

## APPENDIX

## APPENDIX – PART B

### APPENDIX -PART B.1. Bogota’s case

Bogota, apart from being the capital of Colombia, is the largest and the most important city of Colombia: on it concentrates most of the economic and political activities of Colombia. Bogota has more than 7 million inhabitants approximately (15% of the Colombian population approximately) (DANE, 2019). It is administrated as Capital District as being a territorial entity of the first order (the same administrative status as departments of Colombia). Bogota was founded in 1538 as “Santafé” when Colombian territory was part of *Viceroyalty of New Granada* (Spanish colony). After the Colombian independence, it was called “Bogota” in honor of the name that *Muisca* culture used to call to this region “*Bacata*”. The *Muisca*s were the native culture that had been settled in this region before the arriving of Spanish conquer (Vasco & Iriarte, 1998; Blanco, 2017). Bogota is the third highest capital of South America (average altitude of 2625 meters above the sea level), and it is located in the center of Colombia in a natural region called “savannah of Bogota” which is part of the eastern cordillera of the Andes Mountain range. Bogota is boarded to the east by the Eastern Cordillera of the Andes Mountains range and to the west by the Bogota’s river (Blanco, 2017).

#### B.1.1. Local assessment standard

*Table 1. Structural defects and their scores according to NS-058*

CODE	DEFECT'S TYPE	DEFECTS	SCORE
1.1.1.1	Deformation or deflection	Vertical (>3% and 7.5%; >7.5% and 12.5%; or > 12.5%)	20, 80 or 165
		Horizontal (>12.5%)	165
1.1.1.2	Crack or facture	Superficial crack (circular, complex, helicoidal, or longitudinal)	2
		Crack (circular, longitudinal, complex, or helicoidal)	10 or 80
		Fracture (circular, longitudinal, complex, or helicoidal)	40 or 80
1.1.1.3	Breakage or collapse	Breakage (<1/4; or +1/4)	80 or 165
		Collapse (complete loss)	165
1.1.1.4	Seal material introduced in the sewer asset	The seal is a ring (visible displacement, less than a half, more than a half, broken)	1, 2, 5 or 8
		Other seal (<5%; 5%- 20%; or >20%)	1, 2 or 5
		Without seal	5
1.1.1.5	Shifted joint	Longitudinal (1 and 1.5 width; >1.5 width; or displacement joint over NS-073 o visible soil)	1, 2 or 80
		Radial (1 and 1.5 width; >1.5 width; or 10% diameter)	2 or 80
		Angular (1 and 1.5 width; >1.5 width; or 10% diameter)	2 or 80

1.1.1.6	Superficial damages	Roughness, Pelling (mild, moderate, high, or very high)	5, 20, 120 or 165
		Aggregate (visible, leaving on the surface, absent) (mild, moderate, high, or very high)	5, 20, 120 or 165
		Reinforcement (visible, and leaving on the surface or corroded) (mild, moderate, high, or very high)	5, 20, 120 or 165
		Surface abrasion, corrosion waste or porous pipes (mild, moderate, high, or very high)	5, 20, 120 or 165
		Mechanical damage (mild, moderate, high, or very high)	5, 20, 120 or 165
		Chemical Attack - Damage above or below water level (mild, moderate, high, or very high)	5, 20, 120 or 165
		non-obvious cause or other damages (mild, moderate, high, or very high)	5, 20, 120 or 165
1.2.1.1	Defects related to brick or masonry assets	Displacement	80
		Absent bricks (<1/4; or +1/4)	120 or 165
		Collapsing collector in brick	165
1.2.1.2	Lack of mortar	Lack of mortar (< 15mm; 15-50 mm; or >50 mm)	10, 20 or 40

Source: NS-058 (EAAB, 2001)

Table 2. Operational defects and their score according to NS-058

CODE	DEFECT'S TYPE	DEFECTS	SCORE
1.1.2.1	Obstruction by connection	Obstruction by connection (<5%; 5%-20%; 20-50%; 50%-75%; or >75%)	1, 2, 5, 8 or 10
1.1.2.2	Trees' roots	Root blocking connection	5
		Independent fine roots	1
		Complex root mass (<5%; 2%-20%; 20%-50%; 50%-75%; or >75%)	2, 4 or 10
1.1.2.3	Bonded or sedimentary deposits or soil income	Incrustation (<5%; 2%-20%; or >20%)	2, 4 or 10
		Materials glued to the wall (<5%; 2%-20%; 20%-50%; 50%-75%; or >75%)	1, 2, 5, 8 or 10
1.1.2.4	Other obstacles	Brick pieces, broken piece of pipe, other objects in the bottom of the pipe, protuberance through the wall, board wedge or construction inside the structure	10
1.1.2.5	Infiltration	Sweating, drip, jet or pressure water jet	3, 5 or 10

Source: NS-058 (EAAB, 2001)

**Table 3. Classification of structural grades, diagnosis and recommendations by NS-058**

$\Sigma$ structural scores	Grade	Diagnosis	Recommendations
> 10	1	Without o little structural defects which are not important for the structural stability of the system	New inspection within 4 to 5 years to verify the structural state of the sewer asset
10-39	2	The defects found are minor and do not compromise the stability of the network in the short term	Maintenance actions in order to correct the damage found and make a new inspection within 3 to 4 years to analyse the structural risk
40-79	3	Defects that could generate structural problems	Maintenance actions to correct defects by prioritizing them according to their severity or qualification. Make a new inspection within 2 to 3 years to verify with the result, the actions carried out and that the structural risk has not increased
80-164	4	Defects with high importance and could generate structural problems	Rehabilitation actions that prevent the damage propagation by prioritizing defects according to the severity or qualification. Make a new inspection within 1 to 2 years to analyse the performed actions
165+	5	Collapsed sewer asset	Replacement actions of an urgent nature

Source: NS-058 (EAAB, 2001)

**Table 4. Classification of operational grades, diagnosis and recommendations by NS-058**

$\frac{\Sigma \text{operational defects}}{\text{sewer asset's length}}$	Grade	Diagnosis	Recommendations
<0.5	1	Without o little operational defects which are not important for the operation of the system	New inspection within 2 to 3 years to verify the operational state of the sewer asset
0.5 - 0.9	2	The defects found are minor, and do not compromise the operation of the network in the short term	Maintenance actions to correct the most important damage found and make new inspection with 1 to 2 years to analyse the operational risk
1 -2.4	3	The defects found could affect the normal operation of the network	Maintenance actions that avoid the operational failure of the system. New inspection within 1 year to verify the actions' results
2.5 - 4.9	4	The defects found of high importance that could generate operational problems that limit the free water flow	Rehabilitation actions that prevent damage propagation. New inspection within 8 to 12 months to analyse the actions' results
>5	5	Sewer asset has a level of clogging greater than or equal to 60 %, and/or flow of water is slow or zero	Emergency actions of cleaning and unblocked of urgent nature. Make inspections of surrounding networks to determine the clogging cause

Source: NS-058 (EAAB, 2001)



## B.1.2. Distribution of the structural conditions in the collected variables

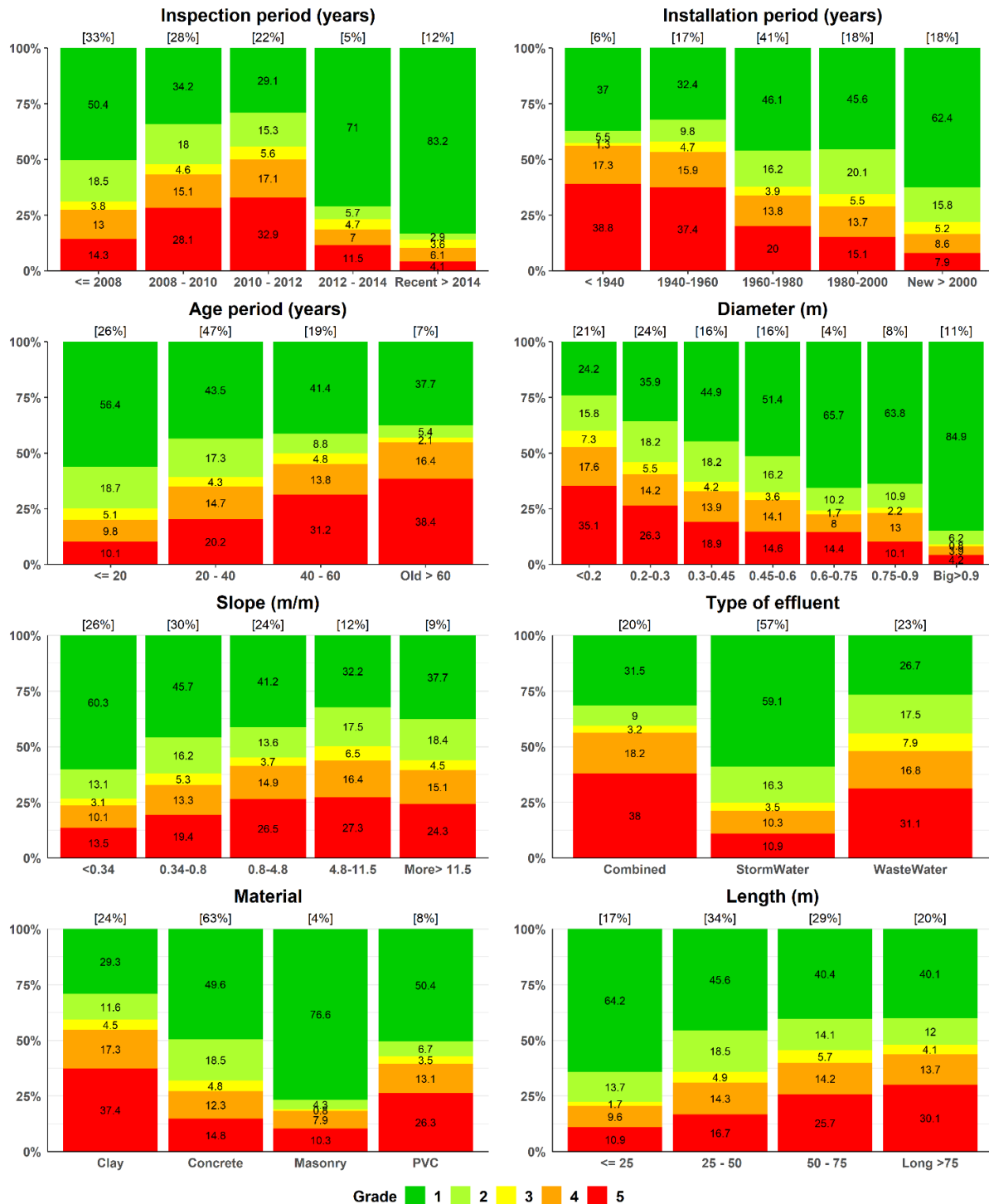


Figure 1. Distribution of the structural condition in the variables such as inspection periods, installation periods, age periods, diameters, materials, types of effluent, lengths and slopes (Part I). Percentage upper each bar plot represents the distribution of factors for each variable in the inspected sewer assets database for Bogota's case. Source: Author

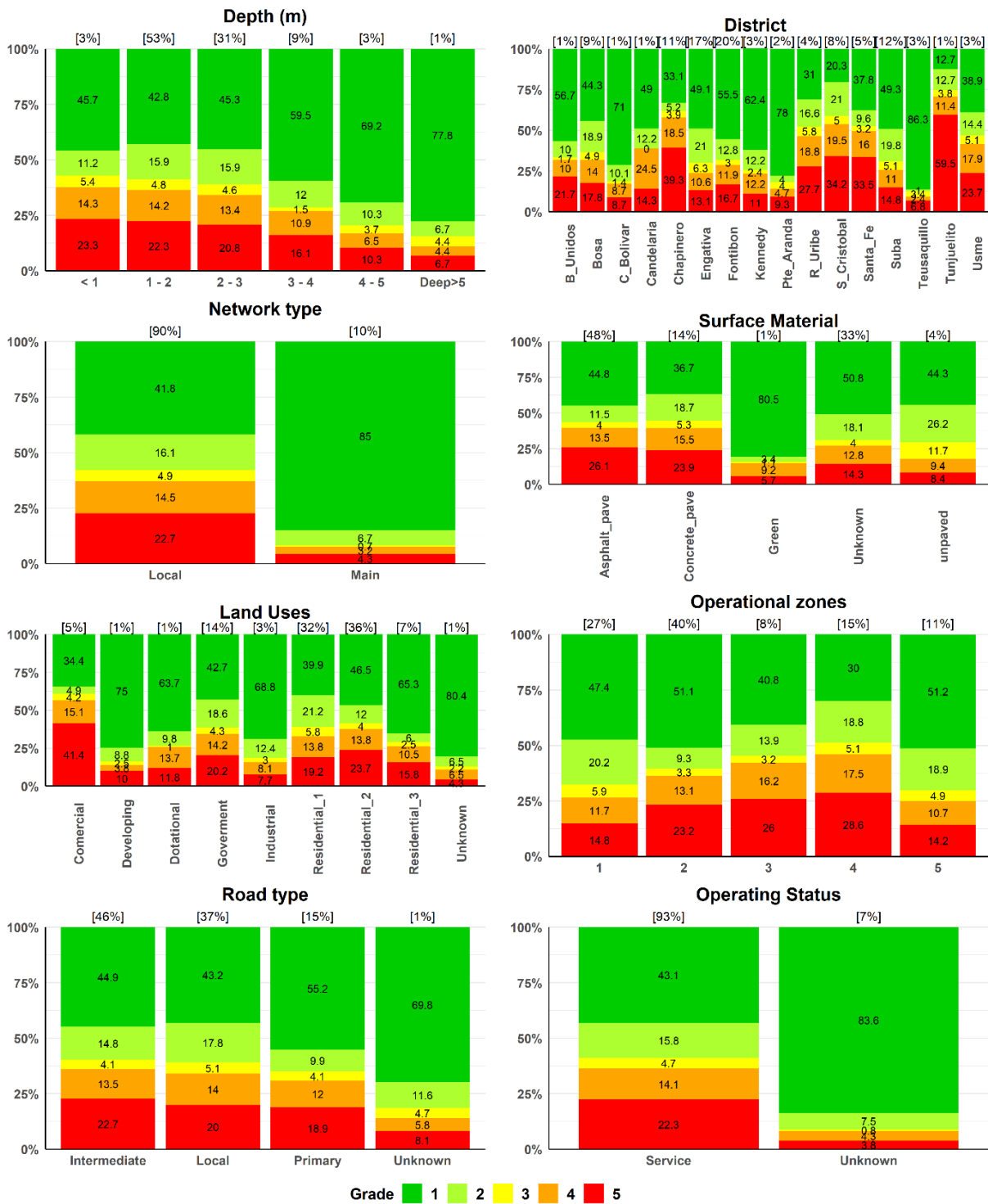
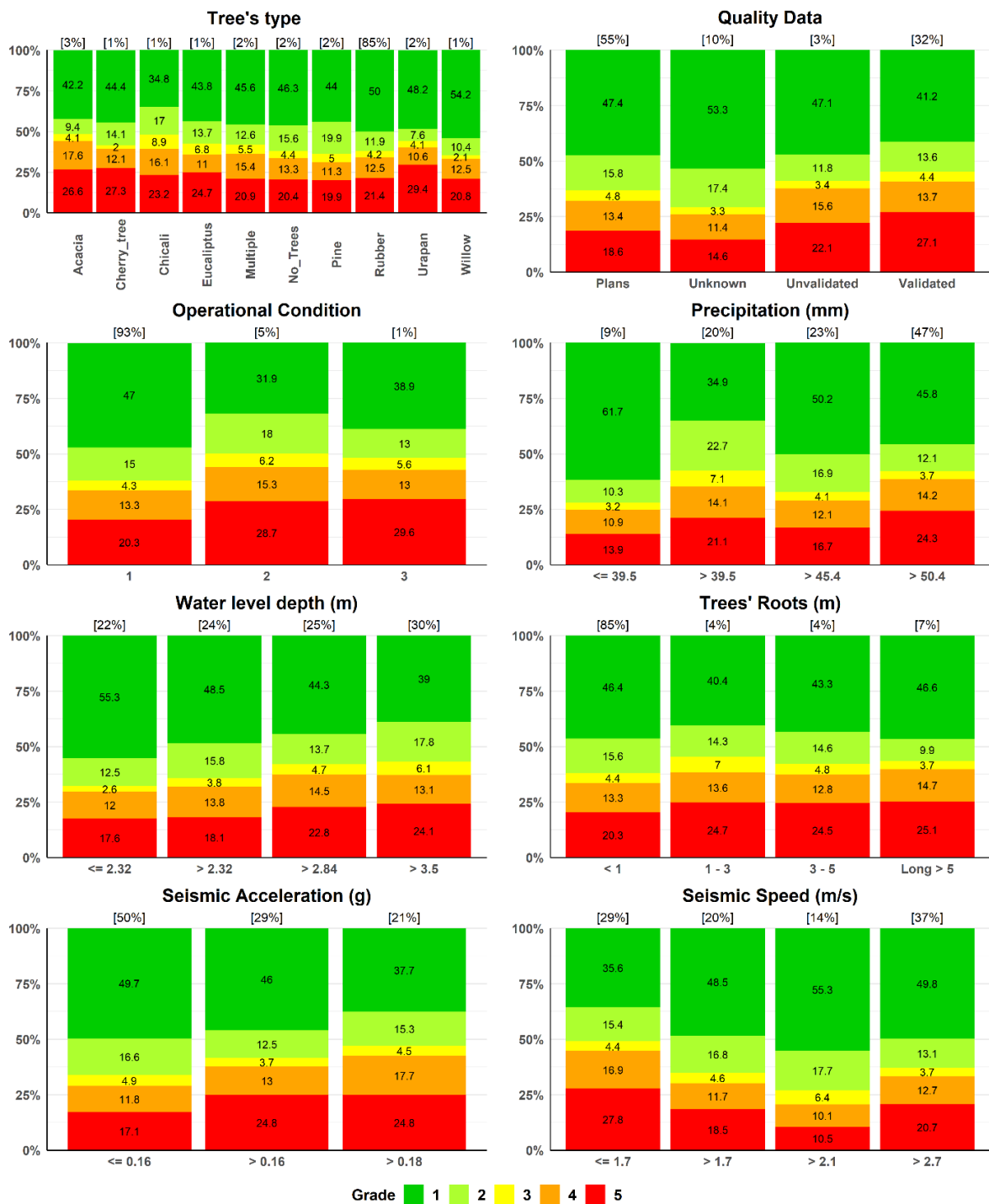


Figure 2. Distribution of the structural condition in the variables such as depths, districts, network types, surface materials, land uses, operational zones, road types, and operating status (Part II). Percentage upper each bar plot represents the distribution of factors for each variable in the inspected sewer assets database for Bogota's case. Source: Author



**Figure 3. Distribution of the structural condition in the variables such as trees' types, quality data, operational conditions, precipitation levels, water level depths, trees' roots, seismic acceleration and seismic speed (Part III). Percentage upper each bar plot represents the distribution of factors for each variable in the inspected sewer assets database for Bogota's case. Source: Author**

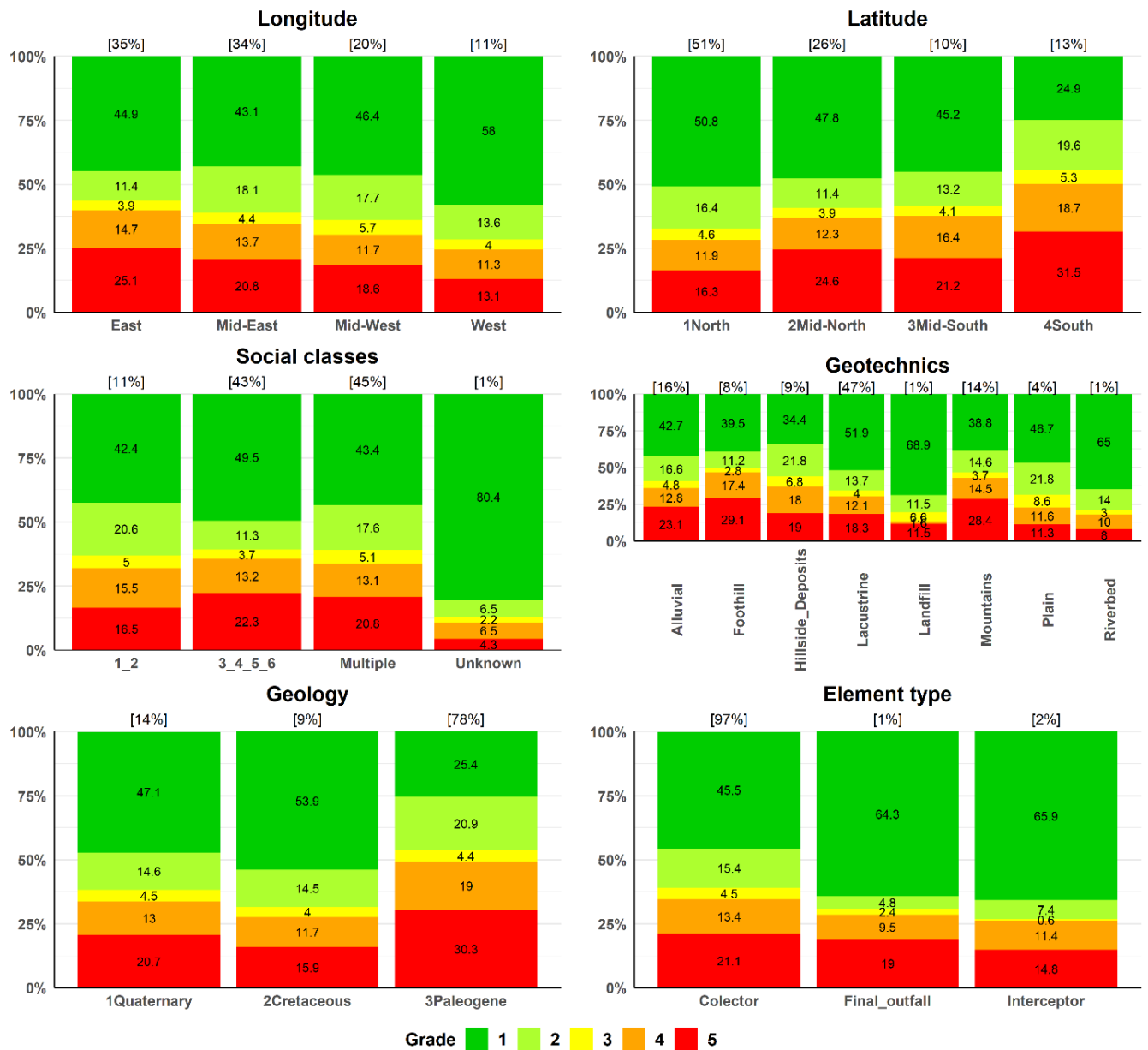


Figure 4. Distribution of the structural condition in the variables such as longitude, latitude, social classes, geotechnics, geology and element type (Part IV). Percentage upper each bar plot represents the distribution of factors for each variable in the inspected sewer assets database for Bogota's case. Source: Author

## **APPENDIX -PART B.2. Medellin's case**

Medellin is a city with 4 million inhabitants (DANE, 2019) approximately and it is located at the Aburra's valley, a central region of The Andes Mountains. Medellin is the second largest urban agglomeration and the second most important city of Colombia (after Bogotá). It is the capital of *Antioquia's* department. The city extends to both sides of Medellín's river which across the city from south to north.

Medellin was founded in 1616 as "Nuestra Señora de la Candelaria de Medellin" when Colombian territory belonged to the Spanish royal (*Viceroyalty of New Granada*). Then after the Colombian independence, it was called "Medellín". In 1826, it was proclaimed as the capital of Antioquia's department because of economic development of Aburra's valley region (*Santafé de Antioquia* had been the Antioquia's capital during the colonial period) (Betancur, 2003). Currently, the metropolitan Medellin city groups ten municipalities: *Medellín, Barbosa, Bello, Caldas, Copacabana, Envigado, Itagüí, La Estrella, Girardota* and *Sabaneta*.

### **B.2.1. Local assessment standard**

The scores are given according to the type of failure, and their location as shown in Tables 4 and 5 for structural and operational failures, respectively. The location description refers to the position of failure along the wall's circumference of the sewer asset. The location is referenced according to the clock hands, it means that: positions from 11 to 1 refer to the above wall of the circumference; positions from 1 to 4 refers to the right wall of the circumference; positions from 4 to 8 refer to the bottom wall of the circumference (in which the waterflood is permanent); and positions from 8 to 11 refer to the left wall of the circumference. According to this location classification, it classifies the severity of the failure: failure located to the high wall of the circumference is low severity, located on the left or right wall of the circumference is medium severity and on the bottom wall of the circumference is a failure of high severity.

Table 5. Structural defects and their scores according to EPM's assessment methodology

DEFECTS' TYPE	CODE	DEFINITION	SCORES				RELEVANCE
			NO LOCATION	LOCATION			
				11-1	(1-4) and (8-11)	4-8	
Fissure	FIL	Longitudinal		25	28	30	1
	FIC or FIM	Circular or multiple		28	31	34	2
	FIE	Spiral		31	34	37	2
Fracture	FRL	Longitudinal		36	40	43	2
	FRC	Circular		42	46	50	2
	FRM	Multiple		63	69	76	3
	FRE	Spiral		125	138	150	3
Breakage or Hole	RO or HU	Breakage or Hole		125	138	150	3
Deformation	DEV	Vertical		50			2
	DEH	Horizontal			50		2
Collapse	CO	Collapse		250			
Joint	JUDH or JUAH	Horizontal displaced or Horizontal open		50		60	2
	JUDV or JUAV	Vertical displaced or Vertical open			55		2
	JUE	Shared					0
Deteriorated surface	SUDR	Rough		25	25	30	1
	SUDAV	Visible aggregate		42	46	50	2
	SUDRV	Visible reinforcement		50	55	60	2
	SUDRP	Steel reinforcement projected on the network		63	69	76	2
	SUDPC	Corrosive products or high temperature				250	3
	SUDAB	Absent of invert level wall				250	3

Source: EPM (2010).

Table 6. Operational defects and their scores according to EPM's assessment methodology

DEFECTS' TYPE	CODE	DEFINITION	SCORES				RELEVANCE
			NO LOCATION	LOCATION			
				11-1	(1-4) and (8-11)	4-8	
Trees roots	RAF	Fine roots		2	4	6	1
	RAG or RAM	Thick roots or Roots in mass		3	6	9	2
Infiltration	IND or ING	Leak or Drip		3	3	4	2
	INF or INP	Filter or Pressure		23	25	30	1
Inflow	EX	Inflow		23	25	30	2
Deposits	DEI	Scales		3	6	9	2
	DEG or DER	Fats or solid waste		3	6	9	1
	DEC, DEA or DET	Concrete, sand or crushed		5	10	15	2
Obstacles	OBT or OBC	Transverse to the pipe or cables		8	9	11	2
Defected packaging	EMV	Visible packing inside to the joint		5	10	15	2
	EME	Network exposed pack		8	16	20	2
Alignment	ALPVS	Superior vertical loss		3			1
	ALPVI	Lower vertical loss				9	1
	ALPHD or APhi	Right or left horizontal loss			6		1
Connections	ACH	With hole	23				3
	ACP	Penetrating	23				3
	ACI	Incorrect position	5				1
	ACO	Clogged	3				1
	ACE	Wrong	8				1
	ACV	With rod	12				1
Punctual repair	REPD	Faulty		8	9	11	2
Fall inspection camera	CACF	Fractured	8				2
	CACO or CACH	Clogged or hole	23				3

Source: EPM (2010).

The operational and structural conditions are calculated according to the defects found by CCTV camera and affectation's probability that could generate a short, medium and long term (relevance), in which the damages are assessed as maximum, median and minimum. Equation

$$Total\ score\ of\ sewer\ asset = \frac{K \sum Scores_{Rmax} + K \sum Scores_{Rmedium} + K \sum Scores_{Rmin}}{...}$$

Equation 1. Total score of the sewer asset to determine the structural or operational condition.

1 shows the calculus to determine the total score of the sewer asset according to the structural or operational condition.

Being K the number of damage for each category,  $\sum Scores_{Rmax}$  is the sum of all the scores of damages found in the sewer asset that represent relevance 3 (high),  $\sum Scores_{Rmedium}$  the sum of all the scores of damages found in the sewer asset that represent relevance 2 (medium); and  $\sum Scores_{Rmin}$  the sum of all the scores of damages found in the sewer asset that represent relevance 1 (low). Table 7 shows the corresponding structural or operational deterioration grade according to the results of the total score of sewer asset given by Equation 1.

*Table 7. Classification of structural and operational grades, diagnosis and recommendations by EPM's assessment methodology (EPM, 2010)*

GRADE	TOTAL STRUCTURAL SCORE	TOTAL OPERATIONAL SCORE	DIAGNOSIS	RECOMMENDATIONS
1	< 1.8	< 0.4	Without o little defects which are not important for the operational or structural stability of the sewer asset	New inspection within 7 to 10 years to verify the operational and structural condition
2	1.8 - 4.1	0.4 - 1.3	Defects with higher importance, but do not compromise the operational or structural stability of the sewer asset to short term	Maintenance actions to correct damages found and new inspection within 5 to 7 years to analyse the structural and/or operational risk
3	4.1 - 9.2	1.3 - 3.3	Defects found could generate operational or structural punctual problems, corrective and preventive actions should be taken in order to minimize the failure probability	Maintenance actions with the purpose of correcting damages found, prioritizing them by their severity or score. Besides a new inspection within 3 to 5 years to verify the structural and/or operational risks have not been increased with the performed actions' results
4	9.2 - 21.6	3.3 - 8.6	Punctual or sectorized defects found of great importance and compromise the operational and/or structural condition of sewer assets	Preventive or corrective measures that perform maintenance actions that prevent a generalization of the damage, prioritizing the actions regarding the severity or score of the defects. New inspection within 1 to 3 years to analyse the performed actions' results
5	>= 21.6	>= 8.6	Defects of great importance along the sewer asset that requires urgent operational and/or structural interventions	Structural and/or operational maintenance actions of urgent nature to leave the affected sewer asset in operation. It should be analysed the reposition or rehabilitation possibility of the sewer asset.

Source: EPM (2010)



## B.2.2. Distribution of the structural conditions in the collected variables

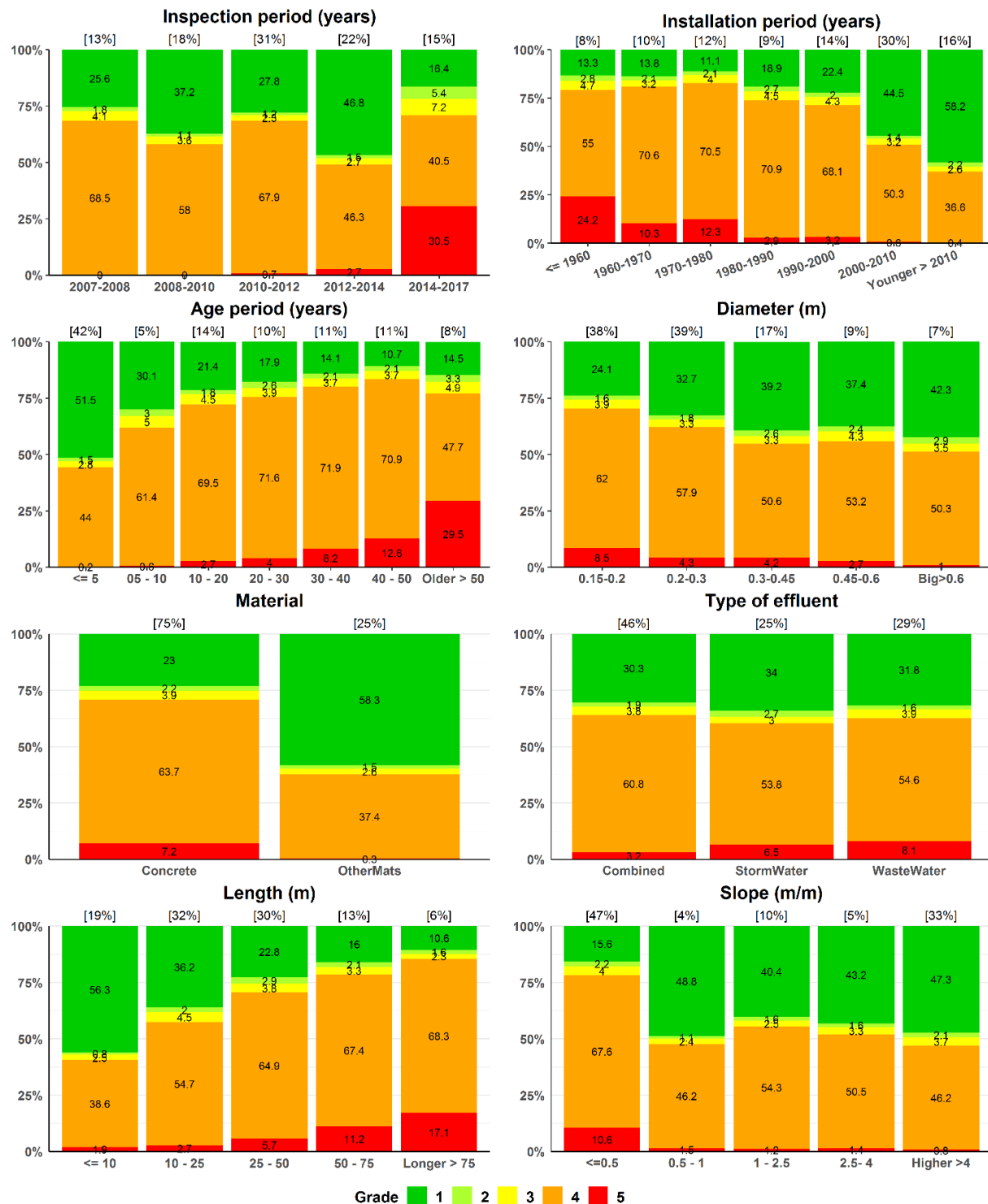


Figure 5. Distribution of the structural condition in the variables such as inspection periods, installation periods, age periods, diameters, materials, types of effluent, length and slopes (Part I). Percentage upper each bar plot represents the distribution of factors for each variable in the inspected sewer assets database for Medellin's case. Source: Author

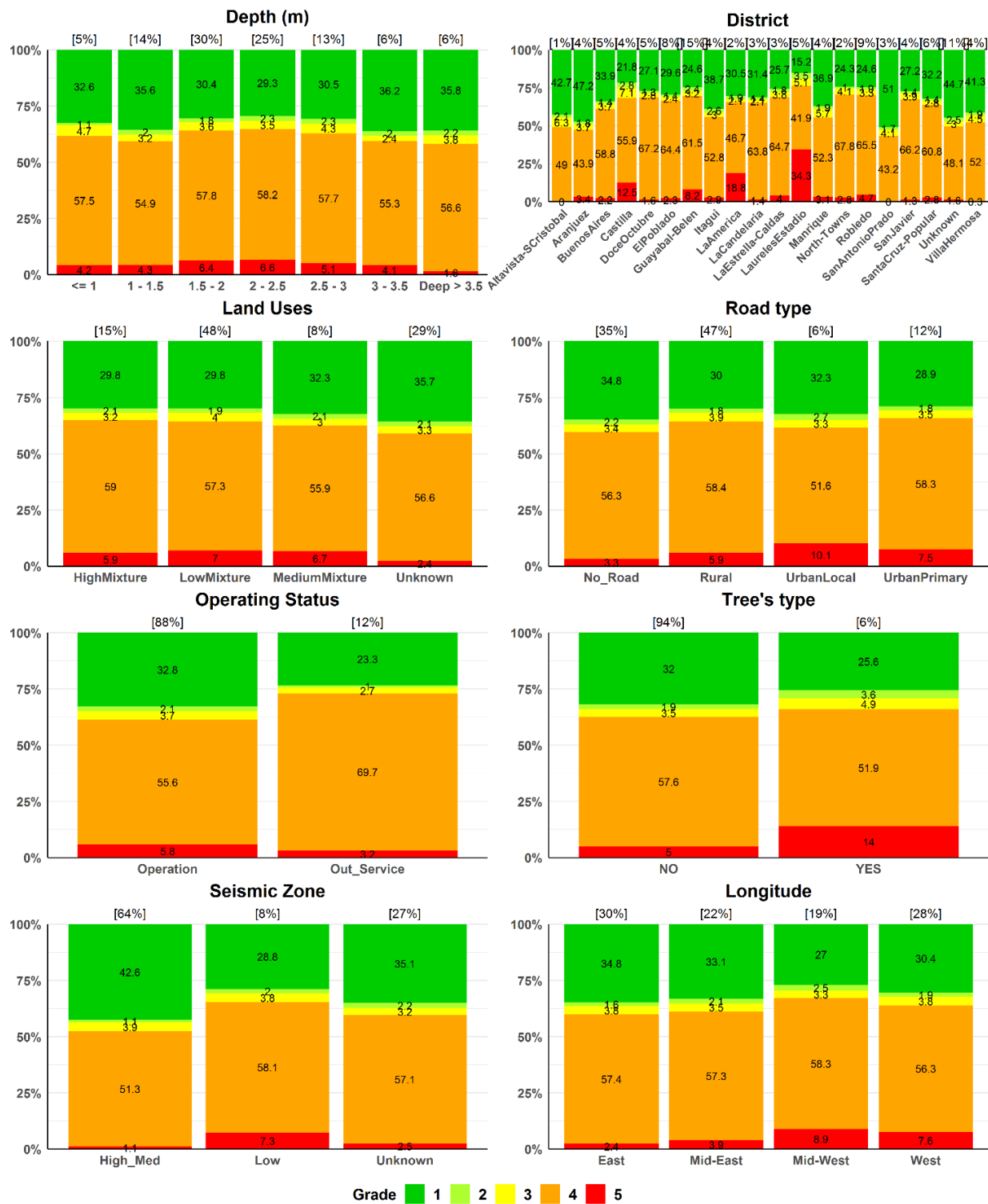


Figure 6. Distribution of the structural condition in the variables such as depths, districts, land uses, road types, operating status, tree-s types, seismic zones, and longitudes (Part II). Percentage upper each bar plot represents the distribution of factors for each variable in the inspected sewer assets database for Medellin's case. Source: Author

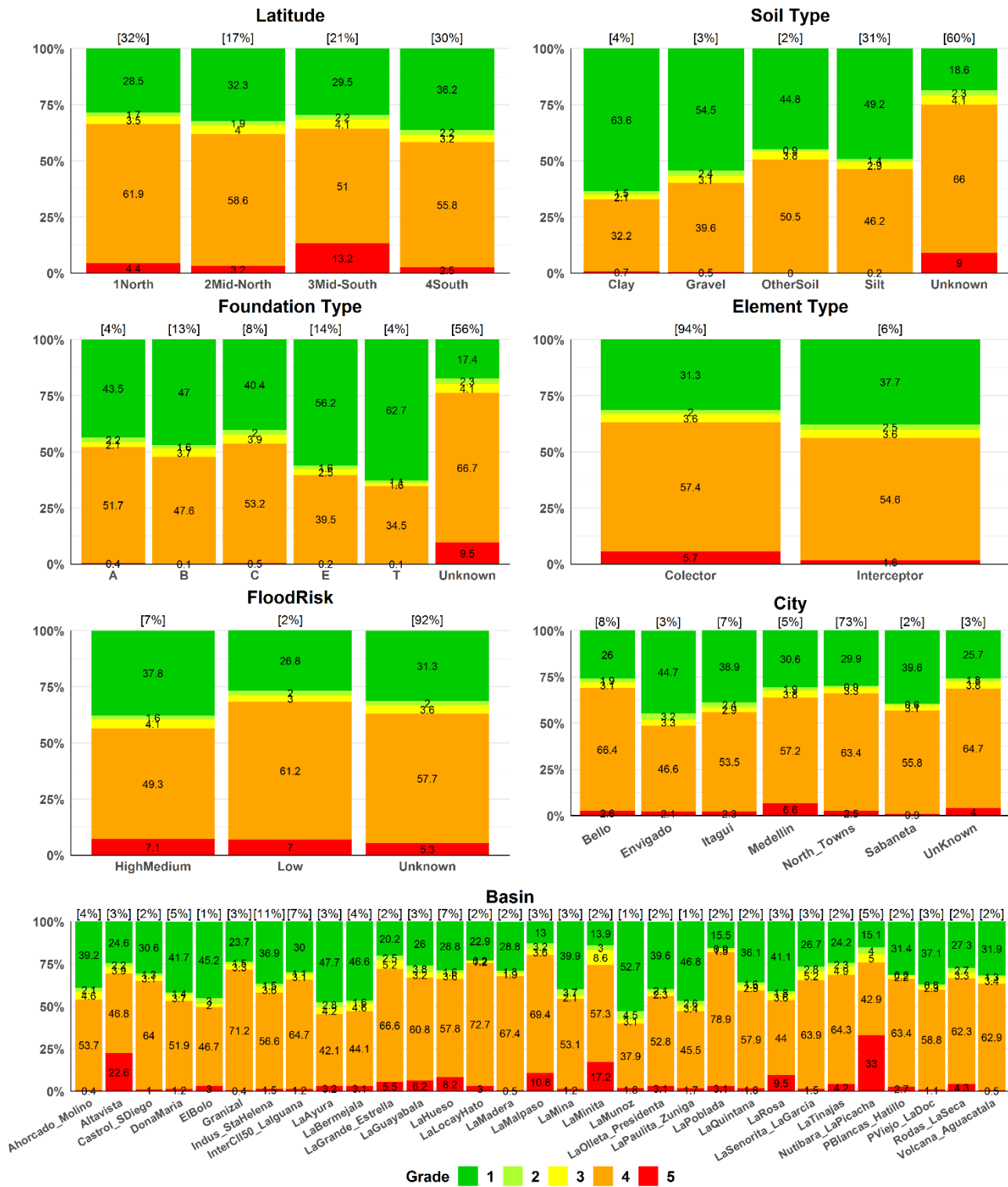


Figure 7. Distribution of the structural condition in the variables such as latitudes, soil types, foundation types, element types, flood risk zones, cities and basins (Part III). Percentage upper each bar plot represents the distribution of factors for each variable in the inspected sewer assets database for Medellin's case. Source: Author

## APPENDIX – PART C

This appendix shows a first attempt of the application of the developed tools of the chapter 8 of the Part C of this manuscript for developing a methodology that integrates the selection of appropriate prediction models for two sewer asset management objectives, as well as the selection of the enough variables and training data to maximize the prediction quality of models. This methodology was developed by the Master student Julián Guzmán who was directed by the supervisor and the author of this doctoral thesis. This methodology was a first attempt to integrate the selection of deterioration models with the sewer asset management objectives. The products of this methodology were (i) 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), and (ii) the base in the development of the proposed methodology of this manuscript (Chapter 9 of Part C).

This methodology integrates two deterioration models and the proposed performance metrics and the optimisation methodology (chapter 8). The chosen deterioration models were the two models based on machine learning methods with the highest performance predictions in the exploration carried out previously for Bogota’s and Medellin’s cases, exploration reported in Hernández et al., (2017a, b and c; 2018a; 2019b). The selection of models based only in machine learning methods was chose to integrate the optimisation methodology and metrics proposed in the chapter 8. For more details about this exploration see item 6.1.2 of the Part B and the given results in the Part D of this document.

The present methodology is the result of the master thesis of the student Julián Guzmán which was directed by both the supervisor and the author of this PhD thesis. This work was submitted on the Journal of Infrastructure systems in November 2019 (Guzmán-Fierro et al., 2019c).

The aim of work was developing a methodology for selecting the variables and the most appropriate prediction models and training data necessary to maximize the prediction quality of models oriented to support two different sewer asset management objectives.

Due to the lack of methodologies for integrating prediction models, training data subsets and variables that could influence the structural condition of sewer pipes, this work proposes a five-step methodology. The methodology could be applied to different case studies for the

development of prediction models oriented to support sewer asset management whose objectives are related to the sewer predictions at network and pipe levels.

- Step 1 - Data collection: as shown in Figure 8, the proposed methodology begins with the collection of data from CCTV inspections, information of physical characteristics of the sewer pipes and environmental factors through geo-referenced databases. From this information, two subsets are created: i) sewer pipe structural conditions and physical factors and ii) sewer pipe structural conditions, physical and environmental factors.
- Step 2 - Structural Condition Scenarios -SCS- Creation: different structural condition scenarios –SCS– are created to identify in the next step (Step 3) the scenario that provides the highest predictive capacity for a specific model. 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.

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).

- Step 3 SCS selection: for each scenario defined in Step 2, SVM and RF models (Hernández et al., 2017a and c; 2018a; 2019 a and b) are built considering two types of input data (variables) to train the model: (i) only physical variables which are easily available for sewerage utilities; and ii) physical and environmental variables to explore if the inclusion of external variables could increase the performance prediction of the deterioration models for support the management objectives. In the end, four models should be created: (a) SVM trained only with the physical variables; (b) SVM trained with physical and environmental variables; (c) RF trained with physical variables; and (d) RF trained with physical and environmental variables. For each model, 1000 random selections (Monte-Carlo simulations) are trained and evaluated by different calibration/validation percentages. As well as, the methodology proposed in chapter 7, 1000 Monte-Carlo Simulations are carried out to find a balance between the computational costs and enough quantity of random data selection to assess the possible prediction performance that the models could reach. Likewise, Cohen's Kappa Coefficient was chosen because of their robust evaluation of measure inter-rate agreement for predicted and observed conditions, considering the agreement occurring by chance (Vieira et al., 2010). Then, Cohen's Kappa Coefficient (See 4.1 of the Part A) (Kappa) is calculated for the validation data to measure the agreement rate between predicted and observed structural conditions. Therefore, for each model, 1000 Kappa are obtained. Then, for each

SCS, it is compared to the obtained Kappa's set by SVM and RF models using boxplot analysis and Wilcoxon test. Wilcoxon test is used to define the statistically significant difference ( $p\text{-value} < 0.05$ ) with the other Kappa's set related to the models of the other SCS.

For selecting the SCS that provides the higher capacity, the following criteria are considered: it is chosen the SCS that shows highest Kappa set for validation data and significant differences with the Kappa's sets of other scenarios. In the case that there are no significant differences among the scenarios, it is chosen the SCS with the lowest variability and highest Kappa's set.

- Step 4 Calibration/Validation percentage subset selection: considering the chosen SCS from step 3, a new SVM and RF models are trained and validated by five calibration/validation percentage subsets (50%/50%, 60%/40%, 70%/30%, 80%/20% and 90%/10%) using 1000 random selections for each percentage subset. As well as the proposed methodology of chapter 7, the steps of 10% of increasing and decreasing calibration and validation percentage subsets is defined by the user. Kappa evaluates each model in the validation data. In the end, Kappa's sets are obtained by each model and validation set. For each validation set, Kappa's sets are compared using boxplot analysis and Wilcoxon test ( $p\text{-value} < 0.05$ ). The calibration/validation percentage subsets are chosen according to the following criteria: it is chosen the calibration/validation percentage subset that shows the highest Kappa's sets and significant differences with the other validation Kappa's sets obtained with the other calibration/validation percentage subsets and the lowest variability.

In the case that the above criteria fulfil, but the variability is the highest, it is chosen the subsets with the second-high Kappa with lower data in the calibration percentage subset.

In the case that there is no significant difference among the Kappa's subsets, it is chosen the calibration/validation percentage subset that requires the lowest data number for training (calibration subset).

- Step 5 Knet and Kpipe optimised models: with the chosen SCS (step 3) and the calibration/validation percentage (subsets) chosen in step 4, the following models (Table 8) are trained and evaluated with *Knet* and *Kpipe* performance metrics.

Table 8. Trained and evaluated models by *Knet* and *Kpipe* metrics

Models \ Variables	Physical (PV)		Physical and Environmental (EV)	
	RF with default package hyperparameters	<b>KnetPV1</b>	<b>KpipePV1</b>	<b>KnetEV1</b>
SVM with default package hyperparameters	<b>KnetPV2</b>	<b>KpipePV2</b>	<b>KnetEV2</b>	<b>KpipeEV2</b>

Source: Guzmán-Fierro et al. (2019c)

According to Table C2, **KnetPV1** and **KnetPV2** are the *Knet* values and **KpipePV1** and **KpipePV2** are the *Kpipe* values obtained from RF and SVM models (being model 1 and 2 respectively) considering only physical variables and default hyperparameters suggested by *randomForest* and *ksvm* functions of the libraries *randomForest* (RcolorBrewer & Liaw, 2018) and *kernlab* (Karatzoglou et al., 2018) libraries of R software (See the description of this functions and libraries in the item 6.2.1 of the Part B of this manuscript). Likewise, **KnetEV1** and **KnetEV2** are the *Knet* values and **KpipeEV1** and **KpipeEV2** are the *Kpipe* values obtained from RF and SVM models considering the physical and environmental variables and defaults hyperparameter suggested by *randomForest* and *ksvm* functions of the R software.

Within the eight implemented models from in Table C2, it is chosen two models that show the lowest values of *Knet* and *Kpipe* (performance metrics). These chosen models are optimised to raise the predictive capacity of the prediction models. The DE method is used to find the combination of hyperparameters that best minimize the objective function, following the optimisation methodology given in subchapter 8.1 of this Part (Caradot et al. 2018; Hernández et al. 2019c).

Finally, after the optimisation process, two models for predicting the structural condition sewer pipes are obtained: an optimised model for the network-level objective (for supporting decision-making at the network level) and an optimised model for the pipe-level objective (for supporting decision-making at the pipe level).

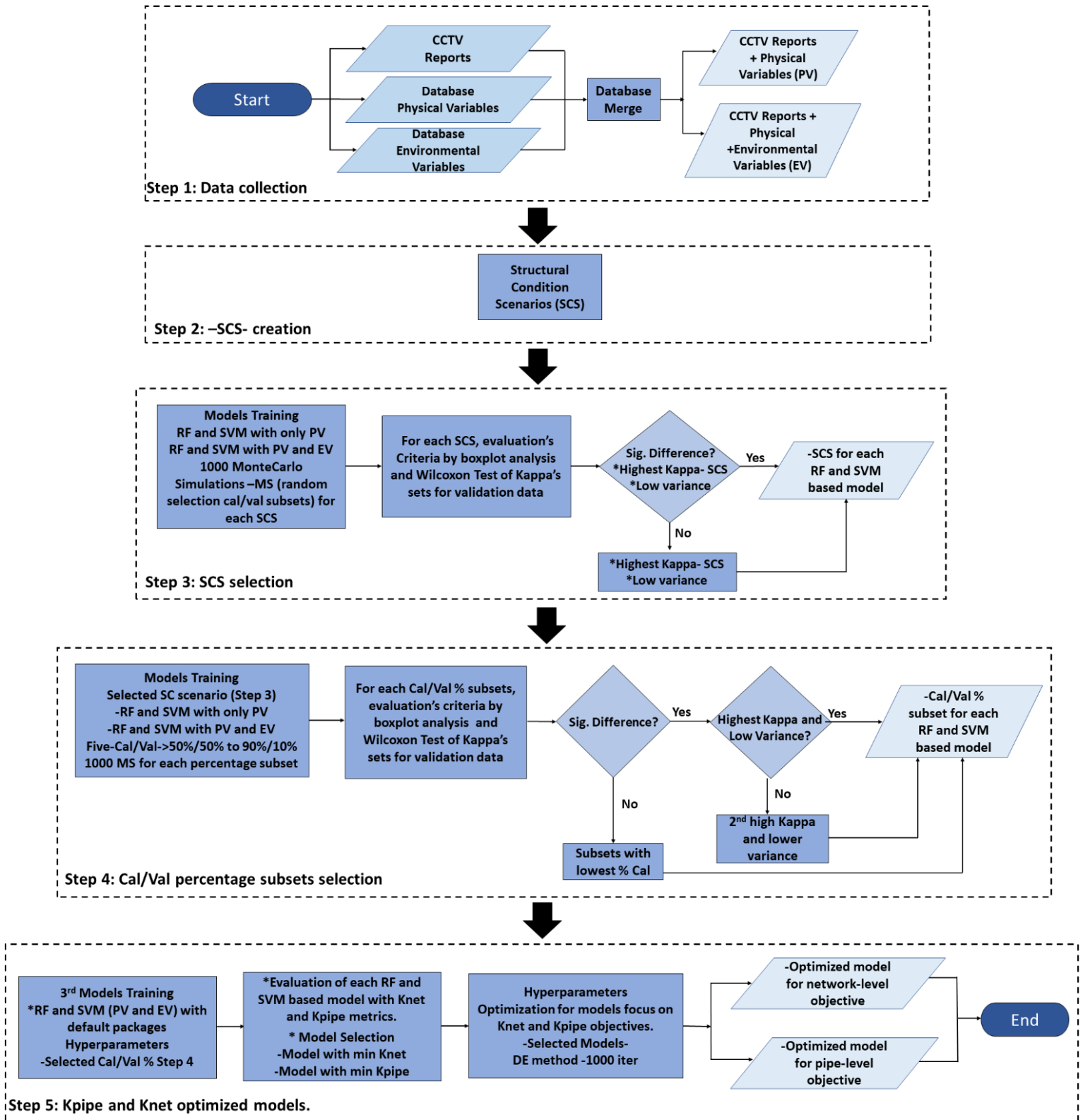


Figure 8. Flowchart of Methodology for achieving two management objectives (Antecedent methodology to the proposed one in this doctoral thesis). Source: Guzmán-Fierro et al. (2019c)



## APPENDIX – PART D

This appendix shows the results of the application of the proposed methodology (Chapter 9) in both case studies: Bogotá and Medellín.

### APPENDIX – Part D.1. Bogota's case

This appendix shows the results of the application of the proposed methodology in Bogota's case in detail. This subchapter consists of three parts: (i) the hierarchy of the most influential variables over the structural condition obtained after applying the methodology described in chapter 9.1.(Part C); (ii) the optimisation of the selected deterioration models for management objectives, methodology described in chapter 9.2. (Part C); and (iii) the results of the optimised deterioration models for management objectives, methodology described in chapter 9.2. (Part C).

Each part shows the results for each structural condition scenario described in Table D.9. (Part D) of the manuscript.

#### D.1.1. Hierarchy of the most influential variables

##### *D.1.1.1. Five structural grades*

Table 9 shows the variables' relationships hierarchy considering the structural condition as the local assessment standard for Bogota's city (EAAB, 2001). According to the Bayesian Network-based methodology, from the 31 studied variables for Bogota's case, 19 variables show a non-depreciable relationship with the five structural grades (median  $\geq 0.05$ ). Variables such as material and network type of the sewer assets, surface material in the superficial infrastructure over the sewer systems, road type, operating status of the sewer assets, quality data, length trees roots, element type of the sewer asset, longitude and latitude coordinates were variables that do not show influence over the structural condition of the sewer assets, when the five structural grades are considered for prediction purposes.

**Table 9. Classification of the variables' relationship with five structural grades (first structural condition scenario)**

Relationship Type	Order	Variables	Median	Q1	Q3	IQR	median/IQR
First (Parent variables)	1	Inspection Year ("IY")	0.63	0.46	0.70	0.24	<b>2.63</b>
	2	Diameter ("Diam")	0.87	0.63	0.99	0.36	<b>2.42</b>
	3	Installation Year ("CY")	0.15	0.04	0.24	0.20	<b>0.71</b>
	4	Length (Length")	0.06	0.01	0.10	0.09	<b>0.63</b>
	5	Type of effluent ("Sew")	0.13	0.01	0.35	0.35	<b>0.36</b>
	6	Age ("Age")	0.06	0.00	0.39	0.39	<b>0.16</b>
Second (GParent variables)	7	District ("District")	1	1	1	0	<b>1000</b>
	8	Social Classes ("SocialC")	1	1	1	0	<b>1000</b>
	9	Land Uses ("LandUse")	0.98	0.84	1	0.16	<b>6.09</b>
	10	Depth ("Depth")	0.98	0.09	1	0.91	<b>1.08</b>
	11	Seismic shear wave velocity ("Vel")	0.15	0.03	0.23	0.20	<b>0.74</b>
	12	Seismic Acceleration ("Acc")	0.25	0.02	0.44	0.41	<b>0.59</b>
	13	Presence of trees (Tree")	0.10	0.04	0.25	0.22	<b>0.47</b>
	14	Slope ("Slope")	0.07	0.01	0.20	0.19	<b>0.39</b>
Third (GGParent variables)	15	Operational Zones ("Zones")	1	1	1	0	<b>1000</b>
	16	Type of intrusive trees ("TreeType")	1	1	1	0	<b>1000</b>
	17	Geotechnical zones ("GeoTec")	1	1	1	0	<b>1000</b>
	18	Geological zones ("Geo")	0.21	0.00	0.50	0.49	<b>0.43</b>
	19	Precipitation levels ("Prec")	0.07	0	0.19	0.19	<b>0.35</b>

*Source: Author*

Figure 9 shows a Bayesian Network that illustrates the predecessor variables of the five structural grades considering non-depreciable relationships among the variables (Boxplot median  $\geq$  0.05). The name of the variables shown in Figure 9. **Error! Reference source not found.** are depicted according to the abbreviations shown in Table 9.

According to Figure 9, District and Operational Zone are the roots of the Bayesian Networks: most of the other variables are related in some way to them. Variables such as geological zones, geotechnical zones, precipitation levels and trees are not related to the District and Zone, however these variables have successor variables that links other variables that show a direct and indirect relationship with structural condition. Most of variables that show a direct relationship with the five structural conditions are physical characteristics of the sewer assets and variables related to the age of the sewer assets. Coming back to the bar plot analysis of the item 5.1.2.3 of Part B, the

variables related to the age and district had an apparent strong relationship with the deterioration if the structural condition; in Figure 9 **Error! Reference source not found.**, it is possible to see the relationship between the age of the variables with the districts.

Moreover, there are variables that show an unusual relationship because of their different natures such as: Seismic velocity with social classes and precipitation levels with seismic velocity.

