DEFECT-LEVEL CONDITION ASSESSMENT OF SEWER PIPELINES IN AUCKLAND

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Abstract

CCTV plays an essential role in keeping sewer pipe performance at a desirable level. A sewer pipe condition score is normally assigned to each sewer pipe based on the type, quantity, and extent of defects observed through CCTV inspections. While the impact of different factors on the condition score has been considered in several studies, the impact of these factors on the underlying defects has not been investigated. The aim of this study was to investigate the effect of various factors, including age, material, diameter, and groundwater level, on the prevalence of eight defect categories in the transmission sewer network of Auckland, New Zealand. A cleaned dataset with the defects identified through recent CCTV inspections of 2780 sewers was gathered and linked to a range of physical and environmental factors. Defects were grouped into the following eight categories: material damage, gas attack, infiltration, roots, debris, total joint, structural, and dipped pipe. Correlations between different factors and defects were analyzed, respectively, followed by an investigation of the impact of each factor on each defect category and, finally a comparison of the normalized linear regression slopes for statistically significant relationships.

In addition, multi-parameters models were developed in order to study the relationship between various factors and each defect category. Two models, including binary logistic regression and gradient boosting trees, were developed as statistical and artificial intelligence models, respectively. These models were selected based on several reasons, such as the performance to predict categorical outcomes, the capability to be trained by nominal and categorical variables, and the clarity of achieved results.

This study showed the value of underlying defects and highlighted the importance of applying this approach in the future in the city of Auckland and all around the world in order to provide new insights into the drivers of deterioration processes in sewer pipes. The results of this study may be utilized for prioritization of inspection planning and renewal programs in managing the sewer pipeline network in the city of Auckland.

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List of Abbreviations and Symbols

ABS	acrylonitrile butadiene chloride
AC	asbestos cement
Alum	aluminium
ASCE	Journal of American Society of Civil engineers
CCL	Large circumferential crack
CER	ceramic
CI	cast iron
CIP	cast in place
CLCI	concrete-lined cast iron
CLS	concrete-lined steel
Conc	concrete
EW	earthenware
FRP	fiberglass reinforced plastic
GL	groundwater level
GPIMNZ	Gravity Pipe Inspection Manual Standard of New Zealand
HDPE	high-density polyethylene
LFB	lateral sealing faulty broken
LS	liquefaction susceptibility index
PD	population density
PE	polyethylene
PVC	polyvinyl chloride
RC	reinforced concrete
RCRRJ	reinforced concrete-rubber ring joint
RCSRJ	reinforced concreate-skid ring joint
RIM	Medium root intrusion
SS	stainless steel
VC	vitrified clay
WWTP	Wastewater Treatment Plant

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Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work. Tizmaghz, Z., Zyl, J.E. van.,Hennig, T.F.P. 2022. Consistent classification system for sewer pipe deterioration and asset management.Journal of Water Resources Planning and Management., 2022, 148(5): 04022011 DOI: 10.1061/(ASCE)WR.1943-5452.0001545.

Nature of contribution by PhD candidate	Data study, analysis, and manuscript writing
Extent of contribution by PhD candidate (%)	70

CO-AUTHORS

Name	Nature of Contribution
J.E . van Zyl	Clarification of existing inconsistencies and definitions, Proposing the classification systems including all categories and subcategories and defining all the involved components, Reviewing the paper, corresponding with the Journal, and revised
Theuns Henning	Commented on the manuscript draft

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and
- that the candidate wrote all or the majority of the text.

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Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.	
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CO-AUTHORS

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Theuns Henning	Commented on the manuscript draft
Nathan Donald	Contributed with gathering data set and commented on the manuscript draft
Purvi Pancholy	Commented on the manuscript draft

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The undersigned hereby certify that:

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1 INTRODUCTION

1.1 Background

Sewage collection systems are designed to collect sewage from residential, commercial, and industrial parts of cities and transfer it to wastewater treatment plants. It is necessary to convey wastewater in the proper way to minimize the potential hazardous impacts which can be caused by sewage (Hawari et al., 2020).

As sewer pipelines reach the end of their useful lives in megacities, they are becoming one of the main concerns of utilities. More strict environmental and health standards, increasing population, and limited operating budget make dealing with this issue harder (Saeed Moradi & Zayed, 2017).

Hawari et al. (2020) stated that sewage systems have amongst the poorest condition in comparison with other infrastructure systems. For example, sewer pipeline condition in the US is graded as D: Poor, by the American Society of Civil engineers (ASCE) (Herrmann, 2013). Besides, the Canadian Infrastructure Report Card (2016) evaluated sewer pipelines condition in Canada as poor and very poor (Saeed Moradi & Zayed, 2017). Also, in the UK, in one year (2014 – 2015), two severe and 71 less serious sewerage-related pollution incidents for every 10,000 km were reported (Myrans et al., 2018).

These limitations are forcing utilities to consider proactive asset management strategies instead of reactive ones (Grigg, 2012; Salman & Salem, 2012). A reactive method is an approach when utilities have to do rehabilitations and renovations of pipelines after the emergence of failures. However, failures of sewer pipelines may affect cities negatively by causing catastrophic damage to communities and the environment. Thus, proactive strategies are utilized to address possible problems before they arise which lead to serve utilities in saving time, money, and energy (Fenner et al., 2000; López-Kleine et al., 2016).

The most important key elements of a proactive strategy are data collecting, being aware of the current asset condition, and the ability to predict the future condition of sewer segments (Hawari et al., 2020). Thus, the inspection of sewer pipelines has appeared as a critical task for contributing utilities for collecting data and being informed about asset states. For fulfilment of this step, various inspection technologies have been implemented, which will be discussed in the literature review. Meanwhile, utilities need to prioritize the inspection of sewer pipelines since inspecting all sewer pipelines is prohibitively expensive and time-consuming.

To facilitate the prioritization procedure of inspection for utilities, many decision-support tools have been proposed (Gc et al., 2011). These methods include deterioration models, prediction of the future condition of sewer pipelines to estimate their failure times, and a consequence model for determining the impact of failures on people and the environment. By merging all these tools, utilities are able to have a risk-based prioritizing tool (Hansen et al., 2020). These prediction models can lead municipalities to schedule short-term and long-term asset management strategies (Hoseingholi & Moeini, 2023).

The deterioration processes of sewer pipelines are complicated as many factors can affect them (Hansen et al., 2020; Mohammadi et al., 2019). Therefore, many deterioration models have been assessed and optimized in order to predict the sewer pipeline condition according to various factors. Deterministic, statistical, and artificial intelligence (AI) or machine learning approaches are three classes of methods that have been used to assess the process of deterioration in sewer pipelines (Hansen et al., 2020).

A common aspect in all research done in this field is the use of a condition score as the dependent variable. A condition score is a number (usually from 1 to 5) that is assigned to each sewer pipe based on the type, quantity, and extent of defects observed through CCTV inspections. The condition score generally increases with the increasing number and extent of defects (Khazraeializadeh, 2012).

1.2 Knowledge Gap

While several statistical and machine learning deterioration models have been used to predict the condition of sewer pipelines all around the world (Egger et al., 2013; Hansen et al., 2020), there is no study on predicting the condition of sewer pipelines in the city of Auckland, New Zealand.

Sewer condition models normally study the impact of various variables on the codition scores of sewer pipes. While the condition score is a simple and useful measure for the overall sewer condition, it provides no insight into the underlying mechanisms responsible for the deterioration of a pipe. A given condition score may result from a vast range of underlying defect types and their frequency and severity. Given that the underlying defects are identified and classified as part of CCTV inspection process, this information may provide an opportunity to gain a more detailed understanding of the causes and patterns of sewer pipe deterioration in a particular system.

To the best of my knowledge, there have not been any studies investigated the defects underlying condition scores and their correlation with various factors. Additionally, no statistical and artificial intelligence models have been developed to investigate the relationship between underlying defects and different physical and environmental factors.

Malekmohammadi. (2019) recommended that more research is needed to develop condition prediction models by considering more independent variables related to the surrounding environment, installation procedure, and maintenance schedules. In this study, a range of factors is considered in order to investigate the possible effect of the surrounding environment on the deterioration of sewer pipelines. The studied factors included pipe age, material, diameter, depth, slope, length, groundwater level, population density, and liquefaction susceptibility.

Malekmohammadi. (2019) recommended that more research is needed on deep learning algorithms to model deterioration in sewer pipeline systems. Also, Tscheikner et al. (2019) stated that results obtained from different models that have been performed for the same cities showed that machine learning models surpass statistical models in recognizing pipes in critical conditions. Thus, machine learning models are included in this study to provide better insight into the deterioration processes of sewer pipelines.

1.3 Objectives

The aim of this study was to investigate the prevalence of defects identified by CCTV inspection and study the relationship between these defects and various factors. Also, correlations between different factors and defects were analyzed, respectively, followed by an investigation of the impact of each factor on each defect category.

In addition, two prediction models, including logistic regression and gradient boosting trees, were developed in order to predict the prevalence of eight defect categories. A better understanding of physical and environmental factors affecting pipe defects provides a better insight for municipalities to manage their assets and make efficient CCTV inspection decisions in terms of planning and future installations (Laakso et al. 2018).

The specific objectives of this study were to:

- Present the state of the art of the current knowledge on sewer condition assessment and deterioration models and how it relates to the city of Auckland.
- Develop a structured framework for classifying different components involved in deterioration processes in order to make the deterioration procedure of sewer pipelines more understandable.
- Investigate the most influential factors such as age, diameter, material, etc. affecting the prevalence of defects in sewer pipelines in the city of Auckland.
- Explore and evaluate multivariate sewer prediction models for each defect category to prioritize inspection and rehabilitation planning of sewers in the city of Auckland.

1.4 Scope

The scope of this thesis is restricted to the closed-circuit television (CCTV) inspection report of gravity transmission sewer pipelines provided by Watercare Ltd. Not any physical investigations were implemented to improve the quality of the dataset. The classification of various defects in sewers is based on the Gravity Pipe Inspection Manual Standard of New Zealand (Water New Zealand, 2019).

1.5 Layout

Figure 1 shows the order of the research methodology based on the following chapters in this dissertation. After providing an introduction in terms of the background, main objectives, and possible gaps in chapter one, a literature review on the effect of deterioration reasons on sewer systems and condition assessment approaches were provided in chapter two. Based on the literature review, a consistent classification system for sewer pipe deterioration was proposed and considered as one of the main contributions of this study. In the next step and chapter four of the study, data gathering and cleaning were described, followed by an investigation of the impact of each factor on each defect category.

It is noteworthy to add that the chapter three and four are mainly part of published and submitted papers, respectively. Both papers in the original format are provided in Appendixes A and B.

Followingly, statistical and artificial intelligence models were developed in order to study and predict the relationship between various factors and each defect category in chapter five. Finally, in chapter six, the conclusions of the study are stated.

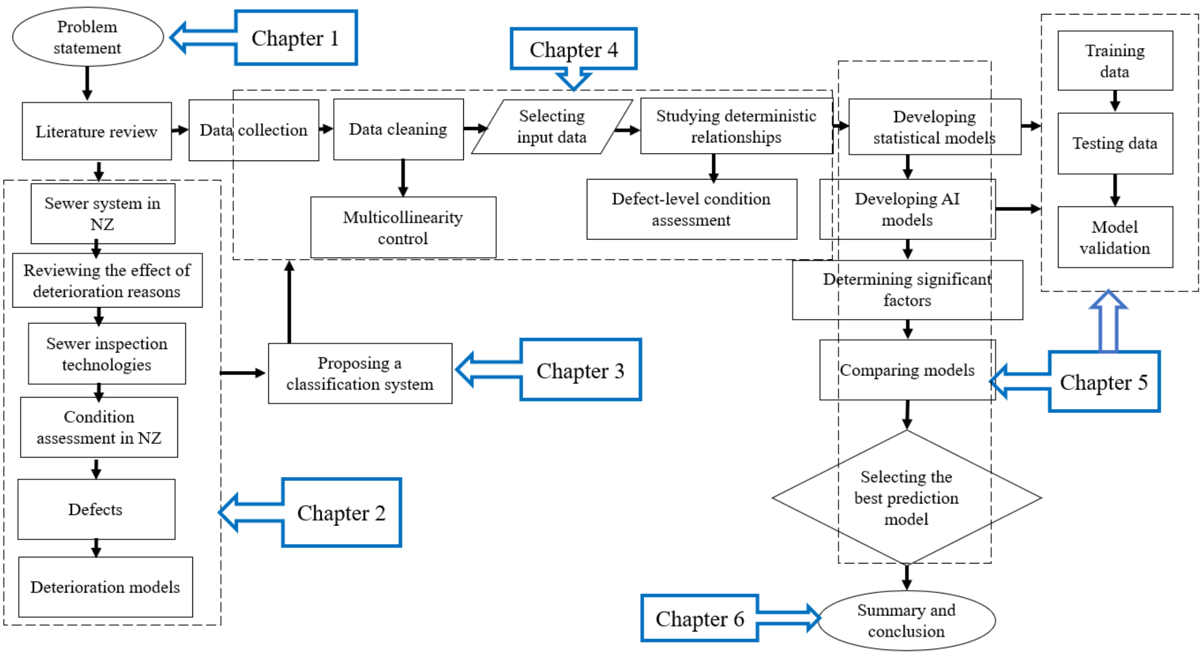


Figure 1. Research methodology

2 LITERATURE REVIEW

2.1 Overview

Minimizing the total cost of owning and operating infrastructure assets while delivering the desired service levels to customers are the main objectives of proactive asset management strategies (Environmental & Epa, 2017; Roghani et al., 2019). One of the key elements of an effective proactive asset management process is the ability to accurately predict the current and future condition of sewer segments to facilitate decision-making processes. Thus, assessment of the condition of sewer segments is a vital component of any proactive program which is usually evaluated by condition assessment models (Mohammadi et al., 2019; Roghani et al., 2019). Condition assessment models are based on data that is recorded by municipalities and might have an impact on sewer pipeline degradation. Determining the deterioration state of pipes by condition assessment models have been made these models powerful tools for utilities to consider prioritization and rehabilitation plans which form proactive asset management strategies (Hawari et al., 2020)

The whole proactive asset management process for sewer networks consists of the following components, i) data collection and processing, ii) deterioration models, iii) condition assessment models, iv) Proactive asset management, v) Implementation.

Data collection and processing play an important role as the initial step in acquiring more reliable condition assessment models (Hyeon-Shik et al., 2006; Roghani et al., 2019; Yin, Chen, Bouferguene, & Al-Hussein, 2020). Understanding factors that affect sewer pipelines performance, inspection of the infrastructure’s physical and functional conditions manually or with different technologies such as CCTV, GPR, SSET, etc., and analyzing data with professional and trained operators or automated defect detection models can be included in this step (Saeed Moradi et al., 2019; Yin, Chen, Bouferguene, Zaman, et al., 2020).

Deterioration models are utilized to evaluate the progression of any defects to make informed decisions about complementary investigations, maintenance, repair, or potential replacement by considering influencing factors (Hyeon-Shik et al., 2006).

Both data collection and processing and deterioration models feed into condition assessment models to describe the current situation and predict the future condition of an asset. These steps all support proactive asset management, which is evaluating the infrastructure performance over time and making the best decisions on pipe rehabilitation or replacement. The asset management strategy is then implemented, and the process is repeated. The above cycle is described in this literature review. Figure 2 shows the structure of the literature review, which is as follows:

- A history of the establishment of the sewer system in New Zealand and its importance is summarized.
- Different reasons that might influence the deterioration of sewer pipeline is discussed.
- Failure definitions and their classifications in sewer pipelines are reviewed.
- Common sewer inspection technologies are reviewed, and the significance of CCTV is stated.
- Different condition scoring standards all over the world are briefly discussed and New Zealand condition grading standards are reviewed in detail in order to clarify the process that pipes in the received dataset are graded based on the observed defects.
- The role of defects in determining the condition scores of sewers is studied.
- The overall structure of implemented deterioration models in this study is reviewed.

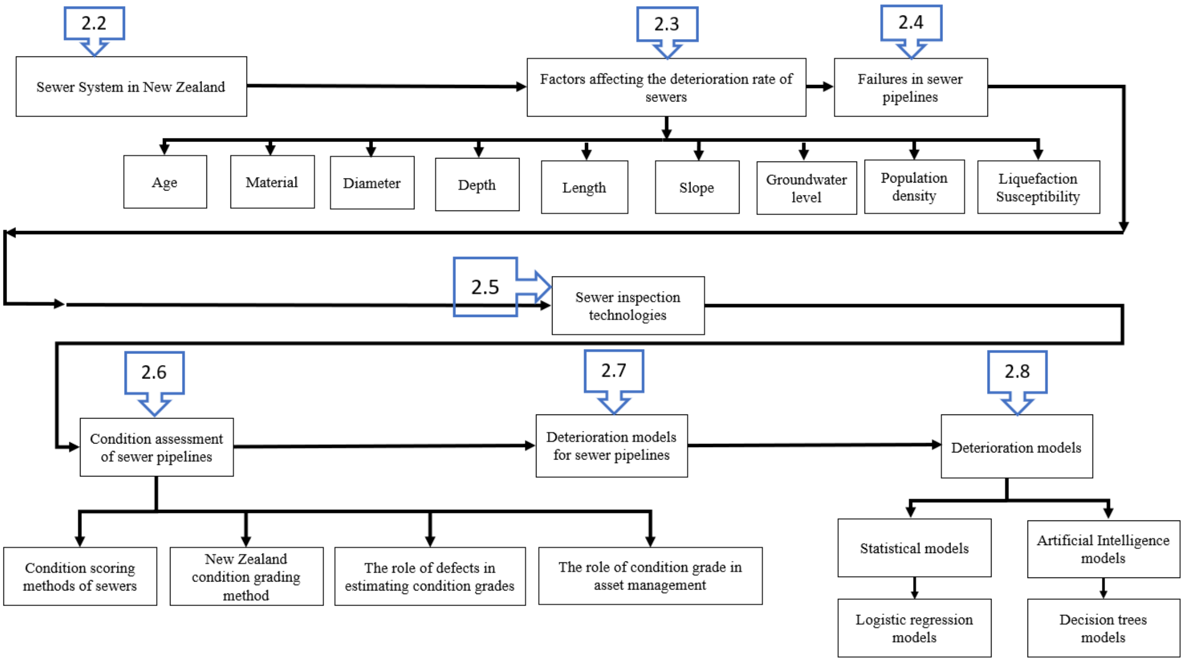


Figure 2. An overview on the literature review

2.2 Sewer Systems in New Zealand

Before 1878, the common form of wastewater disposal in Auckland city was 'nightsoil' collection, i.e., collecting waste from individual households usually in the night by a horse-drawn 'night cart'. By growing the population, the traditional form of wastewater disposal became unacceptable as sanitation problems increased considerably. By increasing the population from 30,000 to 100,000 between 1878 and 1903 and doubling diseases related to poor sanitation, the need for providing an overall wastewater drainage collection system raised noticeably. In 1903, Auckland City Council started the construction of a comprehensive sewer drainage system to handle both storm and wastewater in the city to address the sanitation problems (Roskill et al., 2010). At present, Watercare Services limited owned by Auckland Council is in charge of water and wastewater services in the Auckland region, with a population of around 1.7 million. Every day almost 400 million liters of wastewater is collected through almost 8000 kilometers of wastewater pipelines and treated to a very high standard in two main wastewater treatment plants in Rosedale and Mangere at the north and south of Auckland, respectively (Roskill et al., 2010). In Auckland city still, two types of sanitary sewer systems, including Combined Sewer Systems (CSS) and Separate Sewer Systems (SSS), have been working (Environmental Guide, 2019). While in Combined Sewer System, sewer and stormwater are conveyed through the same pipe, in Separate Sewer Systems, these two flows are separated from each other to be transferred to a selected disposal location. Implementing Combined Sewer Systems leads to designing larger pipe diameters and more complicated and equipped water treatment plants. Therefore, these days due to economic reasons there is a stronger inclination for Separated Sewer Systems.

2.3 Factors affecting the deterioration rate of sewers

Buried sewer pipes are exposed to deterioration due to external and internal reasons. A general schematic of these reasons is shown in Figure 3 (Angkasuwansiri et al., 2013). As it can be seen from the figure, the factors are from an extensive range of reasons such as age, material, diameter, joint types, pipe length and section, corrosion, water consumption, the amount of fat-oil-grease (FOG), groundwater table, ground movement, construction and installation procedure, dead and live load, trench backfill features, soil characteristics, and tree roots.

A brief description of the main and most common factors studied in several developing deterioration models is reported in this section.

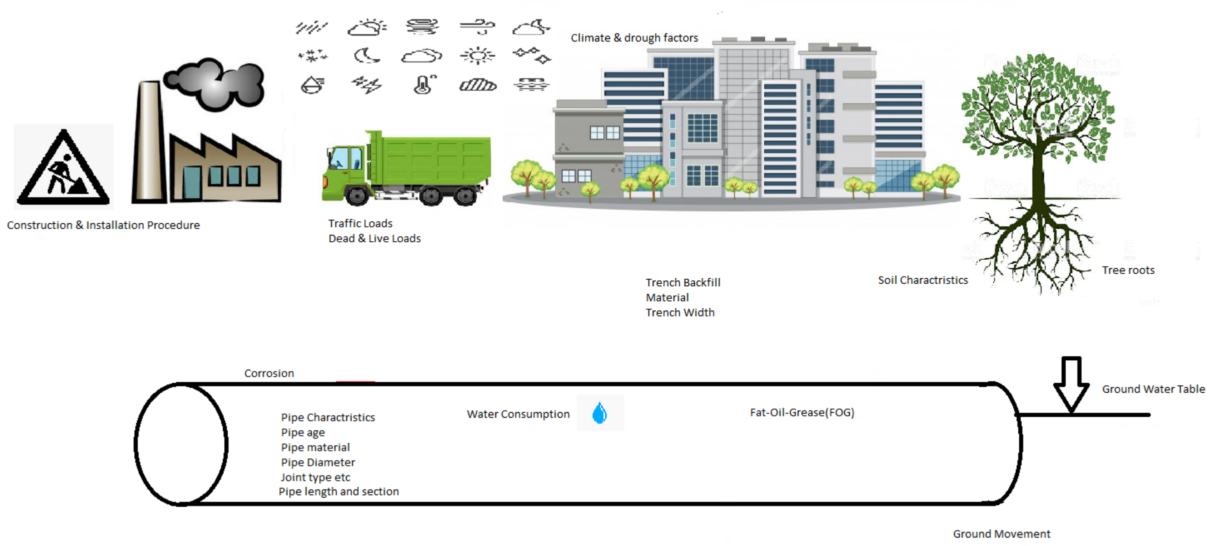


Figure 3. General factors affecting sewer pipelines performance (Angkasuwansiri et al., 2013)

2.3.1 Age

The aging of pipes starts from the installed date, and it can affect the deterioration rate of sewer pipelines. The bathtub curve shown in Figure 4 illustrates the rate of failures based on the age of pipes and is divided into three phases. In the first phase, which is coincident with time after installation, the number of failures is high due to several reasons, such as human errors, impairment of pipes during construction and installation, and using unsuitable pipe materials (Serajiantehrani et al., 2020). In the middle phase, the useful life of the pipe, the rate of failure is relatively low and constant. During this period, different physical, operational and environmental factors can speed up the finishing of the useful life of the pipe. Near the end of useful life, the pipes enter the third phase, and the rate of failures increases due to pipe deterioration and the aging process.

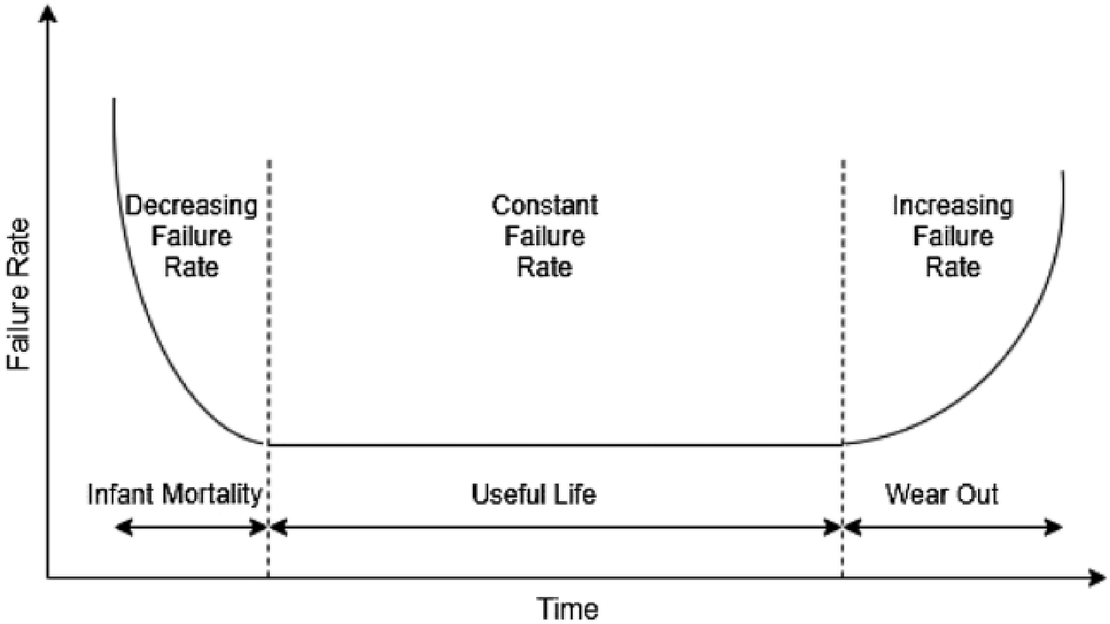


Figure 4. Bath-tub curve (Serajiantehrani et al., 2020)

Pipe age has been found as a noteworthy factor in various studies (Ahmadi et al., 2014; Ana et al., 2009; Cigada et al., 2011). O'REILLY et al. (1989) claimed that more defects will present in older sewer pipelines. Laakso et al. (2018) reported an upward trend in the deterioration rate of sewer pipelines after the age of 45 years. Harvey and McBean (2014) stated that pipes more than 50 years old have more chance of being in poor condition. These results align with the general trend that is expected since aging causes fatigue and wear in the structure of sewers which makes them more prone to structural defects.

Pohls et al. (2004) indicated that the number of blockages from 30 to 60 years is the highest, and surprisingly the number of blockages decreases after 60 years of pipe age. This may be due to decreasing debris ingress and increasing sewer flow rate over the years as the construction of new properties decreases and the number of sewer connections increases. Debris is one of the main causes leading to blockages in sewers (Marlow et al., 2011).

2.3.2 Material

Several studies pointed out that material characteristics affect pipe condition (Ahmadi et al., 2014; Ana et al., 2009; Nicolas Caradot et al., 2017; Cigada et al., 2011; Duchesne et al., 2013; Micevski et al., 2002). Khan et al. (2010) reported substantial differences in pipes of different types of concrete. Syachrani et al. (2013) found essential differences between the deterioration of vitrified clay (VC) pipes and PVC pipes. Marlow et al. (2011) reported that concrete and VC pipes have a higher blockage rate in comparison with PVC and polyethylene (PE) pipes.

Laakso et al. (2018) argued that concrete and polyethylene high-density (PEH) sewer pipeline materials are more connected with defects in comparison with other materials studied, including polyethylene (PE) and polyvinyl chloride (PVC). A possible interpretation for this difference referred to the initial low quality of certain batches of PEH. Additionally, according to utility's experiences, concrete pipes are usually selected for inspections as they often are in poor condition (Laakso et al., 2018).

The analysis done by Ana et al. (2009) showed that brick sewers are more prone to deterioration than concrete sewers. It is claimed that the procedure of construction is the main reason on influencing this trend. As concrete pipes are normally constructed in factories, in a controlled environment, the pipes would be more durable with higher quality. In contrast, brick pipes are made on-site in a difficult workmanship environment (Ana et al., 2009).

2.3.3 Diameter

Different results regarding the effect of pipe diameter on sewer deterioration are reported. Many studies reported deterioration rate of smaller pipes is faster than larger ones (Baur &

Herz, 2002; Davies, Clarke, Whiter, & Cunningham, 2001; Micevski et al., 2002; O'REILLY et al., 1989).

Laster & Farrar (1979) pointed out there is a slight connection between pipe diameter and the recurrence of defects. Pohls et al. (2004) reported that 70 % of all tree-associated blockages in an Australian sewer system were related to smaller diameter pipes in shallower depths, usually less than one meter from the surface. Beattie & Engineer (2007) revealed that blockages rate are three times more in pipes smaller than 150 mm in diameter.

Harvey and McBean (2014) noted that pipes with a diameter smaller than almost 250 mm are more prone to higher deterioration. Moreover, Davies et al. (2001) noted that as the installation of larger diameter pipes is done with experienced experts and supervised cautiously in a more controlled environment, the rate of deterioration rate for larger diameter pipes is less than smaller ones (Davies, Clarke, Whiter, & Cunningham, 2001). In research by Laakso et al. (2018), fewer defects were reported in pipes with a larger diameter than 1500 mm and pipes with a diameter of about 300 mm.

However, the opposite is stated in a few numbers of studies, i.e., the deterioration rate of larger pipes is faster in comparison with smaller pipes (Hyeon-Shik et al., 2006; Khan et al., 2010).

Khan et al. (2010) claimed smaller diameters experience less deterioration compared to larger diameters. Also, Hyeon-Shik et al. (2006) pointed out that larger diameter pipes deteriorate faster as they have more surface area exposed to sewage and neighboring soil, which makes them more susceptible to deterioration.

Lastly, Ana et al. (2009) reported that sewer pipe diameter did not influence sewer deterioration in their study.

Various outcomes reported from the above-reviewed studies might be due to the overall and specific conditions governed by each studied sewer network. The correlation of different factors in each network might influence the effect of a particular variable on sewer structural deterioration.

2.3.4 Depth

Researchers found contradictory results in terms of the effect of depth on sewer deterioration. Laster and Farrar (1979) reported that the number of sewer defects decreases with increasing depth. O'Reilly et al. (1989) stated that the defect rate decreases with the increase of the pipeline depth till the depth of 5.5 meters; after that, the defect rate increases by increasing depth. The decreasing rate of defects as sewer cover depth increases is attributed to the decreasing influence of surface factors such as road traffic and surface maintenance activities on sewers. However, for sewers that are buried deeper, the increasing effect of soil overburden pressure causes an increase in sewer defect rate (Ana et al., 2009).

Kaddoura and Zayed (2019) reported that deeper pipelines provide higher static pressures because they can form higher soil interactions. Also, it is shown that pipeline depth could influence the erosion voids surrounding the pipeline. In this study, the depth is categorized into five groups, and it is reported that pipes deeper than 5 meters are considered in excellent condition, and pipes shallower than 1.25 meters are categorized in critical condition (Kaddoura & Zayed, 2019).

In contrast, Khan et al. (2010) observed that any increase in depth has a negative effect on the pipe condition. Pipes in deeper depths are liable to have more deterioration than those at shallower depths. The logic of this behavior is that increase in depth implies a greater dead load over the pipe, in addition to a higher probability of groundwater table affecting pipes (Khan et al., 2010).

2.3.5 Length

Length is a common variable studied in different deterioration models. Ana et al. (2009) reported that as sewer pipeline length increases, the probability of deterioration increases. Harvey and McBean (2014) reported a downward condition trend in the pipe with a length of more than 33 meters. Laakso et al. (2018) stated that pipes with a length of more than 40 meters are more prone to have at least one defect. The potential reason for the increase of structural defects in longer pipes might be related to the presence of more laterals connected directly to sewer mains which enhances the probability of failures. Some studies reported that joint defect is one of the most common defects in sewer pipelines, e.g., Park and Lee (1998) reported that 27.5% of sewers inspected in Seoul had joint defect issues. Furthermore, as sewer pipelines become longer, the likelihood of differential settlement multiplies, which causes sediment deposition and blockage. The mentioned defects can be responsible for exacerbating sewer pipeline conditions. Additionally, longer pipes are more exposed to bending stresses (Fazel Chughtai & Zayed, 2008).

On the other hand, Khan et al. (2010) observed no relationship between length and pipe condition for pipes shorter than 70m. However, for pipes longer than this length a better condition than shorter pipes were reported. The possible reason was attributed to the reduced density of end joints which are the main source of break, dislocation, infiltration, and exfiltration (Khan et al., 2010).

Besides, Baik et al. (2006) reported a similar result i.e., that longer pipes are less susceptible to deterioration in comparison with shorter ones. Likely, this is attributed to the fact that longer pipes have fewer bends in which less debris can be accumulated, leading to fewer blockages or damage that can occur due to the standing sewage (Baik et al., 2006).

2.3.6 Slope

Several researchers studied the effect of pipe slope on pipe deterioration. Tscheikner-Gratl et al. (2014) stated that pipes with steeper slopes deteriorate at a slower rate. Laakso et al. (2018) reported that more debris accumulation on flatter pipes could be expected due to the inadequate rinsing of sewers.

However, some researchers found a positive relationship between deterioration rate and pipe slope. Reasons for this finding was attributed to several reasons, such as the higher flow velocities, lower pipe stability, development of voids in the soil, soil movements and the higher prevalence of pipe joint defects (Jeong et al., 2005; Salman & Salem, 2012; Tran et al., 2006).

2.3.7 Groundwater Level

A few numbers of researchers studied the effect of groundwater level on pipe condition. Davies et al. (2001) reported that the presence of groundwater around sewer pipes can cause or exacerbate different defects, such as cracks and infiltration. Indeed, the availability of groundwater around the pipe cause formation of voids which leads to unsuitable soil support. Malek Mohammadi (2019) reported groundwater level as a significant independent variable which is positively affecting the deterioration of sewers. Generally, sewers located below the groundwater level are more prone to fail in comparison with ones above the groundwater (Serajiantehrani et al., 2020).

2.4 Failures in sewer pipelines

The definition of failure may vary based upon the required or desired level of service provided by the pipe. Opila (2011) defined a failed pipe when an action ranges from rehabilitation to replacement or maintenance needs to return the pipe condition to the desired level of service. Failure can range from a small leak to a complete pipe collapse inhibiting the conveyance of flow. It is argued that most pipe failures are caused by several contributing factors rather than a single cause of failure (Davies, Clarke, Whiter, Cunningham, et al., 2001). For instance, the age of the pipe can strengthen or weaken the effect of other factors that may cause failures. For instance, while a load disturbance in the soil may cause a deteriorated pipe to crack, the same disturbance may have a minimal impact on a new pipe. Opila (2011) reported that failures in wastewater are classified into four categories, namely, structural, operation and maintenance, hydraulic capacity, and economic. The definition of each of these failures and their main causes and examples are shown in Table 1.

Table 1. The failure classification systems used in Opila (2011)

Category	Definition	Reasons referred to	Examples
Structural	incorporated compromises in the structural integrity of the pipe itself	-	Pipe collapses, Breaks, Cracks, and Corrosion
Operations and maintenance	a physical cause that may be remediated by a maintenance procedure, the structural integrity of the pipe remains intact in this failure	-	Debris deposits, roots, infiltration, and obstacles
Hydraulic capacity	the hydraulic capacity of the pipe itself is insufficient and is not caused by structural or operations and maintenance failure.	- change in the pipe wall's friction factor -Subsidence and the resulting decrease of slope in gravity pipes -increased water reaching the pipe due to a change in catchment characteristics,	

		-increased infiltration and inflow upstream of the pipe -change in rainfall characteristics -change in the design standards or regulatory requirements
Economic	a failure in which the economic cost of maintaining the pipe over some time horizon exceeds the economic cost of replacing the pipe	-

Stanic (2014) applied a HAZard and OPerability (HAZOP) approach using several expert groups and an expert review to identify the main processes responsible for the structural/operational failures of sewer elements. The HAZOP results were applied in a fault-tree analysis for risk estimation, and the top level of the hierarchy is described as 'top failure events' and categorized into two main groups: system and element performance. System failures occur when the load exceeds the capacity of the pipe or the pipe capacity is not enough for the imported load. In element failures, the load exceeds the strength of the pipe, or the pipe strength is not sufficient for the imported load and causes sewer systems to collapse.

2.5 Sewer Inspection Technologies

2.5.1 Introduction

Inspection technologies provide information about the condition of sewer pipelines and facilitate planning in terms of maintenance, rehabilitation, and renovation. Gathering appropriate data about asset conditions can be the most precious resource for utilities since it can demonstrate the present and future condition of their asset. Thus, inspections of sewer pipelines condition need to be scheduled through a reliable periodic assessment to guarantee an acceptable performing level of service (Guo, Soibelman, & Garrett, Jr., 2009).

Inspection of sewer pipelines was a difficult task before the 1960s because of the small pipe diameters (Reyna et al., 1994). However, sewer inspection techniques have been developing during recent decades through different inspection approaches such as closed-circuit television (CCTV), sewer scanning and evaluation technology (SSET), electro-scanning, ground-penetrating radar (GPR), etc. (Saeed Moradi et al., 2019).

Among all technologies listed, using CCTV cameras is a common technology for the inspection of sewer pipelines. Implementing CCTV and interpretations of CCTV videos are expensive and time-consuming and normally, it is feasible to perform an inspection of 10 percent of the sewer pipelines drainage system each year (Anbari et al., 2017; S. Moradi & Zayed, 2017). The objective of this section is to introduce common technologies for sewer pipelines inspection and assessment and emphasize CCTV as the most common procedure.

2.5.2 Inspection Tools in Sewers

The sewer networks are often known as the most invisible infrastructure as it is challenging to get access to it through manual inspection due to buried & small diameter pipes with an unsafe, unhealthy, and odorous environment. Defects in the sewer pipeline have an extensive spectrum and inspecting and recognizing them with outdated methods is impossible. The broad spectrum of defects leads researchers to use various inspection tools for sewer pipeline assessment. Sewer pipeline inspection techniques can be categorized into camera-based, structural, defect detection, and hybrid technologies, which are a combination of two or more of mentioned techniques; this categorization is illustrated in Figure 5 (Saeed Moradi et al., 2019). The definition of each technology with strengths and drawback points has been summarized in the next section.

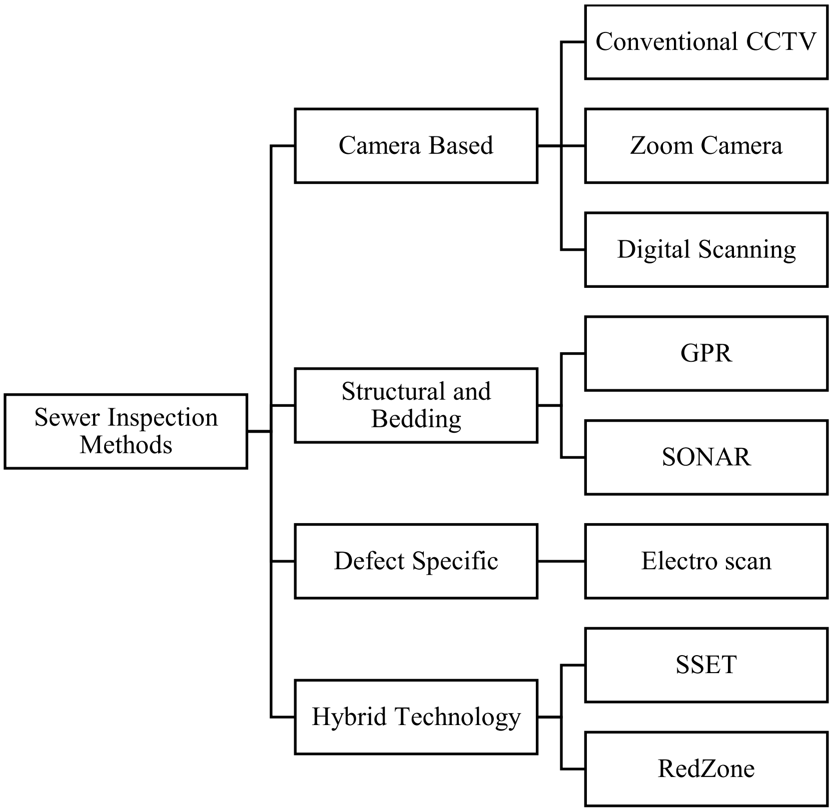


Figure 5. Different sewer pipeline inspection techniques (Saeed Moradi et al., 2019)

2.5.2.1 Camera-Based Technologies

Manual inspection of sewer pipelines is limited due to the reasons mentioned in the previous section. Usually, a broad range of inspections of sewer pipelines is performed with camera-based technologies. Closed-circuit television (CCTV) inspection, zoom camera inspection, and digital scanning are the most regular techniques in camera-based technologies (Saeed Moradi et al., 2019).

Sewer pipeline inspection with CCTV was first introduced in the 1960s. The CCTV includes television cameras mounted on robots, video recorders, and video monitors, which are administrated and interpreted by an operator (Hao et al., 2012). Defects recorded by CCTV footage and interpreted with operators used to collect a survey report for assessment of the sewer pipeline conditions. The footage is often recorded and transferred to the office, where operators can watch and interpret them. Also, CCTV video interpretation can be performed online, which allows the surveyor to control the camera more precisely when defects are distinguished (Myrans, 2018). The main benefit of this technique is providing documentation by capturing pictures and recording videos of defects by acceptable resolution. Information gathered from CCTV inspection demonstrate the condition of actual defects such as cracks, debris, holes, sapling large, collapse, open joint, broken, deformed, etc., besides their locations (Edwards & Flintsch, 2012b; Saeed Moradi et al., 2019; Su et al., 2011). Figure 6 shows some common sewer defects.

Despite the emergence of several new sewer inspection technologies over the past 40 years, municipalities have been using CCTV as the main tool to inspect the internal surface of "non-man-entry" sewers (Ékes et al., 2014; R. & Jantira, 2014). The popularity of CCTV inspection can be due to several reasons, including lower upfront cost, simplicity of usage, and familiarisation of contractors to utilize this method (Kumar et al., 2018).

However, CCTV is not free of limitations; the main drawback is that this method is time-consuming as operators need to stop and turn the camera every time the region of interest (ROI) is faced. This reason forces municipalities to not inspect all sections of their networks due to financial limitations (Harvey & McBean, 2014). Besides, inconsistency in defect reports which is done by operators, is another drawback of this method (Dirksen et al., 2013). Driksen et al. (2012) reported that 25% of defects could not be recognized by operators. The experience, skill, and bias of operators can considerably influence inspection reports (Dirksen et al., 2012). Following standardized reporting formats like the European standard (EN 13508-2) and Pipeline Assessment Certification Program (PACP) from the American National Association of Sewer Service Companies (NASSCO) can lessen these inconsistencies (Haurum & Moeslund, 2020).

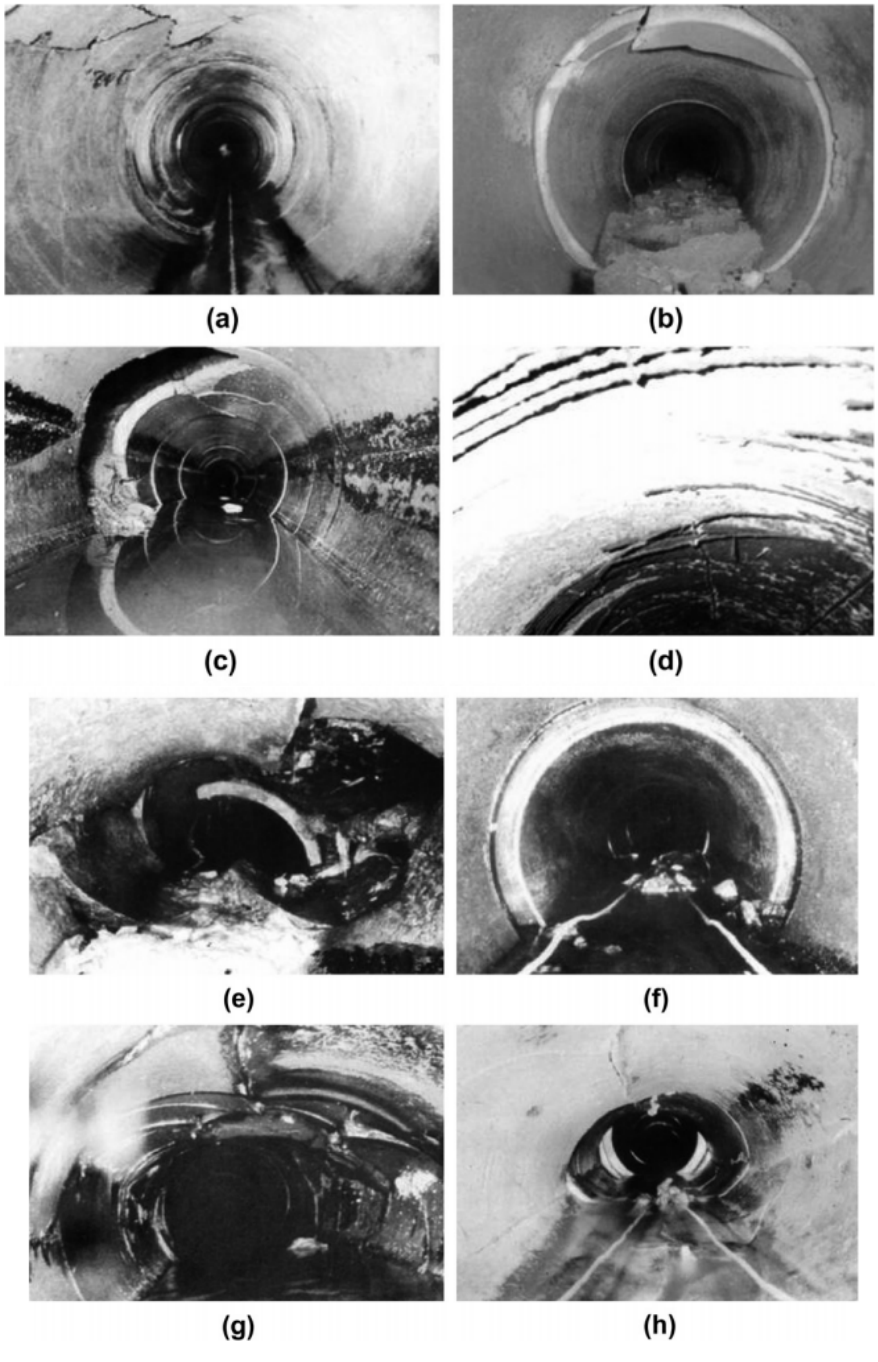


Figure 6. Grey level CCTV images of typical sewer defects (a) cracks (b) debris, (c) holes, (d) sapling large, (e) collapse, (f) open joint, (g) broken, and (h) deformed sewer (Su et al., 2011).

Although CCTV is widely applied and considered a cost-effective technology across the world, it has some drawbacks. Firstly, it might be considered as a laborious task with a slow pace if it is done by an operator. Secondly, the slow nature of interpretation by the operator can make that costly. Thirdly, merely the condition of the pipe above the waterline can be provided by

CCTV, like all camera-based technologies. Lastly, the structural pipe wall integrity and the soil supporting information cannot be provided by CCTV technology (Ariamalar et al., 2014).

Zoom cameras are raised as another screening technique that can be used to have a primary inspection by a fixed camera inside a manhole which is mounted on a pole without going into the pipe. The basic performance is like the traditional CCTV techniques, including the recording of pipe footage. The main difference between a zoom camera and CCTV is that the zoom camera is stationary mounted on a pole and located at a manhole and looks down into a pipe without passing through the pipe. Zoom cameras can be utilized as a main and primary inspection technique tool for pipelines since the sewer pipe does need to be cleaned which is an essential step before CCTV recording helping to avoid delays of crawler-mounted CCTV camera motion which caused by different obstacles such as roots, deposits, etc (Ariamalar et al., 2014). Therefore, prioritization of the pipes, which should be cleaned to inspect more accurately with CCTV, can be done by Zoom cameras (Saeed Moradi et al., 2019).

Classically, zoom cameras are used for manhole inspections and a few meters down the pipe. However, zoom cameras have been developed recently and can zoom further down pipes. While zoom cameras are considered a cost-effective technology for assessing sewer pipelines, they have some limitations. The main disadvantage of zoom cameras is that defects cannot be measured and located accurately, specifically where pipes have deviations due to shifting or impaired installation. Also, similar to other camera-based technologies, defects below waterlines cannot be seen (Selvakumar et al., 2014).

Digital scanning, also called optical scanning, is another camera-based technology that uses high definition (HD) cameras to provide an accurate visual assessment of pipe condition above the waterline (Edwards & Flintsch, 2012a; Iseley & Ratliff, 2002). Like traditional CCTV, digital cameras are carried through sewer pipelines on crawlers, and videos are recorded and transmitted to interpret (Karasaki et al., 2001). The difference between digital scanners and conventional CCTV is that they use more than one digital camera with high resolution and wide-angle lenses on the front and the rear side to collect HD videos (Knight et al., 2009). The resolution of digital scanners, like other vision-based technologies, decreases as pipe diameter increases due to lighting issues (Edwards & Flintsch, 2012a; Selvakumar et al., 2014).

2.5.2.2 Structural and Bedding Inspection Technologies

Unlike vision-based technologies, hidden defects related to under waterlines, soil bedding conditions, and pipe wall integrity can be evaluated by this category of technologies. GPR, ground-penetrating radar, is a technology that can detect defects without limitation by comparing the velocity of transmitting and reflecting electromagnetic radiations. Detecting soil voids, leakages, and assessing rebar in reinforced concrete with precise details can be done by GPR. One of the disadvantages of this technology can be requiring the experienced operator to interpret the data attained by GPR (Edwards & Flintsch, 2012a).

Sonar is another non-visual-based inspection technology used for detecting defects below flooded sections and estimating sediment accumulation (Selvakumar et al., 2014). Sonar is a technique that transmits a burst of high-frequency sound waves and measures the time it takes to travel from the source to the target and back again. Traditionally, this technology is used to provide complementary information, below waterlines, alongside CCTV technology (Andrews, 1998). One advantage of this technology is that it can be utilized in pressurized force mains without shutting down the system, this can be helpful in siphons that cannot be dewatered (Selvakumar et al., 2014). Some drawbacks of sonar are as follows: it cannot be applied simultaneously in both water and air, also detecting longitudinal cracks is difficult with this technology (Edwards & Flintsch, 2012a). Additionally, like GPR technology, the interpretation of data resulting from sonar technology is not straightforward and needs experienced interpreters (Saeed Moradi et al., 2019).

2.5.2.3 The Defect-Specific Technology (Electro-Scanning)

Due to the limitation of visual methods in detecting and evaluating the magnitude of specific types of defects like infiltration and exfiltration, special technologies such as electrical leak location systems have been recommended. This method also is known as electrical leak detection or electro-scanning, as it measures the leakage based on estimating the electrical resistance of the pipe wall (Andrew, 2020; Saeed Moradi et al., 2019). This method applies to pipes material which are electrical insulators, i.e. plastic, concrete, clay, and brick (Edwards et al., 2012).

2.5.2.4 Hybrid Technologies

The combination of two or more technologies leads to a more reliable strategy for detecting defects in sewer pipelines. Limitations of different technologies, like not providing any condition data under the waterline in CCTV technology, can be offset by implementing this category of technologies (Saeed Moradi et al., 2019). The Sewer Scanner and Evaluation Technology (SSET) comprises a set of CCTV technology, an optical scanner, and gyroscopic technology to provide a full-circumference scanned image of the pipe wall and a CCTV video record (ECT Team, 2007; Haurum & Moeslund, 2020; Jin et al., 2001). RedZone is considered another hybrid technology that combines laser and CCTV technologies to probe defects in large pipelines (Guo, Soibelman, & Garrett, 2009). Technologies like pipe inspection real-time assessment techniques known as PIRAT and KARO are multi-sensing technologies that can automatically detect and interpret defects in sewer pipelines (Jin et al., 2001; Tuccillo et al., 2011). As another example, the INNOKANIS project introduces a new tool that combined optical and acoustic technologies, including a zoom camera and SewerBatt, to compensate for the limitations faced in CCTV technology (Plihal et al., 2016).

2.6 Condition Assessment of Sewer pipelines

Condition assessment is a vital component of any sewer asset management program that evaluates the condition of the asset base on the data collected by municipalities. Particularly, the term “condition assessment” relates to evaluating the current physical condition, recognizing the deterioration procedure, and determining the potential failure of an asset (Khazraeializadeh, 2012).

The basic concept of condition assessment is comparing the present structural and operational condition of a sewer pipeline with an intact or new counterpart to assign a numerical condition score to its present condition. These condition scores facilitate making decisions about maintenance prioritization programs that are based on the risks associated with sewer pipelines’ failures (Khazraeializadeh, 2012).

2.6.1 Condition Scoring Methods of Sewer Pipelines

Many standards all over the world have been developed to score the condition of pipelines, including the MSCC from the British Water Research Center (WRc), PACP from the American National Association of Sewer Service Companies (NASSCO), NRC in Canada, WSA05 in Australia, European standard EN 13508-2, New Zealand Gravity Pipe Inspection Manual (NZGPIM) from Water New Zealand (Haurum & Moeslund, 2020; *NZGPI*, 2019). These standards adjust a set of descriptions according to their countries' requirements to classify defects and features and finally score the condition of pipes. Usually, they are an adaption of each other; e.g., PACP is based on the MSCC guide. NZGPIM 4th edition is an initial source for identifying defects within sewer pipelines in this study which will be discussed in the next section.

2.6.2 NZGPIM Condition Grading Method

New Zealand gravity pipe inspection manual standard (NZGPIM) was created in 1989 to unify a standard approach for overall condition gradings in sewer and stormwater gravity pipelines. The NZPGIM 4th edition is the only standard for CCTV inspection and condition assessment in use in New Zealand, which is supported by Council asset owners, CCTV contractors, and industry suppliers (*NZGPI*, 2019; Prepared, 2016). The main objective of NZGPIM is making proper decisions regarding the management of gravity assets which is based on condition assessment.

2.6.3 The role of defects in estimating condition scores in NZ code

In the GPIMSNZ 4th edition, an observation coding system for the specification and classification of features and defects in gravity pipes is presented. “Features are attributes or components of the pipe or information related to the inspection being undertaken that are not defects”. Defects are defined “as faults in the pipeline that deteriorate the strength, durability, water tightness, or hydraulic performance of the pipeline”. Defects are classified into two groups namely, structural related to strength characteristics, and service related to performance features “in terms of effects on the conveyance of water through the pipe”. According to this coding system, defects are quantified, and weighted scores are assigned to them to determine the condition score of individual pipes, whereas features do not. Table 2 shows this observation classification with its categories and subcategories.

Table 2. Observation classification in gravity pipe inspection manual standard of New Zealand

observations	categories	Subcategories
Features	-	Liner Construction, lateral connections, inspection points
Defects	Structural	Surface damage (such as corrosion and damage on pipe surface), cracked pipes (such as cracks, broken pipe, pipe holes, deformed pipes, and collapses in rigid pipes), deformation in flexible pipes, masonry pipes, roots, joint faulty, lateral faulty.
	Service	debris greasy, encrustation deposits, root intrusion, obstruction, blocked pipes, dipped pipes, exfiltration, infiltration, and water level.

The observation data fields used in New Zealand are based on those used in the European Standard, EN 13508-2 “Investigation and assessment of drain and sewer systems outside buildings – Visual inspection coding system”, and WSA 05, Conduit Inspection Code of Australia.

