonal models are valid for a particular road section type over an annual period, such as for high trafficked segments with low slope, the annual number of grading activities required to maintain a selected HRI maintenance trigger can be assumed to be the sum of the number of the number of grading activities required over the wet and dry season.

Where only one seasonal model is valid for a particular road section type over an annual period, such as for low trafficked road segments, the annual number of grading activities required to maintain a selected HRI maintenance trigger can be conservatively assumed to be twice the number of grading activities required for valid seasonal model.

Thus, the number of annual grading activities required to maintain various road section types over an annual period is provided in Table 4-7.

Table 4-7: No. of annual grading activities for various grading triggers and road section types

Section type	No. of annual grading activities				
	4 (m/km)	4.5 (m/km)	5 (m/km)	5.5 (m/km)	6 (m/km)
High traffic, low slope	5.2	3.2	2.4	1.9	1.6
Low traffic, high slope	13.5	8.7	6.4	5.0	4.1
Low traffic, low slope	3.4	2.1	1.5	1.2	1

4.7.2 Maintenance cost models

The average cost of vehicle hire for a grading activity undertaken by the agricultural organisation was R 1 040 per hour. Figure 4-62 represents the annual hourly cost required to grade various road section types at selected HRI trigger values. These models are calculated by multiplying the maintenance cost per hour by the quotient of the number of days in a year divided by the number of days required to activate maintenance for various HRI trigger values (provided in equations 4-2 to 4-4).

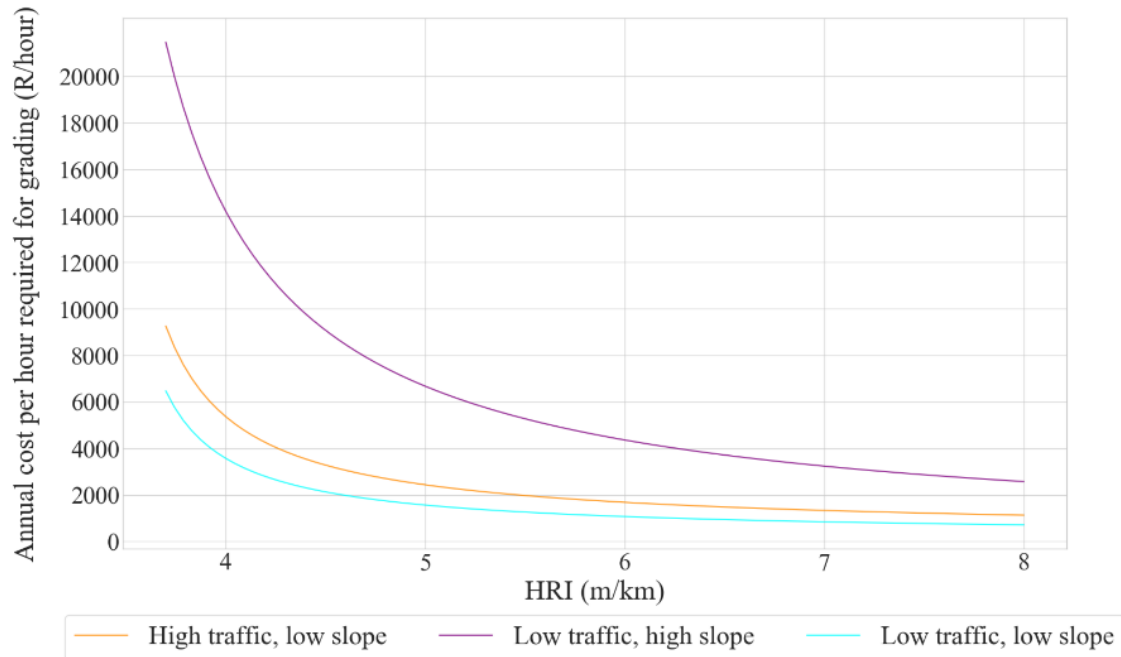


Figure 4-62: Graph showing the annual hourly cost required to grade the road vs HRI

4.7.3 Tomato shelf-life models

Shelf-life models for tomatoes of varying degrees of ripeness transported over roads with constant roughness for a period of 10 minutes simulated by Pretorius (2017) are provided in Figure 4-63.

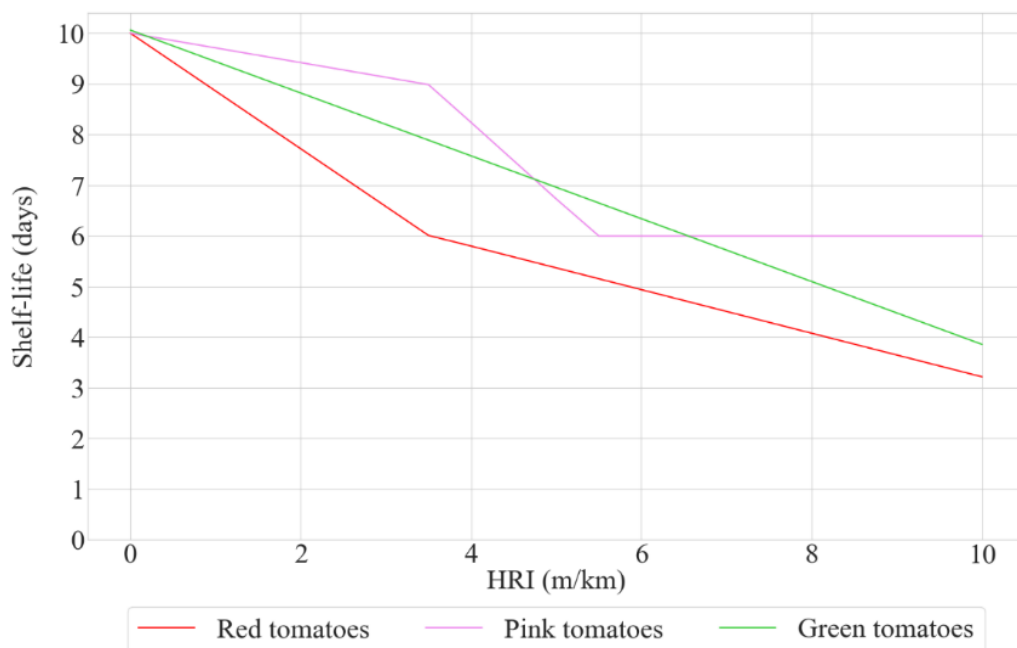


Figure 4-63: Shelf-life deterioration of tomatoes transported on an unpaved road for 600 seconds

4.7.4 Optimization of annual grading cost vs tomato shelf-life

The annual grading cost curves for various road section types as well as the shelf-life models for tomatoes of varying degrees of ripeness were plotted on a single chart for graphical representation only and are shown in Figure 4-64.

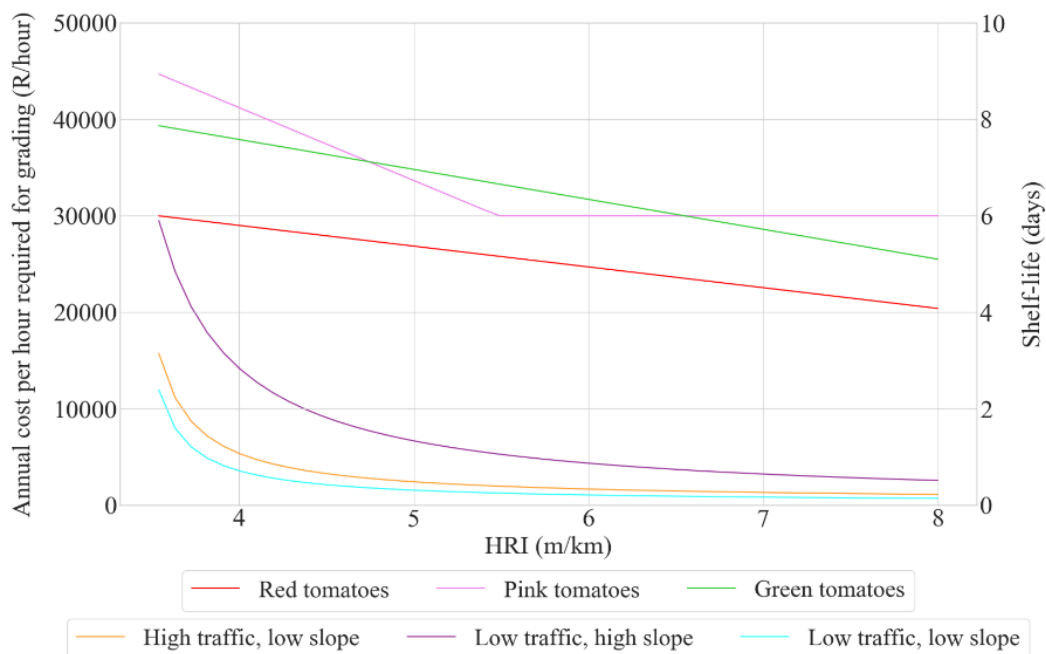


Figure 4-64: Graphical representation of annual grading cost and shelf-life vs HRI

The optimum HRI values that can be used to trigger grading operations on unpaved roads can be determined by finding the HRI that simultaneously gives a minimum of the annual grading cost and a maximum of the tomato shelf-life. The optimum HRI trigger values were calculated by finding the point at which the difference between the annual grading cost curve and shelf-life curve was at a maximum. The results are provided in Table 4-8 to 4-10.

Table 4-8: Optimum HRI values to trigger the grading of unpaved roads

Section type	Red tomatoes	Pink tomatoes	Green tomatoes
High traffic, low slope	4.6	4.0	4.4
Low traffic, high slope	5.6	4.4	5.1
Low traffic, low slope	4.4	3.9	4.2

Table 4-9: Annual grading cost measured per hour required for a single grading to obtain optimum HRI

Section type	Red tomatoes	Pink tomatoes	Green tomatoes
High traffic, low slope	R 3 113	R 5 373	R 3 684
Low traffic, high slope	R 5 160	R 9792	R 6 308
Low traffic, low slope	R 2 405	R 4 444	R 2 865

Table 4-10: Target shelf-life corresponding to optimum HRI trigger values

Section type	Red tomatoes	Pink tomatoes	Green tomatoes
High traffic, low slope	5.6 days	8.2 days	7.4 days
Low traffic, high slope	5.1 days	7.6 days	6.9 days
Low traffic, low slope	5.65 days	8.4 days	7.5 days

5 DISCUSSION AND ANALYSIS

This chapter will discuss and interprets the significance of the results presented in Chapter 4 by analysing the findings in terms of their applicability and reliability.

5.1 ROAD NETWORK CHARACTERISTICS

The portion of the unpaved road network used in the analysis of the study is not extensive in length and covers a relatively small area thus the results are suitable for regions of similar ground and climate conditions. However, the three roads selected differ significantly in terms of steepness and traffic conditions, thus, conclusions drawn from the effects of these factors on the optimum frequency of grading may be more widely applicable.

5.2 ROAD CONDITION

Figure 4-7 clearly shows that the range of the road roughness represented by the change in HRI over time decreases as the length of the HRI data record increases. This is possibly due to the effect of averaging as a decreased proportion of outliers is less likely to skew the data. Thus, it is important to obtain data records sufficient in length to minimise the effect of outliers. However, it is clear that the roads used in the analysis have achieved similar average HRI minimum values of approximately 2.9 m/km. The excellent riding quality shown by these roads may be caused by excellent maintenance, or the regular application of water. The maximum average HRI values reached over the 16-month analysis period were approximately 6.4 m/km for Houtbosdorp Road, 5.2 m/km for Vreedsaam Road and 4 m/km for Jachtpad Road. The factors contributing to the differences in the maximum average HRI values achieved for the roads are analysed further by investigating the individual sections forming the length of the roads.

5.2.1 Houtbosdorp Road

The Houtbosdorp Road is the longest road selected for the analysis containing the highest number of sections and the shortest data record. When analysing the change in HRI over time for the individual segments forming the length of the road as provided in Figure 4-8, it is clear that the segments show a similar trend with HRI increasing and decreasing uniformly over time, thus it can be argued that the average HRI of the road is a true reflection of the condition of the individual sections forming the length of the road and that the factors contributing to the roughness of the road are heavily time-dependent.

5.2.2 Vreedsaam Road

The Vreedsaam Road is the shortest road used in the analysis and comprises four sections. An analysis of Figure 4-9 representing the change in HRI over time for the individual segments forming the length of the road, it is clear that a disparity exists between the individual HRI measurements achieved over time for sections with vastly varying data record lengths. The section located at the start of the road (17100023044624) contains the highest number of measurements and shows the lowest range in HRI values achieved over time. The section located at the end of the road (17100024046817) has the lowest data record length and shows the largest range in HRI values over time. However, when looking at the sections collectively, it becomes clear that although the individual measurements are vastly different for sections of varying data record lengths, the general trend marking where the HRI values increase and decrease over time is similar for all the sections, thus, a general trend of the change in HRI of the Jachtpad Road can be obtained from the sections forming the length of the road.

5.2.3 Jachtpad Road

The Jachtpad Road is the highest trafficked road with the longest data record used in the analysis. Figure 4-10 shows that the first (17100023402227), second (1710002348190) and fourth (17100024819125) segments are highly uniform in terms of HRI value and trend. Interestingly, the third segment (17100022256372) deviates significantly from the segments preceding and succeeding it in terms of the HRI values obtained and the HRI trend over time. This particular section is positioned at the intersection of the head office of the agricultural organisation and the Jachtpad Road, thus the high HRI values obtained for this section may be attributed to the difficulty in achieving an accurate HRI measurement when making a sharp turn as well as the poor condition of the road surface at the intersection due to the increased shearing forces exerted by the heavy trucks and small vehicles making a 90 degree turn into the entrance of the head office and primary packing house. The collective condition of this road does not accurately reflect the conditions of the segments it is comprised of.

