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Asset Management of Wastewater Interceptors Adjacent to Bodies of Water

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Abstract: Pipeline asset management derives from pipelines' physical conditions, condition rating, and serviceability through investigating, monitoring, and analyzing the rupture history. The remaining asset life and structural condition of the pipeline network running near and under bodies of water are often hard to predict. In case of a pipeline failure, major damage may occur to the surrounding environment, adding up to disruptions in service and repair costs. This paper develops multinomial logistic regression (MLR) and binary logistic regression models to predict how the bodies of water could affect the soil surrounding wastewater interceptors. The models were developed based on data from the City of Fort Worth, Texas. This study concludes that the pipe diameter, pipe age, location of the pipeline with reference to bodies of water (far or near), and the pipe material are the most significant variables that affect the surrounding conditions and remaining life of wastewater interceptors. In future, a clearer perception through increased software development and machine learning for managing pipeline asset management would provide impacts on different parameters on pipelines' expected life.

Keywords: asset management; wastewater; artificial intelligence; pipelines; multinomial logistic regression; binary logistic regression

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1. Introduction and Background

Utility and pipeline systems form one of the most capital-intensive infrastructure systems, and they are aging, overused, possibly mismanaged, and neglected [1]. Most wastewater systems are gravity systems; flow is transferred by natural forces rather than complicated pumping technology. The United States' wastewater network consists of over 800,000 miles of public sewers and 500,000 miles of private lateral sewers that connect homes and businesses to public sewer lines. The typical lifespan expected for wastewater pipes is 50 to 100 years [2].

The biggest challenges of maintaining wastewater systems are that the process is out of view [3]. The latest 2021 infrastructure report card, published by the American Society of Civil Engineering (ASCE), reveals incremental progress toward restoring our nation's infrastructure. For the first time, our infrastructure GPA went up from D+ in 2017 to C- in 2021 [2]. Furthermore, most municipal sewer systems are at least 60 years old, and some utilities assume that newer pipes must be in good condition compared with older pipes, which is not the case, since many examples show 80-year-old pipes in excellent condition and 30-year-old pipes near failure [3].

An estimation of how much pipe of each size in each region must be repaired and rehabbed in the coming 40 years is compiled by combining the demographically based pipeline inventories with the projected service lifetime for each region [4]. The effects that are associated with pipeline failures can be extended to impact other infrastructures, so many utilities have adopted new technologies in pipeline asset management to enhance proactive asset management strategies [5]. Moreover, the U.S. utilities must meet all National Pollutant Discharge Elimination System (NPDES) permit requirements and innovative the geographic information system (GIS)'s cloud-based data combined with mapping technologies within utility asset management planning to begin the next step of risk analysis based on the condition assessment [6].

Evaluating pipe management strategies with an Envision pre-assessment checklist resulted in three main strategies, as explained below [6,7]:

- A run-to-failure strategy is recommended only if the pipe failure consequences are minimal with financial shortfalls.
- A pre-emptive replacement strategy is shared and reduces the impact of pipe failures. Pipe replacement should be based on the actual condition; otherwise, some pipes will be replaced even when they have a remaining useful life.
- Under a balanced approach strategy, repair and rehabilitation decisions will be based on the pipe condition factor.

Asset management is a comprehensive plan for managing infrastructure assets to deliver a satisfying service level and minimize operating and ownership costs. A comprehensive asset management plan can help municipalities turn from a reactive approach to a proactive approach while providing life cycle cost analysis based on cost–benefit analysis [7].

Many pipelines that cross under bodies of water are buried deep underneath the soil and must regularly be inspected and evaluated. Once the pipeline conditions are available, asset management, repair, and rehabilitation decisions will be made. Asset management strategies start with reviewing the available historical pipeline data and understanding the failure and deterioration models [8]. Repair and rehabilitation decisions control the continual performance of pipeline systems. A proactive asset management system will overwhelm the reactive system to stay within the cost-effective choices and keep the system at an acceptable level.

Local municipalities use geographical information systems (GISs) for archival, revenue, and information retrieval purposes, but the use of GISs varies among municipalities within each state. Effective asset management requires evaluating pipeline systems and identifying pipelines with a high risk of failure. A geographic information system (GIS) data set consisting of pipe age, length, material, and previous repairs will allow municipalities to make asset management decisions while continuously updating the GIS data set [9].

2. Pipeline Condition Assessment

2.1. Phases of Condition Assessment Projects

Condition assessment projects typically have four phases: preliminary investigations, field investigations, integrity assessments, and post-processing condition assessments. Generally, various tools and techniques will be used, since no single tool can provide all the required information for the condition assessment. Once the main pipeline details such as diameter, length, age, and failure history are available, technique selection will be uncomplicated [10].

