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METHODOLOGY FOR IDENTIFYING THE KEY AND ENOUGH FACTORS FOR ACHIEVING OBJECTIVES IN SEWER ASSET MANAGEMENT

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DOCTORAL THESIS

METHODOLOGY FOR IDENTIFYING THE KEY AND ENOUGH FACTORS FOR ACHIEVING OBJECTIVES IN SEWER ASSET MANAGEMENT

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GENERAL INTRODUCTION

The Main Problem

The nearly unmitigated growth of cities has placed ever-greater pressure on urban water systems in terms of climate change, environmental pollution, resource limitations, and infrastructure ageing (Ferguson et al., 2013). Currently, urban drainage systems are presenting alarming rates of aging and deterioration in both developed and developing countries (Osman, 2012). The cities have faced several problems, because of the increasing of the deterioration probability of the sewer networks (Micevski et al., 2012; Liu & Kleiner, 2013; Osman, 2012): flooding on the streets, suffering in the buildings, traffic disturbances, environmental impacts, damage in other infrastructures and other problems that affect the users directly (Saegrov, 2006).

Literature Review

According to the literature, the authors have contributed to different fields of sewer asset management with the purpose to build proactive management. In the following, it is sum up the main contributions:

(i) Building new technologies and methods to collect GIS and inspection information in which experts on electronic devices and software developers are working with the purpose of improving the quality of collected data by inspection technologies (Cherqui et al., 2008; Schilperoort & Clemens, 2009; Feeney et al., 2009; Yang et al., 2011; Hao et al., 2012; Plihal et al., 2016; Stanic et al., 2017), developing software to automatize the collected inspection information with the assessment protocols (Knolmar & Szabo, 2003; Sinha & Fieguth, 2006; Duran et al., 2007; Yang & Su, 2008; Sarchar et al., 2009; Elamin, 2017), and collecting and integrating environmental, physical, economic and social information characteristics to simulate the cities' dynamics in Geographical Information Systems (GIS) tools which could be open and adapted for any professional, scientist or student who works in topics related to Infrastructure Asset Management, urban developing, civil and environmental engineering, climate change, among others (Halfway et al., 2002; Möderl et al., 2009; Steiniger & Hunter, 2012; ESRI, 2012; Mair et al., 2012; Sinha et al., 2017).

(ii) Developing or improving the methodologies for assessing the condition of sewer assets whose objective is to evaluate the sewer assets according to the structural and operational failures collected by inspection technologies (particularly, CCTV inspection technologies) (EAAB, 2001; Thronhill & Wildbore, 2005; Le Gauffre, 2007; EPM, 2010;

Chughtai & Zayed, 2011; Ennaouri & Fuamba; 2011; Khazraeializadeh, 2012; Ahmadi et al., 2014; Daher, 2015), the factors that could affect the operational or structural condition (Koo & Ariaratman, 2006; Le Gauffre, 2007; Islam et al., 2009; Ennaouri & Fuamba; 2011; Kandasamy & Prasad, 2017), and the consequences that could happen whether the sewer asset is not rehabilitated timely (Stein et al.2004; Stein et al., 2006; DWA, 2013; Park & Kim, 2013; Anbari et al., 2017). Some of these methodologies, particularly those that only consider the observed structural and operational failures by CCTV are already national or local standards (protocols) (EAAB, 2001; EPM, 2010; WRC, 2013; NASSCO, 2015; CEN, 2011; Zhao et al., 2001; CERIU, 2004; NZWAA, 2006). The idea of these assessments is to guide the decision-making to carry out rehabilitation activities, and thus, prevailing the level-service of urban drainage and other infrastructures in the cities (Thornhill & Wildbore, 2005).

(iii) Identifying the influential factors over the operational and structural condition by application of statistical methods (El-Housni et al., 2017, Torres-Caijao et al., 2017; Angarita et al., 2017; López-Kleine et al., 2016; Rokstad & Ugarelli, 2015; Fuchs-Hanusch et al., 2012; Tscheikner-Gratl et al., 2014; Ugarelli et al., 2013; Salman & Salem, 2011; Younis & Knight, 2010; Ana et al., 2009; Chughtai & Zayed, 2008; Tran et al., 2006; Baik et al., 2006; Micevski et al., 2002; Davies et al., 2001; Ariaratnam et al., 2001), entropy’s concepts (Hernández et al., 2016), Bayesian inferences (Anbari et al., 2017), and machine learning tools (Laakso et al., 2018; Khan et al., 2009; Tran et al., 2007) to find the factors that cause the most common failures or influence the deterioration of the structural condition of sewers. The presented studies have centred in those defects related to the structural condition since these also affect the sewer flow capacity (operational state): structurally deteriorated pipes with cracks and breaks have a rougher inner surface that increases the risk of debris accumulation (Chughtai & Zayed, 2008; Tran et al., 2007; Davies et al., 2001). Among the variables that have been found as influential factors are included: physical sewer characteristics (size, material, slope, length, shape, depth), age, sewer type, surrounding variables (trees presence, road traffic, soil type, bedding type, geographical locations), and social characteristics (construction time and land use). Furthermore, the criteria to choose the most influential factors have been the significance (p-value) of different statistical tests, redundancy with the sewer condition, and the accuracy’s performance of the deterioration models.

(iv) Developing deterioration or predictive models to forecast the condition or probability in future time (Tran et al., 2008; Le Gat, 2008; Scheidegger et al., 2011; Egger et al., 2013; Kleidorfer et al., 2013; Vitorino et al., 2014; Caradot et al., 2015) or predicting the current condition of uninspected pipes (Mashford et al., 2010; Ennaouri & Fuamba, 2011; Rockstad & Ugarelli, 2015; Hernández et al., 2018; Hernández et al., 2019a; Hernández et al., 2019b; Stanic et al., 2017).

(v) Designing proactive management proposals (PMPs) to support the making-decisions of this infrastructure is based on stakeholders' and operators' expertise (Van Riel et al., 2016a, Van Riel et al., 2016b), deterioration models' outputs (Ahmadi et al., 2014; Ahmadi et al., 2015; Khan & Tee, 2016), and multi-objective optimisation models focused on support the operational conditions developed by machine learning techniques (Diogo et al., 2017; Fontecha et al., 2016), and developing proactive management of multiple infrastructures (Tscheikner-Gratl et al., 2016; Mikovits et al., 2017; Marzouk & Osama, 2017; Kielhauser & Adey, 2017).

Justification

Even though the above contributions, some gaps are still open, such as:

(i) The need of the development of technologies will be economically accessible to the utilities for inspection activities and the automation the inspections information with the assessment protocols (Cherqui et al., 2008; Schilperoort & Clemens, 2009; Feeney et al., 2009; Yang et al., 2011; Hao et al., 2012; Plihal et al., 2016; Stanic et al., 2017; Knolmar & Szabo, 2003; Sinha & Fieguth, 2006; Duran et al., 2007; Yang & Su, 2008; Sarchar et al., 2009; Elamin, 2017).

(ii) The current protocols have shortcomings since studies of factors that could affect the operational and structural condition of assets are still developing (Angarita et al., 2017; El-Hosni et al., 2017), the integration of methodologies as decision-making tools for choosing the proper rehabilitation activity has not been included in these protocols (Stein et al., 2004; Stein et al., 2006; DWA, 2013; Anbari et al., 2017) and the generated uncertainty by inspection technologies and the way of grouping the defects and their severities in grades which, in the end, is the output of these protocols (Dirksen et al., 2013; Caradot et al., 2017). It is essential to clarify that the protocols are still in developing until the time that the research gaps close, and these protocols become part of a local, national or international management program with enough information to make decisions effectively and timely (Ana & Bauwens, 2007).

(iii) Most of the cases, some physical characteristics of pipes, environmental and operational characteristics, where the pipes are embedded, have been identified such as factors that could influence over the structural and operational conditions of the sewer assets by statistical models and analysis (Chughtai & Zayed, 2011; Tran et al., 2007; Davies et al., 2001). However, depending on the case study, the number of variables could differ: the dynamism of infrastructure assets depends on the characteristics of each urban area. Thus, some factors could be influential in some cities and others not (Chornet, 1994). Each urban area is different because of the integration of environmental (topographic, climatic, soil type conditions, bending soil types, surrounding infrastructure, external loads that could support the sewers), social (land uses, population density), and system operation logistics. Furthermore, the expert knowledge, the available information (Angarita et al., 2017; Kabir et al., 2016), and the ease of collection (costs and time) (Angkasuwansiri & Sinha, 2013) are some of the strategies for choosing the variables that could influence over the sewer condition. For example, Angkasuwansiri & Sinha (2013) determined that almost 60 variables could affect the performance of the pipes, other studies included between 5 and 16 variables that contribute directly to the deterioration of the sewerage network (Ariaratnam et al., 2001; Baah et al., 2015; Kabir et al., 2016; Laakso et al., 2018; Rokstad & Ugarelli, 2015). Alternatively, other studies use only one variable to explain structural damage, such as Xu et al. (2018). They developed a statistical model to represent the relationship between sewer pipes' structural condition and pipes age. Moreover, Laakso et al. (2018) state that in some studies are not deeply explained the selection criteria, leaving outside the uncertainties in the methodological procedure to select the appropriate variables. Therefore, it is necessary to develop rational methods or methodologies to identify the influential factors over the deterioration of the structural condition, the evaluation of their inclusion for support tools of decision makings in sewer asset management, and the evaluation of their addition for specific management objectives.

The deterioration models are not precise enough in their prediction because of the low available or erroneous information that feeds them (Scheidegger & Maurer, 2012; Chughtai & Zayed, 2011). Moreover, most of the variables involved in the models are chosen from other experiences or by criteria of intuition of experts (Van Riel et al., 2014a; Van Riel et al., 2016a; López-Kleine et al., 2016). As well, training the deterioration models with the structural condition could generate uncertainty: since a structural condition represents several failures whose degradation process could be different and the model could not catch the degradation behaviour (Dirksen et al., 2013; Caradot et al., 2013; Van Riel et al., 2014b). And finally, most of the proactive management proposals (PMPs), developed to address efficiently and rationally the management activities, are based on the deterioration model outputs, the identification of influential deterioration factors, and failures consequences (Frone & Frone, 2012; Ahmadi et al., 2014, 2015; Khan & Tee, 2016). Due to the lack in the identification of the influential factors which could reduce the deterioration models' performance, the effectiveness of the PMPS could decrease.

According to the above gaps, the identification of factors that affect the condition of sewer could be the key, and this selection should link with the management objectives and the ease costs of their collection.

On the other hand, the prediction performance used to carried out by accuracy tools (Cohen's Kappa coefficient, ROC curve, true positive rates, accuracy, among others), leaving aside the main objective of development of these deterioration models: guiding strategically the decision making to fulfil with the management objectives of this infrastructure.

Although the identification of deterioration factors was left aside in the last decade for prioritizing the exploration of deterioration models and designing PMPs, this topic once again becomes relevant since the performance of deterioration models and PMPs depend on the input data (factors and inspection assessments). Thus, research on the suitable tools to identify the key factors that influence the deterioration of sewer assets is still opening, the outcomes in this topic could help to understand the deterioration behaviour of sewer pipes and address the deterioration modelling to have a high prediction performance. As mentioned by Chornet (1994), the dynamism of infrastructure assets depends on the characteristics of each urban area, and thus some factors could be influential in some cities and others not.

Research Questions

According to the above, research questions appear around this topic, such as:

(i) Could the factors identified as influential over the sewer condition and deterioration model vary according to own distinct characteristics of cities?;

(ii) Could the factors identified as influential over the sewer condition and deterioration model vary according to the management objectives such as investment plans (i.e. prediction of the number of assets to rehabilitate per year), prioritisation plans for assets rehabilitation (i.e. the identification of which assets need a replacement immediately), or inspection plans?;

(iii) Is it possible to hierarchize the key factors to develop deterioration models for minimising collection costs and the error prediction?;

(iv) and Is it possible to infer information from other factors (not identified) that could affect the structural condition of the sewers?

Therefore, the importance of proposing a methodology lies in identifying the key factors to build proper deterioration models, developing appropriate deterioration models with the enough and available information and developing precise deterioration models looking for fulfilling the management objectives that utilities have to face to apply a proactive sewer asset management.

Main objective

The purpose of this research is to develop a methodology for determining which factors are enough and necessary to achieve specific objectives in sewer asset management, considering the quantity and quality of the available information.

Structure of the manuscript

The following manuscript consists of four parts: Part A depicts the theoretical framework of the main concepts, tests, methods, and metrics used as the basis for developing the proposed methodology; Part B concerns the description of materials (case studies and computer-based tools) and the scientific arguments of the choosing methods for developing the proposed methodology; Part C is the most essential part of this manuscript because it describes the developed sewer asset management tools and the proposed methodology, objective of this doctoral thesis; and Part D illustrates the results of the proposed sewer asset management tools and the application of the proposed methodology in two case studies.

Main contributions

During my doctoral studies, I explored and developed sewer asset management tools which are described in Part C. These tools are classified in antecedent tools and the proposed methodology in this doctoral thesis.

According to the antecedent tools, I developed:

1. A Bayesian Network-based methodology for selecting a cost-effective sewer asset management model as a feature selection tool;
2. Performance metrics linked with management objectives in sewer asset management;
3. An optimisation methodology for machine learning-based models to find the optimal hyperparameters for achieving management objectives; and
4. Building deterioration models based on different statistical and machine learning methods on different case studies, evaluating the predictions from different perspectives.

Thanks to the results of the above, I developed the proposed methodology for this doctoral thesis. This methodology consists of two parts:

1. Bayesian Network-based methodology for selection feature hierarchically
2. Methodology for the selection of the deterioration model for achieving a management objective

From the above contributions, I already published some articles on International Journals from the results of the developed sewer asset management tools. These articles are:

- Hernández N., Caradot N., Sonnerberg H., Rouault P and Torres A (2020). Support Vector Machines used for the prediction of the structural conditions of pipes in Bogota's sewer system. Accepted on Ingeniería y Universidad Journal in March 2020.
- Hernández, N., Caradot, N., Sonnenberg, H., Rouault, P., & Torres, A. (2020). Optimizing SVM models as predicting tools for sewer pipes conditions in the two main cities in Colombia for different sewer asset management purposes. Structure and Infrastructure Engineering, 1-14.
- Tscheikner-Gratl, F., Caradot, N., Cherqui, F., Leitão, J. P., Ahmadi, M., Langeveld, J. G., ... & Lepot, M. (2019). Sewer asset management–state of the art and research needs. Urban Water Journal, 16(9), 662-675.
- Hernández, N., Caradot, N., Sonnenberg, H., Rouault, P., & Torres, A. (2018). Support tools to predict the critical structural condition of uninspected pipes for case studies of Germany and Colombia. Water Practice & Technology, 13(4), 794-802.
- Caradot, N., Riechel, M., Fesneau, M., Hernández, N., Torres, A., Sonnenberg, H., ... & Rouault, P. (2018). Practical benchmarking of statistical and machine learning models for predicting the condition of sewer pipes in Berlin, Germany. Journal of Hydroinformatics, 20(5), 1131-1147.

For more information about my contributions during my doctoral studies, see my curriculum vitae in the appendix of this manuscript.

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PART A THEORETICAL FRAMEWORK

Part A of this manuscript describes the theoretical framework of the concepts, definitions, and description of the tests, methods, and techniques mentioned along with the doctoral document. The idea is to give a theoretical background of these tools to understand the procedures of the proposed methodology.

This part consists of four chapters. Chapter 1 illustrates the concept of sewer asset management (SAM), the general context about sewerage, the stages to achieve a SAM based on the ones of infrastructure asset management (IAM), the origin of the leading research topics in SAM, and a brief state-of-art of the worldwide contributions on each SAM research topic.

Chapter 2 depicts the theoretical framework of the used statistical tools, such as Homogeneity and normality tests (Shapiro-Wilk and Bartlett tests), tests of significant difference between samples (Wilcoxon-signed rank test), boxplot analysis, the cross-validation method, Bayesian Networks, binary, ordinal and multinomial logistic regressions, and linear discriminant analysis. Statistical tools were useful to develop tools for feature selection, deterioration models, and analysis of some results, and from their application, the proposed methodology could be developed (Part C).

Chapter 3 holds machine learning tools as support vector machines (SVM) and random forest (RF), and differential evolution algorithm (DE). Machine learning tools were useful to develop deterioration models and an optimisation methodology which is described further in Part C of this manuscript.

And finally, chapter 4 describes the used performance measures to validate the developed tools. Among these measures are the Cohen's Kappa coefficient, ROC space, Performance curve, and deviation analysis. Thanks to their application in the prediction evaluation of deterioration models, these were the basis for proposing the performance metrics depicted in chapter 8 of Part C.

Further, subchapter 6.1. (Part B - Materials and Methods) describes the scientific pertinence of choosing the depicted methods and techniques.

CHAPTER 1: SEWER ASSET MANAGEMENT

Urban drainage systems are one of the most critical urban infrastructures because of their adverse consequences and effects of inadequate performance. Failure events can sometimes lead to disrupting part of a city's functioning. These systems may operate at a lower level than desirable for extended periods before appearing evidence of existing problems. Structural or hydraulic failures may be unknown for a long time until service disruptions, road collapse, or basement flooding emerge (Anbari et al., 2017; Khan et al., 2009).

Urban drainage infrastructures, including collection pipes and treatment facilities, represent an enormous investment in physical assets. In the last 30 years, most municipalities have invested in sewerage expansion to meet growth and treatment plant upgrades; they still allocated a relatively small proportion of the budget to sewer rehabilitation (AWWA, 2012). According to the distribution of infrastructure investment by sector during the 2003-2012 period in Latin-America, energy, and transportation infrastructures are the ones with most investment capital, then telecommunication and last water and sewer systems (less than 0.3% Gross Domestic Product - GDP) (Lardé & Sánchez, 2014). As a result, most cities face the problem of ageing infrastructure in need of extensive and ongoing repair, rehabilitation, or renewal (Caradot et al., 2017b).

The rehabilitation of existing sanitary sewer networks is essential in many circumstances to ensure acceptable operating conditions and to safeguard public health and natural resources. Rehabilitation is frequently an expensive task requiring a significant investment of public funds (Diogo et al., 2017). To invest these funds rationally, often operators are under pressure to minimize their maintenance costs while keeping the risk of failures at an acceptable level (Stanic et al., 2017).

Traditionally it has been economically feasible to apply reactive management strategies, repairing when failures occur; however, this strategy becomes less viable as the systems age and the funding gap increases (Rokstad & Ugarelli, 2015): In the USA, the American Society of Civil Engineers (ASCE) estimated the required capital investment to maintain and upgrade water infrastructure at $91 billion, however, only $36 billion of this $91 billion needed was funded, leaving a capital funding gap of nearly $55 billion (ASCE, 2011; Caradot et al., 2017b); In Germany, over the last years, annual investment for sewer rehabilitation was about 4 billion € whereas the capital need is estimated to more than 7 billion €, indicating a capital deficit of a least 3 billion € (Branchenbild, 2011; IPK,2014); and The new Latin-American governments recognize that investment is too low because it is estimated that is needed around $60 and $70 billion of funds to achieve the need levels of water and wastewater investment, but the actual inversion is about $18 billion (CG/LA Infrastructure, 2006). In consequence, the rehabilitation of sewerage systems has been a civil engineering area of particular importance in relatively recent times and currently (see, for instance, EPA, 1991; WRC & WAA, 1986; WRC & WAA, 2004; Werey et al., 2006; Almeida & Cardoso, 2010; ASCE, 2011, Black & Veatch 2013), given that many networks are in an inefficient or degraded state and that it is imperative to manage the public funds and the wastewater infrastructures assets rationally (Diogo et al., 2017).

Recalling the stages of Infrastructure Asset Management (IAM) is essential for achieving Sewer Asset Management (SAM) (Ana & Bauwens, 2007). These stages allow building strategic operation and maintenance (O&M) programs with enough information for rational decision-making considering diverse actors such as budget constraints, environmental regulations and public water benefits (Anbari et al., 2017; Cardoso et al., 2012; Younis & Knight, 2012; Baik et al., 2006). From the stages of IAM proposed by Lemer (1999), the research topics in SAM have born to achieve strategic operation and maintenance programs. Figure A1 shows a review of the leading research topics in SAM linked to the stages of IAM.

According to Figure A.1., the research topics in SAM born from the need to develop proactive management for the sewer systems following the steps of IAM. Figure A.1. shows three boxes related to the first four stages of IAM.

The first box is related to the collection of Geographical Information Systems and inspected information which includes new inspection technologies, development of standards for assessing the condition of sewer assets and identifying the influential factors over the deterioration of structural, and operational conditions of the sewer assets. By the first research topic, the researchers have developed different technologies to inspect the sewer assets have been developed based on Visual (Koo & Ariaratnam, 2006; Allouche & Freure, 2002), electromagnetic (Hao et al., 2012; Mukhopadhyay & Srivastava, 2000; Saha et al., 2010; Khodayari-Rostamabad et al., 2009; Markar & Changon, 1999; Roubal, 1999; Kuras et al., 2007), acoustic (Feeney et al., 2009; Plihal et al., 2016) and thermic techniques (Schilperoort & Clemens, 2009). The most used has been the visual techniques such as Closed-Circuit Television (CCTV) in which is focused the industry standards for sewer system inspection and structural performance evaluation (Schilperoort et al. 2014). Furthermore, information about the characteristics of the terrain that could be recorded by Geographical Information Systems (GIS) (Steiniger & Hunter, 2012; ESRI, 2012). From this computational tool, it is possible to integrate spatial infrastructure data with inventory data to query, explore, visualise, and analyse the infrastructure data in its spatial context (Halfway et al., 2002).

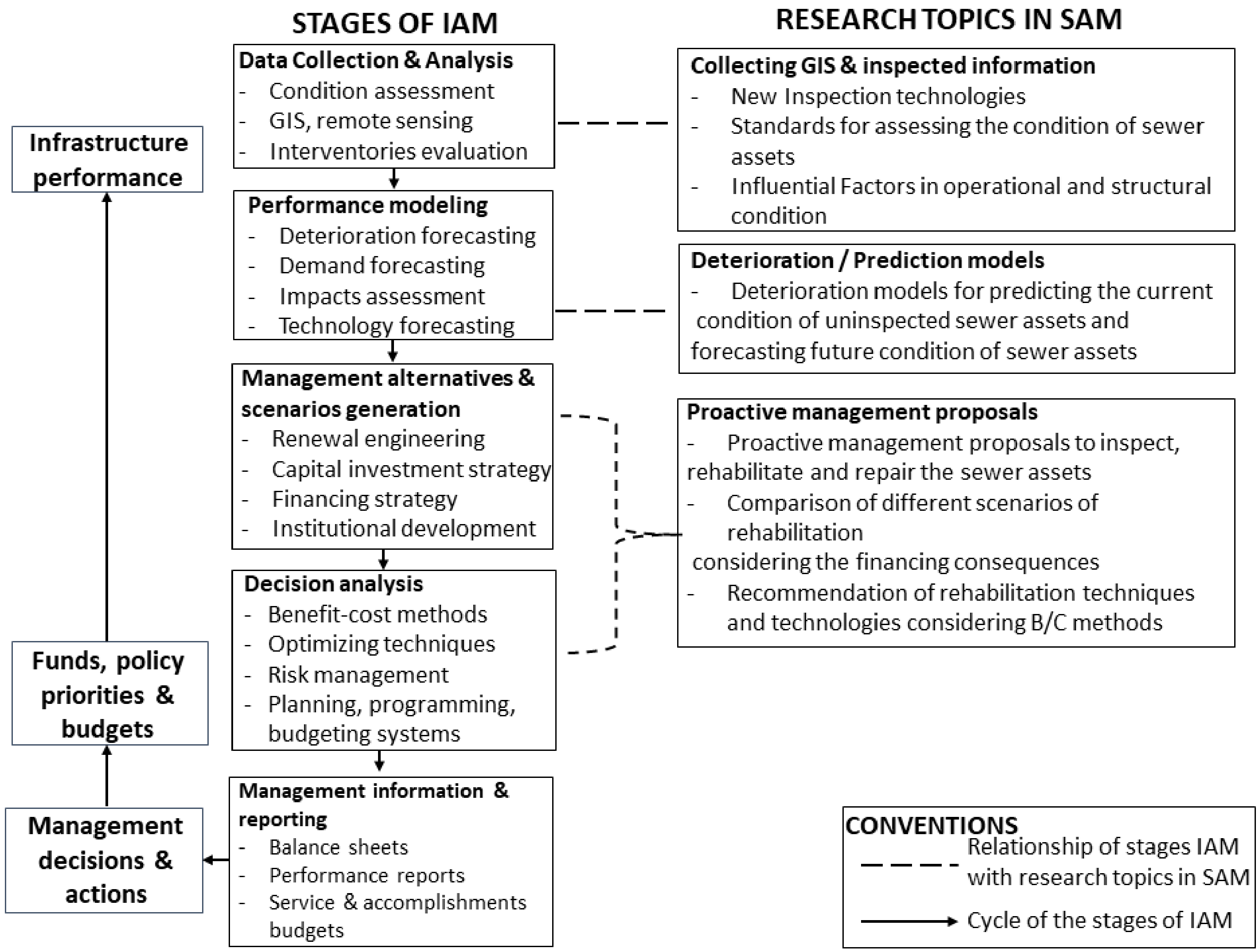

Figure A.1. Conceptual map of origin the main research topics in Sewer Asset Management (SAM) based on the stages of Infrastructure Asset Management (IAM) proposed by Lemer, 1999.

The second research topic, in the first box, is related to the development of standards for assessing the condition of sewer assets. UK was a pioneer in proactive management (1978) with the application of the CCTV technologies to inspect sewer pipes. The Water Research Centre (WRC) developed a codification to score the structural and operational state of sewer pipes, becoming a technical standard in this country (Thornhill & Wildbore, 2005; Daher, 2015). The manual of sewer condition classification (MSSC) has had five versions with the last update in 2013. Based on this manual, cities of other countries have developed own standards such as PACP in the USA (NASSCO, 2004), *Manuel de standardization des Observations*, in Canada (CERIU, 2004), EN13508 in European Union (CEN, 2003; Le Gauffre et al., 2007), Australian Conduit Evaluation Manual (Board, 1991), among others. Moreover, different researchers have developed methodologies based on priorities and substance-based methodologies. The methodologies based on priorities consider operational and environmental factors to assess the structural condition of sewer assets (Le Gauffre 2004, 2007; Chughtai & Zayed, 2011; Ennauri & Fuamba, 2011 and Daher, 2015). The substance-based methodologies consist of classifying the sewer assets considering in the quantity and rehabilitation type (see some examples in DWA, 2013 and Stein et al., 2004, 2006).

And the third research topic related to the first stage of the IAM concerns the identification of the influential factors over the deterioration of the sewer assets. Factors such as physical characteristics of the sewer assets, environmental and surrounding infrastructure to the sewer assets, urban and operational features of the cities, type of effluent, age of the sewer assets, climate change, land use's changes, and demographic growth have been reported as influential over the operational and structural conditions (Davis et al., 2001a; Davis et al., 2001b; Ariaratnam et al., 2001; McDonald & Zhao, 2001, Moore et al., 1987, Marzouk & Osama, 2017, Baur & Herz, 2002; Saegrov & Konig, 2005; Salem & Salam, 2012; Post et al.,2016; Anbari et al., 2017; Torres et al., 2017; Kleidorfer et al., 2013). Statistics methods, entropy's concepts, and Bayesian inferences have been used to find these influential factors. Davies et al. (2001b) applied logistic regression utilizing a stepwise selection method to identify the crucial parameters that affect the deterioration of rigid pipes: the analysis was related to those pipes in critical conditions. Likewise, Salem & Salman (2011) developed deterioration models from the estimation of the probability of failure values for sewer sections based on ordinal regressions, multinomial logistic regression, and binary logistic regression methods. Other experiences explored tools such as PCA and k-means clusters to identify the relationship between the intrusive trees and the observed sewer failures (Torres et al., 2017) and find connections between physical pipes characteristics and the structural conditions of the sewer pipes (López-Kleine et al.,2016; Angarita et al., 2017). Joint entropy, average mutual information (AMI), and redundancy were the entropy's concept explored by Hernández et al. (2016) to find relationships between characteristics of sewer pipes and their structural condition assessing the quantity of shared information.

Recently, Bayesian Networks were used by Anbari et al. (2017) to develop a risk assessment model for prioritizing sewer pipes to inspect: they calculated the consequences of failure values from a weighted average method guided by experts' opinion and computing the failure probability.

The fourth research topic in SAM, linked to the second stage of IAM (second box), is related to the development of deterioration models. Deterioration modelling is a powerful tool to support utilities in planning efficient sewer rehabilitation strategies since from this tool it is possible to (i) predict the current sewer condition of uninspected sewers and (ii) forecast the evolution of the sewer condition. Researchers around the world have developed methods and methodologies based on different approaches (Hernández et al., 2017a; Santos et al., 2017; Ana & Bauwens, 2010; Mashford et al., 2010; Le Gat, 2008; Saegrov & Konig, 2005). According to Caradot et al. (2013), these modelling approaches are generally classified into three groups (deterministic, statistical, and machine learning models) regarding their mathematical base. Deterministic models describe the deterioration process by evaluating the physical ageing mechanism. Linear and exponential regression models are used to explain the deterioration of sewer pipes (i.e. Saegrov, 2006; Alegre & Céu Almeida, 2007). The basis of statistical models is the data concerning the evolution of the sewer condition and pipe deterioration. Survival functions and Markov chains are methods used to quantify in probability values the ageing and the deterioration process to simulate the transition of the deterioration process: i.e. Gompitz model (Le Gat, 2008; Rokstad & Ugarelli 2015; Caradot et al., 2017b) which mix survival functions (Gompertz function) and non-homogeneous Markov chains, and others which consider one of both methods (Baik et al., 2006; Tran et al. 2008; Scheidegger et al., 2011; Duschesne et al., 2013; Egger et al., 2013) or other distribution functions such as mutinormal distribution (Del Giudice et al., 2016). Other methods such as logistic regression and discriminant analysis are used to find the relationship between influential factors and the sewer condition status in probabilistic values (Wright et al., 2006; Tran, 2007; Salman, 2010; Ahmadi et al., 2014; Tscheikner-Gratl et al., 2016; Fuchs-Hanusch et al., 2012; Hernández et al., 2017). Machine learning models could identify the complex and non-linear relationship between deterioration factors and sewer condition states by "learning" the deterioration behaviour of pipes from inspection data. Therefore, the knowledge of the sample data (CCTV data) is generalized to predict the evolution of the condition. Some machine learning methods used as deterioration models are Decision Trees (Santos et al., 2017), Random Forest (Harvey & McBean, 2014; Vittorino et al., 2014), Support Vector Machines (Mashford et al.., 2010; Hernández et al., 2017a,b), and Neuronal Networks (Tran et al. 2007, Khan et al. 2010; Jiang et al., 2016), among others.

The last research topic in SAM, linked to the third stage of IAM, is related to the proactive management proposals (PMPs). From the deterioration model outputs, it is possible to build strategic plans for rehabilitation purposes. Model outputs, in particular, may provide crucial information to operators and municipalities for the scheduling of inspection programs (i.e. the detection of sewers in critical condition) and the planning of rehabilitation budgets (i.e. the comparison of different sewer rehabilitation scenarios and the evaluation of necessary investment rates) (Caradot et al., 2017b). In practice, the strategies of proactive management used for Decision-Making have based on the companies or municipalities employees experience: their intuition and knowledge of the system play an essential role in decision-making (Van Riel et al., 2016a; Van Riel et al., 2016b). However, considering all the management tasks in a limited time is not possible (López-Santana et al., 2016): proper maintenance planning defines the set of tasks, time intervals, and resource consumption for each maintenance series (Duffuaa, 2000). Considering that the deterioration models are still in developing (the optimisation, adaptation, and lack of information is still the Achilles heel for the development of these models), many researchers have developed PMPs for particular case studies based on the integration of limited information available of CCTV data and influential factors, deterioration models (taking into account their uncertainty), budget restrictions, and rehabilitation activities. For instance, Ahmadi et al. (2014, 2015) propose a systematic approach using a deterioration model to predict the structural condition of sewers to improve the efficiency of sewer inspection programs. The PMP consists of choosing only a portion of pipes predicted with structural failures (10% of pipes with a high probability of structural failure by a logistic regression model) and a random selection of uninspected sewer pipes to build the annual inspection plan considering the budget available for that activity. The advantages of this PMP are that it takes advantage of the prediction of the logistic regression model and feeds the CCTV database to recalibrate the deterioration model for the next annual inspection plan. Another experience, Khan et al. (2016) used the computational optimisation algorithm Subset Simulations (SS) to develop a risk-cost optimisation of flexible underground pipeline networks from a time-dependent reliability analysis. This optimisation algorithm is based on the integration of artificial probability density functions (PDF), Markov chains, and Monte-Carlo simulations which simulate the degradation process of pipe defects caused by corrosion. Then, the minimization of life-cycle cost (LCC) function gives information of the optimal intervention year, and the last, a criterion for pipe renewal is based on identifying the degree of impact of an underground sewer failure considering six influential factors: location, embedment soil, buried depth, pipe size, functionality, and seismic zone.

Furthermore, some researchers have developed PMPs considering a group of different infrastructure types (such as road, water, and sewer systems) as one element for management tasks (Kelly et al., 2013; Makropoulos et al., 2008; Tscheikner-Gratl et al., 2016; Mikovits et al., 2017; Willuweit & O'Sullivan, 2013; Marzouk & Osama, 2017). These PMPs are in developing, identifying areas where rehabilitation is technically necessary but also economically recommendable. Criteria such as structural resiliency, the vulnerability of the network, capital value, infrastructure components, rehabilitation techniques, rehabilitation costs, and costs due to the loss in the level of service play a vital role in decision-making for cities' rehabilitation plans (Tscheikner-Gratl et al., 2016). Examples of this research approach are the works of Marzouk & Osama (2017) and Tscheikner-Gratl et al. (2016).

CHAPTER 2: STATISTICAL TOOLS

This chapter contains the used statistical tools for developing the proposed methodology. Bayesian Networks and statistical tests were useful to build feature selection tools that support the proposed methodology. While, Linear Discriminant Analysis, Binomial, Multinomial and Ordinal logistic regressions helped develop deterioration models.

2.1. STATISTICAL TESTS

2.1.1. SHAPIRO-WILK TEST

Shapiro-Wilk test is a test for determining normality in the data. This test detects the departures from normality due to either skewness or kurtosis, or both (Razali & Wah, 2011). As the null-hypothesis of this test is that the data is normally distributed, if the p-value is less than 0.05, then the null hypothesis is rejected, and there is evidence that the data is not normally distributed (Henderson, 2006).

2.1.2. BARTLETT'S TEST

Bartlett's test is a test to determine the homogeneity of variances in the data. Bartlett's test is designed to test for equality of variances across groups against the alternative that variances are unequal for at least two groups. Therefore, this test assumes that variances are equal across groups or samples of the data. Bartlett's test is sensitive to departure from normality. That is, if the samples come from non-normal distribution, then Bartlett's test could be testing for non-normality (NIST/SEMATECH, 2012).

The null hypothesis of this test assumes homogeneity in the variances ($H_0 = \sigma_1^2 = \cdots = \sigma_k^2$. If the p-value is lower than 0.05 (significance level) the null hypothesis is refused; therefore, the variance is not the same for all the k samples (Li et al., 2015).

2.1.3. BOXPLOT AND WILCOXON SIGNED-RANK TEST

A boxplot is a statistical tool that depicts graphically a summary statistic for univariate variables, where observations are ordered from the smallest value to the largest to define median, quartiles, the minimum and maximum, and detects outliers. The distribution of the data by quartiles measures and identifies outliers (Genton et al., 2015). A boxplot consists of two parts, a box, and whiskers (see Figure A.2.).

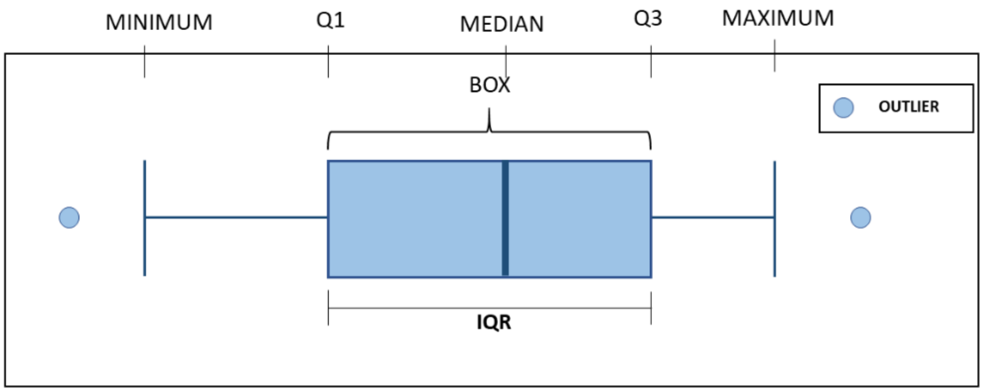

Figure A.2. Description of a box plot. Source: Author

According to Figure A.2., Q1 refers to the first quartile of the data and represents the 25% of the data that have lower values than this limit Q1; Median (bold black line) represents the middle quartile of the data; Q3 refers to the third quartile of the data and represents the 75% of the data that have lower values the value of Q3 (Hofmann et al., 2017). IQR is the interquartile range calculated as Q3-Q1 (size of the box). The values of the whiskers which are depicted in Figure A.2. as a minimum (MIN) and maximum (MAX) values corresponds to the following data which is inside of the rank after calculating Q1-1.5*IQR for minimum constraint and Q3+1.5*IQR for maximum constraint. The values outside of the whiskers are considered outliers (Zamora & Torres, 2014).

Wilcoxon signed-rank test is a rank test in nonparametric statistics, and it is the alternative of the t-test. It compares the locations of two populations, to determine if one shift to another. The method employed is a sum of ranks comparison (Liu, 2017). The procedure is as follows. First, it calculates the difference between each pair of data. The differences are then ranked. Next, the ranks are assigned then sign (+) of the corresponding difference, and then two sums are computed: the sum of the positive signed-ranks (T+) and the sum of the absolute values of the negative signed-ranks (T-). Therefore, the null hypothesis is true when the absolute value of negative and positives sums is equal, and as a result, there are no differences between that pair of data. Conversely, there are statistical differences (Reynolds, 1998). Quantitatively, when the p-value is lower than 0.05, it rejects the null hypothesis of this test which means that the pair of data is significantly different (Laake & Benestad, 2015).

2.1.4. CROSS-VALIDATION METHOD AND GRID SEARCH TECHNIQUE

Cross-validation provides a simple and effective method for model selection and performance evaluation. Under k-fold cross-validation, the data are randomly partitioned to form K disjoint subsets of approximately equal size. In the *ith* fold of the cross-validation procedure, the *ith* subset is used to validate the model trained by the K folds (Cawley & Talbot, 2010).

Grid search is a technique used for finding the optimal hyperparameters of a model which results in the most accurate predictions. When the global optimisation problem involves continuous variables, there is an infinite number of points in the domain, and complete enumeration is impossible (Zabinsky, 2013). Grid Search is a common approach to perform an essential discretisation of the domain. A grid search creates an equally spaced grid of points over the feasible regions and evaluates the objective function at each point. If the grid search indicated that the function is fat over a wide range, there is little reason to proceed with sophisticated methods. If the grid search suggests that there are multiple local optimal, then it is needed to work hard to find the global optimum (Judd & Judd, 1998).

2.2. BAYESIAN NETWORKS

Bayesian Networks is a probabilistic graphical model that represents a set of variables and their conditional dependencies (joint probability distribution). The structure of the network consists of a direct acyclic graph (DAG), integrated by nodes that represent random variables (Xi) with several possible states and arrows that connect pairs of nodes to display their probabilistic cause-effect relationship (Liu et al., 2013). These dependencies are based on process understanding, statistical, or other types of associations. Conditional probabilistic distribution tables are the qualitative representation of the dependencies: they describe the probability distribution of each child node, which is conditioned by the combination of the probability distribution of its parent nodes. If a variable does not have parents, it means that this node has a marginal probability distribution (Pollino & Hart., 2006). These probabilities of each node could be evaluated from historical data, expert judgment, or their combination (Liu et al., 2013).

The main objective of learning the structure of a BN from data is finding the network that best matches the training set. Therefore, learning algorithms are the best option to learn the structure of BN. There are two kinds of learning algorithms based on two general approaches: (i) methods based on conditional independence tests, and (ii) methods based on scoring function and a search procedure (De Campos & Castellano, 2007).

(i) Methods based on conditional independence tests: causal graphical models are the basis of these algorithms, which provide a framework for learning a DAG using conditional independence tests. The used tests are mutual information (Kraskov et al., 2004) and the exact t-tests for correlation (Kim, 2015), to detect the Markov blanket of the variables, which in turn calculate the structure of the Bayesian Network. The Markov blanket for a node contains all the variables shield the node from the rest of the network. It means that the Markov Blanket of a node is the only knowledge needed to predict the behaviour of that node and its children (Scutari & Nagarajan, 2011, Scutari, 2014).

(ii) Methods based on scoring function and a search procedure: these algorithms attempt to find a DAG that maximises a score. These algorithms use a scoring function, which measures the fit between the DAG and the data, in combination with a search method to measure the goodness of each explored structure from the space of feasible solutions (De Campos & Castellano, 2007). Some of the algorithms that belong to this approach are Hill-Climbing and Tabu (Scutari & Nagarajan, 2011). Hill-Climbing algorithm is a grid search of Hill-Climbing on the space of the direct graphs. The optimised implementation uses score caching, score decomposability, and score equivalence to reduce the number of duplicated tests (Scutari & Nagarajan, 2011). Tabu algorithm is a modified Hill-Climbing algorithm able to escape local optimal by scaling a network that minimally decreases the score function (Scutari & Nagarajan, 2011). For both algorithms, the scores more used are Multinomial log-likelihood, the Akaike's entropy-based Information Criterion (AIC), and Bayesian Information Criterion (BIC).

2.3. BINOMIAL LOGISTIC REGRESSION

Logistic Regression is a statistical method that represents a simple linear or multiple regression where the dependent variable is dichotomous (0 or 1). This method is a particular regression that is useful for predicting a categorical variable based on many independent variables. The following logit function (Equation A.1.) is the log of the odds that an event occurs (category 1). The coefficients (b) depicts how much the logit changes based on the values of the predictor variables (X):

$$logit(p) = ln\left(\frac{p}{1-p}\right) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \cdots + b_kX_k$$

Equation A.1. Logit Function for logistic regressions

According to the Equation. A.1., *p* is the probability of an event occurring depending on the values of the independent variables. The parameters b_i are obtained from Maximum likelihood estimation (Hosmer & Lameshow, 2004). The logit transformation is defined as the logged odds: $\frac{p}{1-p}$, by the formula shown in Equation A.2. (Hernández et al., 2018).

$$p = \frac{1}{1-e^{-logit\,(p)}}$$

Equation A.2. Logit transformation to probability

2.4. ORDINAL LOGISTIC REGRESSION

An ordinal variable is a type of categorical variable that has a natural ordering of classes, but the distances between these are not known. Ordinal regression models are an extension of logistic regression considering more than two categories (polychotomous) as the response variable. The unique condition is that the response variable must be ordinal (Younis & Knight, 2010). There are several types of ordinal logistic regression models; however, the most frequent is the "proportional odds model" (Hosmer & Lemeshow, 2004). The ordinal logistic regression assumes that the coefficients that describe the relationship between the lowest versus all higher categories of the response variable are the same as those that describe the relationship between the next lowest category and all the higher categories, etc. Equation A.3. states the proportional odds model:

$$logit[P(Y \leq k)] = b_0 - b_ix, k = 1, \ldots, K-1$$

Equation A.3. Mathematical definition of proportional odds model

being *k* the level of an ordered category with *K* categories, and therefore, *K-1* logit equations.

It is essential to clarify that proportional odds models perform the probability of being in one category (or lower) versus being in categories above it (Harrel, 2015).

Then, when $logit[P(Y \leq k)]$ is converted in $P(Y \leq k)$ using Equation A.3., this probability is a cumulative probability and not the probability of $p(Y = k)$. Equation A.4. shows the probability of being in a particular category k.

$$P(Y = k) = P(Y \leq k) - P(Y \leq k - 1)$$

Equation A.4. Probability of being in category k

According to Equation A.4., the probability of being in category K is not calculated, because, in this model, the highest level returns a probability of 1. Therefore, Equation A.5. is a modification of Equation A.4. to obtain the probability of being in the highest category K (Harrel. 2015).

$$P(Y = K) = 1 - P(Y \leq k)$$

Equation A.5. Probability of being in higher category

2.5. MUTINOMIAL LOGISTIC REGRESSION

Multinomial logistic regression is the regression analysis to conduct when the dependent variable is nominal with more than two levels. This regression is useful to predict categorical placement in or the probability of category membership on a dependent variable based on multiple independent variables (Starkweather & Moske, 2011). If the dependent variable consists of K categories, one of them is chosen as the reference category (Salman & Salem, 2011). The remaining (K-1) categories generate (K-1) logit equation, as shown in the Equation A.6.

$$\log\left[\frac{P\left(Y = i \middle| X_1,\ X_2, \dots, X_p\right)}{P(Y = k|X_1, X_2, \dots, X_p)}\right] = \alpha_i + \beta_{i1}X_1 + \beta_{i2}X_2 + \cdots + \beta_{ip}X_p$$

Equation A.6. Mathematical definition of logit for multinomial logistic regression

In which $i = 1, 2, \dots, (K-1)$ corresponds to the categories of the dependent variable that has the total K variables; α_i corresponds to the intercept term for the *ith* level of the dependent variable; $X_1, X_2, \dots, X_p$ correspond to the independent variables; and $\beta_1, \beta_2, \dots, \beta_p$ correspond to the regression coefficients for the respective independent variables. As the binary, ordinal, and multinomial logistic regression parameters are estimated by using the MLE method (Salman & Salem, 2011).

2.6. LINEAR DISCRIMINANT ANALYSIS

The independent variables are continuous, and the dependent variable is categorical. LDA classifies an object in a category if the Mahalanobis distance is minimum between this object and the centroid of the data group that corresponds to this category. LDA assumes that covariance matrices are the same for all groups. Assuming that if there are two categories

(K1 and K2) for which are known X explanatory variables, it is possible to construct a linear function of the X variables to predict whether a new observation belongs to a group or another with the determined probability (Friedman et al., 2001). Equation A.7. defines the general linear function of linear discriminant analysis.

$$Z = \lambda_0 + \sum_{i=1}^{k} \lambda_1 x_1$$

Equation A.7. Mathematical definition of linear discriminant analysis (LDA)

The problem of discriminant analysis function from the analysis of variance is to answer the question if two or more groups are significantly different from each other concerning the average of a single variable. In the case that the mean of a variable is significantly different for several groups, it can be stated that this variable discriminated between groups (Friedman et al., 2001).

CHAPTER 3: MACHINE LEARNING TOOLS

Chapter 3 presents the theoretical framework of Random Forests and Support Vector Machines methods, which were the base for developing deterioration models for estimating the structural conditions of sewer assets. Also, a differential evolution optimisation algorithm was helpful to build a methodology that determines the combination of hyper-parameters that most fit in the deterioration models based on machine learning tools for reaching a management objective (See Part C).

3.1. RANDOM FOREST

Random Forest (RF) is a machine learning algorithm based on an ensemble of decision trees. RF is used to solve classification and regression problems (Caradot et al., 2018). The basis of this method consists of the construction of multiple decision trees (weak learners), using a randomly selected subset of training samples and variables (Belgiu & Dragut, 2016). These multiple decision trees are assembled (strong learner) for gaining prediction capacity (Hernández et al., 2019). The trees draw a subset of training samples through the replacement of variables (bagging approach). It means that the same sample can be selected several times, while others may not select at all (Belgiu & Dragut, 2016). In a decision tree, each internal node represents a rule (or variable), each branch represents a possible outcome of the rule (or attributes of the variable), and each terminal node denotes a label or class (Breinman, 2001). In the RF algorithm, it divides each tree's node by selecting the best predictor subset that strengthens the tree learning capacity. This characteristic makes this learning algorithm robust against overtraining, giving an advantage over other classifiers such as discriminant analysis and neural networks (Breinman, 2001). In addition to this advantage, RF is a simple algorithm to use since it requires only three hyper-parameters to work: i) the number of the trees: the number of observation samples chosen; ii) the node size: the minimum number of nodes that each tree can take at the end (tree depth); and iii) the number of variables: the number of attributes to be considered during the split (Caradot et al., 2018). Besides, RF has been used to feature selection, due to it measures the importance of each feature (variable) by reduction of the accuracy of the model (mean decrease accuracy - MDA) when the feature is not included (Sylvester et al., 2016; Hasan et al., 2016).

3.2. SUPPORT VECTOR MACHINES

SVM is a machine learning method commonly used in classification problems (Betancourt, 2005), and it has an extension for also solving regression problems. SVM is a machine learning developed in the mid-1960s by Vladimir Vapnik (Kuhn & Johnsons, 2013). With the application of Kernel functions, SVM increases the data dimensionality to find a hyperplane that could separate them correctly (Hernández et al., 2019). Among the kernel functions are linear, polynomial, Gaussian, sigmoid Bessel, Laplace, Polynomial, Vanilla or linear, Tangent, and Anova (Karatzoglou et al., 2004; Genton, 2001). The most used kernel function for classification is the Radial Basis Function (RBF) (Genton, 2001). The principle of the SVM is the resolution of binary classification problems which considers a large number of predictor attributes. In cases where there are more than two classes, SVM uses "one-to-one" or "pairwise" methods (Betancourt, 2005) to find the optimum separation hyperplane that maximizes the separation margins between each class. The support vectors are the training samples that define the optimal separation hyperplane and are the most difficult points to classify (Duda et al., 2012).

The hyperplane equation is defined by the Equation A.8.:

$$\left|ß_0 + ß^T x\right| = 1$$

Equation A.8. Mathematical definition of the separation hyperplane of the support vectors

being $ß_0$ the bias, β a weight vector and x the support vectors.

The distance between x and the hyperplane is defined by Equation A.9. and the hyperplane's margin is defined by Equation A.10.:

$$\frac{\left|ß_0 + ß^T x\right|}{||ß||} = \frac{1}{||ß||}$$

Equation A.9. Distance between support vectors (x) and hyperplane

$$M = \frac{2}{||ß||}$$

Equation A.10. Hyperplane's margin

The minimization function that maximizes the hyperparameter's margin is defined by Equation A.11.:

$$\min_{ß,ß_0} L(ß) = \frac{1}{2}\|ß\|^2 \text{ depending of } y_i\left(ß^T x_i + ß_0\right) \geq 1 \quad \forall i,$$

Equation A.11. Minimization function for finding the optimal separation hyperplane

being *y* each label or data class, and Lagrange multipliers are used to find the values of $ß_0$ and β.

The hyperparameters that condition the SVM performance depend on the type of kernel and the soft margin parameter *C*. *C* controls the compensation between the training errors and the separation surface which determines the width of hyperplane margins (Hernández et al., 2019).

3.3. DIFFERENTIAL EVOLUTION (DE) ALGORITHM OPTIMISATION

DE is a heuristic optimisation method (requires little or no assumption for searching a solution) developed by Storn & Price in 1997.

A global optimisation problem is defined by an objective function $\min f(x)$, a decision vector consisting of variables $x = [x_1, x_2, \dots, x_D]$, and constrained bounds in $x_j \in [a_j, b_j], \forall j = 1, 2, \dots, D$ which a_j, and b_j are the lower and upper bounds for each decision variable (Mohamed, 2015).

An initial random population consists of NP (population size) vectors $x, \forall\ i = 1, 2, \dots, NP$ which are generated by the boundaries (see Equation A.12.):

$$x_{ij}^0 = a_j + rand_j(b_j - a_j)$$

Equation A.12. Initial population for a search optimisation

where $rand_j$denotes a uniformly distributed number between [0,1], generating a new value of each decision parameter. These individuals are evolved by DE operators (mutation and crossover) to generate a trial vector. A comparison between the parent and its trial vector is then made to select the vector which should survive to the next generation (Mohamed, 2015).

The mutation operator is utilized to generate the mutant vector of Equation A.13.:

$$\boldsymbol{v_i^{G+1} = x_{ri}^G + F\left(x_{r2}^G - x_{r3}^G\right), \quad r_1 \neq r_2 \neq r_3 \neq i}$$

Equation A.13. Mutation operator for Differential Evolution (DE)

in which G is the generation, x_i^G is the target vector, v_i^{G+1} is the mutant vector, $r_1, r_2, r_3 \in \{1,2,\dots,NP\}$ are the randomly chosen indices. F is a real number to control the amplification of the difference vector $x_{r2}^G - x_{r3}^G$. If a component of a mutant vector violates the search space, then the value of this component is generated anew using Equation A.13. (Mohamed, 2015; Yi, 2016).

The binomial crossover operator (which is the most used) can be selected to generated the vector u_{ij}^{G+1}, between x_i^G and v_i^G which can be expressed by Equation A.14.

$$\boldsymbol{u_{ij}^{G+1} = \begin{cases} v_i^{G+1}, & rand(j) \leq CR \quad or \quad j = rand\ (i) \\ x_i^{G+1}, & rand(j) > CR \quad and \ \ j \neq rand(i) \end{cases}}$$

Equation A.14. Crossover operator (binomial) for Differential Evolution

where $j = 1,2,\dots,D, rand(j) \in [0,1]$ is the *j*th evaluation of a uniform random generator number. $CR \in [0,1]$ is the crossover rate, $rand(i) \in \{1,\ 2,\dots,D\}$ is the randomly chosen index which ensures that u_{ij}^{G+1} gets at least one element from v_i^{G+1}; on the other hand, no new parent vector would be produced and the population is not altered (Mohamed, 2015; Yi, 2015).

CHAPTER 4: PERFORMANCE MEASURES

This chapter describes the theoretical framework of the used methods to evaluate the prediction capacity of the explored deterioration models. Besides, these methods were the antecedent metrics of the *Knet* and *Kpipe* metrics also proposed in this work (see Part C).

4.1. COHEN'S KAPPA COEFFICIENT (K)

Cohen's kappa coefficient is an index that measures inter-rater reliability for qualitative terms. Cohen's Kappa measures the agreement between two rates which each classifies N items into mutually exclusive categories (Cerda & Villaroel, 2008; Shan & Wang, 2017). Equation A.15. defines the Cohen's kappa coefficient mathematically.

$$K = \frac{p_0 - p_e}{1 - p_e} = 1 - \frac{1 - p_o}{1 - p_e}$$

Equation A.15. Mathematical definition of Cohen's kappa coefficient (K)

In which p_0 is the proportion of rater pairs exhibiting agreement and p_e is the proportion expected to exhibit agreement by chance alone. Thus, the perfect agreement would indicate $K = 1$, and no agreement $K = 0$. For k categories, N observation to categorize and n_{ki} the number of times rater i predicted category k (Wang & Xia, 2019). Therefore, p_e is calculated following the Equation A.16.

$$p_e = \frac{1}{N^2} \sum_k n_{k1} n_{k2}$$

Equation A.16. Calculation of the proportion expected to exhibit agreement by chance alone (p_e)

4.2. ROC SPACE

It is the space in which draws the Receiver Operating Characteristic (ROC) curve. The ROC space is a two-dimensional space in which is defined by False Positive Rate (FPR) and True Positive Rate (TPR) as x and y axes, respectively. This space is a graphical representation of a confusion matrix that compares the predicted classes versus the observed ones from a binomial classification (positive and negative labels). According to a binomial classification, the confusion matrix contains four outcomes which analysis the correct classifications and miss-classifications: (i) True Positives (TP) refer to the instances classified correctly in the positive label; (ii) True Negatives (TN) represent the instances classified correctly in the negative label; (iii) False Positives (FP) refer to the instances wrongly classified in the positive label; and False Negatives (FN) represent the instances improperly classified in the negative label (Saito & Rehmsmeier, 2015). Dividing the TP over the total positive instances in the real classification obtains the TPR; and dividing the FP over the total negative

instances in the actual classification obtains the FPR (Fawcett, 2006). A ROC space depicts trade-offs between benefits (TPR) and costs (FPR). Therefore, if the TPR value (y-axis) is higher than the FPR value (x-axis) means that the model prediction is better than a random one; if the TPR and FPR values are the same means that the model prediction is equal that a random one; and if the TPR value (y-axes) is lower than FPR value (x-axis) means that the model prediction is worse than a random one.