5.3 RAINFALL

The distribution of rainfall over a small area is known to be highly variable. Due to the fact that data from six different rain gauge stations positioned around the roads of interest was available for analysis, an attempt was made to calculate the distribution of rainfall landing on each road segment by weighting the measured rainfall according to the relative distance of the rain gauge station to the centre of the road segment. The rainfall was then weighted according to the length of the road segments to obtain an average rainfall for each road which is represented by Figures 4-11 to 4-13. When comparing the graphs, it can be noted that the distribution of rainfall over time throughout the analysis period is identical for all the roads however, the Jachtpad Road experienced the heaviest daily rainfall, followed by the Vreedsaam Road and the Houtbosdorp Road over the analysis period.

5.4 ROAD MAINTENANCE HISTORY

The primary maintenance activity performed on the selected roads consists of grading using a mechanical grader followed by compaction using a vibratory roller. Grading was frequently performed on all three of the selected roads. Table 4-2 shows that the Houtbosdorp Road is the most expensive to grade, requiring the largest number of days of plant and vehicle hire due to the long length of the road. The Vreedsaam road received the least number of grading activities due to its light traffic and was the least expensive to grade per grading activity due to the short length of the road.

The effect of the grading activities performed on the Houtbosdorp Road represented by Figure 4-15 shows that the grading activities typically resulted in a reduction in the average HRI ranging between 0.3 m/km and 3.4 m/km. The greatest reduction in HRI was obtained when grading was performed after the road had reached a maximum of 6.4 m/km. The minimum HRI achieved was 2.9 m/km.

The effect of the grading activities performed on the Vreedsaam Road represented by Figure 4-16 show that the grading activities typically resulted in a reduction in the average HRI ranging between 0.2 m/km and 1.5 m/km with the exception of the grading performed at the end of May 2018 which resulted in an increase in HRI. This can be caused by an inexperienced grader operator cutting too deeply into the road surface resulting in further roughening. The minimum HRI achieved after grading was 2.7 m/km.

The effect of the grading activities performed on the Jachtpad Road represented by Figure 4-17 shows that the grading activities typically resulted in a reduction in the Average HRI ranging between 0.5 and 1.5 m/km with the greatest improvement occurring after the maximum HRI was reached. The minimum HRI achieved was 2.5 m/km.

5.5 ROAD ROUGHNESS PROGRESSION TRENDS

The road roughness progression isolated between the grading activities are provided in Figures 4-18 to 4-20. The figures show a predominantly increasing trend in roughness over time with a few exceptions showing a decrease in roughness over time. This may be due to the effect of compaction from vehicle loading shortly after a maintenance activity which may be further enhanced by the saturation of the road surface material due to rainfall and watering activities performed daily on the roads as a dust control measure.

5.5.1 Normalised roughness progression trends

The normalised roughness progression trends for the various roads provided in Figures 4-21 to 4-23 indicate a general net increase in roughness over the deterioration period although the trend is not uniformly increasing and it is common for the measured roughness to decrease for a period after grading has been conducted before increasing again. This may be caused by settlement and latent compaction of the road surface material due to traffic loading. Furthermore, if the material is stony, grading will loosen the stones causing roughness which are then moved to the side of the road by traffic, decreasing the roughness. It is clear from the graphs that grading activities were scheduled regularly without allowing the road to deteriorate by more than 1.5 m/km with the exception of two instances along the Houtbosdorp road. Thus, the scheduling of the maintenance activities was relatively consistent even though the scheduling was not informed by the direct measurement of the road surface roughness. It is clear that the roads have been well maintained and that the maintenance activities performed on the roads have been effective in preserving the condition of the road surface.

5.5.2 Normalised roughness progression trends isolated by rainfall

The normalised roughness progression trends were isolated by rainfall season to investigate the effect of rainfall on the deterioration of the roads and are provided in Figures 4-24 to 4-26. When comparing the roughness progression over the dry and wet seasons, it is clear that the net roughness increase was higher over the dry season than over the wet season for the Houtbosdorp and Vreedsaam roads. This is attributed to the formation of corrugations during the dry season. The Jachtpad road showed similar net deteriorations over both seasons. An explanation for the higher deterioration experienced over the wet season on the Jachtpad road relative to the Houtbosdorp and Vreedsaam roads may be due to the heavy traffic and higher shearing forces experienced at the entrance to the head office and packing house causing increased deterioration. It is necessary to isolate the roughness progression trends further to identify the effect of the relative traffic level and slope of the roads on the deterioration of the road surfaces over the dry and wet seasons.

5.5.3 Normalised roughness progression trends isolated by the slope

The normalised road roughness progression isolated into flat and mountainous sections (slope greater than 6 per cent) for the Houtbosdorp Road are presented in Figure 4-27. The figure shows great variability in the road roughness progression trend for the flat section of the Houtbosdorp road. The mountainous section, however, indicated similar net deterioration over the deterioration period although the trends were variable. It is necessary to isolate the trends further by rainfall season to investigate the combined effect of the road steepness and rainfall on the roughness progression trends. The deterioration of the Houtbosdorp road isolated by rainfall and slope is provided in Figures 4-28 and 4-29. The roughness progression trend over the dry season remains highly variable for both flat and mountainous sections although it can be noted that a smaller increase in roughness was experienced over the wet season for flat sections of the Houtbosdorp Road. The effect of rainfall on the mountainous sections of the Houtbosdorp remains unclear as the data collected was not sufficient to plot more than one trend.

5.5.4 Normalised roughness progression trends for high trafficked sections

The change in road roughness for highly trafficked road sections is presented in Figures 4-30 to 4-32 which show a similar net increase over the deterioration period. However, the roughness progression trend showed great variability for the Houtbosdorp and Vreedsaam roads, which experienced periods of increasing and decreasing roughness. This may be due to the latent compaction under traffic loading or possibly due to the Data Capturing Vehicle avoiding areas of high roughness by aligning the vehicle centre to the left or to the right of the lane centre line. This possibility must be considered due to the roads having a wide width to accommodate large vehicles. The maintenance activities were well scheduled for the Houtbosdorp and Jachtpad roads. The delay in grading the Vreedsaam road resulted in cost-saving self-correcting behaviour for three of the deterioration periods. The Jachtpad road showed a near-uniform trend of increasing surface roughness over time.

5.5.5 Normalised roughness progression trends for high trafficked sections isolated by traffic and rainfall

The roughness progression of the highly trafficked sections isolated by rainfall season provided in Figure 4-33 to Figure 4-35 did not show a uniform progression trend. Figure 4-33 shows that the road experienced the greatest deterioration for one period over the dry season although the road roughness remained fairly constant for the remaining two deterioration periods. Over the wet season, the road segment showed similar roughness progression trends, with the roughness increasing consistently to a net increase of approximately 0.8 m/km.

Figure 4-34 shows that the road roughness trend was not consistent over the dry period with half of the deterioration periods experiencing a net decrease in road roughness over the deterioration period. However, over the wet season, the trend was similar to the road segment experiencing periods of increasing and decreasing roughness with the net roughness remaining fairly consistent for two deterioration periods and decreasing for one. Figure 4-35 shows a uniform trend of increasing roughness over the dry season with a net increase of approximately 0.45 m/km over the deterioration period. However, over the wet season, no uniform roughness progression trend was displayed.

5.5.6 Normalised roughness progression trends for low trafficked sections isolated by traffic and rainfall

The roughness progression of the road segments experiencing the least traffic provided in Figure 4-36 to Figure 4-38. The graphs show similar trends with the measured roughness remaining fairly consistent over all the deterioration periods with 4 out of 14 trends showing a net increase in the road surface roughness and 10 out of 14 trends showing a net decrease. It is evident that grading activities were scheduled too frequently on the road sections experiencing low traffic.

5.5.7 Normalised roughness progression trends for low trafficked sections isolated by traffic and rainfall

The roughness progression of the low trafficked sections isolated by rainfall season provided in Figure 4-39 to Figure 4-41 shows that one roughness progression trend had a net increase in road roughness, four remained constant and five experienced a net decrease in road roughness over the dry season. Over the wet season, two trends showed a net increase in roughness, one remained constant and three showed a net decrease over the deterioration period. Thus, the frequency of grading activities performed on low trafficked road segments was too high and can be improved by confining the extent of planned grading activities by selected chainage intervals. Rainfall did not have a significant effect on the roughness progression of low trafficked road segments.

5.6 DETERIORATION MODELS

The road deterioration models were developed by grouping datasets of road segments with similar traffic and slope and fitting logarithmic, linear and exponential functions to the measured data using linear and non-linear regression. The results of the regression analysis are provided in the following sections.

5.6.1 Deterioration model for high traffic, low slope segments over the wet season

The results of the linear regression analysis on the deterioration data for road segments with low slope experiencing high traffic over the wet season provided in Figure 4-42 show that none of the fitted models displayed a high “goodness-of-fit” although the exponential curve had the best fit with an R^2 of 0.0108. The low coefficient of determination shows that the roads did not deteriorate significantly.

5.6.2 Deterioration model for low traffic, high slope segments over the wet season

The results of the linear regression analysis on the deterioration data for road segments with high slope experiencing low traffic over the wet season provided in Figure 4-43 show that the linear curve displayed the best “goodness-of-fit” with the data an R^2 of 0.6267. The low coefficient of determination shows that the roads did not deteriorate significantly.

5.6.3 Deterioration model for low traffic, low slope segments over the wet season

The results of the linear regression analysis on the deterioration data for road segments with low slope experiencing low traffic over the wet season provided in Figure 4-44 show that none of the fitted models displayed a high “goodness-of-fit” with the data although the linear curve had the best fit with an R^2 of 0.0012. The low coefficient of determination shows that the roads did not deteriorate significantly.

5.6.4 Deterioration model for high traffic, low slope segments over the dry season

The results of the linear regression analysis on the deterioration data for road segments with low slope experiencing high traffic over the dry season provided in Figure 4-45 show that none of the fitted models displayed a high “goodness-of-fit” with the data although the exponential curve had the best fit with an R^2 of 0.2282. The low coefficient of determination shows that the roads did not deteriorate significantly.

5.6.5 Deterioration model for low traffic, high slope segments over the dry season

The results of the linear regression analysis on the deterioration data for road segments with low slope experiencing low traffic over the dry season are provided in Figure 4-46. None of the fitted models displayed a high “goodness-of-fit” with the data although the exponential curve had the best fit with an R^2 of 0.065. The low coefficient of determination shows that the roads did not deteriorate significantly.

5.6.6 Deterioration model for low traffic, low slope segments over the dry season

The results of the linear regression analysis on the deterioration data for road segments with low slope experiencing low traffic over the dry season provided in Figure 4-44 show that none of the fitted models displayed a high “goodness-of-fit” with the data although the exponential curve had the best fit with an R^2 of 0.0293. The low coefficient of determination shows that the roads did not deteriorate significantly.

5.7 EVALUATION OF DETERIORATION MODELS

The deterioration models were evaluated by plotting the residuals versus the predicted values for the various curves fitted to the data. The models were further evaluated by comparing curves fitted using both linear and non-linear regression. The results are compared in the following sections.

5.7.1 Evaluation of deterioration models for high traffic, low slope segments over the wet season

The results of the linear and non-linear regression models for road segments with high slope and low traffic are provided in Figure 4-48 and Figure 4-49 respectively. The linear regression models performed better than the non-linear regression models. The logarithmic function was a poor predictor of the variability in the data which was better described by the linear and exponential function.

5.7.2 Evaluation of deterioration models for low traffic, high slope segments over the wet season

The results of the linear and non-linear regression models for road segments with high slope and low traffic are provided in Figure 4-50 and Figure 4-51 respectively. The results show that the linear regression models performed slightly better on the data in comparison to the non-linear regression models. The functions performed similarly in predicting the variability in the data.

5.7.3 Evaluation of deterioration model for low traffic, low slope segments over the wet season

The results of the linear and non-linear regression models for road segments with low slope and low traffic are provided in Figure 4-52 and Figure 4-53 respectively. The results show that the linear regression models performed slightly better on the data in comparison to the non-linear regression models. The logarithmic and exponential functions are poor predictors of the variability in the data which is best predicted using the linear function.

5.7.4 Evaluation of deterioration models for high traffic, low slope segments over the dry season

The results of the linear and non-linear regression models for road segments with high slope and low traffic are provided in Figure 4-54 and Figure 4-55 respectively. The results show that the linear and non-linear regression models performed similarly. The logarithmic function performed poorly in predicting the variability in the data which was better described by the linear and exponential function.

5.7.5 Evaluation of deterioration models for low traffic, high slope segments over the dry season

The results of the linear and non-linear regression models for road segments with high slope and low traffic are provided in Figure 4-50 and Figure 4-57 respectively. The results show that the linear regression models performed slightly better on the data in comparison to the non-linear regression models. The functions performed similarly in predicting the variability in the data.

5.7.6 Evaluation of deterioration models for low traffic, low slope segments over the dry season

The results of the linear and non-linear regression models for road segments with low slope and low traffic are provided in Figure 4-58 and Figure 4-59 respectively. The linear regression models performed better than the non-linear regression models. The logarithmic function performed poorly in predicting the variability in the data which was better described by the linear and exponential function.

5.8 FINAL DETERIORATION MODELS

The final deterioration models were chosen from the linear regression models as the linear regression consistently performed better in predicting the data when compared to the non-linear regression models. The functions that best described the deterioration of the road segments were chosen based on the “goodness-of-fit” and suitability of the function in predicting the variability in the data. The final deterioration models are provided in Figure 4-60. Exponential functions best described the deterioration of road segments with low slope experiencing high traffic for both the dry and the wet season. Linear functions best described the deterioration of road segments with low traffic over the wet season regardless of the slope of the road segment. Exponential functions best described the deterioration of low trafficked road segments over the dry season regardless of the slope of the segment.