The main difference between the New Zealand standard with other standards is the additional code “P”, which shows the circumferential location of a defect. The observation data fields used in New Zealand in order are:

- Main code: main defect or feature code
- Characterization: extra code that describes the defect in more detail
- Quantification: extra code that quantifies the severity of the defect by Small (S), Medium (M), and Large (L)
- Longitudinal Distance: The distance measured from the start point to the feature or defect

- Measurement From: Specifying the start node from which the longitudinal distance is measured from which shows by a unique code U/D, i.e., the Upstream and Downstream, respectively.
- Circumferential location, Position From & Circumferential location, Position to: Locating the circumferential location of a defect or features by assigning a or two clock face references typically occurring at points: 3 O'clock, 6 O'clock and 9 O'clock, 12 O'clock.
- Continuous Observation Code: meaning a feature or defect that occurs for a distance longer than one-meter length.
- Remarks: text explains other aspects of the feature or defect that cannot be described in any other way.

An example representing the location of defects reported by inspection methods and the observation data fields used in New Zealand code is shown in Figure 7 and Table 3.

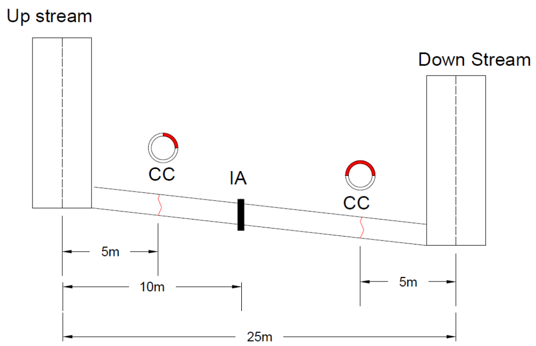


Figure 7. Representing the location of defects from Up-Stream and Down-Stream manholes

Table 3. The observation data field used in New Zealand code

Longitudinal Distance	Measured From	Main Code	Characterization Sub-Code	Quantification Sub-Code	Position From	Position To	Remarks
0	U	IS					Centre of upstream manhole
5	U	CC		M	12	3	
10	U	IA					Stopped by protruding lateral
0	D	IS					Re-start at the center of the Downstream manhole
5	D	CC			9	3	Lifting eye
15	D	IA					Ends at previous abandonment

The first step in the Scoring Analysis process is to determine three Key Condition Indicators for structural and service conditions, including Total Score, Peak Score, and Mean Score, defined as below:

A- Total score: is the sum of all the individual scores related to the defects recorded during the inspection; defects can be points or continuous ones. Calculating continuous defects are classified as follows:

- Per meter continuity: the score is calculated by multiplication of the assigned value of the weighted score on the length of the continuous defect. E.g.: the value of a large circumferential crack (CCL) that continues for a length of 3 meters is 36 (12 extracted from table multiplied by 3).

- Per defect continuity, the score is the assigned value of the weighted score for the defect regardless of the length of the continuous defect. E.g.: the values of a medium severity of root intrusion (RIM) that continuous for 10 meters is 30 according to the table.

It is essential to consider that the total score depicts the magnitude and number of defects in the pipe without considering the total length of the pipe. Therefore, the same Total Score in a short and long pipe does not indicate the same severity of the deterioration.

B- Peak Score: is the value of the worst single defect or mixture of defects in each one-meter length of the pipe. For calculating this score, the sum of scores of different defects is calculated in each one-meter length of the pipe, and then the largest score determines as the Peak Score.

C- Mean Score is the numerical mean of the defect score per meter of the pipe inspected. It is determined by dividing the Total Score by the Inspected Length. Mean Score = Total Score/Inspected Length

Figure 8 represents an example of calculating the structural score based on the pipe inspection reports.

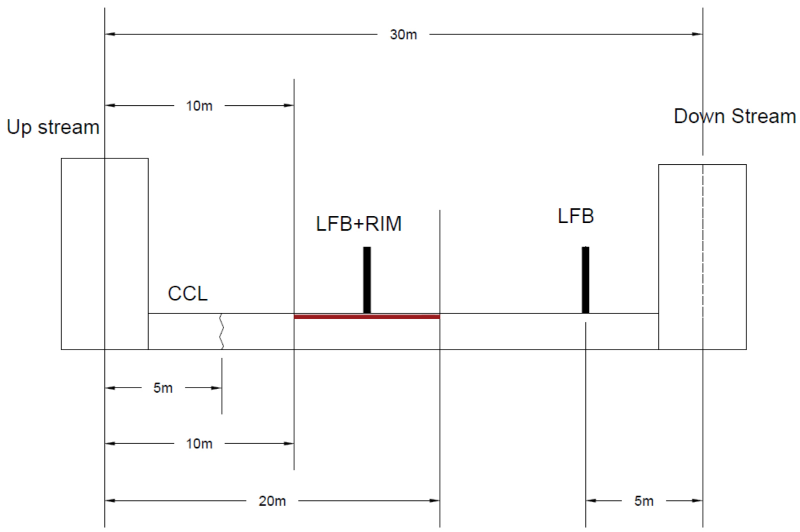


Figure 8. Defects observed in a completed pipe inspection

Table 4. Assigning initial structural defect scores to observed defects according to GPIMSNZ

Longitudinal distance	Continuity	Main+ characterization codes	Quantification	Structural defect Score
0.0		IS		0
5		CC	L	12
10	S.1	SAM		50
15		LFB	L	30
15		RIM	M	10
20	F.1	SAM		50
25		LFB	M	20
30		IE		0

The Total, Peak, and Mean structural scores calculated for the above example pipe inspection are in the following ways:

- Total Score = sum of all individual defect scores + Per meter Continuity score= (12+30+10+20) + (50×10) = 572
- Peak Score = The maximum score over any 1m of pipe, according to Figure 9) = 90
- Mean Score = Total score/ Inspected Length = 572/30 = 19.07

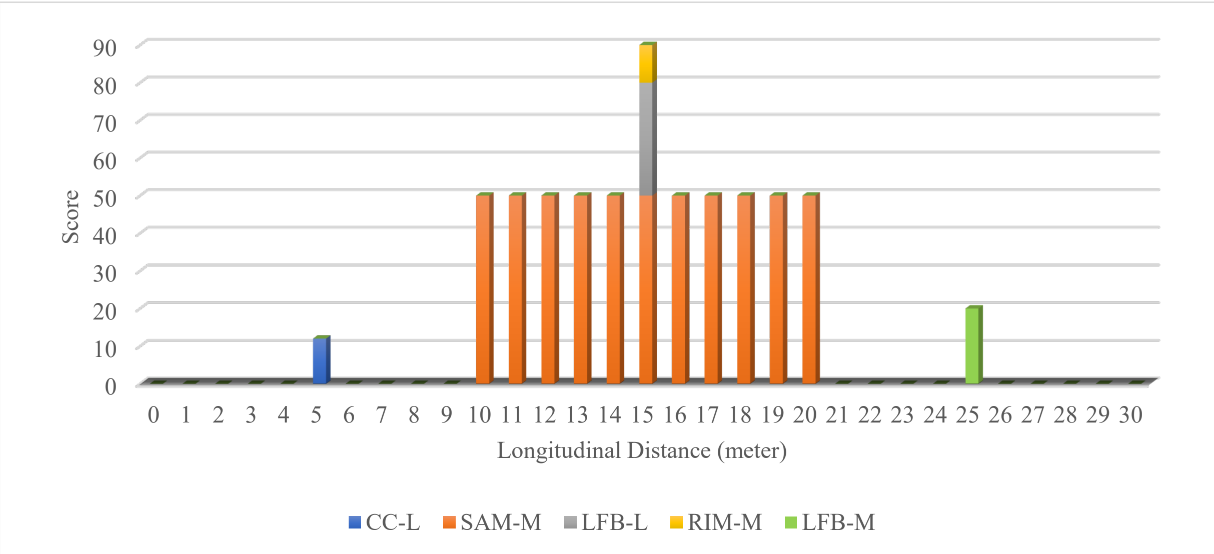


Figure 9. Determining Peak Score by representing the summed scores within each meter of the pipe length

The structural and service defect scores for pipes are specified in GPIMSNZ. Table 5 represents some structural defect scores for structural and service code types used in the previous example.

Table 5. Pipe structural and service scores

Code Type	Main code	Char.	Description	Structural Score for structure code type			Structural Score for service code type		
				Small	Medium	Large	Small	Medium	Large
Cracks Circumferential	CC			2	7	12			
		C	Crack edge chipped		15				
		D	Crack faces are displaced		22			2	
Lateral Sealing Faulty	LF			2	6	15			
		C	Cracked	1	6	15			
		B	Broken	10	20	30			
		D	Damaged	3	5	17			
		X	Seal	1	6	10			
Root Intrusion	RI			3	10	10	10	33	70
		F	Fine roots	3	10	10	5	15	25
		M	Mass of mostly fine roots	3	10	10	15	35	60
		T	Tap roots	3	10	10	12	22	55
		RF	Recently cut fine roots	3	10	10	5	10	20
		RB	Recently cut root beard	3	10	10	15	25	60
		RT	Recently cut tap roots	3	10	10	10	21	50
Surface Damage	S	D	Damage	6	21	61	6	8	23
		W	Wall roughened		6			2	
		S	Spalling		26			5	
		PM	Pipe missing		125			35	
		AE	Aggregate exposed	6	15	20	5	6	7

	AP	Aggregate projecting	18	30	36	6	7	8
	AM	Aggregate missing	30	50	60	7	8	9

GPIMSNZ evaluates the service and structural condition of pipes on a scale of 1 to 5 based on the peak scores assigned to the pipe. Structural condition 1 specifies that the pipe does not have any structural defects and it is in very good condition, and structural condition 5 specifies that structural failure is forthcoming or has already happened and so the pipe is in very poor condition. Service condition 1 determines that the pipe's hydraulic performance is excellent, and the pipe is in very good condition, and Service condition 5 determines that service failures like blockage or surcharging are forthcoming or have already happened and so the pipe is in very poor condition. Condition grading according to structural, and service condition definitions is presented in Table 6.

Table 6. Condition grading according to structural and service condition definitions based on the Gravity Pipe Inspection Manual Standard of New Zealand

Preliminary Condition Score	Description	Structural Definition	Service Definition	Peak Score
1	Very Good	No structural defects	A low probability of overflow or surcharge	0 to 5
2	Good	Some structural defects have begun minor deterioration	A minor probability of overflow or surcharge	5.1 to 20
3	Moderate	Structural defects causing moderate deterioration	A moderate probability of overflow or surcharge	20.1 to 35
4	Poor	Significant defects that lead to serious deterioration	A serious probability of overflow or surcharge	35.1 to 60
5	Very Poor	Structural failures are forthcoming or have already happened	The pipe is blocked and overflow and/or surcharging is forthcoming or has already happened.	>60

2.6.4 The Role of Condition Score in Asset Management

The type and magnitude of defects lead to determining condition scores of pipes which is an essential concept in different steps of the asset management field as below:

- Tracking the rate of pipe deterioration over time
- Understanding how deteriorations appear and how they are different
- Providing information for planning asset rehabilitation or renewals
- Confirming the need to renew the pipelines that have approached their end of useful lives
- Allowing the depreciation of pipes to be controlled in a steady process
- Providing a consistent basis for reporting asset conditions (*NZGPI*, 2019)

For planning for rehabilitation and renewal of non-critical pipelines, either condition score or remaining useful life is considered. The relationship between condition scores and remaining useful life for a pipe in a 'typical' condition is reported according to GPIMSNZ in Table 7.

Table 7. The relationship between condition scores and remaining useful life and reference to the planning cycle (*NZGPI*, 2019)

Grade	Useful Remaining Life	Planning cycle
1	>50 years	Outside 30-year infrastructure planning cycle
2	30-50 years	Outside 30-year infrastructure planning cycle
3	10-30 years	Inside 30-year planning cycle, but outside long-term plan, 3-year planning cycle
4	3-10 years	Inside 10-year planning cycle, but outside long-term plan, 3-year planning cycle
5	<3 years	Inside 10-year planning cycle, but outside long-term plan, 3-year planning cycle

*Note: The table is based on a 50+years expect useful life.

2.7 Deterioration models for sewer pipelines

While inspection technologies lead to a better understanding related to sewer pipeline conditions, they are not sufficient to provide a complete image of the real condition of sewer systems, since they represent a limited picture in a certain time of the pipe's condition. Predicting the current and future condition of sewer pipelines based on the available past conditions is essential to implement proactive management strategies (Baik et al., 2006). Deterioration models using optimization methods have shown a highlighted role in contributing utilities to reach the proper time for an inspection and to make a decision whether rehabilitation or replacement is needed (Baik et al., 2006).

Many quantitative deterioration models have been developed in the last decade to evaluate the deterioration procedure of sewer pipelines (Baik et al., 2006). Results of these deterioration models, which are based on the assessment of the current sewer pipeline conditions, have been used to plan short-term rehabilitation programs and predict the future condition of the system under long-term decision planning. Deterioration models can be categorized according to the assessed methods used into three different groups, namely, deterministic, statistical, and artificial intelligence (AI) models (Tscheikner-Gratl et al., 2019).

Deterministic models contribute to the comprehension of physical procedures that cause sewer deterioration. Currently, the applicability of these models decreases since they are too simple to show the complexity of deterioration mechanisms simulated with inadequate data (Kleiner & Rajani, 2001). Statistical methods have been developed to conquer the difficulties of deterministic models to determine the structural deterioration procedures of sewer pipelines. Statistical sewer deterioration models are based on relationships between factors considered random variables that affect the deterioration procedure (Rokstad & Ugarelli, 2015).

There are several principal statistical approaches, including survival analysis, Markov chain, Logistic regression, and discriminant analysis. Between all the statistical deterioration models mentioned, survival analysis and Markov chain are the most common models on a network level (Tscheikner-Gratl et al., 2019). Regression approaches have been developed in many studies to specify the probability of failure of each distinctive sewer pipe.

In comparison with statistical models, dependent outputs in Artificial Intelligence (AI) models are classified from a set of relationships between independent input variables and learning from the available data instead of following any model (Scheidegger et al., 2011). While determining non-linear relationships between input variables is the most advantageous of these models, needing a large amount of data to generate these models is considered the biggest disadvantage (Tscheikner-Gratl et al., 2019). In these models, sewer condition states of pipes are determined according to learning from deterioration behaviours of pipes gathered by inspection processes. In the next step, the complex relationships achieved from inspected pipes are generalized to pipes not inspected. Figure 10 shows a classification of various deterioration models used to assess the condition of sewer pipelines.

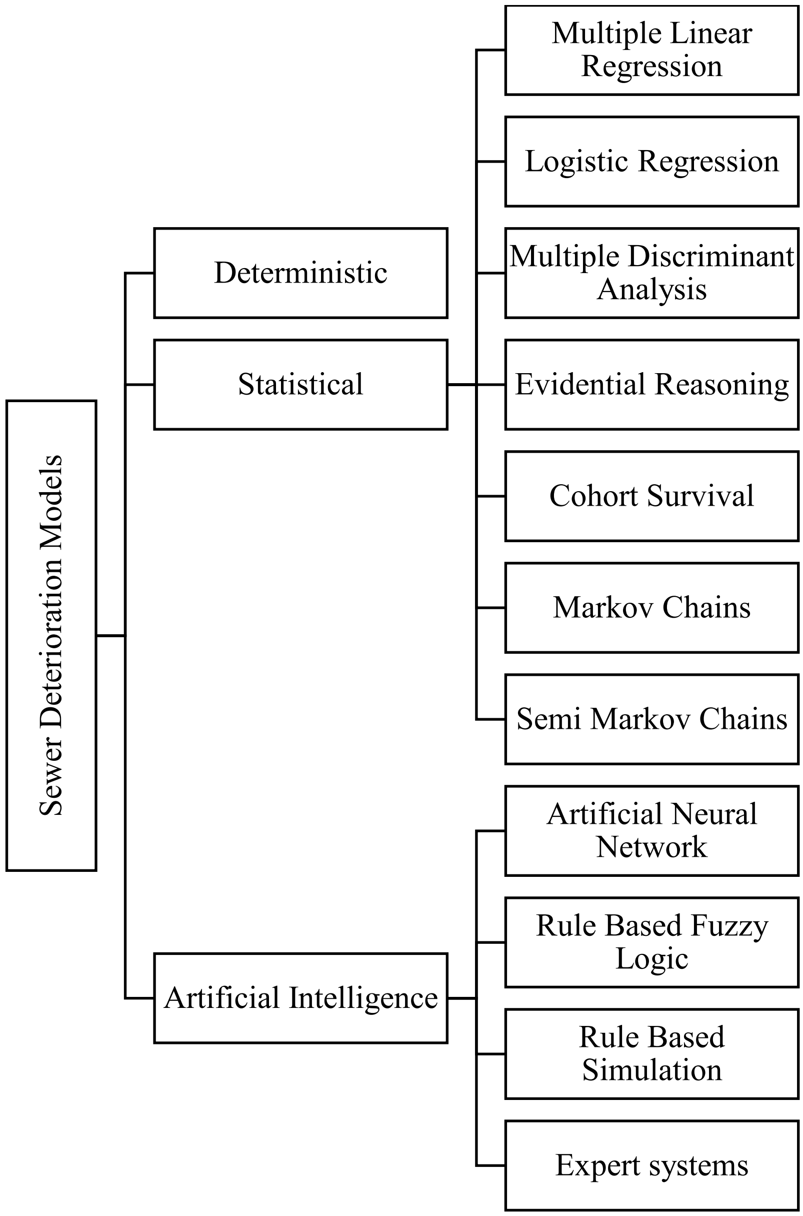


Figure 10. Sewer deterioration model classifications (Hawari et al., 2020)

It is not simple to compare the performances of different deterioration models for several reasons, including a great number of modelling methods, the different types and sizes of network systems, the different amounts of available inspected datasets, and finally, the different metrics that have been used to assess the deterioration models' performances.

According to modelling goals, the model performance can be assessed at two distinct levels, including either the network level or the pipe level (Ana & Bauwens, 2010). At the network level, the main goal is to simulate the progress of the deterioration of the system over time to support long-term strategic rehabilitation and renovation programs. At this level, metrics show how much the model can be accurate in predicting the condition of the whole network, i.e., the percentage of pipes in a certain condition state.

At the pipe level, the goal is to recognize pipes in critical condition to support rehabilitation strategies. The metrics at this level represent the consistency of the model in predicting the condition class of every single pipe.

Several studies tried to compare the performance of deterioration models in simulating the condition distribution of the network. It is pointed out that even in the shortage of data, survival analysis and Markov models surpass a simple random model to predict the condition distribution of the network (Caradot et al., 2018; Duchesne et al., 2013; Hernández et al., 2018; Ugarelli et al., 2013).

Caradot et al. (2018) developed statistical and machine learning models at the network level to predict the condition of the entire network, including 95,547 sewer pipes in Berlin, Germany. They showed that statistical models provide a better simulation of the condition distribution at the network level in comparison with machine learning models (N. Caradot et al., 2018). It is reported that the discrepancies between predicted and inspected condition distributions at the network level were below 1% and 5% for statistical and machine learning models, respectively (N. Caradot et al., 2018).

Several studies assessed the reliability of the model performance at the pipe level (Caradot et al., 2018; Fuchs-Hanusch et al., 2015; Harvey & McBean, 2014; Hernández et al., 2018; Laakso et al., 2018; Mashford et al., 2010; Salman & Salem, 2012; Sousa et al., 2014). Principal metrics used in these studies are statistical ones and, including:

- Chi-square statistic

- Goodness of fit
- Root Mean Square Error
- Coefficient of determination

Moreover, several indicators were used in these studies, including:

- True Positive Rate (TPR) means the percentage of pipes inspected in critical condition and correctly predicted in critical condition.
- Positive Predictive Value (PPV) means the percentage of pipes predicted in critical condition and they have been inspected in critical condition.
- False-Positive Rate (FPR) means the percentage of pipes inspected in good condition and wrongly predicted in critical condition (Tscheikner-Gratl et al., 2019).

Table 8 shows the efficiency of several deterioration models in a number of studies according to the above indicators at the pipe level (Nicolas Caradot et al., 2018; Harvey & McBean, 2014; Hernández et al., 2018; Laakso et al., 2018; Mashford et al., 2010; Salman & Salem, 2012).

Table 8. Efficiency of deterioration models on pipe level according to indicators (Tscheikner-Gratl et al., 2019)

Author	Year	Model	PPV	TPR	FPR
Mashford et el.	2010	Support Vector Machine	88%	74%	1%
Salman and Salem	2012	• Multinomial Logistic Regression • Logistic Regression	• 53% • 55%	• 73% • 45%	• 29% • 22%
Harvey and McBean	2014	Random Forest	30%	89%	25%
Sousa, Matos, and Matias	2014	• Artificial Neural Network • Support Vector Machine • Logistic Regression	• 67% • 69% • 62%	• 71% • 60% • 39%	• 18% • 19% • 16%
Caradot et al.	2018	Random Forest	42%	67%	26%
Hernandez et al.	2018	• Random Forest • Logistic Regression • Multinomial Logistic Regression	• 53% • 60% • - • -	• 57% • 38% • 71% • 70%	• 17% • 7% • 21% • 20%

		• Linear Discriminant Analysis • Support Vector Machine	• 52%	• 67%	• 22%
Laakso et al.	2018	Random Forest	-	80%	53%

According to a list of studies in Table 8, the range of PPV is between 30% and 88%, TPR is between 38% and 89%, and FPR is between 1% and 53%.

By considering these different indicators, it is difficult to select the best modelling approach at the pipe level as model performance is significantly changing in different case studies. However, Tscheikner et al. (2019) stated that results obtained from different models that have been performed for the same cities show that machine learning models surpass statistical models in recognizing pipes in critical conditions.

2.8 Deterioration Models

Different deterioration models from statistical and artificial intelligence categories are developed to study the effect of various variables on sewers' conditions. In this section, binary logistic regression and decision trees, as the most common statistical and artificial intelligence models, are briefly reviewed, respectively.

2.8.1 Logistic Regression Models

Logistic models or logit models are utilized to analyse the relationship between multiple independent variables and a categorical dependent variable. The probability of occurrence of an event can be estimated by fitting data to a logistic curve. Dependent variable Y might either be binary (only two categories, usually success/fail) or multinomial (several categories). In both cases, the independent variables x_i might be categorical or continuous.

The probability of Y occurring is related directly to the independent variables through a logistic regression model. Estimating unknown coefficients is the main goal of the regression model. These coefficients indicate the degree of association between each independent variable and the dependent variable Y. The regression coefficient represents the expected change in the dependent variable for a one-unit increase in one independent variable, assuming all other independent variables in the model are constant. For achieving the best result, a model needs to be created to include all independent variables, which probably can be effective on the outcome or dependent variable.

Logistic regression has been broadly used in different studies concerning the modelling deterioration of sewer pipelines (Ana et al., 2009; Ariaratnam et al., 2001; Davies, Clarke, Whiter, Cunningham, et al., 2001; Fuchs-Hanusch et al., 2015; Koo & Ariaratnam, 2006). In these studies, logistic regression is used to analyse and develop a prediction model and identify the factors that have the most effect on the sewer's structural condition. The main and common feature of all mentioned studies is that the sewer condition as the dependent variable was categorized into two nominal levels, including poor and good conditions. Generally, in the first step of the study, all independent factors were considered, and then through stepwise forward and backward methods, significant factors were determined. Significant factors are those that can influence the structural deterioration of sewer pipes.

2.8.2 Decision Trees

In tree-based models, the predictor space is split up into several small and simple regions, making them more comprehensible. For example, where Y is a continuous dependent variable and there are two independent variables of x_1 and x_2, the predictor space of Y is divided into several regions until achieving the best fit, and then the model is developed based on the average of the dependent variable (Y) in each region. The above example is shown in Figure 11 where x_1 is divided into t_1 and t_3 and x_2, is divided into t_2 and t_4. And the final output (Y) is divided into five regions R_1, R_2, …, R_5 (Hastie et al., 2017).

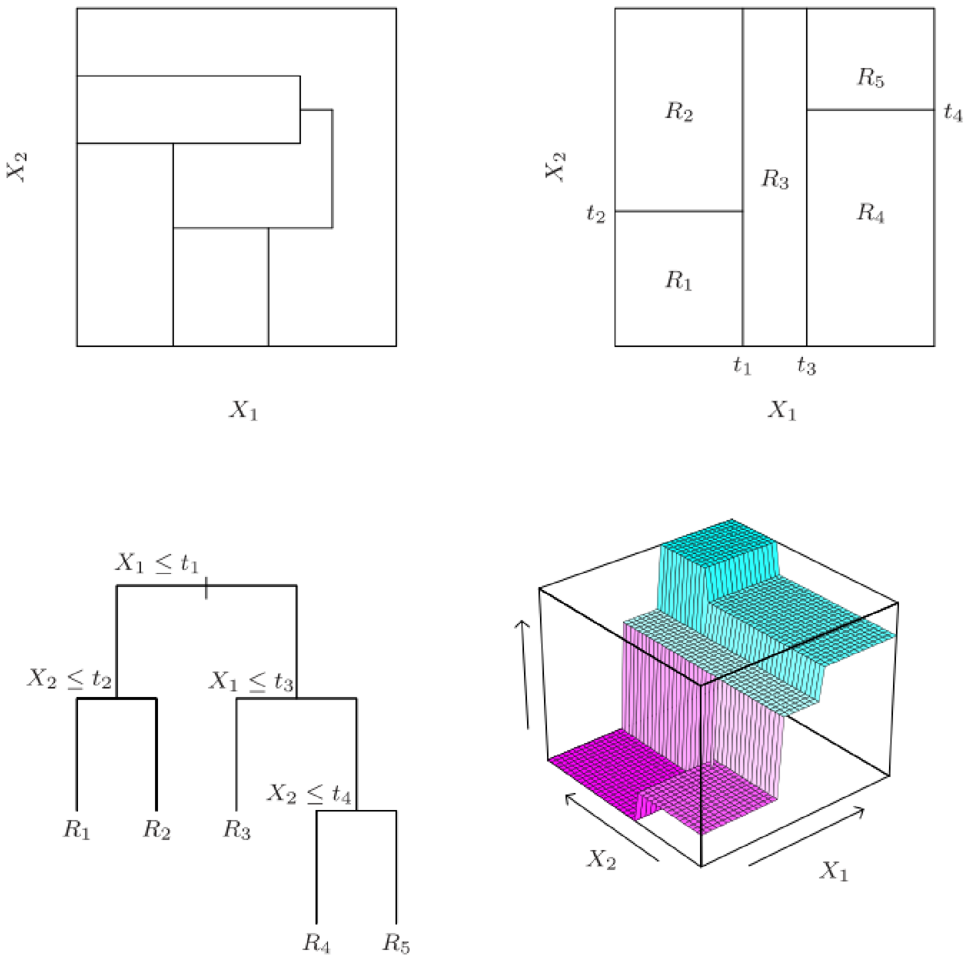


Figure 11. Tree based partitions (Hastie et al., 2017)

When the dependent variable or target takes discrete values 1, 2,…,K, classification trees are developed as predictive models (Hastie et al., 2017). While in regression trees, the squared-error node is used to divide the outcome space into separate areas, in classification trees, different criteria such as impurity-based criteria, information gain, and Gini index are used. Among mentioned criteria, the Gini index is the most common method, measuring the divergences between the probability distributions of the dependent variable's values. Indeed, it measures how often a random event can be determined incorrectly; hence, a variable with a lower Gini index is more desirable (Hastie et al., 2017).

Implementation of decision trees is very common for classification, since they provide us with graphical results which are facilitating the interpretation of the outcomes.

It has been proven that an ensemble model consisting of several trees can have better predictive performance than single trees for developing deterioration models (Harvey & McBean, 2014). The most common method to generate ensemble classifiers are random forest and boosting. The main difference between these methods lies in how the decision trees are created and aggregated.

Overall, gradient boosting performs better than random forests (Elyassami et al., 2020). Random forest is used to develop several deterioration models to predict the condition of sewer pipelines (N. Caradot et al., 2018; Harvey & McBean, 2014; Hernández et al., 2018; Laakso et al., 2018). However, gradient boosting trees have only been used in one study to assess the deterioration of sewer pipelines. Malek Mohammadi. (2019) developed a gradient boosting trees model to develop a prediction model and rank the importance of factors influencing 30,000 sewer pipes in Tampa city. The Sewer condition was grouped into poor and good conditions, and various variables were considered for developing the model.

3 CONSISTENT CLASSIFICATION SYSTEM FOR SEWER PIPE DETERIORATION AND ASSET MANAGEMENT

3.1 Introduction

Sewer pipe deterioration is driven by a finite number of root causes and processes. Thus, it should be both feasible and advantageous to have a uniform classification system that can be universally applied in sewer deterioration modelling and asset management. However, the literature review revealed several problems and inconsistencies, and no widely adopted system. This chapter proposes a uniform classification system that can be used for different purposes in the fields of gravity pipe deterioration and asset management.

This chapter has been adopted from a paper published in the Journal of Water Resources Planning and Management, ASCE. Tizmaghz, Z., van Zyl, J. E., & Henning, T. F. P. (2022). Consistent Classification System for Sewer Pipe Deterioration and Asset Management. Journal of Water Resources Planning and Management, 148(5), 1–10. https://doi.org/10.1061/(asce)wr.1943-5452.0001545.

The first section of this chapter gives the background and motivations for the purpose of this study. Followingly, existing classification systems in the sewer asset management domain are grouped by purpose and then discussed. The existing systems are compared, and problems, such as a lack of clearly defined concepts, internal inconsistencies, and contradictions between systems, are discussed. A new classification system is then proposed with clear definitions of all terms and consistent categories and subcategories. The proposed system is discussed, pointing out potential weaknesses and improvements, and demonstrating its application. While this chapter focuses on separated sewer systems, the same principles apply to combined sewers and stormwater systems, which can be adapted to these systems with ease.

3.2 Background

The critical role of sewer pipelines in the sewer collection system has forced utilities to consider proactive asset management strategies (Grigg, 2012; Salman & Salem, 2012). Utilities are willing to invest in efficient, proactive asset management strategies in order to minimize the cost of owning and operating infrastructure assets while delivering the desired service levels to customers (Roghani et al., 2019). The main goals of a proactive asset management strategy are avoiding catastrophic failures, optimizing maintenance and rehabilitation strategies, and accurately planning for future requirements (Hawari et al., 2020).

The proactive asset management process for sewer networks consists of the following components, i) data collection and processing, ii) deterioration models and condition assessment, iii) proactive asset management and iv) implementation.

Data collection and processing play an important role as the initial step in acquiring more reliable condition assessment irrespective of frameworks used (Yin, Chen, Bouferguene, & Al-Hussein, 2020). This includes investigating factors affecting sewer pipes performance, an inspection of the infrastructure's physical and functional condition manually or with different technologies such as CCTV, GPR, SSET, and analyzing data with professional and trained operators or automated defect detection models (Saeed Moradi et al., 2019; Yin, Chen, Bouferguene, Zaman, et al., 2020).

Deterioration models and condition assessment facilitate the decision-making process by predicting sewer segments' current and future condition. In other words, deterioration models provide condition assessment by evaluating the deterioration of sewer pipes, considering certain influencing factors to make informed decisions about complementary investigations, maintenance, repair or potential replacement (Hawari et al., 2020; Hyeon-Shik et al., 2006).

Deciding whether and when rehabilitation or replacement is needed constitutes the proactive asset management step. The asset management strategy is then implemented, and the process is repeated.

Performance classification systems are used to make sense of the large range and complexity of the parameters involved in sewer asset management. A review of the literature published showed that several classification systems have been proposed to investigate the variables that affect sewer pipeline performance (Ana and Bauwens 2010; and others). Each classification system was developed for different purposes within the asset management process. While there are similarities between them, significant differences and inconsistencies limit their wider application. Besides the fact that different numbers and types of categories are used, few systems provide clear definitions for the classes. In addition, there are often internal contradictions within a system and contradictions between different systems. As a result, there is no widely accepted and consistent classification system for sewer asset management parameters.

Given that all the classification systems are applied to some aspect of the pipe deterioration and asset management cycle, it should be both feasible and advantageous to define a uniform classification system that can be universally applied in the deterioration modelling and asset management fields. Benefits of a uniform classification system include (adapted from Finisdore et al. 2020):

- a unifying language
- a consistent basis for selecting or categorizing parameters
- the consistent basis for developing metrics and functional relationships
- the ability to compare the results of different studies
- improved knowledge transfer and management.

The development of such a new classification system is the main aim of this chapter.

The proposed system is based on existing classification systems but is different from anything currently in existence. It is based on three top-level categories of failures, defects, and factors. Each of these categories is clearly defined according to their subcategories and components that can be unambiguously applied.

At the heart of the proposed system is the realization a) the condition of sewer pipes is affected by many factors that are not problems in themselves and b) most problems (for example a crack in a pipe) in sewer pipes do not constitute a failure in themselves. Thus, the term 'factor' is defined as a parameter that may influence the condition of a sewer pipe but is not a problem in itself. 'Defect' is defined as a problem in a sewer system that is undesirable and may require monitoring but does not require immediate action. Finally, 'failure' is defined as a problem on which society would expect immediate action.

3.3 Current Classifications Approaches

The literature reviewed in this chapter is based on publications that apply classification systems of parameters affecting sewer pipe performance published in peer-reviewed journals, conferences, codes, and other sources since 2001. The distribution of publications reviewed is as follows; 5 from peer reviewed journals, 4 from conference papers, 3 from codes, and finally 2 from research theses. The publications were grouped by the purpose of the classification system according to the following asset management cycle steps: data collection and processing, deterioration models and condition assessment, proactive asset management, and implementation. A summary table and a brief description of the classification systems are provided under each heading.

3.3.1 Data Collection and Processing

Understanding and collecting parameters affecting the deterioration process of sewer pipelines is the first step of implementing any asset management strategy (Angkasuwansiri et al., 2013). A summary of the data collection and processing papers and their classification systems is provided in Table 9.

Table 9. Classification systems used in the data collection and processing

Source	Main categories	Subcategories	Parameters
Angkasuwansiri et al., 2013	Alphabetical list of parameters	None	Age, backup flooding, bedding condition, blockage, cathodic protection, closeness to trees, coating, condition, connection density, cover depth, design life, diameter, dissimilar materials, disturbances, exfiltration, extreme temperatures, failing utilities, FOG (fat-oil-grease), flow velocity, frost penetration, function, groundwater table, hydrogen sulfide gas (H2S), inflow and infiltration (I&I), installation, joint type, lateral, length, lining, live load, location, manhole, manufacture, material type, moisture content, odors, operational pressure, overflow, precipitation, seismic activity, slope, slope stability, soil corrosivity, soil PH, soil redox potential, soil resistivity, soil sulfides, soil type, stray currents, surcharging, tidal influences, thrust restraint, trench backfill, trench width, type of cleaning, vintage, wall thickness, wastewater quality, wet/dry cycles
PACP (NASSCO, 2001)	Features	Construction	Tap, intruding sealing material, line, access point
		Miscellaneous	General observation, joint length, lining change, material change, shape /size change, water level, not visible
	Defects	Continuous	Truly (extends more than 1m), repeated (appears in a length of pipe in at least 3 out of 4 of the joints)
		Structural	Cracks, fractures, broken, hole, deformed, collapse, joint, surface damage, lining features, weld failure, point repair, brickwork
		Operation and maintenance	Deposits, roots, infiltration, obstacle obstructions, vermin, grout test & seal
Moradi et al., 2019 (based on PACP)	Defects	Structural	Cracks (longitudinal, circumferential, multiple, spiral), joint (offset, angular, fracture, separated), deformed, hole, collapsed, broken
		Construction	-
		Operation and maintenance	Roots, deposits, infiltrations, obstacles
	Features	-	Liner construction, lateral connections, inspection points

Gravity Pipe Inspection Manual Standard of New Zealand, 2019	Defects	Structural	Surface damage (such as corrosion and damage on pipe surface), cracked pipes (such as cracks, broken pipe, pipe holes, deformed pipes, and collapses in rigid pipes), deformation in flexible pipes, masonry pipes, roots, joint faulty, lateral faulty.
		Service	Debris greasy, encrustation deposits, root intrusion, obstruction, blocked pipes, dipped pipes, exfiltration, infiltration, and water level.
Stannic et al., 2012 **(see Figure 1)**	Top failure events	System failure (load > capacity)	Flooding, frequent CSOs (Combined Sewer Overflows), soil contamination, exposure to health hazards
		Element failure (load > strength)	The collapse of structural elements, breakdown of mechanical elements.

Angkasuwansiri *et al*. (2013) noted that a complete list of parameters that affect sewer pipes does not exist and compiled an alphabetical list from available literature, providing a brief description and the potential impact for different pipe materials. They also provide a table summarising potential sources of data for the parameters. Although the paper notes that failures depend on pipe characteristics, the surrounding environment (internal and external), and operational practices, no attempt is made to further classify the parameters.

A number of guidelines for pipe inspection have been published, including EN-135082 in Europe (EN, 2011), Pipeline Assessment Certification Program (PACP) in the US (NASSCO, 2001), Conduit Reporting Code (WSA05) in Australia (WSA, 2020), and the Gravity Pipe Inspection Manual Standard of New Zealand (Water New Zealand, 2019). Each of these guidelines provide a procedure for documenting present condition and defects in pipelines. These codes are related to each other, for example, the New Zealand's code is based on EN 13508-2 and WSA05. In Table 9, the New Zealand's code and NASSCO's classification systems are presented. These standards specify an agreed set of descriptors to classify defects and features in pipelines and impose a universally compatible process for the transfer of data (Water New Zealand, 2019).

PACP classifies defects and features into five groups, namely continuous defects, structural defects, operational and maintenance defects, construction features, and miscellaneous features (NASSCO, 2001). PACP's defect and feature classification have been applied in other studies, for example, in a review on automizing sewer inspection using computer vision models by Moradi et al. (2019).

In the Gravity Pipe Inspection Manual Standard of New Zealand (2019), a coding system for describing features and defects observed in gravity pipes is presented. 'Features' are defined as attributes or components of pipelines or any information gathered by inspection that cannot be classified as defects. 'Defects' are defined as faults that weaken the strength, durability, water tightness, or hydraulic performance of pipelines. Defects are classified into two groups, namely structural (related to strength characteristics), and service (related to performance). According to this coding system, defects are quantified, and weighted scores are assigned to them to determine the condition grade of individual pipes.

Stanic (2014) applied a HAZard and OPerability (HAZOP) approach to identify the main processes responsible for the structural or operational failures of sewer elements, as well as the possibility of obtaining information on them. The HAZOP results were applied in a fault-tree analysis for risk estimation as shown in Figure 12. The top-level of the hierarchy is described as 'top failure events' and categorized into two main groups: system and element performance. System failures were defined as occurring when the load exceeds the pipe capacity, or the pipe capacity is inadequate for the imposed load. In element failures, the load exceeds the pipe strength, or the pipe strength is insufficient for the imposed load, causing sewer collapse. It is argued that element failures do not necessarily lead to system failures, which seems unlikely to be the case in practice.

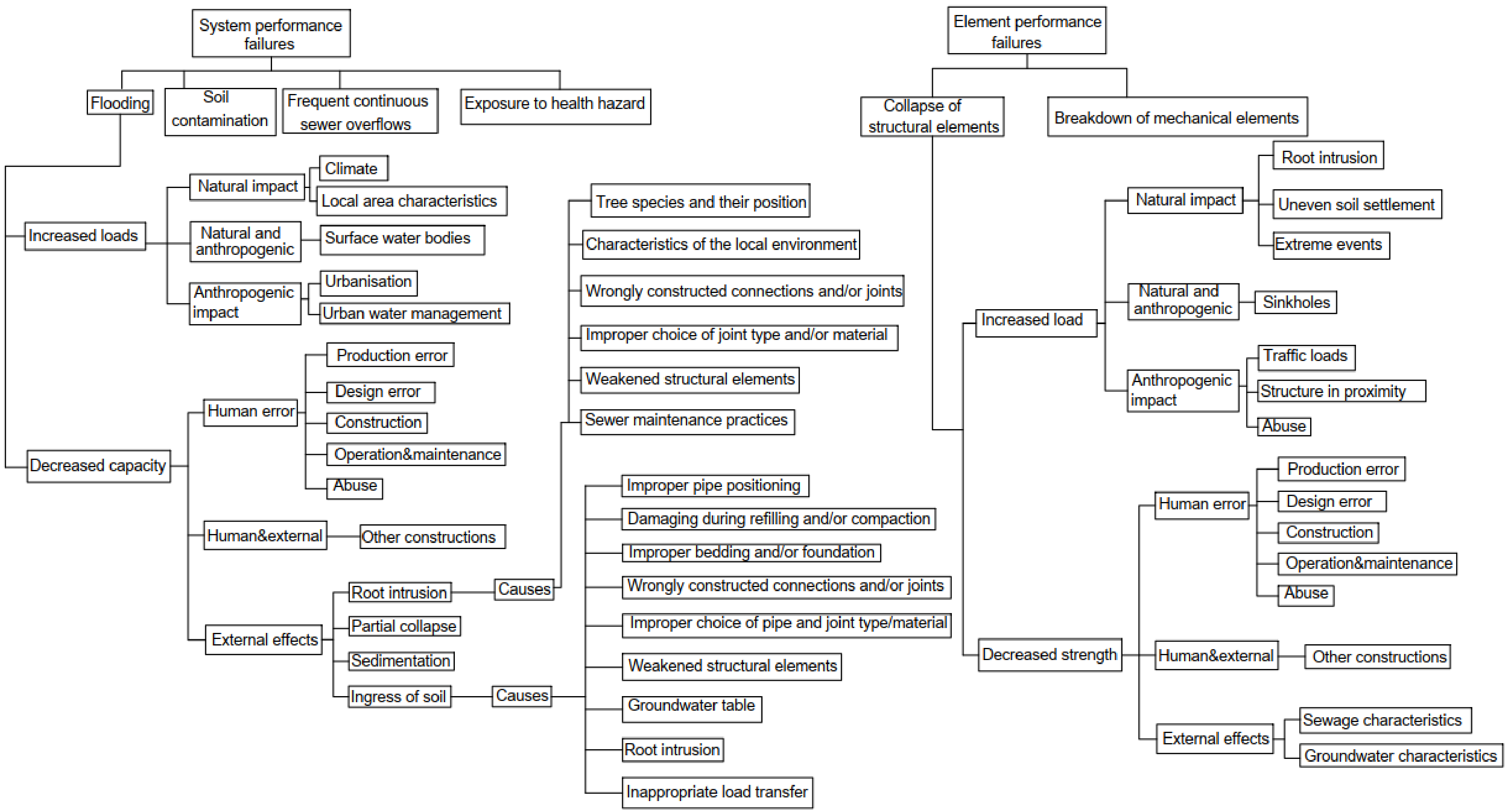


Figure 12. Fault tree for failure mechanisms in sewer systems obtained through a HAZOP analysis (adapted from Stanić et al., 2012)

3.3.2 Deterioration Modelling and Condition Assessment

Significant efforts have been made to develop deterioration models and condition assessment approaches to better understand the performance of sewer pipes. Condition assessment supports decisions on repair, rehabilitation or renovations of assets for utilities (Mohammadi et al., 2019). Deterioration modelling and condition assessment papers with their classification systems are summarized in Table 10.

Table 10. Classification systems used in deterioration modelling and condition assessment

Source	Main categories	Subcategories	Parameters
Davies et al., 2001	Factors	Construction	Load transfer, standard of workmanship, sewer size, sewer depth, sewer bedding, sewer material, sewer joint type and material, sewer pipe section length, sewer connections
		Local external	Surface use, surface loading and surface type, water main burst/leakage, ground disturbance, groundwater level, soil/backfill type, root interference
		Other factors	Sewage characteristics, inappropriate maintenance methods, asset age
Ana & Bauwens, 2010	Factors	Physical	Pipe age, pipe shape, pipe size, sewer depth, sewer length, sewer material, sewer slope, sewer type, joint type, and material
		Environmental	Groundwater level, infiltration/exfiltration, presence of trees, soil, backfill type, traffic, and surface loadings
		Operational	Sediment level, sewage characteristics, maintenance and repair strategies
		Construction	Installation method, the standard of workmanship
Chughtai & Zayed, 2007a	Structural factors	Physical	Pipe age, pipe diameter, pipe length, pipe material, pipe depth, pipe gradient.
		Operational	Maintenance and repair strategies
		Environmental	Type of soil, type of wastes, bedding condition, frost factor, the proximity of other utilities, traffic volume, and groundwater
Chughtai & Zayed, 2007b	Operational factors	Hydraulic	Inadequate flow capacity, infiltration and inflow, inadequate sewer gradients
		Non-hydraulic	Random blockage, debris-fats-greases, and roots, pumping station/screening equipment failure, operational and maintenance history
Hawari et al., 2017	Factors	Physical	Pipeline age, pipeline diameter, pipeline length, pipeline material, pipeline coating conditions, installation quality
		Operational	Flow rate, blockages (ex: roots, sediments), infiltration and inflow, corrosive impurities, maintenance and break strategies, operating pressure in pressurized pipelines

		Environmental	Soil type, bedding conditions, location (ex.: traffic load), groundwater level, ground disturbance (ex.: construction work)
Laakso et al., 2018	Factors	Pipe attributes	Age, installation year, diameter, material, location, depth, length
		Attributes related to pipe environmental	Soil type, road class, intersections with other pipes, distance to a tree
		Attributes related to the network structure	Estimated annual sewage flow, water consumption of all water users upstream of the pipe

Davies et al. (2001) identified and described the factors that influenced the structural stability of a rigid sewer pipe and categorized them into three main groups, namely construction features, local external factors and other factors. The influence of each parameter is discussed comprehensively in the study. It is concluded that a sewer pipe must be considered as a composite structure consisting of the pipe itself, the ground in which it is buried, and the local environment.

In a review of statistical models used for predicting structural deterioration of urban drainage pipes by Ana and Bauwens (2010), factors that lead to sewer structural deterioration are grouped into four categories: physical factors related to the pipe attributes, environmental factors related to the characteristics of the surrounding environment, operational factors related to how pipes operate, and construction factors related to the manner of construction.

Chughtai & Zayed (2007a) conducted a study on predicting sewer pipeline conditions for prioritizing detailed inspections. Factors that may influence the structural condition of pipes are grouped into three main categories: physical, operational and environmental. In another paper by the same authors, factors that can affect operational conditions are grouped into two categories: non-hydraulic and hydraulic. Hydraulic problems occur if the sewer capacity is inadequate to handle high flows, while non-hydraulic problems are not due to a lack of flow capacity (Chughtai & Zayed 2007b).

In a study by Hawari et al. (2017), a simulation-based condition assessment model for sewer pipes is presented to accurately evaluate and assess their condition. Factors were categorized into three main categories: physical, operational, and environmental. Seventeen factors affecting gravity pipeline performance and one other factor affecting pressure sewers are included in the model. Factors are weighted through a distributed questionnaire and included in a model. A detailed description and definition for each factor are provided. However, the 'factor' and 'category' terms are not defined. It is not clear how factors are selected and incorporated into categories.

Laakso et al. (2018) combined inspection results with weighted influencing factors to predict the sewer pipe condition and locate pipes with serious defects that need urgent renovation or replacement. This study divided influencing factors into three categories: pipe attributes, attributes related to the pipe environment and attributes related to network structure. While the study states that the installation year represents the quality of construction work, it is categorized as a pipe attribute.

3.3.3 Proactive Asset Management

The classification systems of the two studies identified as being aimed at proactive asset management are summarised in Table 11.

Table 11. The classification systems used in implementing proactive asset management in sewer pipelines

Source	Main categories	Subcategories	Parameters
Opila, 2011	Factors	Pipe design and installation	Pipe structural properties, manufacturing- storage- handling of pipes, pipe material- thickness- diameter- length, joining

			plastic to metal/concrete pipes
		Quality of installation	Jointing techniques, bedding material, and placement
		Ongoing environmental / operational	Internal physical loading (including operational pressure, operating cycles, external physical loading (including soil overburden, traffic patterns, traffic loads), chemical, biochemical, electro-chemical environment (including internal (water-pipe interactions), external (soil-pipe or groundwater-pipe interactions), Changes in ground condition (including weather condition, shrinking or swelling of the soil, frost loads, local disturbance (including nearby digging, soil erosion, changes in the water table, root intrusion)
	Failures	Structural	Sub-causes: pipe collapses, breaks, cracks, and corrosion
		Operations and maintenance	Sub-causes: debris deposits, roots, infiltration, and obstacles
		Hydraulic capacity	Sub-causes: wall friction change, subsidence, changing catchments, infiltration, rainfall, guideline changes
		Economic	
		Water quality	
Wastewater Renewal Framework for Gravity Pipelines in New Zealand (McFarlane, 2018)	Service failures	Operational	Sub-causes: silt, fat, and roots
		Strength	Sub-causes: degradation sections of pipelines, deterioration of the pipe wall, shock events
		Containment	Sub-causes: joint leakage, leakage through cracked and damaged pipes, infiltration.
		Capacity	Sub-causes: wet weather flow, growth in upstream areas

Opila (2011) used the structural condition scores of buried sewer pipes for risk-based decision making. Factors leading to failures were categorized into three groups: pipe design and installation, quality of installation and ongoing environmental or operational. Also, a failed pipe was defined as one requiring action ranging from rehabilitation to replacement to return the pipe condition to the desired level of service. Thus, the occurrence of a failure may vary depending on the required level of service provided by the pipe. A failure can range from a small leak to a complete pipe collapse. It is argued that most pipe failures are caused by several contributing factors rather than a single factor. Failures are classified into five categories: structural, operation and maintenance, hydraulic capacity, economic and water quality.

The wastewater renewal framework for gravity pipelines in New Zealand (McFarlane, 2018) defines and categorizes service failures. These failures occur when the wastewater system is incapable of providing the intended service. They are grouped into four categories: operational, strength, containment and capacity. Operational failures occur when a sewer pipe is unable to convey the quantity of flow that it was designed to convey. Strength failures occur when a sewer is unable to withstand the forces applied to it either during normal operation or shock events such as earthquakes. Containment failures occur when a sewer is unable to stop water ground leaking in or wastewater leaking out. Finally, capacity failures occur when a sewer is unable to convey the required quantity of flow.

3.4 Discussion

The literature review shows that, while there are similarities, there is no consistent approach to the classification of sewer system deterioration modelling or asset management. The inconsistency in approaches means that it is hard to interpret and compare different studies to build a consistent and scientific understanding of how sewer pipes deteriorate and fail.

Despite the fact that the classification systems discussed were developed for different purposes, they consider the same underlying problem of sewer pipe deterioration and thus, it should be possible to develop a consistent classification system that can be applied for different purposes.

This section discusses the main differences and problems in the reviewed classification systems, including inconsistent terminology, missing or inconsistent definitions, and inconsistent classifications.

3.4.1 Inconsistent terminology

The classification systems studied used a wide range of terms to describe their categories, including ‘parameters’, ‘features’, ‘defects’, ‘factors’ and ‘failures’. Figure 13 illustrates the range of terms used by publications in different steps of the asset management process. While papers on Deterioration Models and Condition Assessment consistently used the term ‘factors’, both ‘factors’ and ‘failures’ are used in Proactive Asset Management and four different terms in Data Collecting and Processing.

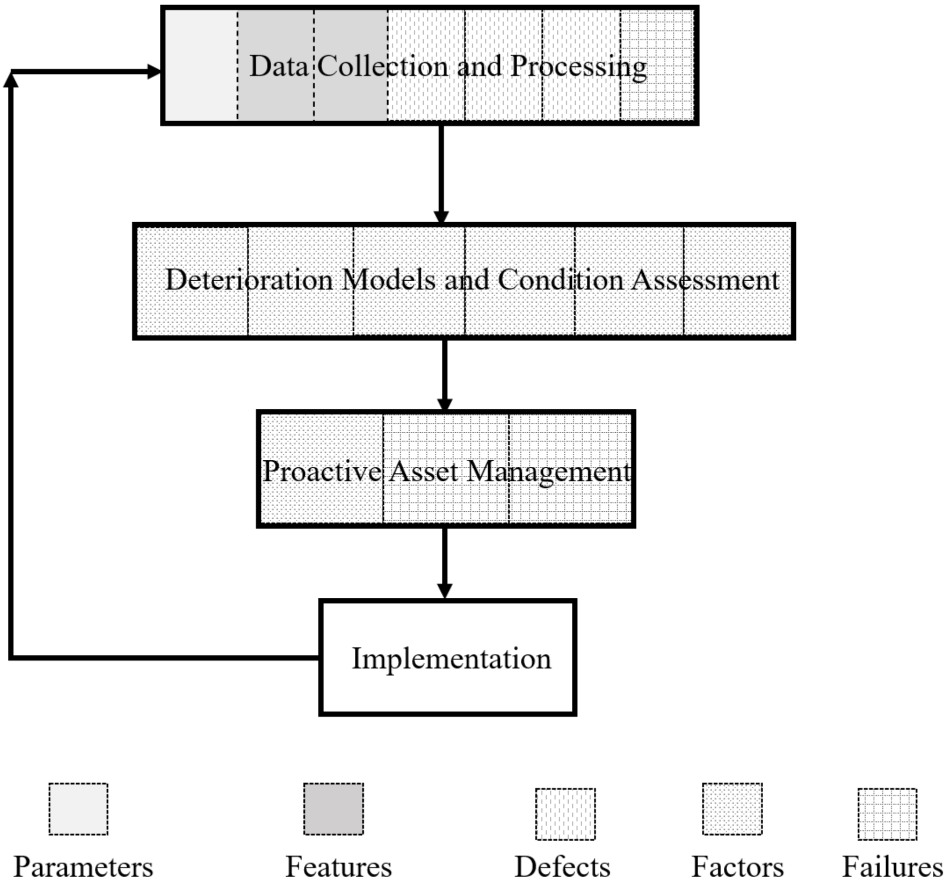


Figure 13. The frequency of terms used in different steps of the asset management process

As can be expected, there are similarities in what is grouped under the same term by different studies. However, in some cases, different terms are used for the same concept, while others use the same term for different concepts. For instance, Angkasuwansiri *et al* (2013) use the term 'parameter' as an umbrella term that includes infiltration and overflows, while Stanic et al (2012) classified overflow as a 'failure'. Hawari *et al* (2013) uses 'factor' as an umbrella term that includes infiltration and blockage, while Laakso et al (2018) limits 'factor' to attributes related to pipe, environment and network structure.

3.4.2 Missing or inconsistent definitions

The problem with inconsistent terminology is exacerbated by the fact that terms are mostly not explicitly defined. Only three of the thirteen papers reviewed defined all classification terms used, and one defined some of the terms used. Stanic et al (2012) defined all terms related to failure and its classification. The guidelines studied define all terms related to defects and features and their classifications. Chughtai & Zayed (2008) defined terms used in their classification systems, including ‘physical’, ‘operational’ and ‘environmental’ but didn’t define ‘factor’.

Where terms are defined, the definitions are sometimes inconsistent. For instance, the New Zealand gravity pipe inspection manual standard defines ‘defects’ as “faults in the pipeline that deteriorate the strength, durability, water tightness, or hydraulic performance of the pipeline”, while Marne (2013) defines ‘defects’ “as deviations that can be seen in the physical state of the sewer pipeline”. Not only do these two definitions of defects differ in content, but “deviations” in the second definition is subjective and leaves significant room for interpretation.

There are significant inconsistencies in the definition of ‘failures’. Stanic (2012) categorizes ‘failures’ in terms of pipes' capacity and strength specifications, while Opila (2011) defines ‘failures’ in terms of the desired level of service. A particular difficulty with ‘failures’ is how to distinguish between failures that have little or no impact on the operational capacity of the pipe (such as a crack), and failures that lead to blockage of the pipe and sewage spills (such as a pipe collapse).

3.4.3 Inconsistent classification

Several inconsistencies in the way that terms are classified were observed. For instance, Ana and Beuwens (2010) and Hawari et al. (2017) classify age as a physical pipe feature, while Davies et al. (2001) classify age under other factors.

