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Enhancing Pavement Sustainability: Prediction of the Pavement Condition Index in Arid Urban Climates Using the International Roughness Index

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Abstract: Municipalities and transportation departments worldwide are striving to keep road pavement conditions acceptable, thus enhancing pavement sustainability. Although the pavement condition index (PCI) is widely used to assess distress conditions, traditional visual surveys used for PCI estimation can be laborious, expensive, and time-consuming. The international roughness index (IRI) can be measured more economically and conveniently than PCI; however, it does not directly indicate the surface condition of the pavement. In this study, a PCI–IRI correlation is proposed for urban roads located in the New Beni-Suef region, Egypt. For this purpose, a total of 44 km of urban roads was divided into homogenous sections. A visual distress survey was conducted to measure PCI considering typical distress patterns. The IRI values for the same sections were measured using an ultrasonic distance sensor mounted on an automobile. An exponential model was proposed to capture the relationship between IRI and PCI. With a coefficient of determination of 0.82, the exponential model seems to outperform reported IRI-PCI correlations. Model validation, along with a comparison to the existing models, supports its applicability to a wide range of roads. The proposed model provides a cost-effective means for accurately predicting PCI based on IRI, which is particularly useful for pavement maintenance management programs on limited budgets.

Keywords: pavement sustainability; IRI; correlation; PCI; urban flexible roads

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1. Introduction

Ensuring the durability of flexible pavements poses a crucial challenge for sustainable cities, particularly in countries with constrained budgets for road maintenance programs. Roads play a vital role in the development and growth of modern societies. Over time, pavements undergo gradual deterioration and specific forms of distress progress throughout their lifespan. This degradation not only impacts the ride quality but also increases the likelihood of road traffic accidents [1]. Consequently, it undermines the overall sustainability of the pavement infrastructure. The damage rate, however, can be reduced by adopting efficient maintenance management [2]. Urban roads do not typically receive proper attention in maintenance programs compared to rural roads due to the growing interest in the latter. As a result, the performance of urban roads is often mediocre and necessitates frequent maintenance and rehabilitation. With the typically limited funds allocated for upkeeping urban roads, transportation agencies worldwide face serious financial challenges in the maintenance and rehabilitation of flexible pavement networks [3]. This is of particular concern in developing countries, which have extremely scarce financial resources and relatively limited collected information about road conditions needed for adequate condition detection and due rehabilitation [4,5]. This necessitates a continuous evaluation of depressions and other surface deformations through comprehensive field monitoring programs [6].

The public work department in Malaysia routinely collects pavement performance data for their standard pavement maintenance management system (PMMS), but the core issue is the lack of funds for road maintenance as per the set PMMS. In Iraq, pavement condition surveys were developed to evaluate the current condition of the pavement network to assist in minimizing current distress [7]. The survey included network evaluation, project future condition, maintenance and rehabilitation needs, assessing repair costs, and repair programs. The pavement network in this study has unacceptable surface conditions and is in a state of constant deterioration; however, a PMMS system is yet to be established due to the lack of data.

There are several pavement indices for evaluating pavement surface conditions, including the pavement condition index (PCI), falling weight deflectometer (FWD), international roughness index (IRI), and British pendulum number (BPN) [8,9]. PCI is, perhaps, the most universally recognized index for evaluating pavement performance and condition. PCI is an index established by the U.S. Army Corps of Engineers [10,11] and mathematically expressed between 0 and 100, with 0 being the worst possible pavement condition and 100 being the best possible pavement condition. While PCI rating is widely used in transportation engineering to evaluate pavement conditions, measuring it is not always convenient [12]. PCI can be measured using either visual or automated surveys [13]. The visual survey is based on identifying 19 different distress types and patterns [14]. The process is tedious and lengthy as it necessitates collecting huge field data sets. Additionally, the safety of the survey participants may be compromised. The automated survey, however, requires advanced and costly equipment, and it uses a fully equipped vehicle to collect digital data on road surface conditions [4].

1.1. Utilization of IRI in PMMS

The IRI is a measure of pavement roughness [3,15]. It is common to view roughness in terms of distortion of the pavement surface, which contributes to an undesirable or uncomfortable ride. As such, the IRI reflects passengers' and drivers' comfort and measures their experience with the pavement surface. It can also indirectly reflect the response of vehicles to road conditions [16]. The IRI correlates well with other riding aspects, including safety, vehicle vibration, functioning speed, and fuel consumption [3,17]. The IRI can be measured by calculating the distortion of the pavement surface along the longitudinal profile of the vehicle wheel path [18]. Developing IRI-based models for performance prediction is common as pavements deteriorate [3,19,20]. Increasing fuel consumption, greenhouse gas emissions, decreasing vehicle efficiency, and causing traffic accidents are well-correlated with increasing pavement roughness, which collectively costs USD one million every year [18,21–23]. Owed to its versatility, the IRI became a key performance index in pavement management systems (PMSs) in many countries, especially for estimating vehicle operating costs [19]. To this end, the IRI is adopted by most road agencies across the world as an indicator of pavement performance [20,24].

In the Swedish specifications for calculating the IRI, 20 m road segments are utilized to determine individual IRI values. The average IRI value and the standard deviation, known as sIRI, are then calculated based on 400 m road segments. IRI specifications vary with the sIRI value, such that a 400 m segment of greater sIRI value has more stringent IRI specifications. National standards define different IRI thresholds for accepting new roads at the end of the warranty period and equally for accepting reconstructed roads. Remarkable differences have been found in the IRI specifications in various countries. IRI thresholds are, for example, 1.1 mm/m in Sweden (120 km/h), 1.9 mm/m for highways and expressways in Slovakia, 1.2 mm/m for a 20 m interval of main road in Hungary, and 2.2 mm/m for 100 m intervals of first class highways in Russia [25]. Figure 1 depicts the

IRI thresholds for new or reconstructed roads in different countries. The values are plotted against the respective segment length (L) they were developed for.