Low trafficked segments with high slope experienced the highest deterioration of all the segments over the wet season, followed by high trafficked segments with low slope over the dry season. Interestingly, low trafficked segments with low slope over the dry season performed almost identically to high trafficked segments with low slope over the wet season possibly due to the compaction under vehicular loading of high trafficked road segments.

The data collected for low trafficked segments with low slope over the wet season as well as for low trafficked segments with high slope over the dry season resulted in models predicting a decrease in road roughness over time. The models are not suitable for predicting road deterioration. The unsuitable models developed from the data are possibly a result of the poor scheduling of grading activities and low frequency of data collection. It is obvious that these models are not suitable for extrapolation over an annual period, thus these models were not evaluated further.

The models showing an increase in roughness over time were deemed valid for extrapolation over an annual period for the purpose of analysis, however, it is recommended that data be captured for roads that are left to deteriorate over a period of 12 months or greater to more accurately quantify the deterioration over an annual period. The deterioration models extrapolated over an annual period provided in Figure 4-60 show a maximum increase in road roughness from 3.1 m/km to 15.2 m/km over an annual period for the deterioration trend experienced on low trafficked, high slope road segments over the wet season and a minimum roughness increase from 3.3 m/km to 6.1 m/km over an annual period for both low trafficked segments with low slope over the dry season and highly trafficked segments with low slope over the wet season.

5.9 MAINTENANCE COST MODELS

The maintenance cost models were developed by analysing the number of grading activities that would be required over an annual period to maintain the surface roughness of various types of road sections based on selected grading triggers ranging between 4 m/km to 6m/km. The results presented in Table 4-7 show that a maximum of 13.5 annual grading activities would be required to maintain road segments with low traffic and high slope below 4 m/km. A minimum of 1 annual grading activity would be required to maintain roads with low traffic and low slope below a roughness of 6 m/km.

Annual maintenance cost curves were developed from the deterioration curves based simply on the number of required annual grading activities required to maintain the road below a given roughness threshold and the fixed hourly rate of vehicle hire for a grading activity conducted by the agricultural organisation. The results presented in Figure 4-62 show decreasing logarithmic functions with a maximum annual cost of R 24 000 for vehicle hire, per hour required to conduct a grading activity to maintain a segment with low traffic and low slope below a roughness of 3.5 m/km.

5.10 TOMATO SHELF-LIFE MODELS

The tomato shelf-life models developed by Pretorius (2017) show the shelf-life deterioration of tomatoes of varying degrees of ripeness after being transported over a road of fixed roughness for a period of 10 minutes as simulated by vibrations under laboratory conditions are presented in Figure 4-63. It is interesting to note that pink tomatoes retained a higher shelf-life than green tomatoes except for conditions in which the HRI values ranged between 4.4 m/km and 6.3 m/km. This is possibly due to market factors suggesting that pink tomatoes are in greater demand than green tomatoes or that bruising may have been less obvious on pink tomatoes in comparison to green tomatoes.

5.11 OPTIMISATION OF MAINTENANCE COST AND SHELF-LIFE

The tomato shelf-life models developed by Pretorius (2017) were used to determine optimum trigger values for the grading of various types of road sections with similar characteristics to the roads analysed in this study. The optimum HRI values that simultaneously resulted in the maximum shelf-life and minimum annual grading cost are presented in Table 4-8. The results show that the minimum optimum HRI trigger value was 3.9 m/km for the transportation of pink tomatoes on road sections with low slope experiencing low traffic, resulting in an estimated shelf-life of 8.4 days. A maximum optimum grading trigger of 5.6 m/km was obtained for red tomatoes transported on road segments with low traffic and high slope, resulting in an estimated shelf-life of 5.1 days.

The cost of the annual vehicle hire per hour required for grading corresponding to the optimum trigger values is presented in Table 4-9. The results show that the greatest expense corresponds to roads with low traffic and high slope, thus, it is economically beneficial to avoid transporting tomatoes, or other soft-skinned produce, on roads with high slope. If the minimisation of the annual road maintenance cost is the predominant priority of the agricultural entity, it is most beneficial to transport red tomatoes thereby minimising the cost of grading while forgoing an extended shelf-life.

The expected shelf-life of the transported tomatoes corresponding to the optimum HRI trigger values is presented in Table 4-10. The results show that longest optimum shelf-life is obtained when transporting pink tomatoes that may reach a maximum expected shelf-life of 8.4 days and a minimum expected shelf-life of 7.6 days depending on the types of roads over which the tomatoes are transported. Thus, if extending the shelf-life of the tomatoes is the predominant priority of the agricultural entity, it is most economical to transport pink tomatoes which results in a maximum optimum shelf-life while incurring a higher annual grading cost in comparison to red tomatoes.

The transportation of green tomatoes does not result in the lowest optimum annual road maintenance cost nor the highest shelf-life achieved at the market. However, if there was a high market demand for green tomatoes and the agricultural entity chose to transport green tomatoes, it would be optimal to use a grading trigger value of 4.4 m/km for roads with high traffic and low slope, 5.1 m/km for roads with low traffic and high slope and 4.2 m/km for roads with low traffic and low slope.

6 CONCLUSIONS

This section presents the conclusion of this study to explain whether the objects of the project were reached and present the key findings of the data analysis.

6.1 MOST SUITABLE MODEL FORM

The most appropriate mathematical model to predict the road roughness progression from data collected using a Response-type road roughness measurement system (RTRRMS) was determined to be an exponential curve fitted using linear regression analysis. Linear functions were most suitable for the prediction of roughness deterioration on road segments with a slope of less than 6 per cent in the wet season. Logarithmic functions were not suitable for any of the road sections analysed in the study. Non-linear regression analysis did not result in an improved model fit for any of the functions.

ANN's were not suitable for the purpose of the project as the model does not have an explicit form that can be easily implemented by agricultural communities with the added drawback of being complex to optimise, time-consuming to run and require great computing power. It must be emphasized that although ANN models may initially seem appropriate for the analysis of vast quantities of data, once the dataset is split into appropriate categories, the length of the datasets may be vastly reduced thus the benefits of using ANN's may no longer be realised.

6.2 FINAL DETERIORATION FUNCTIONS

6.2.1 Effect of Rainfall

In general, rainfall had a significant effect on the rate of roughness progression. It was not unusual for the road roughness to decrease for a short period after a grading activity was completed on roads with a slope of less than 6 per cent over the wet season due to the compactibility of the saturated roads under the action of traffic. For road segments experiencing low traffic, linear functions were best suited to model the roughness progression over the wet season whereas exponential functions were more suitable over the dry season. The high rate of deterioration occurring on flat, low trafficked roads over the dry season in comparison to the deterioration occurring over the wet season may be attributed to the loss of material fines and excessive dust generation occurring over the dry season.

6.2.2 Effect of traffic

Traffic volume had a significant effect on the rate of roughness progression with highly trafficked segments generally exhibiting more rapid deterioration in comparison to low trafficked segments. The deterioration of highly trafficked roads occurred more rapidly over the dry season than over the wet season and was most appropriately modelled using an exponential curve. The deterioration of low trafficked segments was significantly affected by the steepness of the road with mountainous sections experiencing the most rapid deterioration and flat sections experiencing the least deterioration of all.

6.2.3 Effect of Slope

Road segments with a high slope of greater than 6 per cent displayed the most rapid deterioration of all the roads analysed in this study over the wet season. The same road segments experienced the least amount of deterioration of all the roads during the dry season. Thus, the deterioration of steep road sections is significantly affected by the rainfall season with rapid deterioration occurring under wet conditions. Interestingly, highly trafficked flat segments under wet conditions performed almost identically to low trafficked flat segments over the dry season indicating that slope has a significant influence on deterioration under low traffic conditions.

6.3 OPTIMISATION OF MAINTENANCE SCHEDULING

It is misleading to analyse a road as a single unit without investigating the individual characteristics of the segments forming the length of the road. Weak trends that were evident when assessing the bulk of the collected data for each road become more noticeable and distinct when the data were separated according to matching road segment characteristics, thus it is beneficial to disaggregate a road into maintenance sections with similar characteristics in order to achieve optimised maintenance scheduling.

6.4 OPTIMUM ROAD ROUGHNESS GRADING THRESHOLD VALUES

The optimum HRI roughness values that are recommended to be used as thresholds to trigger grading are dependent upon the characteristics of the road segment to be graded as well as the ripeness of the tomatoes to be transported. In general, road segments with slopes greater than 6 per cent required the most frequent maintenance with grading thresholds ranging between 4.4 m/km for pink tomatoes and 5.6 m/km for red tomatoes. Low trafficked, flat road segments required the least maintenance with grading thresholds ranging between 3.9 m/km for pink tomatoes and 4.4 m/km for red tomatoes.

The annual grading costs associated with the optimum trigger values are the highest for pink tomatoes, which optimally require the smoothest riding quality, and are the lowest for red tomatoes. The expected shelf-life corresponding to the optimised grading threshold values was the highest for the pink tomatoes ranging between 8.4 and 7.6 days while being the lowest for red tomatoes reaching a maximum of 5.7 days and a minimum of 5.1 days.

It can be concluded that the grading triggers of unpaved roads with varying characteristics are governed by market factors. If there is a high market demand and a low shelf-life will suffice, it is most economical to harvest red tomatoes and to employ grading trigger values of 4.6 m/km for road segments with low slope high traffic, 5.6 m/km for road segments with high slope and 4.4 m/km for road segments with low slope experiencing low traffic. If the market demand for tomatoes is low and a high-shelf life is required, it is most economical to harvest pink tomatoes and to employ grading trigger values of 4.0 m/km for road segments with low slope experiencing high traffic, 4.4 m/km for roads with high slope and 3.9 m/km for roads with low slope experiencing low traffic. The difference between these two scenarios results in an average shelf-life increase of 48 per cent while increasing the maintenance cost by an average of 82 per cent.

It is possible that the market demand for tomatoes may increase specifically for tomatoes of a particular ripeness, in this event, it is simple to adjust the maintenance strategy by using the optimal grading triggers for each type of road segment corresponding to the selected tomato ripeness provided in Table 4-8. In general, it is recommended that dynamic maintenance scheduling be employed by adjusting the maintenance trigger values depending on market demand.

7 RECOMMENDATIONS

It is recommended that grading activities scheduled on flat road segments over the wet season be delayed at least one month after the threshold roughness value has been reached in order to facilitate the opportunity for the road segments to be compacted under traffic action.

The deterioration trends represented by the road roughness progression database can be extended to represent far more severe deterioration by collecting data on roads of low priority that are left to deteriorate for extended periods of time. This will improve the ability of the models to accurately predict the future roughness condition over extended periods of time.

More roads with varying characteristics, such as the surface material type, road width and type of pavement, and steep road sections can be investigated to develop deterioration models that are appropriate for a greater variety of roads with different characteristics experiencing different climates and rainfall conditions.

The maintenance cost models can be improved by including all of the costs associated with road maintenance and be expanded to include various types of maintenance activities in addition to grading.

The grading triggers recommended for the transportation of tomatoes can be expanded by investigating the shelf-life of various types of produce so that maintenance triggers can be dynamically recommended depending on the market requirements.

Although the road roughness data collected over the 16 month analysis period was sufficient to produce the deterioration models presented in this dissertation, the accuracy and fit of the models can be vastly improved with the addition of more data, thus it is recommended that the models be regularly updated by incorporating newly collected data into the historical database at regular intervals.

It is recommended that the Skytrax telematics device be used to collect the road roughness data be installed in more vehicles and potentially different types of vehicles if effective calibration can be achieved. This will allow the data to be collected to be accelerated with the benefit of recording the roughness for vehicles of different axle widths thus showing a greater representation of the condition of the lane cross-section.

The road roughness progression trends and resulting deterioration models are highly dependent on the integrity of the data used in the analysis, thus it is recommended that the road roughness data capturing method, rainfall data collection and road maintenance history record be controlled by a formal quality system to assure the accuracy and consistency of the data collection methods and records.

The script used to analyse the data can be incorporated into an online tool with a simple user interface that the agricultural organisation can use to periodically update the models as the road condition database increases.

The segmentation of the roads can be improved by generating segments with a dynamic length so that maintenance can be scheduled on isolated deteriorated road segments that are long enough to economically justify the maintenance activity.