Additionally, while Opila (2011) classifies a sewer pipe's installation quality as an independent category, Hawari et al. (2017) classify it as a physical attribute and Davies et al. (2001) and Ana & Bauwens (2010) as a construction attribute.

3.5 Proposed Classification System

This section proposes a consistent classification system for deterioration modelling and asset management of gravity sewer pipes. The classification system is partly based on previous systems but aims to avoid the problems and inconsistencies of existing systems. It identifies categories and subcategories based on conceptual or functional groupings. A flow diagram for classifying any parameter into a primary factor, defect or failure category is given in Figure 14. Note that where a parameter can be placed in more than one category, the flow diagram is meant to only identify the primary category, while secondary effects are discussed later this section.

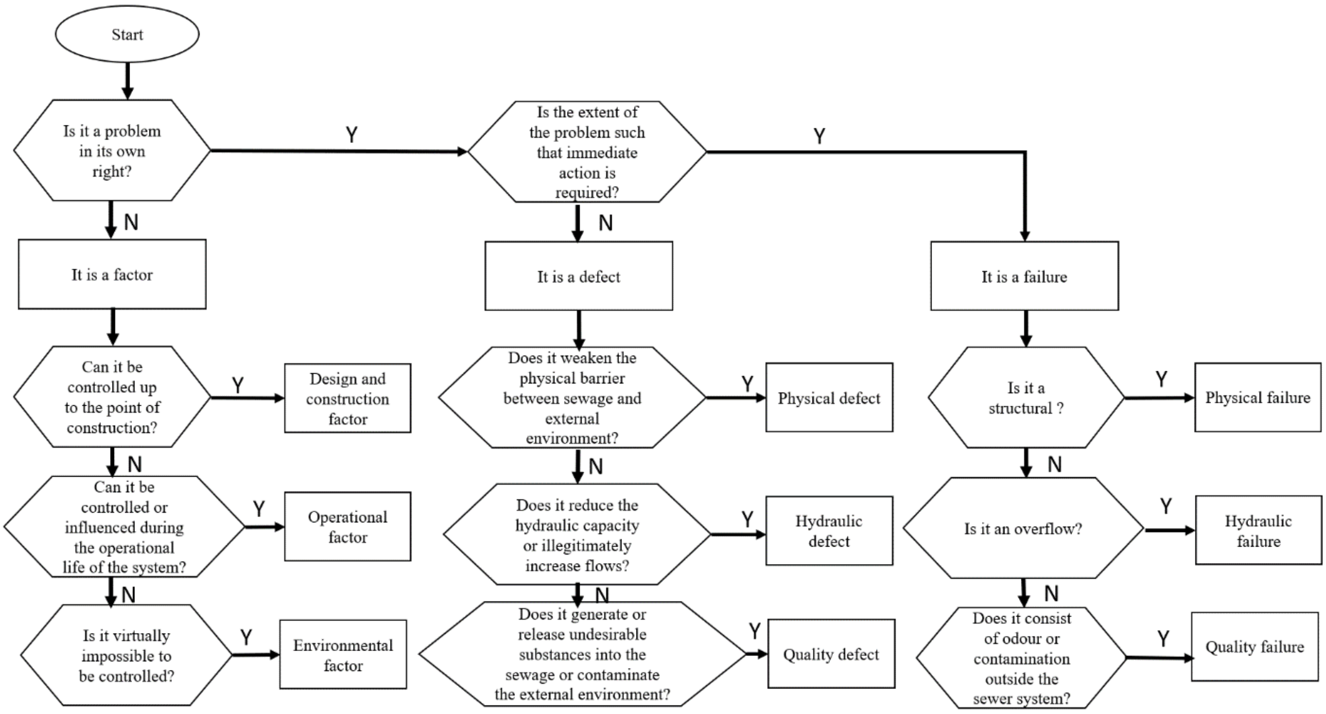


Figure 14. Flow diagram for the proposed classification system

3.5.1 Main Categories

Sewer failures generally don't occur suddenly in an otherwise perfect system but happen at the end of a long and complex deterioration process. They are influenced by several parameters, some that are problems in themselves (e.g., sedimentation or pipe wall cracks) and others that are not (e.g., rainfall or urban densification). Based on these observations, three main categories are proposed, namely failures, defects and factors.

In some cases, the difference between a defect and failure may only be a matter of degree. For instance, sewage leaking through a pipe crack may result in limited and localized soil contamination (a defect) or contaminate a nearby drinking water supply (a failure). Thus, to clearly demarcate the boundary between defects and failures, failures are defined in terms of societal expectations, i.e., a problem that society would expect immediate action on.

The following definitions are proposed for the main categories:

- ***Failure:*** *a failure is defined as a state or event that has a negative impact on people, property or the environment* <u>*and*</u> *which society would expect immediate remedial action on.* Examples include sewer pipe collapse, sewage overflows, groundwater contamination and disagreeable odours.
- ***Defect:*** *a defect is defined as an undesirable problem or condition in the sewer system that does not constitute a failure in its own right*. Examples include pipe cracks, sediment buildup and hydrogen sulphate production. Defects often worsen over time and may interact with other defects or factors to cause failures. Defects are common in most sewer systems and, while they aren't desirable and may be monitored or used as the basis for prioritizing maintenance interventions, they are generally tolerated.
- ***Factor:*** *a factor is defined as a property, condition or event that may contribute to a defect or failure but isn't a problem in its own right.* Examples of factors include pipe material, sewage composition and rainfall.

3.5.2 Subcategories

Subcategories were defined for each of the three main categories based on the most appropriate conceptual or functional grouping.

The concept of system integrity, defined for water distribution systems in a National Research Council (2006) report, provided a valuable basis for further classifying failures and defects. This report defined three integrity domains in which system failures may occur, namely physical, hydraulic and quality, which were adapted to sewer systems through the following definitions:

- ***Physical Integrity*** *refers to the maintenance of a physical barrier between the sewer system interior and the external environment.*
- ***Hydraulic Integrity*** *refers to the maintenance of a desirable sewer flow capacity, minimum and maximum velocities and sewage age.*
- ***Quality Integrity*** *refers to maintaining acceptable sewage quality inside the sewer system, avoiding the release of undesirable substances or generation of undesirable byproducts and avoiding contamination of the external environment.*

The value of adopting this sub-classification is that, while the different types of integrity are interrelated, each integrity can be lacking despite the other two being intact. Thus, all three have to be intact to ensure full system integrity. For instance, a system may have perfect physical integrity (no pipe breaks or cracks) and quality integrity (no undesirable substances in the sewage) but lack hydraulic integrity due to insufficient pipe flow capacity, resulting in an overflows during a peak wet weather event. It is worth noting that system lacked hydraulic integrity (and thus overall integrity) even before the overflow failure occurred due to the lack of adequate flow capacity to handle a foreseeable peak flow event. Once the overflow failure occurred, multiple additional failures will result, such as land and surface water contamination. However, the primary cause of the failure was the lack of hydraulic integrity that was present even before the failure occurred.

3.5.3 Failure Subcategories

Failures can be classified into the following categories based on the type of integrity loss they are primarily caused by:

Physical Failures *occur when sewer components structurally fail through a break or collapse to the extent that immediate remedial action is required.*

Hydraulic Failures *occur when the flow in system components exceed their hydraulic capacity to the extent that this leads to sewage overflows.*

Quality Failures *occur when releases into the sewage, internal sewage processes, exfiltration or overflows lead to contamination or odors inside or outside the system to the extent that immediate remedial action is required.*

Table 12 provides a classification for the primary cause of failures that occur in sewage systems. As noted in the table, different types of failures are strongly linked. In particular, physical failures (pipe collapse or pipe break) will generally result in a blockage or flow path to the surface, leading to a hydraulic failure (overflow). In turn, hydraulic failures will invariably result in quality failures in the form of land and surface water contamination, and sometimes also coastal contamination and odor.

Table 12. Classification of sewage system failures

Category	System Failure
Physical	Pipe collapse*
	Pipe break*
Hydraulic	Overflow#
Quality	Odor
	Groundwater contamination
	Land contamination
	Surface water contamination
	Coastal contamination

Note: * very likely to cause hydraulic failure through sewage overflow

very likely to cause quality failures through land and surface water contamination, possibly also coastal contamination and odor.

3.5.4 Defect Subcategories

Similar to failures, defects are classified based on the type of integrity they primarily impact on using the following categories:

- ***Physical Defects*** *weaken or breach the physical barrier between the sewage and the surrounding environment.* This includes internal and external damage to pipes, linings and joints.
- ***Hydraulic Defects*** *reduces the capacity of sewer components to carry legitimate sewage flows.* Legitimate sewage flows include all inflows that the sewage system is designed to carry, such as industrial and household wastewater. Hydraulic defects include problems that reduce the hydraulic capacity of system components (deposits and obstructions) and problems that illegitimately increase sewage flows, such as connections to the stormwater system, private drainage connections and groundwater ingress.
- ***Quality Defects*** *reduces the quality integrity of the system through or the release or generation of undesirable substance inside the sewage or contamination of the external environment.* Undesirable substances refer to fluids or items that consumers should not release into the sewage, such as engine oil, cooking oil, wipes and sanitary products. It excludes releases that would be considered normal, such as fats and oil from dishwashing. The problem with undesirable substances is related to the quality or makeup of the sewage rather than the volume of fluid (which would constitute a hydraulic defect).

In some cases, defects also affect another category, such as physical defects that also act as hydraulic defects, including pipe deformation, misalignments and seals or liners that obstruct the flow path. Another example is some hydraulic defects that also act as quality defects, such as sediments or roots providing additional surface area for slime layers that convert sulfates in the sewage into ionic sulfides. Table 13 provides a classification for the main defects that occur in sewage systems.

It should be noted that the defects that affect more than one category are either primarily structural with a secondary hydraulic impact, or hydraulic with a secondary quality impact. In each case, the primary classification also appears first in the flow diagram (Figure 17), with secondary categories obtained from Table 13 or engineering judgment.

Table 13. Classification of sewage system defects based on the type of integrity they primarily impact on and grouped by where they occur

Defect Category	Defect Group	Defect
Physical	Pipe	cracks
		holes
		fractures
		internal corrosion
		external corrosion
		deformation*
		scouring
		undetected construction damage
		third-party damage
	Joints	• cracks/holes/fractures
		• damaged seal
		• pulled out
		• extruding seal*
		• misalignments*
	Linings	• tears/breaks
		• scouring
		• corrosion
		• delamination*
		• bulging*
	Bedding	• voids
Hydraulic	Deposits	• sediments#
		• FOG#

	Obstructions	• debris[#]
		• roots[#]
	Undesirable inflows	• groundwater infiltration
		• stormwater cross-connections
		• rainwater ingress (including on private properties)
		• pool backwash releases
Quality	Release of undesirable substances	• oil
		• fat
		• grease
		• wipes
		• paper
		• rubbish
		• sanitary products
	H_2S production and release	• dissolved sulphide
		• turbulence
		• splashing
	Exfiltration	

Note: * also act as hydraulic defects; # also act as quality defects.

3.5.5 Factor subcategories

Factors are (by definition) not problems in their own right but may contribute to defects or failures. Thus, factors are not amenable to categorization through the integrity classification used for failures and defects. After considering different strategies, it was decided to categorize factors according to whether and when they can be influenced in the following way:

Design and Construction Factors *can be controlled up to the point of construction and then cannot be changed without major work.* Costs associated with design and construction factors would normally be classified as capital costs. Examples include pipe material, diameter and slope.

Operational Factors *can be controlled or influenced during system's operational life, whether by the sewer service provider or the municipal authority.* Costs associated with operational factors would normally be classified as operational costs. Examples include household water consumption, products allowed into the sewer system, inspection frequency and maintenance actions.

Environmental Factors *are factors that cannot be controlled or influenced.* This includes in-situ soil properties, rainfall and natural disasters.

Table 14 provides a classification of the main factors in sewage systems.

Table 14. Classification of factors affecting sewage systems based on whether and when they can be influenced

Factor Category	Factor Group	Factor
Design and Construction	Planning and design	• land use
		• user connection density
		• approach (combined / separate)
		• pipe layout
		• traffic loads
		• construction loads
		• interaction with other services
	Pipe characteristics	• shape
		• diameter
		• section length
		• material
		• lining (internal)
		• coating (external)
		• joint type
		• design life
	Installation properties:	• installation date (age)
		• installation method
		• installation quality
		• trench width
		• slope
		• distance between manholes
		• cover depth
		• pipe bedding

		• trench backfill
		• restraints
Operational	Water consumption	
	Sewage composition	• corrosive impurities
		• sediments
		• acceptable fat, oil, and grease (FOG) load
	Maintenance strategies	• inspection regime
		• frequency of sewer cleaning
		• sewer cleaning methods
		• quality of repairs
	Temporary loading	
	Trees near system	
Environmental	Soil	• expansive properties
		• deficit index
		• corrosivity
		• sulphides
		• Ph
		• redox potential
		• moisture content
		• groundwater level
		• wet/dry cycles
		• tidal influences
		• movements
		• frost penetration
		• sinkholes
	Climate	• rainfall
		• temperature
	Catastrophic events	• earthquakes
		• wildfires

3.6 Discussion

It is possible to classify the deterioration of sewer pipe systems in different ways depending on the purpose and parameters considered, as is evident from the literature. The aim of this chapter is to propose a single consistent and rational classification system that can be used for different purposes in modelling sewer pipe deterioration or assert management processes. It is based on the premise that the different studies are subject to the same underlying parameters and processes, and that the benefits of adopting a single classification system far outweighs the cost.

No classification system is perfect, and thus it is necessary to adopt a pragmatic approach, adopting a system with the best overall fit and lowest number of anomalies considering the range of possible applications.

In developing the proposed classification system, particular challenges were finding a suitable classification structure, demarcating categories and subcategories, formulating definitions, and fitting known parameters into the proposed system. It took several iterations to develop the proposed system and further adjustments may be necessary, for instance if new parameters are identified that the system can't classify.

It should be recognized that there are interactions within and between categories and that a mix of factors and defects will influence most failures. To illustrate the complexity of these interactions and influences, the proposed classification system is applied to illustrate the processes responsible for overflow failures due to sedimentation. This is illustrated in Figure 18 and can be described as follows, working back from the failure event:

<u>Overflow failures due to sedimentation in a given pipe occurs when:</u>

1. Sewage flow exceeds the capacity of the pipe
    - A. Increased sewage flow is determined by:
        - i. Sewage production, which is at a maximum during certain times of the year and day
        - ii. Cross connections to the stormwater system, which increases flow during rainfall events

iii. Rainwater ingress, which increases flow during rainfall events

iv. Groundwater infiltration, which is caused by

a. Cracks, holes and fractures in the system, combined with

b. High groundwater level

B. Reduced hydraulic capacity due to sedimentation, which is caused by:

i. Small pipe slopes that reduce flow velocity

ii. High sediment loads in sewage, which is caused by

a. High sewage sediment loads

b. High groundwater level infiltrating through cracks, holes and fractures, carrying soil particles into the pipe

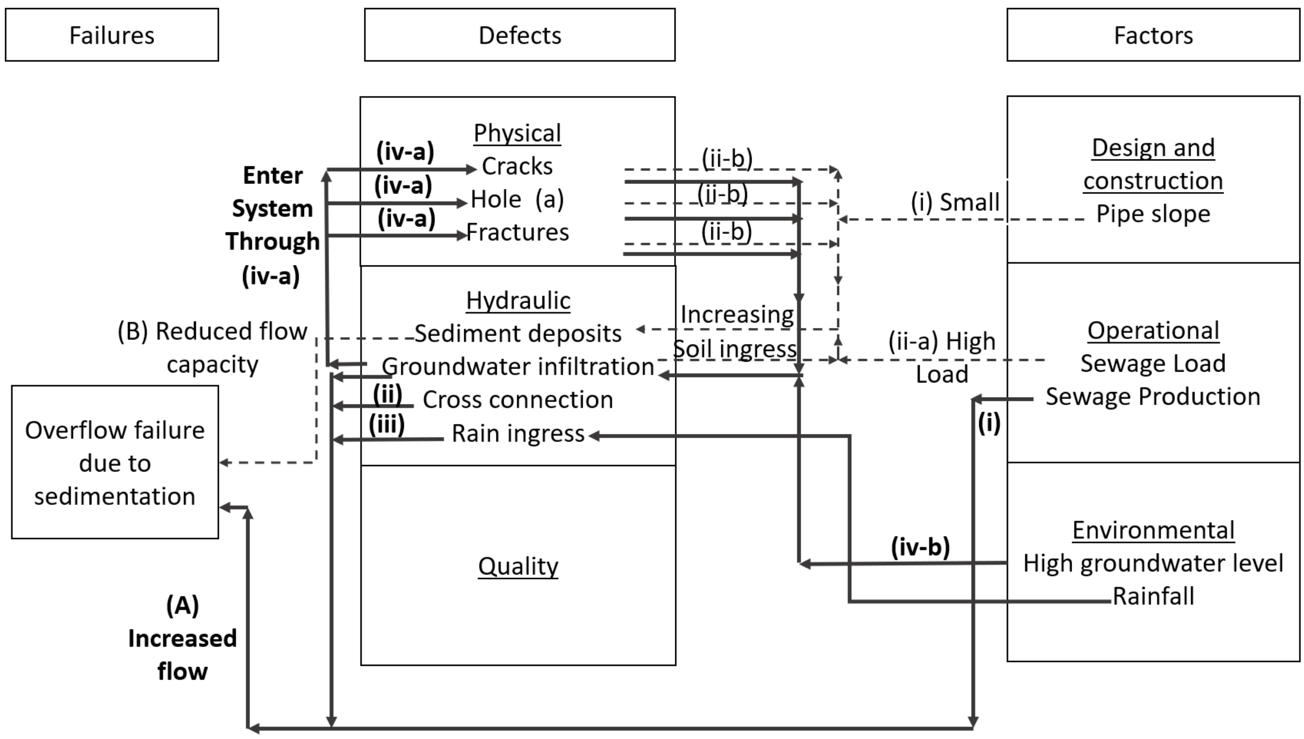


Figure 15. Schematic illustration of the causes of sewage overflows due to sedimentation

3.7 Chapter Summary

This chapter highlights the large differences and inconsistencies in classification systems used in different studies in the sewer deterioration and asset management fields. It then proposes a classification system based on three top-level categories of factors, defects and failures. Each of these categories and subcategories is clearly defined, and a flow diagram is provided to guide the user in classifying any given parameter. Sewer systems are highly complex with a large array of components, loads, deterioration processes and impacts on society and the environment. This makes the classification of parameters that affect or are affected by sewer systems a challenging task, as is evident from the number of different classification systems available from the literature.

Despite a significant number of objectives that analyses of sewer system deterioration or asset performance may have, these analyses are all influenced by the same factors, deterioration processes and failure types. Thus, it should be possible to develop a consistent classification system that can be applied in a broad range of deterioration or asset management studies. The purpose of this chapter is to propose a uniform classification system that may fulfil this purpose or form the basis for an improved unified classification system.

It should be stated that no classification system will be without its weaknesses, and it is unlikely that a perfect system can ever be found. Decisions on whether to change a system should be taken on the basis of whether the benefits outweigh the costs, rather than whether it is devoid of any problems or inconsistencies.

Far more important than a perfect classification system, is the need for researchers and practitioners in sewer systems to use the same classification system. This will allow the body of professional in sewer asset management to communicate more effectively by speaking same language, make it possible to compare different studies and build up a consistent knowledge base to move the understanding and management of sewer systems forward.

4 IMPACT OF FACTORS ON DEVELOPMENT OF DEFECTS IN AUCKLAND SEWERS

4.1 Introduction

The aim of this chapter is to investigate the effect of various factors, including age, material, diameter, and groundwater level, on the prevalence of eight defect categories. A cleaned dataset with the defects identified through recent CCTV inspections of 2780 sewers was gathered and linked to a range of physical and environmental factors.

The main part of this chapter has been adopted from a submitted paper to the Journal of Infrastructure Systems, ASCE. Tizmaghz, Z., van Zyl, J. E., Henning, T. F. P., Donald, N., & Pancholy, P. (2022). Defect-Level Condition Assessment of Sewer Pipes. Journal of Infrastructure Systems, Under Review.

This chapter is organized as follows; in the first section, the background of the study is presented. In the next section, the Auckland sewer system, CCTV dataset, and the factors and defects investigated are described, as well as correlations between factors and defects. The impact of a range of factors on eight defect categories is then presented. Finally, the results and potential of this approach for sewer deterioration modelling are discussed.

4.2 Background

CCTV plays an essential role in monitoring, assessing, and condition scoring of sewer pipes. A condition score is normally assigned to each sewer pipe based on the type, quantity, and extent of defects observed through CCTV inspections.

Condition scores can be assigned through different condition assessment methodologies, e.g., (CEN, 2003), (NASSCO, 2001), (WSA, 2020), and the Gravity Pipe Inspection Manual Standard in New Zealand (Water New Zealand, 2019). For the last two decades, studies have identified and described various factors that affect the condition score of sewers by accepting it as a comprehensive index for the overall condition. A broad range of deterioration models, including logistic regression, Markov chain, decision trees, and support vector machines, have been utilized to study the relationship between factors and the condition score.

Mohammadi (2019) published a list of studies with their characteristics that have been conducted in this field, which has been expanded and updated in Table 15. Studies are grouped by the models used for each study, and the number of sewer pipes, assessment methodology, and the condition scale considered are stated. Figure 16 shows the frequency of significant factors based on the results of the 22 studies reviewed in Table 15.

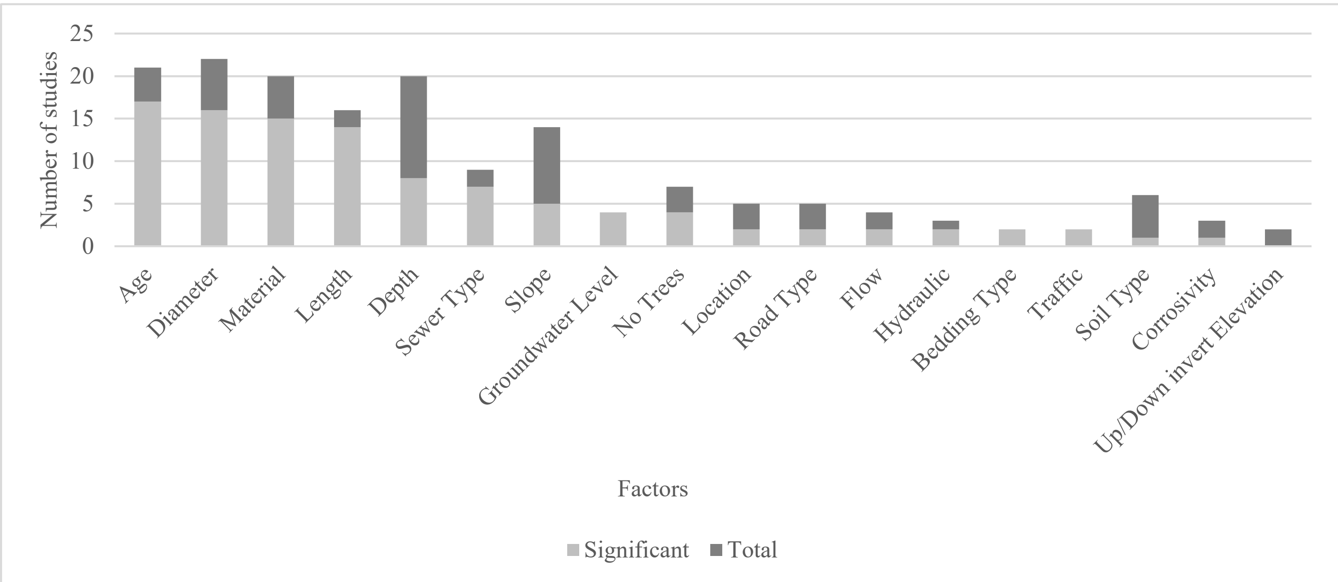


Figure 16.Factors included in published sewer pipe deterioration studies

Table 15. Sewer Deterioration Models

Model	Authors	Number of Pipelines, training/test	Condition Assessment Methodology	Condition Grade Output	Factors	Significant Factors
Logistic Regression	Davies et al. (2001)	12,000	WRc	0: 1,2,3,4 1: 5	Age, material, diameter, depth, length, sewer type, groundwater, corrosivity, road type, number of trees, other factors	Material, diameter, length, sewer type, groundwater, corrosivity, number of trees
	Ariaratnam et al. (2001)	748	WRc	0: 1,2,3 1: 4, 5	Age, material, diameter, depth, sewer type	Age, diameter, sewer type
	Koo and Ariaratnam (2006)	579	PACP	0: 1,2,3 1: 4, 5	Age, velocity, flow	Age, flow
	Ana et al. (2009)	1316	NEN3399	0: 1,2,3 1: 4, 5	Age, material, diameter, depth, length, slope, sewer type, location	Age, material, length
	Lubini and Fuamba (2012)	459	PACP	1,2,3	Age, diameter, length, slope, material	Age, diameter, and material (different in various condition states)
	Fuchs-Hanusch (2015)	4577	Other	0: 1,2,3 1: 4, 5	Material, vintage, sewage type, profile type, width, hight, length, depth	Material, length, width, vintage, profile type
Markov Chain	Wirahadikusumah et al. (2001)	-	Other	1,2,3,4,5	Material, depth, soil type, groundwater	Material, depth, soil type, groundwater
	Micevski et al. (2002)	497	Other	1,2,3,4,5	Diameter, material, soil type, exposure (distance to coastline), serviceability	Diameter, material, soil type, exposure (distance to coastline)
Neural Network	Najafi and Kulandaivel (2005)	-	PACP	1,2,3,4,5	Age, material, diameter, depth, length, slope, sewer type	-
	Tran et al. (2006)	583	WSAA	1,2,3	Age, diameter, depth, slope,	Hydraulic condition

					location, soil type, number of trees, hydraulic condition, other factors	
	Khan et al. (2010)	200	WRc	1,2,3,4,5	Age, material, diameter, depth, length, bedding type	Age, material, diameter, depth, length, bedding type
Support Vector Machine	Mashford et al. (2010)	1441	others	1,2,3,4,5	Diameter, construction year, road, slope, up/down invert elevation, material, delta of angle, soil corrosivity, sulphate soil, groundwater	-
Decision trees **Support Vector Machine**	Harvey and McBean (2014)	1825	WRc	0: 1,2,3 1: 4, 5	Age, material, sewer type, diameter, length, slope, down elevation depth, road coverage, watermain breaks	- Age, depth, length, diameter, watermain breaks
Neural Network **Support Vector Machine** **Logistic regression**	Sousa et al. (2014)	745	PACP	0: 1,2,3 1: 4, 5	Age, material, diameter, depth, length, slope	Age, material, depth, length
Markov chain **Survival Analysis** **Random Forest**	Caradot et al. (2018)	102,258	ATV M 143-2	1,2,3	Construction year, material, sewer type, width, length, depth, slope, tree density, city district	Material, city district, shape, sewer type
Logistic Regression **Random Forest** **Support Vector Machine** **Discriminant analysis**	Hernandez et al. (2018)	4633	NS-058	1,2,3,4	Age, material, type of effluent, depth, diameter, slope, type of road	-

Random Forest **Binary Logistic Regression**	Laakso et al. (2018)	6700	EN-13508-2	0: 0,1,2 1: 3, 4	Age, material, diameter, depth, length, slope, sewer type, location, road type, number of trees, flow, other factors	Age, depth, length, slope, sewer type, location, number of trees, flow
Logistic Regression **Gradient Boosting Tree** **K-Nearest Neighbours**	Mohammadi (2019)	19766	PACP		Age, diameter, flow, depth, slope, length, soil sulphate, soil PH, groundwater, hydraulic, corrosivity	Age, material, diameter, length, groundwater Age, material, diameter, length, groundwater Age, material, diameter, length, depth
Neural Network **Linear Regression**	Yin et al. (2020)	9892	PACP	1,2,3,4,5	Age, diameter, length, material, average LOF, waste type, up/down invert elevation, up/down depth, repair history, capacity, category	Age, diameter, length, material, waste type, category Age, tree density, and traffic in the average LOF factor

While the pipe condition score is a simple and useful measure for overall sewer condition, it provides no insight into the underlying mechanisms responsible for its deterioration. A given condition score may result from a vast range of underlying defect types and their frequency and severity. For instance, it is impossible to discover that a particular mechanism, such as gas attack, may be the dominant deterioration mechanism of a certain cluster of sewer pipes from an analysis of pipe condition score, and thus the opportunity to impede or prevent such deterioration in future may be missed. Given that the underlying defects are identified and classified as part of the CCTV inspection process, this may provide an opportunity to gain a more detailed understanding of the causes and patterns of sewer pipe deterioration in a particular system.

The aim of this study was to investigate the distribution of defects identified by CCTV inspection and study the correlation of these defects with various factors in order to provide better insight into the sewer deterioration process. A better understanding of physical and environmental factors affecting pipe defects can provide insights for municipalities to better manage their asset by making efficient CCTV inspection decisions and optimizing maintenance and installation strategies (Laakso et al., 2018).

4.3 Methodology

4.3.1 Auckland Sewer System

The study dataset was obtained from Watercare Service limited; a council-owned entity responsible for managing Auckland's 9800 km of sewer pipes. Sewer pipes are grouped into two main categories; distribution sewers are smaller and less critical pipes that are usually run until failure. Transmission sewers, on the other hand, play the most important role in conveying sewage from different parts of the network to the wastewater treatment plants and are assessed regularly to minimize the probability of failures. CCTV datasets for main transmission sewers are done every five years, and the latest available reports were used as the basis of this study. The Watercare transmission sewer dataset consisted of 4870 pipes with a total length of 246 km, representing about 3% of the whole network. Table 16 provides a summary of sewers' main features in the City of Auckland based on the dataset received from Watercare. Also, Figure 17 demonstrates the sewer pipeline system in the city of Auckland.

The age profiles for the different pipe materials in the transmission sewer network are shown in Figure 18.

Table 16. Overall sewer specifications in Auckland city

Characteristic	Specification
The total length of sewers	9,815 km
Number of gravity sewers	451,123
Number of main transmission sewers	4912
Length of transmission sewers	246 km
Range of pipe diameter	100-3700 mm
Pipe Materials	Conc, RC, RCRRJ, CIP, PE, EW, CLS, PVC, AC, CER, CI, VC, RCSRJ, ABS, FRP, SS, CLCI, Alum, HDPE

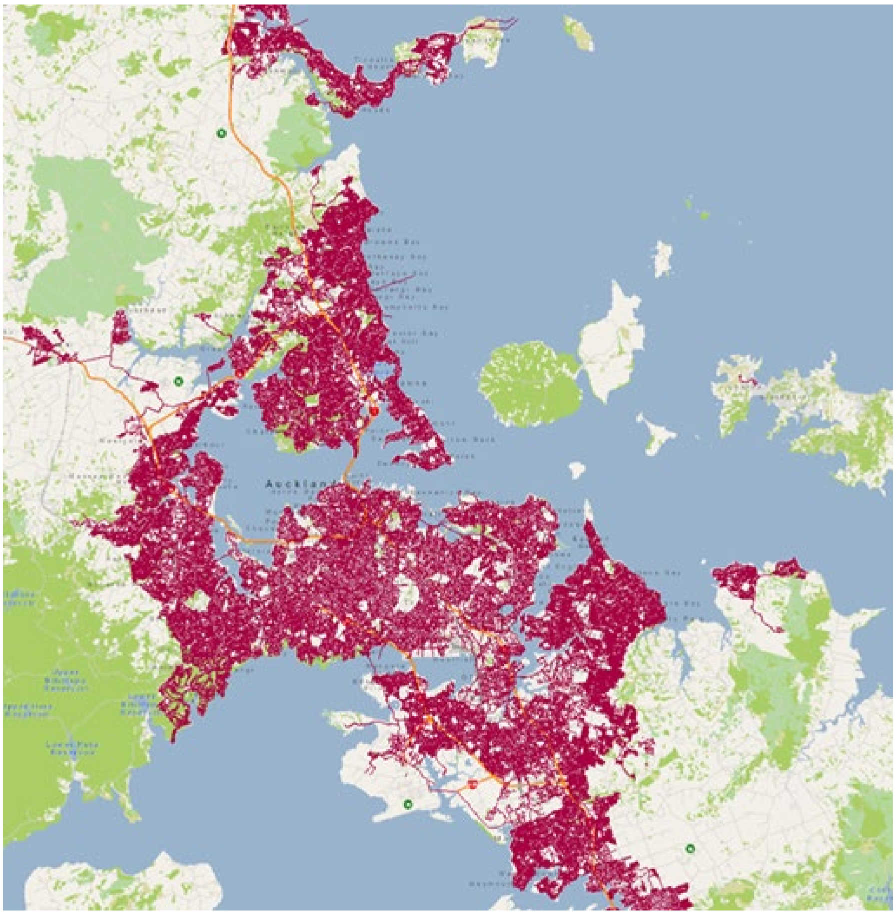


Figure 17. The sanitary sewer pipeline in Auckland city

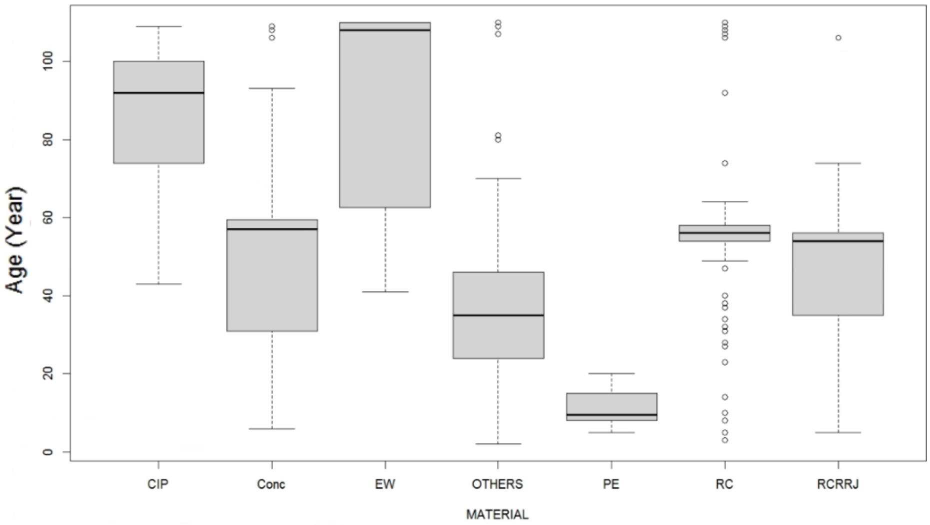


Figure 18. The age profiles of the main pipe materials in the Auckland sewer network: cast in place (CIP), concrete (Conc), earthenware (EW), other materials (OTHERS), Polyethylene (PE), reinforced concrete (RC), reinforced concrete rubber ring joint (RCRRJ)

4.3.2 CCTV dataset

The CCTV dataset was received from Watercare which is in charge of managing water and wastewater networks for the City of Auckland. Watercare has been performing CCTV investigations for all main transmission pipelines every five years as part of its asset management strategy. The gathered CCTV dataset for this study is based on the latest CCTV dataset, which was available for all main transmission sewers between 2015 and 2020.

CCTV is performed by an operator by passing a CCTV camera through the pipe and filling the related report, including the most highlighted features. In the next step, the recorded videos and reports are scrutinized by Watercare's experts to determine the occurrence of various defects and provide more details, such as the severity of defects and their locations.

The CCTV dataset was received in the form of various spreadsheets, including all gravity transmission pipes with their condition scores and all possible defects that might be present in sewers. Indeed, CCTV spreadsheets are gathered from 49 areas on the north shore and 100 areas in the south of Auckland. In this study, all CCTV spreadsheets were combined to become the basis for this study. The received CCTV spreadsheets contain 22 columns shown in Table 17.

Table 17. CCTV spreadsheet columns

Item	Name	Description
1&2	Start manhole & end manhole	The manholes in which the pipe begins and ends, respectively.
3	Material & diameter	Indicating the material and diameter of the pipe
4 to 19	4.gas attack, 5. erosion, 6. exposed aggregate, 7. delaminated, 8. infiltration, 9. roots, 10. dipped pipe, 11. open joint, 12. displacement joint, 13. joint defect, 14. broken pipe, 15. cracking, 16. liner defects, 17. debris, 18. exposed steel, 19. Hole	Different defects based on the defects code of the Gravity Pipe Inspection Manual Standard of New Zealand (Water New Zealand, 2019)
20	Equipment ID	An identification code that is exclusive to every pipe and allows pipes to be distinguished from each other
21	Condition score	Includes the condition score of sewers scored according to the Gravity Pipe Inspection Manual Standard of New Zealand from 1 to 5. The number of condition scores is increasing with increasing defects numbers. While a condition score of one indicates a pipe contains few defects or lack of any, the condition score of five shows that the number or extent of defects are considerable, and immediate action is needed to address the problem.
22	Remarks	General notes

4.3.2.1 General simplification

Detailed datasets such as the distance and quantity of each defect were provided in corresponded spreadsheets in the CCTV spreadsheets. For simplification, defects details and counts were ignored, and all detailed information was transformed to a binary variable indicating whether the defect is present in the pipe. Particularly, “1” represents the existence of one or more of the related defects, and “0” represents the non-existence of the related defect.

Table 22 shows an overview of the CCTV report in Auckland with corresponding defects after simplification. As an example, in Table 18, the pipe with equipment ID of 10088201 has only two types of defects namely gas attack and debris and a condition score of 2.

Table 18. Simplified table indicating the types of defects present in each pipe

Equipment ID	Gas attack	Erosion	Exposed aggregate	Delaminated	Infiltration	Root s	Dipped pipe	Open joint	Displa cement joint	Joint defect	Broken pipe	Cracking	Liner defects	Debris	Exposed steel	Hole	Condition-score
10088196	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2
10088197	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	2
10088198	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	3
10088199	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	4
10088200	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	2
10088201	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2

4.3.2.2 Simplification and Categorization

Figure 19 illustrates the frequency of different defect types in Auckland's main transmission sewers. Generally, there are 16 defect types; gas attacks and broken pipes have the highest and lowest frequency in the main transmission sewers, respectively. A brief definition for each defect is presented in Table 19.

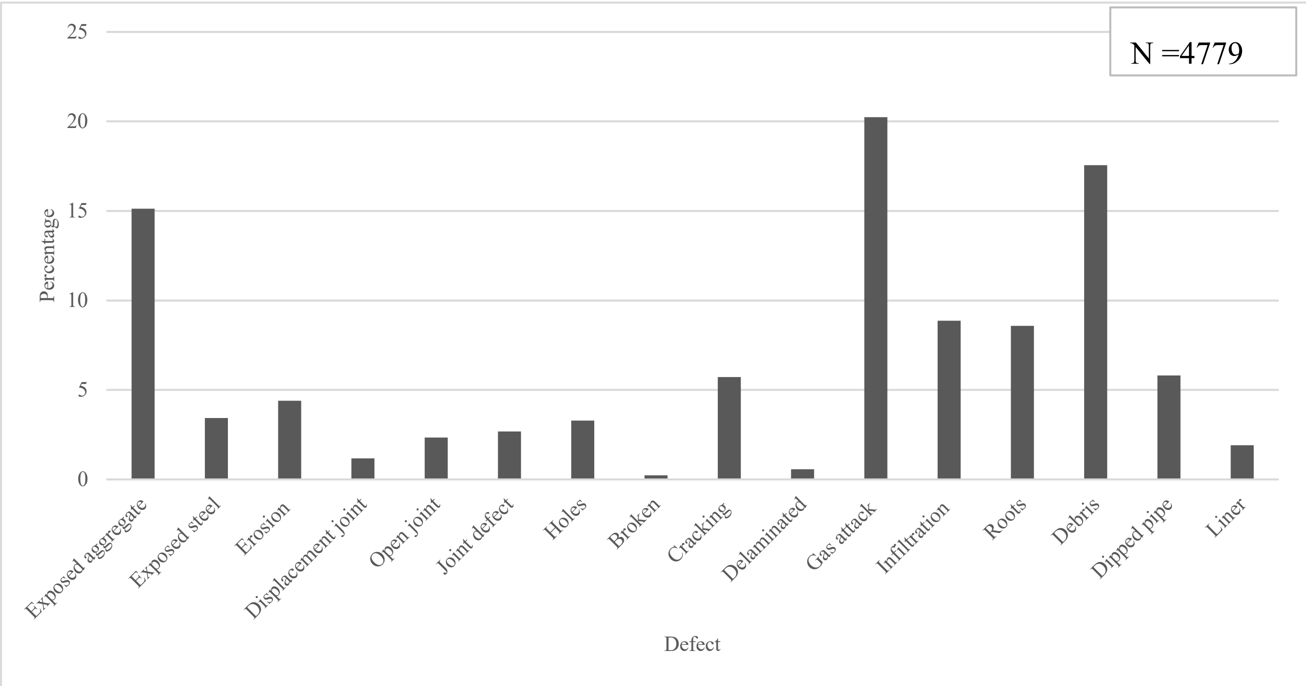


Figure 19. The percentage of sewer transmission pipes with different defects based on the CCTV footage

Table 19. Defect types identified in the CCTV footage

Defect	*Description*
Exposed aggregate	Any rough pieces of aggregate which are left exposed on the surface of the concrete
Exposed steel	Any steels which are left exposed on the surface of the reinforced concrete
Erosion	The process by which the internal surface of a pipe deteriorates
Displacement joint	The process of displacing joints from their proper place
Open joint	The process of opening a joint
Joint defect	Any visible defects that might appear in joints
Holes	Any hollow place in a pipe body
Broken	Any breaks or gaps in a pipe body
Cracking	Any lines on the surface of pipe along which it has split without breaking apart
Delaminated	Divided into layers
Gas attack	The process of realising gas attacks in sewers
Infiltration	The process of entering water into sewers
Roots	The process of penetrating tree roots into sewers
Debris	The scattered pieces of rubbish or remains
Dipped pipe	The process of displacing down of pipe in some spots from their straight direction
Liner	Any defects that might appear on the lining of sewers

For facilitating the analysis, the number of defects was reduced from 16 to 8 by grouping similar defects into one category. The defect categories are listed in Table 20.

Table 20. The simplified defects categories

Category	Including
Gas attack	Gas attack
Material damage	Exposed aggregate, exposed steel, and erosion defects.

Infiltration	Infiltration
Roots	Roots
Debris	Debris
Total joint	Displacement joint, open joint, and joint defects.
Structural	Holes, broken, cracking, and delaminating
Dipped pipe	Dipped pipe

Figure 20 provides the prevalence of all defects in the dataset and how they were grouped into eight categories. The first three categories, including material damage, gas attack, and debris show the highest frequencies in order, and they are more likely to be dominant in the Auckland sewers network in comparison with other defects categories.

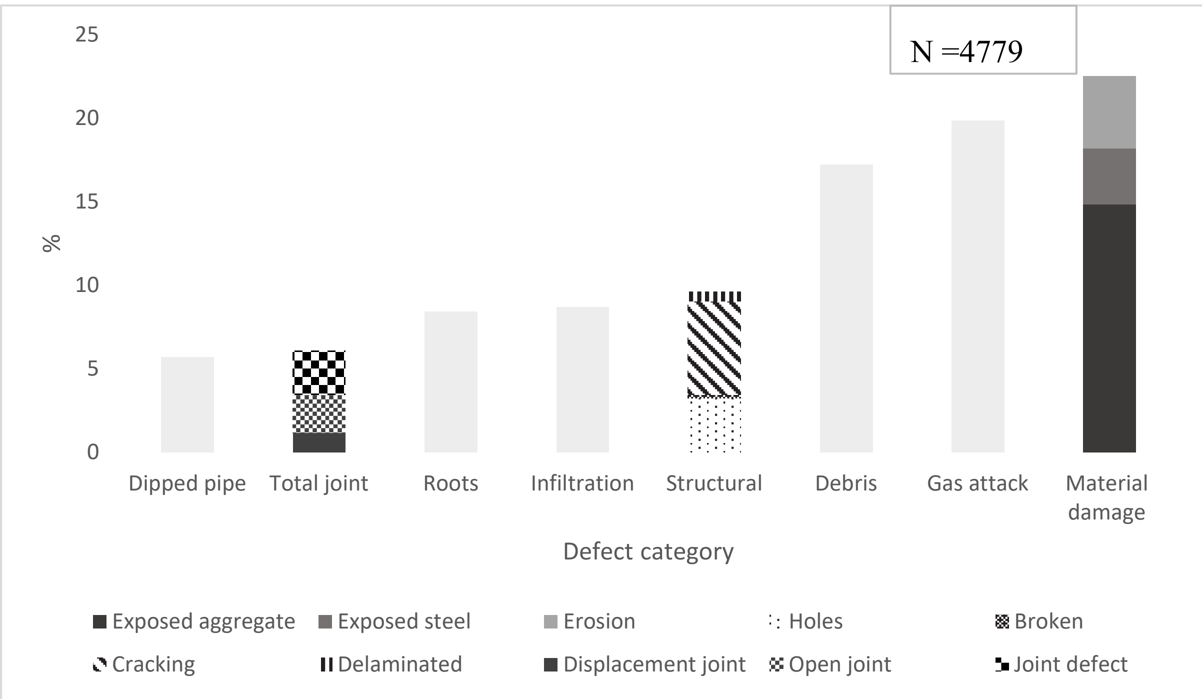


Figure 20. Prevalence of defects in the Auckland transmission sewer network, grouped into eight categories

In the next step, the merged defect dataset was linked to a range of factors. The procedure of gathering the required factors and cleaning them is presented in the next section.

4.3.3 Other data sources

Besides the CCTV records, several additional sources of information were gathered through a list of data layers that are readable, compatible, and adjustable with ArcGIS software (Geographic Information System) as follows:

- Sewer pipe features
- Liquefaction susceptibility index
- Population density
- Groundwater

Sewer pipe features, as the main source of the dataset, are provided by Watercare as a shapefile, including 451,123 individual manholes to manhole pipe segments. A list of pipe features such as equipment IDs, diameter, material, linings data, installation date, upstream and downstream invert levels, and length of pipes was provided in the records.

The liquefaction susceptibility index and population density dataset were obtained from the Land Information New Zealand website through raster files adjustable and readable in GIS software (LINZ, 2021). Both of these factors were specified based on the location of each pipe.

The groundwater dataset was the last dataset source of this study which was collected through a raster file that is readable and adjustable in GIS software. Groundwater inventory was collected based on the latest groundwater dataset provided by Westerhoff et al. (2018), who studied and prepared the latest changes in the groundwater level in New Zealand.

4.3.4 Merging and Preparation

Prior to study the existing relationships between factors and each defect category, data need to be merged and prepared. Data preparation is a series of strategies that are done to increase the accuracy of the model and study. In this section, the procedure of merging and preparing of CCTV dataset and other data sources is explained to provide an overview of how the required dataset for conducting this study was compiled.

For merging physical factors such as diameter and material with environmental factors, including liquefaction susceptibility, population density, and groundwater level, the spatial join feature in the ArcGIS software was used. A spatial join is a GIS operation that affixes data from one feature layer's attribute table to another from a spatial perspective (Mohammadi, 2019). After merging all these factors, the simplified CCTV defect data were merged using unique equipment IDs.

Prior to looking at the procedure of emerging defect categories based on the variability of different factors, gathered and combined datasets needed to be cleaned and prepared. Preparation of the gathered dataset is an essential step at the beginning of any numerical research, including a series of strategies that can increase the study's accuracy (Pyle, 1999).

For performing the following data preparation, several techniques, which are explained in detail in the rest of this section, were conducted.

Firstly, pipes with missing information were identified and omitted. Secondly, pipes that come with lining need to be omitted since they show longer durability in comparison with other pipes influencing the deterioration rate of sewers. Thirdly, pipes with a negative dataset, such as negative age and length were omitted. Fourthly, the box plot technique is used to remove outliers which are those data that are typically larger or smaller than other observed present continuous datasets (Seo, 2006).

To develop this study, different factors, including pipe age, diameter, depth, slope, length, groundwater level, and population density are considered as continuous numeric variables, and two factors, including pipe material and liquefaction susceptibility index, are considered as discrete variables.

In summary, the following steps were applied to conduct the data preparation. In the first step, after merging all CCTV inspection datasets, 4912 pipes were included in the dataset. Secondly, all pipes without equipment IDs which is the essential feature in distinguishing individual pipes from each other, were excluded. Consequently, the number of pipes in datasets decreased to 3596. Thirdly, pipes with unknown ages that are one of the studied features are excluded. After this step, the remained number of pipes was reduced to 3174. In the next step, all pipes with a lining were removed from the dataset; after this exclusion, the number of records was reduced to 3041.

Following that, all outliers in depths, slopes, and length features were excluded. After this exclusion, the number of pipes was reduced to 2818. Box plot method used for excluding outliers, for instance, the length box plot used to exclude length's outliers. Box plot is a way for graphically depicting groups of numerical data through lower and upper quartiles beside their median and minimum, and maximum amount. Removing outliers contributes to achieving a better correlation between independent and dependent variables (Mohammadi, 2019).

Finally, the final dataset contains 2780 main gravity sewer transmission pipelines, including recorded corresponding defect categories, overall related condition scores, and physical and environmental features. An extract of the gathered dataset is shown in Table 21 in order to represent how the compiled inventory looks like. In this table, all information related to each main transmission sewer pipe, including equipment ID, the presence of different defect categories (including gas attack, material damage, debris, structural, infiltration, roots, total liner, total joint), condition score, material, diameter, length, age, depth, slope, groundwater level, liquefaction susceptibility, and population density were provided. In the next section, the distribution of sewer pipes based on various factors with data cleaning details for each factor is reported.

Table 21. An extract of the gathered dataset

EQUIP_ID	Age	Diameter	MATERIAL	Length	Pipe depth	Slope	groundwater level-Pipe depth	Population density	Liquefaction index	CONDITION	Material damage	Gas Attack	Infiltration	Structural	Roots	Debris	Total joint	Dipped pip
10004040	63.0	900	RC	62.2	4.5	7.2	2.2	1887.3	-2.2	2	1	1	0	0	0	0	0	0
10004037	63.0	900	RC	507.5	6.0	1.2	5.3	1558.8	-2.3	3	1	1	0	0	1	0	0	0
10004050	110.0	750	OTHERS	87.6	0.0	0.0	0.0	637.8	-2.5	3	0	1	0	1	1	1	0	1
10004052	110.0	750	RC	11.7	0.0	0.0	0.0	518.2	-2.5	3	2	0	0	0	0	1	0	0
10004056	110.0	450	EW	44.4	0.0	0.0	-7.6	578.3	-2.5	3	0	0	0	0	1	0	0	0
10004057	110.0	450	EW	7.4	3.0	40.5	-4.6	578.3	-2.5	3	0	0	0	0	0	0	0	1
10004058	110.0	450	EW	26.6	3.0	11.2	-4.0	578.3	-2.5	3	0	0	0	0	0	0	0	0
10004060	110.0	450	EW	25.8	1.8	6.8	-5.3	578.3	-2.5	3	0	0	0	0	0	0	1	0
10004059	110.0	450	EW	51.8	1.7	3.2	-5.4	752.0	-2.5	3	0	0	0	0	0	0	0	0
10004061	110.0	450	EW	100.4	1.2	1.2	-5.8	944.3	-2.6	3	1	0	0	1	1	0	0	0
10004062	110.0	600	EW	36.7	1.2	3.2	-5.8	962.8	-2.6	3	0	0	0	0	1	0	0	0
10004063	110.0	600	EW	61.4	2.7	4.3	-4.4	1044.9	-2.6	3	0	0	0	0	0	0	0	1
10004064	110.0	525	EW	140.8	2.7	1.9	-7.6	1126.9	-2.6	4	0	0	0	1	1	0	0	0

4.4 Detailed Statistics

Data on a large range of factors that may influence sewer pipe deterioration were collected and grouped into two categories; design and construction and environmental (Tizmaghz et al., 2022). Table 22 provides a summary of the factors and their properties.

The main goal of this table is to display a quick review of variables and their main features in the sewer database.

Table 22. Factors included in the study

Category	Factor	Type	Minimum	Maximum	Mean
Design and Construction	Material	Categorical	-	-	-
	Diameter (mm)	Continuous quantitative	150	2550	685
	Depth (m)	Continuous quantitative	0.2	19.34	2.44
	Slope (%)	Continuous quantitative	0	49.9	4.78
	Length (m)	Continuous quantitative	1	930	88.5
	Age (year)	Continuous quantitative	2	110	51
	Population density (Number of people per square kilometre)	Continuous quantitative	0	17221	4727
Environmental	Groundwater level (m)	Continuous quantitative	-56.1	19	2.27
	Liquefaction Susceptibility	Categorical	-	-	-

4.5 Data Analysis

Correlations between different factors and defects were investigated respectively to identify any interdependencies. The relationships between each factor and each of the defect categories were then investigated. Each factor was split into a convenient number of groups, and the fractions of pipes with each defect were calculated for each group as a basis for the analysis.

Table 23 shows the correlation coefficients between factors. For continuous quantitative variables, The Pearson correlation coefficient was used for categorical features, Crammer's V or Theil's U correlation coefficient, and for categorical-continuous variables, the correlation ratio (Boslaugh, 2012; Court et al., 2015). The strongest positive correlations (between 0.5 and 0.7) were found between pipe material and population density, pipe material and age, and pipe depth and slope. The strong correlation between pipe material and age is likely due to the use of specific pipe materials in different periods of time and that of pipe material and population density to the usage of certain kinds of materials in different suburbs. The reason for the strong correlation between pipe depth and pipe slope is not immediately clear.

Table 23. Correlation coefficients for factors

variables	Age	Diameter	Depth	Length	Slope	Groundwater	Population	Liquefaction	Material
Age	1	0.23*	0.07*	0.01	0.01	-0.06*	-0.38*	0.132*	0.576*
Diameter		1	0.01	0.3*	-0.12*	0.09*	-0.18*	0.226*	0.287*
Depth			1	0.16*	0.50*	0.32*	0.13*	0.140*	0.222*
length				1	-0.29*	0.04	-0.12*	0.168*	0.150*
Slope					1	0.14*	0.22*	0.188*	0.274*
Groundwater						1	0.12*	0.256*	0.145*
Population							1	0.403*	0.680*
Liquefaction								1	0.201*
Material									1

Correlation is significant at the 0.05 level

*Correlation is significant at the 0.1 level

The correlation coefficients between the different defects are shown in Table 24. The results don't show any strong correlations between defects, indicating that they are mostly independent of each other. The highest coefficient (0.24) was found between gas attack and material damage, possibly due to gas attack damage facilitating other material damage mechanisms.

Linear regression was used to describe the relationships between continuous quantitative variables and defects since there was no indication that more sophisticated methods would provide better descriptions of the underlying trends. Data outliers were identified and excluded using Tukey's fences method (Thompson, 2000), i.e. any point that lies more than 1.5 times the interquartile range outside the interquartile range (Dümbgen & Riedwyl, 2012).

The statistical significance of different defect categories as dependent variables was approximated through the p-value, which checks the null hypothesis (Dahiru, 2008). For evaluating the p-value, the significance level of 0.05 was considered, indicating only a 5% probability of an observed difference when there is no actual difference. To increase the accuracy, categories with less than 30 (approximately 1%) of the total number of pipes were excluded from the regression analysis.