2.2. Factors Impacting Pipeline Service Life

The ability of the pipeline to carry external and in-service loads forms the pipeline's structural integrity. Pipeline structural integrity must be assessed during condition assessment to determine the level of deterioration. For example, the pipeline material could react with the environment, causing corrosion that can vary along the pipeline. The corrosion mechanism could act entirely differently inside and outside the pipe [10]. Figure 1 illustrates water seepage and movement of soil when the pipeline is installed using trenchless technology methods and is under or near bodies of water.

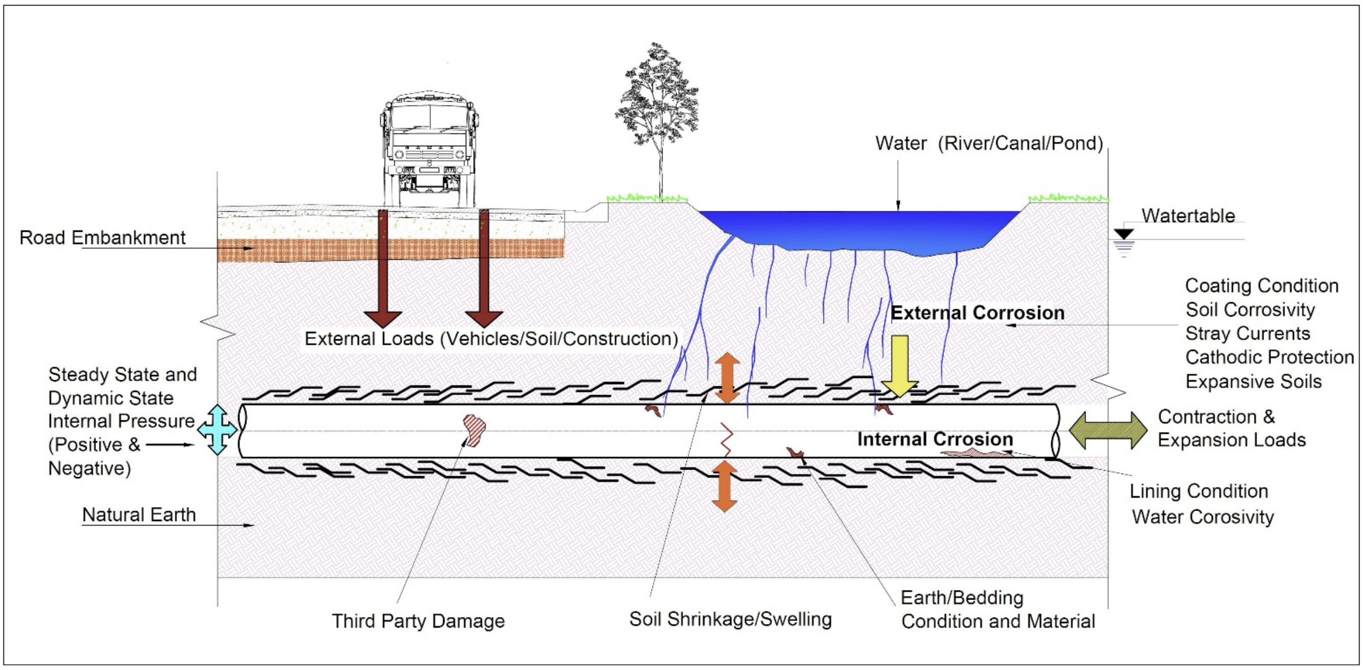

Figure 1. Factors impacting pipelines' service life.

2.3. Asset Management Strategies

Infrastructure asset management is the continual assessment of the operations and maintenance history and projected life expectancy, with a long-range plan for financing asset rehabilitation or replacement (R&R); this results in prioritizing infrastructure assets and incorporating assets into the annual capital improvement planning [4].

Condition assessment will enable municipalities to understand the current structural condition of pipelines and implement the predictive-level strategy [11]. The traditional asset management strategies are operative (reactive), inspection (condition-based), proactive (preventive), and predictive (advanced). Each strategy has a specific role in the asset management methodologies series. In general, asset management strategies fall under four main categories, as shown in Table 1.

Table 1. Categories of asset management strategies [11].

Operative (reactive)	• Municipalities often make decisions based on practical experience. • It is emergency repairs and rehabilitation. • In a simple approach, the pipe section will consume its full-service life. • It causes interruptions in traffic and services.
Inspection (condition-based)	• Municipalities monitor pipelines periodically. • Pipelines are classified based on their condition rating. • It recognizes the current pipeline condition without failure consequences.

Table 1. *Cont.*

Proactive (preventive)	• Repair and rehabilitation are carried out before failure. • It needs more time to choose the best cost-effective repair.
Predictive (advanced)	• Cities provide economic analysis support for the proactive approach. • It provides the ability to choose between regular maintenance and rehabilitation. • It indicates long-term implications on life cycle cost.

