

Metal Culvert Renewal Prioritization Framework Using Fuzzy Inference System [†]

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Abstract: Saskatchewan boasts an extensive road network, spanning over 250,000 km and featuring more than 26,500 culverts that facilitate the flow of water. Ensuring the timely replacement of these culverts is of paramount importance to prevent potential disasters and safeguard water quality. This research focuses on the prioritization of infrastructure renewal, with a particular emphasis on metal culverts. This study undertakes a rigorous evaluation of two statistical and computational methods—ordinal logistic regression and a fuzzy inference system—through an exhaustive examination of 1000 metal culverts situated along Saskatchewan’s highway network. Performance evaluation metrics, including area under the curve, percentage of correct predictions, confusion matrix analysis, accuracy, precision, recall, and the F1 score, consistently highlight the fuzzy inference system method as the superior and most efficacious approach for prioritizing culvert renewal within this crucial infrastructure context.

Keywords: culvert renewal; ordinal logistic regression; fuzzy inference system; road infrastructure; water flow management



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1. Introduction

In the realm of crisis management, the precise control of surface water flow is paramount, particularly at intersections with crucial transportation routes. Culverts, serving as conduits beneath roadways, play a pivotal role in this context [1]. These structures, fashioned from metal, concrete, or plastic, exhibit varying material and design characteristics dictated by factors such as hydraulic performance and location [2]. This study zeroes in on the prioritization of infrastructure renewal, emphasizing metal culverts. The examination comprehensively scrutinizes two statistical and computational methodologies—ordinal logistic regression and a fuzzy inference system—applied to 1000 metal culverts situated along Saskatchewan’s extensive highway network. Rigorous performance evaluation metrics consistently underscore the fuzzy inference system as the preeminent and most efficacious approach for prioritizing culvert renewal within this vital infrastructure context.

2. Literature Review

The literature presents an array of systems for prioritizing culvert renewal. Masada et al. [3] pioneered a risk assessment method for adjusting the structural rating of metal culverts. Najafi et al. [4] introduced field protocols and a decision support system for culvert management. Salem et al. [5] utilized binary logistic regression for a deterioration model, and Werbelow and Ksaibati [6] prioritized culvert repair using a comprehensive methodology. While these studies offer valuable insights, challenges, such as incomplete parameters, biased culvert selection, and scalability issues, persist. To advance precision

and effectiveness in culvert assessment and prioritization methodologies, further research is warranted, considering diverse factors and addressing study-specific limitations (Table 1).

Table 1. List of studies related to culvert renewal prioritization.

Reference	Effective Factors														Method	Culvert Material	
	Culvert Age	Culvert Depth	Land Type	Crossing Type	Culvert Material	Culvert Diameter	Culvert Length	Metal Corrosion	Joint Separation	Metal Shape	Concrete Spalling	Concrete Cracking	Concrete surface	Plastic Shape			End Deformation
Masada et al., 1976 [3]	X					X	X	X	X	X					X	risk assessment method	Metal
Najafi et al., 2008 [4]	X	X	X		X	X	X	X	X		X	X	X	X		combination of methods	M*, C*, P*
Hunt et al., 2008 [7]					X	X	X	X	X	X	X	X		X	X	decision-making tools	M, C, P
Najafi and Bhattachar, 2011 [8]		X	X	X	X	X	X		X	X	X	X	X	X	X	AHP	M, C, P
Yang, 2011 [9]	X	X		X	X			X	X	X	X	X		X	X	Markov model	M, C, P
Salem et al., 2012 [5]	X							X	X	X					X	binary logistic regression	M
Werbelow and Ksaibati, 2015 [6]		X		X	X		X	X	X	X	X	X	X	X	X	inspection procedures	Not specified
Reagan, 2015 [10]		X	X	X												road crossing life optimization	Not specified
Jin and Stoner, 2016 [11]			X	X				X	X	X	X	X		X		failure risk-based model, AHP	M, C, P
Piratla et al., 2019 [12]			X		X	X	X	X	X	X		X			X	failure risk-based model, AHP	M, C
Amiri et al., 2019 [13]			X													AHP, ANP, and TOPSIS	Not specified
Vladeanu and Matthews, 2019 [14]	X	X	X	X		X	X									failure consequences and AHP	Not specified
Truhlar et al., 2020 [15]			X	X		X	X									ArcGIS- and Python-based tool	Not specified
Gao and Elzarka, 2021 [16]				X		X	X								X	machine learning models	Not specified
Marsili and Bödefeld, 2021 [17]	X		X	X											X	integrating MCDA with data mining	Not specified
Mohammadi et al., 2023 [18]	X		X	X	X	X	X	X	X	X	X	X		X	X	risk-based prioritization	M, C, P

* Note. M = Metal, C = Concrete, P = Plastic.