Table 24. Spearman Rank Correlation Coefficients for defects

Defects	Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe
Gas attack	1	0.24*	0.06*	-0.03	0.05*	0.00	-0.05**	0.10*
Material damage		1	0.09*	0.03	0.06*	-0.01	0.06*	0.03**
Infiltration			1	0.03	0.02	0.12*	0.19*	0.08*
Roots				1	0.04**	0.07*	0.15*	0.02
Debris					1	0.03	-0.01	0.10*
Total joint						1	0.08*	0.11*
Structural							1	0.02

Total liner	1

Correlation is significant at the 0.05 level

*Correlation is significant at the 0.01 level

4.5.1 Relationships Between Factors and Defects

In this section, the effect of the various factors on each defect category is described and interpreted in relation to previous research. To demonstrate the process and typical results, the analysis of pipe age is discussed in detail. For the other factors, only a summary of the main findings is presented and discussed. However, details for all factors are provided in Appendix A.

4.5.1.1 Age

Pipe age was calculated as the difference between the years of the CCTV inspection and installation. The distribution of pipe age, based on 5-year intervals, is shown in Figure 21.

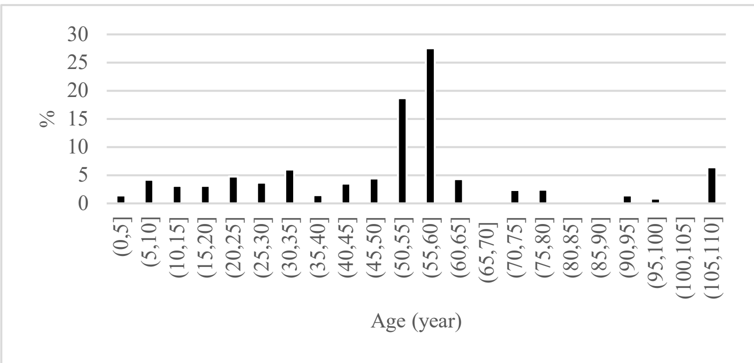


Figure 21. Distribution of sewer ages

To study the impact of age, the fractions of pipes with each defect were calculated and then plotted as shown in Table 25 and Figure 22.

Table 25. The number of pipes with defects in 5-year age intervals

Age interval	Total no of pipes	Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe	Total no of defects
(0,5]	39	9	1	0	0	11	4	2	1	28
(5,10]	116	8	9	6	5	42	9	5	11	95
(10,15]	86	27	18	8	2	45	4	2	18	124
(15,20]	87	8	21	13	8	35	3	7	4	99
(20,25]	133	52	51	19	27	44	13	12	17	235
(25,30]	103	12	28	9	12	40	16	10	5	132
(30,35]	167	70	55	16	30	51	48	21	21	312
(35,40]	41	26	26	9	6	13	2	5	2	89
(40,45]	98	11	11	12	14	22	21	17	3	111
(45,50]	123	52	56	15	21	44	8	17	20	233
(50,55]	520	257	222	78	61	113	46	66	59	902
(55,60]	765	331	428	104	104	237	56	116	68	1444
(60,65]	120	52	44	36	36	40	23	28	30	289
(65,70]	6*	1	2	1	5	5	1	0	0	15
(70,75]	66	34	24	20	10	6	0	2	0	96
(75,80]	68	0	6	4	0	29	6	12	0	57
(80,85]	0*	0	0	0	0	0	0	0	0	0
(85,90]	0*	0	0	0	0	0	0	0	0	0
(90,95]	40	8	12	27	6	8	9	25	2	97
(95,100]	23*	3	9	10	9	12	8	15	1	67
(100,105]	0*	0	0	0	0	0	0	0	0	0
(105,110]	179	6	74	37	54	42	19	106	16	354
Total	**2780**	**967**	**1097**	**424**	**410**	**839**	**296**	**468**	**278**	**4779**

* The categories with less than 1% of the total number of pipes are excluded from significance estimations

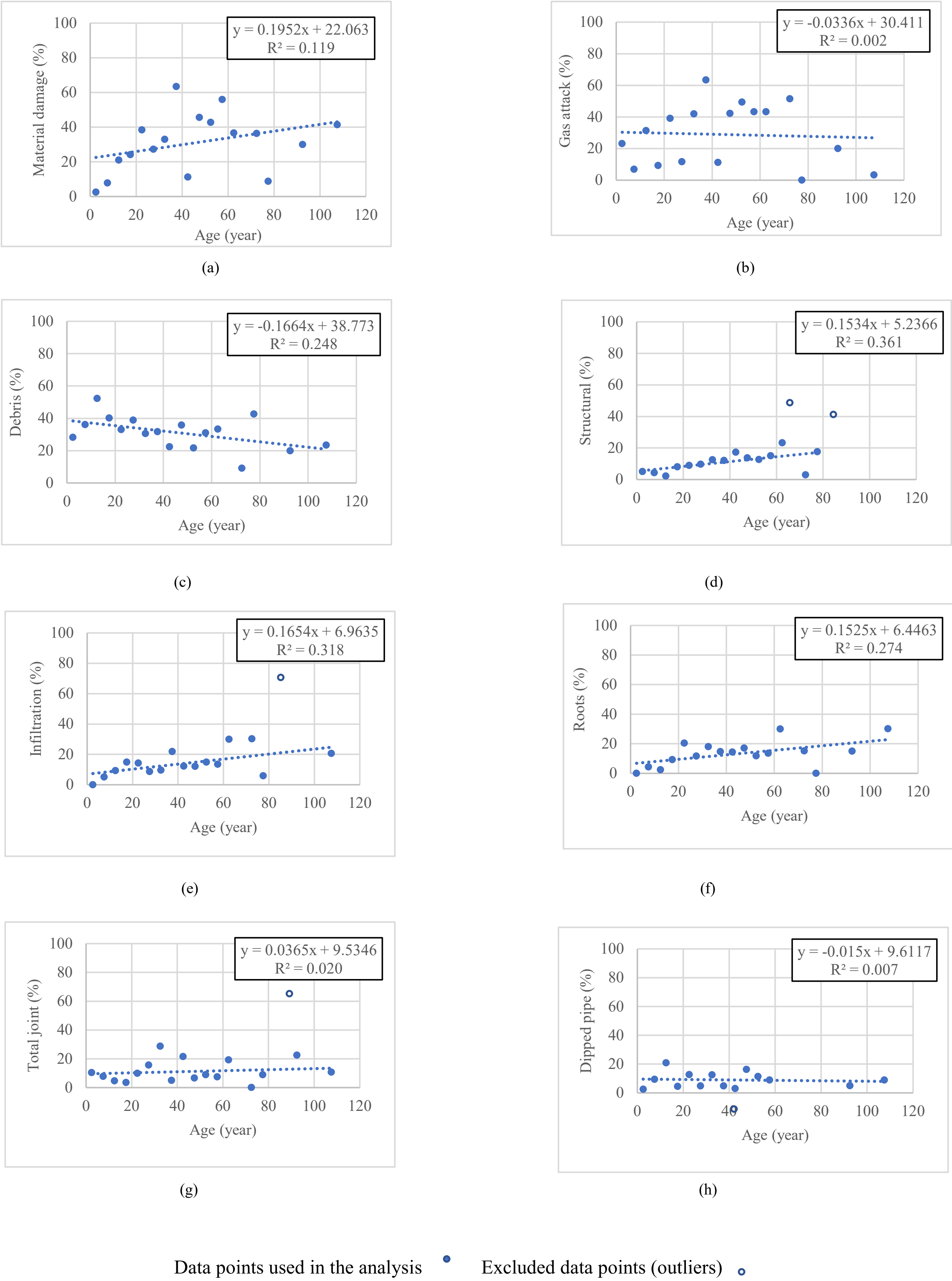


Figure 22. The fraction of pipes with different defects as a function of age: a) material damage b) gas attack c) debris d) structural e) infiltration f) roots

Clear trends between age and four of defect categories, debris, structural, infiltration and roots are evident from the graphs. By analyzing the graphs, it was observed that, while significant scattering is evident in the full material damage range (Figure 22 (a)) there is a clear positive trend for pipes younger than 60 years. It is possible that in older pipes, high levels of material damage may have led to the worst pipes being replaced, leaving only the best pipes in the system and skewing the results.

Significant scattering is also evident in the gas attack (Figure 22 (b)) results. However, for younger pipes, a bifurcated pattern is visible, with succeeding data points plotting on either an upper or lower imagined trend lines. Given that gas attack results through a physical corrosion mechanism, it is highly unlikely that a bifurcated pattern with a five-year period could result naturally. Thus, the bifurcation was assumed to result from the way the data was gathered or documented, and the analysis was repeated for pipes younger than 60 years using a time interval of 10 years.

The results for material damage and gas attack for pipes younger than 60 years are shown in 10-year intervals in Figure 23. In this representation, both defects display statistically significant and large positive slopes. The significant slopes calculated form the linear regression results between defects and age are summarized in Column 2 of Table 26.

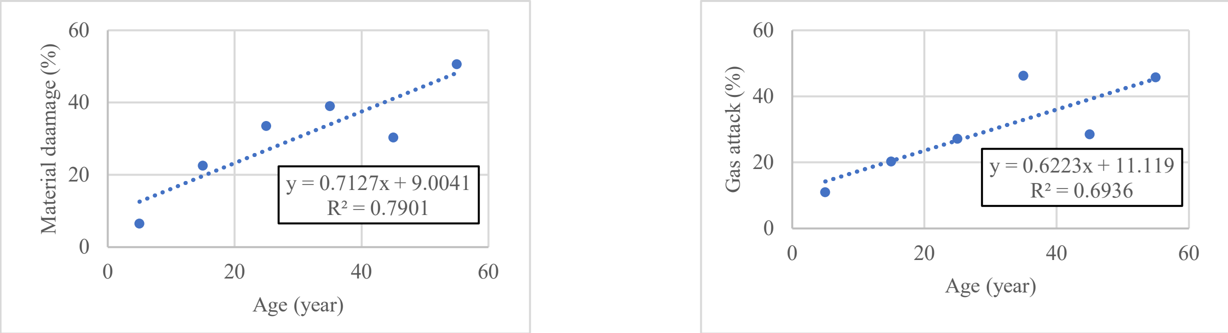


Figure 23. The fraction of pipes, younger than 60 years, with material damage and gas attack defects as a function of age using 10-year intervals

Table 26. Statistically significant linear slopes for the prevalence of defects as a function of different factors

Defect category rank	Age (year)	Diameter (mm)	Depth (m)	Length (m)	Slope (%)	Groundwater (m)	Population density (N/Km2)
1. Material damage	0.622#			0.057*	-1.015		
2. Gas attack	0.712#		-2.934*	0.123	-1.58	-1.116	-0.003
3. Debris	-0.166	-0.009				-1.262	
4. Structural	0.153			0.077	-0.505		-0.001
5. Infiltration	0.165		1.671*	0.047			-0.001
6. Roots	0.152	-0.006		-0.032			
7. Total joint		-0.008				0.481	
8. Dipped pipe		-0.015			-0.448		-0.0006

*Significant at P-value of 0.1

#Calculated based on 10-year intervals below the age of 60 years

The results show that material damage and gas attack (limited to pipes younger than sixty years) are by far the most affected by age, with their prevalence increasing at 0.71 % and 0.62 % per year, respectively. This is followed by infiltration, structural defects, and roots with prevalence growth rates of 0.16%, 0.16%, and 0.15 % per year, respectively. Interestingly, debris displays a significant negative trend, reducing at 0.16 % per year. This may be due to decreasing debris ingress and increasing sewer flow rate over the years as construction of new properties decreases and the number of sewer connections increases. Finally, total joint and dipped pipe defects show no significant trend with age.

The above results align with the trend that can be expected through known physical deterioration mechanisms in sewer pipes, as well as the findings of previous studies showing that pipe age has an adverse effect based on sewer condition scores (Ahmadi et al., 2014; Ana et al., 2009; Cigada et al., 2011). In contrast, Davies et al. (2001) found age not to be a significant variable in their deterioration model. However, they did not have access to sewer pipe age data and used property age as a surrogate, which may have impaired their analysis.

This study provides significant new insights, showing that material damage and gas attack are probably the main causes of the observed reduction in pipe condition with time, with infiltration, structural damage, and roots also playing significant roles.

It is worth adding that while both infiltration and roots defects increase with age, they are unlikely to occur without pipe structural damage, and thus their growth is also an indication of other structural defects (Lubini & Fuamba, 2012). This is supported by the positive correlation between structural damage and both infiltration and roots (0.15 and 0.19 respectively) as shown in Table 24.

4.5.1.2 Diameter

Figure 24 represents the distribution of Auckland transmission sewer diameters, grouping pipes in 150mm diameter intervals. As it can be seen from the figure, Auckland transmission sewer diameter vary between 150 and 2550 mm, with most diameters between 300 mm and 750 mm.

Four defects (dipped pipe, debris, total joint, and roots) displayed statistically significant slopes with diameter. All of these slopes are negative and relatively small, showing a decrease in defect prevalence between 1% and 0.6% per 100-millimetre increase in diameter.

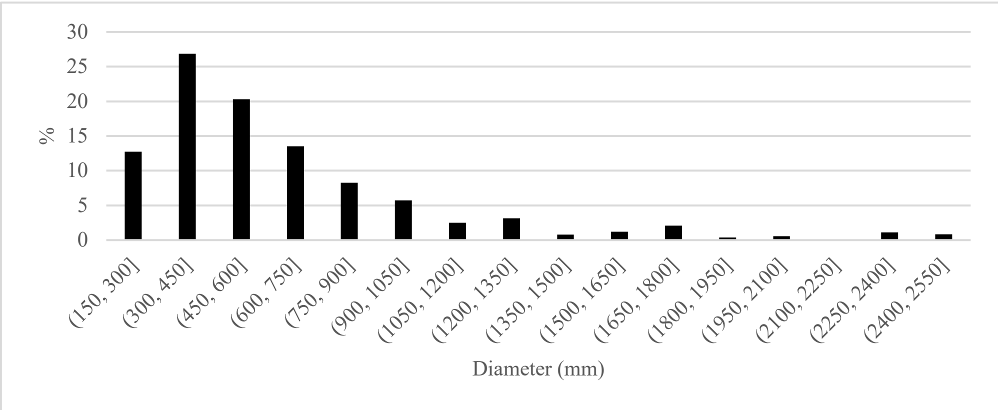


Figure 24. The distribution of sewer diameters

These results align with previous studies, including Davies et al. (2001) and Micevski et al. (2002), who argued that larger diameter pipes have lower deterioration rates due to greater structural strength and cover depths than smaller diameter pipes. Tran et al. (2010) noted that larger diameter pipes are typically installed to higher construction standards, and Lubini and Fauamba (2012) that larger diameter pipes are more likely to continue operating under damage conditions that will prevent flow in smaller diameter pipes.

A number of studies (Jeong et al., 2005; Mohammadi, 2019) made the opposite finding, that larger sewer pipes deteriorate faster due to greater exposure surfaces and more difficult installation procedures related to their bulkier characteristics.

A few studies reported mixed results, such as Khan et al. (2010), who found no diameter effect up to 600 mm, but a decrease in deterioration rate with increasing diameter above 600 mm, and (Laakso et al., 2018), who found that pipes between 300 mm and 1500mm had the best condition.

Finally, two studies such as Tran (2007) and Ana et al. (2009) found no significant impact of diameter on pipe deterioration (Malek Mohammadi et al., 2020). Given the mixed results reported by previous studies and the small slopes observed in this study, it seems likely that diameter is not a major factor in sewer pipe deterioration.

4.5.1.3 Material

The distribution of sewer pipe materials in Auckland is shown in Figure 25, and their age distribution in Figure 18.

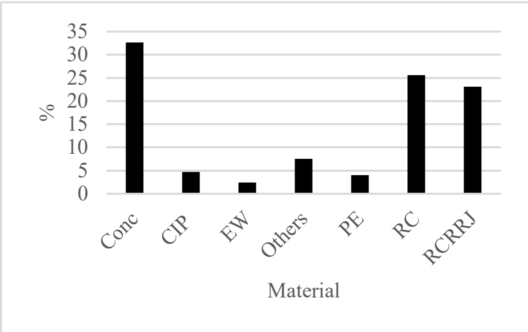


Figure 25.Distribution of sewer materials

A summary of the prevalence of each defect for the various materials is shown in Figure 26.

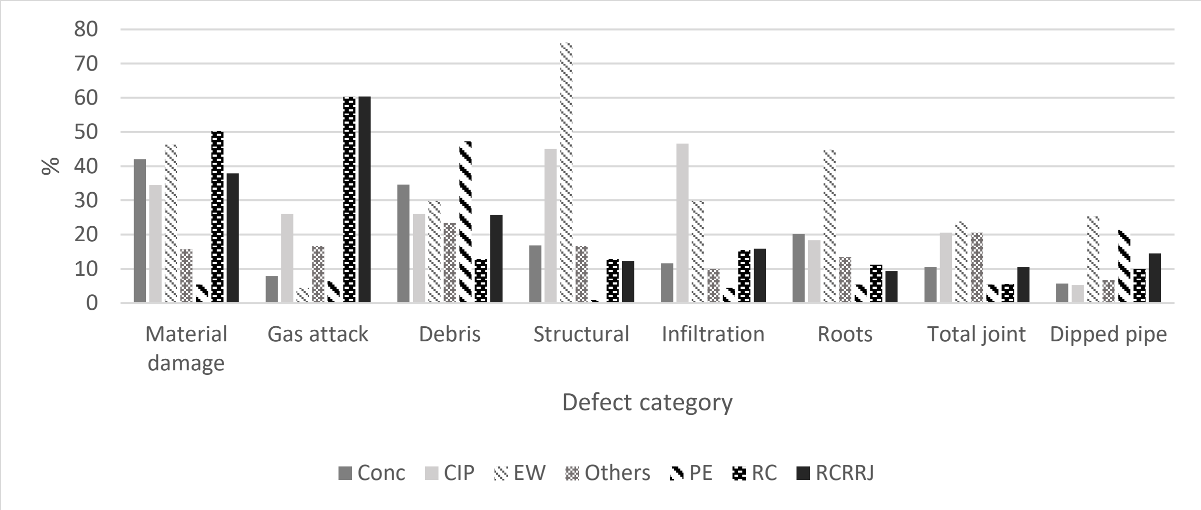


Figure 26. Prevalence of defects for different pipe materials

It is clear from Figure 26 that earthenware is the worst performing material, having the first or second highest prevalence of defects in all categories except gas attack, where it shows the best performance. The reasons for this may be that earthenware is the oldest material in the Auckland sewer network and usage of the shortest pipe sections with greatest number of joints.

Polyethylene, as the youngest among all materials, has the lowest prevalence of less than 6% for five defects, including material damage, structural, infiltration, roots, and total joint indicating the high ductility and strength of this material. However, it has the highest prevalence (47%) of debris which might be due to Polyethylene smaller diameters material mostly used in.

Reinforced concrete (RC) and reinforced concrete rubber ring joint (RCRRJ) pipes presented the highest prevalence of gas attack at almost 55%. According to Figure 18, the median age for RC and RCRRJ pipes is both 65 and thus the similarity of their susceptibility to gas attack is not unexpected. Concrete is particularly susceptible to sulfuric acid, which is created when hydrogen sulfide is release from wastewater and oxidised (Ana et al., 2009; Ayoub et al., 2004). However, it is noted that Conc pipes do not show the same level of susceptibility to gas attack, but the reason for this is unclear. The high susceptibility of concrete to acid attack and the low susceptibility of earthenware aligns with observations made by Micevski et al. (2002) and Ana et al. (2009). In contrast, RC and RCRRJ have the lowest prevalence of all defects apart from gas attack and material damage. This aligns with previous studies, such as Lubini and Fuamba (2012) who argued that reinforced concrete pipes are stronger and more durable than other pipes due to the presence of reinforcement steel that helps prevent structural deterioration.

CIP displayed the highest (46%) infiltration rates, which may be due to their old age a lower quality control in manufacturing.

The lowest impact of pipe material is visible in the debris category, where the range between the highest and lowest prevalence of the defect is narrower than for other defects. This may indicate that debris defects are mainly caused by constituents entering the sewer, rather than from sewer structural deteriorating.

The above results generally align with the trend that can be expected through known physical deterioration mechanisms in sewer pipes, including the findings of previous studies showing that pipe material has a considerable effect on sewer deterioration.

4.5.1.4 Depth

Pipe depth was calculated as the difference between the ground level and the average of the upstream and downstream pipe invert levels.

Figure 27 shows the distribution of sewer pipe depths in two-meter intervals.

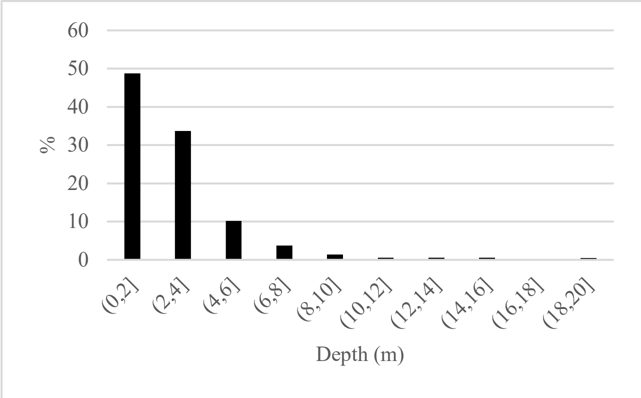


Figure 27. Distribution of sewer depths

Statistically significant slopes for pipe depth are shown in Column 4 of Table 26. No defects had a significant slope at 5% confidence level, but gas attack and infiltration were significant at a 10% confidence level. While the slope for infiltration is positive indicating an increase in infiltration prevalence of 1.7% per meter depth, the slope for gas attack is negative with prevalence decreasing by 2.93% per meter depth. The positive correlation with infiltration may be explained by the higher probability of the groundwater level being in the vicinity of deeper sewers. The negative correlation between gas attack and depth may be due to the higher infiltration rate which dilute the sewage and increases flow rate and reducing the release of hydrogen sulphide from the sewage.

Many studies reported the effect of depth on overall pipe condition. Khan et al. (2010) found pipe depth as a significant variable with a positive correlation to the overall pipe condition. They attributed this to the greater dead load on deeper pipes and higher probability of encountering the groundwater table. However, Mohammadi (2019) stated that generally shallower pipes have higher deterioration rates since they are more prone to surface loads like traffic loads, illegal connections, and tree root intrusion. Laakso et al. (2018) reported that pipes with depth installation between 2 and 3 m had comparatively the best condition. Finally, in a few studies, no significant relationship between depth variable and condition score was reported (Ana et al., 2009; Davies, Clarke, Whiter, Cunningham, et al., 2001). There is no strong indication of consistent effect of pipe depth on the condition of sewers from the literature review. In addition, the dataset showed pipe depth was only significant at p-value of 10% for gas attack and infiltration.

4.5.1.5 Length

The distribution of lengths of the transmission sewer pipes grouped in 50 m intervals is shown in Figure 28. Most pipes are below 100 m in length and the longest pipe has a length of 950 m.

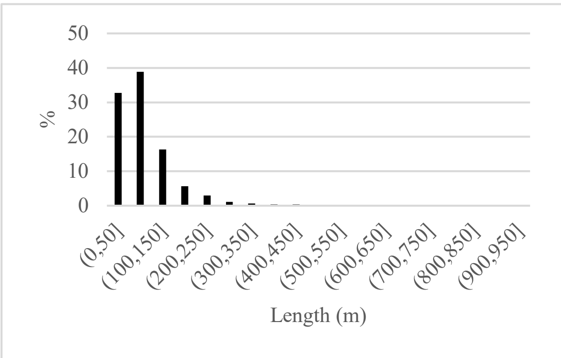


Figure 28. Distribution of sewer lengths

As shown in Column 5 of Table 26, the slopes of four defect categories (gas attack, structural, infiltration, and roots) with pipe length were statistically significant at a 5% level. The slopes are positive and small, except for roots, which has a negative slope. The slope for material damage is significant at the 10% level, showing a small positive correlation.

The positive slopes of gas attack, structural, material damage and infiltration align with what can be expected, as longer pipes have more surface area and joints. Since joints are a significant location for material damage, infiltration, and exfiltration, the probability of failure increases with the number of joints (Ana et al., 2009; Khan et al., 2010). In addition, longer pipes are more prone to blockages and sediment deposition, which will contribute to sewer pipe deterioration (Ana et al., 2009).

On the other hand, Jeong et al. (2005) reported longer sewer pipes are less likely to deteriorate than shorter ones. The reason was attributed to the fact that longer pipes have fewer bends in which less debris can be accumulated, leading to fewer blockages.

Interestingly, the trend for roots, which is also significant, is negative and reducing at 0.03% per meter length. Referring to the determined positive correlation coefficient between length and depth (0.16), it may be interpreted that as the pipe length increases, the pipe depth also increases. And consequently, deeper depths decrease the possibility of tree roots reaching to the pipe.

4.5.1.6 Slope

Figure 29 shows the distribution of pipe slopes in the study sample in 3% slope intervals. It is clear from the figure that most pipes have small slopes with more than half of the pipes having a slope below 3%.

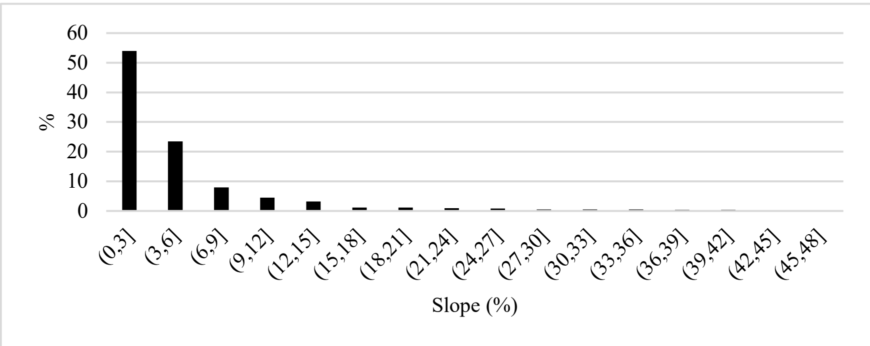


Figure 29. Distribution of sewer slopes

As shown in Column 6 of Table 26, the slope for four defect categories (gas attack, material damage, structural, and dipped pipe) were found to be significant and negative, showing a decrease in defect prevalence of between 0.45% and 1.5 % per percentage slope increase. These trends may be due to higher velocities and thus shorter sewage retention time in pipes with higher slopes. It may also be that the pipe slope is correlated with the location of the pipe in the network, for example slopes may be higher for pipes which are further away from the wastewater treatment plants, corresponding to lower sewage age. These results align with Tscheikner-Gratl et al.'s (2014), who found that pipes with steeper slopes deteriorate at a slower rate.

On the other hand, some researchers found a positive relationship between deterioration rate and pipe slope. Reasons for this finding include higher flow velocities, lower pipe stability, development of voids in the soil, soil movements and the higher prevalence of pipe joint defects (Jeong et al., 2005; Salman & Salem, 2012; Tran et al., 2006).

Finally, while Laakso et al. 2018 reported more debris accumulation on pipes with smaller slopes due to the inadequate rinsing of sewers, no significant correlation between debris and slope was found in this study.

4.5.1.7 Groundwater

The groundwater level was calculated as the difference between the documented absolute groundwater level and pipe depth, and was grouped using 2-meter intervals. A positive groundwater level represents the height of the groundwater above the pipe, and a negative groundwater level indicates the height of groundwater below the pipe. As can be seen from the Figure 30, more than half of the sewer pipes are located below the groundwater level.

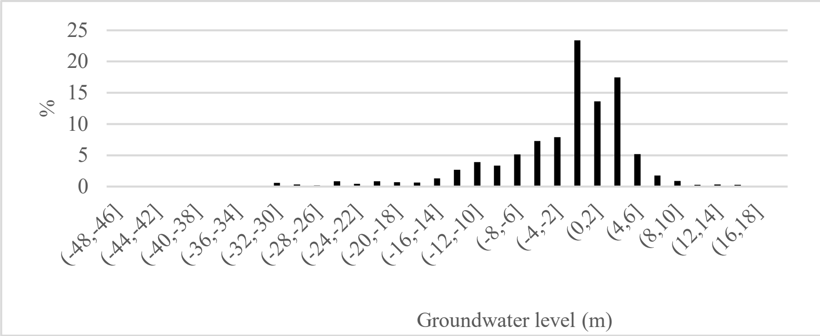


Figure 30. Distribution of groundwater levels

Statistically significant slopes were observed for three defect categories: debris, gas attack, and total joint. While the slope for total joint defect is positive (increasing 0.48% per meter groundwater level), the slopes for debris and gas attack are negative (decreasing around 1.2% per meter groundwater level).

The positive correlation between total joint defects and groundwater level has been confirmed by other studies and may be due to the presence of groundwater facilitating structural deterioration. Davies et al. (2001) noted that groundwater around the pipe can cause loss of soil support and infiltration via cracks or openings. Malekmohamadi (2019) also found a positive correlation between structural deterioration and groundwater level, explaining that a higher groundwater level increases the total structural load on the pipe, leading to soil movement and structural pipe deterioration and subsequently infiltration via structural defects.

The significant negative correlation of debris and gas attack with groundwater level may result from the greater infiltration at higher groundwater levels, increasing flow velocities and diluting the sewage. High sewage velocities will result in a better carrying of debris and dilution of the sewage lead to slowing down of the corrosion process.

4.5.1.8 Other Factors

The impact of two other factors, population density and soil liquefaction susceptibility, on defects were investigated. Population density was measured as the number of people per square kilometer and grouped in 1000 people categories. Liquefaction susceptibility has the potential to cause serious failures after an earthquake due to the lateral ground movement and vertical settlements. This variable was grouped into five severity categories based on the location of each sewer pipe

Statistically significant correlations for population density are provided in Columns 8 of Table 26. Population density displayed negative correlations with gas attack, infiltration, structural, and dipped pipe, which may be due to the better rehabilitation and replacement of the sewer networks in areas with high population density.

Regarding liquefaction susceptibility, mixed results were observed. While four defects (material damage, gas attack, debris, and dipped pipe) had the highest numbers in the high liquefaction susceptibility range, other defects had the lowest number in the same range, therefore, no consistent trend was evident.

4.6 Discussion

The linear regression slopes of the various relationships investigated were normalized by multiplying them by the standard deviation of each data set to allow them to be compared on the same scale. Figure 31 provides a summary of all statistically significant normalized slopes between defects and factors.

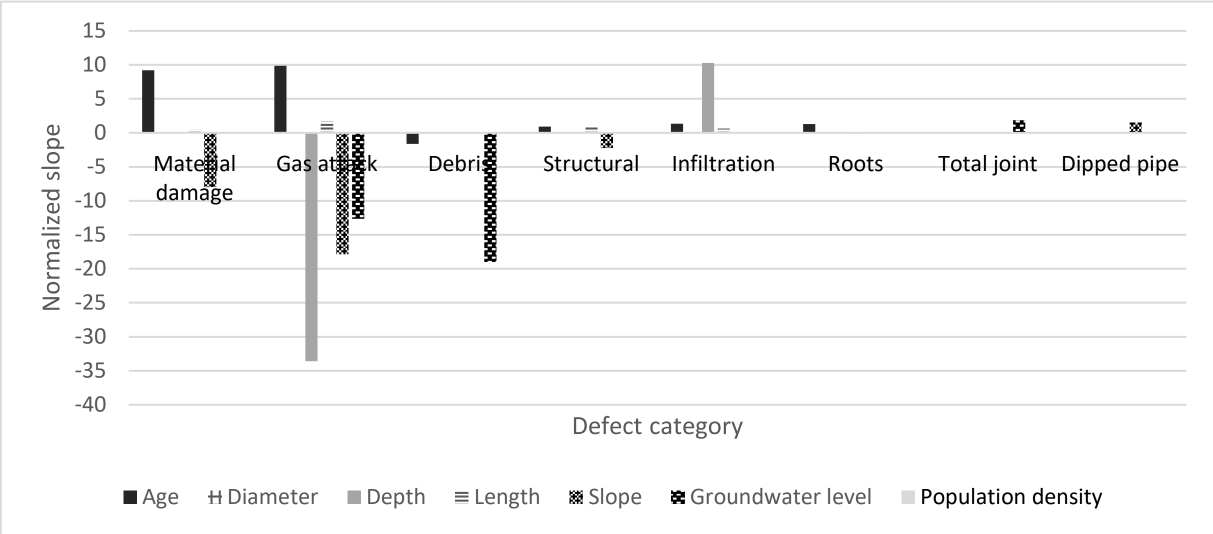


Figure 31. Statistically significant normalized slopes calculated from linear regression results between continuous numeric variables and studied defects

It is clear from the figure there are a few factors that have greatest impact on pipe deterioration. These factors, in order of impact size, are as follows:

- Pipe depth negatively affecting gas attack and positively affect infiltration
- Groundwater level negatively affecting both debris and gas attack
- Pipe age positively affect both material damage and gas attack
- Slope negatively affecting both gas attack and material damage

Considering the normalized regression slopes in the context of the correlation and individual factor analyses, the following main conclusions can be made for the Auckland transmission sewer system:

- EW is clearly the worst performing of all pipe materials, being the oldest pipes in the network and having one of the highest prevalence for virtually all defect categories.
- As expected, gas attack is shown to chiefly affect RC and RCRRJ sewer pipes, and for these pipes is also the most pronounced defect. However, the data also shows that gas

attack is markedly reduced by increasing pipe depths and higher groundwater levels. Both these factors will increase groundwater infiltration, thus diluting the sewage and reducing the release of hydrogen sulfide (pipe depth is positively correlated with infiltration and it is logical that a higher water table will also increase infiltration).

- Debris are markedly decreased by increasing groundwater levels, probably due to the higher infiltration and corresponding higher flow velocities facilitating the removal of debris. Debris are also significantly more prevalent in PE than other pipe materials. This may be due to PE being commonly used in smaller diameters and newer areas, with its combination of construction activities and fewer connections (and thus lower flow rates), as well as lower infiltration rates as a result of fewer joints and better structural condition.
- Infiltration was mostly observed in EW and CIP pipes, which are not only the oldest materials in the Auckland system with the greatest prevalence of both structural and joint defects. To reduce infiltration in the network, it is recommended that refurbishment efforts are focused on EW and CIP pipes with high depths or in areas with high-water tables.
- Finally, material damage similarly affects all materials (prevalent on between 30 and 50% of pipes), except for Others with low, and PE with very low incidences. These are also the two youngest pipe materials in the system and their better performance may be explained by the strong impact of age on material damage.

4.7 Chapter Summary

This chapter investigated how a range of factors, including age, diameter, material, depth, length, slope, groundwater level, population density, and liquefaction susceptibility, affects the prevalence of various defect categories in the transmission sewer network of Auckland, New

Zealand. Defects were grouped into eight categories: material damage, gas attack, debris, structural, infiltration, roots, total joint, and dipped pipe. Correlations between different factors and defects were analyzed respectively, followed by an investigation of the impact of different factors on each defect category and finally a comparison of the normalized linear regression slopes for statistically significant relationships.

The results identified the main impacts on the prevalence of various defects to be as follows (in order of decreasing importance): pipe depth, groundwater level, pipe age, and pipe slope. The strongest positive relationships were observed between pipe depth and infiltration, and between pipe age and material damage and gas attack. The strongest negative relationships were observed between groundwater level and debris and gas attack, and between pipe slope and material damage and gas attack. Several smaller, but statistically significant impacts between factors and defect categories were also identified and quantified.

The results of this chapter show the potential for CCTV inspection data to provide insight into the impact of a range of factors on specific aspects of sewer pipe deterioration. While the pipe condition score gives a good overall estimate of the pipe condition, the underlying defect data can provide more detail of specific deterioration processes and the factors influencing them. These insights, in turn, can support better sewer pipe design, maintenance and lifecycle management. Finally, the results of this chapter are specific to Auckland's transmission sewer network and cannot be generalized to other networks. More studies are required to understand the performance of different systems and identify common trends.

5 MODELLING DEFECTS IN SEWER PIPES

5.1 Introduction

The previous chapter described the sewer dataset, data cleaning procedures and individual deterministic analysis of the acquired dataset for all defect categories. This chapter deals with the details of developing multi-parameters statistical and artificial intelligence models in order to study the relationship between various factors and each defect category.

Two models, including binary logistic regression and gradient boosting trees, were developed as statistical and artificial intelligence models, respectively. These models were selected based on several reasons, such as the performance to predict categorical outcomes, the capability to be trained by nominal and categorical variables, and the comprehensibility of achieved results.

The binary logistic regression, as the statistical model developed in this dissertation is the most used model for predicting categorical dependent variables based on numerical and categorical independent variables (Hosmer et al., 2013). Significant variables influencing the deterioration of sewer pipes can be determined by the development of binary logistic regression.

Gradient boosting trees as an artificial intelligence model is also applied in this chapter. Boosting is one of the most robust learning techniques presented for classification problems in terms of providing support handling categorical features, training faster, especially on larger datasets, and generally being more accurate compared to other models. Gradient boosting is a machine learning technique that can combine weak learners to predict and simulate a single strong learner (Hastie et al., 2017). By developing this model, the prevalence of each defect in sewer pipes and important variables influencing each defect can be predicted and determined, respectively.

In this chapter, the first binary logistic regression model and the gradient boosting trees model are described, developed, and discussed. In addition, the influence of independent variables on the prevalence of each defect category is reported. Finally, overall findings are discussed.

5.2 Binary Logistic regression

In this section, the binary logistic regression method is applied to develop a statistical prediction model. The model is theoretically described, also the details of the development of the model are reported, and finally, summary and results are presented.

5.2.1 Theoretical overview

Logistic models are used to analyse the relationship between multiple independent variables and categorical dependent variables (Hosmer et al., 2013). The probability of occurrence of an event can be estimated by fitting data to a logistic curve. Dependent variable Y might either be binary (only two categories, usually success/fail) or multinomial (several categories). In both cases, the independent variables x_i might be categorical or continuous (Belsley et al., 2005).

If P is the probability of success for a given value of X, the odds of success vs. failure at any value for X is P/(1-P). For instance, if the probability of success is 0.9, then the odds of success is 0.9/1-0.9=9 (Kleinbaum et al., 2002).

The odds ratio is defined as the ratio of the odds of an event occurring in the presence of a variable (X=1) to the odds of the event occurring in the absence of the variable (X=0). An odds ratio of 1, means the occurrence of the event is the same in the presence or the absence of the variable. An odds ratio greater than one shows that the event occurring is associated with the presence of the variable rather than the absence of that. Unlikely, if the Odds ratio is less than

1, showing that the occurrence of the event is negatively associated with the presence of the variable (X=1) (Hosmer et al., 2013).

$$Odds\ ratio = \frac{ODDS_{The\ event\ occuring\ in\ the\ presence\ of\ the\ variable(X=1)}}{ODDS_{\ The\ event\ occuring\ in\ the\ absence\ of\ the\ variable(X=0)}} = \frac{\frac{P_{X=1}}{1-P_{\ X=1}}}{\frac{P_{X=0}}{1-P_{\ X=0}}}$$

The natural log of this odds ratio is known as logit (P)

Logit(P) = ln [odds ratio]

The logistic regression model form for predicted probabilities is expressed as the natural logarithm (ln) of the odds ratio. In other words, the odds ratio is the result of logistic regression analysis, which is able to estimate the probability of success over the probability of failure (Hosmer et al., 2013).

$$ln\left[\frac{P(Y)}{1-P(Y)}\right] = b + \alpha_1 x_1 + \alpha_2 x_2 + \cdots \alpha_n x_n \tag{5.1}$$

$$\frac{P(Y)}{1-P(Y)} = e^{b+a_1x_1+a_2x_2+\cdots a_nx_n} \tag{5.2}$$

$$P(Y) = e^{b+a_1x_1+a_2x_2+\cdots a_nx_n} - P(Y)e^{b+a_1x_1+a_2x_2+\cdots a_nx_n} \tag{5.3}$$

$$P(Y) = \frac{e^{b+a_1x_1+a_2x_2+\cdots a_nx_n}}{1+e^{b+a_1x_1+a_2x_2+\cdots a_nx_n}} \tag{5.4}$$

Where:

- Y is the dependent variable
- $x_1, x_2, \ldots, x_n$ are the independent variables
- $a_1, a_2, \ldots, a_n$ are the regression model coefficients
- b is the intercept

In equation 5.4, the probability of Y occurring is related directly to the independent variables through a logistic regression model. Estimating unknown coefficients is the main goal of the regression model. These coefficients indicate the degree of association between each independent variable and the dependent variable Y. The Regression coefficient signifies the expected change in the dependent variable for a one-unit increase in the independent variable, assuming all other independent variables in the model are constant. To achieve the best result, the model needs to include all possible independent variables that can affect the outcome or dependent variable (Belsley et al., 2005).

The dependent variables in this study are the eight specified defect categories, respectively. The binary logistic regression is applied since the number of defects in each category was not enough to build a multinomial logistic regression. Dependent variables were categorized into two levels by classifying pipes without the specified defect in good condition (level 0) and pipes with any number of the specified defect in poor condition (level 1). For instance, when the dependent variable is the total joint defect, then for a pipe, including the specified defect, the binary level is categorized as poor condition. The defect levels considered for binary regression in the study dataset are shown in Table 27.

Figure 32 shows the frequency of each defect in the total number of datasets specified in good and poor conditions by representing them in the binary level of 0 and 1.

Table 27. Pipe condition levels in binary logistic regression

the specified defect levels	Binary levels
Without	0 (good)
With	1 (poor)

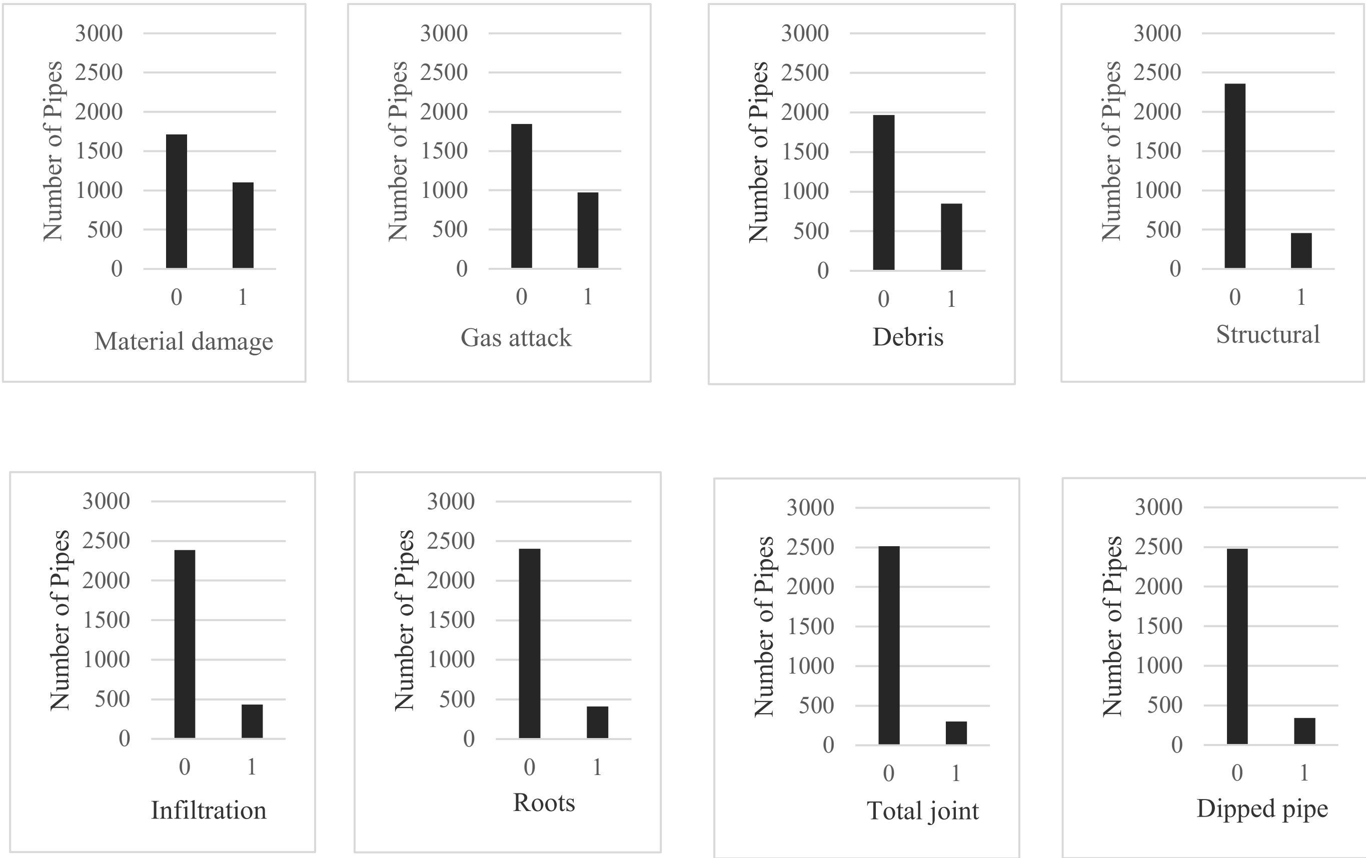


Figure 32. The frequency of binary levels in the dataset

According to the feature of output, which has two levels, one regression equation is developed to predict the specified defect of each pipe as represented in the following equation.

$$
\begin{aligned}
ln\left[\frac{P(Y=1)}{1-P(Y=1)}\right] \\
&= b + \alpha_1 \times \text{Age} + \alpha_2 \times \text{Diameter} + \alpha_3 \times \text{Depth} + \alpha_4 \times \text{Slope} \\
&+ \alpha_5 \times \text{Length} + \alpha_6 \times \text{PD} + \alpha_7 \times \text{GL} + \alpha_8 \times D_{RC} + \alpha_9 \times D_{RCRRJ} \\
&+ \alpha_{10} \times D_{Conc} + \alpha_{11} \times D_{CIP} + \alpha_{12} \times D_{EW} + \alpha_{13} \times D_{PE} + \alpha_{14} \times D_O \\
&+ \alpha_{15} \times LS_{vl} + \alpha_{16} \times LS_l + \alpha_{17} \times LS_M + \alpha_{18} \times LS_H + \alpha_{19} \times LS_{VH}
\end{aligned}
\tag{5.5}
$$

Where b is the intercept, $\alpha_1, \alpha_2, \ldots, \alpha_n$ are regression coefficients, and D_i is a dummy variable to refer various values to categorical independent variables. Table 28 shows the categories of dummy variables used in this study to develop binary logistic regression.

Table 28. Description of dummy variables

Independent variable	Dummy variable	Category
Pipe material	D_{RC}	RC pipes
	D_{RCRRJ}	RCRRJ pipes
	D_{Conc}	Concrete pipes
	D_{CIP}	CIP pipes
	D_{EW}	EW pipes
	D_{PE}	PE pipes
	D_O	Others pipes
Liquefaction susceptibility	LS_{vl}	Liquefaction susceptibility group very low
	LS_l	Liquefaction susceptibility group low
	LS_M	Liquefaction susceptibility group medium
	LS_H	Liquefaction susceptibility group high
	LS_{VH}	Liquefaction susceptibility group very high

80% of the total number from sewer pipes was used for training binary logistic regression, and 20% of the remaining dataset was used to test the accuracy of the developed model. In binary logistic regression which the dependent variable includes two categories, one category is selected as the reference category. For the development of binary logistic regression model in this study, level 0 was used as the reference category.

5.2.1.1 The basics of coefficient estimation

Maximum Likelihood Estimation is used to estimate the regression coefficients in the model. The method of estimating the coefficients and the intercept follows a well-developed theory of maximum likelihood estimation. This theory estimates the unknown coefficients β in a way to maximize the probability of achieving the observed result value (Menard, 2002). The maximum likelihood estimators of independent variables are the value that maximizes the likelihood function of the observed result value, which is the dependent variable. The equation represents the general form of maximum likelihood estimation (Menard, 2002).

$$l(\beta) = \prod_{i=1}^{n} \pi(x_i)^{y_i}[1 - \pi(x_i)]^{n_i - y_i} \tag{5.6}$$

Where:

n_i is total number of observations

β is coefficient parameters

y_i is number of success

And n is total number of observations

After estimating the coefficients, the main concern will be assessing the significance of the variables in the fitted model. Determining the significance of independent variables in the model is the formulation and testing of a statistical hypothesis that can ascertain whether the independent variables are significantly related to the result variable (Hosmer et al., 2013).

5.2.1.2 The significance of independent variables

The significance of independent variables can be determined through the log-likelihood test, Wald-test, and P-test (Kleinbaum et al., 2002). The log-likelihood function is used in the log-likelihood test to compare the observed and predicted values. Log-likelihood function is as follows:

$$G = -2\ln\left[\frac{likelihood\ without\ the\ variable}{likelihood\ with\ the\ variable}\right]$$

$$G = 2\{\sum_{i=1}^{n}[y_i \ln \pi\ (x_i) + (1 - y_i)\ln(1 - \pi(x_i)] - [\,n_1 \ln(n_1) + \ n_0 \ln(n_0) - n \ln\ (n)]\} \qquad 5.7$$

Where: $n_1 = \sum y_i$ and $n_0 = \sum(1 - y_i)$ (Harrell, 2001).

Also, the Wald test can be used to determine the significance of variables in the logistic regression model. Wald test is the ratio of maximum likelihood estimate and the standard error shown as follows:

$$w_j = \left(\frac{\beta_j}{SE(\beta_J)}\right) \qquad 5.8$$

Where:

(β_J) is the coefficient of the predictor variable and SE is the standard error of the coefficient.

While a Wald test of zero for an independent variable shows that the variable is insignificant and can be removed from the model, the non-zero Wald test shows the variable is significant and should be included in the model (Hosmer et al., 2013).

P-test is the most common method used to determine the significance of independent variables.

In this study, for determining the significance of independent variables, Wald-test and P-test are used with a significance level of 0.05.

The significance level is the probability of rejecting the null hypothesis when it is true. If the p-value for a variable is less than the considered significance level, the sample data provide adequate evidence to reject the null hypothesis for the entire population i.e., there is a non-zero correlation (Dahiru, 2008).

Backward and forward stepwise selection methods are applied to select the significance of the independent variables. These methods are statistically developed to keep the variables powerfully affecting the dependent variable and remove the remained variables. Forward stepwise selection begins with a model that includes no variables (called the Null model), and then the most significant variables are added in order. Whereas the backward stepwise selection method begins with all independent variables, and then the insignificant variables that have the least effect on the outcome are removed from the model (Hastie et al., 2017).

For each studied defect, a binary logistic regression model was developed. Seven numerical variables are used to develop the first binary logistic regression model, including age, diameter, depth, slope, length, groundwater level, and population density are used. Two variables, including liquefaction susceptibility and pipe material, are categorized as dummy variables. A dummy variable is one that takes only the value of 0 or 1 to show the absence or presence of a category of a categorical independent variable.

5.2.1.3 The significance of model

For investigating the significance of the developed binary regression model, the Chi-square test is used, that is calculated by equations 5.9 and 5.10.

Deviance = -2× log-Likelihood (LL) 5.9

Chi-square = (($Deviance_{null}$)) - (($Deviance_{current}$)) = $2LL_{current}$- $2LL_{null}$ 5.10

Where $LL_{current}$ is the log-likelihood of the final model with all independent variables, and $2LL_{null}$ is the log-likelihood of the model without considering any independent variables.

As shown in equation 5.10, the Chi-square test estimates the difference of doubled log-likelihood of the model, including all independent variables, and the doubled log-likelihood model without any coefficients that are called null.

Also, Akaik Information Criteria (AIC) is used to compare the accuracy of different models calculated by equation 5.11.

AIC = -2× log-Likelihood (LL) + 2K 5.11

Where K is the number of predictor variables.

For representing the percentage of correct predictions by the logistic regression models, the classification table is utilized. This table compares the predicted values of the outcome (success/failure) based on the fitted logistic regression models to the real values in the dataset.

For achieving the classification table, considering a cut-off point is necessary. The cut-off point is the point that will be considered the border between success and failure. The cut-off point of 0.5 is considered due to the common usage in similar studies, and it is compared to each computed probability (Hosmer et al., 2013).

While a calculated probability higher than the cut-off point is considered a success, a calculated probability less than the cut-off point is signified as failure (Hosmer et al., 2013).

5.2.2 Binary logistic regression in sewer deterioration modelling

Binary logistic regression has been used in different studies concerning modelling the deterioration of sewer pipelines, considering the condition score as the dependent variable. Davies et al. (2001) developed a binary logistic regression analysis to develop a prediction model and identify the factors that have the most effect on the structural sewer condition. The sewer condition as the dependent variable was categorized into two nominal levels, including poor and good conditions. In the first step, 18 independent factors were considered, then through stepwise forward and backward methods ten factors, including debris, pipe length, pipe size, sewer use, soil fracture potential, soil corrosivity, sewer location code, groundwater regime, sewer material, and flow were used to develop the model. The results showed that seven out of ten factors were determined as significant, which means they can influence the structural deterioration of sewer pipes. These factors include physical factors such as pipe material, diameter, and length; operational factors such as sewer type; and environmental factors such as location, groundwater level, and soil corrosivity.

Ana et al. (2009) developed a binary logistic regression to study the effect of physical sewer features on structural deterioration. Results showed that out of 10 independent variables considered, three of them, including age, material, and length, were significantly affecting the structural deterioration of sewer pipes. The main deficiency of these two studies was that the accuracy of the model was not mentioned, and merely a p-test was used to ascertain the significance of independent variables.

Fuchs-Hanusch et al. (2015) developed binary logistic regression in order to predict the condition of individual sewers in order to support a decision on inspection frequencies and priorities. It was reported five independent variables, including material, length, width, vintage, and profile type, out of total 8 variables considered, were significant. A cross-validation process was used to achieve accurate prediction of sewer failure.

5.2.3 Developing binary logistic regression models

This section represents the details of developing the binary logistic regression model as a statistical model for all defect categories. In this section, a procedure regarding developing the binary logistic regression model and details like training and testing of the model is described. This is only done for the material damage defect category. The same procedure was applied for the rest of the defect categories; however, to shorten the chapter and avoid repetitions, the whole developed models for all defect categories are reported in Appendix B.

For the development of the binary logistic regression model, the static package R with an application of the computing library of "glm" was used.

5.2.3.1 Material damage

As described, 80% of the data was utilized for training the binary logistic regression by static package R. The first binary logistic regression model was developed for the material damage defect category. In logistic regression, if the dependent variable includes N categories, one of the categories is selected as the reference category. For the development of binary logistic regression in this study, level 0 for the material damage defect was selected as the reference category. Pipe age, diameter, depth, length, slope, groundwater, population density, and liquefaction susceptibility were selected as independent variables to develop binary logistic regression.

Maximum Likelihood Estimation was used to estimate the coefficient of independent variables in the model. The significance of the independent variables was specified by Wald test and P-test with a confidence interval of 95%.

A backward stepwise variable selection method was utilized to identify the independent variables that have more predictive power to predict the prevalence of material damage defect of sewer pipes. In this method, a full model started by considering all nine independent variables and then the variables representing the least influence were excluded from the model. The independent variables with the highest P-value were nominated for exclusion from the model. The procedure of removing independent variables continues until the lowest Chi-square is achieved.

The first model was applied with the presence of all independent variables. The regression coefficient of independent variables for the first developed model is shown in Table 29. Also, standard deviation error, Wald test and P-value are reported in order to represent the degree of significance of each independent variable coefficient. The significance of the independent variables was reported by P-value with a confidence interval of 95%.

Three of the variables by P-value less than 0.05 are determined as significant. According to Table 29, two variables, including age and length, which are numerical variables, were identified as significant. In pipe material, which is a categorical variable, all materials, apart from earthenware and RCRRJ, were determined as significant with a P-value less than 0.05.

