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Reliability Investigation of Pavement Performance Evaluation Based on Blind-Number Theory: A Confidence Model

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Abstract: The evaluation of in-service pavements' performance is a complex system that encompasses a variety of uncertain factors. These uncertainties include random, fuzzy, gray, and unascertained information, and their interrelationships are intricate, making comprehensive quantification unachievable. Nonetheless, current highway management organizations rely on a comprehensive indicator, namely, the Pavement Quality Index (PQI), to assess the level of pavement performance. This paper introduces a novel approach that employs blind number theory to evaluate the reliability of pavement performance test data. The proposed method aims to enhance the representativeness of PQI and is demonstrated using detection data from highway asphalt pavements in Hunan Province. The method takes into account the probability distribution characteristics of evaluation metrics and incorporates the blind number representation format of PQI. A confidence model for pavement performance evaluation is established to assess the reliability of pavement detection results. The method also integrates expert empowerment and entropy weight to consider both the subjectivity of evaluation and the objectivity of measured data. The method presented in this study has demonstrated superior performance compared to traditional evaluation index systems. This is attributed to the effective utilization of blind information to accurately characterize the discreteness of pavement performance indexes. Consequently, pavement performance can be quantitatively graded based on anticipated issues and data.

Keywords: pavement performance evaluation; reliability study; confidence model; entropy weight method; blind-number theory



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1. Introduction

In the field of pavement engineering, one crucial aspect that affects the grade of pavement performance is the occurrence of distresses or diseases in asphalt pavements over time [1]. These distresses can manifest in various forms, such as cracks, potholes, rutting, and surface deterioration [2]. The pavement management system (PMS) encompasses a comprehensive range of interconnected activities, including road planning, design, construction, maintenance, evaluation, and research [3]. Its primary objective is to optimize the utilization of various resources such as capital, labor, machinery, materials, and energy [4]. Within the PMS framework, the maintenance management system plays a crucial role. It aims to maximize available resources to maintain optimal pavement performance throughout the entire life cycle [5]. Evaluating the service performance of pavements at different stages of their life cycle is essential to proactively address necessary repairs before they reach critical failure conditions [6]. By implementing maintenance management systems, it becomes possible to reduce maintenance and repair costs while ensuring

the safety of transportation networks [7]. The assessment of pavement performance is a key component of maintenance management and directly impacts the quality of highway service [8]. Therefore, accurately evaluating the grade of pavement performance is of paramount importance.

To enhance the objectivity and persuasiveness of the evaluation process, numerous quantitative analysis studies have been conducted to assess pavement performance. Majidifard et al. [9] employed novel machine learning techniques to predict rut depth, thereby enhancing the accuracy of rut curves. Fan and Dai [10] devised a comprehensive pavement performance evaluation method that considers five performance indexes. Olowosulu et al. [11] utilized a fuzzy evaluation method, presenting a novel framework for accurate assessment and analysis of flexible pavement performance. Li et al. [12] proposed an enhanced entropy weight analytic hierarchy process for evaluating pavement maintenance. In recent years, evaluation models have expanded to machine learning models, including the BP neural network [13], NARX neural network [14], and TOPSIS theory [15]. These models employ single or comprehensive evaluation indexes to gain insights into the actual pavement condition, thereby providing a scientific foundation for maintenance decision-making schemes and designs [16,17]. However, current research on pavement performance evaluation primarily focuses on single evaluation indexes, with limited consideration given to the weight of individual evaluation indexes, comprehensive evaluation methods, and reliability analysis of comprehensive evaluation indexes.

With the rapid expansion of highway transportation demand in China, there has been significant construction of highway infrastructure, leading to increased research on pavement performance evaluation methods [18]. The Pavement Quality Index (PQI) is a comprehensive indicator that encompasses sub-indexes such as the Pavement Condition Index (PCI), Riding Quality Index (RQI), Rutting Depth Index (RDI), and Skidding Resistance Index (SRI) [19]. These sub-indexes are weighted to derive the comprehensive evaluation index, which provides an overall assessment of pavement condition [20]. In engineering applications, the evaluation of pavement performance often relies on the average value and discrete grade of the performance indexes [21]. The average value approach calculates the mean of the observed data along the entire road section, while the discrete grade approach involves statistical analysis to determine the proportions of excellent, good, fair, poor, and very poor road conditions based on unit pavement performance evaluation results [22]. However, the evaluation method based on the average value tends to compress the information contained in the data, potentially leading to the neglect of important details. Predictions based solely on the average value may result in symmetric dispersion around the average index value, which can misrepresent the actual pavement condition [23]. Moreover, the process of converting continuous unit-kilometer metrics to discrete pavement levels can mask detailed information about pavement performance, further contributing to evaluation inaccuracies [24]. To address these limitations, it is important to consider more advanced evaluation methods that capture the variability and nuances of pavement performance [25]. This may involve incorporating additional factors, such as the weight of individual evaluation indexes, the use conditions of each measuring point, and the reliability analysis of the comprehensive evaluation index [26]. Utilizing more sophisticated techniques can improve the objectivity and accuracy of pavement performance evaluation, providing a solid foundation for maintenance decision-making and design.