3. Proposed Framework

The framework outlined in this study seeks to address the gaps identified in the existing literature. Through a meticulous literature review, relevant factors influencing culvert failure were identified, paving the way for data collection from VEMAX, a specialized asset/data management software. With a focus on metal culverts in Saskatchewan highways due to data abundance and regional prevalence, these factors were quantified and ranked. Culvert condition was assessed through two distinctive methodologies—ordinal logistic regression and a fuzzy inference system (FIS). Performance evaluation metrics guided the selection of the optimal method based on multiple measures. The resulting ranked culvert conditions were employed for renewal prioritization (Figure 1). This framework not only enables accurate prediction of culvert conditions but also aids in effective resource allocation for renewal initiatives.

3.1. Ordinal Logistic Regression

Ordinal logistic regression, as a sophisticated statistical technique, scrutinizes the intricate relationship between an ordinal dependent variable and independent variables when the dependent variable features three or more ordered categories [19]. The model accommodates the ordered nature of response categories, employing proportional odds with a general form [20]. The framework encompasses meticulous data collection, preparation, model development utilizing maximum likelihood estimation, and evaluation through metrics such as the likelihood ratio test and AIC. This comprehensive approach ensures a nuanced understanding of the relationships governing culvert conditions [21].

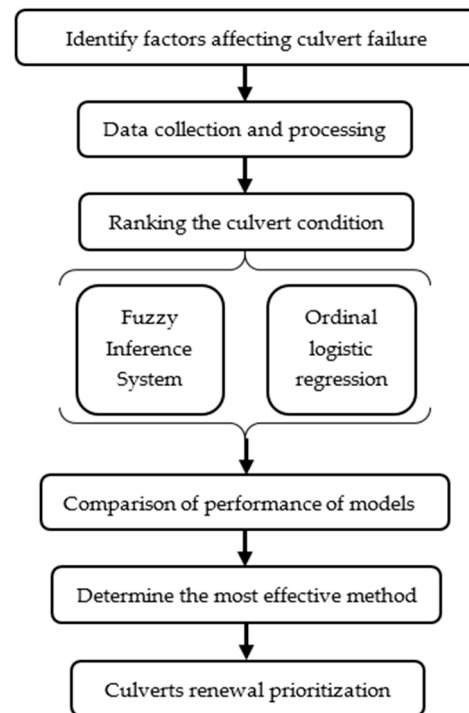


Figure 1. Key steps of culvert renewal prioritization.

3.2. Fuzzy Inference System

The fuzzy inference system (FIS), positioned as a robust computational framework, models uncertain systems using fuzzy logic to represent linguistic terms with fuzzy sets, effectively mapping input to output [22]. Comprising fuzzification, rule formulation, inference (employing methods like Mamdani and Sugeno), and defuzzification (employing methods like centroid, maxima, and height), the FIS excels in decision-making within uncertain environments. Its application extends to control systems, pattern recognition, and decision-making, showcasing adaptability across diverse domains [22].

3.3. Analytic Hierarchy Process (AHP)

The analytic hierarchy process (AHP), conceptualized by Saaty in the 1970s, employs pairwise comparisons for decision-making—a methodology widely embraced in engineering, finance, and management [23]. Structured in steps, including problem structuring, pairwise comparison, normalization, and aggregation, the AHP relies on expert opinions to assess the importance of factors affecting culvert conditions. This powerful decision-making tool finds successful applications in diverse domains, such as transportation planning, project management, and environmental decision-making [23].

4. Model Implementation

4.1. Data Collection and Processing

Prioritizing the renewal of Saskatchewan culverts necessitates the identification of effective factors contributing to culvert failure. The literature review, presented in Table 2, guided the determination of the most critical factors. The data collected from VEMAX, a specialized asset/data management software, provide a comprehensive dataset for analysis. Emphasizing the significance of metal culverts in Saskatchewan highways, the dataset focuses on 1000 culverts. During implementation, 70% of this dataset is dedicated to model training, 15% is dedicated to model testing, and the remaining 15% is dedicated to model validation. This structured division facilitates rigorous testing and validation, ensuring the robustness of the predictive models.