Table 29. Regression coefficients and their features of binary logistic regression model for material damage

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-1.226e+00	3.086e-01	-3.973	0.000
Age	6.081e-03	2.353e-03	2.584	0.009

Diameter	-1.085e-05	1.067e-04	0.102	0.919
Depth	-3.518e-02	2.061e-02	-1.707	0.087
Length	2.163e-03	5.799e-04	3.730	0.000
Slope	-1.324e-02	8.043e-03	-1.646	0.099
Groundwater level	2.326e-04	6.196e-03	0.038	0.970
Population Density	-1.957e-06	1.582e-05	0.124	0.901
Liquefaction Susceptibility (High) (Reference)	0	-	-	-
Liquefaction Susceptibility (low)	-5.965e-03	5.379e-01	-0.011	0.991
Liquefaction Susceptibility (Moderate)	-9.240e-02	1.036e-01	-0.892	0.372
Liquefaction Susceptibility (Very High)	-1.368e+01	2.643e+02	-0.052	0.958
Liquefaction Susceptibility (Very low)	3.936e-01	2.390e-01	1.647	0.099
Material-factor CIP (Reference)	0	-	-	-
Material-factor (Conc)	6.665e-01	2.237e-01	2.979	0.002
Material-factor (EW)	3.968e-01	3.158e-01	1.257	0.208
Material factor (OTHERS)	-6.506e-01	2.884e-01	-2.256	0.024
Material-factor (PE)	-1.852e+00	4.881e-01	-3.794	0.000
Material-factor (RC)	8.398e-01	2.161e-01	3.886	0.000
Material-factor (RCRRJ)	3.415e-01	2.268e-01	1.506	0.132

Table 30. Accuracy of binary logistic regression for material damage

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	3723		2777		
Current model	3496	227	2760	0.000	3532

In the next step, variables with a high P-score (higher than 0.05) are removed through a few backward stepwise selection procedures and achieving the lowest Chi-square.

Table 31 represents the coefficients of significant variables of the binary logistic regression model after removing insignificant variables and implementing a few backward stepwise selection procedures.

As represented in Table 31, slope, length, population density, and material are determined as significant variables.

Table 31. Regression coefficients and their features after backward stepwise method in the binary logistic regression model for material damage

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-4.982e-01	2.217e-01	-2.247	0.024
Slope	-2.085e-02	8.952e-03	-2.329	0.019
Length	1.768e-03	6.124e-04	2.888	0.003
Population density	-4.159e-05	1.378e-05	-3.017	0.002
Material-Conc	9.755e-01	2.498e-01	3.905	0.000
Material-PE	-1.935e+00	5.377e-01	-3.598	0.000
Material-RC	7.147e-01	2.331e-01	3.066	0.002

The significance of the binary logistic regression model was determined based on the Chi-square test. This test estimates the difference of doubled log-likelihood of the model, including all independent variables, and the model without any coefficients that are called null.

The significance values of the current binary regression model are shown in Table 32. According to the table and comparing Chi-square values, the current model with three independent variables surpasses the first binary model. As represented in Table 32, the significance level of the model is less than 0.05; therefore, our current model surpasses the null model.

Table 32. Accuracy of binary logistic regression after the backward stepwise method for material damage

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	2018		1480		
Current model	1901	117	1474	0.000	1915

5.2.3.1.1 Confusion Matrix

The confusion matrix is useful in representing the number of correct and incorrect samples that are predicted per class. In the confusion matrix, the actual class of each sample in the test dataset is compared to the predicted class obtained from the trained classifier. The confusion matrix is shown in Table 33. While true positive and true negative (TP/TN) represents the number of samples that are predicted correctly, false positive and false negative (FP/FN) shows the number of samples that are predicted incorrectly.

Table 33. Confusion Matrix

	Predicted positive	Predicted Negative
Actual Positive Sample (P)	True positive (TP)	False negative (FN)
Actual Negative Sample (N)	False positive (FP)	True negative (TN)

Based on the confusion matrix, below performance measurements can be calculated (O. Maimon et al., 2010):

True positive rate also called as sensitivity: (TP) / (FN+TP)

False positive rate: (FP) / (TN+FP)

True negative rate also called as specificity: (TN) / (TN+FP)

False negative rate: (FN) / (FN+TP)

Accuracy: (TN+TP) / (TP+FN+FP+TN)

The actual values and predicted values for the final binary logistic regression developed for material damage defect category are illustrated in Table 34.

Table 34. Accuracy of binary logistic regression after the backward stepwise method for material damage

Actual values	**Predicted values**		**Accuracy**
	0	1	
0	176	43	59%
1	111	51	

Table 39 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 35. Binary logistic regression model performance for material damage

Rates	Values
True positive rate (TPR)	80%
False positive rate (FPR)	68%
True negative rate (TNR)	31%
False negative rate (FNR)	20%

5.2.4 Summary and Results

The details for developing binary logistic regression models for the material damage defect category are reported in this chapter. The same procedure was implemented for other defect categories, and all detail tables are available in Appendix B.

In this section, the archived results from all developed binary logistic regression models are summarized in Table 37. The table represents the coefficient estimation (α) of significant independent variables achieved from all binary logistic regression models.

Table 36. Summary of coefficient estimation (α) of significant independent variables in all binary logistic regression models

Independent variable	**Dependent variable**							
	Material damage	Gas attack	Debris	Structural	Infiltration	Roots	Total joint	Dipped pipe
Intercept	-0.4982	-4.3710	-0.0807	-1.8791	-1.676	-2.9810	-0.8814	0.7486
Age	-	-	-	0.0167	0.0079	0.0245	-	-
Diameter	-	-	-0.0005	-	-	-0.0009	-0.0007	-0.0026
Depth	-	-	-	-	0.0388*	-	-	-
Length	0.0017	0.0015	0.0011	0.0018	0.0027	-	0.0021	0.0029
Slope	-0.0208	-	-	-	-	-	-	-0.0633
Groundwater level	-	-0.025	-0.0213	-	-	-	0.0490	0.0774
Population Density	-0.0001	0.0005	0.0004	-	-	0.0001	0.0001	-0.0001
Liquefaction Susceptibility (low)	-	-	-	-	-	-	-	-

Liquefaction Susceptibility (Moderate)	-	-	-	-	-	-	-	-
Liquefaction Susceptibility (High)-(Reference)	-	-	-	-	-	-	-	-
Liquefaction Susceptibility (Very High)	-	-	-	-	-	-	-	-
Liquefaction Susceptibility (Very low)	-	-	-	-	-	-	-	-
Material-factor CIP (Reference)	-	-	-	-	-	-	-	-
Material-factor (Conc)	0.9755	-0. 961	-	-	-1.6048	-	-2.0636	-
Material-factor (EW)	-	-	-	1.6519	-	-	-	-
Material factor (OTHERS)	-	-	-	-	-1.4091	-	-1.4240	-
Material-factor (PE)	-1.935	-2.5480	-	-2.8304	-2.3728	-	-2.8484	-
Material-factor (RC)	0.7147	1.8140	-	-1.1452	-1.3946	-	-2.1606	-
Material-factor (RCRRJ)	-	2.4960	-	-0.9615	-1.3609	-	-1.2395	-

For better illustration and in order to make the comparison of coefficients easier, Figure 33 shows a summary of coefficient estimation (α) of significant numerical independent variables achieved from all developed binary logistic regression models.

It is clear from the figure there are a few factors that have the greatest impact on pipe deterioration. These factors, in order of impact size, are as follows:

- Groundwater level positively affecting dipped pipe and total joint defects and negatively affecting debris
- Slope negatively affecting both material damage and dipped pipe
- Pipe depth positively affecting infiltration

- Pipe age positively affecting structural and roots

While length, population density, and diameter significantly affecting some of the defect categories, their effects were not noticeable in comparison with the above-reported factors.

Figure 34 shows a summary of coefficient estimation (α) of the only significant categorical variable, material, achieved from all developed binary logistic regression models. Considering CIP as the reference material, in order of impact size, the following results are achieved:

- Pipes built from PE are less prone to material damage, gas attack, structural, infiltration, and total joint.
- Pipes built from RC and RCRRJ are more prone to material damage and gas attack defects and less exposed to three defects, including structural, infiltration, and total joint.
- Pipes built from EW are more exposed to structural defects.

Liquefaction susceptibility was another categorical independent variable studied. However, no significant relationship between this variable and any of the defect categories was achieved.

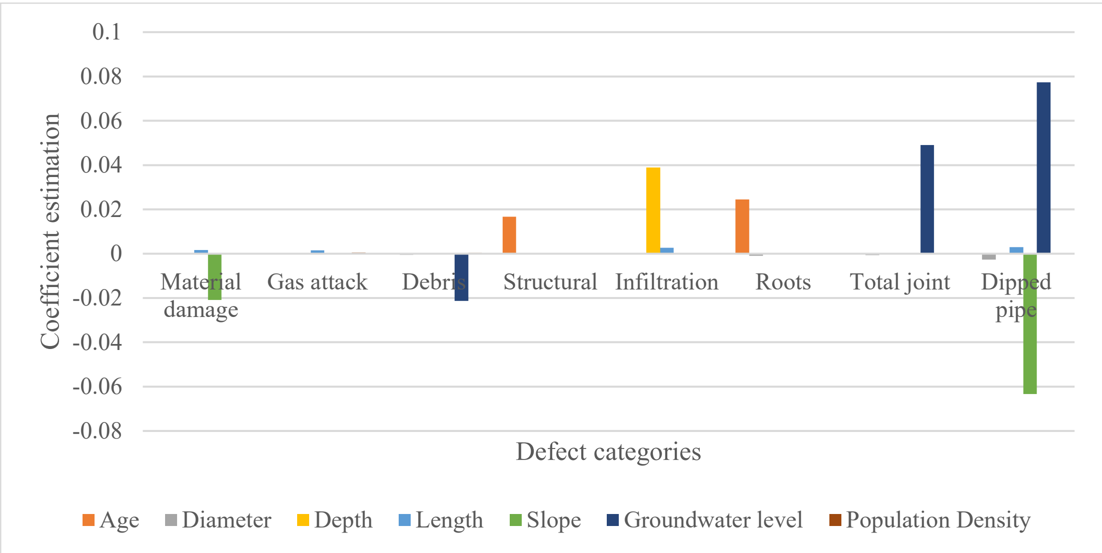


Figure 33. Coefficient estimation (α) of significant numerical independent variables of all developed binary logistic regression models

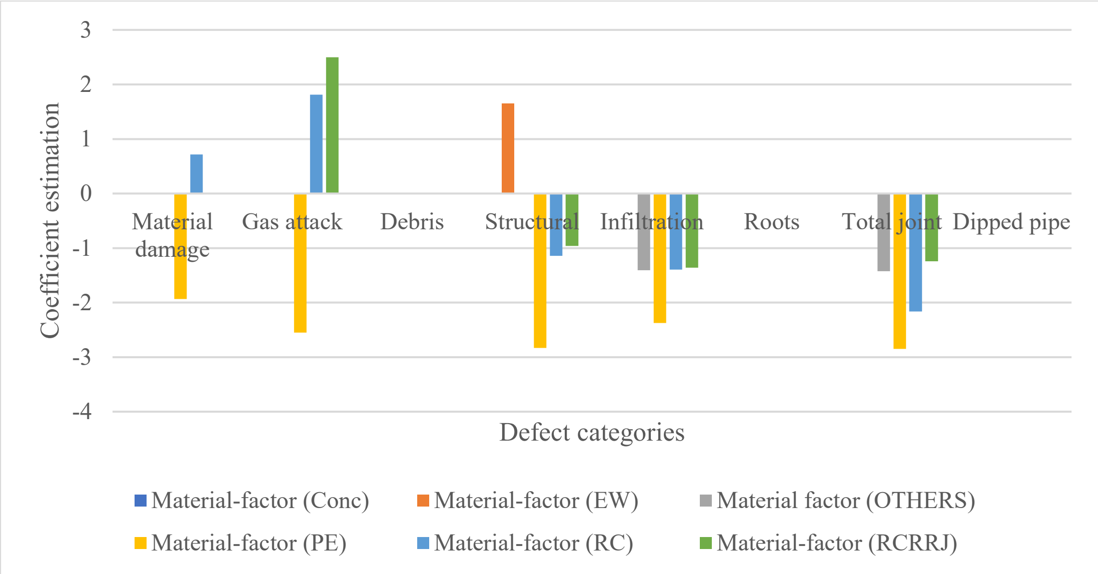


Figure 34. Coefficient estimation (α) of different levels of pipe material achieved from all developed binary logistic regression models, considering CIP as the reference material.

5.3 Gradient Boosting Trees

In this section, the gradient boosting trees model is used to develop a prediction model as an artificial intelligence model. The model is theoretically described; also, the details of the development of the models are reported, and finally, a summary and results are presented.

5.3.1 Theoretical overview

Gradient boosting is a machine learning technique used for classification problems and regressions. In this method, for developing the classifiers, the training dataset is grouped to a number of sub-samples. After a week learner is run repeatedly on sub-samples of the training dataset and all achieved classifiers are combined into a single strong classifier in order to obtain a higher accuracy. In fact, a gradient boosting tree is an ensemble model which can work better than a single prediction model.

The most popular boosting algorithm is AdaBoost.M1 (Freund & Schapire, 1997). Consider an output variable $Y \in \{-1, 1\}$. The error rate upon the training sample can be calculated as follows:

$$\overline{err} = \frac{1}{N}\sum_{i=1}^{N} I\left(y_i \neq G(x_i)\right) \tag{5.12}$$

The error rate of a weak classifier is slightly better than random guessing.

Based on the main goal of boosting, various weak classification algorithms are repeatedly applied in order to modify the versions of the data on all the subsets of training datasets. After producing weak classifiers $G_m(x)$, all of them are combined by weighting them through α_m to produce the final prediction. The AdaBoost.M1 procedure is illustrated in Figure 35.

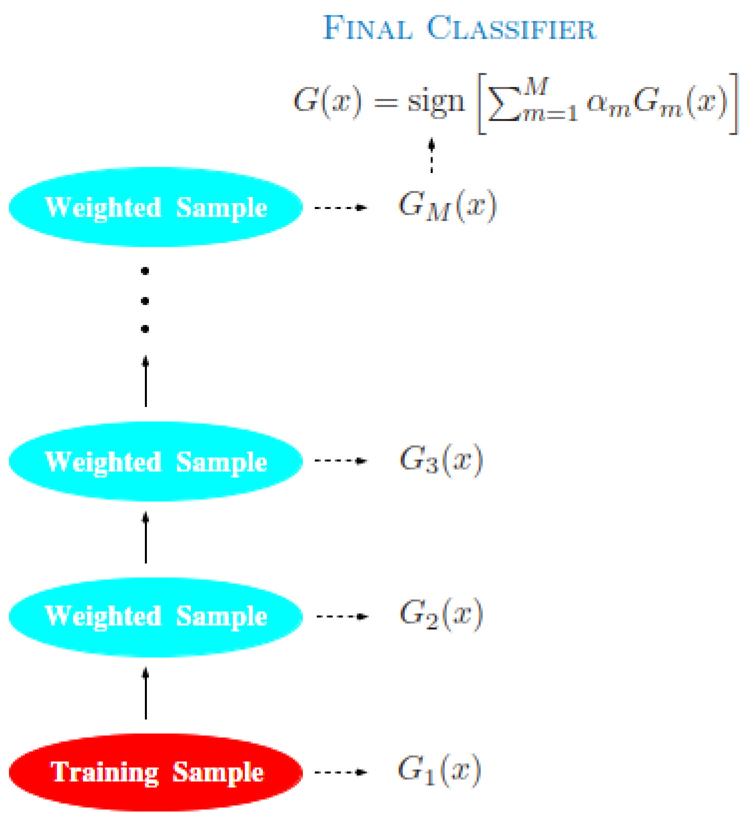


Figure 35. Schematic general of AdaBoost procedure (Hastie et al., 2017)

And the equation is as follows:

$$G(x) = \mathrm{sign}(\sum_{m=1}^{M} \alpha_m G_m(x)) \qquad 5.13$$

Where α_1, α_2, …., α_m are the weight of contribution of classifiers and are computed by the boosting algorithm.

5.3.1.1 Fitting of Gradient Boosting-Tree

Boosting is a method of fitting additive expansions by employing a set of elementary functions (Hastie et al., 2017). Equation 5.14 shows the elementary function expansion form.

$$f(x) = \sum_{m=1}^{M} \beta_m \mathrm{b}(x; \gamma_m) \qquad 5.14$$

Where:

β_m are the expansion coefficients

And $\mathrm{b}(x; \gamma_m)$ are simple functions of the multiple argument x, characterized by a set of parameters γ.

For fitting gradient boosting trees, typically, methods such as the squared error or a likelihood-based function are used. The common feature of mentioned methods is the minimization of the loss function, which is a machine learning approach to assess the performance of the prediction model. While a high value of the loss function shows the low accuracy of the prediction model, a lower value of that indicates a higher accuracy of the model. Hence, minimizing the loss function is a method to enhance the prediction model performance.

Equation 5.15 represents the calculation of minimizing loss function in gradient boosting trees (Hastie et al., 2017).

$$min_{\{\beta_m,\gamma_m\}} \sum_{i=1}^{N} \mathrm{L}\ (y_i, \sum_{m=1}^{M} \beta_m \mathrm{b}(x_i;\gamma_m)) \qquad 5.15$$

5.3.1.2 Importance of independent variables

One of the critical features of the decision trees model is the capability to rank the importance of independent variables. Conventionally, two methods called Mean Decrease Impurity (MDI) and Mean Decrease Accuracy (MDA), are used to estimate the significance of independent variables. MDI method estimates the weighted decrease of impurity from splitting on the independent variable and averaging over all trees (Mohammadi, 2019). Equation 5.16 shows the MDI measuring.

$$MDI(X^{(j)}) = \frac{1}{M}\sum_{l=1}^{M} \sum_{t\epsilon\tau_l}^{M} p_{n,t}L_{class,n}\left(\mathrm{j}_{n,t}^{*}, \mathrm{z}_{n,t}^{*}\right) \qquad 5.16$$

Where:

$p_{n,t}$ is the fraction of observations falling in node t

$\{\tau_l\}_{1\leq l\leq M}$ is the collection of trees in the forest

And $\left(\mathrm{j}_{n,t}^{*}, \mathrm{z}_{n,t}^{*}\right)$ the split that maximizes the empirical criterion in node t

Mean decrease accuracy (MDA) is based on the idea stating that if the variable is not important, then reordering its values should not decrease the accuracy of the prediction model. MDA for a set of variables x= () measures by averaging the difference in out-of-bag error estimation before and after the permutation over all trees. Equation 5.17 shows the mathematical form of MDA.

$$MDA(X^{(j)}) = \frac{1}{M}\sum_{l=1}^{M}[R_n[m_n(.\,;\Theta_l), D_{l,n}^{j}] - R_n[m_n(.\,;\Theta_l), D_{l,n}]\,] \qquad 5.17$$

Where:

$D_{l,n}$ is out-of-bag dataset of lth tree

$D_{l,n}^{j}$ is the same dataset when the values of X (j) variable have been randomly permuted (Biau & Scornet, 2016).

5.3.1.3 Evaluation of Gradient Boosting Tree performance

For estimating the accuracy of the gradient boosting tree model, several methods such as confusion matrix, Receiver Operating characteristic (ROC) curve and Area Under curve (AUC) are used.

5.3.1.3.1 Confusion Matrix

The confusion matrix is previously represented in section 5.2.3.1.1.

5.3.1.3.2 Receiver Operating Characteristic Curve

ROC curve is a standard method for summarizing classifiers' performance based on the true positive percentage or rate (sensitivity) on the Y-axis and false positive rates (specificity) on the X-axis. The Area under ROC curve is called AUC.

A perfect model, including a 100% true positive rate and 0% false negative rate, would have an AUC of 1 and would be the dashed line that passes through the upper left corner of the plot in Figure 36. An unsuccessful model, which is not better than randomly guessing, would have an AUC of 0.5 and is represented by the diagonal line in Figure 36 (Harvey & McBean, 2014; O. Maimon et al., 2010).

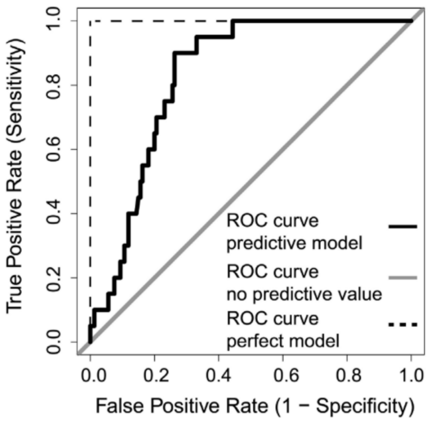


Figure 36. The receiver operating characteristic (ROC) curve (Harvey & McBean, 2014)

Hosmer et al. (2013) provided a general guideline in order to describe the level of discrimination of the model based on the area under the ROC curve, which is represented in Table 37.

Table 37. The level of discrimination of models based on the area under the ROC curve (Hosmer et al., 2013)

Area under the ROC curve range	Level of discrimination
AUC = 0.5	Not acceptable
0.5<AUC< 0.7	Poor
0.7 ≤AUC< 0.8	acceptable
0.8 ≤AUC< 0.9	excellent
AUC≥ 0.9	Outstanding

5.3.2 Gradient Boosting Trees in Sewer Deterioration Modelling

Gradient boosting trees is an ensemble model consisting of several decision trees which have better predictive performance than single trees for developing deterioration models (Harvey & McBean, 2014). The most common methods to generate ensemble classifiers from decision trees are random forest and boosting. The primary difference between these methods lies in how the decision trees are created and aggregated. Unlike random forests, the decision trees in gradient boosting are built additively, i.e., each decision tree is built one after another to improve the overall model. However, in random forests, each decision tree is built and calculated independently. Another key difference between random forests and gradient boosting is how they aggregate their results. While in random forests, the results of decision trees are aggregated at the end of the process, in gradient boosting, results are aggregated for each decision tree along the way to calculate the final result (Krauss et al., 2017).

Overall, gradient boosting performs better than random forests (Elyassami et al., 2020). Random forest is used to develop several deterioration models to predict the condition of sewer pipelines (N. Caradot et al., 2018; Harvey & McBean, 2014; Hernández et al., 2018; Laakso et al., 2018). However, gradient boosting trees have only been used in one study to assess the deterioration of sewer pipelines. Malek Mohammadi. (2019) developed a gradient boosting trees model to develop a prediction model and rank the importance of factors influencing 19,766 sewer pipes in Tampa city. The Sewer condition was considered the dependent variable and categorized into two levels, including poor and good conditions.

The results showed that five out of 13 different independent variables considered are critically important in predicting the overall condition of sewer pipes. These factors include age, material, diameter, length, and water table. In general, older and longer sewers had higher probability of being in poor condition. In addition, water table was another influence variable in the gradient boosting tree model, and sewers are in worse condition when the water table is higher in the surrounding sewers.

Finally, the effect of pipe diameter on pipe condition identified that smaller diameter sewers had more probability of being in poor condition in comparison with larger sewers. Accuracy is defined as the number of classifications a model correctly predicts divided by the total number of predictions made. An overall accuracy of 87.4% was achieved for predicting the condition of sanitary sewer pipes. More specifically, 93 % of sewer pipes in good condition and 71% of sewer pipes in poor condition were predicted correctly, indicating a high accuracy. In addition, the AUC, the area under ROC curve, was 0.93 representing the high reliability of the model.

5.3.3 Developing Gradient Boosting Trees

This section represents the details of developing the gradient boosting tree model as an artificial intelligence model for all defect categories.

For better representation, details like training and testing of the model, besides the degree of influence of studied variables on various dependent defect categories, are reported.

To reduce the risk of uncertainty and overfitting, a five-fold cross-validation method was utilized. In this method, the dataset is divided into two groups of 80% and 20% for training and validation purposes.

Through cross-validation technique, the dataset is divided into K equal size folders during the training and testing of the model. For instance, if there are 100 datasets and five folds, there will be 20 datasets in each folder. To develop gradient boosting tree in this study, a five-fold cross-validation method was considered to randomly select 80% of the dataset for training and 20% for testing of the model.

In five-Fold cross-validation, five separate learning iterations were developed. In each iteration approximately, including 550 datasets with 110 datasets in each folder, one folder was selected as the testing set, and the rest four folders were combined to create the training set. This procedure was repeated in five iterations, and the mean value was determined as the result of the model. Figure 37 represents the detail of the five-Fold cross validation method in a different iteration of the development of the model.

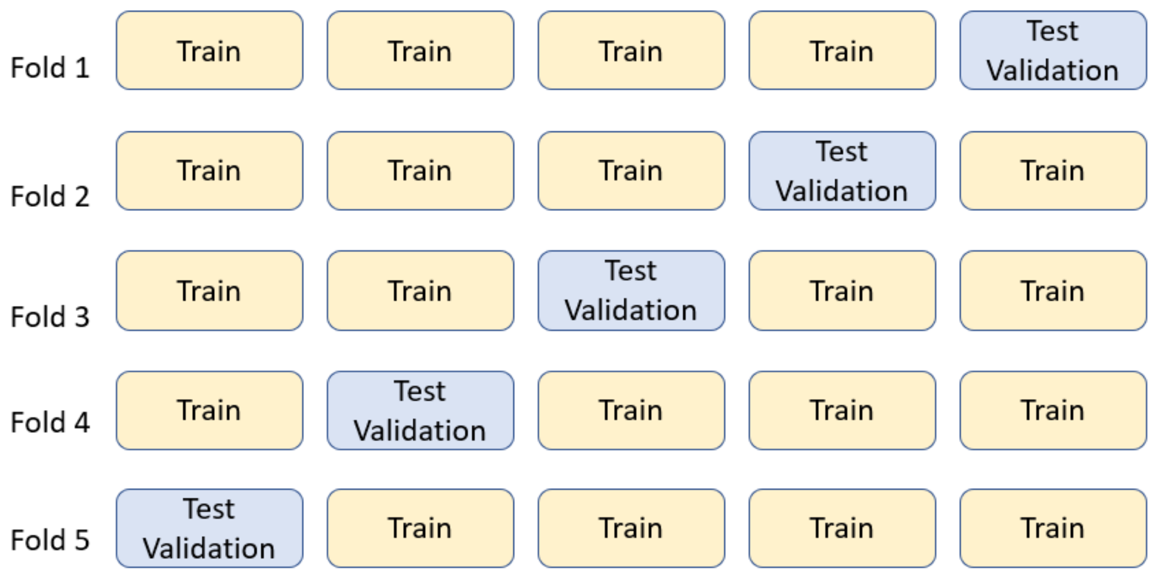


Figure 37. Five-fold cross validation

For the development of the gradient boosting tree model, the static package R with various applicable computing libraries such as “rplot”, “caret”, and “gbm” was used.

The gradient boosting tree technique provides a prediction model by improving the performance of a weak learner by repeating them on different training data to develop classifiers. Followingly, the gathered classifiers are combined into a strong classifier to attain a higher accuracy (O. Z. Maimon & Rokach, 2014).

In the following section, only the gradient boosting tree model for the material damage defect category is discussed in detail, and the same procedure was applied for all other defect categories, and results are provided in Appendix C.

5.3.3.1 Material damage

All details regarding applying and developing the gradient boosting trees model for the material damage defect category were discussed and presented in section 5.3.3. In the following sub-sections, the achieved results from the model are reported.

5.3.3.1.1 Validation of the model

The performance of the gradient boosting tree model was determined using the confusion matrix and ROC curve. The confusion matrix was utilized to represent the number of pipes correctly or incorrectly, including the predicted specific defect categories. In the confusion matrix, the observed or actual class in the test classifier is compared to the predicted class that was achieved by the trained classifier. Table 38 shows the result of the confusion matrix for the gradient boosting tree model developed for the material damage defect category.

Table 38. Gradient boosting tree confusion matrix for material damage

Actual values	**Predicted values**		**Accuracy**
	0	1	
0	279	65	72%
1	86	116	

According to the result of the confusion matrix, overall, 72% Of the material damage prevalence was predicted correctly by the gradient boosting tree model. 81% of pipes with no presence of material damage defects and 57% of pipes with the presence of material damage defects were predicted correctly.

Table 39 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 39. Gradient boosting tree model performance for material damage

Rates	Values
True positive rate (TPR)	81%
False positive rate (FPR)	42%
True negative rate (TNR)	57%
False negative rate (FNR)	18%

Additionally, the performance of the gradient boosting tree model was evaluated by Receiver Operating Characteristic (ROC) curve. ROC curve is based on true positive rate (TPR) and false positive rate (FPR), on the vertical and horizontal axis, respectively. The area under the curve shown with AUC represents the model performance, where AUC close to 1 indicates a perfect prediction, and the AUC close to 0.5 represents a random prediction. Conventionally, AUC greater than 0.7 represents an acceptable model (Hosmer et al., 2013).

Figure 38 shows the ROC curve for the gradient boosting tree model developed for the material damage defect category.

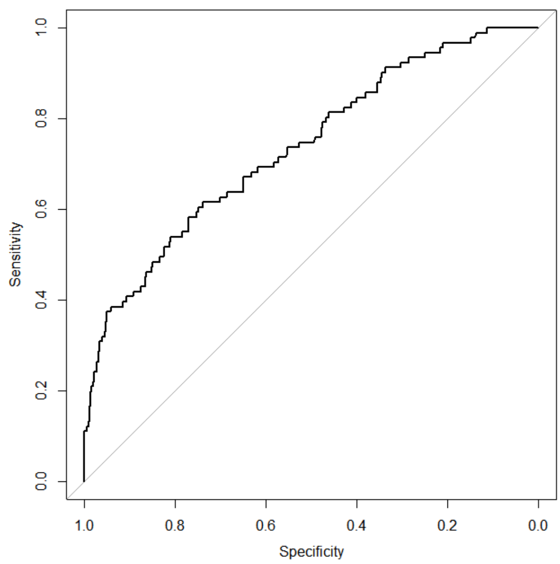


Figure 38.Gradient boosting tree ROC curve

The AUC of ROC curve is 0.78, indicating that gradient boosting tree model results are acceptable and can be used to predict the prevalence of material damage defect of sewer pipes that have not been inspected yet.

5.3.3.1.2 Feature importance

The importance of independent features can be ranked through the gradient boosting tree model.

Feature importance is shown with a score indicating the weight of the independent variable in the implementation of the model. Importance is calculated for each developed tree by the amount that independent variable split points improve the prediction performance of the gradient boosting tree model. Figure 39 shows the feature importance in the gradient boosting tree model for the material damage defect.

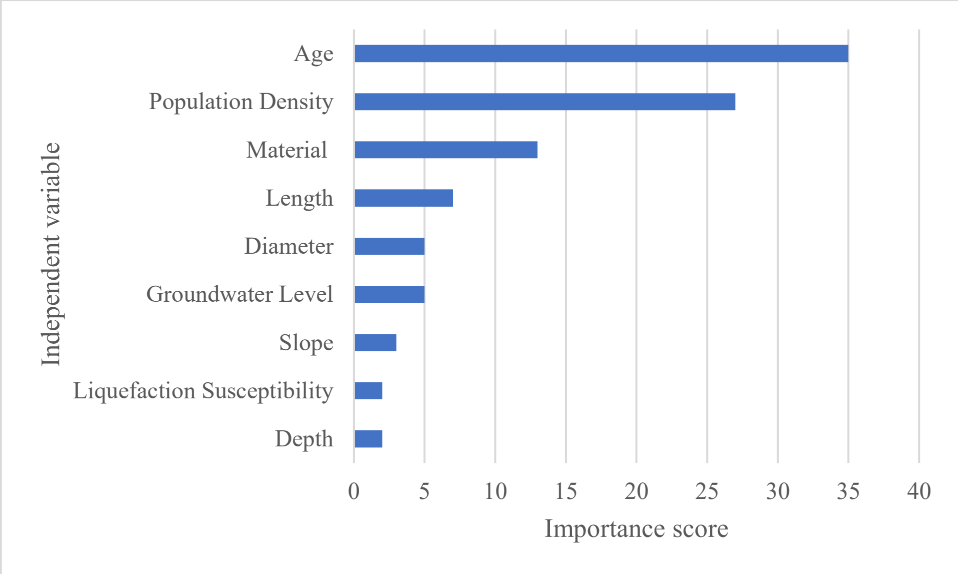


Figure 39. Feature importance in gradient boosting tree model for material damage

According to the results of feature importance, age, population density, material, and length are the most critical independent variable for the prediction of material damage defects in sewer pipes in the Auckland dataset.

5.3.3.1.3 Gradient boosting tree plot

The gradient boosting tree model provides a decision tree plot based on the importance of independent variables in the dataset. This plot illustrates different layers of the decision tree and split decision of independent variables based on their importance in the model. Different layers in the decision tree plot include branches and leaves representing the role of independent variables on the prediction of the target, which is various defect categories in this study. In the gradient boosting tree model, several decision trees are developed in order to determine the relationship between independent variables and the prediction of the target.

Figure 40 shows the first created decision tree plot in the gradient boosting tree model for material damage as the first target.

The branches and leaves of the decision tree provide insight into the role of independent variables in determining the prevalence of various defect categories. Since developed decision trees are very extensive, just a couple of branches for more illustrations are explained.

The first split of the tree shows the influence of age on the prevalence of material damage defects within pipes. Sewer pipes are divided into two groups of pipes with an age of more or less than 22 years. In the left node and where the age is less than 22 years, age again is filtered to more or less than 10 years, and in the next layers, again is filtered to smaller parts. Finally, the decision tree illustrates that 1% of pipes between 16 years and 22 years have a 68% chance of including material damage defects.

In the second layer, for pipes more than 22 years, pipes are filtered based on the population density with more or less than 14000 people. In the third layer, pipe length is appeared as the next influence variable in the model divided into more or less than 46 meters. Followingly, for pipes less than 46 meters, population density is filtered to more or less than 8559 people. In the next layer, material and age are the influence variables. Finally, the decision tree shows that 1% of sewers with the population density of more than 8559 and older than 59 years have a high probability of 83% to include material damage defects.

The results of the gradient boosting tree partly supported the outcomes of the deterministic method and binary logistic regression model. In general, longer pipes had more chance of including material damage defects in deterministic, logistic and tree models. Additionally, the probability of material damage occurrence is higher in pipes built from concrete and RC material which is in line with binary logistic regression results. Population density was also an influence variable in the gradient boosting tree model, and generally sewer pipes have more chance to contain material damage when the population density is higher around the pipe, supporting the logistic model results. Moreover, the influence of pipe diameter on material damage demonstrated that larger diameter pipes had higher probability of including material damage defects rather than the smaller pipes in the gradient boosting tree model, however, it was not supported by other models. While in the gradient boosting tree model, the older pipes had more chance of including material damage defects and this was supported with the achieved deterministic relationships, this could not be supported by the developed binary logistic regression models.

It is noteworthy to state that the decision tree uses “if and then clause” and split different independent variables until reaching the best prediction model. This means that some of the influence variables in the developed gradient boosting tree models might have only a small effect on the target, but still, they might be considered as an influencing and important variable. Therefore, they might not be as important as variables determined as significant in the developed binary logistic regression models. In addition, the important variables which were shown from developed gradient boosting tree models are obtained based on the first decision tree; however, many decision trees are developed to achieve ultimate prediction in this model.

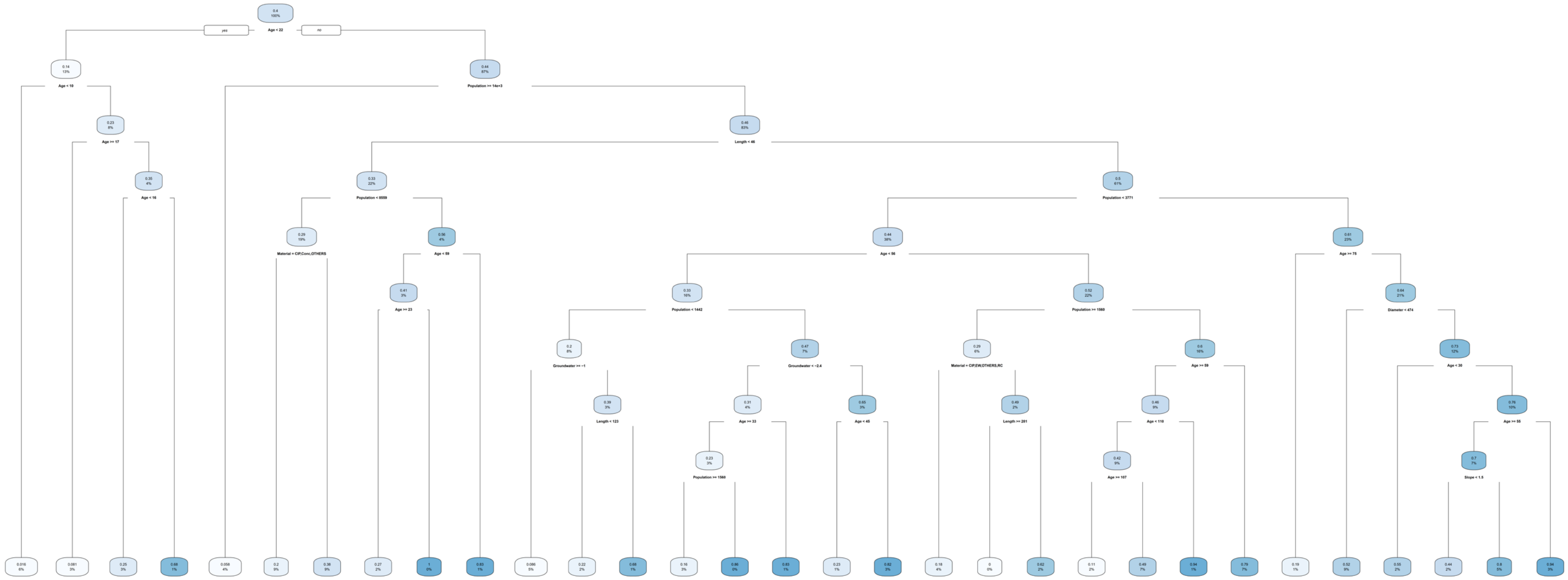


Figure 40. Gradient boosting tree plot for material damage

5.3.4 Summary and Results

The details for developing the gradient boosting trees model for the material damage defect category are reported in this chapter. The same procedure as material damage was implemented for all other defect categories, and all detailed tables and figures are provided in Appendix C.

In this section, the archived results from all gradient boosting tree models are briefly summarized and discussed.

Unlike logistic regression models, the gradient boosting tree model cannot provide any coefficients for studied independent variables and the scoring logic for this model is based on the conditional clause, which was illustrated in decision tree plots. Therefore, comparing the impact of independent variables on different defect categories and ranking them based on the impact size is not possible for this model. As a substitute, a summary of the first four independent variables, called critical independent variable, based on the feature importance rankings achieved from developed gradient boosting tree models for all defect categories is provided in Table 40. In addition, the accuracy and Area Under Curve (AUC) for each model were summarized in this table.

While accuracies for all defects were higher than 70%, which is desirable, the area under ROC curve is bigger than 0.7 for just two defect categories, i.e., material damage and gas attack. Referring to Table 37, the area under the curve is less than 0.7, representing a model with a poor level of discrimination. So, gradient boosting tree models developed for six defects are categorized in a poor discrimination level, i.e., debris, structural, infiltration, roots, total joint, and dipped pipe. The possible reason for not achieving an acceptable level of discrimination in the mentioned defect categories might be due to the low number of these defect categories in the initial dataset.

The effect of independent variables on all defect categories based on reported decision tree plots in Appendix C is as follows:

- Aging was recognized as an important independent variable which is positively affecting all defect categories apart from dipped pipe.
- Material was determined as an important variable affecting most of the defects, including material damage, gas attack, debris, infiltration, and total joint. Referring to Figure 40, sewer pipes built from concrete and RC had a higher probability of including material damage defects. In addition, referring to Figure 59, pipes built from RC and RCRRJ had more chance of including gas attack. Finally, referring to Figure 65 and Figure 69, pipes built from cementitious materials and PE had less chance of including infiltration and total joint defects.
- Pipe slope was another influence variable affecting the prevalence of only gas attack defects, demonstrating that pipes that are flatter had more probability of having gas attack defects rather than steeper pipes.
- Groundwater level was determined as an important variable affecting debris defects; however, no clear relationship between these two could be directly interpreted from the related decision tree (Figure 61).
- Length was determined as an important variable positively affecting material damage, infiltration, total joint, and dipped pipe defects.
- Diameter was identified as an important variable in two defects, i.e., roots and dipped pipe. In general, smaller pipes had more chance of including dipped pipe defects in tree models. No clear relationship between diameter and prevalence of roots defect could be directly interpreted from the achieved gradient boosting tree plots.
- Population density was another influence independent variable in the gradient boosting tree models. Generally, sanitary sewer pipes have more chance to include material

damage, gas attack, debris, infiltration, and total joint when the population density is higher around the pipe.

- Depth and Liquefactions susceptibility were not determined as critical independent variables (those are between one and fourth ranking in the feature importance list) affecting defects.

Table 40. Summary of first four important independent variables in all gradient boosting tree models and accuracies

Feature importance	Dependent variable							
	Material damage	Gas attack	Debris	Structural	Infiltration	Roots	Total joint	Dipped pipe
1	Age	Material	Population density	Age	Material	Diameter	Material	Diameter
2	Population density	Population density	Age	Material	Length	Age	Population density	Length
3	Material	Age	Groundwater level	-	Population density	-	Length	-
4	Length	Slope	diameter	-	Age	-	Age	-
Accuracy	72	81	71	82	85	84	87	90
ROC	78	89	67	65	65	60	63	60

5.4 Discussion

Binary logistic regression and gradient boosting trees were developed to predict the prevalence of eight defect categories of sewer pipes in this chapter.

Development of both models was implemented using static package R. Several techniques, such as cross-validation and feature importance, were used to minimize the risk of overfitting and uncertainty. Both models were validated using validation techniques, including confusion matrix and ROC curve. Figure 41 shows the accuracy of both developed models for all defect categories. Generally, the achieved accuracies in both models for all defects apart from material damage were close to each other. As shown in the figure, while the binary logistic regression model for material damage obtained the lowest accuracy of 59%, developed gradient boosting for the same defect category had an accuracy of 72%.

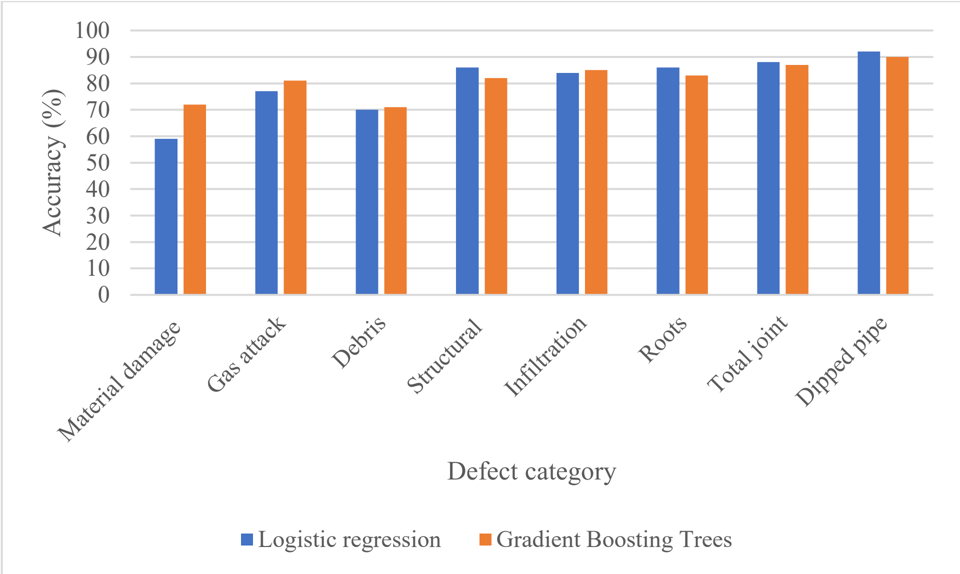


Figure 41. Comparison of models' accuracy for all studied defect categories

The accuracy of both models is shown with TPR and TNR concepts in Figure 42. The results showed that pipes without defects (TPR) could be predicted better in both models. However, the prediction of pipes with defects (TNR) had different percent correct values. The possible reason for a higher rate of predicting pipes without defects might be due to the fact that a number of these pipes was approximately five to seven times more than pipes including defect categories. As stated in chapter four (Figure 20), the frequency of defect categories, in order from the highest to the lowest, is as follows: material damage, gas attack, debris, structural and infiltration, roots, total joint, and dipped pipe.

While both models, binary logistic regression and gradient boosting trees, had high TPR in all of the defects, they showed low TNR for six defect categories, i.e., debris, structural, infiltration, roots, total joint, and dipped pipe, which are the defect categories from the third to eighth ranks in the defect frequency list. Therefore, it can be concluded that while both models can be considered reliable in predicting material damage and gas attack, they cannot be efficient in predicting the rest of the defect categories. The possible reason for not achieving high TNR for six defect categories, i.e., debris, structural, infiltration, roots, total joint, and dipped pipe in both models, might be due to the low number of these defect categories in the initial dataset.

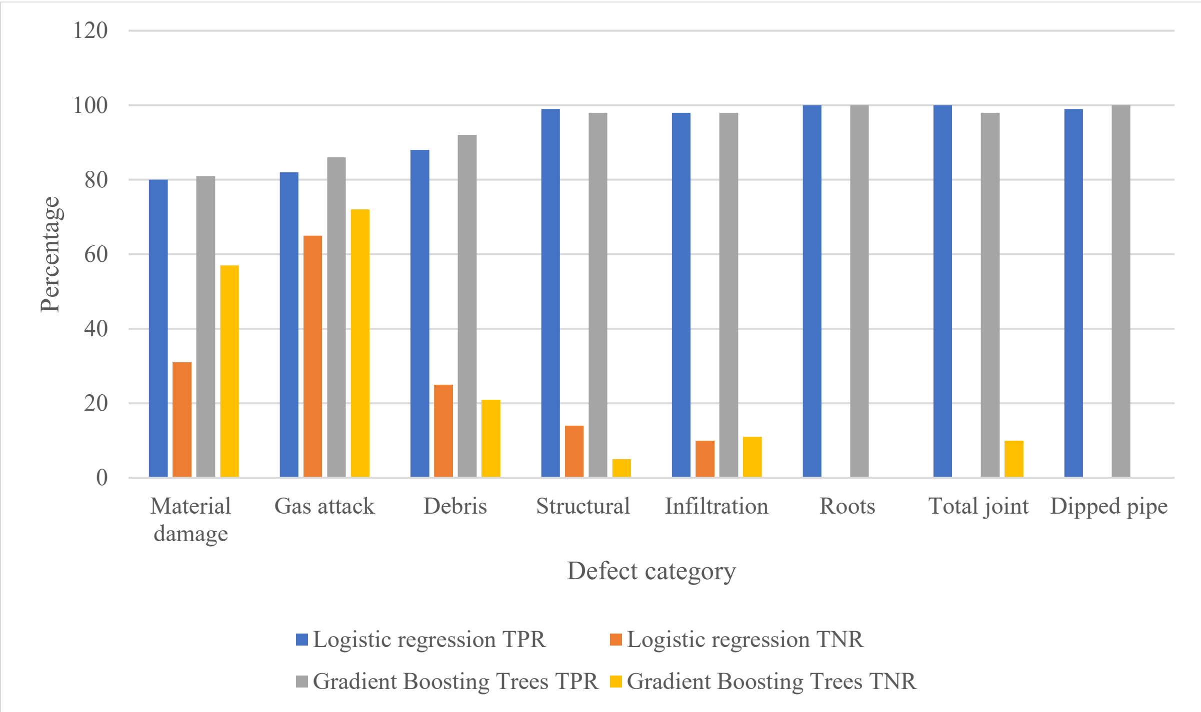


Figure 42. Comparison of TPR and TNR for developed models

The influence of independent variables on the deterioration of sewer pipes was determined in both binary logistic regression and gradient boosting tree models.

Table 41 illustrates the results in terms of important and significant variables in both models. These variables showed strong relationships with studied defect categories and excluding each one of them from the models can reduce the achieved accuracies.

While significant variables reported from binary logistic regression models are those with a p-value less than either 0.05 or 0.1, important variables are those obtained from developed gradient boosting tree models and are first four variables listed in the feature importance ranking.

The effect of independent variables on all defect categories based on the results achieved from developed binary logistic regression and gradient boosting trees models developed is summarized as follows:

- While in the gradient boosting tree model, age was an influential variable in predicting all defect categories except dipped pipe, in the binary logistic regression model, it was significant just in three defect categories, i.e., structural, infiltration, and roots.
- Material was identified as an important variable in both binary logistic regression and gradient boosting tree models in predicting five defect categories, i.e., material damage, gas attack, structural, infiltration, and total joint.
- Diameter was also determined as another important variable in both binary logistic regression and gradient boosting tree model in predicting four defect categories, i.e., debris, roots, total joint and dipped pipe.
- Length was identified as important variable in predicting material damage, infiltration, total joint, and dipped pipe in both binary logistic regression and gradient boosting tree models. It was also significant not only in the four mentioned defects but also in gas attack, debris, and structural defects in the binary logistic regression model.
- While depth was not identified as an important variable to predict any defect categories in gradient boosting tree models, it was identified as a significant variable with a significance level of 0.1, for predicting infiltration in the binary logistic regression model.

- Slope was identified as an important variable in predicting gas attack in gradient boosting trees. It was also identified as significant in predicting two defects, i.e., material damage and dipped pipe, in the binary logistic regression model.
- Groundwater level was determined as an influential variable in predicting debris in both binary logistic regression and the gradient boosting tree models. It was also identified as a significant variable in predicting gas attack, total joint, and dipped pipe in the binary logistic regression model.
- Population density was identified as an effective variable in predicting four defect categories, i.e., material damage, gas attack, debris, and total joint for both models. In addition, it was identified as important in predicting infiltration in gradient boosting trees and as a significant variable in predicting roots and dipped pipe in the binary logistic regression model.
- Finally, liquefaction susceptibility was not identified as an important variable in any of the studied models.

The possible reason for achieving different results in terms of the influence of independent variables on predicting various defects in both models might be due to the differences between the concept of binary logistic regression and gradient boosting tree models. While in binary logistic regression models, the significant variable can be distinguished based on the P-value, important variables reported from gradient boosting models are based on the first four variables listed in the feature importance rankings.

Table 41. Influence variables affecting prevalence of defect categories within sewers: A: Binary logistic regression model, B: Gradient boosting trees model, significant variable: ✓, insignificant variable: ✗

Defect category	**Material damage**		**Gas attack**		**Debris**		**Structural**		**Infiltration**		**Roots**		**Total joint**		**Dipped pipe**	
Variables	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
Age	✗	✓	✗	✓	✗	✓	✓	✓	✓	✓	✓	✓	✗	✓	✗	✗
Material	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✗	✗	✓	✓	✗	✗
Diameter	✗	✗	✗	✗	✓	✓	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓
Length	✓	✓	✓	✗	✓	✗	✓	✗	✓	✓	✗	✗	✓	✓	✓	✓
Depth	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗
Slope	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗
Groundwater	✗	✗	✓	✗	✓	✓	✗	✗	✗	✗	✗	✗	✓	✗	✓	✗
Population density	✓	✓	✓	✓	✓	✓	✗	✗	✗	✓	✓	✗	✓	✓	✓	✗
Liquefaction susceptibility	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗

5.5 Chapter Summary

The chapter presented detailed overviews of validating binary logistic regression and gradient boosting tree models and the influence of different independent variables on eight defect categories.

Generally, the accuracies achieved in both statistical and artificial intelligence models for all mentioned defects were close to each other and higher than 70%. While both models showed high TPR in predicting all defects, the model showed low TNR in all defects apart from material damage and gas attack. The possible reason for not achieving high TNR for six defect categories might be due to the low number of mentioned defects in the initial dataset.

Influence variables and the order of their importance affecting the prevalence of different defect categories on sewers were determined in order to optimize the useful life of sewer pipes.

6 CONCLUSION

6.1 Summary and significant findings

The main objective of this study was to investigate the effect of various physical and environmental factors, including age, diameter, and groundwater level, on the prevalence of eight defect categories in the transmission sewer network of Auckland, New Zealand.

After conducting a literature review, several differences and inconsistencies between classification systems used in published studies in the sewer deterioration and asset management fields were identified. Since no widely adopted classification system is available, a classification system is proposed based on three top-level categories of factors, defects, and failures. Each category and subcategory are clearly defined, and a flow diagram is provided to guide the user in classifying any given parameter.

Developing a consistent classification system that can be applied in a broad range of deterioration or asset management studies can have several benefits. It is the need for researchers and practitioners in sewer systems to use the same classification system. This will allow the body of professionals in sewer asset management to communicate more effectively by speaking the same language, make it possible to compare different studies and build up a consistent knowledge base to move the understanding and management of sewer systems forward.

The study dataset was obtained from Watercare Service limited. A cleaned dataset with the defects identified through recent CCTV inspections of 2780 sewers was gathered and linked to a range of physical and environmental factors. Defects were grouped into eight categories: material damage, gas attack, debris, structural, infiltration, roots, total joint, and dipped pipe. In the first step, correlations between different factors and defects were analyzed respectively, followed by an investigation of the impact of each factor on each defect category and, finally, a comparison of the normalized linear regression slopes for statistically significant relationships. In the next step, multi-parameters statistical and artificial intelligence models were developed in order to study the relationship between various factors and each defect category. Two models, binary logistic regression and gradient boosting trees were developed as statistical and artificial intelligence models, respectively. These models were selected based on several reasons, such as the performance to predict categorical outcomes, the capability to be trained by nominal and categorical variables, and the comprehensibility of achieved results.

The following findings were drawn from the development of individual deterministic relationships, binary logistic regression, and gradient boosting tree models. The main findings of each mentioned category were reported separately for a better understanding of the performance of the models.

- **Individual deterministic relationships:**

❖ Correlation coefficient between different factors and defects were analyzed. The strongest positive correlations were found between pipe material and population density, pipe material and age, and pipe depth and slope. The strong correlation between pipe material and age is likely due to the use of specific pipe materials in different periods of time and that of pipe material and population density to the usage of certain kinds of materials in different suburbs. The reason for the strong correlation between pipe depth and pipe slope is not immediately clear.

❖ Results indicated that there are a few factors that have the greatest impact on pipe deterioration. These factors, in order of impact size, are as follows:

- Pipe depth negatively affects gas attack and positively affects infiltration. Both gas attack and infiltration were significant at a 10% confidence level. While the slope for infiltration is positive, indicating an increase in infiltration prevalence of 1.7% per meter depth, the slope for gas attack is negative, with prevalence decreasing by 2.93% per meter depth. The positive correlation with infiltration may be explained by the higher probability of the groundwater level being in the vicinity of deeper sewers. The negative correlation between gas attack and depth may be due to the higher infiltration rate, which dilutes the sewage and increases the flow rate, and reduces the release of hydrogen sulphide from the sewage.

- Groundwater level negatively affects both debris and gas attack. This may result from the greater infiltration at higher groundwater levels, increasing flow velocities and diluting the sewage. High sewage velocities will result in a better carrying of debris, and dilution of the sewage, lead to slowing down of the corrosion process.
- Pipe age positively affects both material damage and gas attack. The results show that material damage and gas attack (limited to pipes younger than sixty years) are by far the most affected by age, with their prevalence increasing at 0.71 % and 0.62 % per year, respectively.
- Slope negatively affects both gas attack and material damage. These trends may be due to higher velocities and thus shorter sewage retention time in pipes with higher slopes reducing the rate of the corrosion process.