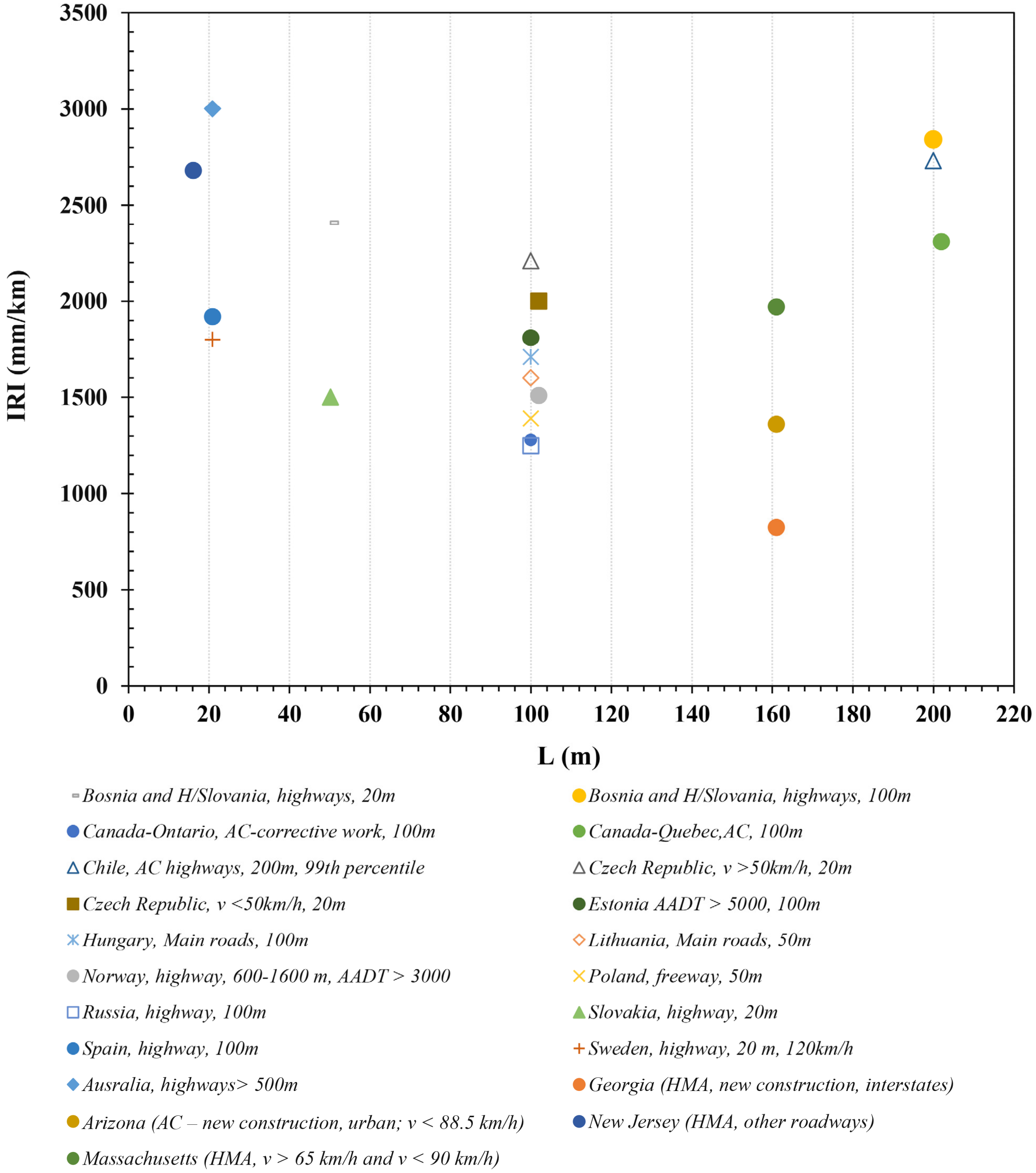

Figure 1. IRI limit values for new or reconstructed roads as a function of segment length (L). (after [25]).

1.2. PCI versus IRI

The IRI and PCI have an inverse relationship—as the pavement gets worse, PCI decreases, and IRI increases. The correlation quality captured by R^2 drops as the pavement deteriorates [3]. Several studies attempted to build reliable correlations between the IRI and PCI [15]. Dewan and Smith [26] developed a linear regression model to assess the IRI using the PCI for urban roads in the San Francisco Bay Area. The distresses include alligator cracking, longitudinal and transverse cracking, depression and rutting, patching, and utility cut patches. The mainstream of the measured IRI values was less than 3000 mm/km. Different mathematical models were used in this study to evaluate the relationship between the PCI and IRI; only the linear regression was satisfactory.

Park et al. [27] proposed a correlation between the PCI and IRI using data collected from The DataPave 3.0 software over an extended area in the United States (Delaware, Maryland, New Jersey, New York, Vermont, Virginia) and Canada (Ontario, Quebec, and Prince Edward Island). The data based on the long-term pavement performance (LTPP) study were from the early 1980s onwards. The study was performed by the National Research Council's Transportation Research Board (TRB), with the support of the Federal Highway Administration (FHWA) and the American Association of State Highway and Transportation Officials (AASHTO). The R^2 value of the model was 0.66 [27]. Adeli, Najafi moghaddam Gilani, Kashani Novin, Motesharei and Salehfard [3] developed a regression model for which a reasonable correlation between the IRI and PCI was observed. Linear, power, and exponential regressions were used for this purpose. The latter seems to be the most successful for the used dataset. R^2 values of 0.75, 0.76, and 0.59 were reported for IRI values of 2.5–3.5 m/km, 3.5–5 m/km, and 5–8 m/km, respectively. Hasibuan and Surbakti [10] also reported a relationship between the PCI and IRI for a road segment in Medan City, Indonesia. The exponential correlation was adopted with an R^2 value of 0.59.

The studies mentioned earlier had reported weak correlations between the IRI and PCI, with R^2 values ranging from 0.59 to 0.75. Therefore, this study attempted to create a more reliable regression model to capture the relationship between the PCI and IRI with a relatively higher R^2 value.

2. Study Area

2.1. Location and Climate

The study area selected in this research is comprised of a 44 km network of urban flexible pavement roads located in the New Beni-Suef region, Egypt, as shown in Figure 2. The city of New Beni-Suef is an extension of the old city of Beni-Suef as part of the government's ambitious plan to expand to the east. The study area is administratively affiliated with the district of the housing and development authority, the New Beni-Suef region, in the road management sector. This study's pavement section's age is approximately 10 to 12 years, with reasonable maintenance activities applied. As such, the overall pavement condition index is relatively high. The road condition of this network exhibits limited variation in traffic, age, location, environmental condition, subgrade, and maintenance activity. Days in Beni-Suef are commonly warm or hot, and nights are relatively mild or cool. Temperatures range from an average minimum of 6.60 °C in the winter to an average maximum of 36.9 °C in the summer. Beni-Suef receives fewer than eighty millimeters of precipitation annually in most areas [28,29]. The near-surface soil in this area is classified as Typic Torripsamments or Lithic Torripsamments [30].

2.2. Traffic

The traffic volume of the road sections of the study area is not calculated routinely by the Authority of Road Sector in Beni-Suef. Therefore, the authors have conducted a dedicated traffic survey in the study area. The manual count method was used at different times of the day over two months to enable the identification of the vehicle types and the respective traffic volume with confidence. The roads of the selected network experience moderate-volume traffic. The peak hour traffic volumes were enlarged by a K-factor. This factor is the proportion of AADT on a roadway segment or link during the design hour, i.e., the hour in which the 30th highest hourly traffic flow of the year takes place [8]. The annual average daily traffic (AADT) volumes were estimated accordingly. Using a K value of 0.12, as recommended in the highway capacity manual [31,32], the collected traffic seems to be comparable. Passenger cars constituted approximately 89%, buses were 8%, and trucks were merely 3% of the total traffic. While the low percentage of trucks has a limited impact in this study, it may be useful for developing a pavement deterioration model. The geometric and traffic characteristics of the roads in this study are summarized in Table 1.

Figure 2. The study area (* roads used for validation).

Table 1. Traffic volumes of the roads used in the study.

Road	Road Length (km)	AADT	Design Hourly Volume (DHV)
Ashabab	12.5	12,734	1528
El-Cornish	11.5	14,829	1780
Zamzam	5.4	13,598	1632
Al-Amal *	9	11,583	1390
Al-Andalus *	5.6	14,536	1744

* roads partially used for validation purposes.

3. Data Collection

This study attempts to develop a simple and affordable method for estimating the PCI based on this IRI. It is intended to economically, but accurately, collect the IRI values for the study area and subsequently use them to build an enhanced correlation with the PCI. A targeted low-budget approach is appealing for use when other traditional methods are costly and inconvenient. A correlation between the IRI and PCI was being developed for the network of flexible urban roads in the study area. Data collection included visible distress in pavement surfaces from the 44 km of urban roads in the study area.