The Positive Likelihood Ratio (PLR) is an index obtained dividing TPR over FPR, and it quantifies how likely it is to have a correct prediction than a wrongly one (Hernández et al., 2018).

4.3. PERFORMANCE CURVE

The performance curve is a technique based on Le Gat et al. (2008). The main goal is analysing if the probabilities of sewer assets predicted in most deteriorated conditions are really in these conditions. The procedure is sorting in decreasing order the probabilities of being in critical conditions of all the sewer assets. Then these assets are ranking in percentages: it means that the 1% represent the sewer assets with the highest probability of being in the cost deteriorated states. Suddenly, it compares the probability of being in critical conditions and the actual one (observed condition by CCTV): the probabilities of being in critical conditions are in the x-axes, while the percentage of the real condition is in y-axes, and from them is building the performance curve. Figure A3 shows an example of the performance curve.

The main idea of the performance curve is to visualize the performance prediction in estimating the most deteriorated assets to make decisions for rehabilitation plans. For example, coming back to Figure A.3., it is possible to visualize the proportion of the conditions of the 10% assets with the highest probability to be in critical conditions.

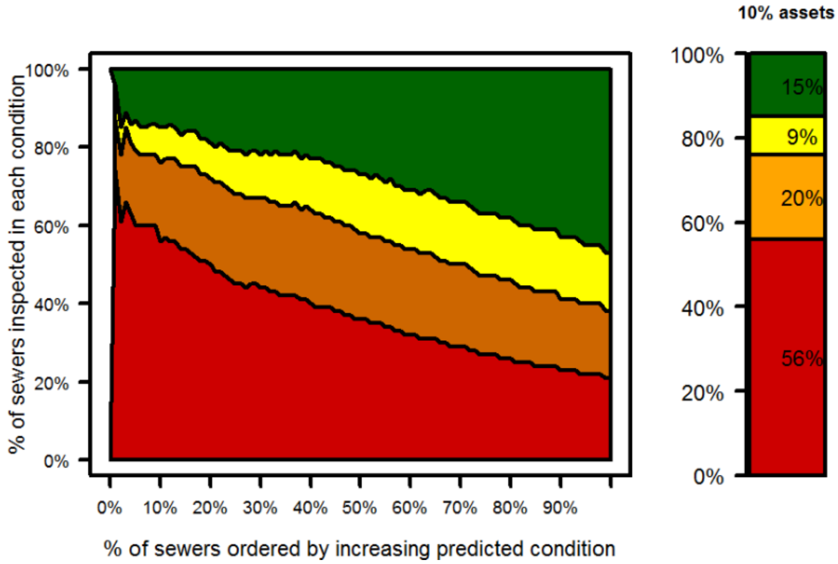

Figure A.3. Example Performance Curve

4.4. DEVIATION ANALYSIS

Deviation analysis is an analysis technique proposed by Caradot et al. (2015). It measures the deviation between the proportion of observed and predicted assets on each condition and by each age period. It means that this technique only analyses the difference in the number of assets predicted on each condition by each age period.

Figure A.4. depicts three graphics: (i) the top plot shows the conditions' distributions of the sewer assets, by each age period, found by CCTV inspections; (ii) the centre plot shows the conditions' distribution of the sewer assets, by each age period, obtained by a deterioration model's predictions; and (iii) the below plot shows boxplots that summarized the deviations of the four conditions and a red circle that depicts the deviation of the critical conditions by each age period. Hence, according to the Figure A.4., when the deviation is negative, it means that the prediction overestimated the structural condition (the model predicted in better conditions than are the sewer assets); and when the deviation is positive, it means that the prediction underestimated the structural condition (the model predicted in worse conditions than are the sewer assets).

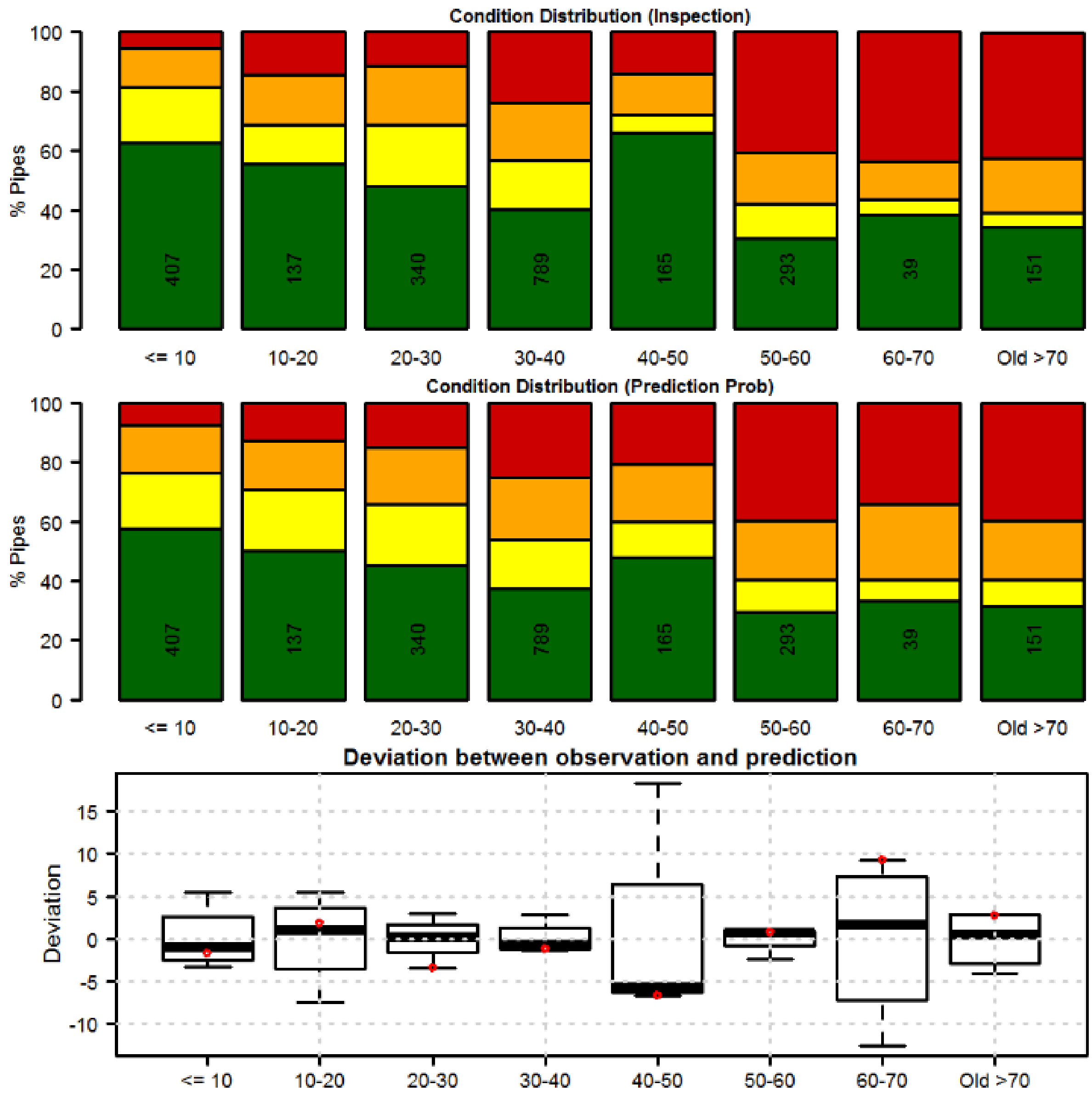

Figure A.4. Deviation analysis plot example

CONCLUSIONS PART A

The importance of the theoretical framework in this doctoral manuscript consists of giving a conceptual background about the used concepts, mathematical and statistical definitions for developing the proposed methodology. According to Part A, a wide range of notions, mathematical, statistical, and machine learning methods have supported the construction of sewer asset management. The concept of Sewer Asset Management (SAM) is based on the generalist concept of the Infrastructure Asset Management (IAM), and from, the stages to reach an effective IAM, the research topics in SAM born. Even though the general introduction has a brief state-of-the-art to justify the objective of this doctoral thesis, Chapter 1 shows more detailed information about the contributions of the worldwide authors for each SAM research topics.

Interestingly, the developed tools are based on methods of different natures (mathematical, statistical, and machine learning) which during the doctoral manuscript are going to be integrated and modified to develop feature selection and predictive tools support strategies at the sewer asset management. Understanding the theoretical background of the methods, the author could identify the advantages and disadvantages of the explored methods, tests, or techniques.

As well, it identified the properties of some methods to develop optimisation tools to complement those methods used for building feature selection and predictive tools, making more robust, precise, and reliable the proposed methodology.

Besides, Part A presents four performance measures to evaluate the predictions of the developed deterioration models based on different focusses. Deviation analysis and ROC space are focused on the prediction of sewer asset at the network level, while Cohen's Kappa coefficient and Performance curve evaluate the prediction of each sewer element. Thanks to the above, the assessment of the deterioration models should focus on two aims, and in turn, these support the management objectives on sewer asset management. Therefore, the author developed two metrics based on these four performance measures to achieve two management objectives. In Part C of this manuscript, the author depicts the two developed performance metrics that link with two management objectives (objectives related to the sewer network and single sewer asset) in detail.

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PART B MATERIALS AND METHODS

Part B of this manuscript consists of the description of the materials and methods to develop the proposed methodology for this doctoral thesis. The depiction of the case studies, computational tools, and the reasons for the chosen methods to build the present doctoral thesis is the objective of this part.

The selected case studies for the development of the present doctoral thesis need to fulfil with the following criteria: (i) large percentage of sanitation coverage on the city; (ii) to have georeferenced information about each asset that belongs to the sewer network; (iii) to have an assessment protocol to classify the structural and operational state of the sewer assets on grades from visual inspections; and (iv) to have information about a non-depreciable quantity of inspected and assessed sewer assets.

The author considered two case studies randomly to apply the proposed tools of this doctoral thesis to identify the influential factors on the structural conditions of both sewer systems. The main idea is to apply the methodology proposed in this doctoral thesis to identify if really the influential variables over the structural conditions vary according to the own characteristics of the cities (first research question). According to the closeness and availability, the chosen case studies were Bogota and Medellin: the two most populated and important Colombian cities. Colombia is one of the Latin-American countries with the highest coverage in water supply and sewerage after Chile and Mexico (IDB, 2019): around 90% of sanitation coverage in urban areas, 70% in rural areas, and 88% of sewerage coverage in the national territory (IDB, 2019; DNP & MAVDT, 2018). Currently, Bogotá and Medellín are the Colombian cities that have their assessment protocols to qualify the structural and operational conditions of the sewer assets from CCTV inspections.

According to the above, chapter 5 consists of the description of Bogota's and Medellin's case, subchapter 5.1., and 5.2. respectively. Each subchapter consists of two items: (i) information about the sewer system; and (ii) collected of surrounding variables to the sewer assets (operational, environmental, and urban characteristics of the city), a brief description of the assessment protocol and description of the CCTV inspected data.

The collection of the information depends on (i) the variables found as influential in the deterioration of the structural conditions of the sewer assets in other case studies; (ii) their availability; and (iii) the variables that have been not studied yet as possible influential variables over the structural conditions in sewer assets. The sewer systems, as any underground infrastructure, represent radiography of the city's conditions, thus the sewer systems cannot be considered as a single infrastructure, but part of a complex system called the city.

Hence, it seems crucial to evaluate the influence of other infrastructures, as well as environmental, urban, and operational conditions over the structural and operational conditions of the sewer assets. The focus of this thesis is the structural conditions of sewer assets because of the severity of their consequences. Physical sewer characteristics (diameter, length, slope, material, and depth in which is located the sewer asset), the age, type of effluent that transport the sewer assets, surrounding characteristics(trees presence, road traffic, soil type, bedding type, and geographical locations, and districts), and social features (installation period, land uses) are some of the variables which have been selected as influential over the structural conditions of sewer assets in other experiences (Ariaratman et al., 2001; Baik et al., 2006; Younis & Knight, 2010; Tscheikner-Gratl et al., 2014; López-Kleine et al., 2016; Torres-Caijao et al., 2017; Hernández et al., 2018b; Hernández et al., 2019a; Hernández et al., 2019b). Moreover, the seismicity, social classes, information quality, geology, water level depth, precipitation levels, basins, and flood risk, also were considered because these variables are part of the environment dynamism in which are immersed the sewer assets. Also, it contemplates the seismicity and geology because of the displacements and breakage in the sewer assets after telluric movements. Besides, water level depth, precipitation levels, the closeness with the basins, and flood risk are variables that could increase the flow's capacity of the sewer assets and/or generate pressure to the assets 'structure, making breakage and collapse in the sewer system. Information about social classes and information quality could complement the information about urban dynamism and the operational behaviour of the utilities.

Finally, chapter 6 depicts the literature review and pertinence of the selected methods and techniques to develop the tools proposed in this doctoral thesis (subchapter 6.1.) and a brief description of the used computational tools (subchapter 6.2). Subchapter 6.1. justifies the selection of the used methods from literature reviews and results of their exploration by the author during her doctoral studies, and subchapter 6.2. shows a description of the used software, main libraries and functions to apply the mentioned methods in subchapter 6.1.

Thanks to the explorations written in subchapter 6.1., the following publications and participations in conferences were carried out: (i) participation with an oral presentation at LESAM conference 2017 entitled "*Support tools to predict the critical structural condition of uninspected sewer pipes in Bogota DC*" (Hernández et al., 2017a); (ii) participation with two oral presentations at ICUD 2017 entitled "*Support Vector Machines used for the prediction of the structural conditions of pipes in Bogota's sewer system*" (Hernández et al., 2017b) and "*Support tools to predict the critical structural condition of uninspected pipes for case studies of Germany and Colombia*" (Hernández et al., 2017c); (iii) publication on the Water Practice and Technology Journal under the title "Support tools to predict the critical structural condition of uninspected pipes for case studies of Germany and Colombia" (Hernández et al., 2018a); (iv) submission on the *Ingeniería y Universidad* Journal in March 2019 under the title "*Support Vector Machines used for the prediction of the structural conditions of pipes in Bogota's sewer system*" (Hernández et al., 2019a); (v) submission on the Journal of Modelling in Management in October 2019 under the title "*Is it possible developing reliable prediction models considering only the pipe's age for decision-making in sewer asset management?*" (Hernández et al., 2019b) in which compared the prediction performance considering only the age and considering the age together with other sewer characteristics as input variables in the deterioration for two Colombian case studies; and (vi) the selection of the most pertinent models to predict the structural condition of uninspected sewer assets for the case studies considered in the present thesis (Part D). A summary of these results is shown in Part D of this manuscript.

CHAPTER 5: CASE STUDIES

Bogota and Medellin are the case studies considered in this doctoral thesis, due to are the main Colombian cities that contain most of 90% of installed sewer assets in Colombia. This chapter consists of two subchapters related to Bogota's and Medellin's case studies.

Each subchapter contains two items about the description of sewer systems and the description of the collected surrounding and CCTV inspection information. The second item describes the collected information about environmental, urban and operational characteristics, a summary of their assessment standards of the sewer assets conditions, and a description of the data collected by CCTV inspections.

5.1. BOGOTA'S CASE STUDY

Subchapter 5.1 contains two items: (i) a description of the Bogota's sewer systems and the basic characteristics of installed sewer assets; (ii) description of the collected information about the surrounding information of Bogota's city, a summary of the local sewer assessment standard used in Bogota to classify the structural condition of sewer assets and a description of the collected CCTV sewer inspections. For more information about Bogota's case, please see appendix-Part B.1.

5.1.1. DESCRIPTION OF THE BOGOTA'S SEWERAGE

Bogota's sewer system has three main drainage basins that drain sanitary and rainwater, from the east to the west, through separate and combined sewer systems (EAAB, 2006). In the central and southeast zones of Bogota, the combined sewer system is working, and then it connects with the sanitary system to the rest of the zones of the city (EAAB, 2006). The Bogota's residual water treatment plant (*PTAR Salitre*) locates at the west of the city close to the Bogota's river. This plant cleans most of the residual water of the city and then it discharges over Bogota's river. Likewise, each system is divided into main and local assets. The main assets correspond to the interceptor assets in which all local assets converge. Figure B.1. shows the sanitary and stormwater systems in Bogota.

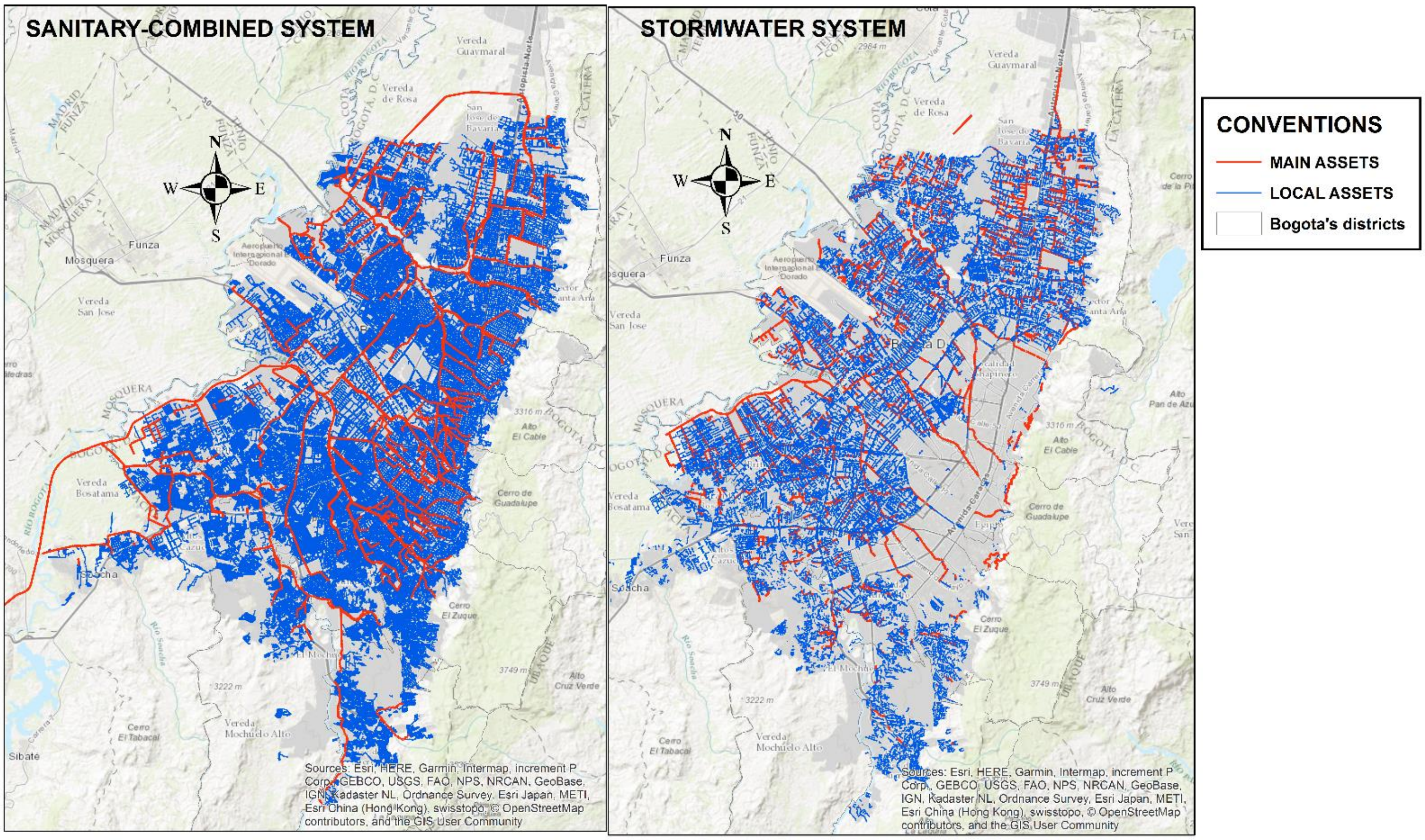

Figure B.1. Bogota's sewer systems. Map on the left shows sanitary and combined sewer systems and on the right stormwater system. The main assets are in red colour and local assets in blue colour. Source: Author

In summary, the sanitary system contains 146763 installed assets (6615.3 km) between main (500.5 km) and local (6115.3 km) networks, and the stormwater system includes 71278 installed assets (3001 km) between main (536.1 km) and local (2464.9 km) networks. In total, Bogota contains 10479.9 km of the installed sewer assets (DNP & Superservicios, 2018) that represents around 98.5% of sewerage coverage in the city.

Table B.1. shows a summary of the basic characteristics contained in the database of the Bogota's sewer system. According to this database, the variables contained were: (i) type of effluent, (ii) shape; (iii) material; (iv) type of the element according to its functionality, (v) diameter (in meters), (vi) length (in meters) of the sewer assets, (vii) installation periods when were installed, (viii) depths (in meters) where is located (average between sewer level upstream and downstream), and (ix) slope (in m/m) of the sewer assets. Besides, some factors of the variables were grouped because the amount was minimum compared to other factors. The numerical variables were categorized to visualize their proportion on the sewer system.

Table B.1. Description of the basic characteristics contained in the Bogota's sewer systems database

Variables	Factors	Proportion	Variables	Factors	Proportion
Type of effluent	Combined	20.3%	Length (m)	< 25	30.0%
	Sanitary	**46.3%**		**25 - 50**	**34.7%**
	Stormwater	33.4%		50 - 75	21.2%
Shape	**Circular**	**98.6%**		75 - 100	10.2%
	Other shapes	1.4%		> 100	3.9%
Material	Clay	25.7%	Installation Period (years)	< 1930	5.9%
	Concrete	**58.2%**		1930 - 1960	13.1%
	Masonry	2.9%		**1960 - 1980**	**26.8%**
	PVC	8.6%		1980 - 2000	15.8%
	Other materials	4.6%		> 2000	38.3%
Element type	**Collector**	**93.9%**	Depth (m)	< 1	5.8%
	Interceptor	4.7%		**1 - 2**	**48.3%**
	Other Elements	1.4%		2 - 3	28.9%
Network type	Main	7.0%		3 - 4	9.4%
	Local	93.0%		4 - 5	2.9%
Diameter (m)	< 0.2	34.9%		> 5	3.9%
	0.2 - 0.45	**41.6%**	Slope (m/m)	< 0.34	26.0%
	0.45 - 0.6	9.4%		**0.34 - 0.8**	**26.6%**
	0.6 - 0.75	3.3%		0.8 - 4.8	24.4%
	0.75 - 0.9	3.7%		4.8 - 11.5	10.4%
	> 0.9	7.1%		> 11.5	12.6%

Source: Author

According to Table B.1., most of the sewer assets are pipes (circular areas – 99%) in concrete and clay materials (84%), with diameters lower than 0.45m (75% approximately). Furthermore, the most important installation period of the sewer assets was after 1955 when the company of water and sewerage *("Empresa de Acueducto y Alcantarillado de Bogotá – EAAB")* was established as a public company (Jiménez & Gomez, 2003). Currently, EAAB had been the private-public company responsible for the water supply and sewerage service for Bogota's city.

EAAB provided the information shown in Table B.1. concerning the installed sewer assets. However, this database has inaccuracies in the proportioned information because there is no information about some replacement assets, the new characteristics and the replacement dates.

5.1.2. COLLECTED INFORMATION OF BOGOTA'S CITY.

This subchapter contains three items. The first one describes the collected information about environmental, urban and operational characteristics of Bogota gathered from different public institutions. The second item depicts the Bogota's assessment standard that the utility uses for qualifying the operational and structural conditions of CCTV inspected sewer assets. And the last item shows a description of the CCTV inspection information carried out between 2007 and 2017.

5.1.2.1. Surrounding characteristics of Bogota's city

Databases of different public institutions, reports and other sources were collected to capture the characteristics of the city. The collected variables were: (i) database of geotechnical zoning in 2010, provided by Bogotá's institution for risk management and climate change (*Institución distrital de gestion de riesgo y cambio climático - IDIGER*), which describes the soil conditions and geomorphology; (ii) database of intrusion trees in Bogotá for the year 2017 provided by Bogota's Botanical Garden (*"Jardín Botánico de Bogotá - JBB"*); (iii) land use database of the year 2016; (iv) databases of social classes classified by zonal planning units (*Unidades de Planeamiento Zonal - UPZ*) ; (v) road database that contains information about road classification according to the type of traffic and its material surface for year 2016; (vi) database of the 20 districts of Bogotá in the year 2017 collected by Bogota's integrated infrastructure of spatial data (*"Infraestructura integrada de datos especiales para el distrito capital - IDECA"*); (vii) database of Bogota's urbanization growth from 1923 to 2013, collected by Gorani (2017); (viii) database of precipitation levels collected by Institute of hydrology, meteorology and environmental studies (*Instituto de hidrología, meteorología y estudios ambientales - IDEAM*); and (ix) database of operational zone, data quality and operational status of the sewer assets collected from EAAB. Table B.2. shows a summary of the collected information.

The information shown in Table B.2. was cleaned-up and pre-processed to feed the database. The information about urban growth areas was used to correct the installation year of some sewer assets with doubtful years of installation. The calculus about trees root length was carried out theoretically by the influence area of growth radios of the trees' roots (Torres-Caijao et al., 2017): 1.3 times of equatorial diameter (tree's crown diameter). The social classes and land uses are discriminated by ZPU -Zonal planning unit (*UPZ - Unidad de planeamiento zonal*). The social levels in Colombia vary from 1 to 6 category, being 6th category the highest social class in which lives people with the most top economic resources, and first the lowest social level in which lives people with the most inferior financial resources (SDP & UNAL, 2009). Further, the land uses are categorized according to the most predominant economic activity as shown in Table B.2., such as (i) Commercial, which means business areas; (ii) Developing, indicates an integrated urban development of projects that combines residential, public and business areas; (iii) Institutional, areas with hospitals, schools, and parks that give a service to the community; (iv) Government it is the land use that refers to the public and historic buildings; (v) Industrial, areas with manufacturing companies; and (vi) three types of residential lands (SDP, 2017; Preciado-Beltran, 2010). The three types of residential lands refer to: the first one, residential areas with infrastructure deficits (social classes 1 and 2); the second, domestic areas of middle social classes with land-use changes; and third, domestic areas of middle and high social levels with properly infrastructure's conditions (SDP, 2017; SDP, 2011).

Table B.2. Description of collected information from Bogota's city

Source	Type of variables	Variables	Description
Bogotá's institution for risk management and climate change (*IDIGER*)	Environmental	Geotechnical zone	Eight geotechnical zones: Alluvial, Foothill, Lacustrine, Landfill, Plain, Riverbed, Hillside deposit, Mountains
		Soil Type	Seven soil types: clay, Foothill, Landfill, Residual soil, wetlands rivers, rocks and sand
		Geology period	Cretaceous, Paleogene, and Quaternary
		Water level depth (m)	0 - 13.78
		Seismic shear wave speed(m/s)	1.3 - 3.5
		Seismic Acceleration (gravity field intensity - g) (Return period of 475 years)	0 - 0.26
Bogota's Botanical Garden (*JBB*)	Environmental	Type of Intrusive trees	Acacia, Cherry Tree, Chicali, Eucaliptus, Pine, Rubber, Willow, and others
		Root trees length (m)	0.78 - 15.54
Bogotá's integrated infrastructure of spatial data (*IDECA*)	Urban	District	19 Urban districts: *Antonio Nariño, Barrios Unidos, Bosa, Ciudad Bolivar, Candelaria, Chapinero, Engativa, Fontibon, Kennedy, Martires, Puente Aranda, Rafael Uribe, SanCristobal, Santafe, Suba, Teusaquillo, Tunjuelito, Usaquén, Usme*
		Land use	Commercial, Developing, Institutional, Government, Industrial, Residential (1,2 and 3)
		Social classes	Classes 1 and 2; Classes from 3 to 6; and Multiple
		Surface material	Unpaved, concrete pavement, asphalt pavement, green, and others
		Road type	Primary, Intermediate, Local, and Supplementary
Gorani (2017)	Urban	Urban Growth periods	Developed urban areas to 1923, 1938, 1958, 1976, 1985, and 2013 year.
Institute of hydrology, meteorology and environmental studies (*IDEAM*)	Environmental	Levels of precipitation of 6hr and return period of 10 years (mm) (Information until 2014)	0.14 - 61.48

Bogota's Water and Sewerage Company (*EAB*)	Operational	Operational zone	Five operational zones which are grouped according to districts: Zone 1 - *Suba* and *Usaquén* districts; Zone 2 - *Engativá, Chapinero, Teusaquillo* and *Barrios Unidos* districts; Zone 3 - *Santafé, San Cristóbal, Tunjuelito, Fontibón, Antonio Nariño, Puente Aranda, Rafael Uribe Uribe, Mártires, Antonio Nariño* and *La Candelaria* districts*;* Zone 4 - *San Cristóbal, Usme, Tunjuelito, Kennedy, Puente Aranda, Rafael Uribe Uribe* and *Ciudad Bolívar* districts; Zone 5: *Kennedy* and *Bosa* districts
		Data quality	Information collected from maps, unvalidated, validated and unknown
		Operational status	Out of service and on service
		Latitude coordinate	North, mid-north, mid-south, and south
		Longitude coordinate	East, mid-east, mid-west and west

Source: Author

Other variables included by the author was the geographical coordinates of the sewer systems (latitude and longitude). The calculus of these variables lies in the average of longitude and latitude coordinates of the location upstream and downstream of sewer assets. Finally, they were categorized into four factors, as shown in Table B.2.

Furthermore, the variables related to the seismicity correspond to the seismic answer of the soils considering the reported earthquakes until 2010 with a return period of 475 years. The seismic variables (acceleration and wave speed) are the ones used for Seism-resistant Construction Regulations for Colombia NSR-10 (MAVDT, 2010). IDIGER and Garzón-Casares (2011) provided the above information.

5.1.2.2. Local assessment standard

Bogota's water and sewerage company has its sewer assessment standard (NS-058 – "Technical Aspects for Inspection of Sewer Networks and Structures") since 2001, updated three times (EAAB, 2001). The standard regulates the circuit-camera television technology's (CCTV) inspection guidelines in which classifies the found defects in operational and structural defects. At the same time, each category is ranked in the defect's types. According to the defect's type, the severity and the defect's location, the standard gives a score from 0 to 165 points for structural defects and from 0 to 10 for operational defects (See Tables 1 and 2 of the appendix - Part B.1.1.).

Once the scores are given to each defect found in the sewer asset, the standard provides a categorization of the structural and operational conditions for each sewer asset. Both structural and operational states rank into five grades. However, the ranking differs from its calculation: the calculus of the structural grade focus on the sum of the scores of all structural defects found in the sewer asset and then categorized (See Table 3 of the appendix – Part

B.1); while the calculus of the operational grade lies on the quotient between the sum of the scores of all operational defects found in the sewer asset and the sewer asset' length, then this rate is categorized (See Table 4 of the appendix -Part B.1). In both rankings, grade 1 represents excellent structural or operational conditions of the sewer assets while grade 5 means critical structural or operational conditions of the sewer assets. For more details about the diagnosis of each grade and suggested recommendation by NS-058, please see Tables 3 and 4 of the appendix – Part B.1.2.

5.1.2.3. CCTV Inspected data

EAAB provided the records of CCTV inspections and CCTV inspection reports of Bogota's sewer assets carrying out from 2007 to 2017. The CCTV inspection database contains information about the ID of the sewer assets, the physical characteristics of the inspected sewer assets, inspection date, surface material over the sewer asset's location, and its structural and operational conditions (in grades). The author assessed part of CCTV inspection data provided during 2017 and 2017 following the NS-058 standard by the visualized failures of the inspection reports. A data clean-up of the CCTV inspection data was carried out, removing wrong information about incoherent values of slopes, diameters, lengths, dates of inspection (before 2007), and depths. After CCTV inspection data clean-up, 8349 consistent inspections (representing 430 km) were linked to 7968 sewer assets (around 3% of the total sewer system). Figure B.2. shows the inspected sewer assets and the whole Bogota's sewer system.

According to the inspected sewer assets, it was found that 45.8% are in excellent structural conditions (grade 1), 14.9% are in good structural conditions (grade 2), 4.7% in moderate structural conditions (grade 3), 13.5% in poor structural conditions (grade 4), and 21.1% in critical conditions (grade 5). Besides, 93% in excellent operational conditions (grade 1), 5.5% in good operational conditions (grade 2), 1.3% in moderate operational conditions (grade 3), 0.16% in poor operational conditions (grade 4) and 0.1% in critical operational conditions (grade 5).

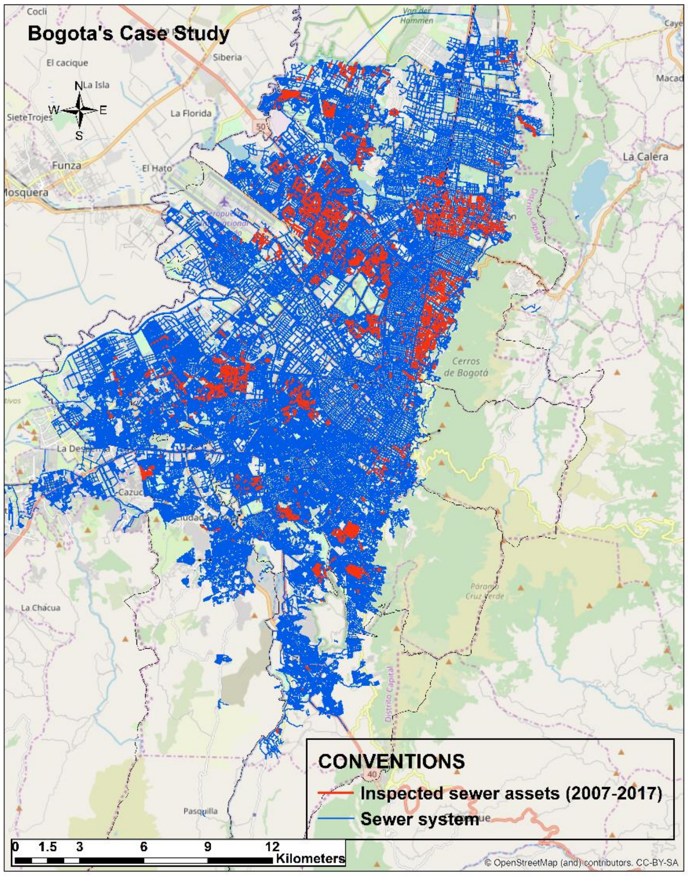

Figure B.2. Bogota's inspected sewer assets between 2007 and 2017. Whole sewer systems in blue lines and inspected sewer assets in red lines. Source: Author

A big database was built by merging the Bogota's sewer systems information (subchapter 5.1.1) and the collected information of Bogota's city (subchapter 5.1.2) related to surrounding characteristics of Bogota's city and CCTV inspection reports. Figures from 1 to 4 of the appendix – Part B.1.2. show bar plot analysis that depict the distribution of the structural condition regarding the collected variables to observe an apparent relationship between the deterioration of the structural condition of sewer assets and the collected data.

From the above bar plot analysis, it is possible to observe that the deterioration of structural condition does not show an apparent relationship with inspection year periods, land uses, road types, operating status, trees' types, quality data, precipitation levels, social classes, geology, and element types. Table B.3. a summary of the variables presenting an apparent relationship with the deterioration of the structural condition of the sewer assets.

Table B.3. Summary of variables that apparently show a relationship with the deterioration of the structural condition of sewer assets according to the bar plots shown in Figures from 1 to 4 of the appendix – Part B.1.2.

Variables	**Relations with the deterioration of the structural condition**
Installation periods	Older installation period, higher percentage of deteriorated sewer assets
Age periods	Older sewers' age period, higher percentage of deteriorated sewer assets
Diameter	Smaller sewer assets, higher percentage of deteriorated sewer assets
Material	Higher percentage of deteriorated sewer assets in clay and PVC sewers
Type of effluent	Higher percentage of deteriorated sewer assets in sanitary and combined sewers
Length	Longer sewer assets, higher percentage of deteriorated sewer assets
Slope	Higher slopes of sewer assets, higher percentage of deteriorated sewer assets
Depth	Shallow sewer assets, higher percentage of deteriorated sewer assets
Districts	Older districts (*Santafe, Chapinero, San Cristobal,* and *Rafael Uribe Uribe*), higher percentage of deteriorated sewer assets. (*Teusaquillo* and *Tunjuelito* districts were not considered as relevant information because of the lower information of inspected sewer assets in these districts)
Network type	Main sewer assets are in better structural conditions than local sewer assets
Surface material	Sewer assets located behind pavement area show a higher percentage of deteriorated sewer assets.
Operating zones	2, 3 and 4 zones are the zones were more population density of Bogota's city and these zones were the ones with the highest percentage of deteriorated sewer assets
Operational condition	Higher operational grade (lower hydraulic operation condition), higher structural deterioration on sewer assets (inspected sewer assets do not show 4 or 5 operational conditions grades)
Water level depth	Deeper water levels, higher structural deterioration sewer assets
Trees roots' length	From 1 m of roots' length, higher structural deterioration of sewer assets
Seismic acceleration	Over 0.16 g shows higher structural deterioration on sewer assets
Seismic shear wave speed	Higher structural deterioration lower 1.7 m/s and higher 2.7 m/s
Longitude coordinate	Higher structural deterioration at the east zone
Latitude coordinate	Higher structural deterioration on the south and mid-north zones of the city
Geotechnical Zones	Higher structural deterioration in Foothill and mountains zones

Source: Author

According to Table B.3., the physical characteristics of the sewer assets show apparently relationship with the deterioration of structural condition as reported in other studies (Ariaratnam et al. 2001; Baik et al., 2006; Tscheikner-Gratl et al., 2014). The apparent relationship of the deterioration of the structural conditions of the sewer assets with latitude and longitude coordinates, geotechnical zones, type of effluent, water level depths and districts show that the geographical localisation of the sewer assets influent over the deterioration of the structural conditions of the sewer assets: sewer assets close to the mountains (east zone of the city) show higher deterioration. However, it is essential to clarify that Bogota’s city has grown from the east to the north, west and south of the city, it means that the oldest sewer assets are located on the east of the city. This fact is confirmed analysing the relationship with the age and installation year periods variables: older sewer assets show higher deterioration on the structural condition of the sewer assets. In other studies of different case studies, the age has a strong influence over the structural condition, because of the lifetime of the sewer assets (Davis et al., 2001a; Baik et al., 2006; Le Gat, 2008; Ana et al., 2009; Rokstad & Ugarelli, 2015; El-Housni et al., 2017; Caradot et al., 2018).

Environmental variables such as roots trees length also show apparently influence over the structural condition of sewer assets which supports the findings of Torres-Caijao et al., (2017) in which more giant trees (longer roots lengths) cause more damage in sewer assets than small trees (shorter roots lengths). As well, the surface material over the sewer assets shows that pavement areas influence over the deterioration of the sewer assets, which means that the road infrastructure could be the cause of the deterioration of the sewer assets.

Seismic shear wave speed and acceleration also show an apparent relationship with the deterioration of the structural condition of sewer assets; however, it is not possible to assure this relationship because could depend on the location of the sewer assets. The relationship between the structural condition of the sewer assets and the seismic variables has not been studied deeply.

Besides, operational conditions of sewer assets also show an apparent influence over the structural conditions of the sewer assets: higher operational conditions, higher deterioration. This result could be explained, because of the reduction of the hydraulic capacity of the sewer assets and in the events of water flow's peaks could generate pressure on the sewer asset causing breakage on the structure.

5.2. MEDELLIN'S CASE STUDY

Subchapter 5.2 consists on the description of three subchapters related to this thesis: (i) a description of the Medellin's sewer system and the basic characteristics of installed sewer assets; (ii) description of the collected CCTV sewer inspections and the collected information about the surrounding information of metropolitan Medellin city; and (iii) a summary of the local sewer assessment standard used the Metropolitan city of Medellin to classify the structural condition of sewer assets. For more information about Medellin, please see appendix-Part B.2.

5.2.1. DESCRIPTION OF THE MEDELLIN'S SEWERAGE

The city extends along of the natural axis of Medellin river in which converge 25 gorges: *Doña María, La Jabalcona, La Guayabala, Altavista, La Picacha, Ana Diaz, La Hueso, La Iguana, Malpaso, La Quintana, La Cantera, Minitas, La Zuñiga, La Aguacatala, La Volcana, La Sucia, La Presidenta, La Poblada, La Asomadera, El Indio, Santa Helena, El Ahorcado, El Molino, La Bermejala, La Rosa* and *La Seca*. EPM (Medellin public companies - *Empresas Públicas de Medellín*) is the company that provides water supply, sewerage, energy and natural gas to metropolitan Medellin city (*Bello, Envigado, Itagüi, La Estrella, Medellín, Sabaneta, Copacabana, Girardota, Caldas* and *Barbosa)* (Alcaldía de Medellín, 2017). The Medellin's sewer system contains 151063 sewer assets (corresponding to 4367 km). Medellin's sewer system contains three types of sewers: combined, sanitary and stormwater. The combined system, which was the first system constructed in Medellin, consists of secondary collector assets that transport water to the collector sewers. These collectors are located parallelly to the gorges to collect the discharge and transport the sanitary and stormwater (combined sewer system) to the interceptor assets. The interceptor is located parallelly to Medellin's river to transport the residual water to the "San Fernando" wastewater treatment plant - WWTP (Superservicios, 2014). The separate sewer system was constructed around the 1950s' decade in the new neighbourhoods without sewer service. As Bogota's case study, the sanitary system is connected to the combined system which discharge to the WWTP and stormwater system is discharged in the gorges and Medellin's river (Superservicios, 2014; Arboleda & Bayona, 2015). Figure B.3. shows the sanitary and stormwater systems in Medellin.

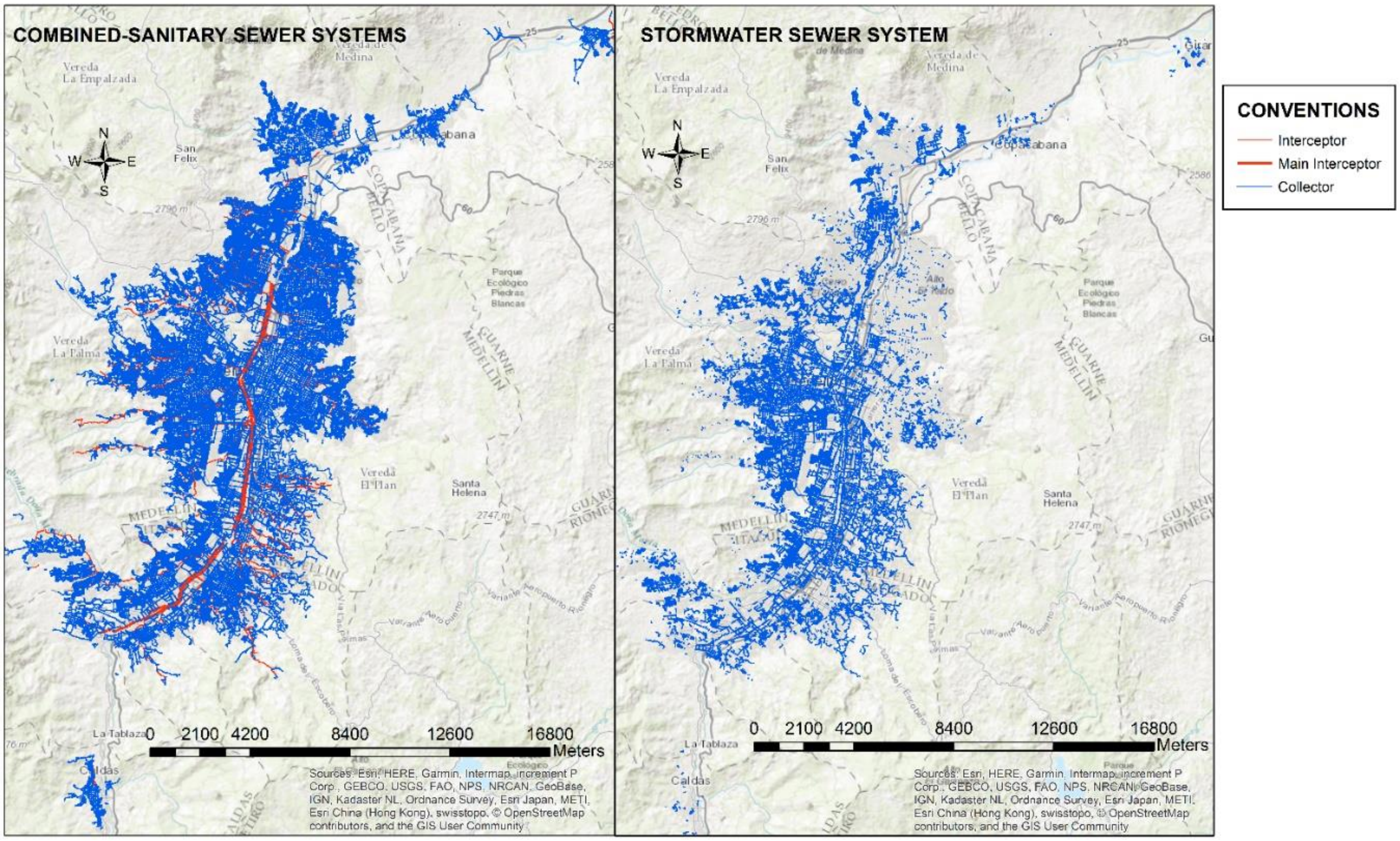

Figure B.3. Medellin's sewer system. Map on the left shows sanitary and combined sewer systems and on the right side shows the stormwater system. In red colour are the main assets (or interceptor sewers) and in blue colour the collector sewers. Source: Author

In summary, the combined and sanitary systems contain 134000 installed assets (3887.2 km), and the stormwater system includes 44876 installed assets (1434.5 km) which represent around 89% of sewerage coverage of Medellin's city (Alcaldía de Medellin, 2016). Table B.4. shows a summary of basic characteristics contained in the Medellin's sewer system database and their proportion. According to this database, the provided variables are (i) Type of effluent that transport the sewer assets; (ii) Material of the sewer assets; (iii) Element type of the sewer assets; (iv) Diameter (in meters) of the sewer assets (sewer assets are pipes); (v) Length (in meters) of the sewer assets; (vi) Installation periods; (vii) Depth (in meters) in which located the sewer assets (mean depth between sewer level upstream and downstream); and (viii) Type of foundation implemented in the sewer assets. As well as Bogota's case, the numerical variables were categorized to visualize their proportion on the sewer systems, and some factors were grouped because their portion was smaller in comparison with other factors.

Table B.4. Description of the basic characteristics of the Medellin's sewer systems database

Variables	Factors	Proportion
Type of Effluent	Combined	42%
	Sanitary	**32.70%**
	Stormwater	25.30%
Material	Concrete	88.40%
	Other materials	11.60%
Element type	Interceptor	0.30%
	Collector	8.60%
	Secondary collector	**91.10%**
Diameter (m)	< 0.15	0.6%
	0.15 - 0.2	**40.40%**
	0.2 - 0.3	26.10%
	0.3 - 0.45	15.90%
	0.45 -0.6	9.40%
	> 0.6	7.60%
Length (m)	< 10	19.70%
	25-Oct	30.50%
	25 - 50	29.50%
	50 -75	13.70%
	> 75	6.60%
Foundation Type	A	2.20%
	B	7.90%
	C	6.60%
	E	13.40%
	P	0.30%
	T	1.90%
	Unknown	**67.70%**

Variables	Factors	Proportion
Installation period (years)	< 1960	7.80%
	1960 - 1970	10.50%
	1970 - 1980	12.60%
	1980 - 1990	14.50%
	1990 - 2000	**24.30%**
	> 2010	4.60%
Depth (m)	< 1m	7.10%
	1m - 1.5m	15.40%
	1.5m - 2m	**29.10%**
	2m - 2.5m	**24.20%**
	2.5m - 3m	12.50%
	3m -3.5m	5.90%
	> 3.5m	5.80%
Slope (m/m)	**< 1**	**63.50%**
	1 - 2%	4.60%
	2 - 4%	5.60%
	4 - 8%	7.20%
	8% - 12%	4.90%
	> 12%	11.50%

Source: Author

According to Table B.4., most of the sewer assets are pipes in concrete (88.4%) with diameters lower than 0.3 m. Besides, the most important installation period of the sewer assets was after 1960 and almost 70% of sewer assets do not report the installed foundation type. The information presented in Table B.4. was provided by EPM. Likewise, as EAAB (Bogota's case), EPM does not report the assets' replacement, the new characteristics, and the replacement dates.

5.2.2. COLLECTED INFORMATION OF METROPOLITAN CITY OF MEDELLIN.

The item 5.2.2. refers to the additionally collected information of the Metropolitan city of Medellin that was useful to develop the present document. It contains the following items: (i) a description of the collected information about environmental, urban and operational characteristics of metropolitan Medellin city which provided by different public institutions; (ii) a description of the Medellin's assessment standard that the utility uses for qualifying the operational and structural condition of CCTV inspected sewer assets; (iii) a description of the CCTV inspection information carried out between 2010 and 2017.

Databases of two different public institutions were collected to gather environmental, urban and operational characteristics of the metropolitan city. EPM gives additional information about trees presence close to the sewer assets, the operational status of sewer assets and hydrographic basins. On the other hand, the municipality of Medellin gives information about the soil type of Aburra's valley, districts (which are the 16 districts of Medellín and the towns that belong to metropolitan Medellin's city), and the closest cities of Aburra's valley; land uses of urban areas (which are categorized in high, medium, low land mixtures and public space), the risk for by movements of mass for Aburra's valley (which refers to the seismic zoning), road database that contains information about road classification according to the type of traffic; the probability of flood risk in Aburra's valley (which is already categorized in high, medium, low and very low flood risk); and finally geographic location (latitude and longitude coordinates). Table B.5. shows a summary of the above variables.

The information about land uses of Medellin's case is categorized in a different way than Bogota's case. According to the territorial ordinance plan for metropolitan Medellin's city (Alcaldía de Medellín, 2014), the land uses classifies in low, medium and high mixture land areas and public space. Along with land mixtures areas in the following is the meaning of each land mixture area: (i) low land mixture area means that predominates residential uses; (ii) medium land mixture areas refer to transition zones, institutional uses (schools, hospitals, and others), a higher percentage of population density and neighbourhood services; (iii) high land mixture areas denote areas of economic activity in transformation and economic and industrial areas. Besides, the information of risk for movements of mass means descending movements, at different speeds, of a volume of soil and/or rock on one or several rupture surfaces, under the action of gravity that can be activated by water, earthquakes and anthropic actions (UNAL, 2009). The categorization of the risk for movements of mass is ranked from the values of maximum ground acceleration (MGA) at rock level, which corresponds to a return period of 475 years according to the results of INGEOMINAS & UNAL (2010) and Salgado et al., (2010). Therefore, the risk of movements of mass was categorized as the following: (i) very low risk corresponds to a MGA from 0 to 100 cm/s2; (ii) low risk, from 100 to 150 cm/s2; (iii) medium risk, from 150 to 200 cm/s2; (iv) high risk, from 200 to 300 cm/s2; and (v) high risk, MGA's values higher than 200 cm/s2 (SGC & EAFIT, 2014; SGC, 2013).

Table B.5. Description of collected information from metropolitan Medellin city

Institution	**Variable**	**Description**
Medellin's public companies (Empresas Públicas de Medellín-EPM)	Trees presence	Yes and No
	Operational status	Construction, Design, operation and out of service
	Basin	*Aguas calientes, Altavista, Castrol Indio y Asomadera, Centro parrilla, Interceptor Occidental-Naranjal, Interceptor Occidental - Nutibara, Interceptor Oriental Industriales, Distrito1, Doña María, El Ahorcado, El Bolo, El Hatillo, El Molino, El Salado, Granizal, Interceptor Occidental Calle 50, La Aguacatala, La Ayura, La Bermejala, La Doctora, La Estrella, La García, La Grande, La Guayabala, La Hueso, La Iguana, La loca y hato, La lopez, La madera, La Malpaso, La Miel Sur, La Mina, La Minita, La Muñoz, La Olleta, La Paulita, La Picacha, La Poblada, La Presidenta, La Quintana, La Rosa, La Seca, La Señorita, La Sucia, La Tinajas, La Valeria Norte, La Valeria Sur, La Volcana, La Zuñiga, Loreto-San Diego Calle 31, Piedras Blancas, Pueblo Viejo, Rio Medellín, Rodas, Santa Helena,* and *Tasajera*
Municipality of Medellín (Alcaldía de Medellín) GeoMedellin Web	Soil type	Clay, Colluvium, Gravel, Sand, Silt, and Stone
	District	16 Medellin's districts: *Popular, Santa Cruz, Manrique, Aranjuez, Castilla, Doce de Octubre, Robledo, Villahermosa, Buenos Aires, La Candelaria, Laureles – Estadio, La América, San Javier, El Poblado, Guayabal* and *Belén*, 7 towns: *Barbosa, Bello, Caldas, Copacabana, Itagüí, La Estrella* and *Girardota*.
	City	*Barbosa, Bello, Copacabana, Girardota, Itagüí, La Estrella, Caldas* and *Medellín*
	Land uses	High, medium, low mixture and public space
	Risk for movements of mass (Seismic zoning)	Very High, High, medium, low and very low risk
	Road type	Highway, national street, regional street, rural primary, rural local, urban primary and urban local
	Flood Risk	High, medium, low, and very low probability flow risk
	Latitude Coordinate	East, mid-east, mid-west and west
	Longitude Coordinate	North, mid-north, mid-south, and south

Source: Author

Furthermore, the climatic zoning (IDEAM, 2001) calculates the information about Flood risk from the maximum daily rain (MDR) evaluated with a return period of 25 years. Therefore, the categorization of flood risk was: (i) very low risk corresponds to a DMR's values from 0 to 100 mm; (ii) low risk, from 50 to 100 mm; (iii) medium risk, from 100 to 150 mm; (iv) high risk, from 150 to 220 mm; and (v) very high risk with DMR's values higher than 220 mm (SGC & EAFIT, 2014).

5.2.2.2. Local assessment standard

Medellin public companies (EPM) has its methodology for assessing the condition of sewer assets ("*Methodology for diagnosis and evaluation of sewage networks with CCTV*") since 2010 (EPM, 2010). The methodology guides the CCTV inspections of the sewer assets and then qualifies each sewer asset according to the severity of failures found. An assessment system qualifies each sewer asset according to the failures found and established criteria for determining the deterioration level or grade regarding a collapse probability of the asset.

As well as Bogota's case, for Medellin's sewer system, the standard classifies the operational and structural condition of the sewer assets in five grades, being grade 1 which represents the sewer assets in excellent conditions, and grade 5 the critical conditions. For more details about this assessment, please see appendix – Part B.2.1.