- **Binary logistic regression:**

❖ Binary logistic regression models showed acceptable overall accuracies and high accuracies in predicting pipes including defects (TPR). However, the models showed low accuracies for the prediction of pipes without defects (TNR) for all defect categories, apart from gas attack and material damage. The possible reason for not achieving a high accuracy for predicting pipes without defects (TNR) for most of defect categories might be due to the low number of mentioned defects in the dataset.

❖ Results showed that there are a few numerical factors that have the greatest impact on several defects. These factors, in order of impact size, are as follows:

- Groundwater level positively affects dipped pipe and total joint and negatively affects debris. While the coefficient for dipped pipe and total joint is positive, indicating an increase in both defects' prevalence of 4.9% and 7.7% per meter, respectively, the coefficient for gas attack and debris is negative, with prevalence decreasing by approximately 2.2% per meter.
- Slope negatively affects dipped pipe and material damage indicating a decrease in both defects with a coefficient of 6.3% and 2% per percentage, respectively. This may result from the fast sewage velocities, which reduce the release of hydrogen sulphide from the sewage and lead to less corrosion.
- Depth positively affects infiltration with a coefficient of 4% per meter. The reason may be explained by the higher probability of the groundwater level being in the vicinity of deeper sewers.
- Age positively affects two defects, structural and roots, with an approximate coefficient of 2% per year.

❖ For pipe material, considering CIP as the reference material, the following results are achieved:

- Pipes built from PE are less prone to material damage, gas attack, structural, infiltration, and total joint.
- Pipes built from RC and RCRRJ are more prone to material damage and gas attack defects and less exposed to three defects, i.e., structural, infiltration, and total joint.
- Pipes built from EW are more exposed to structural defects.

❖ Generally, the binary logistic regression model results supported the findings from individual deterministic relationships, i.e., studying one factor and one defect at a time. The same significant variables were identified in both models, including depth, groundwater, age, and slope. However, the order of significance for these variables was not the same, which might be due to the correlation between variables overlooked in individual deterministic relationships. In addition, while studying the significance of material was not possible in individual deterministic relationships, the results from binary logistic regression showed that material is a significant variable affecting the prevalence of the defect categories.

- **Gradient boosting trees:**

❖ While all models provide high accuracies and TPR, low TNR was reported for all models apart from material damage and gas attack. Likewise, while accuracies for all defects were higher than 70%, which is desirable, the area under ROC curve is bigger than 0.7 for only two defect categories, i.e., material damage and gas attack. Referring to Table 37, the area under the curve is less than 0.7, representing a model with a poor level of discrimination. So, gradient boosting tree models developed for six defects are categorized in a poor discrimination level, i.e., debris, structural, infiltration, roots, total joint, and dipped pipe. The possible reason for not achieving an acceptable level of discrimination in the mentioned defect categories might be due to the low number of these defect categories in the initial dataset.

❖ The effect of independent variables on all defect categories based on achieved featured importance rankings and decision tree plots are as follows:

- Aging was recognized as an important independent variable positively affecting all defects apart from dipped pipes.

- Material was determined as an important variable affecting most of the defects, including material damage, gas attack, debris, infiltration, and total joint. In general, sewer pipes built from concrete and RC had a higher probability of including material damage defects. In addition, pipes built from RC and RCRRJ had more chance of including gas attacks. Pipes built from cementitious materials and PE had less chance of including infiltration and total joint defects. The achieved results from gradient boosting tree models in terms of material were generally supported by binary logistic regression results.
- Pipe slope was another influence variable affecting the prevalence of only gas attack defects, demonstrating that pipes that are flatter had more probability of having gas attack defects rather than steeper pipes.
- While groundwater level was determined as an important variable affecting debris defects, no clear relationship between these two could be directly interpreted from the decision tree.
- Length was determined as an important variable positively affecting material damage, infiltration, total joint, and dipped pipe defects. These results were supported by results achieved from binary logistic regression models.
- Diameter was identified as an important variable in two defects, i.e., roots and dipped pipe. In general, smaller pipes had more chance of including dipped pipe defects in both binary logistic and tree models. No clear relationship between diameter and prevalence of roots defect can be directly interpreted from the gradient boosting tree model.
- Population density was also an influence variable in the gradient boosting tree model, and generally, sewer pipes have more chance to contain material damage, gas attack, debris, infiltration, and total joint when the population density is higher around the pipe, supporting the results achieved from binary logistic regression models.

- Depth and Liquefactions susceptibility were not identified as critical independent variables affecting defects.

❖ Generally, the achieved results from developed gradient boosting tree models were supporting results from developed binary logistic regression models. Some minor discrepancies were seen as follows:

- Pipe slope was seen as an influence variable negatively affecting the gas attack defect. However, based on the binary logistic regression model results, pipe slope only negatively affects dipped pipe and material damage. The reason was attributed to the less release of hydrogen sulphide from the sewage leading to less corrosion in sewers. Based on the positive and strong correlation coefficient of 0.24 achieved between material damage and gas attack, this can be interpreted that these two defects have a direct relationship with each other. Therefore, the above results are more or less alike.
- Groundwater level was determined as an important variable affecting debris defects; however, no clear relationship between these two could be directly interpreted from the related decision tree. However, based on the binary logistic regression model results, groundwater level not only had a negative effect on gas attack and debris but also had a positive effect on total joint and dipped pipe defects.

6.2 Limitations

Any research might have several limitations that can affect the achieved results, two of the main limitations regarding implementing this study were as follows:

- Not having access to all possible factors that might influence the prediction of the prevalence of defects in sewers in developed models, such as sewage age, the sequence of flow through sewers, flow rate, soil features or the quality of installation.

- Limited access to CCTV datasets and therefore not having enough numbers of defects for some categories such as debris, infiltration, roots, structural, total joint, and dipped pipe.

6.3 Contribution to the sewer networks

A structured framework was proposed for classifying different components involved in deterioration processes in order to make the deterioration procedure of sewer pipelines more understandable. The most significant factors affecting the prevalence of defects in sewer pipelines in the city of Auckland were investigated. In addition, multivariate sewer prediction models were developed and evaluated to illustrate the extent and importance of different factors affecting each defect category. The results from this study can contribute to municipalities scheduling CCTV inspections more efficiently in the Auckland sewer network. Moreover, determining the importance of influence variables is a crucial outcome that can be fed into the optimization of planning and installation strategies which consequently amend the useful life of sewers.

6.4 Recommendations for future research

The work presented in this dissertation can be developed by additional research. Some of the areas of potential future development include:

- The deterioration models can be expanded by adding other independent variables, such as flow, soil corrosivity, soil type, soil pH, backfill type, installation method, and pipe shape.

- The results from the prediction models can be used to develop a more efficient CCTV inspection schedule for sewers in Auckland, NZ. Prioritizing sewers in critical condition for inspection will save time and energy, speed up the rehabilitation and maintenance process, and consequently avoid abrupt failures. A cost-benefit analysis can represent the cost saving of this schedule in comparison with regular inspection plans.
- Further prediction models, particularly machine learning methods, can be developed in order to compare the performance of models.
- This study can be done for more cities like Wellington and Christchurch in NZ, and consequently, the achieved results can be compared with the presented study. Applying the study widely in NZ will help to determine the effective variables more accurately. Also, all developed models for all cities can be combined in order to develop a major singular prediction model for the entire NZ.

7 APPENDIX A: RELATIONSHIPS BETWEEN EACH FACTOR AND EACH INDIVIDUAL DEFECT CATEGORY

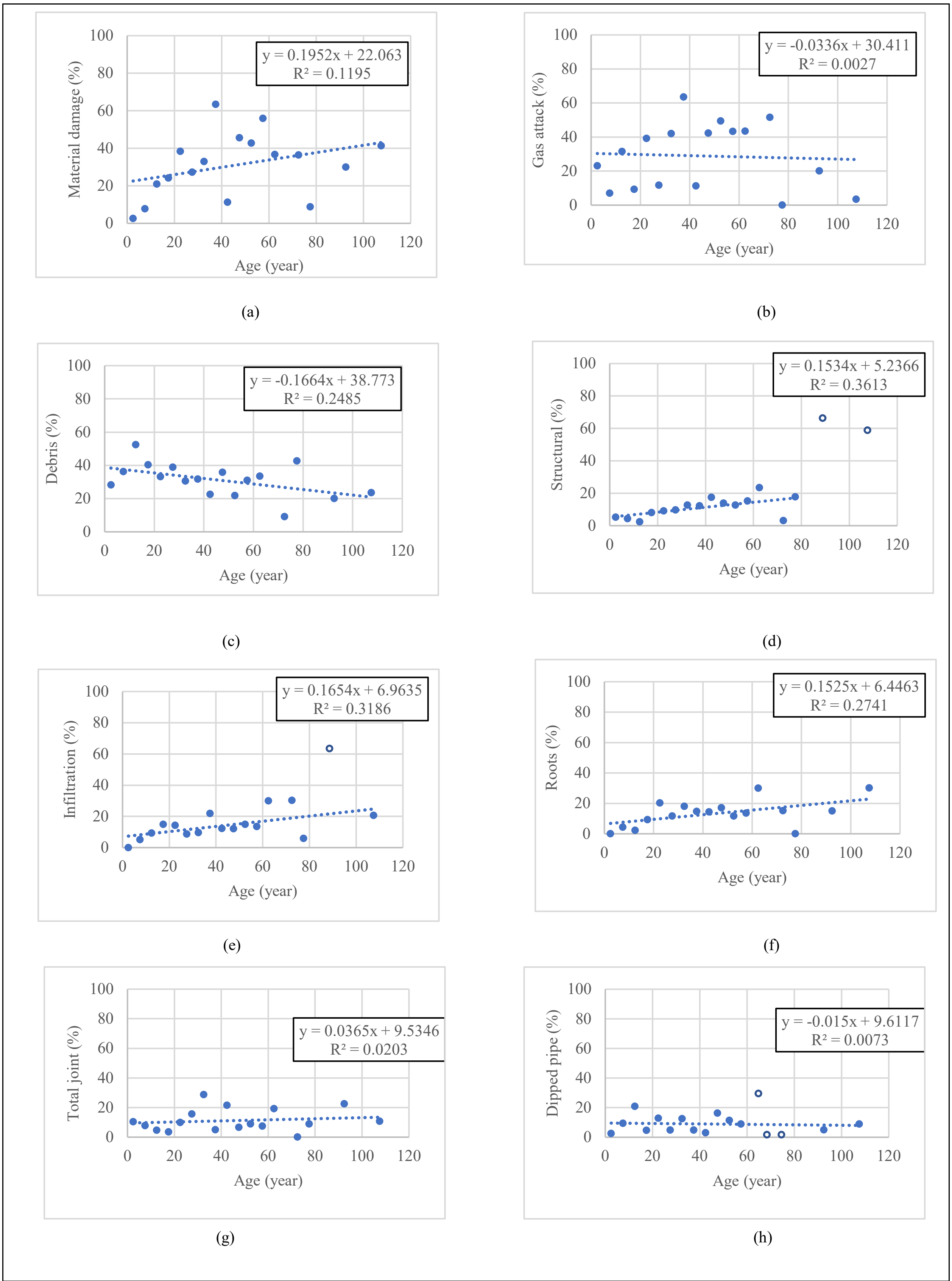
7.1 Age

To study the impact of pipe age, pipes were grouped using 5-year intervals, and the number of pipes with each defect was determined for each group as shown in Table 26. The table does not include age intervals between 80 and 90 years, and between 100 and 105 years, since no records were included in these ranges in the dataset. The fractions of pipes with each defect were then plotted against the age, as shown in Table 43.

Table 42. The number of pipes with defects in 5-year age intervals

Age interval	Total no of pipes	No of pipes with defect								Total no of defects
		Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe	
(0,5]	39	9	1	0	0	11	4	2	1	28
(5,10]	116	8	9	6	5	42	9	5	11	95
(10,15]	86	27	18	8	2	45	4	2	18	124
(15,20]	87	8	21	13	8	35	3	7	4	99
(20,25]	133	52	51	19	27	44	13	12	17	235
(25,30]	103	12	28	9	12	40	16	10	5	132
(30,35]	167	70	55	16	30	51	48	21	21	312
(35,40]	41	26	26	9	6	13	2	5	2	89
(40,45]	98	11	11	12	14	22	21	17	3	111
(45,50]	123	52	56	15	21	44	8	17	20	233
(50,55]	520	257	222	78	61	113	46	66	59	902
(55,60]	765	331	428	104	104	237	56	116	68	1444
(60,65]	120	52	44	36	36	40	23	28	30	289
(65,70]	6*	1	2	1	5	5	1	0	0	15
(70,75]	66	34	24	20	10	6	0	2	0	96
(75,80]	68	0	6	4	0	29	6	12	0	57
(80,85]	0	0	0	0	0	0	0	0	0	0
(85,90]	0	0	0	0	0	0	0	0	0	0
(90,95]	40	8	12	27	6	8	9	25	2	97
(95,100]	23*	3	9	10	9	12	8	15	1	67
(100,105]	0	0	0	0	0	0	0	0	0	0
(105,110]	179	6	74	37	54	42	19	106	16	354
Total	**2780**	**967**	**1097**	**424**	**410**	**839**	**296**	**468**	**278**	**4779**

* The categories with less than 1% of the total number of pipes are excluded from significance estimations



y = 0.1952x + 22.063
R² = 0.1195
Material damage (%)
Age (year)
(a)
y = -0.0336x + 30.411
R² = 0.0027
Gas attack (%)
Age (year)
(b)
y = -0.1664x + 38.773
R² = 0.2485
Debris (%)
Age (year)
(c)
y = 0.1534x + 5.2366
R² = 0.3613
Structural (%)
Age (year)
(d)
y = 0.1654x + 6.9635
R² = 0.3186
Infiltration (%)
Age (year)
(e)
y = 0.1525x + 6.4463
R² = 0.2741
Roots (%)
Age (year)
(f)
y = 0.0365x + 9.5346
R² = 0.0203
Total joint (%)
Age (year)
(g)
y = -0.015x + 9.6117
R² = 0.0073
Dipped pipe (%)
Age (year)
(h)

Data points used in the analysis • Excluded data points (outliers) ∘

Figure 43. The fraction of pipes with different defects as a function of age: a) material damage b) gas attack c) debris d) structural e) infiltration f) roots g) total joint h) dipped pipe

A summary of the linear regression results for each category, including the intercept, slope, and a p-value is presented in Table 25, separated by level of significance and ordered by decreasing absolute value of slope. The p-value is less than the 5% significance level (i.e. a 95 % probability of a non-zero correlation in the data) in four defect categories: debris, infiltration, structural, and roots. Apart from debris, all other three slopes are positive and relatively small, showing growth in defects between 0.15% and 0.17% per year. The Debris category has a negative slope that indicates a decrease in the debris of 0.15 % per year.

The slopes for the total joint, gas attack, and dipped pipe defects are all very small (below 0.036 %/year) and not statistically different from zero, indicating that these defects are not affected by age.

Table 43. Linear regression results for different defect categories as a function of age

Defect category rank	Intercept	Slope	P-value	Relationship
1. Debris	38.773	-0.166	0.041	Significant
2. Infiltration	6.963	0.165	0.022	Significant
3. Structural	5.236	0.153	0.017	Significant
4. Roots	6.446	0.152	0.031	significant
5. Material damage	22.063	0.195	0.174	Insignificant
6. Total joint	9.534	0.036	0.585	Insignificant
7. Gas attack	30.411	-0.033	0.843	Insignificant
8. Dipped pipe	9.611	-0.015	0.771	Insignificant

While the overall results for Material damage do not display a statistically significant trend, it seems clear from Figure 16(a) that a significant positive trend exists for younger pipes, which is disrupted by lower Material damage values for pipes older than 60 years. It is not clear why this is the case, but it is likely that in older pipes, high levels of Material damage may have led to the worst pipes being replaced, leaving only the pipes with lower susceptibility to material damage in the system.

For Gas attack data (Figure 16(b)), an increase with age is also evident for younger pipes, although in a bifurcated pattern, with succeeding data points plotting on either an upper or lower imagined trend line. Given that Gas attack results through a physical corrosion mechanism, it is highly unlikely that a bifurcated pattern with a five-year resolution could result naturally. Thus, the bifurcation was assumed to be due to the way the data was gathered or documented, and the analysis was repeated using time intervals of 10 years.

The data for Material Damage and Gas Attack is shown up to the age of 60 years in 10-year intervals in Figure 23, and the corresponding trend data is given in Table 45. Both defects display a statistically significant, large positive slope.

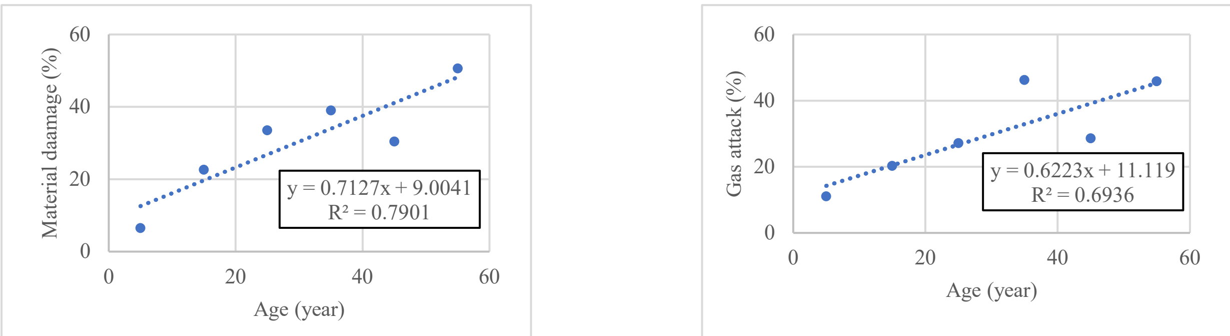


Figure 44. The fraction of pipes with material damage and gas attack defects as a function of age with the 10-year interval before age of 60 years with previous

Table 44. Material damage and gas attack values by considering 10 year-intervals, below the age of 60 years

Defect category	Intercept	Slope	P-value	Relationship
Material damage	11.119	0.622	0.039	Significant
Gas attack	9.004	0.712	0.017	Significant

The restricted age and 10-year data intervals were not applied to the other defects, as it is clear from Figure 16 that this would not have made a significant difference to the results.

7.2 Diameter

To study the impact of pipe diameter, pipes were grouped using 150mm diameter intervals, and the number of pipes with each defect was specified for each group, as shown in Table 46. The table does not include a diameter interval of (2100,2250] since no records were included in this range in the dataset. The fractions of pipes with each defect were then plotted against the pipe diameter, as shown in Figure 45.

Table 45. The number of pipes with defects in each 150mm diameter interval

Diameter interval	Total no of pipes	No of pipes with defect								Total no of defects
		Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe	
(150, 300]	354	107	115	58	88	108	58	60	55	649
(300, 450]	746	286	279	99	112	242	106	145	124	1393
(450, 600]	565	193	236	92	82	175	76	65	64	983
(600, 750]	376	81	142	48	50	124	21	41	17	524
(750, 900]	230	89	73	17	18	74	7	20	11	309
(900, 1050]	159	93	72	43	33	56	7	40	5	349
(1050, 1200]	69	45	38	8	4	19	0	9	1	124
(1200, 1350]	87	35	70	18	3	8	2	14	1	151
(1350, 1500]	22*	2	8	2	9	2	0	10	0	33
(1500, 1650]	33	15	15	6	2	0	1	6	0	45
(1650, 1800]	58	1	23	5	6	19	3	29	0	86
(1800, 1950]	11*	0	0	10	0	2	6	3	0	21
(1950, 2100]	16*	2	1	3	1	7	2	4	0	20
(2100, 2250]	0*	0	0	0	0	0	0	0	0	0
(2250, 2400]	31	8	10	4	2	3	0	13	0	40
(2400, 2550]	23*	10	15	11	0	0	7	9	0	52
Total	**2780**	**967**	**1097**	**424**	**410**	**839**	**296**	**468**	**278**	**4779**

* The categories with less than 1% of the total number of pipes are excluded from significance estimations

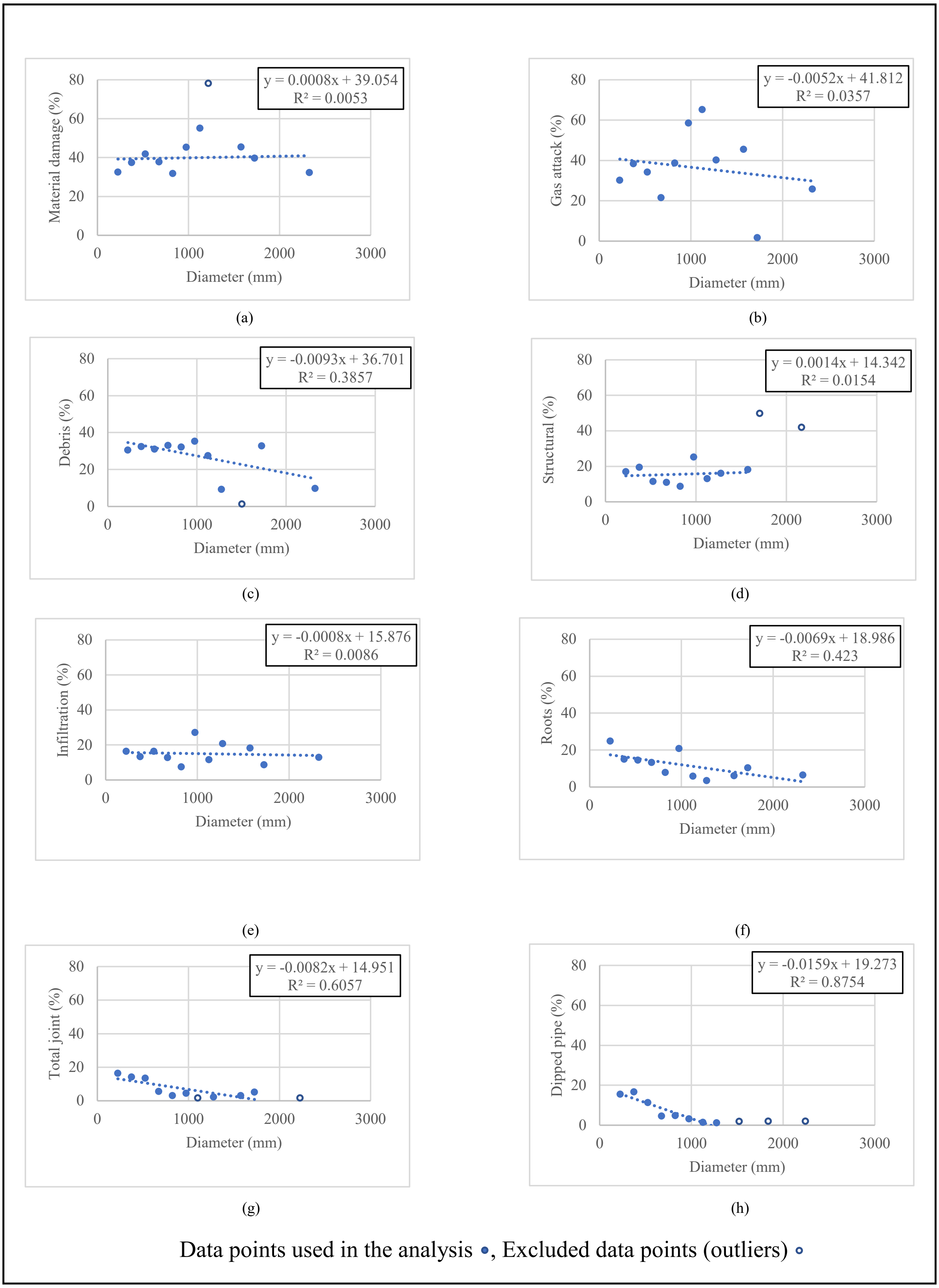


Figure 45. The fraction of pipes with different defects as a function of pipe's diameter a) material damage b) gas attack c) debris d) structural e) infiltration f) roots g) total joint h) dipped pipe

A summary of the linear regression results for each defect category, including the intercept, slope, and p-value, is presented in Table 47, separated by level of significance and ordered by decreasing absolute value of slope. The p-value is less than the 5% significance level in four defect categories: dipped pipe, debris, total joint, and roots. All significant slopes are negative and relatively small, showing a decrease in defects between 0.01% and 0.006% per each millimetre diameter increase.

The slopes for gas attack, structural, material damage and infiltration defects are all not statistically different from zero, indicating that these defects are not affected by diameter.

Table 46. Parameter estimations of the linear regression between defect categories and pipe diameter with a 5% significance level

Defect category rank	Intercept	Slope	P-value	Relationship
1. Dipped pipe	19.273	-0.015	0.0006	Significant
2. Debris	36.701	-0.009	0.055	Significant
3. Total joint	14.951	-0.008	0.013	Significant
4. Roots	18.986	-0.006	0.03	Significant
5. Gas attack	41.812	-0.0052	0.577	Insignificant
6. Structural	14.342	0.001	0.75	Insignificant
7. Material damage	39.054	0.0008	0.841	Insignificant
8. Infiltration	15.876	-0.0008	0.786	Insignificant

7.3 Depth

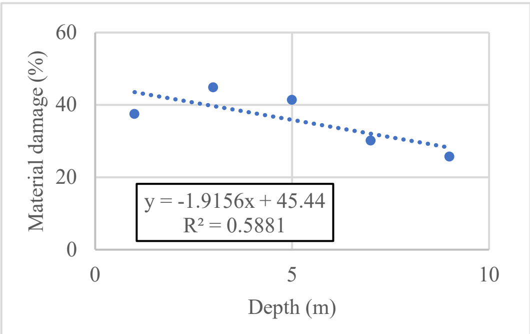
To investigate the effect of pipe depth, pipes were grouped using 2-meter intervals, and the number of pipes with each defect was specified for each group, as shown in Table 48. The fraction of pipes with each defect was then plotted against the depth, as shown in

Figure 46.

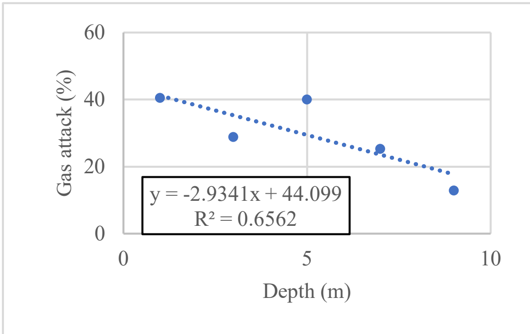
Table 47. The number of pipes with defects in 2-meter depth intervals

Depth Interval	Total no of pipes	No of pipes with defect								Total no of defects
		Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe	
(0,2]	1356	548	508	162	173	408	146	212	136	2293
(2,4]	936	269	419	159	174	273	93	163	110	1660
(4,6]	283	113	117	53	36	91	31	44	17	502
(6,8]	103	26	31	29	13	35	12	20	2	168
(8,10]	39	5	10	9	6	12	8	17	2	69
(10,12]	16*	2	3	7	1	6	2	6	3	30
(12,14]	15*	3	1	1	1	1	1	2	3	13
(14,16]	15*	1	6	2	5	6	1	2	3	26
(16,18]	5*	0	1	0	0	5	0	0	1	7
(18,20]	12*	0	1	2	1	2	2	2	1	11
Total	**2780**	**967**	**1097**	**424**	**410**	**839**	**296**	**468**	**278**	**4779**

* The categories with less than 1% of the total number of pipes are excluded from significance estimations

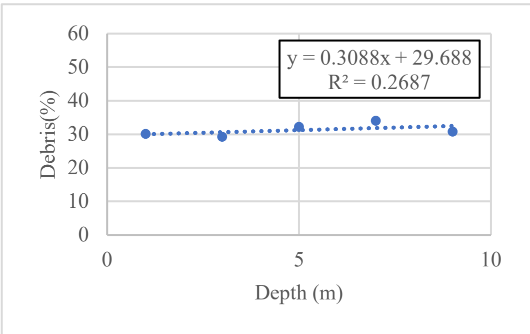


Material damage (%)
60
40
20
0
0
5
10
Depth (m)
y = -1.9156x + 45.44
R² = 0.5881

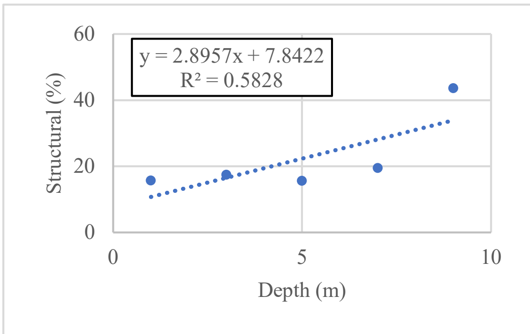


Gas attack (%)
60
40
20
0
0
5
10
Depth (m)
y = -2.9341x + 44.099
R² = 0.6562

(a) (b)

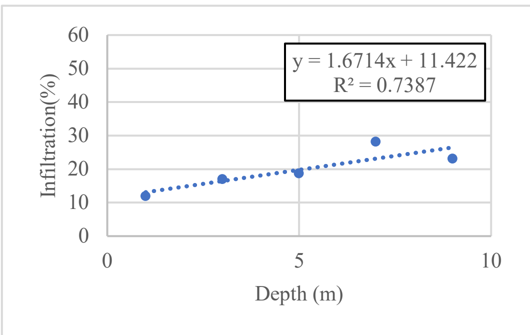


Debris(%)
60
50
40
30
20
10
0
0
5
10
Depth (m)
y = 0.3088x + 29.688
R² = 0.2687

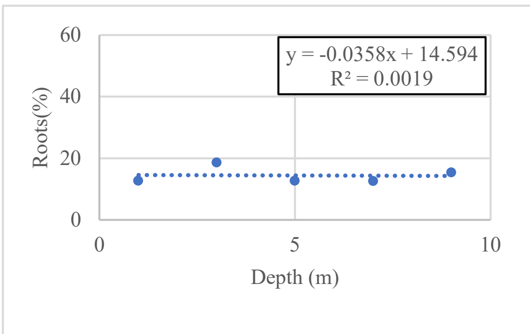


Structural (%)
60
40
20
0
0
5
10
Depth (m)
y = 2.8957x + 7.8422
R² = 0.5828

(c) (d)

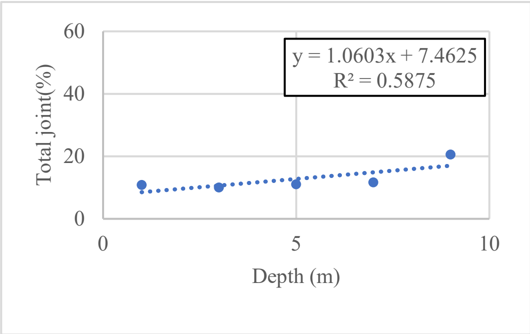


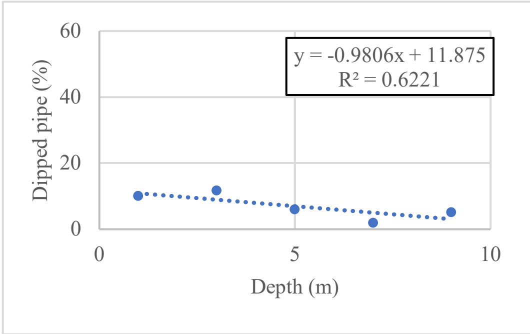
Infiltration(%)
60
50
40
30
20
10
0
0
5
10
Depth (m)
y = 1.6714x + 11.422
R² = 0.7387



Roots(%)
60
40
20
0
0
5
10
Depth (m)
y = -0.0358x + 14.594
R² = 0.0019

(e) (f)





(g) (h)

Data points used in the analysis ●, Excluded data points (outliers) ○

Figure 46. The fraction of pipes with different defects as a function of depth: a) material damage b) gas attack c) debris d) structural e) infiltration f) roots g) total joint h) dipped pipe

A summary of the linear regression results for each category, including the intercept, slope, and p-value, is presented in Table 49, separated by level of significance and ordered by decreasing absolute value of slope. All slopes for various defects are not statistically different from zero, indicating that these defects are not affected by depth.

Table 48. Linear regression results for different defect categories as a function of depth

Defect category rank	Intercept	Slope	P-value	Relationship
1. Gas attack	44.099	-2.934	0.09	Insignificant
2. Structural	7.842	2.895	0.133	Insignificant
3. Material damage	45.44	-1.915	0.13	Insignificant
4. Infiltration	11.422	1.671	0.06	Insignificant
5. Total joint	7.462	1.06	0.13	Insignificant
6. Dipped pipe	11.875	-0.98	0.122	Insignificant
7. Debris	29.688	0.308	0.37	Insignificant
8. Roots	14.594	-0.035	0.944	Insignificant

7.4 Length

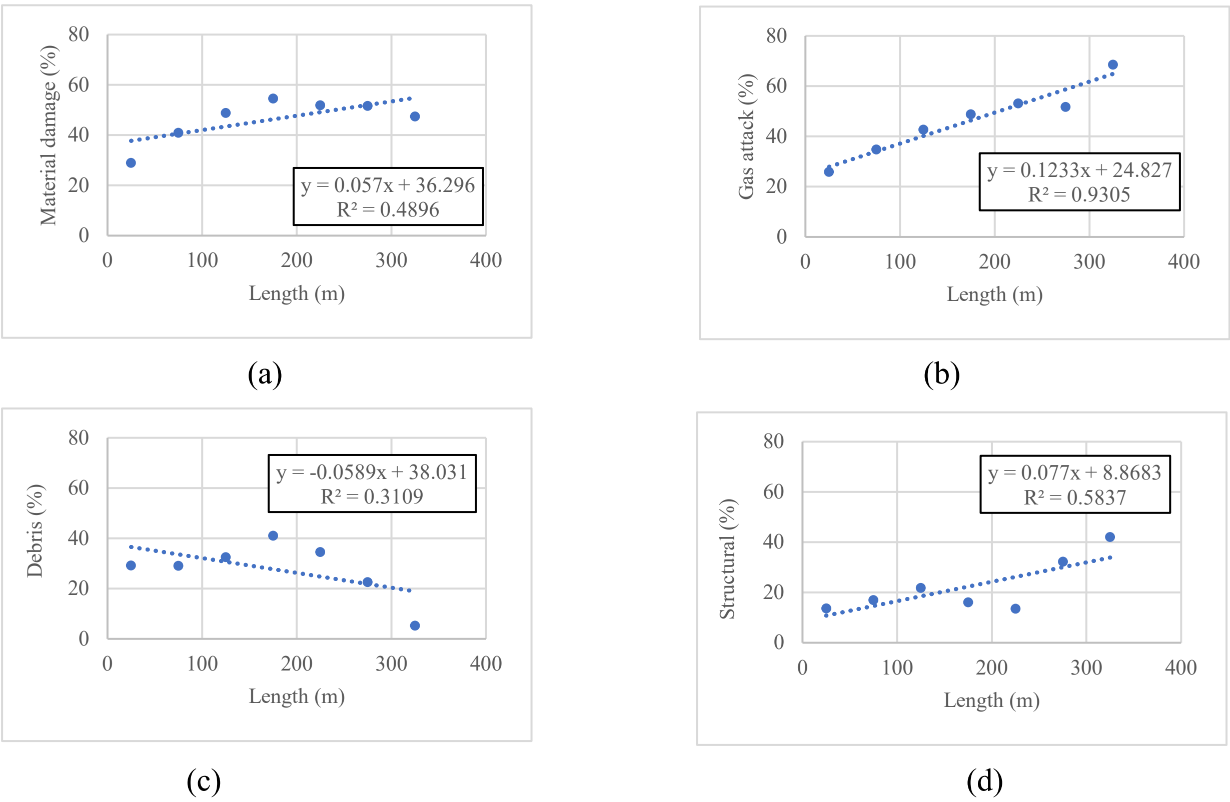
To determine the impact of pipe length, pipes were grouped using 50 meters length intervals, and the number of pipes with each defect was specified for each group, as shown in Table 50. The fractions of pipes with each defect were then plotted against the pipe length, as shown in Figure 47.

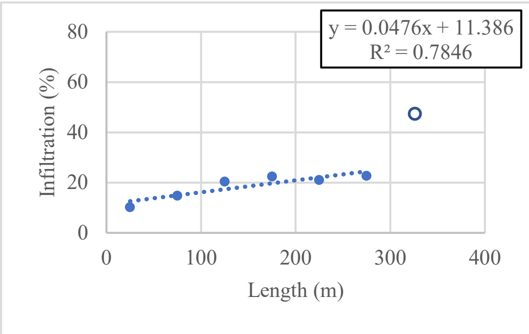
Table 49. The number of pipes with defects in 50-meter length intervals

Length Interval	Total no of pipes	No of pipes with defect								Total no of defects
		Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe	
(0,50]	910	234	263	92	137	265	94	124	40	1249
(50,100]	1080	374	442	159	169	314	124	183	126	1891
(100,150]	453	193	221	92	69	147	43	99	75	939
(150,200]	156	76	85	35	16	64	22	25	23	346
(200,250]	81	43	42	17	9	28	5	11	8	163
(250,300]	31	16	16	7	3	7		10	3	62
(300,350]	19*	13	9	10	1	1	4	8	0	46
(350,400]	10*	3	5	2	1	3	1	1	0	16
(400,450]	10*	3	4	1	0	2	1	2	0	13
(450,500]	7*	5	1	2	0	2	1	1	1	13
(500,550]	3*	1	1	0	2	0	0	1	0	5
(550,600]	5*	1	2	1	0	2	0	0	1	7
(600,650]	3*	0	1	1	1	1	1	0	0	5
(650,700]	3*	2	2	2	0	1	0	1	1	9
(700,750]	2*	0	1	0	1	0	0	0	0	2
(750,800]	3*	0	1	1	0	1	0	1	0	4

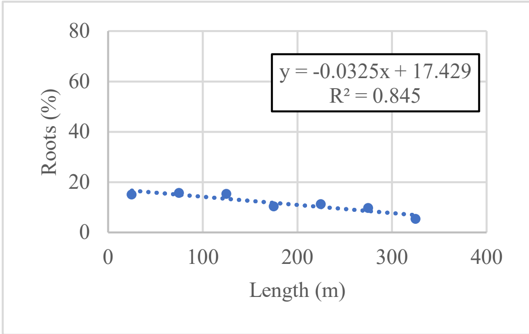
(800,850]	0*	0	0	0	0	0	0	0	0	0
(850,900]	2*	2	0	2	1	0	0	1	0	6
(900,950]	2*	1	1	0	0	1	0	0	0	3
Total	**2780**	**967**	**1097**	**424**	**410**	**839**	**296**	**468**	**278**	**4779**

* The categories with less than 1% of the total number of pipes are excluded from significance estimations

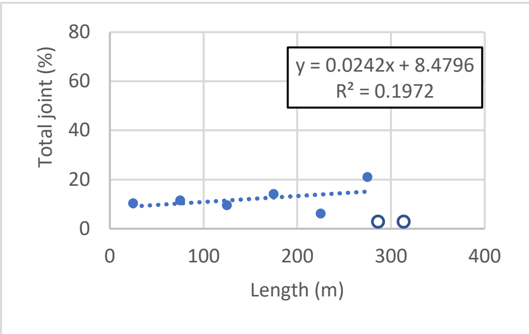




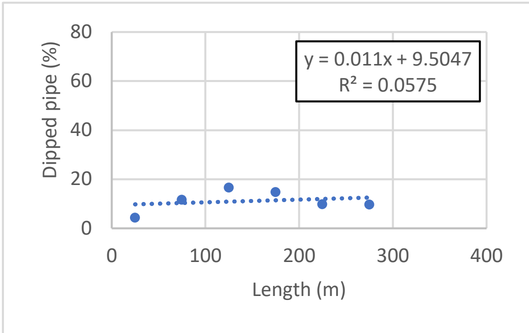
(e)



(f)



(g)



(h)

Data points used in the analysis ●, Excluded data points (outliers) ○

Figure 47. The fraction of pipes with different defects as a function of length: a) material damage b) gas attack c) debris d) structural e) infiltration f) roots g) total joint h) dipped pipe

A summary of the linear regression results for each defect category, including the intercept, slope, and p-value, is presented in Table 51, separated by level of significance and ordered by the absolute value of decreasing slope. The p-value is less than the 5% significance level in four defect categories: gas attack, structural, infiltration, and roots. Except for roots, all other three slopes are positive and small, showing an increase in defects between 0.04% and 0.012 % per meter length increase.

The slopes for debris, material damage, total joint, and dipped pipe defects are all small (below 0.05 % per meter length) and not statistically different from zero, indicating that these defects are not affected by length.

Table 50. Linear regression results for different defect categories as a function of length

Defect category rank	Intercept	Slope	P-value	Relationship
1. Gas attack	12.827	0.123	0.0004	Significant
2. Structural	8.686	0.077	0.045	Significant
3. Infiltration	11.386	0.047	0.018	Significant
4. Roots	17.429	-0.032	0.003	Significant
5. Debris	38.031	-0.058	0.193	Insignificant
6. Material damage	36.296	0.057	0.08	Insignificant
7. Total joint	8.479	0.024	0.261	Insignificant
8. Dipped pipe	9.504	0.011	0.647	Insignificant

7.5 Slope

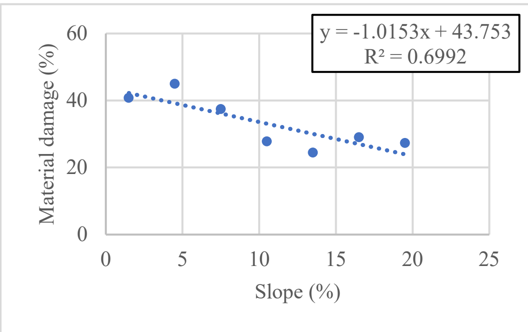
To study the impact of pipe diameter, pipes were grouped using 3% slope intervals, and the number of pipes with each defect was specified for each group, as shown in Table 52.The fractions of pipes with each defect were then plotted against the pipe slope, as shown in Figure 48.

Table 51. The number of pipes with defects in 3% slope intervals

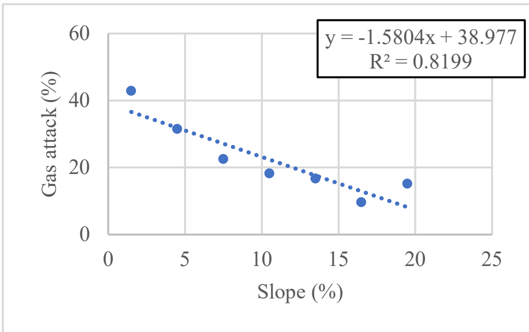
Slope Interval	**Total no of pipes**	**No of pipes with defect**								**Total no of defects**
		Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe	
(0,3]	1501	644	612	223	182	445	154	251	172	2683
(3,6]	654	206	294	107	127	206	71	109	70	1190
(6,9]	222	50	83	50	36	72	29	47	16	383
(9,12]	126	23	35	20	17	37	15	23	13	183
(12,15]	90	15	22	10	20	30	13	14	3	127

(15,18]	31	3	9	5	7	2	4	3	2	35
(18,21]	33	5	9	3	5	7	2	3	1	35
(21,24]	26*	4	9	1	1	8	0	6	1	30
(24,27]	22*	2	2	1	7	6	1	3	0	22
(27,30]	14*	3	6	0	3	4	0	2	0	18
(30,33]	14*	2	7	1	1	5	2	2	0	20
(33,36]	14*	2	1	1	1	3	3	2	0	13
(36,39]	12*	1	4	0	1	5	0	0	0	11
(39,42]	10*	6	3	1	0	5	0	2	0	17
(42,45]	5*	1	1	1	2	1	0	0	0	6
(45,48]	6*	0	0	0	0	3	2	1	0	6
Total	2780	967	1097	424	410	839	296	468	278	4779

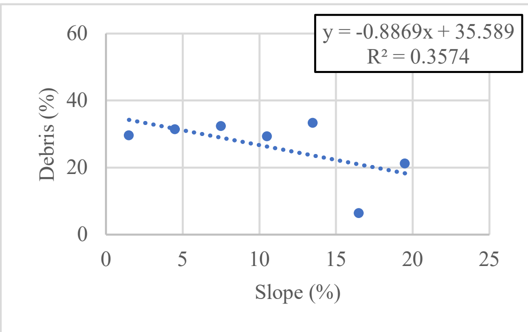
* The categories with less than 1% of the total number of pipes are excluded from significance estimations



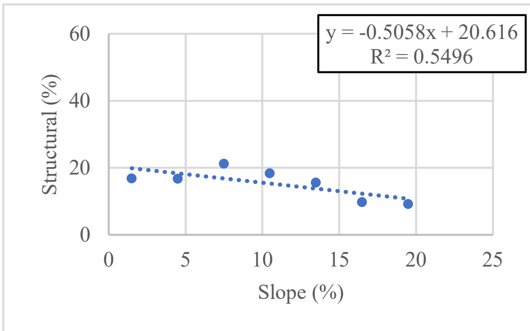
(a)



(b)



(a)



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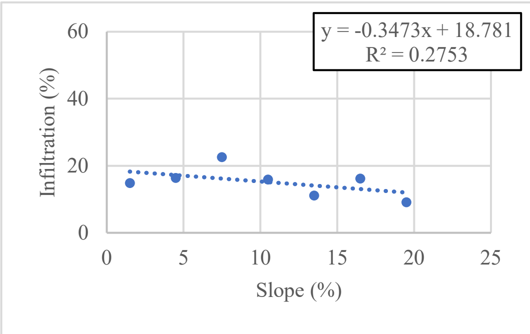
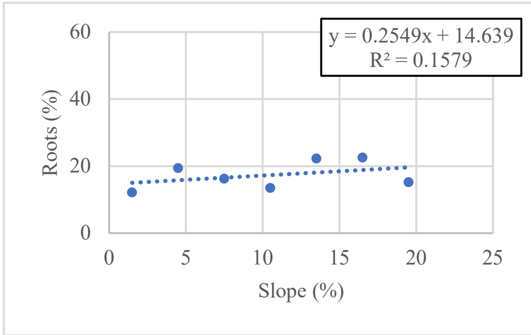
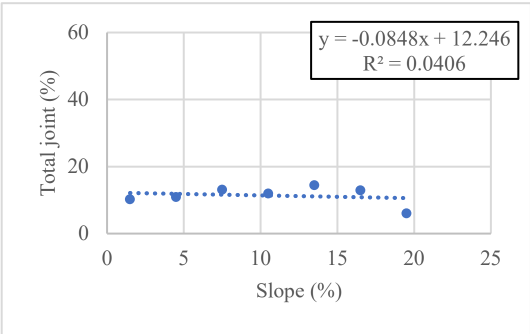


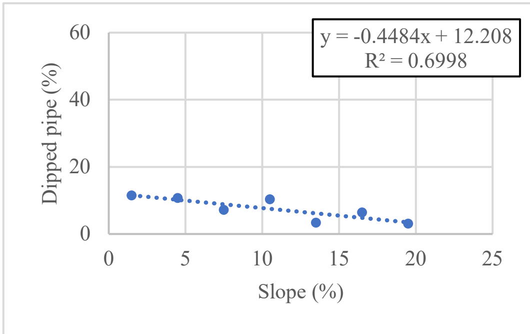
(a)



(b)



(g)



(h)

Data points used in the analysis ●, Excluded data points (outliers) ○

Figure 48. The fraction of pipes with different defects as a function of slope: a) material damage b) gas attack c) debris d) structural e) infiltration f) roots g) total joint h) dipped pipe

A summary of the linear regression results for each defect category, including the intercept, slope, and p-value, is presented in Table 53, separated by level of significance and ordered by decreasing slope. The p-value is less than the 5% significance level in four defect categories, including gas attack, material damage, structural, and dipped pipe. All four slopes are negative and relatively large, showing a decrease in defects between 0.45% and 1.5 % per 1.5% slope increase.

While the slopes for debris, infiltration, roots, and total joint are not small (below 0.08% and 0.88% slope), they are not statistically different from zero, indicating that these defects are not affected by the slope.

Table 52. Linear regression results for different defect categories as a function of slope

Defect category rank	Intercept	Slope	P-value	Relationship
1. Gas attack	38.977	-1.58	0.005	Significant
2. Material damage	43.753	-1.015	0.019	Significant
3. Structural	20.616	-0.505	0.056	Significant
4. Dipped pipe	12.208	-0.448	0.018	Significant
5. Debris	35.589	-0.886	0.156	Insignificant
6. Infiltration	18.781	-0.347	0.226	Insignificant
7. Roots	14.639	0.254	0.377	Insignificant
8. Total joint	12.246	-0.084	0.664	Insignificant

7.6 Groundwater

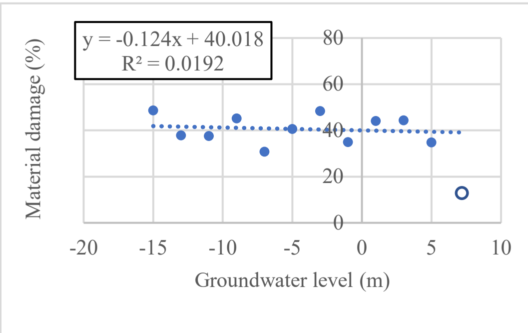
Groundwater level is defined relative to the pipe level. A positive groundwater level represents that groundwater level is above the pipe versus a negative value shows the groundwater level is below the pipe. Groundwater levels were grouped using 2 meters intervals, then the number of pipes with each defect was specified for each group as shown in Table 54. The fractions of pipes with each defect were then plotted against groundwater level as shown in Figure 49. The figures don't include any points after groundwater level of 10-meter and any points before minus 16-meter, since the number of records included in these ranges is all less than 1% of the total number of pipes that were excluded.

Table 53. The number of pipes with defects in 2-meter groundwater intervals

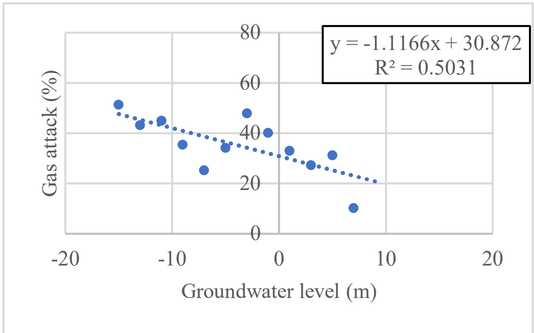
Groundwater level Interval	Total no of pipes	No of pipes with defect								Total no of defects
		Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe	
(-48,-46]	2*		1	0	1	2	0	0	0	4
(-46,-44]	0*		0	0	0	0	0	0	0	0
(-44,-42]	2*		1	0	0	0	0	0	1	2
(-42,-40]	0*		0	0	0	0	0	0	0	0

(-40,-38]	1*		0	1	0	0	0	1	0	2
(-38,-36]	0*		0	0	0	0	0	0	0	0
(-36,-34]	4*		4	0	0	0	0	0	0	4
(-34,-32]	2*		0	0	0	0	0	1	0	1
(-32,-30]	17*	2	4	1	4	3	0	3	0	17
(-30,-28]	9*	3	3	2	1	1	0	1	1	12
(-28,-26]	5*	3	3	1	2	1	0	1		11
(-26,-24]	23*	11	8	2	2	5	3	3	1	35
(-24,-22]	12*	5	7	1	4	2	3	6	1	29
(-22,-20]	24*	9	6	5	5	10	1	5	4	45
(-20,-18]	19*	7	10	1	2	2	2	5	2	31
(-18,-16]	18*	10	7	3	2	11	1	7	4	45
(-16,-14]	37	19	18	7	8	22	2	6	2	84
(-14,-12]	74	32	28	16	13	25	5	14	7	140
(-12,-10]	109	49	41	16	18	17	5	10	7	163
(-10,-8]	93	33	42	12	13	36	6	13	9	164
(-8,-6]	143	36	44	21	11	52	13	18	10	205
(-6,-4]	202	69	82	23	36	67	23	44	20	364
(-4,-2]	219	105	106	38	26	206	17	43	24	565
(-2,0]	651	261	227	87	76	134	75	114	69	1043
(0,2]	379	125	167	49	68	153	45	37	38	682
(2,4]	485	132	215	80	84	54	57	84	55	761
(4,6]	144	45	50	36	16	14	18	22	11	212
(6,8]	49	5	8	9	7	10	9	11	2	61
(8,10]	25*	2	5	6	6	5	7	11	2	44
(10,12]	8*	1	3	3	0	2	1	3	3	16
(12,14]	10*	1	3	1	2	2	2	2	4	17
(14,16]	8*	1	4	2	2	2	1	2	1	15
(16,18]	2*	1	0		1	0	0	0	0	2
(18,20]	4*		0	1	0	1	0	1	0	3
Total	**2780**	**967**	**1097**	**424**	**410**	**839**	**296**	**468**	**278**	**4779**

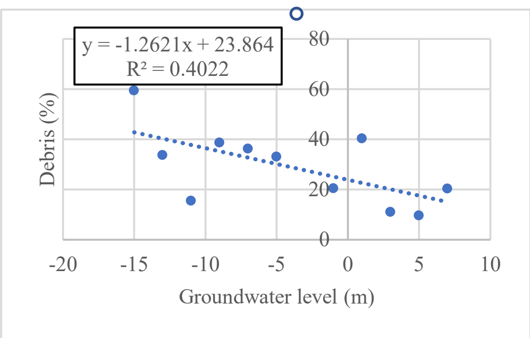
* The categories with less than 1% of the total number of pipes are excluded from significance estimations

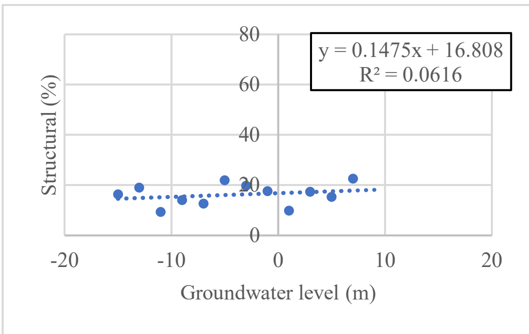

y = -0.124x + 40.018
R² = 0.0192
Material damage (%)
Groundwater level (m)
0
20
40
60
80
-20
-15
-10
-5
0
5
10

(a)

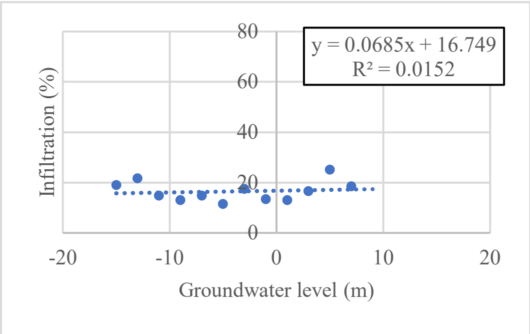

y = -1.1166x + 30.872
R² = 0.5031
Gas attack (%)
Groundwater level (m)
0
20
40
60
80
-20
-10
0
10
20

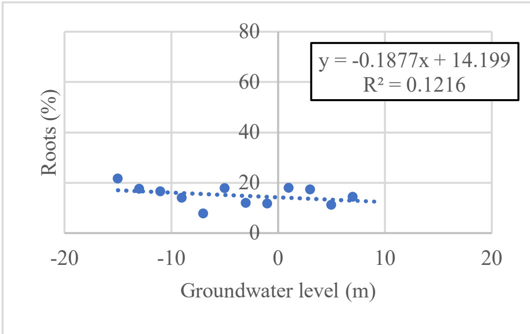
(b)


y = -1.2621x + 23.864
R² = 0.4022
Debris (%)
Groundwater level (m)
0
20
40
60
80
-20
-15
-10
-5
0
5
10

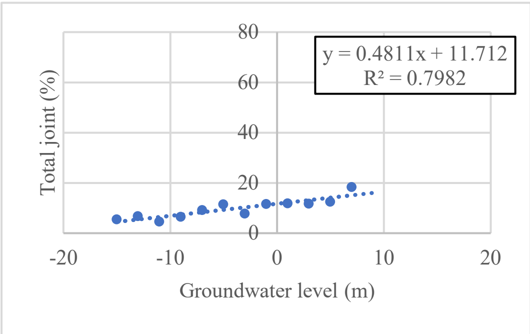

y = 0.1475x + 16.808
R² = 0.0616
Structural (%)
Groundwater level (m)
0
20
40
60
80
-20
-10
0
10
20

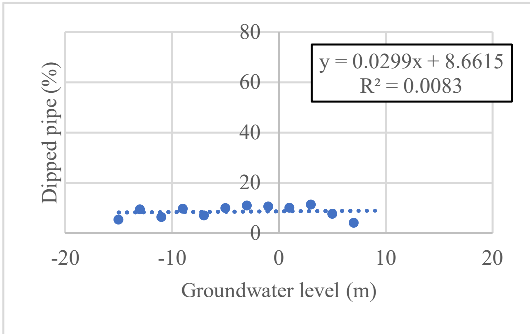
(c) (d)





(e) (f)





(g) (h)

Data points used in the analysis ●, Excluded data points (outliers) ○

Figure 49. The fraction of pipes with different defects as a function of groundwater level: a) material damage b) gas attack c) debris d) structural e) infiltration f) roots g) total joint h) dipped pipe

A summary of the linear regression results for each category, including the intercept, slope, and p-value, is presented in Table 55, separated by level of significance and ordered by decreasing absolute value of slope. The p-value is less than the 5% significance level in three defect categories which are debris, gas attack, and total joint. While the slope for total joint defect is positive, showing a constant increase of 0.48% per meter groundwater level, the slope for debris and gas attack is negative, showing a decrease of 1.26% and 1.11% per meter groundwater level.