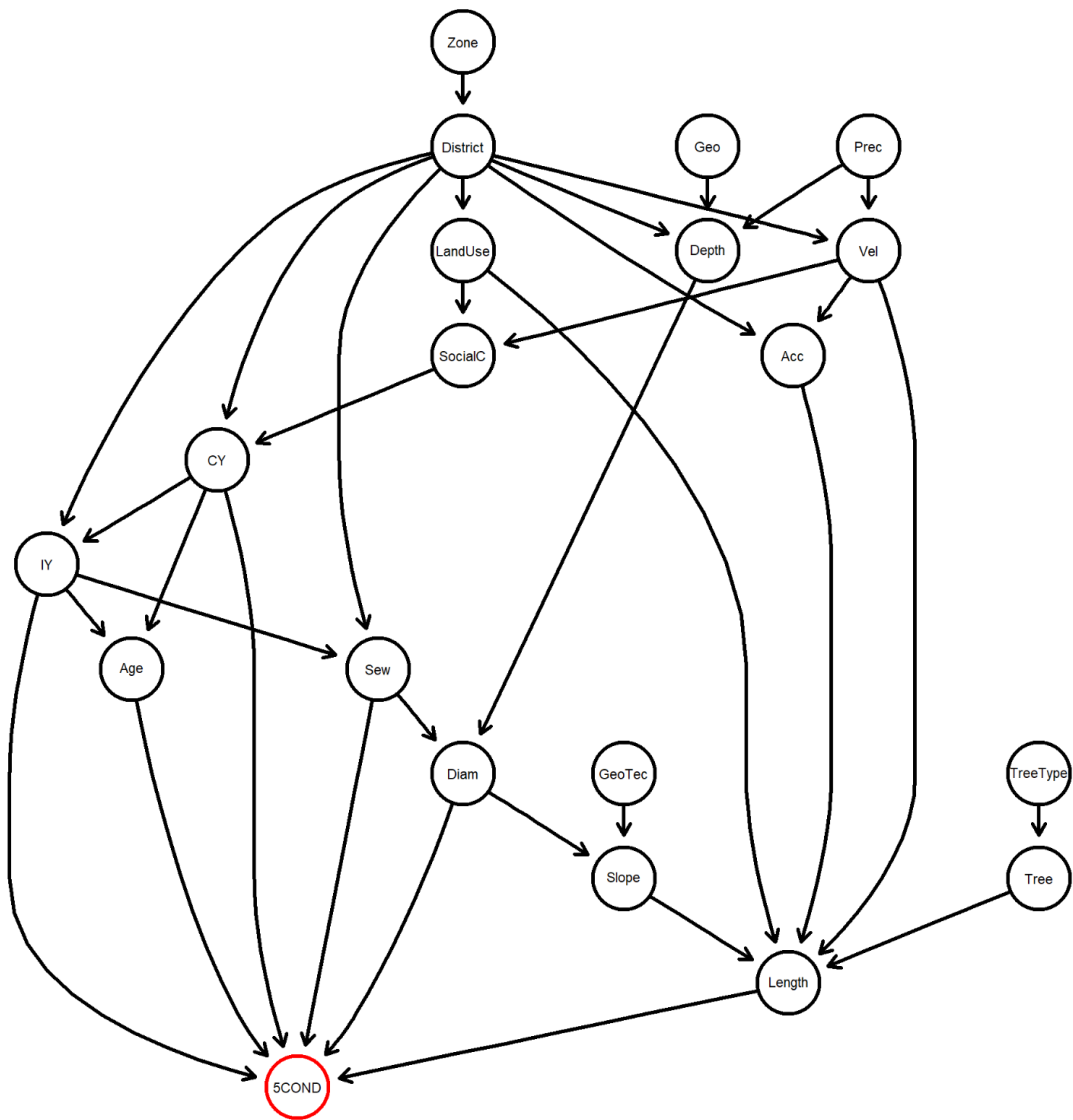


Figure 9. Bayesian Network that illustrates the different relationship of the studied variables with five structural grades, leaving aside variables that show depreciable relationship (boxplot median < 0.05). Source: Author.

### D.1.1.2. Three structural categories

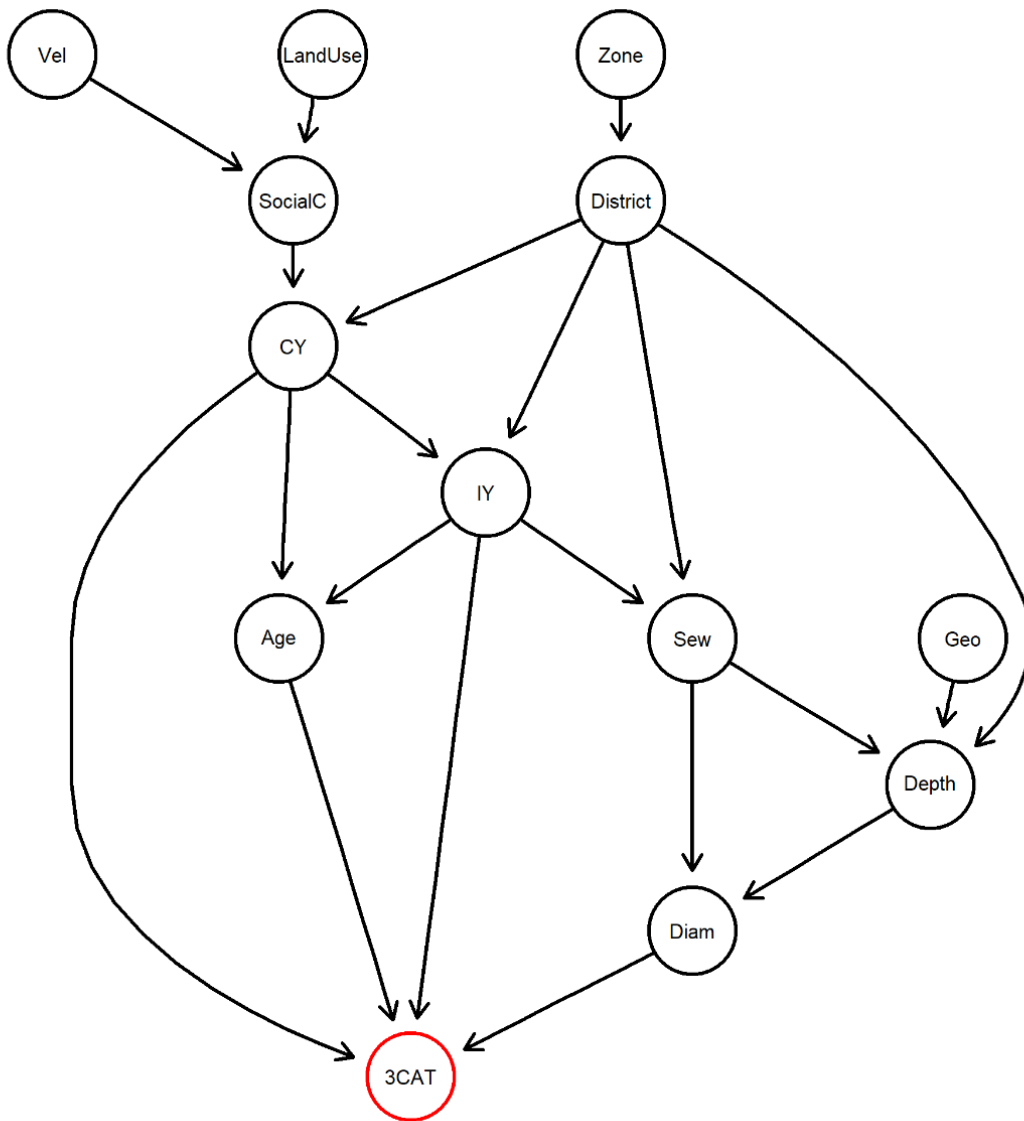
According to Table 10, only 13 variables show relationship with the three built structural categories. Comparing with Table 9, variables such as precipitation levels, closeness to the intrusive trees, type of intrusive trees, seismic acceleration, length and slope of the sewer assets that were chosen as influential to the deterioration of the structural of the sewer assets when the five structural grades, do not show a non-depreciable relationship with the structural condition of the sewer assets grouping the structural condition in three categories.

**Table 10. Classification of the variables' relationship with the three structural categories (second structural condition scenario)**

Relationship Type	Order	Variables	Median	Q1	Q3	IQR	Median/IQR
First (Parent variables)	1	Inspection Year ("IY")	0.74	0.72	0.77	0.05	<b>14.04</b>
	2	Diameter ("Diam")	0.99	0.88	1	0.12	<b>8.50</b>
	3	Age ("Age")	0.16	0.03	0.25	0.22	<b>0.73</b>
	4	Installation Year ("CY")	0.26	0.16	0.70	0.54	<b>0.48</b>
Second (GParent variables)	5	District ("District")	1	1	1	0	<b>1000</b>
	6	Social Classes ("SocialC")	1	1	1	0	<b>1000</b>
	7	Type of Effluent ("Sew")	1	0.99	1	0	<b>500</b>
	8	Depth ("Depth")	0.98	0.09	1	0.92	<b>1.07</b>
Third (GGParent variables)	10	Land Uses ("LandUse")	1	1	1	0	<b>1000</b>
	11	Operational Zone ("Zone")	1	1	1	0	<b>1000</b>
	12	Geological Zone ("Geo")	0.14	0	0.42	0.42	<b>0.34</b>
	13	Seismic shear wave velocity ("Vel")	0.14	0	0.88	0.88	<b>0.16</b>

*Source: Author*

Figure 10 shows the Bayesian Network built according to the relationships of the variables found after the Boxplot analysis (Boxplot's median  $\geq 0.05$ ). Variables related to the age of the sewer assets continue to present a direct relationship with the structural condition. However, the type of effluent and length lose the direct relationship with the structural condition; the first one shows an indirect relationship (second grade) and the latter does not show any relationship with the structural condition. Moreover, the variable District is not related to urban characteristics such as the land uses and social classes. However, together with age, District continues to be one of the most important predecessor variables of the structural condition. Unusual relationship such as the one between seismic velocity and social classes are still present.



**Figure 10 Bayesian Network that illustrates the different relationship of the studied variables with three structural conditions, leaving aside variables that show depreciable relationship (boxplot median < 0.05). Source: Author.**

#### *D.1.1.3. Two structural categories*

Table 11 illustrates the variables that show a relationship with structural condition; these variables are grouped into two categories (without and with structural failures) and are almost the same variables shown in Table 9 (five structural grades). The variable age is not considered as an influential variable in this classification.

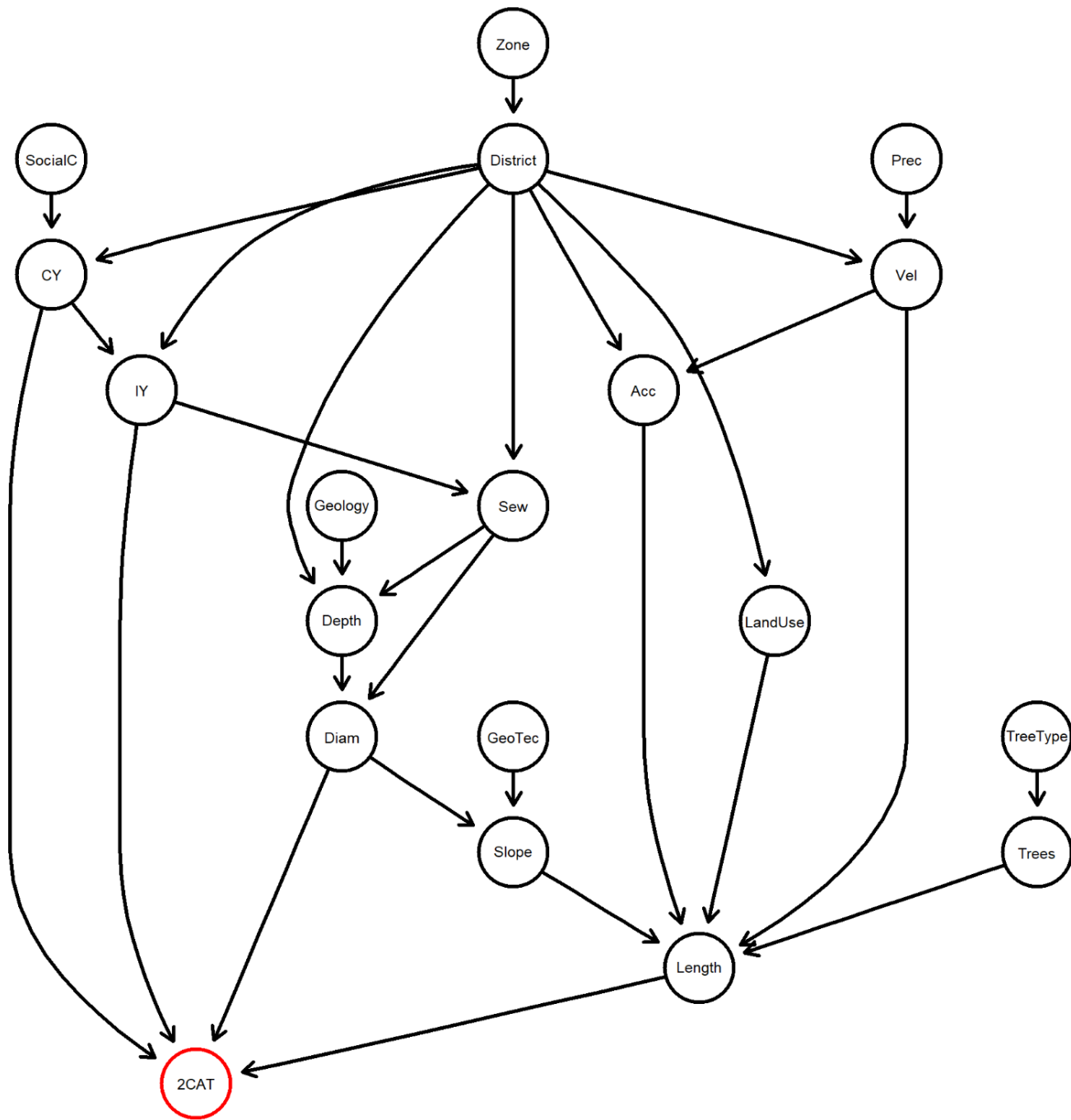
**Table 11. Classification of the variables' relationship with the two structural categories (third structural condition scenario)**

<b>Relationship Type</b>	<b>Order</b>	<b>Variables</b>	<b>Median</b>	<b>Q1</b>	<b>Q3</b>	<b>IQR</b>	<b>Median/IQR</b>
First (Parent variables)	1	Diameter ("Diam")	1	1	1	0.01	<b>200</b>
	2	Inspection Year ("IY")	1	0.98	1	0.02	<b>53.19</b>
	3	Installation Year ("CY")	0.74	0.06	0.80	0.74	<b>1</b>
	4	Length ("Length")	0.11	0.04	0.18	0.14	<b>0.76</b>
Second (GParent variables)	5	District ("District")	1	1	1	0	<b>1000</b>
	6	Social Classes ("SocialC")	1	1	1	0	<b>1000</b>
	7	Type of Effluent ("Sew")	1	1	1	0	<b>555.56</b>
	8	Land Uses ("LandUse")	0.96	0.78	1	0.22	<b>4.35</b>
	9	Depth ("Depth")	0.98	0.10	1	0.90	<b>1.08</b>
	10	Seismic Acceleration ("Acc")	0.25	0.04	0.39	0.36	<b>0.69</b>
	11	Presence of trees ("Tree")	0.07	0.00	0.10	0.10	<b>0.68</b>
	12	Seismic shear wave velocity ("Vel")	0.18	0.05	0.32	0.27	<b>0.66</b>
13	Slope ("Slope")	0.12	0.03	0.29	0.26	<b>0.47</b>	
Third (GGParent variables)	14	Operational Zone ("Zone")	1	1	1	0	<b>1000</b>
	15	Geotechnical zones ("GeoTec")	1	1	1	0	<b>1000</b>
	16	Type of intrusive trees ("TreeType")	1	1	1	0	<b>1000</b>
	17	Precipitation levels ("Prec")	1	1	1	0	<b>1000</b>
	18	Geological Zone ("Geo")	0.23	0.00	0.43	0.43	<b>0.53</b>

*Source: Author*

Despite the variables that influence the deterioration of the structural condition in the third scenario (2 categories) are almost the same as those chosen in the first scenario (5 structural grades), their relationship classification slightly varied for this structural condition scenario: the type of effluent does not show a direct relationship with the structural condition, for this scenario, it shows a relationship of second level (Grandparent variable) (See Tables 9 and 11).

According to Figure 11, the variable social class does not show a relationship with seismic shear wave velocity for the third scenario as the first and second scenarios do. The only one relationship is with installation year which in turn is influenced by the district. Precipitation levels only have influence over seismic shear wave velocity for this scenario. And the type of effluent has influence over the depth in which the sewer asset is located.



**Figure 11** Bayesian Network that illustrates the different relationship of the studied variables with two structural conditions, leaving aside variables that show depreciable relationship (boxplot median < 0.05).  
 Source: Author

#### D.1.1.4. Excellent and critical structural conditions

For the scenario that only considers the sewer asset in excellent and critical structural conditions, some variables are included and their importance changes evidently comparing with the other scenarios that considers the intermediate structural conditions: i.e., the type of network, material of the sewer assets, water level depth and quality of data gain importance and are included as influential variable over the structural condition of sewer assets given a direct relationship (Parent variable) for the first, a relationship of the second order (grandparent variable) for the second and a relationship of the third order (Grand-grandparent variable) for the third and fourth variables; while age lose their importance showing a relationship of third order (grand-grandparent variable) with the deterioration of the structural condition (See Table 12).

**Table 12. Classification of the variables' relationship with the two structural categories that considers only excellent and critical conditions (forth structural condition scenario)**

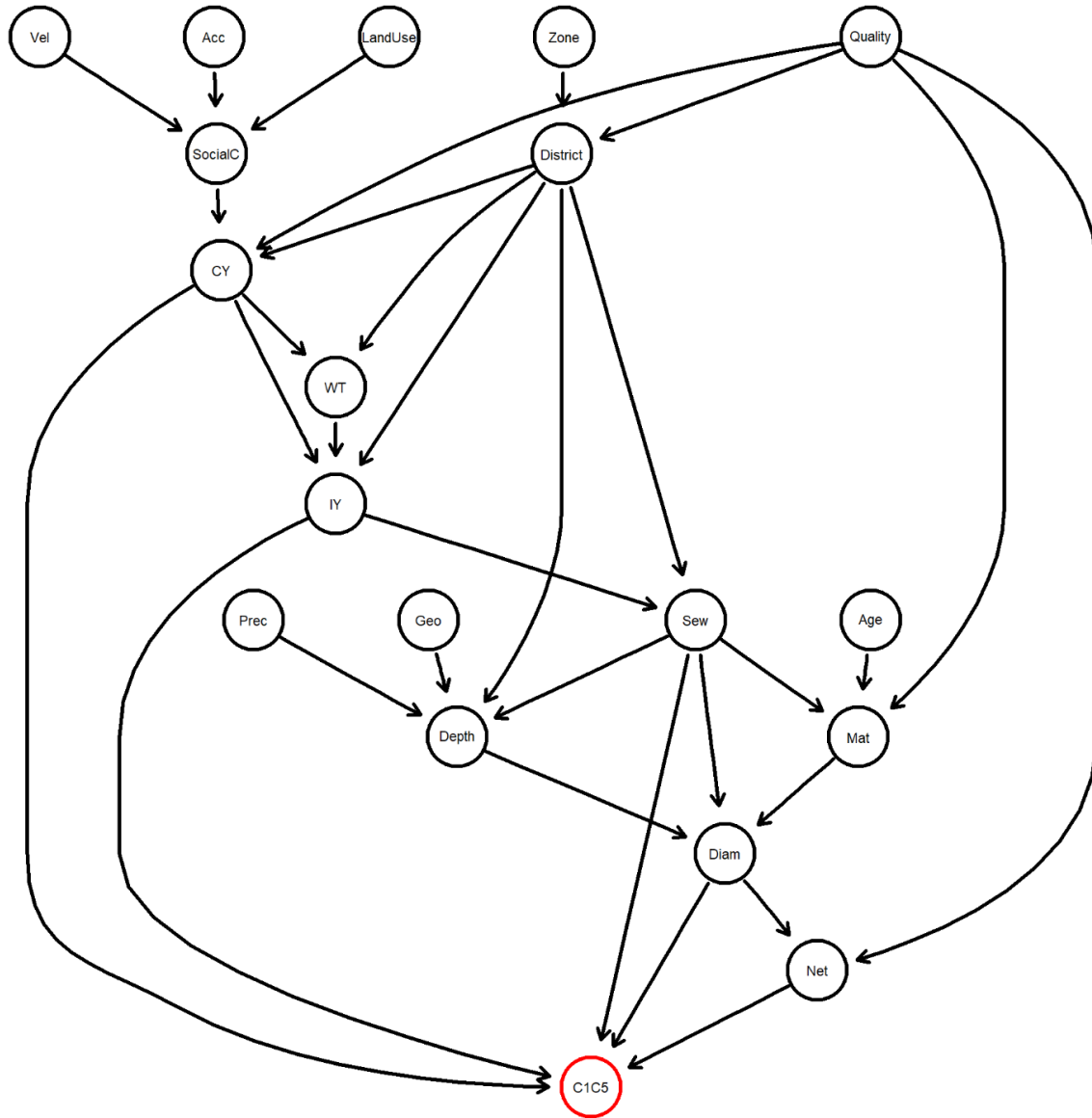
Relationship Type	Order	Variables	Median	Q1	Q3	IQR	Median/IQR
First (Parent variables)	1	Type of Effluent ("Sew")	0.76	0.69	0.79	0.10	<b>7.74</b>
	2	Inspection Year ("IY")	0.68	0.38	0.75	0.37	<b>1.86</b>
	3	Diameter ("Diam")	0.22	0.11	0.30	0.19	<b>1.15</b>
	4	Installation Year ("CY")	0.15	0.02	0.25	0.23	<b>0.66</b>
	5	Network type ("Net")	0.11	0.01	0.40	0.39	<b>0.27</b>
Second (GParent variables)	6	District ("District")	1	0.99	1	0.01	<b>156.01</b>
	7	Social Classes ("SocialC")	1	0.97	1	0.03	<b>34.72</b>
	8	Depth ("Depth")	0.14	0.00	0.81	0.81	<b>0.17</b>
	9	Material ("Mat")	0.11	0.00	0.73	0.73	<b>0.15</b>
Third (GGParent variables)	10	Operational Zones ("Zone")	1	1	1	0	<b>1000</b>
	11	Land Uses ("LandUse")	1	1	1	0	<b>1000</b>
	12	Seismic shear wave velocity ("Vel")	0.99	0.98	1	0.02	<b>40.49</b>
	13	Age ("Age")	1	0.97	1	0.03	<b>32.47</b>
	14	Quality data ("Quality")	0.09	0.06	0.11	0.06	<b>1.48</b>
	15	Seismic Acceleration ("Acc")	0.95	0.01	0.99	0.98	<b>0.96</b>
	16	Geological zones ("Geo")	0.28	0.00	0.61	0.61	<b>0.47</b>
	17	Precipitation levels ("Prec")	0.05	0	0.18	0.18	<b>0.28</b>
	18	Water level depths ("WT")	0.06	0	0.37	0.37	<b>0.17</b>

Source: Author

Figure 12 shows the Bayesian Networks that depicts the relationship of the influential variables over the structural condition considering only excellent and critical conditions. According to this figure the quality of data shows importance over the district, installation year, type of the network and material of the sewer assets. The land uses, seismic velocity and acceleration influence over

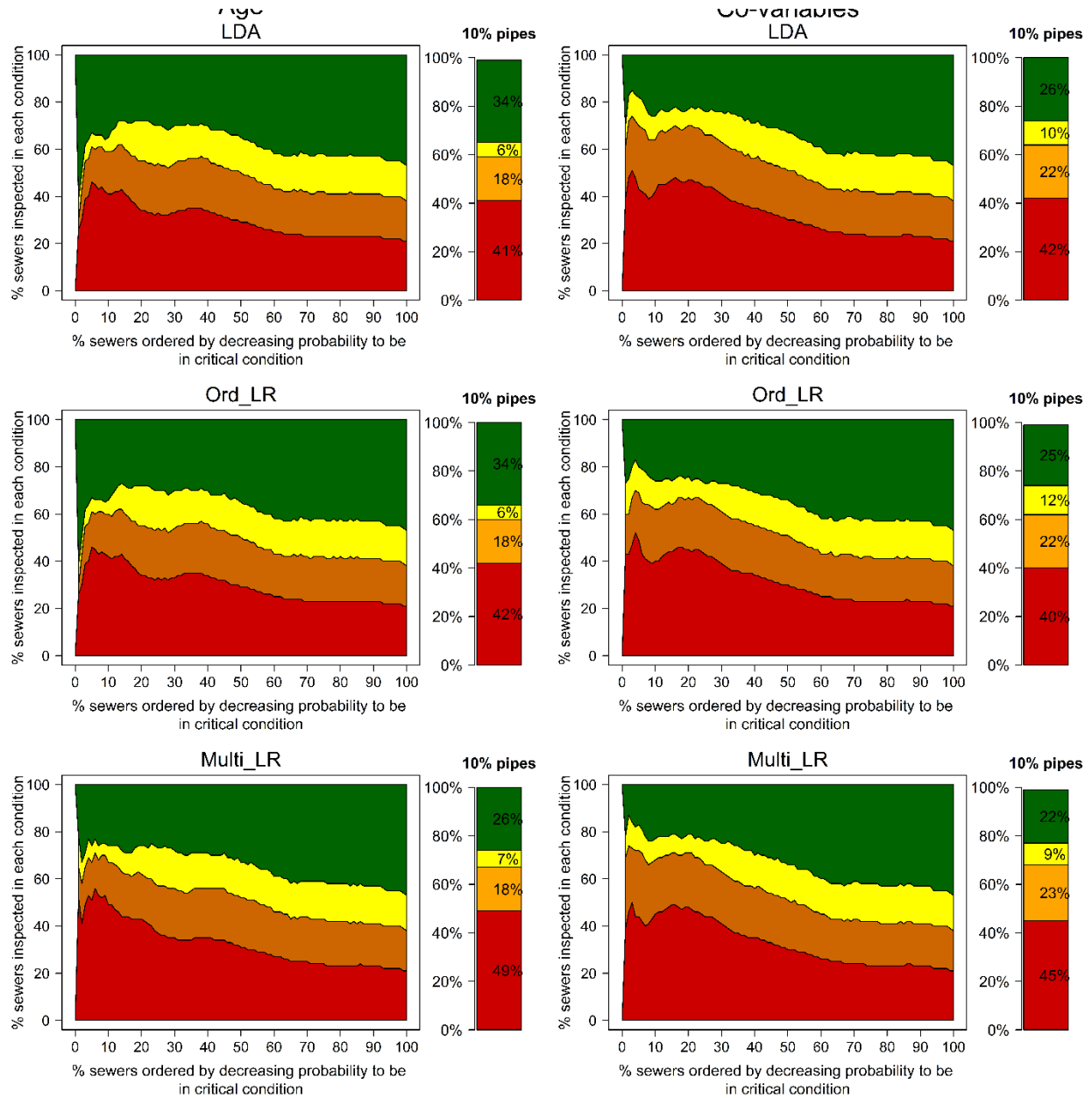


the social classes. And the predecessors of the water level depth are related to the district and installation year of the sewer asset and their predecessor is the inspection year. Moreover, the age influences the material which in turn have influence over the diameter of the sewer assets.



**Figure 12. Bayesian Network that illustrates the different relationship of the studied variables with two structural conditions considering only excellent and critical structural conditions, leaving aside variables that show depreciable relationship (boxplot median < 0.05). Source: Author**

## D.1.2. Exploration of deterioration models



**Figure 13.** LDA, Ord\_LR and Multi\_LR performance curves with a sample on its right of 10% pipes. Left: scenario 1 (considering only the age as influential variable); right: scenario 2 (considering the age and other variables as influential variables) for Bogota's case

Table 13. Summary of the optimised models

Model	Method	SCS	Variables included	Objective	Model	Method	SCS	Variables included	Objectives	Model	Method	SCS	Variables included	Objective	
1	SVM-RBF	5_COND	All	Network	33	SVM-Laplace	5_COND	All	Network	65	RF	5_COND	All	Network	
2				Pipe	34				Pipe	66				Pipe	66
3			GGParent	Network	35			GGParent	Network	67			GGParent	Network	67
4				Pipe	36				Pipe	68				Pipe	68
5			Gparent	Network	37			Gparent	Network	69			Gparent	Network	69
6				Pipe	38				Pipe	70				Pipe	70
7			Parent	Network	39			Parent	Network	71			Parent	Network	71
8				Pipe	40				Pipe	72				Pipe	72
9		3_CAT	All	Network	41		3_CAT	All	Network	73		3_CAT	All	Network	73
10				Pipe	42				Pipe	74				Pipe	74
11			GGParent	Network	43			GGParent	Network	75			GGParent	Network	75
12				Pipe	44				Pipe	76				Pipe	76
13			Gparent	Network	45			Gparent	Network	77			Gparent	Network	77
14				Pipe	46				Pipe	78				Pipe	78
15			Parent	Network	47			Parent	Network	79			Parent	Network	79
16				Pipe	48				Pipe	80				Pipe	80
17		2_CAT	All	Network	49		2_CAT	All	Network	81		2_CAT	All	Network	81
18				Pipe	50				Pipe	82				Pipe	82
19			GGParent	Network	51			GGParent	Network	83			GGParent	Network	83
20				Pipe	52				Pipe	84				Pipe	84
21			Gparent	Network	53			Gparent	Network	85			Gparent	Network	85
22				Pipe	54				Pipe	86				Pipe	86
23			Parent	Network	55			Parent	Network	87			Parent	Network	87
24				Pipe	56				Pipe	88				Pipe	88
25		C1C5	All	Network	57		C1C5	All	Network	89		C1C5	All	Network	89
26				Pipe	58				Pipe	90				Pipe	90
27			GGParent	Network	59			GGParent	Network	91			GGParent	Network	91
28				Pipe	60				Pipe	92				Pipe	92
29			Gparent	Network	61			Gparent	Network	93			Gparent	Network	93
30				Pipe	62				Pipe	94				Pipe	94
31			Parent	Network	63			Parent	Network	95			Parent	Network	95
32				Pipe	64				Pipe	96				Pipe	96

### **D.1.3. Optimisation of the selected deterioration models for management objectives**

Table 13 shows the models that were optimised applying the proposed methodology (chapter 8 and 9).

#### *D.1.3.1. First SCS: Five structural grades*

Regarding the first Structural Condition scenario, Tables 14 and 15 show the combination of hyperparameters found following the optimisation methodology proposed in Chapter 8 and 9 of Part C of this manuscript.

These tables show the combination of hyperparameters found for support vector machines with Radial Basis (RBF) and Laplace Kernel functions and Random Forest.

According to Table 14 the *Sigma* values are lower and *C* values are higher for SVM- RBF than for SVM-Laplace (except for the models that considers only the parent variables), and the weights do not show a particular behaviour of the proportion of the distribution data of the five structural grades. The depicted *Knet* values obtained from the cross-validation of 1000 searchers were lower than 5 for all deterioration models (except for SVM-Laplace considering all studied variables).

Furthermore, these *Knet* values do not show any order when including or not variables in the developed deterioration models. RF-based model was the one whose *Knet* values are lower among the other machine learning methods for achieving network level purposes.

Table 14. Optimal hyperparameters found at Network level for the first SCS.

SVM-RBF									
Variables	Sigma	C	W1	W2	W3	W4	W5	Knet (CV)	
All	0.0057	199.3981	3.0337	5.8319	8.0985	9.4955	9.9070	1.864	
GGParent	0.0099	721.3487	4.1703	7.8932	6.5210	8.6372	8.2102	2.001	
GParent	0.0363	1541.3640	3.8700	7.4853	8.6678	8.3353	9.8147	2.084	
Parent	1.1462	2255.7940	4.0461	6.6816	8.8699	5.8770	11.6349	1.787	
SVM-Laplace									
Variables	Sigma	C	W1	W2	W3	W4	W5	Knet (CV)	
All	0.2391	320.9986	6.1015	8.3007	5.3909	1.6328	7.5990	5.123	
GGParent	0.0300	1516.4860	8.5632	11.3013	3.6817	4.3180	10.6450	3.203	
GParent	0.3047	2508.5009	4.3694	1.6525	5.1216	10.7853	6.7942	3.297	
Parent	0.1363	607.5105	8.1229	8.4233	5.4784	6.6891	11.7905	1.833	
RF									
Variables	Ntrees	NodeSizes	mtry	W1	W2	W3	W4	W5	Knet (CV)
All	4511	14	18	9.4348	6.7514	4.5975	8.4407	4.3161	1.899
GGParent	4802	10	13	11.6628	8.9497	7.9117	10.8018	6.3049	1.876
GParent	2704	17	12	9.0566	6.7228	5.1588	6.2199	4.6043	2.106
Parent	2314	11	6	11.0860	7.0396	4.0461	7.9498	7.5970	1.741

Source: Author

According to Table 15, Sigma values and C values show the same behaviour for SVM-RBF and SVM-Laplace as Table 14: SVM-RBF shows lower sigma values and higher C values than SVM-Laplace. For SVM-based models, W2 is the weight with the highest values among other weights, however this behaviour was not the same for Random Forest (RF). According to the final *Kpipe* value obtained for each model, SVM models shows lowest values ( $Kpipe < 32$ ) than Random Forest ( $Kpipe < 36$ ) for this structural condition scenario.

Table 15. Optimal hyperparameters found at sewer asset level for the first SCS.

SVM-RBF									
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>W4</i>	<i>W5</i>	<i>Kpipe (CV)</i>	
All	0.0032	7.2735	2.3563	10.9406	2.2558	3.1169	5.1871	31.342	
GGParent	0.0022	99.0282	2.2114	9.8638	2.9808	1.1926	5.5399	31.811	
GParent	0.0013	263.5201	2.5441	9.6768	1.1192	3.5189	5.2191	31.334	
Parent	0.0246	1042.7930	3.3745	11.8044	6.9111	8.6056	8.3303	31.279	
SVM-Laplace									
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>W4</i>	<i>W5</i>	<i>Kpipe (CV)</i>	
All	0.0087	5.6832	1.8612	8.6178	8.9577	5.6379	8.2445	31.943	
GGParent	0.0126	5.8179	2.5724	10.9069	6.2944	6.7877	5.3980	31.865	
GParent	0.0371	1.5441	2.3130	9.7527	4.9917	1.5754	4.6487	30.996	
Parent	0.0105	20.2142	1.7487	7.6183	9.0776	2.2253	3.5087	31.188	
RF									
Variables	<i>Ntrees</i>	<i>Nodesizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>W4</i>	<i>W5</i>	<i>Kpipe (CV)</i>
All	1229	40	28	1.1936	3.5385	10.6300	9.8794	7.8599	38.408
GGParent	2707	48	6	1.9507	9.2522	11.7685	4.1599	5.5250	37.997
GParent	1304	40	1	2.7106	4.9956	10.8712	4.5908	6.0043	37.681
Parent	4308	291	5	1.1813	1.0909	6.3160	1.3514	3.6831	36.263

Source: Author

Comparing the hyperparameters found for both metrics, it was found that the *sigma* and *C* values of SVM-based models are lower for sewer asset level management objectives (*Kpipe*) than for network level management objectives (*Knet*). Moreover, the *nodesizes* values of RF based models are higher for *Kpipe* than *Knet* purposes.

#### D.1.3.2. Second SCS: three structural categories (Excellent, intermediate and critical conditions)

According to Table 16, there is not a particular behaviour between the hyperparameters found for SVM-RBF and SVM-Laplace based models. The weighting of the weights depends on the number of variables considered on each model. The obtained *Knet* values from the cross validation after 1000 searchers are lower than 3, being SVM-Laplace models the ones with the lowest values (except for the model that considers GGParent variables).

**Table 16. Optimal hyperparameters found at Network level for the second SCS.**

<b>SVM - RBF</b>						
<b>Variables</b>	<b>Sigma</b>	<b>C</b>	<b>W1</b>	<b>W2</b>	<b>W3</b>	<b>Knet (CV)</b>
All	0.0007	2525.4614	8.0474	9.0662	7.9112	2.587
GGParent	1.4263	509.6316	1.7701	8.7754	10.0173	1.881
GParent	0.8096	1089.2846	4.0811	8.1542	10.3349	1.898
Parent	12.6749	504.7703	8.7171	8.8265	8.9335	2.396

<b>SVM-Laplace</b>						
<b>Variables</b>	<b>Sigma</b>	<b>C</b>	<b>W1</b>	<b>W2</b>	<b>W3</b>	<b>Knet (CV)</b>
All	0.1316	1338.4469	9.5010	5.8163	7.5671	2.314
GGParent	0.0327	1422.7110	6.4250	6.5630	10.2909	2.020
GParent	0.6073	1476.4961	4.0567	7.6841	6.9856	1.596
Parent	2148.4601	1238.2452	9.5837	11.6909	11.7862	0.713

<b>RF</b>							
<b>Variables</b>	<b>Ntrees</b>	<b>NodeSizes</b>	<b>mtry</b>	<b>W1</b>	<b>W2</b>	<b>W3</b>	<b>Knet (CV)</b>
All	1933	6	13	10.3544	10.0674	6.2450	2.774
GGParents	3314	2	10	8.9263	9.8548	5.2711	2.206
GParents	1086	2	5	10.8509	11.7046	7.4118	1.865
Parents	338	3	4	8.1770	6.8504	4.4067	2.500

*Source: Author*

In accordance to Table 17, SVM-RBF based models shows lower sigma values and higher C values than SVM-Laplace, despite of both models shows similar *Kpipe* values. However, RF-based models are the ones that shows lower *Kpipe* values for this SCS.

According to the weighting of the weights in the models, the second category (intermediate conditions) is the one with the highest ponderation and the lowest is first category (excellent conditions).

Table 17. Optimal hyperparameters found at sewer asset level for the second SCS.

SVM - RBF							
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>Kpipe (CV)</i>	
All	0.0003	365.3769	3.2928	6.0723	8.8248	30.665	
GGParent	0.0057	130.8594	4.3774	7.1956	8.8077	32.679	
GParent	0.0022	1302.0238	3.9220	7.6562	10.1046	32.113	
Parent	0.0252	3468.2439	5.0121	8.4880	11.8315	32.893	
SVM – Laplace							
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>Kpipe (CV)</i>	
All	0.0008	81.5828	3.1903	5.9262	8.8561	30.846	
GGParent	0.0346	3.1474	3.2451	6.9685	10.4112	32.301	
GParent	0.0136	11.1256	3.1702	5.7778	8.5086	32.146	
Parent	906.1947	1267.7997	3.4581	7.5014	10.6281	34.609	
RF							
Variables	<i>Ntrees</i>	<i>Nodesizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>Kpipe (CV)</i>
All	2818	20	7	6.0103	9.1038	7.1763	28.050
GGParent	2623	47	8	7.7965	10.8501	9.0301	31.006
GParent	1760	70	2	6.9574	9.3489	8.6035	30.694
Parent	4845	76	5	5.5908	8.4076	7.0809	32.389

Source: Author

Comparing the hyperparameters obtained by each management objective for this scenario, it found was that:

- SVM-Laplace models show *C* values lower for *Kpipe* purposes than *Knet* purposes.
- SVM-RBF models show *sigma* values lower for *Kpipe* purposes than *Knet* purposes.
- *Nodesize* hyperparameter is higher for *Kpipe* purposes than for *Knet* purposes.



*D.1.3.3. Third SCS: two structural categories (without and with structural failures)*

Table 18 shows the combination of hyperparameters that most minimize the *Knet* value for each developed deterioration model. According to the hyperparameters found at network level management objective for this scenario, SVM-Laplace models show higher *C* values than SVM-RBF models. *Knet* values found in RF and SVM-based models varies around 0.7 and 1.4.

*Table 18. Optimal hyperparameters found at Network level for the third SCS.*

<b>SVM - RBF</b>						
<b>Variables</b>	<b>Sigma</b>	<b>C</b>	<b>W1</b>	<b>W2</b>	<b>Knet (CV)</b>	
All	0.0329	1090.4467	7.6651	7.5846	0.822	
GGParent	0.5909	28.5160	1.2685	6.8996	0.808	
GParent	0.5041	33.2466	5.8800	9.5546	1.169	
Parent	4.2661	458.0269	9.0244	7.6101	0.762	
<b>SVM – Laplace</b>						
<b>Variables</b>	<b>Sigma</b>	<b>C</b>	<b>W1</b>	<b>W2</b>	<b>Knet (CV)</b>	
All	0.8148	3987.6418	6.5948	9.5214	1.657	
GGParent	1.0253	1111.6469	9.6124	1.4127	0.899	
GParent	0.3108	3569.1822	8.7966	9.7416	0.956	
Parent	0.2413	3114.8132	1.6668	7.0771	0.884	
<b>RF</b>						
<b>Variables</b>	<b>Ntrees</b>	<b>Nodesizes</b>	<b>mtry</b>	<b>W1</b>	<b>W2</b>	<b>Knet (CV)</b>
All	3860	37	23	6.5607	7.3345	0.163
GGParent	2392	3	13	6.6315	6.4479	1.390
GParent	3241	6	10	9.0019	8.5804	0.849
Parent	3294	1355	2	9.5161	9.9295	0.823

*Source: Author*

According to Table 19, *C* values for both kind of SVM models show values between 30 and 90, except for the deterioration models that take into account the GParent variables (*C* values higher than 1000). In addition, the *C* values for the SVM-based deterioration models which consider the parent variables their values are lower than 10. RF-based deterioration models are the ones with lowest *Kpipe* values (*Kpipe* values < 23.5). SVM-Laplace based models showed *Kpipe* values evidently higher than the other methods for this scenario.

Moreover, comparing the *Kpipe* values of Tables 17 and 19, grouping the structural conditions in two categories increases the performance prediction, since the *Kpipe* reduced from 38 to 24 approximately. It supports the findings of Ariaratman et al. (2001) and López-Kleine et al., (2016).

Table 19. Optimal hyperparameters found at sewer asset level for the third SCS.

SVM - RBF						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Kpipe (CV)</i>	
All	0.0006	30.9657	5.0938	4.7439	23.683	
GGParent	0.0004	87.3042	10.9720	9.5701	24.348	
GParent	0.0003	2370.2090	8.4072	8.3829	24.090	
Parent	1.2690	0.5302	9.0254	7.9931	24.226	
SVM – Laplace						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Kpipe (CV)</i>	
All	0.0054	46.7437	1.8317	8.7661	43.665	
GGParent	0.0027	63.9469	1.4942	7.8659	36.018	
GParent	0.0001	1167.4810	2.1407	10.4928	36.101	
Parent	0.0855	7.4284	1.3937	8.1708	37.150	
RF						
Variables	<i>Ntrees</i>	<i>NodeSizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>Kpipe (CV)</i>
All	3560	10	5	10.8882	10.0267	20.194
GGParent	1295	3	4	8.6257	9.2835	21.833
GParent	3366	16	5	6.7017	8.2151	22.271
Parent	2482	31	2	5.6047	6.3591	23.503

Source: Author

Comparing the hyperparameters found for both management objectives purposes. It was found that:

- For achieving *Kpipe* management objectives, the sigma values are evidently lower than for achieving *Knet* management objectives.
- For achieving *Kpipe* management objectives, *nodesizes* are lower than for achieving *Knet* management objectives.
- For minimizing *Kpipe* metrics, number of variables are lower than for minimizing *Knet* metrics
- This scenario shows values of *Knet* and *Kpipe* lower than first and second scenarios, which considers more than two categories for the classification of the structural condition.

#### D.1.3.4. Fourth SCS: excellent and critical structural conditions

Tables 20 and 21 show the combination of hyperparameters found for each deterioration models based on the selected machine learning methods for both management objectives represented by *Knet* and *Kpipe* metrics for the fourth scenario.

According to Table 20, there are not evident difference between the hyperparameters of SVM-based models. Both kind of models found low Sigma values for deterioration models that considers more variables than only Parent variables. For the deterioration models that considers only parent variables, sigma hyperparameter is appreciably higher. For RF and SVM models, the *Knet* values obtained from the cross-validation of the 1000 searchers oscillate from 0.064 to 1.96, being RF models the ones with lowest *Knet* values.

Table 20. Optimal hyperparameters found at Network level for the fourth SCS.

SVM-RBF						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Knet (CV)</i>	
All	0.0182	296.5413	8.8192	10.2899	0.926	
GGParent	0.0674	4269.0540	2.8267	1.7913	0.886	
GParent	0.4395	461.3621	11.8020	11.4435	1.033	
Parent	19.0656	3102.7432	7.3075	8.9432	1.113	
SVM – Laplace						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Knet (CV)</i>	
All	0.1201	1991.8271	2.8653	1.2196	1.735	
GGParent	0.1296	1864.3010	4.1757	6.8160	1.960	
GParent	0.0954	4256.4030	9.2923	10.9953	1.080	
Parent	2163.7801	2165.9065	5.2799	8.2495	1.060	
RF						
Variables	<i>Ntrees</i>	<i>NodeSizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>Knet (CV)</i>
All	644	10	25	9.3787	7.8859	0.064
GGParent	540	28	10	11.6202	6.9123	0.975
GParent	3315	5	6	8.8704	5.6720	1.032
Parent	2603	31	4	10.0921	6.6171	0.940

Source: Author

According to Table 21, RF-based models are the ones that also minimize the *Kpipe* metric. Also, RF-based models show a behaviour ascendant of the *Kpipe* value when the variables are less: being, the deterioration model that considers all studies variables with the lowest *Kpipe* values, and the highest *Kpipe* value is obtained by the deterioration model that considers only parent variables.

**Table 21. Optimal hyperparameters found at sewer asset level for the fourth SCS.**

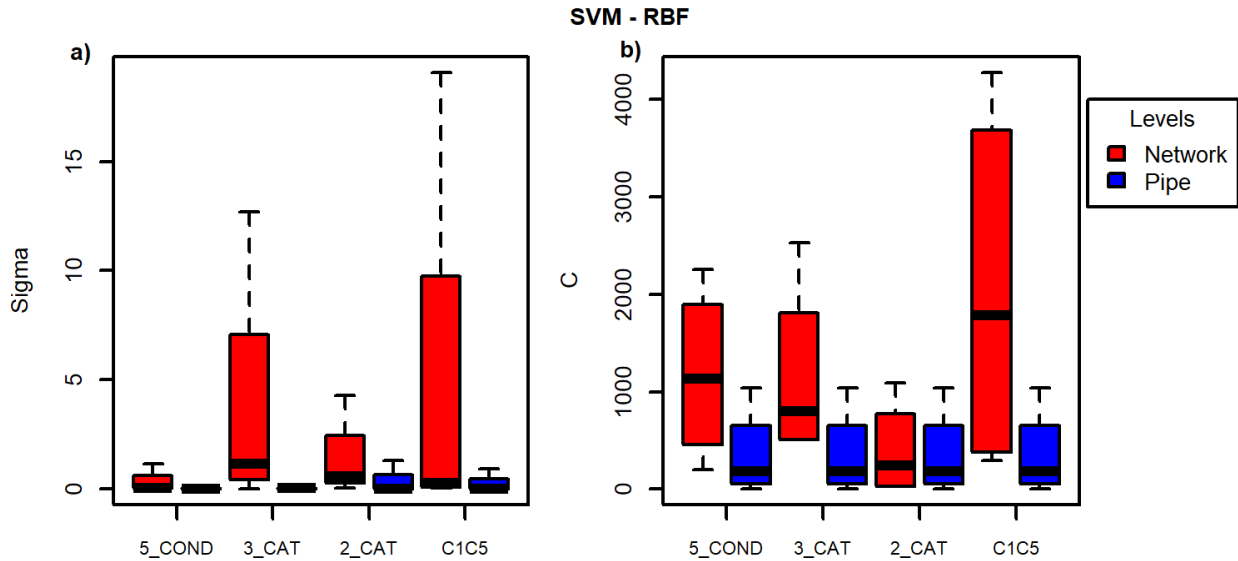
<b>SVM-RBF</b>						
<b>Variables</b>	<b><i>Sigma</i></b>	<b><i>C</i></b>	<b><i>W1</i></b>	<b><i>W2</i></b>	<b><i>Kpipe (CV)</i></b>	
All	0.0017	54.1259	2.7498	4.2334	23.237	
GGParent	0.0011	351.4729	4.3223	8.8372	23.426	
GParent	0.0038	1491.4246	4.5991	7.5609	23.459	
Parent	0.9179	3.9887	4.7527	8.4575	23.697	
<b>SVM – Laplace</b>						
<b>Variables</b>	<b><i>Sigma</i></b>	<b><i>C</i></b>	<b><i>W1</i></b>	<b><i>W2</i></b>	<b><i>Kpipe (CV)</i></b>	
All	0.0001	3383.2910	1.9651	3.6182	22.928	
GGParent	0.0007	411.2865	1.4372	3.3573	24.716	
GParent	0.0034	703.4809	6.8587	11.6476	23.249	
Parent	1.6250	2962.8930	7.5398	10.6394	25.760	
<b>RF</b>						
<b>Variables</b>	<b><i>Ntrees</i></b>	<b><i>NodeSizes</i></b>	<b><i>mtry</i></b>	<b><i>W1</i></b>	<b><i>W2</i></b>	<b><i>Kpipe (CV)</i></b>
All	1037	7	5	6.9896	10.7658	19.867
GGParent	3679	12	8	8.8233	9.7266	21.787
GParent	1030	20	3	6.2908	4.4440	22.378
Parent	3060	14	3	11.8785	9.3154	23.437

*Source: Author*

For the first and second structural condition scenarios (5 structural grades and three structural categories), the explored and optimised models were based on SVM with RBF kernel function, SVM with kernel function, Random Forest (RF), and Ordinal logistic Regression (Ord\_LR). For the third and fourth structural condition scenario (two structural categories and considering only excellent and critical structural conditions), the explored models were based on SVM with RBF kernel function, SVM with Laplace kernel function, Random Forest (RF), and Binomial logistic Regression (LR).

Despite the Laplace kernel function was the one with the highest performance results obtained in the exploration depicted in 11.1.2. (for more details, see Hernández et al., 2019b), the author suggested also optimising the SVM based on Radial Basis Function (RBF) because of the successful results in the preliminary results of the item 10.2.1. (Hernández et al., 2017a).

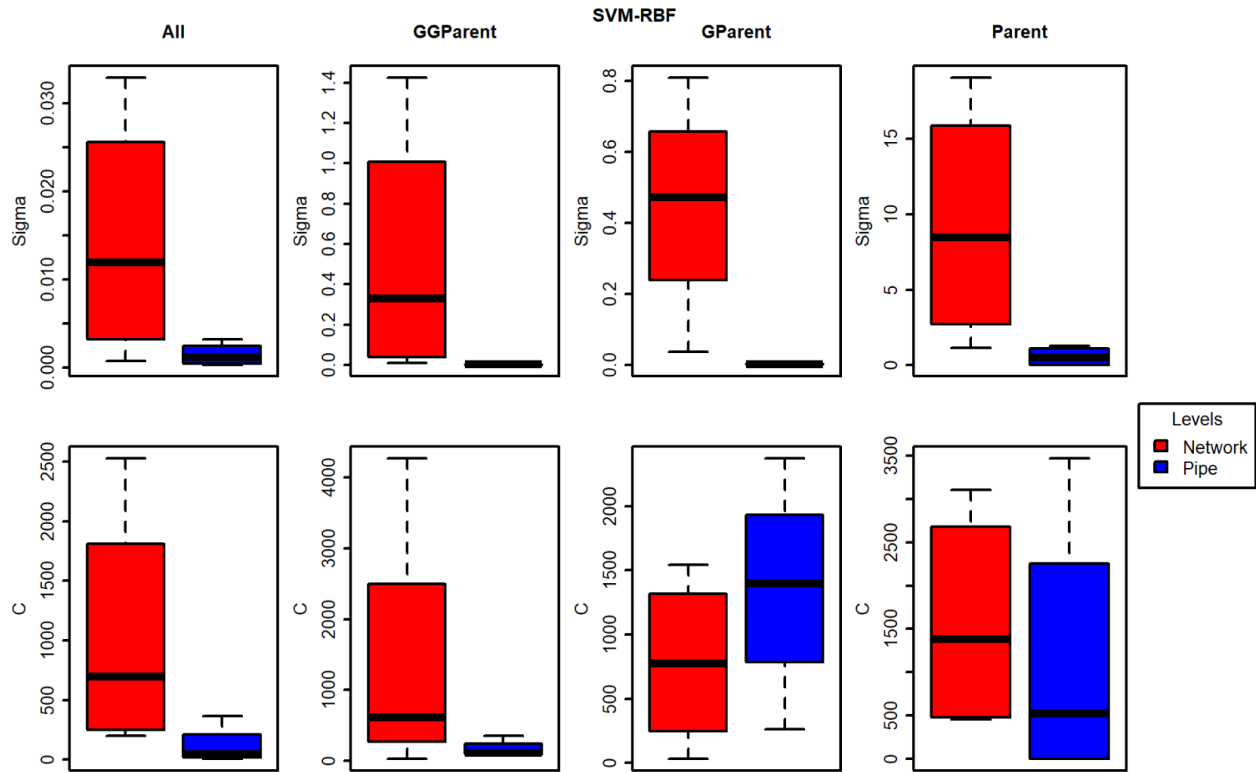
For each method and SCS, four deterioration models were developed and optimised to achieve a management objective considering: (i) the parent variables (*Par*); (ii) parent and grandparent variables (*GPar*); (iii) parent, grandparent and grand-grandparent variables (*GGPar*); and (iv) all variables (see Tables B.1 and B.2., Part B ) from the classification of each structural condition scenario given in Table D.9.



**Figure 14. Boxplot analysis of the Sigma (a) and C (b) hyperparameters obtained for each SCS after applying the proposed optimisation methodology for SVM considering RBF kernel function. Red boxplots refer to the Sigma and C values obtained at the network level (*Knet*) and blue boxplots refer to the Sigma and C values obtained at the pipe level (*Kpipe*). Source: Author**

According to Figure 14, it is possible to observe that the values of Sigma and C of the models built to achieve the network level objective tend to be higher than those hyperparameters for pipe level objectives. According to theory (Hornik et al., 2006), a larger sigma implies a smaller ( $\gamma = 1/(2 \cdot \sigma)$ ). Therefore, the SVM-based model for the network level objective is more constrained, and the data is less complex than the SVM-based model for the pipe level objective (Figure 14.a). 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 hyper-parameter (Figure 14.b), the margin and surface function of separation were more complex for *Knet*; while C values obtained for *Kpipe* show a simpler decision surface function.

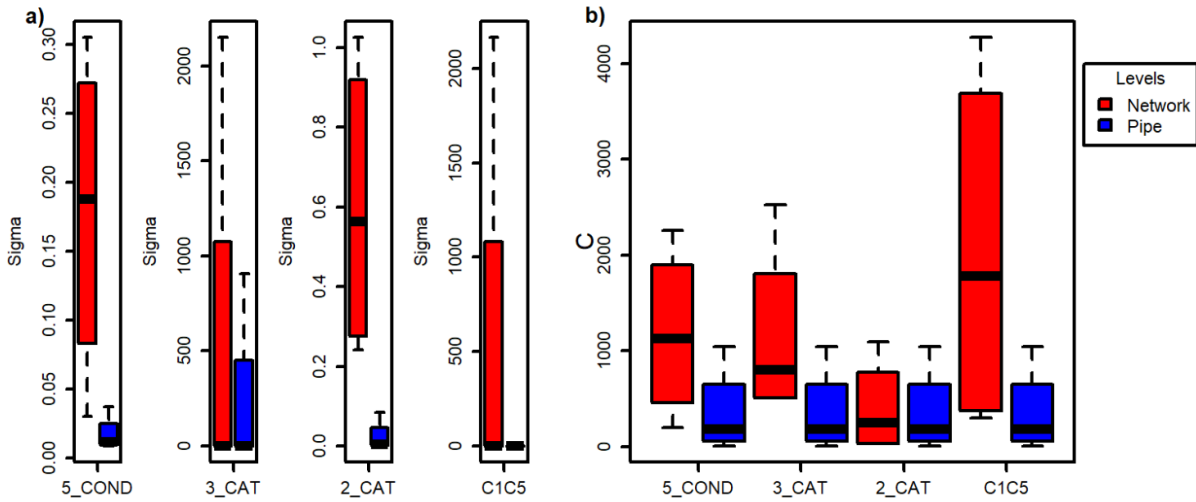
Besides, for the fourth SCS (excellent and critical conditions), the sigma and C values are the highest for the network level objectives, while for the third SCS (without and with any relevant structural failures) are the lowest.



**Figure 15. Boxplot analysis of the Sigma (graphics showed at the top) and C (graphics showed at the bottom) hyperparameters obtained considering each group of variables after applying the proposed optimisation methodology for SVM considering RBF kernel function. Red boxplots refer to the Sigma and C values obtained at the network level (Knet) and blue boxplots refer to the Sigma and C values obtained at the pipe level (Kpipe). Source: Author**

According to Figure 15, the values of Sigma for the network level objectives are higher than for pipe level objectives considering all the groups of variables: all variables, third (GGPar), second (GPar) and first (Par) grade of relationship with structural conditions independently of the SCS. Furthermore, the values of C for the network level objectives are higher than for the pipe levels objectives (except for those models that consider the GParent and Parent variables). It is essential to clarify that the models that consider GParent variables include the variables of the first (Parent) and second-grade relationship with the structural condition. The variability of C values between network and pipe level objectives for models that only consider the variables with a direct relationship with the structural condition is not as different as the C values of the models that consider more variables than the second-grade relationship: All and GGPar variables.