3. Research Needs

The focus of this paper is based on buried wastewater interceptors' asset management adjacent to bodies of water. Wastewater assets have long life cycles. Furthermore, a wide assortment of studies has been carried out to demonstrate the asset management of wastewater pipelines. The following recent research highlights the need for inspection and monitoring of pipelines:

- Ref. [6] encouraged municipalities to enhance affordable resources such as GIS in conducting asset management planning to plan well-conceived projects properly.
- Ref. [12] indicated that the surrounding soil condition has a vital role in the pipeline loads, which is more important to expose than the visible condition.
- Ref. [13] recommended that wastewater utilities use timely information technologies to address the most critical infrastructure needs, since inspecting and rehabilitating large-diameter wastewater systems is expensive.
- Ref. [14] recommended that integrating GISs during inspection of pipe segments would help map the critical pipelines and condition assessment.

4. Objectives

The main objective of this paper is to evaluate the life of wastewater interceptors considering the long-term impacts of surrounding soil conditions for operational and maintenance tasks. The secondary objective is to evaluate the significant factors that affect the condition levels of assets. Furthermore, the objective is to compare the wastewater interceptors surrounding soil elevations from 2010 through to 2015. The comparison will be between wastewater interceptors that are adjacent (less than 10 ft) to bodies of water and the interceptors that are further away (more than 10 ft) from bodies of water.

5. Methodology and Scope

The models developed in this study will be used to link the dissimilarity between wastewater interceptors near to and away from bodies of water by considering physical and environmental factors. The following steps present an approach to developing the outcome of this research. Figure 2 presents the detailed research methodology.

- Step 1: Problem definition;
- Step 2: Literature review;
- Step 3: Data collection;
- Step 4: Data analysis;
- Step 5: Model development;
- Step 6: Model validation;
- Step 7: Model comparison;
- Step 8: Selecting the best model based on the results;
- Step 9: Asset management strategy recommendations.

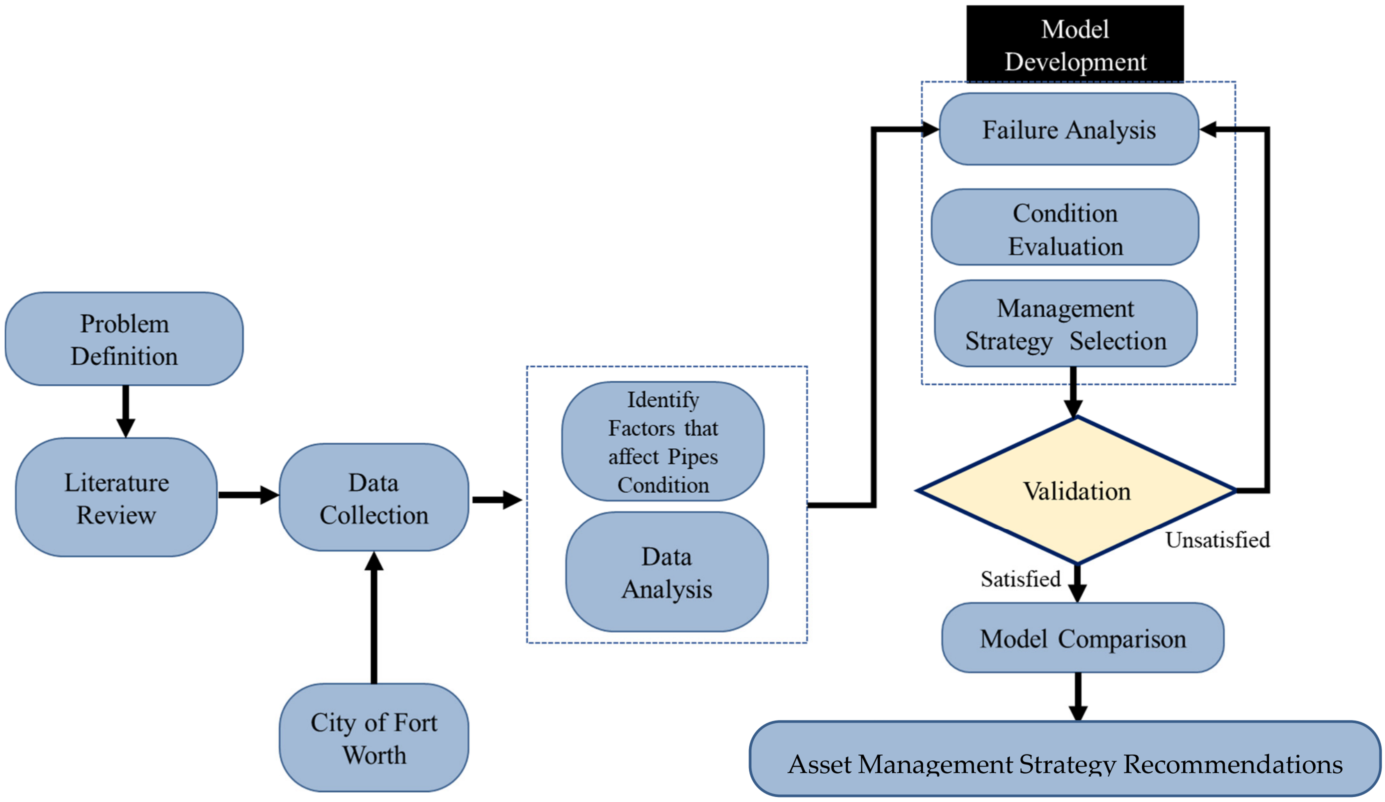

Figure 2. Research methodology.