Table 2. Summary of raw and processed data.

	Raw Data	Processed Data	Number	Percentage		Raw Data	Processed Data	Number	Percentage
Emergency Rating	Good	0	268	26.80%	Culvert Diameter (mm)	0–600	0	300	30.00%
	Fair	1	417	41.70%		601–900	1	465	46.50%
	Poor	2	271	27.10%		901–1200	2	73	7.30%
	Critical	3	44	4.40%		1201–2000	3	137	13.70%
Land Type	Undeveloped	[1,0,0]	738	73.80%		2001–3000	4	23	2.30%
	Cultivated	[0,1,0]	251	25.10%		Over 3000	5	2	0.20%
	Urban	[0,0,1]	11	1.10%					
Crossing Type	Drainage	[1,0,0,0]	507	50.70%	Metal Corrosion	Good	0	303	30.30%
	Seasonal Flow	[0,1,0,0]	159	15.90%		Fair	1	261	26.10%
	Standing Water	[0,0,1,0]	113	11.30%	Metal Shape	Poor	2	436	43.60%
	Flowing Water	[0,0,0,1]	221	22.10%		Good	0	808	80.80%
Length Group	0–10 m	0	14	1.40%	Metal Joint Separation	Fair	1	15	1.50%
	10–20 m	1	692	69.20%		Poor	2	177	17.70%
	20–30 m	2	238	23.80%		Good	0	789	78.90%
	30–40 m	3	26	2.60%	End Deformation	Fair	1	21	2.10%
	40–50 m	4	18	1.80%		Poor	2	190	19.00%
	50–60 m	5	4	0.40%		None	0	618	61.80%
	60–70 m	6	5	0.50%		Right/Left	1	191	19.10%
	70–80 m	7	2	0.20%		Both	2	191	19.10%
	Over 100 m	10	1	0.10%					

The raw data extracted from VEMAX, characterized by categorical variables, are transformed into processed data with numerical values. This transformation is essential for the application of advanced analytical techniques. Descriptive statistics offer a concise overview of the processed data, shedding light on key parameters and trends. The careful processing of raw data ensures the reliability and accuracy of subsequent analyses.

4.1.1. Input Factors

Factors influencing culvert failure, including land type, crossing type, culvert length, culvert diameter, metal corrosion, metal shape, metal joint separation, and end deformation, were identified based on the literature review and expert feedback. The states and scales of each factor were outlined based on the Ministry of Highways culvert inspection handbook (Table 2). Land type is categorized into undeveloped, cultivated, and urban based on traffic volume. Crossing type is divided into drainage, seasonal flow, standing water, and flowing water based on water flow characteristics. Culvert size (diameters) is classified into various diameter ranges. Culvert length is categorized into length groups based on highway widths. Metal corrosion is assessed as good, fair, or poor based on corrosion rate. Metal shape is assessed as good, fair, or poor based on the shape condition. Metal joint separation is classified as good, fair, or poor based on joint condition. End deformation is categorized into none, right/left, or both based on deformation. The detailed categorization of these factors contributes to a nuanced analysis of their impact on culvert conditions.

4.1.2. Culvert Condition Rating

The Culvert Condition Rating System, classifying culverts as good, fair, poor, or critical, serves as the benchmark for evaluating the effectiveness of the predictive models. The raw data extracted from VEMAX, which include categorical variables related to culvert condition assessments, undergo a meticulous processing stage. The processed data assign

numerical values to each category, enabling a more structured and comprehensive analysis of culvert conditions.

4.1.3. Correlation Analysis

Correlation analysis delves into the relationships between input parameters and the culvert condition rating. The Pearson correlation coefficient is employed to ascertain the strength and direction of linear relationships. While the correlation between the length of the culvert exhibits a relatively lower magnitude, its significance is acknowledged based on prior research and expert insights. This study acknowledges the limitation of sample size and anticipates enhanced correlation with additional data.

The identified independent variables—land type, crossing type, culvert length, culvert diameter, metal corrosion, metal shape, metal joint separation, and end deformation—pave the way for the application of ordinal logistic regression (Figure 2).