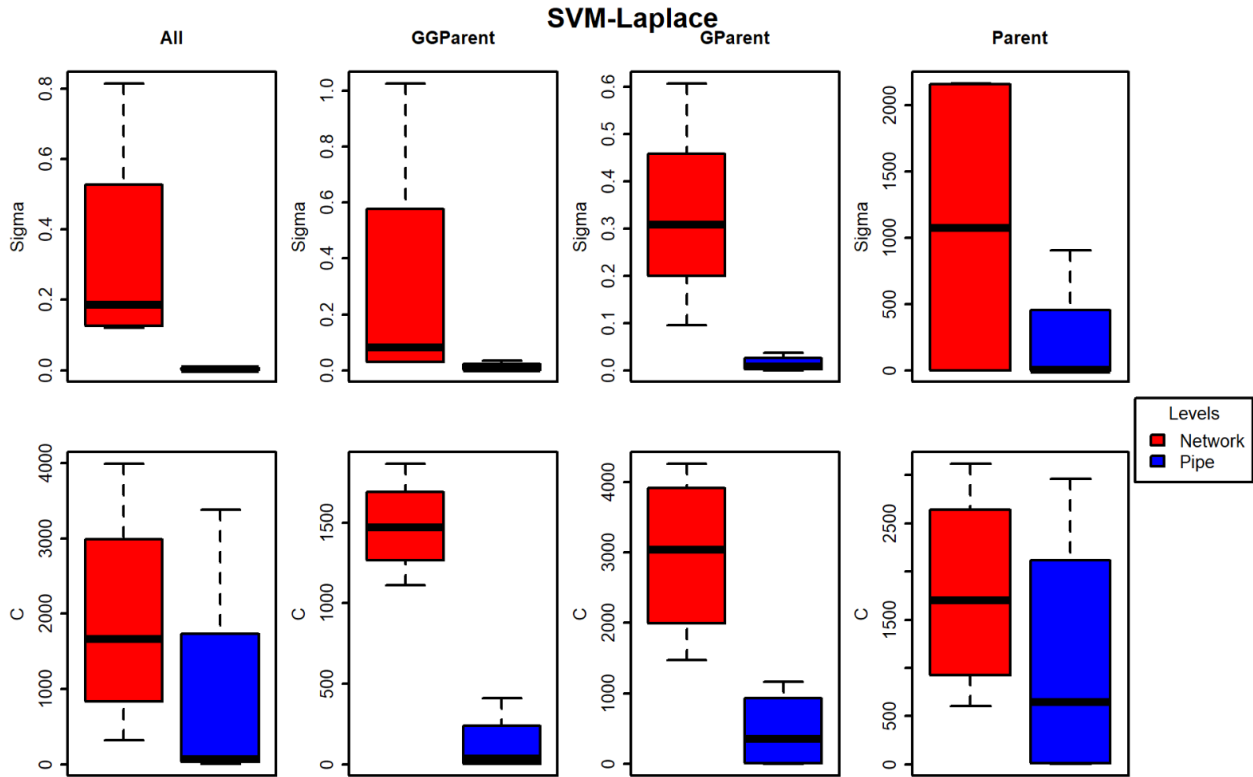
## SVM - Laplace Kernel Function



**Figure 16. Boxplot analysis of the Sigma (Figure a) and C (Figure b) hyperparameters obtained for each SCS after applying the proposed optimisation methodology for SVM considering Laplace kernel function. Red boxplots refer to the Sigma and C values obtained at the network level (Knet) and blue boxplots refer to the Sigma and C values obtained at the pipe level (Kpipe). Source: Author**

As well as results of Figure 14, Figure 16 shows that the values of Sigma and C are higher for the network level objectives (Knet) than for the pipe level (Kpipe) ones independently of the SCS. According to the Sigma values (Figure 16.a.), the first (five structural grades – 5\_COND) and third (two structural categories – 2\_CAT) SCS are relatively similar; and the Sigma values of second (three structural categories – 3\_CAT) and fourth SCS (excellent and critical structural conditions – C1C5) are also relatively similar. On the other hand, the C values of the pipe level objectives are similar independently of the SCS (see Figure 16.b.).

According to Figure 17, Sigma and C hyperparameters show higher values for the network level objectives than for the pipe level objectives independently of the number of variables or hierarchy of influential variables of the structural condition of the sewer assets. The Sigma value of these models is lower for the models that consider more variables than the one of the first relationship grade (Parent variables) for both management level objectives (Network and pipe). It means that SVM models (considering Laplacian kernel function) with only the variables that show first relationship grade with the structural condition of the sewer assets have higher variance making larger radii of influence. It implies less complexity in the shape of the data (Genton, 2001; Hornik et al., 2006).



**Figure 17.** Boxplot analysis of the *Sigma* (graphics showed at the top) and *C* (graphics showed at the bottom) hyperparameters obtained considering each group of variables after applying the proposed optimisation methodology for SVM considering Laplace kernel function. Red boxplots refer to the *Sigma* and *C* values obtained at the network level (*Knet*) and blue boxplots refer to the *Sigma* and *C* values obtained at the pipe level (*Kpipe*). Source: Author

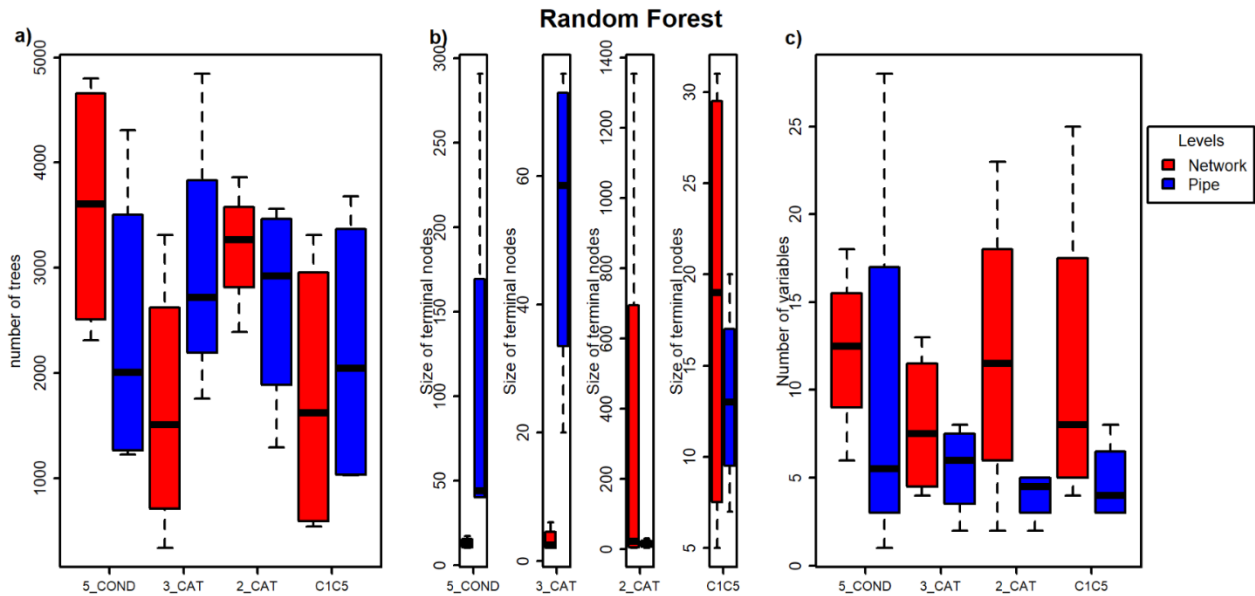
Figures 18 and 19 show the results of the RF hyperparameters found after applying the proposed methodology (chapter 8 and chapter 10 of Part C) considering their variability according to each SCS (Figure 18) and each group of variables chosen from the hierarchization obtained in subchapter 11.1.1. (Figure 19).

According to Figure D.18.(a), the number of trees is higher for the first (5 structural grades – 5\_COND) and third (three structural categories – 3\_CAT) SCS for the network level objective (*Knet*) than the pipe level objective (*Kpipe*). On the other hand, the number of trees is higher for the second (two structural categories – 2\_CAT) and fourth (excellent and critical structural condition – C1C5) SCS for the pipe level objective (*Kpipe*) than for the network level objective (*Knet*). Furthermore, the difference between the number of trees of the network and the pipe level objectives is lower for the third (two structural categories – 2\_CAT) and fourth (excellent and critical structural condition – C1C5) SCS. Besides, the number of trees is lower for the second (three structural categories – 3\_CAT) and fourth (excellent and critical structural conditions – C1C5) SCS for both management objectives.



On the other hand, Figure 18 (b) shows that the size of terminal nodes that it is larger for the pipe level objective than for the network level objective for the first (five structural grades – 5\_COND) and second (three structural categories – 3\_CAT) SCS, while for the third (two structural categories – 2\_CAT) and fourth (excellent and critical structural conditions -C1C5) SCS, the size of terminal nodes (including their variability) is larger for the network level objective (*Knet*) than for the pipe level objective (*Kpipe*). The fourth (excellent and critical structural conditions -C1C5) SCS is the one with the lowest variability of the size of terminal nodes between both management objectives.

Finally, Figure 18.(c). shows that the number of variables (*mtry*) is higher for the network level objective (*Knet*) than for the pipe level objective (*Kpipe*) for the four SCS, despite the variability of the number of variables is higher for the pipe level objective (*Kpipe*) for the first (five structural grades -5\_COND) SCS. Also, the third (two structural categories – 2\_CAT) and fourth (excellent and critical structural conditions -C1C5) SCS need a lower number of variables (less than 8) for achieving the pipe level objective (*Kpipe*).



**Figure 18. Boxplot analysis of the Number of trees (Figure a), Size of terminal nodes (Figure b) and Number of variables (Figure c) hyperparameters obtained for each SCS after applying the proposed optimisation methodology for Random Forest. Red boxplots refer to the number of trees, the size of terminal nodes and the number of variables values obtained at the network level (*Knet*) and blue boxplots refer to the Sigma and C values obtained at the pipe level (*Kpipe*). Source: Author**

According to the Figure 19, the number of trees is higher for the models developed for the network level objectives (*Knet*) when they consider more variables than the first relationship grade (from GPparent to all studied variables). Furthermore, the number of trees for achieving the pipe level objectives are the highest (from 2500 to 4800) for the models that consider only the variables that

show the first grade of relationship with the structural conditions (Parent variables). In accordance of the size of terminal nodes (graphics in the centre of Figure D.19.), their values are lower for models developed for achieving the network level objectives (*Knet*) than for the pipe level objectives (*Kpipe*), despite the variability of this hyperparameter is higher for reaching the network level objectives (*Knet*) when the model only considers the parent variables. Finally, the number of variables is higher for models developed for the network level objective and considers more than parent variables. According to the models that only consider the parent variables (first grade relationship) for RF-based models, it is observed that the number of random variables on each tree of the RF is almost the same for the network (*Knet*) and the pipe (*Kpipe*) level objectives (boxplot median equal to 4).

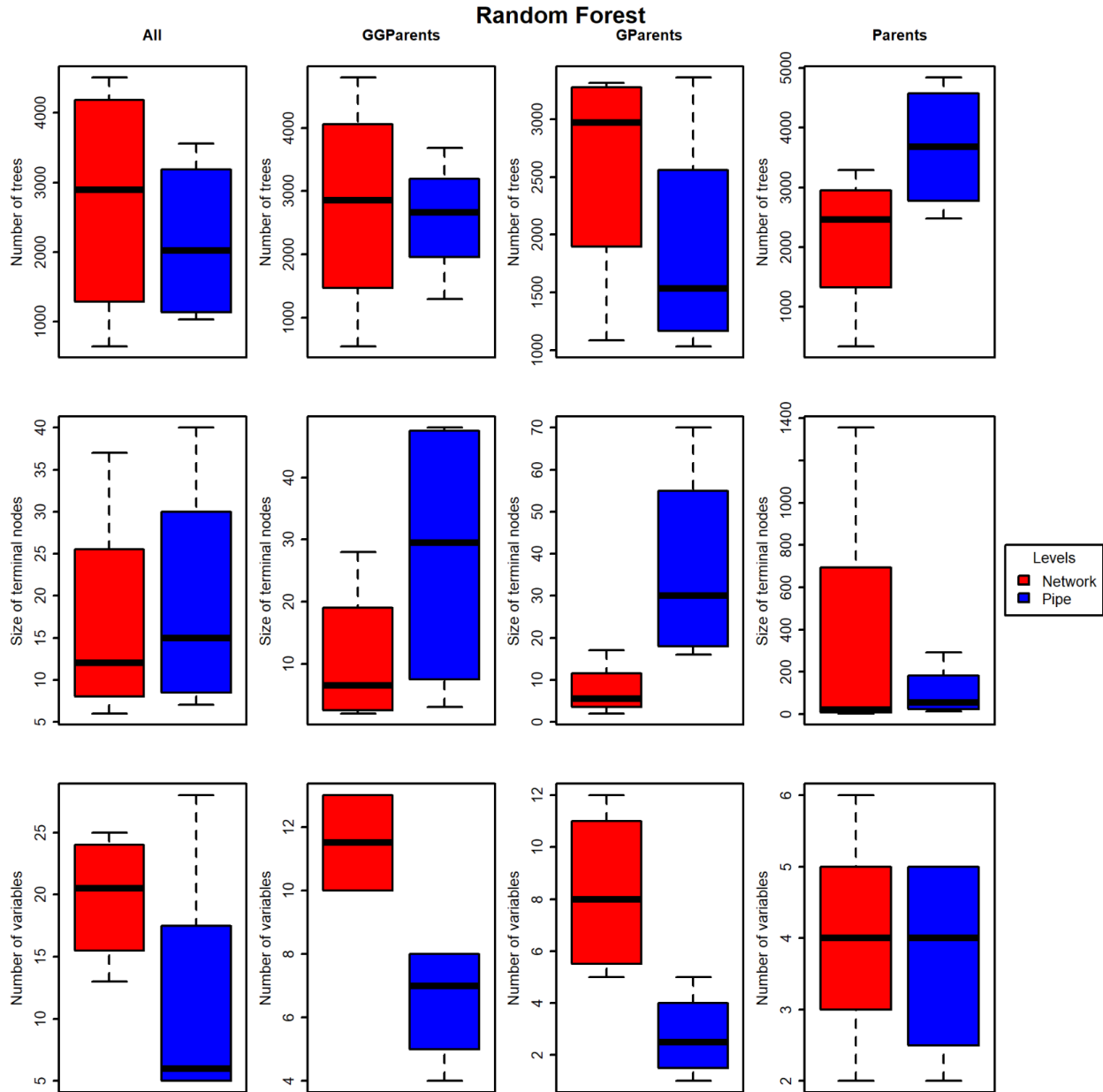


Figure 19. Boxplot analysis of the Number of trees (graphics showed at the top), sizes of terminal nodes (graphics in the centre) and Number of variables (graphics showed at the bottom) hyperparameters obtained considering each group of variables after applying the proposed optimisation methodology for Random Forest. Red boxplots refer to the Sigma and C values obtained at the network level (Knet) and blue boxplots refer to the Sigma and C values obtained at the pipe level (Kpipe). Source: Author

### D.1.4. Results of the optimised deterioration models for management objectives

The following figures show the results of the optimised deterioration models based on SVM-RBF, SVM-Laplace, and RF including each group of variables and by each SCS and management objective (network and pipe level, *Knet* and *Kpipe* metrics respectively). Each figure displays a boxplot analysis and a table that shows the p-values obtained after the Wilcoxon test to find significantly statistical difference between the results of the models depicted in the boxplot analysis. At the end, it shows a boxplot that compares the most suitable models for each optimised method to choose the most suitable for each SCS.

#### D.1.4.1. First SCS: five structural grades

Figure 20 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 9) based on the optimised SVM considering RBF kernel function for network level management objective (see the hyperparameters set in these models in Table 14) for the first SCS.

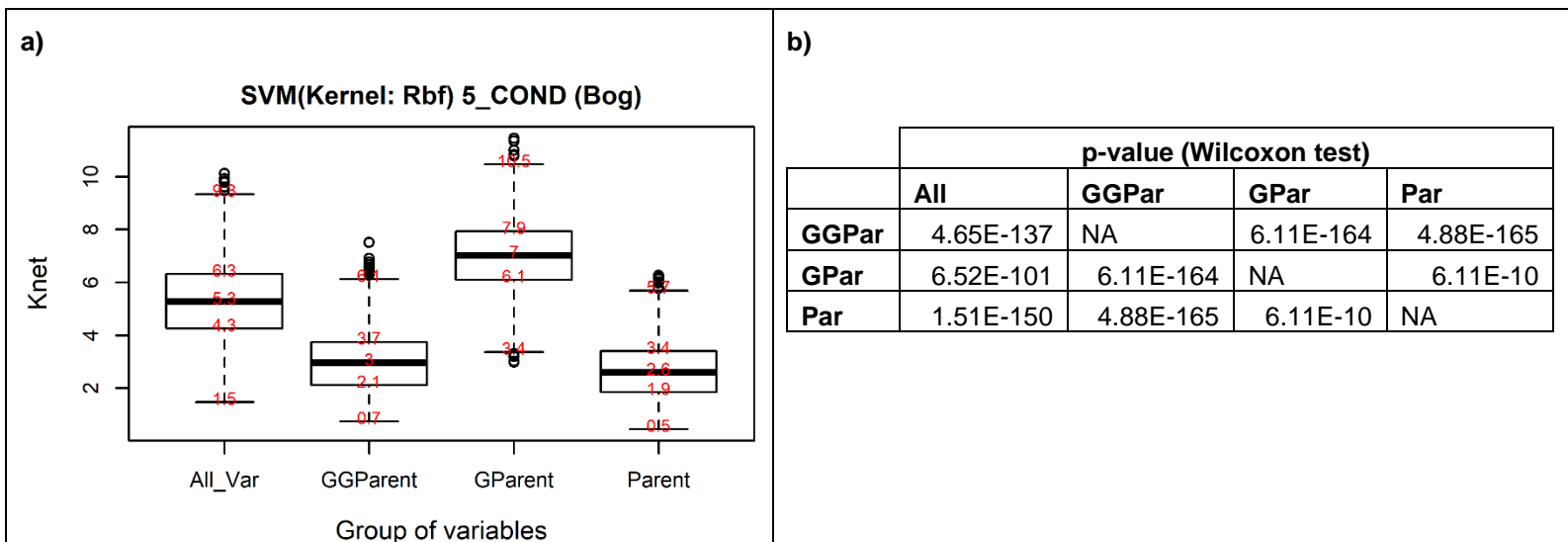


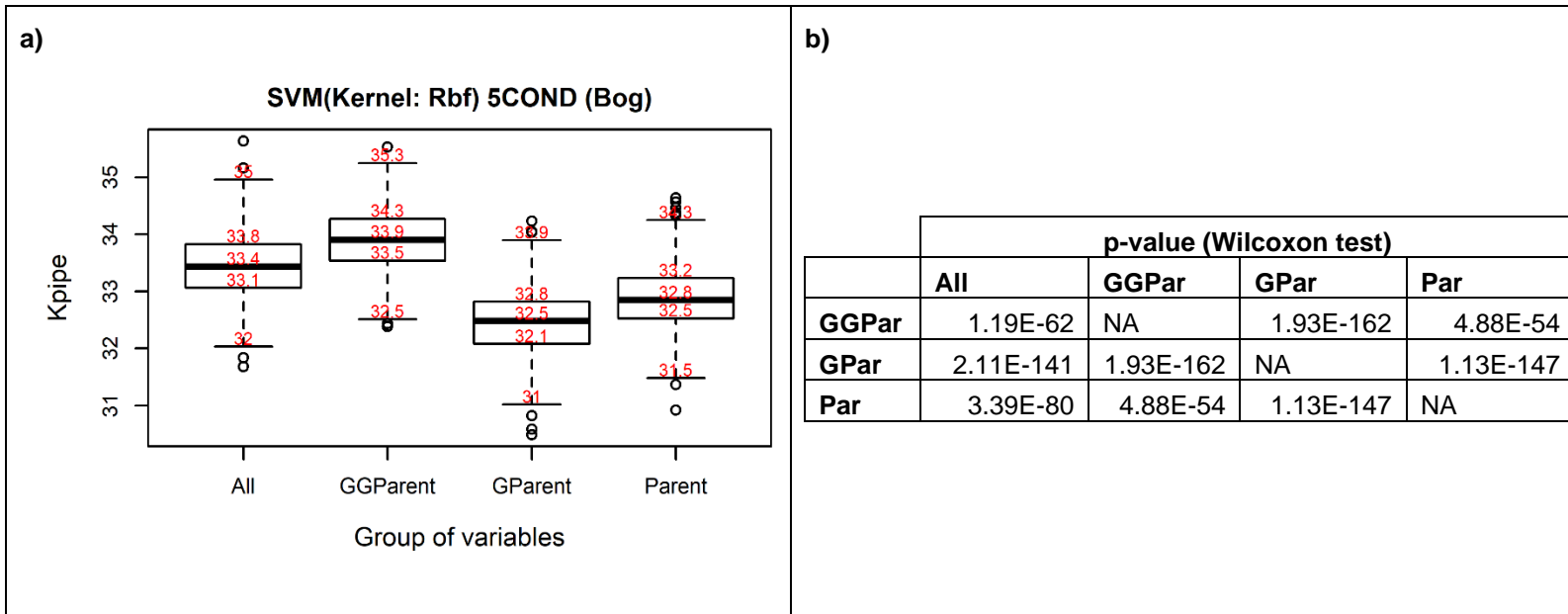
Figure 20. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the network level objective (*Knet*) and first SCS (five structural grades – NS-0.58). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 20, the SVM-RBF-based model that most minimize the *Knet* metric is the one that includes only the variables that shows the first relationship grade with the structural condition (Parent variables), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 21 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 9) based on SVM considering

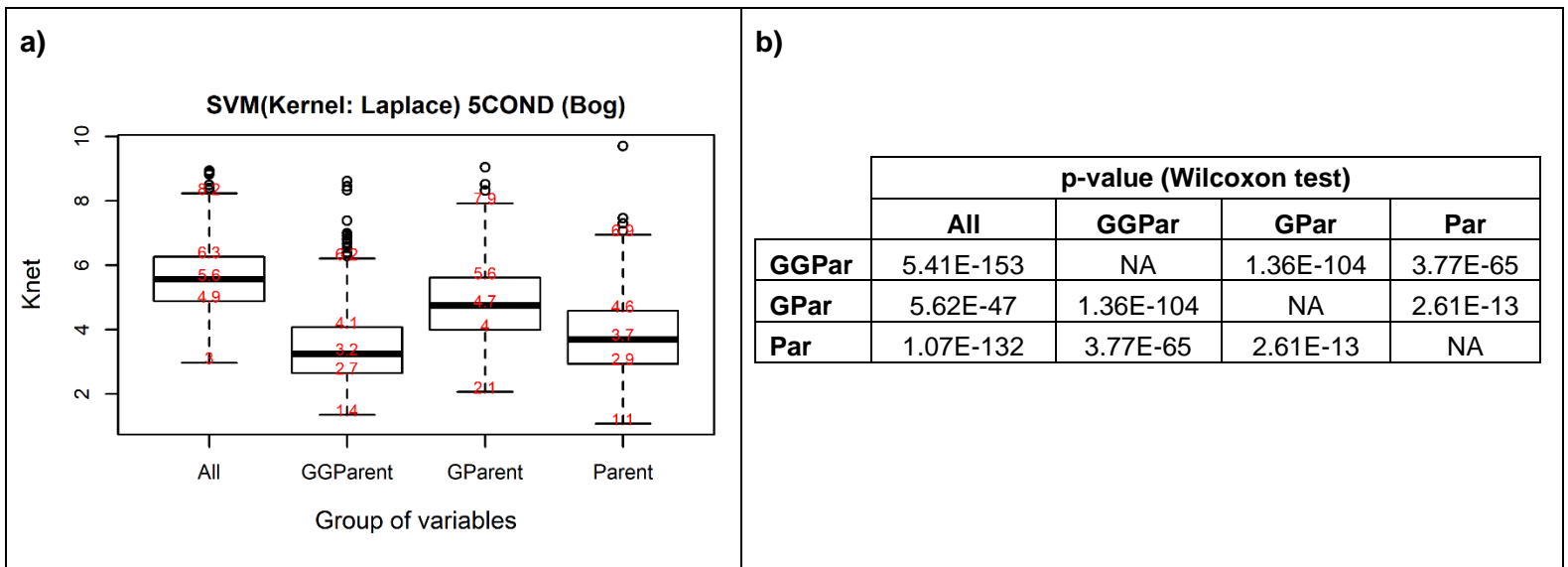
RBF kernel function for pipe level management objective see the hyperparameters set in these models in Table 15) for the first SCS.

According to Figure 21, the SVM-RBF-based model that most minimize the  $K_{pipe}$  metric is the one that includes only the variables that shows the first and second relationship grade with the structural condition (GParent variables), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).



**Figure 21. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the pipe level objective ( $K_{pipe}$ ) and first SCS (five structural grades – NS-0.58). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the  $p$ -values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

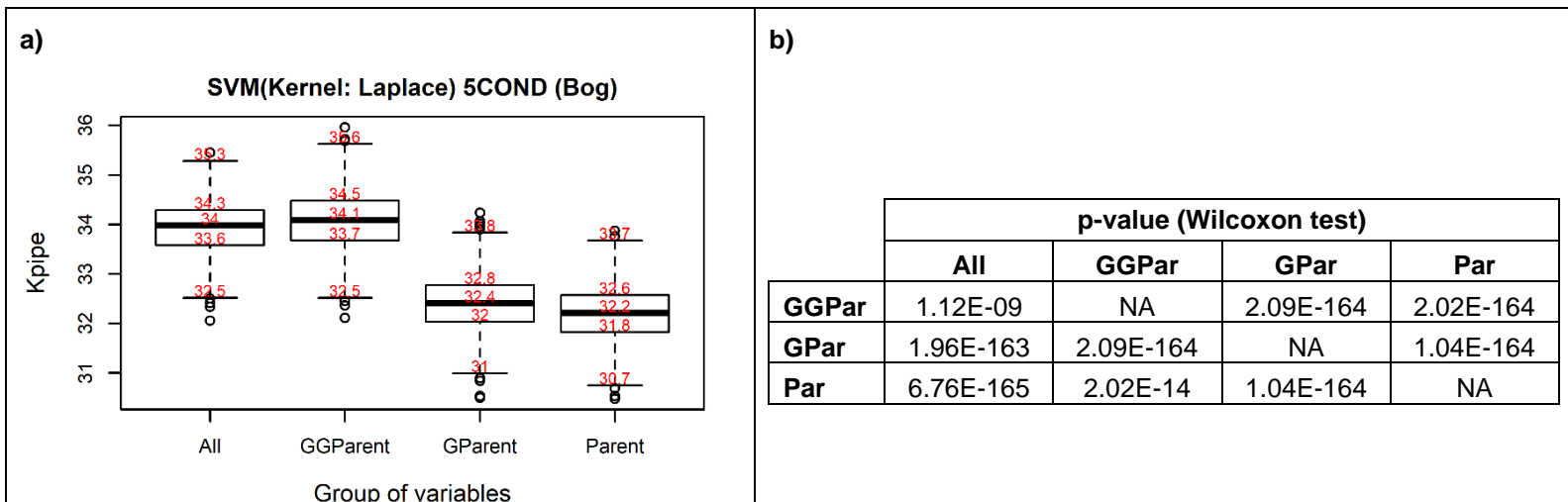
Figure 21 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 9) based on the optimised SVM considering Laplace kernel function for network level management objective (see the hyperparameters set in these models in Table 14) for the first SCS.



*Figure 22. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the network level objective (Knet) and first SCS (five structural grades – NS-0.58). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 22, the SVM-Laplace-based model that most minimize the *Knet* metric is the one that includes the variables that shows any relation of the first, second and third grade with the structural condition (GGParent variables), and this model shows significant statistical difference with the other models (p-value <0.05).

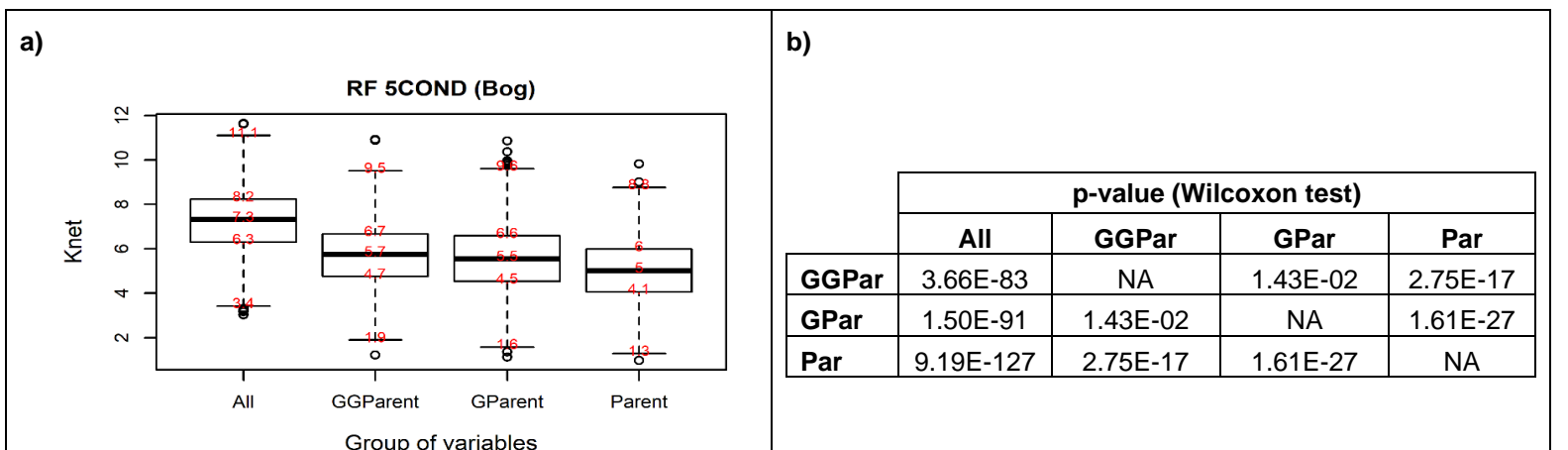
Figure 23 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 9) based on the optimised SVM considering Laplace kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 15) for the first SCS.



**Figure 23. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the pipe level objective ( $K_{pipe}$ ) and first SCS (five structural grades – NS-0.58). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 23, the SVM-Laplace-based model that most minimize the  $K_{pipe}$  metric is the one that includes the variables that only showed the first relationship grade with the structural condition (Parent variables), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).

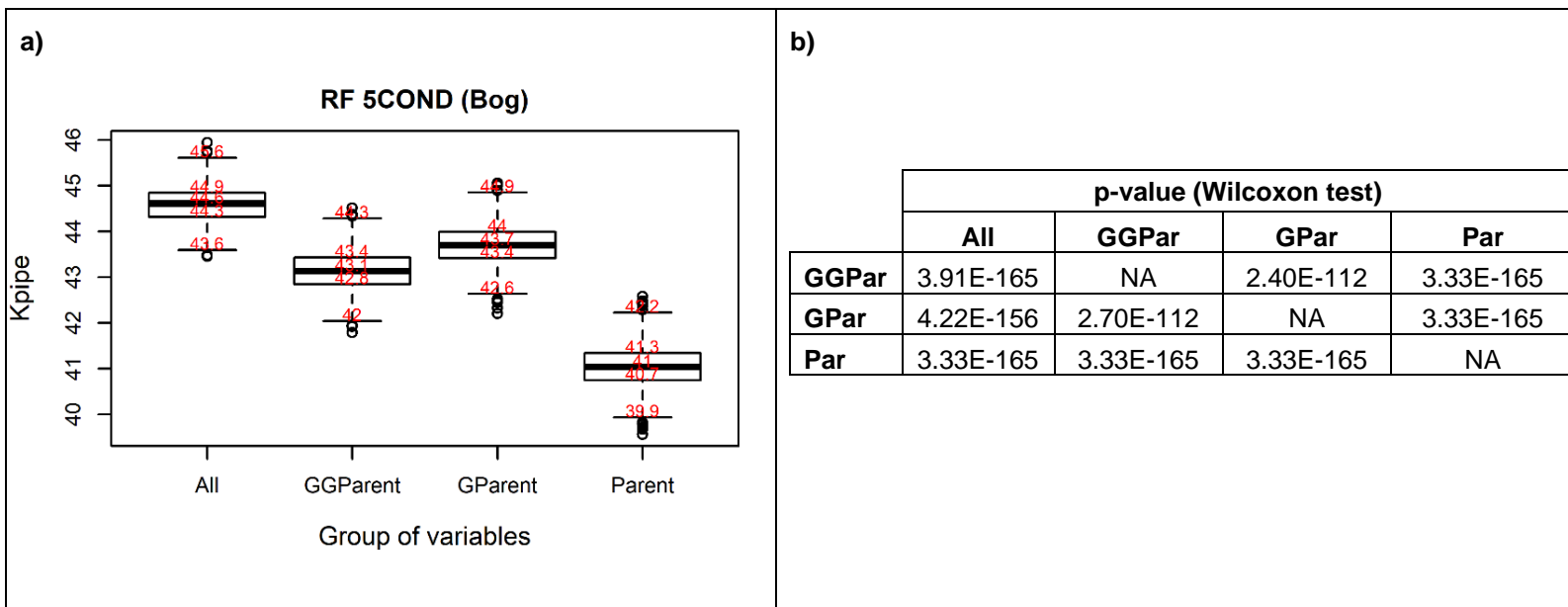
Figure 24 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 9) based on the optimised random forest (RF) for the network level management objective (see the hyperparameters set in these models in Table 14) for the first SCS.



**Figure 24. Results of the validation data of the RF-based deterioration models for the network level objective ( $K_{net}$ ) and first SCS (five structural grades – NS-0.58). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 24, the RF-based model that most minimize the *Knet* metric is the one that includes the variables that only showed the first relationship grade with the structural condition (Parent variables), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 25 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 9) based on the optimised random forest (RF) for the pipe level management objective (see the hyperparameters set in these models in Table 15) for the first SCS.



**Figure 25. Results of the validation data of the RF-based deterioration models for the pipe level objective (*Kpipe*) and first SCS (five structural grades – NS-0.58). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 25, the RF-based model that most minimize the *Kpipe* metric is the one that includes the variables that only showed the first relationship grade with the structural condition (Parent variables), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 26 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 9) based on the Ordinal Logistic regression (Ord\_LR) for the network level management objective for the first SCS.



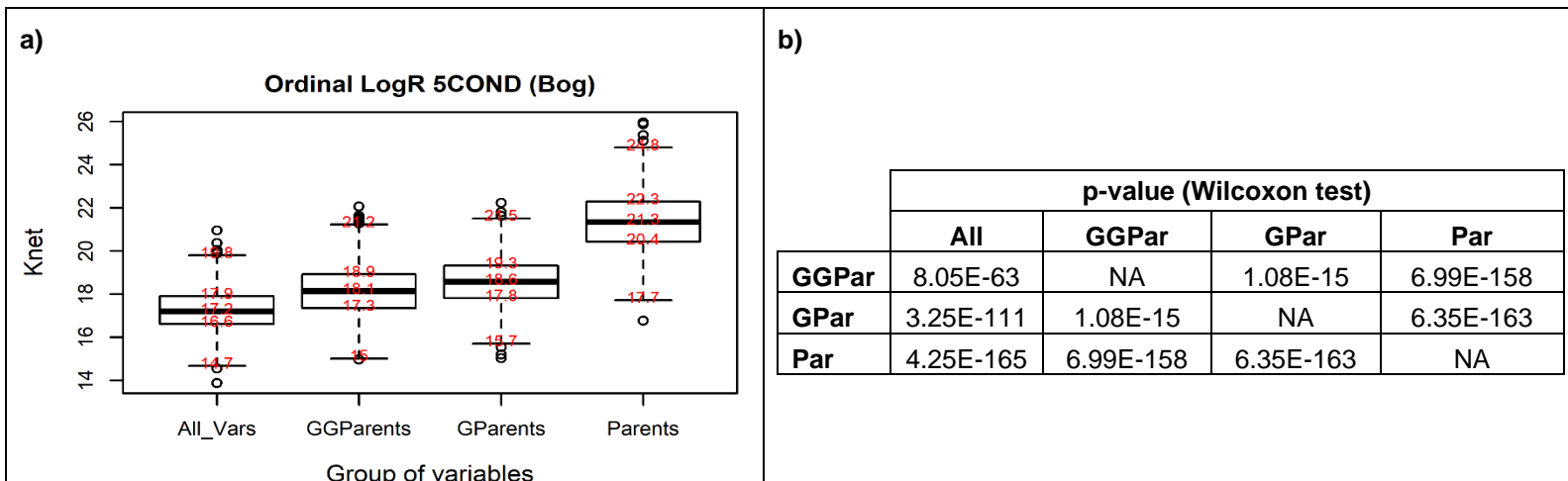


Figure 26. Results of the validation data of the Ord\_LR-based deterioration models for the network level objective (Knet) and first SCS (five structural grades – NS-0.58). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 26, the Ord\_LR-based model that most minimize the Knet metric is the one that includes all the studied variables, and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 27 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 9) based on the Ordinal Logistic regression (Ord\_LR) for the pipe level management objective for the first SCS.

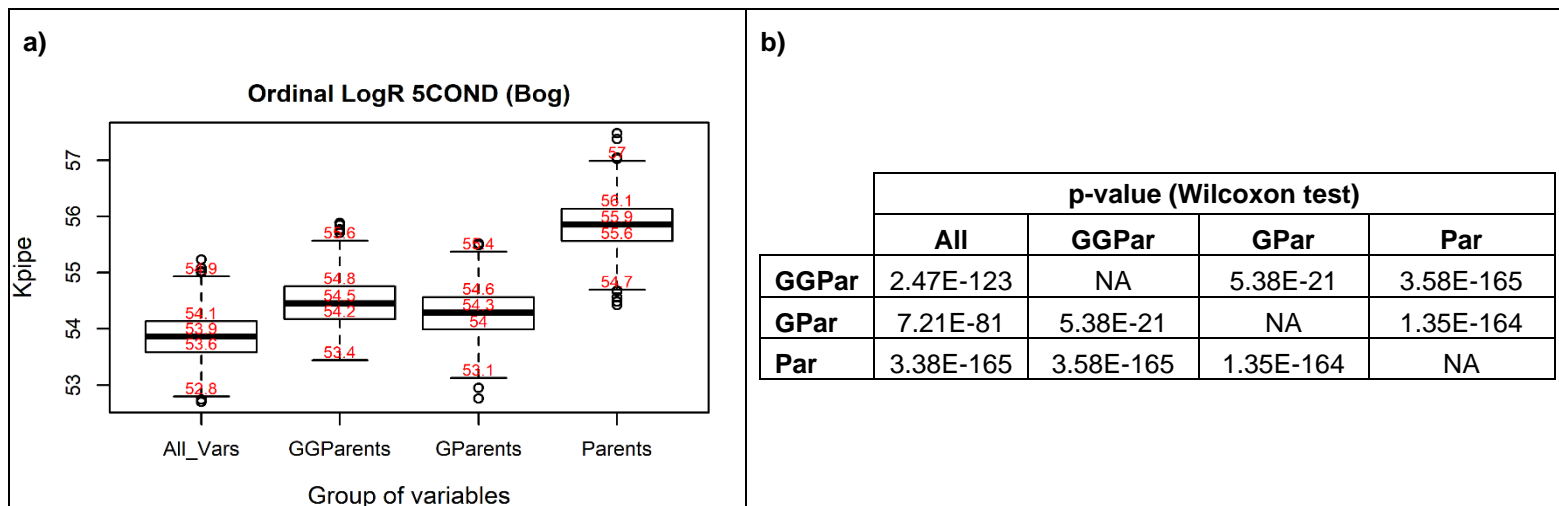
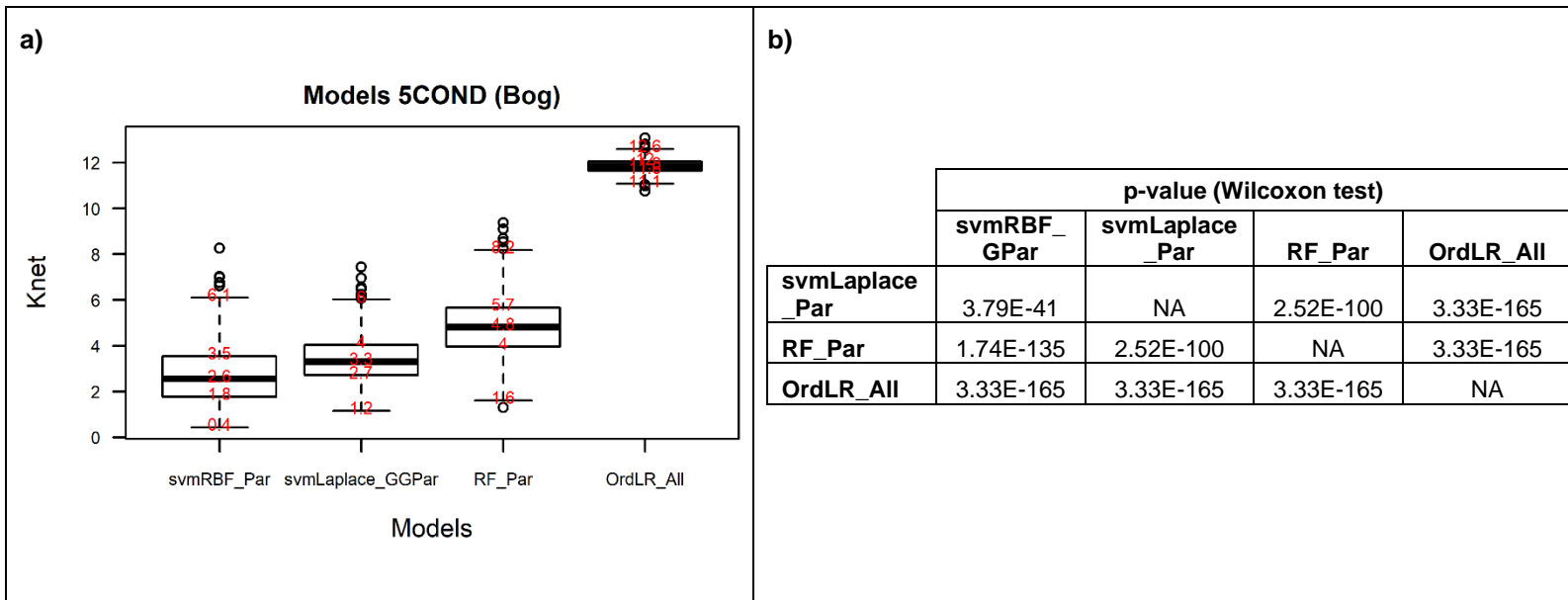


Figure 27. Results of the validation data of the Ord\_LR-based deterioration models for the pipe level objective (Kpipe) and first SCS (five structural grades – NS-0.58). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 27, the Ord\_LR-based model that most minimize the *Kpipe* metric is the one that includes all the studied variables, and this model shows significant statistical difference with the other models (p-value <0.05).

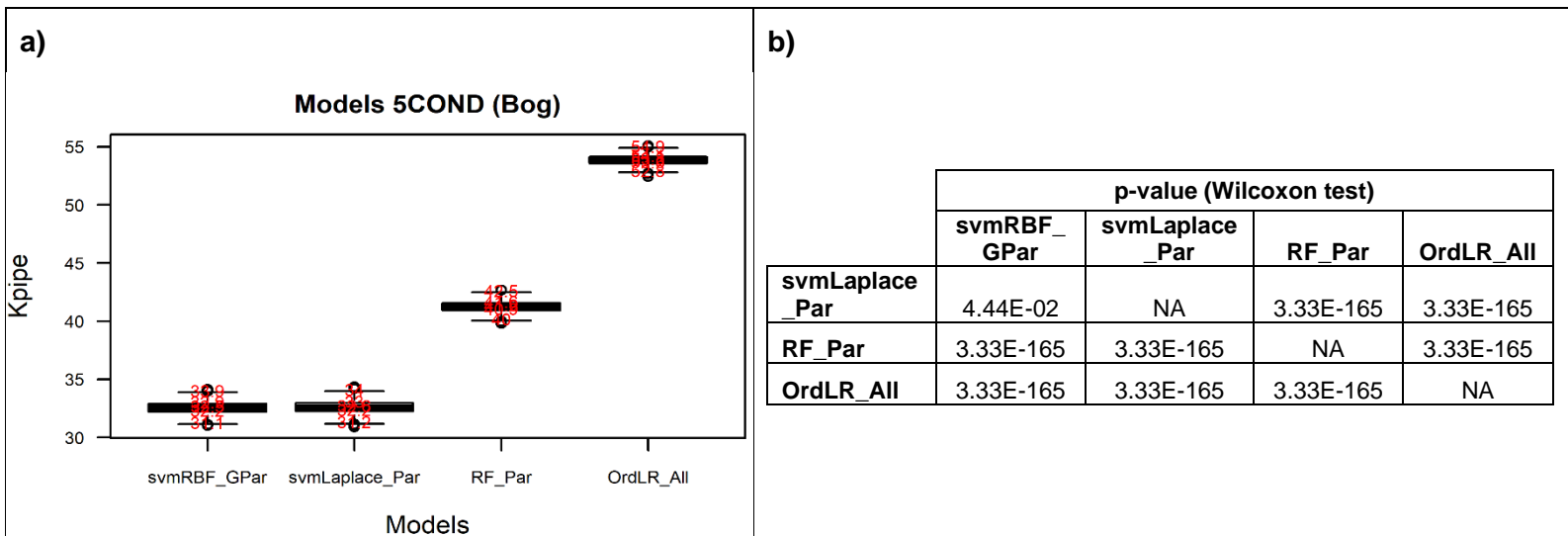
In summary, for the first SCS, the deterioration models that most minimize the *Knet* were: (i) SVM-RBF-based model that considers only the first grade relationship variables (Par); (ii) SVM-Laplace-based models that considers first, second and third grade relationship variables (GGPar); (iii) RF-based models that only considers first grade relationship variables (Par); and Ord\_LR-based model that considers all the studied variables (See Figure 28).



**Figure 28. Comparison of the most suitable deterioration model to achieve the management objective at network level for the first structural condition scenario (5 structural grades). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 28, SVM-RBF model that considers only the first relationship grade variables are the one that most minimize the *Knet* metric increasing performance prediction at network level for the first SCS (see Figure 28.a). The predictions of this model show significant statistical differences with the predictions of the other models (p-values lower than 0.05) (see Figure 28.b).

On the other hand, the deterioration models that most minimize the *Kpipe* metric in the validation data were: (I) SVM-RBF-based deterioration models considering the first and second grade relationship variables (GPar); (ii) SVM-Laplace based deterioration models considering the first relationship grade variables (Par); (iii) RF based deterioration models considering the first relationship grade variables (Par); and (iv) Ordinal logistic models considering all the studies variables (see Figure 29).

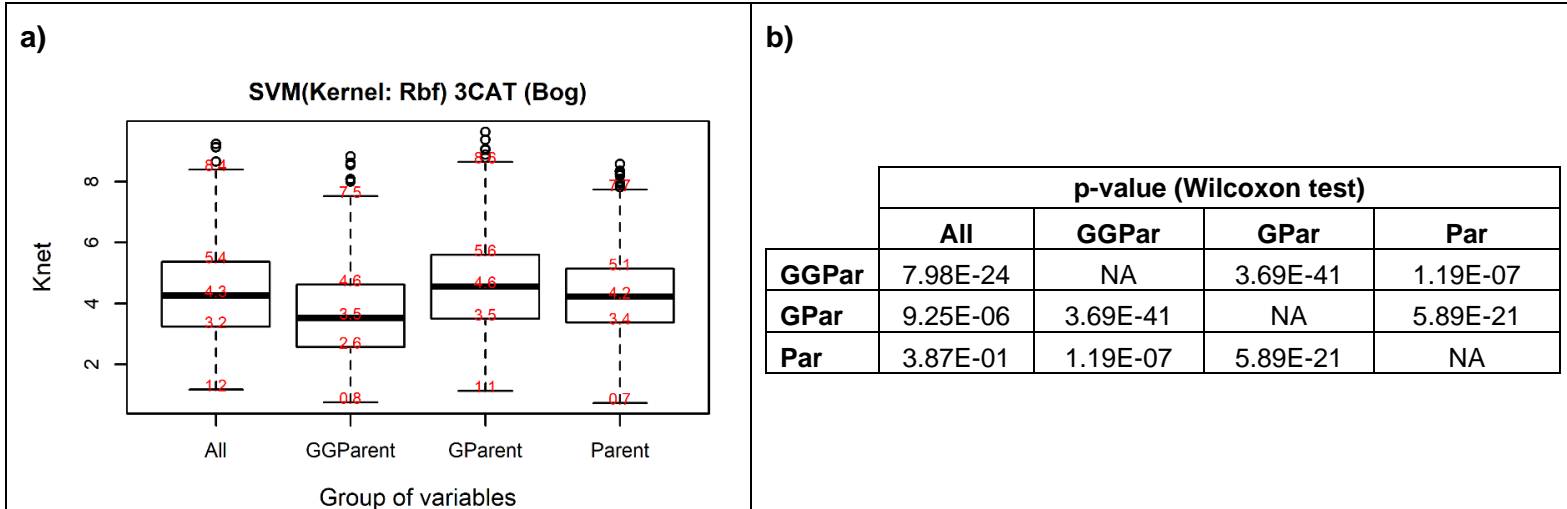


**Figure 29. Comparison of the most suitable deterioration model to achieve the management objective at the pipe level for the first structural condition scenario (5 structural grades). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 29.a., SVM-based deterioration models shows similar *Kpipe* values, being SVM-RBF based model the one with the lowest values. To identify if there is a significant difference between both models, Figure 29.b. shows the p-values after carrying out the Wilcoxon test. From the Wilcoxon test, the p-value between SVM-RBF and SVM-Laplace based models, shows that there is a significant statistical difference between both *Kpipe* samples values (p-value <0.05).

#### *D.1.4.2. Second SCS: three structural categories*

Figure 30 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 10) based on the optimised SVM considering RBF kernel function for the network level management objective (see the hyperparameters set in these models in Table 16) for the second SCS.

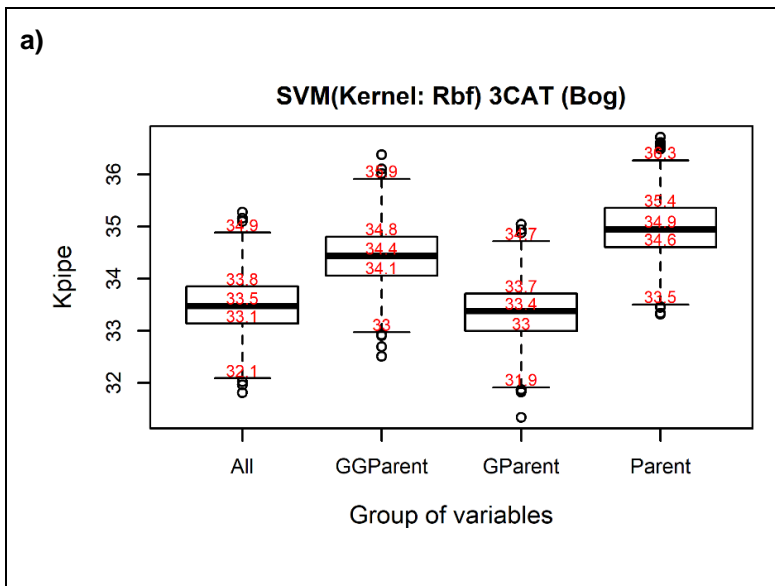


**Figure 30. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the network level objective (*Knet*) and second SCS (three structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the *p*-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 30, the SVM-RBF-based model that most minimize the *Knet* metric is the one that includes the variables that show any relationship of the first, second and third grade with the structural condition (GGParent variables) for the second SCS (three structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ).

Figure 31 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 10) based on the optimised SVM considering RBF kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 17) for the second SCS.

According to Figure 31, the SVM-RBF-based model that most minimize the *Kpipe* metric is the one that includes the variables that show first and second relationship grade with the structural condition (GParent variables) for the second SCS (three structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ).

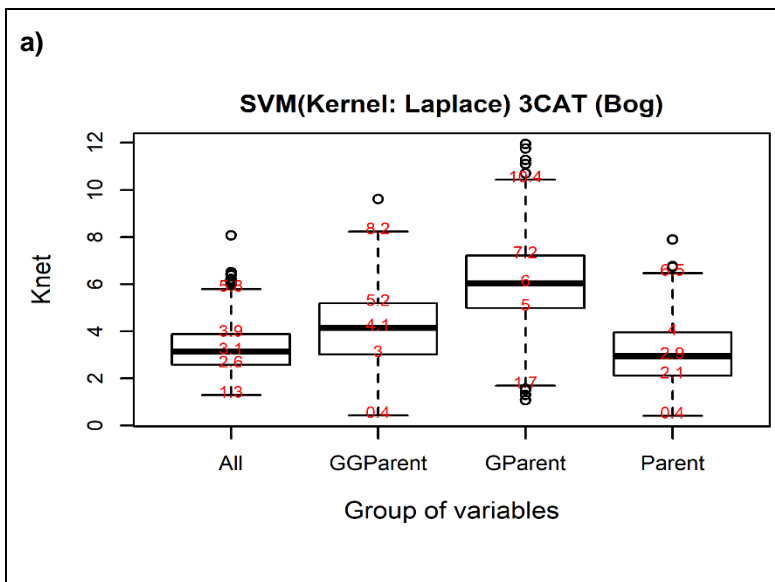


b)

	p-value (Wilcoxon test)			
	All	GGPar	GPar	Par
GGPar	1.56E-136	NA	3.85E-149	9.63E-163
GPar	6.66E-07	3.85E-149	NA	1.80E-72
Par	4.93E-163	9.63E-165	1.80E-72	NA

Figure 31. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the pipe level objective (Kpipe) and second SCS (three structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

Figure 32 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 10) based on the optimised SVM considering Laplace kernel function for the network level management objective (see the hyperparameters set in these models in Table 16) for the second SCS.



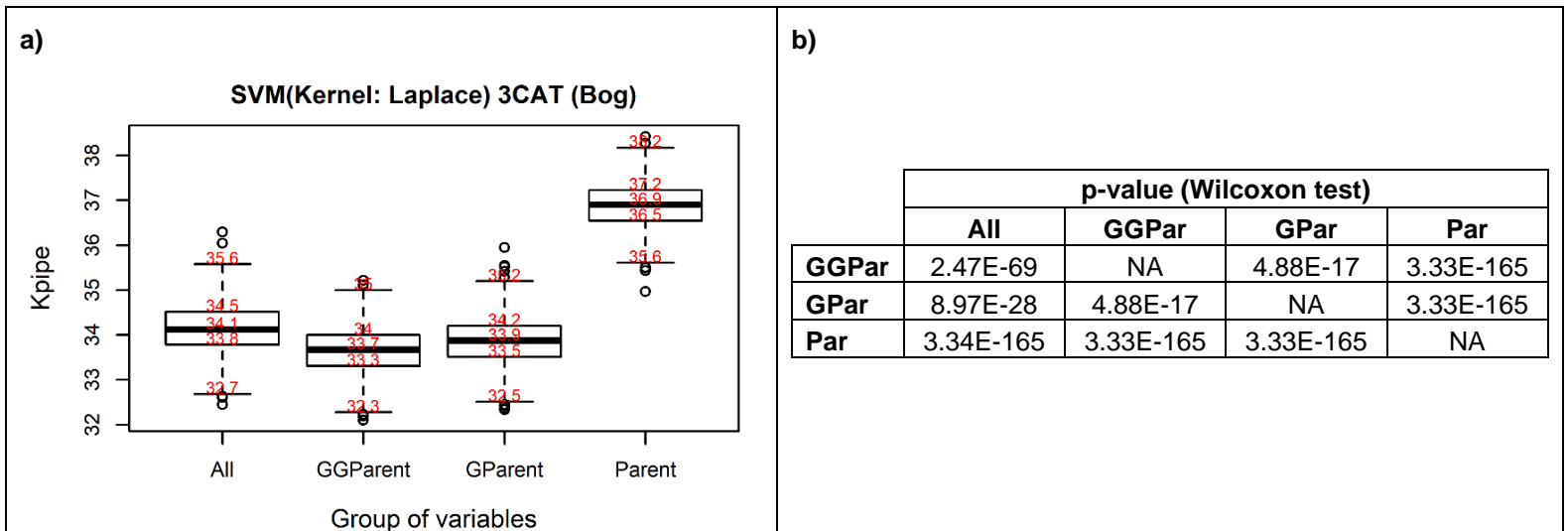
b)

	p-value (Wilcoxon test)			
	All	GGPar	GPar	Par
GGPar	2.72E-38	NA	2.84E-101	1.82E-149
GPar	1.76E-148	2.84E-101	NA	1.87E-51
Par	2.71E-05	1.82E-149	1.87E-51	NA

Figure 32. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the network level objective (Knet) and second SCS (three structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 32, the SVM-Laplace-based model that most minimize the *Knet* metric is the one that includes the variables that show only the variables that show the first relationship grade with the structural condition (Parent variables) for the second SCS (three structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

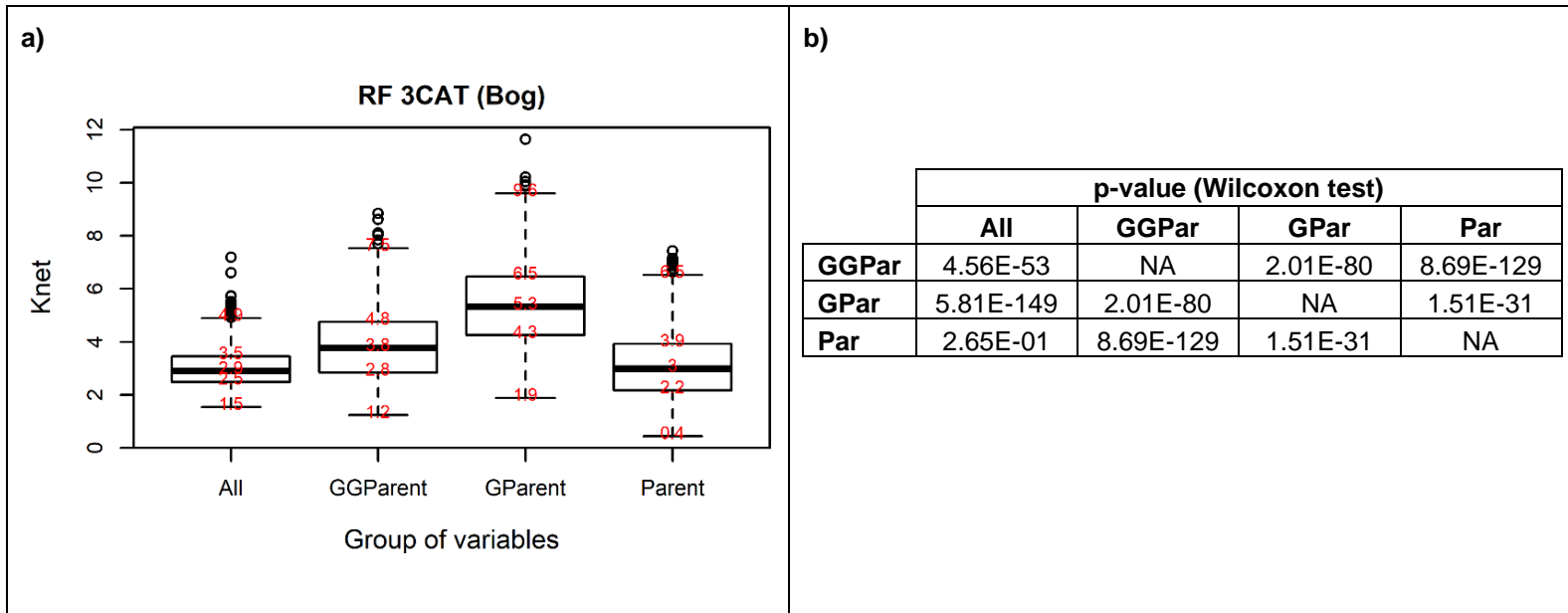
Figure 33 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 10) based on the optimised SVM considering Laplace kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 17) for the second SCS.