6. Data Analysis

Based on the available historical data, it is conceived that planning and managing wastewater interceptors through bodies of water is an exceptional task, taken on to provide municipalities and governments with the needed resources and obtain the highest benefit–cost ratio for the plans. Therefore, the following section explains the development and validation of the research model.

6.1. Binary Logistic Regression

The dependent variable must be only two different values (e.g., 0 and 1) regarding the binary logistic regression. If the dependent variable is categorical or numerical, the corresponding variable must be dummy-coded into two values before employing the binary logistic regression.

Binary logistic regression generates a model to account for relationships between log odds of the dependent and independent variables.

Log likelihood is used to determine whether the binary model is significant. In this methodology, the model is developed by including the variable of interest. By eliminating that variable, followed by comparing those data sets by using a chi-square distribution corresponding to the degree of freedom, it equals the number of eliminated variables. Meanwhile, if the independent variable is categorical and takes on more than one value, the degree of freedom will be the number of categorical values minus one.

After developing the logistic regression model, Equation (1) provides the prediction elevation difference over the years 2010–2015.

$$\begin{gathered} g(x) = \ln\left(\frac{P(C=1)}{1-P(C=1)}\right) = \\ -6.73 + 0.004 \times \text{Age} - 0.001 \times \text{Diameter} + 0.12 \times \text{DMaterial} = \text{HDPE} + 0.185 \\ \times\text{DMaterial} = \text{CI} - 0.12 \times \text{DMaterial} = \text{DI} + 0.101 \times \text{DMaterial} = \text{PVC} + 0.227 \\ \times\text{DMaterial} = \text{Concrete} + 0.09 \times \text{DFar/Near Bodies of Water} \end{gathered} \tag{1}$$

where

$$P(C=1) = \frac{1}{1+e^{-g(x)}} \tag{2}$$

$$P(C=0) = 1 - P(C=1) \tag{3}$$

The next step is to go under the validation phase by identifying the predicted results. The remaining 20% of the data will be used for validation. A cut-off value is determined and then compared with the estimated probability. If it is greater than the cut-off value, it is assigned to class one. Otherwise, it will be given a class zero. Usually, the cut-off value for the binary dependent variable is 0.5.

The percentage of correct predictions is calculated based on a classification table using the below Equation (4):

$$\text{Percentage of correct predictions} = \frac{100(\text{A11}+\text{A22})}{(\text{A11}+\text{A12}+\text{A21}+\text{A22})} \tag{4}$$

Table 2 presents the classification table for the binary logistic regression.

Table 2. Classification for binary logistic regression model.

Observed	**Predicted**	
	0	**1**
0	267	52
1	68	251

Based on Table 2, the percentage of correct predictions is illustrated in Figure 3.

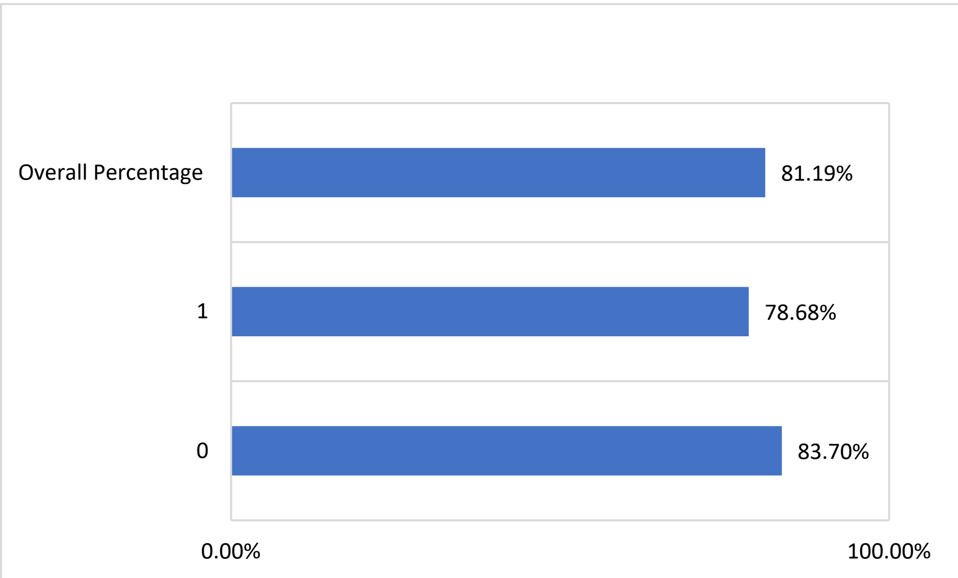

Figure 3. Binary logistic overall correct percentages.