5.2.2.3. CCTV Inspected data

EPM provided the collected CCTV inspections: records of CCTV inspections carrying out from 2010 to 2017. The CCTV inspection database contains information about the ID and the address of the sewer assets, the inspection date, and its structural conditions (in grades). After CCTV inspection data clean-up, 17293 consistent inspections (representing 536 km) were linked to 16684 sewer assets (around 12% of the total sewer system). Figure B.4. shows inspected sewer assets of the whole Medellin's sewer system.

According to the inspected sewer assets, 31.7% are in excellent structural conditions (grade 1), 2% are in good structural conditions (grade 2), 3.6% in moderate structural conditions (grade 3), 57.4% in poor structural conditions (grade 4), and 5.5% in critical conditions (grade 5).

A big database was built based on the Medellin's sewer systems information (item 5.2.1) and the collected information of Medellin's city (item 5.2.2) related to surrounding characteristics of Medellin's city and CCTV inspection reports. Figures from 5 to 7 of the appendix – Part B.2.2. show bar plot analysis that depicts the distribution of the structural condition regarding the collected variables to observe an apparent relationship between the deterioration of the structural condition of sewer assets and the collected data.

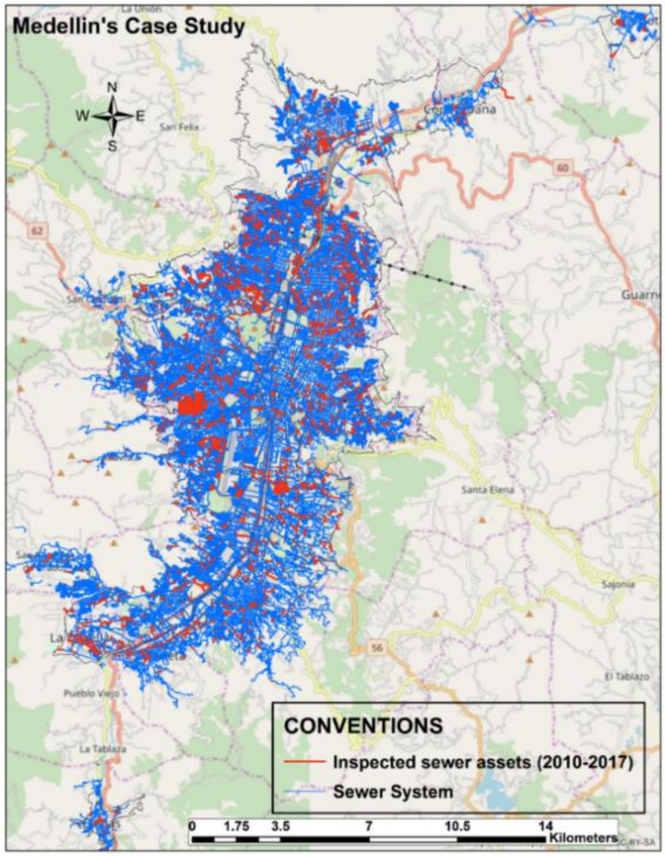

Figure B.4. Medellin's inspected sewer assets between 2010 and 2017. Whole sewer system in blue lines and inspected sewer assets in red lines. Source: Author

From the bar plot analysis (Figures from 5 to 7 of the appendix – Part B.2.2), it is possible to observe that the deterioration of structural condition does not show an apparent relationship with depths in which locates the sewer assets, land uses, operating status, soil type, foundation type, flood risk and cities. Table B.6. a summary of the variables presenting apparent relationship with the deterioration of the structural condition of the sewer assets for Medellin's case.

Table B.6. depicts that the physical characteristics of the sewer assets presented an apparently influence over their structural condition for Medellin's case. As well, the age, installation and inspection years periods an apparent shown relationship with the structural condition. Type of effluent and variables related to geographical location (districts, basins, seismic risk areas, longitude and latitude coordinates) also are variables that could influence the deterioration of the structural conditions; these variables show associations with topographic conditions of the terrene and the urban dynamism of the city (Micevski et al., 2002). Closeness with road networks and trees also depicted an apparent relationship with the deterioration of the structural condition of the sewer assets.

Table B.6. Summary of variables that show a relationship with the deterioration of structural condition of sewer assets according to the bar plots from Figure 5 to 7 of the appendix – Part B.2.2.

Variables	Relations with the deterioration of structural condition
Inspection periods	Higher percentage of deteriorated sewer assets in the last inspection period (2014-2017)
Installation periods	Older installation period, higher percentage of deteriorated sewer assets
Age periods	Older sewers' age period, higher percentage of deteriorated sewer assets
Diameter	Smaller sewer assets, higher percentage of deteriorated sewer assets
Material	A higher percentage of deteriorated sewer assets in concrete sewers
Type of effluent	Higher percentage of deteriorated sewer assets in separate systems (sanitary and stormwater)
Length	Longer sewer assets, higher percentage of deteriorated sewer assets
Slope	A higher percentage of deteriorated sewer assets in sewer assets of slopes lower than 0.5 m/m
Districts	A higher percentage of deteriorated sewer assets in sewers located in *Laureles (Estadio), Las Américas* and *Castilla* districts. In fact, the districts at the west side of the river show higher percentage of deteriorated sewer assets
Road Type	A higher percentage of deteriorated sewer assets in assets located in urban roads
Trees presence	A higher percentage of deteriorated sewer assets in assets that have trees presence closeness
Seismic Zones	A higher percentage of deteriorated sewer assets in assets located in low seismic zones
Element Type	A higher percentage of deteriorated sewer assets in collector assets
Basin	A higher percentage of deteriorated sewer assets in assets located in *Altavista, La Picacha-Nutibara, La Poblada, La Malpaso, La Grande-Estrella* and *Granizal* basins
Longitude coordinate	A higher percentage of deteriorated sewer assets in assets located at the west geographical zone
Latitude coordinate	A higher percentage of deteriorated sewer assets in assets located on the mid-south geographical zone

Source: Author likewise as Bogota's case

it is important to highlight that even if, Medellin is a smaller city and its assessment standard is more recent than Bogota's case, the percentage of inspections is higher because of the inspection's routes are centralized. Bogota's utility divides the water supplies and sewerage management into five zones in which each zone is autonomous, which makes that each zone has its own rules and strategies to manage these infrastructures.

The information provided from CCTV inspections was given from both utilities by confidential agreement between "*Pontificia Universidad Javeriana*" and the utilities (EAB and EPM). The agreement states that the author could work with the provided data with the commitment of reporting the results of this thesis doctoral. This fact allows working with real data for contributing to the utilities in the sewer asset management of their cities.

In accordance of bar plot analysis for both cities, variables related to the physical characteristics, age and installation year periods, type of effluent of the sewer assets, and surrounding variables such as closeness with other infrastructures (road networks and trees), the geographical location of the sewer assets (districts, towns, basins, seismic risk areas, longitude and latitude coordinates) shown an apparent relationship with the structural condition. However, this analysis does not assure the sizable influence of these variables over the deterioration of the structure of the sewer assets, because bar plot analysis is a superficial technique and does not show an interaction of the collected variables with the structural condition. It makes impossible to find a hierarchy of the variables regarding their influence over the deterioration of the structural condition of the sewer assets. Nevertheless, this analysis could give clues of the variables that should include within the deterioration models to support their prediction performance. Most of these variables have already reported in other case studies as influential (Ariaratnam et al. 2001; Baik et al., 2006; Tscheikner-Gratl et al., 2014; Davis et al., 2001a; Le Gat, 2008; Ana et al., 2009b; Rokstad & Ugarelli, 2015; El-Housni et al., 2017; Caradot et al., 2018; Baur & Herz et al. 2002; Chughtai & Zayed, 2008; Salman & Salem, 2011; Ugarelli et al. (2013); and Torres-Caijao et al. 2017).

Furthermore, some variables that present an apparent relationship with the deterioration of the structural condition for both case studies shown that relation in a different way, such as type of effluent: for Bogota's case the structural deterioration was related to the combined and sanitary sewers, while for Medellin's case the structural deterioration was associated with the separate sewers (stormwater and sanitary). It could happen because, in Medellin, the sewer operators have been carried out rehabilitation activities in the oldest zone (historic centre) of the city the last years. And other variables showed an apparent influence over the structural condition in a case study and the other not: depth and inspection period years showed influence for Medellin's case and Bogota's case does not. It implies that the found variables are not always influential over the deterioration of the structural condition. It depends on each case because the interaction of the physical, urban, environmental and operational characteristics makes unique each city (Chornet, 1994).

Besides, characteristics such as land use, operating status, and those related with flood risk (precipitation levels for Bogota's case) do not show an apparent influence over the damage of the structure of the sewer assets in both cities. However, these relationships should be analysed in-depth since there are relationships with districts for both cities and the operational conditions of the sewer assets for Bogota's case.

CHAPTER 6: SELECTED METHODS

Chapter 6 consists of the description of the arguments of the chosen methods to develop the proposed methodology. The theoretical description of these methods is in Part A. Chapter 6 has two subchapters: subchapter 6.1. describes the arguments of choosing the used methods to become tools for supporting the sewer asset management and subchapter 6.2 describes the used computer-based tools to develop the methods mentioned in subchapter 6.1.

6.1. METHODS USED AS SAM'S TOOLS

This subchapter explains in detail the justification, exploration and analysis of different methods for supporting the development of sewer asset management tools. Here, it describes the input data and information to be considered to handle with the explored methods. Subchapter 6.1 consists of four items according to the method's application in the sewer asset management tools: (i) Bayesian networks as feature selection method, (ii) statistical and machine learning methods as deterioration models for predicting the structural condition of the sewer assets, (iii) methods used to develop optimisation methodologies for finding the combination of hyperparameters that best fit for a management objective, and (iv) the used performance measures to evaluate the accuracy of the developed deterioration models for different performance perspectives.

6.1.1. BAYESIAN NETWORKS AS A FEATURE SELECTION METHOD

In general, some physical characteristics of pipes, environmental and operational features have been identified as factors that could influence the structural and operational conditions of the sewer assets by statistical models and analysis (Chughtai & Zayed, 2011; Tran et al., 2007; Davies et al., 2001a).

In recent years, Bayesian Networks (BN) has become a promising tool for cause-effect analyses, which allows representing uncertain knowledge in probabilistic systems such as risk analysis (Kabir et al., 2015). This tool has proven to be effective in capturing and integrating qualitative (nominal variables) and quantitative information from various sources (see the theoretical framework of Bayesian Networks in subchapter 2.5 of Part A). Therefore, it can strengthen decisions when empirical data are lacking (Kabir et al., 2015; Li et al., 2016). For example, España (2007) developed a model for prioritising the pipes to construct inspection plans based on BN, GIS (Geographical Information Systems) and survival functions. In this model, the BN let incorporating the information in an organised way and limited zones where the information's cost was readily available. Furthermore, this identified the relevant variables to the failure mechanisms and their consequences and determined conceptual relationships among them.

Bayesian Networks have also been successful in experiences related with medical diagnosis (Curiac et al., 2009; Gadewadikar et al., 2010; Bucci et al., 2011) because of the integration of variables of different natures (i.e. numerical, categorical) such as physical findings, laboratory test results and image study findings (Gadewadikar et al., 2010). The identification of cause-and-effect relationships between variables from the calculus of conditional probabilistic of the observed database, which indicates the amount in which one variable influences another (subchapter 2.5 of Part A). Bayesian Networks are useful in contexts where are different interactions of variables of different natures, in which a failure or modification of one variable could affect another variable because both belong to the same system. Thus, the human organs and urban systems are systems that belong to complex systems (human body and city), therefore, sometimes the failure of one of them could be produced from the damage or influence of another system or organ, and this is detectable with the Bayesian Networks. According to the above, Bayesian Networks could be a suitable tool to determine the number of variables that are enough to obtain a satisfactory prediction quality for the structural condition of sewer pipes, to reduce the collection costs of the variables that could influence over the structural condition.

6.1.2. METHODS USED AS DETERIORATION MODELS

Globally, some methodologies and models have already proposed to support the sewer asset management (Vittorino et al., 2014; Baah et al., 2015; Rokstad & Ugarelli, 2015; Saegrov, 2006), especially deterioration models to support the definition of cost-effective inspection and rehabilitation strategies (Caradot et al., 2013) from the prediction of condition of uninspected sewer assets (Mashford et al., 2010; Wright et al., 2006) to the forecasting of the sewer condition (Ana & Bauwens, 2007). Most of these models base on statistical and machine learning approaches (description of the theoretical framework of these methods are in chapter 2 and 3 of part A). According to a literature review (Wright et al., 2006; Mashford et al., 2010; Younis & Knight, 2010; Salman & Salem, 2011; Harvey & McBean, 2014), the explored methods were Binomial Logistic Regression -LR, Random Forest (RF), multinomial logistic regression – Multi_LR, Ordinal logistic regression – Ord_LR, linear discriminant analysis – LDA and support vector machines -SVM.

During the research internship, the author together with researchers of *Kompetenzzentrum Wasser Berlin* (KWB) explored the above-described methods applying them in different case studies of Colombian and German cities, to analyse their performance to support sewer asset management strategies. The internship was supported by a mobility exchange *DAAD – COLCIENCIAS* contract.

Therefore, the explored deterioration models were based on (i) logistic regression - LR, (ii) random forest - RF, (iii) multinomial logistic regression - Multi_LR, (iv) ordinal logistic regression – Ord_LR, (v) linear discriminant analysis - LDA and (vi) support vector machine - SVM).

The input data for all methods were numerical variables. Dummy variables were useful to handle with categorical variables, except for Random Forest, which works well both with categorical and numerical variables. The dependent variable was always categorical. However, for logistic regression, the categorical variable was grouped into two levels to become a dichotomic response. In this case, the structural condition represents critical and non-critical.

For LDA and SVM, different methods exist for estimating the parameters and kernel functions. For the LDA model, four methods for estimating the parameters, such as t-student distribution, mve (minimum volume ellipsoid), moment and mle (maximum likelihood estimation) (Friedman, 2001). According to the results from the deviation analysis and performance curve, t-student distribution and mve were the ones with the highest quality predictions for the validation dataset (Hernández et al., 2019b). Likewise, for the SVM model, seven kernel functions were explored: (Gaussian) radial basis (Rbf), linear (vanilla), polynomial, hyperbolic tangent, Bessel and ANOVA (Genton, 2001). In the end, the Laplacian kernel function was the one with the most successful results according to deviation analysis and performance curve (Hernández et al., 2019b).

The above deterioration models were applied using 2/3 of the data for calibration and the rest for validation. Three techniques were used to analyse the prediction performances obtained by the developed deterioration models: ROC space, Performance Curve, and deviation analysis. For more details about these techniques, see chapter 4 of part A.

From the results of these explorations, the methodology proposed in this doctoral thesis (Part D) includes some methods such as LR, SVM, RF and Ord_LR to build deterioration models because of their successful results in Bogota's and Medellin's case.

6.1.3. METHODS USED AS OPTIMISATION METHOD

Grid search technique and Differential Evolution algorithm optimisation (for a theoretical framework, see in items 2.1.4 and 3.3 of the part A) were used to develop an optimisation methodology for finding the combination of hyperparameters that best fit to reach a management objective. These techniques are often useful to find the optimal hyperparameters for machine learning methods such as SVM and RF. The selection of Grid Search and Differential evolution algorithm optimisation as optimisation methods were chosen by the successful results in finding hyperparameters in other experiences such as Bergstra & Bengio, (2012), Ortiz-García et al. (2014) and Tarmizi et al. (2014) for Grid Search Method and López-Kleine & Torres (2014), Bazi et al. (2013), and Tien et al. (2016) for differential evolution algorithm optimisation. Differential Evolution algorithm (DE) is widely useful since it provides the following advantages over other optimisers: i) it improves a candidate solution by the use of bio-inspired operators (such as crossover and mutation); ii) it does not require a gradient to find the optimal global solution; and iii) it can handle non-differentiable functions, which allows its use in non-continuous problems (Price et al., 2006, Torres et al., 2013). Part C describes in detail a methodology which links both techniques for finding the optimal combination of hyperparameters that best fit to fulfil two management objectives.

6.1.4. METHODS USED AS PERFORMANCE METRICS

Cohen's Kappa coefficient, ROC space, performance curve and deviation analysis are methods used as metrics to measure the prediction performance of the structural condition estimated by deterioration models. These metrics evaluate the prediction under different points of view: (i) Cohen's Kappa coefficient (subchapter 4.1 of Part A) gives a value between 0 and 1 which measures the agreement between the predicted structural conditions and the real structural conditions to evaluate the performance of the prediction robustly, since it considers the agreement occurring by chance (Vieira et al., 2010); (ii) ROC space is used to analyse the performance prediction of an objective (in this case, a structural condition), calculating the True Positive Rate (TPR) and False Positive Rate (FPR) to compare the times that the model predicted correctly and incorrectly the structural condition; (iii) performance curve is a method that specifically analysis the performance of critical conditions by comparing the probability of being in critical conditions with the actual condition reported by CCTV; and (iv) deviation analysis is a technique that compares the condition distribution of the sewer assets on the network and by times period between the predicted and observed conditions, this technique compares the proportions of sewer assets on each condition. ROC Space and Deviation analysis are useful to evaluate the predictions at a global level, that could be useful to develop management strategies at the network level of the sewer system. On the other hand, Cohen's kappa coefficient and performance curve evaluate the performance of the prediction of the structural condition of each single sewer asset. These tools are useful for identifying assets with more urgency to be rehabilitated and supporting strategies for rehabilitation activities.

Based on these four-performance metrics, in subchapter 8.1 of part C, the author proposes performance metrics that englobe four performance perspectives explained before and guides the prediction to two specific management objectives: at the network and single pipe levels.

6.2. COMPUTER-BASED TOOLS

Computer-based tools are software that helps with the handling and processing data, as well as the development of the sewer asset management tools to reach the methodology proposed in this doctoral thesis. R software and ArcGIS were the main used tools during the doctoral thesis. The link between GIS tools and R software is helpful because of the versatility of R software. GIS tools allow collecting and georeferenced the data in order to be handled with R software. Once the thesis 'results were obtained, GIS tools were used one more time, in order to plot in georeferenced maps. This subchapter splits into two items: (i) a description of the primary libraries and functions of R Software for developing the methods described in the subchapter 6.1, and (ii) a description of the leading used tools in ArcGIS for collecting and merging information geographically, and building georeferenced maps to visualize the predictions of the sewer assets.

6.2.1. R SOFTWARE

R software is a language and environment for statistical computing and graphics. R offers a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, classification, clustering, machine learning algorithms, mathematical algorithms, etc.) and graphical techniques, and is highly extensible. R is an integrated suite of software facilities for data manipulation, calculation and graphical displays. One of the most important characteristics of R software is the ease to produce publication-quality plots, including mathematical symbols. R is available as Free Software under the terms of the Free Software Foundation's GNU General Public License in source code form. It compiles and runs on a wide variety of UNIX platforms and similar systems: Linux, Windows and macOS. R could extend via packages: there are about eight packages provided with R distributions and many more are available through the CRAN family of internet sites covering an extensive range of modern tools (R Core Team, 2019).

Besides R, there is a friendly software called “RStudio”. RStudio is an integrated development environment for R. RStudio includes a console, syntaxis-highlighting editor that supports direct code execution, as well as tools for plotting, history, debugging and workspace management. RStudio is also available in open source and commercial edition and runs on the desktop (Windows, Mac or Linux) or in a browser connected to RStudio Server or RStudio Server Pro (for Ubuntu, CentOS, and Linux) (RStudio Core Team, 2019).

6.2.1.1. Libraries used for data pre-processing

Libraries such as *Base*, *Utils* (R Core Team, 2019), *kwb.utils* (KWB, 2017a), *kwb.sema* (KWB, 2017b), *lubridate* (Spinu,2016), and *plyr* (Wickham H & Wickham M.H., 2016a) were helpful to call data from CSV and shapefiles of the collected information of the case studies. For the pre-processing activity, the data were cleaned-up, merged and filtered to consolidate a unique database for each case study. Besides, some variables were calculated, such as the depth and the age of the sewer assets. The numeric data also were categorised (based on boxplot distribution) to analyse their distribution in the database and compare with other variables. Besides, libraries such as *grDevices*, *graphics* (R Core Team, 2019), *ggplot2* (Wickham et al., 2016b), *scales* (Wickham, 2016c), *multipanelfigure* (Graumann & Cotton, 2018) were useful for plotting the cleaned-up database to visualise the distribution of the collected variables with the structural grades and draw the graphics related to the measurement techniques such as performance curve and deviation analysis.

6.2.1.2. Function used as feature selection tool

Library *Bnlearn* is a package that contains Bayesian network structure learning, parameter learning and inference. The package implements constrained-based, pairwise, score-based and hybrid structure learning algorithms for discrete, Gaussian and conditional Gaussian networks, along with many score functions and conditional independence tests (Scutari, 2019). All the learning algorithms need that all input data should be categorical; therefore, the numerical data must be categorised. As Hill-Climbing algorithm was the chosen learning algorithm, this library contains the function *hc* to build a network based on hill-climbing greedy search node ordering. (Scutari, 2019). *hc* worked to develop the proposed feature selection methodologies for both case studies described in Part C.

6.2.1.3. Main functions for deterioration models

Several deterioration models were developed based on seven statistical and machine learning methods. The application of this deterioration models is in Part D of this manuscript. Therefore, the functions of different libraries were applied to develop the deterioration models. In the following, it is describing the used functions for each method:

- ***lda*****:** this function is helpful for developing linear discriminant analysis (LDA) models. This function contains the four methods for estimating the parameters of LDA. *MASS* is the library that holds this function (Ripley et al. 2013). However, it is not the only one library that develops linear discriminant analysis models in R.
- ***polr*****:** polr is the function that fits a logistic or probit regression model to an ordered factor response. The default logistic area is proportional odds logistic regression, after which is named ordinal logistic regression. *polr* belongs to the functions that holds the library *MASS* (Ripley et al., 2013)
- ***glm*****:** this function is useful to fit generalized linear models, specified by giving a symbolic description of the linear predictor and a description of the error distribution. This function helps to develop binomial logistic regression models. *Stats* is the library that contains *glm* function (R Core Team, 2019).
- ***multinom:*** *multinom* is helpful to model nominal outcome variables, in which the log odds of the outcomes generate linear combination of the predictor variables. *nnet* package contains the function *multinom* to develop a multinomial logistic regression model (Ripley & Ripley, 2016).
- ***randomForest:*** This function implements Breiman's random forest algorithm (based on Breiman and Cutler's original Forthan code) for classification and regression tasks. It can also be used in an unsupervised mode for assessing proximities among data points (RcolorBrewer & Liaw, 2018). *randomForest* is included in the functions that offer *randomForest* library, which is used for classification and regression tasks based on a forest of trees using random inputs.
- ***ksvm***: *ksvm* implements Support Vector Machines which are a tool for classification, novelty detection, and regression tasks. *ksvm* support the well-known C-svc, nu-svc, (classification), one-class-svc (novelty), eps-svr, nu-svr (regression) formulations along with native multi-class classification formulations and the bound-constraint

SVM formulations *ksvm* also supports class-probabilities output and confidence intervals for regression. *ksvm* belongs to *kernlab* library (Karatzoglou et al., 2018).

6.2.1.4. Main functions for optimisation tools

To develop the grid search technique and differential evolution algorithms, two libraries were suitable: *caret* (Kuhn, 2012) and *DeOptim* (Mullen et al., 2011). caret package contains functions to streamline the model training process for complex regression and classification problems. From caret package and other packages that support caret packages such as *parallel* (R Core Team, 2019), *do.parallel* (Weston & Calaway, 2019a), *foreach* (Weston, 2019b), and *base* (R Core Team, 2019) packages to develop grid search technique reducing the computational time by splitting the running process in different cores. *DeOptim* package implements the Differential Evolution algorithm for global optimisation for a real-valued parameter vector. The implementation of differential evolution interfaces with code for efficiency.

Moreover, the package is self-contained and does not depend on any other packages (Mullen et al., 2011). The function used to perform the global evolutionary optimisation via differential Evolution algorithm is *DeOptim* (Mullen et al., 2011).

6.2.2. ArcGIS

ArcGIS is a software related to Geographical Information Systems (GIS) for working maps and geographic information. This software helps for creating and using maps, compiling geographic data, analysing mapped information, sharing and discovering geographical information, using maps and geographical information in a range of facilities, and managing geographical information in a database (ESRI, 2019). ArcGIS desktop consists of several integrated applications such as ArcMap, ArcCatalog, ArcToolbox, ArcScene, ArcGlobe and ArcGIS Pro. ArcCatalog is the data management application. ArcMap is the application used to view, edit and query geospatial data, and create maps. ArcToolbox contains geoprocessing tools, data conversion, and analysis tools. ArcScene and ArcGlobe are an application for viewing GIS data in 3-D. And finally, ArcPro allows using ArcPy python scripting for database programming (ESRI, 2019).

For this doctoral thesis, the ArcGis tool was used mainly for extracting information of the collected information of both case studies and building maps. Table B.7. shows the tools that were suitable for the above purpose.

Table B.7. Used tools and functions of ArcGis (ESRI, 2019)

Tools	Functions	Used for
Analysis Toolbox	Extract, overlay, spatial joint and clip	Extract and join information of different shapefiles
Conversion Toolbox	Convert files from KML, PDF, Raster, GPS and WFS files to shapefiles and raster files	Convert the collected information in shapefiles to extract information
Data Management Toolbox	projections and transformations tools, aggregate o delete features, joints merge, rename, sort, find identical, and geometry calculator	One of the most used toolbox: The projections and transformation tools were used to convert geographical data from one map projection to another; also aggregates o delete features into the shapefiles, joint and merge shapefiles (also feature information tables), renames features, sort data, find identical points and Calculates and add information to a feature's attribute fields representing the spatial or geometric characteristics and location of each feature, such as area, length, and x, y and z coordinates
Insert	add shapefile, add legend, add north arrow, add scale bars, and add base maps	Add information to build and visualize data in the ArcMap: Add Shapefiles, add a legend, add data frame (more than 1 map environments), add a north arrow, add scale bars and add base maps (add a background of geographical context of the map that user wants to visualize)
Selection	Selection by attributes	This function allows providing a SQL query expression that is used to select that match the selection criteria

Source: Based on ESRI (2019)

According to Table B.7., these functions help to extract, join and merge information to build an extensive database in which each sewer asset contains information about physical characteristics of sewer assets and surrounding variables. Functions such as Insert and selection help to create maps to show the predictions of the sewer assets geographically on each case study.

CONCLUSIONS PART B

The chosen case studies were Bogotá and Medellin because of their availability and the criteria needed to develop the proposed methodology: (i) large percentage of sanitation coverage on the city; (ii) georeferenced information; (iii) assessment protocol for evaluating the structural and critical conditions of sewer assets; and (iv) non-depreciable quantify of CCTV inspected information.

From the available information (sewer system and CCTV reports) that own the EAB and EPM, the managers can already make decisions in rehabilitation activities. However, these decisions are based on reactive management (making decisions after the damage occurs).

The idea of collecting data of different nature (numerical, categorical, special, and others) represents a challenge for its processing. The development of feature selection and deterioration models should consider this diversity to include all the collected data and take advantage of this variety in the models.

According to the description of the collected data (bar plot analysis), it was possible to observe that the relationship of some variables varies from a case to another. It means that it is not possible to generalize over "universal" variables in sewer asset management. It is essential to handle each case study separately, and it is evident that it is necessary to develop methodologies for being applying to different cases.

Despite some variables presented an apparent relationship with the deterioration of the structural conditions for both case studies, there are doubts about the importance of some variables than others. It difficult to assures if these variables have the same weight within the model or could handle in the same way.

Following the last two conclusions, it is not possible to make conclusive decisions about the key variables to include in the deterioration models because the bar plot analysis is not deep enough. However, variables such as some physical characteristics, age, construction year periods and type of effluent of the sewer assets, as well as closeness with trees and road networks, the geographical location of the sewer assets, and seismic characteristics could include supporting the performance of the deterioration models.

The exploration of deterioration models, based on different statistical and machine learning methods for different case studies, allows analysing the prediction accuracy from different perspectives. According to Hernández et al. (2018) and Hernández et al. (2019b), it was found that there is not a unique model for predicting the structural condition of the sewer assets; there are multiple models that achieve a good prediction quality. Nevertheless, some models could better behave in some case studies than others, because of the specific city's characteristics, assessment standard, collected data of CCTV inspections and management objectives.

On the other hand, some explored methods and computational-based tools could help to the decision-making for (i) including or not specific variables within the deterioration models; and (ii) including or not particular variables within the deterioration models for reaching particular management objectives.

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PART C DEVELOPED SEWER ASSET MANAGEMENT TOOLS

Part C is the most important of this manuscript because it describes the developed tools during the doctoral time and the proposed methodology for identifying the key and enough factors for achieving objectives in sewer asset management. Part C contains first the description of the developed tools independently (Chapter 7 and 8), and their final integration for building the proposed methodology (Chapter 9). The main idea of these tools is answering the research questions of this doctoral thesis. Hence, the developed tools are splitting in two: antecedent tools and the main methodology. The antecedent tools are those developed independently and proved to determine their applicability (chapters 7 and 8), and the main methodology is the integration of all these tools to achieve the objective of this doctoral thesis, and thus answering the open research questions in part D.

Chapter 7 consists of the description of a Bayesian network-based methodology that was the first antecedent of the proposed methodology in this thesis. The Bayesian network-based methodology depicts in this section was carried out together with the support of Master students (Julián Guzmán-Fierro, Sharel Charry, Iván González and Felipe Peña-Heredia), who developed this methodology. The final products of this Bayesian network-based methodology were: (i) participation for an oral presentation at LESAM/PI conference 2019 under the title *"Selecting effective sewer asset management models: a probabilistic inference approach"* (Guzmán-Fierro et al., 2019a); (ii) submission in the International Journal of Critical Infrastructures in November 2019 under the title "*Bayesian network-based methodology for selecting a cost-effective sewer asset management model*" (Guzmán-Fierro et al., 2019b); and finally (iv) the base in the development of the proposed methodology of this manuscript (subchapter 9.1 of this Part).

Chapter 8 has two subchapters: (i) the description of the proposed developed metrics that links with two different sewer asset management objectives: to network and single pipe objectives; and (ii) the description of the optimisation's methodology, based on grid search, Monte-Carlo simulations and Differential Evolutionary (DE) algorithms, that finds the optimal hyperparameters of the machine learning-based deterioration models guided to the two proposed sewer asset management objectives of the proposed developed metrics. In the following, it is shown some products of these developed tools: (i) publication of the paper entitled "*Practical benchmarking of statistical and machine learning models for predicting the condition of sewer pipes in Berlin, Germany*" (Caradot et al., 2018) in the Journal of Hydroinformatics"; (ii) submission of the paper entitled "Optimising SVM models as predicting tools for sewer pipes in the two main cities in Colombia for different sewer asset management purposes" (Hernández et al., 2019c) in Structure and Infrastructure Systems Journal; (iii) participation on UDM conference 2018 as a poster (Hernández et al., 2018b); (iv) application of the proposed metrics and optimisation methodology in Guzman-Fierro et al., (2019c) and finally, (v) application of the proposed metrics and optimisation methodology in the present thesis (Subchapter 9.2 of the present part). The performed work shown in chapter 8 was carried out together with *Kompetenzzentrum Wasser Berlin (KWB)*, during the mobility exchange DAAD-Colciencias contract, celebrated in 2016 and 2017 years.

Chapter 9 describes the methodology for identifying the key and enough factors for achieving objectives in sewer asset management. This methodology consists of two parts: (i) Bayesian Networks (see 6.1.1. of Part B of this manuscript) based methodology as a feature selection tool to develop a methodology that chose and sort the importance of features to influence in the deterioration of the structural condition of the sewer assets (Subchapter 9.1); and (ii) Methodology for selection the deterioration models that best fit two management objectives related to network and single asset purposes (Subchapter 9.2). Both parts integrate the proposed metrics (chapter 8.1) that links with two different management objectives (at the network and single pipe prediction levels), and the proposed optimisation methodology (subchapter 8.2) to find the hyperparameters combination that best fit the management objectives. The methodology could apply to different case studies and for different structural condition scenarios in which is also explored the prediction quality and the advantages of these scenarios in the decisions-making in sewer asset management.

Chapter 9 is the most important chapter of this manuscript. This chapter integrates the different developed tools (Chapter 7 and 8) to develop a complete methodology for determining which factors are enough and necessary to achieve specific objectives in sewer asset management, considering quantity and quality of the available information. Part D shows the application of the proposed methodology in Bogota's and Medellin's cases.

CHAPTER 7: FEATURE SELECTION TOOL

Chapter 7 presents the development of a methodology based on Bayesian networks to select a set of variables that could influence the deterioration of sewer asset management. Thanks to the properties of Bayesian Networks, stated in item 2.5 (Part A) and 6.1.1 (Part B) of this manuscript, could be a suitable tool to determine the number of variables that are enough to obtain a satisfactory prediction quality for the structural condition of the sewer assets.

For the development of this tool, some master students (Julián Guzmán Fierro, Sharel Charry, Ivan González, and Felipe Peña Heredia) participated together with the author of this manuscript to build a methodology based on BN to prioritize and select a minimal number of variables that allows predicting the structural condition of sewer pipes for the management of this type of infrastructure.

From this work, an article was submitted on International Journal of Critical Infrastructures (Guzman-Fierro et al., 2019b), an oral speech was presented in an international conference (LESAM/PI 2019) (Guzman-Fierro et al., 2019a). Subchapter 10.1. (Part D) shows a summary of the results of this methodology.

Bayesian Network-based methodology consists of six steps in which are integrated Bayesian Networks, a statistical measurement of the agreement such as Cohen's Kappa coefficient – Kappa (See 4.1 of Part A of this manuscript), data distribution (boxplots) and statistical tests (Wilcoxon test), as shown in the following:

- ***Step 1 – Data collection:*** as shown in Figure C1, the proposed methodology begins with the collection of data from CCTV inspections (which describe the failures and sewer pipe structural conditions according to a visual inspection and qualification standard), and information of the sewer system corresponding to the physical characteristics of the assets (i.e. diameter, material, length), operational characteristics (i.e. type of wastewater, flow), and environmental factors (i.e. geotechnical and seismic aspects, urban and demographic aspects) obtained by Geographical Information Systems GIS in one database. Then, this information is merged to build one database in which each asset has information of each physical, environmental and operational characteristic together with the structural condition reported by CCTV inspections.

- ***Step 2 – Creation of structural condition scenarios (SCS):*** different structural condition scenarios are created to identify in the next step (step 3) the scenario that provides more predictive capacity. Assessment standards such as MSSC (WRC, 1993) or PACP (NASSCO, 2004), which generally qualify the structural condition in five categories, can be taken as a reference for proposing condition aggrupation such as the one shown in Table C.1.

  The purpose of creating SCS is to discriminate in a better way the structural state to maximize the prediction quality (López-Kleine et al., 2016; Caradot et al., 2016), reducing the uncertainty of wrong evaluation of the operators or the camera quality of CCTV technology (Caradot et al., 2017). Moreover, the reduction of the structural condition of sewer assets in categories could support the management objectives and management activities, considering budget restrictions.

Table C.1. Structural Condition Scenario (SCS) example

Description	Original	Aggrupation
	WRc Protocol (5 grades)	proposal (3 categories)
Acceptable Condition	1	1
Minimal Collapse Risk	2	2
Unlikely collapse in near future	3	2
Likely collapse in near future	4	2
Imminent collapse or collapsed	5	3

Source: Guzmán-Fierro et al. (2019b and c)

- ***Step 3 – Selection of BN learning algorithm:*** Merging the collected data with one of the created SCS, then it is explored different learning algorithms to build a Bayesian Network (BN). 70% of random data is chosen for training the BN, and the rest is used to validate the performance by Cohen's Kappa coefficient. The selected learning algorithm was the one with the highest Cohen's Kappa coefficient.
- ***Step 4 – SCS selection*:** for each scenario proposed in step 2, BN-based models are trained considering 1000 random selections (Monte-Carlo simulations) of different calibration and validation subset (varying percentages randomly from 50% / 50% to 90%/10 % with 10% steps) and all available variables to predict the structural condition range values for each validation sets. 1000 random selections were chosen to apply Monte-Carlo simulations, to find an agreement between the low computational cost and a rank of possible prediction performance that the model

could achieve considering a large amount of random data selection. This agreement also is suggested in the findings of Bauer & Guzy (2004) and Austin (2009). Moreover, the percentages steps for building the different calibration and validation subsets could be according to the user criteria, for this case the authors chose ranks of 10% steps for exploring the significant differences in the performance prediction considering these calibration and validation subsets. Cohen's Kappa Coefficient (See 4.1 of Part A) (Kappa) is used to evaluate the prediction performance of each model because, a part of being a statistical measure of inter-rater agreements for qualitative items (predicted and observed structural conditions), it is a robust measure than simple per cent agreement calculation since it considers the agreement occurring by chance (Vieira et al., 2010; items 4.1 and 6.1.4 of the parts A and B of this manuscript). Then, the K's sets of each scenario are compared to each other by boxplot analysis and statistical tests to determine if there are significant differences (Wilcoxon test). The chosen structural condition scenario is the one that shows the highest Kappa's set, a low variance, and shows differences significantly with the Kappa's sets of the other SCSs. In the case that Kappa's sets do not show differences significantly, it is chosen the SCS with the lowest Kappa's variance and high Kappa's median value.

- ***Step 5 - Calibration/Validation percentage subsets selection:*** considering the chosen SCS from step 3, for each calibration/validation percentage subsets (the varying percentages from 50%/50% to 90%/10% by increasing and decreasing each 10% of the calibration and validation data respectively), 1000 BN-models are trained using Hill-Climbing algorithm (item 2.2 and 6.1.1 of the Parts A and B of this manuscript) with all the available variables to predict the structural condition range values for each validation set. As well as for step 3, Kappa is calculated to measure the model performance, and boxplot analysis and Wilcoxon test are applied to analyse the data distribution and determine significant differences among the Kappa values correspond to each calibration/validation percentages subset. The chosen calibration/validation percentages subset is the one that shows the highest K's set, a low variance, and shows differences significantly with the Kappa's sets of the other calibration/validation percentages subsets. In the case that Kappa's sets do not show a significant difference, it is chosen the calibration/validation percentage subset that needs less data for training the model.

- ***<u>Step 6 – Comparing the prediction performance:</u>*** the “reference model” is constructed with the chosen SCS and the calibration/validation percentage subsets from steps 3 and 4 and with all the available variables. From the reference model, a Bayesian Network is built to extract the variables with a direct relationship (first parenting relation) with the structural condition. Then, a new model is carried out using only these variables (first parenting relationship with the structural condition). Anew, 1000 random selections (Monte-Carlo simulations) of the chosen calibration/validation percentages subsets are carried out in both models (“reference model” and the new model – “reduced variables model”) and these are evaluated by Kappa, creating two Kappa’s sets related to “reference model” and “reduced variable model” respectively. Wilcoxon test is applied for determining if there are significant differences between both Kappa’s sets. If there is not differences significantly, it means that it is possible building a model with few variables that achieve the same capacity prediction than a model considering all available variables; conversely, if there is differences significantly between both models, it is constructed a new model considering the variables with a direct relationship with structural condition (first parenting relationship) and the variables with a direct relationship with the first parenting relationship variables (second parenting relationship with the structural condition variable), and it is carried out again the same comparison procedure. If still, the comparison shows differences significantly between both “reference model” and “reduced variables model”, it is considered the third, fourth and so on parenting relationship variables to build new “reduced variables models” until we find a model that could achieve the same capacity prediction than the “reference model”.

For more details about this methodology, and the corresponding results, discussion and conclusions, see Guzmán-Fierro et al. (2019b).

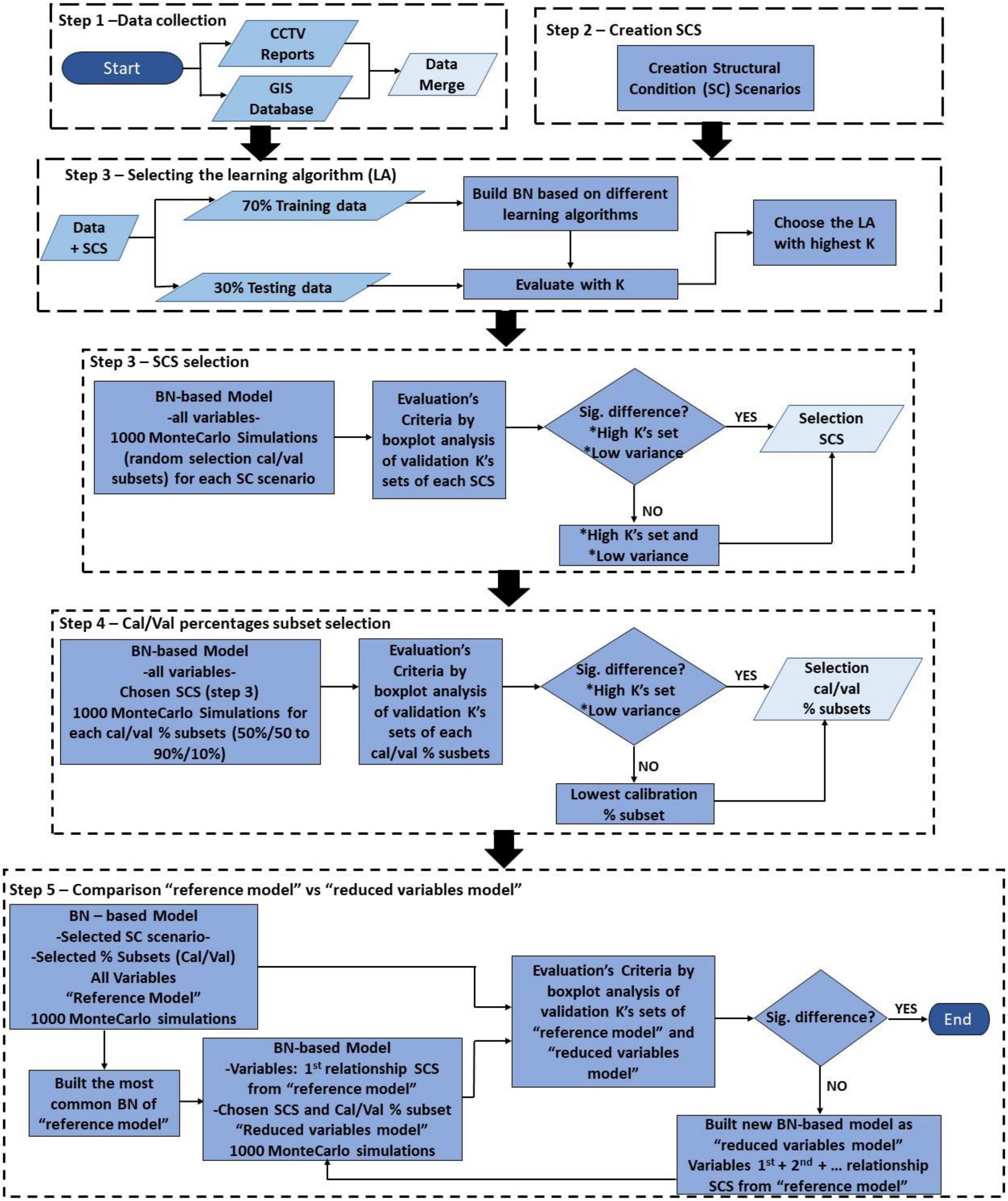

Figure C.1. Flowchart of Bayesian network-based methodology. Source: Guzmán-Fierro et al. (2019b)

CHAPTER 8: PROPOSED OPTIMISATION METHODOLOGY AND METRICS

As well as the exploration carried out in the item 6.1.2 of Part B of this manuscript, the proposed metrics and optimisation methodology in the present chapter was carried out together with *Kompetenzzentrum Wasser Berlin (KWB)* during the mobility exchange DAAD-Colciencias contract.

8.1. PERFORMANCE METRICS PROPOSAL

Thanks to the exploration of different methods (item 6.1.2 of this manuscript) to predict the structural condition and the evaluation of these predictions by different performance techniques (Cohen's Kappa coefficient, ROC space, performance curves, and deviation analysis), the authors found that some methods are more suitable for fulfilling some goals than others (Hernández et al., 2017a, b and c; Hernández et al., 2018a; Hernández et al., 2019a; Hernández et al.. 2019b). Furthermore, it was found that these four performance techniques guide to two prediction perspectives that could support two different objectives in sewer asset management. According to Rokstad & Ugarelli (2015), the accuracy and efficiency of the deterioration models should be analysed considering questions related to condition assessment which frequently arise in the Infrastructure Asset Management (IAM) planning process at the network and single pipe level. According to the above, two performance metrics were developed based on the above performance techniques. These proposed metrics are intuitive, self-explanatory and thus clearly understandable.

The management goal addressed by the network level metric is the extent to which the model can predict the distribution of the condition of the network (i.e., the number of pipes in each categorized condition), as well as the identification of those areas that require rehabilitation more urgently, to design effective investment plans considering the coherent budget routes for rehabilitation (Rokstad & Ugarelli, 2015; Hernández et al., 2019c).

Meanwhile, the management goal addressed by the pipe level metric is related to the actual identification of a structural condition of each sewer asset (identifying with higher importance those assets in critical conditions). From that information, the stakeholders could develop inspection and rehabilitation plans considering additional information about the confidence of the outputs of deterioration models (Caradot et al., 2018; Hernández et al., 2019c).

The first performance metric (*Knet*) is related to the network level. It estimates the deviations between observed and predicted structural conditions –SC–, usually defined by qualification standards such as MSSC (WRC, 1993) or PACP (NASSCO, 2004), for the entire network (K_{DEV_1}, K_{DEV_2},…,K_{DEV_N}) and the deviations of the oldest pipe group for each structural condition –SCO ($K_{OLD(DEV\_1)}$, $K_{OLD(DEV\_2)}$,…,$K_{OLD(DEV\_N)}$). The selection of the oldest pipe group because these are ones with the most urgent need of rehabilitation, as they near the end of their lifespan. In accordance to Moore (2008) and Dirksen et al. (2012), the oldest sewer pipes show more deterioration because the thickness of the inner wall is smaller, as chemical attacks and the sum of structural and operational damages that support the sewers accrue as time passes. Therefore, many utilities take as reference the oldest sewer pipes for prioritizing the renovation of assets (Baur & Herz, 2002; Basu et al., 2013). However, the utility assumes this decision depending on other factors such as the depreciation period of concrete and clay pipes (Caradot et al., 2018).

The purpose of this metric is to estimate the model's ability to predict the distribution of the structural conditions in the sewer network (percentage of pipes under a specific structural condition) focused on the distribution prediction of the old sewers (more priority). Equation C.1. shows the calculation of the *Knet* metric.

$$Knet = \sqrt{\frac{K_{DEV\_1}{}^2 + K_{DEV\_2}{}^2 + \cdots + K_{DEV\_N}{}^2 + K_{OLD(DEV\_1)}{}^2 + K_{OLD(DEV\_2)}{}^2 + \cdots + K_{OLD(DEV\_N)}{}^2}{Number\ of\ total\ K\ indicators}}$$

Equation C.1. Calculation for determining the Knet metric

The second performance metric (*Kpipe*), related to the pipe level, is obtained from a confusion matrix, which compares the predicted and the observed conditions for each pipe, and counts the number of agreements and disagreements. Three types of indicators are calculated in this metric, related to the True Positive Rates – TPR (K_{TPR_1}, K_{TPR_2}, …, K_{TPR_N}), False Positive Rates – FPR (K_{FPR_1}, K_{FPR_2}, …, K_{FPR_N-2}), and False Negative Rates – FNR (K_{FNR_1}, K_{FNR_2}, …, K_{FNR_N-1}), of the confusion matrix. Equation C.2. shows the calculation of the proposed formula to achieve *Kpipe* metric.

$$Kpipe = \sqrt{\frac{(100 - K_{TPR\_1})^2 + \cdots + \left(100 - K_{TPR\_N}\right)^2 + K_{FPR\_1}{}^2 + \cdots + K_{FPR\_N-2}{}^2 + K_{FNR\_1}{}^2 + \cdots + K_{FNR_N-1}}{Number\ of\ K\ indicators}}$$

Equation C.2. Calculation for determining the Kpipe metric

The indicators for TPR refers to the percentage of assets predicted correctly in their structural conditions; meanwhile, the indicators for FPR and FNR refers to the percentage of assets mispredicted. It is vital to observe the indicators of the wrong prediction, as they imply the severe consequences when a decision is made in sewer asset management using wrong predictions.

There are two kinds of possible incorrect predictions: those that predict assets in better structural conditions than they are (overestimation of the structural conditions – FNR), and those that predict assets in worse structural conditions than they are (underestimation of the structural condition – FPR). The most important is taken those indicators in which the seriousness of the consequence could affect the decision-making guided by the deterioration models' outputs in sewer asset management.

The percentage of sewer assets incorrectly predicted (overestimations and underestimations) is essential for asset management decision-making: for overestimated predictions, the utility could assume that urgent actions do not required which could lead to sudden collapses (undesirable situation); while if the prediction model classifies an element in a worse structural condition than it is, the utility does not have unexpected breakdowns in the network. As the severity of the consequences of mispredictions is higher for the overestimated predictions, it considers more indicators that represent these predictions than the underestimated conditions (see Equation C.2.).

It is important to note that the proposed metrics were applied for three or two structural conditions. In the case that the structural conditions consist of more levels (i.e. five structural grades), it is suggested grouping in two or three structural categories assuring data balance in the categories: a similar proportion of data on each category. Many grouping scenarios were created to explore the best grouping assuring that balance, considering as criteria the importance level of the structural conditions and prevailing the same data proportion on each category. The importance level of the structural conditions grouping means that only could be grouped in order of severity that represents the grades: i.e. that grade 1 cannot be grouped with grade 5, or grade 1 cannot be grouped with grades three unless in the group is included grade 2.

The sum of squared difference was the indicator used to evaluate the categories balance (as shown in the Equation C3 with an example of three categories), the chosen aggrupation of categories is the one with the lowest sum of squared differences.

$$\boldsymbol{min \sum x^2 = (C_1 - C_2)^2 + (C_2 - C_3)^2 + (C_3 - C_1)^2}$$

Equation C.3. Sum of squared differences (three categories example)

Being C_1, C_2, and C_3, the length of data for each category.

Hernández et al. (2019c) and Caradot et al. (2018) used the proposed metrics considering three structural categories and Guzmán-Fierro et al. (2019c) considered two structural categories.

The performance metrics used here allow to manage specific objectives and serve as tools to build effective investment plans to maintain the operation of the network or to rehabilitate specific elements that can reach a critical condition (Rokstad & Ugarelli, 2015).

8.2. OPTIMISATION METHODOLOGY

As the machine learning methods have taken relevance for the development of deterioration models because of the successful predictions of structural conditions of the sewer assets (Mashford et al., 2010; Harvey & McBean, 2014; and Rokstad & Ugarelli, 2015), it is essential to increase their prediction capacity, finding the combination of optimal hyperparameters and guiding the prediction to specific management objectives. Among the hyperparameters are included the hyperparameters proper to the machine learning tools and the weights of the structural conditions to give equity to the prediction models, reducing the classification errors provided by the data distribution (Gunn, 1998).

The present optimising methodology suggests two steps for finding the optimal combination of hyperparameters that increase the prediction quality of the deterioration models: the grid search technique (Caradot et al., 2018) and the differential evolution algorithm (DE) technique (Hernández et al., 2019c). For more details about these methods, see item 2.1.4 and subchapter 3.3 of part A and item 6.1.3 of part B.

In this proposal were considered both techniques because: (i) the grid search technique only gives a rank where are located the optimal hyperparameters, and (ii) the DE technique is successful in finding the optimal hyper-parameters combination in the search space that falls into an optimal global solution (Torres et al., 2013; Zhang et al., 2015). Hence, constraining the search space by the grid search technique support the finding of the DE technique. Any objective function works with the present methodology. For this thesis, the minimisation of *Knet* and *Kpipe* metrics are the objectives functions.

The database used for this methodology should contain the covariates (variables chosen as influential over the structural conditions) and the response variable (grades or categories that represent the structural conditions). The database is divided randomly, 70% of the data for calibration and the rest for validation. The calibration data helps to search for the optimal hyper-parameter combination to achieve the management purposes following the next procedures.

8.2.1. GRID-SEARCH TECNIQUE PROCEDURE

This methodology consists of two steps to reduce computation time. The idea is to run a first coarse grid search to find the optimal values rank for the most sensitive parameters, in this case, the weighting factors, and a second fine grid search with thinner weight values to identify the optimal values of the remaining hyperparameters. With this two-step procedure, the computation time for the parameter search can be reduced compared to a full grid search covering all hyperparameters (Bergstra & Bengio, 2012).

- Step 1 – Random Search: a list of 1000 random hyperparameter combinations has been prepared based on the reasonable range of variation of the hyperparameters. For each combination of hyperparameters, a five-fold cross-validation procedure has been performed on the training dataset using the performance metrics defined in the previous section.
  - The calibration dataset is divided into five random equal-sized subsets
  - Of the five subsets, a single subset is retained as the testing data to calculate the performance metrics and the remaining four subsets are used to train the model

  This procedure is repeated five times with each subset as testing data. Finally, it calculates the median of the five sets of performance metrics. It is keeping the hyperparameters ranks in which the performance metrics were the lowest. Finally, the obtained *Knet* and *Kpipe* values are plotting according to tested weigh values of the grid search to identify the weight values rank that could maximize the performance prediction: lowest values of *Knet* and *Kpipe.*

- Step 2 – grid search: It is repeated with fixed values of weights and varying the values of the remaining hyperparameters. Again, the values of the metrics *Knet* and *Kpipe* are plotted against the hyperparameters to identify the combination that maximises the performance: lowest values of the metric *Knet* and *Kpipe.*

The result of this technique is giving ranks of the hyperparameters' values that could provide a search space to find the local solution of their optimal combination.

8.2.2. DIFFERENTIAL EVOLUTION (DE) ALGORITHM METHODOLOGY

Once defined the search space for the optimal combination of the hyperparameters, the DE algorithm optimisation methodology is applied. *Knet* and *Kpipe* metrics are the objective functions that the DE algorithm attempts to minimise. In the following procedure are the steps for this optimisation methodology:

- Step 1- Defining hyperparameter values ranking and objective function: it is given to the DE algorithm the minimum and maximum values of the hyperparameters found by Grid Search technique and the objective function to minimize: *Knet* or *Kpipe* (Equations C1 and C2 respectively)
- Step 2 – Five Monte-Carlo (MC) simulations: as the grid search technique, the calibration data is divided five times randomly, splitting each subset in 70% for training and 30% for testing data.
- Step 3 – Machine learning-based deterioration model: for each MC simulation, the model uses the 70% of the data for training it with the hyperparameters given by the DE algorithm, then with the resulting model is predicted the structural conditions for the testing data and evaluated with observed structural conditions of the testing data by performance metric (*Knet* or *Kpipe*). Into a vector, it saves the five elements of the performance metric values of MC simulations.
- Step 4 – Median of the performance metric: it calculates the median value of the five metric values saved on the vector. From the median value, the DE algorithm search other combination of hyperparameter values in the search space given in step 1.
- Step 5 – 1000 times repetitions: The procedure from steps 2 to 4 repeats 1000 times again searching the combination of hyperparameters that minimize the objective function (*Knet* or *Kpipe*). The DE algorithm proves other hyperparameter values' combination whose result should be the lowest than the median of the last repetition. If the median value is higher or equal to the last median of the last time, the DE algorithm saves the hyperparameters combination that obtained the lowest median of the performance metric and tries other hyperparameters combinations closest to the one that obtained the lowest median performance metric.