The data collection process involved two steps: desk study collection and field collection [33]. Office data collection encompassed the utilization of available soil profiles and reports from prior studies. The data include construction dates, pavement layers, cross-section elements, significant maintenance activities with their respective dates and sizes, traffic volumes derived from permanent and temporary traffic count stations, and relevant environmental data. Field data collection, however, entailed pavement survey data, such as geometry-related data, and pavement distresses. Field data were collected by field inspectors who visually examined the pavement surface conditions considering distress type, severity, and extent. The current study utilized a paver system for distress data collection, which included specific guidelines regarding distress classification, and the quantification of severity and extent in certain measurement units (area or length or number) based on the type of distress [34]. Detailed descriptions of the 19 distress types implemented in this paver system, along with the guidelines, are reported by Shahin, M.Y. (2005) [17].

The conducted full field survey of the asphalt pavement distresses enabled estimating the PCI values. This was followed by measuring the IRI values using a mobile (vehicle-mounted) ultrasonic sensor. A regression model was developed to identify the potential correlation between the IRI and PCI. Several mathematical forms were considered for this purpose, including those used in the common prediction models from the literature. Performance was assessed via a robust validation process and complemented by a comparison with the reported models. The accuracy of the developed model was further investigated through detailed error analysis. Model implication on selected developed countries was performed to gauge its applicability in similar countries. Figure 3 depicts the development process of the model alongside the performance assessment.

3.1. PCI Survey

Distress data collection (i.e., defective areas) has been carried out for the selected urban roads located in the New Beni-Suef region, as shown in Figure 2, to estimate PCI. The identified distresses have been classified based on the 19 distress types listed in the PAVER system [12]. The study roads have been divided into sections with consistent characteristics throughout their length. Each pavement section is divided into sample units for the purpose of pavement inspection. Each sample unit was inspected for distress type, severity, and density. Identified distresses ranged from structural failures such as fatigue cracking, potholes, and depression to functional failures like bleeding and patching.

The study area exhibits a range of distress types, including fatigue cracks, longitudinal cracks, transverse cracks, polished aggregate, bleeding, block cracking, depressions, edge cracking, patching, and potholes. The density of low-severity fatigue cracks was 0.3%, while that of medium-severity fatigue cracks was 0.4%. The density of medium-severity bleeding was 1.2%. The density of medium-severity block cracking was 0.6%, while that of high-severity block cracking was 0.5%. The densities of medium-severity depressions and low-severity polished aggregate were 0.7% and 20%, respectively. The densities of low-severity and high-severity edge cracking were 0.22% and 0.35%, respectively. The densities of low-severity and medium-severity longitudinal and transverse cracking were 1.2% and 1%, respectively. The densities of low-severity and high-severity patching were 6% and 1.5%, respectively. The densities of low-severity, medium-severity, and high-severity potholes were 0.2%, 0.15%, and 0.1%, respectively. Table 2 summarizes the sample pavement distress types, severity, and density along the Al-Aml Road section. After data collection, data entry and processing for PCI calculation were performed using Micro PAVER software Version 3.0, which is a well-established PMS software developed by the Army Corps of Engineers, Washington, DC, USA [12].

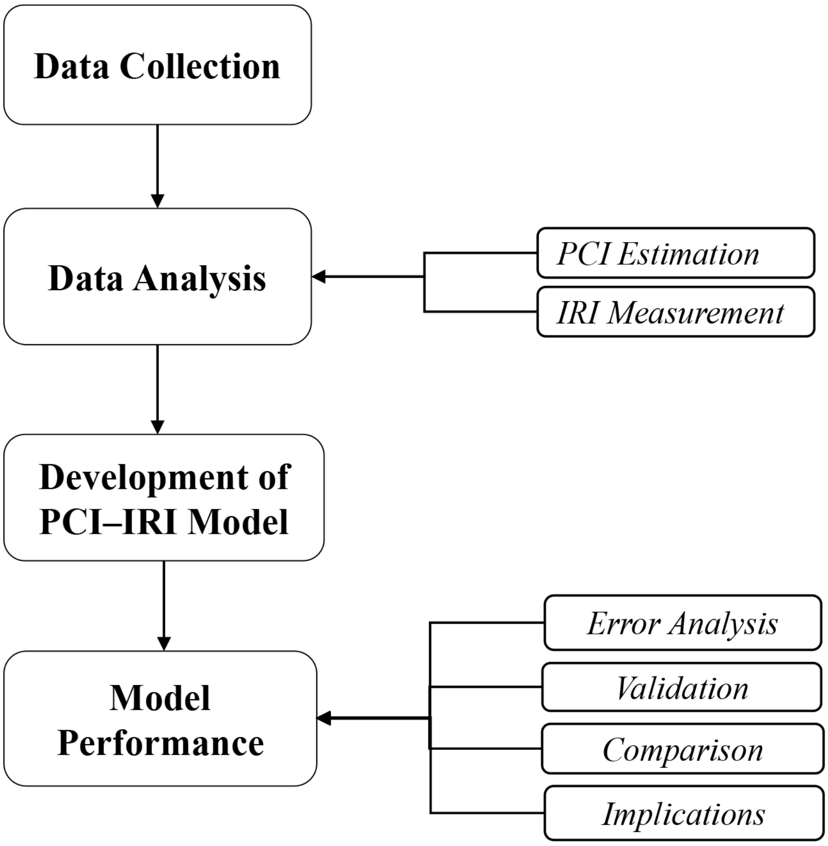

Figure 3. Model development and assessment.

Table 2. Sample of distressing patterns collected from Al-Aml Road.

Distress Type	Quantity	Severity Level
Bleeding (m^2)	30	medium
Depression (m^2)	11.7	high
Longitudinal cracking (m)	17.5	low
Patching (m^2)	68.95	medium
Potholes (No.)	4	low
Edge cracking (m)	70	high
Lane/shoulder drop off (m)	22	medium

The pavement sections were evaluated using a PCI rating system. PCI rating is widely used in transportation and civil engineering to evaluate pavement conditions [12,35]. The PCI rating system in Egypt is approved by the Ministry of Transport and is considered the main system for rating flexible pavements [36]. The identified distress types, severity, and density for the study roads were evaluated using the Micro-PAVER Version 3.0 software, and a database for the corresponding PCI deduct values was then created. Subsequently, the software was used to calculate the total and corrected deduct values, and thus, the PCI for the sample units along each road section. Since all surveyed sample units were selected randomly, the PCI of each road section was calculated by averaging the PCI of its sample units. Figure 4 shows examples for observed sample unit distresses along the urban flexible pavement in the study area.

Figure 4. Typical distress patterns in the flexible pavement of the study network: (**a**) utility patching; (**b**) longitudinal and transverse cracking; (**c**) depression; (**d**) lane-to-shoulder drop off.

3.2. IRI Survey

A mobile ultrasonic distance sensor has been fabricated to capture the pavement profile, as shown in Figure 5. The assembly—comprised of an ultrasonic sensor, Arduino board, and connecting cables—records the distance between the sensor and the surface of the pavement in millimeters. The device was charged through a fixed USB cable connected to a laptop. It was attached to the back bumper of the vehicle at a height of 420 mm from the pavement surface along with a vertical accelerometer to capture the vertical oscillation of the vehicle as it encounters road irregularities such as bumps, potholes, and cracks. The onboard processor removed these vertical oscillations from the sensor data. The IRI was calculated as the accumulated vertical motion along the pavement profile for 1km in the vehicle wheel path. The IRI measurement was conducted in both traffic directions, and the final IRI value of the road section was derived by averaging the two IRI values obtained from each direction.