In this study, the probability function of each evaluation index parameter is established to gain insights into the probability distribution characteristics of pavement performance evaluation metrics. Fitting tests are conducted to analyze various influencing factors. By utilizing probability distribution methods, it becomes possible to analyze potential indicators per kilometer without losing information due to averaging and discretization of evaluation results [27]. This approach ensures the maximum retention and utilization of all indicator data at the unit kilometer level. However, it is important to note that due to the different distribution forms of variables, a unified equation form cannot be adopted when dealing with each index. Each evaluation index may follow a distinct probability

distribution, and therefore, specific distribution functions need to be employed for accurate analysis. Furthermore, pavement performance evaluation often involves uncertain information, including randomness, fuzziness, gray areas, and unascertained factors [28]. Incorporating statistical techniques to handle uncertainty becomes crucial in accurately assessing pavement performance and making informed decisions. By considering the probability distribution characteristics and addressing uncertainties, this study aims to enhance the understanding of pavement performance evaluation and provide a more comprehensive and reliable assessment of the condition of highway pavements.

Therefore, this study presents the concept of blind-number theory and its application in evaluating the performance of pavement surfaces. A reliability framework for the pavement evaluation indicator using blind numbers is proposed. This framework integrates obscured data into the evaluation system, ensuring that it remains unaffected by probability distribution functions. By clearly defining the evaluation grade and its corresponding confidence, the rigor of the evaluation process is enhanced.

2. Testing Methods for Pavement Performances

2.1. Evaluation Indexes and Data Collection Methods

Accurate assessment of pavement performance is crucial in maintenance management, as it plays a pivotal role in determining the condition of pavements. Various factors such as climate, region, traffic load, and pavement materials contribute to the deterioration of pavements, leading to issues like ruts, cracks, pits, and oil flooding. The Highway Performance Assessment Standard (JTG H20) requires the use of the PQI for evaluating pavement performance in China. The PQI is calculated based on the PCI, RQI, RDI, and SRI, as defined in Equation (1).

$$PQI = w_{PCI}PCI + w_{RQI}RQI + w_{RDI}RDI + w_{SRI}SRI \quad (1)$$

where w_{PQI} , w_{RQI} , w_{RDI} , and w_{SRI} are the calculated weights of PCI, RQI, RDI, and SRI, respectively.

The data for the test object were collected using a laser-based 3D road intelligent detection vehicle [29]. This vehicle enabled comprehensive coverage of all the pavement performance indexes mentioned in the study. The collection of pavement condition data was carried out on expressways located in plain, hilly, and mountainous terrains of a province in China. These specific sections were carefully chosen to represent a diverse range of engineering geological conditions, variations in traffic load, complexities in pavement structure, and performance characteristics of pavement materials. The outcomes of the investigation provide valuable insights into how different conditions influence the probability distribution of pavement performance evaluation indicators.

2.2. Probability Distribution Analyses of Evaluation Indexes

In this study, several probability distributions, including Normal, Log-Logistic, Log-Logistic (3P), Logistic, and Lognormal, were used to analyze the probability distribution characteristics of the evaluation indexes. By employing different probability functions [30], probability distribution characteristics of the pavement performance evaluation indexes were determined.

To validate the appropriateness of the selected probability distributions for the evaluation indexes, fitting tests were conducted using the probability functions. These tests aimed to assess how well the probability distributions fit the observed data for the pavement performance evaluation indicators. Table 1 lists three typical fitting methods of probability results, providing insights into the suitability of the probability distributions for the evaluation indexes.

Table 1. Fitting test method of pavement performance evaluation index.

Type	Test Method
Kolmogorov–Smirnov Test	$D = \max_{1 \leq i \leq n} (F(x_i) - \frac{i-1}{n}, \frac{i}{n} - F(x_i))$
Anderson–Darling Goodness Test	$A^2 = -n - \frac{1}{n} \sum_{i=1}^n (2i - 1) \cdot [\ln F(X_i) + \ln(1 - F(X_{n-i+1}))]$
Chi-Squared Goodness Test	$\chi^2 = \sum_{i=1}^k \frac{(O_i - E_i)^2}{E_i}, E_i = F(x_2) - F(x_1)$

In the context of statistical hypothesis testing, H_0 represents the assumption that the observed data conform to the specified distribution, while H_1 suggests that the data deviate from the specified distribution.

Let x_1, \dots, x_n denote a series of random samples extracted from the theoretical probability density function $F(x)$, with n representing the number of sample sequences. Based on the predetermined significance level (typically 0.05) in the hypothesis test, the critical value is determined by referencing the appropriate table. If the test statistic D exceeds the critical value, the null hypothesis H_0 is rejected; otherwise, it is accepted.

$F_n(x)$ represents the empirical cumulative probability density function. By comparing the test statistic A^2 with the critical value size of each distribution cluster, it is determined at the given significance level α (e.g., 0.01, 0.05, etc.) whether to accept or reject the null hypothesis H_0 .

O_i is the observed frequency of the sample falling in the i -th interval, whereas E_i signifies the expected frequency of the sample falling within the same interval. $F(x)$ denotes the probability density function of the calculated sample, and x_1 and x_2 specify the range of interval i .

2.3. Analysis Framework Pavement Performance Reliability

2.3.1. Principle of Blind-Number Theory

According to the degree of completeness, information can be categorized into two types: deterministic information and uncertain information. Deterministic information refers to information that is known to be complete and certain. On the other hand, uncertain information refers to information that is known to be incomplete and uncertain. Specifically, many factors affect pavement performance, such as pavement structure, traffic volume, pavement and base materials, engineering geological conditions, and environmental factors. All of these influencing factors have uncertainty, and their performance on pavement performance varies.