*Figure 33. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the pipe level objective (Kpipe) and second SCS (three structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 33, the SVM-Laplace-based model that most minimize the *Kpipe* metric is the one that includes the variables that show any relationship of first, second and third grade with the structural condition (GGParent variables) for the second SCS (three structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 34 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 10) based on the optimised RF for the network level management objective (see the hyperparameters set in these models in Table 16) for the second SCS.

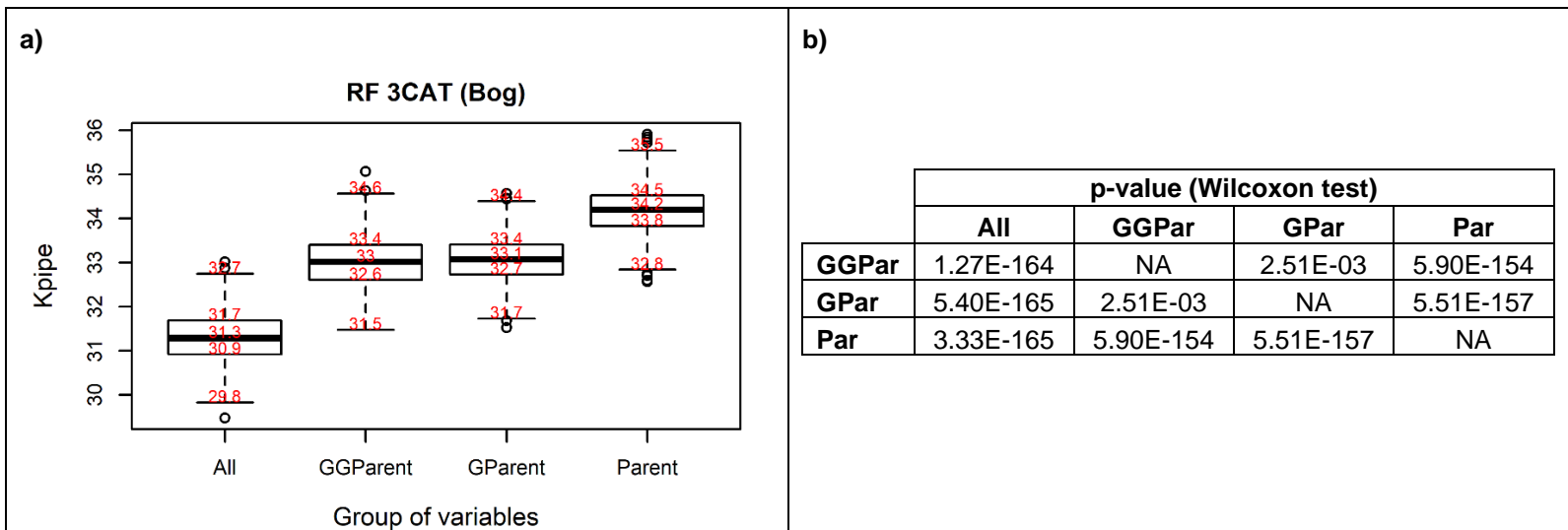


*Figure 34. Results of the validation data of the RF-based deterioration models for the network level objective ( $K_{net}$ ) and second SCS (three structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 34, the RF-based model that most minimize the  $K_{net}$  metric is the one that includes the variables that show the first relationship grade with the structural condition (Parent variables) for the second SCS (three structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).

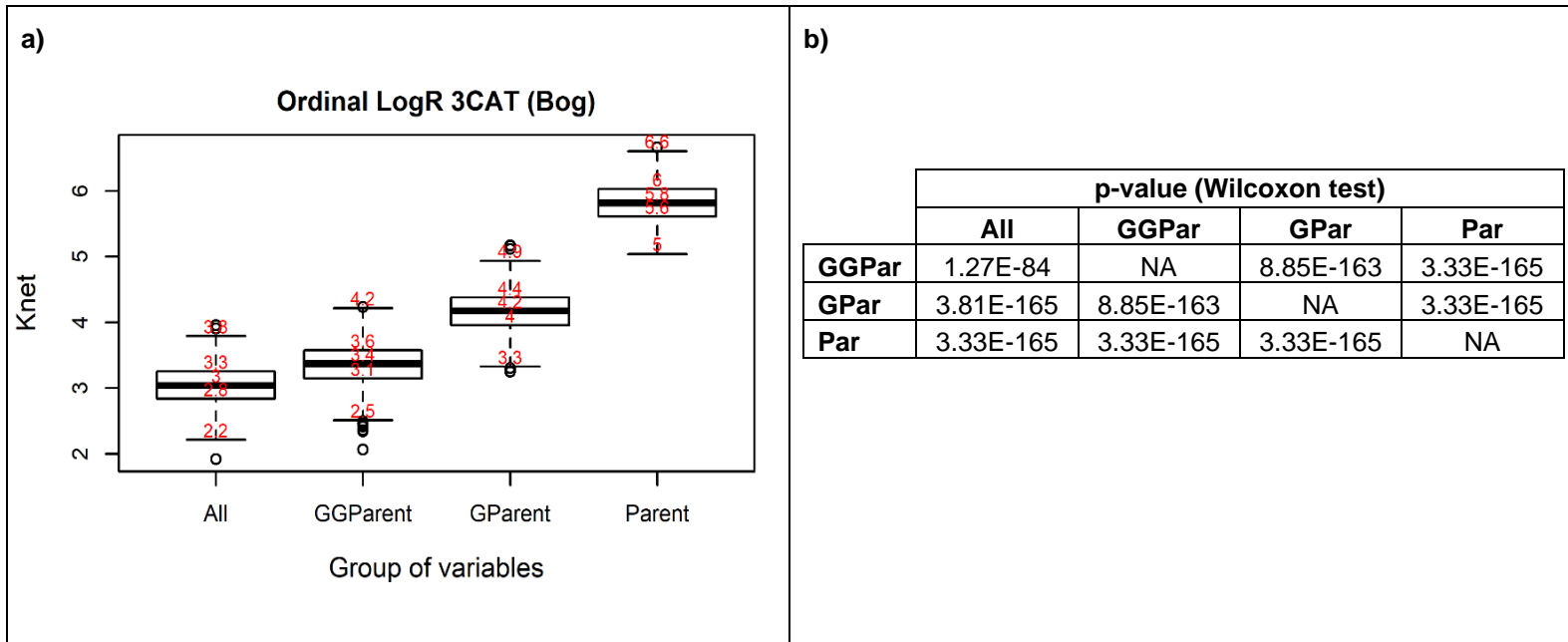
Figure 35 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 10) based on the optimised RF for the pipe level management objective (see the hyperparameters set in these models in Table 17) for the second SCS.

According to Figure 35, the RF-based model that most minimize the  $K_{pipe}$  metric is the one that includes all studied variables for the second SCS (three structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).



**Figure 35.** Results of the validation data of the RF-based deterioration models for the pipe level objective (*Kpipe*) and second SCS (three structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

Figure 36 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 10) based on the Ordinal logistic regressions (Ord\_LR) for the network level management objective for the second SCS.

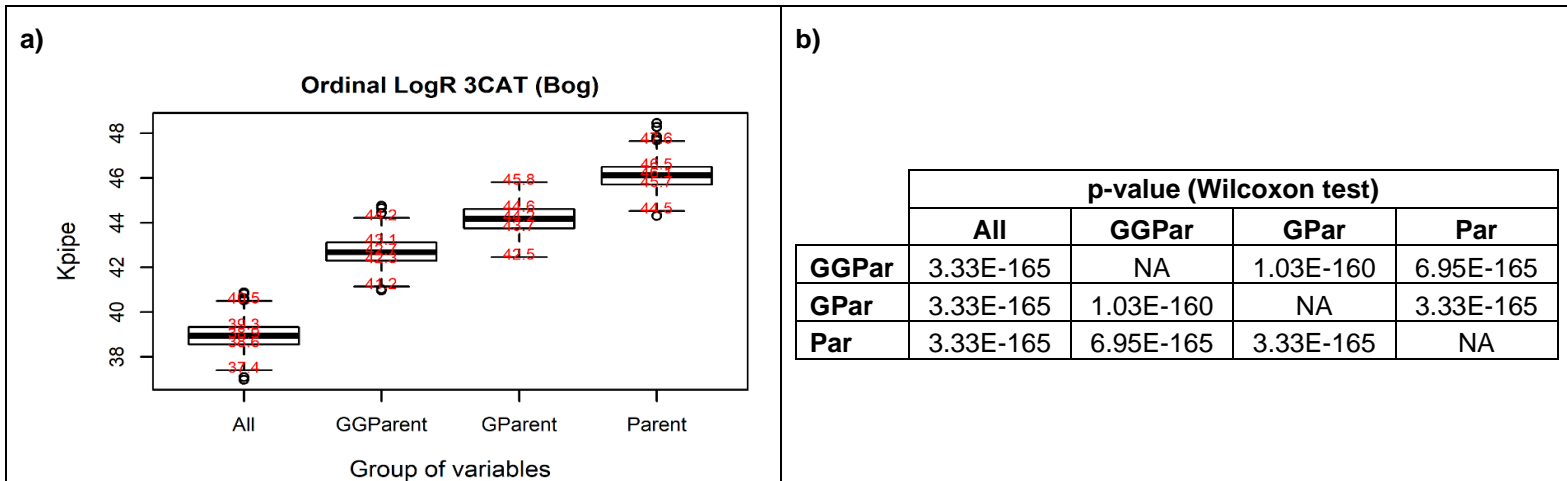


**Figure 36.** Results of the validation data of the Ord\_LR-based deterioration models for the network level objective (*Knet*) and second SCS (three structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author



According to Figure 36, the Ord\_LR-based model that most minimize the *Knet* metric is the one that includes all the studied variables, and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ).

Figure 37 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 10) based on the Ordinal logistic regressions (Ord\_LR) for the pipe level management objective for the second SCS.



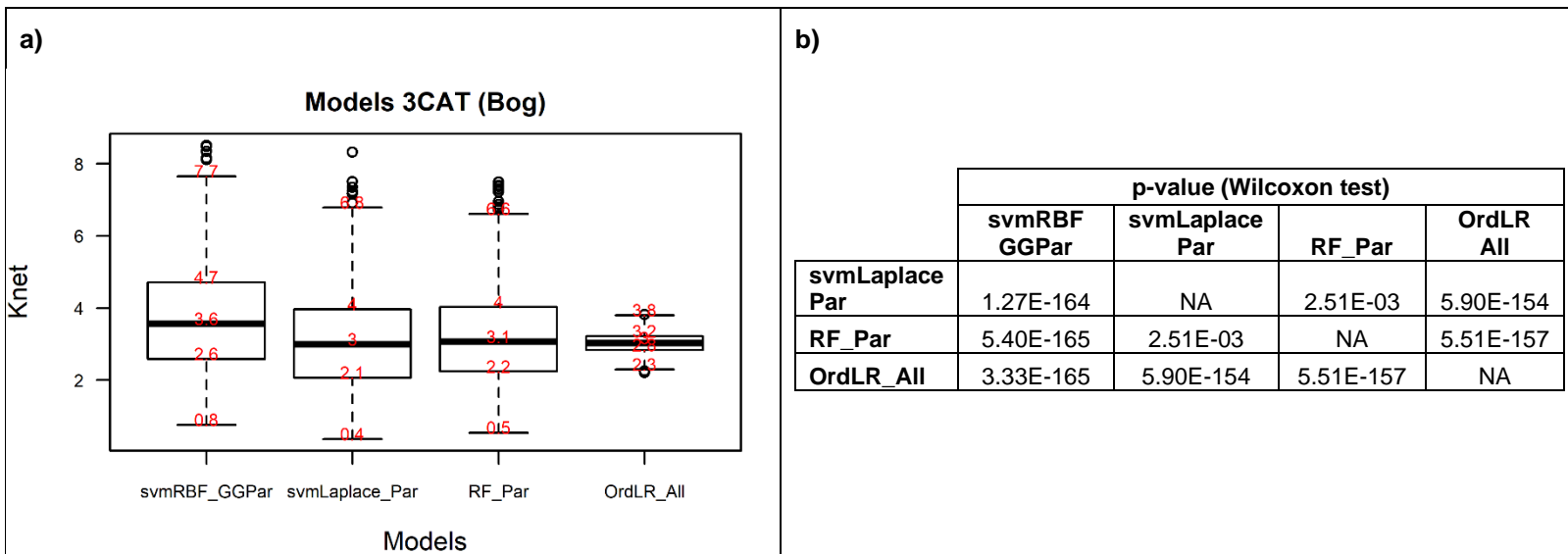
**Figure 37. Results of the validation data of the Ord\_LR-based deterioration models for the pipe level objective (*Kpipe*) and second SCS (three structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the *p*-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 37, the Ord\_LR-based model that most minimize the *Kpipe* metric is the one that includes all the studied variables, and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ).

In summary, for the second structural condition scenario (SCS), the deterioration models that most minimize the *Knet* values in the validation data were: (i) SVM-RBF based deterioration models considering first, second and third relationship grade variables (GGPar); (ii) SVM-Laplace based deterioration models considering only first relationship grade variables (Par); (iii) RF-based deterioration models considering first relationship grade variables (Par); and (iv) Ordinal logistic regression-based deterioration models considering all studied variables (See Figure 38).

According to Figure 38.a. the deterioration models that minimum values of *Knet* shows are SVM-Laplace and RF-based models, both considering only the parent variables. Figure 38.b. shows that these above models have significant difference ( $p$ -value  $<0.05$ ). However, it is interesting the results of Ord\_LR which should be more analysed in detail. Considering that visually the SVM\_Laplace-based model is the one with the lowest *Knet* values is comparing with the Ord\_LR

values. In this analysis is found that both models show a *Knet* median of 3, but the variability of the SVM\_Laplace-based model is higher, making that these model presents also the highest *Knet* values between these both models. Therefore, an analysis of Q1 and Q3 values were carried out for both models to quantify the variability length below of above of the median: Q1 and Q3 are 2.1 and 4 for SVM\_Laplace-based model; 2.8 and 3.2 are for Ord\_LR. Calculating the variability length for SVM\_Laplace-based model is was found that the variability length above (1) the median is higher than variability below (0.9) reaching *Knet* values around 4, while the variability length above and below of the median is 0.2, reaching *Knet* values around 3.2. Thus, it was chosen, for its stability in their *Knet* values, the Ord\_LR model as suitable model considering all studies variables for achieving network level objectives for the second SCS.



**Figure 38. Comparison of the most suitable deterioration model to achieve the management objective at network level for the second structural condition scenario (3 structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

For the same SCS, the deterioration models that most minimize the *Kpipe* values in the validation data were: (i) SVM-RBF based deterioration models considering first and second relationship grade variables (GPar); (ii) SVM-Laplace based deterioration models considering first, second and third relationship grade variables (GGPar); (iii) RF-based deterioration models considering all studied variables (All); and (iv) Ordinal logistic regression-based deterioration models considering all studied variables (See Figure 39).

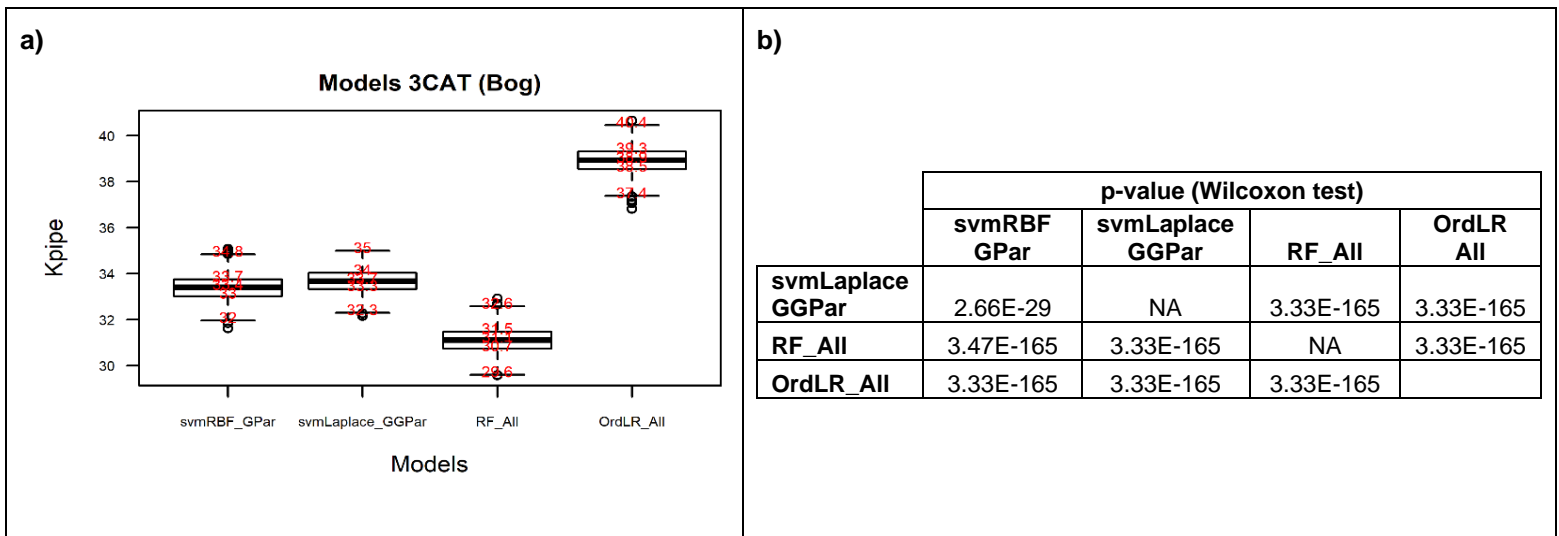


Figure 39. Comparison of the most suitable deterioration model to achieve the management objective at the pipe level for the second structural condition scenario (3 structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 39.a., RF-based deterioration models considering all the studied variables is the one with lowest *Kpipe* values in the validation data. Moreover, Figure 39.b. also shows that all the compared models show significant statistical differences.

#### D.1.4.3. Third SCS: two structural categories

Figure 40 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 11) based on the optimised SVM considering RBF kernel function for the network level management objective (see the hyperparameters set in these models in Table 18) for the third SCS.

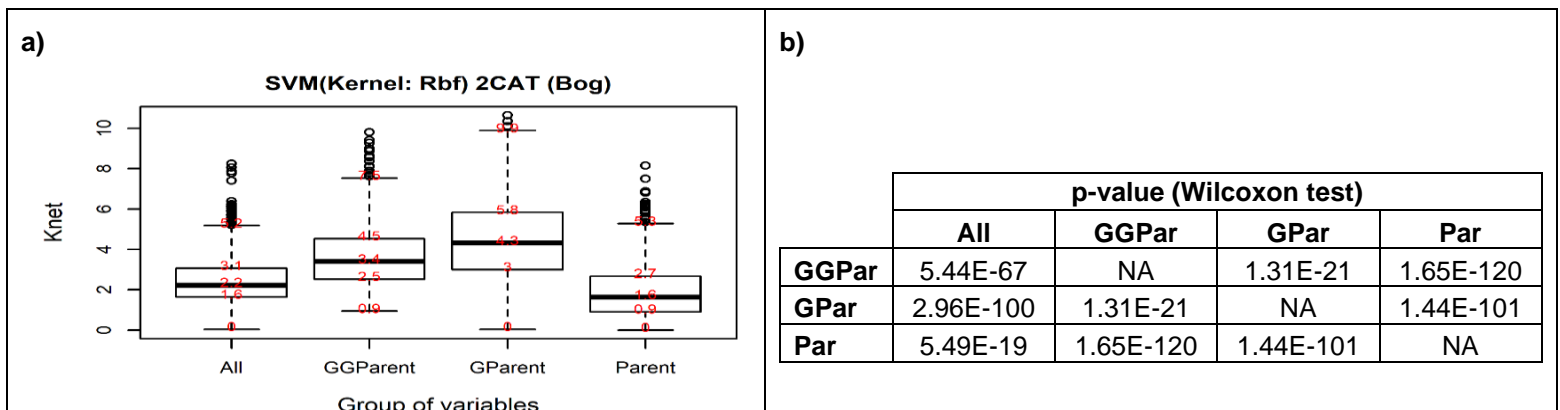


Figure 40. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the network level objective (*Knet*) and third SCS (two structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 40, the SVM-RBF-based model that most minimize the *Knet* metric is the one that includes the variables that show only show the first relationship grade with the structural condition (Parent variables) for the third SCS (two structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 40 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 11) based on the optimised SVM considering RBF kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 19) for the third SCS.

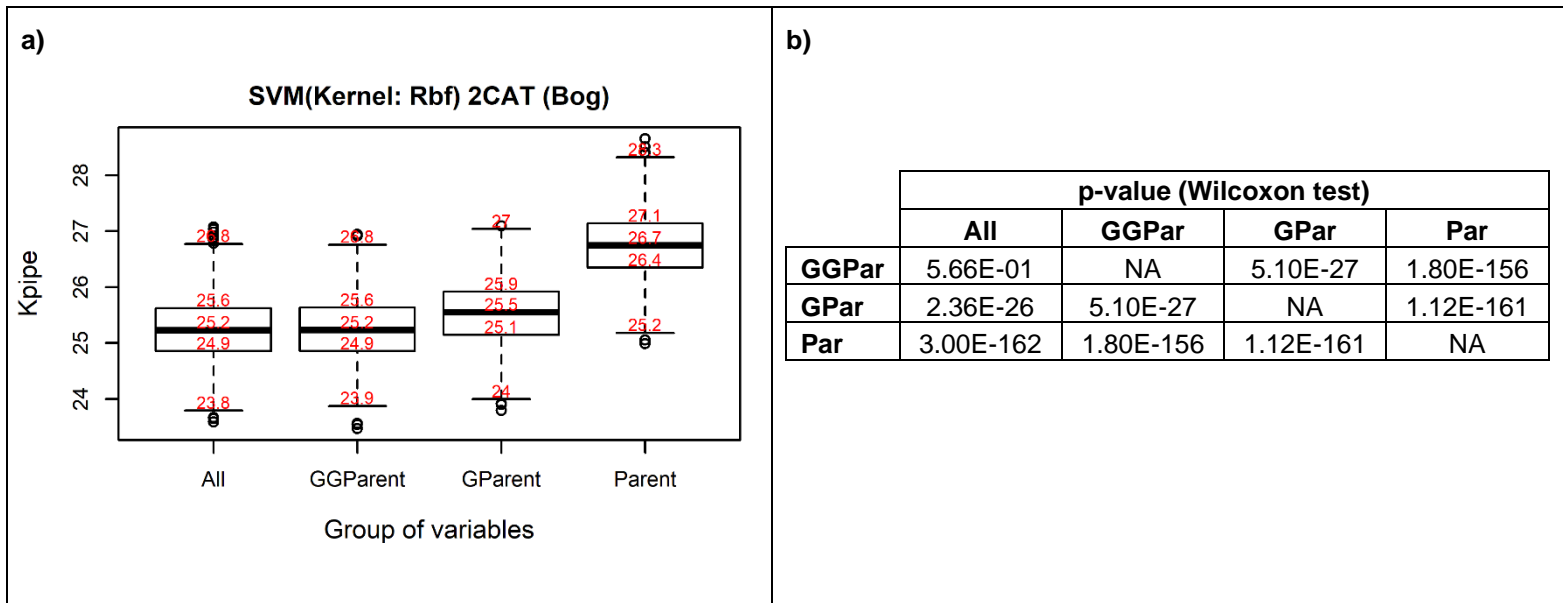
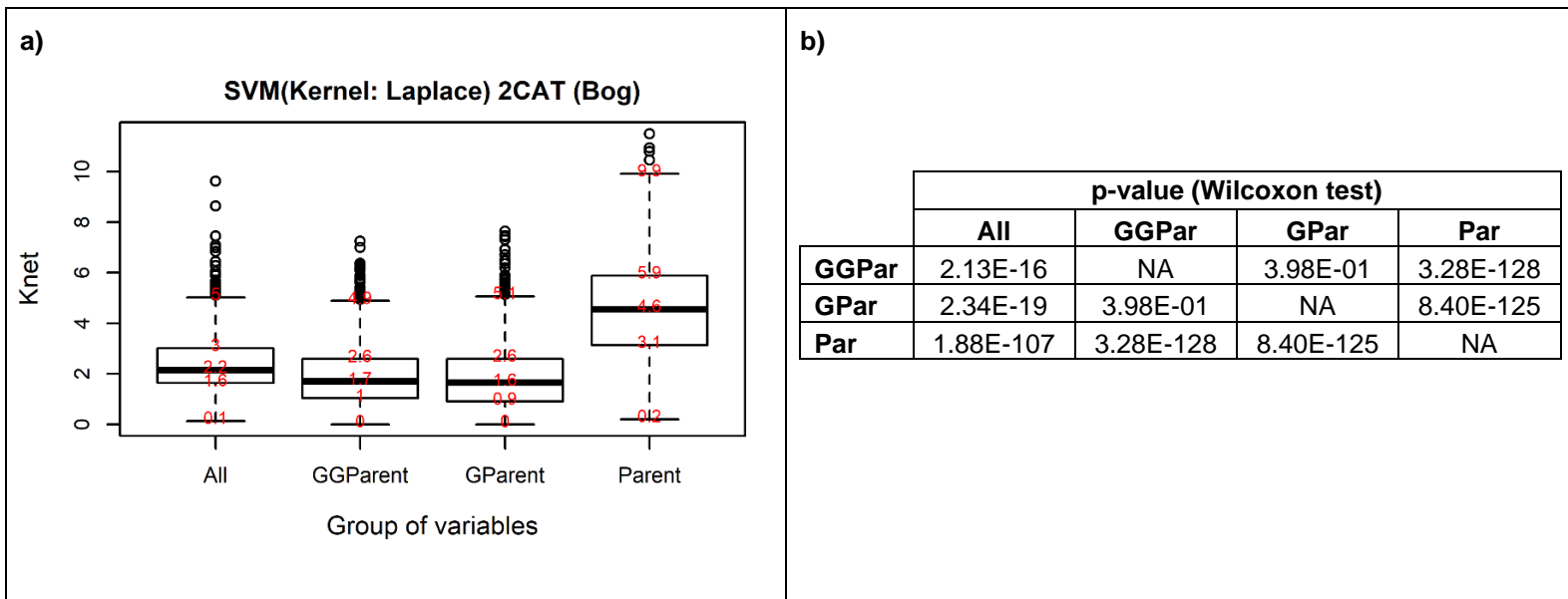


Figure 41. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the pipe level objective (*Kpipe*) and third SCS (two structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 41.a., the SVM-RBF-based models that most minimize the *Kpipe* metric are two models: SVM-RBF that includes all the studies variables and SVM-RBF that includes any relationship of the first, second and third relationship grade (GGParent variables) for the third SCS (two structural categories). Regarding Figure 41.b. there is not significant difference (pvalue > 0.05) between these both models, therefore it is chosen the one that has less variables to reduce the information collection costs.

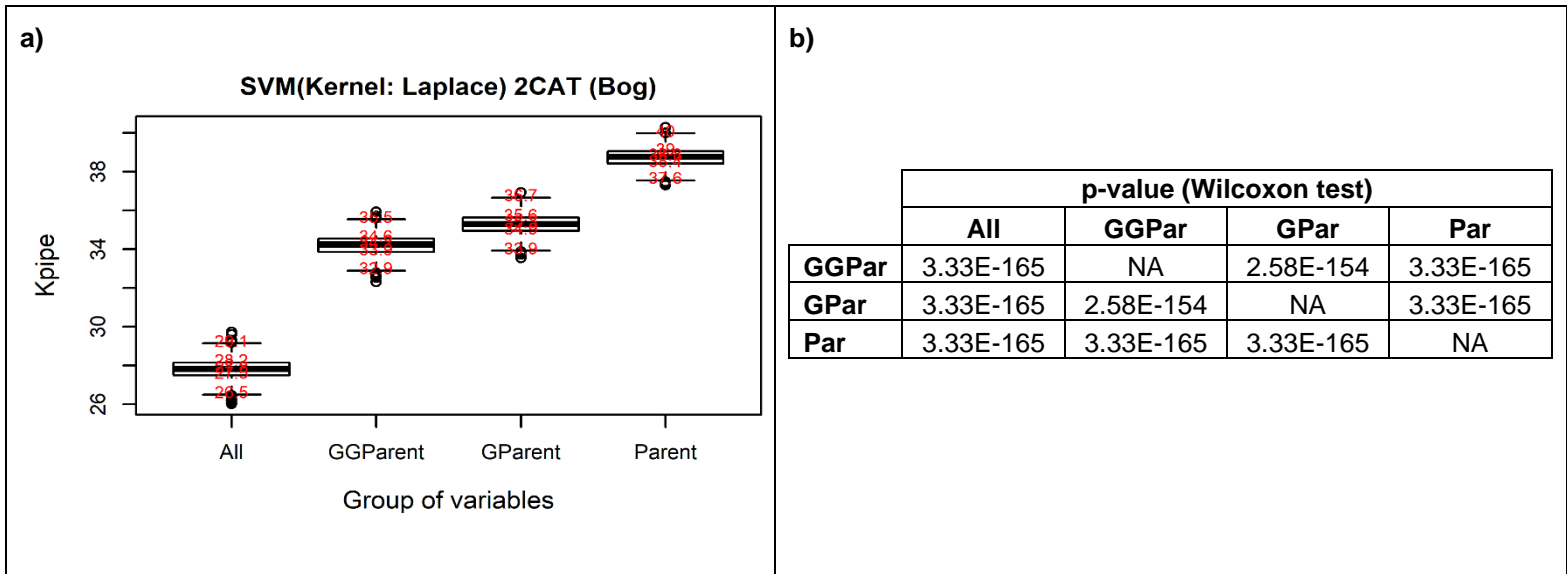
Figure 42 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 11) based on the optimised SVM considering Laplace kernel function for the network level management objective (see the hyperparameters set in these models in Table 18) for the third SCS.

According to Figure 42.a., the SVM-Laplace-based model that most minimize the *Knet* metric is the one that includes the variables that show the first and second relationship grade with the structural condition (GParent variables) for the third SCS (two structural categories). However, Figure 42.b. shows that this model does not show significant difference with the SVM-Laplace based model that includes any relationship of the first, second and third grade with the structural condition. It means, that both models show the same results. Therefore, according to the proposed methodology, it is chosen the SVM-Laplace-based model that includes only the variables that show first and second relationship grade (GParent variables) and this model shows significant statistical difference with the other models (p-value <0.05).



*Figure 42. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the network level objective (Knet) and third SCS (two structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

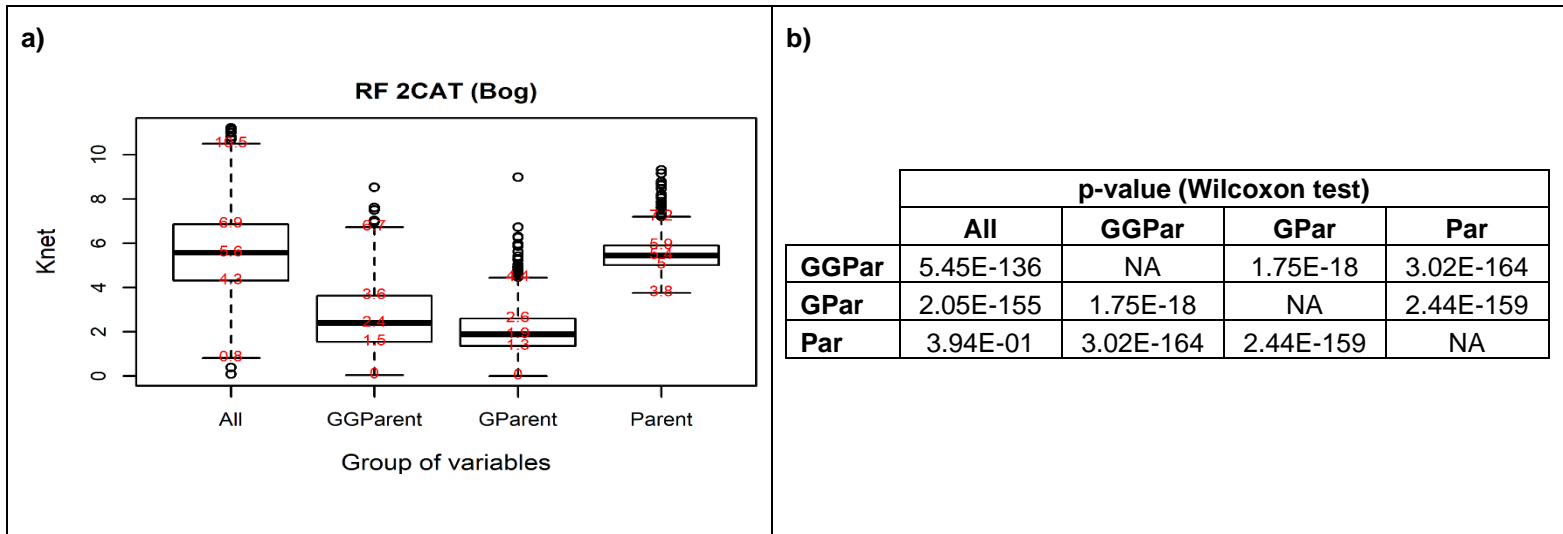
Figure 43 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 11) based on the optimised SVM considering Laplace kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 19) for the third SCS.



*Figure 43. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the pipe level objective ( $K_{pipe}$ ) and third SCS (two structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 43, the SVM-Laplace-based model that most minimize the  $K_{pipe}$  metric is the one that includes the all studied variables for the third SCS (two structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).

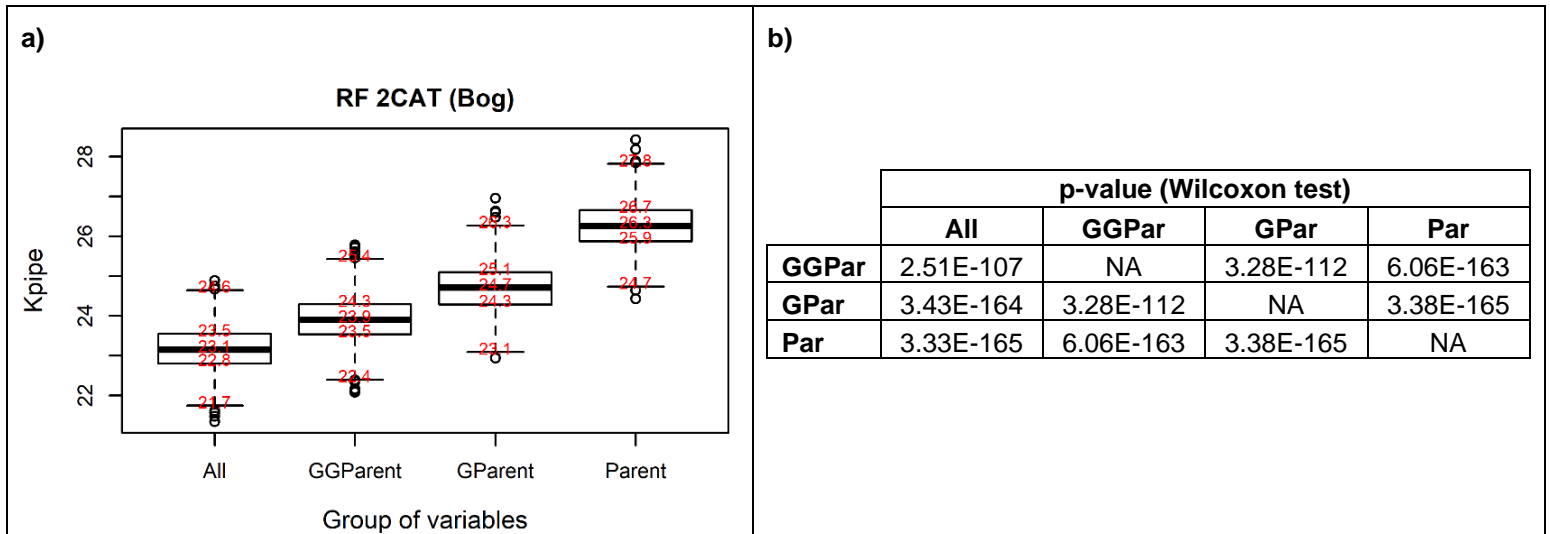
Figure 44 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 11) based on the optimised RF model for the network level management objective (see the hyperparameters set in these models in Table 18) for the third SCS.



**Figure 44. Results of the validation data of the RF-based deterioration for the network level objective (*Knet*) and third SCS (two structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 44, the RF-based model that most minimize the *Knet* metric is the one that includes the variables of the first and second relationship grade (GParent) with the structural condition for the third SCS (two structural categories), and this model shows significant statistical difference with the other models ( $p\text{-value} < 0.05$ ). Furthermore, it is interesting that there is not significant difference ( $p\text{-value} > 0.05$ ) between the RF models that includes all studied variables and only the parent variables (the variables that show the first relationship grade with the structural condition).

Figure 45 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 11) based on the optimised RF model for the pipe level management objective (see the hyperparameters set in these models in Table 19) for the third SCS.

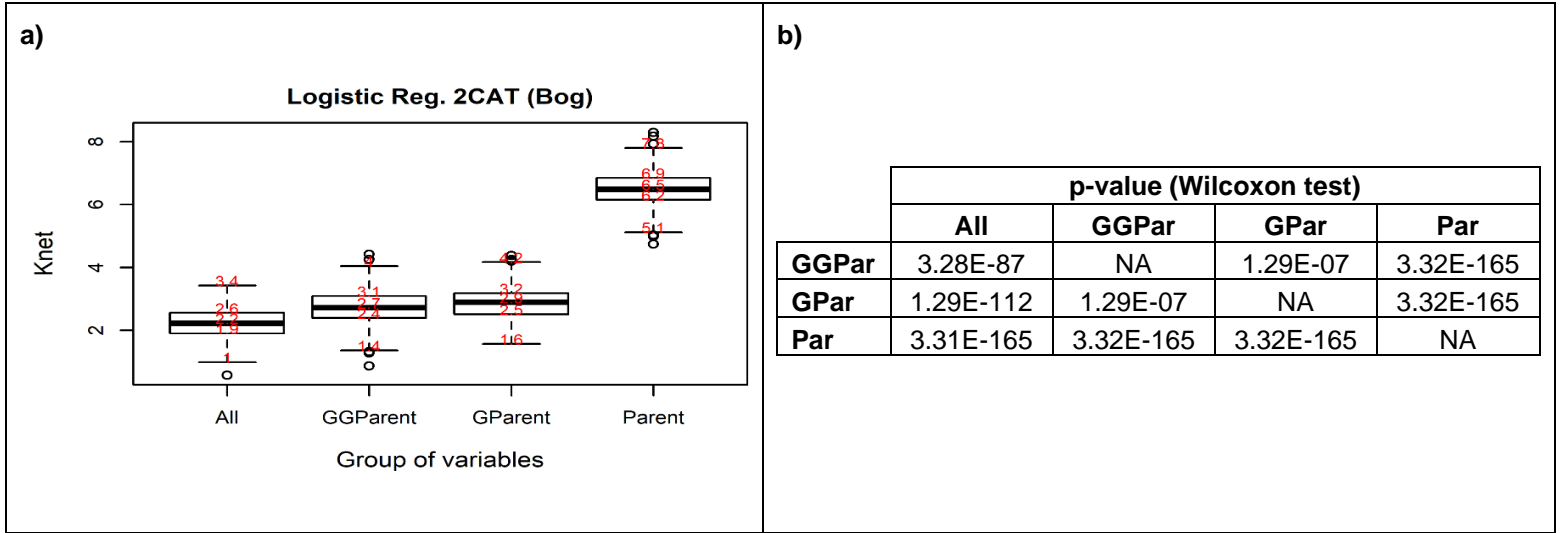


**Figure 45. Results of the validation data of the RF-based deterioration for the pipe level objective ( $K_{pipe}$ ) and third SCS (two structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 45, the RF-based model that most minimize the  $K_{pipe}$  metric is the one that includes all the studied variables for the third SCS (two structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).

Figure 46 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 11) based on the binomial logistic regressions (LR) for the network level management objective for the third SCS.

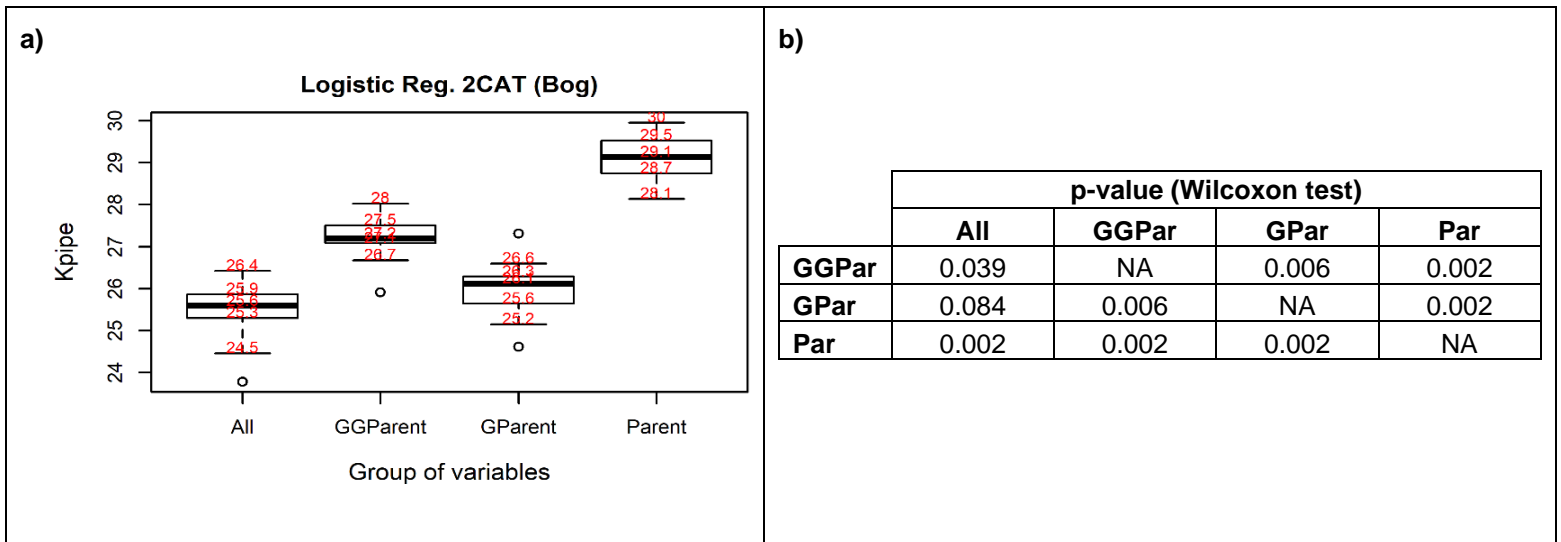




**Figure 46. Results of the validation data of the LR-based deterioration for the network level objective (*Knet*) and third SCS (two structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 46, the LR-based model that most minimize the *Knet* metric is the one that includes all the studied variables, and this model shows significant statistical difference with the other models ( $p\text{-value} < 0.05$ ).

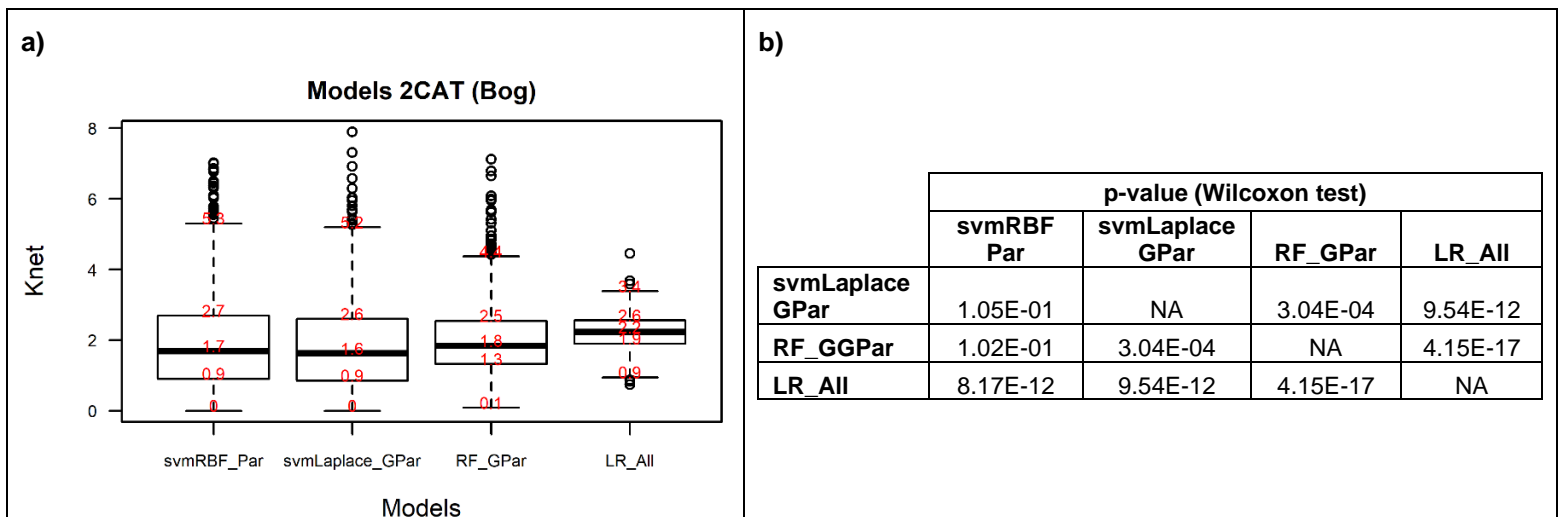
Figure 47 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 11) based on the binomial logistic regressions (LR) for the pipe level management objective for the third SCS.



**Figure 47. Results of the validation data of the LR-based deterioration for the pipe level objective (*Kpipe*) for the third SCS (two structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 47.a., the LR-based model that most minimize the  $Kpipe$  metric is the one that includes all the studied variables. However, this model does not show significant (Figure 47.b.) differences with LR-based model including the variables that show the first and second relationship grade (GPar) with the structural condition for the third SCS.

In summary, for this SCS that groups the structural condition scenarios between sewer assets without and with structural damages, the deterioration models that most minimize the  $Kpipe$  values in the validation data were: (i) SVM-RBF based deterioration models considering only first relationship grade variables (Par); (ii) SVM-Laplace based deterioration models considering first and second relationship grade variables (GPar); (iii) RF-based deterioration models considering first and second relationship grade variables (GPar); and (iv) Ordinal logistic regression-based deterioration models considering all studied variables.

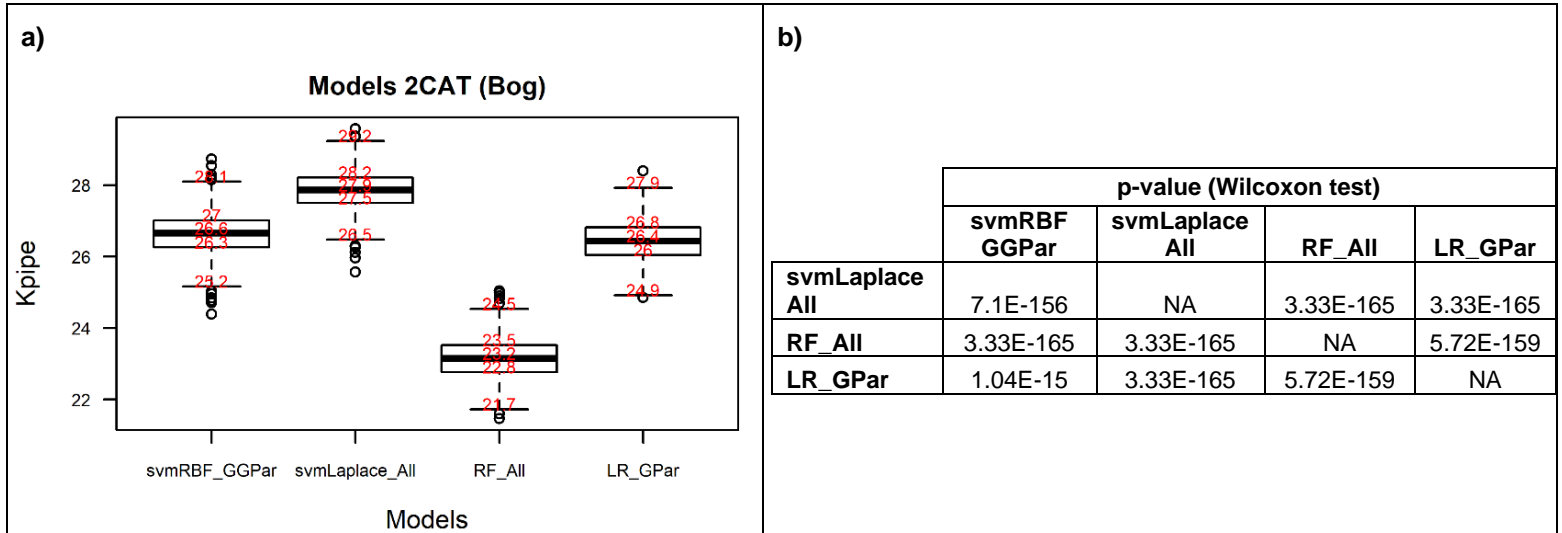


**Figure 48. Comparison of the most suitable deterioration model to achieve the management objective at network level for the third structural condition scenario (2 structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 48.a, SVM-based models are the ones with lowest  $Knet$  values for validation data. However, the boxplots of both models show distribution of  $Knet$  values very similar. Wilcoxon test was carried out to these models and it was found that there are not significant differences between them (Figure 48.b). Therefore, the model chosen for predicting the structural conditions at network level for this scenario was SVM-RBF based model, because it needs less quantity of variables to achieve the lowest values of  $Knet$ .

According to the models chosen for finding the one that most minimize the  $Kpipe$  values for the present SCS, it was explored the best deterioration models of each method. These models were: (i) SVM-RBF based deterioration models considering first, second and third relationship grade

variables (GPar); (ii) SVM-Laplace based deterioration models considering all studied variables (All); (iii) RF-based deterioration models considering all studied variables (All); and (iv) binomial logistic regression-based deterioration models considering first and second relationship grade variables (GPar).



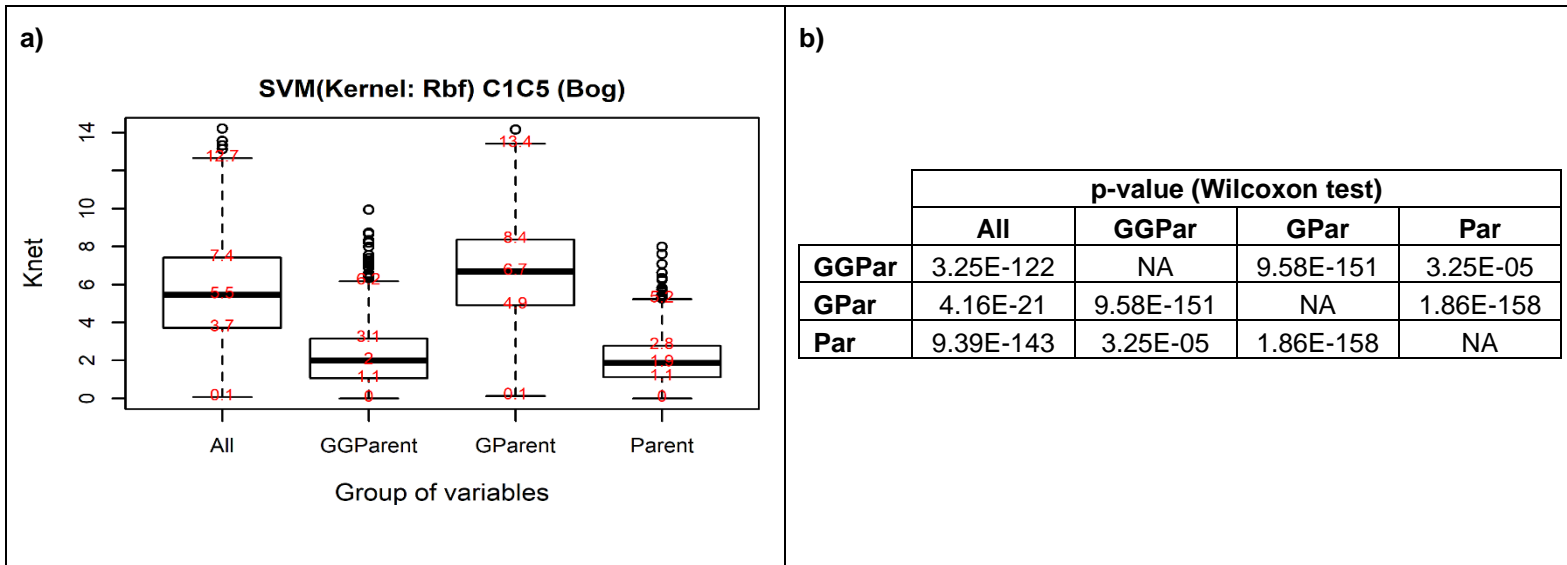
**Figure 49. Comparison of the most suitable deterioration model to achieve the management objective at pipe level for the third structural condition scenario (2 structural categories).** a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 49.a., RF-based model is the one with the lowest *Kpipe* values and shows significant differences with the other models (Figure 49.b). The values shown for this SCS shows that a scenario that groups the structural conditions in two categories arise the performance prediction, due to the rank of *Kpipe* values shown in these boxplots are around between 22.7 and 25.5 for RF-based models while for the scenario that groups the structural condition in three categories shows *Kpipe* values between 29.6 and 33.6 for RF-based models.

**D.1.4.4. Fourth SCS: excellent and critical structural conditions**

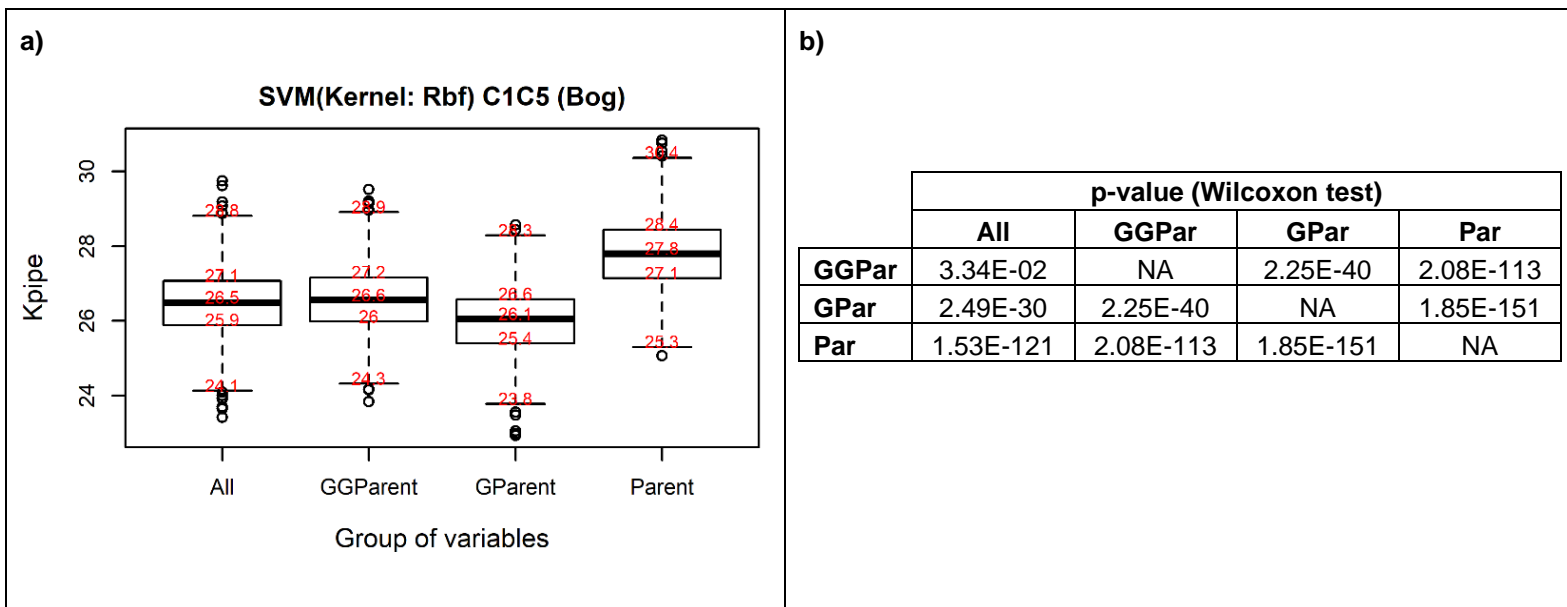
Figure 50 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 12) based on the optimised SVM considering RBF kernel function for the network level management objective (see the hyperparameters set in these models in Table 20) for the fourth SCS.