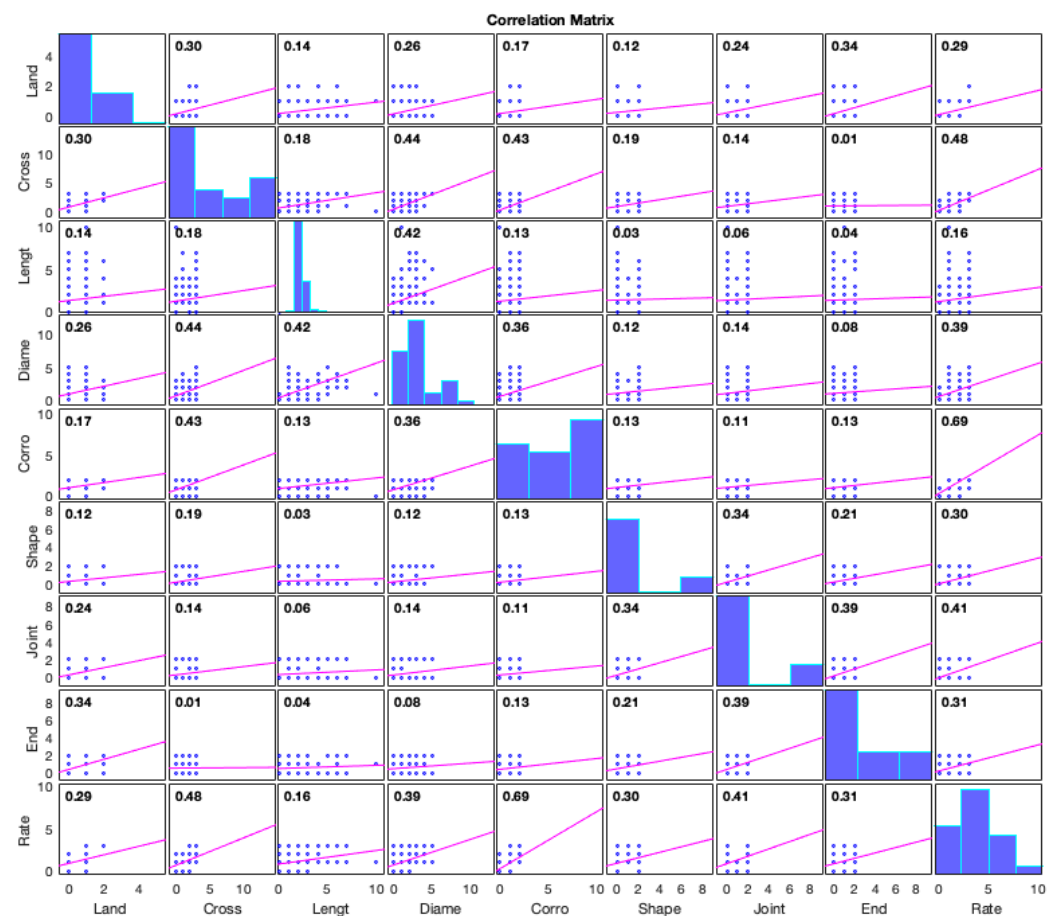


Figure 2. Correlation analysis matrix.

4.2. Ordinal Logistic Regression for Culvert Condition Prediction

Executed in SPSS, the model examines the correlation between the ordinal dependent variable (emergency rating) and the aforementioned independent parameters. Utilizing the logit function, the model successfully predicts emergency rating levels (ranging from 0 to 3), supported by a significant chi-square test statistic ($p < 0.001$) and pseudo-R-squared values ranging from 0.537 to 0.798. The “Goodness-of-Fit” test underscores the well-fitted nature of the model. To compare models, performance metrics, like confusion matrix, accuracy, precision, recall, F1 score, AUC, and PCP, are calculated for training, testing, and validation data. The confusion matrix and evaluation metrics (Tables 3 and 4) depict high accuracy and effectiveness across classes, reinforcing the model’s robustness.

Table 3. Ordinal logistic regression and fuzzy inference system confusion matrix.