When dealing with incomplete and uncertain information, mathematical methods are commonly used to process blind information comprehensively. Blind information refers to information that lacks complete knowledge or certainty. To handle blind information, a mathematical tool called a blind number is utilized. A blind number is essentially a gray function that operates on a set of rational gray numbers, with its value varying between 0 and 1.

The study supposes that $H(I)$ represents the set of interval-type gray numbers formed by the gray interval a_i , where each a_i belongs to $H(I)$. If $\alpha_i \in [0, 1]$ for $i = 1, 2, \dots, n$, the gray function in $H(I)$ can be defined as $f(x)$, as shown in Equation (2). If $i \neq j, a_i \neq a_j$, and $\sum^n \alpha_i = \alpha \leq 1$, the $f(x)$ should be called a blind number, which can be expressed by Equation (3) [30].

$$f(x) = \begin{cases} \alpha_i, & x = a_i \ (i = 1, 2, \dots, n) \\ 0, & \text{other} \end{cases} \tag{2}$$

$$\{[a_1, a_n], f(x)\} \tag{3}$$

where n is the order of $f(x)$; α_i is the confidence of the value a_i of $f(x)$; α is the total confidence of $f(x)$. The greater n , the greater the accuracy of the blind number $f(x)$.

The probability distributions described by Equations (3) and (4) represent the likelihoods associated with various intervals of the blind numbers A^\wedge and B^\wedge . The symbols “ \oplus ” “ \ominus ” “ \otimes ” “ \ominus ” denote the four arithmetic operations applied to the blind numbers. A^\wedge and B^\wedge can be any element within the matrix of possible values, expressed as $A \otimes B$, where $i = 1, 2 \dots k$ and $j = 1, 2 \dots m$. To illustrate the blind number operation using addition, this study considers x_1, x_2, \dots, x_k and y_1, y_2, \dots, y_m as lists of real numbers in descending order, referred to as the sequence of possible values for A^\wedge and B^\wedge . The vertical side of a matrix is denoted by x_1, x_2, \dots, x_k , while the horizontal edge is represented by y_1, y_2, \dots, y_m . The bounded matrix is perpendicular horizontal and vertical axes, and the possible values of A^\wedge and B^\wedge are associated with the edges and matrices, as depicted in Table 2.

$$A^\wedge = f(x) = \begin{cases} \alpha_i, x = x_i (i = 1, 2, \dots, k) \\ 0 \end{cases} \tag{4}$$

$$B^\wedge = g(x) = \begin{cases} \beta_j, x = y_j (i = 1, 2, \dots, m) \\ 0 \end{cases} \tag{5}$$

Table 2. The possible values of A^\wedge and B^\wedge with edge sum matrix.

x_1	$x_1 + y_1$	$x_1 + y_2$	\dots	$x_1 + y_j$	\dots	$x_1 + y_m$
x_2	$x_2 + y_1$	$x_2 + y_2$	\dots	$x_2 + y_j$	\dots	$x_2 + y_m$
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
x_i	$x_i + y_1$	$x_i + y_2$	\dots	$x_i + y_j$	\dots	$x_i + y_m$
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
x_k	$x_k + y_1$	$x_k + y_2$	\dots	$x_k + y_j$	\dots	$x_k + y_m$
	y_1	y_2	\dots	y_j	\dots	y_m

Based on the above assumptions, the confidence of the event $A/B \geq r$, is shown in Equation (6).

$$P\{A/B \geq r\} = \sum_{x_i - y_j \geq r} f(x_i)g(y_j) \tag{6}$$

where B can be the classification threshold of a certain evaluation standard, usually a real value; r is a known real number determined according to the requirements of the actual problem.

Construct the confidence matrix with edge product for A^\wedge and B^\wedge , where $f(x_1), f(x_2), \dots, f(x_k)$ and $g(y_1), g(y_2), \dots, g(y_m)$ represent the vertical and horizontal sides of the matrix with an edge, referred to as the confidence sequence of A^\wedge and B^\wedge . The horizontal and vertical axes of the matrix with an edge are perpendicular lines. The resulting confidence matrix obtained by performing an edge product on A^\wedge and B^\wedge is presented in Table 3.

Table 3. The confidence band-edge product matrix of A^\wedge and B^\wedge .

$f(x_1)$	$f(x_1)g(y_1)$	$f(x_1)g(y_2)$	\dots	$f(x_1)g(y_i)$	\dots	$f(x_1)g(y_m)$
$f(x_2)$	$f(x_2)g(y_1)$	$f(x_2)g(y_2)$	\dots	$f(x_2)g(y_i)$	\dots	$f(x_2)g(y_m)$
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
$f(x_i)$	$f(x_i)g(y_1)$	$f(x_i)g(y_2)$	\dots	$f(x_i)g(y_i)$	\dots	$f(x_i)g(y_m)$
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
$f(x_k)$	$f(x_k)g(y_1)$	$f(x_k)g(y_2)$	\dots	$f(x_k)g(y_i)$	\dots	$f(x_k)g(y_m)$
	$g(y_1)$	$g(y_2)$	\dots	$g(y_i)$	\dots	$g(y_m)$