6.2. True vs. False and Positive vs. Negative

Figure 4 illustrates the different true/false and positive/negative scenarios for the model.

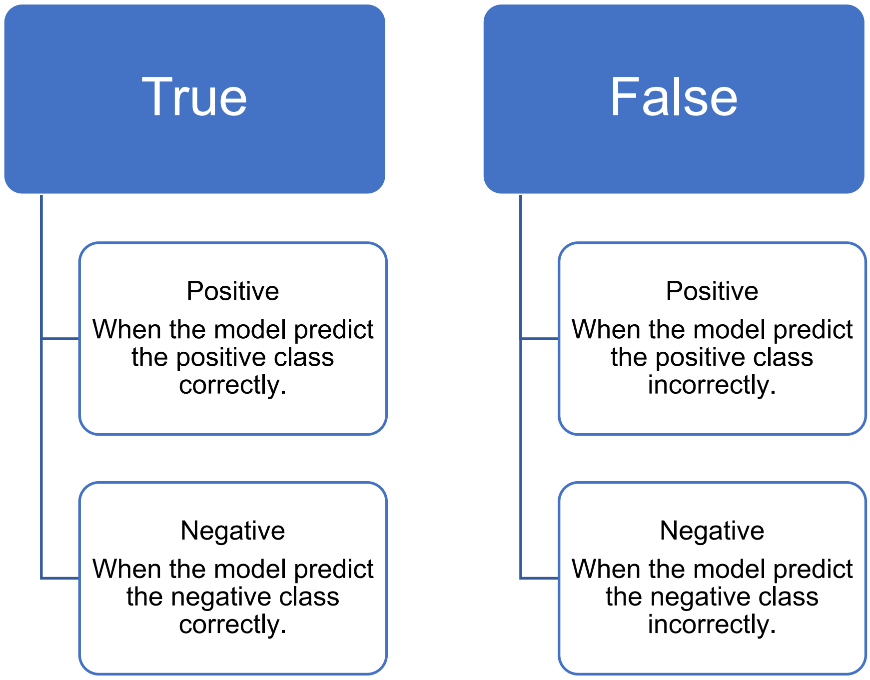

Figure 4. True vs. false and positive vs. negative.

Table 3 summarizes the binary logistic regression model using the confusion matrix that shows the four expected outcomes, and we will evaluate our model classification based on these four outcomes.

Table 3. Confusion matrix for binary logistic regression model.

True Positive (TP):	False Positive (FP):
• Reality: Elevation Increased. • Model Prediction: Elevation Increased. • Outcome: Correct Prediction.	• Reality: Elevation Decreased. • Model Prediction: Elevation Increased. • Outcome: Wrong Prediction.
False Negative (FN):	**True Negative (TN):**
• Reality: Elevation Increased. • Model Prediction: Elevation Decreased • Outcome: Wrong Prediction.	• Reality: Elevation Decreased. • Model Prediction: Elevation Decreased. • Outcome: Correct Prediction.

6.3. Accuracy

One parameter for evaluating classification models is accuracy; this represents the percentage of correct predictions made by our model. The following Equation (5) is the general formula of accuracy:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \tag{5}$$

Accuracy can also be assessed in terms of positives and negatives in our model, as shown below (Equation (6)):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{6}$$

where

TP = True Positives.

TN = True Negatives.

FP = False Positives.

FN = False Negatives.

Based on the above formulas, the degree of accuracy for the binary logistic regression model is 0.812, or 81.2%. Accuracy alone does not convey the whole evaluation classification to understand our model's performance better. The following section will discuss the ROC curve (receiver operating characteristic curve) (Equations (7) and (8)).

6.4. Receiver Operating Characteristic (ROC)

A receiver operating characteristic (ROC) curve is a graph that shows how well a classification model performs across all categorization levels. Two parameters are plotted on this curve:

True Positive Rate (TPR) is a synonym for sensitivity:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{7}$$

False Positive Rate (FPR):

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{8}$$

TPR vs. FPR is plotted on an ROC curve at various categorization levels. As the classification threshold is lowered, more objects are classified as positive, increasing both False Positives and True Positives. A logistic regression model can be analyzed multiple times with different classification criteria to compute the ROC curve points, but AUC is the fastest sorting-based method. AUC stands for "Area under the ROC Curve", which refers to the complete two-dimensional area beneath the entire ROC curve from (0, 0) to (1, 1).