Ordinal Logistic Regression							Fuzzy Inference System						
(a) Training Data							(a) Training Data						
Actual	Predicted					Accuracy	Actual	Predicted					Accuracy
	Good	Fair	Poor	Critical									
	Good	98	40	0	0	71%		Good	138	0	0	0	100%
	Fair	21	246	46	1	78%		Fair	56	226	32	0	72%
	Poor	0	71	141	13	63%		Poor	0	49	174	2	77%
	Critical	0	0	8	15	65%		Critical	0	0	0	23	100%
(b) Validation Data							(b) Validation Data						
Actual	Predicted					Accuracy	Actual	Predicted					Accuracy
	Good	Fair	Poor	Critical									
	Good	58	1	0	0	98%		Good	59	0	0	0	100%
	Fair	0	50	10	0	83%		Fair	13	37	10	0	62%
	Poor	0	12	9	0	43%		Poor	0	8	12	1	57%
	Critical	0	0	7	3	30%		Critical	0	0	0	10	100%
(c) Test Data							(c) Test Data						
Actual	Predicted					Accuracy	Actual	Predicted					Accuracy
	Good	Fair	Poor	Critical									
	Good	68	3	0	0	96%		Good	71	0	0	0	100%
	Fair	3	25	15	0	58%		Fair	9	23	11	0	53%
	Poor	0	17	8	0	32%		Poor	0	11	12	2	48%
	Critical	0	0	3	8	73%		Critical	0	0	0	11	100%

Table 4. Prediction accuracy of ordinal logistic regression and fuzzy inference system model.

Classes	Precision		Recall		F1 Score		AUC		Accuracy		PCP	
	OLR	FIS	OLR	FIS	OLR	FIS	OLR	FIS	OLR	FIS	OLR	FIS
Good	0.958	0.888	0.958	1.000	0.958	0.940	0.820	0.936	0.958	1.000	96%	94%
Fair	0.556	0.677	0.581	0.535	0.568	0.597	0.751	0.662	0.581	0.535	75%	79%
Poor	0.308	0.522	0.320	0.480	0.314	0.500	0.739	0.815	0.320	0.480	77%	84%
Critical	1.000	0.846	0.727	1.000	0.842	0.917	0.977	0.993	0.727	1.000	98%	99%
Average	0.705	0.733	0.647	0.754	0.670	0.739	0.822	0.852	0.727	0.780	79%	79%

4.3. Fuzzy Inference System for Culvert Condition Rating

This segment delineates a sophisticated approach for evaluating culvert conditions through the adept application of the fuzzy inference system (FIS). The comprehensive framework encompasses crucial facets such as culvert location, size, and condition. Each category undergoes meticulous modeling utilizing Mamdani's FIS, with subsequent integration through Sogno's fuzzy system to derive an overarching condition ranking. The subsequent subsections expound upon the intricacies of the methodologies employed.

4.3.1. Mamdani FIS for Culvert Location, Size, and Condition

Assessing culvert locations involves a nuanced examination based on land type and crossing type. Expert opinions and the analytic hierarchy process (AHP) play pivotal roles in parameter weighing. The trimf (triangular) membership function is

strategically employed for its simplicity and interpretability. With two inputs, one output, twelve rules, and the utilization of centroid defuzzification, this system ensures a comprehensive assessment.

Modeling culvert size incorporates parameters such as diameter and length, categorized in alignment with the Ministry of Highways guidelines. Similar to the location model, trimf membership functions are applied. This system comprises two inputs, one output, and sixty-six rules and utilizes centroid defuzzification, ensuring a robust evaluation of culvert size. Culvert condition assessment factors in elements such as metal corrosion, shape, joint separation, and end deformation. The trimf membership function is judiciously applied, resulting in a system with four inputs, one output, eighty-one rules, and centroid defuzzification, facilitating a meticulous evaluation of culvert conditions.

4.3.2. AHP for Factor Prioritization

The analytic hierarchy process (AHP) is instrumental in prioritizing culvert location, size, and condition. Expert opinions, gathered through pairwise comparisons, contribute to the determination of weights. The assessment identifies culvert location as the most pivotal factor, followed by condition and size. A high consistency ratio ($CR = 0.03$) underscores the reliability of this prioritization approach.

4.3.3. Sugeno FIS for Culvert Condition Rating

The Sugeno FIS model seamlessly integrates the outputs from Mamdani FIS models, assigning values from 0 to 3 for an inclusive overall condition rating. The weights derived from the AHP guide the establishment of rules. This meticulous and systematic approach, harnessing advanced tools and fuzzy logic techniques, ensures a precise and objective evaluation of culvert conditions. The performance metrics, including the confusion matrix, accuracy, precision, recall, F1 score, AUC, and PCP, are diligently computed for a thorough model comparison, as depicted in Tables 3 and 4.