The slopes for the rest of the defects are not statistically different from zero, indicating that these defects are not affected by groundwater level.

Table 54. Linear regression results for different defect categories as a function of groundwater

Defect category rank	Intercept	Slope	P-value	Relationship
1. Debris	23.864	-1.262	0.036	Significant
2. Gas attack	30.872	-1.116	0.009	Significant
3. Total joint	11.712	0.481	0.00009	Significant
4. Roots	14.199	-0.187	0.266	Insignificant
5. Structural	16.808	0.147	0.436	Insignificant
6. Material damage	40.018	-0.124	0.684	Insignificant
7. Infiltration	16.749	0.068	0.702	Insignificant
8. Dipped pipe	8.661	0.029	0.778	Insignificant

7.7 Population density

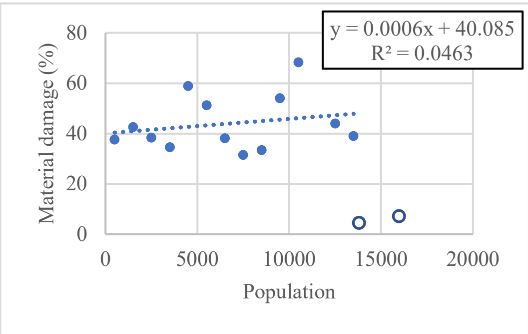
To study the impact of population density, pipes were grouped using 1000-people intervals, and the number of pipes with each defect was specified for each group, as shown in Table 56. The fractions of pipes with each defect were then plotted against the population density, as shown in Figure 50. The figures don't include any dataset higher than a population density of 16000 people per square kilometre of an area since the number of records included in these ranges is all less than 1% of the total number of pipes.

Table 55. The number of pipes with defects in 1000 people per square kilometre population density intervals

Population density Interval	Total no of pipes	No of pipes with defect								Total no of defects
		Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe	
(0,1e+03]	712	280	267	120	80	181	50	163	64	1205
(1e+03,2e+03]	367	163	156	74	54	87	42	87	55	718
(2e+03,3e+03]	248	122	95	59	33	46	24	50	26	455

(3e+03,4e+03]	197	117	68	27	15	66	19	29	28	369
(4e+03,5e+03]	204	122	120	39	37	64	19	26	19	446
(5e+03,6e+03]	172	57	88	13	19	64	19	19	22	301
(6e+03,7e+03]	84	37	32	17	8	31	6	6	8	145
(7e+03,8e+03]	121	1	38	10	22	44	21	27	10	173
(8e+03,9e+03]	171	12	57	21	49	38	12	13	8	210
(9e+03,1e+04]	139	34	75	29	36	78	23	17	29	321
(1e+04,1.1e+04]	63	2	43	1	4	16	4	12	1	83
(1.1e+04,1.2e+04]	28*	4	8	2	7	14	2	2	0	39
(1.2e+04,1.3e+04]	66	15	29	2	9	36	3	4	2	100
(1.3e+04,1.4e+04]	36	1	14	1	4	20	6	2	0	48
(1.4e+04, 1.5e+04]	96	0	3	0	21	27	24	6	3	84
(1.5e+04,1.6e+04]	53	0	3	6	12	17	18	4	2	62
(1.6e+04,1.7e+04]	22*	0	1	2	0	9	3	1	1	17
(1.7e+04,1.8e+04]	1*	0	0	1	0	1	1	0	0	3
Total	**2780**	**967**	**1097**	**424**	**410**	**839**	**296**	**468**	**278**	**4779**

* The categories with less than 1% of the total number of pipes are excluded from significance estimations



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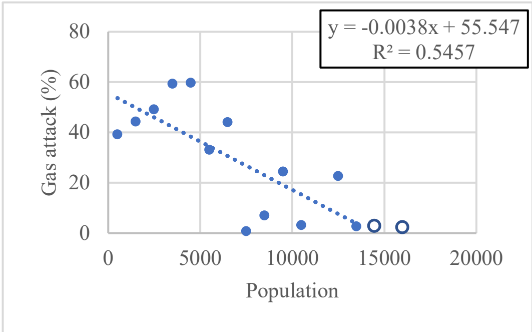

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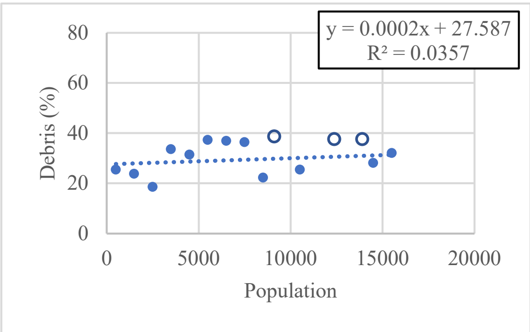

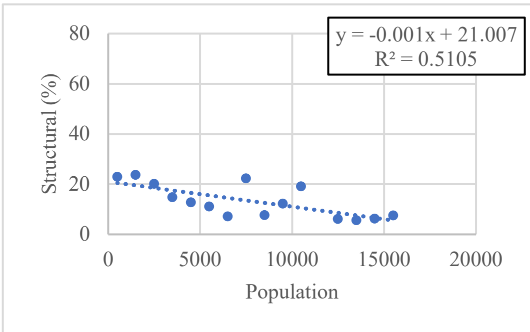

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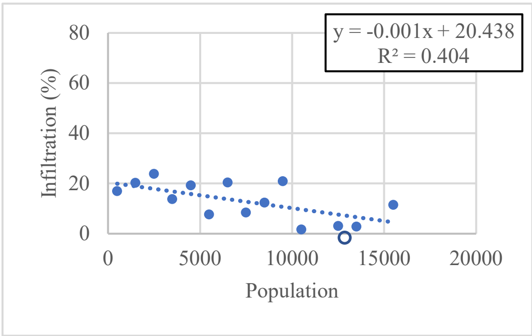

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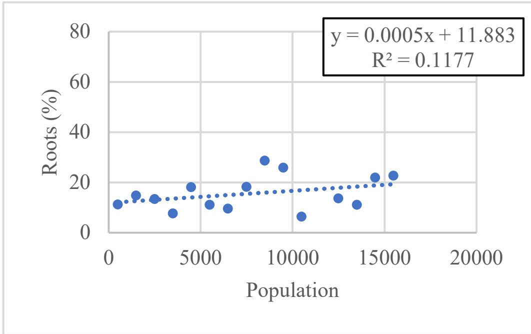

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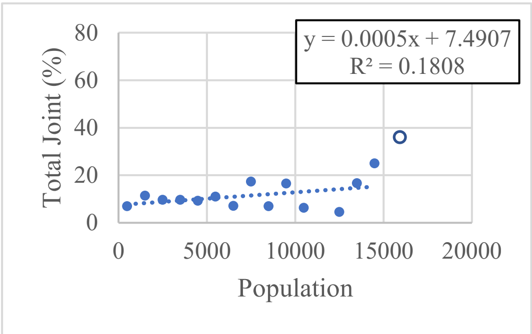

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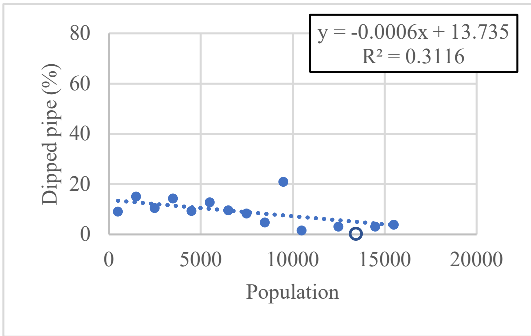


(g) (h)

Data points used in the analysis ●, Excluded data points (outliers) ○

Figure 50. The fraction of pipes with different defects as a function of population: a) material damage b) gas attack c) debris d) structural e) infiltration f) roots g) total joint h) dipped pipe

A summary of the linear regression results for each defect category, including the intercept, slope, and p-value, is presented in Table 57, separated by level of significance and ordered by the absolute value of decreasing slope. The p-value is less than the 5% significance level in four defect categories: gas attack, infiltration, structural, and dipped pipe. All four slopes are negative, showing a decrease in defects between -0.0006% and -0.003 % per person on each square kilometre increase.

The slopes for total joint, material damage, roots and debris defects are all small (below 0.0006% per person on each square kilometre) and not statistically different from zero, indicating that these defects are not affected by the slope.

Table 56.Linear regression results for different defect categories as a function of population density

Defect category rank	Intercept	Slope	P-value	Relationship
1. Gas attack	55.547	-0.003	0.003	Significant
2. Infiltration	20.438	-0.001	0.007	Significant
3. Structural	21.007	-0.001	0.0002	Significant
4. Dipped pipe	13.735	-0.0006	0.038	Significant
5. Material damage	40.085	0.0006	0.48	Insignificant
6. Total joint	7.490	0.0005	0.129	Insignificant
7. Roots	11.883	0.0005	0.21	Insignificant
8. Debris	27.587	0.0002	0.556	Insignificant

7.8 Liquefaction susceptibility

Soil liquefaction has the potential to cause serious failures in infrastructure. The liquefaction susceptibility of different zones of Auckland city is assigned to inspect main transmission sewers according to a geospatial liquefaction map developed by Zhe et al. (2017). This factor is used to represent the effect of the probability of liquefaction on the prevalence of various defects on the main transmission sewers in Auckland city. Zhe et al. believe that geospatial susceptibility maps can be beneficial as preliminary data for regional-scale planning. Based on the geospatial map presented, different ranges representing liquefaction susceptibility are shown in Table 58. According to Figure 51, liquefaction susceptibility in Auckland is mostly categorized into moderate and high ranges. The distribution of liquefaction susceptibility ranges besides the wastewater treatment plants in Auckland is represented in Figure 52. No specific relationship between the location of WWTPs and the liquefaction susceptibility range was visible.

Table 57. Liquefaction susceptibility for different ranges according to Zhe et al. geospatial map (2017)

Range	Susceptibility
-38.1 to -3.2	Very low
-3.2 to -3.15	low

-3.15 to -1.95	Moderate
-1.95 to -1.15	high
-1.15 to 5.30	Very high

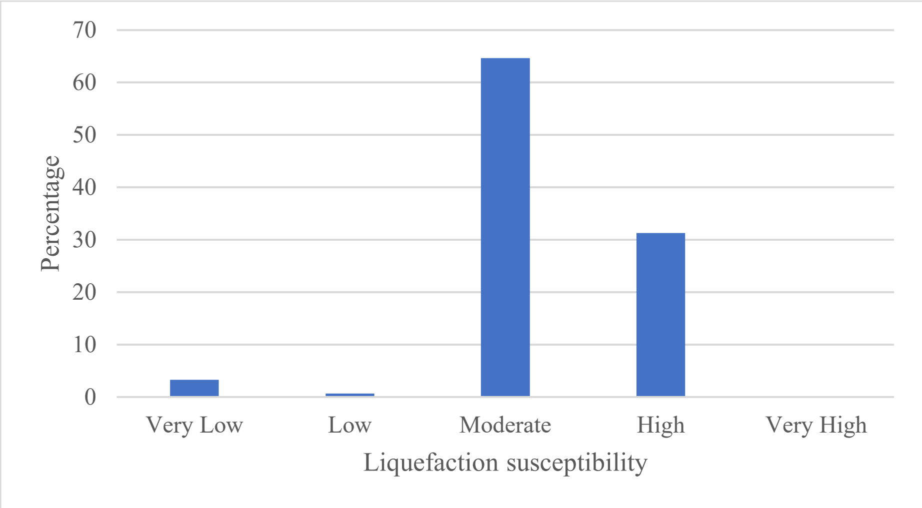


Figure 51. The distribution of liquefaction susceptibility ranges of main transmission sewer pipes

Figure 52. Liquefaction susceptibility ranges in Auckland

To identify the effect of liquefaction susceptibility ranges, the number of pipes defect for each range was determined, as shown in Table 59. The fractions of pipes with each defect were then plotted against the liquefaction susceptibility ranges, as shown in)

Figure 53. The figures don't include any dataset in low and very high ranges since the number of records included in these ranges is less than 1% of the total number of pipes.

Table 58. The number of pipes with defects in different liquefaction susceptibility ranges

Liquefaction susceptibility Interval	Total no of pipes	No of pipes with defect								Total no of defects
		Gas attack	Material damage	Infiltration	Roots	Debris	Total joint	Structural	Dipped pipe	
Very Low	92	33	0	23	14	18	11	25	8	132
Low	18*	1	7	2	0	2	0	2	4	18
Moderate	1797	456	719	270	327	532	222	323	171	3020
High	869	475	371	129	68	287	63	117	94	1604
Very High	4*	2	0	0	1	0	0	1	1	5
Total	**2780**	**967**	**1097**	**424**	**410**	**839**	**296**	**468**	**278**	**4779**

* The categories with less than 1% of the total number of pipes are excluded from significance estimations

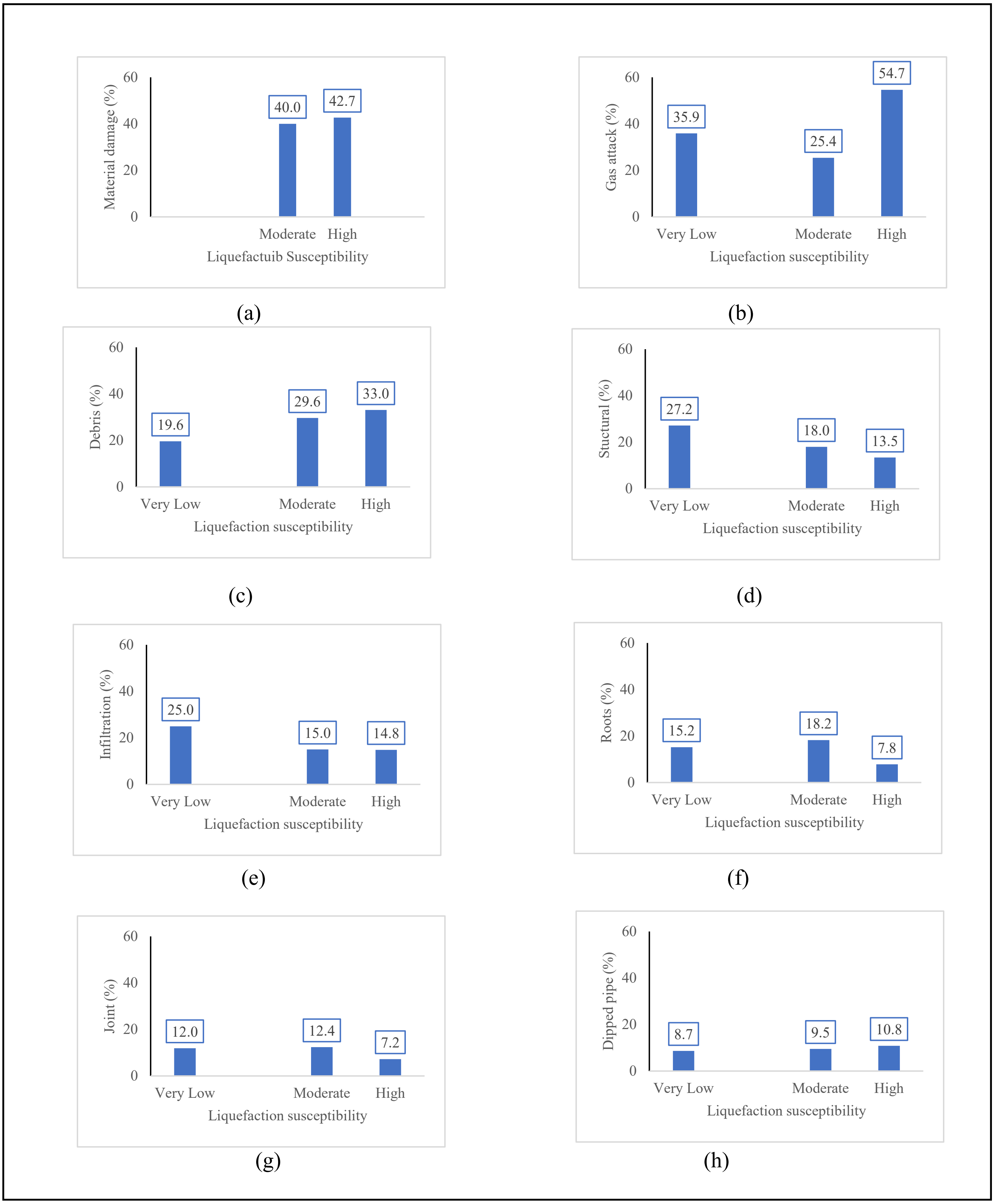


Figure 53. The fraction of pipes with different defects as a function of pipe's material a) material damage b) gas attack c) debris d) structural e) infiltration f) roots g) total joint h) dipped pipe

A general view of liquefaction susceptibility ranges with corresponding percentages for each defect category is summarized in Table 60.

Table 59. A summary of the highest and lowest liquefaction susceptibility ranges for each defect category

Defect category	Very low	Moderate	high
Material damage	-	40	42.7
Gas attack	35.9	25.4	54.7
Debris	19.6	29.6	33.0
Structural	27.2	18.0	13.5
Infiltration	25.0	15.0	14.8
Roots	15.2	18.2	7.8
Total joint	12	12.4	7.2
Dipped pipe	8.7	9.5	10.8

As shown in the above table, while the high liquefaction susceptibility range has the highest percentage in four out of eight defects, including material damage, gas attack, debris, and dipped pipe, it has the lowest percentage (between 7% and 14%) in the rest of defect categories. Therefore, not any specific trends have been specified between liquefaction susceptibility ranges and the number of different defect categories.

8 APPENDIX B: DEVELOPING BINARY LOGISTIC REGRESSION MODELS

8.1 Material damage

The first binary logistic regression model was developed for the material damage defect category. The regression coefficient of mentioned independent variables is shown in Table 29. Three of the variables by P-value less than 0.005 are determined as significant. According to Table 29, two variables, including age and length, which are numerical variables, were distinguished as significant. In pipe material, which is a categorical variable, all materials, apart from earthenware and RCRRJ, were determined as significant.

Table 60. Regression coefficients and their features of binary logistic regression model for material damage

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-1.226e+00	3.086e-01	-3.973	0.000
Age	6.081e-03	2.353e-03	2.584	0.009
Diameter	-1.085e-05	1.067e-04	0.102	0.919
Depth	-3.518e-02	2.061e-02	-1.707	0.087
Length	2.163e-03	5.799e-04	3.730	0.000
Slope	-1.324e-02	8.043e-03	-1.646	0.099
Groundwater level	2.326e-04	6.196e-03	0.038	0.970
Population Density	-1.957e-06	1.582e-05	0.124	0.901
Liquefaction Susceptibility (low)	-5.965e-03	5.379e-01	-0.011	0.991
Liquefaction Susceptibility (Moderate)	-9.240e-02	1.036e-01	-0.892	0.372
Liquefaction Susceptibility (Very High)	-1.368e+01	2.643e+02	-0.052	0.958

Liquefaction Susceptibility (Very low)	3.936e-01	2.390e-01	1.647	0.099
Material-factor CIP (Reference)	0	-	-	-
Material-factor (Conc)	6.665e-01	2.237e-01	2.979	0.002
Material-factor (EW)	3.968e-01	3.158e-01	1.257	0.208
Material factor (OTHERS)	-6.506e-01	2.884e-01	-2.256	0.024
Material-factor (PE)	-1.852e+00	4.881e-01	-3.794	0.000
Material-factor (RC)	8.398e-01	2.161e-01	3.886	0.000
Material-factor (RCRRJ)	3.415e-01	2.268e-01	1.506	0.132

Table 61. Accuracy of binary logistic regression for material damage

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	3723		2777		
Current model	3496	227	2760	0.000	3532

In the next step, variables with a high P-score (higher than 0.05) are removed through a few backward stepwise selection procedures. The coefficients of significant variables of the binary logistic regression model after removing insignificant variables and implementing a few backward stepwise selection procedures are shown in Table 31.

As represented in Table 31, following factors, including slope, length, population density, and material are determined as significant variables.

Table 62. Regression coefficients and their features after backward stepwise method in the binary logistic regression model for material damage

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-4.982e-01	2.217e-01	-2.247	0.024
Slope	-2.085e-02	8.952e-03	-2.329	0.019
Length	1.768e-03	6.124e-04	2.888	0.003
Population density	-4.159e-05	1.378e-05	-3.017	0.002
Material-Conc	9.755e-01	2.498e-01	3.905	0.000
Material-PE	-1.935e+00	5.377e-01	-3.598	0.000
Material-RC	7.147e-01	2.331e-01	3.066	0.002

The significance of the current binary regression model is shown in Table 32. According to the table and comparing AIC, the current model with three independent variables surpasses the first binary model. As represented in Table 32, the significance level of the model is less than 0.05. So, our current model surpasses the null model.

Table 63. Accuracy of binary logistic regression after the backward stepwise method for material damage

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	2018		1480		
Current model	1901	117	1474	0.000	1915

The real values and predicted values for the final model are illustrated in Table 34, used to show the accuracy of the model.

Table 64. Accuracy of binary logistic regression after the backward stepwise method for material damage

Actual values	Predicted values		Accuracy
	0	1	
0	176	43	59%
1	111	51	

8.2 Gas attack

The gas attack defect category was considered the second output variable for developing the binary logistic regression model. The regression coefficient of mentioned independent variables is shown in Table 66. Variables by P-value less than 0.05 are determined as significant. According to Table 66, six variables, including depth, length, groundwater level, and population density which are numerical variables, distinguished as significant. In pipe material, which is a categorical variable, all materials were determined as significant. Also, the liquefaction susceptibility variable signified as significant in two levels, including low and moderate.

Table 65. Regression coefficients and their features of binary logistic regression model for gas attack

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-4.44e-01	3.761e-01	-1.183	0.236
Age	-1.433e-03	3.008e-03	-0.476	0.633
Diameter	-1.570e-04	1.354e-04	-1.616	0.106
Depth	-5.974e-02	2.578e-02	-2.317	0.020
Length	3.164e-03	6.892e-04	4.591	0.000
Slope	-4.441e-03	1.029e-02	-0.432	0.665

Groundwater level	-2.697e-02	7.749e-03	-3.480	0.000
Population Density	6.664e-05	1.950e-05	3.417	0.000
Liquefaction Susceptibility (low)	-2.568e+00	1.080e+00	-2.379	0.017
Liquefaction Susceptibility (Moderate)	-5.303e-01	1.161e-01	-4.568	0.000*
Liquefaction Susceptibility (Very High)	-6.266e-01	1.013e+00	-0.619	0.536
Liquefaction Susceptibility (Very low)	-4.348e-01	2.885e-01	-1.507	0.131
Material-factor CIP (Reference)	0	-	-	-
Material-factor (Conc)	-2.081e+00	2.926e-01	-7.112	0.000
Material-factor (EW)	-2.276e+00	6.391e-01	-3.561	0.000
Material factor (OTHERS)	-1.249e+00	3.323e-01	-3.758	0.000
Material-factor (PE)	-3.030e+00	5.644e-01	-5.369	0.000
Material-factor (RC)	1.014e+00	2.447e-01	4.145	0.000
Material-factor (RCRRJ)	9.413e-01	2.57e-01	3.663	0.000

As represented in Table 67, the significance level of the model is less than 0.05. Thus, our current model surpasses the null model.

Table 66. Accuracy of binary logistic regression for gas attack

	Deviance	**Chi-square**	**Degree of freedom**	**Significance**	**AIC**
Null	3585		2777		
Current model	2626	959	2763	0.000	2656

In the next step, variables with a high P-score are removed through a few backward stepwise selection procedures. The coefficients of significant variables of the binary logistic regression model after removing insignificant variables and implementing a few backward stepwise selection procedures are shown in Table 68.

Table 67. Regression coefficients and their features after backward stepwise method in the binary logistic regression model for gas attack

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-4.371e+00	1.139e+00	-3.839	0.000
Length	1.509e-03	9.185e-04	1.643	0.09
Groundwater	-2.524e-02	9.728e-03	-2.594	0.00948
Population density	5.538e-05	2.501e-05	2.214	0.02681
Material-Conc	-9.619e-01	3.904e-01	-2.464	0.064
Material-PE	-2.548e+00	8.192e-01	-3.111	0.001
Material-RC	1.814e+00	3.197e-01	5.673	0.000
Material-RCRRJ	2.496e+00	3.288e-01	7.591	0.000

As represented in Table 68, length, groundwater level, population density, and material (Conc, PE, RC, RCRRJ) variables were determined as significant. Interestingly, liquefaction Susceptibility (Moderate) which was a significant variable in the first model, transformed into an insignificant variable after eliminating insignificant variables.

The significance of the current binary regression model is shown in Table 69. According to the table and comparing AIC, the current model with six independent variables surpasses the first binary model. As represented in Table 69, the significance level of the model is less than 0.05. So, our current model surpasses the null model.

Table 68. Accuracy of binary logistic regression after the backward stepwise method for gas attack

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	1495		1278		
Current model	1061	434	1271	0.000	1077

The real values and predicted values for the second model are illustrated in Table 70, used to show the accuracy of the model.

Table 69. Accuracy of binary logistic regression after the backward stepwise method for gas attack

Actual values	Predicted values		Accuracy
	0	1	
0	184	40	77%
1	28	54	

8.3 Debris

By considering debris as the output variable, the first binary logistic regression model was developed. The regression coefficient of mentioned independent variables is shown in Table 71. Variables with a P-value less than 0.005 are determined as significant. According to Table 71, three variables, including diameter, groundwater level, and population density, which are numerical variables, were distinguished as significant. Also, the liquefaction susceptibility variable was signified as significant in the very low, low, and moderate levels. Similarly, the material was signified as significant in three levels, including OTHERS, RC, and RCRRJ.

Table 70. Regression coefficients and their features of binary logistic regression model for debris

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	1.965e-01	3.362e-01	0.584	0.558
Age	7.505e-04	2.555e-03	0.294	0.768
Diameter	-7.173e-04	1.275e-04	-5.625	0.000
Depth	-1.075e-02	2.057e-02	-0.523	0.601
Length	1.062e-03	5.681e-04	1.869	0.061
Slope	-5.214e-03	7.905e-03	-0.660	0.509
Groundwater level	-2.110e-02	6.978e-03	-3.024	0.002
Population Density	7.296e-05	1.526e-05	4.782	0.000
Liquefaction Susceptibility (low)	-1.688e+00	7.735e-01	-2.183	0.029
Liquefaction Susceptibility (Moderate)	-6.370e-01	1.131e-01	-5.632	0.000
Liquefaction Susceptibility (Very High)	-1.320e+01	2.660e+02	-0.050	0.960
Liquefaction Susceptibility (Very low)	-6.236e-01	2.881e-01	-2.164	0.030
Material-factor CIP (Reference)	0	-	-	-
Material-factor (Conc)	-4.406e-01	2.421e-01	-1.820	0.068
Material-factor (EW)	-3.243e-01	3.415e-01	-0.950	0.342
Material factor (OTHERS)	-1.164e+00	2.958e-01	-3.936	0.000
Material-factor (PE)	-5.632e-02	3.326e-01	-0.169	0.865
Material-factor (RC)	-5.322e-01	2.359e-01	-2.256	0.024
Material-factor (RCRRJ)	-7.163e-01	2.476e-01	-2.893	0.003

Table 71. Accuracy of binary logistic regression for debris

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	3393.3		2777		
Current model	3255.2	138	2760	0.000	3291.2

In the next step, variables with a high P-score (higher than 0.05) are removed through a few backward stepwise selection procedures. The coefficients of significant variables of the binary logistic regression model after removing insignificant variables and implementing a few backward stepwise selection procedures are shown in Table 73.

As represented in Table 73, diameter, length, groundwater level, and population density are determined as significant variables. Interestingly, length, which was not significant, transformed into a significant variable and material, which was significant in three levels, transformed to insignificant after removing insignificant variables.

Table 72. Regression coefficients and their features after backward stepwise method in the binary logistic regression model for debris

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-8.075e-01	1.349e-01	-4.217	0.000
Diameter	-5.102e-04	1.294e-04	-4.012	0.000
Length	1.169e-03	5.661e-04	2.065	0.038
Groundwater level	-2.130e-02	7.489e-03	-2.844	0.004
Population density	4.894e-05	1.056e-05	4.636	0.000

The significance of the current binary regression model is shown in Table 74. According to table, and comparing AIC, the current model with three independent variables surpasses the first binary model. As represented in Table 74, the significance level of the model is less than 0.05. So, our current model surpasses the null model.

Table 73. Accuracy of binary logistic regression after the backward stepwise method for the debris defect category

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	2730		2232		
Current model	2668.9	62	2228	0.000	2678

The real values and predicted values for the second model are illustrated in Table 75, used to show the accuracy of the model.

Table 74. Accuracy of binary logistic regression after the backward stepwise method for the debris defect category

Actual values	Predicted values		Accuracy
	0	1	
0	337	46	70%
1	107	36	

8.4 Structural

The structural defect category was considered as another output variable, and the first binary logistic regression model defect was developed for that. The regression coefficient of mentioned independent variables is shown in Table 76. Variables with a P-value less than 0.005 are determined as significant. According to Table 76, two variables, including age and population density which are numerical variables, were distinguished as significant. In pipe material, which is a categorical variable, all materials apart from Conc and OTHERS were determined as significant.

Table 75. Regression coefficients and their features of binary logistic regression model for structural

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-2.220e+00	3.691e-01	-6.014	0.000
Age	1.860e-02	3.266e-03	5.694	0.000
Diameter	1.441e-04	1.342e-04	1.074	0.283
Depth	-1.733e-02	2.829e-02	-0.613	0.540
Length	1.234e-03	7.030e-04	1.755	0.079
Slope	-1.179e-02	1.113e-02	-1.059	0.289
Groundwater level	1.565e-02	9.046e-03	1.730	0.083
Population Density	-8.382e-05	2.245e-05	-3.733	0.000
Liquefaction Susceptibility (low)	-5.222e-01	8.217e-01	-0.636	0.525
Liquefaction Susceptibility (Moderate)	2.712e-01	1.452e-01	1.868	0.061
Liquefaction Susceptibility (Very High)	9.572e-01	1.174e+00	0.815	0.415
Liquefaction Susceptibility (Very low)	1.188e-01	3.251e-01	0.365	0.714
Material-factor CIP (Reference)	0	-	-	-
Material-factor (Conc)	-1.400e-01	2.349e-01	-0.596	0.551
Material-factor (EW)	1.830e+00	3.651e-01	5.013	0.000
Material factor (OTHERS)	1.052e-01	2.954e-01	0.356	0.721
Material-factor (PE)	-2.443e+00	1.043e+00	-2.342	0.019
Material-factor (RC)	-9.218e-01	2.345e-01	-3.931	0.000
Material-factor (RCRRJ)	-8.150e-01	2.525e-01	-3.227	0.001

Table 76. Accuracy of binary logistic regression for structural

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	2464.3		2777		
Current model	2093.6	371	2760	0.000	2129.6

In the next step, variables with a high P-score (higher than 0.05) are removed through a few backward stepwise selection procedures. The coefficients of significant variables of the binary logistic regression model after removing insignificant variables and implementing a few backward stepwise selection procedures are shown in Table 78.

As represented in Table 78, age, length, and material (EW, PE, RC, and RCRRJ) are determined as significant variables. Surprisingly, population density which was significant, transformed to insignificant after removing insignificant variables.

Table 77. Regression coefficients and their features after backward stepwise method in the binary logistic regression model for structural

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-1.879166	0.470746	-3.992	0.000
Age	0.016791	0.004925	3.409	0.000
Length	0.001851	0.000857	2.157	0.03100
Material-EW	1.651944	0.366453	4.508	0.000
Material-PE	-2.830469	1.089980	-2.597	0.009
Material-RC	-1.145274	0.278857	-4.107	0.000
Material-RCRRJ	-0.961498	0.308842	-3.113	0.001

The significance of the current binary regression model is shown in Table 79. According to the table and comparing AIC, the current model with three independent variables surpasses the first binary model. As represented in Table 79, the significance level of the model is less than 0.05. So, our current model surpasses the null model.

Table 78. Accuracy of binary logistic regression after the backward stepwise method for structural

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	1240.3		1353		
Current model	1038	202	1347	0.000	1052

The real values and predicted values for the second model are illustrated in Table 80, used to show the accuracy of the model.

Table 79. Accuracy of binary logistic regression after the backward stepwise method for structural

Actual values	Predicted values		Accuracy
	0	1	
0	260	1	86%
1	42	7	

8.5 Infiltration

The first binary logistic regression model was developed by considering the infiltration defect category as another output variable. The regression coefficient of mentioned independent variables is shown in Table 81. Variables with a P-value less than 0.005 are determined as significant. According to Table 81, three variables, including depth, length, and slope, which are numerical variables, distinguished as significant. In pipe material, which is a categorical variable, all materials were determined as significant. Also, the liquefaction susceptibility variable signified as significant at a very low level.

Table 80. Regression coefficients and their features of binary logistic regression model for infiltration

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-7.917e-01	3.694e-01	-2.143	0.032
Age	4.189e-03	3.161e-03	1.325	0.185
Diameter	-1.782e-04	1.407e-04	-1.267	0.205
Depth	7.208e-02	2.543e-02	2.835	0.004
Length	2.722e-03	6.305e-04	4.316	0.000
Slope	-2.924e-02	1.249e-02	-2.341	0.019
Groundwater level	1.252e-02	8.945e-03	1.399	0.161
Population Density	-3.386e-05	2.212e-05	-1.531	0.125
Liquefaction Susceptibility (low)	-1.442e-01	7.872e-01	-0.183	0.854
Liquefaction Susceptibility (Moderate)	1.400e-01	1.413e-01	0.990	0.321
Liquefaction Susceptibility (Very High)	-1.252e+01	2.445e+02	-0.051	0.959
Liquefaction Susceptibility (Very low)	6.137e-01	2.955e-01	2.077	0.037
Material-factor CIP (Reference)	0	-	-	-
Material-factor (Conc)	-1.515e+00	2.504e-01	-6.051	0.000
Material-factor (EW)	-6.708e-01	3.336e-01	-2.011	0.044
Material factor (OTHERS)	-1.532e+00	3.275e-01	-4.680	0.000
Material-factor (PE)	-2.485e+00	5.430e-01	-4.576	0.000
Material-factor (RC)	-1.346e+00	2.318e-01	-5.809	0.000

Material-factor (RCRRJ)	-1.261e+00	2.476e-01	-5.091	0.000

Table 81. Accuracy of binary logistic regression for infiltration

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	2384.0		2777		
Current model	2208.2	176	2760	0.000	2244.2

In the next step, variables with a high P-score (higher than 0.05) are removed through a few backward stepwise selection procedures. The coefficients of significant variables of the binary logistic regression model after removing insignificant variables and implementing a few backward stepwise selection procedures are shown in Table 83.

As represented in Table 83, age, length, depth, and material were determined as significant variables. Surprisingly slope and liquefaction susceptibility, which were significant, turned out to be insignificant after removing insignificant variables.

Table 82. Regression coefficients and their features after backward stepwise method in the binary logistic regression model for infiltration

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-1.167611	0.341579	-3.418	0.000
Age	0.007952	0.003162	2.515	0.011
Length	0.002729	0.000587	4.649	0.000
Depth	0.038819	0.021615	1.796	0.072

Material-Conc	-1.604844	0.244512	-6.563	0.000
Material-OTHERS	-1.409130	0.342778	-4.111	0.000
Material-PE	-2.372804	0.602200	-3.940	0.000
Material-RC	-1.394678	0.246595	-5.656	0.000
Material-RCRRJ	-1.360914	0.263986	-5.155	0.000

The significance of the current binary regression model is shown in Table 84. According to the table and comparing AIC, the current model with three independent variables surpasses the first binary model. As represented in Table 84, the significance level of the model is less than 0.05. So, our current model surpasses the null model.

Table 83. Accuracy of binary logistic regression after the backward stepwise method for infiltration

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	1856		2222		
Current model	1747	109	2214	0.000	1765

The real values and predicted values for the second model are illustrated in Table 85, used to show the accuracy of the model.

Table 84. Accuracy of binary logistic regression after the backward stepwise method for infiltration

Actual values	Predicted values		Accuracy
	0	1	
0	408	5	84%
1	69	8	

8.6 Roots

The roots defect category was considered as another output variable, and the first binary logistic regression model defect was developed for that. The regression coefficient of mentioned independent variables is shown in Table 86. Variables with a P-value less than 0.005 are determined as significant. According to Table 86, three variables, including age, diameter, and population density which are numerical variables, distinguished as significant. In pipe material, which is a categorical variable, two materials, including EW and OTHERS, were determined as significant. Also, the liquefaction susceptibility variable was signified as significant at a moderate level.

Table 85. Regression coefficients and their features of binary logistic regression model for roots

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-2.737e+00	4.216e-01	-6.492	0.000
Age	1.589e-02	3.407e-03	4.665	0.000
Diameter	-6.661e-04	1.716e-04	-3.882	0.000
Depth	-2.895e-02	2.806e-02	-1.032	0.302
Length	6.500e-04	7.744e-04	0.839	0.401
Slope	-3.204e-03	9.970e-03	-0.321	0.747
Groundwater level	1.019e-03	7.908e-03	0.129	0.897
Population Density	4.816e-05	2.018e-05	2.387	0.017
Liquefaction Susceptibility (low)	-1.322e+01	3.340e+02	-0.040	0.968
Liquefaction Susceptibility (Moderate)	5.256e-01	1.622e-01	3.240	0.001
Liquefaction Susceptibility (Very High)	1.244e+00	1.169e+00	1.065	0.287

Liquefaction Susceptibility (Very low)	2.428e-01	3.480e-01	0.698	0.485
Material-factor CIP (Reference)	0	-	-	-
Material-factor (Conc)	1.580e-01	2.836e-01	0.557	0.577
Material-factor (EW)	7.843e-01	3.518e-01	2.230	0.025
Material factor (OTHERS)	7.843e-01	3.518e-01	2.230	0.025
Material-factor (PE)	-8.179e-01	5.351e-01	-1.529	0.126
Material-factor (RC)	-2.062e-01	2.842e-01	-0.726	0.468
Material-factor (RCRRJ)	-2.209e-01	3.037e-01	-0.727	0.467

Table 86. Accuracy of binary logistic regression for roots

	Deviance	**Chi-square**	**Degree of freedom**	**Significance**	**AIC**
Null	2325.2		2777		
Current model	2164.0	161	2760	0.000	2200

In the next step, variables with a high P-score (higher than 0.05) are removed through a few backward stepwise selection procedures. The coefficients of significant variables of the binary logistic regression model after removing insignificant variables and implementing a few backward stepwise selection procedures are shown in Table 88.

As represented in Table 88, age, diameter, and population density remained as significant variables.

Table 87. Regression coefficients and their features after backward stepwise method in the binary logistic regression model for roots

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-2.981e+00	2.385e-01	-12.496	0.000
Age	2.454e-02	3.054e-03	8.037	0.000
Diameter	-8.962e-04	1.756e-04	-5.103	0.000
Population density	9.256e-05	1.512e-05	6.121	0.000

The significance of the current binary regression model is shown in Table 89. According to the table and comparing AIC, the current model with three independent numerical variables, including age, diameter, and population density, surpasses the first binary model. As represented in Table 89, the significance level of the model is less than 0.05. So, our current model surpasses the null model.

Table 88. Accuracy of binary logistic regression after the backward stepwise method for roots

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	1860.6		2234		
Current model	1760.3	100	2231	0.000	1768.3

The real values and predicted values for the second model are illustrated in Table 90, used to show the accuracy of the model.

Table 89. Accuracy of binary logistic regression after the backward stepwise method for roots

Actual values	Predicted values		Accuracy
	0	1	
0	473	0	86%
1	77	0	

8.7 Total joint

Total joint defect category was considered as another output variable, and the first binary logistic regression model defect was developed for that. The regression coefficient of mentioned independent variables is shown in Table 91. Variables with a P-value less than 0.005 are determined as significant. According to Table 91, three variables, including diameter, slope, and groundwater, which are numerical variables, distinguished as significant. In pipe material, which is a categorical variable, all materials apart from EW were determined as significant. In liquefaction susceptibility, another categorical variable, one level, very low, was determined as significant.

Table 90. Regression coefficients and their features for the material damage binary logistic regression model for total joint

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-8.318e-01	4.875e-01	-1.706	0.087
Age	2.592e-03	3.833e-03	0.676	0.498
Diameter	-8.989e-04	2.127e-04	-4.227	0.000
Depth	-3.290e-02	3.229e-02	-1.019	0.308
Length	1.284e-03	8.605e-04	1.493	0.135
Slope	-2.664e-02	1.319e-02	-2.020	0.043
Groundwater level	5.381e-02	1.241e-02	4.334	0.000
Population Density	1.075e-04	2.174e-05	4.943	0.000

Liquefaction Susceptibility (low)	-1.274e+01	3.216e+02	-0.040	0.968
Liquefaction Susceptibility (Moderate)	1.815e-01	1.854e-01	0.979	0.327
Liquefaction Susceptibility (Very High)	-1.297e+01	7.218e+02	-0.018	0.985
Liquefaction Susceptibility (Very low)	8.282e-01	3.798e-01	2.181	0.029
Material-factor CIP (Reference)	0	-	-	-
Material-factor (Conc)	-1.846e+00	3.236e-01	-5.704	0.000
Material-factor (EW)	-1.907e-01	3.853e-01	-0.495	0.620
Material factor (OTHERS)	-9.253e-01	3.694e-01	-2.505	0.012
Material-factor (PE)	-2.546e+00	5.686e-01	-4.478	0.000
Material-factor (RC)	-1.812e+00	3.183e-01	-5.692	0.000
Material-factor (RCRRJ)	-1.028e+00	3.186e-01	-3.227	0.001

Table 91. Accuracy of binary logistic regression for total joint

	Deviance	**Chi-square**	**Degree of freedom**	**Significance**	**AIC**
Null	1897.6		2777		
Current model	1736.1	161	2760	0.000	1772.1

In the next step, variables with a high P-score (higher than 0.05) are removed through a few backward stepwise selection procedures. The coefficients of significant variables of the binary logistic regression model after removing insignificant variables and implementing a few backward stepwise selection procedures are shown in Table 93.

As represented in Table 93, diameter, length, groundwater, population density, and material (Conc, OTHERS, PE, RC, and RCRRJ) are determined as significant variables.

Table 92. Regression coefficients and their features after backward stepwise method in the binary logistic regression model for total joint

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	-0.88140	0.3296806	--2.795	0.005
Diameter	-0.0007338	0.0002155	-3.406	0.000
Length	0.002186	0.0009038	2.419	0.010
Groundwater level	0.0490539	0.0133316	3.680	0.000
Population density	0.0001122	0.0000219	5.124	0.000
Material-Conc	-2.0635559	0.3408350	-6.054	0.000
Material-OTHERS	-1.4240601	0.3849831	-3.699	0.000
Material-PE	-2.8484690	0.5699750	-4.998	0.000
Material-RC	-2.1606400	0.3212782	-6.725	0.000
Material-RCRRJ	-1.2395183	0.2901026	-4.273	0.000

The significance of the current binary regression model is shown in Table 94. According to the table and comparing AIC, the current model with three independent variables surpasses the first binary model. As represented in Table 94, the significance level of the model is less than 0.05. So, our current model surpasses the null model.

Table 93. Accuracy of binary logistic regression after the backward stepwise method for total joint

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	1457		2201		
Current model	1352	105	2192	0.000	1372

The real values and predicted values for the second model are illustrated in Table 95, used to show the accuracy of the model.

Table 94. Accuracy of binary logistic regression after the backward stepwise method for total joint

Actual values	Predicted values		Accuracy
	0	1	
0	522	2	88%
1	59	0	

8.8 Dipped pipe

Dipped pipe defect category was considered as another output variable, and the first binary logistic regression model defect was developed for that. The regression coefficient of mentioned independent variables is shown in Table 96. Variables with a P-value less than 0.005 are determined as significant. According to Table 96, five variables, including diameter, length, slope, groundwater, and population density which are numerical variables, were distinguished as significant. In pipe material, which is a categorical variable, three materials, including Conc, OTHERS, and RC were determined as significant.

Table 95. Regression coefficients and their features of binary logistic regression model for dipped pipe

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	4.010e-01	6.447e-01	0.622	0.533
Age	4.339e-03	3.960e-03	-1.096	0.962
Diameter	-2.897e-03	3.042e-04	-9.523	0.000
Depth	3.386e-02	3.573e-02	0.948	0.343
Length	3.092e-03	7.543e-04	4.099	0.000
Slope	-8.157e-02	2.244e-02	-3.634	0.000
Groundwater level	4.264e-02	1.095e-02	3.893	0.000

Population Density	-7.434e-05	2.420e-05	-3.072	0.002
Liquefaction Susceptibility (low)	8.852e-01	6.484e-01	1.365	0.172
Liquefaction Susceptibility (Moderate)	-1.983e-01	1.535e-01	-1.292	0.196
Liquefaction Susceptibility (Very High)	4.458e-01	1.264e+00	0.353	0.724
Liquefaction Susceptibility (Very low)	4.346e-01	3.608e-01	1.204	0.228
Material-factor CIP (Reference)	0	-	-	-
Material-factor (Conc)	-1.042e+00	3.792e-01	-2.747	0.006
Material-factor (EW)	-9.612e-02	4.031e-01	-0.238	0.811
Material factor (OTHERS)	-1.156e+00	4.238e-01	-2.727	0.006
Material-factor (PE)	-2.467e-01	4.748e-01	-0.520	0.603
Material-factor (RC)	-1.020e+00	3.415e-01	-2.988	0.002
Material-factor (RCRRJ)	-6.432e-01	3.500e-01	-1.838	0.066

Table 96. Accuracy of binary logistic regression for dipped pipe

	Deviance	**Chi-square**	**Degree of freedom**	**Significance**	**AIC**
Null	1790.2		2739		
Current model	1513.5	277	2722	0.000	1549.5

In the next step, variables with a high P-score (higher than 0.05) are removed through a few backward stepwise selection procedures. The coefficients of significant variables of the binary logistic regression model after removing insignificant variables and implementing a few backward stepwise selection procedures are shown in Table 98.

As represented in Table 98, five variables, including diameter, length, slope, groundwater, and population density, remained as significant variables.

Table 97. Regression coefficients and their features after backward stepwise method in the binary logistic regression model for dipped pipe

Independent variable	Coefficient Estimation (α)	Standard Deviation Error	Z-value, Wald test	P-value
Intercept	7.486e-01	4.242e-01	1.071	0.032
Diameter	-2.650e-03	4.173e-04	-6.350	0.000
Length	2.945e-03	1.055e-03	2.792	0.005
Slope	-6.343e-02	2.090e-02	-3.035	0.002
Groundwater level	7.748e-02	1.765e-02	4.389	0.000
Population density	-8.983e-05	2.989e-05	-3.006	0.002

The significance of the current binary regression model is shown in Table 99. According to the table and comparing AIC, the current model with three independent variables surpasses the first binary model. As represented in Table 99, the significance level of the model is less than 0.05. So, our current model surpasses the null model.

Table 98. Accuracy of binary logistic regression after the backward stepwise method for dipped pipe

	Deviance	Chi-square	Degree of freedom	Significance	AIC
Null	881.82		1567		
Current model	746.81	135	1562	0.000	758.81

The real values and predicted values for the second model are illustrated in Table 100, used to show the accuracy of the model.

Table 99. Accuracy of binary logistic regression after the backward stepwise method for dipped pipe

Actual values	**Predicted values**		**Accuracy**
	0	1	
0	343	3	92%
1	27	1	

9 APPENDIX C: DEVELOPING GRADIENT BOOSTING TREE MODELS

Details regarding applying and developing the gradient boosting trees model for all defect categories were discussed and presented in section 5.3.3. In the following sections, the achieved results from all gradient boosting tree models are reported.

9.1 Material damage

9.1.1 Validation of the model

The performance of the gradient boosting tree model was determined using the confusion matrix and ROC curve. The confusion matrix was utilized to represent the number of pipes correctly or incorrectly, including the predicted specific defect categories. In the confusion matrix, the actual class the test classifier is compared to the predicted class that was achieved by the trained classifier. Table 38 shows the result of the confusion matrix for the gradient boosting tree for the material damage defect category.

Table 100. Gradient boosting tree confusion matrix for material damage

Actual	**Predicted**		**Accuracy**
	0	1	
0	279	65	72%
1	86	116	

According to the result of the confusion matrix, overall, 72% Of the material damage prevalence was predicted correctly by the gradient boosting tree model. 81% of pipes with no presence of material damage defects and 57% of pipes with the presence of material damage defects were predicted correctly.

Table 39 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 101. Gradient boosting tree model performance for material damage

Rates	Values
True positive rate (TPR)	81%
False positive rate (FPR)	42%
True negative rate (TNR)	57%
False negative rate (FNR)	18%

Additionally, the performance of the gradient boosting tree model was evaluated by Receiver Operating Characteristic (ROC) curve. ROC curve is based on the True positive rate (TPR) and false positive rate (FPR) on vertical and horizontal axis, respectively. The area under the curve shown with AUC represents the model performance, where AUC close to 1 indicates a perfect prediction, an AUC close to 0.5 represents a random prediction. Conventionally, AUC greater than 0.7 represents an acceptable model (Hosmer et al., 2013).

Figure 38 shows the ROC curve for the gradient boosting tree model for material damage.

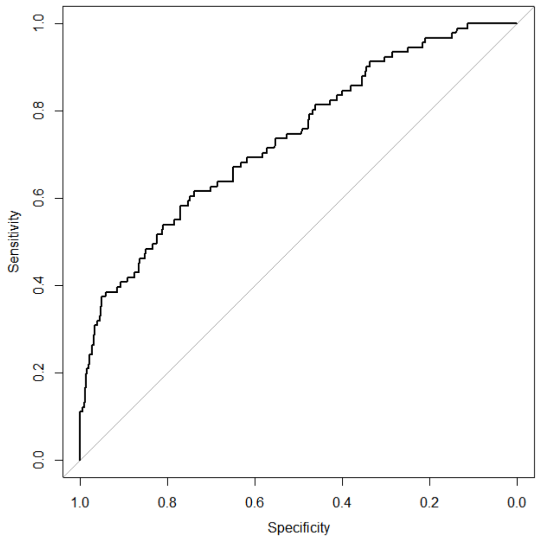


Figure 54.Gradient boosting tree ROC curve

The AUC of the ROC curve is 0.78, indicating that gradient boosting tree model results are acceptable and can be used to predict the prevalence of material damage defect of sewer pipes that have not been inspected yet in the city of Auckland.

9.1.2 Feature importance

The importance of independent features can be ranked through the gradient boosting tree model.

Feature importance is shown with a score indicating the weight of the independent variable in the implementation of the model. Importance is calculated for each developed tree by the amount that independent variable split points improve the prediction performance of the gradient boosting tree model. Figure 39 shows the feature importance in the gradient boosting tree model for the material damage defect.

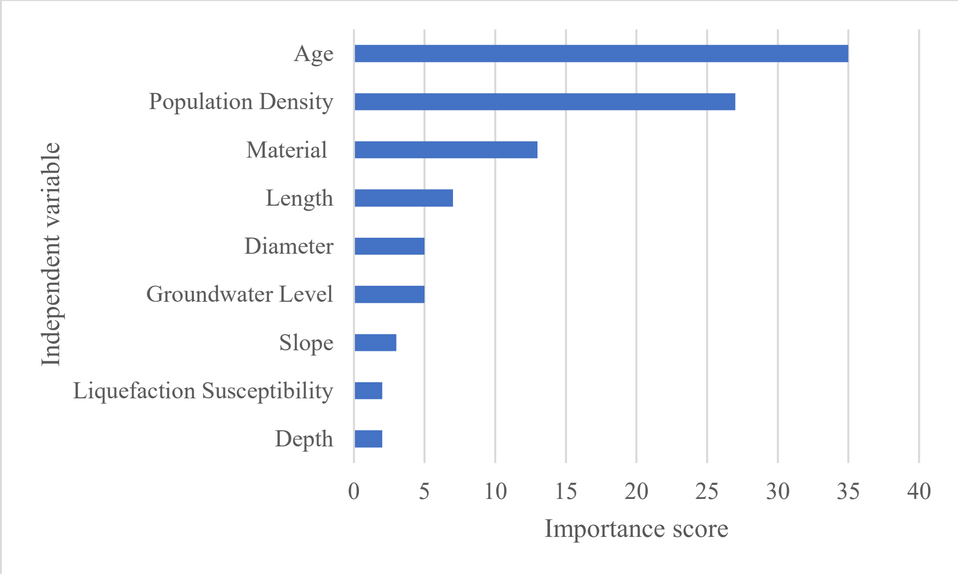


Figure 55. Feature importance in gradient boosting tree model for material damage

According to the results of feature importance, age, population density, material, and length are the most critical independent variable for the prediction of material damage defects in sewer pipes in the Auckland dataset.

9.1.3 Gradient boosting tree plot

The gradient boosting tree model provides a decision tree plot based on the importance of independent variables in the dataset. This plot illustrates different layers of the decision tree and split decisions of independent variables based on their importance in the model. Different layers in decision tree plot include branches and leaves representing the role of independent variables on the prediction of the target, which is various defect categories in this study. In gradient boosting tree model, several decision trees are developed in order to determine the relationship between independent variables and the prediction of the target.

Figure 40 shows the first created decision tree plot in the gradient boosting tree model for material damage as the first target.

The branches and leaves of the decision tree provide insight into the role of independent variables in determining the prevalence of various defect categories. Since developed decision trees are very extensive, just a couple of branches for more illustrations are explained.

The first split of the tree shows the influence of age on the prevalence of material damage defects within pipes. Sewer pipes are divided into two groups of pipes with an age of more or less than 22 years. In the left node and where the age is less than 22 years, age again is filtered to more or less than 10 years, and in next layers, again is filtered to smaller parts. Finally, the decision tree illustrates that 1% of pipes between 16 years and 22 years have a 68% chance of including material damage defects.