8 LIST OF REFERENCES

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9 APPENDIX A

```

#Import libraries:
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import os
import cv2
import csv
import PIL
from PIL import Image, ExifTags
import time
import datetime
from math import degrees, atan2, cos, sin, radians
import shutil

start = time.time()

directory = r"E:\GoPro_video_footage\Test7"

#Move images into single location
head, tail = os.path.split(directory)
destination_allFiles = os.path.join(head, tail+"_GPSdata_&_videos")

listdirectories = []

for dirpath, dirnames, filenames in os.walk(directory):
    listdirectories.append(dirpath)

del listdirectories[0]

if not os.path.exists(destination_allFiles):
    os.makedirs(destination_allFiles)

for folder in listdirectories:
    files = os.listdir(folder)
    for file in files:
        shutil.copy(folder + "\\" + file, destination_allFiles)

#Loop through images in file:
directory_in_str = destination_allFiles
#directory_in_str = Esmefour_folder
head, tail = os.path.split(directory_in_str)

rows = []
rows.append(("File", "Latitude", "Longitude", "Altitude", "Date Time"))

for file in os.listdir(directory_in_str):
    filename = os.fsdecode(file)
    if filename.endswith(".JPG"):
        file_path = os.path.join(directory_in_str, filename)
        #print(file_path)
        image = Image.open(file_path)
        exif = { ExifTags.TAGS[k]: v for k, v in image._getexif().items() if k in ExifTags.TAGS }
        GPSdata = exif["GPSInfo"]

        Latitude_deg = GPSdata[2][0][0]
        Latitude_min = GPSdata[2][1][0]
        Latitude_sec = GPSdata[2][2][0]
        Latitude = -1*(Latitude_deg + (Latitude_min/60) + (Latitude_sec/(1000000*60*60)))

        Longitude_deg = GPSdata[4][0][0]
        Longitude_min = GPSdata[4][1][0]
        Longitude_sec = GPSdata[4][2][0]
        Longitude = (Longitude_deg) + (Longitude_min/60) + Longitude_sec/(1000000*(60*60))

        Altitude = (GPSdata[6][0])/1000

        Date_Time = exif['DateTime']

        rows.append((filename, Latitude, Longitude, Altitude, Date_Time))
    image.close()

Sheetname = '\\GPSData_all.csv'

f = open(directory_in_str + Sheetname, 'wt')
try:
    writer = csv.writer(f, lineterminator = '\n')
    for row in rows:
        writer.writerow(row)
finally:

```

```

f.close()

# Directory
#directory2 = "E:\\GoPro_video_footage\\Test5_GPSdata"
directory2 = destination allFiles
GPSdata = pd.read_csv(directory2 + "\\GPSData_all.csv")

#Destinations
head2, tail2 = os.path.split(directory2)
D617_Houtbosdorp_folder = os.path.join(head2, tail2.split("_")[0] + "_D617_Houtbosdorp")
D839_Vreedsaam_folder = os.path.join(head2, tail2.split("_")[0] + "_D839_Vreedsaam")
D844_Rita_folder = os.path.join(head2, tail2.split("_")[0] + "_D844_Rita")
D1942_Malale_folder = os.path.join(head2, tail2.split("_")[0] + "_D1942_Malale")
D2651_Rietgat_folder = os.path.join(head2, tail2.split("_")[0] + "_D2651_Rietgat")
P100_Chambbers_folder = os.path.join(head2, tail2.split("_")[0] + "_P100_Chambbers")
Out_of_range_folder = os.path.join(head2, tail2.split("_")[0] + "_Not_in_range")
location_list = []

#Limits
D617_Houtbosdorp_latitude_min = -23.7713
D617_Houtbosdorp_latitude_max = -23.5903
D617_Houtbosdorp_longitude_min = 29.95211
D617_Houtbosdorp_longitude_max = 30.131

D839_Vreedsaam_latitude_min = -23.6962
D839_Vreedsaam_latitude_max = -23.6098
D839_Vreedsaam_longitude_min = 29.9895
D839_Vreedsaam_longitude_max = 30.0564

D844_Rita_latitude_min = -23.7576
D844_Rita_latitude_max = -23.7122
D844_Rita_longitude_min = 29.6235
D844_Rita_longitude_max = 29.6710

D1942_Malale_latitude_min = -22.4121
D1942_Malale_latitude_max = -22.3242
D1942_Malale_longitude_min = 30.1351
D1942_Malale_longitude_max = 30.5973

D2651_Rietgat_latitude_min = -23.7147
D2651_Rietgat_latitude_max = -23.6149
D2651_Rietgat_longitude_min = 29.7331
D2651_Rietgat_longitude_max = 29.8113

P100_Chambbers_latitude_min = -23.6962
P100_Chambbers_latitude_max = -23.6395
P100_Chambbers_longitude_min = 29.9895
P100_Chambbers_longitude_max = 30.0418

#Lists
D617_Houtbosdorp_file_names = []
D839_Vreedsaam_file_names = []
D844_Rita_file_names = []
D1942_Malale_file_names = []
D2651_Rietgat_file_names = []
P100_Chambbers_file_names = []
Out_of_range = []

#Variables
#lat = GPSdata['Latitude']
#long = GPSdata['Longitude']
files = GPSdata['File'].tolist()
latitudes = GPSdata['Latitude'].tolist()
longitudes = GPSdata['Longitude'].tolist()

# Iterating through images
for lat, long, file in zip(latitudes, longitudes, files):

    #Booleans to assign images to location lists
    if (((lat >= D617_Houtbosdorp_latitude_min)\
        & (lat <= D617_Houtbosdorp_latitude_max)\
        & (long >= D617_Houtbosdorp_longitude_min)\
        & (long <= D617_Houtbosdorp_longitude_max))\
    ):
        D617_Houtbosdorp_file_names.append(file)

    elif (((lat >= D839_Vreedsaam_latitude_min)\
        & (lat <= D839_Vreedsaam_latitude_max)\
        & (long >= D839_Vreedsaam_longitude_min)\
        & (long <= D839_Vreedsaam_longitude_max))\
    ):
        D839_Vreedsaam_file_names.append(file)

    elif (((lat >= D844_Rita_latitude_min)\
        & (lat <= D844_Rita_latitude_max)\
        & (long >= D844_Rita_longitude_min)\
        & (long <= D844_Rita_longitude_max))\

```

```

    ):
        D844_Rita_file_names.append(file)

    elif ((lat >= D1942_Malale_latitude_min)\
          & (lat <= D1942_Malale_latitude_max)\
          & (long >=D1942_Malale_longitude_min)\
          & (long <= D1942_Malale_longitude_max))\
          ):
        D1942_Malale_file_names.append(file)

    elif ((lat >= D2651_Rietgat_latitude_min)\
          & (lat <= D2651_Rietgat_latitude_max)\
          & (long >=D2651_Rietgat_longitude_min)\
          & (long <= D2651_Rietgat_longitude_max))\
          ):
        D2651_Rietgat_file_names.append(file)

    elif ((lat >= P100_Chambers_latitude_min)\
          & (lat <= P100_Chambers_latitude_max)\
          & (long >=P100_Chambers_longitude_min)\
          & (long <= P100_Chambers_longitude_max))\
          ):
        P100_Chambers_file_names.append(file)

    else:
        Out_of_range.append(file)

# Moving images:
if D617_Houtbosdorp_file_names:
    if not os.path.exists(D617_Houtbosdorp_folder):
        os.makedirs(D617_Houtbosdorp_folder)
        location_list.append(D617_Houtbosdorp_folder)
for image in D617_Houtbosdorp_file_names:
    shutil.move(directory2 + "\\" + image, D617_Houtbosdorp_folder)

if D839_Vreedsaam_file_names:
    if not os.path.exists(D839_Vreedsaam_folder):
        os.makedirs(D839_Vreedsaam_folder)
        location_list.append(D839_Vreedsaam_folder)
for image in D839_Vreedsaam_file_names:
    shutil.move(directory2 + "\\" + image, D839_Vreedsaam_folder)

if D844_Rita_file_names:
    if not os.path.exists(D844_Rita_folder):
        os.makedirs(D844_Rita_folder)
        location_list.append(D844_Rita_folder)
for image in D844_Rita_file_names:
    shutil.move(directory2 + "\\" + image, D844_Rita_folder)

if D1942_Malale_file_names:
    if not os.path.exists(D1942_Malale_folder):
        os.makedirs(D1942_Malale_folder)
        location_list.append(D1942_Malale_folder)
for image in D1942_Malale_file_names:
    shutil.move(directory2 + "\\" + image, D1942_Malale_folder)

if D2651_Rietgat_file_names:
    if not os.path.exists(D2651_Rietgat_folder):
        os.makedirs(D2651_Rietgat_folder)
        location_list.append(D2651_Rietgat_folder)
for image in D2651_Rietgat_file_names:
    shutil.move(directory2 + "\\" + image, D2651_Rietgat_folder)

if P100_Chambers_file_names:
    if not os.path.exists(P100_Chambers_folder):
        os.makedirs(P100_Chambers_folder)
        location_list.append(P100_Chambers_folder)
for image in P100_Chambers_file_names:
    shutil.move(directory2 + "\\" + image, P100_Chambers_folder)

if Out_of_range:
    if not os.path.exists(Out_of_range_folder):
        os.makedirs(Out_of_range_folder)
        location_list.append(Out_of_range_folder)
for image in Out_of_range:
    shutil.move(directory2 + "\\" + image, Out_of_range_folder)

CSV_list = []

#Loop through folders:
for folder in location_list:
    if os.path.exists(folder):

```

```

#Variables
directory_in_str = folder
head, tail = os.path.split(directory_in_str)
rows = []
rows.append(("File", "Latitude", "Longitude", "Altitude", "Date Time"))

# Loop through images in file
for file in os.listdir(directory_in_str):
    filename = os.fsdecode(file)
    if filename.endswith(".JPG"):
        file_path = os.path.join(directory_in_str, filename)
        image = Image.open(file_path)
        exif = { ExifTags.TAGS[k]: v for k, v in image.getexif().items() if k in ExifTags.TAGS }
        GPSdata = exif["GPSInfo"]

        Latitude_deg = GPSdata[2][0][0]
        Latitude_min = GPSdata[2][1][0]
        Latitude_sec = GPSdata[2][2][0]
        Latitude = -1*(Latitude_deg + (Latitude_min/60) + (Latitude_sec/(10000000*60*60)))

        Longitude_deg = GPSdata[4][0][0]
        Longitude_min = GPSdata[4][1][0]
        Longitude_sec = GPSdata[4][2][0]
        Longitude = (Longitude_deg) + (Longitude_min/60) + Longitude_sec/(10000000*(60*60))

        Altitude = (GPSdata[6][0])/1000

        Date_Time = exif['DateTime']

        rows.append((filename, Latitude, Longitude, Altitude, Date_Time))

    image.close()

Sheetname = '\\GPSData_' + tail + '.csv'
CSV_list.append(Sheetname)

f = open(directory_in_str + Sheetname , 'wt')
try:
    writer = csv.writer(f, lineterminator = '\n')
    for row in rows:
        writer.writerow(row)
finally:
    f.close()

destination_folders = []
date_folders = []

#Loop through folders:
for folder, CSV in zip(location_list, CSV_list):
    destinations = []
    if os.path.exists(folder):
        directory3 = folder
        GPSdata = pd.read_csv(directory3 + CSV)

    # Split Date time column
    Dates_series = GPSdata['Date Time'].str.split(expand = True)[0]
    Times_series = GPSdata['Date Time'].str.split(expand = True)[1]

    # Create dataframe with image names and dates
    Images_names = GPSdata['File']
    Dates_Images = pd.concat([Images_names, Dates_series], axis = 1)
    Dates_Images.columns = ['Image', 'Date']
    #type(Dates_Images)

    # Get all unique dates
    Dates = pd.Series(data = Dates_series).unique()

    # Format unique dates
    ReadableDates = pd.Series(Dates).apply(lambda x: x.replace(':', '_'))
    ReadableDates = '_' + ReadableDates.astype(str)
    ReadableDates = pd.Series(ReadableDates).tolist()

    #Destination folders
    for Date in ReadableDates:
        destination_folders.append(os.path.join(directory3, Date))
        date_folders.append(Date)
        destinations.append(os.path.join(directory3, Date))

#Groupby
bydate = Dates_Images.groupby('Date')['Image'].apply(list).tolist()

# Moving images
for images, folder in zip(bydate, destinations):
    if not os.path.exists(folder):
        os.makedirs(folder)

```

```

        for image in images:
            shutil.move(directory3+ "\\\" + image, folder)
#Loop through folders:
for folder in destination_folders:
    if os.path.exists(folder):

        #Variables
        directory_in_str = folder
        head, tail = os.path.split(directory_in_str)

        rows = []
        rows.append(("File", "Latitude", "Longitude", "Altitude", "Date Time"))

        # Loop through images in file
        for file in os.listdir(directory_in_str):
            filename = os.fsdecode(file)
            if filename.endswith(".JPG"):
                file_path = os.path.join(directory_in_str, filename)
                image = Image.open(file_path)
                exif = { ExifTags.TAGS[k]: v for k, v in image._getexif().items() if k in ExifTags.TAGS }
                GPSdata = exif["GPSInfo"]

                Latitude_deg = GPSdata[2][0][0]
                Latitude_min = GPSdata[2][1][0]
                Latitude_sec = GPSdata[2][2][0]
                Latitude = -1*(Latitude_deg + (Latitude_min/60) + (Latitude_sec/(10000000*60*60)))

                Longitude_deg = GPSdata[4][0][0]
                Longitude_min = GPSdata[4][1][0]
                Longitude_sec = GPSdata[4][2][0]
                Longitude = (Longitude_deg) + (Longitude_min/60) + Longitude_sec/(10000000*(60*60))

                Altitude = (GPSdata[6][0])/1000

                Date_Time = exif['DateTime']

                rows.append((filename, Latitude, Longitude, Altitude, Date Time))
            image.close()

Sheetname = '\\GPSData_'+ tail +'.csv'
CSV_list2.append(Sheetname)

f = open(directory_in_str + Sheetname , 'wt')
try:
    writer = csv.writer(f, lineterminator = '\n')
    for row in rows:
        writer.writerow(row)
finally:
    f.close()

# Directory
#Loop through folders:
for Folder, CSV in zip(destination_folders, CSV_list2):
    if os.path.exists(Folder):
        directory4 = Folder

        GPSdata = pd.read_csv(Folder + CSV)

        #Split Date time column
        Times_series = GPSdata['Date Time'].str.split(expand = True)[1]

        #Create dataframe with image names and dates
        Images_names = GPSdata['File']

        # Splitting the images by time
        Dates_Times = pd.concat([Images_names, Times_series], axis = 1)
        Dates_Times.columns = ['Image', 'Time']
        Dates_Times_split = Dates_Times['Time'].str.split(":", expand = True)
        Dates_Times_split.columns = ['Hour', 'Minute', 'Seconds']

        # Finding the differences between consecutive timestamps and creating df Time diff
        a = pd.to_numeric(Dates_Times_split['Hour'])
        b = pd.to_numeric(Dates_Times_split['Minute'])
        c = pd.to_numeric(Dates_Times_split['Seconds'])

        diff_Hours = pd.Series([x - a[i - 1] for i, x in enumerate(a) if i > 0])
        diff_Minutes = pd.Series([x - b[i - 1] for i, x in enumerate(b) if i > 0])
        diff_Seconds = pd.Series([x - c[i - 1] for i, x in enumerate(c) if i > 0])
        Time_diff = pd.concat([Images_names, diff_Hours, diff_Minutes, diff_Seconds, Times_series], axis =
1)

        Time_diff.columns = ['Image', '^Hour', '^Minute', '^Seconds', 'Time']

        # Creating output folders
        Time_folders = []
        number_of_folders = len(Time_diff[((Time_diff['^Seconds'] > 1.0) & (Time_diff['^Seconds'] != 59)) |
(Time_diff['^Minute'] > 1) | (Time_diff['^Hour'] > 1)]) + 1