2.3.2. Confidence Modeling of Pavement Quality Index

Due to the inherent uncertainty in pavement detection information, all indicators of pavement performance evaluation conform to specific probability distributions. Based on the aforementioned blind number theory, if the PCI, RQI, RDI, and SRI are all considered blind numbers, they can be expressed as follows:

$$PCI\hat{I} = \{[PCI_1, PCI_n], f_1(PCI)\} \tag{7}$$

$$RQI\hat{I} = \{[RQI_1, RQI_m], f_2(RQI)\} \tag{8}$$

$$RDI\hat{I} = \{[RDI_1, RDI_i], f_3(PCI)\} \tag{9}$$

$$SRI\hat{I} = \{[SRI_1, SRI_j], f_4(SRI)\} \tag{10}$$

Therefore, this study uses the blind number representation of the pavement quality index, as shown in Equation (10).

$$PQI\hat{I} = w_{PCI} \otimes PCI\hat{I} \oplus w_{RQI} \otimes RQI\hat{I} \oplus w_{RDI} \otimes RDI\hat{I} \oplus w_{SRI} \otimes SRI\hat{I} \tag{11}$$

In reliability calculations, the reliability of the representative value is defined as the ratio of the occurrence frequency of a single indicator to the total frequency. The credibility of the representative value can be determined using the traditional probability density function method. In cases where the amount of data is limited, the frequency of data occurrence can also be analyzed. The thresholds for different performance levels in pavement performance evaluation are established: 90 for excellent, 80 for good, 70 for medium, and 60 for bad. According to the blind number theory, the reliability of pavement serviceability for excellent and good grades can be indicated in Equations (12) and (13).

$$R_{PQI}(90) = \frac{1}{90} \otimes PQI\hat{I} \tag{12}$$

$$R_{PQI}(80) = \frac{1}{80} \otimes PQI\hat{I} \tag{13}$$

3. Analysis of Examples

3.1. Statistical Result Analysis

To fulfill the requirements of probability function analysis and fitting tests for pavement performance evaluation metrics, an operational program was developed for analysis and calculation. The statistical results are shown in Table 4. The probability density and fitting analysis results of PCI, RQI, RDI, SRI, and other indicators are presented in Figure 1. The analysis of the results indicated that when comparing PCI, RQI, RDI, and SRI using the Kolmogorov–Smirnov and Anderson–Darling test methods, the Log-Logistic (3P) distribution provided the most suitable fitting results. When using the Chi-Squared method for comparison, the Log-Logistic (3P) distribution yielded the best fitting results for RQI and RDI. The PCI achieved the best result through Logistic fitting method, followed by Log-Logistic (3P) fitting. However, the SRI obtained the best result through Log-Logistic fitting. By comprehensively comparing the calculation results from all three methods, it can be concluded that the probability density distributions of PCI, RQI, RDI, and SRI can be effectively characterized by the Log-Logistic (3P) distribution.