Figure 5. Mobile ultrasonic distance sensor mounted to a vehicle to estimate IRI values (Arduino board connected to the sensor and housed for mobile data collection).

The device employed in this study utilizes the same profile-based roughness mechanism used in full-scale automated vans. This approach warrants collecting IRI values of high accuracy. Table 3 illustrates the features and specifications of the ultrasonic sensor used. The estimated total cost of the device is USD 16. To this end, in similar studies conducted in the UK by Li et al. [37] and Psarianos, B. et al. [38,39], the price tag of the survey van is estimated to be USD 500,000, which is typically beyond the capacity of pavement management programs in many developing countries.

Table 3. Ultrasonic sensor specs.

Power supply	+5 V DC
Quiescent Current	<2 mA
Working Current	15 mA
Working Frequency	40 Hz
Effectual Angle	<15°
Trigger Input Pulse width	10 uS TTL pulse
Echo Output Signal	TTL pulse proportional to the distance range
Dimensions	45 mm × 20 mm × 15 mm

The accuracy is highly dependent on the response time of the sensor and the vehicle's speed. Therefore, extensive testing and trials were performed to identify the speed of the vehicle at which data could be collected with minimal error and noise. Likewise, the effect of the sensor location on the quality of collected data was examined. Attaching the sensor along with the vertical accelerometer to the rear bumper of the vehicle seems to minimize vibrations and noise that could be generated due to the vehicle's vertical oscillations. As such, the recorded vertical distance is taken after any vehicle's shaking and bouncing is diminished. It should be noted that the vehicle is driven at a speed not exceeding 30 km/h controlled by car cruise control to minimize vibrations and thus enhance the quality of the collected data. The computer code used in measuring distances was developed using Arduino IDE. To this end, the vehicle operates at this optimal constant speed, and the timestamp was recorded to estimate the respective measurement. The accuracy of the IRI measured by the device employed in this study was checked against those obtained from the transportation authorities. These values were treated as a reference measurement. This comparison was conducted for a selected 5 km section from Ashabab Road (Figure 6). The estimated and reference IRI values were sampled at 100 m intervals. The cumulative difference between the estimated and reference IRI values for this section was approximately 442 mm. Approximately 52% of the estimated values (26 of 50 points in this test section) slightly underestimate the IRI reference values; however, the accuracy is quite acceptable. The average ratio between the estimated and reference IRI values (Figure 6) was approximately 0.97, which further supports the observed accuracy.

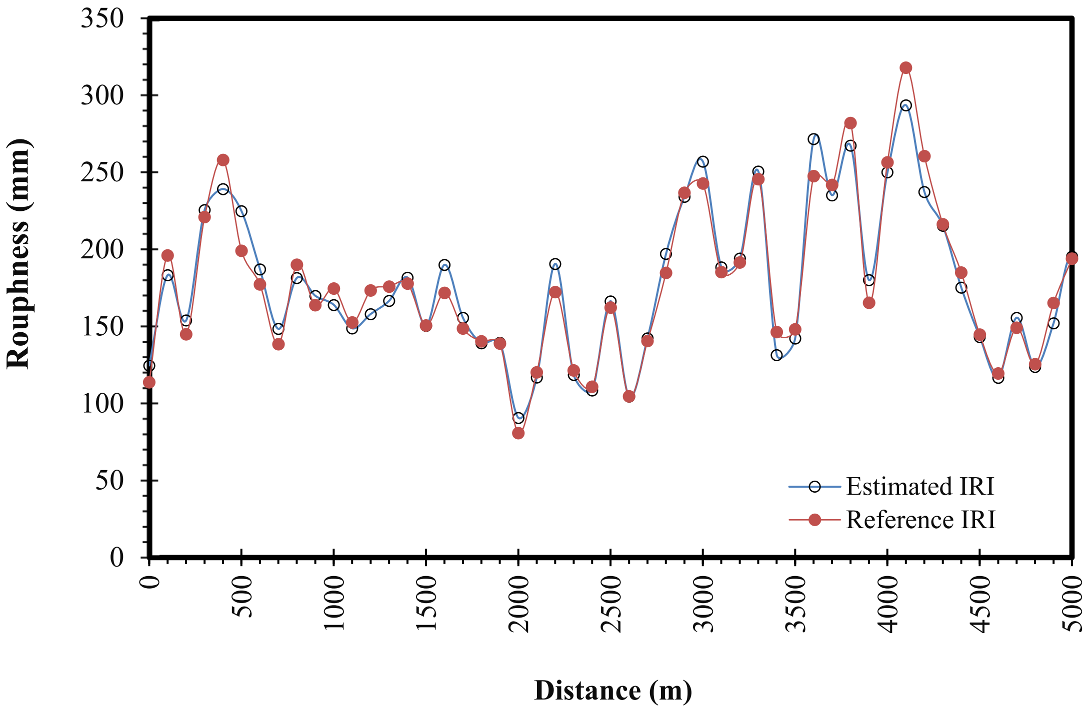

Figure 6. Road surface deformation (average irregularities in wheel paths shown in absolute value) for a 5 km stretch of Ashabab Road for both estimated and reference IRI values.

4. Model Development

Sufficient PCI and IRI data points were collected to build a robust regression and allow for subsequent validation. The database was split into two sets. The first set is for model development, which represents 70% of all data points. The second set is dedicated solely to the validation process, which represents the remaining 30% of the points. This data split is conventional for building correlations and validations and is statistically sound [29,40]. It is important to note that the conditions of the preselected roads for validation (as shown in Table 1) are quite representative of the study area. The statistical evaluation results for all pavement sections are shown in Table 4. The data appear to have a normal distribution, but they statistically fail the normality test. The correlation coefficient between the PCI and IRI is fairly high. The ratio between the standard deviation and standard error (σ/SE) represents the degree of scattering with respect to the line of equality. A ratio less than 0.5 generally indicates low scatter. At σ/SE value of 0.067, the data showed accurate predictions.

Table 4. Statistical evaluation of PCI values for the pavement sections of the study area.

Number of points	221
Minimum	57.00
Maximum	95.00
Median	83.00
Mean	82.59
σ	7.786
SE	0.5237
Coefficient of variation	9.43%
Correlation significant (alpha = 0.05)?	Yes
KS normality test	
KS distance	0.1071
p value	$p < 0.0001$
Passed normality test (alpha = 0.05)?	No

Table 4. *Cont.*

Shapiro–Wilk normality test	
W	0.9533
p value	$p < 0.0001$
Passed normality test (alpha = 0.05)?	No
D'Agostino and Pearson omnibus normality test	
K2	12.18
p value	0.0023
Passed normality test (alpha = 0.05)?	No