```

```

for count in range(1, number_of_folders+1):
    Time_folders.append(os.path.join(directory4, 'Time_lapse_'+str(count)))

# Finding section breaks
Sectioned_images = Time_diff[((Time_diff['^Seconds'] > 1.0) & (Time_diff['^Seconds'] != 59)) |
(Time_diff['^Minute'] > 1) | (Time_diff['^Hour'] > 1)].append(Time_diff.iloc[0])
Sectioned_times = Sectioned_images['Time'].apply(lambda x: x.replace(':', '_')).tolist()

conditions = [
    (Time_diff['^Seconds'] > 1.0) & (Time_diff['^Seconds'] != 59),
    (Time_diff['^Minute'] > 1),
    (Time_diff['^Hour'] > 1)]
choices = [999, 999, 999]
Time_diff['Section'] = np.select(conditions, choices)

# Replacing section breaks with consecutive numbering
for x in range(1, number_of_folders):
    for index, row in Time_diff.iterrows():
        if row['Section'] == 999:
            Time_diff.set_value(index, 'Section', x)

# Generating new columns based on shifts of the consecutively numbered columns and summing the
columns together to get the section number
for r in range(0, len(Time_diff)):
    Time_diff['Section_shift_0'] = Time_diff['Section'].shift().fillna(0)
    Time_diff['Section_shift_%d' % (r+1)] = Time_diff['Section_shift_%d' % r].shift().fillna(0)

col_list = list(Time_diff)
list_to_remove = ['^Hour', '^Minute', '^Seconds', 'Time']
sum_list = list(set(col_list).difference(set(list_to_remove)))
Time_diff['Section_number'] = Time_diff[sum_list].sum(axis=1)

# Generate lists of images for each timelapse using Groupby
bytime = Time_diff.groupby('Section_number')['Image'].apply(list).tolist()

# Making folders
for folder in Time_folders:
    if not os.path.exists(folder):
        os.makedirs(folder)

# Moving images
for images, folder in zip(bytime, Time_folders):
    for image in images:
        shutil.move(directory4 + "\\\" + image, folder)
)

```

10 APPENDIX B

```
# LSTM Model

### Part 1 - Data Pre-processing
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import os
import time

start = time.time()

ts = 60
epochs = 100
neurons = 70
batchsize = 5

road_names = ['D617 Houtbosdorp', 'D678 Jachtpad', 'D839 Vreedsaam', 'D2651 Rietgat', 'P100 Chambers']

for road in road_names:
    directory_Train = r'E:\\DATA\\TRACKER ROAD ROUGHNESS\\TOYOTA BAKKIE\\RNN_Input\\{\\}\\Train'.format(road)
    directory_Test = r'E:\\DATA\\TRACKER ROAD ROUGHNESS\\TOYOTA BAKKIE\\RNN_Input\\{\\}\\Test'.format(road)
    directory2 = r'E:\\DATA\\TRACKER ROAD ROUGHNESS\\TOYOTA BAKKIE\\RNN_Output\\{\\}\\'.format(road)

    # directory = os.fsencode(directory)

    sheets_train = []
    sheets_train_path = []
    segments = []
    for dirpath, dirnames, filenames in os.walk(directory_Train):
        sheets_train.append(filenames)

    for filename in sheets_train:
        for file in filename:
            sheets_train_path.append(os.path.join(directory_Train, file))
            a = file
            b,c,d = a.split("_")
            segments.append(b)

    sheets_test = []
    sheets_test_path = []
    for dirpath, dirnames, filenames in os.walk(directory_Test):
        sheets_test.append(filenames)
    for filename in sheets_test:
        for file in filename:
            sheets_test_path.append(os.path.join(directory_Test, file))

    print(sheets_train)
    print(sheets_test)
    print(sheets_train_path)
    print(sheets_test_path)
    print(segments)

    # Importing the training set
    for sheet_train, sheet_test, segment in zip(sheets_train_path, sheets_test_path, segments):
        dataset_train = pd.read_csv(sheet_train)
        training_set = dataset_train.iloc[:, 2:3].values # Gives numpy array of 1 column

        # Feature Scaling (standardisation vs normalisation)
        from sklearn.preprocessing import MinMaxScaler
        sc = MinMaxScaler(feature_range = (0,1))
        training_set_scaled = sc.fit_transform(training_set)

        # Creating a data structure with 60 timesteps and 1 output
        X_train = []
        y_train = []
        for i in range(ts, len(training_set_scaled)):
            X_train.append(training_set_scaled[i-ts:i,0])
            y_train.append(training_set_scaled[i,0])
        X_train, y_train = np.array(X_train), np.array(y_train)

        X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))

    ### Part 2 - Building the RNN
    # Importing the keras libraries and packages
    from keras.models import Sequential
    from keras.layers import Dense
    from keras.layers import LSTM
    from keras.layers import Dropout

    # Initializing the RNN
    regressor = Sequential()
```

```

# Adding the first LSTM layer and some dropout regularization
regressor.add(LSTM(units = neurons, return_sequences = True, dropout=0.2, input_shape =
(X_train.shape[1], 1)))

#regressor.add(Dropout(0.2)) #20% of the neurons will be ignored during the training (20% of 50 is
10, therefore 10 neurons will be ignored during each iteration of the training)
# Adding a second LSTM layer and some dropout regularization
regressor.add(LSTM(units = neurons, return_sequences = True, dropout=0.2))

#Adding a third LSTM with some dropout regularization
regressor.add(LSTM(units = neurons, return_sequences = True, dropout=0.2))

# Adding a fifth LSTM with some dropout regularization
regressor.add(LSTM(units = neurons, return_sequences = True, dropout=0.2))

#Adding a fourth LSTM with some dropout regularization
regressor.add(LSTM(units = neurons, return_sequences = False, dropout=0.2)) # for the last layer
of the LSTM, return sequences must be false

#Adding the output layer
regressor.add(Dense(units = 1))

# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')

# Fitting the RNN to the Training set
regressor.fit(X_train, y_train, epochs = epochs, batch_size = batchsize) #epochs number obtained by
trial and error until convergence is reached

### Part 3 - Making the predictions and visualising the results

dataset_test = pd.read_csv(sheet_test)
real_HRI_Ave = dataset_test.iloc[:,2:3].values #Gives numpy array of 1 column
dataset_total = pd.concat((dataset_train["HRI_Ave"], dataset_test["HRI_Ave"]), axis=0)
inputs = dataset_total[len(dataset_total) - len(dataset_test) - ts:].values
inputs = inputs.reshape(-1, 1)
inputs = sc.transform(inputs)

X_test = []
for i in range(ts, ts+len(dataset_test)): #60 + 20 = 80 (20 in test set)
    X_test.append(inputs[i-ts:i,0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
predicted_HRI_Ave = regressor.predict(X_test)
predicted_HRI_Ave = sc.inverse_transform(predicted_HRI_Ave)

# Adding dates to axes
Predicted_HRI_df = pd.DataFrame(predicted_HRI_Ave, index=dataset_test['Date'])
Predicted_HRI_df.columns = ['HRI_Ave']
Real_HRI_df = pd.DataFrame(real_HRI_Ave, index=dataset_test['Date'])
Real_HRI_df.columns = ['HRI_Ave']
Plot = pd.DataFrame(Real_HRI_df['HRI_Ave'])
Plot['Pred_HRI_Ave'] = Predicted_HRI_df['HRI_Ave']

import math
from sklearn.metrics import mean_squared_error
rmse = round(math.sqrt(mean_squared_error(real_HRI_Ave, predicted_HRI_Ave)),4)
relative_error = round(rmse/(real_HRI_Ave.max() - real_HRI_Ave.min()),4)

# Visualising the results
fig_name1 = '{0}_{1}_{2}_{3}_{4}_{5}_{6}.png'.format(segment, ts, epochs, neurons, batchsize, rmse,
relative_error)
if not os.path.exists(directory2):
    os.makedirs(directory2)
fig_path1 = os.path.join(directory2, fig_name1)

plt.plot(Real_HRI_df, color = 'red', label = 'Real HRI Average')
plt.plot(Predicted_HRI_df, color = 'blue', label = 'Predicted HRI Average')
plt.ylim(ymin=0)
plt.title('HRI Average Prediction')
plt.xlabel('Days')
plt.xticks(rotation=90)
plt.ylabel('HRI Average')
plt.legend()
plt.savefig(fig_path1, format='png')
plt.close()

print(rmse)
print(relative_error)

print('It took', time.time()-start, 'seconds, ', (time.time()-start)/60, ' minutes,', (time.time()-
start)/60*2, ' hours.')
```

11 APPENDIX C

```

import numpy as np
import pandas as pd
import os
import time
import math
import csv
from math import pi
import matplotlib.pyplot as plt

start = time.time()

#### Pre-processing weather data
# Importing the dataset
directory = "C:\\Users\\Tamryn\\Documents\\MEng_2018\\Data\\Weather\\Station_Data\\"
first_date = '2017-04-01'

BB_Rain_Data_name = 'BB_Rain_Data.xls'
BB_Rain_Data_path = os.path.join(directory, BB_Rain_Data_name)
BB_Rain_Data = pd.ExcelFile(BB_Rain_Data_path).parse("Sheet1")
BB_Rain_Data = (BB_Rain_Data[BB_Rain_Data['Date'] >= first_date]).drop("Station", 1)
BB_Rain_Data.columns = ['Date', 'Rain (mm) BB']

BHB_Rain_Data_name = 'BHB_Rain_Data.xls'
BHB_Rain_Data_path = os.path.join(directory, BHB_Rain_Data_name)
BHB_Rain_Data = pd.ExcelFile(BHB_Rain_Data_path).parse("Sheet1")
BHB_Rain_Data = (BHB_Rain_Data[BHB_Rain_Data['Date'] >= first_date]).drop("Station", 1)
BHB_Rain_Data.columns = ['Date', 'Rain (mm) BHB']

DENNH1_Rain_Data_name = 'DENNH1_Rain_Data.xls'
DENNH1_Rain_Data_path = os.path.join(directory, DENNH1_Rain_Data_name)
DENNH1_Rain_Data = pd.ExcelFile(DENNH1_Rain_Data_path).parse("Sheet1")
DENNH1_Rain_Data = (DENNH1_Rain_Data[DENNH1_Rain_Data['Date'] >= first_date]).drop("Station", 1)
DENNH1_Rain_Data.columns = ['Date', 'Rain (mm) DENNH1']

# DODDINGTON_Rain_Data_name = 'DODDINGTON_Rain_Data.xls'
# DODDINGTON_Rain_Data_path = os.path.join(directory, DODDINGTON_Rain_Data_name)
# DODDINGTON_Rain_Data = pd.ExcelFile(DODDINGTON_Rain_Data_path).parse("Sheet1")
# DODDINGTON_Rain_Data = DODDINGTON_Rain_Data[DODDINGTON_Rain_Data['Date'] >= first_date].drop("Station", 1)
# DODDINGTON_Rain_Data.columns = ['Date', 'Rain (mm) DODDINGTON']

EDEN_Rain_Data_name = 'EDEN_Rain_Data.xls'
EDEN_Rain_Data_path = os.path.join(directory, EDEN_Rain_Data_name)
EDEN_Rain_Data = pd.ExcelFile(EDEN_Rain_Data_path).parse("Sheet1")
EDEN_Rain_Data = EDEN_Rain_Data[EDEN_Rain_Data['Date'] >= first_date].drop("Station", 1)
EDEN_Rain_Data.columns = ['Date', 'Rain (mm) Eden']

ES_Rain_Data_name = 'ES_Rain_Data.xls'
ES_Rain_Data_path = os.path.join(directory, ES_Rain_Data_name)
ES_Rain_Data = pd.ExcelFile(ES_Rain_Data_path).parse("Sheet1")
ES_Rain_Data = ES_Rain_Data[ES_Rain_Data['Date'] >= first_date].drop("Station", 1)
ES_Rain_Data.columns = ['Date', 'Rain (mm) ES']

PD_Rain_Data_name = 'PD_Rain_Data.xls'
PD_Rain_Data_path = os.path.join(directory, PD_Rain_Data_name)
PD_Rain_Data = pd.ExcelFile(PD_Rain_Data_path).parse("Sheet1")
PD_Rain_Data = PD_Rain_Data[PD_Rain_Data['Date'] >= first_date].drop("Station", 1)
PD_Rain_Data.columns = ['Date', 'Rain (mm) PD']

VZ_Rain_Data_name = 'VZ_Rain_Data.xls'
VZ_Rain_Data_path = os.path.join(directory, VZ_Rain_Data_name)
VZ_Rain_Data = pd.ExcelFile(VZ_Rain_Data_path).parse("Sheet1")
VZ_Rain_Data = VZ_Rain_Data[VZ_Rain_Data['Date'] >= first_date].drop("Station", 1)
VZ_Rain_Data.columns = ['Date', 'Rain (mm) VZ']

VZNH2_Rain_Data_name = 'VZNH2_Rain_Data.xls'
VZNH2_Rain_Data_path = os.path.join(directory, VZNH2_Rain_Data_name)
VZNH2_Rain_Data = pd.ExcelFile(VZNH2_Rain_Data_path).parse("Sheet1")
VZNH2_Rain_Data = VZNH2_Rain_Data[VZNH2_Rain_Data['Date'] >= first_date].drop("Station", 1)
VZNH2_Rain_Data.columns = ['Date', 'Rain (mm) VZNH2']

WP_Rain_Data_name = 'WP_Rain_Data.xls'
WP_Rain_Data_path = os.path.join(directory, WP_Rain_Data_name)
WP_Rain_Data = pd.ExcelFile(WP_Rain_Data_path).parse("Sheet1")
WP_Rain_Data = WP_Rain_Data[WP_Rain_Data['Date'] >= first_date].drop("Station", 1)
WP_Rain_Data.columns = ['Date', 'Rain (mm) WP']

# Getting dates
weather_dates = pd.concat([BB_Rain_Data['Date'], BHB_Rain_Data['Date'], DENNH1_Rain_Data['Date'],
EDEN_Rain_Data['Date'], ES_Rain_Data['Date'], PD_Rain_Data['Date'], VZ_Rain_Data['Date'],
VZNH2_Rain_Data['Date'], WP_Rain_Data['Date']], axis=0)
weather_dates = pd.DataFrame(weather_dates.unique())
weather_dates.columns = ['Date']
weather_all = pd.merge(weather_dates, BB_Rain_Data, on = 'Date', how = 'outer').merge(BHB_Rain_Data, on =