According to Figure 50, the SVM-RBF-based model that most minimize the *Knet* metric is the one that includes the variables that show first relationship grade (Parent) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).



*Figure 50. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the network level objective (Knet) and fourth SCS (excellent and critical structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

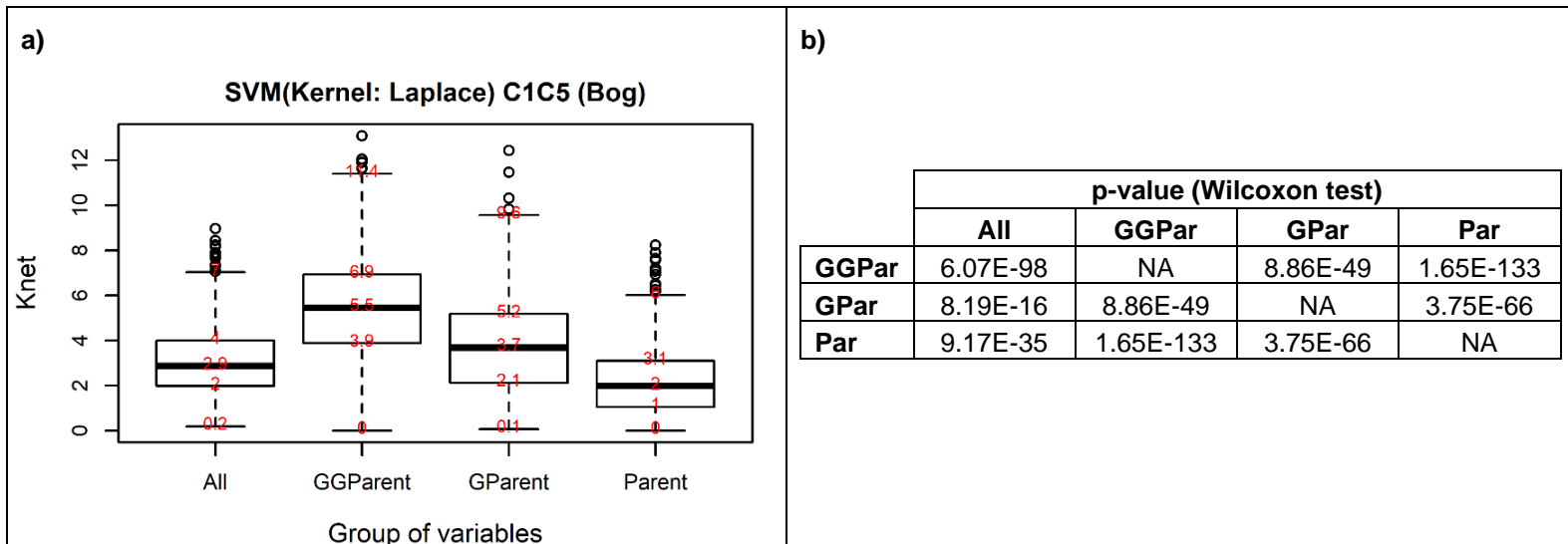
Figure 50 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 12) based on the optimised SVM considering RBF kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 21) for the fourth SCS.



*Figure 51. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the pipe level objective (Kpipe) and fourth SCS (excellent and critical structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 51, the SVM-RBF-based model that most minimize the *Kpipe* metric is the one that includes the variables that show first and second relationship grade (GParent) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).

Figure 52 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 12) based on the optimised SVM considering Laplace kernel function for the network level management objective (see the hyperparameters set in these models in Table 20) for the fourth SCS.



*Figure 52. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the network level objective (Knet) and fourth SCS (excellent and critical structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 52, the SVM-Laplace-based model that most minimize the *Knet* metric is the one that includes the variables that only show first relationship grade (Parent) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).

Figure 53 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 12) based on the optimised SVM considering Laplace kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 21) for the fourth SCS.

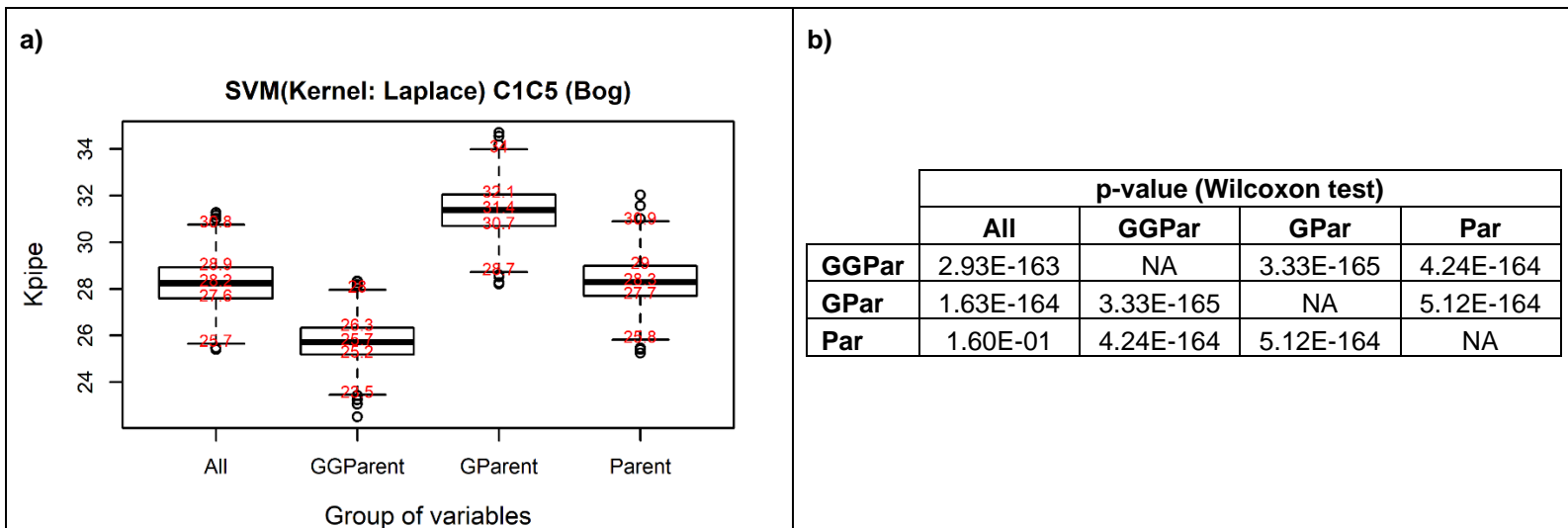
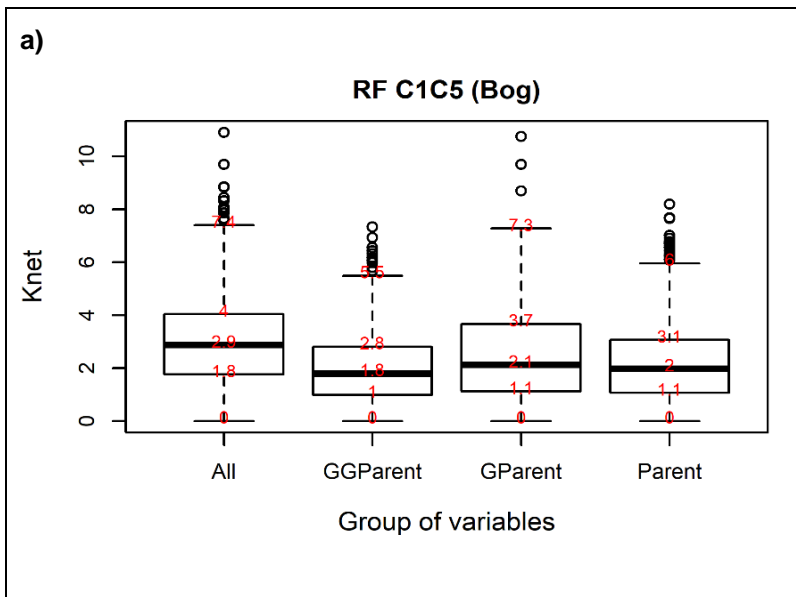


Figure 53. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the pipe level objective ( $K_{pipe}$ ) and fourth SCS (excellent and critical structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 53, the SVM-Laplace-based model that most minimize the  $K_{pipe}$  metric is the one that includes the variables that show any relationship of first, second and third grade (GGPar) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ). Furthermore, it is interesting that the prediction results of the SVM-Laplace-based models that includes all the studied variables and only the first relationship grade (Parent variables) with the structural condition do not show significant differences.

Figure 54 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 12) based on RF for the network level management objective (see the hyperparameters set in these models in Table 20) for the fourth SCS.

According to Figure 54, the RF-based model that most minimize the  $K_{net}$  metric is the one that includes the variables that any relationship of first, second and third grade (GGParent variables) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ).

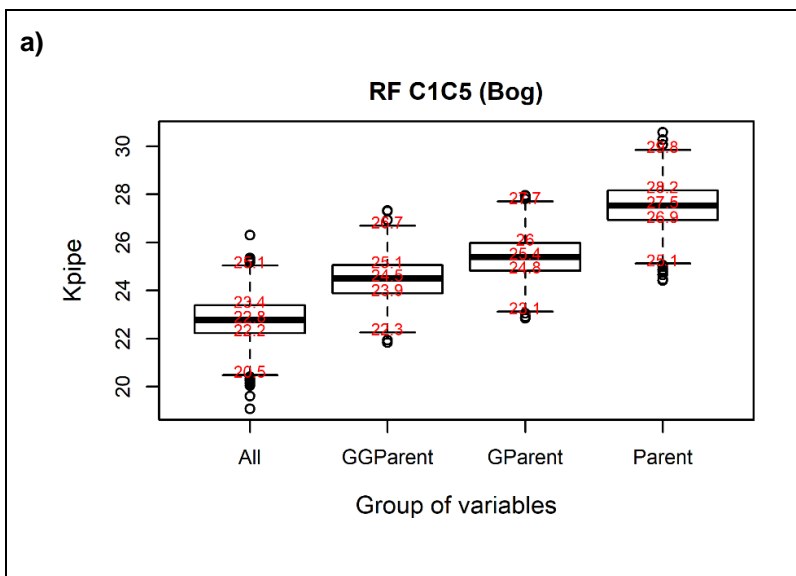


b)

	p-value (Wilcoxon test)			
	All	GGPar	GPar	Par
GGPar	1.1E-46	NA	6.91E-22	7.96E-09
GPar	1.01E-07	6.91E-22	NA	1.59E-05
Par	1.53E-21	7.96E-09	1.59E-05	NA

Figure 54. Results of the validation data of the RF-based deterioration models for the network level objective (Knet) and fourth SCS (excellent and critical structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

Figure 55 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 12) based on RF for the pipe level management objective (see the hyperparameters set in these models in Table 21) for the fourth SCS.



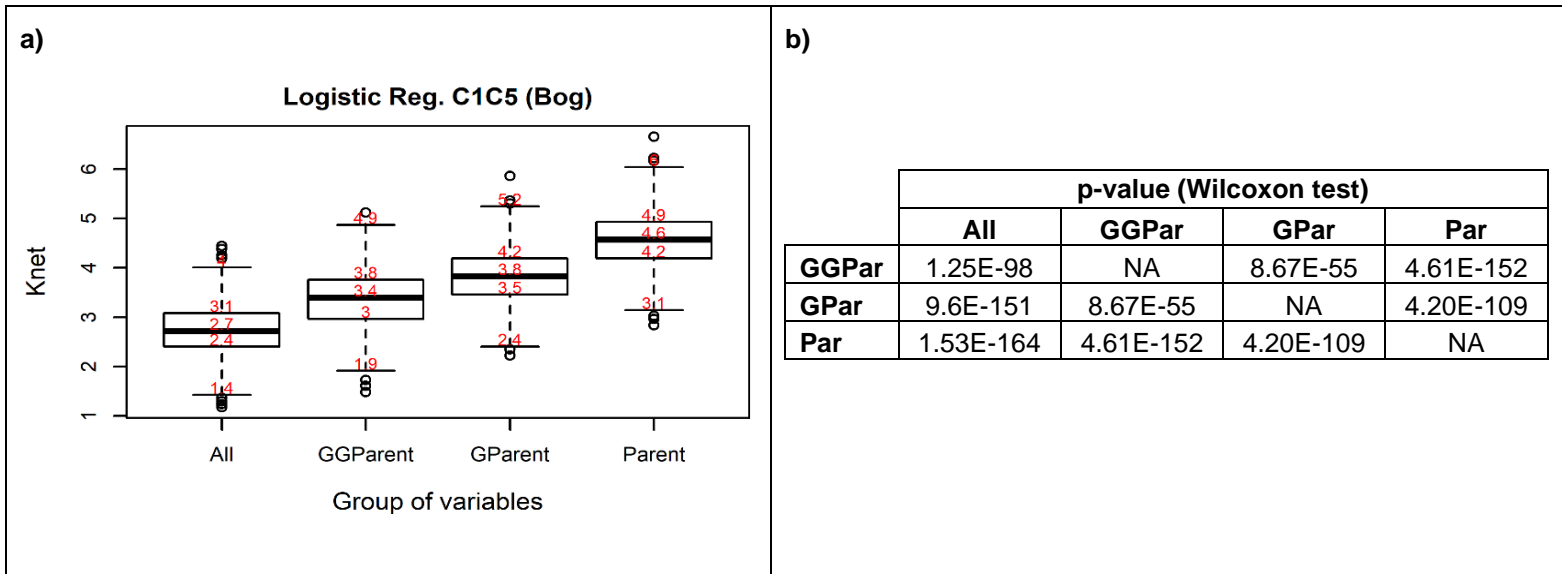
b)

	p-value (Wilcoxon test)			
	All	GGPar	GPar	Par
GGPar	6.85E-146	NA	1.46E-83	1.86E-157
GPar	3.99E-164	1.46E-83	NA	6.07E-165
Par	3.36E-165	1.86E-157	6.07E-165	NA

Figure 55. Results of the validation data of the RF-based deterioration models for the pipe level objective (Kpipe) and fourth SCS (excellent and critical structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 55, the RF-based model that most minimize the  $K_{pipe}$  metric is the one that includes the all studied variables for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 56 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 12) based on LR for the network level management objective for the fourth SCS.

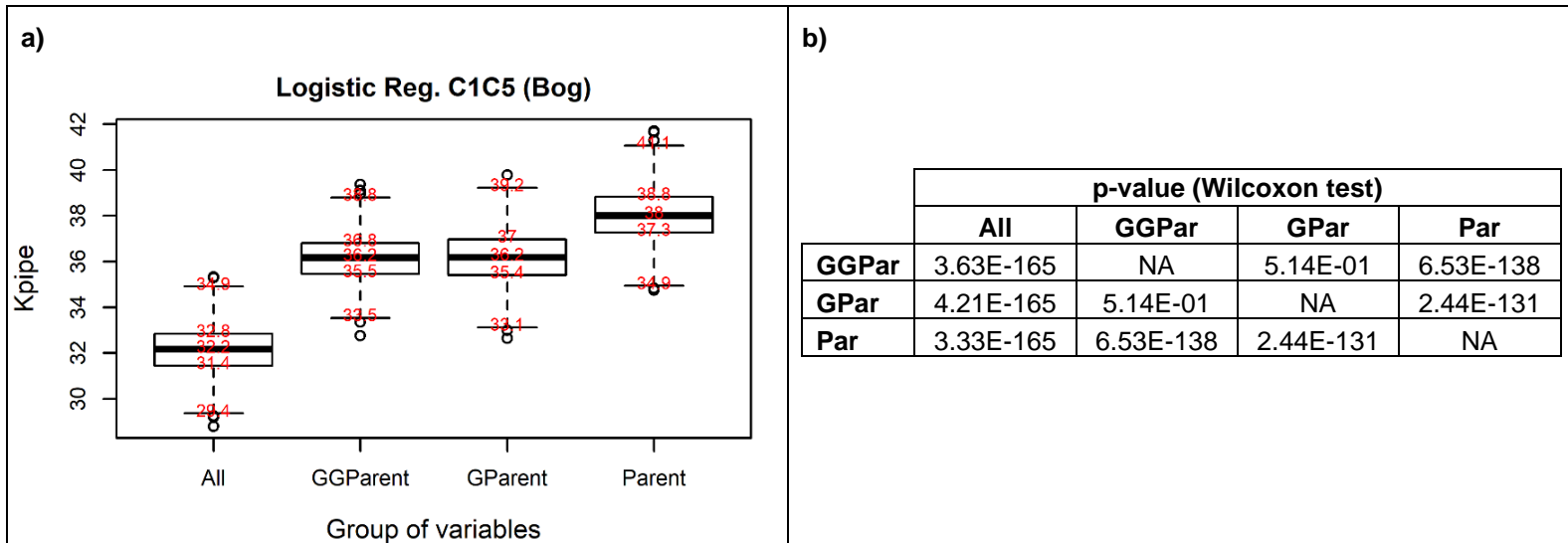


**Figure 56. Results of the validation data of the LR-based deterioration models for the network level objective ( $K_{net}$ ) and fourth SCS (excellent and critical structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 56, the LR-based model that most minimize the  $K_{net}$  metric is the one that includes the all studied variables for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 57 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 12) based on LR for the pipe level management objective for the fourth SCS.

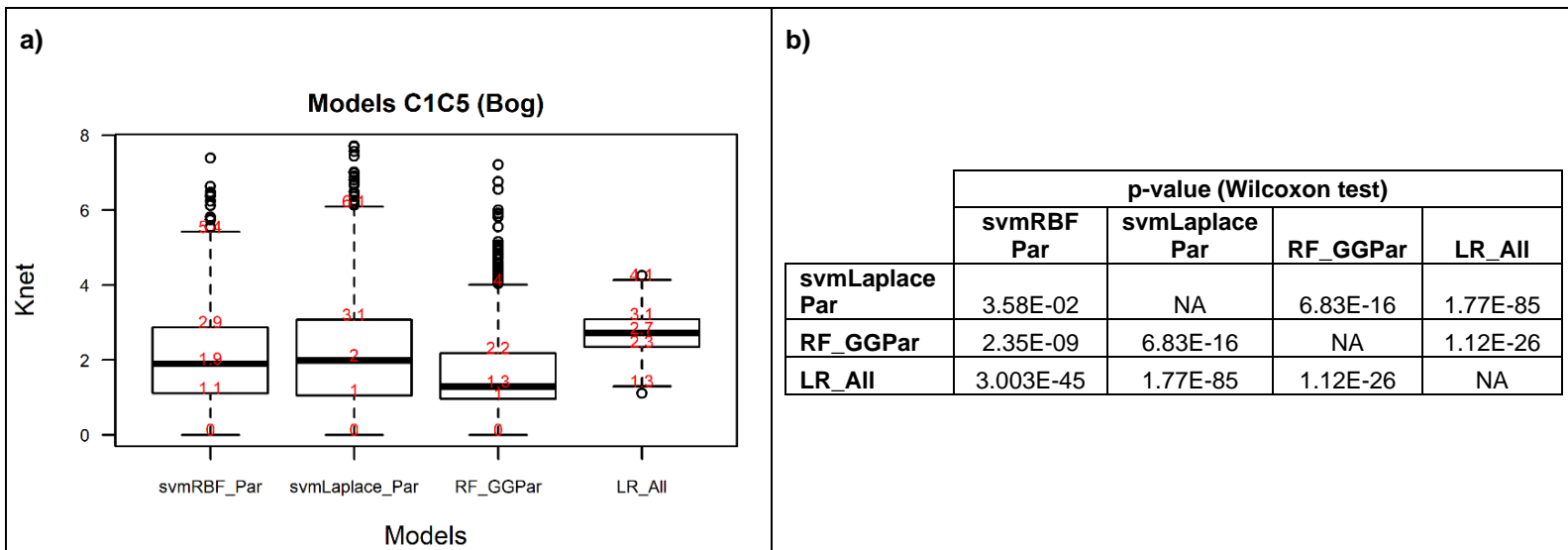




**Figure 57. Results of the validation data of the LR-based deterioration models for the pipe level objective ( $K_{pipe}$ ) and fourth SCS (excellent and critical structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 57, the LR-based model that most minimize the  $K_{pipe}$  metric is the one that includes the all studied variables for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

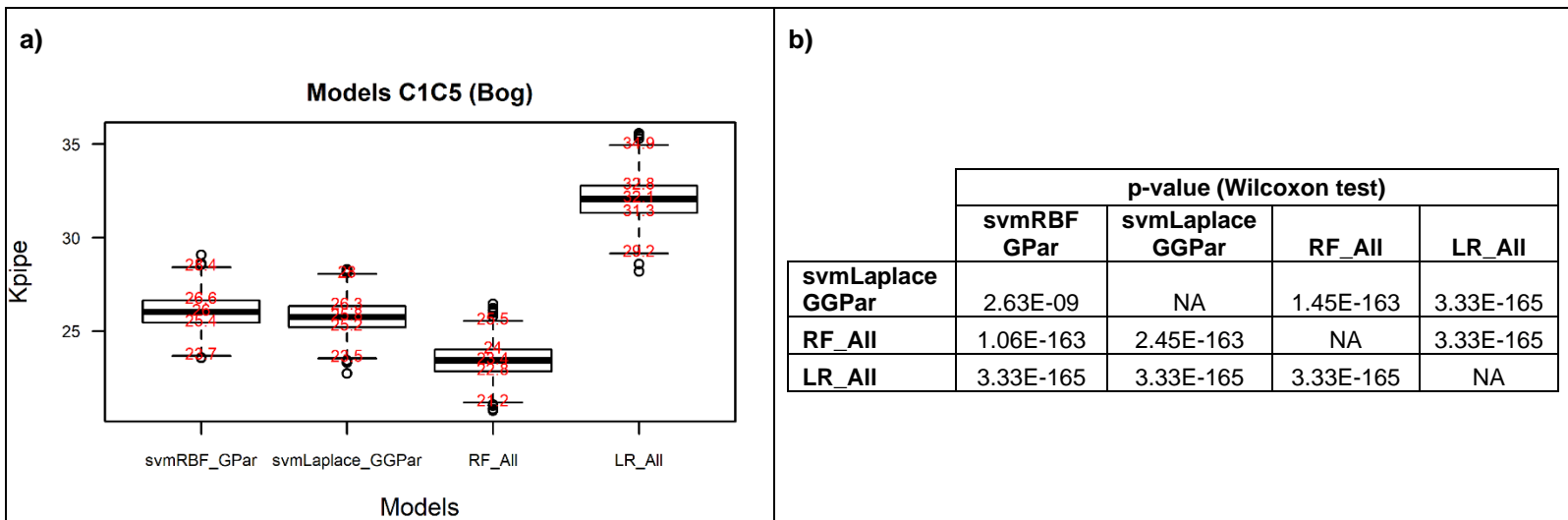
For the last structural condition scenario (SCS), excellent and critical structural conditions, the deterioration models that most minimize the  $K_{net}$  values in the validation data were: (i) SVM-RBF based deterioration models considering only first relationship grade variables (Par); (ii) SVM-Laplace based deterioration models considering only first relationship grade variables (Par); (iii) RF-based deterioration models considering first, second and third relationship grade variables (GGPar); and (iv) Binomial logistic regression-based deterioration models considering all studied variables.



*Figure 58. Comparison of the most suitable deterioration model to achieve the management objective at network level for the fourth structural condition scenario (excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 58.a., RF-based deterioration models is the one with the lowest *Knet* values, however the *Knet* values of SVM-models have close values. Figure 58.b shows that RF-based model has significant difference with the other evaluated models, therefore RF-based model considering the grand-grandparent variables are the chosen for achieving *Knet* management objectives for this SCS.

For achieving pipe level objectives, the deterioration models that most minimize the *Kpipe* values in the validation data were: (i) SVM-RBF based deterioration models considering the first and second relationship grade variables (GPar); (ii) SVM-Laplace based deterioration models considering the first and second relationship grade variables (GGPar); (iii) RF-based deterioration models considering all studied variables (All); and (iv) binomial logistic regression-based deterioration models considering all studied variables.



**Figure 59. Comparison of the most suitable deterioration model to achieve the management objective at pipe level for the fourth structural condition scenario (excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 59.a., RF-based deterioration model is also the one that increase the performance predictions for achieving pipe level objectives over other models (p-value<0.05 – Figure 59.b.).

*D.1.4.5. Analysis of the most suitable models for management objectives*

**Table 22. p-values obtained by the comparison of the deterioration models by Wilcoxon test (Knet) for the four SCS.**

	p-value (Wilcoxon test)			
	5_COND	3_CAT	2_CAT	C1C5
3_CAT	7.69E-17	NA	7.45E-85	5.72E-115
2_CAT	4.34E-35	7.45E-84	NA	9.54E-07
C1C5	1.41E-56	5.72E-115	9.54E-07	NA

Source: Author

**Table 23. p-values obtained by the comparison of the deterioration models by Wilcoxon test (Kpipe) for the four SCS.**

	p-value (Wilcoxon test)			
	5_COND	3_CAT	2_CAT	C1C5
3_CAT	5,74E-149	NA	3,33E-151	3,33E-151
2_CAT	3,33E-151	3,33E-151	NA	6,96E-01
C1C5	3,33E-151	3,33E-151	6,96E-01	NA

Source: Author

## APPENDIX – Part D.2. Medellín’s case

This appendix shows the results of the application of the proposed methodology in Medellín’s case in detail. This subchapter consists of three parts: (i) the hierarchy of the most influential variables over the structural condition obtained after applying the methodology described in chapter 9.1.(Part C); (ii) the optimisation of the selected deterioration models for management objectives, methodology described in chapter 9.2. (Part C); and (iii) the results of the optimised deterioration models for management objectives, methodology described in chapter 9.2. (Part C).

Each part shows the results for each structural condition scenario described in Table D.16. (Part D) of the manuscript.

### D.2.1. Hierarchy of the most influential variables

#### D.2.1.1. Five structural grades

Table 24 shows the variables' relationships hierarchy considering the structural condition as the local assessment standard for Medellín’s city (EPM, 2010). According to the Bayesian Network-based methodology, from the 23 studied variables for Medellín’s case, 7 variables show a non-depreciable relationship with the five structural grades (median  $\geq$  0.05). Variables such as diameter, length, slope, depth, soil type, type of element, operational status, districts, city, land uses, seismic zone, road type, closeness of trees, flooding zones, and longitude and latitude coordinates were variables that do not show influence over the structural condition of the sewer assets, when the five structural grades are considered for prediction purposes.

*Table 24. Classification of the variables' relationship with five structural grades (first SCS)*

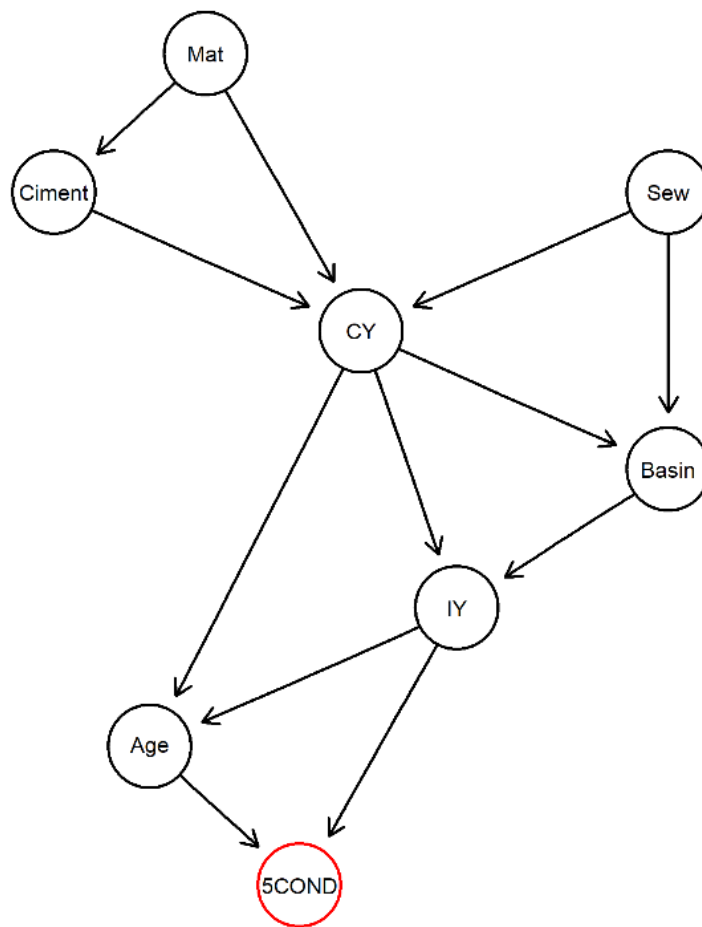
Relationship Type	Order	Variables	Median	Q1	Q3	IQR	Median/IQR
First (Parent variables)	1	Inspection Year (“IY”)	1	1	1	0	<b>1000</b>
	2	Age (“Age”)	1	0.98	1	0.02	<b>48.03</b>
Second (GParent variables)	3	Installation Year (“CY”)	1	0.99	1	0.01	<b>76.34</b>
	4	Basin (“Basin”)	0.15	0	0.74	0.74	<b>0.20</b>
Third (GGParent variables)	5	Material (“Mat”)	1	1	1	0	<b>1000</b>
	6	Foundation Type (“Ciment”)	1	1	1	0	<b>1000</b>
	7	Type of effluent (“Sew”)	0.37	0	1	1	<b>0.37</b>

*Source: Author*

Figure 60 shows a Bayesian Network that illustrates the predecessor variables of the five structural grades considering non-depreciable relationships among the variables (Boxplot median

$\geq 0.05$ ). The name of the variables shown in Figure 53. **Error! Reference source not found.** are depicted according to the abbreviations shown in Table 24.

According to Figure 60, Material (“Mat”), type of effluent (“Sew”) and foundation type (“Ciment”) are the roots of the Bayesian Networks: most of the other variables are related in some way to them. Most of variables that show a direct relationship with the five structural conditions are the variables related to the age and inspection year of the sewer assets. Coming back to the bar plot analysis of the item 5.2.2.3 of Part B, the variables related to the age had an apparent strong relationship with the deterioration if the structural condition; material (“Mat”), type of effluent (“Sew”) and basin (“Basin”) also display relationship with structural condition in particular those sewer assets in concrete and separate sewer system kinds that shown higher percentages of sewer deterioration. Foundation Type (“Ciment”) did not show any relationship with the structural condition in the previous bar plot analysis.



*Figure 60. Bayesian Network that illustrates the different relationship of the studied variables with five structural grades (first SCS), leaving aside variables that show depreciable relationship (boxplot median < 0.05). Source: Author.*

### D.2.1.2. Three structural categories

Table 25 shows the variables' relationship hierarchy considering the structural condition in three structural categories that group the structural condition in acceptable, poor and critical structural conditions in accordance with the Equation C.3. (Part C), as it is shown in Table D.16. (Part D). According to the Bayesian Network-based methodology, from the 23 studied variables for Medellín's case, 9 variables show a non-depreciable relationship with the three structural categories (median  $\geq 0.05$ ). Variables such as diameter, slope, depth, soil type, type of element, operational status, city, land uses, seismic zone, road type, closeness of trees, flooding zones, and longitude and latitude coordinates were variables that do not show influence over the structural condition of the sewer assets, when the structural condition consists of three categories.

**Table 25. Classification of the variables' relationship with three structural categories (second SCS)**

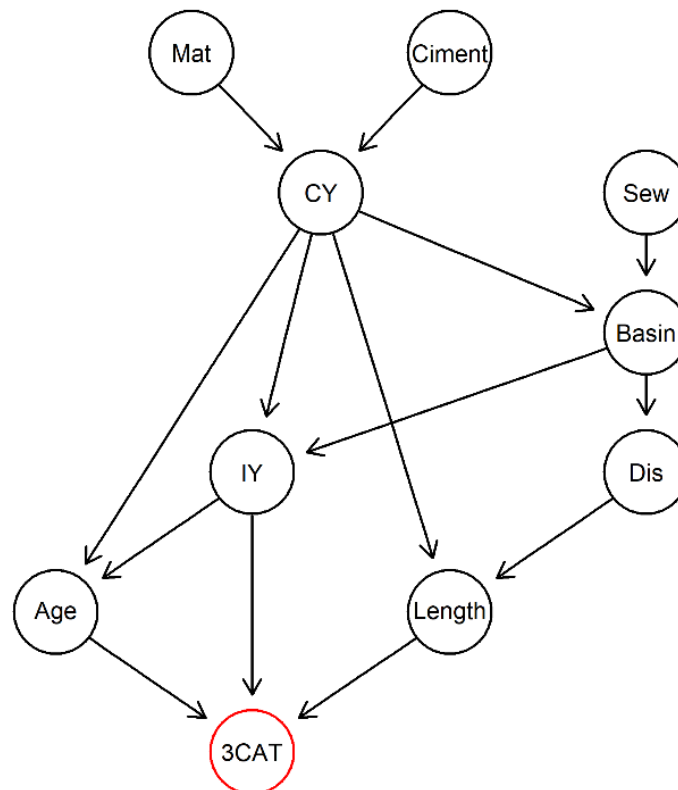
Relationship Type	Order	Variables	Median	Q1	Q3	IQR	median/IQR
First (Parent variables)	1	Inspection Year ("IY")	1	1	1	0	<b>1000</b>
	2	Age ("Age")	1	0.98	1	0.02	<b>48.03</b>
	3	Length ("Length")	0.12	0.00	0.34	0.34	<b>0.34</b>
Second (GParent variables)	4	District ("Dis")	1	0.75	1	0.25	<b>4</b>
	5	Installation Year ("CY")	1	0.98	1	0.02	<b>61.73</b>
	6	Basin ("Basin")	0.14	0	0.71	0.71	<b>0.20</b>
Third (GGParent variables)	7	Material ("Mat")	1	1	1	0	<b>1000</b>
	8	Foundation Type ("Ciment")	1	1	1	0	<b>1000</b>
	9	Type of effluent ("Sew")	0.464	0	1	1	<b>0.46</b>

*Source: Author*

Figure 55 shows a Bayesian Network that illustrates the predecessor variables of the three structural categories considering non-depreciable relationships among the variables (Boxplot median  $\geq 0.05$ ). The name of the variables shown in Figure 55 **Error! Reference source not found.** are depicted according to the abbreviations shown in Table 25.

According to Figure 55, Material ("Mat"), type of effluent ("Sew") and foundation type ("Ciment") are also the roots of the Bayesian Networks: most of the other variables are related in some way to them. Most of variables that show a direct relationship with the three structural categories are the variables related to the age, inspection year and length of the sewer assets. Moreover, for this SCS the variable district ("Dis") took relevance reinforced the premise together with Basin ("Basin") that the location in which is located the sewer assets influence over the deterioration of sewer assets. However, basin ("Basin") and districts ("Dis") shows a relation of second and third level grade with the structural condition, while variables related to age ("IY", "CY" and "Age") show

a relationship of first level grade. It means that the fact that basin and district influence on the deterioration of the sewer assets depend on the evolution of the urban growth of the city: the oldest sewer assets are in the first settled areas. Coming back to the bar plot analysis of the item 5.2.2.3 of Part B, length (“Length”), age (“Age”) and inspection year (“IY”) show an apparent strong relationship with structural condition, as well as basin (“Basin”), district (“Dis”), type of effluent (“Sew”) and material (“Mat”) of the sewer assets. Nevertheless, foundation type (“Ciment”) did not show any relationship with the structural condition in the previous bar plot analysis.



**Figure 61. Bayesian Network that illustrates the different relationship of the studied variables with three structural categories (second SCS: acceptable, poor and critical structural conditions), leaving aside variables that show depreciable relationship (boxplot median < 0.05). Source: Author.**

### D.2.1.3. Two structural categories

Table 26 shows the variables' relationship hierarchy considering the structural condition in two structural categories that group the structural condition in acceptable and poor-critical structural conditions in accordance with the Equation C.3. (Part C), as it is shown in Table D.14. (Part D). According to the Bayesian Network-based methodology, from the 23 studied variables for Medellín's case, 9 variables show a non-depreciable relationship with the two structural categories (median  $\geq 0.05$ ). Variables such as diameter, slope, depth, soil type, type of element, operational

status, city, land uses, seismic zone, road type, closeness of trees, flooding zones, and longitude and latitude coordinates were variables that do not show influence over the structural condition of the sewer assets, when the structural condition consists of two categories.

Furthermore, Table 26 shows that more variables have a direct relationship with the structural condition for the third SCS in comparison with the SCS that group the structural condition in more than two categories. Therefore, variables such as inspection year (“IY”), construction year (“CY”), material (“Mat”), length (“length”) and (“Age”), relationships that are visible in Figure 62.

**Table 26. Classification of the variables' relationship with two structural categories (third SCS: Acceptable and poor-critical structural conditions)**

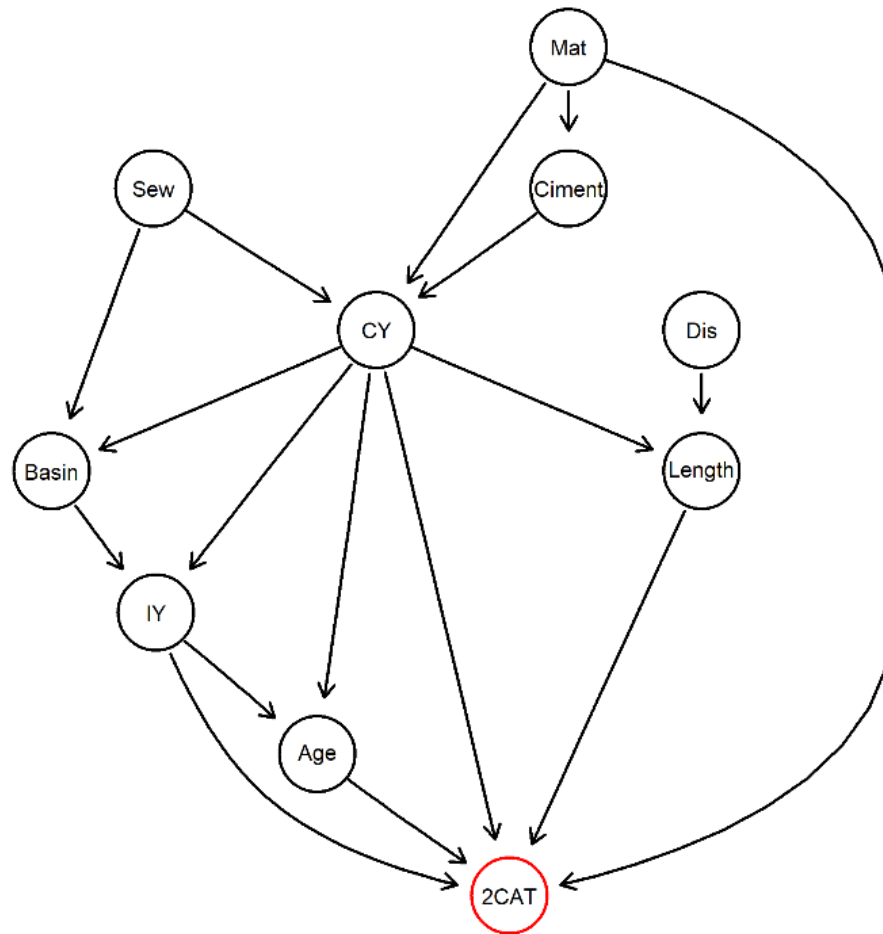
Relationship Type	Order	Variables	Median	Q1	Q3	IQR	median/IQR
First (Parent variables)	1	Inspection Year (“IY”)	1	0.996	1	0.004	<b>238.10</b>
	2	Installation Year (“CY”)	0.91	0.75	0.98	0.23	<b>3.99</b>
	3	Material (“Mat”)	0.65	0.14	0.75	0.61	<b>1.06</b>
	4	Length (“Length”)	0.24	0.06	0.35	0.29	<b>0.82</b>
	5	Age (“Age”)	0.09	0.03	0.20	0.17	<b>0.54</b>
Second (GParent variables)	6	Basin (“Basin”)	0.14	0	0.72	0.72	<b>0.19</b>
	7	Foundation Type (“Ciment”)	1	1	1	0	<b>1000</b>
	8	District (“Dis”)	1	0.12	1	0.88	<b>1.14</b>
Third (GGParent variables)	9	Type of effluent (“Sew”)	0.33	0	1	1	<b>0.33</b>

*Source: Author*

According to Figure 62, the root variables of the Bayesian Network are the type of effluent (“Sew”), districts (“Dis”) and material (“Mat”) of the sewer assets which have relationship with the other variables that do not show a depreciable relationship (boxplot median > 0.05). Some relationships that the Bayesian Network shows are: (i) type of effluent (“Sew”) with the age (“Age”) of the sewer assets and the basin (“Basin”) in which are the sewer assets; (ii) material (“Mat”) of the sewer assets and foundation type (“Ciment”) of the sewer assets; and (iii) District (“Dis”) and length (“length”) of the sewer assets.

The variables that show any relationship with structural condition of the sewer assets for the third SCS (two structural categories: acceptable and poor-critical conditions) are the same that for second SCS (three structural categories: acceptable, poor and critical conditions), however, the relationship grade is different: for the third SCS the variables show stronger relationship with the structural condition, except the type of effluent (“Sew”) that remained in the third relationship level grade.





**Figure 62. Bayesian Network that illustrates the different relationship of the studied variables with two structural categories (third SCS: acceptable and poor-critical structural conditions), leaving aside variables that show depreciable relationship (boxplot median < 0.05). Source: Author.**

#### *D.2.1.4. Excellent and critical structural conditions*

Table 27 shows the variables' relationship hierarchy considering the structural condition in two structural categories that only considered sewer assets in excellent and critical structural conditions, leaving aside the intermediate conditions (good, acceptable and poor). According to the Bayesian Network-based methodology, from the 23 studied variables for Medellín's case, 11 variables show a non-depreciable relationship with these two structural conditions (median  $\geq 0.05$ ). Variables such as length, slope, soil type, type of element, city, land uses, road type, closeness of trees, flooding zones, type of effluent, and longitude and latitude coordinates were variables that do not show influence over the structural condition of the sewer assets, when the structural condition consists on these two structural conditions. Furthermore, the variables that

show direct relationship with the structural for this SCS are the ones related with the age of the sewer assets: inspection year (“IY”), construction year (“CY”) and age (“Age”) of the sewer assets.

*Table 27. Classification of the variables' relationship with two structural categories (fourth SCS: excellent and critical conditions)*

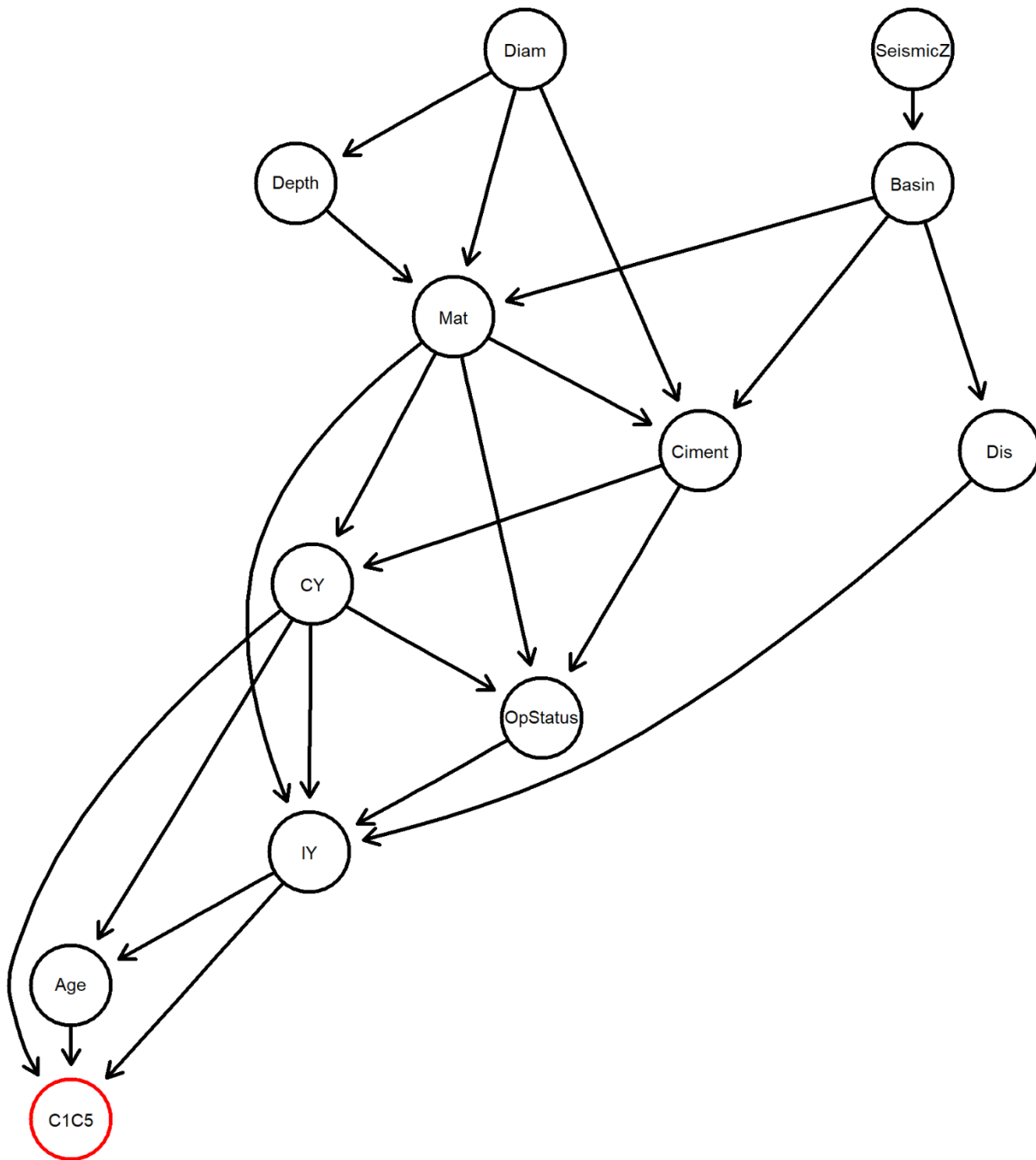
Relationship Type	Order	Variables	Median	Q1	Q3	IQR	median/IQR
First (Parent variables)	1	Inspection Year (“IY”)	0.99	0.82	1	0.179	5.55
	2	Installation Year (“CY”)	0.93	0.55	1.00	0.449	2.08
	3	Age (“Age”)	0.06	0.00	0.23	0.226	0.27
Second (GParent variables)	4	Foundation Type (“Ciment”)	1	1	1	0	1000
	5	Material (“Mat”)	1.00	0.934	1	0.07	15.13
	6	Operational Status (“OpStatus”)	0.15	0.006	0.33	0.32	0.47
	7	Districts (“Dis”)	0.39	0.021	0.86	0.83	0.46
Third (GGParent variables)	8	Diameter (“Diam”)	1	0.992	1	0.01	121.95
	9	Basin (“Basin”)	1	1	1	0	1000
	10	Depth (“Depth”)	0.09	0.05	0.15	0.10	0.84
	11	Seismic Zone (“SeismicZ”)	0.78	0.06	1	0.94	0.84

*Source: Author*

Figure 63 shows a Bayesian Network that illustrates the predecessor variables of these two structural conditions non-depreciable relationship among the variables (boxplot median > 0.05).

According Figure 63, the root variables of the Bayesian Network are diameter (“Diam”), depth (“Depth”) and seismic zones (“SeismicZ”), which are the variables that have relationship with other variables that do not show a depreciable relationship with the structural conditions. Moreover, physical characteristics such as diameter (“Diam”), depth (“Depth”), and material (“Mat”) of sewer assets show a relationship with the structural condition which in turn these are related with the age variables; likewise, variables related to the location (seismic zones – “SeismicZ”, basin – “Basin” and districts – “Dis”) of sewer assets show also a relationship with the structural condition which in turn present with the age variables. In comparison with the other SCS, the fourth SCS (excellent and critical structural conditions) does not consider the type of effluent (“Sew”) and length (“Length”) as influential variables for the excellent and critical conditions for Medellin’s case.

In addition, this figure shows unexpected relationships such as: (i) material (“Mat”) and foundation type (“Ciment”); (ii) material (“Mat”) and operational status (“OpStatus”); and (iii) construction year (“CY”) with operational status (“OpStatus”).



*Figure 63. Bayesian Network that illustrates the different relationship of the studied variables with two structural categories (fourth SCS: excellent and critical structural conditions), leaving aside variables that show depreciable relationship (boxplot median < 0.05). Source: Author.*

## D.2.2. Exploration of deterioration models

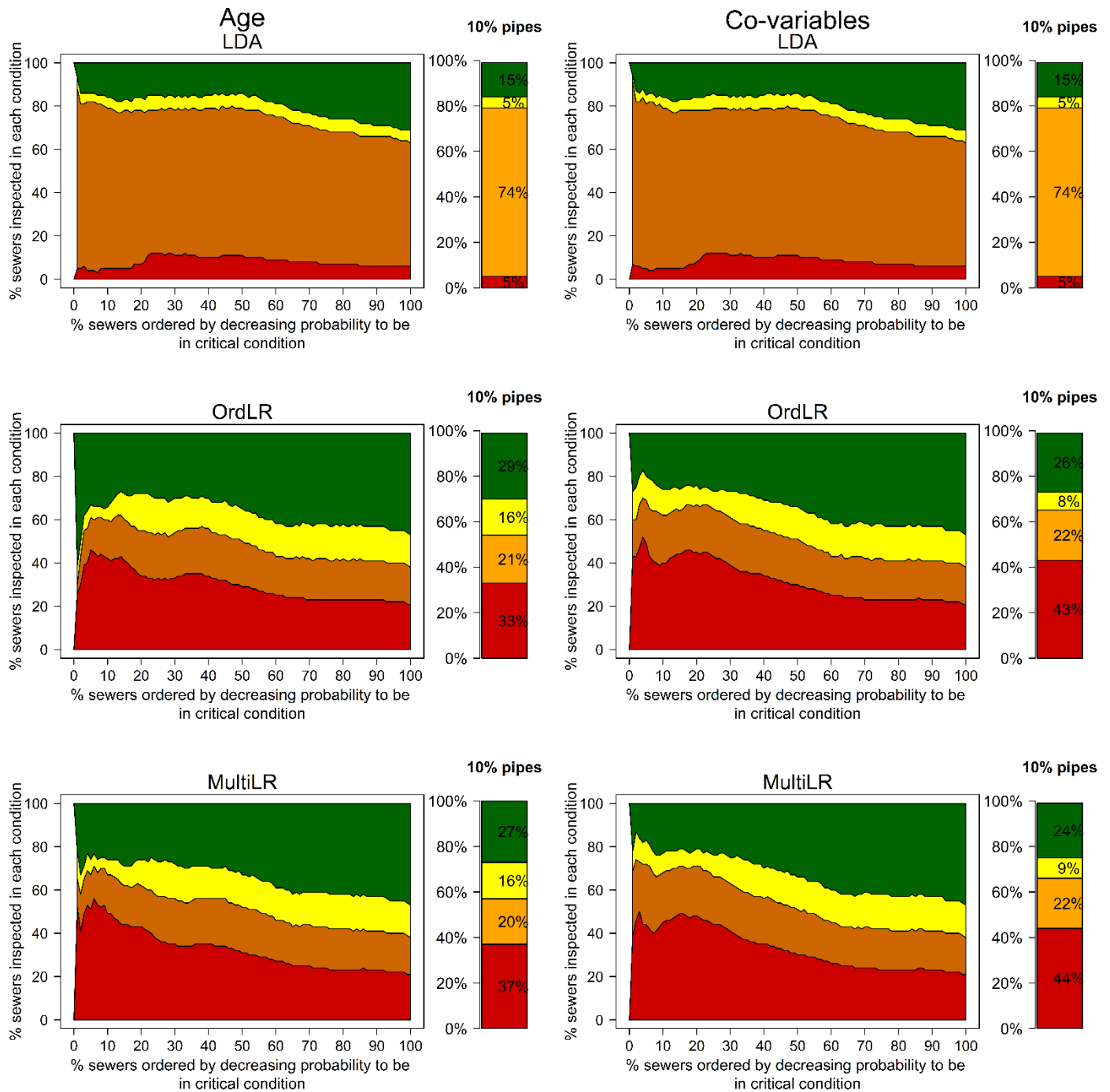


Figure 64. LDA, Ord\_LR and Multi\_LR performance curves with a sample on its right of 10% pipes. Left: scenario 1 (considering only the age as influential variable); right: scenario 2 (considering the age and other variables as influential variables) for Medellín's case

### D.2.3. Optimisation of the selected deterioration models for management objectives

Likewise, as Bogota's case, the models showed in Table 13 were the optimised one applying the proposed methodology (chapters 8 and 9) for Medellin's case.

#### D.2.2.1. First SCS: Five structural grades

Regarding the first Structural Condition scenario, Tables 28 and 29 show the combination of hyperparameters found following the optimisation methodology proposed in Chapter 8 and 9 of Part C of this manuscript.

These tables show the combination of hyperparameters found for support vector machines with Radial Basis (RBF) and Laplace Kernel functions and Random Forest.

*Table 28. Optimal hyperparameters found at Network level for the first SCS.*

SVM-RBF									
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>W4</i>	<i>W5</i>	<i>Knet (CV)</i>	
All	0.03514	8.9172	5.8014	5.9396	7.8708	6.7521	6.5186	0.744	
GGParent	1947.388	1659.651	5.3024	10.1236	8.6048	3.4676	2.6648	1.459	
Gparent	491.267	3410.949	5.7046	11.0196	11.4141	4.9837	2.6506	1.276	
Parent	482.862	1830.1692	2.6319	10.4158	8.3109	1.8787	2.1080	1.353	
SVM-Laplace									
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>W4</i>	<i>W5</i>	<i>Knet (CV)</i>	
All	0.0232	3442.4109	10.0080	4.4721	11.0038	11.8148	5.8807	3.028	
GGParent	924.275	4228.1393	6.9147	10.1391	10.1634	3.9302	2.7182	1.400	
Gparent	4170.247	3371.4481	5.4387	11.6392	11.3041	4.8493	2.8162	1.189	
Parent	3655.688	429.4686	3.3899	11.9917	10.8910	2.6951	2.6799	1.093	
RF									
Variables	<i>Ntrees</i>	<i>NodeSizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>W4</i>	<i>W5</i>	<i>Knet (CV)</i>
All	1654	15	11	8.7403	6.2832	8.2827	11.6520	1.0036	1.069
GGParent	3271	60	2	8.9108	3.0647	4.9924	11.5423	1.4767	2.168
Gparent	2777	182	4	8.5173	3.2720	4.7449	11.5023	1.1057	2.074
Parent	1008	37	2	6.9744	2.7299	4.0128	9.3013	1.3152	2.092

*Source: Author*

According to Table 28, the Sigma values for SVM-models (considering RBF and Laplace kernel functions) are higher in comparison to the ones obtained for Bogota's case under the same SCS and management objective (except for those models that considered all the collected variables). The C values are higher than 1600 for SVM\_RBF-based models (except for the model that

considers all collected variables) and 3300 for SVM\_Laplace-based models (except for the model that considers only the variables that show the first relationship grade – Parent variables). Regarding the weights obtained for both kind of SVM -based models, the weights W1, W4 and W5 are the ones with the lowest values and W2 and W3 are the ones the highest values (except for the SVM-based models that considers all variables). This behaviour is consistent with the percentage of data on each grade in the CCTV inspected data (see Figures in the section B.2.2. of the appendixes). The depicted *Knet* values obtained from the cross-validation of 1000 searchers were lower than 1.5 for all SVM-based deterioration models (except for SVM-Laplace considering all studied variables). Furthermore, these *Knet* values do not show any order when including or not variables in the developed deterioration models.

In accordance with RF-based models, the number of trees (*Ntrees*) and node of terminal sizes (*NodeSizes*) are lower for the models that considers all studied variables and those variables that only show the first relationship grade with the structural condition. Regarding number of random variables (*mtry*) on each tree, it is interesting that the models that considers Parent and GGPparent variables selects two variables to build each tree. The lowest weight values are related to grade 2 and 5 (W2 and W5). The displayed *Knet* values obtained from the cross-validation of 1000 searchers are lower than 2 for RF-based models.

Comparing the obtained *Knet* values, it is showed that SVM-based models are the ones that most minimize the *Knet* metric, rising the prediction quality at the network level for the first SCS.

According to Table 29, Sigma values are lower for SVM\_RBF-based models than SVM\_Laplace-based models, however Sigma values of both SVM-based models considering all variables are evidently lower than the other models. C values are higher without a particular behaviour. Regarding to the weights, those relative to critical conditions (grade 5) are the ones that show the highest values for minimizing the *Kpipe* values after 1000 searches. The depicted *Kpipe* values obtained from the cross-validation of 1000 searchers were lower than 25.5 for all SVM-based deterioration models. Furthermore, the SVM-based models that considers all studied variables and GGPparent variables show lower *Kpipe* values, being the model that include all the variables the one with the lowest *Kpipe* values.

Table 29. Optimal hyperparameters found at Pipe level for the first SCS.