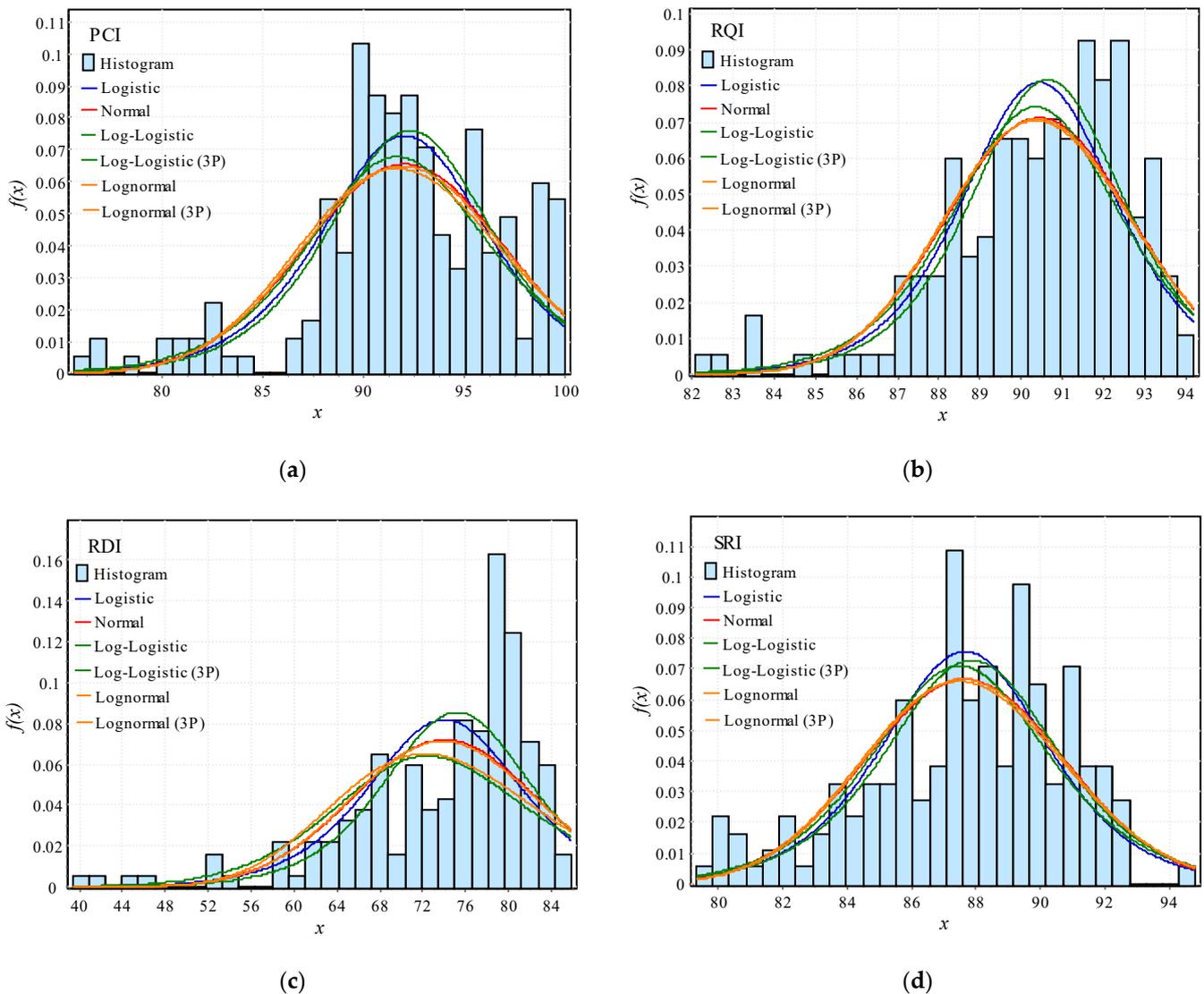


Figure 1. Comparison of probability density of pavement performance indexes and fitting analysis results: (a) PCI; (b) RQI; (c) RDI; (d) SRI.

The cumulative probability density functions of PCI, RQI, RDI, and SRI, as well as the comparison between measured values and fitting values, are presented in Figures 2 and 3. In the case of the PCI, the Log-Logistic (3P) fitting is not effective in the range of [80, 85], meaning that the fitted function does not accurately represent the distribution of the index within this range. However, the fitting becomes stable and reliable in the range of [85, 100], indicating that the fitted function accurately represents the distribution of the PCI within this range. For the RQI, the Log-Logistic (3P) fitting is not effective in the ranges of [82, 87] and [93, 94], suggesting that the fitted function does not accurately represent the distribution of the index within these ranges. However, the fitting becomes stable and reliable in the range of [87, 93], indicating that the fitted function accurately represents the distribution of the RQI within this range. The overall trend of the RDI obtained through Log-Logistic (3P) fitting to the cumulative probability density function is evident. This suggests that the fitted function accurately represents the distribution of the RDI across its entire range. Similarly, the cumulative probability density function of the SRI obtained through Log-Logistic (3P) fitting shows an ideal effect within the range of [84, 92] and is stable and reliable. This indicates that the fitted function accurately represents the distribution of the SRI within this range.

The measured and fitted values of pavement performance indicators are compared using Log-Logistic (3P) fitting. In the range of the PCI [0, 0.6], the fitting results fluctuate significantly, and the fitting effect is poor. In the range of [0.6, 0.9], the fitting results fluctuate slightly and are distributed on both sides of the line, indicating relative reliability and stability. For the RQI, in the range of [0, 0.2] and [0.5, 1], the fitting results fluctuate greatly, and the fitting effect is poor. However, in the range of [0.2, 0.5], the fitting results fluctuate slightly and are distributed on both sides of the straight line, indicating stability and reliability. The fitting values obtained for the RDI fluctuate around the actual values, with local fluctuations being significant. In the range of the SRI [0.4, 0.9], the fitting values exhibit a high correlation with the measured values, indicating a better effect.