In the end, it is chosen the hyperparameter values combination that the DE algorithm could search after 1000 searching.

CHAPTER 9: METHODOLOGY FOR IDENTIFYING THE KEY AND ENOUGH FACTORS FOR ACHIEVING OBJECTIVES IN SEWER ASSET MANAGEMENT

The developed tools described in chapter 7 and 8 were relevant due to fulfilling different goals: (i) identification of the main variables that influence over the structural condition; and (ii) finding the optimal combination of hyperparameters of the machine learning-based deterioration models for two management objectives linked to two performance metrics(subchapter 8.1).

The first attempt of integration was developed in a methodology to select the appropriate prediction models for two sewer asset management objectives, as well as the selection of enough variables and training data to maximise the prediction quality of models. In this methodology, two deterioration models, the proposed performance metrics, and the optimisation methodology are integrated (chapter 8). The results showed the importance of selecting variables and methods for implementing prediction models for specific case studies and orienting to management objectives (Guzmán-Fierro et al.,2019c). This methodology was developed together with the Master student Julián Guzmán who was directed by the supervisor and the author of this doctoral thesis. The products of this methodology were the direction of the master thesis entitled "*Methodology for selecting suitable variables, prediction models and data subsets to maximize the prediction capacity of decision-making support models for different sewer asset management objectives*", which was defended in July 2019, and submitted as a paper on the Journal of Infrastructures Systems in November 2019 (Guzmán-Fierro et al., 2019c). For more details about this methodology, please see appendix -Part C.

From the advantage of the above methodology, the principal proposed methodology of this doctoral thesis born. This methodology consists of two parts: (i) Bayesian Network-based methodology for selecting features hierarchically described in subchapter 9.1.; and a methodology to choose the deterioration model for achieving a management objective described in subchapter 9.2. From this methodology, it is possible to determine which factors are enough and necessary to achieve specific goals in sewer asset management, considering the quantity and quality of the available information. This methodology could be applied in any case study that owns its local assessment standard.

9.1. BAYESIAN NETWORK BASED METHODOLOGY FOR SELECTING FEATURE HIERARCHICALLY

Thanks to the properties (Item 6.1.1.) and successful results using the Bayesian Networks (BN) tool as a feature selection method in Guzmán-Fierro et al. (2019a) (Chapter 7), it proposes a second BN-based methodology that establishes a relationship with the structural condition in different importance levels: first, second and third-grade relation. The idea with this classification is exploring the prediction quality of the deterioration models adding each variables group that represents the different importance levels in the deterioration of sewer assets.

The first-grade relationship refers to those variables that display a direct relationship with the structural condition, and these variables are called *"Parent variables"*; the second-grade relationship refers to those variables that show a direct relationship with the parent variables, and these are called *"Grand-Parent Variables"*; and the third-grade relation are those variables that depict direct relationship with the Grand-Parents variables, and these variables are called *"Grand-Grand Parent variables"*.

The proposed methodology consists of the following five steps:

- ***Step 1 - Definition of the data:*** the database should contain the collected variables and the variable that represent the structural condition. Whole variables should be categorical variables. Numerical variables are categorized by to boxplots' analysis with the purpose to make a fair categorization.
- ***Step 2 - random selections of data sets:*** it creates different data sets that vary from 2% to 100% of data with 2% steps and 1000 random selection for each set to find the first, second and third-grade relationship variables with the structural condition for each subset. In the end, it chooses randomly 1000 data from these 50 sets. 1000 random selections were chosen for applying Monte-Carlo simulations, to find an agreement between the low computational cost and a rank of possible prediction performance that the model could achieve considering a large amount of random data selection. This agreement also is suggested in the findings of Bauer & Guzy (2004) and Austin (2009). Moreover, the criteria of choosing the percentages steps to build the different subsets are according to the user decision, for this case the authors chose ranks of 2% steps for exploring the dynamic of the relationship of the variables with the structural condition considering the size of the subsets.

- ***Step 3 –Probability of relationship with the structural condition:*** It builds a BN following any structure learning algorithm to find the first, second, and third-grade relationship variables with the structural condition for each data subset. 1000 Monte-Carlo simulations (MC) are making, according to the 1000 selected data for each subset. When it finishes the Monte-Carlo simulations, it is counting the number of times each variable has first, second and/or third-grade relationships with the structural condition to calculate their probability: number of times of each relationship grade over 1000.
- ***Step 4 – Summary of the probabilities:*** according to the results from step 3, it summarises the probabilities of the variables that present first, second and third-grade relationship with the structural condition in boxplots: it summarises each variable's relationship with the structural condition in a boxplot, The boxplot contains the probabilities of that relationship considering the different data subsets (from 2% to 100% of data by 2% steps). The purpose of this sum up is to identify that, regardless that the percentage of data changes, the studied variables show any relationship grade with the structural condition.
- ***Step 5 – Classification of the variables according to the relationship importance level with the structural condition:*** it analysis the above boxplots beginning with the probabilities of the variables that present a first-grade relationship. It selects the variables whose boxplot's median is over 0.05, and the others are leaving aside. The chosen variables are called "parent variables". The cut-off was in 0.05 because it shows that the relationship between variables is non-depreciable, and it selects the median because it is the most representative value of the data that characterises the boxplot. Then, it carries out the same procedure with the boxplots that represent the variables that show the second-grade relationship with the structural condition; however, it does not consider the variables (boxplot median higher than 0.05) are called "grandparent variables". Likewise, this procedure repeats with the boxplots that represent the variables that show the third-grade relationship with the structural condition leaving aside the variables already chosen as parent and grandparent variables. The selected variables for this last boxplot analysis are called "grand-grandparent variables" and the variables whose boxplot median below 0.05 represent the variables that do not show any relationship with the structural condition.

This methodology could be applied for different structural condition scenarios (SCS) to evaluate their importance on the structural deterioration following the management plan that managers would like to develop, for example, structural condition scenarios considering: (i) the five structural grades provided by the local standards that give parameters to manage the sewer assets; (ii) three categories in which classify in excellent, intermediate and critical structural conditions to re-address management parameters; two categories in which classifies in two conditions types (i.e. excellent and critical structural conditions, acceptable and poor structural conditions, sewer assets without structural failures, and with structural failures). The aggrupation of the structural conditions in (SCS) follows the equation C.3 of the subchapter 8.1 of this manuscript to keep a balance among the categories of the SCS.

Figure C.2. shows a flowchart describing the above methodology graphically.

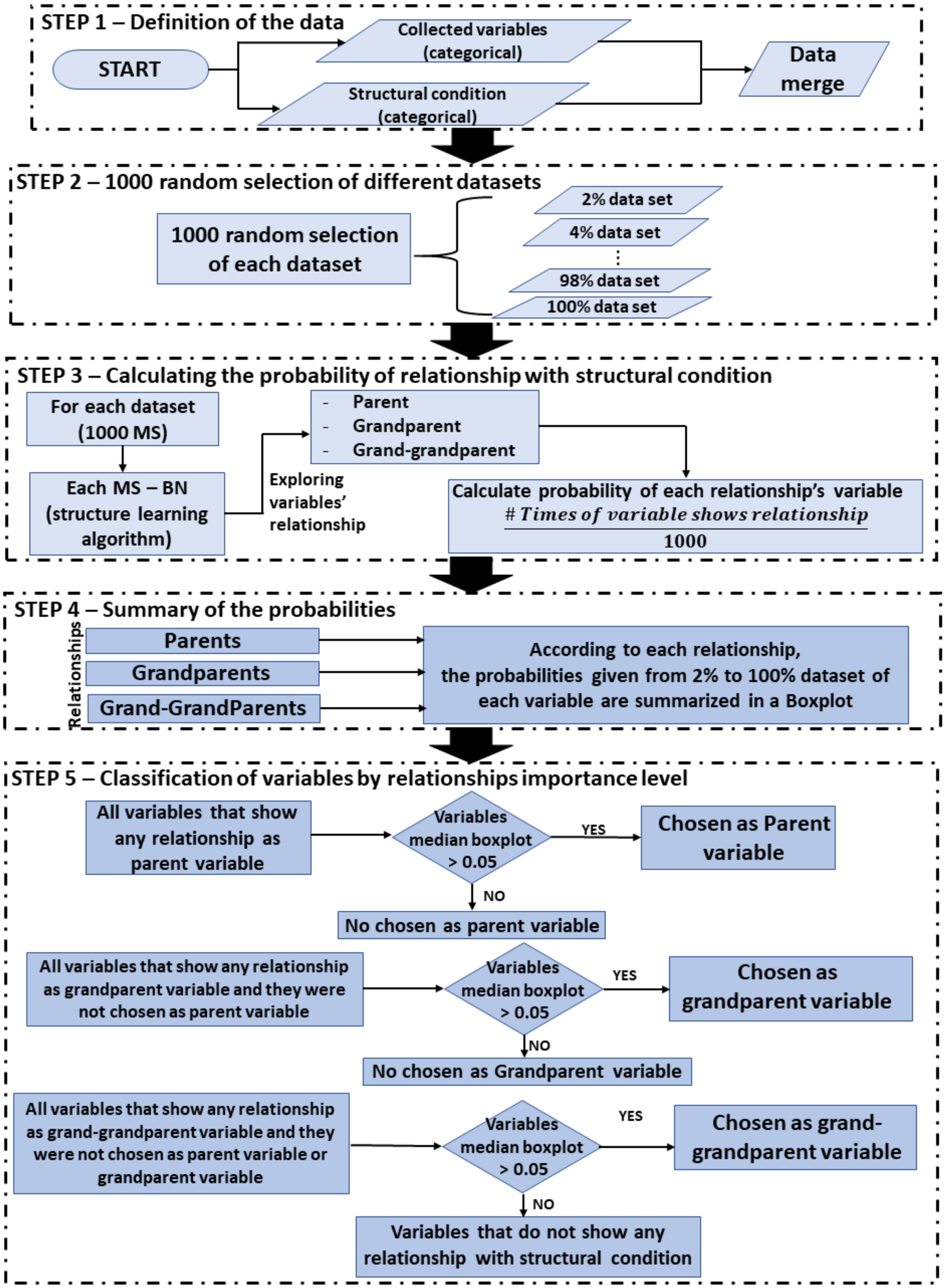

Figure C.2. Flowchart of the Bayesian Network-based methodology for selecting features hierarchically. Source: Author

9.2. METHODOLOGY FOR THE SELECTION OF THE DETERIORATION MODEL FOR A MANAGEMENT OBJECTIVE

According to the classification of influential variables suggested by the BN-based methodology, proposed in subchapter 9.1., the deterioration models are built and optimised considering each level importance of variables group: Parent, Grandparents, Grand-grandparents, and all variables. Then, it carries out a boxplot analysis to select the most appropriate model. Machine learning and statistical methods such as Random Forest (RF), Support Vector Machines (SVM)), linear discriminant analysis (LDA), and binomial (LR), multinomial (Multi_LR) and Ordinal logistic regressions (Ord_LR) were the basis of the explored deterioration models. Their selection was focused on their application in other case studies with successful predictions results in predicting the structural condition of the sewer assets (Wright et al. 2006; Mashford et al., 2010; Salman & Salem, 2011; Younis & Knight, 2010; Harvey and McBean, 2014; Rokstad & Ugarelli, 2015). Experiences reported in item 6.1.2. of Part B.

This methodology contains the following three steps:

- ***Step 1 - Exploration of different deterioration models:*** according to the literature, it explores different deterioration models (see items 2.6, 2.7, 2.8, 2.9, 3.1, and 3.2 of Part A and 6.1.2. of Part B) evaluated by different performance metrics such as Cohen's Kappa coefficient, ROC space, Performance curve and Deviation analysis (Chapter 4 and item 6.1.4 of Part A and B) to identify the prediction advantages of each model. According to the conclusions of Part B, there is not a unique model for predicting the structural condition of the sewer assets; there are multiple models that could achieve good prediction qualities, it depends on which is the most adapted to each case study and to the management objective. Hence, the exploration of different deterioration models is fundamental.
- ***Step 2 – Optimisation of the chosen deterioration models:*** once are chosen the methods that give the highest performance quality to develop deterioration models; new deterioration models are built considering Parents, Grandparents, Grand-grandparents and all variables. For increasing the performance quality of the deterioration model to reach a management objective, it applies the methodology proposed in subchapter 8.2 for the 70% of the data (training data) to find the optimal hyperparameters' combination for models whose basis are machine learning methods. There is one change in the application of the methodology described in

subchapter 8.2.: instead of five-fold cross-validations, it carries out ten-fold cross-validations in step 2 related to the Differential Evolution (DE) algorithm methodology to rise reliability for finding the proper combination of the hyperparameters. This change was made following the criteria of the author of this thesis to increase the reliability for finding the proper combination of the hyperparameters, but not increasing meaningfully the computational costs. Regarding to models related to Logistic Regression models, the hyperparameters to find are related to the coefficients of the considered variables in the model. As it is shown in the items 2.3, 2.4 and 2.5 of Part A, the logistic regression models fit as linear regressions because of the transformation in odds functions. Therefore, the optimisation of these models is handling with numeric methods such as Maximum Likelihood estimation and Newton-Raphson methods (Hilbe, 2009). The functions of the R's libraries *glm*, *nnet* and *MASS* fits the models using the above numeric methods by default (see item 6.2.1.3 of Part B).

- Step 3 – Selection of the model: Once found the combinations of hyperparameters that most minimise the *Knet* and *Kpipe* metrics for each developed deterioration models, again 70% of the data are choosing as training data to develop this step. 1000 random selections of 70% and 30% of the training are choosing as calibration and validation subsets respectively, to apply the deterioration models considering the combination of hyperparameters found. Anew, it carries out 1000 Monte-Carlo Simulations to find the balance between the computational costs and enough quantity of random data selection to assess the possible prediction performance rank that could reach the model (procedure also implemented in the methodologies of chapter 7, and subchapters 8.2 and 9.1 and appendix – Part C, suggested by Vieira et al., (2010)). Depending on the management objective (*Knet* or *Kpipe*) for the deterioration model was developed, 1000 *Knet* (or *Kpipe*) values are obtained for each deterioration model, and these values are plotted in boxplots to visualize the ranks of *Knet* (or *Kpipe*) values obtained by the deterioration models. Then, Wilcoxon-signed rank tests are applied to measure statistically significant differences among the *Knet* (or *Kpipe*) values obtained by the evaluated deterioration models: the Wilcoxon-signed rank test is evaluated by pairs of samples, it means that all models are compared by pairs building a matrix that shows the p-values of these comparisons. The model chosen for the management objective is the one that: (i) its boxplot depicts the lowest values of *Knet* (or *Kpipe*); and (ii) shows significant differences with the values of the other deterioration models. In the case that the *Knet* (or *Kpipe*) values of the deterioration models do not show significant differences, it is chosen the model with fewer needed variables to be built.

The above methodology is carried out by each deterioration model that looks for reaching a management objective that links with the *Knet* and *Kpipe* metrics. Likewise, this methodology could be applied considering different SCS for achieving the same management objective. In the end, it chooses the most suitable SCS comparing the obtained *Knet* (or *Kpipe*) values by the Wilcoxon signed-rank test to find differences significantly. If there are differences significantly between the *Knet* (or *Kpipe*) values, it chooses the one whose boxplot shows the lowest *Knet* (or *Kpipe*) values. On the contrary, it chooses the model with fewer needed variables to be developed.

Figure C.3. shows a flowchart that describes graphically the current methodology.

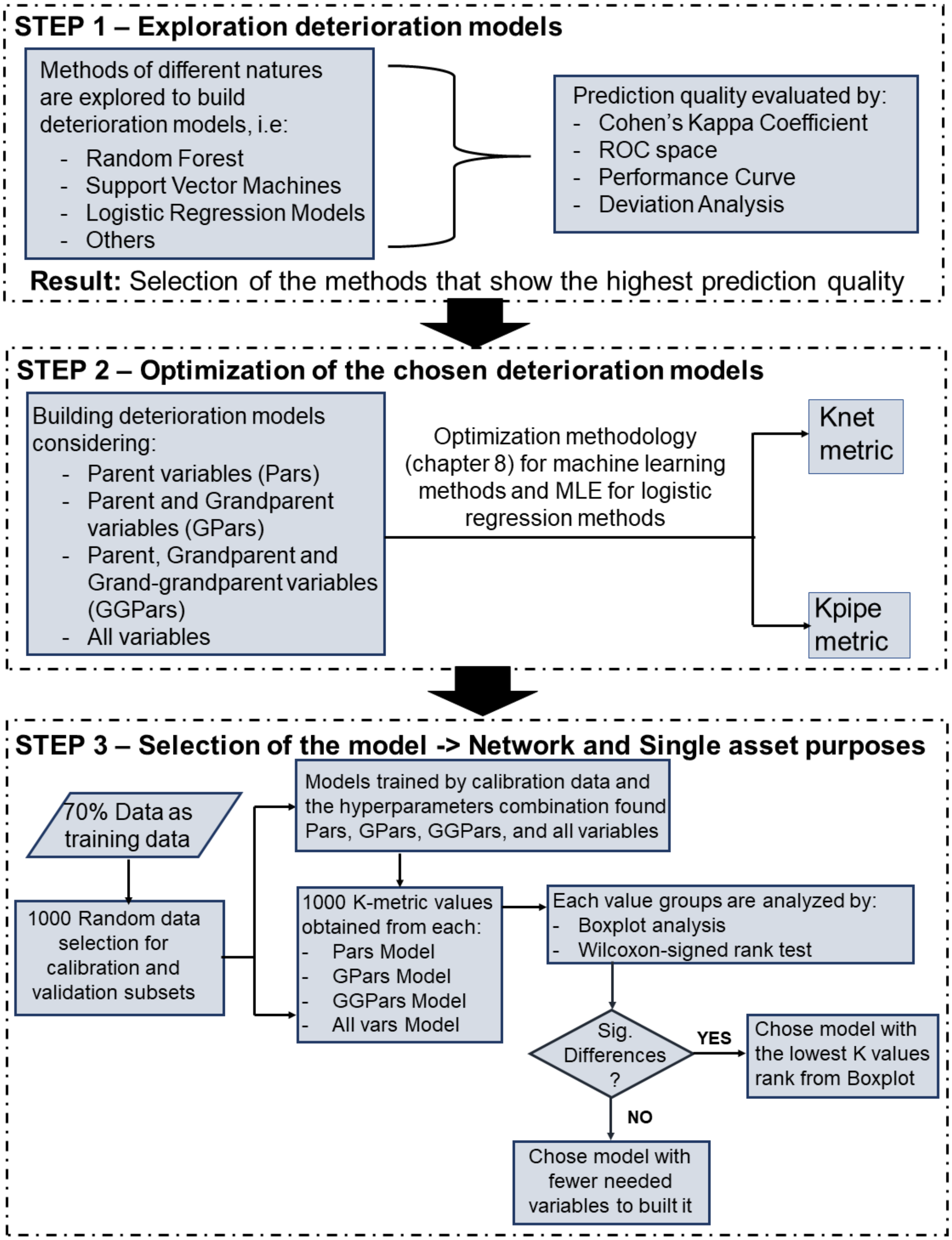

Figure C.3. Flowchart of the methodology for selecting the deterioration model for a management objective

CONCLUSIONS PART C

The following conclusions show the contribution of the developed tools in the sewer asset management field. The development of these tools was vital for developing the principal methodology proposed for this doctoral thesis (Part D).

It develops a methodology based on methodology Bayesian Network as a feature selection method to prioritise and select the minimum and enough variables that allow predicting the structural condition of sewer pipes with the same prediction performance as a model that considers several variables. The selection and reduction of the number of variables diminish the quantity of information to collect, and therefore, a lower amount of investment resources re-addresses to data collection. The use and integration of agreement measure, statistical tests and Monte-Carlo simulations allows measuring in a simple, direct and robust way the prediction assessment of the model, the existence of significant differences between one or another, and decreasing probabilities of random effects. It makes a model more trustworthy for being used for the utilities in a sewer system of any city. As well, Bayesian Networks was a proper tool for integrating qualitative and quantitative information by cause-effects analysing, removing limitations of the type of data (Guzmán-Fierro et al., 2019b).

According to the above, performance metrics were developed with the purpose to link these metrics with specific management objectives. The development of each metric was based on the ones found in the literature for measuring the accuracy of the predictions such as ROC space, Cohen's Kappa coefficient, performance curve, and deviation analysis. It shows the development of two metrics following the management objectives that search the managers currently: for developing investment plans (predictions at the network levels) and rehabilitation plans (predictions at the pipe level) (Rokstad & Ugarelli, 2015; Caradot et al., 2018, Hernández et al., 2019c). Besides, the development of specific metrics for each management objective allows evaluating the accuracy of the developed deterioration models under two different perspectives. As each metric links to a particular management objective, it makes easier the optimisation of deterioration models, guiding the predictions for achieving a specific management objective. It this way, the metric works as an objective function in the optimisation method.

Additionally, it proposes an optimisation methodology linking two main techniques: Grid Search and Differential Evolutionary algorithm. Both techniques are complementary, due to Grid Search finds a rank where could be the global solution, and the Differential Evolutionary algorithm could find the global solution of that rank. Moreover, both techniques consider Monte-Carlo simulations for avoiding overtraining problems (Caradot et al., 2018; Hernández et al., 2019c). The proposed optimisation methodology could be applied to find a suitable combination of hyper-parameters for deterioration models based on machine learning tools (Hernández et al., 2019c).

From the results of the developed tools of chapter 7 and 8, it was possible to build a complete methodology that integrates these tools. This methodology consists of two parts whose objective is determining which factors are enough and necessary to achieve specific management objectives in sewer asset management, considering the quantity and quality of the available information.

The first part of this methodology is a Bayesian Networks based methodology that proposes to classify the importance of influential variables in the deterioration of the structural conditions of sewer assets. This classification allows focusing on the collection of the most influential variables, reducing the information collecting costs. Moreover, the integration of boxplots analysis, the application of Monte-Carlo simulations, and the study of the variables by different sizes of data subset in this methodology assure the reliability and robustness of this classification.

Regarding the second methodology of the complete one, whose goal is selecting the most appropriate deterioration model to support a management objective, allows identifying the advantages of some deterioration models over others for specific sewer asset management objectives. The exploration of methods of different mathematical approaches and their evaluation under different management perspectives confirms that there is not only one method that could fulfil the requirements to support different sewer asset management objectives. Also, the integration of optimisation methodologies, the application of Monte-Carlo simulations with cross-validation techniques strengthens the methodology of selection, reducing the overtraining process and outlier's prediction results.

The above methodology is flexible because: (i) some decisions depends on the user criteria; (ii) it could be implemented in different case studies with any restrictions of the inclusion of characteristics of different nature; and (iii) it could be applied for different aggrupation of structural conditions of the sewer assets (Structural Conditions Scenarios – SCS). It implies that the methodology could be reproduced in other databases to support sewer asset management or other infrastructure asset management.

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PART D METHODOLOGY'S APPLICATION FOR CASE STUDIES

Part D presents the results of this doctoral thesis. This part has two chapters: (i) Chapter 10 depicts the results obtained from the antecedent tools (chapters 7 and 8 of Part C); and (ii) Chapter 11 shows the results of the methodology proposed in this PhD thesis for Bogota's and Medellin's cases (see description of the methodology in chapter 9 of Part D).

The importance of presenting the results of the antecedent tools lies in the fact that from their successful results, the author made decisions on integrating and modifying some of them to build the proposed methodology (describes in chapter 9). Chapter 10 contains: (i) the results of the proposed method of chapter 7 for prioritising some variables over others to achieve the same prediction quality as if the model had been considered all collected variables for Bogota's case; (ii) the results from the exploration of different machine learning and statistical methods for developing deterioration models to predict the structural conditions of the sewer assets for Colombian and German case studies; and (iii) the results from the application of the optimisation methodology (chapter 8, Part C) for SVM-based models to support two objectives for the sewer asset management of Bogota's sewer network. These results are published in Hernández et al. (2017a, b and c; 2018a, b; 2019b and c), Caradot et al., (2018) and Guzmán-Fierro et al. (2019a, b and c).

According to the results of chapter 10, the methodology proposed of chapter 9 was developed. From the results of chapter 10, it was identified the use of some methods for: (i) selecting and hierarchising the importance of some characteristics over the deterioration of the structural condition of the sewer assets; (ii) achieving the prediction of uninspected sewer assets for different management perspectives; and (iii) the effectivity of finding the optimal hyperparameters to increase the prediction for a specific management objective.

Therefore, the methodology proposed in chapter 9 integrates all these methods to develop a complete methodology able to find which variables are needed and under which deterioration model could achieve a specific management objective. This methodology was applied for two Colombian case studies which contain enough information to develop it. Thanks to this integration, it is possible to answer the research question mentioned in the general introduction. The first part of the methodology (subchapter 9.1) gives a hierarchisation of the key factors to develop deterioration in the second part of the methodology, and from their application in the two case studies (Bogotá and Medellín), it is possible to identify the influential factors on each case study and analysing if these vary according to the own characteristics and management objectives.

Chapter 11 depicts the results of the application of the methodology proposed in chapter 9 in Bogota's and Medellin's cases. The methodology was developed for different management objectives and structural condition scenarios (SCS) that support the management plans. Prediction at network and pipe level were the objectives proposed to support investment and rehabilitation plans. As well, the exploration of different SCS was suggested because of (i) the exploration of the prediction quality and (ii) to facilitate the decision-making in sewer asset management. Four structural conditions scenarios were built for both case studies to evaluate the most suitable configuration for prediction purposes.

Chapter 11 contains the subchapters 11.1. and 11.2 which show the results of the application of the proposed for Bogota and Medellin. Each subchapter contains: (i) the hierarchy of the variables that influence the structural condition for each SCS; (ii) the exploration and identification of which statistical and machine learning methods are more suitable for predicting the structural condition under different perspectives (at network and pipe sewer asset level); (iii) the optimal hyperparameters found for each machine learning method to achieve a management objective (at network and pipe sewer asset levels); and finally (iv) the selection of the most suitable deterioration model for the two evaluated management objective for each SCS. Maps at network and pipe sewer asset level are shown to design financial plans and rehabilitation activities for both case studies. Subchapter 11.3 presents a discussion of the obtained results in the application of the proposed methodology for Bogota's and Medellin's cases (subchapters 11.1 and 11.2).

CHAPTER 10: FIRST RESULTS

The results shown in chapter 10 are related to the developed tools depicted in chapter 7 and 8 of Part C and the exploration of different statistical and learning machine methods to develop deterioration models (6.1.2). This chapter consists of four subchapters: (i) Results of feature selection tool based on Bayesian Networks (Guzmán-Fierro et al., 2019a, b); (ii) Results of the exploration of different deterioration models (Hernández et al. 2017a,b,c; 2018a and 2019a,b); and (iii) Results of the application of the proposed optimisation methodology (Hernández et al., 2018b, 2019c).

Most of the results of chapter 10 are written in more detail in some published articles (Guzmán-Fierro et al., 2019b, Hernández et al., 2019a, b and c) and articles in submitted status (Hernández et al. 2017a, b, c; 2018a; 2018b; Caradot et al., 2018; Guzmán et al. 2019a). From the results of this chapter, it was possible to make decisions for constructing the methodology, the main objective of this PhD thesis.

10.1. RESULTS OF FEATURE SELECTION TOOL

A BN-based methodology reported in Guzmán-Fierro et al. (2019a) and described in chapter 7 (Part C) of this manuscript was applied for Bogota's sewer system. This first methodology was developed to prioritize and select a minimal number of variables that allows predicting the structural condition of sewer pipes.

The Bayesian Network (BN)-based method has been used to develop methodologies for finding the variables that influence the structural condition. During the doctoral period, two methodologies were developed using this method.

Chapter 7 (Part C) depicts a methodology to prioritize and select a minimal number of variables that allows predicting the structural condition of sewer pipes (methodology reported on Guzmán-Fierro et al. (2019a, b)) and Chapter 9 (Part C) depicts a methodology that establishes a classification that gives different relationship levels of some variables with the structural condition for prediction purposes, a methodology that being part of the principal methodology proposed in this PhD thesis. This subchapter shows only the most relevant results obtained using the first developed Bayesian Network-based methodology described in chapter 7 (Part C).

This methodology applies for Bogota's sewer system, and the considered variables for this study were physical characteristics of the sewer assets such as material ("Mat"), length

("Leng"), diameter ("Diam"), type of effluent ("Sew"), network type ("Net"), age ("Age"), depth ("Depth") and slope ("Slope"); and surrounding variables such as geotechnical zones ("Geotech"), water level depths ("W_T_D"), districts ("Distr"), land uses ("Land_U"), surface material ("Mat_R"), road type ("Road_Typ"), closeness to water bodies ("Water_B") and intrusive trees ("Tree"). The performance quality of three structural condition scenarios was analysed considering (i) the five structural grades given by NS-058 (EAAB, 2001); (ii) two structural categories discriminating the critical conditions with the others (suggested by Ariaratnam et al., 2001); and (iii) two structural categories evaluating only the critical and excellent conditions, leaving aside intermediate conditions (following the suggestions of López-Kleine et al. 2016). Furthermore, the chosen learning algorithm was Hill-Climbing because of its successful predictions in the exploration.

According to the results of this methodology, Figure D.1. shows in boxplots the K values obtained from validation data of each SCS to visualise the performance and the variability that each model could reach.

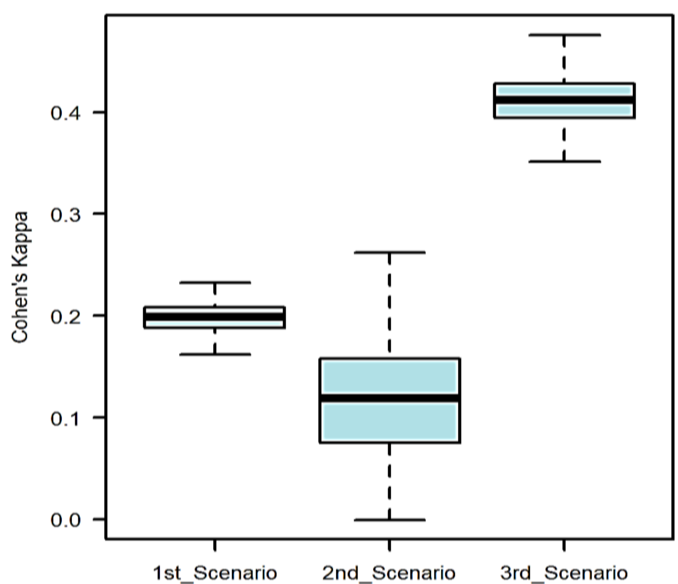

Figure D.1 Boxplots of validation Cohen's Kappa values obtained from the three SCS proposed in Guzmán-Fierro et al. (2019b). Source: Guzmán-Fierro et al. (2019b)

According to Figure D.1. the K's set of the third scenario shows a median of 0.41 which is significantly higher (Wilcoxon test, p-value <0.001) than the first and second scenarios whose K's medians are around 0.19 and 0.12 respectively. Consistent with the classification of the association agreement, that represents K, proposed by Cerda & Villarroel, (2008), the third scenario shows a moderate association agreement (K's values around of 0.41-0.60) between the prediction and observation data, while the other scenarios show K's values that correspond to a low association agreement (0.1 - 0.2). Therefore, the third scenario was chosen based on these results and considering that the methodology seeks to increase the prediction capacity of the BN model.

The above results confirm the findings of Ariaratnam et al. (2001), who suggests that two categories are sufficient to correctly classify the status of the infrastructure: non-deficient status (sewers without any failures) and deficient status (sewers with failure); and López-Kleine et al. (2016) who, for the same case study of the present work, found a better prediction quality of the structural condition of sewer pipes considering only structural grades 1 and 5 instead of the five structural grades described in NS-058 standard (EAAB, 2001).

Also, once it was chosen the SCS with the highest performance quality (third scenario), this methodology tested different calibration/validation percentage subsets to evaluate which subsets significantly increase the prediction quality of the BN-based model. Figure D.2. shows the boxplot analysis of Cohen's Kappa coefficient obtained from the validation results of the different calibration/validation percentage subsets.

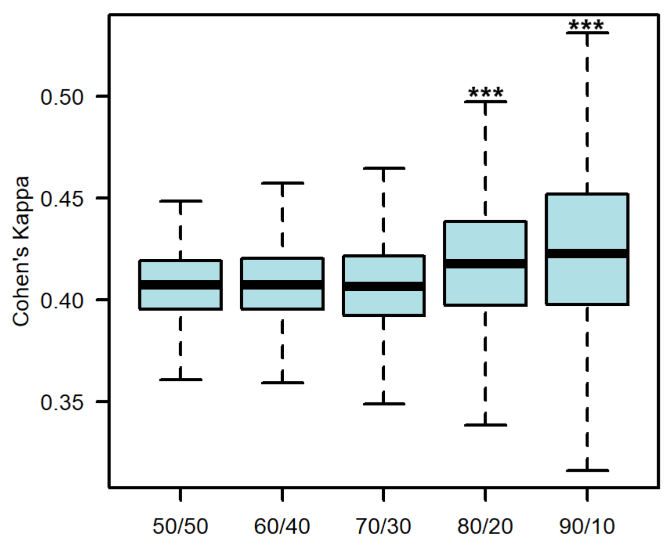

*Figure D.2 Boxplots of Cohen's Kappa values obtained from models that considered calibration/validation percentage subsets between 50%/50% and 90%/10% (***p-value <0.001). Source: Guzmán-Fierro et al. (2019b)*

According to Figure D.2, the validation K's set related to 90%/10% percentage subsets shows significantly highest values in comparison to the other groups of percentages subsets, with a median K's value of 0.420 (Figure D.2). However, the variation of this percentage subsets group is the largest of all groups with K's values (varies from 0.320 to 0.530), which makes it less favourable to predict the structural condition of sewer pipes.

On the other hand, the boxplot related to the 80%/20% calibration/validation percentages subsets results show a K's median around 0.417 with lower variability than the 90%/10% percentage subsets group, and it requires less information to calibrate the prediction model; therefore, the group of subsets of 80%/20% for calibration/validation data was chosen for the BN-based model. Figure D.3 shows the most common Bayesian Network (BN) obtained (from 1000 trained) for the 80%/20% calibration/validation percentage subsets considering the structural condition scenario that only predicts the excellent and critical structural conditions of the sewer assets.

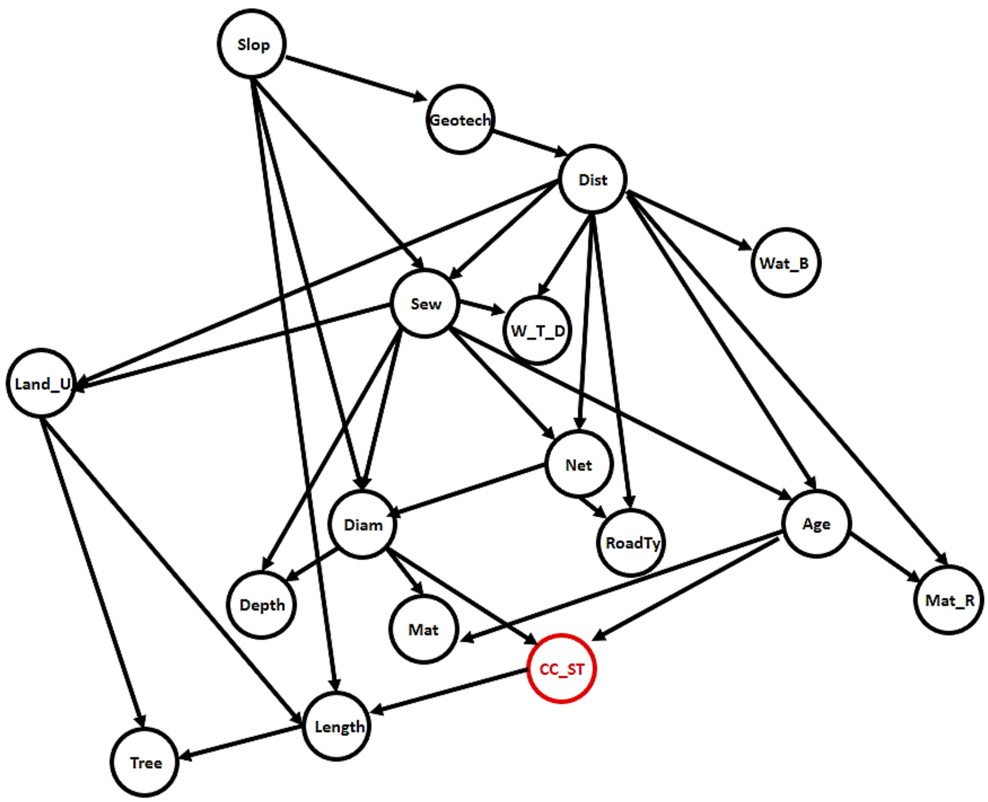

Figure D.3 The most representative BN model with 1000 random selections following 80%/20% calibration/validation percentage and all available variables. Source: Guzmán-Fierro et al. (2019b)

As shown in the BN (Figure D.3), the age and the diameter are the variables with a direct relationship with the structural condition (first parenting nodes of the structural condition). The first dependence relationships found in this BN with the structural condition, for the case study, agrees with studies such as Ariaratman et al. (2001), Yan & Vairavamoorthy (2003), Chughtai & Zayed (2011) and Salman (2010) that show that these two variables play a significant role in the structural deterioration of sewer pipes and therefore in their structural condition.

In the end, two BN-based models were built considering (i) all the studied variables "reference model" (16_var), and (ii) only the variables with direct a relationship with the structural condition, age and diameter of the sewer assets "reduced variables model" (2_var). Figure D.4. shows the comparison of both models by boxplot analysis.

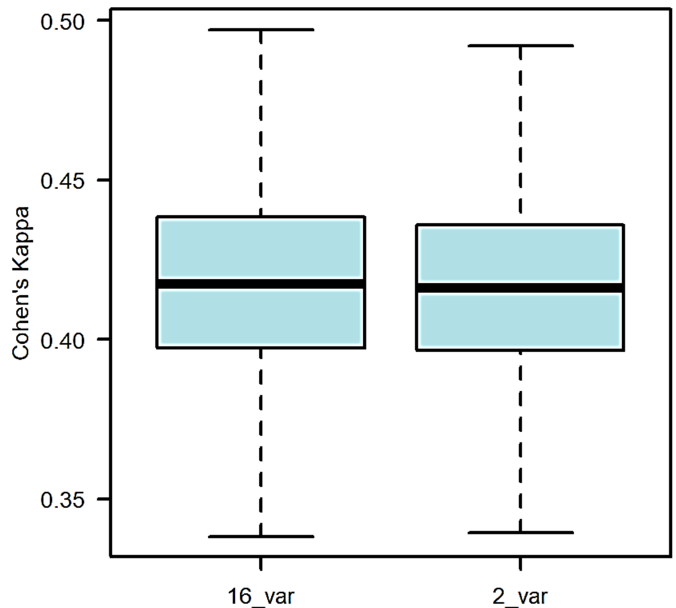

Figure D.4 Boxplots of validation K's sets obtained by the "reference model" (16_var) and the "reduced variables model" considering only the first parenting variable relationships with the structural condition (2_var): age and diameter of sewers

According to Figure D.4, the K's set related to "reference model" shows a median of 0.438 that is not significantly higher (Wilcoxon test p = 0.08) than the median of the K's set related to the "reduced variables model" (K's median of 0.432). This result shows that only considering the diameter and the age of sewer assets; it is possible to build a prediction model, using BN, that achieve the same prediction capacity (K's> 0.4 - moderate association agreement between predicted and observed structural conditions) than a model based on BN that considers more variables. For more details about the prediction application in Bogota's case, please see Guzmán-Fierro et al. (2019a, b).

10.2. RESULTS OF DIFFERENT DETERIORATION MODELS

This subchapter consists of depicting the results of the exploration of different statistical and machine learning methods. This exploration was vital and gave clues to develop the methodology proposed in this manuscript. Other works such as Hernández et al. (2017b;

2019a; 2019d) include an exploration of some methods such as SVM and Logistic regression for estimating the structural states of uninspected sewer assets.

Subchapter 10.2. consists of two items: (i) Results of the exploration of different statistical and machine learning methods to develop deterioration models in sewer asset management for Bogota's case (Hernández et al., 2017a); and (ii) the results of the comparison of two deterioration models in a Colombian and a German case study (Hernández et al. 2017a; 2018a).

10.2.1. RESULTS OF EXPLORATION OF DETERIORATION MODELS FOR BOGOTA'S CASE

It shows a first exploration of statistical and machine learning-based methods to develop deterioration models that support the sewer asset management for Bogota's sewer system. Logistic regression (LR), Random Forest (RF), Multinomial logistic regression (Multi_LR), linear discriminant analysis (LDA) and support vector machines (SVM) were the explored methods for developing deterioration models and analysing their advantages or disadvantages to predict the critical conditions of the sewer assets under two study options: (i) considering only age as influential variable over the deterioration of the structural condition of the sewer assets; and (ii) considering the age together with other variables such as material, type of effluent, depth, length, slope and diameter of the sewer assets as influential variables over the deterioration of the structural conditions of the sewer assets. Table D.1. shows the ROC space analysis (True Positive Rate -TPR and False Positive Rate -FPR and their relationship by Positive Likelihood Rate PLR) of the explored deterioration models for Bogota's case.

Table D.1. ROC space coordinates (TRP and FPR) and PLR index from the prediction results by each method with (i) option 1: only the variable age; and (ii) option 2: age together with other covariates.

Method	option 1			option 2		
	TPR	FPR	PLR	TPR	FPR	PLR
Random Forest (RF)	0.62	0.22	2.82	0.57	0.15	3.80
Logistic Regression (LR)	0.07	0.04	1.75	0.38	0.07	5.43
Multinomial Logistic Regression (Multi_LR)	0.32	0.15	2.13	0.71	0.21	3.38
Linear Discriminant Analysis (LDA)	0.32	0.15	2.13	0.7	0.2	3.50
Support Vector Machine (SVM)	0.32	0.15	2.13	0.66	0.17	3.88

Source: Hernández et al. (2017a)

For option 1, results obtained with Multi_LR, LDA and SVM were the same (Table E.1) because Multi_LR and LDA estimate the same statistical significant coefficients (0.048) and SVM uses the same discriminant function such as the function of the hyperplane that best separates the data in a high dimensionality due to the data transformation by RBF kernel function. Furthermore, it is possible to observe the for LR results (TPR = 0.07 and FPR =0.04) are close to coordinates (0, 0) in ROC space, which means that this model has a low probability to predict any pipe in critical condition. The RF results show the highest values of TPR and PLR for model 1 (0.62 and 2.82, respectively). It means that RF has 62% of probability to predict the critical structural condition correctly, and it has 2.82 times more probability to predict this condition correctly than wrongly.

On the other hand, the prediction results considering all the co-variables (see Table D.1 - option 2), show that including more variables the prediction's capacity improves. The ROC space's coordinates are quite similar for all methods (except for LR): around 60-70% for TPR and 15-20% for FPR. The main difference among these four methods is in the PLR value: SVM and RF methods have higher values (around 4). Although TPR values for SVM and RF are lower than for LDA and Multi_LR, PLR index assures the prediction effectivity of SVM and RF methods: for 60 of pipes predicted in critical conditions, 15 pipes are mispredicted by SVM, and RF (PLR is 4) and 20 pipes are mispredicted by Multi_LR and LDA (PLR is 3). LR results show the lowest values of TPR and FPR; however, the PLR value is the highest (PLR is 5): for 60 pipes predicted in critical conditions, 12 are wrongly predicted.

The prediction results of the option 1 and 2 show that the five methods predicted more pipes correctly than wrongly, it could be due to the linear relationship between the structural condition and the variable age for both options: the older is the pipe, higher is the probability to be in critical condition (Davis et al., 2001). However, there are some notable differences among the methods' prediction for each option which are analysed in the following:

- For option 1, it is observed three behaviours: (i) the linear relationship between structural condition and the variable age (LDA, SVM, Multi_LR), (ii) the weak linear relationship between variable age and logit of the structural condition (LR); and (iii) the classification of the structural condition in a specific time period by the intuitive decision rules (RF). Although Multi_LR is based on a non-linear method (LR), the results are quite different from LR, probably because Multi_LR assumes independence among the groups of the dependent variable (structural condition).

This condition implies that when it is not valid, Multi_LR estimates unrealistic coefficients (it could guide method to be linear) which make an imperfect separation and could guide method to be linear (Melter & Vannata, 2015). In our case, the structural condition is an unreliable value, because this qualification depends on the quantity and seriousness of the found failures in the CCTV inspections; therefore these conditions are ordinal variables (EAAB, 2001).

- For option 2, the behaviour of Muti_LR and LDA is similar, but SVM does not. The behaviour of the SVM method considering other variables together with age is not linear due to the nature of the other variables and their interaction. Hence the SVM, Random Forest and Logistic Regression are the methods that ensure a high percentage of pipes predicted correctly in critical conditions (TPR) with a high performance (PLR) due to these are non-linear methods.

From the above results, Figure D.5 shows the performance curves obtained from the LR, RF and SVM-based deterioration models.

According to option 1 (Figure D.5., left), the RF's performance curve shows a high percentage of success for pipes with high probability to be in critical conditions. Likewise, it is possible to observe that the rate of success decreases when the probability of being in critical condition also decreases. In contrast, LR and SVM prediction results do not show a high percentage of success for pipes with high probabilities to be in critical conditions: these peaks are located respectively at 13 and 7% of pipes with high probability to be in critical conditions. These results suggest that is not possible to use this technique as a tool to prioritize the rehabilitation of most critical sewer pipes because the percentage of success is not the highest for the pipes with the highest probability to be in critical conditions.

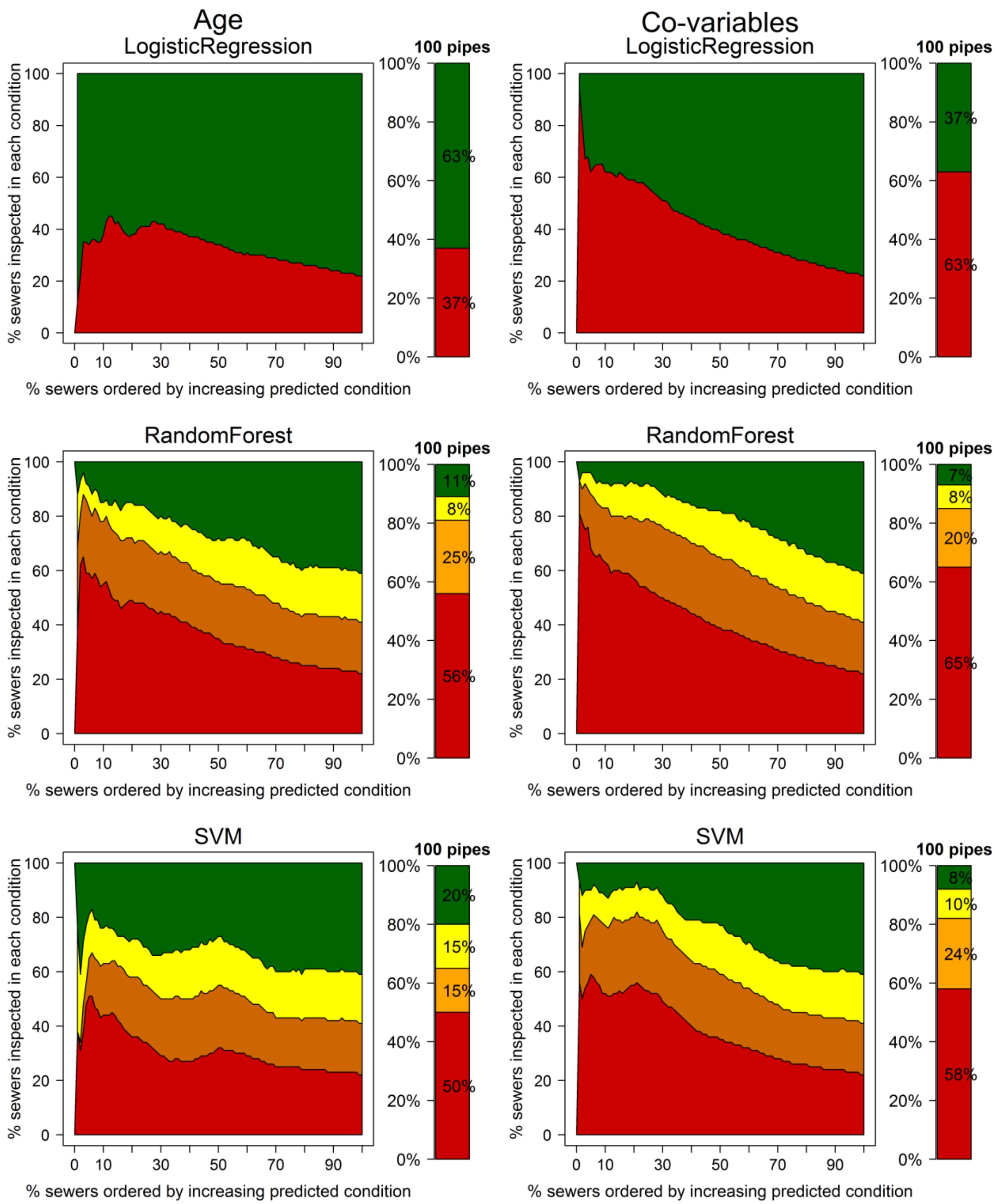

Figure D.5 LR, RF and SVM performance curve with a sample on its left of 100 pipes. On the left side are results of the option 1 (Considering only the variable age as influential variable in the models) and on the right, the option 2 (considering all variables as influential variables in the models). Source: Hernández et al., (2017a)

On the other hand, the LR and RF performance curves of option 2 (Figure D.5., right) show high percentages of successful for pipes with a high probability of being in critical conditions. Likewise, these performance curves show that when the probability of being in critical condition decreases, also the success's percentage decreases. However, the SVM performance curve (option 2) shows two peaks of percentages of successful located at 7% and 22% of the pipes with high probabilities to be in critical condition. SVM method is not a suitable method for the objective that follows the performance curve because this method does not give a probability to be in critical condition.

The LDA and Multi_LR prediction results are not displayed because their performance curves do not show remarkable peaks of success's percentage, and neither a particular behaviour of this percentage with the high probability to be in critical conditions.

The bar plots on the right side of each performance curve show a sample of the percentage of success for the first 100 pipes with high probabilities to be in critical condition (around 10% of validation data). For option 1, RF is the method with the highest percentage of successful (56%) following by SVM and LR, with 50% and 37% respectively. These two last percentages show that these predictions tend to be random when the age is the only input variable in the models. On the other hand, the bar plots for option 2 show percentages over 50%, it means that the three predictions show better results than a random scenario. In this model, RF also shows the highest rate of effectivity (65%) to predict the critical structural conditions in those pipes with high probability to be in that condition following by LR and SVM with 63% and 58% of successful respectively.

In general, it is observed that considering more attributes as input variables (option 2) improves the prediction of the critical structural condition in the present case study, in particular for the LR method: according to the bar plots (first 100 pipes with high probabilities to be in critical condition of the option 1 and 2) the success's percentage increases from 37% (option 1) to 63% (option 2).

10.2.2. RESULTS OF THE EXPLORATION OF DETERIORATION MODELS FOR COLOMBIAN AND GERMAN CASES

This exploration consist of the application of Random Forest and Logistic regression-based deterioration models for a Colombian and German sewer systems, and then it compares their prediction results. The purpose of this prediction was focus on predicting the critical structural condition of the sewer assets by Positive Likelihood Ratio (PLR), Performance curve and deviation analysis.

According to the obtained PLR (Table D.2), the models of both approaches have PLR's value higher than 1 for the Colombian city's case, which means that both models give better predictions than a random prediction (True Positive Rate TPR > False Positive Rate FPR). However, for the German city's case, only RF's model gives PLR's value higher than 1, the PLR's value was assumed to be zero for LR's model. Besides, for each model, it was found that: (i) LR prediction shows that the PLR value is higher for the Colombian city (5.43) than for the German one (0.02); and (ii) RF prediction shows the opposite result: 3.8 and 5.2 for the Colombian and the German cities respectively. The RF's results are interesting to highlight the importance of PLR because even though the proportion of pipes predicted correctly for the Colombian city's case is higher (TPR = 0.57) than the German city's one (TPR = 0.26). Likewise, the proportion of pipes predicted wrongly is also higher for the Colombian city (FPR = 0.15) than for the German city (FPR = 0.05).

Therefore, PLR of the critical condition's prediction shows that LR is more adapted for the prediction of the Colombian city's sewer system's critical conditions, and RF for the German one.

Table D.2. PLR index of the critical conditions of sewer pipes in Colombian and German case studies using RF and LR.

	German City			Colombian City		
	TPR	**FPR**	**PLR**	**TPR**	**FPR**	**PLR**
RF	0.26	0.05	5.2	0.57	0.15	3.8
LR	0.02	0	0	0.38	0.07	5.43

Source: Hernández et al. (2018a)

The performance curves presented in Figures D.6. and D.7. show that both methods (RF and LR) exhibit similar behaviour, but different results for each case study. According to the performance curves analysis of RF's prediction shown in Figure D.6 for both cities, RF predicts correctly 63% of pipes in critical condition (or 83% of pipes in critical and poor conditions) for the first 10% of pipes with high probability to be in this condition for the

Colombian city's case (Figure D.6., left). While for the German city's case, RF predicts 33% of the first 10% of pipes (or 63% of pipes in critical and poor conditions) with high probability to be in critical condition correctly (Figure D.6., right). Although the behaviour of the curves concurs to the fact the probability to be in critical condition decreases when the success's percentage does it, the prediction results show more accuracy to identify those pipes in the critical condition for the Colombian city's case.

On the other hand, in accordance to Figure D.7., the performance curves of LR prediction results, for both cities, show lower accuracy than the RF prediction results: according to the bar plots on the right side of each performance curve (Figure D.7.) which represent the 10% of pipes with the highest probability to be in critical condition, the accuracy is around 62% and 27% for the Colombian and the German cases respectively.