Error measures must be chosen wisely to assess the model's performance. Numerous error measures have been used in the literature for this purpose. The root mean square error (RMSE) and the mean absolute error (MAE) as error measures are very common in modeling. RMSE is unit-dependent, which does not allow for error normalization. MAE is usually a good indicator of bias; however, it cannot tell the direction of the bias, nor does it come with a cap (upper limit). For that reason, these error norms are deemed insufficient for holistic error analysis [41]. The coefficient of determination (R^2) is used to measure the proportion of variance in the dependent variable. R^2 is more sensitive to outliers than to the near mean measurements, which leads to an appreciable bias toward extreme events [42,43]:

$$R^2 = \left(\frac{\sum_{i=1}^{n} \left[(PCI_m)_i - \underline{PCI_{s-m}} \right] \left[(PCI_p)_i - \underline{PCI_p} \right]}{\left[\sum_{i=1}^{n} \left((PCI_m)_i - \underline{PCI_m} \right)^2 \right]^{0.5} \left[\sum_{i=1}^{n} \left((PCI_p)_i - \underline{PCI_p} \right)^2 \right]^{0.5}} \right)^2 \tag{1}$$

where PCI_m is measured PCI, and PCI_p is predicted PCI. Model evaluation is instrumental in gauging its utility, which requires error estimation [41]. In addition to the use of R^2 for developed regressions, bias (B) and index of agreement (I_a) can provide more insight into error distribution. Bias refers to the tendency of the model to overestimate or underestimate the prediction relative to the corresponding metric. The bias in this study is expressed as a ratio between the predicted and measured PCI values:

$$B = \frac{PCI_p}{PCI_m} \tag{2}$$

The Willmott index of agreement (I_a) is defined as the ratio between the mean square error (MSE) and the potential error (PE). The index of the agreement generally offers a better measure of the model performance since it encompasses both MSE and PE [44].

$$I_a = 1 - \frac{\sum_{i=1}^{n} \left[(PCI_m)_i - (PCI_p)_i \right]^2}{\sum_{i=1}^{n} \left[\left| (PCI_p)_i - \underline{PCI_m} \right| + \left| (PCI_m)_i - \underline{PCI_m} \right| \right]^2} = 1 - \mathrm{n}\frac{MSE}{PE} \tag{3}$$

Figure 7 shows the histogram of the field-collected PCI values. As depicted in the figure, most of the PCI values are within the 65 to 95 range, which generally indicates good pavement quality. This is expected given the age of the roads considered in the study. Approximately 40% (96/221) of the PCI values were in the range of 85 to 95, which can be classified as excellent. More than 39% (87/221) of the pavement sections are very good (70 to 85), and the rest of the data (35/221) were in the range of 65 to 75, which can be classified as good to very good [4].

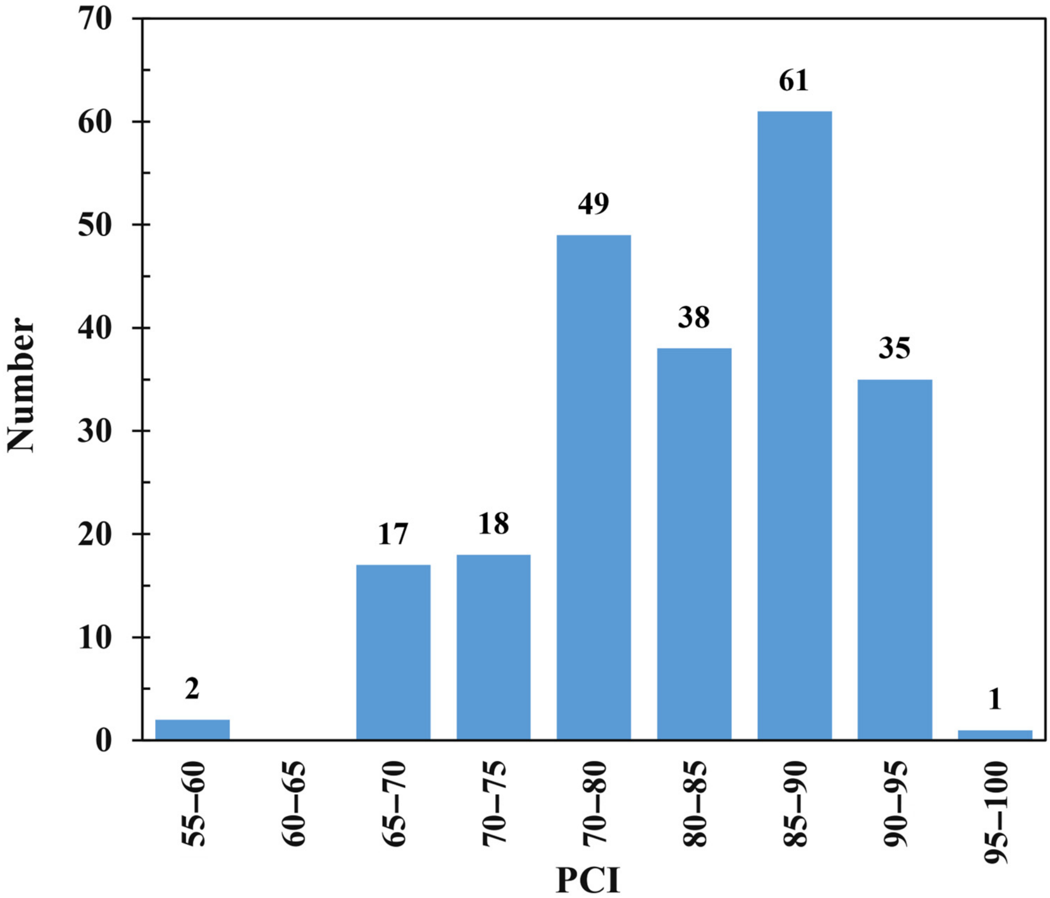

Figure 7. Distribution of the calculated PCI values (221 data points) for the roads of the study area.

The calculated *PCI* and *IRI* values for the 221 sections of the study area are shown in Figure 8. Several mathematical forms were considered to build a robust correlation between the *PCI* and *IRI* values. The variety allows for identifying the most appropriate regression and warrants generality. The *PCI* predictions of the models developed by Adeli, Najafi moghaddam Gilani, Kashani Novin, Moteshareі and Salehfard [3], Dewan and Smith [26] and Arhin et al. [45] were poor. The developed models by Ali, Hossain, Hussein, Swarna, Dhasmana and Hossain [2], Elhadidy, El-Badawy and Elbeltagi [4], Hasibuan and Surbakti [10], Park, Thomas, and Wayne Lee [27] yielded good estimates of the *PCI*. Although the sigmoid function is widely used for similar applications in pavement management [46], it does not seem to capture the relationship between the *PCI* and *IRI* in this study. Upon close examination of the performance of models from the literature, the logarithmic function has proven to provide the best fit. The proposed correlation between the *IRI* (in mm/km) and *PCI* can be expressed as follows:

$$PCI\,\% = -14.94 ln(IRI) + 189.95 \tag{4}$$

El-Cornish and Al-Amal sections are mostly in excellent condition, with *PCI* values higher than 75%, whereas Al-Andalus and Zamazam sections represent most of the low *PCI* values. Ashabab sections cover a wide range of *PCI* values. The coefficient of determination $\left(R^2\right)$ was estimated to be 0.82, which suggests a strong correlation between *PCI* and *IRI*.