SVM-RBF									
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>W4</i>	<i>W5</i>	<i>Kpipe (CV)</i>	
All	0.0008	190.2696	4.4146	1.8667	2.2772	2.7787	10.2757	22.828	
GGParent	63.1692	243.6046	7.3259	6.1712	3.1379	4.5970	10.6497	24.339	
Gparent	3572.6	3899.3593	5.5482	4.6321	2.4616	3.7427	9.7424	23.517	
Parent	400.1027	4037.3129	3.0230	3.9437	1.1504	2.3422	11.7437	25.516	
SVM-Laplace									
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>W4</i>	<i>W5</i>	<i>Kpipe (CV)</i>	
All	0.000163	623.6701	2.9205	2.9940	3.1101	1.8744	8.9509	22.971	
GGParent	3962.714	2383.5877	5.4568	4.8373	3.9488	3.1400	9.6211	24.369	
Gparent	3091.316	644.0035	6.2363	10.2742	3.4028	4.3704	11.5522	23.429	
Parent	3115.402	2704.8395	2.4229	3.4675	1.9468	1.7798	11.5101	25.350	
RF									
Variables	<i>Ntrees</i>	<i>NodeSizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>W4</i>	<i>W5</i>	<i>Kpipe (CV)</i>
All	2640	4668	1	3.4510	10.7077	6.8534	10.7563	7.0052	37.183
GGParent	3470	2217	1	4.8357	5.1296	4.2002	9.2953	2.6715	39.530
Gparent	3000	3030	1	11.6491	2.0326	2.4744	10.5558	2.3522	40.722
Parent	2452	3198	1	10.7162	6.9155	4.2836	10.5705	3.8995	40.023

Source: Author

Regarding RF-based models, the hyperparameters related to number of trees (*Ntrees*) and size of terminal nodes (*NodeSizes*) are high values without any particular behaviour. Moreover, it is interesting that RF-based models need only one random variable for each constructed tree of the random forest (*mtry*) for minimizing *Kpipe* value to increase the prediction quality at pipe level objective.

Comparing *Kpipe* values obtained from the cross-validation of the 1000 searches to minimize the *Kpipe* metric and thus raising the prediction performance at the pipe level, it is observed that SVM-based models more minimize the *Kpipe* values than RF-based models.

#### D.2.2.2. Second SCS: Three structural categories (Acceptable, poor and critical conditions)

Regarding the second Structural Condition Scenario (SCS), Tables 30 and 31 show the combination of hyperparameters found for Medellin's case following the optimisation methodology proposed in Chapter 8 and 9 of Part C of this manuscript. These tables show the combination of hyperparameters found for support vector machines with Radial Basis (RBF) and Laplace Kernel functions and Random Forest.

**Table 30. Optimal hyperparameters found at Network level for the second SCS.**

<b>SVM-RBF</b>							
<b>Variables</b>	<b>Sigma</b>	<b>C</b>	<b>W1</b>	<b>W2</b>	<b>W3</b>	<b>Knet (CV)</b>	
All	0.0033	2745.2637	6.8985	7.6525	7.0057	1.075	
GGParent	0.9345	4965.9666	7.5013	2.3118	6.0440	0.847	
GParent	1.0166	4149.9523	7.7379	8.4807	5.8622	1.117	
Parent	40.4771	2259.1025	2.8014	2.6816	11.0769	1.257	
<b>SVM-Laplace</b>							
<b>Variables</b>	<b>Sigma</b>	<b>C</b>	<b>W1</b>	<b>W2</b>	<b>W3</b>	<b>Knet (CV)</b>	
All	0.0003	1449.7342	11.8812	1.9594	2.1673	1.614	
GGParent	0.0159	179.8795	8.3824	6.0381	11.5924	1.180	
GParent	0.0837	3664.127	3.2332	5.3953	4.3038	0.924	
Parent	0.9716	2990.9073	7.5891	4.4406	3.8227	1.154	
<b>RF</b>							
<b>Variables</b>	<b>Ntrees</b>	<b>NodeSizes</b>	<b>mtry</b>	<b>W1</b>	<b>W2</b>	<b>W3</b>	<b>Knet (CV)</b>
All	1307	63	10	9.1272	11.5011	1.0391	1.301
GGParent	1640	173	8	8.2036	10.4690	1.0516	1.219
GParent	2676	2	6	9.6740	11.8655	1.1290	1.196
Parent	360	51	2	8.7611	9.9889	1.1616	1.313

*Source: Author*

According to Table 30, Sigma values are evidently lower than the ones obtained for the first SCS, while C values are similar. The weights values do not show a particular behaviour. The minimum *Knet* values after the optimisation were lower than 1.6 for both kind SVM-based models. Regarding RF-based models, the number of trees that contains each RF - based model are higher than 1300 (except for the model that consider only parent variables), while the size of the terminal nodes are lower than for the first at the same management level objective. The weights values are lower for the one related to the critical conditions (W3). The *Knet* values obtained for RF-based models varies between 1.2 and 1.3.



**Table 31. Optimal hyperparameters found at Pipe level for the second SCS.**

SVM-RBF							
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>Kpipe (CV)</i>	
All	0.0010	112.9593	3.1927	2.4082	11.5090	22.926	
GGParent	0.0042	82.0730	5.5117	3.9723	11.6124	23.483	
GParent	0.0059	255.5995	3.5700	3.0575	9.1002	24.449	
Parent	0.1965	3153.8227	3.0156	2.5066	11.6335	25.125	
SVM-Laplace							
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>Kpipe (CV)</i>	
All	0.0001	1029.4037	1.6479	1.3955	7.8314	22.880	
GGParent	0.0058	31.8292	2.9999	2.5174	6.6062	23.096	
GParent	0.0017	115.8326	3.6858	2.9079	10.6361	23.627	
Parent	0.0225	45.0334	1.8951	1.3851	7.2946	25.101	
RF							
Variables	<i>Ntrees</i>	<i>NodeSizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>W3</i>	<i>Kpipe (CV)</i>
All	2528	3212	2	6.6656	10.6053	5.3258	38.967
GGParent	1779	2425	1	4.5484	7.9887	3.0830	39.181
GParent	2564	2337	1	6.1637	8.2305	2.0314	39.139
Parent	2759	4325	1	6.5534	10.0058	3.3542	39.656

*Source: Author*

According to Sigma values found for both kind of SVM-based models are lower than the Sigma values obtained for first SCS at pipe level objective. It is interesting for SVM\_RBF-based models that the sigma is lower when the model considers higher number of variables. The found weight values for *Kpipe* level objective shows a particular behaviour comparing with the ones obtained for *Knet* level objective for SVM-based models. Regarding to RF-based models, the number of random variables for each tree continues to be minimum (1 or 2) as well as for the first SCS. Furthermore, the weights related to poor conditions (*W2*) are the highest to achieve most minimum *Kpipe* value. The *Kpipe* values of SVM-based models are lower with SVM-based models than RF-based models.

#### *D.2.2.3. Third SCS: Two structural categories (Acceptable and poor-critical conditions)*

Regarding the third Structural Condition Scenario (SCS), Tables 32 and 33 show the combination of hyperparameters found for Medellín's case following the optimisation methodology proposed in Chapter 8 and 9 of Part C of this manuscript. These tables show the combination of hyperparameters found for support vector machines with Radial Basis (RBF) and Laplace Kernel functions and Random Forest.

According to Table 32, SVM\_RBF-based models show lower Sigma values than SVM\_Laplace-based models, while C values are higher for SVM\_RBF-based models than SVM\_Laplace-based models for achieving network level objectives (*Knet* lower than 0.8, except for SVM\_Laplace-based model considering all the variables).

**Table 32. Optimal hyperparameters found at Network level for the third SCS.**

SVM-RBF						
Variables	Sigma	C	W1	W2	Knet (CV)	
All	0.0493	4412.3200	9.4009	5.1630	0.676	
GGParent	0.9634	1125.3794	10.1695	4.2620	0.625	
GParent	2.5361	2765.8007	8.0647	3.6874	0.723	
Parent	109.7640	1142.1558	7.8176	3.9478	0.660	
SVM-Laplace						
Variables	Sigma	C	W1	W2	Knet (CV)	
All	0.0667	1931.2357	6.3572	2.9155	2.116	
GGParent	0.2646	80.9554	8.4611	1.4238	0.527	
GParent	0.1431	180.4422	6.1752	1.7804	0.697	
Parent	0.3737	3467.3142	11.0771	6.1896	0.736	
RF						
Variables	Ntrees	NodeSizes	mtry	W1	W2	Knet (CV)
All	11	13	21	6.5422	6.0707	2.407
GGParent	4	2	9	11.6762	7.1364	1.412
GParent	411	3	6	9.7742	1.0316	0.975
Parent	3684	2	5	11.5212	8.4251	0.843

*Source: Author*

Furthermore, the number of trees considered are higher those RF-models that considers less variables, and the size of terminal nodes (*NodeSizes*) are evidently lower than the above SCS (first and second) for network level objectives. Once more, the *Knet* obtained from SVM-based models are lower than for RF-based models. Moreover, the weight values are higher for *W1* than *W2*, according to the data distribution to balance the model for achieving suitable predictions: 37% and 63% data in Category 1 and 2, respectively.

Table 33. Optimal hyperparameters found at Pipe level for the third SCS.

SVM-RBF						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Kpipe (CV)</i>	
All	0.0007	141.7570	7.5109	4.8862	24.569	
GGParent	0.0147	171.3113	6.1817	4.0202	24.856	
GParent	0.0054	2743.5170	6.1701	4.2150	24.885	
Parent	0.3654	360.3727	8.0553	5.9956	25.868	
SVM-Laplace						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Kpipe (CV)</i>	
All	0.0001	986.4581	7.2403	4.3789	24.347	
GGParent	0.0002	657.4987	11.8217	8.3152	24.646	
GParent	0.0241	13.1705	4.1383	2.7434	24.347	
Parent	0.0124	22.8379	4.8259	3.4911	25.580	
RF						
Variables	<i>Ntrees</i>	<i>NodeSizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>Kpipe (CV)</i>
All	3758	10	5	9.6034	7.9076	21.381
GGParent	4599	17	2	6.8438	6.5469	22.205
GParent	3177	16	2	7.6313	7.8012	22.345
Parent	2669	62	2	7.2699	8.7466	25.355

Source: Author

D.2.2.4. Fourth SCS: Excellent and critical structural conditions

Table 34. Optimal hyperparameters found at Network level for the fourth SCS.

SVM-RBF						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Knet (CV)</i>	
All	0.0289	1031.1749	6.8878	2.4500	0.725	
GGParent	0.4258	3056.5442	7.2038	10.4251	0.636	
GPparent	4136.3113	1335.1313	11.3553	7.4147	1.262	
Parent	4526.4880	4709.3527	11.7970	7.0446	1.146	
SVM-Laplace						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Knet (CV)</i>	
All	0.0564	3699.5740	4.5786	2.9444	1.070	
GGParent	0.0199	3046.3160	10.3341	5.5273	0.608	
GPparent	4891.1424	4260.0966	11.0468	7.5546	1.342	
Parent	825.7562	4728.2415	9.1904	5.0108	1.190	
RF						
Variables	<i>Ntrees</i>	<i>NodeSizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>Knet (CV)</i>
All	436	20	20	10.3859	2.2247	0.562
GGParent	4413	15	10	11.5261	1.5855	1.100
GPparent	824	4	5	10.3576	1.2150	1.311
Parent	4400	228	2	9.6753	1.7514	2.973

**Table 35. Optimal hyperparameters found at Pipe level for the fourth SCS.**

SVM-RBF						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Kpipe (CV)</i>	
All	0.0040	20.6020	5.1932	7.7038	11.299	
GGParent	0.0016	155.0461	3.6354	6.8256	12.435	
GParent	11.9815	2690.4697	7.9153	11.2701	11.520	
Parent	1651.0838	2568.3387	2.9798	5.5817	12.624	
SVM-Laplace						
Variables	<i>Sigma</i>	<i>C</i>	<i>W1</i>	<i>W2</i>	<i>Kpipe (CV)</i>	
All	0.0591	3282.4621	3.6872	5.0298	12.031	
GGParent	0.0023	33.1812	3.0528	7.6871	12.010	
GParent	0.0355	2463.9700	4.2763	6.5637	11.073	
Parent	2168.1890	3919.9058	3.3031	6.1025	12.386	
RF						
Variables	<i>Ntrees</i>	<i>NodeSizes</i>	<i>mtry</i>	<i>W1</i>	<i>W2</i>	<i>Kpipe (CV)</i>
All	3011	4	11	9.0425	3.2174	8.648
GGParent	1027	4	6	1.5717	3.7883	9.602
GParent	2342	3	5	10.8707	2.5134	10.332
Parent	1305	6	2	6.7173	2.2933	12.905

For the first and second SCS (5 structural grades and 3 structural categories), SVM based on RBF kernel function, SVM based on Laplace kernel function, Random Forest (RF), and Ordinal logistic Regression (Ord\_LR) were the optimised models. For the third and fourth SCS (two structural categories and considering only excellent and critical structural conditions), SVM based on RBF kernel function, SVM based on Laplace kernel function, Random Forest (RF), and Binomial logistic Regression (LR) were the optimised models.

SVM-based models were considered Laplace and Radial Basis (RBF) kernel functions because of the successful results shown in 11.2.2. (for more details, see Hernández et al., 2019b) and the suggestions of Genton (2001).

For each method and SCS, four deterioration models were developed and optimised to achieve a management objective considering: (i) the parent variables (*Par*); (ii) parent and grandparent variables (*GPar*); (iii) parent, grandparent and grand-grandparent variables (*GGPar*); and (iv) all variables (see Tables B.4 and B.5., Part B ) from the classification of each structural condition scenario (SCS) given in Table D.14.

Figures 65. and 66 show the Sigma and C values obtained for SVM\_RBF-based models at network and pipe level objectives considering the four SCS and the four group of variables respectively.

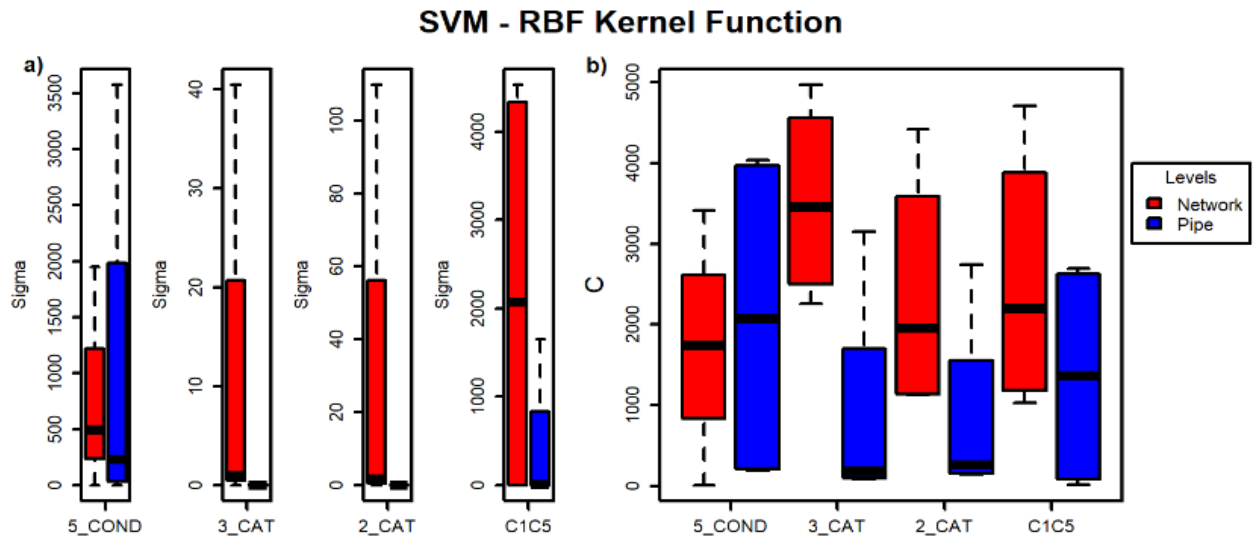
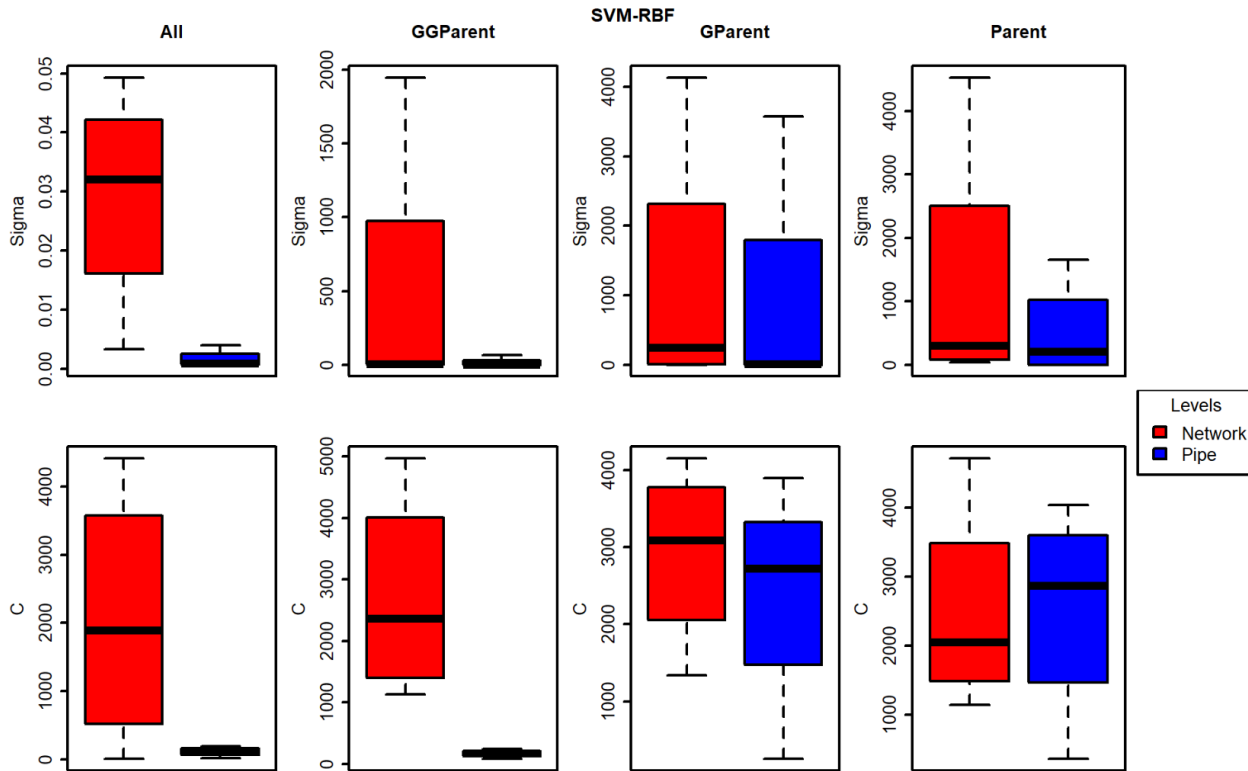


Figure 65. Boxplot analysis of the Sigma (a) and C (b) hyperparameters obtained for each SCS after applying the proposed optimisation methodology for SVM considering RBF kernel function for Medellin's case. Red boxplots refer to the Sigma and C values obtained at the network level ( $K_{net}$ ), and blue boxplots refer to the Sigma and C values obtained at the pipe level ( $K_{pipe}$ ) for Medellin's case. Source: Author

According to Figure 65, the Sigma values are higher for the models related to achieving the network level objective than for the models associated with achieving the pipe level objective (except for the first SCS-5\_COND). It means that the classification is simpler for the SVM-based models, considering RBF kernel function, related to reaching network-level objectives than the SVM-based models related to reaching pipe level objectives. However, it is interesting that for the SVM-RBF-based models for the first SCS, the sigma values are higher for reaching pipe level objectives than for the network level objectives. It means that the location of the data is simpler for achieving pipe level objectives, despite that  $K_{net}$  metric is less demanding than  $K_{pipe}$ .

Besides, Sigma values of the first and fourth SCS are higher than 200. It means that the corresponding SVM-based models considering RBF kernel function are more constrained and the data is less complex than the SVM-based models of the second and third SCS.

According to the obtained C values, Figure 65 shows that C values related to minimising the  $K_{net}$  metric are higher than the C values of the models related to minimizing  $K_{pipe}$  (except for the first SCS -5\_COND).



**Figure 66. Boxplot analysis of the Sigma (graphics showed at the top) and C (graphics showed at the bottom) hyperparameters obtained considering each group of variables after applying the proposed optimisation methodology for SVM considering RBF kernel function for Medellin’s case. Red boxplots refer to the Sigma and C values obtained at the network level (Knet), and blue boxplots refer to the Sigma and C values obtained at the pipe level (Kpipe). Source: Author**

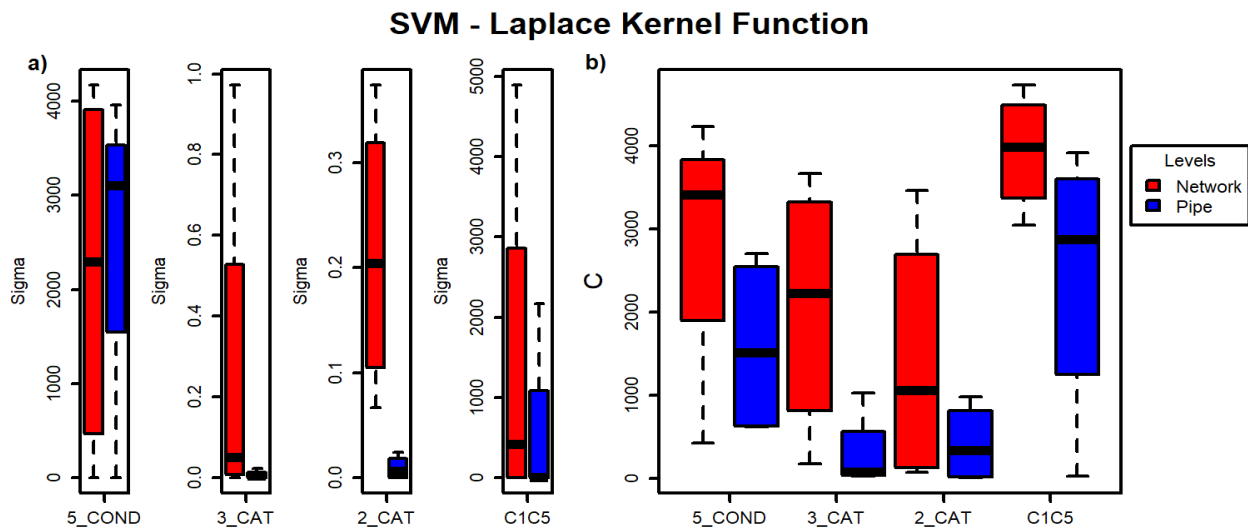
According to Figure 66, the Sigma values for achieving network-level objectives are higher than the ones for pipe level objectives independently of the type or number of considered variables in the model. Comparing to Figure D.35., the above means that the size of Sigma values is less dependent on the included variables in the models than on the grouping of the structural conditions (SCS) for SVM\_RBF-based models developed for Medellin’s case.

On the other hand, the C values show evident differences between the models that look for achieving network and pipe level objectives. However, the differences are higher when the models consider several variables (all studied variables or all the variables that presented any relationship with the structural condition -GGPar): for the models that most minimise the *Knet* metric, the C values are higher than for the models that most minimise *Kpipe* metric. It means that models that reduce the *Knet* metric have thinner margins and a 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).

Regarding the models that consider the variables that present only the first (parent variables – Par) or the first and second relationship grades (grandparent variables - GPar), the model for achieving the network level objective considering parent variables (Par) is lower than the model (considering Par variables) for achieving the pipe level objective; while for the model considering grandparent variables (GPar) for achieving the network level objective is higher than the model (considering GPar variables) for achieving pipe level objective

According to the above, the obtained Sigma values are intuitive because of the evaluation that leads the network level objective is not as exigent in their predictions as the evaluation that leads the pipe level objective.

Figures 67 and 68 show the Sigma and C values obtained for SVM\_Laplace-based models at network and pipe level objectives considering the four SCS and the four groups of variables, respectively.

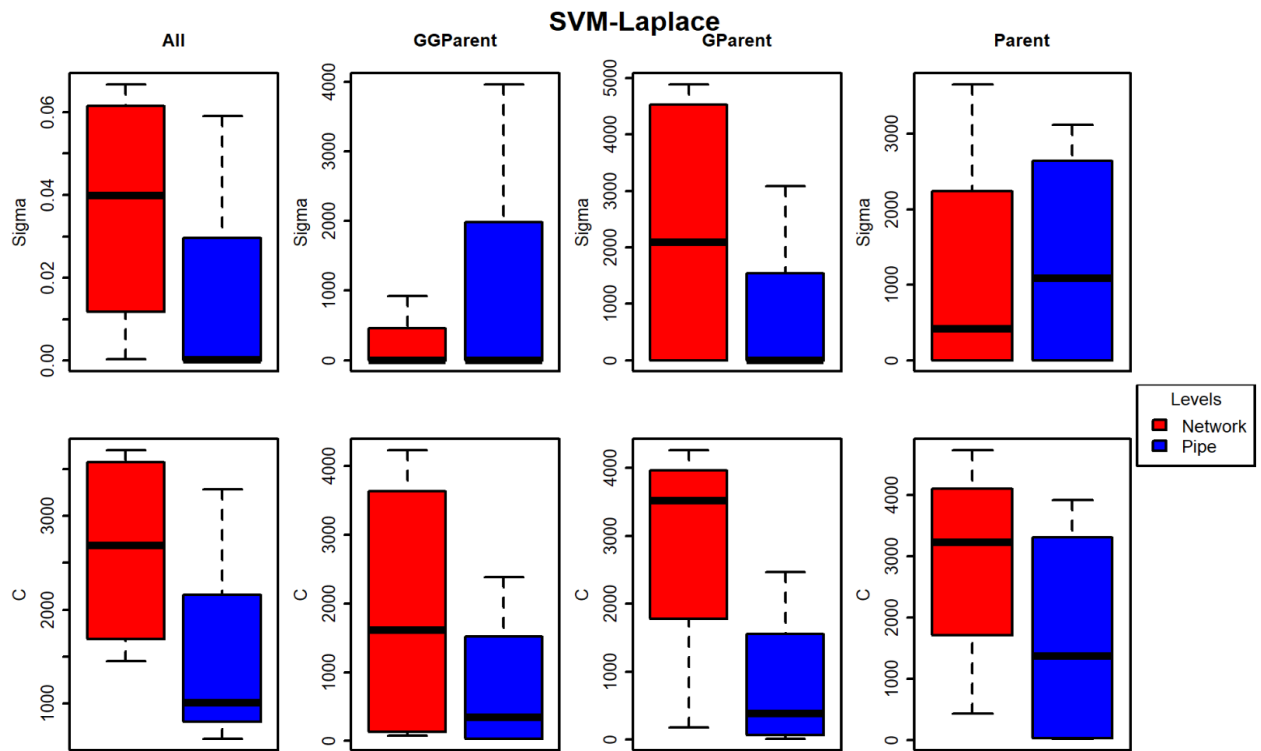


**Figure 67. Boxplot analysis of the Sigma (graphics showed at the top) and C (graphics showed at the bottom) hyperparameters obtained considering each group of variables after applying the proposed optimisation methodology for SVM considering Laplace kernel function. Red boxplots refer to the Sigma and C values obtained at the network level (Knet), and blue boxplots refer to the Sigma and C values obtained at the pipe level (Kpipe) for Medellin's case. Source: Author**

As for SVM\_RBF-based models, for SVM\_Laplace-based model, the Sigma values for achieving the network level objectives are evidently higher than the Sigma values for achieving pipe level objectives. Also, Figure 67 shows that the C values for achieving the network level objective are higher than the C values for achieving pipe level objectives. It means that independently of the SCS, the data is less complex, and the margin is thinner for models related to the network level objectives.



Figure 68 shows that sigma values vary according to the type and the number of considered variables in the models, but the C values continue being higher for models that lead network than those for pipe level objectives. It is interesting to highlight that the Sigma values obtained from models that consider all the studied variables are significantly lower (at network and pipe level objectives) than the other models that consider other groups of variables (GGPar, GPar and Par variables).

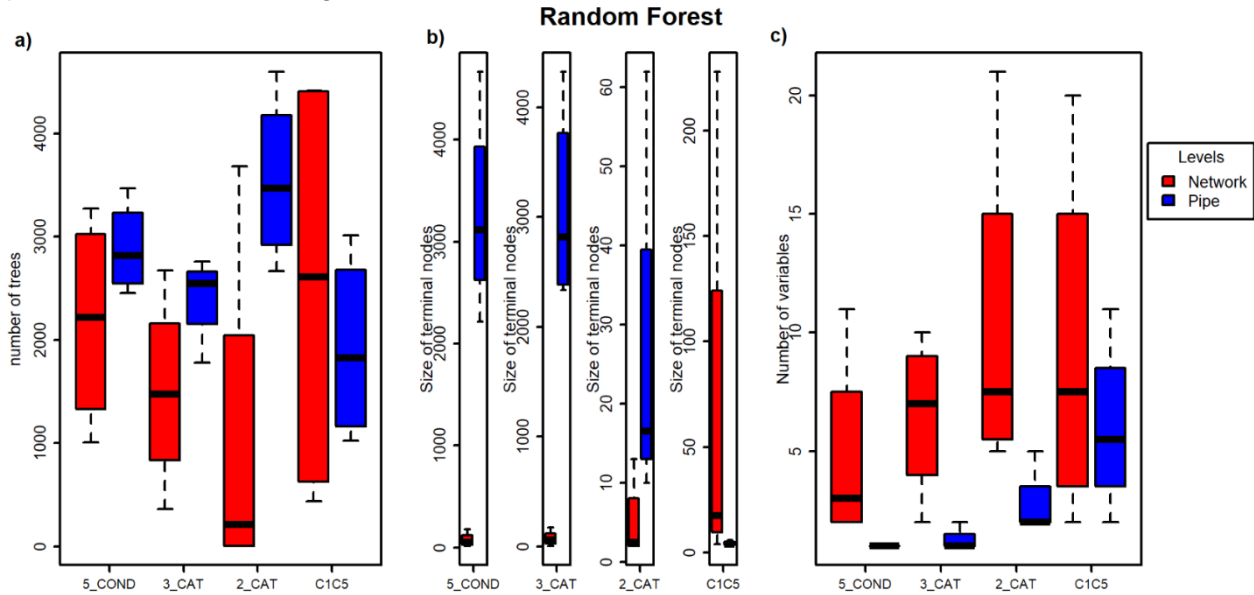


**Figure 68.** Boxplot analysis of the Sigma (Figure a) and C (Figure b) hyperparameters obtained for each SCS after applying the proposed optimisation methodology for SVM considering Laplace kernel function. Red boxplots refer to the Sigma and C values obtained at the network level (Knet), and blue boxplots refer to the Sigma and C values obtained at the pipe level (Kpipe) for Medellin's case. Source: Author

Figures 69 and 70 show the results of the RF hyperparameters found after applying the proposed methodology (chapter 8 and 9, Part C) considering their variability according to each SCS (Figure D.39.) and each group of variables chosen from the hierarchization obtained in section 11.2.1.

According to Figure 69(a), the number of trees and size of terminal nodes SCS for three of SCS at the network level objective (Knet) is lower than at the pipe level objective (Kpipe). It means that for achieving network-level objectives, the RF-based models need fewer trees and smaller sizes of terminal nodes. Furthermore, the models related to the network level objectives need a larger number of random variables on each tree for all SCS. The above suggests that if an RF-based model needs a larger number of random variables on each tree, the number of trees could be

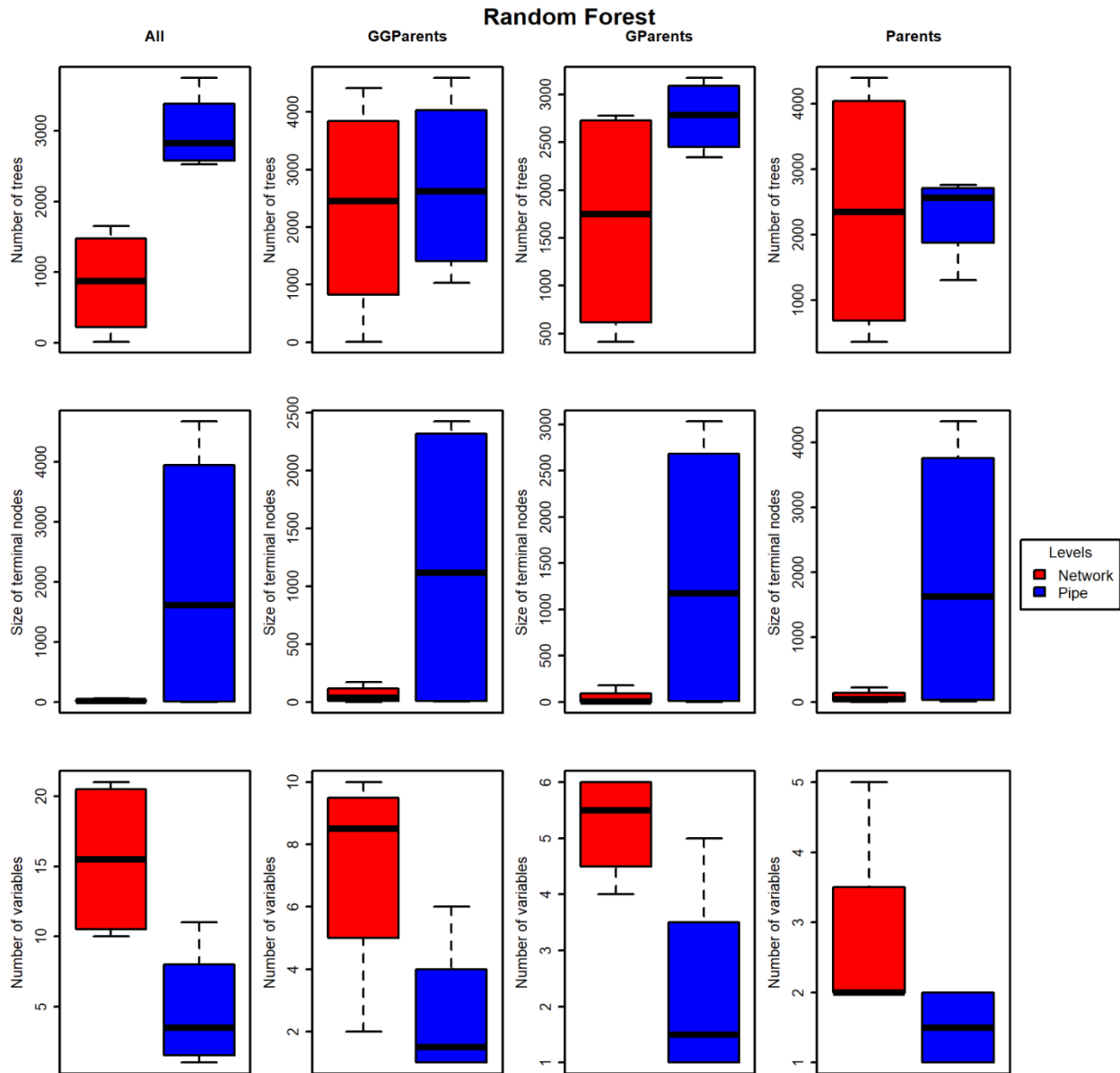
less. This kind of simple models is enough for achieving network-level objectives. Nevertheless, for RF-models that achieves the pipe level objectives should be more robust (smaller number of random variables on each tree and more trees in the model) and complex because their predictions are more exigent.



**Figure 69. Boxplot analysis of the Number of trees (Figure a), Size of terminal nodes (Figure b) and Number of variables (Figure c) hyperparameters obtained for each SCS after applying the proposed optimisation methodology for Random Forest. Red boxplots refer to the number of trees, the size of terminal nodes and the number of variables values obtained at the network level (Knet), and blue boxplots refer to the Sigma and C values obtained at the pipe level (Kpipe) for Medellin’s case. Source: Author**

It is interesting to highlight that for the fourth SCS (excellent and critical conditions) the behaviour changes: higher number of trees, the bigger size of terminal nodes and more random variables are required for achieving network-level objectives than for achieving pipe level objectives.

The same behaviour of Figure 69 is shown in Figure 70., related to the type and number of variables, the size of terminal nodes and the number of random variables on each built tree for the RF-models. Important facts to highlight are: (i) RF-based models at the pipe level that consider the Par variables show a smaller number of trees than RF-based models at the network level considering the same variables; and (ii) the size of terminal nodes for RF-based models at pipe level are bigger than the ones obtained for RF-based models at the network levels, which implies that the size of terminal nodes is less dependent on the type and number of included variables than on the SCS considered.



**Figure 70.** Boxplot analysis of the Number of trees (graphics showed at the top), sizes of terminal nodes (graphics in the centre) and Number of variables (graphics showed at the bottom) hyperparameters obtained considering each group of variables after applying the proposed optimisation methodology for Random Forest. Red boxplots refer to the Sigma and C values obtained at the network level (*Knet*), and blue boxplots refer to the Sigma and C values obtained at the pipe level (*Kpipe*) for Medellin's case. Source: Author

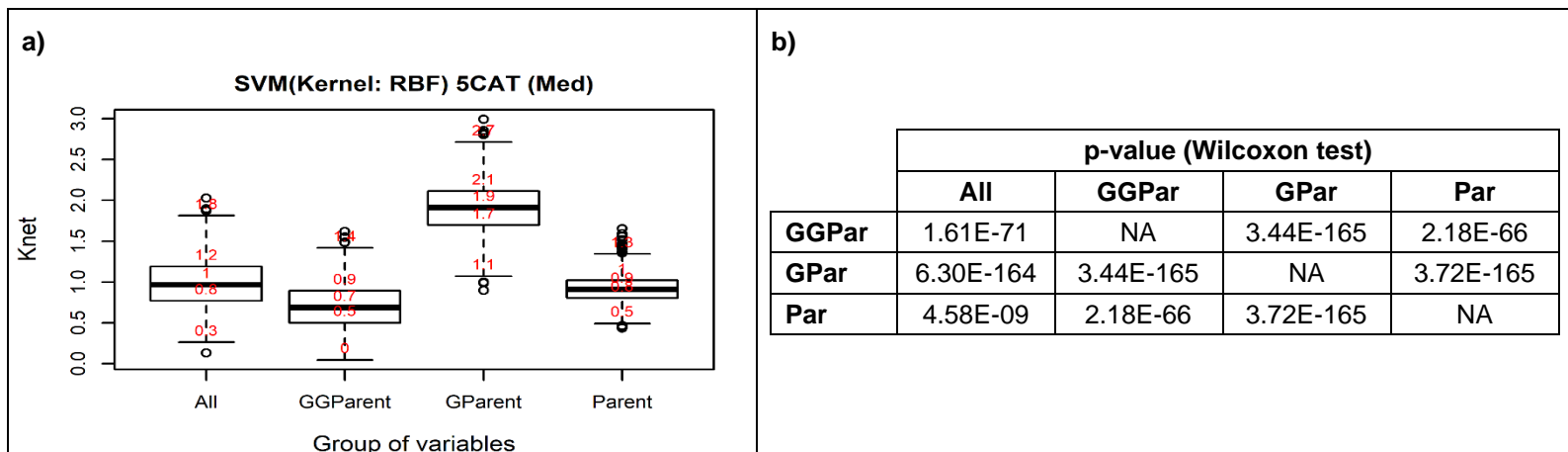
#### D.2.4. Results of the optimised deterioration models for management objectives

The following figures show the results of the optimised deterioration models based on SVM-RBF, SVM-Laplace, and RF including each group of variables and by each SCS and management objective (network and pipe level, *Knet* and *Kpipe* metrics respectively) for Medellin's case. Each figure displays a boxplot analysis and a table that shows the p-values obtained after the Wilcoxon test to find significantly statistical difference between the results of the models depicted in the

boxplot analysis. At the end, it shows a boxplot that compares the most suitable models for each optimised method to choose the most suitable for each SCS.

#### D.2.4.1. First SCS: five structural grades

Figure 71 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 24) based on the optimised SVM considering RBF kernel function for network level management objective (see the hyperparameters set in these models in Table 28) for the first SCS.

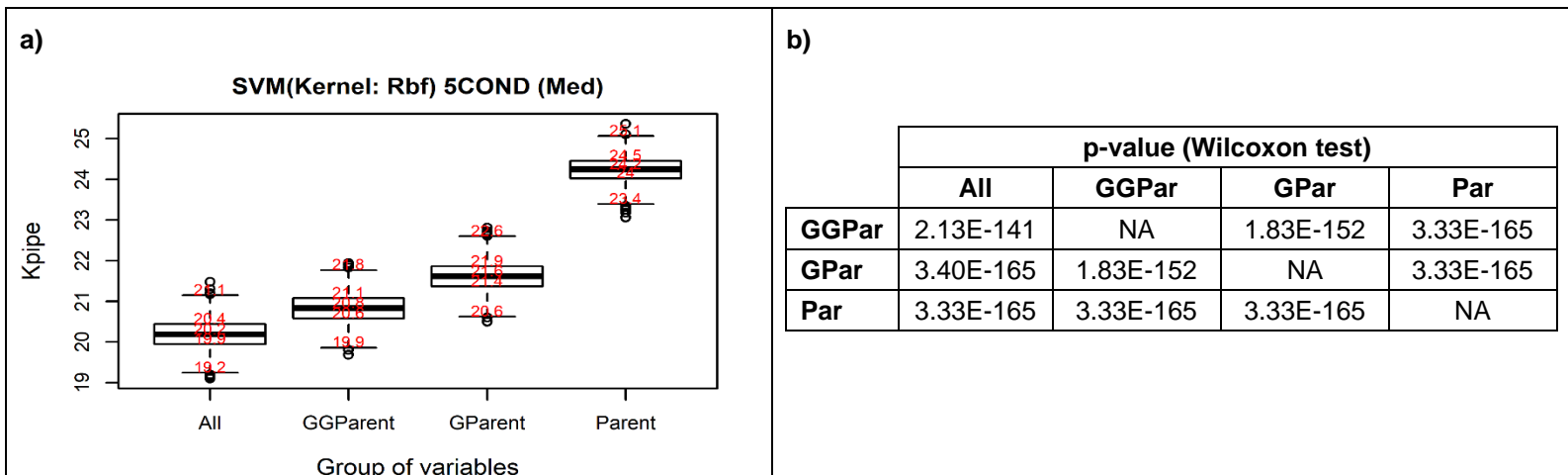


**Figure 71. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the network level objective (Knet) and first SCS (five structural grades – EPM,2010). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 71, the SVM-RBF-based model that most minimize the *Knet* metric is the one that includes the variables that shows any relationship grade with the structural condition (GGParent variables), and this model shows significant statistical difference with the other models (p-value <0.05).

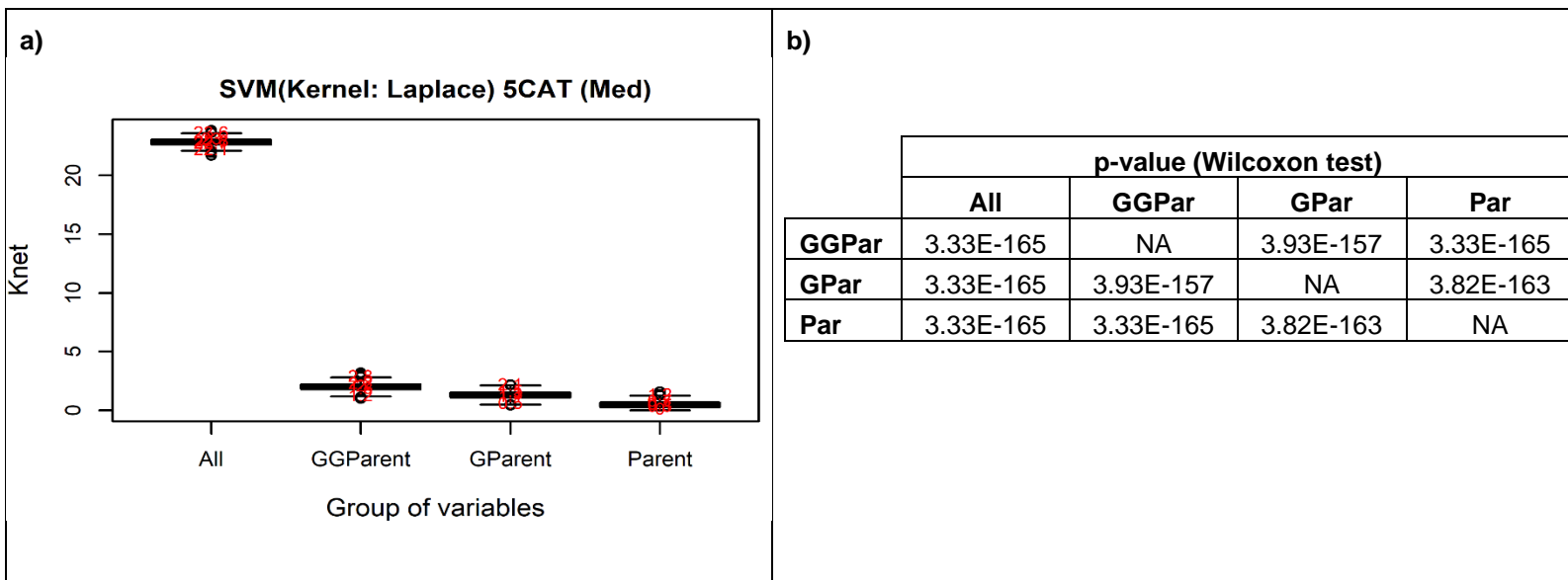
Figure 72 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 24) based on SVM considering RBF kernel function for pipe level management objective see the hyperparameters set in these models in Table 29) for the first SCS.

According to Figure 72, the SVM-RBF-based model that most minimize the *Kpipe* metric is the one that includes all studied variables and this model shows significant statistical difference with the other models (p-value <0.05).



**Figure 72.** Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the pipe level objective (*Kpipe*) and first SCS (five structural grades – EPM,2010). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

Figure 72 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 24) based on SVM considering Laplace kernel function for network level management objective see the hyperparameters set in these models in Table 28) for the first SCS.

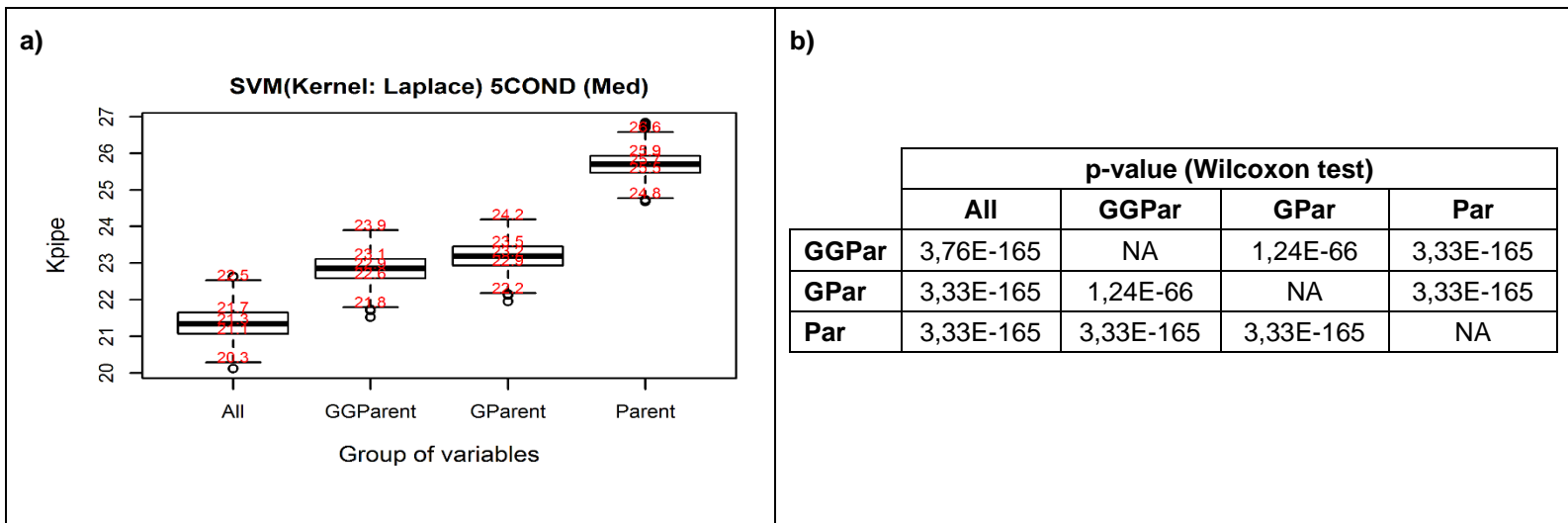


**Figure 73.** Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the network level objective (*Knet*) and first SCS (five structural grades – EPM,2010). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 73, the SVM-Laplace-based model that most minimize the *Knet* metric is the one that only includes the variables that show the first relationship grade with structural condition

(Parent variables), and this model shows significant statistical difference with the other models (p-value <0.05).

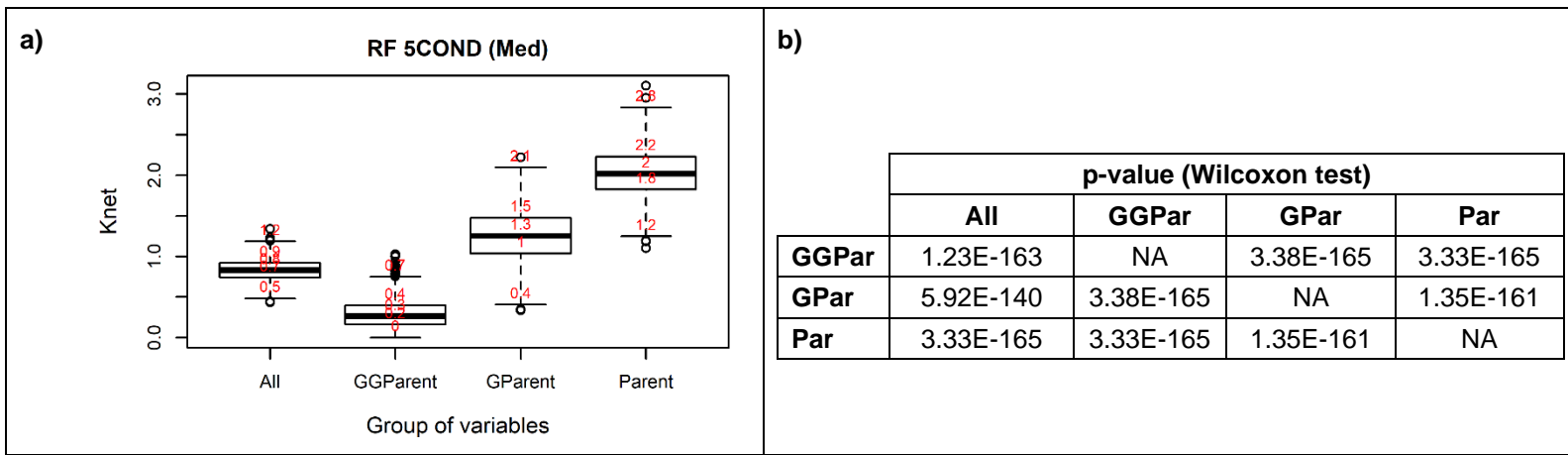
Figure 74 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 24) based on SVM considering Laplace kernel function for pipe level management objective see the hyperparameters set in these models in Table 29) for the first SCS.



**Figure 74. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the pipe level objective ( $K_{pipe}$ ) and first SCS (five structural grades – EPM,2010). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 74, the SVM-Laplace-based model that most minimize the  $K_{pipe}$  metric is the one that includes all the studied variables and this model shows significant statistical difference with the other models (p-value <0.05).

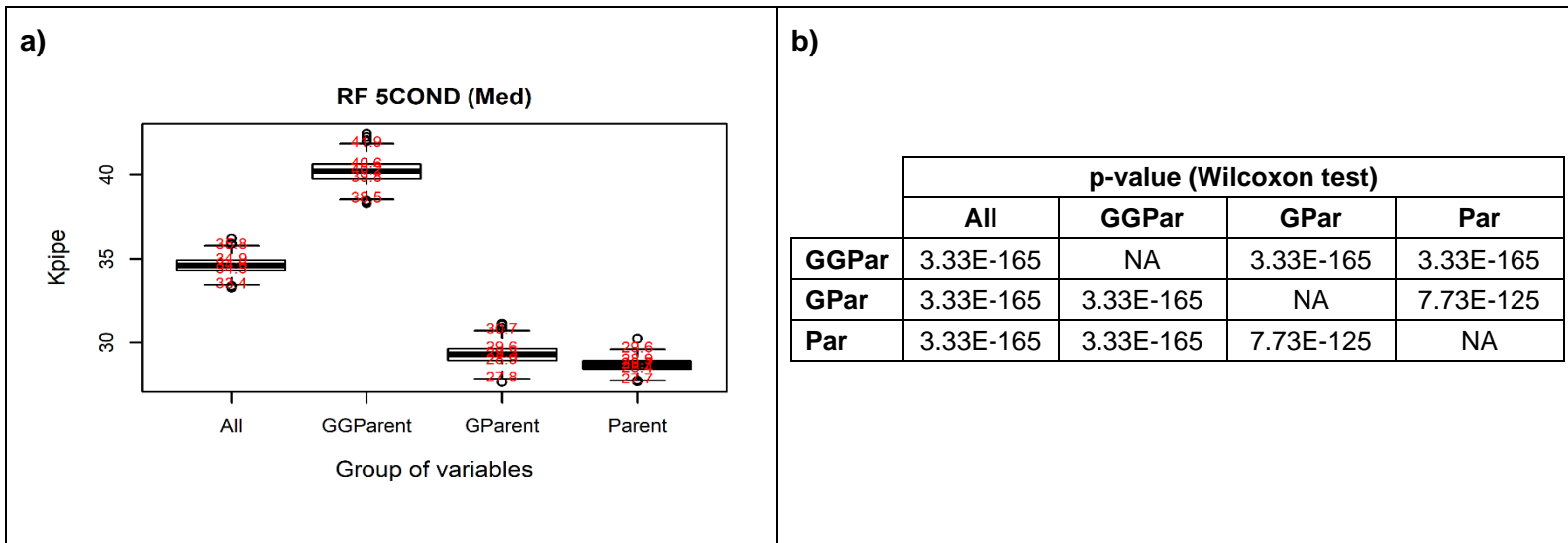
Figure 75 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 24) based on RF for the network level management objective see the hyperparameters set in these models in Table 28) for the first SCS.



**Figure 75. Results of the validation data of the RF-based deterioration models for the network level objective (Knet) and first SCS (five structural grades – EPM,2010). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 75, the RF-based model that most minimize the *Knet* metric is the one that the variables that show any relationship grade with structural condition (GGPar), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).

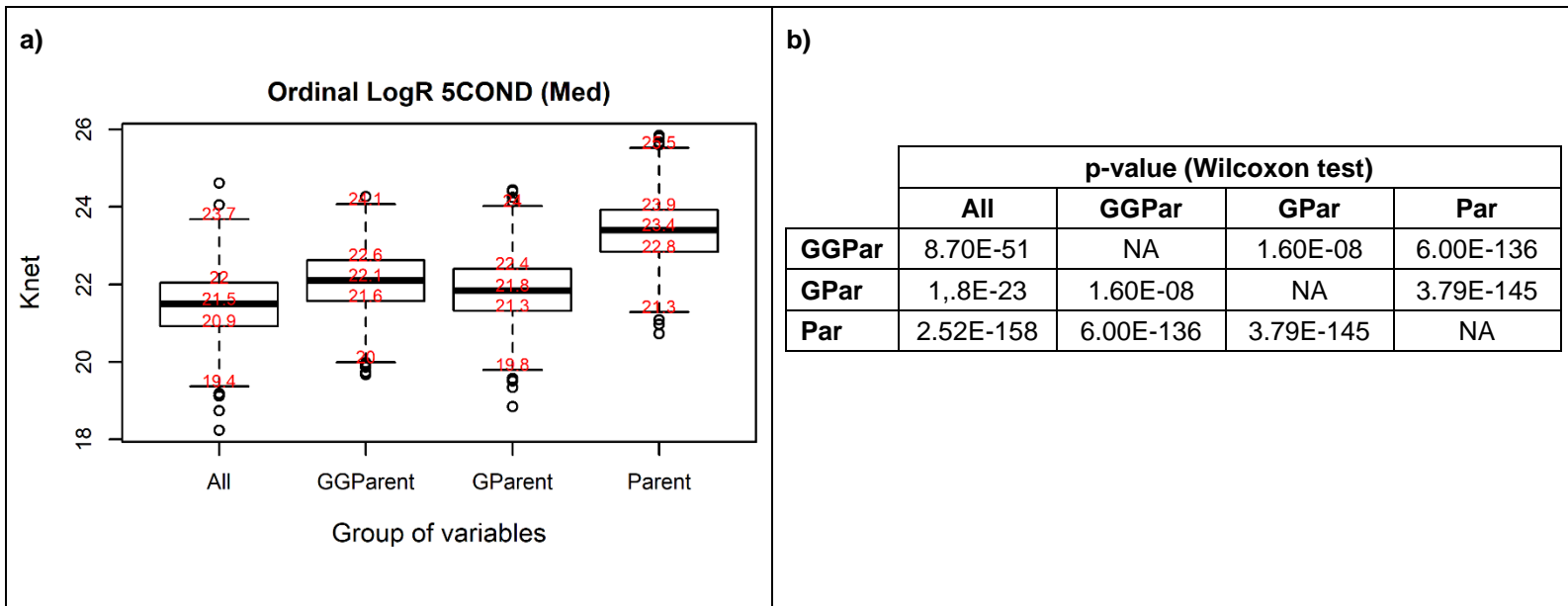
Figure 76 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 24) based on RF for the pipe level management objective (see the hyperparameters set in these models in Table 29) for the first SCS.



**Figure 76. Results of the validation data of the RF-based deterioration models for the pipe level objective (Kpipe) and first SCS (five structural grades – EPM,2010). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 76, the RF-based model that most minimize the *Kpipe* metric is the one that the variables that only includes the first relationship grade with structural condition (Parent variables), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 77 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 24) based on ordinal logistic regression (Ord\_LR) for the network level management objective for the first SCS.