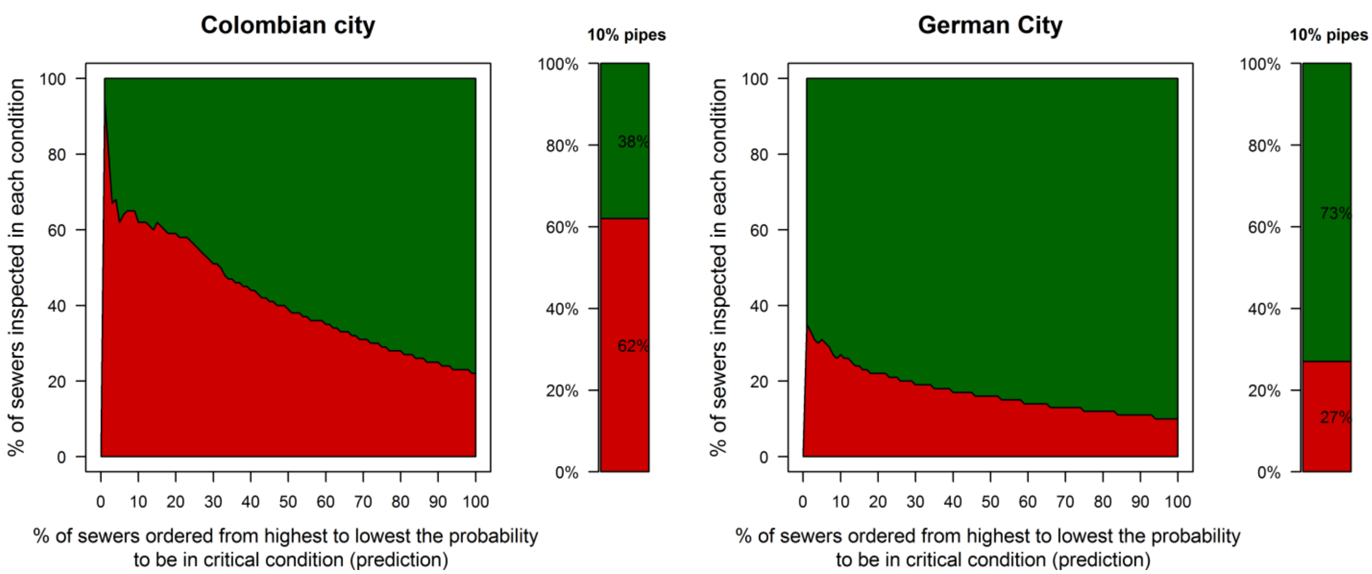

Figure D.6. Performance curves with 10% pipes sample bar plot on its right of LR prediction results for the Colombian city (on the left) and the German city (on the right). X-axes: predicted pipes ordered from the highest to the lowest probability to be in critical conditions. Y-axes: the real structural condition observed by CCTV. The bar plot (right side): 10% of pipes-sample with the highest probability to be in critical conditions. Red: critical condition, and green: excellent condition. Source: Hernández et al. (2018a)

For the Colombian city's case, the accuracy in identifying those pipes with a high probability to be in a critical condition is similar for both RF and LR methods. However, for the German city's case, this accuracy is worse than a random selection for both models (RF and LR), which matches with TPR results shown in Table D.2.

The above performance curves' analysis shows that the models based on RF and LR could be useful to identify the critical conditions correctly for the Colombian's case: Colombian city's stakeholders could make strategic plans of rehabilitation choosing that 10% of pipes with the highest probability to be in critical condition ensuring to find more than 60% of success for critical condition and more than 83% (according to RF) for critical or poor structural condition (red and orange stripes, Figure D.6. left).

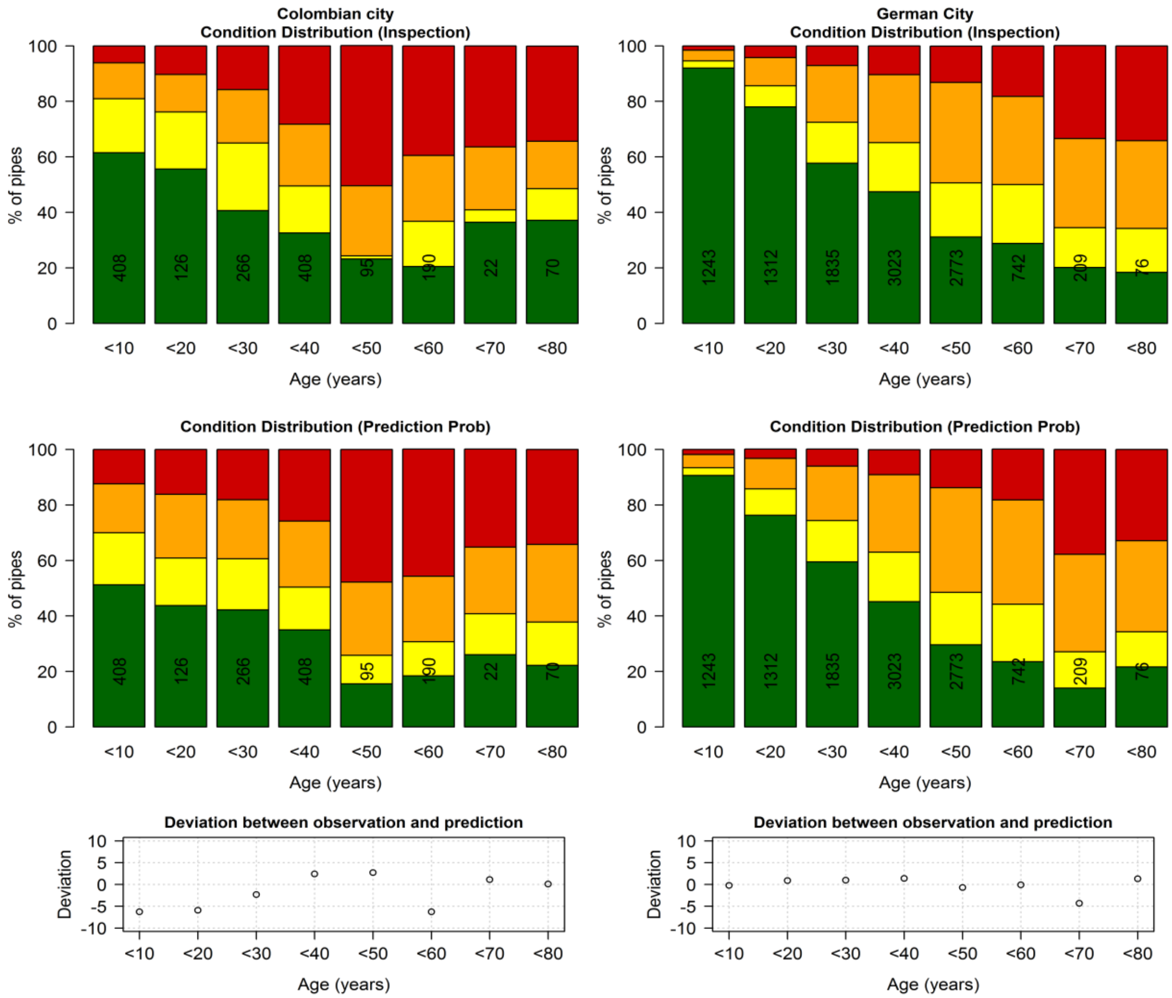

Figure D.7 Deviation analysis of the RF prediction results vs inspection data results for the Colombian city's case (left) and the German city's case (right). Top-graph: bar plots of structural condition's distribution by each period given by CCTV inspections; Middle-graph: bar plots of structural condition's distribution by each period given by the predicted conditions; Bottom-graph: mean deviation (of all structural conditions) between the Top-graph and the Middle-graph. Source: Hernández et al. (2018a)

Figures D.7. and D.8. show the deviation analysis of the prediction results of both methods (RF and LR, respectively). According to the analysis of RF, the Colombian's city´s case results show higher deviation in the prediction of critical condition for each period of 10 years (Figure D.7., left) than the German city's case ones (Figure D.7, right). It is essential to observe that for the Colombian city, for pipes with ages between 40 and 50 years, the model overestimates the critical condition, predicting these pipes in better conditions (orange, yellow and green stripes), but for the young pipes (age <20 years) and 50-60-year-old pipes the model underestimates the critical condition, predicting some pipes in critical condition which actually are not in that condition. According to the distribution conditions of both case studies, it is possible to observe (graphs on the top of Figures D.7. and D.8.) that the deterioration depends on the age, making directly proportional with the criticality of the assets. This behaviour is observed for the German case (deviation lower than 5%) and the Colombian case for assets younger than 60 years old (deviation lower than 7%). Therefore, the model represents the same behaviour in the prediction. However, for pipes older than 60 years old in the Colombian case, this behaviour changes, in which the model underestimates the prediction of these pipes. The author assumes that the atypical behaviour of the pipes older than 60 years for the Colombian case depends on the reliability of the data, the old construction methods, the lack of information about the rehabilitation dates and if these assets have been rehabilitated and these rehabilitations have not been reported. These gaps should be explored in future research works, and the analysis should be careful with the information of the oldest sewer pipes.

On the other hand, the deviation analysis of LR (Figure D.9.) shows higher deviations for both cities (Figure D.9.) compared with those obtained with RF (Figure D.8). Nevertheless, the deviation is still higher for Colombian city´s case. For the Colombian city´s case, LR also tends to overestimate pipes whose ages are between 40 and 50 years, while pipes younger than 30 years and older than 60 years-old pipes are underestimated. For the German city´s case, the deviation on each period is lower than +/- 5%, except for 70-year-old pipes.

Figure D.9. shows a clear relationship between the distributions of conditions and the pipes' age, in particular for the German case. However, even if LR's prediction represents this behaviour is not as accurate as RF' prediction.

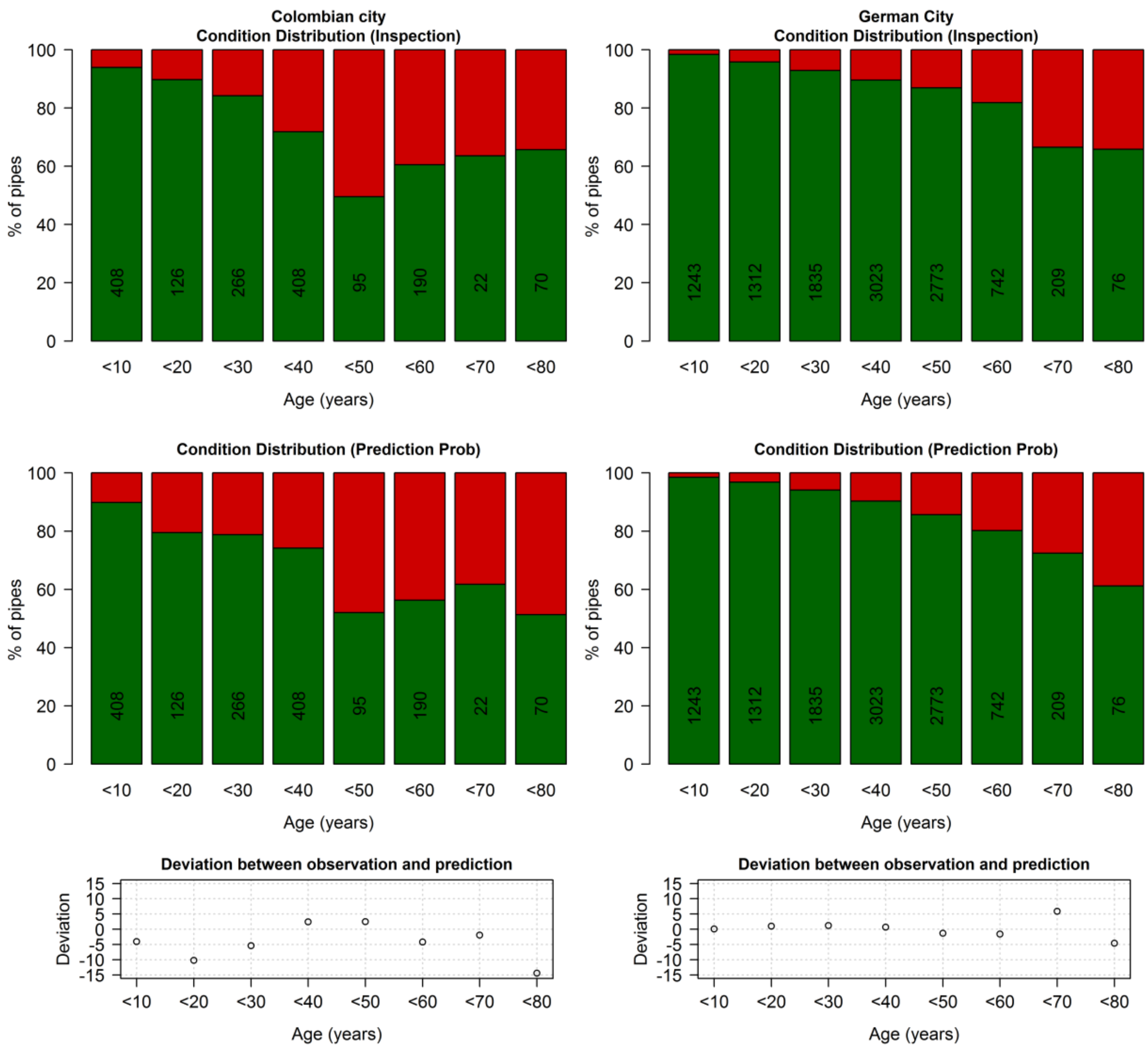

Figure D.8 Deviation analysis of the RF prediction results vs. inspection data results for the Colombian city's case (left) and the German city's case (right). Top-graph: bar plots of structural condition's distribution by each period given by CCTV inspections; Middle-graph: bar plots of structural condition's distribution by each period given by the predicted conditions; Bottom-graph: the mean deviation (of all structural conditions) between the Top-graph and the Middle-graph.

According to the general prediction´s approach, both methods are suitable to predict the structural condition; however, it depends on each case study. According to the ROC space analysis, RF was the method with a higher effectiveness rate (PLR) to predict the critical structural condition for the German city's case, while Logistic Regression (LR) was the suitable one for Colombian city´s case. Nevertheless, in the analysis with the Performance curve and deviation analyses, Random Forest (RF) was the one with adequate results in both cases: based on the performance curve analysis, RF was appropriate for identifying the pipes in critical condition with an accuracy of 63% for the Colombian city´s case, and based on the deviation analysis, RF had the lowest deviation (<+/-5%) on each 10-years' pipes for the German city's case.

The reason because RF prediction results are more appropriate in both cases lies in the fact that RF does not expect linear features or direct interactions as LR do it. Although the PLR´s index showed that LR has greater correct predictability for the Colombian city´s case, there were not so many pipes predicted in critical condition (True Positive Rate = 0.38), while for the same case study, the True Positive Rate was around 0.57 for RF.

Since the Random Forest prediction results are different from both case studies, it is possible to analyse in which way the stakeholders could take advantage of these predictions: (i) for the German city's case, the stakeholders could design strategic budget plans having an approach based on the number of pipes in critical condition taking into account their age; and (ii) for the Colombian city's case, the stakeholders could be concerned in developing support tools to predict the current structural condition of uninspected sewers and to prioritise the management of those in worst conditions. For more details about these results, see Hernández et al. (2017b and 2018a).

10.3. RESULTS OF APPLICATION OF OPTIMISATION METHODOLOGY

According to the optimisation methodology proposed in chapter 8 (Part C), the first procedure related to grid search was applied in the frame of the collaboration project with (*Kompetenzentrum Wasser Berlin*) KWB colleagues for sewer systems of a German city, and their results were published in Caradot et al. (2018), and the second procedure related to the differential evolutionary (DE) optimisation algorithm was applied for Bogota's and Medellin's sewer systems and the results are in Hernández et al. (2019c). Hence, this subchapter consists of the results of both procedures for these case studies.

10.3.1. RESULTS OF THE GRID-SEARCH METHODOLOGY'S PROCEDURE

According to the procedure shown in Caradot et al. (2018), Random Forest and Gompitz were the models used to find the rank of hyperparameters combination which rise the prediction performance to fulfil two management objectives related to both the network and single pipe level. However, in this item, it is shown only the results of Random Forest since the grid search methodology for this machine learning method focus on finding the hyperparameters of the model. In contrast, for Gompitz the hyperparameters were related to the survival functions of the covariates. The considered variables as covariates in this model were age, material, type of effluent, diameter, depth and districts.

For assess the structural condition of the sewer assets, the utility of the studied German city follows a local standard similar to the German guideline ATV M 143-2 (1999). This standard classifies the structural condition of the sewer assets on six levels: being grade 1, which represents the sewer assets in critical conditions and grade 6, which represents the sewer assets in excellent conditions. For this study, the structural conditions were grouped in three categories: C1 which represents the sewer assets in excellent and good conditions (Grades 5 and 6); C2, the sewer assets in intermediate conditions (Grades 3 and 4); and C3 the ones in critical and poor structural conditions (Grades 1 and 2).

The following hyperparameters were considered to set up for finding their optimal combination to achieve the management objectives, objectives represented in *Knet* and *Kpipe* metrics (see subchapter 8.1 of Part C):

- *nodesize*: minimum size of terminal nodes
- *mtry*: number of variables randomly sampled as a candidate at each split
- *ntree*: number of trees in the forest
- *w1*, *w2* prior (i.e., weights) of the categories C1 and C2. *w3* is not defined as a parameter since its value can be calculated form other priors (w*1*+*w2*+*w3* =1)

The tested ranges of the hyperparameters were: *nodesize*: 4-1808; *mtry*: 1-12; *w1*: 0.2-3; and *w2*: 0.2-3. According to the grid search, Table D.3. shows the best combination of hyperparameters at both network and pipe levels. For more details about sensitive analysis for selecting these hyperparameters, see Figure 3 and 4 in Caradot et al. (2018)

Table D.3. Best combinations of hyperparameters at both network and pipe levels

Hyperparameter	Best model at network level	Best Model at pipe level
ntree	100	100
nodesize	7	55
mtry	10	11
w1	2	1
w2	1	0.8
w3	1	1

Source: Caradot et al. (2018)

Once the combination of hyperparameters was chosen for each model, Figure D.10 shows a deviation analysis for analysing the model at the network level.

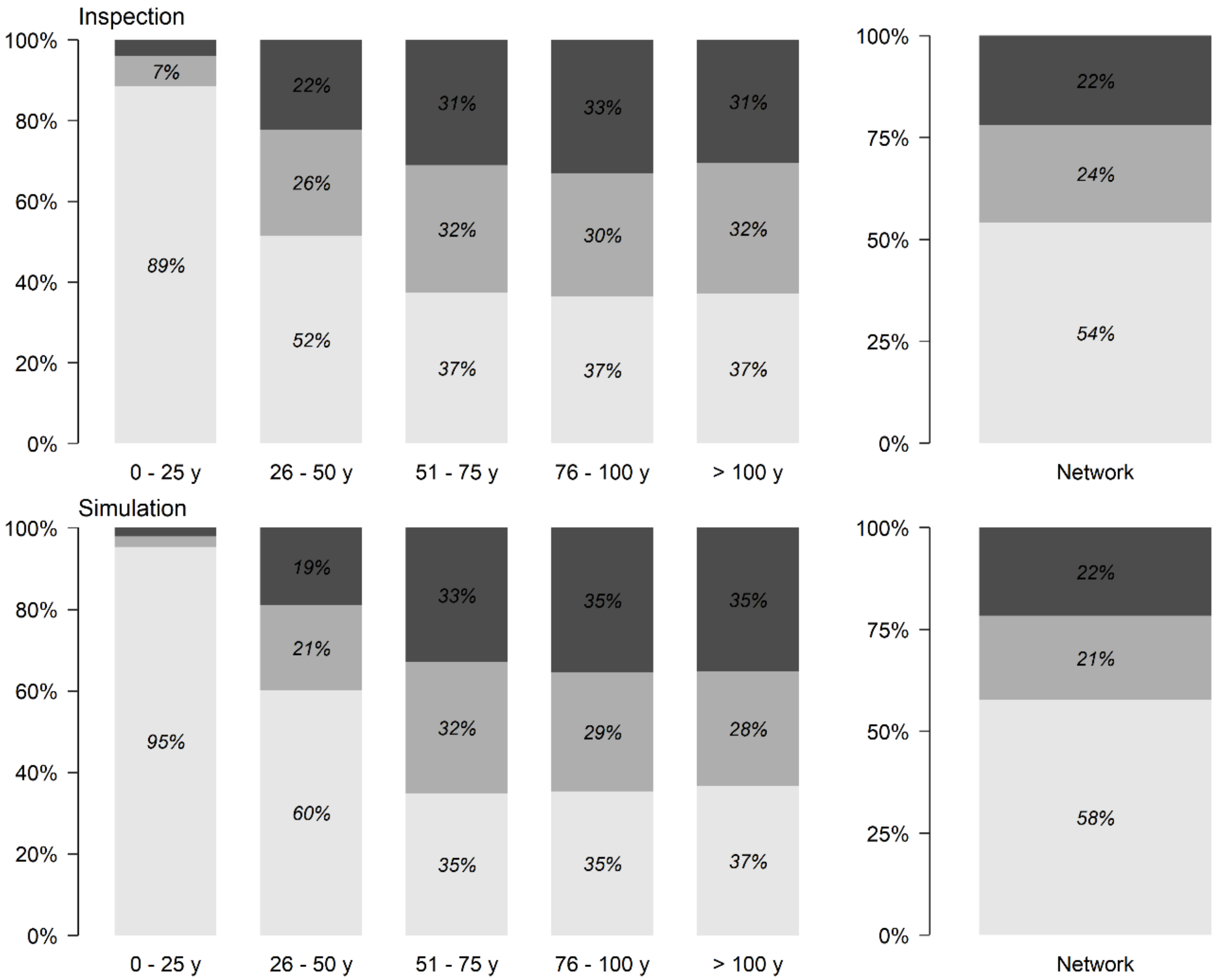

Figure D.9 Deviation analysis of the inspected and predicted condition distribution for the entire network (right) and for each age group (left). The colours light grey, medium grey and dark grey represented good, medium, and poor conditions, respectively. Source: Caradot et al. (2018)

Table D.4. shows a summary of the value of the metrics obtained on the test data. The metrics have been calculated with the best models at both network and pipe levels.

According to Table D.4. the deviations at the network level are relatively low, below 5%. At pipe level, 64% of the pipes inspected in excellent conditions have been predicted correctly (K_{TPR_1}), 40% of the pipes inspected in intermediate conditions have been predicted correctly (K_{TPR_2}), and 66.7% of the pipes in critical conditions have been predicted correctly (K_{TPR_3}). 17.1% of the pipes inspected in intermediate conditions and 9.5% of the pipes inspected in critical conditions have been wrong predicted in critical conditions (K_{FNR_21}, K_{FNR_31}). 28.3% of the pipes inspected in excellent conditions have been mispredicted in critical conditions.

Table D.4. Summary of performance metrics for the two models on the test data

Metrics	Goal		Metrics	Goal	
K_{DEV_1}	Minimize	-3,50%	K_{TPR_1}	Maximize	64%
K_{DEV_2}		3,40%	K_{TPR_2}		40%
K_{DEV_3}		0,10%	K_{TPR_3}		66,70%
$K_{OLD(DEV\_1)}$		2%	K_{FNR_21}	Minimize	17,10%
$K_{OLD(DEV\_2)}$		-0,10%	K_{FNR_31}		9,50%
$K_{OLD(DEV\_3)}$		1,90%	K_{FPR_13}		28,30%
Knet		2,3	***Kpipe***		34,5

Source: Caradot et al. (2018)

For more details about these results and conclusions, please see Caradot et al. (2018).

10.3.2. Results of Differential Evolutionary (DE) algorithm methodology's procedure

The differential Evolutionary algorithm methodology's procedure was applied for findings the combination of hyperparameters of Support Vector Machines (SVM) models that best fit to minimise *Knet* and *Kpipe* metrics to achieve management objectives at network and pipe levels for Bogota's and Medellin's sewer systems. The results of this study are in more detail in Hernández et al. (2019c). In this article, the main objective was comparing the performance predictions of SVM models optimising the hyperparameters by the proposed methodology and considering by the default optimisation carried out by *ksvm* function (see 6.2.1.3 of Part B) of R software (which optimises only the hyperparameter related to the used kernel function). The variables considered for each case study were chosen by Cramer's test and redundancy concepts (cut-off = 0.05, representing a 95% probability that the results are extreme enough for supporting dependence between the variables): age, type of effluent, diameter, material, network type, districts, and surface material were selected for Bogota' case as influential variables over the deterioration of structural conditions of the sewer assets; and age, length, diameter, depth, slope, type of effluent, and districts were selected for Medellin's case. Regarding the analysed hyperparameters to fit SVM models are:

- *sigma*: hyperparameter related to Radial Basis (RBF) kernel function
- *C*: hyperparameter that trades off misclassification of training samples for simplicity in the decision surface and determines the hyperplane margin's width.

- *W1, W2, W3, W4* and *W5*: weights related to the structural grade 1, 2, 3, 4 and 5, respectively.

Tables D.5. and D.6. show a comparison of the values of the hyperparameters for the conventional model (default SVM optimisation by R function) with the optimal SVM hyperparameters found by the proposed optimisation methodology at the network (*Knet*) and the pipe (*Kpipe*) levels for Bogota and Medellin respectively.

Table D.5.Optimal SVM hyperparameters for Bogota's case

Models	Hyper-Parameters for Bogota						
	Sigma	***C***	***W1***	***W2***	***W3***	***W4***	***W5***
Conventional SVM model	0.039	1	1	1	1	1	1
DE-optimised SVM model at network level *Knet*	3.171	101.31	2.975	4.554	3.253	5.044	4.279
DE-optimised SVM model at pipe level *Kpipe*	0.097	6.543	1.336	4.360	2.653	1.749	2.227

Source: Hernández et al. (2019c)

Table D.6. Optimal SVM hyperparameters for Medellin's case

Models	Hyper-Parameters for Medellin						
	Sigma	***C***	***W1***	***W2***	***W3***	***W4***	***W5***
Conventional SVM model	0.022	1	1	1	1	1	1
DE-optimised SVM model at network level $Knet_t$	0.955	211.56	7.643	5.893	7.324	5.430	5.567
DE-optimised SVM model at pipe level *Kpipe*	0.019	95.92	2.131	9.365	9.903	1.012	1.207

Source: Hernández et al. (2019c)

From the results shown in Tables D.5. and D.6, it is possible to determine that the values of *sigma* and *C* are far higher when trying to obtain the minimum *Knet* than for the minimum *Kpipe*. For the data, a *sigma* of 3.17 for Bogotá and of 0.95 for Medellin gave the minimum *Knet*, while a σ of 0.097 and 0.019 for each case gave minimum values of *Kpipe*; and a similar trend was noted for the *C* hyper-parameter. According to theory (Hornik et al., 2006), a larger σ for a minimal *Knet* than *Kpipe* implies a smaller γ for the former than the latter. Therefore, the DE-optimised SVM model at the network level is more constrained, and the data is less complex than the DE-optimised SVM model for *Kpipe*. Likewise, a larger *C* hyper-parameter means a thinner margin and smaller chance of misclassification from the complexity of the surface function of the separation hyperplane, which is built choosing more data as support vectors (Hornik et al., 2006). The results of the *sigma* hyper-parameter are intuitive since the objective of the *Knet* metric is describing the deviation between the predicted and the inspected condition distributions, while the objective of *Kpipe* is evaluating whether the model predicts the pipes' condition correctly. According to the *C* hyperparameter, the margin and surface function of separation were more complex for *Knet*, with values lower than 1.89; while *C* values obtained for *Kpipe* show a simpler decision surface function. Additionally, each case study is weighted differently, as this is dependent on the grade distribution into our conditions for optimisation. As shown in Tables D.5 and D.6, the lower weight values were applied to those conditions with the most pipes per grade in inspection data.

For Bogota's case, *W1* is the smallest weight, which corresponds to grade 1, alone in condition 1, which had 45% of all information in the dataset. *W5*, corresponding to grade 5, alone in condition 3, corresponds to 21% of the information, is the second smallest, given that *W2*, *W3* and *W4* are grouped into a single category. This proportional relationship is harder to observe when it comes to grades 2 through 4, as *W2*, *W3* and *W4* were grouped into condition 2 in the optimisation function and accounted for 33% of all data.

For Medellin's data, two structural grades were grouped for each of the intermediate (grades 2 and 3) and critical (grades 4 and 5) conditions. According to the database, those pipes deemed to be in critical condition account for 70% of all data, and so, in Table D.6, it is clear that they were given the lowest *W* values. As for the other conditions, it is not easy to discern the balancing effect of the given weights.

According to the hyper-parameters shown in Tables D.5. and D.6., the DE-optimised SVM model was trained in an RBF kernel function, using 70% of the data as calibration, and 30% as validation data. Table D.7. shows the deviation results (*K* indicators) and the *Knet* obtained for the test data for each city, which were then compared for both case studies between the conventional SVM model and the DE-optimised SVM model.

Table D.7. SVM models' performance results at the network level for both case studies

Model	**Indicators for validation data**						
	K_{DEV_1}	K_{DEV_2}	K_{DEV_3}	$K_{OLD(DEV\_1)}$	$K_{OLD(DEV\_2)}$	$K_{OLD(DEV\_3)}$	$\boldsymbol{K_{net}}$
Bogota - Conventional model	-18.64	26.16	-7.52	-15.09	19.81	-4.72	19.05
Bogotá – DE-optimised model at network level	1.37	2.67	-4.04	3.64	1.82	-5.45	2.91
Medellin – conventional model	15.75	6.72	-22.47	12.76	10.46	-23.21	16.31
Medellín -DE-optimised model at network level	-1.58	1.74	-0.15	-4.59	2.3	2.3	1.36

Source: Hernández et al. (2019c)

This comparison shows an undoubted and evident difference, with the lowest deviations occurring in the optimised model (about 6 and 5% respectively for each city). In contrast, the conventional model reaches deviations of 20 and 23% respectively.

To better understand the trends of the *K* indicators of the DE-optimised SVM model for both case studies in detail, the distribution of each complete network (right) and each age group (left) was plotted, shown as Figures D.11 and D.12 respectively for each city, with the inspection data shown at the top and the predicted values at the bottom.

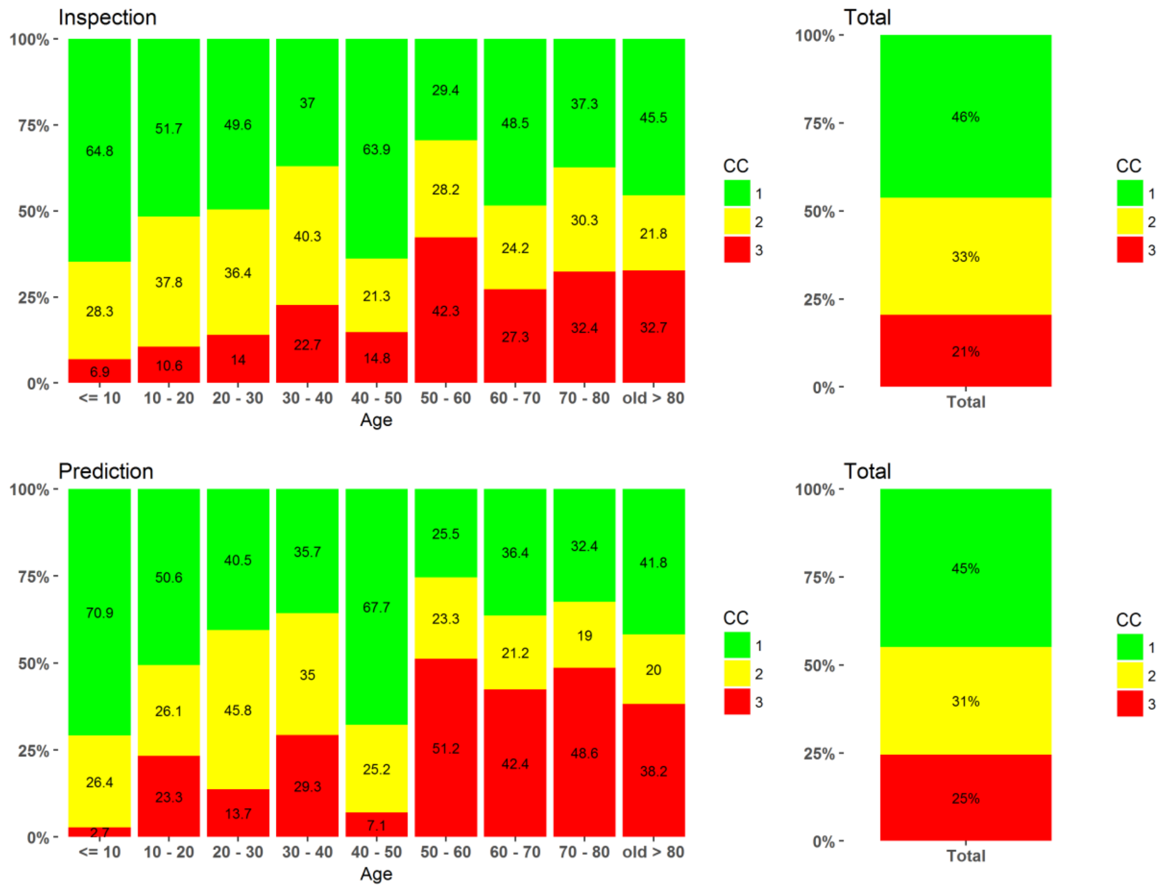

Figure D.10 Inspected and predicted distribution of data in DE-optimised SVM model at the network level for Bogota's case. Total network (Right) and broken down by age group (Left). The colours green, yellow and red represent excellent, intermediate and critical structural conditions. Source: Hernández et al. (2019c)

A positive K value (Table D.7) shows that the model underestimated the percentage of pipes that are actually in each condition, while a negative value indicates overestimation. Figure D.11. shows these under and overestimations for Bogotá in richer detail. Most pipes were overestimated to be in critical condition and underestimated to be in an intermediate condition, except for those that are 40-50, 20-30 or <10 years old. Interestingly, there is an abrupt change in the distribution of the sewer's structural condition at pipes aged 40-50 years, which could reflect the evident changes that happened due to the arrival of both new technologies and materials allowing the evolution of construction processes, as well as accelerated population growth from the 1960s. Furthermore, it is worth noting that the model attempted to simulate this atypical behaviour, which displays SVM's advantages when handling non-linear data behaviour.

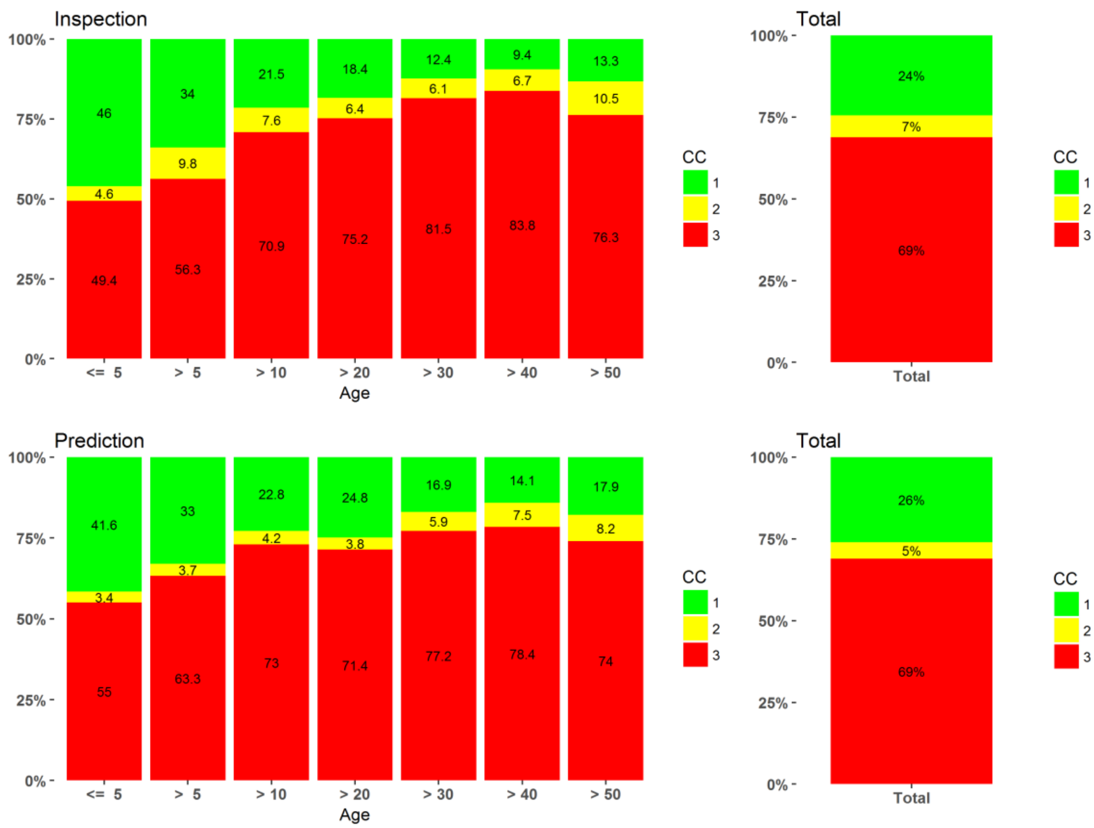

Figure D.11 Inspected and predicted distribution of data in DE-optimised SVM model at the network level for Medellin's case. Total network (Right) and broken down by age group (Left). The colours green, yellow and red represent excellent, intermediate and critical structural conditions. Source: Hernández et al. (2019c)

For Medellín's case, the condition of pipes older than 10 years was overestimated (negative K_{DEV_1} and $K_{OLD(DEV\_1)}$, Table D.7), predicting an excellent condition, while pipes younger than that are underestimated (Figure D.12.). The lowest *K*-indicators are seen for those pipes in critical condition (0.15% and 2.30% for K_{DEV_3} and $K_{OLD(DEV\_3)}$ respectively), which were underestimated with the exception again being those pipes installed in the last ten years, that were overestimated with a deviation close to 7% to be in intermediate or excellent condition.

Onto analysing the adequacy of our model, Table D.8. shows the *K* indicators obtained by the confusion matrices of the validation data and the respective *Kpipe* for each case study. This table compares the *K* indicators and *Kpipe* obtained by i) conventional SVM models ii) our DE-optimised SVM model.

Table D.8.SVM model performance results at pipe levels for both case studies.

Model	**Indicators for validation data**							
	K_{TPR_1}	K_{TPR_2}	K_{TPR_3}	$K_{FNR\_1\text{-}2}$	$K_{FNR\_1\text{-}3}$	$K_{FPR\_3\text{-}1}$	***Kpipe***	***Kappa***
Bogota without optimisation by DE methodology	82.94	12.88	56.21	56.99	36.88	23.09	49.9	0.26
Bogotá - optimised model	53.81	54.19	54.04	20.05	12.62	25.46	35.48	0.3
Medellin without optimisation by DE methodology	21.83	0	95.8	6.74	4.2	20.91	52.65	0.18
Medellín- optimised model	53.55	32.58	65.4	23.6	17.17	14.25	38.63	0.26

Source: Hernández et al. (2019c)

Contrary to the *Knet* values (Table D.7.), *Kpipe* values are very similar in both DE optimised and conventional models, with slightly smaller values in the DE-optimised SVM model than in the conventional SVM model for both case studies. Furthermore, the K_{TPR_1} and K_{TPR_3} (except, K_{TPR_1} for Medellín) are higher for the conventional SVM model, which shows the result of only optimising the σ hyper-parameter in both the condition predicted and its corresponding data distribution. Besides the *Kpipe* metric, Cohen's Kappa coefficient (Kappa) (Kraemer, 1982) was calculated to find the degree of agreement between observed and predicted conditions. From these calculations, we can observe how the DE-optimised SVM model improves agreement in both scenarios, and in Medellín's case it does so enough to rise from slight (0 – 0.2) to fair agreement (0.2 – 0.4) (Cerda & Villarroel, 2008).

In Bogotá's case, the DE-optimised SVM model presents more homogenous TPR values (53.81-54.19%), despite the conventional model having higher K_{TPR_1} and K_{TPR_3} values than it. Said TPR values are also significantly higher than those expected from a random prediction, which would be around 33%. When looking at FNR values ($K_{FNR\_1\text{-}2}$ and $K_{FNR\_1\text{-}3}$), those from the DE-optimised model are lower than those from the conventional model, both overall and for the most critical overestimation ($K_{FNR\_1\text{-}3}$). The exception is the False Positive Rate (FPR) value shown by $K_{FPR\_3\text{-}1}$ which is lower for the conventional SVM model (23%) than for the DE-optimised model (25%); however, this indicator is the least critical of all measured, as underestimating the condition of assets leads to less critical incorrect decisions than overestimation. Cleaning and inspection activities needed before carrying out rehabilitation would only result in minor costs to be assumed by the utility due to a wrong prediction, with stakeholders realizing that the condition is not as critical as predicted by the model. For more details about this study and results about the performance prediction of these models, please see Hernández et al. (2019c).

CHAPTER 11: RESULTS METHODOLOGY

The methodology was applied for each case study considering four structural conditions scenarios (SCS). The idea was to find the models that most support the management objectives for each case study.

Therefore, the results for each case study contains: (i) the hierarchy of the most influential variables, (ii) the exploration of the prediction performance of different methods to develop deterioration models; (iii) the construction and optimisation of the deterioration models based on the statistical and machine learning methods that showed high predictive performance in the exploration for each case study; and (iv) the results of the suitable deterioration models to fulfil two management objectives (at network and sewer asset level).

11.1. RESULTS FOR BOGOTA’S CASE

This subchapter contains the results of the proposed methodology (described in chapter 9, part C) for Bogota’s sewer system. In chapter 9, this methodology is described considering only one structural condition scenario. However, for this thesis, four structural conditions scenarios were created to support the management objectives and activities. Therefore, Table D.9. presents the built structural condition scenarios considering: (i) the five structural grades given by NS-058; (ii) three structural categories that classify the structural condition in excellent, intermediate and critical conditions; (iii) two categories that classify the structural condition in sewers without defects and with any defect; and (iv) two categories that only consider the sewer assets in excellent and critical conditions.

Table D.9. Description of structural condition scenarios (SCS) for Bogota's case

Original	**Groups**		
NS-058 (EAAB, 2001)	**3 Categories**	**2 Categories**	**2 Categories**
1	C1	C1	C1
2	C2	C2	-
3			-
4			-
5	C3		C2

Source: Author

It chooses three and two structural categories because the first simplifies the decision making in sewer asset management that offers the local standard to design management plans to short, medium and long term and following the Equation C.3. (Part C). The structural conditions were grouped in excellent, intermediate and critical structural conditions to look for balance in the data. Also, two more scenarios were created grouping the structural conditions in two categories, following the suggestions of Ariaratman et al. (2001) and López-Kleine et al. (2016). Therefore, the scenario of two categories was created following the recommendations of Equation C.3. (Part C) which suggest grouping the structural conditions in excellent and with any structural damage (See Table D.9); and another scenario was created considering only excellent and critical structural conditions, leaving aside intermediate conditions, from the findings of Guzmán-Fierro et al. (2019a, b, and c), in which leaving outside those sewer assets in intermediate conditions could reduce the mispredictions due to the uncertainty by qualification for sewer assets in intermediate conditions. Besides, grouping the structural conditions in two categories is useful to develop management plans for sewer assets that need urgent repair.

11.1.1. HIERARCHY OF THE KEY VARIABLES FOR THE DETERIORATION OF THE SEWER ASSETS FOR BOGOTA'S CASE

According to the first methodology described in subchapter 9.1., Table D.10. shows a summary of the hierarchy of the variables that have the most influence over the deterioration of the structure of the sewer assets for each structural condition scenario for Bogota's case.

The hierarchy shown in Table D.10. was chosen by each variable's relationship grade (first, second and third relation grade) with the structural condition of the sewer assets and the boxplot analysis of the Monte-Carlo simulations suggested in the Methodology (see subchapter 9.1., Part C). The relationship between each variable was hierarchically sorted according to the ratio between the median value and the interquartile range of the given boxplot (Q3-Q1). For more details, please see appendix – Part D.1.1.

According to Table D.10., from the 32 studied variables for Bogota's case, 23 variables show a non-depreciable relationship with the four structural condition scenarios (boxplot median >= 0.05). Only to remember, the boxplots summarized the probabilities in which each variable has any relationship (first, second and third grade) with the structural condition. Therefore, the variables whose boxplot median is lower than 0.05 means a depreciable relationship with the structural condition, according to the evaluated relationship (first, second and third grade). Variables such as soil type, trees roots length, surface material over the sewer assets, operational status, element type, road type, operational condition of the sewer assets and longitude and latitude coordinates where is located the sewer asset do not show any relationship with the structural condition in the four studied structural condition scenarios.

Table D.10. Summary of the hierarchy of the influential variables the over structural condition by each structural condition scenario (SCS)

Relationship grade	**Variables**			
	First SCS: 5-structural grades	**Second SCS: 3-structural categories**	**Third SCS: 2-structural categories**	**Forth SCS: Excellent and critical structural conditions**
First (Parent variables)	Inspection Year (“IY”)	Inspection Year (“IY”)	Diameter (“Diam”)	Type of Effluent (“Sew”)
	Diameter (“Diam”)	Diameter (“Diam”)	Inspection Year (“IY”)	Inspection Year (“IY”)
	Installation Year (“CY”)	Age (“Age”)	Installation Year (“CY”)	Diameter (“Diam”)
	Length (Length”)	Installation Year (“CY”)	Length (“Length”)	Installation Year (“CY”)
	Type of effluent (“Sew”)			Network type (“Net”)
	Age (“Age”)			
Second (GParent variables)	District (“District”)	District (“District”)	District (“District”)	District (“District”)
	Social Classes (“SocialC”)	Social Classes (“SocialC”)	Social Classes (“SocialC”)	Social Classes (“SocialC”)
	Land Uses (“LandUse”)	Type of Effluent (“Sew”)	Type of Effluent (“Sew”)	Depth (“Depth”)
	Depth (“Depth”)	Depth (“Depth”)	Land Uses (“LandUse”)	Material (“Mat”)
	Seismic shear wave velocity (“Vel”)		Depth (“Depth”)	
	Seismic Acceleration (“Acc”)		Seismic Acceleration (“Acc”)	
	Presence of trees (Tree”)		Presence of trees (“Tree”)	
	Slope (“Slope”)		Seismic shear wave velocity (“Vel”)	
			Slope (“Slope”)	
Third (GGParent variables)	Operational Zones (“Zones”)	Land Uses (“LandUse”)	Operational Zone (“Zone”)	Operational Zones (“Zone”)
	Type of intrusive trees (“TreeType”)	Operational Zone (“Zone”)	Geotechnical zones (“GeoTec”)	Land Uses (“LandUse”)
	Geotechnical zones (“GeoTec”)	Geological Zone (“Geo”)	Type of intrusive trees (“TreeType”)	Seismic shear wave velocity (“Vel”)
	Geological zones (“Geo”)	Seismic shear wave velocity (“Vel”)	Precipitation levels (“Prec”)	Age (“Age”)
	Precipitation levels (“Prec”)		Geological Zone (“Geo”)	Quality data (“Quality”)
				Seismic Acceleration (“Acc”)
				Geological zones (“Geo”)
				Precipitation levels (“Prec”)
				Water level depths (“WT”)

Source: Author

Variables such as Inspection Year (“IY”), Installation Year (“CY”), and diameter (“Diam”) of the sewer assets show a direct relationship (first relation grade or parent variable) with the four SCS. The Age (“Age”) shows a direct relationship with the structural condition in the first two SCS (five structural grades and three structural categories); in the third SCS (two structural categories), it does not show any relation, and for the fourth structural condition scenario, the variable Age shows a relationship of the third grade. And the variable length of the sewer assets (“Length”) shows a direct relationship with the structural condition in the first two SCS (five structural grades and three structural categories); while in the other scenarios do not show any relationship.

Variables that show a relationship of second grade (Grandparent variables) in the four structural condition scenarios were district (“District”), social classes (“Social_C”) and depth (“Depth”) in which are located the sewer assets. The type of effluent (“Sew”) was positioned in the first and second relation grade (Parent and GParent variables).

Operational (“Zone”) and geological (“Geo”) zones show relationships of third grade (Grand-Grandparents) in the four structural condition scenarios. Land use (“LandUse”) shows a relationship of second and third grade (grandparents and grand-grandparent variables), as well the seismic shear velocity (“Vel”) which shows the relationship of second and third grade (grandparents and grand-grandparent variables). Furthermore, precipitation levels (“Prec”) and seismic acceleration (“Acc”) also show a relationship of third grade in three of the four SCS. Geotechnical zones shows a relationship of third grade in the first and third SCS.

Variables related to trees showed a relationship with the structural condition in the first and third SCS (five structural grades and two structural categories). This confirms the findings of Torres-Caijao (2017) with the same case study. The hierarchy of variables of the first and third SCS are similar.

The fourth SCS showed a relationship of the first, second and third grade with variables that were not considered in the other SCS, such as the network type ("Net"), the material of the sewer assets ("Mat"), data quality ("Quality") and water level depths ("WT").

Comparing the results of Table D.10. with Table B.3. (Part B of the manuscript), it is possible to confirm that installation years, type of effluent, age, length, diameter and type of effluent show a direct relationship with the structural condition and their behaviour is explained according to the stated in Table B.3. Variables such as districts, seismic variables, geological and operational zones show relationships of second and third grade with the structural condition, which confirms that these relationships depend on other variables that link them with the structural condition. The above mentioned is showed in the Bayesian Networks plotted in figures 9 to 12 of the appendix – Part D.1.1, in which those variables that act as a link between the above variables and the structural conditions are installation year ("CY") and age ("Age") of the sewer assets. Coming back to the analysis of Table B.3. in which it was not evident to know which variables between geographical or age ones were the most influential over their structural deterioration, with the results of the proposed methodology is confirmed that it is more influential the age variables (installation period and age) of the sewer assets. It reinforces the findings of other studies in which the age has a strong influence over the structural condition, because of the lifetime of the sewer assets (Davis et al., 2001a; Baik et al., 2006; Le Gat, 2008; Ana et al., 2009; Rokstad & Ugarelli, 2015; El-Housni et al., 2017; Caradot et al., 2018).The physical characteristics of the sewer assets such as length, diameter and slope showed relationships of the first and second grade (Parent and GParent variables). However, the material of the sewer assets only had a relationship in the fourth SCS in which the sewer assets with intermediate conditions were not considered. Comparing these results with the bar plot analysis (Table B.3.), the variable material showed influence over the structural deterioration of the sewer assets: sewer assets in clay and PVC showed a higher percentage of structural deterioration. The fact that physical characteristics and variables related to the age of the sewer assets show a relationship of first and second grade (Parent and GParent variables) confirms that these variables show a great influence over the structural condition of the sewer assets, as it has been reported in other case studies (Ariaratnam et al. 2001; Baik et al., 2006; Tscheikner-Gratl et al., 2014).

Furthermore, variables such as Precipitation levels (“Prec”), Geological zones and land uses show relationships of third grade that were not detected in the bar plot analysis (Table B.3.).On the other hand, variables that showed an apparent relationship with the structural condition in the bar plot analysis (Table B.3.) such as longitude and latitude coordinates, operational conditions, surface material and trees roots’ length do not show any relationship with the structural condition from the application of the proposed methodology.

In summary, physical characteristics and variables related to the age show a direct relationship with the structural condition. In contrast, the surrounding variables were positioned in a second and third level relationship with the structural condition. Information about road infrastructure does not show any relationship over the deterioration of the structure of the sewer assets for Bogota's case.

11.1.2. Exploration of deterioration models

An exploration of statistical and machine learning tools was carried out to develop deterioration models for Bogota's case. Methods such as support vector machines (SVM), random forest (RF), lineal discriminant analysis (LDA), binomial (LR), multinomial (Muti_LR) and ordinal (Ord_LR) logistic regressions were explored by two different scenarios considering only the age as influential variable over the structural conditions (scenario 1) and age together with other characteristics such as material, type of effluent, depth, length, slope, and diameter for estimating the critical structural condition (scenario 2). In this study, the five structural conditions were grouped into four structural categories looking for the same proportion of data on each structural category. Therefore, grades 3 and 4 were grouped. Figure D.13. shows a deviation analysis for estimating the critical structural condition.

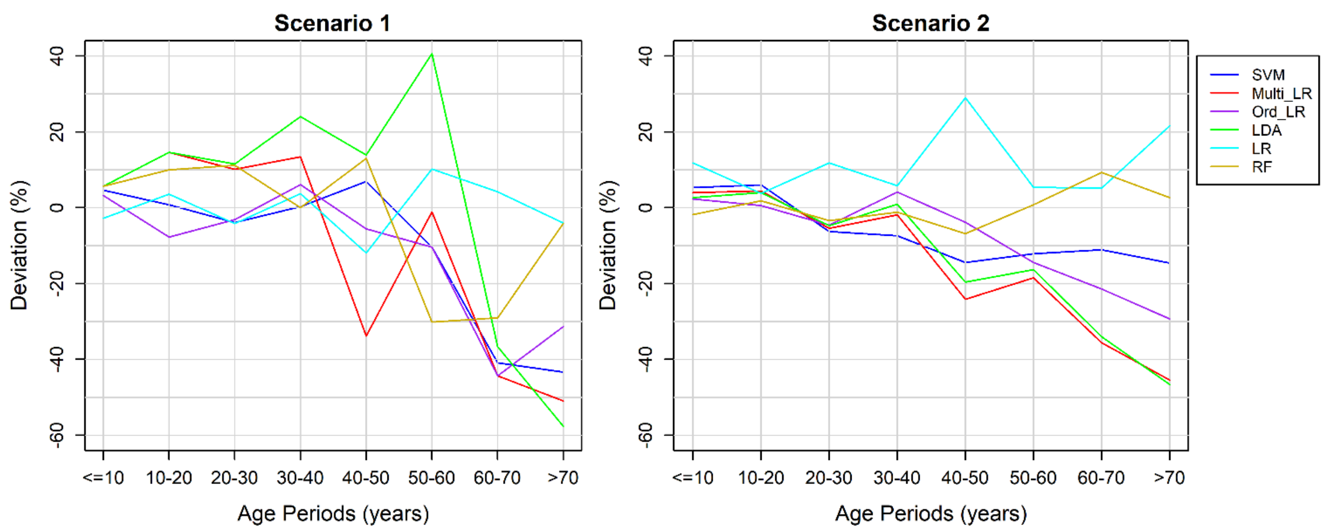

Figure D.12 Deviation analysis of the models' prediction vs inspection data results for Bogota's case considering the scenario 1 (on the left) and scenario 2 (on the right).

According to Figure D.13., most of the models have higher deviations when these consider scenario 1 (only age as a predictor variable), except LR. The highest overestimation (positive deviation values) and underestimation (negative deviation values) were obtained for the 40-years old group for both scenarios.

The prediction results of RF and SVM models show the lowest deviation for both scenarios, especially when these models consider scenario 2: RF exhibits deviations lower than +/-10% and SVM lower than +/-15%. However, the prediction results of Ord_LR (scenario 2) are not as different as the SVM and RF ones (scenario 2) for pipes with less than 60 years.

Furthermore, it is interesting to observe that SVM and RF models change the sign of deviation (from overestimation (+) to underestimation (-)) for the 30-50 years groups for SVM and the 20-50 years groups for RF for both scenarios 1 and 2. It implies that when the models mispredict the first one (considering scenario 1), they were wrongly predicted in better conditions than really they are; and the second (considering scenario 2) mispredicted some pipes in critical conditions when they really were in a better condition. The results obtained with LDA and Multi_LR models show similar behaviour, mainly, for scenario 2. In comparison to scenario 1, these models reduce the percentage of overestimated predictions but increase the percentage of underestimated predictions. However, the underestimation of scenario 2 does not exceed the percentage of underestimation of scenario 1: except for 50-60 years group for Multi_LR model.

LR model results exhibit deviations lower than +/- 10% for all the age groups for scenario 1; however, the results obtained with the RF model for scenario 2 are the ones with the lowest deviation among all results. Although the RF model results (scenario 2) show lower deviation than the LR model ones (scenario1), LR models are simpler than the RF models, due to it only needs the age to make a successful prediction at the network level. Also, it is possible to observe that the LR model under scenario 2 does not behave in the same way as the LR model under scenario 1, because the obtained results show that adding more covariates reduces the prediction capacity, overestimating predictions. Furthermore, the LR model under scenario 2 is the only one that overestimates the mispredictions while the other models under the same scenario underestimate the mispredictions (including Ord_LR and Multi_LR). This fact could be because the LR model works as a linear function with the log-odds ($log_b \frac{p(y)}{1-p(y)} = \beta_0 + \beta_1 x_2$) considering only the age. It means that the LR model catches the behaviour of the deterioration pipes through the time by a logarithmic function, and it is expressed by the probability to be in critical condition. On the other hand, if more variables are included, the log-odds' linear function is more complex, and a logarithmic function would not be the function that could explain the deterioration behaviour. The probability of being in critical condition could be distorted. It is important to remember that this analysis does not show the identification of the critical condition of each sewer; this analysis shows the performance of the model detecting the number of pipes on each age period. Meanwhile, RF, SVM, and LDA are machine learning models whose classification way is different: these models need the training data to separate the categories by decision trees or hyperplanes, while LR uses the training data to build a logarithm function for making a regression.