4.4. Model Comparison

This study endeavors to predict culvert failure and prioritize renewal by evaluating two methodologies: ordinal logistic regression and the fuzzy inference system (FIS). Performance metrics, including AUC, PCP, confusion matrix, accuracy, precision, recall, and F1 score, are employed for an exhaustive assessment. The results unequivocally underscore the superiority of the FIS over the ordinal logistic regression method. Across various metrics, such as AUC, PCP, precision, recall, F1 score, and accuracy, the fuzzy inference system consistently outperforms its counterpart (Table 4). This robust performance affirms the efficacy of the FIS in providing a nuanced and accurate prediction of culvert conditions.

4.5. Culvert Prioritization

The application of the FIS on a dataset comprising 1000 culverts in Saskatchewan highways facilitates the assignment of final scores for prioritizing renovations. Notably, the analysis identifies 49 culverts in critical condition, surpassing the accuracy of the existing system. Visualized in Figure 3, a comparative representation highlights the efficacy of the proposed method in emphasizing the need for prioritizing renovations on culverts in poor and critical conditions. This critical information serves as a valuable guide for decision-makers in allocating resources effectively to address areas with the utmost urgency.

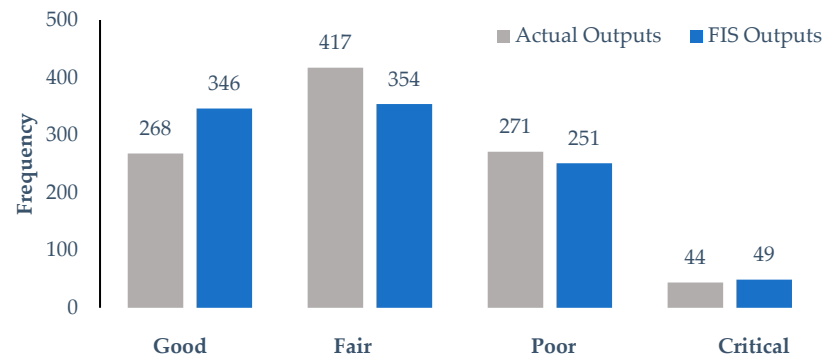


Figure 3. Comparison of culvert renewal prioritization with the result of the existing method.

5. Results and Discussions

This research proposes two methodologies for prioritizing culvert renewal for Saskatchewan highways. Method 1 leverages ordinal logistic regression within SPSS, and method 2 integrates Mamdani and Sugeno’s fuzzy inference system (FIS) through MATLAB’s fuzzy toolbox. The evaluation of both methodologies against key criteria—AUC, PCP, precision, recall, F1 score, and accuracy—provides valuable insights into their effectiveness. A model’s excellence is often gauged by its high performance across metrics, such as AUC, PCP, precision, recall, F1 score, and accuracy. In the context of this study, as depicted in Table 4, the FIS consistently outperforms ordinal logistic regression, underscoring its prowess in addressing uncertainties and imprecisions inherent in the data.

However, researchers are urged to meticulously weigh the advantages and limitations of each method, aligning their choice with the specific nuances of their research context and questions. Ordinal logistic regression, with its aptitude for handling ordinal relationships, may be a prudent choice, while the FIS’s adeptness at managing uncertainty renders it valuable in contexts where data imprecision is a prevalent challenge. This nuanced consideration of method strengths and weaknesses is imperative for the judicious selection of the most fitting approach.

6. Conclusions and Recommendation

This study unveils a comprehensive culvert replacement prioritization framework tailored for Saskatchewan, grounded in real data from the VEMAX database. Through a meticulous identification of factors influencing culvert failure, derived from a literature review and expert feedback, a synthesis of statistical and soft computing methods is employed for condition prediction. This study accentuates the pivotal role of the culvert’s appearance condition, with the fuzzy inference system emerging as the most effective approach for renewal prioritization. While acknowledging certain limitations, such as data dependency on inspection forms and inspectors’ opinions, a lack of installation time information for many culverts, and applicability restricted to metal culverts, this study sets the stage for potential future enhancements. Future research endeavors could extend the framework to diverse infrastructures, encompass different culvert types, and explore alternative mathematical theories, such as the adaptive neuro fuzzy inference system (ANFIS).

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