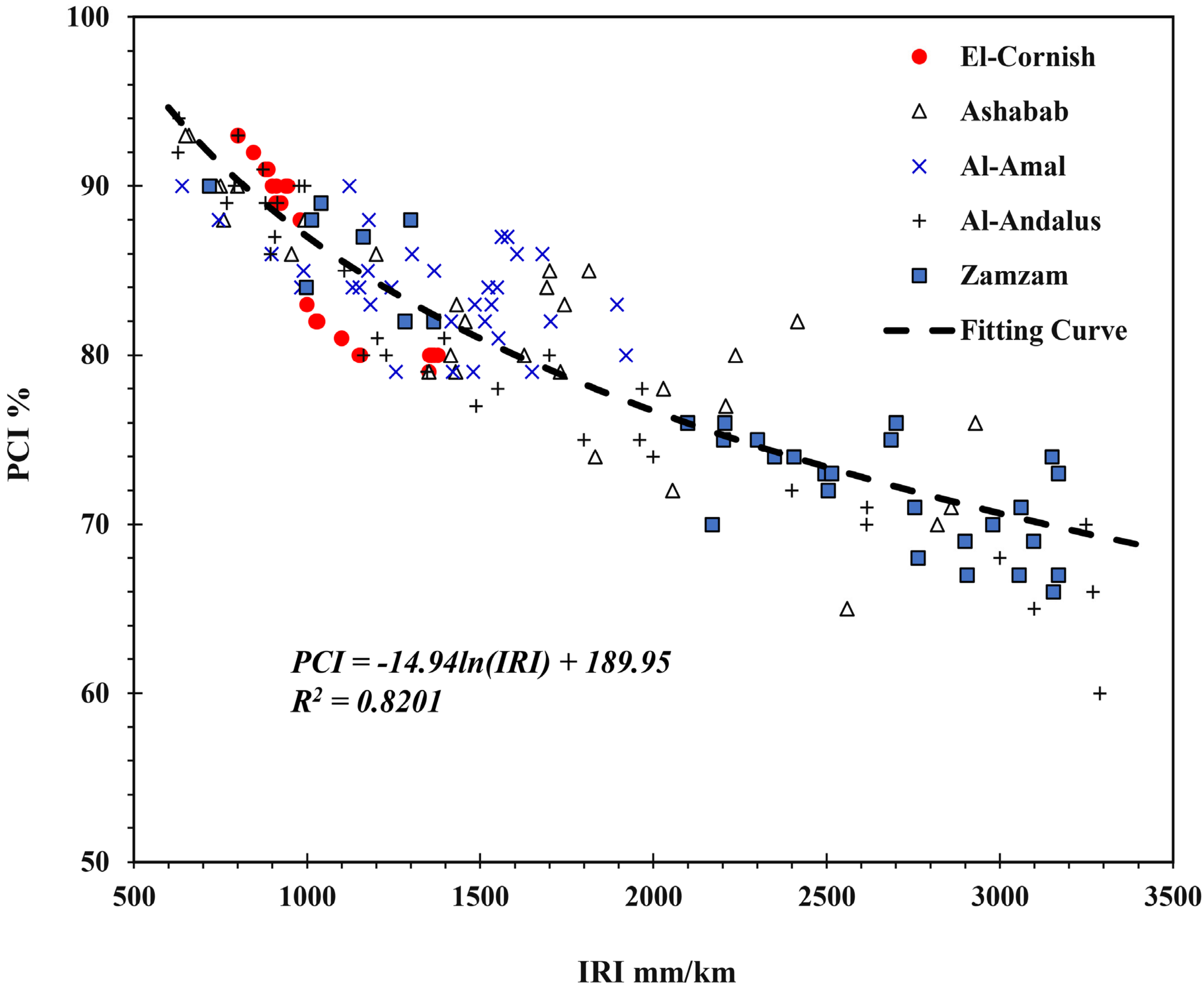

Figure 8. Proposed correlation for the collected IRI and PCI values.

5. Model Performance

The performance of the developed model was assessed via validation, error analysis, and comparison with similar regression models. Error analysis encompasses error norms for the developed model. The suitability of the model was gauged to predict PCI for two developed countries.

5.1. Error Analysis

Three error norms (R^2, B, I_a) were considered in comparing the proposed model against those well-behaving from the literature: [2,4]. Figure 9 displays the statistical performance and quality of predictions of this study's model. It was clear that the index of agreement and average bias for the developed model are both notably superior to those of the two other models. However, the coefficients of determination for the three models are nearly equal. As such, the 0.95 index of agreement and the near 1.0 average bias are more profound indications of accuracy than the coefficient of determination.

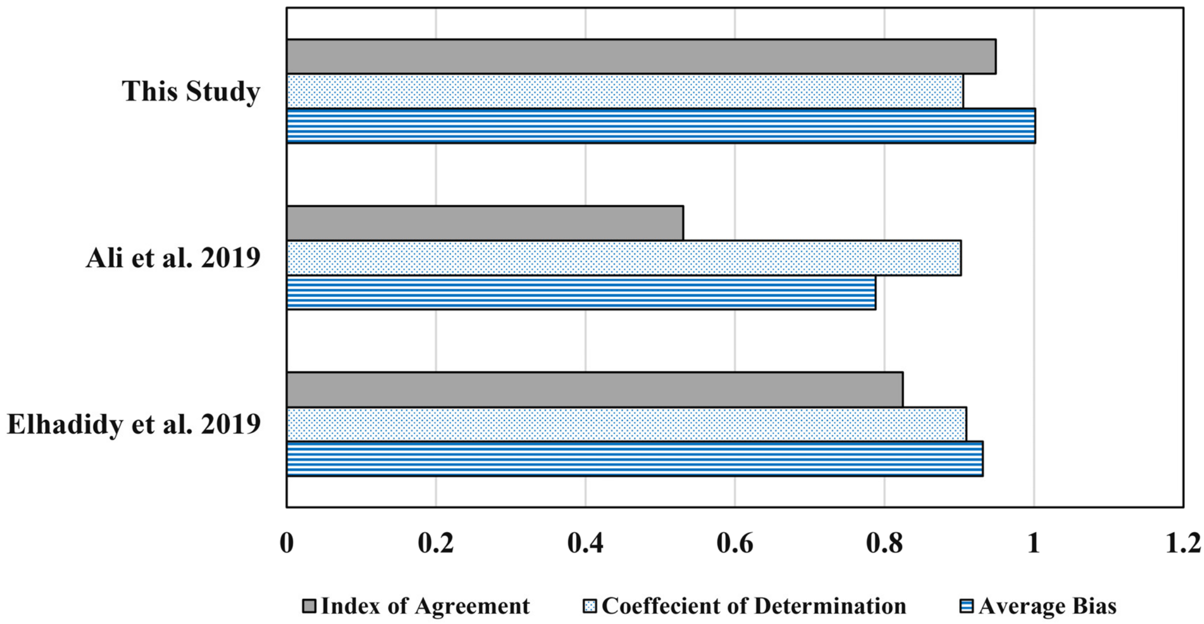

Figure 9. Error norms for the developed model versus the existing models [2,4].

5.2. Validation

The validation process was carried out using a dataset (30% of all available data points) other than that used in the development process. Figure 10 shows the relationship between the predicted and measured PCI corresponding to the same IRI values collected along Al-Amal and Al-Andalus roads. Approximately 62.5% and 37.5% of sections of Al-Amal and Al-Andalus roads, respectively, were used for this purpose. The PCI values in the validation dataset varied significantly, ranging from 57% to 95%. Similarly, the IRI values showed a wide range from merely 711 mm/km to 3288 mm/km. Such wide ranges reflect various road surface conditions in the validation dataset, and could subsequently warrant representativeness. As shown in the figure, the proposed model satisfactorily fits most of the data, starting from IRI values of 500 to 2000 mm/km, which indicates the validity of the model for forecasting the PCI. In contrast, the predictions are unable to capture the scatter beyond IRI values of 2000 to 2500 mm/km. One possible explanation for this discrepancy could be attributed to data quality, possibly human or systematic errors. Higher IRI values are associated with pronounced vertical oscillations of the vehicle, which may not have been accurately captured by the vertical accelerometer used to collect the data.