On the other hand, the prediction of Ord_LR and Multi_LR models differ from those obtained with the LR model because Ord and Multi_LR have many objectives, not only one as the LR model: Ord_LR measures the probabilities of being in any condition from accumulative probabilities, as the order starts from C1 when it arrives at the critical condition (C4), the probability depends on the probabilities of the previous conditions (Gelman & Hill, 2006) and the probability of being in critical condition could be mispredicted compared to the one obtained with the LR model; and Multi_LR assumes independence among the conditions (it means that C1, C2, C3 and C4 are independent each other, which is not true, see the local assessment standard of Bogota, making that it could estimate unrealistic coefficients leading to a wrong separation (Melter & Vannata, 2015).

Figure D.14. shows the performance curves for LR, SVM and RF prediction results, under scenarios 1 and 2, since these models were the most successful ones in predicting the percentage of sewer pipes with the highest probabilities to be in critical conditions.

According to Figure D.14., it is possible to observe that the performance curves for LR, SVM and RF results show higher successful percentages detecting sewer pipes in critical condition considering the scenario 2. Furthermore, for scenario 1 the behaviour of performance curves of the models tend to be flat, which means that the models do not correlate the sewers with high probability to be in critical condition with the successful percentage to be in that condition. Meanwhile, models considering the scenario 2 correlate the successful percentage with the probability to be in critical conditions (mainly for LR and RF models). The bar plots, on the right side of each performance curve, show a sample of the success percentage for the first 10% of sewers with the highest probabilities to be in critical condition. According to these bar plots, for scenario 1, LR, SVM and RF results show similar successful predictions around 42%; while for scenario 2, the highest successful prediction results are around 55% for LR and RF. Even though the SVM model under scenario 2 improves the prediction quality compared to the SVM model under scenario 1, for which the corresponding performance curve tends to be flat.

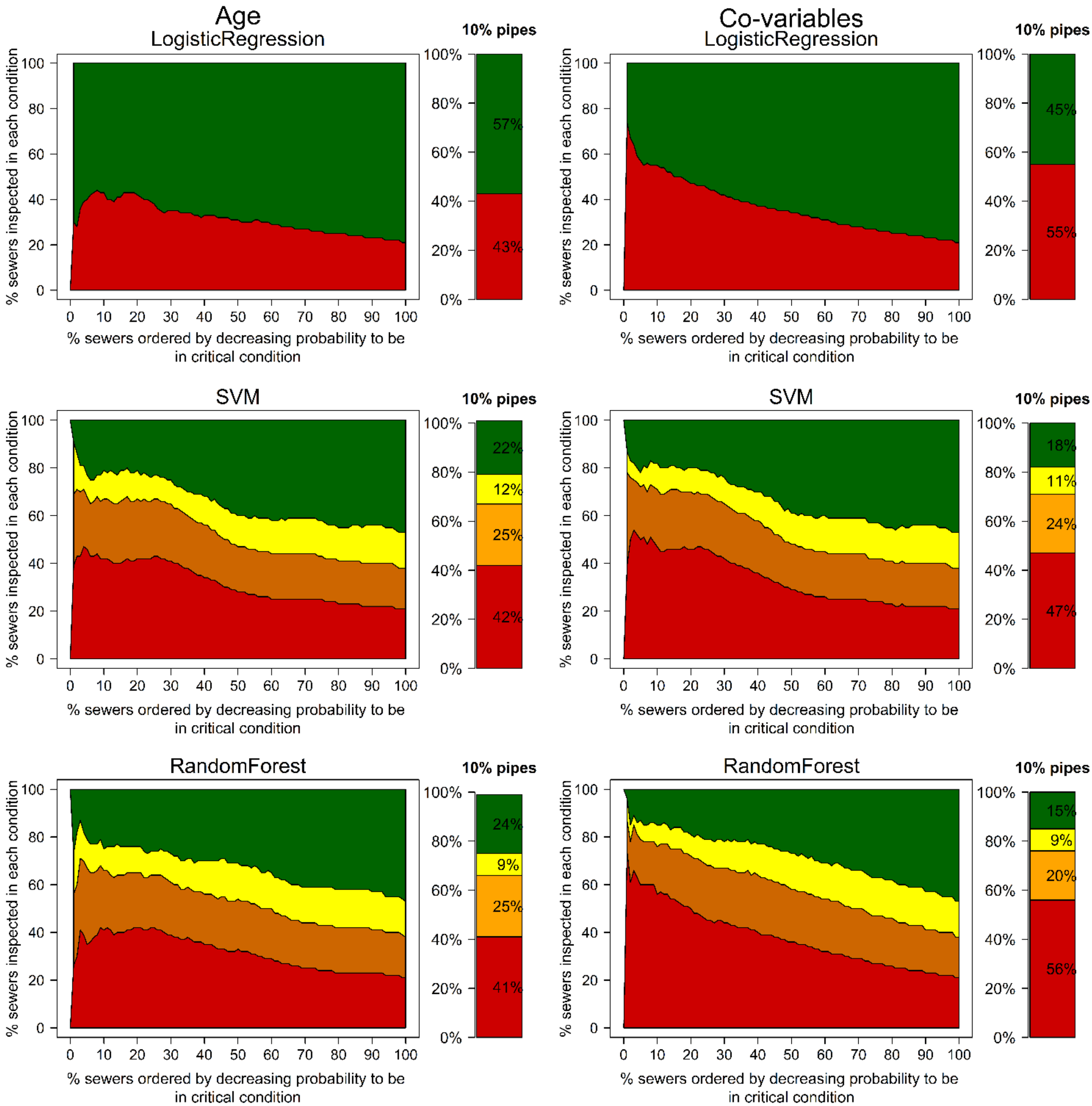

Figure D.13. LR, RF and SVM performance curves with a sample on its right of 10% pipes. Left: scenario 1 (considering only the age as an influential variable); right: scenario 2 (considering the age and other variables as influential variables)

Here, it does not show the performance curves obtained by LDA, Ord_LR and Multi_LR model predictions because their prediction quality is lower than RF, SVM and LR model predictions (see Appendix – Part D.1.2.).

It is essential to highlight that even if Ord_LR and SVM show similar deviation results under both scenarios, the performance curves of Ord_LR tend to be flatter than SVM ones in both cases. Furthermore, the success percentage to be in critical condition of the first 10% of pipes with the highest probability to be in that condition was lower for Ord_LR (44%) than for SVM (47%) under scenario 2.

According to the above results, Support Vector Machines (based on Laplace kernel functions), Random Forest and Binomial Logistic regressions are the selected methods for developing deterioration models for Bogota' case. Moreover, it also considers Ordinal Logistic Regression in the case that structural condition consists of more than two structural categories. For more details about this exploration, see Hernández et al., 2019b.

11.1.3. SUITABLE DETERIORATION MODELS FOR MANAGEMENT MODELS FOR BOGOTA'S CASE

After finding the above hyperparameters' combinations for the machine learning-based deterioration models, it carries out 1000 Monte-Carlo simulations for all the selected deterioration models (based on both statistical and machine learning methods). The idea of this is to estimate the prediction rank of validation data for the structural condition of the sewer assets focused on the two analysed management objectives.

It compares the predictions of each method-based deterioration model to finding the one that most significantly minimises the *Knet* and *Kpipe* metrics (see Appendix-D.1.4, Figures from 13 to 52). Based on the proposed methodology (Chapter 9 of part C), when the models do not show a significant difference in their prediction results, it is chosen the one with the lowest number of needed variables to achieve the management objective.

Figure D.14. shows the most suitable models to achieve the network level management objective (*Knet*) for each SCS: (a) five structural grades (5_COND), (b) three structural categories (3_CAT), (c) two structural categories (2_CAT), and (d) excellent and critical structural conditions (C1C5).

According to Figure D.14., the statistical-based deterioration models such as ordinal (Ord_LR) and binomial (LR) logistic regression are the ones with the lowest variance, but with the highest *Knet* median (except for the second SCS). Furthermore, the SCS that showed the lowest *Knet* values are related to SCS that groups the structural condition in two categories (third – 2_CAT and fourth SCS -C1C5): *Knet* median varies between 1 and 2. In contrast, the *Knet* median of the SCS that groups the SCS in more than two categories (first – 5_COND and second SCS – 3_CAT) varies from 3 to 6.

According to Figure D.14., the statistical-based deterioration models such as ordinal (Ord_LR) and binomial (LR) logistic regression are the ones with the lowest variance, but with the highest *Knet* median (except for the second SCS). Furthermore, the SCS that showed the lowest *Knet* values are related to SCS that groups the structural condition in two categories (third – 2_CAT and fourth SCS -C1C5): *Knet* median varies between 1 and 2. In contrast, the *Knet* median of the SCS that groups the SCS in more than two categories (first – 5_COND and second SCS – 3_CAT) varies from 3 to 6.

Furthermore, there are interesting results in the selection of the most suitable model for the second and third SCS. According to Figure D.14.(b). SVM_Laplace and Ord_LR -based models, they have *Knet* medians of 3; however, the variability is higher for SVM_Laplace-based model. Therefore, as the proposed methodology (chapter 9, Part C) suggests to choose the one with the lowest *K* metric value and it presents a statistically significant difference with the other models (Figure 31.b. of the appendix – Part D.1.4.), the SVM_Laplace-based model should be the selected. However, also the SVM_Laplace-based model shows the highest *Knet* values between both models (SVM_Laplace and Ord_LR). Therefore, it was analysed the Q1 and Q3 values of the boxplots to verify the variability below or above the median. Regarding this analysis, it was found that the variability above the median is higher than the one below of the median for the SVM_Laplace-based model. Thus, it was chosen the Ord_LR-based model as the most suitable model for the network level objective and the second SCS.

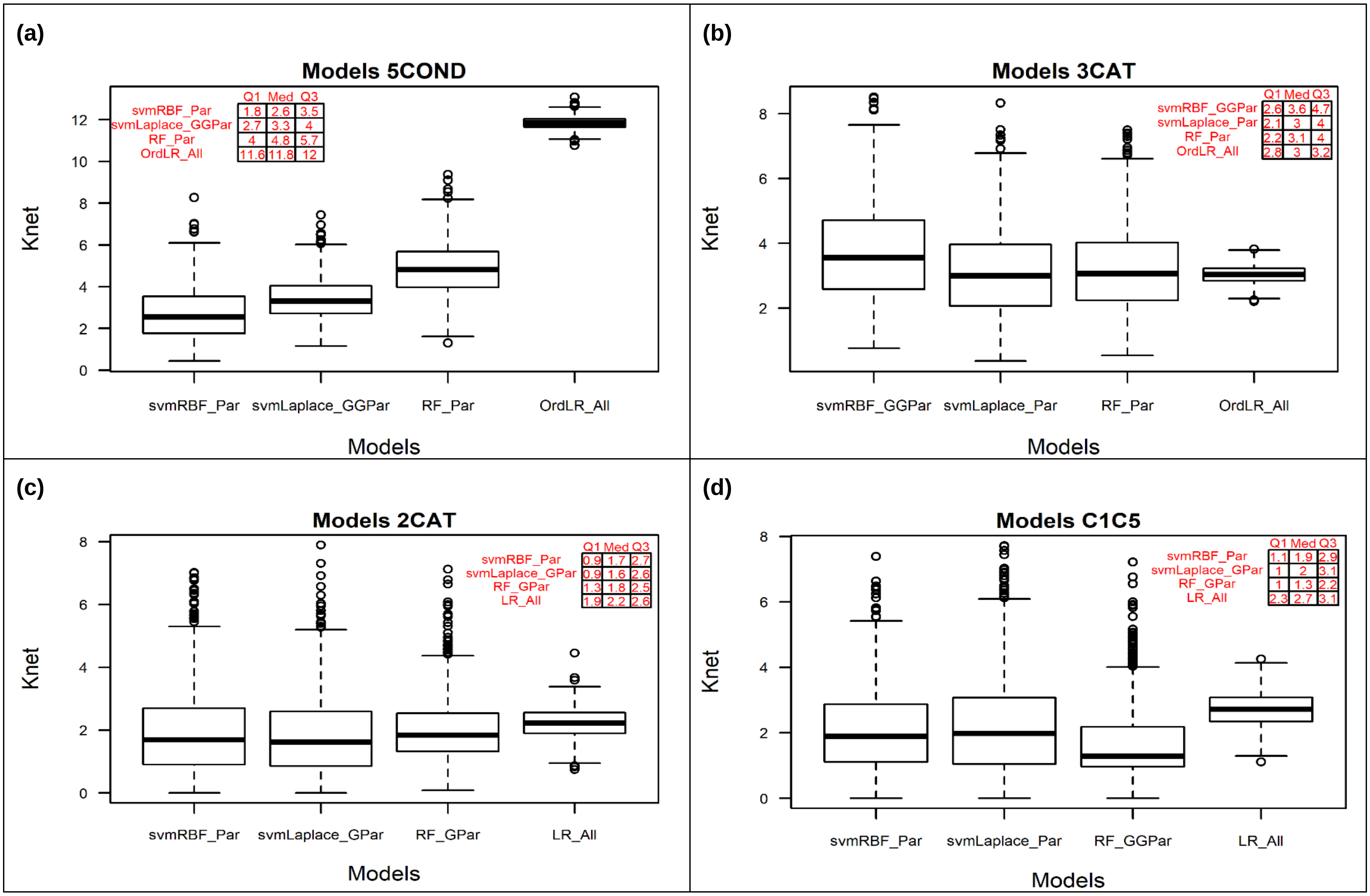

Figure D.14. Comparison of the most suitable deterioration models to achieve the management objective at the network level for the first (a), second (b), third (c) and fourth (d) SCS. Source: Author

On the other hand, Figure D.14.(c) shows that SVM-based models depict similar results considering a different number of variables, and according to Figure 42.b. of the Appendix-Part D.1.4., the results of both models do not show significant statistical differences (p-value > 0.05. Therefore, it was chosen the one that needs a fewer number of variables to achieve the lowest *Knet* values (SVM_RBF considering any relationship of first, second and third grade with the structural conditions – GGParent variables).

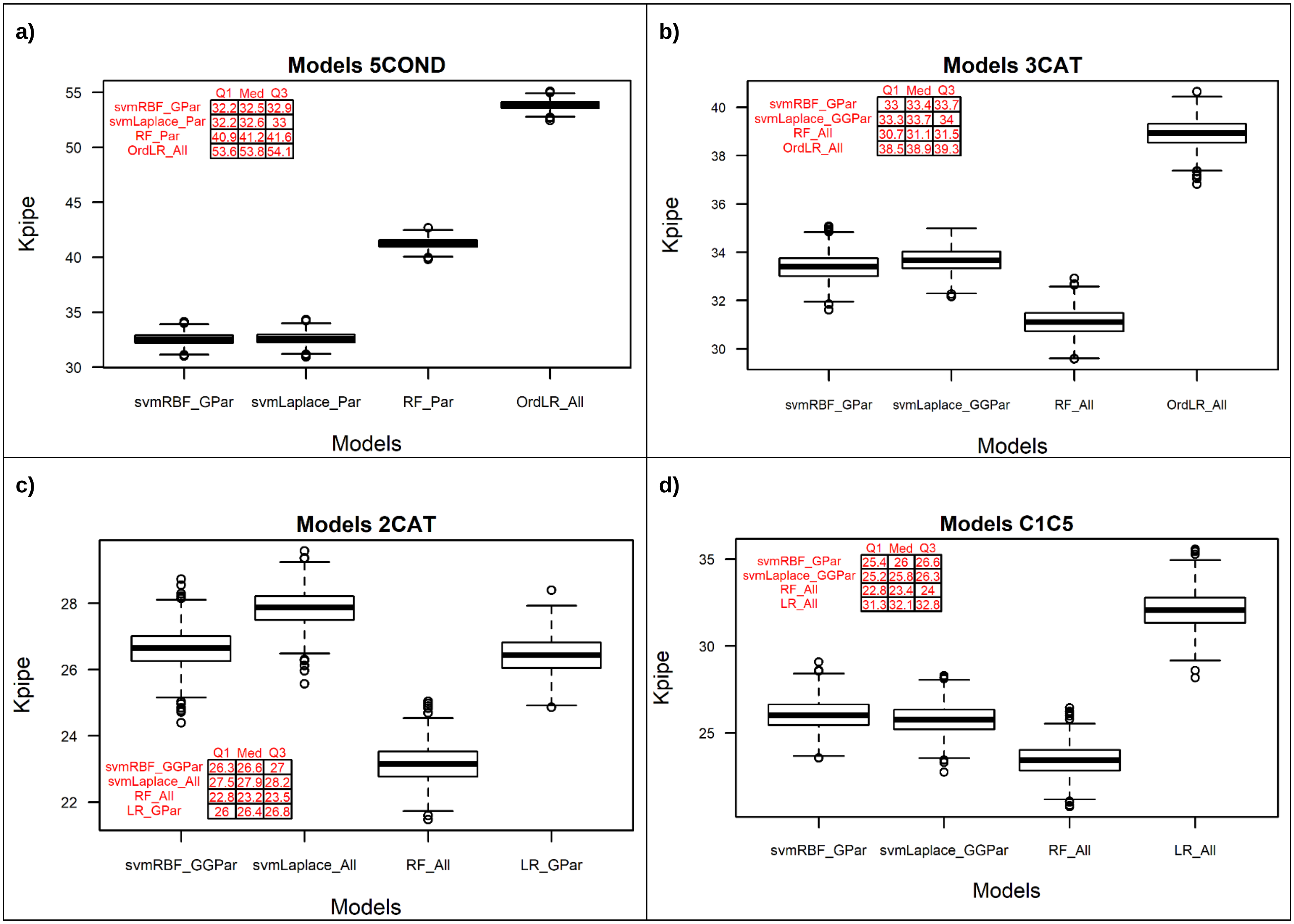

Figure D.15. Comparison of the most suitable deterioration model to achieve the management objective at the pipe level for the first (a), second (b), third (c) and fourth (d) SCS. Source: Author

According to Figure D.15. SVM and RF-based models were the ones that show the lowest *Kpipe* values; however, the RF-based models considering all the studied variables are the ones chosen to achieve the pipe level objective. According to Figure D.15. SVM and RF-based models were the ones that show the lowest *Kpipe* values; however, the RF-based models considering all the studied variables are the ones chosen to achieve the pipe level objective for the second, third and fourth SCS. The appendix-Part D.1.4. shows in detail the analysis of the selection of the most suitable models for each SCS.

Table D.11. shows the summary of the most suitable model for each SCS and each management objective.

Table D.11. The chosen deterioration models for each SCS and management objective after the analysis of boxplots and Wilcoxon tests showed in appendix – D.1.4.

SCS	Management objective	Method-based deterioration model	Type of hierarchy	Variables
First: five structural grades (5_COND)	network	SVM-RBF	First relationship grade (Parent) variables	Inspection year, diameter, installation year, length, type of effluent and age (6 variables)
	pipe	SVM-RBF	First and second relationship grade (GParent) variables	Inspection year, diameter, installation year, length, type of effluent, age, districts, social classes, land uses, depth, seismic shear wave velocity, seismic acceleration presence of trees and slope (14 variables).
Second: three structural categories (3_CAT)	network	Ord_LR	All studied variables	See Table B.1 and B.2 of Part B
	pipe	Random Forest	All studies variables	See Table B.1 and B.2 of Part B
Third: two structural categories (2_CAT)	network	SVM-RBF	First relationship grade (Parent) variables	Diameter, inspection year, installation year and length (4 variables).
	pipe	Random Forest	All studies variables	See Table B.1 and B.2 of Part B
Fourth: Excellent and critical structural conditions (C1C5)	network	SVM-RBF	First, second and third relationship grade (GGParent) variables	Type of effluent, inspection year, diameter, installation year, network type, district, social classes, depth, material, operational zones, land uses, seismic shear wave velocity, age, data quality, seismic acceleration, geological zones, precipitation levels, and water level depths (18 variables)
	pipe	Random Forest	All studies variables	See Table B.1 and B.2 of Part B

Source: Author

According to Table D.11., it is possible to observe that machine learning-based models are the most suitable to develop deterioration models for the prediction of the structural conditions for Bogota's sewer system after applying the proposed optimisation methodology (chapter 8). However, no one method or model leads to a specific sewer asset management objective. It confirms the hypothesis of this PhD thesis that the performance of the deterioration models to predict the structural conditions of sewer assets depends on the case study, the management objective and the information included in the model identified as key factors. Furthermore, Table D.11. shows that the models related to the network level need fewer variables than the models related to the pipe level for achieving their respective objectives.

Furthermore, variables such as inspection year, installation year and diameter of the sewer assets are considered in all the chosen models. In addition, according to the variables considered on the chosen models of each SCS, it was found that: (i) for the first SCS (5_COND), it is enough to consider Inspection year, diameter, installation year, length, type of effluent, age, districts, social classes, land uses, depth, seismic shear wave velocity, seismic acceleration presence of trees and slope for achieving the network and pipe level objectives; (ii) for the second SCS (3_CAT), it is necessary to considers all the studied variables for achieving both management objectives; (iii) for the third SCS (2_CAT), it is enough to consider only four variables (diameter, inspection year, installation year and length) for achieving the network level objectives and necessary to include all the studied variables for achieving the pipe level objective; and (iv) for the fourth SCS (C1C5), all the variables that show any relationship with the structural condition (GGPar) are necessary for achieving the network level objective and all the studied variables for achieving the pipe level objective.

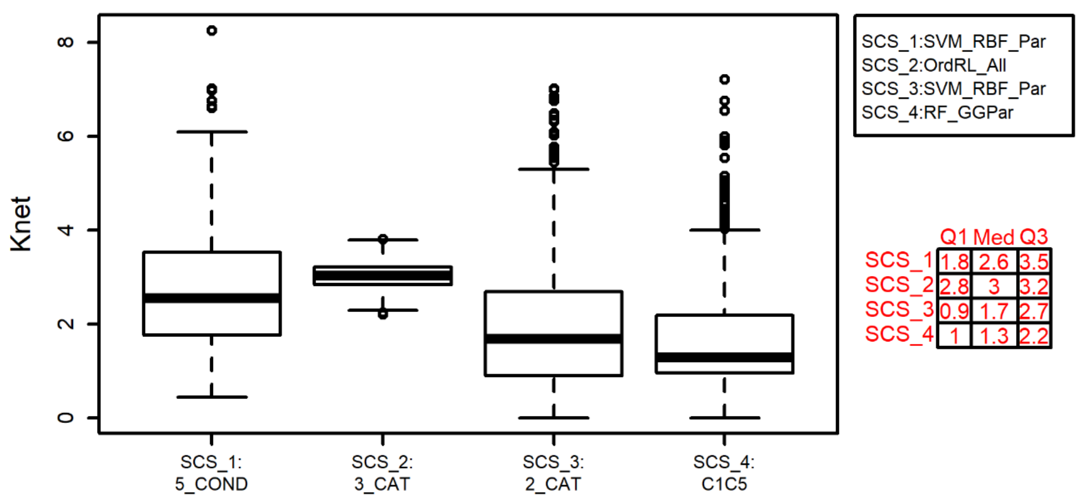

Figure D.16. Comparison of the most suitable deterioration model to achieve the management objective at the network level for the four SCS. Source: Author

From the models depicted in Table D.11., Figures D.16. and D.17. show the boxplot analysis of the *Knet* and *Kpipe* values obtained for the validation data to visualise which model and SCS showed the highest performance quality. As well, Tables D.12. and D.13. show the p-values obtained after applying the Wilcoxon analysis to find significant differences in the prediction results among the models of the different SCS shown in Figures D.16. and D.17. respectively.

According to Figure D.16., the third (two structural conditions – 2_CAT) and fourth (excellent and critical structural conditions - C1C5) SCS are the ones with lower *Knet* values than the ones obtained from the first (5_COND) and second (3_CAT) SCS. It confirms the findings of Ariaratman et al. (2001), López-Kleine et al. (2016) and Guzmán-Fierro et al. (2019a, b and c): grouping the structural conditions in two categories increases the performance prediction quality independently of the deterioration model (in this case SVM considering RBF and Laplace kernel function and Random Forest) and the variables included as predictors in the models (Parent and GGParent variables). The advantage in sewer asset management on grouping the structural conditions in two categories to support the investment plans at the network level is focused on identifying the number of sewer assets in critical conditions for feeding investment plans of short term. Besides, the figure shows that leaving aside the sewer assets in intermediate conditions (fourth SCS – C1C5), more significantly (see Table 22 – appendix – Part D.1.4.5.) increases the prediction performance (the lowest *Knet* values) to estimate the number of sewer assets in excellent and critical conditions.

On the other hand, the results of *Knet* values of the model chosen as suitable for the first SCS (five structural grades -NS-058, 5_COND) are significantly lower (see Table 22 – appendix – Part D.1.4.5) that the *Knet* values of the model chosen as suitable for the second SCS (three structural categories – 3_CAT). It means that the SVM_RBF-based model considering only parent variables (first relationship grade with the structural condition) and the five grades achieves the network level objective to find the number of sewer assets on each structural grade to develop investment plans of medium and long term and follow the recommendations given by EAAB (Table 1 of the Appendix – Part B.1.1) for management planning.

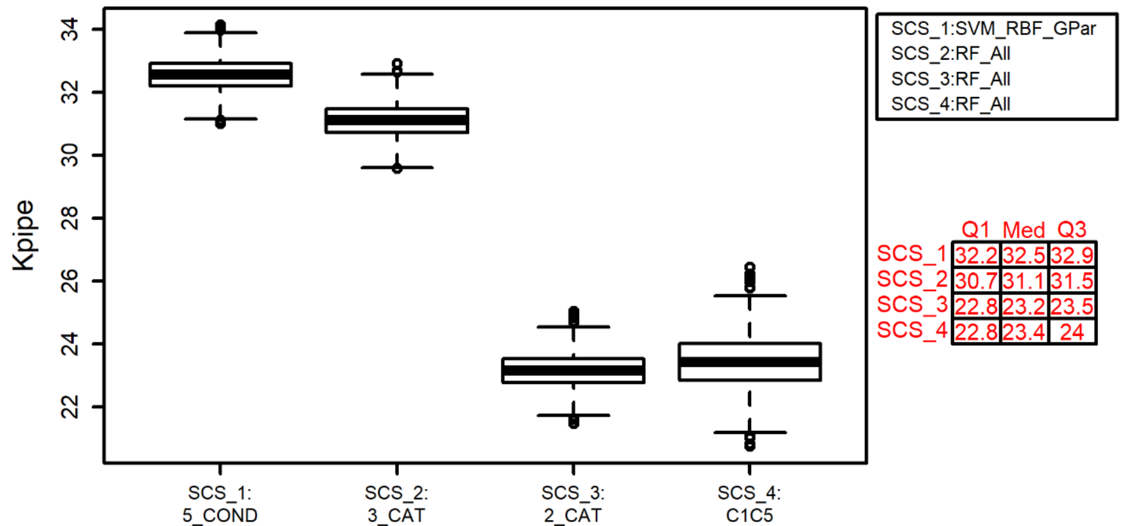

Figure D.17. Comparison of the most suitable deterioration model to achieve the management objective at the pipe level for the four SCS. Source: Author

According to Figure D.17., the models that show the lowest *Kpipe* values are the ones that group the structural condition in two categories (third and fourth SCS). The results for the network level objectives, these results confirm the findings of Ariaratman et al. (2001), López-Kleine et al. (2016) and Guzmán-Fierro et al. (2019a, b and c): the performance quality increases when the structural conditions are grouped in only two categories. According to the Wilcoxon test (p-values showed in Table 23 of the appendix - Part D.1.4.5), there is not a statistically significant difference (p-value > 0.05) between the models chosen for the third and fourth SCS. The above means that the most suitable model for identifying the sewer assets with any structural damage (third SCS) or in critical condition (fourth SCS) is an RF-based model considering all the collected variables in Table B.1 and B.2 of part B.

Regarding the first (5_COND) and second (3_CAT) SCS, the SCS that groups the structural condition in three categories (second SCS) has more prediction performance quality than the one that considered the structural condition as the assessment of the Bogota's standard – NS-058 (EAAB, 2001). Therefore, the selected model to prioritise the activities in sewer asset management is the one based on RF considering all the studied variables (Tables B.1. and B.2). This model allows a hierarchy on the management activities in three levels, according to their importance: replacement (C3 – critical structural conditions), rehabilitation (C2 – intermediate structural conditions) and cleaning (C1 -excellent structural conditions).

From the chosen models to fulfil the network level objectives (Figure D.16.), Table D.12. shows the *K* indicators and *Knet* metric obtained from the selected models for the first and fourth SCS. According to this table for the first SCS (5 structural grades – 5_COND), the deviations for the whole network were not higher than 5.4, being poor and critical conditions (the model overestimated the poor condition and underestimated the critical condition) the ones with the highest deviations. Moreover, the deviations for the oldest sewer assets (ages between 70 -80 years old) are higher for those assets predicted in good and acceptable conditions (the model underestimated the good condition while overestimated the acceptable condition). In the end, the *Knet* for validation data was 2.88. Moreover, regarding the fourth SCS (excellent and critical conditions - C1C5), the deviations are visible in the total sewer system, while there is no deviation for the oldest sewer assets, giving a *Knet* of 0.084.

Table D.12. K indicators and Knet metric for validation data obtained from the chosen models of the first and fourth SCS for Bogota's case.

SCS	**Deviation total sewer system**					**Deviation old sewer assets: 70-80 years**					***Knet***
	K_{DEV_1}	K_{DEV_2}	K_{DEV_3}	K_{DEV_4}	K_{DEV_5}	$K_{OLD(DEV\_1)}$	$K_{OLD(DEV\_2)}$	$K_{OLD(DEV\_3)}$	$K_{OLD(DEV\_4)}$	$K_{OLD(DEV\_5)}$	
SCS_1: 5_COND	0.29	0.29	0.29	4.33	-5.19	0.76	-5.34	2.29	1,53.	0.76	2.88
	K_{DEV_1}				K_{DEV_5}	$K_{OLD(DEV\_1)}$				$K_{OLD(DEV\_5)}$	
SCS_4: C1C5	-0.12				0.12	0				0	0.084

Source: Author

The above results are visualized in the bar plots of Figure D.18 and D.19. of the SVM-based model considering parent variables and the five structural grades; and RF-based model considering GGParent variables and only excellent and critical structural conditions.

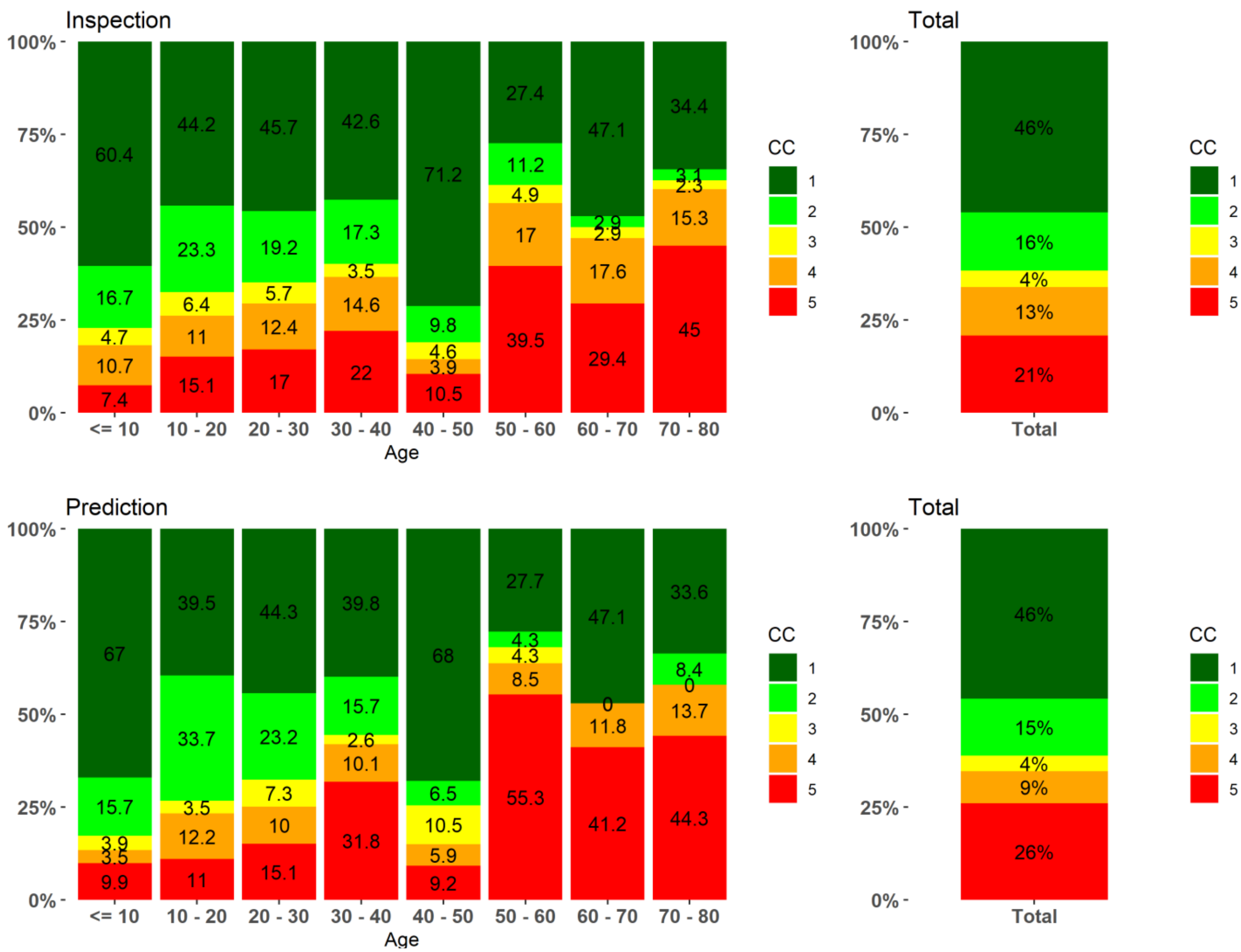

Figure D.18. Inspected and predicted distribution of validation data (SVM-model) considering only parent variables at the network level for Bogota's case. Total network (right) and broken down by age group (left). The colours dark green, green, yellow, orange and red represent excellent (CC1), good (CC2), acceptable (CC3), poor (CC4) and critical (CC5) structural conditions. Source: Author

According to Figure D.18., the SVM-based model chosen for the first SCS at the network level tends to capture the distribution of the structural conditions by each age periods. The great differences are that the model underestimates the structural conditions of acceptable and poor sewers (CC3 and CC4 -yellow and orange colours) in critical conditions (CC5-red colour) for 50-70- and 30-40-years old sewer assets; while it overestimated the structural conditions of recent (<30 years old), and 40-50 years old sewer assets and the oldest sewer assets predicting in better conditions than really they are.

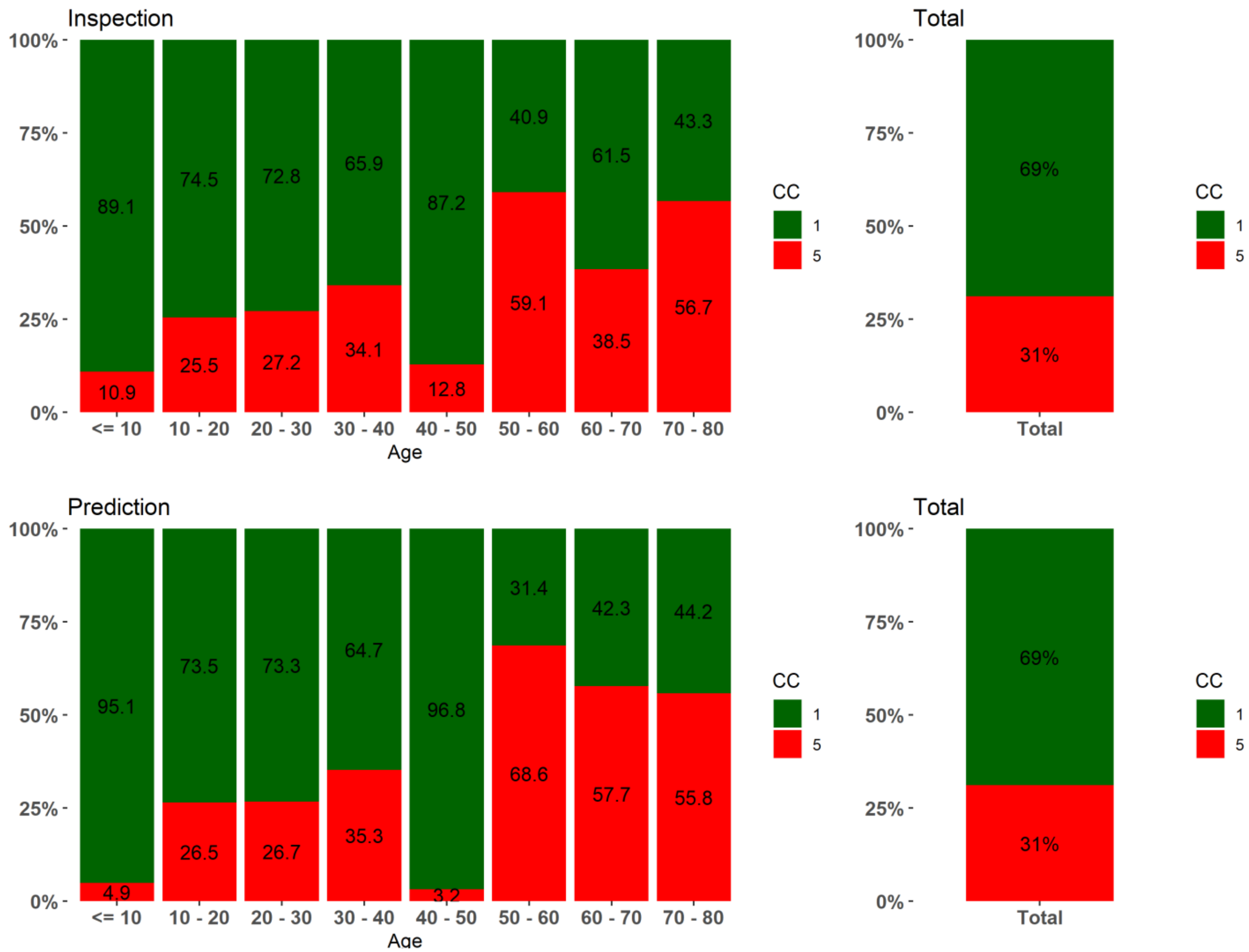

Figure D.19. Inspected and predicted distribution of validation data (RF-model) considering GGParent variables at the network level for Bogota's case. Total network (right) and broken down by age group (left). The colours dark green, green, yellow, orange and red represent excellent (CC1), good (CC2), acceptable (CC3), poor (CC4) and critical (CC5) structural conditions. Source: Author

Regarding Figure D.19., RF-based model chosen for predicting the structural condition at the network level for the fourth SCS also manages to capture the distribution of the structural condition of the observed data. Furthermore, as well as Figure D.18., this model underestimates the structural conditions for the 50-70 and 30-40-year-old sewer assets; and it overestimates the structural conditions of recent sewer assets (<30 years old), 40-50-year-old sewer assets and the oldest sewer assets (70-80-year-old).

From the successful results for validation data, the above models were used to predict the structural condition of the whole sewer system to visualise areas in which the sewer assets are in critical condition and from them, developing investment plans. Therefore, Figure D.20. shows the maps with the prediction of the total sewer system for both models at the network level considering both structural condition scenarios (5_COND and C1C5).

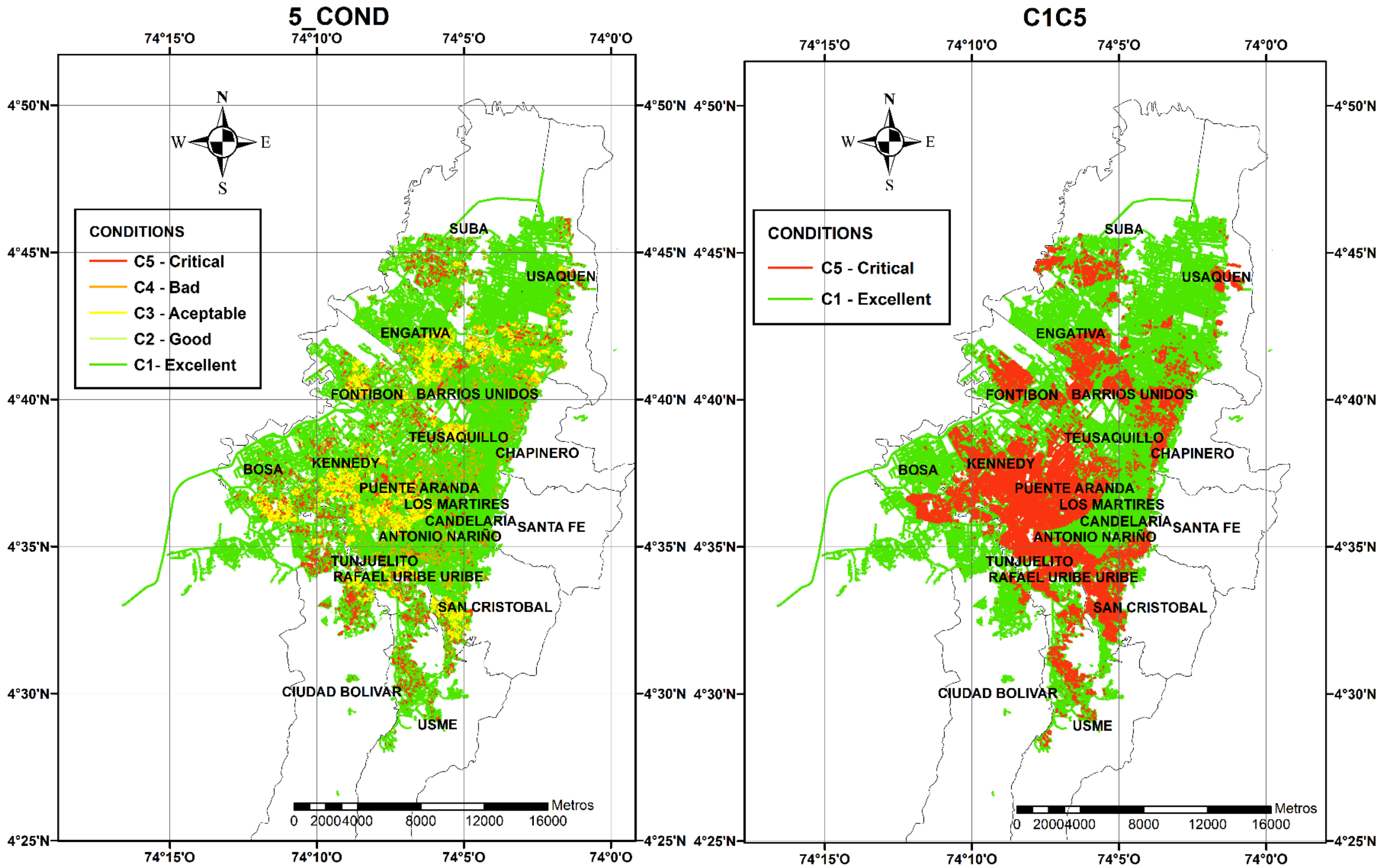

Figure D.20. Maps overview of the predicted structural condition of Bogota's sewer system at network level from SVM-RBF model considering only parent variables and the five structural grades or first SCS (on the left) and RF model considering GGParent variables and two structural conditions (excellent and critical – fourth SCS) (on the right)

According to the maps of Figure D.20., districts such as *Usaquén* and *Engativá* depicted vast areas of sewer assets in excellent conditions for both predictions, likewise districts such as *Suba* and *Kennedy* depict areas with sewer assets in critical conditions. It is essential to observe that both models (SVM and RF) considering different SCS and variables could achieve almost the same prediction result. Moreover, even if these models are guided by the same objective (prediction at the network level for investment plans), the results could support different perspectives of the investment plans at short (Figure D.27., map on the right), medium and long term (Figure D.26., map on the left).

Regarding the map of Figure D.20. on the left, apart from *Suba* and *Kennedy* districts that need investment in replacement actions of an urgent nature, *Puente Aranda*, *Bosa*, *Los Mártires*, *Fontibon*, *San Cristobal*, and *Rafael Uribe* are districts in which investment plans should be built for maintenance, rehabilitation and inspection actions of short and medium term, according to the recommendations of the standard NS-058 (see Table 3 of Appendix – B.1.1).

Table D.13. shows the *K* indicators and *Kpipe* metric obtained from the prediction for validation data from the chosen model in Figure D.24. for the pipe level objectives.

Table D.13. K indicators and Kpipe metric of validation data obtained from the chosen models of the second and third SCS

SCS	K_{TPR_1}	K_{TPR_2}	K_{TPR_3}	K_{FPR1_3}	K_{FNR2_1}	K_{FNR3_1}	***Kpipe***
SCS_2: 3_CAT	62	58,9	55,9	19,24	18,77	9,61	31,34
	K_{TPR_1}	K_{TPR_2}		K_{FPR1_2}	K_{FNR2_1}		
SCS_3: 2_CAT	76,5	74,8		21,17	25,23		23,83

Source: Author

According to Table D.13., RF-based model considering the second SCS (3_CAT) shows True Positive Rate -TPR values above f 56%. It means that most than 56% of sewer assets were correctly predicted in the observed condition. It implies that the model predicts and identifies the structural condition of the sewer assets better than a random model (TPR = 33%) for the three structural categories. Moreover, the overestimation of mispredictions that implies severe consequences ($\mathbf{K_{FNR3\_1}}$: Model predicted in excellent condition those sewer assets that really are in critical condition) is less than 10% given a *Kpipe* value of 31.34.

Furthermore, RF-based model considering the third SCS (2_CAT) shows TPR values around 75%, which implies that more than 75% of sewer assets were correctly predicted in excellent and critical conditions, given a *Kpipe* value of 23.83.

Figures D.21 and D.22. show performance curves for validation data considering the models of both SCS (3_CAT and 2_CAT). These curves were built from calculating the probability of each sewer asset of being in critical conditions (the strip in red colour).

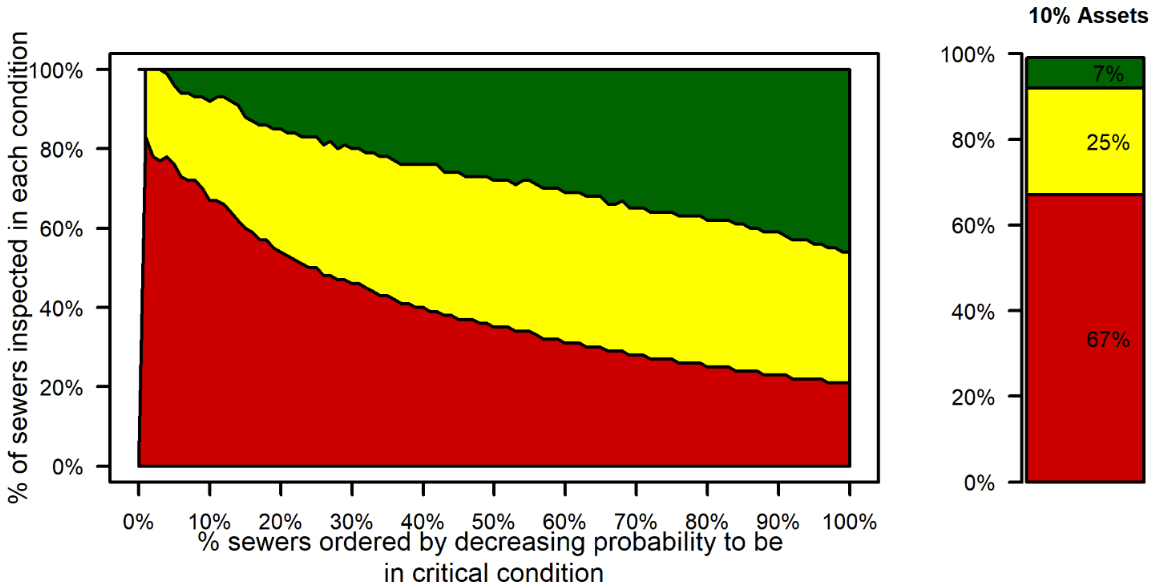

Figure D.21. Performance curve with a sample on its right of 10% sewer assets for validation data obtained from RF-based model considering all studied variables and second SCS (3_CAT) for the pipe level objective. Excellent, intermediate and critical conditions in green, yellow and red strips. Source: Author

According to Figure D.21., the performance curve shows a decreasing behaviour when the probability of being in critical condition reduces. It means that the prediction of RF-based model helps to prioritise the replacement of the sewer assets with the highest probability of being in critical condition with the reliability of being in that condition. The sample on its right shows the 10% of sewer assets with the highest probability of being in critical condition. This bar-plot shows that 69% of the sewer assets are effectively in critical conditions, 24% in intermediate conditions and 7% in excellent conditions. The above means that if the budget for replacement is low, there is no need to inspect all the sewer systems to develop replacement/rehabilitation activities plans. For instances, in accordance with the prediction of this model, the managers could rehabilitate 10% of the sewer assets with the highest probability of being in critical condition with a reliability of 69% that the sewer assets need urgent replacement activities and 93% of reliability that need any management activity. Figure D.29. shows a comparison between the structural conditions, grouped under the second SCS, found on CCTV data inspections (observed conditions), and the probability of being in critical conditions from the RF-based model prediction.

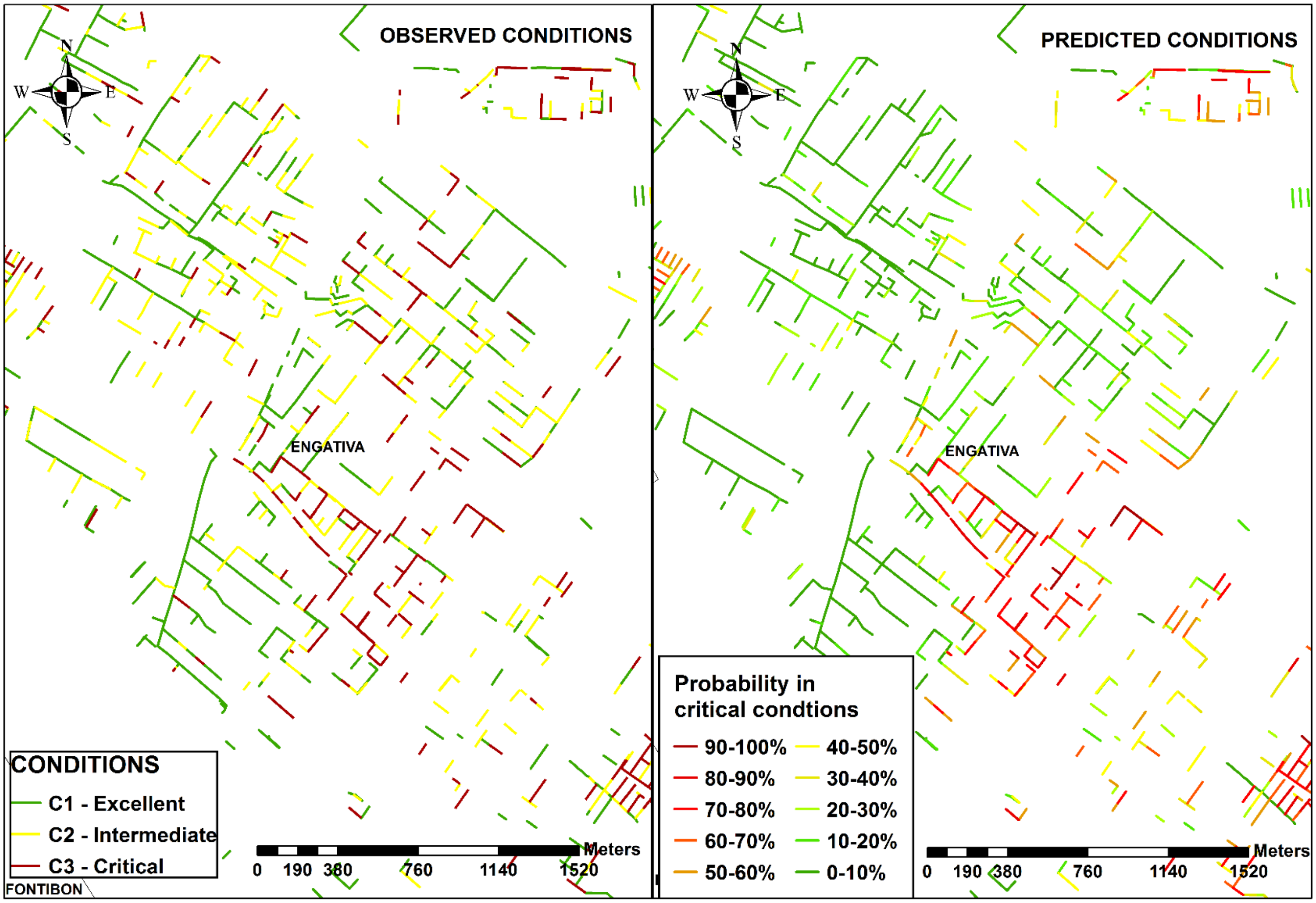

Figure D.22. Comparison between the conditions found by CCTV inspection data grouped according to the second SCS (left) and prediction of the probability of being in critical conditions (right) for Bogota's case, magnified onto Engativá district. Source: Author

According to Figure D.22., it is found that the sewer assets in red scale that represent the higher probability of being in critical conditions (probability >70%) from the map "predicted conditions" really are in critical conditions in the map "observed data". As well, the sewer assets in green scale that represent the lowest probabilities of being in critical conditions (probability <20%) really are in excellent structural conditions. The sewer assets in median probabilities of being in critical conditions are the ones that it is difficult to intuit. However, the RF-based model also gives the probabilities of being on each structural category. The relevant fact from the above comparison is visualising the performance of the chosen model for rehabilitation activities to prioritise the management activities in some sewer assets over others.

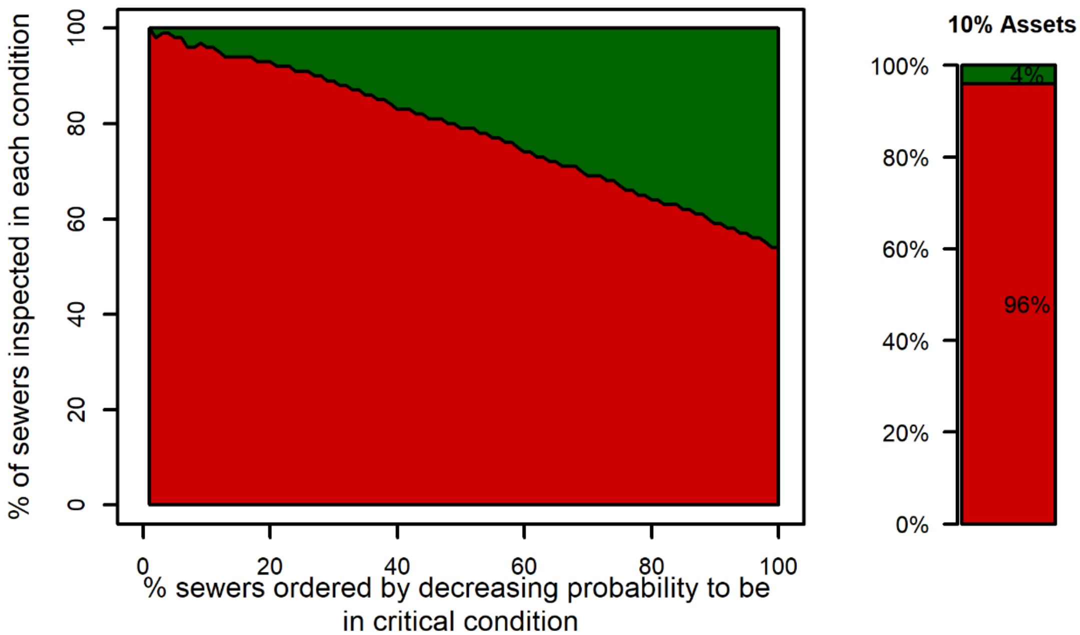

Figure D.23. Performance curve with a sample on its right of 10% sewer assets for validation data obtained from RF-based model considering all studied variables and third SCS (2_CAT) for the pipe level objective. Green and red strips represent without and with structural damage in the sewer assets. Source: Author

Figure D.23. shows that the performance curve depicts a decreasing behaviour when the probability of a sewer asset has any structural damage also diminishes. This result is positive due to the model could address rehabilitation plans prioritising those sewer assets with the highest probability of presenting any structural damage. Supposing that the budget for rehabilitation is limited, it is suggested rehabilitating the 10% of sewer assets with the highest probability of present any structural damage with a 96% of reliability.