```

```

'Date', how = 'outer')).merge(DENNH1_Rain_Data,on = 'Date', how = 'outer'))\
    .merge(EDEN_Rain_Data, on = 'Date', how = 'outer')).merge(ES_Rain_Data, on = 'Date', how =
'outer')).merge(PD_Rain_Data, on = 'Date', how = 'outer')).merge(VZ_Rain_Data,on = 'Date', how = 'outer'))\
    .merge(VZNH2_Rain_Data,on = 'Date', how = 'outer')).merge(WP_Rain_Data,on = 'Date', how =
'outer')).sort_values(['Date']).fillna(0)

# Pre-processing weather data
def condition(value):
    if value >= 150:
        #return value/100
        return 0
    return value

for column in weather_all.drop(['Date'], axis=1):
    weather_all[column] = weather_all[column].apply(condition)

# Creating dataframe of distances from road segments to rain gauge stations
dataset_distances =
pd.ExcelFile('C:\\Users\\Tamryn\\Documents\\MEng_2018\\Data\\Weather\\Distances_from_roads_to_weather_stati
ons.xlsx')

D617_Houtbosdorp_distances = dataset_distances.parse("Houtbosdorp")
D617_Houtbosdorp_distances.drop(D617_Houtbosdorp_distances.columns[[1, 2, 3, 4, 6]], axis=1, inplace=True)
D839_Vreedsaam_distances = dataset_distances.parse("Vreedsaam")
D839_Vreedsaam_distances.drop(D839_Vreedsaam_distances.columns[[1, 2, 3, 4, 6]], axis=1, inplace=True)
D2651_Rietgat_distances = dataset_distances.parse("Rietgat")
D2651_Rietgat_distances.drop(D2651_Rietgat_distances.columns[[1, 2, 3, 4, 6]], axis=1, inplace=True)
P100_Chambers_distances = dataset_distances.parse("P100")
P100_Chambers_distances.drop(P100_Chambers_distances.columns[[1, 2, 3, 4, 6]], axis=1, inplace=True)
D678_Jachtpad_distances = dataset_distances.parse("Jachtpad")
D678_Jachtpad_distances.drop(D678_Jachtpad_distances.columns[[1, 2, 3, 4, 6]], axis=1, inplace=True)

Total_distances = [D617_Houtbosdorp_distances, D839_Vreedsaam_distances, D2651_Rietgat_distances,
P100_Chambers_distances, D678_Jachtpad_distances]
Total_distances_clipped = [D617_Houtbosdorp_distances[['Segment_ID', 'Sum']],
D839_Vreedsaam_distances[['Segment_ID', 'Sum']], D2651_Rietgat_distances[['Segment_ID', 'Sum']],
P100_Chambers_distances[['Segment_ID', 'Sum']], D678_Jachtpad_distances[['Segment_ID', 'Sum']]]

###Pre-processing the road condition data
start = time.time()
dataset_new1 = pd.ExcelFile('E:\\DATA\\TRACKER ROAD ROUGHNESS\\TOYOTA
BAKKIE\\2017\\toyota_roughness_2017.xlsx')
dataset_new2 = pd.ExcelFile('E:\\DATA\\TRACKER ROAD ROUGHNESS\\TOYOTA
BAKKIE\\2018\\toyota_roughness_2018.xlsx')

# Load a sheet into a DataFrame by name: df1
df_New1 = dataset_new1.parse("toyota_roughness_2017")
df_New2 = dataset_new2.parse("toyota_roughness_2018")
df_New = pd.concat([df_New1, df_New2], axis=0)

#Defining road segments for each road
D617_Houtbosdorp_Segments = ["17100022050121", "17100022064666", "17100022165429",
"17100022176107", "17100022275362", "17100023349369", "17100024083528", "17100024776586", "17100023399786",
"17100023838534", "17100024063171", "17100023733686", "17100024272752", "17100024418609", "17100024809472",
"17100024741876", "17100023031026", "17100024809479"]
D839_Vreedsaam_Segments = ["17100023044624", "17100022758644", "17100024046817", "17100024072076"]
D2651_Rietgat_Segments = ["17100022944802", "17100022960713", "17100022990611", "17100023033470",
"17100024432762", "17100024604711", "17100024935185"]
P100_Chambers_Segments = ["17100024083528", "17100022758644"]
D678_Jachtpad_Segments = ["17100023402227", "17100022256372", "17100024819125", "17100023199273",
"17100023438190"]
Road_Segments = [D617_Houtbosdorp_Segments, D839_Vreedsaam_Segments, D2651_Rietgat_Segments,
P100_Chambers_Segments, D678_Jachtpad_Segments]

Dataframe_columns_new = ['Segment_ID', 'Segment Length (m)', 'From Latitude (Decimal Degrees)', 'From
Longitude (Decimal Degrees)', 'To Latitude (Decimal Degrees)', 'To Longitude (Decimal Degrees)', 'Unit ID',
'Customer Vehicle ID', 'Vehicle Make', 'Vehicle Model', 'Date', 'Season', 'Day of Week', 'Time', 'Latitude
(Decimal Degrees)', 'Longitude (Decimal Degrees)', 'Segment Distance (m)', 'Odometer (km)', 'Speed (km/h)',
'Speed Limit (km/h)', 'Heading (Degrees)', 'Direction', 'Estimated HRI (m/km)', 'HRI Condition', 'Layer 1 &
2 Green (Days)', 'Layer 2 & 3 Green (Days)', 'Layer 5 & 6 Green (Days)', 'Layer 1 & 2 Pink (Days)', 'Layer
2 & 3 Pink (Days)', 'Layer 5 & 6 Pink (Days)', 'Layer 1 & 2 Red (Days)', 'Layer 2 & 3 Red (Days)', 'Layer 5
& 6 Red (Days)', 'Roll (Degrees)', 'Pitch (Degrees)']

road_names = ["D617 Houtbosdorp", "D839 Vreedsaam", "D2651 Rietgat", "P100 Chambers", "D678 Jachtpad"]

D617_Houtbosdorp = pd.DataFrame(df_New[df_New['Segment_ID'].isin(D617_Houtbosdorp_Segments)])
D617_Houtbosdorp.columns = Dataframe_columns_new
D617_Houtbosdorp.drop(['Layer 1 & 2 Green (Days)', 'Layer 2 & 3 Green (Days)', 'Layer 5 & 6 Green (Days)',
'Layer 1 & 2 Pink (Days)', 'Layer 2 & 3 Pink (Days)', 'Layer 5 & 6 Pink (Days)', 'Layer 1 & 2 Red (Days)',
'Layer 2 & 3 Red (Days)', 'Layer 5 & 6 Red (Days)', 'Unit ID', 'Customer Vehicle ID', 'Vehicle Make',
'Vehicle Model'],axis=1, inplace=True)
D839_Vreedsaam = pd.DataFrame(df_New[df_New['Segment_ID'].isin(D839_Vreedsaam_Segments)])
D839_Vreedsaam.columns = Dataframe_columns_new
D839_Vreedsaam.drop(['Layer 1 & 2 Green (Days)', 'Layer 2 & 3 Green (Days)', 'Layer 5 & 6 Green (Days)',
'Layer 1 & 2 Pink (Days)', 'Layer 2 & 3 Pink (Days)', 'Layer 5 & 6 Pink (Days)', 'Layer 1 & 2 Red (Days)',
'Layer 2 & 3 Red (Days)', 'Layer 5 & 6 Red (Days)', 'Unit ID', 'Customer Vehicle ID', 'Vehicle Make',
'Vehicle Model'],axis=1, inplace=True)
D2651_Rietgat = pd.DataFrame(df_New[df_New['Segment_ID'].isin(D2651_Rietgat_Segments)])