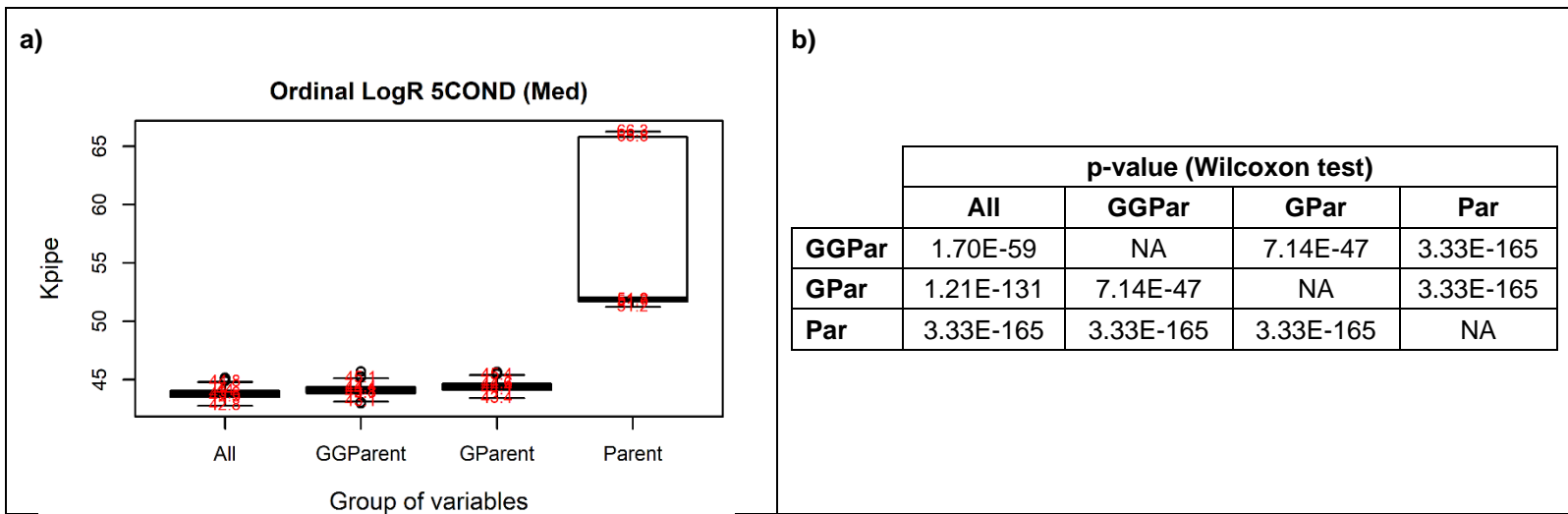
*Figure 77. Results of the validation data of the Ord\_LR-based deterioration models for the network level objective (Knet) and first SCS (five structural grades – EPM,2010). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 77, the Ord\_LR-based model that most minimize the *Knet* metric is the one that includes all studied variables and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 78 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 24) based on ordinal logistic regression (Ord\_LR) for the pipe level management for the first SCS.

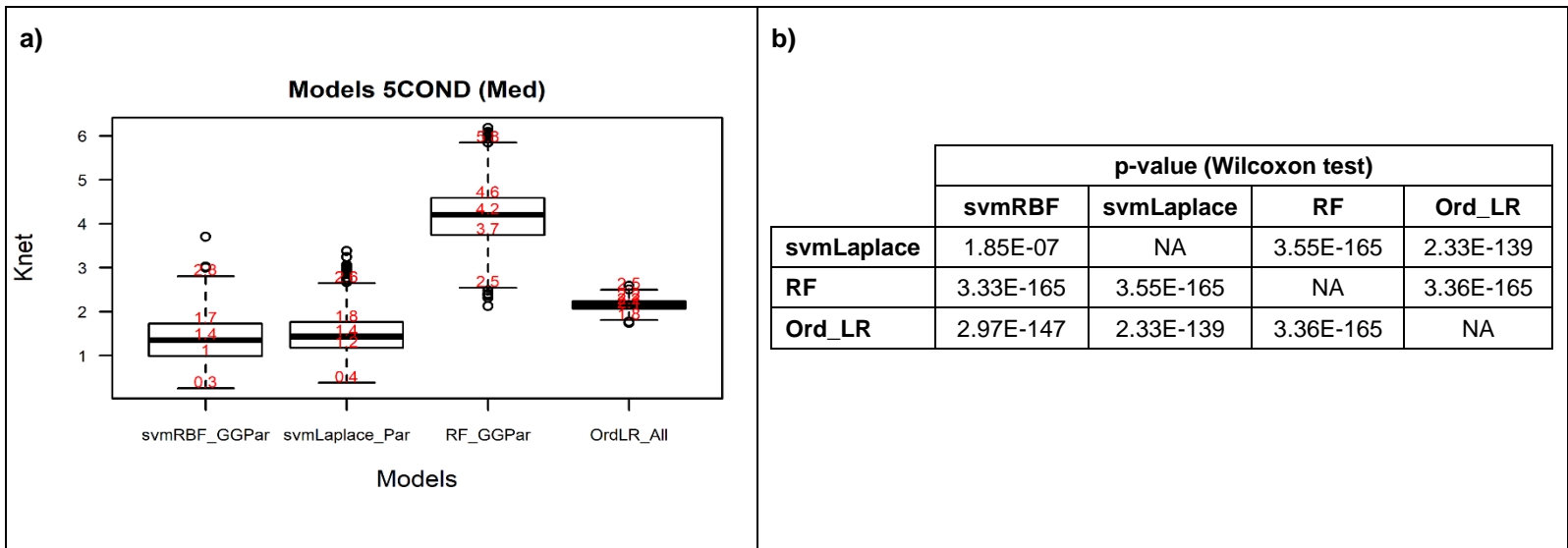
According to Figure 78, the Ord\_LR-based model that most minimize the *Kpipe* metric is the one that includes all studied variables and this model shows significant statistical difference with the other models (p-value <0.05).





*Figure 78. Results of the validation data of the Ord\_LR-based deterioration models for the pipe level objective (Kpipe) and first SCS (five structural grades – EPM,2010). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

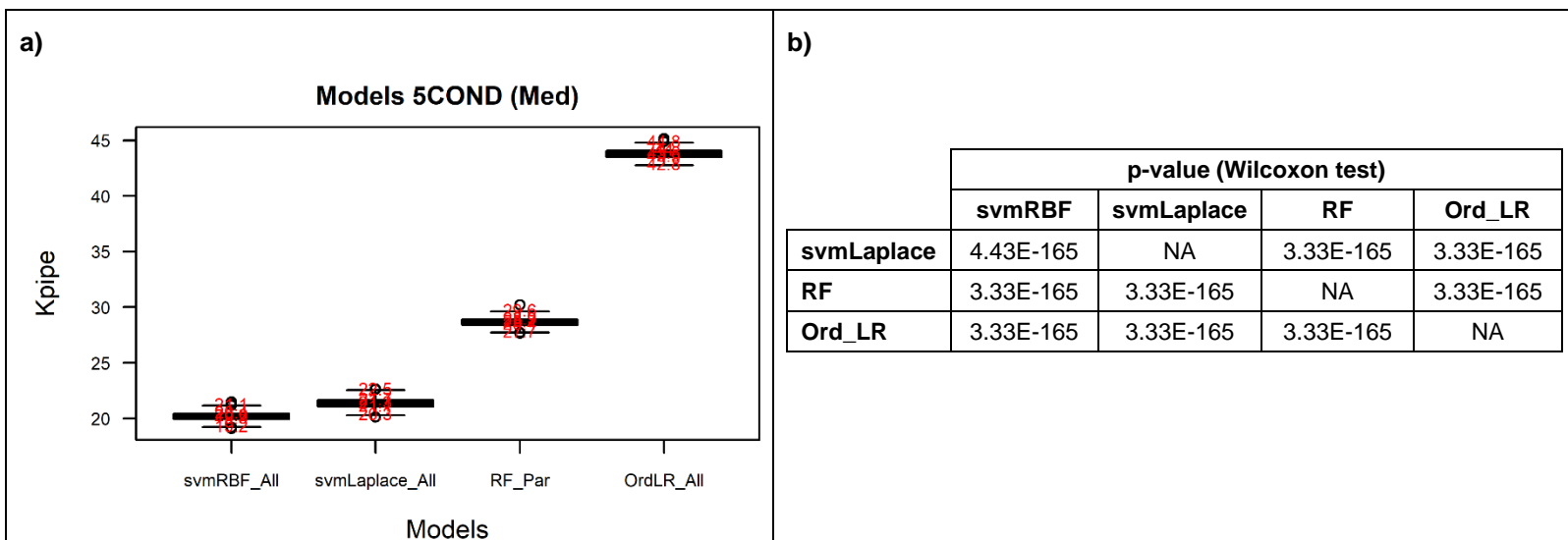
In summary, for the first SCS, the deterioration models that most minimize the *Knet* were: (i) SVM-RBF-based model that considers the variables that showed any relationship with structural condition (GGPar); (ii) SVM-Laplace-based models that only considers the variables that shows the first relationship grade with the structural condition (Par); (iii) RF-based models considers the variables that showed any relationship with structural condition (GGPar); and Ord\_LR-based model that considers all the studied variables (See Figure 67).



*Figure 79. Comparison of the most suitable deterioration model to achieve the management objective at network level for the first structural condition scenario (5 structural grades). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 79, SVM-RBF model that considers only the first relationship grade variables are the one that most minimize the *Knet* metric increasing performance prediction at network level for the first SCS (see Figure 79.a). The predictions of this model show significant statistical differences with the predictions of the other models (p-values lower than 0.05) (see Figure 79.b).

On the other hand, the deterioration models that most minimize the *Kpipe* metric in the validation data were: (i) SVM-RBF-based deterioration models considering all studied variables; (ii) SVM-Laplace based deterioration models considering all the studied variables; (iii) RF based deterioration models considering the first relationship grade variables (Par); and (iv) Ordinal logistic models considering all the studies variables (see Figure 80).



**Figure 80. Comparison of the most suitable deterioration model to achieve the management objective at network level for the first structural condition scenario (5 structural grades). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 80, SVM-RBF model that considers all the studied variables are the one that most minimize the *Kpipe* metric increasing performance prediction at pipe level for the first SCS (see Figure 80.a). The predictions of this model show significant statistical differences with the predictions of the other models (p-values lower than 0.05) (see Figure 80.b).

D.2.4.2. Second SCS: Acceptable, poor and critical structural conditions

Figure 81 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 25) based on the optimised SVM considering RBF kernel function for network level management objective (see the hyperparameters set in these models in Table 30) for the second SCS.

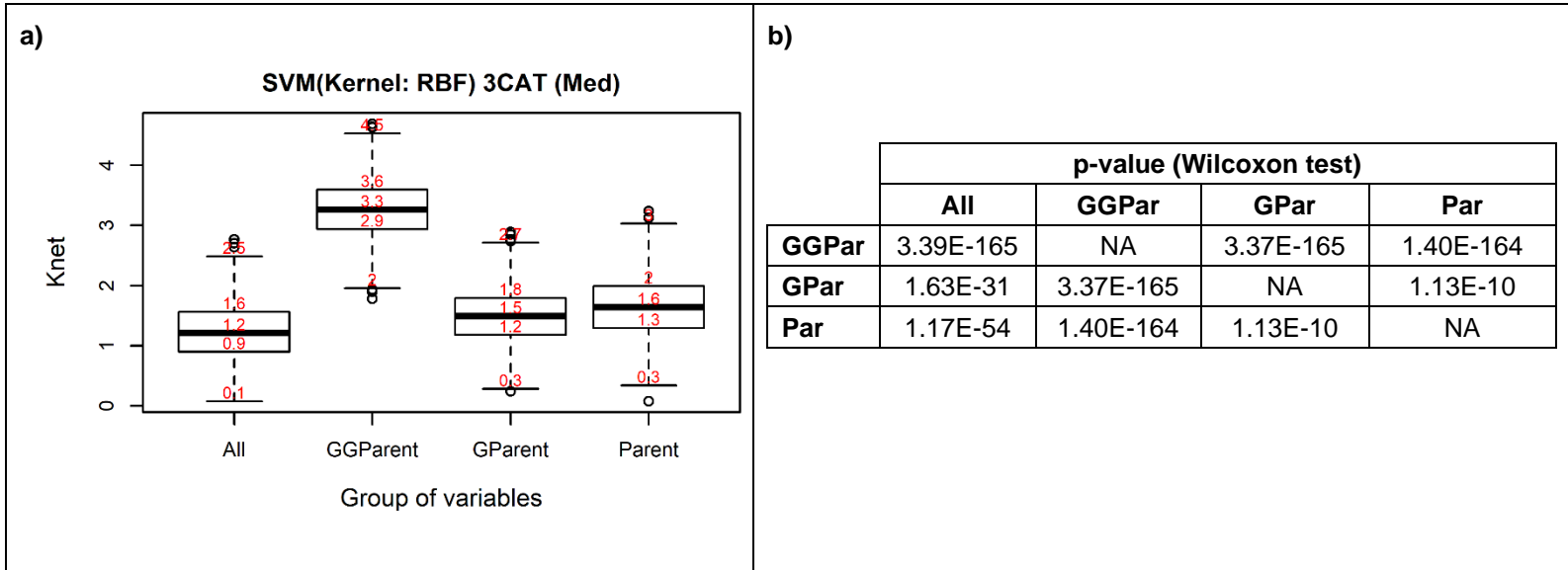
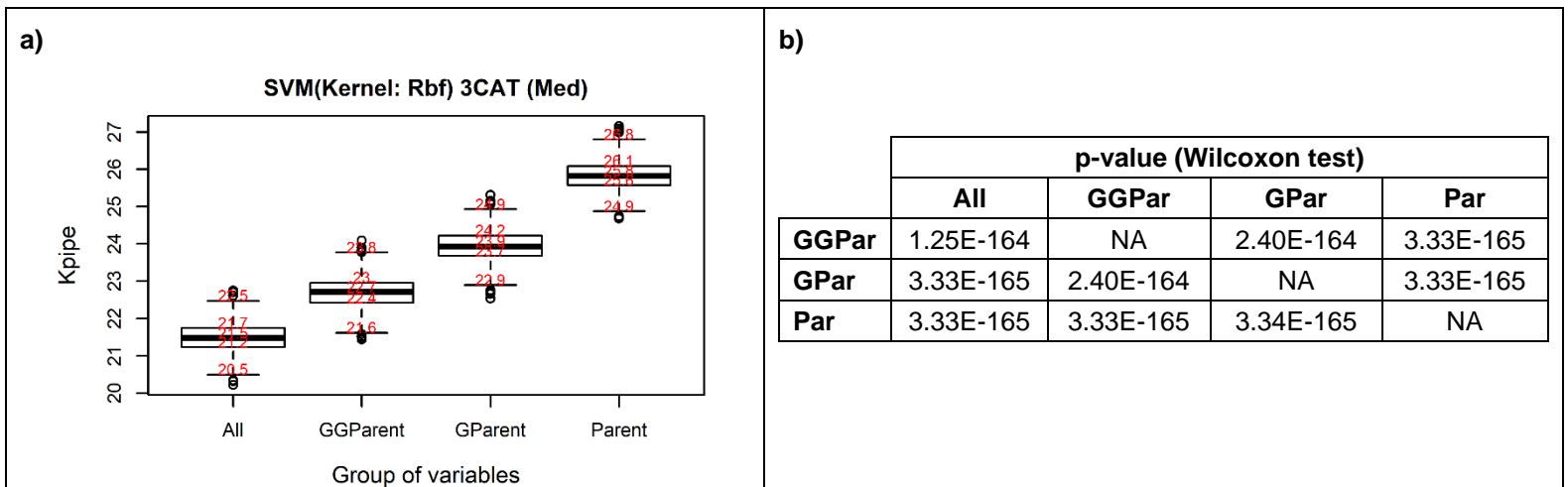


Figure 81. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the network level objective (*Knet*) and second SCS (three structural categories– acceptable, poor and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 81, the SVM-RBF-based model that most minimize the *Knet* metric is the one that includes all studied variables and this model shows significant statistical difference with the other models (p-value <0.05).

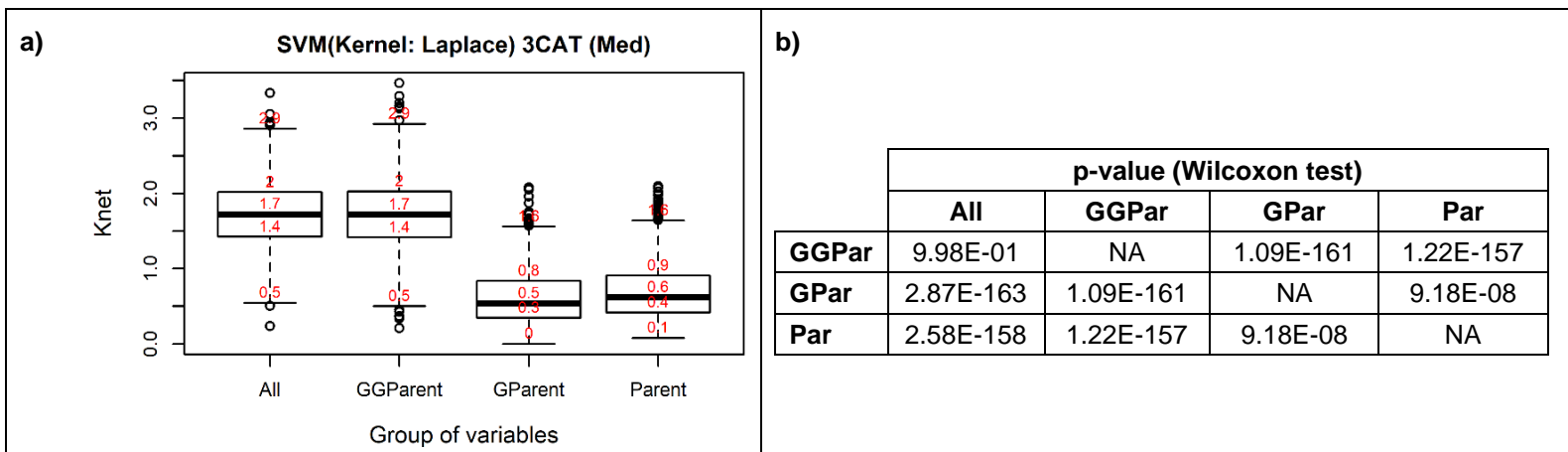
Figure 82 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 25) based on SVM considering RBF kernel function for pipe level management objective see the hyperparameters set in these models in Table 31) for the second SCS.



**Figure 82.** Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the pipe level objective ( $K_{pipe}$ ) and second SCS (three structural categories– acceptable, poor and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 82, the SVM-RBF-based model that most minimize the  $K_{pipe}$  metric is the one that includes all studied variables and this model shows significant statistical difference with the other models (p-value <0.05).

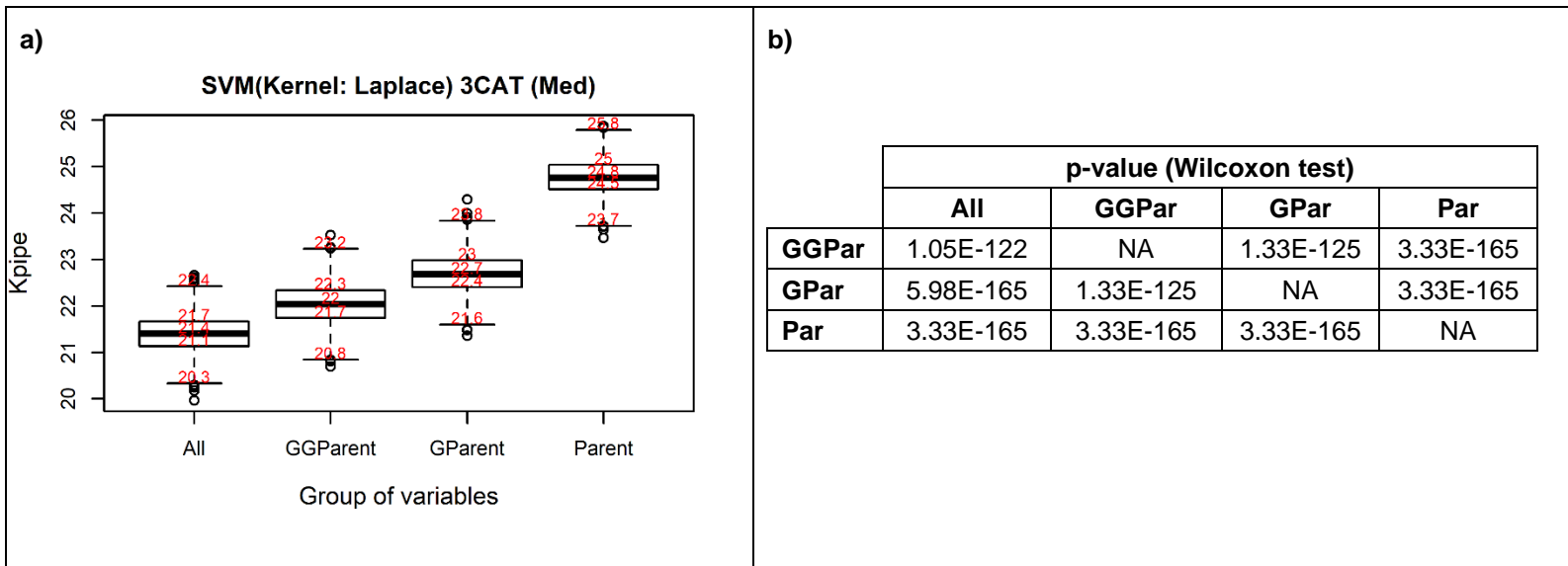
Figure 83 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 25) based on SVM considering Laplace kernel function for network level management objective see the hyperparameters set in these models in Table 30) for the second SCS.



**Figure 83.** Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the network level objective ( $K_{net}$ ) and second SCS (three structural categories– acceptable, poor and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 83, the SVM-RBF-based model that most minimize the *Knet* metric is the one that includes the variables that present the first and second relationship grade with the structural condition (GParent variables) and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ). Although the SVM-RBF-based models that considers all studied variables and the variables that presented any relationship with structural condition (GParent variables) do not show the lowest *Knet* values, it is important to highlight that there is not difference significantly ( $p$ -value  $>0.05$ ). It means, that both models show the same prediction results including or nor the variables that do not show any relationship with the structural condition.

Figure 84 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 25) based on SVM considering Laplace kernel function for the pipe level management objective see the hyperparameters set in these models in Table 31) for the second SCS.

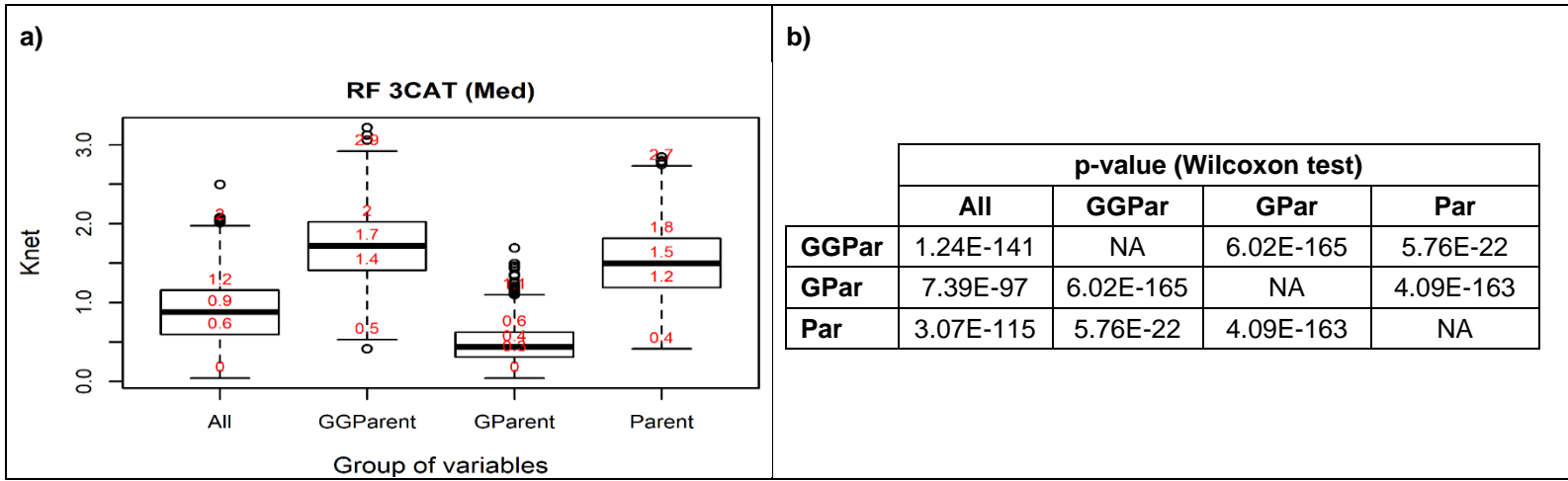


**Figure 84. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the pipe level objective (*Kpipe*) and second SCS (three structural categories– acceptable, poor and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the  $p$ -values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 84, the SVM-Laplace-based model that most minimize the *Kpipe* metric is the one that includes all studied variables and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ).

Figure 85 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 25) based on RF for the

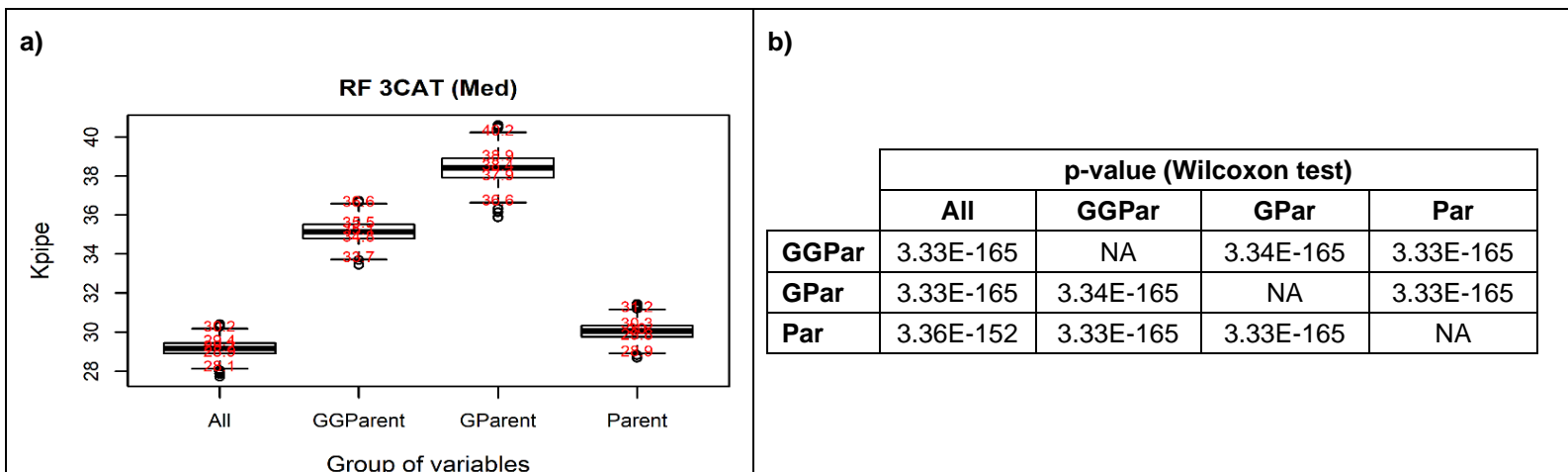
network level management objective see the hyperparameters set in these models in Table 30) for the second SCS.



**Figure 85. Results of the validation data of the RF-based deterioration for the network level objective (*Knet*) and second SCS (three structural categories– acceptable, poor and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 85, the RF-based model that most minimize the *Knet* metric is the one that includes the variables that present the first and second relationship with the structural condition (GParent variables), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).

Figure 86 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 25) based on RF for the pipe level management objective see the hyperparameters set in these models in Table 31) for the second SCS.



**Figure 86. Results of the validation data of the RF-based deterioration for the pipe level objective (*Kpipe*) and second SCS (three structural categories– acceptable, poor and critical structural conditions). a) figure that**

shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 86, the RF-based model that most minimize the  $K_{pipe}$  metric is the one that includes all the studied variables and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ). It is interesting to highlight that the lowest  $K_{pipe}$  values (with differences significantly) are the RF-based models that consider all studied variables and those variables that present only the first relationship with the structural condition (Parent variables).

Figure 87 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 25) based on Ord\_LR for the network level management objective for the second SCS.

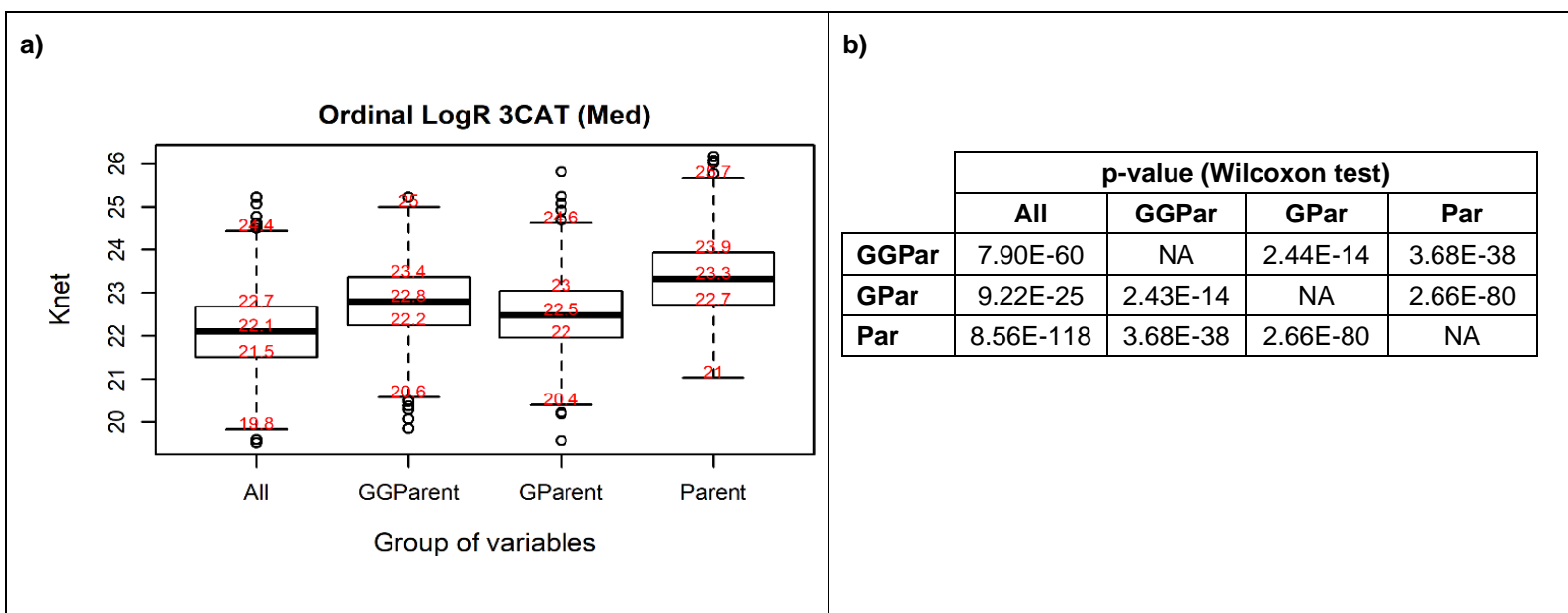


Figure 87. Results of the validation data of the OrdLR-based deterioration for the network level objective ( $K_{net}$ ) and second SCS (three structural categories– acceptable, poor and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 87, the OrdLR-based model that most minimize the  $K_{net}$  metric is the one that includes all the studied variables and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ).

Figure 88 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 25) based on Ord\_LR for the pipe level management objective for the second SCS.

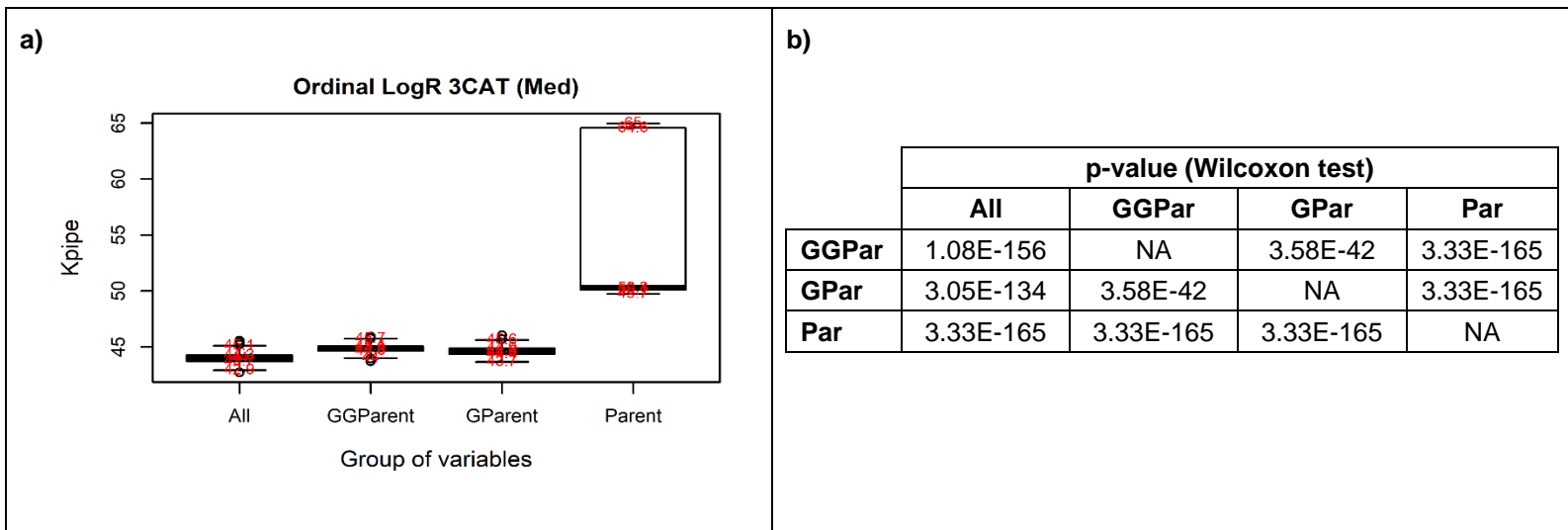
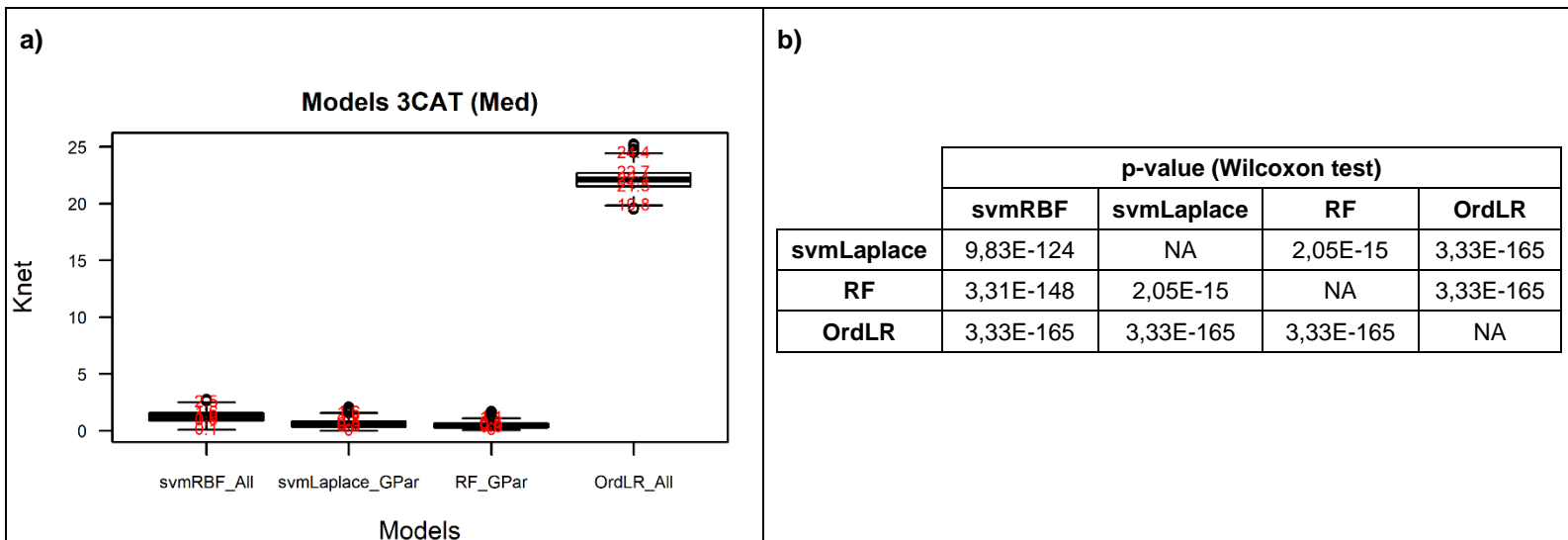


Figure 88. Results of the validation data of the OrdLR-based deterioration for the pipe level objective (*Kpipe*) and second SCS (three structural categories– acceptable, poor and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 88, the OrdLR-based model that most minimize the *Kpipe* metric is the one that includes all the studied variables and this model shows significant statistical difference with the other models (p-value <0.05).

In summary, for the second SCS, the deterioration models that most minimize the *Knet* were: (i) SVM-RBF-based model that considers all the studied variables; (ii) SVM-Laplace-based models that considers the variables that shows the first and second relationship grade with the structural condition (GPar); (iii) RF-based models that considers the variables that shows the first and second relationship grade with the structural condition (GPar); and Ord\_LR-based model that considers all the studied variables (See Figure 89).



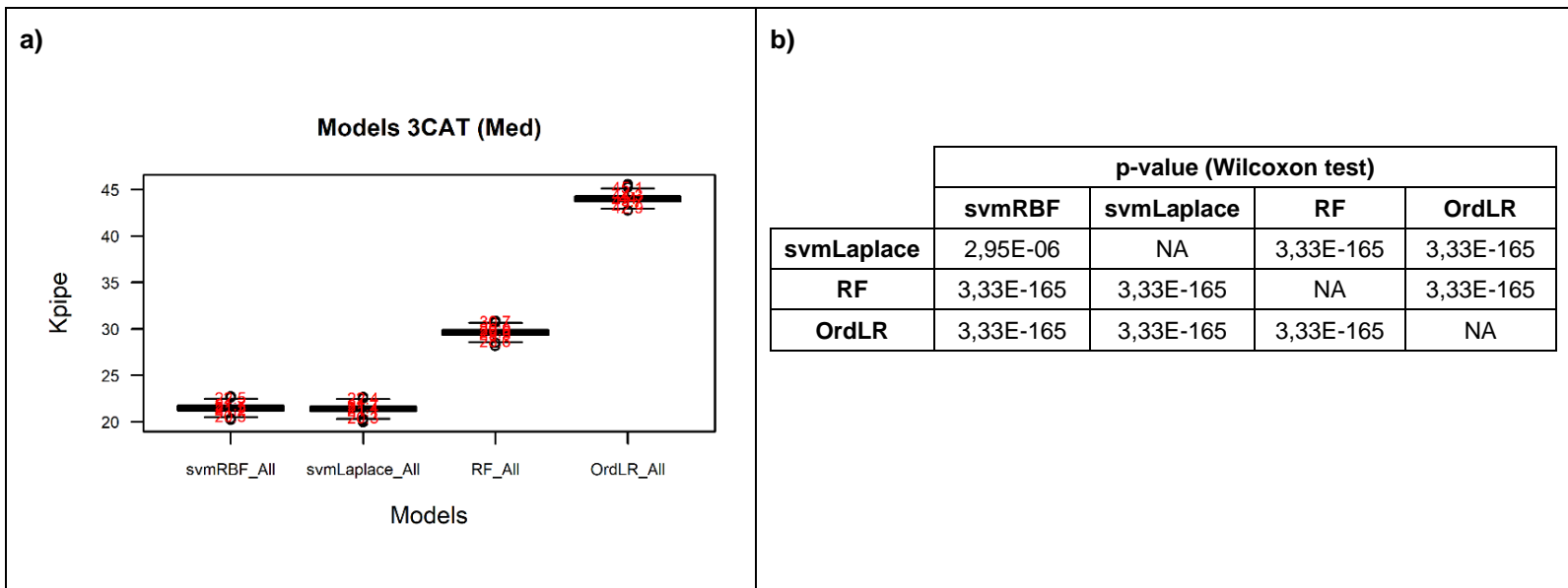


**Figure 89.** Comparison of the most suitable deterioration model to achieve the management objective at network level for the second structural condition scenario (3 structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right) for Medellin's case. Source: Author

According to Figure 89, R-based model that considers the variables that presented the first and second relationship grade with the structural conditions are the one that most minimize the *Knet* metric increasing performance prediction at network level for the second SCS (see Figure 77.a). The predictions of this model show significant statistical differences with the predictions of the other models (p-values lower than 0.05) (see Figure 77.b).

On the other hand, the deterioration models that most minimize the *Kpipe* metric in the validation data were: (i) SVM-RBF-based deterioration models considering all studied variables; (ii) SVM-Laplace based deterioration models considering all the studied variables; (iii) RF based deterioration models considering the first relationship grade variables (Par); and (iv) Ordinal logistic models considering all the studies variables (see Figure 90).

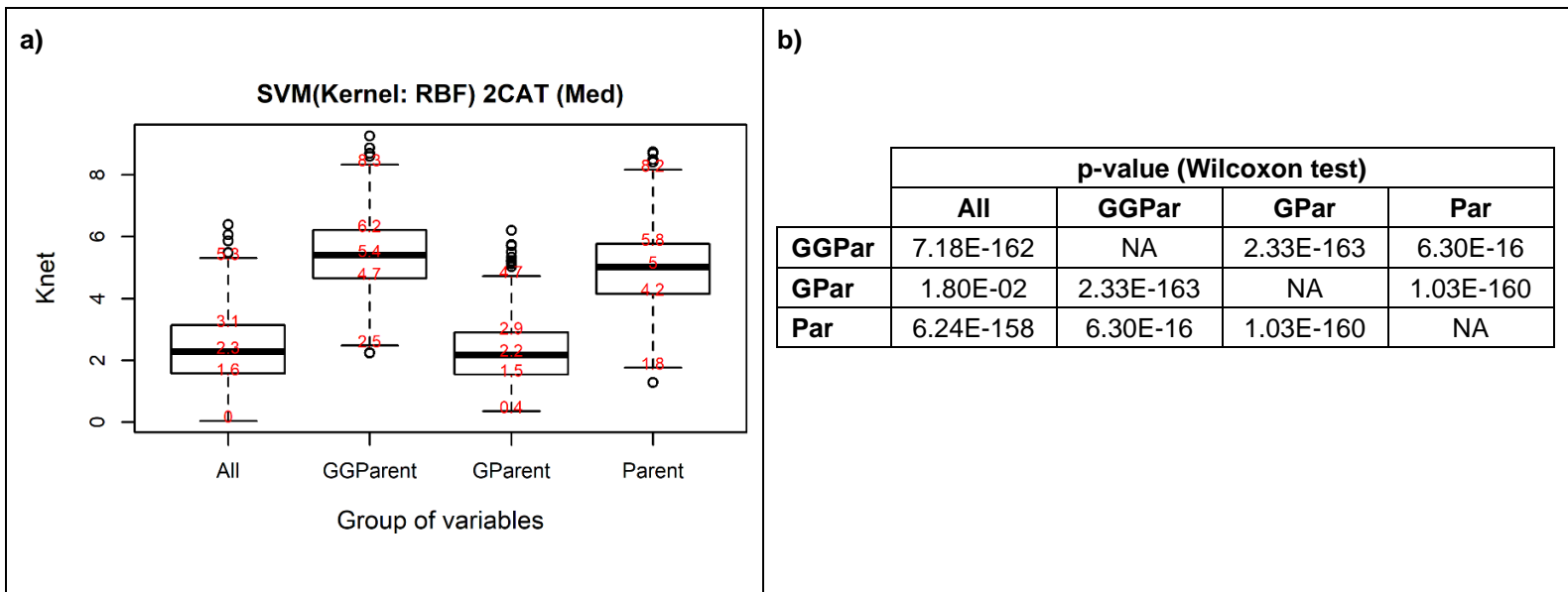
According to Figure 90, SVM\_Laplace-based model that considers all the studied variables is the one that most minimize the *Kpipe* metric increasing performance prediction at pipe level for the second SCS (see Figure 90.a). The predictions of this model show significant statistical differences with the predictions of the other models (p-values lower than 0.05) (see Figure 90.b).



*Figure 90. Comparison of the most suitable deterioration model to achieve the management objective at pipe level for the second structural condition scenario (3 structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right) for Medellin's case. Source: Author*

*D.2.4.3. Third SCS: Acceptable and poor-critical structural conditions*

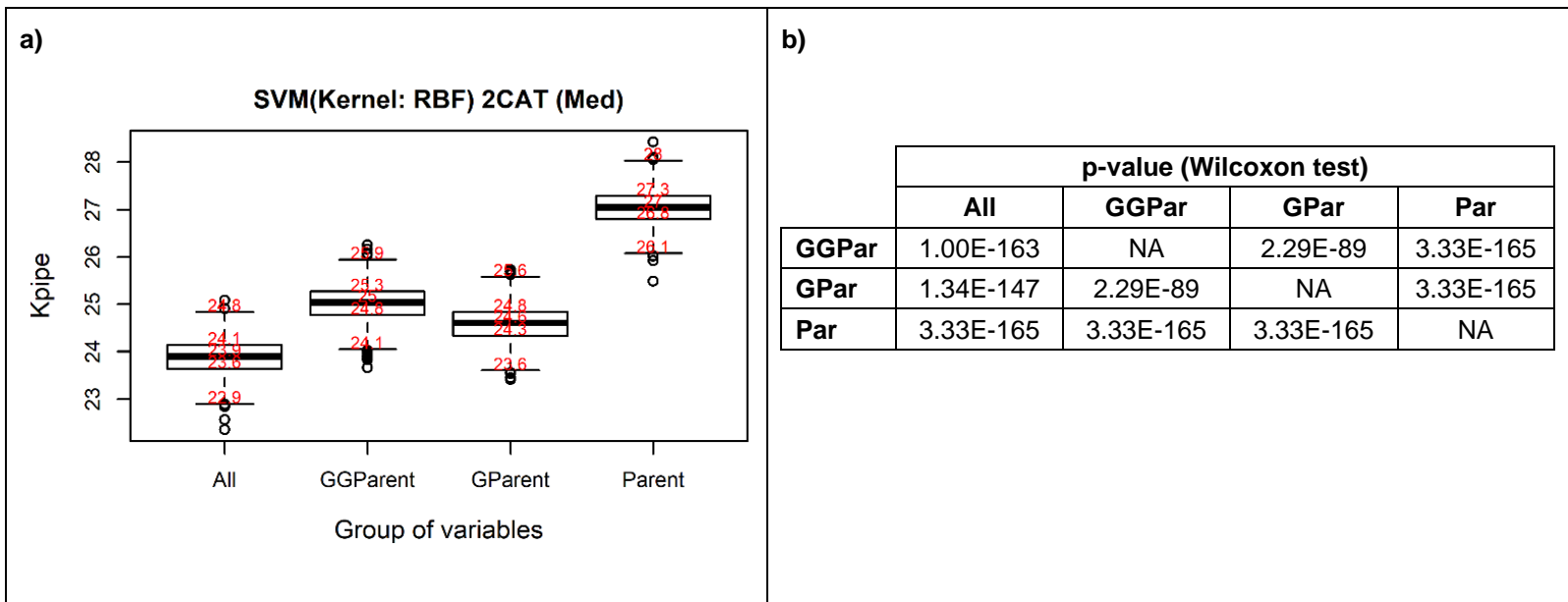
Figure 91 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 26) based on the optimised SVM considering RBF kernel function for network level management objective (see the hyperparameters set in these models in Table 32) for the third SCS.



*Figure 91. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the network level objective (Knet) and third SCS (two structural categories– acceptable and poor-critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 91, the SVM-RBF-based model that most minimize the *Knet* metric is the one that includes the variables that presented the first and second relationship with the structural condition (GPARENT), and this model shows significant statistical difference with the other models (p-value <0.05).

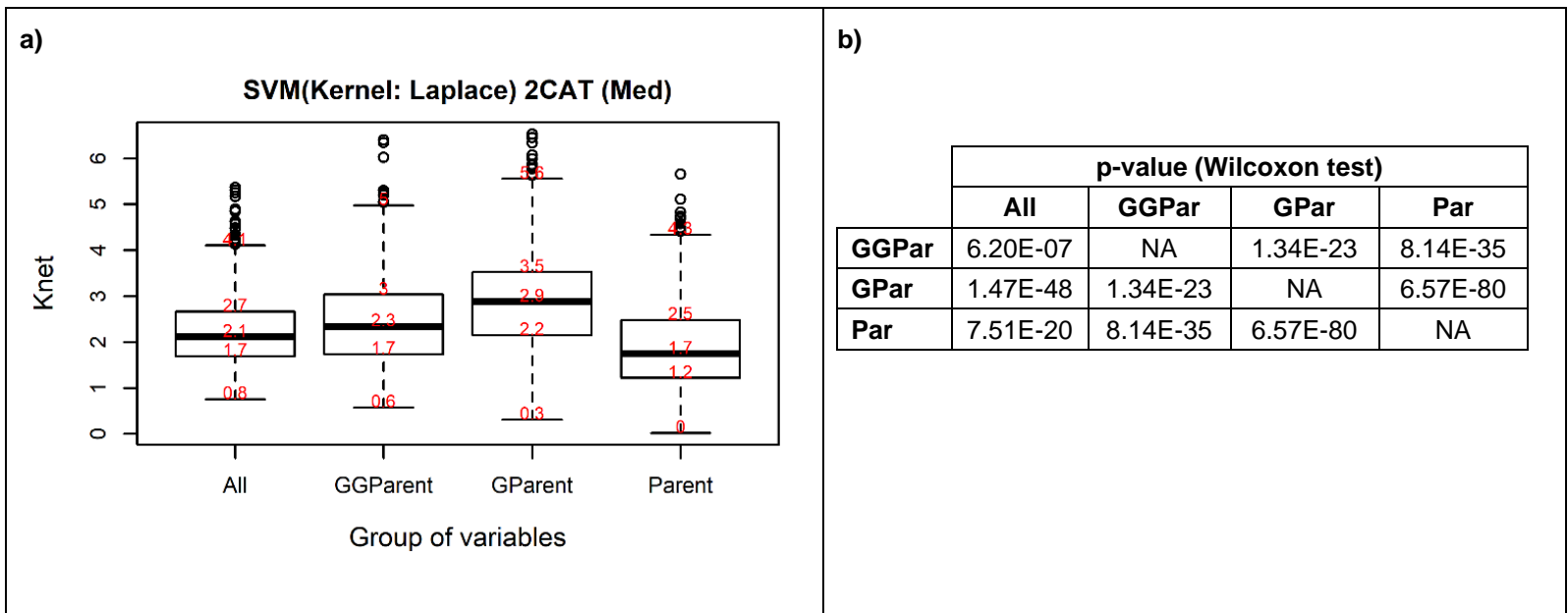
Figure 92 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 26) based on the optimised SVM considering RBF kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 33) for the third SCS.



*Figure 92. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the pipe level objective (Kpipe) and third SCS (two structural categories– acceptable and poor-critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 92, the SVM-RBF-based model that most minimize the *Kpipe* metric is the one that includes all the studied variables and this model shows significant statistical difference with the other models (p-value <0.05).

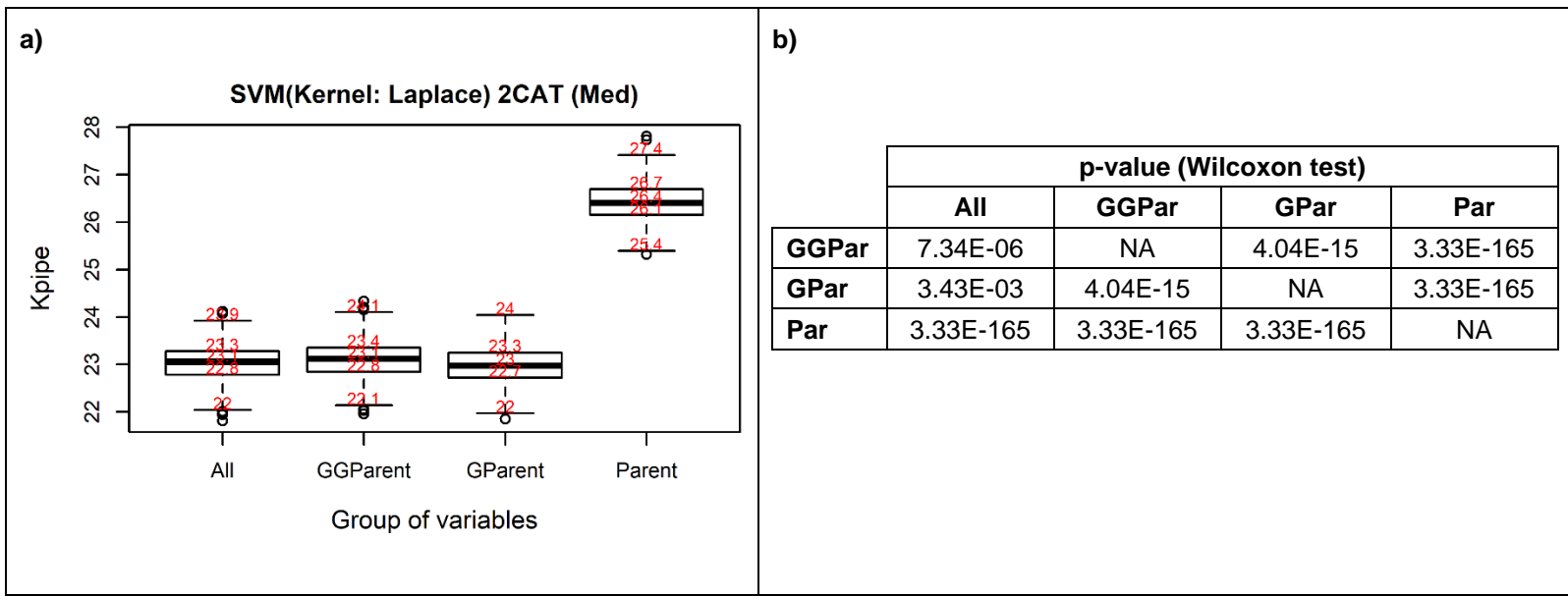
Figure 93 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 26) based on the optimised SVM considering Laplace kernel function for the network level management objective (see the hyperparameters set in these models in Table 32) for the third SCS.



*Figure 93. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the network level objective (Knet) and third SCS (two structural categories– acceptable and poor-critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 93, the SVM-Laplace-based model that most minimize the *Knet* metric is the one that includes only the variables that show the first relationship grade with the structural conditions (Parent variables), and this model shows significant statistical difference with the other models (p-value <0.05).

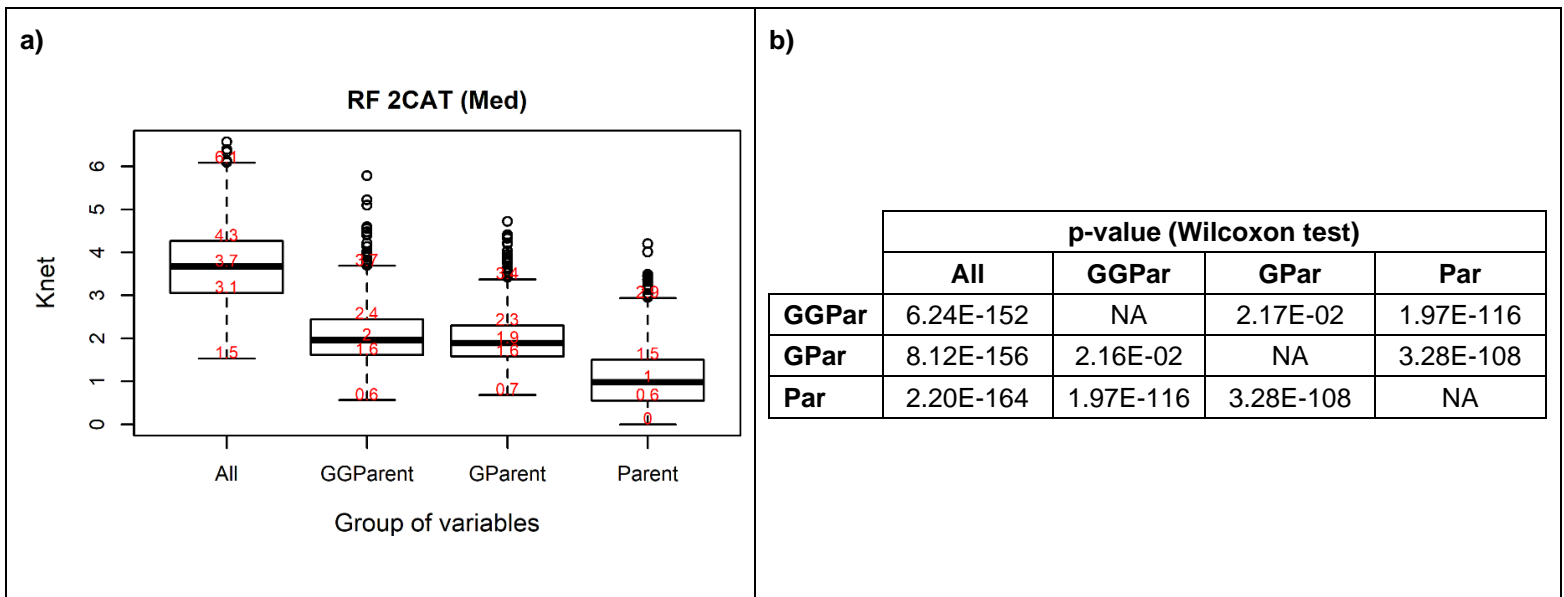
Figure 94 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 26) based on the optimised SVM considering Laplace kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 33) for the third SCS.