In the second layer, for pipes more than 22 years, pipes are filtered based on the population density with more or less than 14000 people. In the third layer, pipe length is appeared as the next influence variable in the model divided into more or less than 46 meters. Followingly, for pipes less than 46 meters, population density is filtered to more or less than 8559 people. In the next layer, material and age are the influence variables. The decision tree shows that 1% of sewers with a population density of more than 8556 and older than 59 have a high probability of 83% to include material damage defects.

The results of the gradient boosting tree model partly supported the outcomes of the deterministic method and binary logistic regression model. In general, longer pipes had more chance of including material damage defects in deterministic, logistic and tree models. Additionally, the probability of material damage occurrence is higher in pipes built from concrete and RC material which is in line with binary logistic regression results. Population density was also an influence variable in the gradient boosting tree model and generally, sewer pipes have more chance to contain material damage when the population density is higher around the pipe, supporting the logistic model results. Moreover, the influence of pipe diameter on material damage demonstrated that larger diameter pipes had more probability of including material damage defects rather than the smaller pipes in the gradient boosting tree model; however it was not supported by other models. While in the gradient boosting tree model, the older pipes had more chance of including material damage defects and were supported with the deterministic method, this could not be supported by the binary logistic regression model.

It is noteworthy to state that the decision tree uses the “if and then clause” and split different independent variables until reaching the best prediction model. This means that some of the influence variables in the developed gradient boosting tree models might have only small effect on the target; however, still they might be considered as an influencing and important variable. Therefore, they might not be as important as variables determined as significant in the developed binary logistic regression models. In addition, the important variables which were shown from developed gradient boosting tree models are obtained based on the first decision tree; however, many decision trees are developed to achieve ultimate prediction in this model.

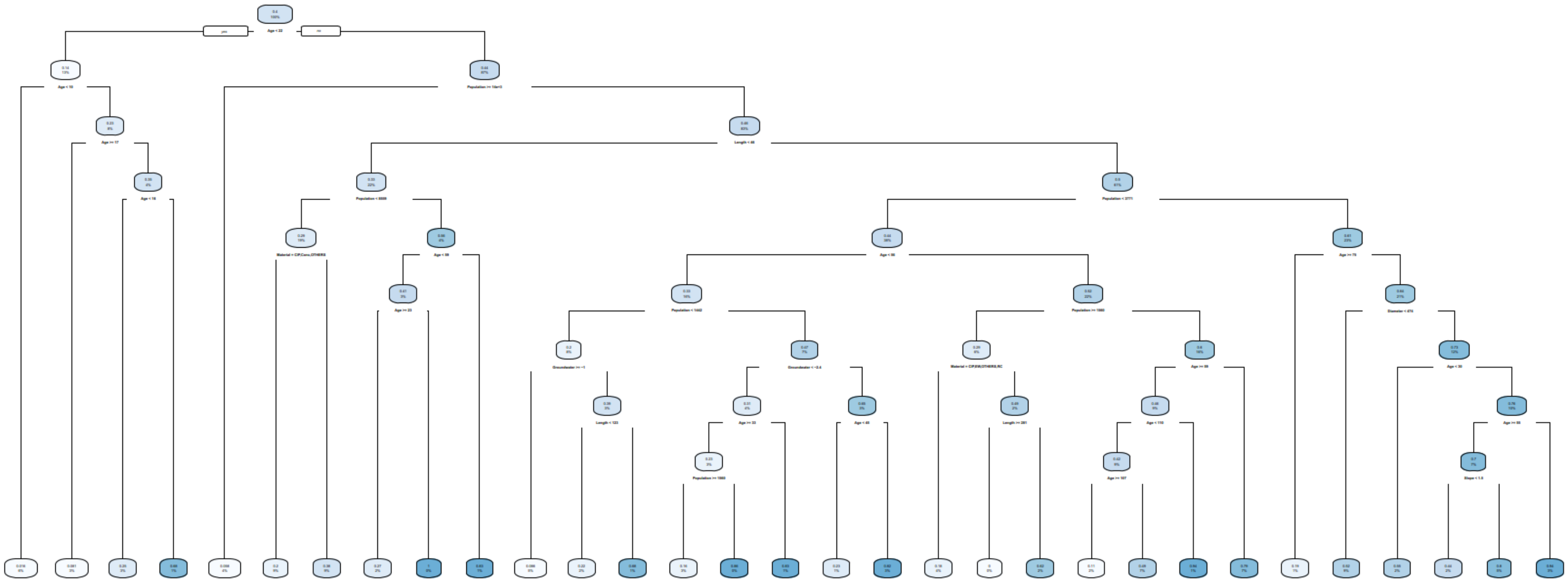


Figure 56. Gradient boosting tree plot for material damage

9.2 Gas attack

9.2.1 Validation of the gradient boosting tree model

Table 103 shows the result of the confusion matrix for the gradient boosting tree for the gas attack defect category.

Table 102. Gradient boosting tree confusion matrix for gas attack

Actual value	Predicted value		Accuracy
	0	1	
0	300	50	81%
1	55	141	

According to the result of the confusion matrix, overall, 81% of the gas attack prevalence was correctly predicted by the gradient boosting tree model. 86% of pipes with no presence of the gas attack defects and 72% of pipes with the presence of the gas attack defect were correctly predicted.

Table 104 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 103. Gradient boosting tree model performance for gas attack

Rates	Values
True positive rate (TPR)	86%
False positive rate (FPR)	28%
True negative rate (TNR)	72%
False negative rate (FNR)	14%

Figure 57 shows the ROC curve for gradient boosting tree model for gas attack.

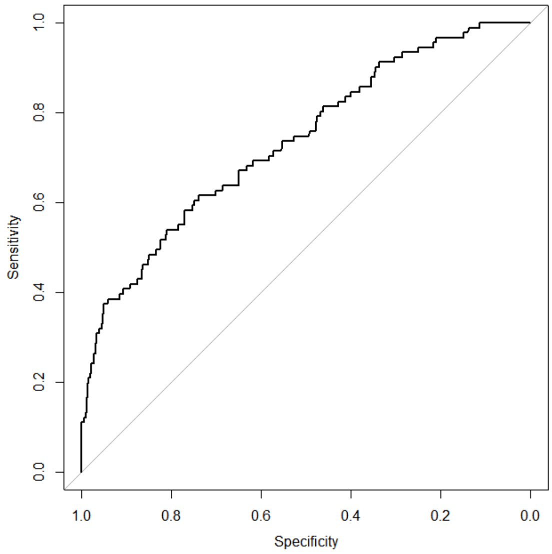


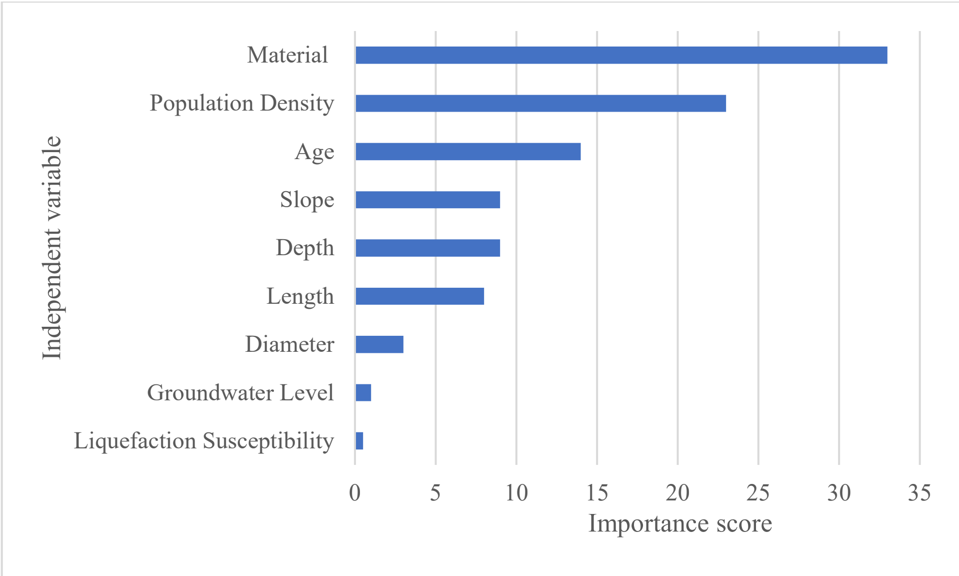
Figure 57. ROC curve for gas attack

The AUC of the ROC curve is 0.89, indicating that gradient boosting tree model results is acceptable and can be used to predict the prevalence of gas attack defect of sewer pipes that have not been inspected yet.

9.2.2 Feature importance

Figure 58 shows the feature importance in the gradient boosting tree model for the gas attack defect.

Figure 58. Feature importance in gradient boosting tree model for gas attack



According to the results of feature importance, material, population, age, slope, and depth are the most critical independent variables for the prediction of gas attack defects in sewer pipes in Auckland city.

9.2.3 Gradient boosting tree plot

Figure 59 shows the first created decision tree plot in the gradient boosting tree model for the gas attack defect category.

The first split of the tree illustrates the influence of age on the prevalence of gas attack defects within pipes. Sewer pipes are divided into two groups of pipes built from RC and RCRRJ and another group with the rest of the materials. In the second layer of the tree, for RC and RCRRJ pipes, population density is filtered as the next influence variable with more or less than 578 people. In the left node, when the population density is less than 578 people, diameter is filtered to more or less than 655mm. In the next layer, in the right node and where pipes are larger than 655 mm, shows that 2% of pipes with RC material have a 78% chance to include gas attack defects.

After appearing population density in the second layer as the influence variable for RC and RCRRJ pipe, in the third layer, on the right side and when population density is higher than 578 people, age is appeared as the next influence variable in the model divided to more and less than 10 years. While for pipes less than 10 years, the decision tree shows a very low probability of 6.7% to include gas attack defects, for older pipes illustrate, 9% of sewers have a higher chance of 50% to include gas attack defects.

The results of the gradient boosting tree partly supported the outcomes of the deterministic method and binary logistic regression model. In general, RC and RCRRJ pipes had more chance of including gas attack defects in both logistic and tree models. Additionally, the probability of containing gas attack is higher when population density is higher in both logistic and tree models. Age was also an influence variable in the gradient boosting tree model, and sewer pipes deteriorate faster when they are older. While this was not supported by the logistic regression model, it was in line with achieved results from deterministic results.

Moreover, the influence of pipe slope on gas attack demonstrated that pipes that are flatter had more probability of having gas attack defects rather than steeper pipes; this was also supported by deterministic results. Regarding depth, while it is illustrated as an influence variable, no specific and clear relationship between depth and prevalence of gas attack could be seen since the branched-out probabilities were close to each other. Finally, length is also another influence variable in the gradient boosting tree model, and as pipes are longer, the probability of including gas attack within sewers goes higher, supporting both deterministic and logistic regression model results.

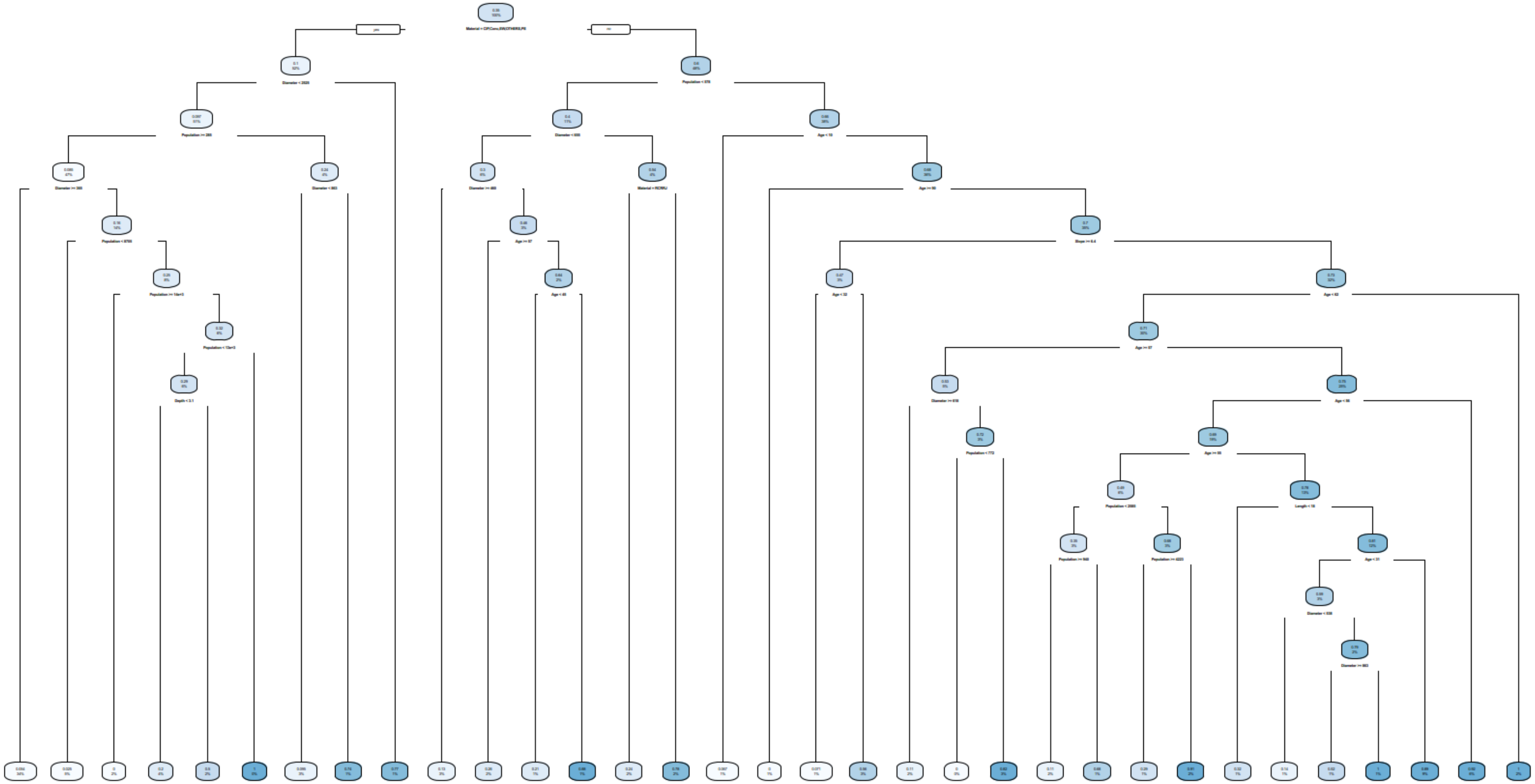


Figure 59. Gradient boosting tree plot for gas attack

9.3 Debris

9.3.1 Validation of the gradient boosting tree model

Table 105 shows the result of the confusion matrix for the gradient boosting tree for the debris defect category.

Table 104. Gradient boosting tree confusion matrix for debris

Actual value	Predicted value		Accuracy
	0	1	
0	357	28	71%
1	127	34	

According to the result of the confusion matrix, overall, 71% Of the debris prevalence was predicted correctly by the gradient boosting tree model. 92% of pipes with no presence of debris defects and 21% of pipes with the presence of debris defects were predicted correctly.

Table 106 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 105. Gradient boosting tree model performance for debris

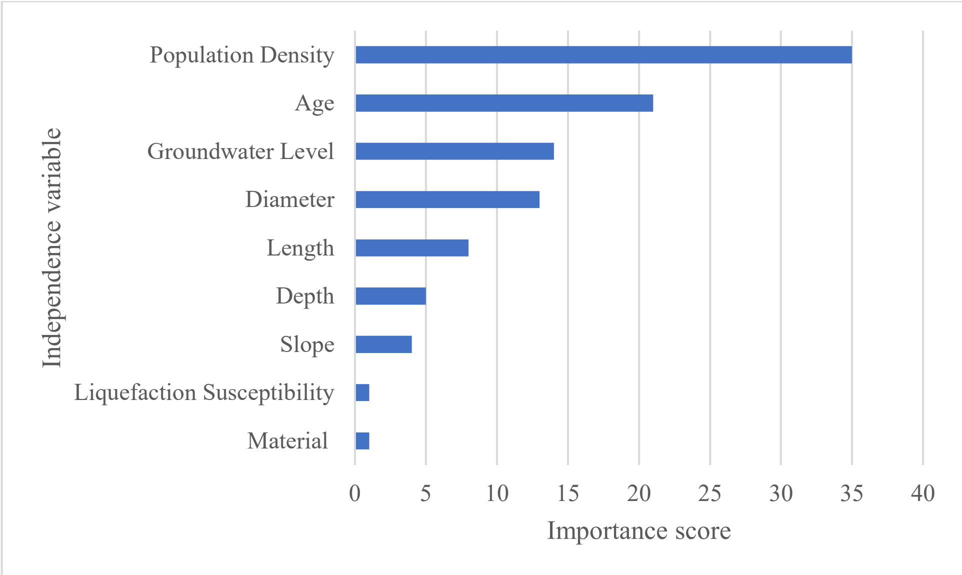
Rates	Values
True positive rate (TPR)	92%
False positive rate (FPR)	78%
True negative rate (TNR)	21%
False negative rate (FNR)	7%

The AUC of the ROC curve is 0.67, indicating that the gradient boosting tree model results are almost acceptable and can be cautiously used to predict the prevalence of debris defect in sewer pipes that have not been inspected yet.

9.3.2 Feature importance

Figure 60 shows the feature importance in the gradient boosting tree model for the debris defects.

Figure 60. Feature importance in gradient boosting tree model for debris



According to the results of feature importance ranking, population, age, groundwater, and diameter are the most critical independent variable for the prediction of debris defects in sewer pipes in the Auckland dataset.

9.3.3 Gradient boosting tree plot

Figure 61 shows the first created decision tree plot in the gradient boosting tree model for debris as another target.

The first split of the tree shows the effect of population density on the prevalence of debris defects within pipes. Sewers pipes are divided into two groups of pipes with a population density of more or less than 3729 people. The second layer of the tree consists of population density and groundwater level as the influence variables. In the right node, where population density is more than 3729 people, population density is again filtered to more or less than 3977 people. The decision tree illustrates that 3% of pipes with a population density higher than 3977 people have a 67% chance of including debris defects.

In the second layer, where the population density is less than 3729 people, pipes are filtered based on the groundwater level with more or less than -3.3 meters. In the third layer, where the groundwater level is higher than -3.3 meters, diameter is appeared as the next influence variable in the model divided into more or less than 1275mm. In the fourth layer, pipes larger than 1275 mm in length is appeared as the next influence variable and filtered to more or less than 114 meters. The decision tree shows that 6% of sewers with a population density less than 3729 and groundwater level higher than -3.3 and larger than 1275mm, and longer than 114 meters have a 48% chance to include debris defects.

The results of the gradient boosting tree partly supported the outcomes of the deterministic method and binary logistic regression model. In general, pipes with higher population density had more chance of including debris defects in both tree and logistic models. Age was also an influence variable in the gradient boosting tree model, and sewer pipes had less probability of including debris when they were older, supporting deterministic results. Moreover, the influence of pipe diameter on debris demonstrated that pipes that are larger had less probability of having debris defects rather than smaller pipes confirming both deterministic and binary logistic regression model results.

Finally, no clear relationship between two independent variables, including length and groundwater level, and prevalence of debris defect could be directly interpreted from the decision tree.

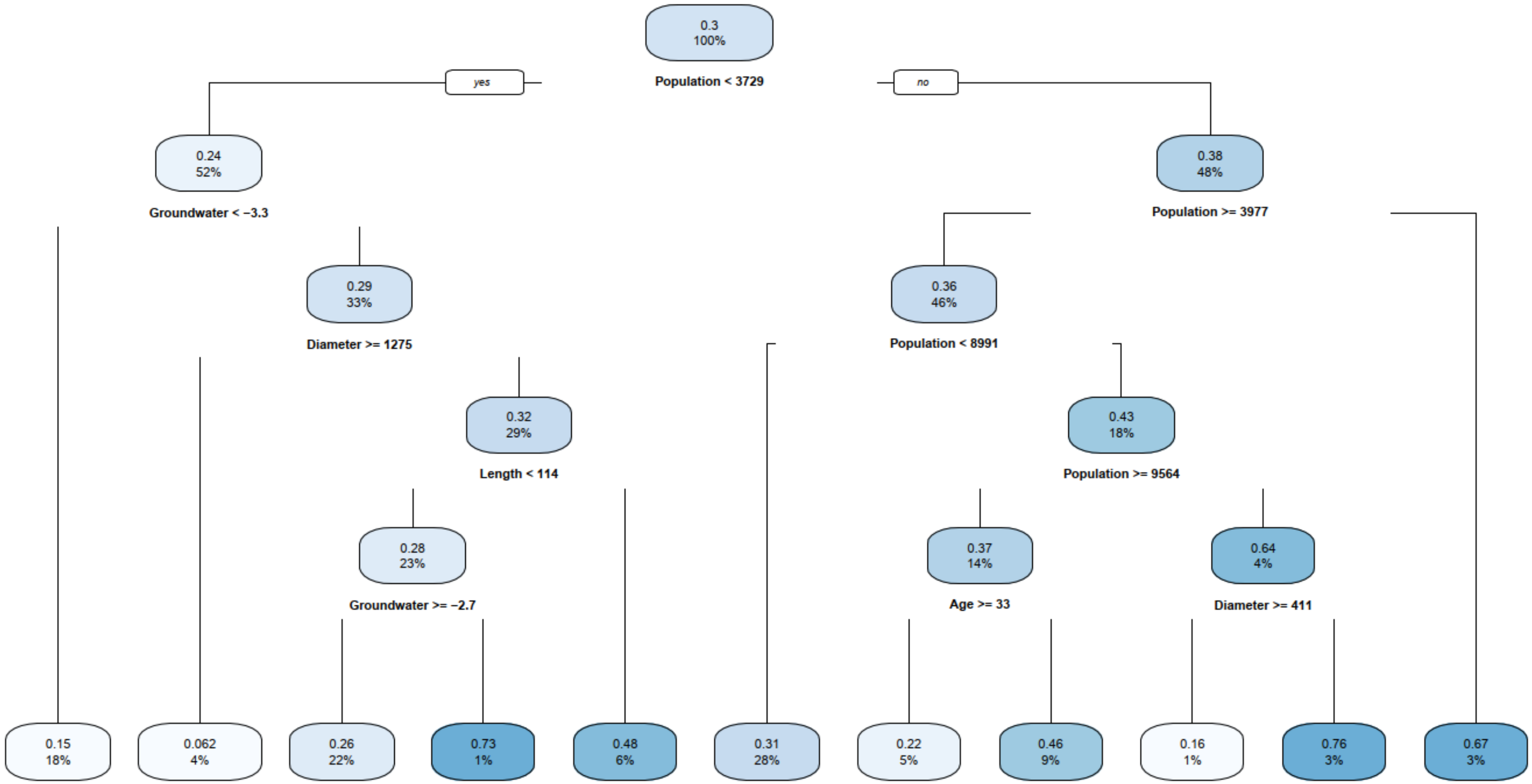


Figure 61. Gradient boosting tree plot for debris

9.4 Structural

9.4.1 Validation of the gradient boosting tree model

Table 107 shows the result of the confusion matrix for the gradient boosting tree for the structural defect category.

Table 106. Gradient boosting tree confusion matrix for structural

Actual value	Predicted value		Accuracy
	0	1	
0	446	9	82%
1	86	5	

According to the result of the confusion matrix, overall, 82% Of the structural prevalence was predicted correctly by the gradient boosting tree model. 98% of pipes with no presence of structural defects and 5% of pipes with the presence of structural defects were predicted correctly.

Table 108 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 107. Gradient boosting tree model performance for structural

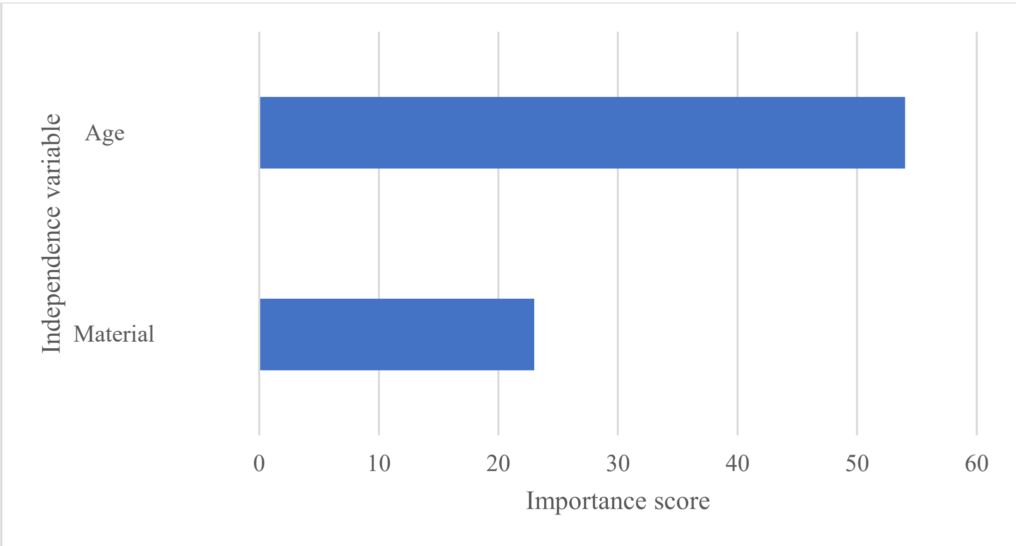
Rates	Values
True positive rate (TPR)	98%
False positive rate (FPR)	94%
True negative rate (TNR)	5%
False negative rate (FNR)	1%

The AUC of the ROC curve is 0.65, indicating that the gradient boosting tree model results is almost acceptable and can be cautiously used to predict the prevalence of structural defect in sewer pipes that have not been inspected yet.

9.4.2 Feature importance

Figure 62 shows the feature importance in the gradient boosting tree model for the structural defects.

Figure 62.Feature importance in gradient boosting tree model for Structural



According to the results of feature importance, age and material are the most critical independent variable for the prediction of structural defects in sewer pipes in the Auckland dataset.

9.4.3 Gradient boosting tree plot

Figure 63 shows the first created decision tree plot in the gradient boosting tree model for structural defects.

The first layer of the tree shows the effect of age on the prevalence of structural defects within pipes, and age is filtered to more or less than 86 years.

In the second layer of the tree, sewer pipes are divided into two groups of pipes built specifically from RC and another group built from all other materials apart from EW. The decision tree shows that 8% of pipes not built from RC and older than 86 years have a 66% chance of including structural defects.

In the second layer, on the left side, pipes are filtered based on all materials apart from EW. For EW pipes, the decision tree shows 1% of pipes have the probability of 69% to include structural defects.

The results of the gradient boosting tree partly supported the outcomes of the binary logistic regression model. In general, the probability of including structural defects is higher when pipes are older. Additionally, EW pipes had more chance of including structural defects in both logistic and tree models.

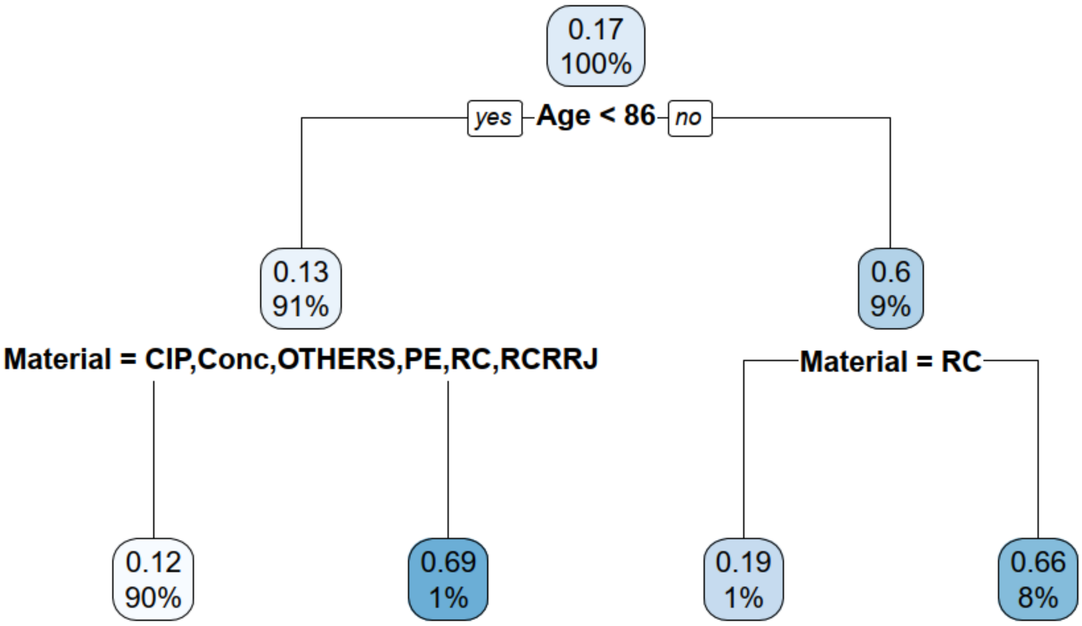


Figure 63.Gradient boosting tree plot for structural

9.5 Infiltration

9.5.1 Validation of the model

Table 109 shows the result of the confusion matrix for the gradient boosting tree for the infiltration defect category.

Table 108. Gradient boosting tree confusion matrix for infiltration

Actual value	Predicted value		Accuracy
	0	1	
0	457	7	85%
1	72	9	

According to the result of the confusion matrix, overall, 85% of the infiltration prevalence was predicted correctly by the gradient boosting tree model. 98% of pipes with no presence of gas attack defects and 11% of pipes with the presence of infiltration defects were predicted correctly.

Table 110 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 109. Gradient boosting tree model performance for infiltration

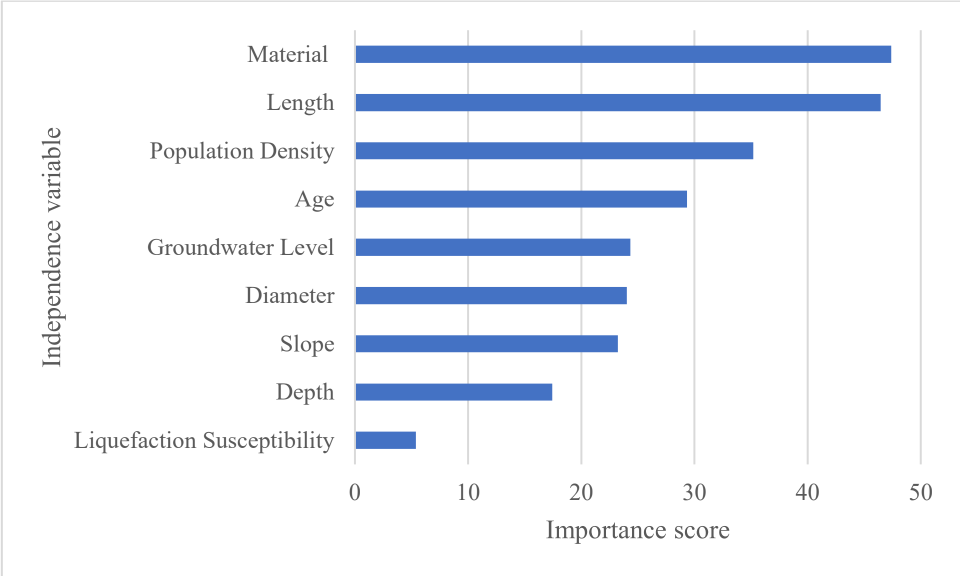
Rates	Values
True positive rate (TPR)	98%
False positive rate (FPR)	88%
True negative rate (TNR)	11%
False negative rate (FNR)	1%

The AUC of the ROC curve is 0.65, indicating that the gradient boosting tree model results are almost acceptable and can be cautiously used to predict the prevalence of infiltration defects in sewer pipes that have not been inspected yet.

9.5.2 Feature importance

Figure 64 shows the feature importance in the gradient boosting tree model for infiltration defects.

Figure 64. Feature importance in gradient boosting tree model for infiltration



According to the results of feature importance, length, population, groundwater, and age are the most critical independent variables for the prediction of infiltration defects in sewer pipes in the Auckland dataset.

9.5.3 Gradient boosting tree plot

Figure 65 shows the first created decision tree plot in the gradient boosting tree model for infiltration defects.

The first split of the tree shows the effect of material on the prevalence of infiltration defects within pipes. Sewer pipes are divided into whether they are being built from the following materials RC, RCRRJ, concrete, PE, and others or not. In the second layer, where pipes are built from one of RC, RCRRJ, concrete, PE, and others, length is shown as the influencing variable with being filtered to more or less than 85 meters. In the next layer, for pipes longer than 85 meters, the population density was shown as the influencing variable and divided into more or less than 9935 people. In the same layer, for pipes shorter than 85 meters, age was shown as the next influence variable and is divided into more or less than 86 years. In the fourth layer, for pipes older than 86 years, diameter emerged as another influence variable and filtered to more or less than 1125mm. The decision tree shows that all mentioned materials which are shorter than 85 meters, older than 86 years and larger than 1125 mm, including 1% of pipes, have a chance of 68% to include infiltration defects.

In the second layer, at the right node, age is filtered to more or less than 109 years. In the next layer, for pipes younger than 109 years and in the right node, the length is filtered to more or less than 41 meters. Followingly, for pipes longer than 41 meters, the population density appears as the next influence variable and is filtered to more or less than 280. Results show that 3% of pipes built from EW and CIP, older than 109 years, longer than 41 meters, with a population density more than 280 people have 70% chance to include infiltration defects.

The results of the gradient boosting tree partly supported the outcomes of the deterministic method and binary logistic regression model. In general, pipes built from the following materials RC, RCRRJ, PE, Concrete, and others pipes had less chance of including infiltration defects in both logistic and tree models. Additionally, the probability of including infiltration is higher when the pipe is longer. Age was also an influence variable in the gradient boosting tree model, and sewer pipes contain more infiltration when they are older. Length and age results from gradient boosting tree models are supported by achieved results from the deterministic method, and the binary logistic regression model. While diameter was not significant in the deterministic method and the binary logistic regression model, it was shown as an influence variable in the gradient boosting tree model, and results showed that generally, sewers include higher infiltration when they are larger.

The population density was also an influence variable in the gradient boosting tree model, and sewer pipes contain more infiltration when the population density is higher, which was supported just by deterministic method results. Moreover, the influence of pipe slope on infiltration demonstrated that pipes that are steeper have more probability of including infiltration defects rather than flatter pipes.

Finally, while groundwater level was identified as an influential variable affecting infiltration defects in the gradient boosting tree model, no clear and strong relationship between groundwater level and infiltration was directly interpreted from the decision tree.

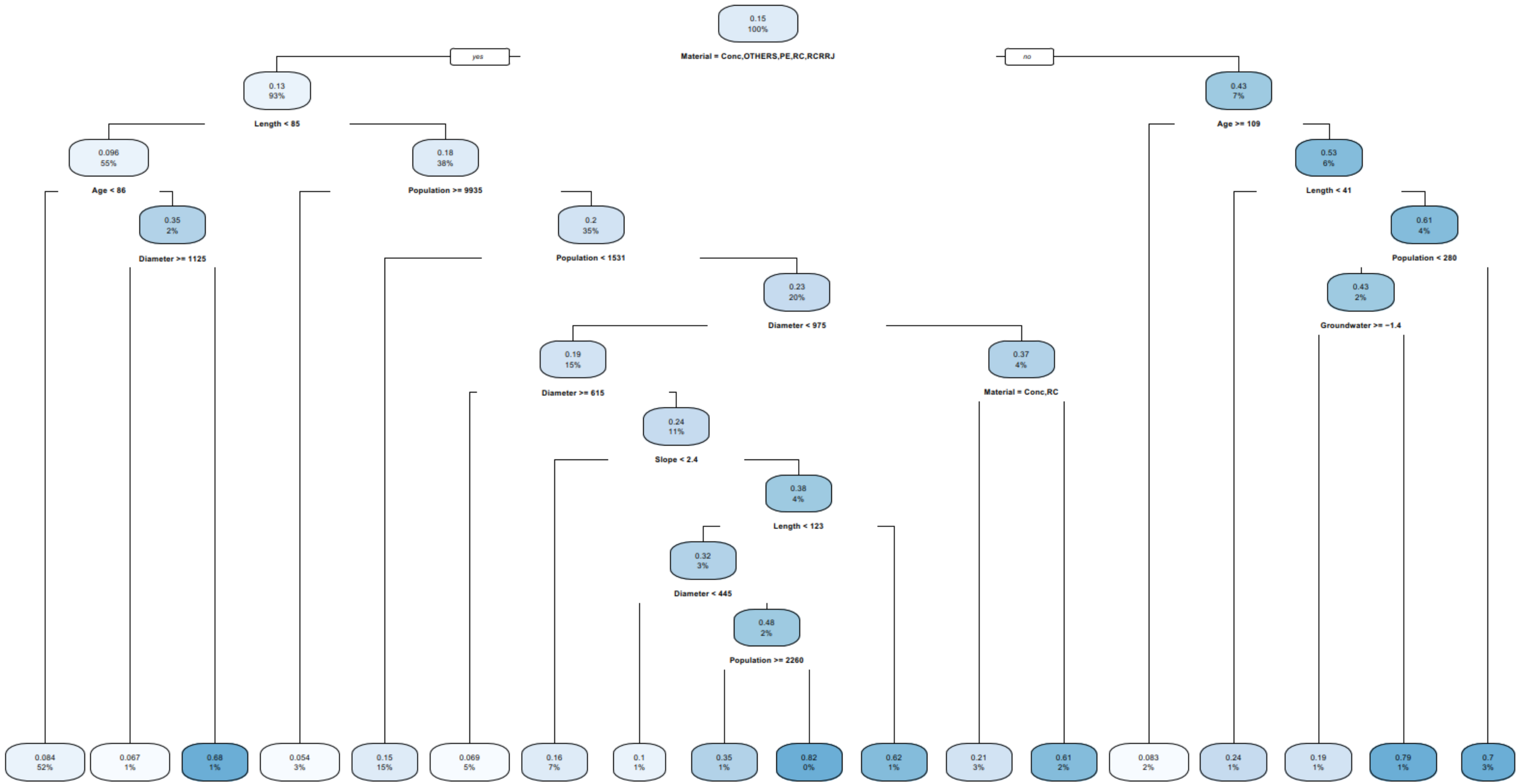


Figure 65. Gradient boosting tree plot for infiltration

9.6 Roots

9.6.1 Validation of the gradient boosting tree model

Table 111 shows the result of the confusion matrix for the gradient boosting tree for the roots defect category.

Table 110. Gradient Boosting Tree Confusion Matrix for roots

Actual value	Predicted value		Accuracy
	0	1	
0	457	0	84%
1	89	0	

According to the result of the confusion matrix, overall, 84% of roots prevalence was predicted correctly by the gradient boosting tree model. 100% of pipes with no presence of roots defects and 0% of pipes with the presence of roots defects were predicted correctly.

Table 112 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 111. grading boosting tree model performance for roots

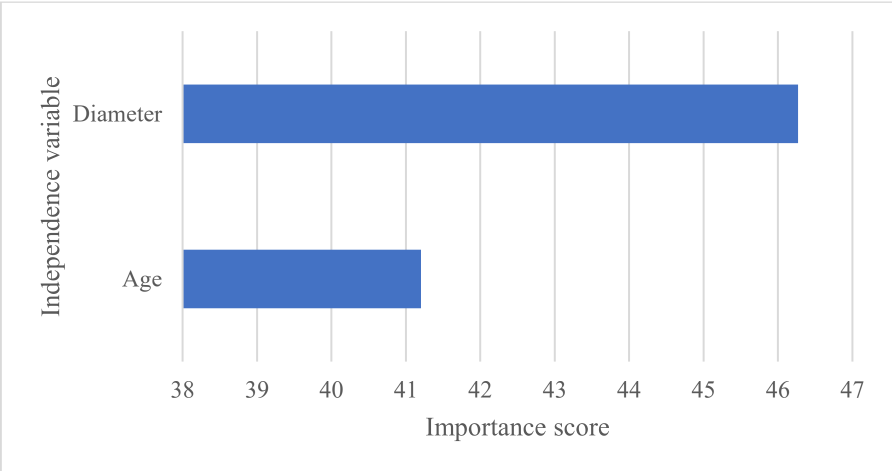
Rates	Values
True positive rate (TPR)	100%
False positive rate (FPR)	100%
True negative rate (TNR)	0%
False negative rate (FNR)	0%

The AUC of the ROC curve is 0.6, indicating that the gradient boosting tree model results are unacceptable and cannot be used to predict the prevalence of roots defect in pipes that have not been inspected yet.

9.6.2 Feature importance

Figure 66 shows the feature importance in the gradient boosting tree model for roots defects.

Figure 66. Feature importance in gradient boosting tree model for roots



According to the results of feature importance, diameter and age are the most critical independent variables for the prediction of roots defects in sewer pipes in the Auckland dataset.

9.6.3 Gradient boosting tree plot

Figure 67 shows the first created decision tree plot in the gradient boosting tree model for roots defects.

Since the number of sewer pipes, containing roots in the initial dataset was less than 10% of the whole dataset, all achieved outputs in the gradient boosting tree model are predicted without roots, and therefore gradient boosting trees are unable to provide us with an acceptable prediction result.

The first split of the tree shows the effect of diameter on the prevalence of roots defects within pipes. Sewer pipes are divided into two groups of pipes with a diameter of more or less than 365 mm. The decision tree shows that sewers larger than 365 mm, including 18% of sewers, have a chance of 24% to include roots defects.

The second layer of the tree consists of age filtered with more or less than 97 years. While pipes older than 97 years, including 7% of entire sewers, have 29% include debris defects, pipes younger than 97 years, consisting of 75% of whole sewers, have 11% include roots defects. Since all probabilities are less than 50% and close to each other, the decision tree is not useful for predicting roots defects.

Also, no clear relationship between diameter and age and prevalence of roots defects could be directly interpreted from the decision tree.

The results of the gradient boosting tree supported the outcomes of the deterministic method and the binary logistic regression model. In both mentioned models, age and diameter were determined as significant variables in order to predict roots defects.

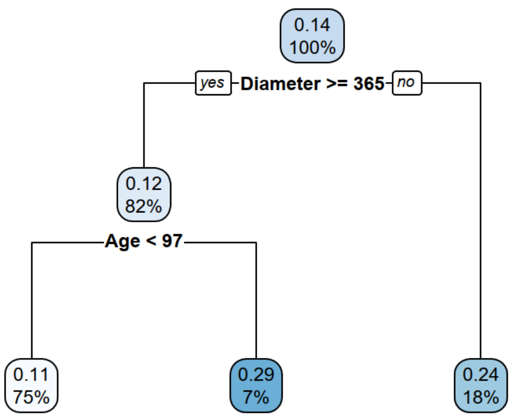


Figure 67. Gradient boosting tree plot for roots

9.7 Total joint

9.7.1 Validation of the gradient boosting tree model

Table 113 shows the result of the confusion matrix for the gradient boosting tree for the total joint defect category.

Table 112. Gradient boosting tree confusion matrix total joint

Actual value	**Predicted value**		**Accuracy**
	0	1	
0	473	7	87%
1	59	7	

According to the result of the confusion matrix, overall, 87% of the total joint prevalence was predicted correctly by the gradient boosting tree model. 98% of pipes with no presence of total joint defects and 10% of pipes with the presence of total joint defects were predicted correctly.

Table 114 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 113. Gradient boosting tree model performance for total joint

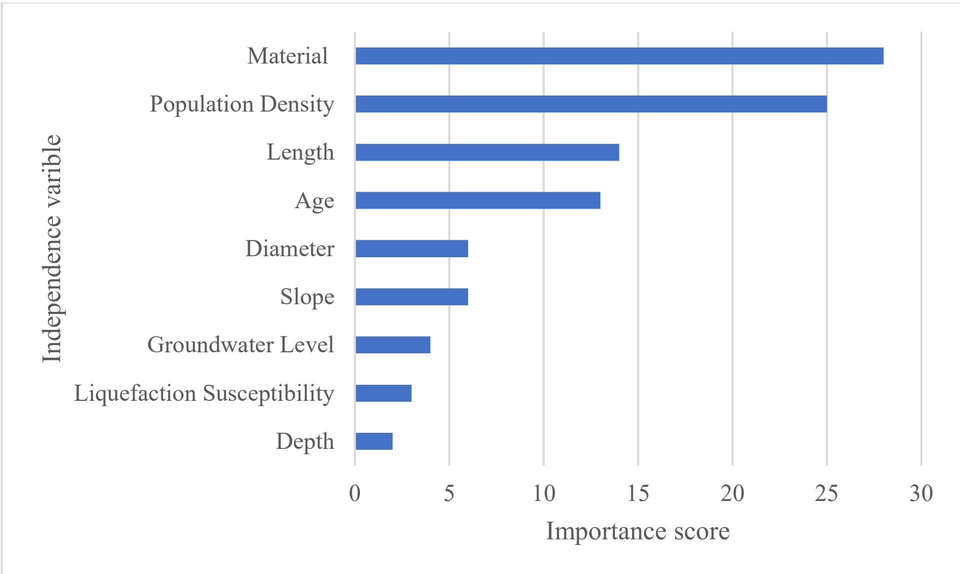
Rates	**Values**
True positive rate (TPR)	98%
False positive rate (FPR)	89%
True negative rate (TNR)	10%
False negative rate (FNR)	1%

The AUC of the ROC curve is 0.63, indicating the low reliability of the model, and therefore, the results cannot be used to predict the prevalence of the total joint defects within sewer pipes that have not been inspected yet.

9.7.2 Feature importance

Figure 70 illustrates the feature importance in the gradient boosting tree model for total joint defects.

Figure 68. Feature importance in gradient boosting tree model for total joint



According to the results of feature importance, material, population, age, slope, and depth are the most critical independent variable for the prediction of total joint defects in sewer pipes in the Auckland dataset.

9.7.3 Gradient boosting tree plot

Figure 69 shows the first created decision tree plot in the gradient boosting tree model.

Since developed decision trees are very extensive, just a couple of branches of the below decision tree will be explained.

The first split of the tree is divided into two groups of pipes whether being built from the following materials; RC and RCRRJ, PE, and concrete or not. The second layer of the tree, where the pipes are built from EW, others, and CIP, consists of population density, appears as the influencing variable, and it is filtered to more or less than 15000 people. In the third layer, where population density is less than 15000 people, age is filtered to more or less than 59 years. In the next layer, where pipes are older than 59 years, again, population density appears, and it is filtered to more or less than 1137 people. Followingly, for pipes with a population density higher than 1137 people, the length is filtered to more or less than 59 meters. The decision tree represents that by following the above branch, 2% of pipes longer than 59 meters have a 60% chance of including total joint defects.

The results of the gradient boosting tree partly supported the outcomes of the deterministic method and binary logistic regression model. In general, RC, RCRRJ, PE, and concrete pipes had less chance of including total joint defects in both logistic and tree models. Additionally, the probability of including total joints is higher when population density is higher. The Length was also determined as an influence variable in the gradient boosting tree model, and sewer pipes are deteriorated faster in terms of total joint defects when pipes were longer. Both achieved results for population density and length were supported with binary logistic regression results. Age was also an influence variable in the gradient boosting tree model, and sewer pipes have more total joint defects when they are older; however, this was supported by neither the deterministic method nor the binary logistic regression model.

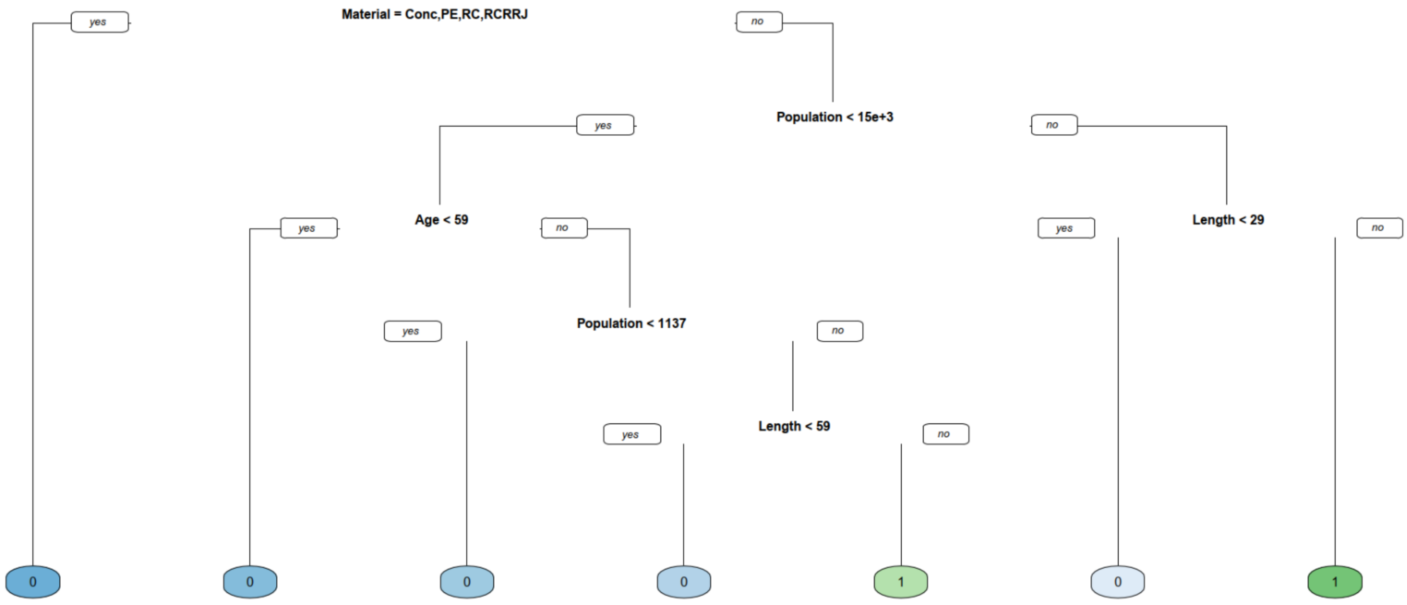


Figure 69. Gradient boosting tree plot for total joint

9.8 Dipped pipe

9.8.1 Validation of the gradient boosting tree model

Table 115 shows the result of the confusion matrix for the gradient boosting tree for the dipped pipe defect category.

Table 114. Gradient boosting tree confusion matrix for dipped pipe

Actual value	Predicted value		Accuracy
	0	1	
0	493	0	90.2%
1	53	0	

According to the result of the confusion matrix, overall, 90.2% of the dipped pipe prevalence was predicted correctly by the gradient boosting tree model. All pipes with no presence of dipped pipe defects and no pipes with the presence of dipped pipe defects were predicted correctly.

Table 116 reports the result of calculating true positive, true negative, false positive, and false negative rates.

Table 115. Gradient boosting tree model performance for dipped pipe

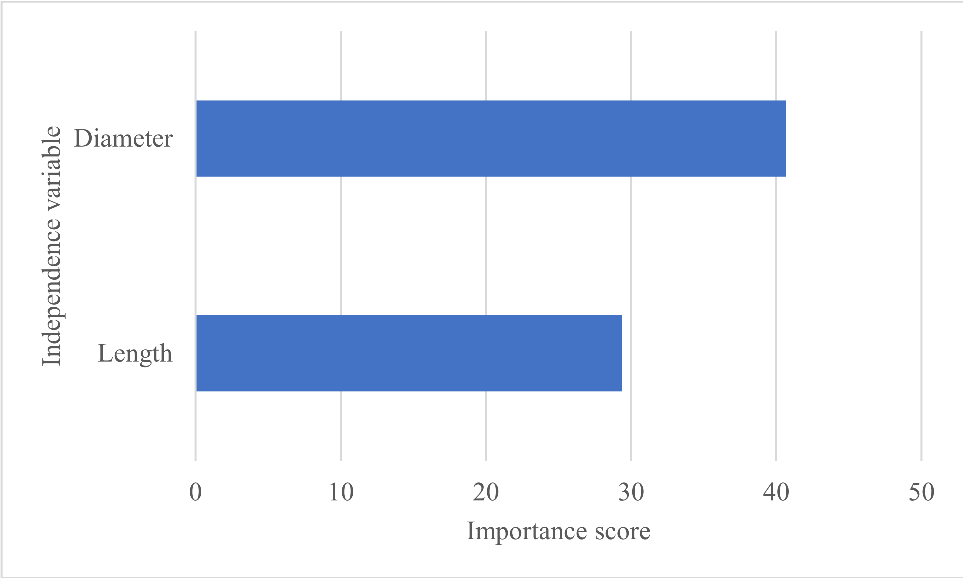
Rates	Values
True positive rate (TPR)	100%
False positive rate (FPR)	100%
True negative rate (TNR)	0%
False negative rate (FNR)	0%

The AUC of the ROC curve is 0.6, indicating the low reliability of the gradient boosting tree model. Therefore, the results of this model cannot be reliable in predicting the prevalence of dipped pipe defects within sewers that have not been inspected yet.

9.8.2 Feature importance

Figure 70 shows the feature importance in the gradient boosting tree model for dipped pipe defects.

Figure 70. Feature importance in gradient boosting tree model for Dipped pipe



According to the results of feature importance, diameter and length are the most critical independent variables for the prediction of dipped pipe defects in sewer pipes in the Auckland dataset.

9.8.3 Gradient boosting tree plot

Figure 71 shows the first created decision tree plot in the gradient boosting tree model for the dipped pipe defect category.

The first split of the tree shows the effect of diameter on the prevalence of dipped pipe defects within sewers. Sewer pipes are divided into two groups of pipes with a diameter of more or less than 717mm. The second layer of the tree consists of length as the influencing variable, which is filtered with more or less than 66 meters. The decision tree shows that 34% of pipes smaller than 717 mm and longer than 66 meters have a 22% chance of including dipped pipe defects.

The results of the gradient boosting tree partly supported the outcomes of the deterministic method and binary logistic regression model. In general, smaller pipes had more chance of including dipped pipe defects in the tree model and both other studied models. Additionally, the probability of including dipped pipe is higher when pipes are longer, supporting binary logistic regression results.

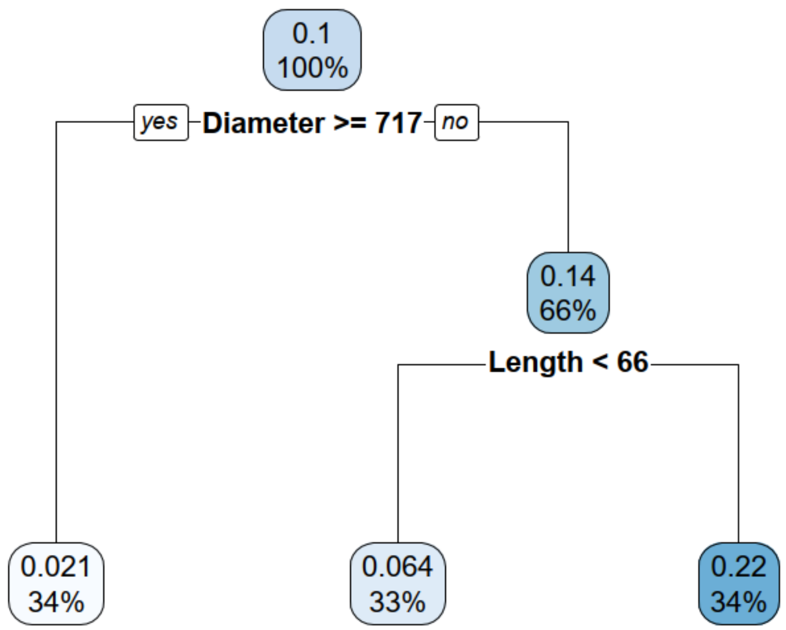


Figure 71. Gradient boosting tree plot for dipped pipe

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