```

```

D2651_Rietgat.columns = Dataframe_columns_new
D2651_Rietgat.drop(['Layer 1 & 2 Green (Days)', 'Layer 2 & 3 Green (Days)', 'Layer 5 & 6 Green (Days)',
'Layer 1 & 2 Pink (Days)', 'Layer 2 & 3 Pink (Days)', 'Layer 5 & 6 Pink (Days)', 'Layer 1 & 2 Red (Days)',
'Layer 2 & 3 Red (Days)', 'Layer 5 & 6 Red (Days)', 'Unit ID', 'Customer Vehicle ID', 'Vehicle Make',
'Vehicle Model'],axis=1,inplace=True)
P100_Chambers = pd.DataFrame(df_New[df_New['Segment ID'].isin(P100_Chambers_Segments)])
P100_Chambers.columns = Dataframe_columns_new
P100_Chambers.drop(['Layer 1 & 2 Green (Days)', 'Layer 2 & 3 Green (Days)', 'Layer 5 & 6 Green (Days)',
'Layer 1 & 2 Pink (Days)', 'Layer 2 & 3 Pink (Days)', 'Layer 5 & 6 Pink (Days)', 'Layer 1 & 2 Red (Days)',
'Layer 2 & 3 Red (Days)', 'Layer 5 & 6 Red (Days)', 'Unit ID', 'Customer Vehicle ID', 'Vehicle Make',
'Vehicle Model'],axis=1, inplace=True)
D678_Jachtpad = pd.DataFrame(df_New[df_New['Segment ID'].isin(D678_Jachtpad_Segments)])
D678_Jachtpad.columns = Dataframe_columns_new
D678_Jachtpad.drop(['Layer 1 & 2 Green (Days)', 'Layer 2 & 3 Green (Days)', 'Layer 5 & 6 Green (Days)',
'Layer 1 & 2 Pink (Days)', 'Layer 2 & 3 Pink (Days)', 'Layer 5 & 6 Pink (Days)', 'Layer 1 & 2 Red (Days)',
'Layer 2 & 3 Red (Days)', 'Layer 5 & 6 Red (Days)', 'Unit ID', 'Customer Vehicle ID', 'Vehicle Make',
'Vehicle Model'],axis=1, inplace=True)

# Creating a list of road data frames
road_dataframes = [D617_Houtbosdorp, D839_Vreedsaam, D2651_Rietgat, P100_Chambers, D678_Jachtpad]

for dataframe in road_dataframes:
    a = pd.to_numeric(dataframe['Latitude (Decimal Degrees)']).astype(float)
    b = pd.to_numeric(dataframe['Longitude (Decimal Degrees)']).astype(float)
    c = a.shift(-1).fillna(0)
    d = b.shift(-1).fillna(0)

    a2s = a / 360.0 * 2 * pi
    b2s = b / 360.0 * 2 * pi
    a3s = c / 360.0 * 2 * pi
    b3s = d / 360.0 * 2 * pi

    delta_phis = (a3s - a2s).tolist()
    delta_lambdas = (b3s - b2s).tolist()
    a2s.tolist()
    a3s.tolist()

    distance = []
    alphas = []

    for a2, a3, delta_phi, delta_lambda in zip(a2s, a3s, delta_phis, delta_lambdas):
        alpha = np.sin((delta_phi / 2.0) ** 2 + np.cos(a2) * np.cos(a3) * np.sin(delta_lambda / 2.0) ** 2)
        e = 2 * 6371000 * math.atan2(np.sqrt(alpha), np.sqrt(1 - alpha))
        alphas.append(alpha)
        distance.append(e)

    frame = pd.DataFrame({'a': a, 'b': b, 'c': c, 'd': d, 'a2s': a2s, 'b2s': b2s, 'a3s': a3s, 'b3s': b3s,
'delta_phis': delta_phis, 'delta_lambdas': delta_lambda, 'alphas': alphas, 'distance': distance})
    dataframe['Calculated Distance (m)'] = frame['distance']
    # D839_Vreedsaam['Distance from speed (m)'] = (D839_Vreedsaam['Speed (km/h)'] / 3.6)

# Merging distances onto road condition data
D617_Houtbosdorp_all_data = pd.merge(left=D617_Houtbosdorp, right=D617_Houtbosdorp_distances,
left_on='Segment_ID', right_on='Segment_ID')
D839_Vreedsaam_all_data = pd.merge(left=D839_Vreedsaam, right=D839_Vreedsaam_distances,
left_on='Segment_ID', right_on='Segment_ID')
D2651_Rietgat_all_data = pd.merge(left=D2651_Rietgat, right=D2651_Rietgat_distances, left_on='Segment_ID',
right_on='Segment_ID')
P100_Chambers_all_data = pd.merge(left=P100_Chambers, right=P100_Chambers_distances, left_on='Segment_ID',
right_on='Segment_ID')
D678_Jachtpad_all_data = pd.merge(left=D678_Jachtpad, right=D678_Jachtpad_distances, left_on='Segment_ID',
right_on='Segment_ID')

# Getting weighted rainfall
A = D617_Houtbosdorp_all_data.drop(['Segment Length (m)', 'From Latitude (Decimal Degrees)', 'From
Longitude (Decimal Degrees)', 'To Latitude (Decimal Degrees)', 'To Longitude (Decimal Degrees)', 'Season',
'Day of Week', 'Time',
'Latitude (Decimal Degrees)', 'Longitude (Decimal Degrees)', 'Segment Distance (m)', 'Odometer (km)',
'Speed (km/h)', 'Speed Limit (km/h)', 'Heading (Degrees)', 'Direction', 'Estimated HRI (m/km)', 'HRI
Condition', 'Roll (Degrees)', 'Pitch (Degrees)',
'Calculated Distance (m)', 'Length', 'DODDINGTON'], axis=1)
AA = pd.merge(A, weather_all)
B = AA.groupby(['Date', 'Segment_ID']).mean().reset_index()
C = pd.merge(B, pd.DataFrame(Total_distances_clipped[0]), on='Segment_ID')
C.columns = ['Date', 'Segment_ID', 'BB', 'BHB', 'DENNH1', 'EDEN', 'ES', 'PD', 'VZ', 'VZNH2', 'WP', 'Sum_x',
'Rain_BB', 'Rain_BHB', 'Rain_DENN1', 'Rain_Eden', 'Rain_ES', 'Rain_PD', 'Rain_VZ', 'Rain_VZNH2', 'Rain_WP',
'Sum_y']
C['Weighted_Rainfall'] = C.apply(lambda x: (x.BB*x.Rain_BB + x.BHB*x.Rain_BHB + x.DENN1*x.Rain_DENN1 +
x.EDEN*x.Rain_Eden + x.ES*x.Rain_ES + x.PD*x.Rain_PD + x.VZ*x.Rain_VZ + x.VZNH2*x.Rain_VZNH2 +
x.WP*x.Rain_WP)/x.Sum_y, axis=1)
D617_Houtbosdorp_all_data = pd.merge(D617_Houtbosdorp_all_data, pd.DataFrame(C[['Weighted_Rainfall',
'Segment_ID', 'Date']]), on = ['Segment_ID', 'Date'])

A = D839_Vreedsaam_all_data.drop(['Segment Length (m)', 'From Latitude (Decimal Degrees)', 'From Longitude
(Decimal Degrees)', 'To Latitude (Decimal Degrees)', 'To Longitude (Decimal Degrees)', 'Season', 'Day of

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Week', 'Time',
'Latitude (Decimal Degrees)', 'Longitude (Decimal Degrees)', 'Segment Distance (m)', 'Odometer (km)',
'Speed (km/h)', 'Speed Limit (km/h)', 'Heading (Degrees)', 'Direction', 'Estimated HRI (m/km)', 'HRI
Condition', 'Roll (Degrees)', 'Pitch (Degrees)',
'Calculated Distance (m)', 'Length', 'DODDINGTON'], axis=1)
AA = pd.merge(A, weather_all)
B = AA.groupby(['Date', 'Segment_ID']).mean().reset_index()
C = pd.merge(B, pd.DataFrame(Total_distances_clipped[1]), on='Segment_ID')
C.columns = ['Date', 'Segment_ID', 'BB', 'BHB', 'DENNH1', 'EDEN', 'ES', 'PD', 'VZ', 'VZNH2', 'WP', 'Sum_x',
'Rain_BB', 'Rain_BHB', 'Rain_DENNH1', 'Rain_Eden', 'Rain_ES', 'Rain_PD', 'Rain_VZ', 'Rain_VZNH2', 'Rain_WP',
'Sum_y']
C['Weighted_Rainfall'] = C.apply(lambda x: (x.BB*x.Rain_BB + x.BHB*x.Rain_BHB + x.DENNH1*x.Rain_DENNH1 +
x.EDEN*x.Rain_Eden + x.ES*x.Rain_ES + x.PD*x.Rain_PD + x.VZ*x.Rain_VZ + x.VZNH2*x.Rain_VZNH2 +
x.WP*x.Rain_WP)/x.Sum_y, axis=1)
D839_Vreedsaam_all_data = pd.merge(D839_Vreedsaam_all_data, pd.DataFrame(C[['Weighted_Rainfall',
'Segment_ID', 'Date']]), on = ['Segment_ID', 'Date'])

A = D2651_Rietgat_all_data.drop(['Segment Length (m)', 'From Latitude (Decimal Degrees)', 'From Longitude
(Decimal Degrees)', 'To Latitude (Decimal Degrees)', 'To Longitude (Decimal Degrees)', 'Season', 'Day of
Week', 'Time',
'Latitude (Decimal Degrees)', 'Longitude (Decimal Degrees)', 'Segment Distance (m)', 'Odometer (km)',
'Speed (km/h)', 'Speed Limit (km/h)', 'Heading (Degrees)', 'Direction', 'Estimated HRI (m/km)', 'HRI
Condition', 'Roll (Degrees)', 'Pitch (Degrees)',
'Calculated Distance (m)', 'Length', 'DODDINGTON'], axis=1)
AA = pd.merge(A, weather_all)
B = AA.groupby(['Date', 'Segment_ID']).mean().reset_index()
C = pd.merge(B, pd.DataFrame(Total_distances_clipped[2]), on='Segment_ID')
C.columns = ['Date', 'Segment_ID', 'BB', 'BHB', 'DENNH1', 'EDEN', 'ES', 'PD', 'VZ', 'VZNH2', 'WP', 'Sum_x',
'Rain_BB', 'Rain_BHB', 'Rain_DENNH1', 'Rain_Eden', 'Rain_ES', 'Rain_PD', 'Rain_VZ', 'Rain_VZNH2', 'Rain_WP',
'Sum_y']
C['Weighted_Rainfall'] = C.apply(lambda x: (x.BB*x.Rain_BB + x.BHB*x.Rain_BHB + x.DENNH1*x.Rain_DENNH1 +
x.EDEN*x.Rain_Eden + x.ES*x.Rain_ES + x.PD*x.Rain_PD + x.VZ*x.Rain_VZ + x.VZNH2*x.Rain_VZNH2 +
x.WP*x.Rain_WP)/x.Sum_y, axis=1)
D2651_Rietgat_all_data = pd.merge(D2651_Rietgat_all_data, pd.DataFrame(C[['Weighted_Rainfall',
'Segment_ID', 'Date']]), on = ['Segment_ID', 'Date'])

A = P100_Chambers_all_data.drop(['Segment Length (m)', 'From Latitude (Decimal Degrees)', 'From Longitude
(Decimal Degrees)', 'To Latitude (Decimal Degrees)', 'To Longitude (Decimal Degrees)', 'Season', 'Day of
Week', 'Time',
'Latitude (Decimal Degrees)', 'Longitude (Decimal Degrees)', 'Segment Distance (m)', 'Odometer (km)',
'Speed (km/h)', 'Speed Limit (km/h)', 'Heading (Degrees)', 'Direction', 'Estimated HRI (m/km)', 'HRI
Condition', 'Roll (Degrees)', 'Pitch (Degrees)',
'Calculated Distance (m)', 'Length', 'DODDINGTON'], axis=1)
AA = pd.merge(A, weather_all)
B = AA.groupby(['Date', 'Segment_ID']).mean().reset_index()
C = pd.merge(B, pd.DataFrame(Total_distances_clipped[3]), on='Segment_ID')
C.columns = ['Date', 'Segment_ID', 'BB', 'BHB', 'DENNH1', 'EDEN', 'ES', 'PD', 'VZ', 'VZNH2', 'WP', 'Sum_x',
'Rain_BB', 'Rain_BHB', 'Rain_DENNH1', 'Rain_Eden', 'Rain_ES', 'Rain_PD', 'Rain_VZ', 'Rain_VZNH2', 'Rain_WP',
'Sum_y']
C['Weighted_Rainfall'] = C.apply(lambda x: (x.BB*x.Rain_BB + x.BHB*x.Rain_BHB + x.DENNH1*x.Rain_DENNH1 +
x.EDEN*x.Rain_Eden + x.ES*x.Rain_ES + x.PD*x.Rain_PD + x.VZ*x.Rain_VZ + x.VZNH2*x.Rain_VZNH2 +
x.WP*x.Rain_WP)/x.Sum_y, axis=1)
P100_Chambers_all_data = pd.merge(P100_Chambers_all_data, pd.DataFrame(C[['Weighted_Rainfall',
'Segment_ID', 'Date']]), on = ['Segment_ID', 'Date'])

A = D678_Jachtpad_all_data.drop(['Segment Length (m)', 'From Latitude (Decimal Degrees)', 'From Longitude
(Decimal Degrees)', 'To Latitude (Decimal Degrees)', 'To Longitude (Decimal Degrees)', 'Season', 'Day of
Week', 'Time',
'Latitude (Decimal Degrees)', 'Longitude (Decimal Degrees)', 'Segment Distance (m)', 'Odometer (km)',
'Speed (km/h)', 'Speed Limit (km/h)', 'Heading (Degrees)', 'Direction', 'Estimated HRI (m/km)', 'HRI
Condition', 'Roll (Degrees)', 'Pitch (Degrees)',
'Calculated Distance (m)', 'Length', 'DODDINGTON'], axis=1)
AA = pd.merge(A, weather_all)
B = AA.groupby(['Date', 'Segment_ID']).mean().reset_index()
C = pd.merge(B, pd.DataFrame(Total_distances_clipped[4]), on='Segment_ID')
C.columns = ['Date', 'Segment_ID', 'BB', 'BHB', 'DENNH1', 'EDEN', 'ES', 'PD', 'VZ', 'VZNH2', 'WP', 'Sum_x',
'Rain_BB', 'Rain_BHB', 'Rain_DENNH1', 'Rain_Eden', 'Rain_ES', 'Rain_PD', 'Rain_VZ', 'Rain_VZNH2', 'Rain_WP',
'Sum_y']
C['Weighted_Rainfall'] = C.apply(lambda x: (x.BB*x.Rain_BB + x.BHB*x.Rain_BHB + x.DENNH1*x.Rain_DENNH1 +
x.EDEN*x.Rain_Eden + x.ES*x.Rain_ES + x.PD*x.Rain_PD + x.VZ*x.Rain_VZ + x.VZNH2*x.Rain_VZNH2 +
x.WP*x.Rain_WP)/x.Sum_y, axis=1)
D678_Jachtpad_all_data = pd.merge(D678_Jachtpad_all_data, pd.DataFrame(C[['Weighted_Rainfall',
'Segment_ID', 'Date']]), on = ['Segment_ID', 'Date'])

Road dataframes all data = [D617_Houtbosdorp all data, D839_Vreedsaam all data, D2651_Rietgat all data,
P100_Chambers_all_data, D678_Jachtpad_all_data]

# Setting date as datetime object
for dataframe in road_dataframes:
    dataframe.Date = pd.to_datetime(dataframe.Date)

# Segment lengths for each road
for road_name, dataframe in zip(road_names, road_dataframes):
    print(road_name + " Segment Lengths (m): ")
    print(dataframe['Segment Length (m)'].unique())
    print("")

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# Quantity of data per road
for road_name, road_dataframe in zip(road_names, road_dataframes):
    print(road_name, " Number of points: ", len(road_dataframe))
    print("")

# Number of days of data
for road_name, road_dataframe in zip(road_names, road_dataframes):
    print(road_name + " Number of days of data:")
    print(len(road_dataframe.Date.unique()).tolist())
    print(road_dataframe.Date.unique())
    print("")

# Looking at roads by date
by_date_dataframes = []
for road_dataframe in road_dataframes:
    a = road_dataframe.groupby('Date')['Estimated HRI (m/km)'].mean().reset_index(name="Average Estimated HRI (m/km)")
    b = road_dataframe.groupby('Date')['Estimated HRI (m/km)'].max().reset_index(name='Max Estimated HRI (m/km)')
    c = road_dataframe.groupby('Date')['Estimated HRI (m/km)'].min().reset_index(name='Min Estimated HRI (m/km)')
    d = road_dataframe.groupby('Date')['Estimated HRI (m/km)'].size().reset_index(name='Total No. of Readings')
    j = road_dataframe.groupby('Date')['Calculated Distance (m)'].size().reset_index(name='Sum Distance (m)')
    f = road_dataframe.groupby('Date')['Odometer (km)'].max().reset_index(name='Odometer_max')
    e = road_dataframe.groupby('Date')['Speed (km/h)'].mean().reset_index(name='Average Speed (km/hour)')
    g = road_dataframe.groupby('Date')['Odometer (km)'].min().reset_index(name='Odometer_min')
    k = road_dataframe.groupby('Date')['Segment Distance (m)'].size().reset_index(name='Segment Distance (m)')
    h = (f.Odometer_max - g.Odometer_min).reset_index(name='Total Distance (km)').merge(g.Date.to_frame(), left_index=True, right_index=True).drop('index', 1)