As well as Figure D.21., Figure D.23. shows a comparison between the observed structural categories (from CCTV inspections), grouped under the third SCS (two categories sewer assets without and with structural damages) and the probability of the sewer assets have any structural damage.

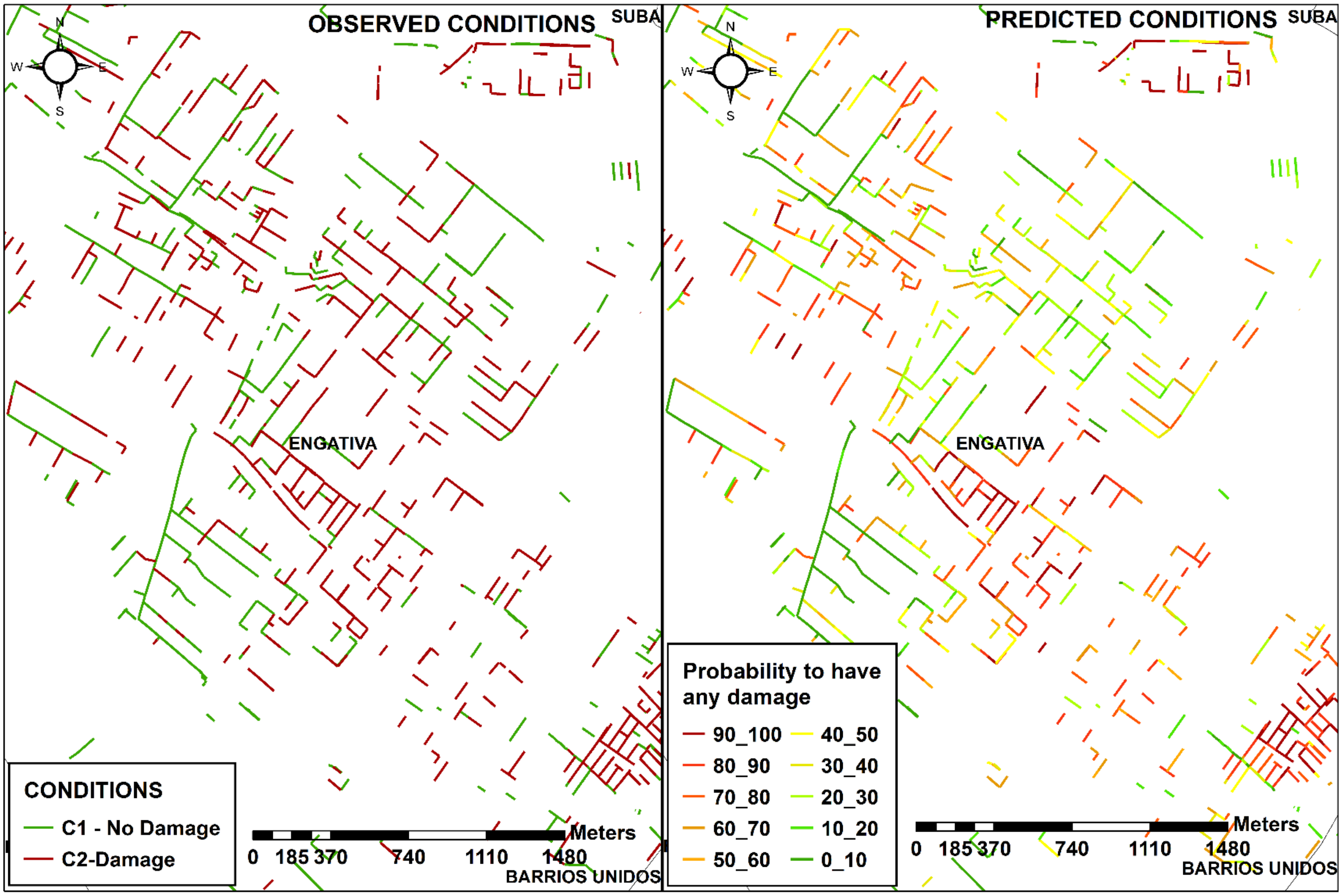

Figure D.24. Comparison between the conditions found by CCTV inspection data grouped according to the third SCS (left) and prediction of the probability of being in critical conditions (right) for Bogota's case, magnified onto Engativá district. Source: Author

According to Figure D.24., the sewer assets in red-orange scales (map of predicted conditions) that represent the highest probability that the sewer assets have any structural damages really have any structural damage. As well, the sewer assets are in yellow colour have more prediction mistakes. Likewise, the sewer assets in green scales are the ones that have higher probabilities of being in excellent structural conditions (no damages). From the above comparison, it confirms the successful predictions of the chosen RF-model geographically together with the performance curve of Figure D.23.

From the above successful results, the model for the pipe level objectives was used to predict the structural condition of the whole Bogota's sewer system to simulate in detail the structural condition of sewer assets and support rehabilitation plans. Figure D.24. shows a segment of the prediction of the structural condition of Bogota's sewer system in Kennedy district obtained from RF models considering all studied variables and the second (three structural categories: excellent, intermediate and critical) and two (without and with damages) SCS.

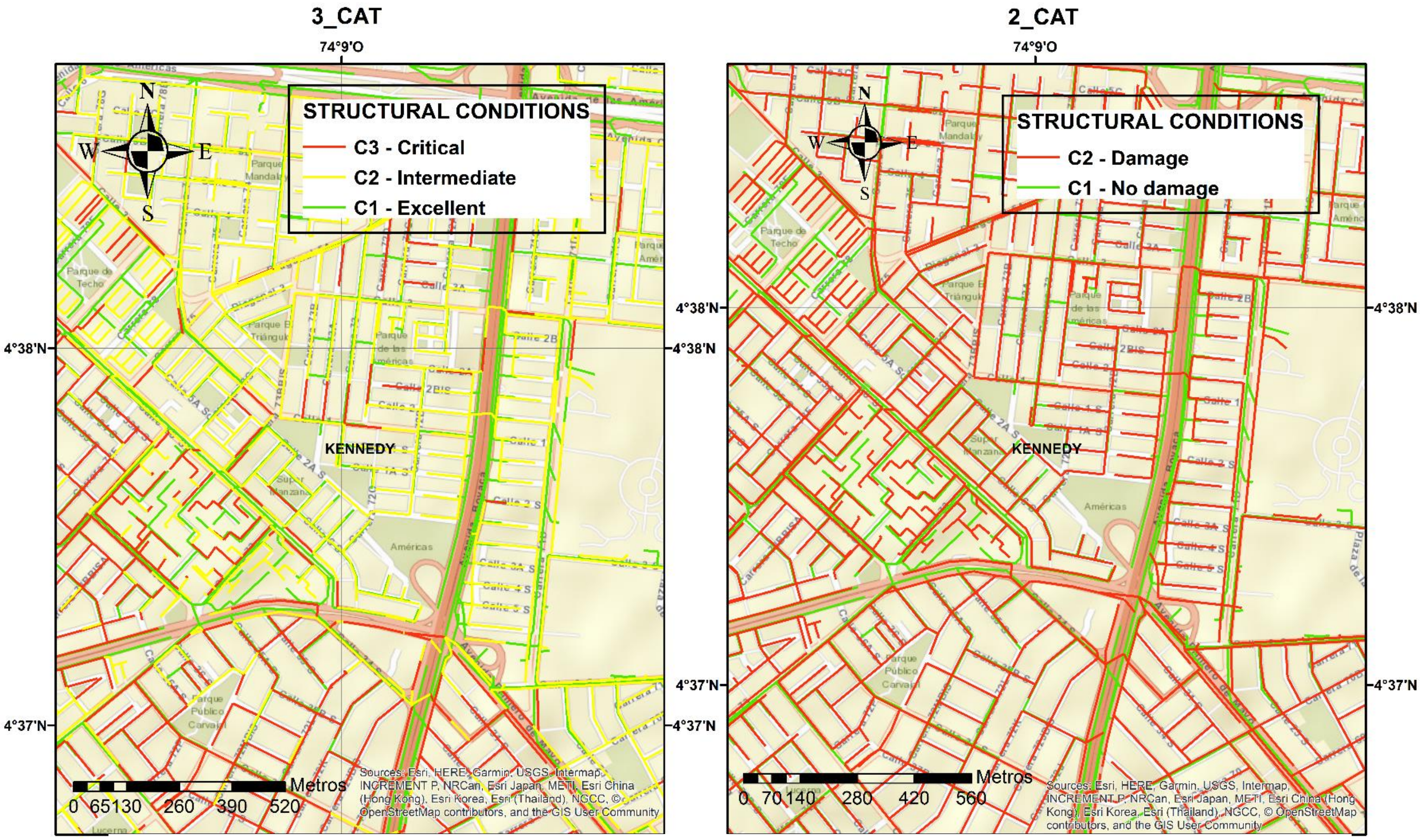

Figure D.25. Example of maps overview of predicted structural condition of Bogota's sewer system (magnified onto Kennedy district) at pipe level from RF-model considering all the studied variables and the three (excellent, intermediate and critical – second SCS) (on the left) and two structural conditions (without and with structural damages – third SCS) (on the right)

According to Figure D.24., both maps predict the same sewer assets in excellent conditions (green lines), as well the sewer assets that have any structural damage have painted in yellow or red for the map of the second SCS (map on the left) and in red for the third SCS (map on the right). From the above results, the rehabilitation plans could be addressed from two perspectives: (i) prioritisation of the most important sewer assets of being replaced and (ii) identification of sewer assets that need rehabilitation activities and tracing in inspection activities.

11.2. RESULTS FOR MEDELLIN'S CASE

This subchapter contains the results of the proposed methodology (described in chapter 9, part C) for Medellin's sewer system. As well as for Bogota's case, four structural conditions scenarios were created to support the management objectives and activities (Table D.14.): (i) the five structural grades given by Medellin's standard (EPM, 2010); (ii) three structural categories that classify the structural condition in acceptable, poor and critical conditions; (iii) two categories that classify the structural condition in sewers in acceptable and poor structural conditions; and (iv) two categories that only considers the sewer assets in excellent and critical conditions.

Table D.14. Description of structural condition scenarios (SCS) for Medellin's case

<table>
<tr><th>Original</th><th colspan="3">Groups</th></tr>
<tr><th>EPM (2010)</th><th>3 Categories</th><th>2 Categories</th><th>2 Categories</th></tr>
<tr><td>1</td><td rowspan="3">C1</td><td rowspan="3">C1</td><td>C1</td></tr>
<tr><td>2</td><td>-</td></tr>
<tr><td>3</td><td>-</td></tr>
<tr><td>4</td><td>C2</td><td rowspan="2">C2</td><td>-</td></tr>
<tr><td>5</td><td>C3</td><td>C2</td></tr>
</table>

Source: Author

Three and two structural categories were chosen because it simplifies the decision making in sewer asset management that offers the local standard. These clusters support the designing of management plans to short, medium and long term. The use of Equation C.3. (Part C) allows for balancing the data in the structural condition for prediction purposes. Therefore, the best way was grouping the structural conditions in acceptable, poor and critical structural conditions. Also, two more scenarios were created grouping the structural conditions in two categories, following the suggestions of Ariaratman et al. (2001) and López-Kleine et al. (2016). Therefore, the third SCS was created following the recommendations of Equation C.3. (Part C) which suggest grouping the structural conditions in acceptable and bad-critical structural conditions (See Table D.14.) and the fourth SCS was created according to the findings of Guzmán-Fierro et al. (2019a, b, and c) for Bogota's case: estimating only the excellent and critical structural conditions (leaving aside intermediate conditions) increases the prediction quality because it reduces the qualification uncertainty in the intermediate conditions. Besides, grouping the structural conditions in two categories is useful to develop management plans for sewer assets that need urgent repair.

11.2.1. HIERARCHY OF THE KEY VARIABLES OF THE DETERIORATION OF THE SEWER ASSETS FOR MEDELLIN'S CASE

According to the first methodology described in subchapter 9.1., Table D.15. shows a summary of the hierarchy of the variables with the most influence over the deterioration of the structure of the sewer assets for each structural condition scenario for Medellin's case.

As well as for Bogota's case, Table D.15. shows a hierarchy was chosen according to the relationship of each variable with the structural condition. The relationship showed in this table has three levels that represent the first, second and third relationship grade with the structural condition. These relationships were obtained after a boxplot analysis of 1000 Monte-Carlo simulations of the BN results of the suggested methodology in subchapter 9.1 (Part C). The relationship between each variable was sorted hierarchically according to the ratio between the median value and the interquartile range of the given boxplot (Q3-Q1). For more details about these hierarchies, please see appendix – Part D.2.1.

Table D.16. depicts that 13 variables of the 23 studied variables showed a non-depreciable relationship with the four structural condition scenarios (boxplot median > = 0.05). Reminding the proposed methodology (subchapter 9.1., part C), the boxplots summarized the probabilities in which each variable has any relationship (first, second and third grade) with the structural condition. Therefore, variables such as inspection year, age, installation year, basin, material, and foundation type are variables that have any relationship with the structural condition in the four SCS for Medellin's case.

Variables related to the age (inspection year, installation year and age) occupied the first relationship in all SCS. Physical and surrounding (urban, environmental and operational) characteristics of sewer assets showed similar relationships with the structural deterioration of sewer assets. Physical and surrounding characteristics showed second and third grades relationships with the structural condition (except for the third SCS). However, from the physical characteristics only length and material were relevant in more than two SCS. Variables such as basin showed stronger relationship with the structural condition than the district (district showed a relationship with the structural condition for the second, third and fourth SCS); even both variables could represent area characteristics. It could happen because the area of the basin is smaller than the district, and this variable would characterise in a better way the inclusion of some unknown variables. Furthermore, the relevance of the foundation type on the structural deterioration of the sewer assets is related to relationship with the material variable, which also was relevant to the structural deterioration of the sewer assets. It happens because the foundation type is chosen from the material of the sewer assets according to the standard of sewer design given by EPM (EPM, 2013).

The type of effluent showed a relationship with the structural condition in the first, second and third SCS (SCS, considering intermediate conditions). In contrast, the operational status, the diameter of sewer assets, the depth and seismic zones showed a relationship with the structural condition for the fourth SCS when the intermediate structural conditions were not considered.

Table D.15. Summary of the hierarchy of the influential variables over the structural condition by each SCS for Medellin's case.

Relationship grade	**Variables**			
	First SCS: 5-structural grades	**Second SCS: 3-structural categories**	**Third SCS: 2-structural categories**	**Fourth SCS: Excellent and critical structural conditions**
First (Parent variables)	Inspection Year ("IY")	Inspection Year ("IY")	Inspection Year ("IY")	Inspection Year ("IY")
	Age ("Age")	Age ("Age")	Installation Year ("CY")	Installation Year ("CY")
		Length ("Length")	Material ("Mat")	Age ("Age")
			Length ("Length")	
			Age ("Age")	
Second (GParent variables)	Installation Year ("CY")	District ("Dis")	Basin ("Basin")	Foundation Type ("Ciment")
	Basin ("Basin")	Installation Year ("CY")	Foundation Type ("Ciment")	Material ("Mat")
		Basin ("Basin")	District ("Dis")	Operational Status ("OpStatus")
				Districts ("Dis")
Third (GGParent variables)	Material ("Mat")	Material ("Mat")	Type of effluent ("Sew")	Diameter ("Diam")
	Foundation Type ("Ciment")	Foundation Type ("Ciment")		Basin ("Basin")
	Type of effluent ("Sew")	Type of effluent ("Sew")		Depth ("Depth")
				Seismic Zone ("SeismicZ")

Source: Author

According to the first exploration of bar plot analysis (Table B.6., Part B), variables related with the age of the sewer asset (inspection year, age, installation year), as well as the basin, districts, seismic zones, type of effluent, material, length and diameter of sewer assets were identified in this exploration as influential over the deterioration of the structural condition. According to this bar plot analysis (Table B.6, Part B),

the following criteria could be alert to identify assets in poor structural conditions and could eventually be used to support a preliminary decision-making in a simplified manner: (i) the oldest sewer assets; (ii) sewer assets inspected between 2014 and 2017; (iii) the smallest sewer asset (diameters < 0.3 m); (iv) sewer assets located in low seismic zones; (v) separate sewer systems; (vi) concrete sewer assets; (vii) the extended sewer assets (lengths > 50 m); and (viii) sewer assets located on the west (particularly *Laureles*, *Las Américas* and *Castilla* districts, and *Altavista*, *La Picacha-Nutibara*, *La Poblada*, *La Malpaso, La Grande-Estrella* and *Granizal* basins). However, variables identified in the bar plot analysis with an apparent relationship with the structural condition such as slope, road type, the closeness to trees, element type and longitude and latitude coordinates do not show any relationship with the structural condition, according to the proposed methodology. While variables such as foundation type, operational status, and depth of the sewer assets, that did not show any apparent relationship with the structural condition by the bar plot analysis, were found as related with the structural condition (second and third relation grade) by the proposed methodology (Table D.15.)

In summary, as well as for Bogota's case and other experiences in the literature (Davis et al., 2001a; Baik et al., 2006; Le Gat, 2008; Ana et al., 2009; Rokstad & Ugarelli, 2015; El-Housni et al., 2017; Caradot et al., 2018), the variable age is a key factor for the deterioration of the structure of the sewer assets.

11.2.2. EXLORATION OF DETERIORATION MODELS

As well as for Bogota's case, for Medellin's case was explored the same statistical and machine learning methods to develop deterioration models for predicting the structural condition of uninspected sewer assets: support vector machines (SVM), random forest (RF), lineal discriminant analysis (LDA), binomial (LR), multinomial (Muti_LR) and ordinal (Ord_LR) logistic regression. These models also were explored by two scenarios (scenario 1 considering only the age as an influential variable, and scenario 2 considering the age, material, type of effluent, depth, length, slope, and diameter) for estimating the critical structural condition. For this case study, grades 2 and 3 were grouped because of the low of sewer assets qualified in these grades. Figure D.26. shows a deviation analysis for estimating the critical structural condition.

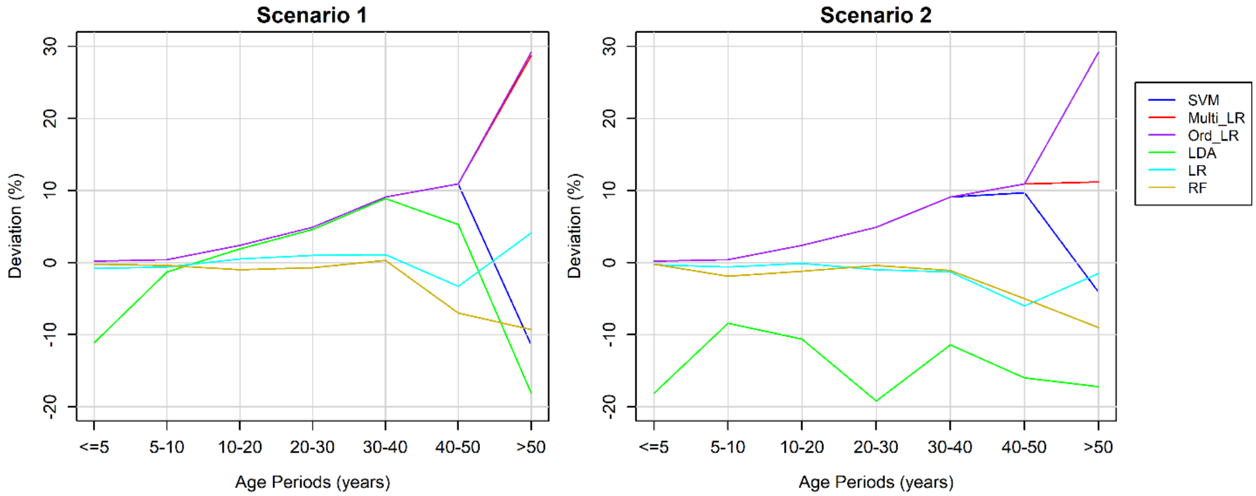

Figure D.26. Comparison models prediction of the critical structural condition for Medellin's case by deviation analysis. Left: results for scenario 1. Right: results for scenario 2

According to Figure D.26., there is a lighter improvement (lower deviation) when the models consider the sewer characteristics together with age (scenario 2) as input variables, in particular for sewers with more than 40 years (except for LDA and Ord_LR models). This figure shows that LR and RF-based models are the ones with the closest deviation to zero: lower than 2% deviation for sewer assets with less than 40 years and lower than 10% for sewer assets with more than 40 years. However, LR-based model results present lower deviations considering only the age as the predictor variable over the critical condition of the sewer pipes. The prediction results of SVM, Multi_LR and Ord_LR are similar for sewers with less than 40 years for both scenarios. However, for sewer assets with more than 40 years, SVM and Multi_LR-based models, for scenario 2, predict more sewer assets in critical condition correctly, reducing the deviation percentage. The Ord_LR-based model does not show any change between both scenarios. On the other hand, even if the prediction results given by LDA-based model, are not the best in comparison with the results obtained with the other models, it is important to highlight that the closest deviation to zero was obtained under the first scenario. The above results indicate that under certain circumstances, some models need more information for achieving a particular management objective.

In summary, the models that show higher prediction capacity are the ones based on LR and RF for Medellin's case. However, it is interesting to highlight some facts: (i) RF, SVM and Multi_LR improve their capacity prediction when the model considers more variables than only the age (scenario 2); (ii) LR shows higher prediction considering only the sewer age as input variable; (iii) LR models show higher prediction quality than Multi_LR; and (iv) Multi_LR and LDA show similar prediction results (scenario 1 for Medellin).

Figure D.27. shows the performance curves of LR, SVM and RF prediction results, under both scenarios 1 and 2, since results obtained with these models were the ones with the highest success percentage to be in critical conditions. Besides, this figure shows that LR and RF under scenario 2 show the highest success percentages: according to the sample of the first 10% of sewer assets with the highest probability to be in critical condition, RF and LR identify 34% and 29% of sewer assets in that condition. The performance curves result of the SVM-based model is not as successful as LR and RF ones. However, it is important considering that the SVM-based model shows a higher success percentage under scenario 1 (only age): according to the bar plot that shows the sample of the first 10% of sewers with the highest probability to be in critical condition, the SVM-based model under scenario 1 identifies 20% of sewers in that condition while the SVM under scenario 2 identifies only 17%.

Furthermore, the models under scenario 1 do not tend to be flat. It means that any of SVM, LR or RF models could be considered to support decision-making for rehabilitation plans. However, it is recommendable to consider the results obtained from LR and RF-based models under scenario 2 for identifying more pipes in that condition. The performance curves obtained by LDA, Multi_LR and Ord_LR model predictions are not shown because their prediction quality does not show remarkable peaks of success percentage (flat tendency) (see appendix – Part D.1.2). For more details about this exploration, please see Hernández et al., 2019b.

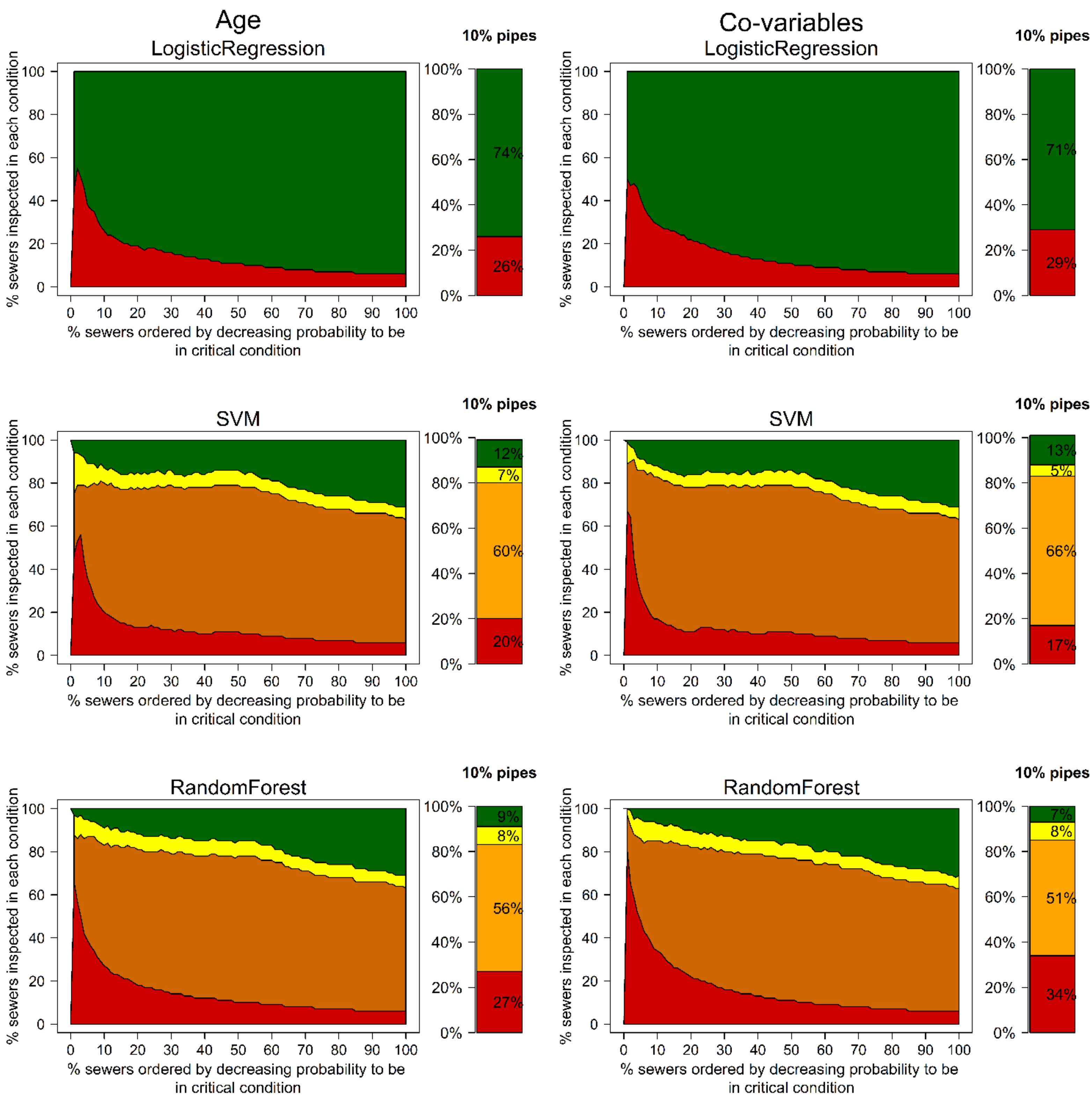

Figure D.27. Performance curves of the LR, RF and SVM-based models with a sample on its right of 10% sewer pipes. Left: scenario 1 (considering only the input variable age as an influential variable); right: scenario 2 (considering the age and other variables as influential variables) for Medellin's case. Source: Author

11.2.3. SUITABLE DETERIORATION MODELS FOR MANAGEMENT OBJECTIVES FOR MEDELLIN'S CASE

After finding the above hyperparameters' combinations for the machine learning-based deterioration models, 1000 Monte-Carlo simulations were carried out for all the selected deterioration models (based on both statistical and machine learning methods) to estimate the prediction rank of validation data for the structural condition of the sewer assets focused on the two analysed management objectives (at the network and pipe level).

It compares all the predictions obtained with the deterioration models to find the one that most significantly minimises the *Knet* and *Kpipe* metrics (see Appendix-D.2.4, Figures 59-98). Based on the proposed methodology (Chapter 9, Part C), when the models do not show a significant difference in their prediction results, it is chosen the one with the lowest number of needed variables to achieve the management objective.

Figure D.28. shows the most suitable models to achieve the network level management objective (*Knet*) for each SCS: (a) five structural grades (5_COND), (b) three structural categories (3_CAT), (c) two structural categories (2_CAT), and (d) excellent and critical structural conditions (C1C5).

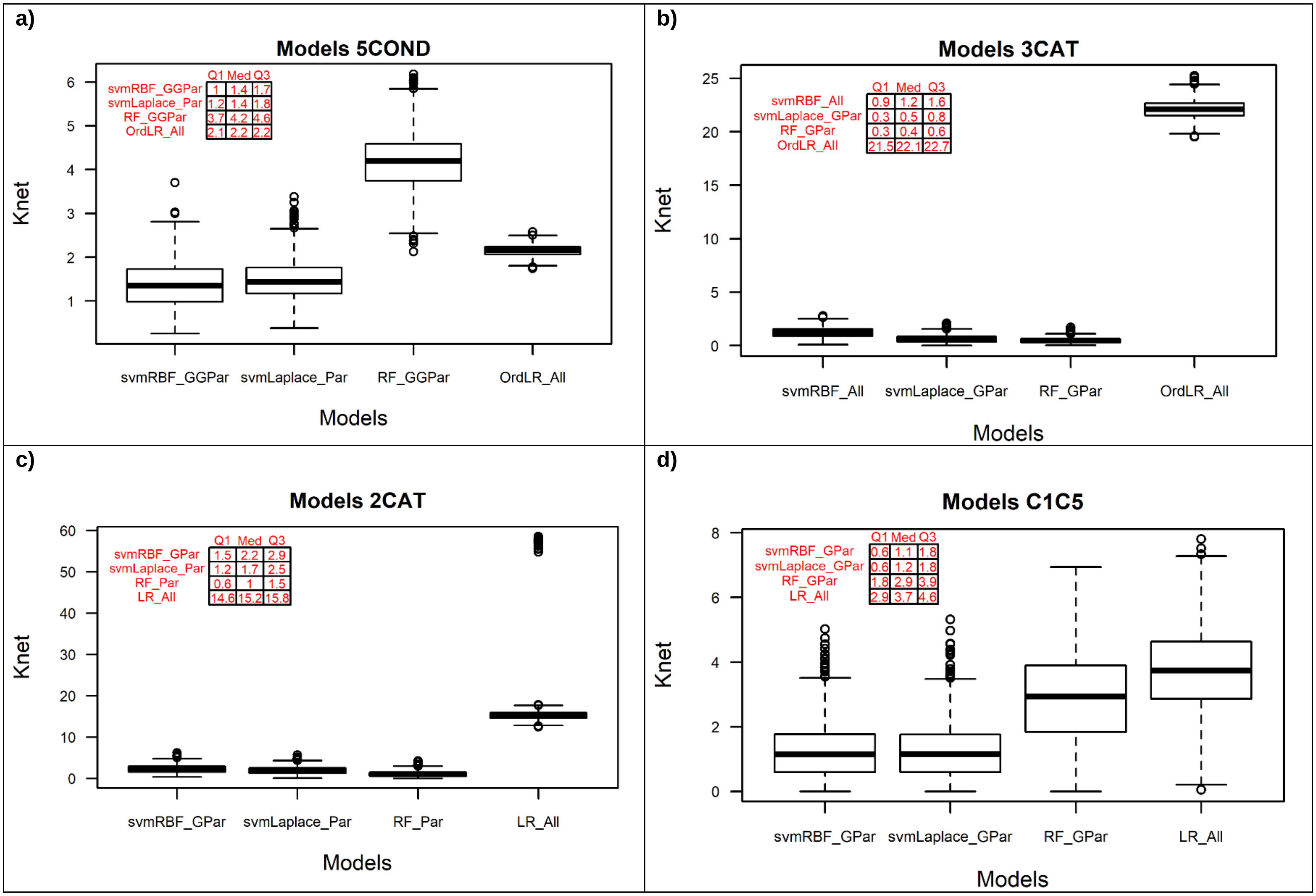

Figure D.28. Comparison of the most suitable deterioration models to achieve the management objective at the network level for the first (a), second (b), third (c) and fourth (d) SCS for Medellin's case. Source: Author

According to Figure D.28., the statistical-based deterioration models such as ordinal (Ord_LR) and binomial (LR) logistic regression are the ones with the lowest variance (except for the fourth SCS), but with the highest *Knet* median. In fact, all the optimised machine learning-based models gave *Knet* values below 5 (except for the fourth SCS, with a median of 3.7 for the LR-based model). Comparing with Bogota's case, for Medellin's case, the SCS that groups the structural condition in two categories do not show the lowest *Knet* values for validation data.

As a summary of the analysis carried out in the Appendix -Part D.2.4., it was found that: (i) the prediction results of SVM-based models for the first SCS (5_COND) are very close, however the Wilcoxon test showed that there are significant differences between both models, being the SVM_RBF-based model considering the variables that show any relationship with the structural condition (GGPar) the one with the lowest *Knet* values for the validation data; (ii) the predictions of SVM_Laplace and RF-based models showed closer *Knet* values; however, according to the Wilcoxon test, there is a significant difference between both models, being the RF-based model that considers the variables that presented the first and second relationship grades with the structural condition (GPar) the one with the lowest *Knet* values for the second SCS (3_CAT); (iii) the predictions obtained with the RF-based model that considers the variables with the first relationship grade with the structural condition (Par) is the one with the lowest *Knet* values for the third SCS (2_CAT), and all the models (SVM, RF and Ord_LR-based models) present significant differences among them; and (iv) the prediction results obtained with SVM-based models are the ones with the lowest *Knet* values for the fourth SCS (C1C5), and after testing significant differences between both models (SVM-based models considering RBF and Laplace kernel functions), it was found that there are not significant differences between them: any of both SVM-model could be chosen because both consider the same number and type of variables (first and second grades relationships with the structural condition -GPar).

Moreover, Figure D.29. shows the most suitable models to achieve the pipe level management objective (*Knet*) for each SCS: (a) five structural grades (5_COND), (b) three structural categories (3_CAT), (c) two structural categories (2_CAT), and (d) excellent and critical structural conditions (C1C5).

According to Figure D.29., Ord_LR and LR-based models are the ones that gave the highest values of *Kpipe* values for the validation data. Furthermore, it is interesting to highlight that the *Kpipe* values for the SCS that groups the structural condition in two categories presented lower *Kpipe* values than the SCS that group the structural condition in more categories, for all the models. It confirms the findings of Ariaratman et al. (2001) and López-Kleine et al. (2016). Furthermore, the lowest *Kpipe* values for the validation data obtained with all the models are related to the fourth SCS (critical structural conditions), leaving outside the predictions of sewer assets in intermediate conditions.

In accordance with the analysis carried out in appendix -Part D.2.4., it was found that all the models show significant differences.

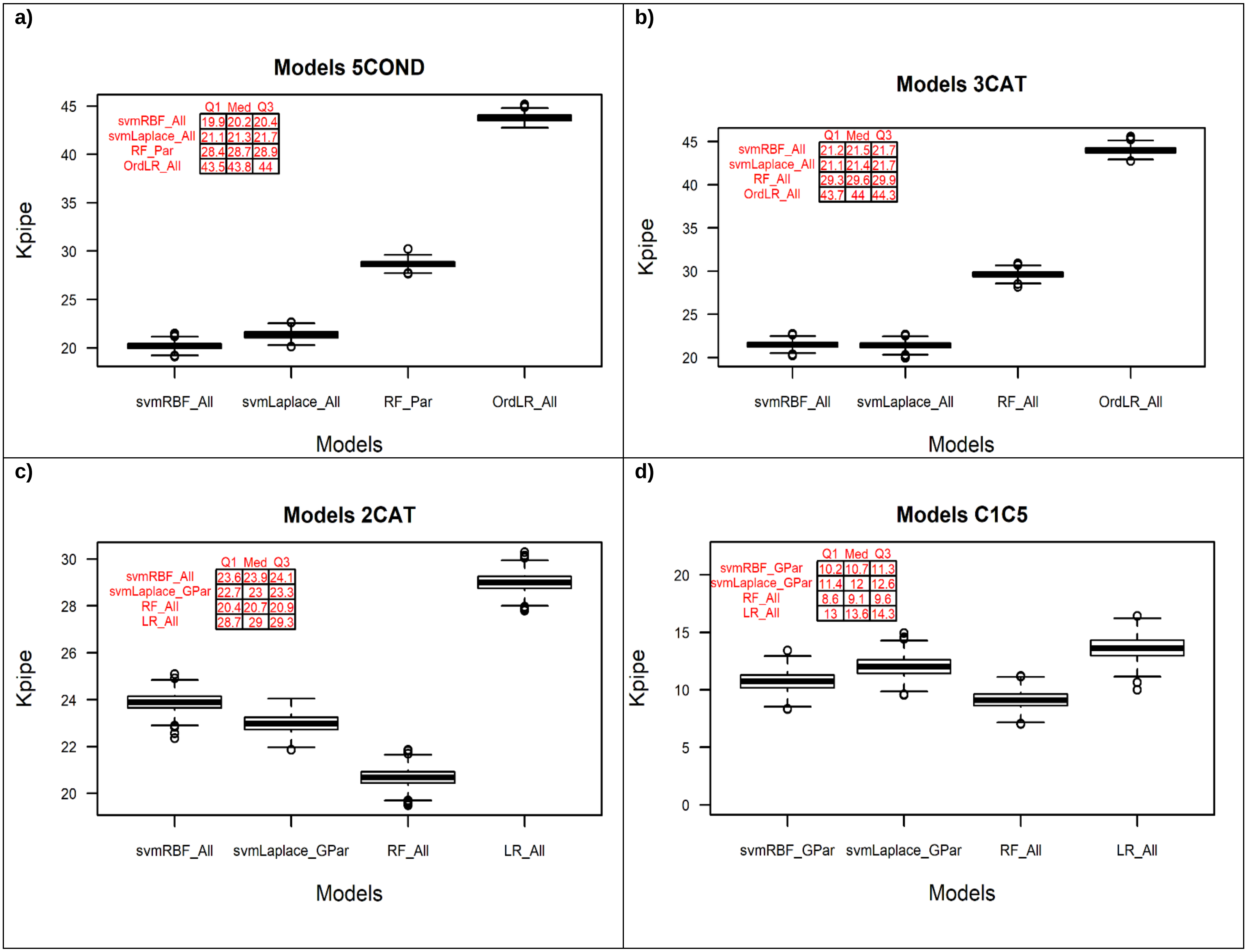

Figure D.29. Comparison of the most suitable deterioration models to achieve the management objective at the pipe level for the first (a), second (b), third (c) and fourth (d) SCS for Medellin's case. Source: Author

Table D.16. shows the summary of the most suitable model for each SCS and each management objective for Medellin's case.

Table D.16. The chosen deterioration models for each SCS and management objective for Medellin's case after the analysis of boxplots and Wilcoxon tests showed in appendix – D.2.4.

SCS	Management objective	Method based deterioration model	Type of hierarchy	Variables
First: five structural grades (5_COND)	network	SVM_RBF	Variables that show any relationship with the structural condition (GGPar)	Inspection year, age, installation year, basin, material, foundation type and type of effluent (7 variables)
	pipe	SVM_RBF	All studied variables	See the variables of Tables B.4 and B.5.
Second: three structural categories (3_CAT)	network	Random Forest	First and second relationship grade variables (GPar)	Inspection year, age, length, districts, installation year and basin (6 variables).
	pipe	SVM_Laplace	All studied variables	See the variables of Tables B.4 and B.5.
Third: two structural categories (2_CAT)	network	Random Forest	First relationship grade variables (Par)	Inspection year, installation year, material, length and age (5 variables).
	pipe	Random Forest	All studied variables	See the variables of Tables B.4 and B.5.
Fourth: Excellent and critical structural conditions (C1C5)	network	SVM_RBF or SVM_Laplace	First and second relationship grade variables (GPar)	Inspection year, installation year, age, foundation type, material, operational status and districts (7 variables).
	pipe	Random Forest	All studied variables	See the variables of Tables B.4 and B.5.

Source: Author

According to Table D.16., it is possible to observe that machine learning-based models are the most suitable to develop deterioration models for the prediction of the structural conditions for Medellin's sewer system after applying the proposed optimisation methodology (chapter 8). Nevertheless, there is not one unique model that achieves a specific sewer asset management objective. It confirms the hypothesis of this PhD thesis that the performance of the deterioration models to predict the structural conditions of sewer assets depends on the case study, the management objective and the input variable included in the model identified as key factors. Furthermore, Table D.16. shows that the models related to the network level need fewer variables than the models related to the pipe level for achieving their respective objectives. It could happen because the predictions objectives at pipe level are more rigorous since it should identify the structural condition of each single sewer asset.

Also, all chosen models consider variables such as inspection year, age and installation year of the sewer assets. Furthermore, for achieving the pipe level objectives is necessary to include all the studied variables. Besides, regarding the variables considered on chosen models of each SCS for achieving the network level objectives, it was found: (i) for the first SCS (5_COND), it is enough to consider variables such as basin, material, foundation type and type of effluent additional to variables related to age in the models; (ii) for the second SCS (3_CAT), it is enough to consider variables such as length, districts and basin additional to variables related to age in the models; (iii) for the third SCS, it is enough to consider also material and length together with the variables related to age in the models; and (iv) for the fourth SCS (C1C5), it is enough to consider variables such as foundation type, material, operation status and districts together with the variables related to age for achieving network-level objectives.

From the models depicted in Table D.16., Figures D.30. and D.31. show the boxplot analysis of the *Knet* and *Kpipe* values obtained for the validation data for Medellin's case to visualise which model and SCS showed the highest performance quality. As well, Tables D.19. and D.20. show the p-values obtained after applying the Wilcoxon analysis to find significant differences in the prediction results among the models of the different SCS shown in the above figures respectively.

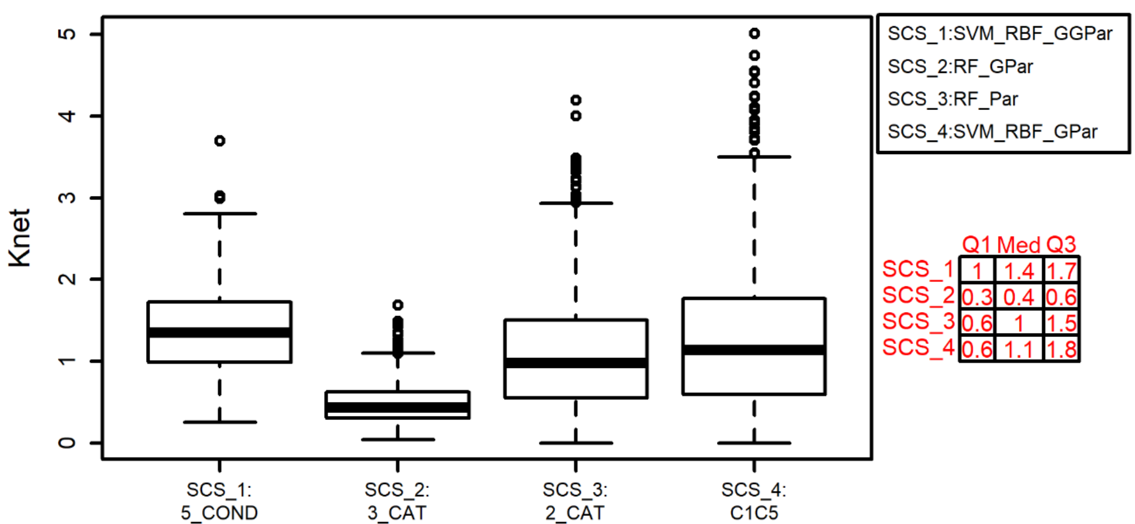

Figure D.30. Comparison of the most suitable deterioration model to achieve the management objective at the network level for the four SCS for Medellin's case. Source: Author

According to Figure D.30., the models that most minimise the *Knet* metric for achieving the network level objectives are the ones related to the second (3_CAT) and third (2_CAT) SCS that correspond to RF-based models considering the variables that presented first and second relationship with the structural condition (GPar) for the second SCS (3_CAT) and only considering the variables that presented the first relationship grade with the structural condition (Par) for the third SCS (2_CAT). It is interesting to highlight that the model that most minimises the *Knet* metric is the one obtained for the second SCS (3_CAT), contrasting the results for Bogota's case: for Bogota's case, the models that most minimise the Knet metrics were the related with the SCS that groups the structural condition in two categories, especially the SCS that only considers excellent and critical structural conditions, leaving out the intermediate conditions.

Table 36 of appendix – Part D.2.4.5. shows the obtained p-value from a Wilcoxon test, in which the models related to the first, second and third SCS depicted differences significantly among them (p-value < 0.05). However, the models related to third and fourth SCS do not have differences significantly in their prediction of the validation data (p-value > 0.05). In this case, it is chosen the third SCS because this model is more robust (needs fewer variables to achieve the network level objective) than the model chosen for the fourth SCS. For the network level objective, it is important to highlight that the intermediate conditions (be more specified in poor condition) is a relevant condition for Medellin's case because the majority of the inspected sewer assets are qualified in this condition by the Medellin's assessment standard (EPM, 2010).

As a result, the RF-based model chosen for the second SCS (RF_GPar) is the suitable one for developing investment plans of medium and long term readdressing the recommendation given by EPM (Table 7 of the appendix – Part B.2.1) for management planning; while RF-based model chosen (RF_Par) for the third SCS (two categories: acceptable and poor-critical conditions) is the appropriate one for developing investment plans at short term, since it identifies the number of sewer assets in poor and critical conditions.

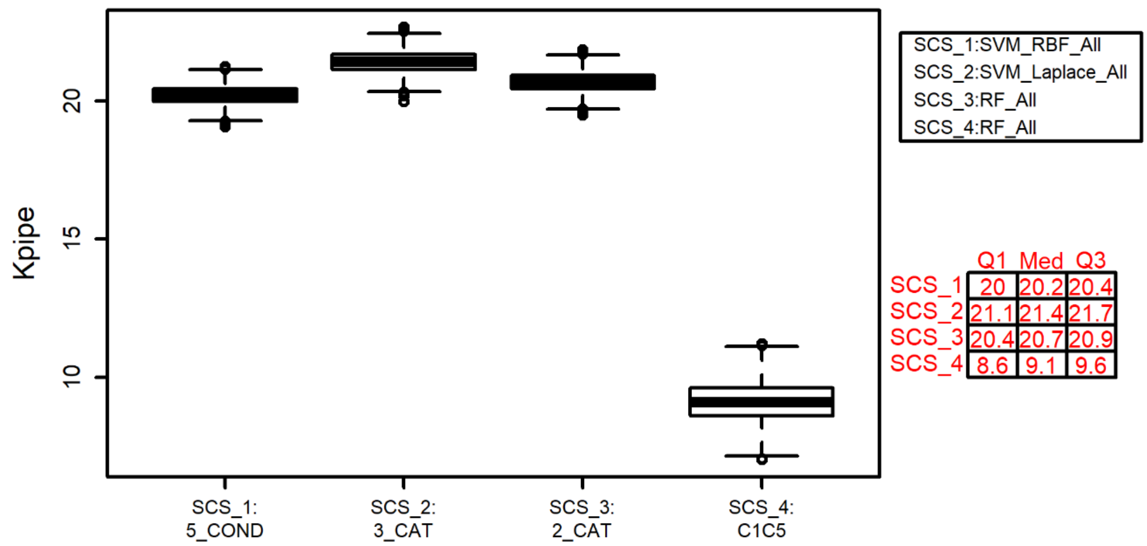

Figure D.31. Comparison of the most suitable deterioration model to achieve the management objective at the pipe level for the four SCS for Medellin's case. Source: Author

According to Figure D.31., the model that most minimises the *Kpipe* metric is the chosen one for the fourth SCS (excellent and critical conditions -C1C5) with a median lower than 10; while the *Kpipe* boxplot median of the models chosen for the other SCS varies between 20 and 25. Furthermore, Table 37 of the appendix – Part D.2.4.5. shows that all models showed differences significantly in their predictions results (p-value <0.05). Therefore RF-based model with all the studied variables is the most suitable for identifying the sewer assets in critical conditions and thus, developing routing plans for sewer assets replacement for Medellin's case.

Besides, the suitable model for prioritising the management activities is the one that considers the five structural grades (first SCS), because it was the model that depicted lower *Kpipe* values for validation data than the model chosen for the second SCS (three categories: acceptable, poor and critical structural conditions -3_CAT). From this result, the prioritising management activities could be guided by the recommendations given in the Medellin's assessment standard (EPM, 2010) (see Table 7 of the appendix – Part B.2.1).

From the chosen models to fulfil the network level objectives (Figure D.30.), Table D.17. shows the *K* indicators and *Knet* metric obtained from the chosen models for the second and third SCS. According to this table, for the second SCS (three structural categories– 3_CAT), the deviations for the whole network were not higher than 0.5. Moreover, the deviations for the oldest sewer assets (more than 50 years old) are higher for those assets predicted in poor conditions. In the end, the *Knet* for validation data was 2.13. Moreover, regarding the third SCS (acceptable and poor-critical conditions – 2_CAT), the deviations are closer to zero in the total sewer system, while for oldest sewer assets, there is a deviation of 1.21, giving a *Knet* of 0.86.

Table D.17. K indicators and Knet metric for validation data obtained from the chosen models of the second and third SCS for Medellin's case.

<table>
<tr><th rowspan="2">SCS</th><th colspan="3">Deviation total sewer system</th><th colspan="3">Deviation old sewer assets: > 50 years</th><th>Knet</th></tr>
<tr><th>K_{DEV_1}</th><th>K_{DEV_2}</th><th>K_{DEV_3}</th><th>$K_{OLD(DEV\_1)}$</th><th>$K_{OLD(DEV\_2)}$</th><th>$K_{OLD(DEV\_3)}$</th><th></th></tr>
<tr><td>SCS_2: 3_CAT</td><td>-0,33</td><td>-0,12</td><td>0,44</td><td>-2,91</td><td>4,13</td><td>-1,21</td><td>2,13</td></tr>
<tr><td></td><td colspan="2">K_{DEV_1}</td><td>K_{DEV_2}</td><td colspan="2">$K_{OLD(DEV\_1)}$</td><td>$K_{OLD(DEV\_2)}$</td><td>Knet</td></tr>
<tr><td>SCS_3: 2_CAT</td><td colspan="2">0,17</td><td>-0.17</td><td colspan="2">-1.21</td><td>1.21</td><td>0,86</td></tr>
</table>

Source: Author

The above results are visualised as bar plots (Figures D.32. and D.33.) for (i) the RF-based model considering the variables that showed the first and second relationship grades with the structural condition (GPar) and the second SCS (acceptable, poor and critical conditions); and (ii) the RF-based model considering only the variables that showed the first relationship grade with the structural condition (Par) and the third SCS (acceptable and poor-critical structural conditions).

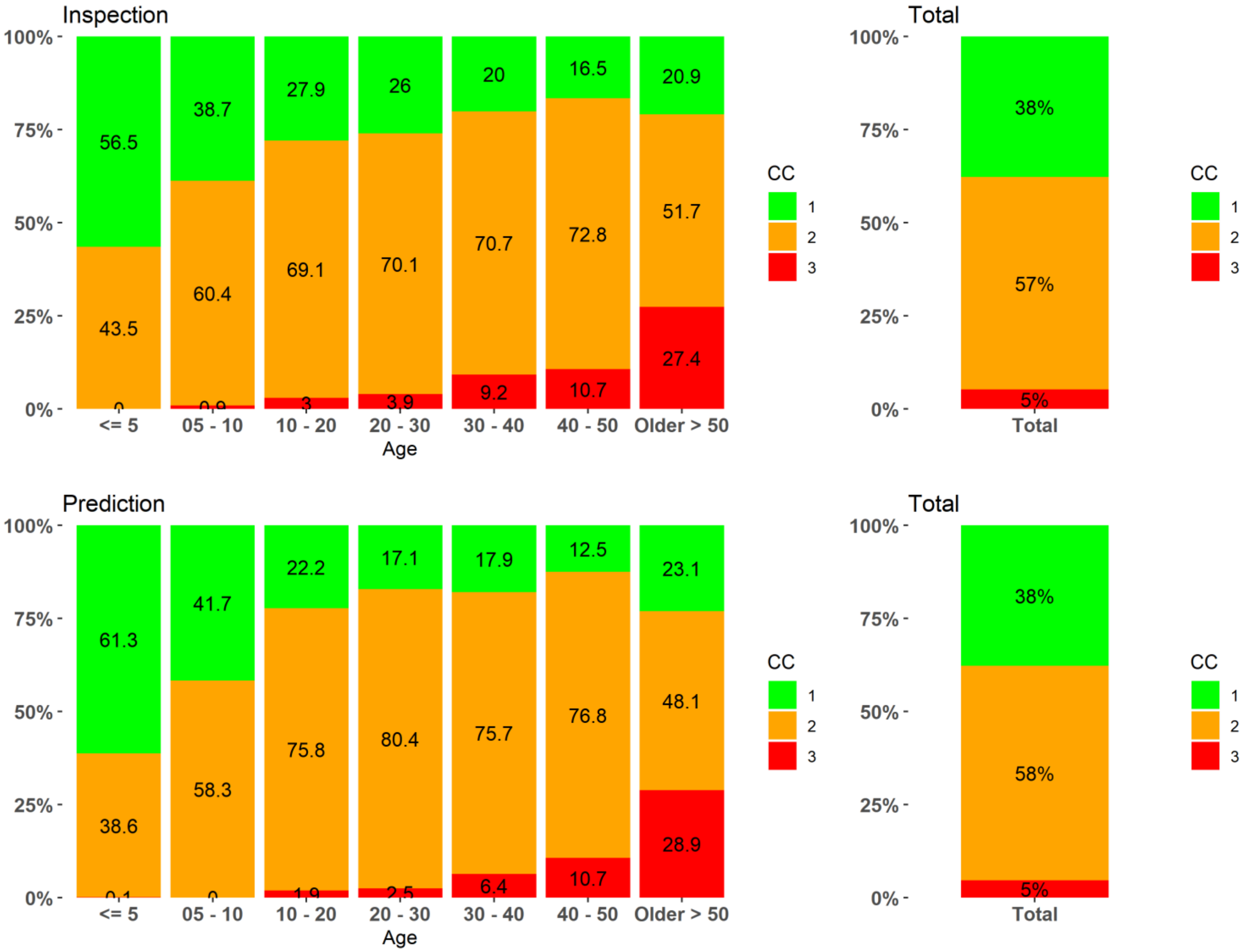

Figure D.32. Inspected and predicted distribution of validation data (RF-model), considering variables that showed the first and second relationship grade with the structural condition (GPar), at the network level objective for Medellin's case. Total network (right) and broken down by age group (left). The colours green, orange and red represent acceptable (CC1), poor (CC2) and critical (CC3) structural conditions. Source: Author

According to Figure D.32., the RF-based model chosen for the second SCS at the network level, for Medellin's case, also tends to capture the distribution of the structural conditions by each age periods and for the whole Medellin's sewer system (see inspected and predicted bar plots on the right of the figure). Furthermore, the deviations at whole network (right bar plots of Figure D.32.) are almost imperceptible.