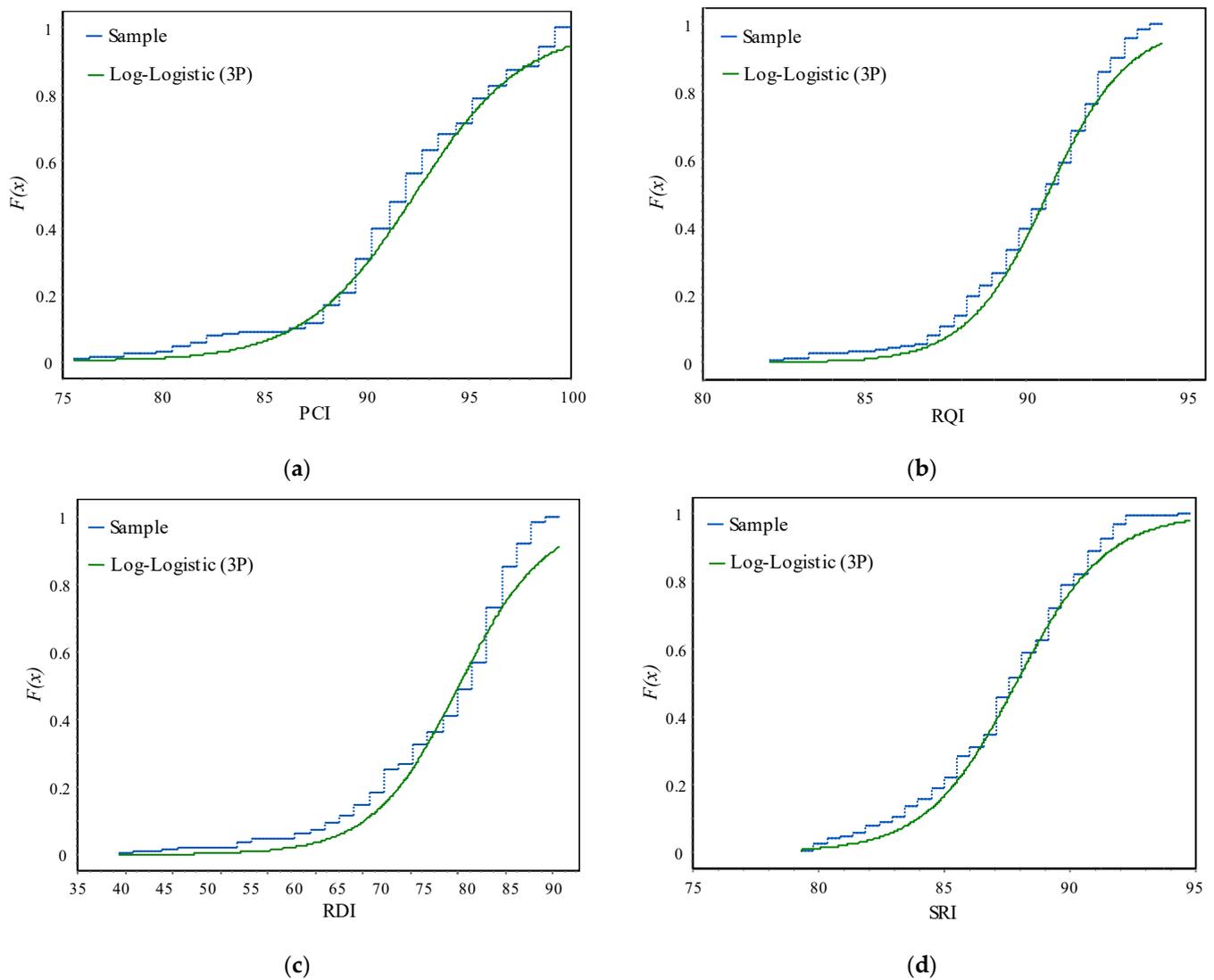


Figure 2. Cumulative probability density function of pavement performance evaluation indexes: (a) PCI; (b) RQI; (c) RDI; (d) SRI.

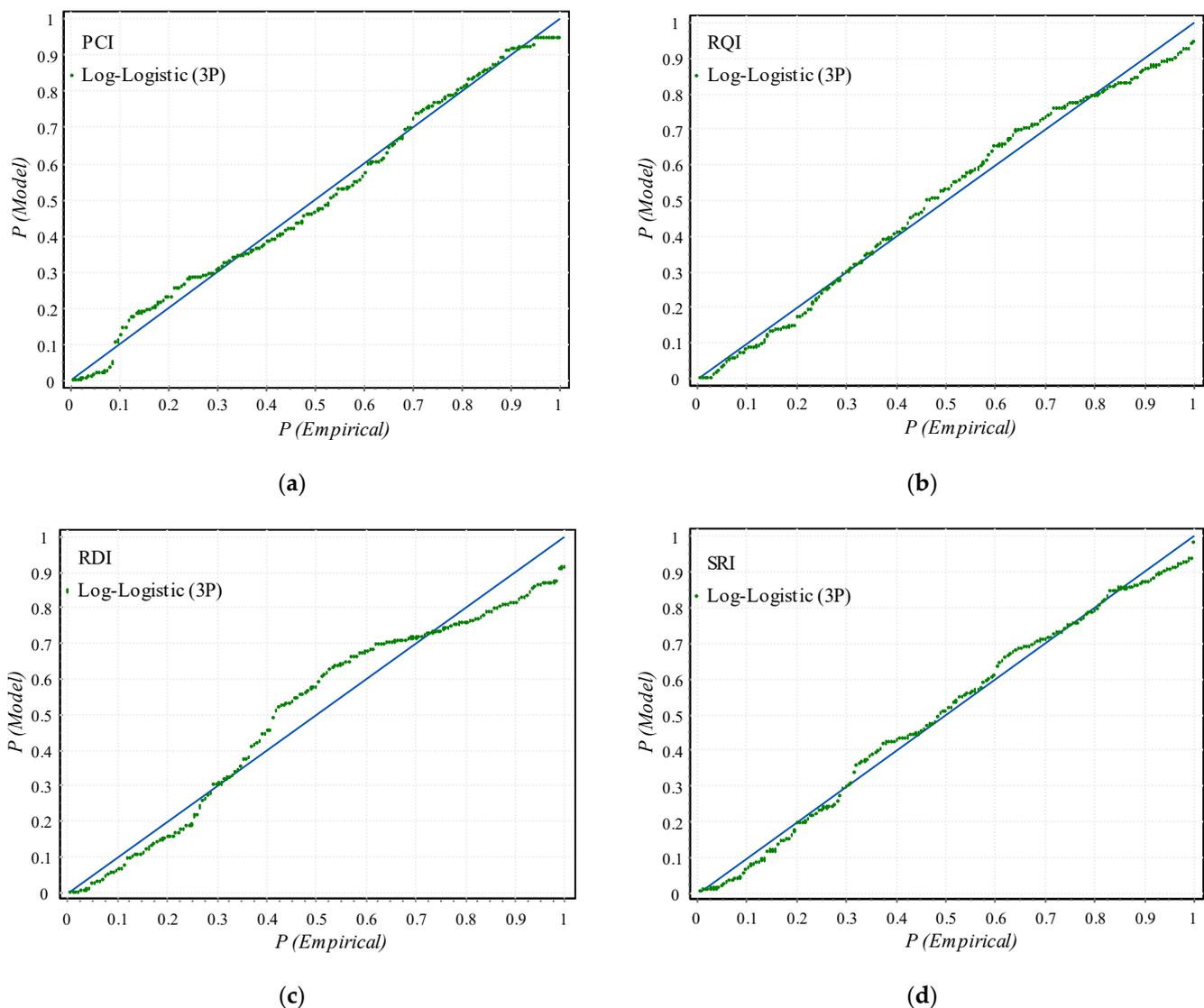


Figure 3. Comparison of measured values and fitting values of pavement performance indexes: (a) PCI; (b) RQI; (c) RDI; (d) SRI.