6.5. Sensitivity and Specificity

Other alternatives for checking the model performance are sensitivity and specificity. Sensitivity represents how effectively the classifier predicts positive samples, whereas specificity expresses how well classifiers detect negative samples (Equations (9)–(11)).

Sensitivity is a synonym for the True Positive Rate (TPR):

$$\mathrm{Sensitvity} = \mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{9}$$

Specificity:

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{FP} + \mathrm{TN}} \tag{10}$$

$$\mathrm{FPR} = 1 - \mathrm{Specificity} = 1 - \frac{\mathrm{TN}}{\mathrm{FP} + \mathrm{TN}} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{11}$$

Based on the above formulas, the sensitivity and specificity for our model are as follows (Figure 5):

$$\mathrm{Sensitvity} = \mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} = \frac{251}{251 + 68} = 78.68\%$$

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{FP} + \mathrm{TN}} = \frac{267}{52 + 267} = 83.70\%$$

True Positive (TP): 251 False Positive (FP): 52

False Negative (FN): 68 True Negative (TN): 267

$$\mathrm{TPR} = \mathrm{Sensitvity} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} = \frac{251}{251+68} = 78.68\%$$

$$\mathrm{FPR} = 1 - \mathrm{Specificity} = \frac{\mathrm{FP}}{\mathrm{FP+TN}} = \frac{52}{52+267} = 16.30\%$$

$$\mathrm{AUC} = 0.879$$

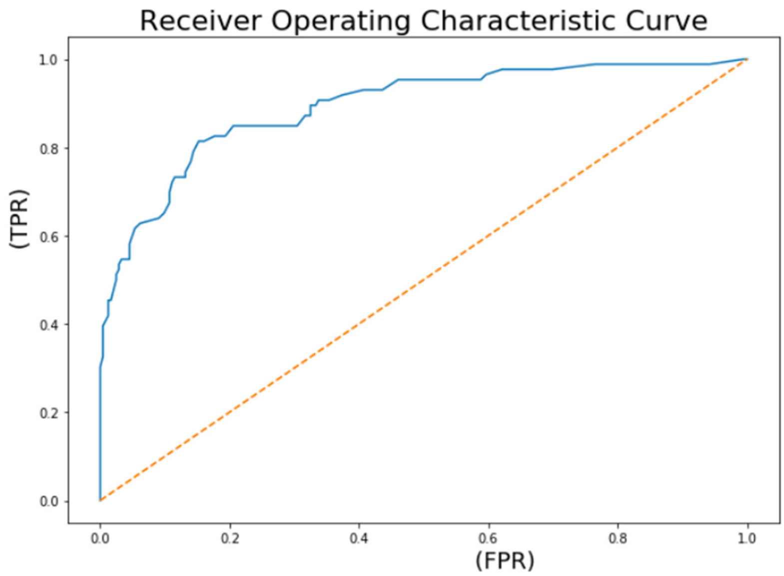

Figure 5. Binary logistic regression model performance.

The area under the ROC curve for the binary logistic regression model is 0.879, indicating acceptable results. As a result, the logistic regression equation can forecast the surrounding conditions of wastewater interceptors that are adjacent to bodies of water.

6.6. Significant Variables

The significant variables for the final model were eight only, as shown in Figure 6.

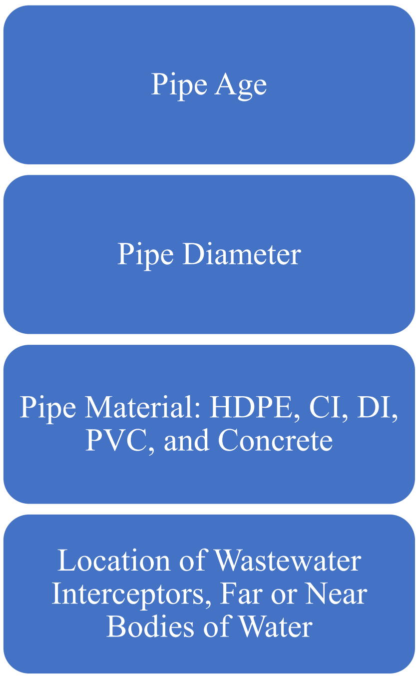

Figure 6. Significant variables.

6.7. Insignificant Variables

According to the backward stepwise analysis, the insignificant variable for the binary logistic regression model was Material (VC or Steel). Several aspects must be addressed to assess the influence of pipe lengths, including the soil type, water table, pipe material, and pipe diameter.

Different materials used in wastewater interceptors react differently to the environment. For example, abrasion resistance is vital in concrete pipes, and acid resistance is high in clay pipes. Other pipes have superior resistance to acidic and alkaline wastes, but they can distort excessively under strain. Corrosion of steel pipes affects pipe strength, resulting in leaks, breaks, low water pressure, blockages, and other issues.