Besides, the RF-based model overestimated some sewer assets in critical conditions and underestimated some sewer assets in acceptable conditions, predicting them in poor conditions for the oldest sewer assets (older than 50 years old). Furthermore, for sewer assets between 10 and 50 years old, the model underestimates the structural condition of some sewer assets in acceptable conditions (less than 10% of sewer assets with these ages), predicting them in poor conditions. Finally, for the youngest sewer assets (younger than 10 years old), the model overestimates the structural conditions of some sewer assets that were in poor conditions, predicting in acceptable conditions (less than 5% of the youngest sewer assets).

Figure D.33. depicts that the RF-based model considering the variables that presented the first relationship grade with the structural condition for the third SCS (acceptable and poor-critical conditions) can correctly predict the number of sewer assets in acceptable and poor-critical conditions with a deviation of 1% for the whole Medellin's sewer network. According to the deviation of the distribution of the structural conditions by each age period, the RF-based model tends to capture their distribution which few differences: (i) for the oldest and youngest sewer assets (older than 50 years old and younger than 10 years old), the RF-based model underestimated the structural conditions of some sewer assets (less than 5%); and (ii) for sewer assets between 10 and 50 years old, the RF-based model overestimated the structural conditions of them (less than 10%).

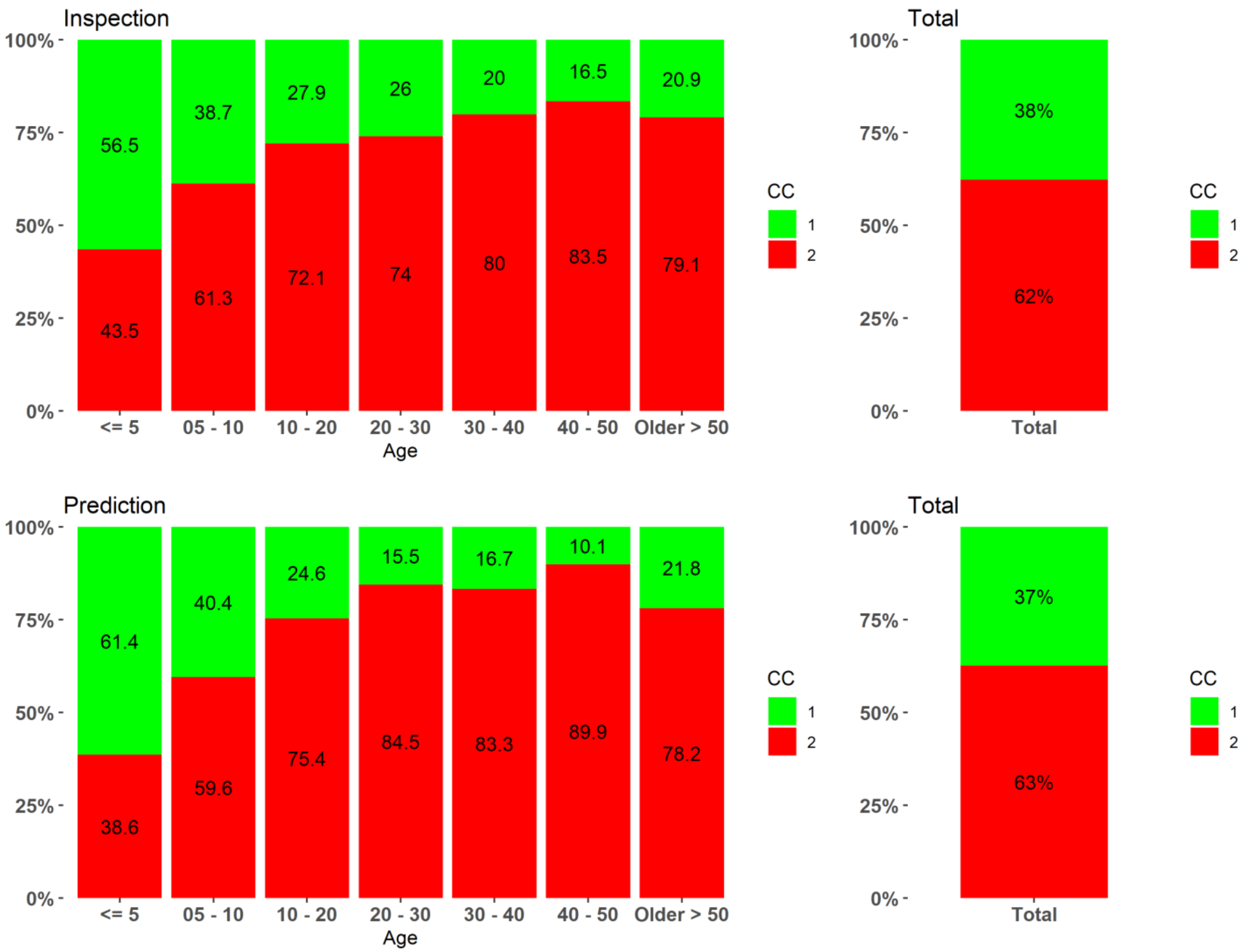

Figure D.33. Inspected and predicted distribution of validation data (RF-model), considering only parent variables at the network level objective for Medellin's case. Total network (right) and broken down by age group (left). The colours green and red represent acceptable (CC1) and poor-critical (CC2) structural conditions. Source: Author

From the successful results for validation data, the above models were used to predict the structural condition of the whole Medellin's sewer network to visualise the areas in which the sewer assets are in critical condition and, from them, developing investment plans. Therefore, Figure D.33. shows the maps with the prediction of the total sewer system for both models at the network level considering both structural condition scenarios (3_CAT and 2_CAT).

According to Figure D.33., districts such as *La America*, *Laureles-Estadio*, *San Javier*, *La Candelaria*, and *La Estrella* presented considerable areas of sewer assets in critical conditions for both predictions. Likewise, districts such as *Robledo* and *Villa Hermosa* shows areas with sewer assets in acceptable conditions. Both models achieve similar prediction results at the network level. The model for the third SCS could support the investment plans at short, intermediate and large term because it predicts the critical structural condition giving a percentage of sewer assets that need urgent replacement and specifying in which districts need these investments. The RF-based model for the third SCS gives the percentage of sewer assets in poor and critical conditions if the management perspective is also prioritising their rehabilitation.

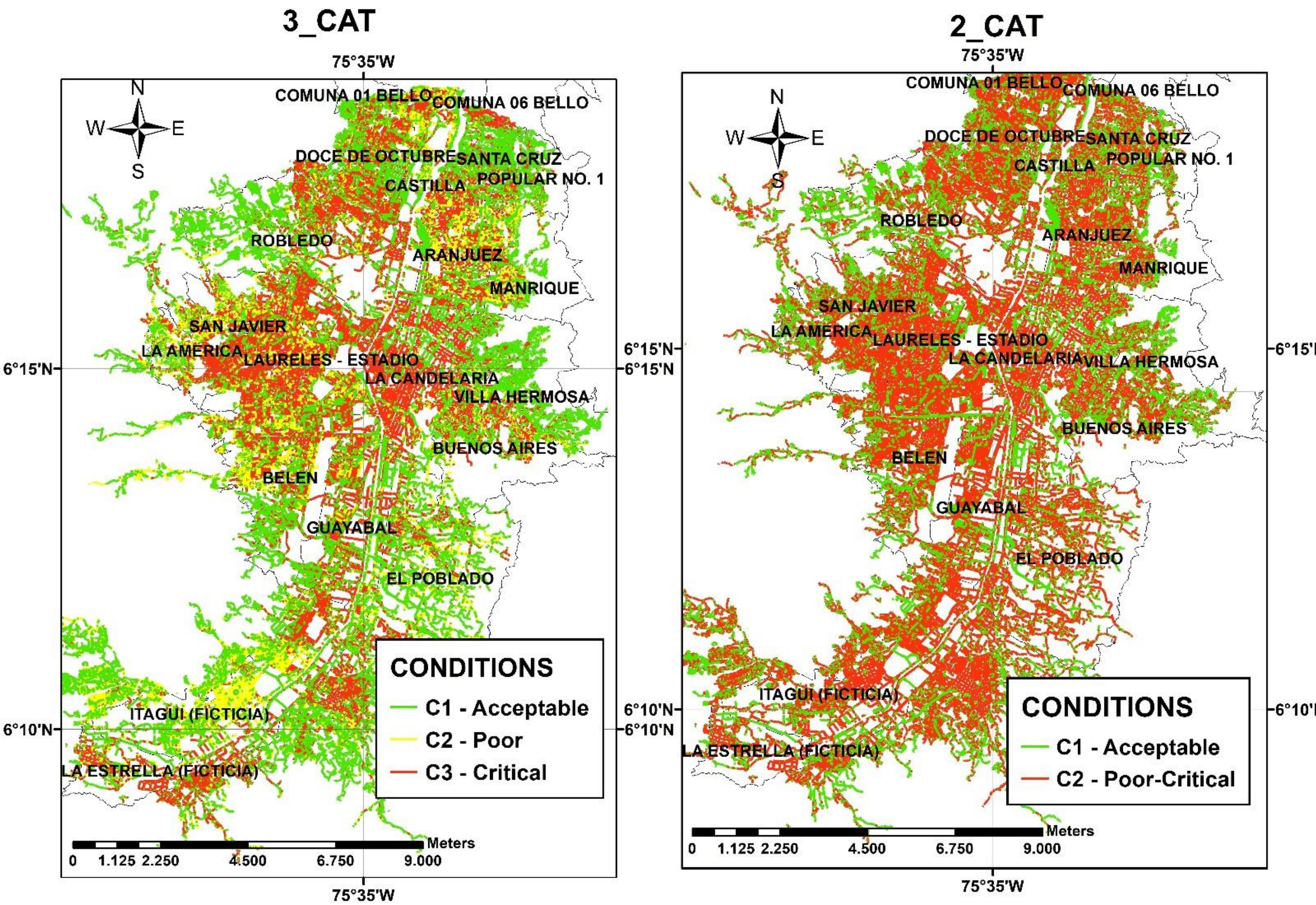

Figure D.34. Maps overview of the predicted structural condition of Medellin's sewer system at network level from RF model considering the variables that showed the first and second relationship with the structural condition (GPar) and the second SCS (on the left) and RF model considering only parent variables and two structural conditions (acceptable and poor-critical – third SCS) (on the right)

Table D.18. shows the *K* indicators and *Kpipe* metric obtained from the prediction for validation data from the chosen model in Figure D.31. It is important to clarify that the percentage of inspected sewer assets in grades 2 and 3 are around 2% and 3.6 % respectively. Hence, the optimisation of the RF-based model for the first SCS was addressed with the same aggrupation of the second SCS. It means, the model predicted the five structural grades, but in the optimisation, these grades were grouped in acceptable, poor and critical conditions. The SVM-based model for the first SCS (5_COND) shows that the model predicts more than 68% (TPR > 68%) of sewer assets correctly for these three structural grades, being the critical conditions with TPR close to 87%. The TPR related to the structural grades 2 (good conditions) and 3 (acceptable conditions) is 0%, because in the optimisation process, the grades 1, 2 and 3 were grouped in one category due to the low quantity of sewer assets qualified in these grades in calibration data. Furthermore, the 14.05% of sewer assets that were found in excellent, good or acceptable conditions were underestimated in critical conditions by the SVM-based model (FPRacceptable_critical). And 20.28% and 2.61% of sewer assets were overestimated, predicting in excellent, good or acceptable conditions those sewer assets observed in poor (FNRpoor_acceptable) and critical (FNRcritical_acceptable) conditions. The above results gave a *Kpipe* value of 20.16.

Table D.18. K indicators and Kpipe metric for the validation data obtained from the chosen models of the first and fourth SCS for Medellin's case.

SCS	$K_{TPR\_(excellent-good-acceptable)}$	K_{TPR_poor}	$K_{TPR\_critical}$	$K_{FPRacceptable\_critical}$	$K_{FNRpoor\_acceptable}$	$K_{FNRcritical\_aceptable}$	***Kpipe***
SCS_1: 5_COND	67.9	75.2	86.6	14.05	20.28	2.61	20,16
	$K_{TPR\_excellent}$		$K_{TPR\_critical}$	$K_{FPRcritical\_excellent}$		$K_{FNRexcellent\_critical}$	***Kpipe***
SCS_4: C1C5	97.5		92.2	14.53		7.84	9.215

Source: Author

In accordance with the fourth SCS (C1C5), the RF-based model considering all studied variables achieves TPR values higher than 92%, with FPR of 14.53 and FNR of 7.84.

The fact that for both above models the TPR are higher than 33.3% and 50% for the first (5_COND) and fourth (C1C5) SCS means that the predictions with both models were better than random models under the same aggrupation of the structural conditions. Furthermore, for both models, FPR values are higher than the FNR values, which means that when the model mispredicts, it tries to predict the sewer asset in a worse condition than really it is.

Figures D.35 and D.38. show performance curves for validation data considering the models of both SCS (5_COND and C1C5). These curves were built from calculating the probability of each sewer asset of being in critical condition (stripe in red). It is important to clarify that for the SVM-based model (Figure D.35 and D.36) cannot predict the probabilities when the weights are optimised. Therefore, these figures show their predictions considering only the optimised values of Sigma and C.

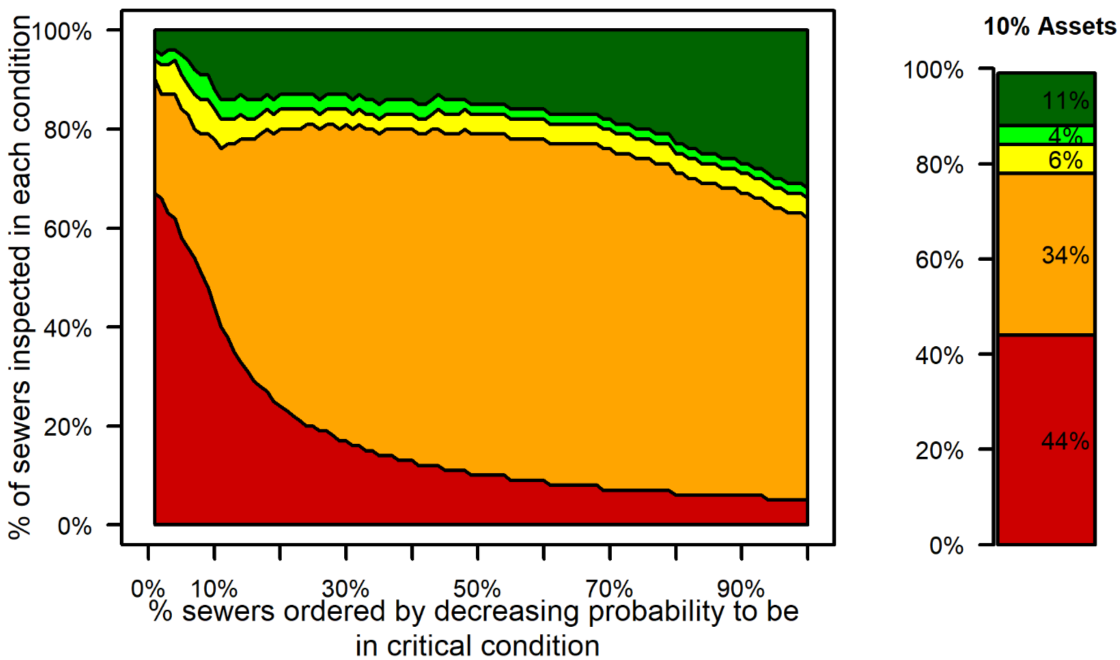

Figure D.35. Performance curve with a sample on its right of 10% sewer assets for validation data obtained from SVM-based model considering RBF kernel function and all studied variables and first SCS (5_COND) for the pipe level objective for Medellin's case. Excellent, good, intermediate, poor and critical conditions in dark green, green, yellow, orange and red stripes. Source: Author

According to Figure D.35., the performance curve shows a strong decreasing behaviour when the probability of being in critical condition decreases. It means that the sewer assets that show the highest probability of being in critical condition have a higher probability of being in that condition, supporting the prioritisation plans for rehabilitation activities. However, the figure shows also a large percentage of sewer assets predicted in poor conditions independently of the probability of being in critical condition. The bar plot on the right shows the first 10% of sewer assets with the highest probability in critical conditions, meaning that these sewer assets have 44% of success in being in critical conditions and 78% to be in critical or poor conditions.

The above means that if the budget for replacement is low, there is no need to inspect all the sewer systems to develop replacement/rehabilitation plans: the managers could rehabilitate only the 10% of the sewer assets with the highest probability of being in critical condition with a reliability of 78% that the sewer assets need urgent replacement or rehabilitation activities.

Figure D.36. shows a comparison between the structural grades found on CCTV data inspections (observed conditions), and the probability of being in critical conditions from the SVM-based model prediction for the first SCS (5_COND), for Medellin's case.

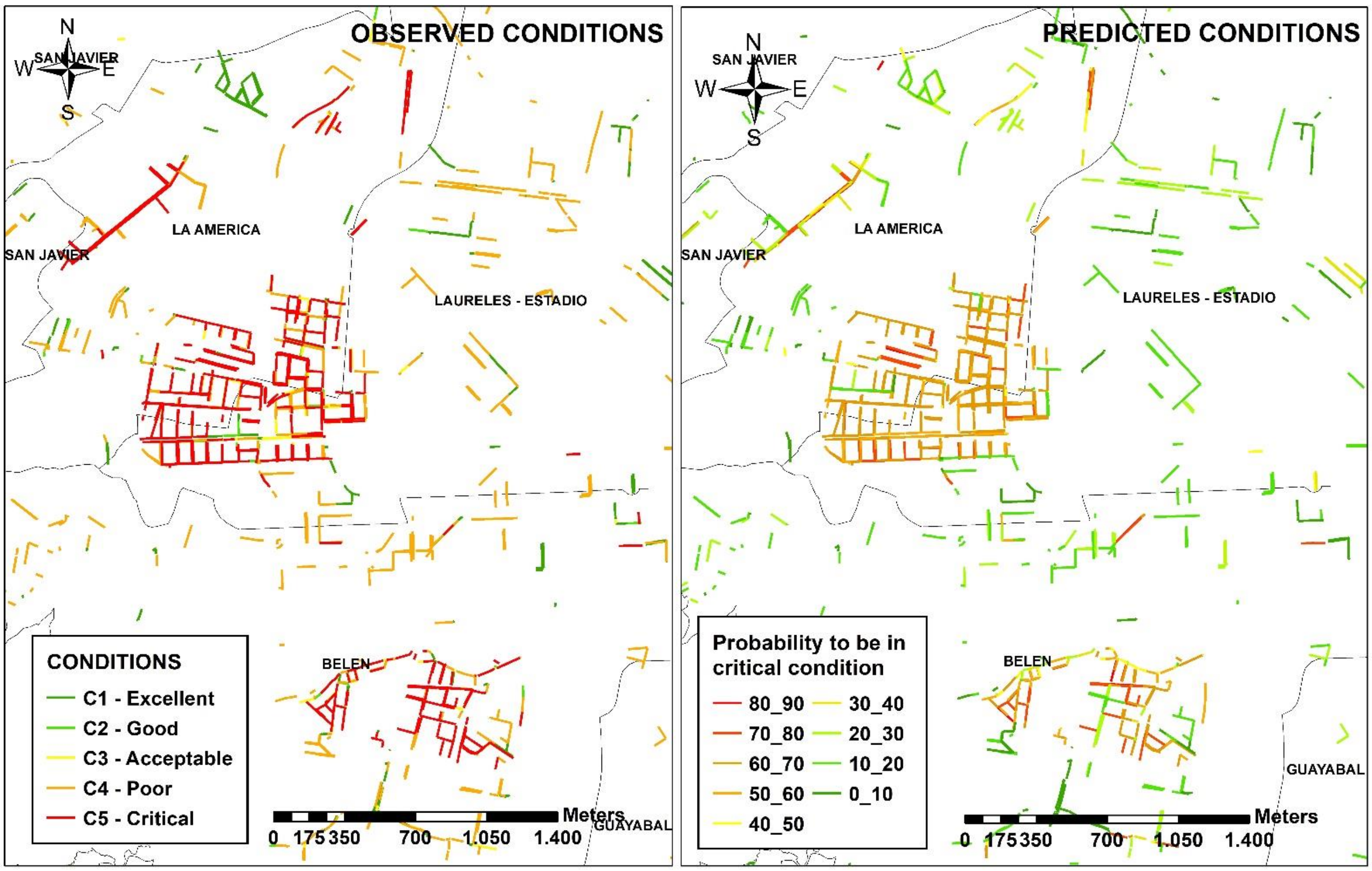

Figure D.36. Comparison between the conditions found by CCTV inspection data according to the first SCS (left) and prediction of the probability of being in critical conditions (right) for Medellin's case, magnified onto Laureles-Estadio, La America and Belen districts. Source: Author

According to Figure D.36., the sewer assets in red scale that represent the highest probability of being in critical conditions (probability >70%) from the map "predicted conditions" are in critical conditions in the map "observed data". Nevertheless, the sewer assets that were in green scales on the predicted map (map on the right, Figure D.49.) are not in good and excellent conditions on the observed map (map on the left, Figure D.49). In fact, the observed map shows most of these sewer assets in poor structural conditions, confirming the results of the performance curve of Figure D.35.

Figure D.37. shows the comparison of the validation data of the inspected (on the left) and predicted (on the right) sewer grades by SVM-based model considering all studied variables and all the optimised hyperparameters (including the weight values). According to this figure, the predicted and inspected maps show correspondence in structural grades of the sewer assets.

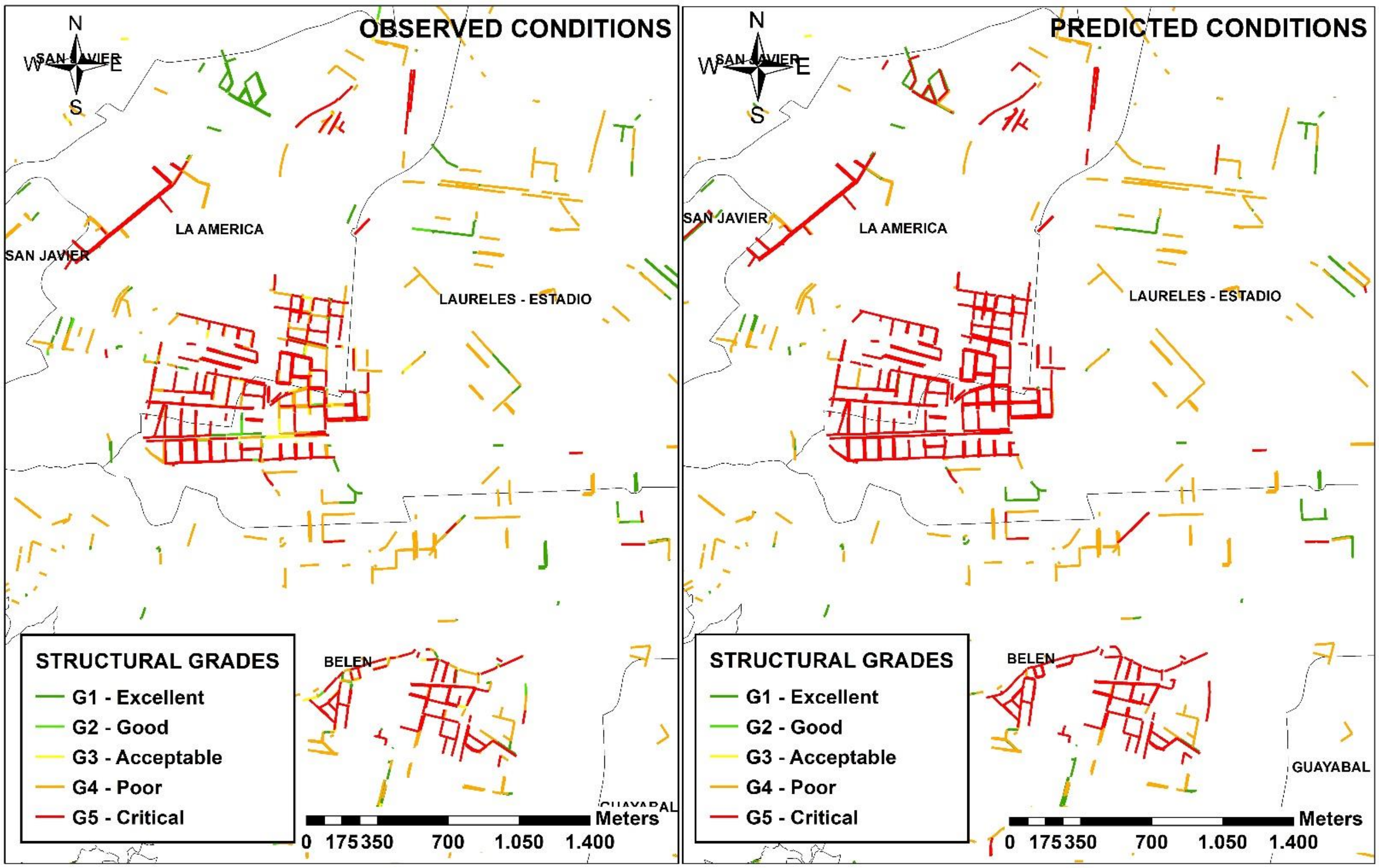

Figure D.37. Comparison between the conditions found by CCTV inspection data according to the first SCS (left) and prediction of the structural grades for Medellin's case, magnified onto Laureles-Estadio, La America and Belen districts. Source: Author

On the other hand, Figure D.38. shows the performance curve of the chosen model for the fourth SCS (RF-based model considering all the studied variables). According to this figure, the performance curve shows a strong decreasing behaviour as the probability of being in critical condition reduces. This result is satisfactory because the model could support rehabilitation plans prioritising the sewer assets with the highest probability of being in critical conditions. Supposing that the budget for rehabilitation is limited, it is suggested rehabilitating the 10% of the sewer assets with the highest probability of presenting any structural damage with 94% of reliability.

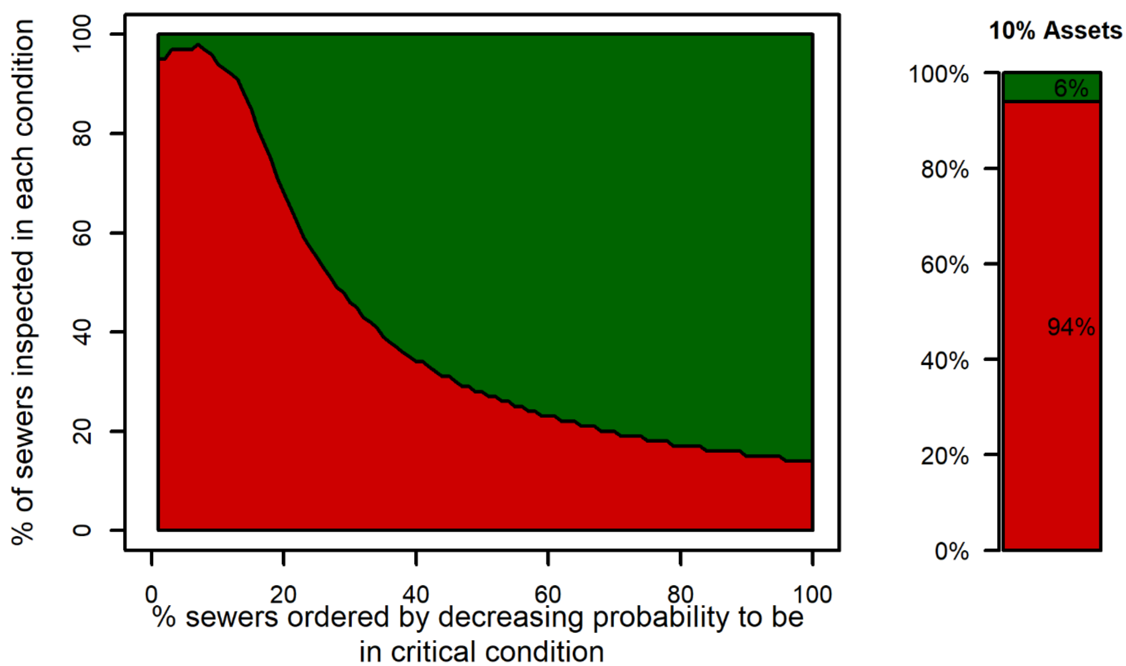

Figure D.38. Performance curve with a sample on its right of 10% sewer assets for validation data obtained from RF-based model and all studied variables and the fourth SCS (C1C5) for the pipe level objective for Medellin's case. Excellent and critical conditions in dark green and red stripes. Source: Author

Figure D.39. shows a comparison between the observed structural categories (from CCTV inspections), grouped under the fourth SCS (excellent and critical structural conditions) and the probability of being in critical conditions.

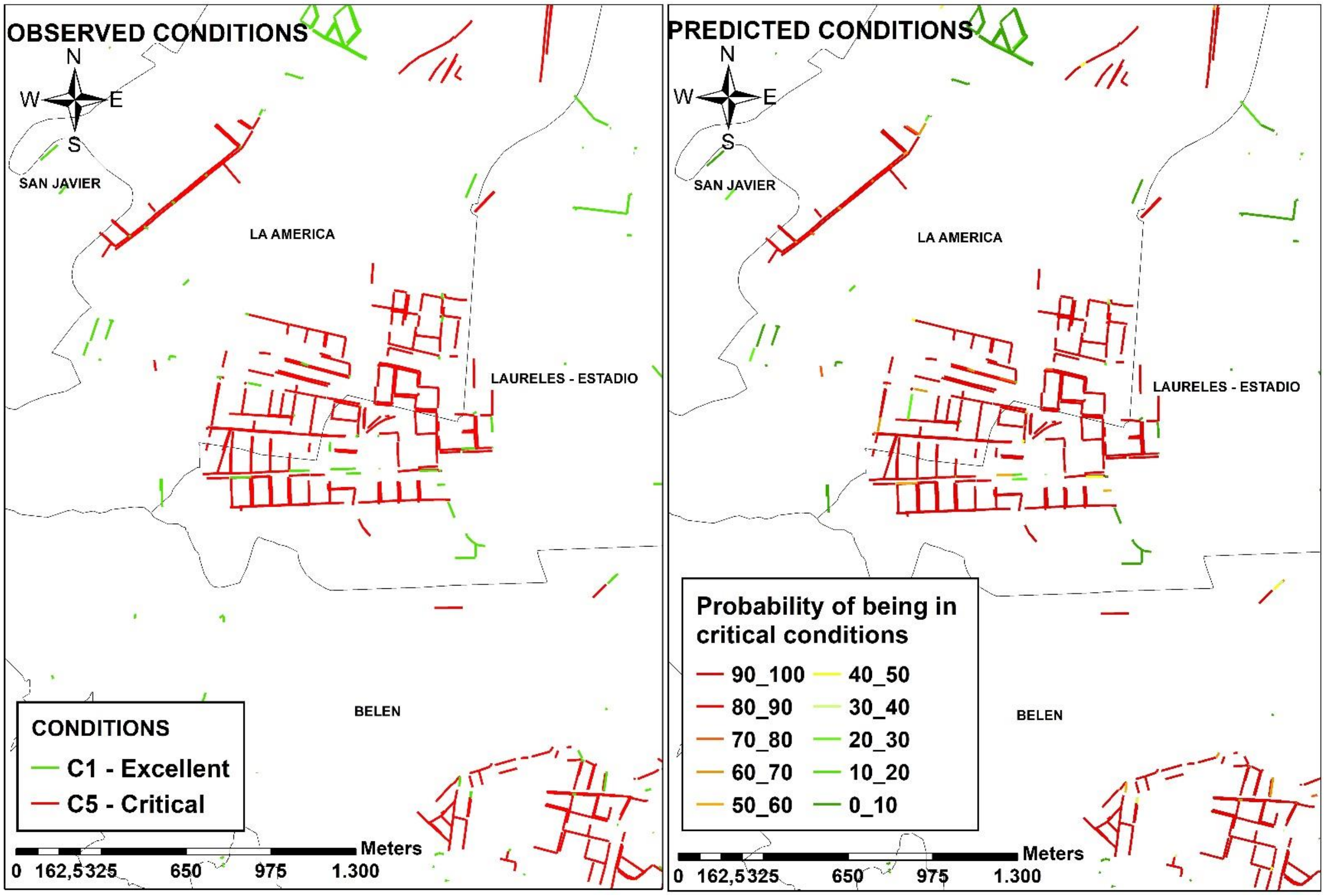

Figure D.39. Comparison between the conditions found by CCTV inspection data according to the fourth SCS (left) and prediction of the probability of being in critical conditions (right) for Medellin's case, magnified onto Laureles-Estadio, La America and Belen districts. Source: Author

According to Figure D.39., the sewer assets with the highest probability of being in critical conditions (probabilities > 80%) are really in critical conditions. Likewise, the sewer assets with the lowest probability of being in critical conditions (green lines) are really in excellent conditions. The above comparison confirms the successful predictions of the chosen RF-model graphically, together with the performance curve of Figure D.38.

From the above successful results, the model for the pipe level objectives was used to predict the structural condition of the whole Medellin's sewer system to simulate in detail the structural condition of sewer assets. Figure D.39. shows a segment of the prediction of the structural condition of Medellin's sewer system in the area of *Laureles, La America, Candelaria* and *Belen* districts obtained from the RF-based model considering all studied variables and the first (five structural grades) and fourth (excellent and critical structural conditions) SCS.

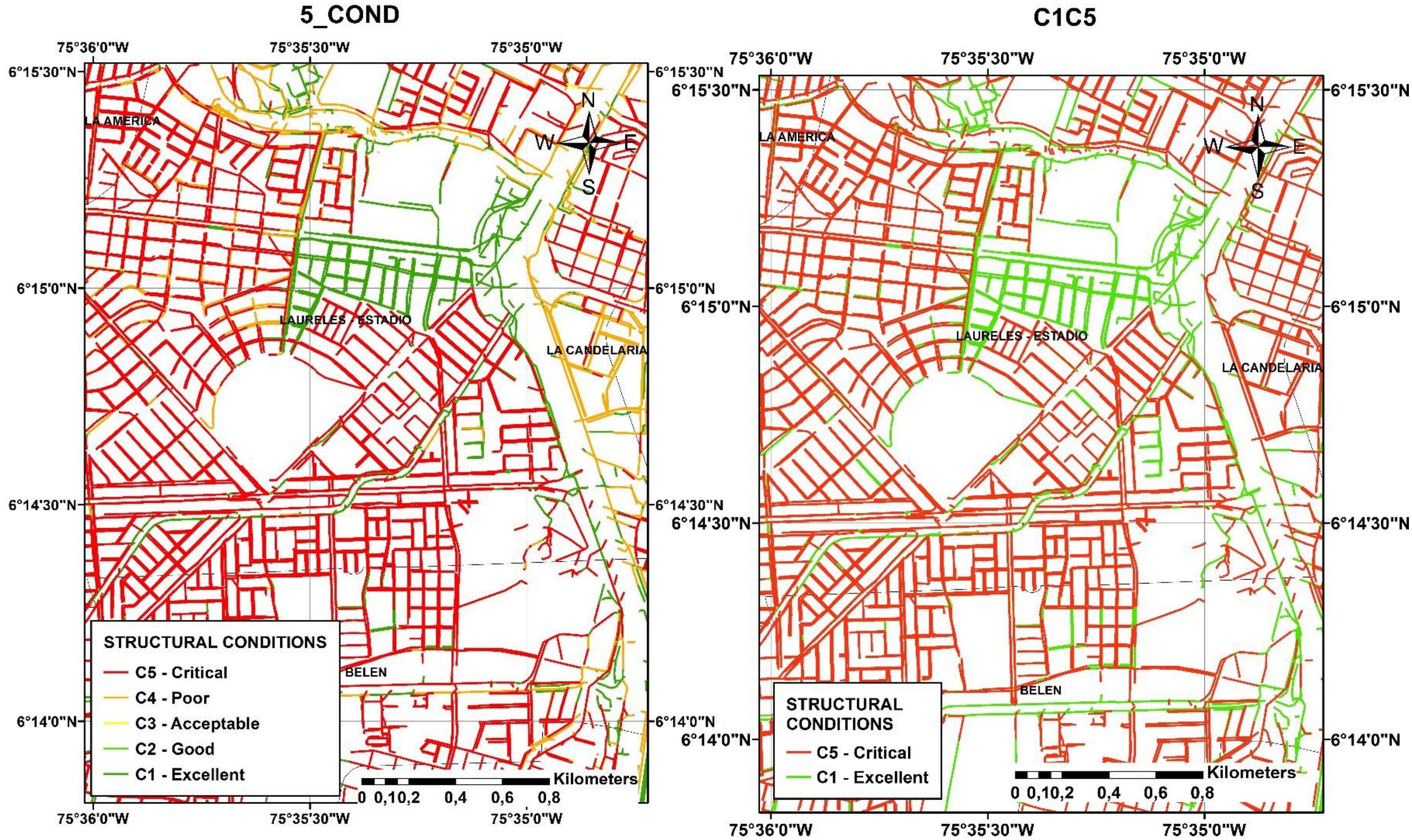

Figure D.40. Example of maps overview of predicted structural condition of Medellin's sewer system (magnified onto Laureles-Estadio, La Candelaria, Belén and La América districts) at the pipe level from the RF-based model considering all the studied variables and the five structural grades (excellent, good, intermediate, poor and critical – first SCS) (on the left) and considering only excellent and critical conditions (fourth SCS) (on the right). Source: Author.

According to Figure D.40., both maps predict the same sewer assets in excellent conditions (green lines). The sewer assets in critical conditions have been painted in orange or red for the first SCS (map on the left) and in red for the fourth SCS (map on the right). From the above results, the rehabilitation plans could be addressed from two perspectives: (i) prioritisation of the most important sewer assets of being replaced and (ii) identification of sewer assets that need rehabilitation activities and tracing in inspection activities.

11.3. DISCUSSION ABOUT RESULTS OBTAINED IN CASE STUDIES

Although four structural conditions scenarios (SCS) were built for Bogota's and Medellin's cases, their groups were different because of the quantity of the inspected sewer assets in the structural grades (see items 5.1.2.3 and 5.2.2.3 for Bogota's and Medellin's respectively, Part B): for the second and third SCS, the structural conditions were grouped in excellent, intermediate and critical conditions; and without and with structural damages for Bogota's case; while for Medellin's case, the structural conditions were grouped in acceptable, poor and critical conditions; and acceptable and poor-critical conditions. It is important to highlight that a large number of sewer assets in excellent and poor conditions for Bogota's and Medellin's cases conditioned the creation of these SCS. Furthermore, in spite of the predictions performance increase significantly grouping the structural grades in the SCS, the management perspectives of the investment or rehabilitation plans change: i.e. predicting which sewer assets have any structural damage or not could help to identify the sewer assets that only need activities of cleaning for Bogota's case; while predicting which sewer assets are in poor-critical conditions identifies the sewer assets that need rehabilitation and replacement activities for Medellin's case. Naturally, the quantity of sewer assets classified on each structural grade depends on the assessment standard and the administrative and operational procedures for the inspection activity of each city, which could indicate that the structural grades of Bogota do not represent the same structural grades of Medellin at all. Therefore, the comparison between which city has a sewer network in better conditions is superfluous.

On the other hand, it was possible to hierarchise by importance levels the influence of some variables over others with the structural conditions, answering one of the research questions. According to the hierarchisation of the variables for both case studies, It was possible to answer the research question variables related to if the influential variables could vary according to the own characteristics of cities. The answer is some variables vary and other not. The age and physical characteristics of the sewer assets showed direct a relationship with the structural conditions in both case studies (also considering the different structural condition scenarios), which confirms the findings of different authors in other case studies (Davis et al., 2001a; Ariaratnam et al. 2001; Baik et al., 2006; Le Gat, 2008; Ana et al., 2009; Tscheikner-Gratl et al., 2014; Rokstad & Ugarelli, 2015; El-Housni et al., 2017; Caradot et al., 2018). However, not all the physical characteristics showed a direct or indirect relationship with the structural conditions and neither the same physical characteristics for all the structural condition scenarios (SCS) and case studies: diameter and length of the sewer assets showed a direct relationship with the structural conditions for Bogota's case and length and material of the sewer assets showed a direct relationship with the structural conditions for Medellin (the length of the sewer assets showed direct relationship only in two SCS). Furthermore, some variables such as District and basin show a relationship with the structural condition. However, they were not linked with age variables, other infrastructures, land uses, and neither geographical coordinates. It is interesting because these variables give information that it is still unknown, but relevant. This answer the research question about the possibility of inferring information from other factors (not identified) that could affect the structural condition of sewer assets.

Moreover, thanks to the exploration of different statistical and machine learning methods as deterioration models evaluated by two different prediction objectives (at network and pipe levels), it was possible to answer if the influential variables and deterioration models vary according to the management objectives. The answer was that there is not only one method that could be suitable for achieving prediction objectives for any city. However, from this exploration, it was possible to identify that Logistic Regression (LR), Random Forest (RF) and Support Vector Machines (SVM)- based models could predict more sewer assets correctly in critical conditions evaluated by different prediction perspectives for Bogota and Medellin cases. Therefore, these models were chosen to include in the proposed methodology. In spite of Ordinal Logistic Regression models (Ord_LR) do not show relevant prediction performance as binomial logistic regression models in the above-mentioned exploration, they were included for SCS that contained more than two structural categories to compare the prediction of machine learning-based models with logistic regression models. The Ord_LR were chosen over Multinomial Logistic Regression models (Multi_LR) because prediction performances of Ord_LR were better than Multi_LR. Besides, the exploration of the prediction performance of the above six methods was the turning point in determining that the method was not the basis to build strategic deterioration models. Also, the included variables could increase or decrease the prediction performance of the deterioration models for achieving a specific management objective.

Even though, the objectives of this thesis do not consist on analysing in detail the obtained hyperparameters after applying the optimisation methodology for achieving network and pipe level objectives; it is important to highlight that Sigma and C values of SVM-based models are higher for achieving network-level objectives than for pipe-level objectives, independently of the structural condition scenarios (SCS) for both case studies (except for the SVM_RBF-based model considering the first SCS and RBF kernel function for Medellin's case). But, while both SVM-based models (at network and pipe level objectives) consider fewer variables, the C values are closer for both case studies. According to the above, in general, the SVM-based models built for the network level objectives are more constrained, and data is less complex than the SVM-based models for achieving pipe level objectives, as well as the margin of the hyperplane's separation is thinner, and the surface function of the separation hyperplane is more complex, choosing more data as support vectors. But as the model includes fewer variables, the separation hyperplane's margin is wider, and the surface function of the separation hyperplane is less complex, choosing less data as support vectors. These results are intuitive because of (i) prediction requirement for minimizing *Knet* metric is not as demanding as for minimizing *Kpipe* metric and (ii) while the model needs fewer variables, the classification task is easier for the model. For the values of the hyperparameters obtained for RF-based models, there is not a behaviour regarding the RF-based models at network or pipe level objectives and SCS for both cities. The hyperparameters' values are different in each case. However, when the values of hyperparameters are analysed according to the number of variables included on each model, the RF-based models for achieving pipe level objectives have a bigger size of terminal nodes and less number of random variables on each tree than the RF-based model for achieving network objectives, independently of the number of variables included for both case studies.

Furthermore, from the chosen models at network and pipe levels for Bogota's and Medellin's case, machine learning-based models achieve the studied management objectives, especially the SVM-based models considering RBF kernel function and the RF-based models. According to the chosen models results, it found that it is necessary the use of the methodology for hierarchisation (Chapter 9.1, Part C) for finding the variables that most influence the deterioration of the sewer assets, and from that selection the prediction performance at network level objective increases; while for achieving pipe level objectives, the models should include the greatest amount of information available for increasing the prediction performance at pipe level objective. Besides, grouping the structural condition in two categories increases the performance predictions of the sewer assets for Bogota and Medellin case studies, confirming the findings of Ariaratman et al. (2001), López-Kleine et al. (2016) and Guzmán-Fierro et al. (2019a, b and c). Nevertheless, for the application of the proposed methodology in Bogota and Medellin case studies, the author also considered the SCS with more than two structural categories to include management plans at the short, medium and long term. Moreover, it is interesting to highlight those chosen models for Medellin's case showed the highest performance at network and pipe level (the lowest *Knet* and *Kpipe* metrics) objectives than for Bogota's case, despite the fact that the information's availability was more restricted for Medellin's case than for Bogota's case. The above confirms the hypothesis that the infrastructure of each city behaves differently, and some cities need less information for achieving specific management objectives than others.

As a relevant specific result for the case studies, it found that RF-based models were the most suitable for achieving network and pipe level results considering two structural categories (grouping the structural condition in two categories or considering only the excellent and critical conditions), as well as for models that consider the five structural grades the most suitable model was based on SVM considering RBF kernel functions. The inclusion of the SCS that consider only the sewer assets in excellent and critical conditions, leaving outside the intermediate structural grades, was helpful for both case studies. For Bogota's case, it increases the prediction performance at the pipe level objective, while for Medellin's case, it increases the prediction performance at the network level objective. Furthermore, the prediction results of statistical methods such as Logistic Regression and Ordinal logistic regression were not as suitable as machine learning-based models since the hyperparameters depend on the variables and not depend on the mode: the coefficients of the linear regression of the odds (see subchapters 2.3 and 2.4) are the hyperparameters for building logistic regression models are related to the considered variables, while the hyperparameters of machine learning-based models are related to the kernel function and the properties of separation hyperplane for classifying the structural conditions for building SVM-based models and the number of trees, minimal size of terminal nodes and the random variables of each tree of the random forest for building RF-based models. It does not consider the Gompitz model (Le Gat, 2008) because, in previous explorations, the prediction results were not satisfactory, since it needs sewer systems with a high percentage of inspected sewer assets to predict/forecast their structural condition. Besides, Gompitz needs a reduced number of variables (overall categorical variables) to be built which was not coherent with the objectives of this thesis.

CONCLUSIONS PART D

The following conclusions are related to the application of the proposed methodology (depicted in chapter 9, Part C) in the case studies considered in this doctoral thesis: Bogota's and Medellin's sewer system infrastructure.

From the preliminary results (chapter 10), different methods were explored and selected for developing tools that support the sewer asset management for different activities. These results allow to build a complete methodology that integrates (i) Bayesian Networks as the base for developing a feature selection tool for hierarchizing the most influential variables, (ii) different statistical (Logistic Regression and Ordinal Logistic Regression) and machine learning (Support Vector Machines and Random Forest) methods for developing deterioration models; and (iii) the use of Grid Search, Differential Evolution methods and the proposed performance metrics (chapter 8, Part C) for developing an optimization methodology for finding the optimal combination of hyperparameters. Above steps were done for designing the structure of a complete model that could predict the structural condition for two management objectives.

Furthermore, the use of different structural condition scenarios (SCS) allows identifying the clusters of structural conditions that most increase the prediction performance of the structural condition of the sewer assets for each management objective and case study. Likewise, the creation of SCS supports the design of investment or rehabilitation activities prioritizing and contemplate different management time-terms.

In the results of the proposed methodology, it was possible identifying enough factors for achieving a management objective. This goal was achievable for the management objective at the network level. However, for the management objective at the pipe level that hierarchization was not necessary, because of the deterioration models needed a large quantity of information available for achieving that objective. Therefore, for attaining network-level goals, variables related to the age of the sewer assets, physical characteristics, type of effluent, and districts or specific areas (basins) of the cities were identified as the key variables to achieve this objective. However, not all the physical characteristics were important, neither the same for both case studies or all structural condition scenarios of each city. It confirms the hypothesis that for each city or database is necessary to apply a specific modelling structure to predict the structural condition of the uninspected sewer assets. The fact that districts or basins were identified as key factors, but these do not show a link with other features, suggests that there are unknown characteristics (which were not available in the collected data) that influence the deterioration of the structural condition. The above confirms that even if the age and physical characteristics of the sewer assets have been found as influential in other case studies, the influence depends on the case study, their information and assessment standard and the interaction of the physical characteristics of the sewer assets with operational, urban and environmental characteristics of the sewer assets.

According to the selected deterioration models at the network level objective, it found that the machine learning methods are more robust than the statistical ones for building deterioration models, because of the first needless information to increase their performance predictions for specific management objectives. It implies that the collection of the necessary information must build deterioration models reliable enough.

Also, it was possible to observe that for reaching each management objective, and structural condition scenario, the number of variables could change also depending on the selected deterioration models and clustering of the structural conditions. It confirms the hypothesis that for each management objective, a specific number of variables should be chosen, due to increasing or reducing this number could reduce the performance prediction.

Besides, grouping the structural condition in two categories increases the performance predictions of the sewer assets of the considered case studies, confirming the findings of Ariaratman et al. (2001), López-Kleine et al. (2016) and Guzmán-Fierro et al. (2019a, b and c). However, for the application of the proposed methodology in the case studies, the author also considered the SCS with more than two structural categories to include management plans at the short, medium and long term.

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GENERAL CONCLUSIONS

The methodology for determining which factors are enough and necessary to achieve specific objectives in sewer asset management, considering the quantity and quality of the available information, was developed and applied for two Colombian case studies that met the quantity and quality of information available: Bogota and Medellin. This methodology consists of two parts: (i) a Bayesian Network-based methodology as a feature selection tool for identifying hierarchically the variables that influence the structural deterioration of the sewer assets; and (ii) a methodology for selecting the deterioration models that best fit two management objectives related to network and single asset purposes. However, from the application of the methodology, it was found that the complete methodology was only useful for achieving management objectives at network level perspectives. For pipe level management objectives, the second part of the methodology is useful to increase the prediction performance of the deterioration models considering all the information available. It is important to highlight that even though the methodology for feature selection was not useful for increasing the performance prediction of the deterioration models guided at pipe level objective, it could be considered for reducing collection costs and achieving acceptable predictions.

According to the application results, it confirms the hypothesis that there is not only one model with specific variables to predict the structural condition of the sewer assets in a city. Bogota's and Medellin's case studies are two cities with different assessment standards, different operational management, a different interaction of physical, urban and environmental characteristics that make that each city would be unique. Therefore, their infrastructure behaves differently. It is observable in the fact that even the information collection of Medellin's case was smaller than for Bogota's case, the predictions at the pipe level were better for Medellin's case than for Bogota's case. Here lies the importance of increasing the inspection rates, because whether a model has more data to train, the prediction will increase.

Furthermore, the development of a Bayesian network-based methodology suggests a new tool for the feature selection method to hierarchise the influence of some variables on the structural condition. It allows prioritising the collection of the most influential variables for achieving similar prediction performances with the models that consider several variables, collecting the necessary information for building deterioration models reliable enough.

Furthermore, this tool makes to develop deterioration models more robust and computationally less expensive than the models that consider a large number of variables.

This thesis also proposes two metrics for evaluating the prediction of the deterioration models to support two management objectives: at the network and the pipe level. The predictions at the network level give an overview of the distribution of the structural condition to the whole sewer network, which allows designing investment plans to know the percentage of sewer assets on each structural condition. Furthermore, the predictions at network level identify the areas that contain more sewer assets that need urgent rehabilitation activities. The models at the pipe level give predictions more detailed, determining the structural condition of each sewer asset that has not been inspected previously. With the identification of areas with sewer assets in critical conditions given by the model at the network level, the model at the pipe level identifies the sewer assets that need to be rehabilitated and prioritise the rehabilitation of sewers with the highest probability of being in critical conditions with high reliability of being in that condition. Both metrics support the managers to design rehabilitation and investment plans in the sewer infrastructure rationally and proactively. It is essential to highlight that the author broke away from standard metrics (such as the accuracy) to be able to link the predictions with objectives of the sewer asset management.

Besides, an optimisation methodology for finding the optimal hyperparameters for the machine learning-based models was proposed to increase the prediction quality for achieving two management objectives linked to the above-proposed metrics: *Knet* and *Kpipe*. This optimisation methodology could be applied in other fields that need the development of machine learning tools for developing prediction tools and increase their predictability for a specific objective (by the accuracy or other metrics).

Also, this thesis considered surrounding variables that could give more information about the structural condition of the sewer assets than the physical characteristics. According to the application results, not all the physical features are influential on the deterioration of the structural condition. In contrast, characteristics such as city's districts or basins are more prominent in both case studies.

The developing of the proposed methodology give an alternative to constructing sufficiently accurate and not expensive tools, reducing the computation time and the collection of several variables for feeding the model and have similar prediction performances.

Besides, statistical and machine learning methods were useful for achieving specific tasks in the developed methodology. Bayesian Network helped to the feature selection identifying the variables that influence the deterioration of the structural conditions, Support Vector Machines and Random Forest methods were helpful to develop the deterioration models, and for optimisation task, it was useful the differential evolutionary algorithm. Deviation analysis and confusion matrix was the basis to develop to build the metrics that link with the management objectives. It is important to take into account the identification of methods for each step of the methodology for future applications or improvements.

Besides, deterioration models based on machine learning such as random forest are recommendable tools for predicting the structural condition or failures to support the sewer asset management of any city, thanks to their success predictions and flexibility of providing the prediction in categories or probabilities of being on each category

Furthermore, the creation and exploration of structural condition scenarios indicate there are other clusters of the structural condition that could increase the prediction performance of the deterioration models (Ariaratman et al., 2001, López-Kleine et al.,2016) and Guzmán-Fierro et al.,2019a, b, c). From the creation of the structural conditions scenarios (SCS), it was possible to confirm that the deterioration model could unlink from the standard and regrouping the structural conditions to increase the prediction quality. Furthermore, the inclusion of intermediate conditions could have uncertainty and do not give enough information for building deterioration models reliable enough. It does not mean that the standard is wrongly designed as a guide to support sewer management; it is just that the classification would not be adapted to develop deterioration models with high prediction performances.

It is recommended for further researches to include the analysis of calibration and validation data presented in Guzmán-Fierro et al. 2019 (a, b and c) to increase the prediction quality for achieving any of both management objectives proposed. With this inclusion, the deterioration models could need fewer variables for achieving a specific management objective: i.e. at the pipe level.

It could be interesting for further investigations, to develop sewer asset management tools from the structural failures found on the sewer assets and unlinked these tools from the categorization of the structural condition of the sewer assets. The main aim of the above is removing the uncertainty generated for that categorization and thus build more reliable tools that support sewer asset management.

Also, it is suggested to verify the classification of the structural condition given by the local standards to evaluate if the five structural grades are more informative as a guide for the decision-making in the sewer asset management or reducing the number of categories could give better or equal information for this decision-making.

As a practical recommendation based on the results of this doctoral thesis, it suggests to include surrounding variables of ease collection related to environmental, urban and operational features of the case study to build deterioration models for the sewerage of any city, such as districts, closeness with other infrastructures and operational zones. They give information about the dynamic of the city that influences the structural behaviour of the sewerage.

It is essential to apply this methodology in case studies that fulfil the following criteria: (i) large percentage of sanitation coverage on the city; (ii) to have georeferenced information about each asset that belongs to the sewer network; (iii) to have an assessment protocol to classify the structural and operational state of the sewer assets on grades from visual inspections; and (iv) to have information about a non-depreciable quantity of inspected and assessed sewer assets. From the last item depends on the performance quality of the methodology: while more CCTV inspections has the calibration data to train the models, higher probabilities of success.

It is imperative that utilities focus more on implementing proactive asset management in the sewerage, investing in tools that support their decision makings and preventing future disasters that could affect other infrastructures and the community. Linking the identification of causes (influential variables of the deterioration of sewer assets), rational assessment protocols for the structural and operational condition of sewer assets with the possible damages should be the strategy.

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