Indeed, studying the probability distribution characteristics of asphalt pavement performance evaluation indexes is an important research endeavor. The analysis conducted above indicates that the PCI, RQI, RDI, and SRIes do not follow a normal distribution entirely, and the probability distribution of pavement performance evaluation indexes varies. The gradual decay of pavement performance over time is influenced by various factors such as climate, geology, traffic load, material properties, and structural geometry parameters. Consequently, the probability distribution of pavement performance evaluation indexes will also change throughout different stages of the pavement's life cycle. The current deterministic evaluation method, which employs fixed weights, is insufficient to meet the practical requirements of the project. To ensure accurate and reliable pavement performance evaluation, it is crucial to consider the probabilistic nature of these indexes and incorporate appropriate statistical models or methods for analysis.

Table 4. Comparison of fitting function statistical test results of pavement performance indexes.

Serial Number	Distribution Function	Kolmogorov–Smirnov		Anderson–Darling		Chi-Squared	
		Statistic	Sort	Statistic	Sort	Statistic	Sort
PCI	Log-Logistic	0.10416	5	2.5466	5	18.017	6
	Log-Logistic (3P)	0.05657	1	1.3167	1	8.0729	2
	Logistic	0.07701	2	1.6292	2	6.5873	1
	Lognormal	0.10857	6	3.0129	6	17.641	5
	Lognormal (3P)	0.10026	4	2.5372	4	13.059	4
	Normal	0.09952	3	2.3536	3	13.057	3
RQI	Log-Logistic	0.08961	5	2.83	6	14.394	3
	Log-Logistic (3P)	0.06286	1	1.6038	1	10.768	1
	Logistic	0.09492	6	2.3974	2	11.416	2
	Lognormal	0.08381	4	2.8015	5	19.881	6
	Lognormal (3P)	0.07966	3	2.6147	4	18.457	5
	Normal	0.07928	2	2.4687	3	15.721	4
RDI	Log-Logistic	0.169	6	9.2652	6	79.025	6
	Log-Logistic (3P)	0.10865	1	4.6751	1	41.345	1
	Logistic	0.16246	4	6.3528	2	60.395	2
	Lognormal	0.16794	5	8.9946	5	77.588	5
	Lognormal (3P)	0.15262	2	6.606	4	63.712	4
	Normal	0.15298	3	6.4046	3	62.267	3
SRI	Log-Logistic	0.09108	6	2.1105	6	5.8546	1
	Log-Logistic (3P)	0.0554	1	1.2219	1	8.7292	5
	Logistic	0.07973	2	1.8442	4	10.447	6
	Lognormal	0.08903	5	2.031	5	7.0076	4
	Lognormal (3P)	0.08081	3	1.7982	3	6.5312	3
	Normal	0.08172	4	1.6595	2	6.3648	2

3.2. Confidence Analysis Based on Blind-Number Theory

Taking into account the uncertainty associated with randomness, fuzziness, grayness, and uncertainty in the evaluation of pavement performance, the blind number theory is employed to establish blind number expressions for pavement performance evaluation indexes. Additionally, a confidence model is developed to analyze the confidence of pavement performance. The integration of blind information into the evaluation system ensures that it remains unaffected by probability distribution functions. This approach not only provides a clear assessment grade for pavement performance but also assigns corresponding credibility to the assessment grade, thereby enhancing the scientific nature of the evaluation. The sample data and weight coefficients used in this study are based on the research conducted by Li, Wei, Yao, Hu, and Wang [12]. By utilizing Equations (14)–(16), blind numbers and reliabilities for the pavement performance indexes are computed, as shown in Table 5.

$$PQ\hat{I} = w_{PCI} \otimes PC\hat{I} \oplus w_{RQI} \otimes RQ\hat{I} \oplus w_{RDI} \otimes RD\hat{I} \oplus w_{SRI} \otimes SR\hat{I} \tag{14}$$

$$R_{PQ\hat{I}}(90) = \frac{1}{90} \otimes PQ\hat{I} \tag{15}$$

$$R_{PQ\hat{I}}(80) = \frac{1}{80} \otimes PQ\hat{I} \tag{16}$$

Table 5. Confidence results for intervals of pavement performance.