**Figure 94. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the pipe level objective ( $K_{pipe}$ ) and third SCS (two structural categories– acceptable and poor-critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 94, the SVM-Laplace-based model that most minimize the  $K_{pipe}$  metric is the one that includes the variables that show the first and second relationship grades with the structural conditions (GParent variables), and this model shows significant statistical difference with the other models ( $p$ -value  $< 0.05$ ).

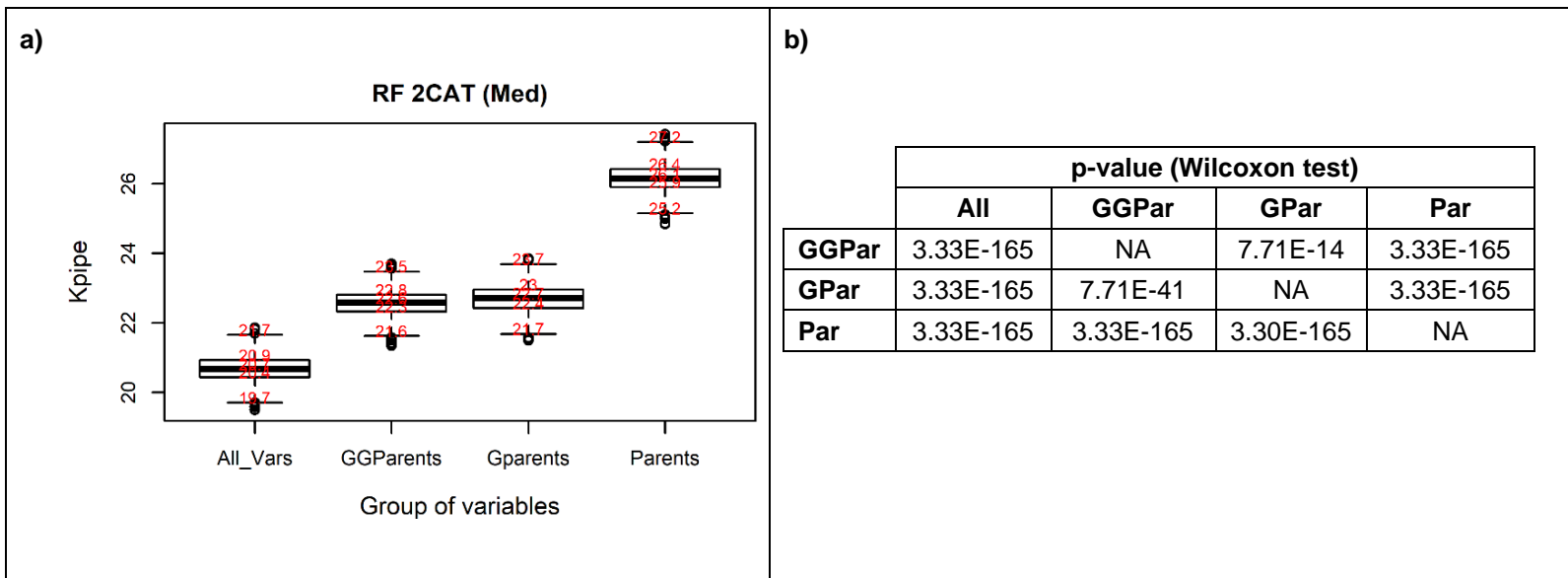
Figure 95 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 26) based on the optimised RF for the network level management objective (see the hyperparameters set in these models in Table 32) for the third SCS.



*Figure 95. Results of the validation data of the RF-based deterioration models for the network level objective (Knet) and third SCS (two structural categories– acceptable and poor-critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 95, the RF-based model that most minimize the *Knet* metric is the one that includes only the variables that show the first relationship grade with the structural conditions (Parent variables), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 96 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 26) based on the optimised RF for the pipe level management objective (see the hyperparameters set in these models in Table 33) for the third SCS.



*Figure 96. Results of the validation data of the RF-based deterioration models for the pipe level objective ( $K_{pipe}$ ) and third SCS (two structural categories– acceptable and poor-critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 96, the RF-based model that most minimize the  $K_{pipe}$  metric is the one that includes all the studied variables and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ).

Figure 97 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 26) based on binomial logistic regression (LR) for the network level management objective for the third SCS.



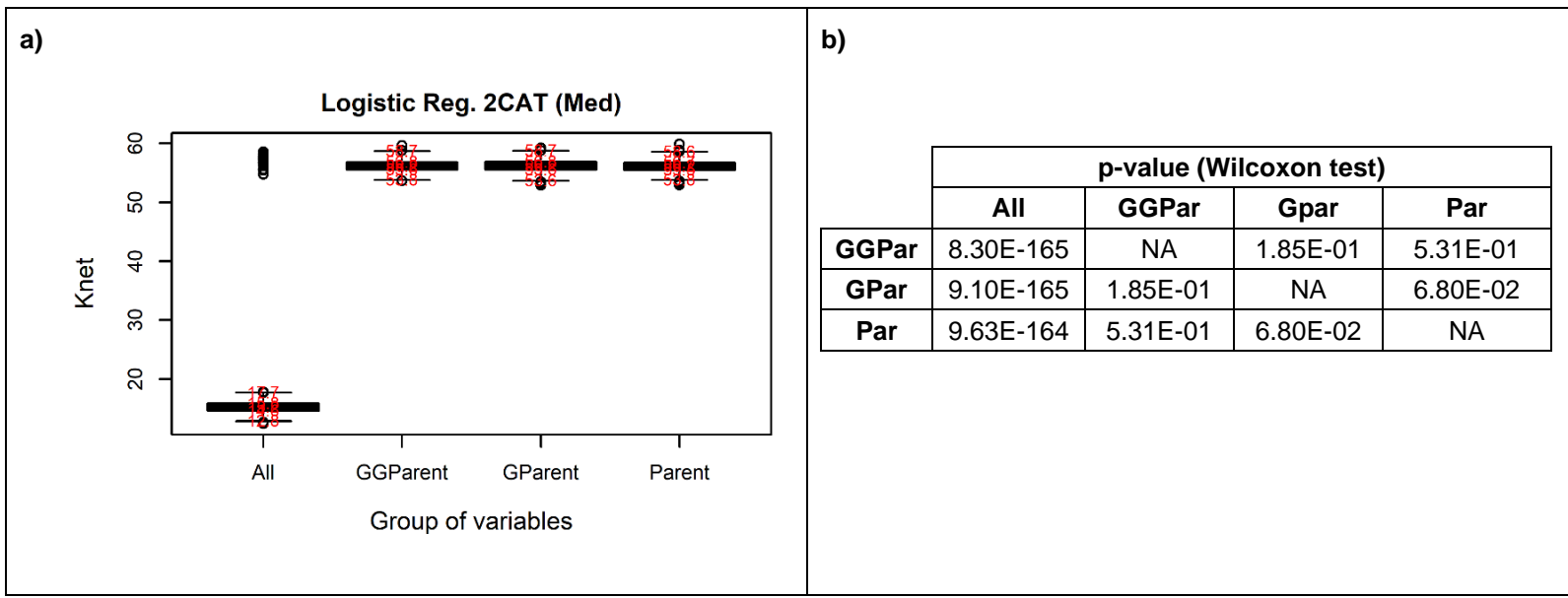
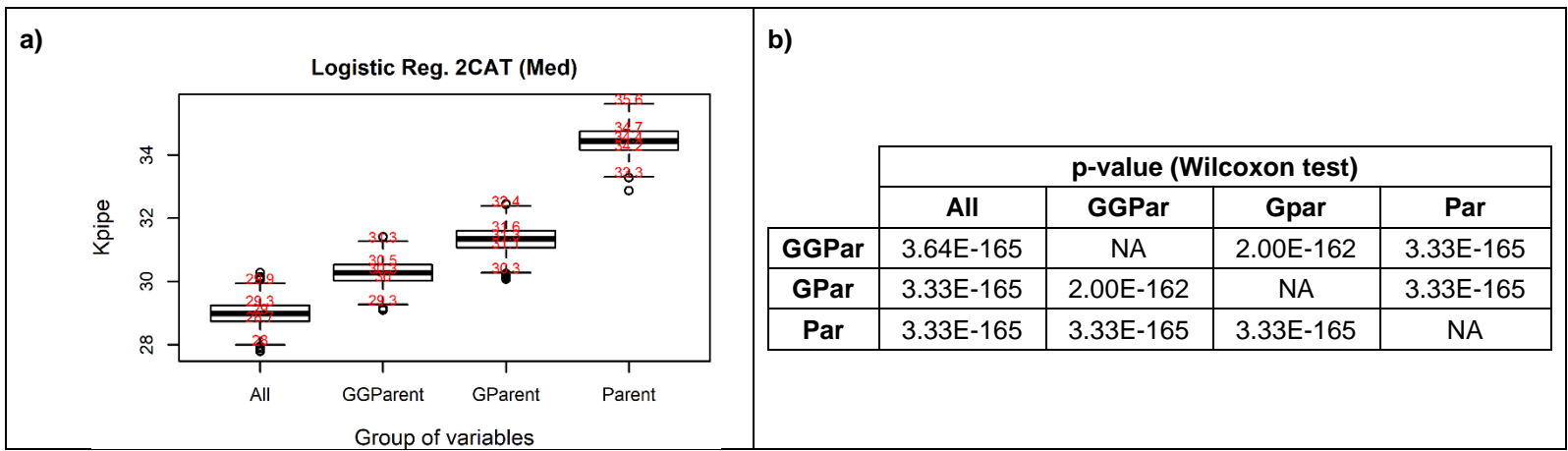


Figure 97. Results of the validation data of the LR-based deterioration models for the network level objective (*Knet*) and third SCS (two structural categories– acceptable and poor-critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 97, the LR-based model that most minimize the *Knet* metric is the one that includes all the studied variables and this model shows significant statistical difference with the other models (p-value <0.05). Besides, there is not differences significantly among the models that considers the variables that represent the Parent, GParent and GGParent variables.

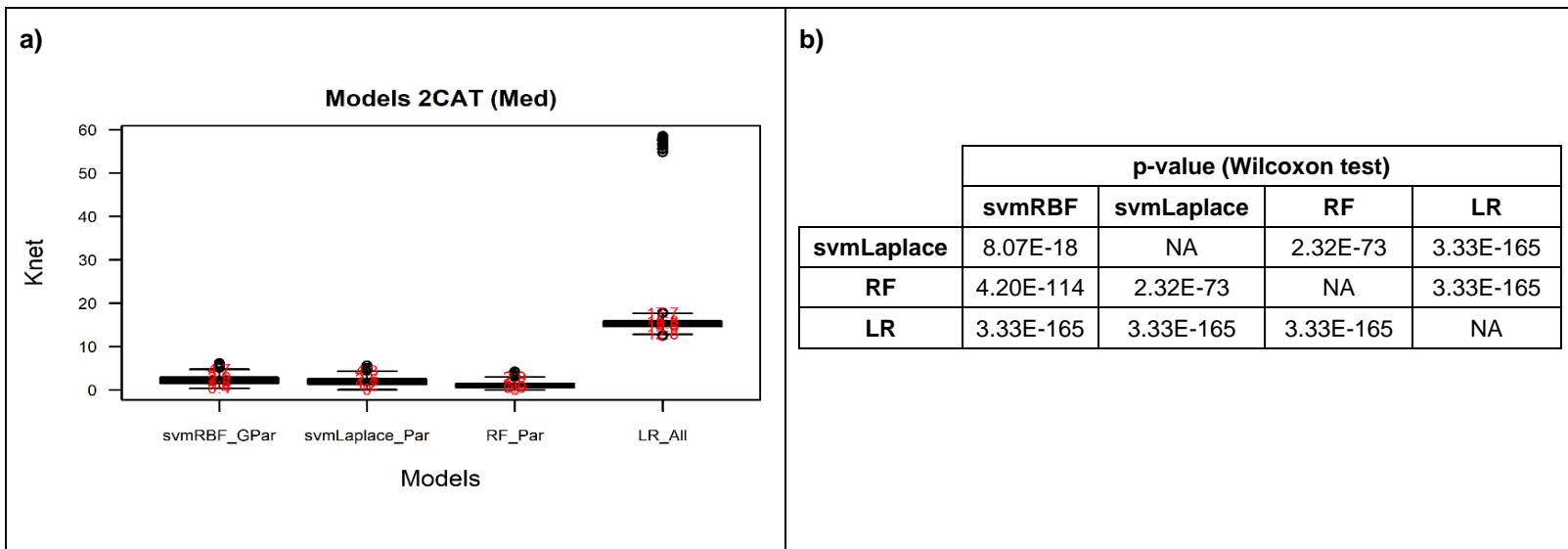
Figure 98 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 26) based on binomial logistic regression (LR) for the pipe level management objective for the third SCS.



*Figure 98. Results of the validation data of the LR-based deterioration models for the pipe level objective (Kpipe) and third SCS (two structural categories– acceptable and poor-critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 98, the LR-based model that most minimize the *Kpipe* metric is the one that includes all the studied variables and this model shows significant statistical difference with the other models (p-value <0.05).

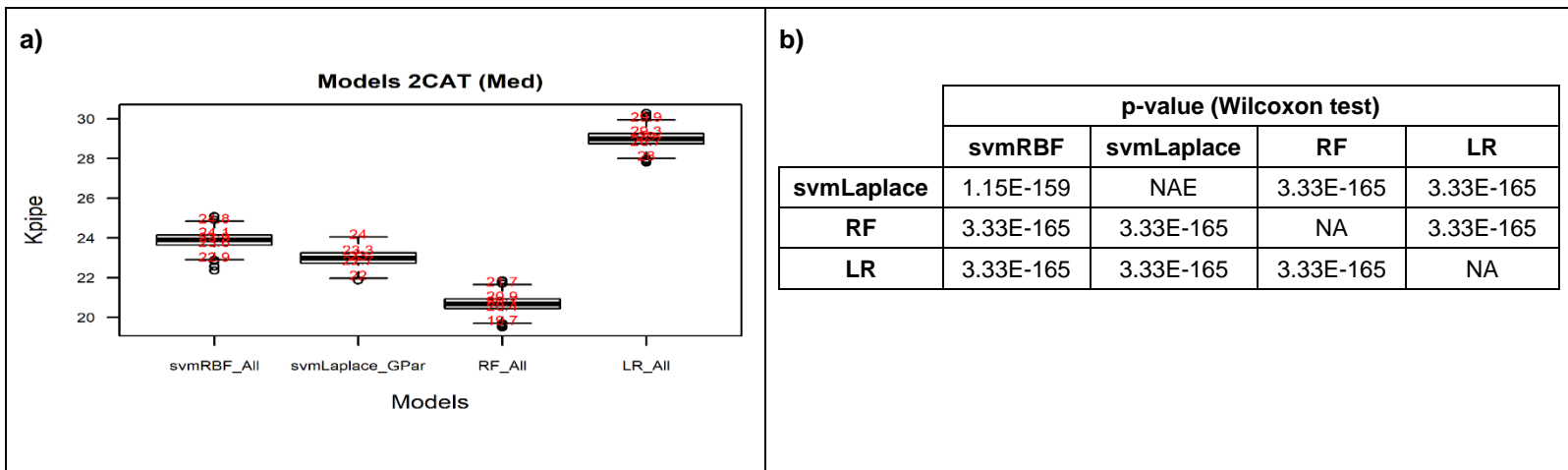
In summary, for the third SCS, the deterioration models that most minimize the *Knet* were: (i) SVM-RBF-based model that considers the variables that present the first and second relationship grade with the structural condition (GPar); (ii) SVM-Laplace-based models that considers only the variables that show the first relationship grade with the structural condition (Par); (iii) RF-based models that only considers the variables that show the first relationship grade with the structural condition (Par); and Ord\_LR-based model that considers all the studied variables (See Figure 98).



*Figure 99. Comparison of the most suitable deterioration model to achieve the management objective at network level for the third structural condition scenario (2 structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right) for Medellin's case. Source: Author*

According to Figure 99, R-based model that only considers the variables that presented the first relationship grade with the structural conditions (Par) is the one that most minimize the *Knet* metric increasing performance prediction at network level for the third SCS (see Figure 99.a). The predictions of this model show significant statistical differences with the predictions of the other models (p-values lower than 0.05) (see Figure 99.b).

On the other hand, the deterioration models that most minimize the *Kpipe* metric in the validation data were: (i) SVM-RBF-based deterioration models considering all studied variables; (ii) SVM-Laplace based deterioration models considering the variables that showed the first and second relationship with the structural conditions (GPar); (iii) RF based deterioration models considering all the studied variables; and (iv) Ordinal logistic models considering all the studies variables (see Figure 99).

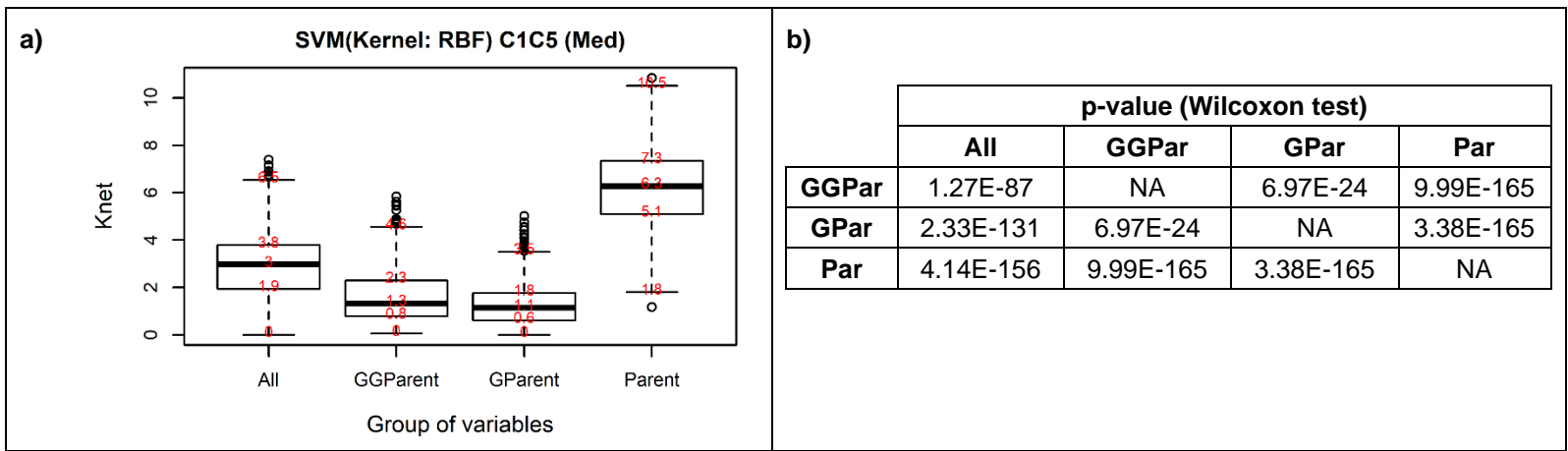


**Figure 100. Comparison of the most suitable deterioration model to achieve the management objective at pipe level for the third structural condition scenario (2 structural categories). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right) for Medellin's case. Source: Author**

According to Figure 100, R-based model that considers all the studied variables is the one that most minimize the *Kpipe* metric increasing performance prediction at pipe level for the third SCS (see Figure 100.a). The predictions of this model show significant statistical differences with the predictions of the other models (p-values lower than 0.05) (see Figure 100.b).

*D.2.4.4. Fourth SCS: excellent and critical structural conditions*

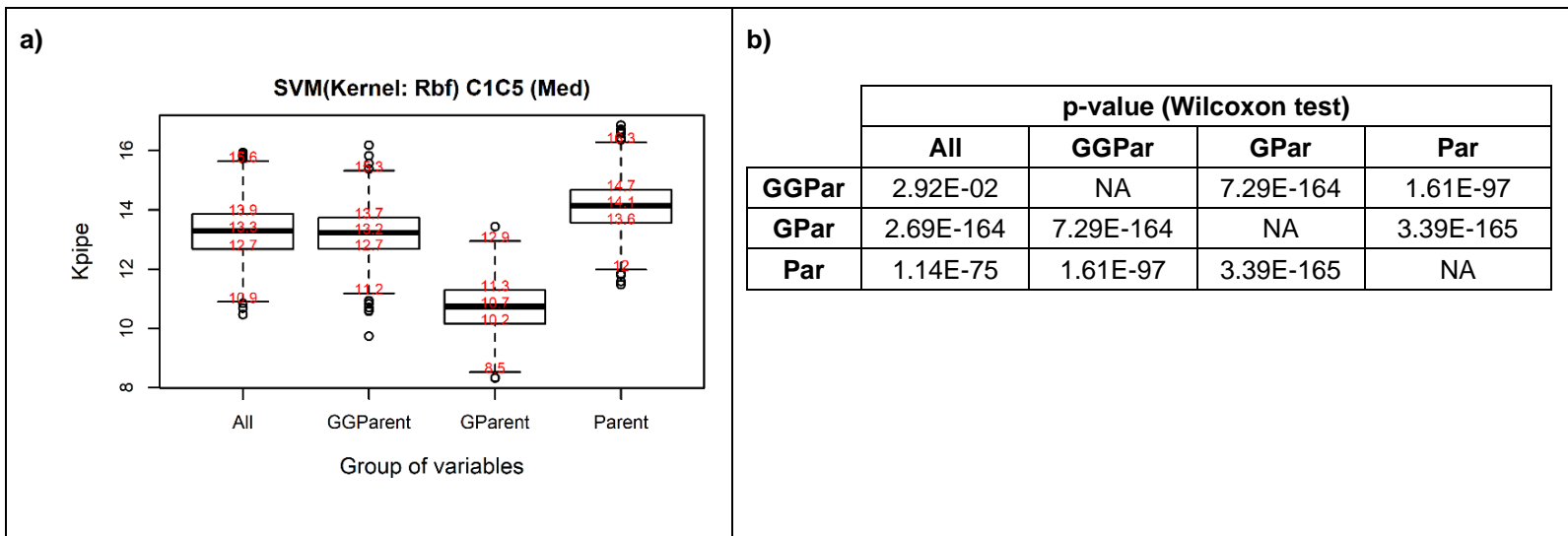
Figure 101 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 27) based on the optimised SVM considering RBF kernel function for the network level management objective (see the hyperparameters set in these models in Table 34) for the fourth SCS.



*Figure 101. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the network level objective (Knet) and fourth SCS (two categories- excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 101, the SVM-RBF-based model that most minimize the *Knet* metric is the one that includes the variables that showed the first and second relationship grades (GPar) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

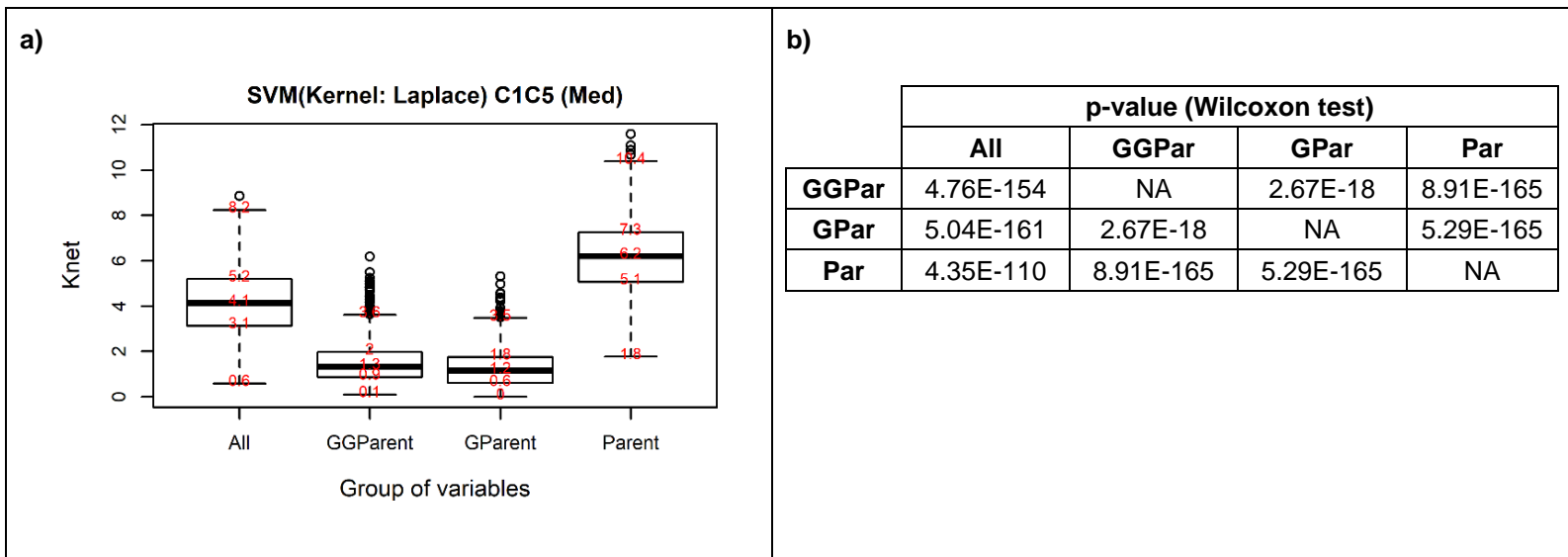
Figure 102 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 27) based on the optimised SVM considering RBF kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 35) for the fourth SCS.



**Figure 102. Results of the validation data of the SVM-based deterioration models considering RBF kernel function for the network level objective (Knet) and fourth SCS (two categories- excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author**

According to Figure 102, the SVM-RBF-based model that most minimize the *Kpipe* metric is the one that includes the variables that showed the first and second relationship grades (GPar) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 103 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 27) based on the optimised SVM considering Laplace kernel function for the network level management objective (see the hyperparameters set in these models in Table 34) for the fourth SCS.



*Figure 103. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the network level objective (Knet) and fourth SCS (two categories- excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 103, the SVM-Laplace-based model that most minimize the *Knet* metric is the one that includes the variables that showed the first and second relationship grades (GPar) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 104 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 27) based on the optimised SVM considering Laplace kernel function for the pipe level management objective (see the hyperparameters set in these models in Table 35) for the fourth SCS.

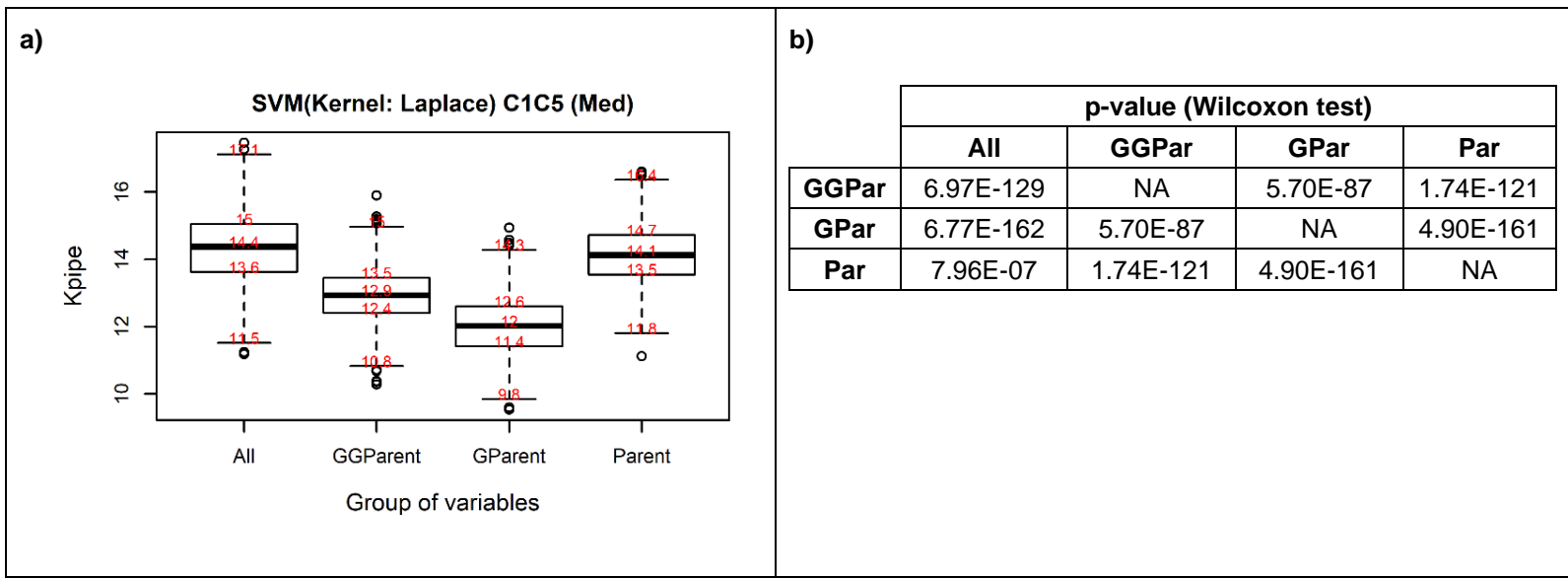


Figure 104. Results of the validation data of the SVM-based deterioration models considering Laplace kernel function for the pipe level objective (*Kpipe*) and fourth SCS (two categories- excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 104, the SVM-Laplace-based model that most minimize the *Kpipe* metric is the one that includes the variables that showed the first and second relationship grades (GPar) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

Figure 105 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 27) based on the optimised RF for the network level management objective (see the hyperparameters set in these models in Table 34) for the fourth SCS.



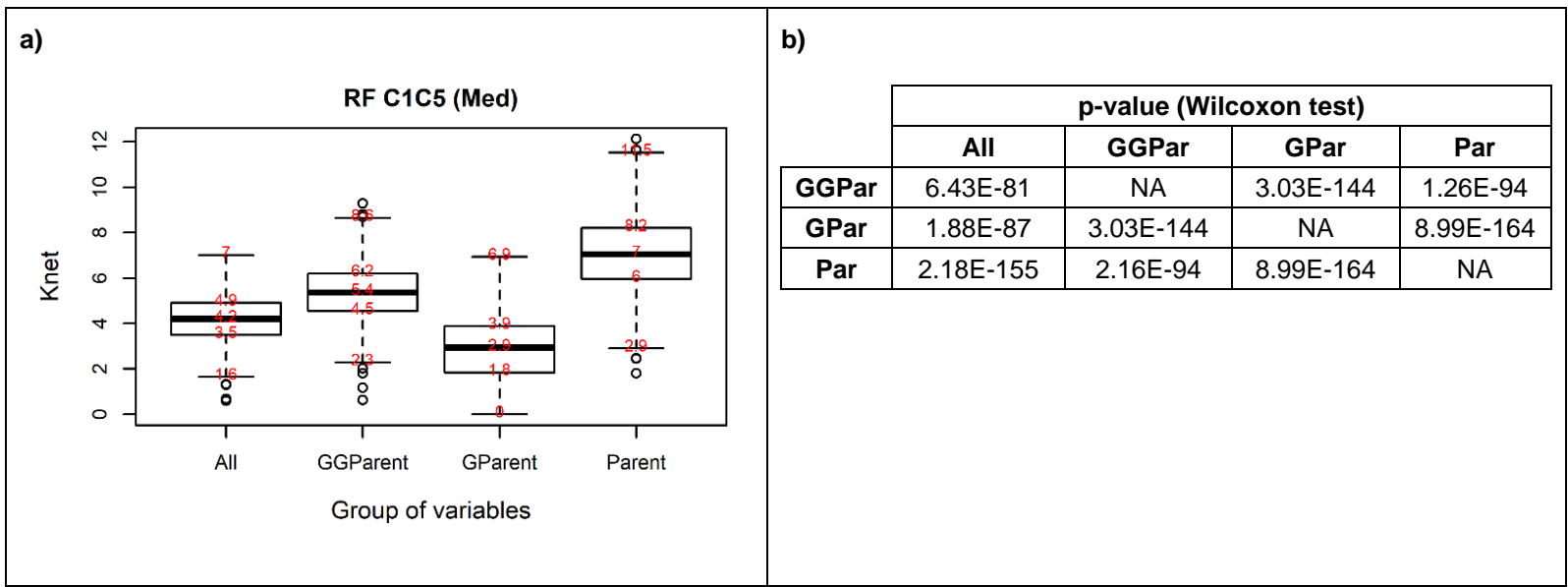


Figure 105. Results of the validation data of the RF-based deterioration models for the network level objective (*Knet*) and fourth SCS (two categories- excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the *p*-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 105, the RF-based model that most minimize the *Knet* metric is the one that includes the variables that showed the first and second relationship grades (GPar) with structural condition for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (*p*-value <0.05).

Figure 106 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 27) based on the optimised RF for the network level management objective (see the hyperparameters set in these models in Table 35) for the fourth SCS.

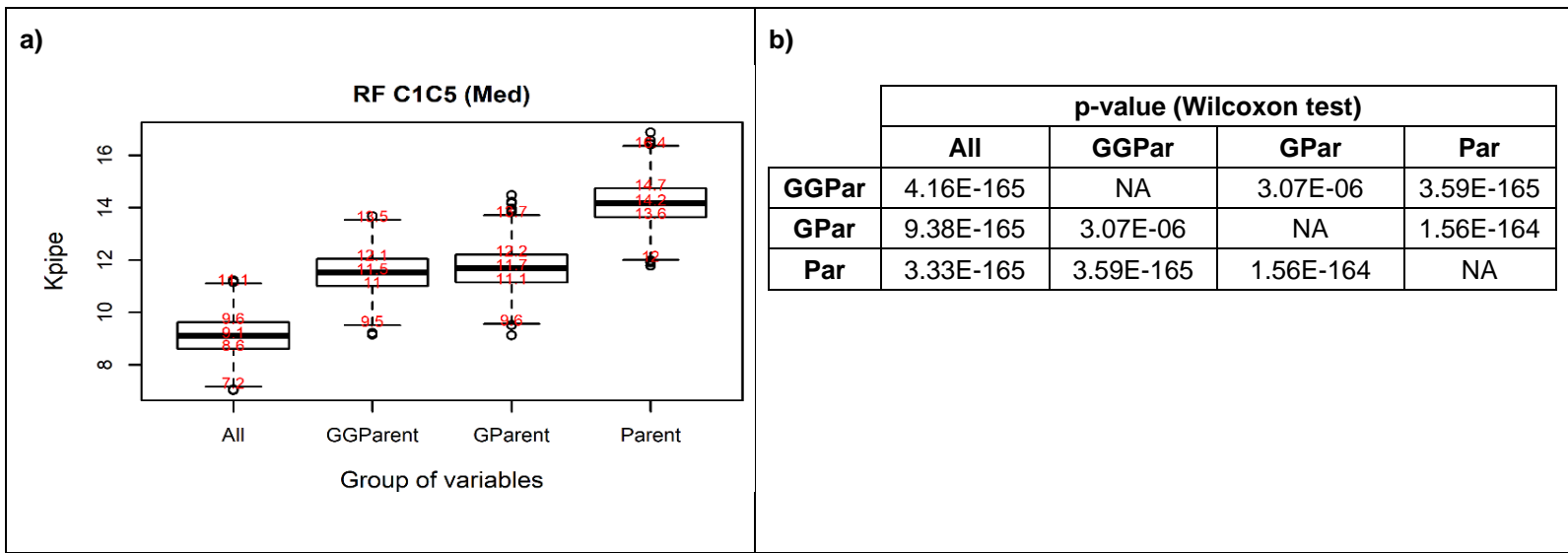
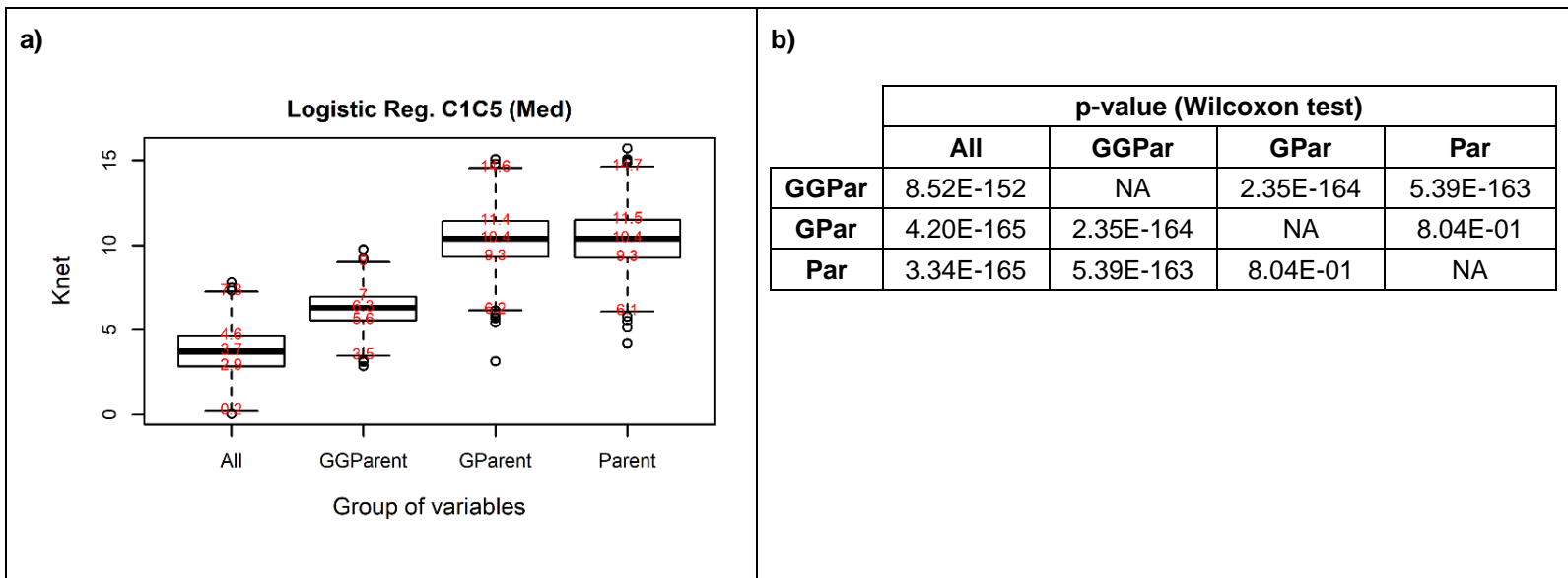


Figure 106. Results of the validation data of the RF-based deterioration models for the pipe level objective ( $K_{pipe}$ ) and fourth SCS (two categories- excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author

According to Figure 106, the RF-based model that most minimize the  $K_{pipe}$  metric is the one that includes all the studied variables for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

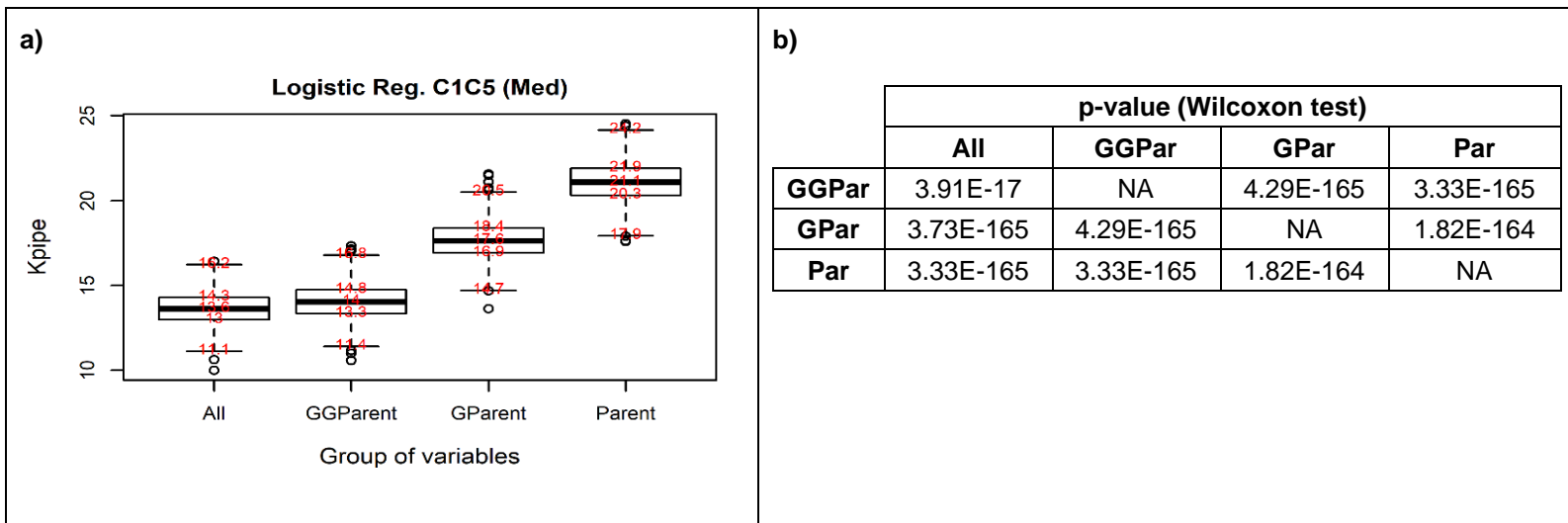
Figure 107 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 27) based on LR for the network level management objective for the fourth SCS.



*Figure 107. Results of the validation data of the LR-based deterioration models for the network level objective (Knet) and fourth SCS (two categories- excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 107, the LR-based model that most minimize the *Knet* metric is the one that includes all the studied variables for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models ( $p$ -value  $<0.05$ ). Moreover, it is interesting to highlight that LR-based models that considers only the variables that present the first relationship grade with the structural condition (Par) and the variables that present the first and second relationship grades with the structural condition (GPar) do not show difference significantly. It means that the inclusion of the variables that showed second grade relationship with the structural condition (GPar) does not present differences in the prediction of the sewer assets in comparison with the LR-based model that considers only the variables that showed the first relationship grade with the structural condition.

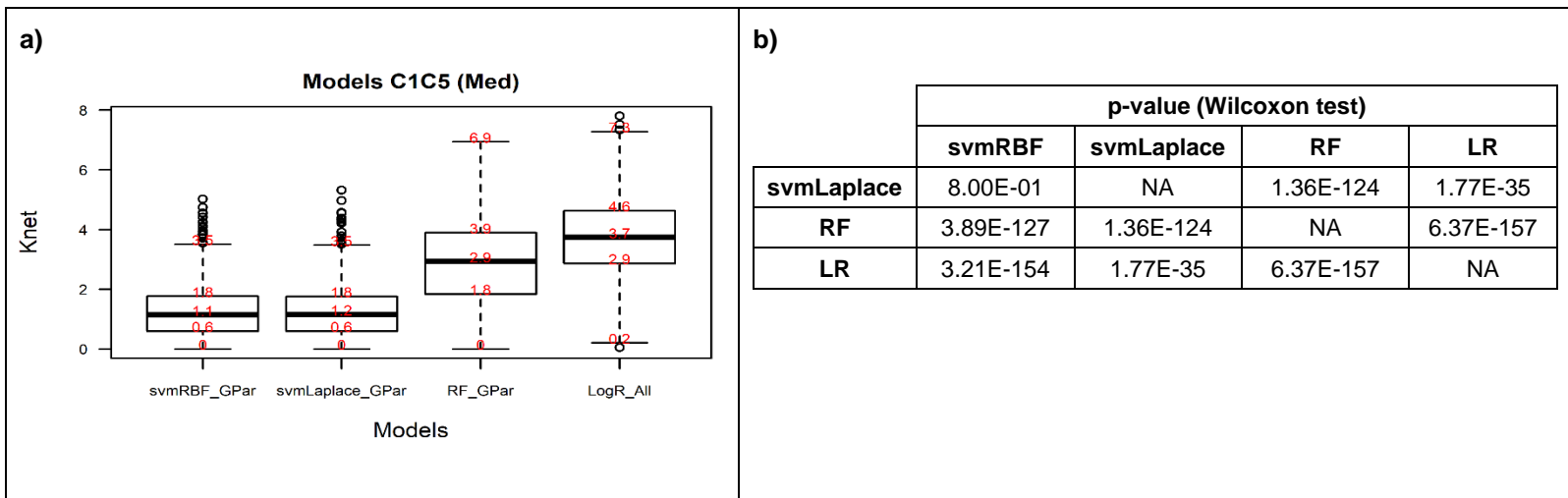
Figure 108 shows the prediction results (validation data) obtained from each model including each group of variables (see hierarchy of variables for this SCS in Table 27) based on LR for the pipe level management objective for the fourth SCS.



*Figure 108. Results of the validation data of the LR-based deterioration models for the pipe level objective ( $K_{pipe}$ ) and fourth SCS (two categories- excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right). Source: Author*

According to Figure 108, the LR-based model that most minimize the  $K_{pipe}$  metric is the one that includes all the studied variables for the fourth SCS (excellent and critical structural categories), and this model shows significant statistical difference with the other models (p-value <0.05).

In summary, for the fourth SCS (excellent and critical structural conditions), the deterioration models that most minimize the  $K_{net}$  were: (i) SVM-RBF-based model that considers the variables that present the first and second relationship grade with the structural condition (GPar); (ii) SVM-Laplace-based models that considers the variables that show the first and second relationship grades with the structural condition (GPar); (iii) RF-based models that considers the variables that show the first and second relationship grades with the structural condition (GPar); and Ord\_LR-based model that considers all the studied variables (See Figure 109).



**Figure 109. Comparison of the most suitable deterioration model to achieve the management objective at network level for the fourth SCS (excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right) for Medellin's case. Source: Author**

According to Figure 109, SVM-based models are the ones that most minimize the *Knet* metric increasing performance prediction at network level for the third SCS (see Figure 109.a). The predictions of these model show significant statistical differences with the predictions of the RF and LR models (p-values lower than 0.05) (see Figure 109.b). However, SVM-based models considering RBF and Laplace kernel functions do not show differences significantly in their predictions for the network level objective (p-values > 0.05). Any of both SVM-based models could be choosing for reaching the network level objective for the fourth SCS, since both need the inclusion of the same variables.

On the other hand, the deterioration models that most minimize the *Kpipe* metric in the validation data were: (i) SVM-RBF-based deterioration models considering the variables that show the first and second relationship grades with the structural condition (GPar); (ii) SVM-Laplace based deterioration models considering the variables that showed the first and second relationship with the structural conditions (GPar); (iii) RF based deterioration models considering all the studied variables; and (iv) Ordinal logistic models considering all the studies variables (see Figure 110).

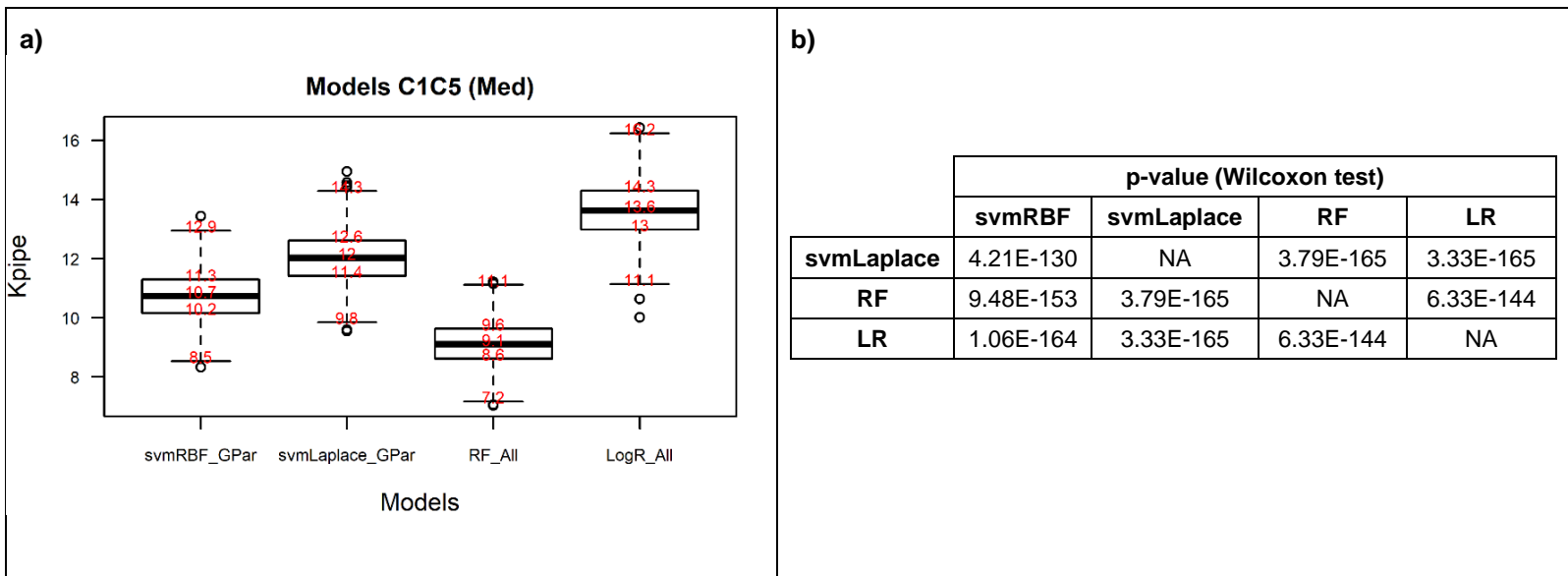


Figure 110. Comparison of the most suitable deterioration model to achieve the management objective at the pipe level for the fourth SCS (excellent and critical structural conditions). a) figure that shows boxplot analysis (figure on the left) and b) table that shows the p-values obtained by the comparison of the deterioration models by Wilcoxon test (figure on the right) for Medellin's case. Source: Author

According to Figure 110, RF-based model considering all the studied variables is the one that most minimize the *Kpipe* metric increasing performance prediction at pipe level for the fourth SCS (see Figure 110.a). The predictions of these model show significant statistical differences with the other models (p-values lower than 0.05) (see Figure 110.b).

*D.2.4.5. Analysis of the most suitable models for management objectives*

Table 36. p-values obtained by the comparison of the deterioration models at the network level objective for Medellin's case by Wilcoxon test (*Knet*) for the four SCS.

	p-value (Wilcoxon test)			
	SCS_1	SCS_2	SCS_3	SCS_4
SCS_2	1.92E-158	NA	3.79E-106	1.51E-93
SCS_3	2.79E-24	3.79E-106	NA	2.90E-01
SCS_4	8.44E-15	1.51E-93	2.90E-01	

Source: Author

Table 37. p-values obtained by the comparison of the deterioration models at the pipe level objective for Medellin's case by Wilcoxon test (*Kpipe*) for the four SCS.

	p-value (Wilcoxon test)			
	SCS_1	SCS_2	SCS_3	SCS_4
SCS_2	6,13E-165	NA	4,95E-144	3,33E-165
SCS_3	5,50E-109	4,95E-144	NA	3,33E-165
SCS_4	3,33E-165	3,33E-165	3,33E-165	NA


Source: Author

# CURRICULUM VITAE

## PERSONAL INFORMATION



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## WORK EXPERIENCE

01/01/2016 – 20/04/2020

### University Doctoral Position

*Pontificia Universidad Javeriana, Bogotá (Colombia)*

Research field focused on Infrastructure Asset Management, specifically Sewer Asset Management.

During the doctoral studies, I focused on:

- Data mining tools
- Exploration of different tools for the feature selection of variables that show a relationship with the structural deterioration of the sewer assets: information theory, statistical and machine learning tools
- Developing of deterioration models based on statistical and machine learning tools: logistic regression, Gompitz, discriminant analysis, Random Forest, Neuronal Networks, and Support Vector Machines
- Developing of optimization methodologies for identifying the optimal combination of hyperparameters to achieve a sewer asset management objective
- Purpose metrics linking with different objective managements
- Use of GIS tools to collect and merge information to build geographical maps

### Other activities:

- Co-director in two Master theses
- Research advisor at university projects related to the development of support tools to sewer asset management and machine learning tools
- Organization's assistant to national and international research events associated to water infrastructure asset management and urban hydrology (ACODAL 2017 and 2018, Cartagena de Indias, Colombia)
- Author of a reviewer book about the main topics and new worldwide advances in sewer asset management. It is a guiding book for professionals, stakeholders, and new generations of engineers interested on this field.
- Coordinator and manager of financial resources given by Colciencias for the research project that support the doctoral studies.

# CURRICULUM VITAE

01/01/2018 – 30/06/2018 **University Teaching Assistant**

*Pontificia Universidad Javeriana, Bogotá (Colombia)*

Course: Fluid Mechanics for Civil Engineering BS.c.

01/01/2016 – 31/12/2017 **Junior Research Internship**

*KompeteZZentrum Wasser Berlin, Berlin (Germany)*

Junior Research Internship into the cooperation framework for the mobility of German and Colombian researchers to develop innovative tools to support efficient sewer asset management strategies in Germany and Colombia (Colciencias – Pontificia Universidad Javeriana and Procol-DAAD)

As it was a mobility contract, the internship was during:

- June and July of 2016; and June to October of 2017

During the internship, the Colombian and German researchers carried out the following activities:

- Exploration and development of deterioration models based on statistical and machine learning tools
- Proposals about optimization methodologies for finding the optimal combination of hyperparameters for deterioration models for achieving management objectives
- Proposals of metrics for achieving management objectives
- Meetings with water utilities and other institutions responsible of sewerage to display the importance of the development of tools to support decision-making in sewer asset management.
- Dissemination of the research results at international events and journals

## EDUCATION AND TRAINING

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01/01/2016 – 20/04/2020 **Engineering (Ph.D.)**

*Pontificia Universidad Javeriana, Bogotá (Colombia)*

Doctoral thesis entitled: Methodology for identifying the key and enough factors for achieving objectives in sewer asset management

Dissertation date: 20/04/2020

Advisor: Prof. Andrés Torres (PUJ, Bogotá, Colombia)

Evaluators: Sveinung Saegrov (NTNU, Trondheim, Norway)

João P. Leitão (Eawag, Dübendorf, Switzerland)

Juan Pablo Rodríguez (UniAndes, Bogotá, Colombia)

Gabriel Penagos (PUJ, Bogotá, Colombia)



# CURRICULUM VITAE

01/01/2014 – 31/12/2015

## Water Systems M.Sc.

*Pontificia Universidad Javeriana, Bogotá (Colombia)*

Master of science focused on hydrology, water systems, water asset management, water quality, water resources, time series analysis, remote sensing, and statistical and machine learning tools

Master thesis entitled: Methodology for classifying uninspected pipes according to their structural condition for Bogota's sewer network

Honorable mention for Master thesis

01/01/2006 – 31/12/2011

## Civil Engineering B.Sc.

*Pontificia Universidad Javeriana, Bogotá (Colombia)*

Bachelor thesis entitled: Markov chains applied for decision-making in Sewer Asset Management

## PERSONAL SKILLS

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Mother language

Spanish

Foreign Language

English (C1)

Italian (B1)

## ADDITIONAL INFORMATION

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### Publications

- 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.
- Tschekner-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., Hernandez, 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.
- Hernández, N., Camargo, J., Moreno, F., Torres, A., & Nossa, L. P. (2017). Arima as a forecasting tool for water quality time series measured with UV-Vis spectrometers in a constructed wetland. *Tecnología y ciencias del agua*, 8(5), 127-139.
- Angarita, H., Niño, P., Vargas, D., Hernández, N., & Torres, A. (2017). Identifying explanatory variables of structural state for optimum asset management of urban drainage networks: a pilot study for the city of Bogota. *Ingeniería e Investigación*, 37(2), 6-16.
- López-Kleine, L., Hernández, N., & Torres, A. (2016). Physical characteristics of pipes as indicators of structural state for decision-making considerations in sewer asset management. *Ingeniería e Investigación*, 36(3), 15-21.

# CURRICULUM VITAE

- Hernandez-Rodriguez, N., Obregon-Neira, N., & Torres, A. (2016). Factor identification of categorical type related to the structural condition Bogota's sewage pipelines stemming from concepts of the information's entropy. *INGENIERIA SOLIDARIA*, 12(19), 63-71.
- Galarza-Molina, S., Gómez, A., Hernández, N., Matthew, B., Fletcher, T. D., & Torres, A. (2016). Online equipment installed in a stormwater harvesting system: calibration procedures, first performance results and applications. *Traitement de la pollution/Pollution treatment-Acquisition de données/Data acquisition*.

## Conferences

- Conference: LESAM/PI Conference 2019. Title: Selecting effective sewer asset management models: a probabilistic inference approach. Rol: Author and Speaker
- Conference: V Simposio Internacional Alianza Asia-Pacífico: Nuevas fronteras para el desarrollo económico y la integración en la cuenca del pacífico (October, 2019). Title: Urban and environmental characteristics of Latin American cities as key factors in the deterioration of sewer systems. Rol: Author and Speaker
- Conference: International Conference on Urban Drainage Modelling (UDM, 2018). Title: Optimizing SVM Model as Predicting Model for Sewer Pipes in the Two Main Cities in Colombia. Rol: Author and Speaker
- Conference: 13th International Conference on Hydroinformatics (HIC 2018). From CCTV data to strategic planning: deterioration modelling for large sewer networks in Germany and Colombia. Rol: Author
- Conference: 61th International ACODAL conference (2018). Titles: Gestión de Activos de Infraestructura: Sistemas de alcantarillado, Introducción del contexto mundial; Historia y contextualización: Protocolos existentes para calificar la condición estructural y operacional; and Herramientas de apoyo para la toma de decisiones en gestión proactiva. Rol: Author and Speaker.
- Conference: 14th International conference on urban drainage (ICUD 2017) Titles: Support Vector Machines used for the prediction of the structural conditions of pipes in Bogota's sewer system and Support tools to predict the critical structural condition of uninspected pipes for case studies of Germany and Colombia. Rol: Author and Speaker
- Conference: LESAM 2017. Title: Support tools to predict the critical structural condition of uninspected sewer pipes in Bogota D.C. Rol: Author and Speaker
- Conference: Coloquio Aguas Urbanas - ACODAL 2017. Title: Aplicación de la regression SVM para predecir la condición estructural de las tuberías no inspeccionadas del sistema de alcantarillado de ogotá. Rol: Author and Speaker.

## Books

Gestión Patrimonial de Alcantarillados  
Editorial Javeriana (to be published in 2020)