6.8. Soil Erosion

The annual global soil erosion is substantially higher than the annual soil replenishment [15]. Soil erosion is the loss of the top layer of soil, which can be caused by various factors, including wind and water.

Streams and rivers are avenues for soil transportation. Watersheds will become prone to floods when vast volumes of soil deposits accumulate in local lakes and reservoirs. This erosion causes valuable agriculture and infrastructure to be destroyed.

Below are some common strategies for effective erosion control:

- Plant Vegetation: Wind can be blocked by trees, bushes, hedgerows, and ground plants. Maintaining continuous ground cover, such as planting cover crops, also aids in binding soil to roots.
- Matting: This ground covering, also known as an erosion control blanket, comprises open-weave, biodegradable materials that insulate the soil while also supporting growing vegetation on bare ground. This erosion control method is generally effective for solar farms and building sites where vast regions are left barren and subject to wind and water erosion.
- Grazing: Rotational grazing involves moving cattle from one pasture plot to the next. Each paddock is given a break and allowed to recover naturally, reducing soil compaction and erosion. Installing fencing and stream crossings to protect pastures from degradation is also practical.

To summarize the recommendations for the City of Fort Worth:

- Future asset management plans must include bodies of water and erosion control methods as essential, and these factors must influence variables of the plan.
- ArcGIS could be the leading platform for the plan, since it can help prioritize time and cost savings.

7. Discussion of Results

Streams and rivers are avenues for soil transportation. Watersheds will become prone to floods. Wastewater systems collect sewage from different types of users. Generally, infrastructures are designed and constructed to serve for many years. Over its life, the system deteriorates, and the likelihood and consequences of pipe failure increase significantly. The asset management plan is the central concept in making the systems' repair and rehabilitation decisions, since inspection and monitoring are time- and budget-consuming tasks. This leads to the need for asset management plans that are developed with statistical tools such as SPSS statistics software based on historical data [16–20].

Variables that influence the surrounding conditions for wastewater interceptors were the pipe age, pipe diameter, pipe material (HDPE, CI, DI, PVC, and concrete), and pipes' location with reference to bodies of water. Future asset management plans must include these influence variables as an essential and practical part of the plan.

Consequently, the surrounding soil elevation for pipelines could be a valuable simple metric compared with a holistic view across the entire wastewater system. A benchmarking approach, every 5 years, could be used to predict the future condition of pipelines based on the condition of similar but older pipelines [21–24].

There is no standard approach for evaluating the structural integrity of wastewater pipelines in sewer system asset management. Different researchers have considered the deterioration of the wastewater pipelines as their model [25–29]. However, the variables used to develop the models were different. Table 4 presents a comparison of variables among recent models.

Table 4. Comparison of variables for recent models.

Current Study	**[18]**	**[30]**	**[14]**
Age	Age	Age	Age
Diameter	Diameter	Diameter	Diameter
Material	Depth	Depth	Slope
Surrounding Soil Elevation	Slope	Slope	Length
Location (with reference to bodies of water)	Length	Length	MAPSCOGRID
-	Soil pH	Soil Sulfate	SUBAREA
	Material	Soil pH	PACP
	Soil Type	Water Table	-
	-	Pipe Flow	
		Material	
		Soil Type	
		Soil Hydraulic Group	
		Soil Corrosivity	

This research developed multinomial logistic regression and binary logistic regression, and the accuracy for the models was 45.29% and 81.20%, respectively. However, it was compared with different models by different authors, as shown in Table 5.

Table 5. Models' accuracy comparison.

Model	**Model Accuracy**	**Author**
Multinomial Logistic Regression	65.8%	[30]
	75%	[18]
	45.29%	**Current Study**
Binary Logistic Regression	84.6%	[30]
	81.2%	**Current Study**
KNN	83.4%	[30]
Neural Networks	85%	[18]

Based on the binary logistic regression model, the influence variables for the wastewater pipelines' surrounding soil were as follows:

- Pipe Age. The coefficient of pipe age is positive in the binary logistic regression equation. With Wald = 2280.199 and p-value = 0.013, the binary logistic regression findings revealed that pipe age has a significant impact on the condition of the surrounding soil condition for wastewater interceptors, as it has a positive coefficient, which indicates that an increase in age will probably result in the surrounding condition to be in a risk condition.
- Pipe Diameter. The coefficient of pipe diameter is negative in the binary logistic regression equation. With Wald = 63.682 and p-value = 0.024, pipe diameter was also found to significantly impact the soil difference elevation over the years for wastewater interceptors near bodies of water. It has a negative coefficient, which means that an increase in the pipe diameter will probably reduce the risk of the pipe's surrounding conditions changing.