5.3. Comparisons with Existing Models

Few studies developed statistical models to correlate the PCI with the IRI [4]. Table 5 summarizes the available correlation models for IRI–PCI from different countries, along with the reported R^2 for each model, as shown in Column 3. These models were applied to the dataset from this study, and R^2 for each model was calculated, as listed in Column 4 of Table 5. The average B and I_a were also calculated to assess the PCI predictions using the reported models, as shown in Columns 5 and 6 of Table 5.

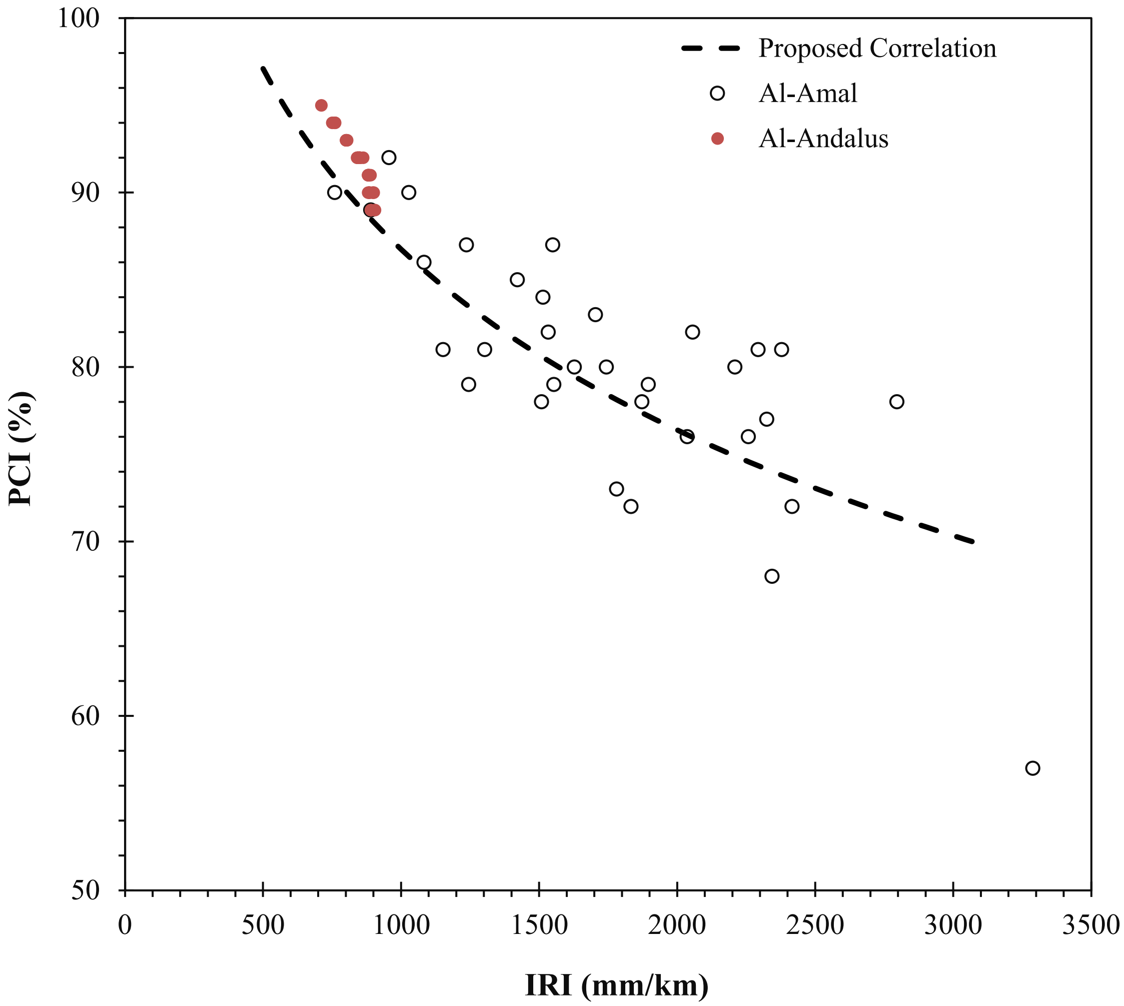

Figure 10. PCI and IRI validation values for Al-Amal and Al-Andalus roads versus the proposed correlation.

Table 5. Commonly developed models for IRI–PCI correlations.

Country	Model	R^2	R^2 (This Study)	B	I_a	Source
USA	$IRI = \frac{79.933}{14.061+exp(0.048\times PCI)}$	0.995	0.826	0.95	0.824	[4]
USA	$PCI = -0.224(IRI) + 120.02$	0.69	0.815	1.41	0.234	[45]
USA	$log\ PCI = -0.101 \times log(IRI) + 2.09$	0.8	0.817	0.94	0.268	[47]
USA	$logPCI = log\ 87.098 - 0.481 log\ IRI$	0.66	0.792	0.95	0.758	[27]
USA	$IRI = 0.0171(153 - PCI)$	0.53	0.815	0.87	0.392	[26]
Canada	$PCI = 81.890 - 11.037 \times IRI$	0.79	0.815	0.79	0.530	[2]
Iran	$PCI = -32.59 ln(IRI) + 132.93$	0.999	0.820	1.48	0.284	[3]
Indonesia	$IRI = 16.074 \times exp^{-0.26\times PCI}$	0.59	0.821	1.16	0.658	[10]

Based on the performance of the models outlined in Table 5, two reliable models developed in the USA and Canada were chosen for comparison due to their high R^2 value (Table 5). Elhadidy, El-Badawy, and Elbeltagi [4] used (LTPP) in the USA and Canada to propose a sigmoidal relationship between the PCI and IRI. The sigmoid mathematical form has been proven suitable for developing IRI–PCI correlations when they follow an S-shaped curve [46]. The correlation has a reported high coefficient of determination (R^2) of 0.995 [4]. Ali, Hossain, Hussein, Swarna, Dhasmana, and Hossain [2] conducted their research in the City of St. John's, Canada, using three types of data, including IRI, PCI, and the present serviceability rating (PSR). A survey involving a number of drivers was conducted to assess their comfort level. A smartphone application referred to as TotalPave was used to collect the IRI data. The IRI data showed a strong correlation with PCI data, while there was no evident relationship between IRI data obtained from TotalPave and PSR, nor between PCI and PSR. Major distresses showed a significant correlation with IRI and PCI indices. The reported correlation coefficient (R^2) was 0.79.