    i = pd.merge(a, b, on='Date').merge(c, on='Date').merge(d, on='Date').merge(e, on='Date').merge(j, on='Date').merge(h, on='Date').merge(k, on='Date')
    by_date_dataframes.append(i)

# Creating road condition data frames by date
D617_Houtbosdorp_by_date = by_date_dataframes[0]
D839_Vreedsaam_by_date = by_date_dataframes[1]
D2651_Rietgat_by_date = by_date_dataframes[2]
P100_Chambers_by_date = by_date_dataframes[3]
D678_Jachtpad_by_date = by_date_dataframes[4]

# Looking at roads by segment
by_segment_dataframes = []
for road_dataframe in road_dataframes:
    a = road_dataframe.groupby(['Segment_ID', 'Date'])['Estimated HRI (m/km)'].mean().reset_index(name = 'Average Estimated HRI (m/km)')
    b = road_dataframe.groupby(['Segment_ID', 'Date'])['Estimated HRI (m/km)'].max().reset_index(name = 'Max Estimated HRI (m/km)')
    c = road_dataframe.groupby(['Segment_ID', 'Date'])['Estimated HRI (m/km)'].min().reset_index(name = 'Min Estimated HRI (m/km)')
    j = road_dataframe.groupby(['Segment_ID', 'Date'])['Calculated Distance (m)'].size().reset_index(name = 'Sum Distance (km)')
    d = road_dataframe.groupby(['Segment_ID', 'Date'])['Estimated HRI (m/km)'].size().reset_index(name = 'Total No. of Readings')
    e = road_dataframe.groupby(['Segment_ID', 'Date'])['Speed (km/h)'].mean().reset_index(name = 'Average Speed (km/hour)')
    f = road_dataframe.groupby(['Segment_ID', 'Date'])['Odometer (km)'].max().reset_index(name = 'Odometer_max')
    g = road_dataframe.groupby(['Segment_ID', 'Date'])['Odometer (km)'].min().reset_index(name = 'Odometer_min')
    h = (f.Odometer_max - g.Odometer_min).reset_index(name = 'Total Distance (km)').merge(g.Date.to_frame(), left_index = True, right_index = True).merge(g.Segment_ID.to_frame(), left_index = True, right_index = True).drop('index', 1)
    i = pd.merge(a, b, on = ['Segment_ID', 'Date']).merge(c, on = ['Segment_ID', 'Date']).merge(d, on = ['Segment_ID', 'Date']).merge(e, on = ['Segment_ID', 'Date']).merge(j, on = ['Segment_ID', 'Date']).merge(h, on = ['Segment_ID', 'Date'])
    by_segment_dataframes.append(i)

#Creating road condition per segment dataframes
D617_Houtbosdorp_by_segment = by_segment_dataframes[0]
D839_Vreedsaam_by_segment = by_segment_dataframes[1]
D2651_Rietgat_by_segment = by_segment_dataframes[2]
P100_Chambers_by_segment = by_segment_dataframes[3]
D678_Jachtpad_by_segment = by_segment_dataframes[4]

### Merging the data

# Merging the weather and road condition dataframes per road
roads_weather_by_date = []
for dataframe in by_date_dataframes:
    dataframe.Date = pd.to_datetime(dataframe.Date)
    a = pd.concat([weather_all['Date'], dataframe.Date], axis =0)
    a = pd.DataFrame(a.unique())
    a.columns = ['Date']

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a = pd.merge(a, weather_all, on = 'Date', how = 'outer').merge(dataframe, on = 'Date', how =
'outer').sort_values(['Date'])
roads_weather_by_date.append(a)

# Converting indices to strings:
for dataframe in roads_weather_by_date:
    dataframe.columns = dataframe.columns.astype(str)

# Creating road weather dataframes
D617_Houtbosdorp_roads_weather = roads_weather_by_date[0]
D839_Vreedsaam_roads_weather = roads_weather_by_date[1]
D2651_Rietgat_roads_weather = roads_weather_by_date[2]
P100_Chambers_roads_weather = roads_weather_by_date[3]
D678_Jachtpad_roads_weather = roads_weather_by_date[4]

# Pivoting segment dataframes for concatenation
dataframes_by_segment_pivot = []
for dataframe in by_segment_dataframes:
    x = dataframe.pivot(index = 'Date', columns = 'Segment_ID', values = "Average Estimated HRI (m/km)")
    dataframes_by_segment_pivot.append(x)

# Creating Dataframes of road condition by segment pivoted:
D617_Houtbosdorp_by_segment_pivot = dataframes_by_segment_pivot[0]
D839_Vreedsaam_by_segment_pivot = dataframes_by_segment_pivot[1]
D2651_Rietgat_by_segment_pivot = dataframes_by_segment_pivot[2]
P100_Chambers_by_segment_pivot = dataframes_by_segment_pivot[3]
D678_Jachtpad_by_segment_pivot = dataframes_by_segment_pivot[4]

# Merging the weather and road condition dataframes per segment
roads_weather_by_segment = []
for dataframe, frame in zip(dataframes_by_segment_pivot, by_date_dataframes):
    frame.Date = pd.to_datetime(frame.Date)
    a = pd.concat([weather_all['Date'], frame.Date], axis = 0)
    a = pd.DataFrame(a.unique())
    a.columns = ['Date']
    a = pd.merge(a, weather_all, on = 'Date', how = 'outer').merge(dataframe, left_on = 'Date',
right_index=True, how = 'outer').sort_values(['Date'])
    roads_weather_by_segment.append(a)

# Converting indices to strings
for dataframe in roads_weather_by_segment:
    dataframe.columns = dataframe.columns.astype(str)

# Creating road weather by segment dataframes
D617_Houtbosdorp_roads_weather_by_segment = roads_weather_by_segment[0]
D839_Vreedsaam_roads_weather_by_segment = roads_weather_by_segment[1]
D2651_Rietgat_roads_weather_by_segment = roads_weather_by_segment[2]
P100_Chambers_roads_weather_by_segment = roads_weather_by_segment[3]
D678_Jachtpad_roads_weather_by_segment = roads_weather_by_segment[4]

# Creating a column for road names:
for dataframe, road in zip(roads_weather_by_segment, road_names):
    dataframe['Road'] = road
roads_weather_by_segment_data = pd.concat(roads_weather_by_segment, sort=False)

# Preparing Data for RNN
Time_series_data = []
for dataframe in Road_dataframes_all_data:
    HRI_Ave = []
    Roll = []
    Pitch = []
    HRI_Max = []
    HRI_Min = []
    Weighted_rainfall = []
    a = dataframe.drop(['HRI Condition', 'Segment Length (m)', 'From Latitude (Decimal Degrees)', 'From
Longitude (Decimal Degrees)', 'To Latitude (Decimal Degrees)',
'To Longitude (Decimal Degrees)', 'Day of Week', 'Time', 'Latitude (Decimal Degrees)', 'Longitude (Decimal
Degrees)', 'Odometer (km)', 'Speed (km/h)', 'Speed Limit (km/h)',
'Heading (Degrees)', 'Direction', 'Calculated Distance (m)', 'Sum'], axis=1)
    a.columns = ['Segment_ID', 'Date', 'Season', 'Segment Distance', 'HRI', 'Roll', 'Pitch', 'Length',
'BB', 'BBB', 'DENNH1', 'DODDINGTON', 'EDEN', 'ES', 'PD', 'VZ', 'VZNH2', 'WP', 'Weighted_rainfall']
    b = a.groupby(['Date', 'Segment_ID'])
    c = lambda x: np.average(x.HRI, weights=x.Segment_Distance)
    d = lambda x: np.average(x.Roll, weights=x.Segment_Distance)
    e = lambda x: np.average(x.Pitch, weights=x.Segment_Distance)
    j = b.HRI.max()
    k = b.HRI.min()
    l = b.Weighted_rainfall.mean()
    f = b.apply(c)
    g = b.apply(d)
    h = b.apply(e)
    HRI_Ave.append(f)
    Roll.append(g)
    Pitch.append(h)
    HRI_Max.append(j)
    HRI_Min.append(k)

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Weighted_rainfall.append(i)
i = pd.DataFrame({'HRI_Ave': HRI_Ave, 'Roll': Roll, 'Pitch': Pitch, 'HRI_Max': HRI_Max, 'HRI_Min':
HRI_Min, 'Weighted_rainfall': Weighted_rainfall})
Time_series_data.append(i)

print(Total_distances[0])
print(Total_distances[0].iloc[0,2])

for i, name, segments, distances in zip(range(0,5), road_names, Road_Segments, Total_distances):
    Directory1 = "E:\\DATA\\TRACKER ROAD ROUGHNESS\\TOYOTA BAKKIE\\Output\\{\\}\\\\".format(name)
    Directory2 = "E:\\DATA\\TRACKER ROAD ROUGHNESS\\TOYOTA BAKKIE\\RNN_Input\\{\\}\\\\".format(name)
    Date = "2018/05/01"

    for x, segment in zip(range(0, len(segments)), segments):
        AAA = pd.DataFrame(Time_series_data[i])
        HRI_Ave = pd.DataFrame(AAA['HRI_Ave'].values.tolist(), index=AAA.index)
        Roll = pd.DataFrame(AAA['Roll'].values.tolist(), index=AAA.index)
        Pitch = pd.DataFrame(AAA['Pitch'].values.tolist(), index=AAA.index)
        HRI_Max = pd.DataFrame(AAA['HRI_Max'].values.tolist(), index=AAA.index)
        HRI_Min = pd.DataFrame(AAA['HRI_Min'].values.tolist(), index=AAA.index)
        Weighted_rainfall = pd.DataFrame(AAA['Weighted_rainfall'].values.tolist(), index=AAA.index)

        HRI_Ave = HRI_Ave.transpose()
        HRI_Ave.reset_index(inplace=True)
        HRI_Ave.columns = ["Date", "Segment_ID", "HRI_Ave"]
        HRI_Ave = HRI_Ave.pivot(index="Date", columns='Segment_ID', values='HRI_Ave').reset_index()

        Roll = Roll.transpose()
        Roll.reset_index(inplace=True)
        Roll.columns = ["Date", "Segment_ID", "Roll"]
        Roll = Roll.pivot(index="Date", columns='Segment_ID', values='Roll').reset_index()

        Pitch = Pitch.transpose()
        Pitch.reset_index(inplace=True)
        Pitch.columns = ["Date", "Segment_ID", "Pitch"]
        Pitch = Pitch.pivot(index="Date", columns='Segment_ID', values='Pitch').reset_index()

        HRI_Max = HRI_Max.transpose()
        HRI_Max.reset_index(inplace=True)
        HRI_Max.columns = ["Date", "Segment_ID", "HRI_Max"]
        HRI_Max = HRI_Max.pivot(index="Date", columns='Segment_ID', values='HRI_Max').reset_index()

        HRI_Min = HRI_Min.transpose()
        HRI_Min.reset_index(inplace=True)
        HRI_Min.columns = ["Date", "Segment_ID", "HRI_Min"]
        HRI_Min = HRI_Min.pivot(index="Date", columns='Segment_ID', values='HRI_Min').reset_index()

        Weighted_rainfall = Weighted_rainfall.transpose()
        Weighted_rainfall.reset_index(inplace=True)
        Weighted_rainfall.columns = ["Date", "Segment_ID", "Weighted_rainfall"]
        Weighted_rainfall['Weighted_rainfall'].fillna(0)
        Weighted_rainfall = Weighted_rainfall.pivot(index="Date", columns='Segment_ID',
values='Weighted_rainfall').reset_index().fillna(0)

        A = pd.concat([HRI_Ave.iloc[:,0], HRI_Ave.iloc[:,x+1], HRI_Max.iloc[:,x+1], HRI_Min.iloc[:,x+1],
Roll.iloc[:,x+1], Pitch.iloc[:,x+1], Weighted_rainfall.iloc[:,x+1]], axis=1)
        A.columns = ['Date', 'HRI_Ave', 'HRI_Max', 'HRI_Min', 'Roll', 'Pitch', 'Weighted_rainfall']
        a = pd.concat([weather_all['Date'], A.Date], axis=0)
        a = pd.DataFrame(a.unique())
        a.columns = ['Date']
        d = pd.DataFrame(list(range(a.min(), a.max())))
        d.columns = ['Date']
        b = pd.merge(d, weather_all, on='Date', how='outer').fillna(0)
        c = pd.merge(d, A, on='Date', how='outer')
        c.interpolate(method="linear", inplace=True)
        B = pd.merge(c, b, on='Date', how='outer')
        B.columns = ['Date', 'HRI_Ave', 'HRI_Max', 'HRI_Min', 'Roll', 'Pitch', 'Weighted_rainfall',
'Rain_BB', 'Rain_BHB', 'Rain_DENNH1', 'Rain_Eden', 'Rain_ES', 'Rain_PD', 'Rain_VZ', 'Rain_VZNH2',
'Rain_WP']
        B['BB'] = distances.iloc[x,2]
        B['BHB'] = distances.iloc[x,3]
        B['DENNH1'] = distances.iloc[x,4]
        B['EDEN'] = distances.iloc[x,5]
        B['ES'] = distances.iloc[x,6]
        B['PD'] = distances.iloc[x,7]
        B['VZ'] = distances.iloc[x,8]
        B['VZNH2'] = distances.iloc[x,9]
        B['WP'] = distances.iloc[x,10]
        B['Sum'] = distances.iloc[x,11]
        B['Weighted_Rainfall_new'] = B.apply(lambda x: (x.BB * x.Rain_BB + x.BHB * x.Rain_BHB + x.DENNH1 *
x.Rain_DENNH1 + x.EDEN * x.Rain_Eden + x.ES * x.Rain_ES + x.PD * x.Rain_PD + x.VZ * x.Rain_VZ + x.VZNH2 *
x.Rain_VZNH2 + x.WP * x.Rain_WP) / x.Sum, axis=1)
        B.drop(['Weighted_rainfall', 'BB', 'BHB', 'DENNH1', 'EDEN', 'ES', 'PD', 'VZ', 'VZNH2', 'WP',
'Sum'], axis=1, inplace=True)
        C = B.loc[0:(len(B)-15),:]
        D = B.loc[(len(B)-15):,:]
        C.dropna(subset=['HRI_Ave'], inplace=True)
        path = os.path.join(Directory1, "{}_RNN_Raw.csv".format(segment))

```

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if not os.path.exists(Directory1):
    os.makedirs(Directory1)
B.to_csv(path)

Directory3 = os.path.join(Directory2, "Train\\")
path = os.path.join(Directory3, "{}_RNN_Train.csv".format(segment))
if not os.path.exists(Directory3):
    os.makedirs(Directory3)
C.to_csv(path)

Directory3 = os.path.join(Directory2, "Test\\")
path = os.path.join(Directory3, "{}_RNN_Test.csv".format(segment))
if not os.path.exists(Directory3):
    os.makedirs(Directory3)
D.to_csv(path)

for x, name in zip(Road_dataframes_all_data, road_names):

    directory = "E:\\DATA\\TRACKER ROAD ROUGHNESS\\TOYOTA BAKKIE\\Check_Weights\\"
    path = os.path.join(directory, "{}.csv".format(name))
    if not os.path.exists(directory):
        os.makedirs(directory)
    x.to_csv(path)

```