- Pipe Material. The Wald and p-values for the significant pipe materials were different. The results of binary logistic regression revealed a moderate significance in High-Density Polyethylene (HDPE), Cast Iron (CI), Ductile Iron (DI), Polyvinyl Chloride (PVC), and concrete materials, as shown in Table 6.
- The location of Wastewater Interceptors. In the binary logistic regression model, wastewater interceptors' location with reference to bodies of water as far or near was also determined to be a significant variable, with Wald = 1.181 and p-value = 0.028. The coefficient is positive, which indicates that as the pipe is nearest to the bodies of water, the risk of the surrounding pipe soil being in a poor condition and, indeed, the pipe failing will increase.

Table 6. Binary logistic regression variables' performance.

Variable	Coefficient (β)	Wald	p-Value	Remarks
Material (1) = Concrete	0.227	0.319	0.047	Positive Coefficient
Material (2) = HDPE	0.120	1.145	0.028	Positive Coefficient
Material (3) = CI	0.185	4.130	0.004	Positive Coefficient
Material (4) = DI	−0.120	0.114	0.054	Negative Coefficient
Material (5) = PVC	0.101	3.313	0.007	Positive Coefficient

8. Practical Applications

The results of this study can help municipalities in managing wastewater interceptors. The model developed in this research may be used to create a wastewater interceptor inspection schedule. A cost–benefit analysis may be conducted to evaluate the cost savings that the model could lead to if used in place of yearly inspection programs. The developed model has a degree of accuracy of 81.2%.

Moreover, the significant variables of the model could be an essential input for developing long-term asset management plans. On the other hand, ArcGIS could be the leading platform for the asset management plan, since it can help prioritize time and cost savings.

This research was based on a 5-year span of data. It is recommended to monitor the wastewater interceptors that are adjacent to bodies of water in short intervals. Frequent inspections (every 5 years or less) are needed for wastewater pipelines when their locations are less than 10 ft away from bodies of water. The distance from a body of water provides a significant variable in the useful life of the pipeline, irrespective of the pipe material, such as, concrete, HDPE, CI, or PVC. Moreover, as the pipeline age increases, the effect on the surrounding soil elevation also increases.

However, the soil surroundings for DI pipelines were found to be more stable, since 69% of these pipelines are installed more than 10 ft away from a body of water. This research also showed that the pipe diameter variable has a negative coefficient, which means that an increase in the pipe diameter will probably reduce the risk of the pipe's surrounding conditions changing. After inspection and analysis of this, wastewater interceptors could be labelled and scored. The high-risk-scored interceptors will have priority in the replacement and rehabilitation plan. Indeed, this will limit the cost and time consumed in inspections or in the case of an unpredicted pipe failure. The model developed in this research could be used for different data years, which can help in defining the areas where the inspection will take place to enhance asset management planning for municipalities.

9. Conclusions

Municipalities would benefit from knowing and predicting how the asset management for wastewater interceptors is different with reference to the location of bodies of water. Two logistic regression models were used to predict how bodies of water can affect the soil surrounding wastewater interceptors. The models were created, verified, and tested. Both models were created using 80% of the data set, chosen at random. In the validation of the model, the remaining 20% of the data were used at random.

According to the model's findings, pipe diameter, age, pipe material, and location with reference to bodies of water were the most important parameters. The multinomial and binary logistic regression performances were 45.29% and 81.20%, respectively.

The binary logistic regression results revealed that the surrounding soil elevation difference over the years 2010 to 2015 near water bodies has decreased compared with the interceptors that are far away from bodies of water. Therefore, the interceptors are at a higher risk of failure. As a result, the binary logistic regression equation is significant, indicating that the area under the ROC curve was 0.879, indicating that the model is reliable.

10. Limitations

The study's base year data were obtained for 2010 to 2015. It is natural to doubt that the relevance of the surrounding condition changes will be detectable enough. The average soil erosion is within the range of 5.6 to 7.7 tons per acre per year [31–34]. The loss of every 5 tons per acre represents 1/32-in. of topsoil [35–38].

This study did not consider other influencing factors, such as the depth and slope of the wastewater interceptors and soil type [39–42]. As a result, the lack of information on these factors is the main limitation of this research.

11. Recommendations for Future Research

Some of the significant prospective future development areas raised in this research that should be addressed are other independent factors, such as the soil type, pipe installation method, and failure history, which can improve the model presented in this research. Further exploration of deep learning algorithms to develop a model will be an important critical component of future efforts. This study is based on data from the City of Fort Worth. To improve the accuracy of models, more inspection data are needed to compare the results of models developed for other cities, which could be an essential part of future work. Future studies should include more data for more years to distribute the findings over more than one five-year span, and the results should be compared with the findings of this study. The model developed in this study can be utilized to create a wastewater interceptor inspection schedule. A cost–benefit analysis can be used to determine the cost savings that the model could lead to if used in place of yearly inspection programs.

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Conflicts of Interest: The authors declare no conflict of interest.

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