The suitability of models developed by Ali, Hossain, Hussein, Swarna, Dhasmana and Hossain [2], and Elhadidy, El-Badawy, and Elbeltagi [4] was examined in the study area. Figure 11a,b depict the PCI predictions of the respective models using the collected IRI in this study (221 data points) alongside the PCI predictions of the proposed model. Ali, Hossain, Hussein, Swarna, Dhasmana, and Hossain [2] model significantly underpredicts PCI values—perhaps because Canada experiences very different climates manifested in substantial precipitation and very low temperatures. Elhadidy, El-Badawy, and Elbeltagi's [4] model, however, shows a mixed behavior: the predictions for PCI are poor for PCI values below 75, and very good matching occurs thereafter. This can probably be attributed to the fact that some states in the south of the USA, such as Arizona and California, enjoy a hot Mediterranean climate similar to that of the study area. Evidently, the developed PCI–IRI model in this study outperforms both models. The percentage of the average error of the developed model in this study is six times smaller than the percentage of the average error obtained by Ali, Hossain, Hussein, Swarna, Dhasmana, and Hossain's [2] model and nearly two times smaller than the percentage of the average error obtained by Elhadidy, El-Badawy, and Elbeltagi's [4] model. The average error (%) was calculated as follows [29]:

$$E_{avg}\ \% = \frac{Predicted\ Value - Measured\ Value}{Measured\ Value} \times 100 \tag{5}$$

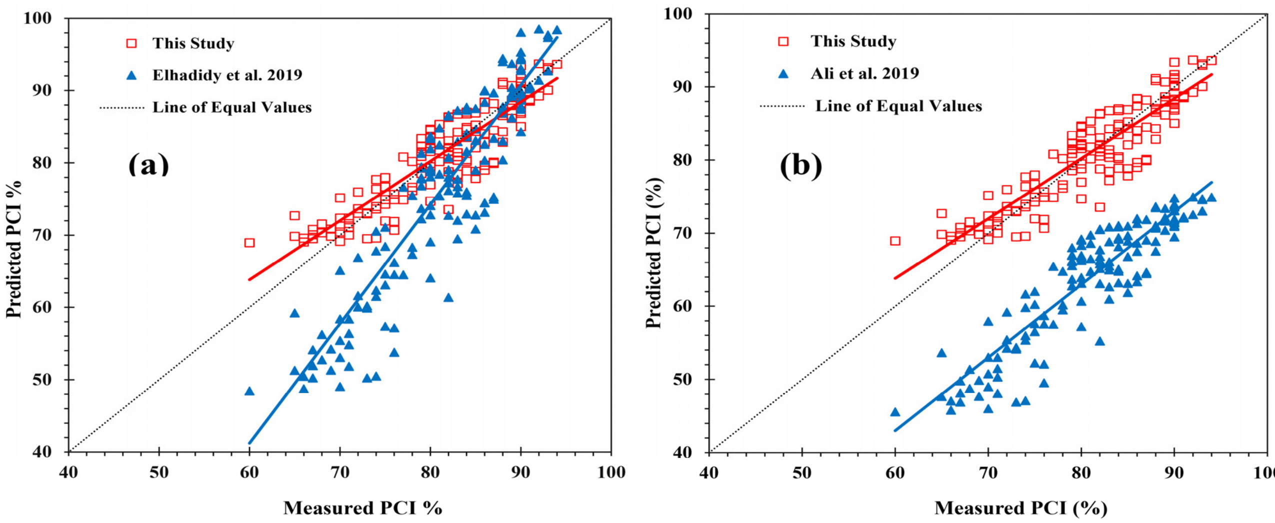

Figure 11. Comparison with reported prediction models performed by (**a**) Elhadidy, El-Badawy, and Elbeltagi [4] and (**b**) Ali, Hossain, Hussein, Swarna, Dhasmana, and Hossain [2].

5.4. Implication on Developing Countries

It is important to examine the applicability of the model to other developing countries such as [3,10,48,49]. Due to the availability of data from Iran and Indonesia [10], the proposed model was applied to the PCI–IRI dataset of selected road networks from Iran [3] and Indonesia [10]. R^2, B, and I_a were calculated once for the original models in [3] and [10], and another time using the developed model in this study. Based on the values of R^2, B, and I_a (Table 6), the developed model yielded fairly acceptable PCI predictions for the case of Indonesia. In Iran's case, some deviation was observed in I_a, perhaps due to ambiguities and irregularities observed in the data. For example, the % PCI values corresponding to the

IRI values from 2500 mm/km to 3500 mm/km are from 90 to 100, which is contradictory to the inverse relationship between these two measures.

Table 6. Comparison between the proposed model and those developed for Iran [3] and Indonesia [10].

	Iran [3]		**Indonesia [10]**	
	Original	**This Correlation**	**Original**	**This Correlation**
R^2	0.873	0.872	0.715	0.714
B	1.002	0.728	0.996	1.216
I_a	0.930	0.146	0.822	0.624

6. Conclusions and Future Direction

This study estimates IRI values for urban roads using a locally fabricated vehicle-mounted device that logs the longitudinal profile of the pavement's surface. The calibration process of the device was carried out using IRI data obtained from the Authority of Road Sector in Beni-Suef. The proposed survey technique is simple and accurate. The collected IRI values are well correlated with the measured PCI in the study area. Several attempts were made to identify the most appropriate mathematical correlation between PCI and IRI. With a coefficient of determination of 0.82, the exponential function fits the data satisfactorily. The study advocates using the average bias and index of agreement as more profound error norms.

Model validation was performed using dedicated data sets different from those used in the development process. The results further support model accuracy. The index of agreement of the proposed model yielded a high value compared to other models from the literature. The coefficients of determination for all models, however, were very similar. The average bias for the proposed models was close to 1.0, which was also notably higher than those of the other models—signaling high accuracy. A comparison is made between the developed model and two common models developed by Elhadidy, El-Badawy, and Elbeltagi [4] and Ali, Hossain, Hussein, Swarna, Dhasmana, and Hossain [2]. The latter model significantly underpredicts the PCI values, while the former performed mediocrely for the entire range of the IRI. The suggested model, thus, outperforms both models. Collectively, the proposed approach is very convenient for estimating the PCI of urban roads in developing countries with arid climates– particularly given the lack of allocated funds and resources. The model applicability was tested using actual measured data from Indonesia and Iran. For Indonesia and Iran, the results indicated that the average error did not exceed 10% and 15%, respectively. The developed model can perhaps be used satisfactorily in countries that share similar management norms and finances.

To this end, the proposed model is, however, limited by the traffic conditions considered in the study. Therefore, the model should be extended to similar arid climates, provided that sufficient traffic data become available. Increasing the number and range of data collection for the study area is necessary to enhance the generality and applicability of the model. Using unmanned aerial vehicles (UAV) to measure the IRI should be considered to improve accuracy and efficiency and minimize risk. The use of UAVs eliminates errors triggered by vehicle vibrations and road imperfections. The use of Light Detection and Ranging (LiDAR) technology can have a remarkable effect on the accuracy of the collected IRI data. Employing artificial intelligence in predicting a model could be instrumental in enhancing the proposed model when large datasets are made available.

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Abbreviations

AADT	Annual Average Daily Traffic
B	Average bias
BPN	British Pendulum Number
DC	Direct current
DHV	Design Hourly Volume
ESAL	Traffic loading represented by Equivalent Single Axle Load
FWD	Falling Weight Deflectometer
HMA	Hot Mix Asphalt
Ia	Index of Agreement
IRI	International Roughness Index
LIDAR	Light Detection and Ranging
LTPP	Long-Term Pavement Performance
MAE	Mean Absolute Error
MSE	Mean Square Error
PCI	Pavement Condition Index
PE	Potential Error
PMMS	Pavement Maintenance Management System
PMS	Pavement Management System
PSR	Pavement Service Rating
RMSE	Root Mean Square Error
R^2	Coefficient of determination
SE	Standard Error
σ	Standard Deviation
UAV	Unmanned Aerial Vehicle

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