No.	PQI (Grade)	PQI ⁺ (Grade)	K _{PQI} ⁺ (90)	K _{PQI} ⁺ (80)
1	83.64	73.31757	0.81464	0.91647
2	83.79	76.23695	0.847077	0.952962
3	84.89	76.85353	0.853928	0.960669
4	85.98	78.84341	0.876038	0.985543
5	84.90	80.23577	0.891509	1.002947
6	87.01	81.69958	0.907773	1.021245
7	84.92	82.01217	0.911246	1.025152
8	85.45	82.64352	0.918261	1.033044
9	84.96	82.85526	0.920614	1.035691
10	87.14	82.93161	0.921462	1.036645
11	84.72	83.26604	0.925178	1.040826
12	87.61	83.40383	0.926709	1.042548
13	87.67	83.48033	0.927559	1.043504
14	86.60	84.10160	0.934462	1.051270
15	86.36	84.60134	0.940015	1.057517
16	87.76	84.83564	0.942618	1.060446
17	87.91	84.84281	0.942698	1.060535
18	87.86	85.12389	0.945821	1.064049
19	88.06	85.74850	0.952761	1.071856
20	89.21	86.82397	0.964711	1.085300
21	89.70	87.03685	0.967076	1.087961
22	89.23	87.35512	0.970612	1.091939
23	89.22	87.47873	0.971986	1.093484
24	88.56	87.48089	0.972010	1.093511
25	89.42	87.75188	0.975021	1.096899
26	88.19	88.27680	0.980853	1.103460
27	89.83	88.34652	0.981628	1.104331
28	89.83	88.36494	0.981833	1.104562
29	90.35	88.42565	0.982507	1.105321
30	90.16	88.50354	0.983373	1.106294
31	89.74	88.56722	0.984080	1.107090
32	90.57	88.84937	0.987215	1.110617
33	89.18	88.98633	0.988737	1.112329
34	90.39	89.02159	0.989129	1.112770
35	90.99	89.17456	0.990828	1.114682
36	91.41	89.56480	0.995164	1.11956
37	90.84	89.72866	0.996985	1.121608
38	91.94	90.05702	1.000634	1.125713
39	92.94	90.97604	1.010845	1.137200
40	92.00	91.01112	1.011235	1.137639

The results of these calculations are presented in Table 4. It is evident that the calculated PQI⁺ results do not align with those obtained using the current standard. The PQI⁺ interval determined by the current standard is [83.64, 92.94], whereas the PQI interval computed is [73.32, 91.01]. Three of the judgment values for the optimal pavement performance evaluation grade exceed 1, indicating that the confidence of judgment values greater than 1 in the sample group is 0.075. There are 36 judgment values for the good pavement performance evaluation grade that surpass 1, signifying a confidence of 0.9 or 90% for judgment values greater than 1 in the sample group. Moreover, confidence is considered as 1 for values exceeding 0.9. According to the current standard, the evaluation outcome indicates that 30 samples are classified as good, while 10 samples are deemed excellent. For instance, considering sample 14, the current standard assigns a PQI evaluation result of 83.64, corresponding to a good evaluation grade. However, when employing the information entropy weight determination calculation for PQI⁺, the result is 73.32, indicating a medium evaluation grade. These evaluation results differ significantly.

Analyzing the pavement performance sample data reveals that the evaluation grade for the RDI is poor, while the PCI, RQI, and SRI receive excellent and good evaluation grades, respectively. The current standard assigns weights of 0.35 and 0.4 to the PCI and RQI, respectively, while the weight assigned to the pavement rutting depth index is relatively small [31]. Consequently, the overall pavement evaluation result becomes overly optimistic. In contrast, Li, Wei, Yao, Hu, and Wang [12] adopt the information entropy weight determination method, which considers the difference in evaluation indexes and reflects the contribution rate of these indexes to the system. This approach leads to an improved weight for the road rutting depth index. By comparing the scores provided by different experts, it is observed that the weight determination using information entropy weight aligns more closely with the actual road condition level.

Through the proposed confidence model for pavement performance analysis, not only is the evaluation level of pavement performance clearly defined, but the corresponding confidence for each evaluation level is also provided. Moreover, it significantly expands the application scope of pavement performance confidence analysis.

4. Conclusions and Outlook

This study has examined the probability distribution characteristics of the evaluation index for asphalt pavement performance and introduced the concept of blind-number theory to investigate the confidence model for analyzing the confidence of asphalt pavement performance. The key findings are as follows:

- (1) The Pavement Condition Index (PCI), Riding Quality Index (RQI), Rutting Depth Index (RDI), and Skidding Resistance Index (SRI) of pavement facilities do not exhibit complete adherence to the normal distribution. Furthermore, the probability distribution of the pavement performance evaluation index differs.
- (2) A blind-number expression for the pavement performance evaluation index is developed in this study. Additionally, a confidence model for analyzing the confidence of pavement performance is constructed using the method of determining the weight information entropy weight of the pavement performance evaluation index. The model effectively integrates blind information into the pavement performance evaluation system, making it independent of the probability distribution function.
- (3) Compared to the traditional method, the proposed confidence model for pavement performance confidence analysis has several advantages. Firstly, it provides a clear evaluation level for pavement performance, allowing for a more precise assessment. Secondly, it also assigns corresponding credibility to the evaluation level, which enhances the scientific and rational nature of the evaluation process. This improvement ensures that the evaluation takes into account the confidence of the data and the assessment results.

Overall, the confidence model significantly enhances the scientific rigor and advanced nature of pavement performance evaluation, thereby expanding the application scope of pavement performance confidence analysis and enabling more accurate and reliable assessments across a wide range of scenarios. In future research, it is highly recommended to expand the sample size to enhance the richness and representativeness of the data. By incorporating a larger number of samples, the confidence model can comprehensively reflect the performance of pavements under diverse road sections and conditions, thereby enhancing its accuracy and reliability. While this study covers several critical pavement performance evaluation indexes, future investigations should consider incorporating additional relevant indexes, such as traffic flow and climate conditions, which also exert significant influence on pavement performance. The careful consideration of these additional factors can further enhance the applicability and prediction capability of the confidence model.

Moreover, future work should focus on expanding and refining the credibility model of pavement performance based on blind number theory, thereby increasing its applicability to road projects in different regions and under varying conditions. This will provide road maintenance activities with more scientific and reliable decision support. By

continuously advancing the credibility model, road engineers can make well-informed decisions regarding maintenance strategies, ensuring the long-term functionality and safety of transportation networks in diverse geographical locations and environmental conditions.

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