District Department of Transportation

Predicting Pavement Condition Index Using International Roughness Index in Washington DC

Final Report

September 29th, 2014

ONE CITY

Disclaimer

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Predicting Pavement Condition Index Using International Roughness Index in Washington DC

Final Report

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Howard University Transportation Research Center

September 29, 2014

Research Project
Final Report 2014-03

TECHNICAL REPORT DOCUMENTATION PAGE

<table>
<tr><td>1. Report No.
DDOT-RDT-14-03</td><td>2. Government Accession No.</td><td colspan="2">3. Recipient's Catalog No.</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
Predicting Pavement Condition Index from International Roughness Index in Washington, DC</td><td colspan="2">5. Report Date
September 29, 2014</td></tr>
<tr><td colspan="2">6. Performing Organization Code
0007977</td></tr>
<tr><td colspan="2">7. Author(s)
Dr. Stephen A. Arhin, P.E., PTOE and Dr. Errol C. Noel, P.E.</td><td colspan="2">8. Performing Organization Report No.
HUTRC-02-2014</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address
Howard University Transportation Research Center (HUTRC)
2300 Sixth Street, NW, Room 2121
Washington, DC 20059</td><td colspan="2">10. Work Unit No. (TRAIS)</td></tr>
<tr><td colspan="2">11. Contract or Grant No.</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Organization Name and Address
District Department of Transportation
Research, Development, & Technology Transfer Program
55 M Street, SE, 5th Floor
Washington, DC 20003</td><td colspan="2">13. Type of Report and Period Covered
July 2013 – September 2014</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code</td></tr>
<tr><td colspan="4">15. Supplementary Notes
Project conducted in Cooperation with the U.S. Department of Transportation, Federal Highway Administration.</td></tr>
<tr><td colspan="4">16. Abstract

A number of pavement condition indices are used to conduct pavement management assessments, two of which are the International Roughness Index (IRI) and Pavement Condition Index (PCI). The IRI is typically measured using specialized equipment that calculates the smoothness and ride quality of the roadway segment based on established computer algorithms, while the PCI is based on subjective rating of the number of pavement distress. The literature suggests that most pavement indices are related, as a result of which several jurisdictions have developed models to predict one index from the other(s). This study used three (3) years of IRI-PCI data obtained from the District Department of Transportation to develop models which could potentially predict PCI from IRI by functional classification and by pavement type. The regression models explored were developed using the ordinary least squares method and were tested on the basis of 5% level of significance. The IRI-PCI models yielded R^2 and adjusted R^2 values between 0.008 and 0.0730, indicating that the models could only explain up to 7.3% of the variations in the data. In addition, the root mean square errors of the models were all determined to be greater than 1. Even though the results of the ANOVA tests indicated that the coefficients were generally statistically significant, the low R^2 values and high RMSEs indicate that the models do not adequately predict PCI from IRI, within the margin of error. A more sophisticated prediction tool, such as artificial neural networks, could be explored to potentially predict PCI from IRI more accurately.</td></tr>
<tr><td colspan="2">17. Key Words
International Roughness Index; Pavement Condition Index</td><td colspan="2">18. Distribution Statement
No restrictions. This document is available from the Research Program upon request.</td></tr>
<tr><td>19. Security Classification (of this report)
Unclassified</td><td>20. Security Classification (of this page)
Unclassified</td><td>21. No. of Pages
60</td><td>22. Price
N/A</td></tr>
</table>

Acknowledgements

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AUTHOR ACKNOWLEDGEMENTS

HUTRC extends its appreciation to the staff at DDOT for contributing to this study, namely, Mr. Edward Carpenter, Mr. Soumya Dey, and Ms. Stephanie Dock. A special thanks also goes to Ms. Carole Lewis for supporting the research team in the management of the study. The Howard University Research staff (Dr. Stephen Arhin and Dr. Errol Noel) recognizes the contribution of the students (Melissa Anderson, Olaolu Dairo, and Asteway Ribbiso) that were involved in the study.

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1.0 EXECUTIVE SUMMARY

The District Department of Transportation (DDOT) conducts pavement condition assessments to determine the physical health of its roadway network and to identify the need for improvements such as maintenance, resurfacing, rehabilitation and reconstruction. There are several types of pavement condition indices that are used by highway agencies to assess the improvement needs, two of which are the International Roughness Index (IRI) and Pavement Condition Index (PCI). IRI is typically determined by using specialized equipment for measuring variations in pavement surfaces that serve as input into established computer algorithms. Meanwhile, PCI is based on subjective rating of observed pavement conditions. Both pavement indices are very important since they collectively provide a comprehensive indication of the structural and functional condition of pavements. DDOT collects IRI and PCI data for the Federal roadway system on an annual basis and on the local system every other year. IRI is the only index required as part of the Highway Performance Monitoring System (HPMS) reporting to the Federal Highway Administration. In addition to IRI, DDOT uses PCI as an input into the agency's asset management and programming decision-making process, especially for local roads.

In order to eliminate the subjectivity in reporting PCI while reducing cost and labor, several jurisdictions and states have modeled the relationships between IRI and PCI so that PCI could be predicted from the IRI (or vice versa). This research was aimed at developing a model for predicting PCI of roads in District of Columbia, using 3 years of IRI and PCI datasets. The data used was obtained from DDOT for 2009, 2010 and 2012; IRI-PCI data for 2011 was not available. The IRI-PCI models were developed by functional classification and by pavement type.

Analyses of descriptive statistics by functional classification (from the mean IRI and PCI values) suggest that freeways have a smoother ride than arterials, followed by collectors and local roads. Similarly, when the data was analyzed by pavement type, the results show that concrete pavements were smoother than composite pavements followed by asphalt pavements in the District.

The regression models developed using Ordinary Least Squares (OLS) method to predict PCI from IRI by both functional classification and pavement type were determined not to be statistically significant within the margin of error (5% level of significance). This was based on the fact that the R^2 values ranged between 0.008 and 0.0730, indicating that the models could explain very small percentages (up to 7.3%) of the variations in the data. In addition, the Root Mean Square Errors (RMSE) for the models were all determined to be greater than 1, indicating that the models do not accurately predict PCI values from IRI even though ANOVA tests showed statistically significant F values ($p < 0.05$). The latter only confirms that the regression coefficients (β_1) are not zero at 5% level of significance.

Regression Models by Functional Classification

Functional Class	Model Equation	R^2	Adj. R^2	ANOVA		t- Statistic		RMSE
				F - value	*p*-value	β_1	*p*-value	
Freeways	$log(PCI_{FWY}) = -0.202[log(IRI_{FWY})] + 2.336$	0.073	0.054	3.8561	0.055	-0.202	0.055	1.250
Arterials	$log(PCI_{ART}) = -0.101[log(IRI_{ART})] + 2.092$	0.021	0.020	184.641	0.000	-0.101	0.000	1.243
Collectors	$log(PCI_{COL}) = -0.077[log(IRI_{COL})] + 2.030$	0.008	0.008	37.507	0.000	-0.077	0.000	1.321
Locals	$log(PCI_{LOC}) = -0.225[log(IRI_{LOC})] + 2.404$	0.035	0.035	365.835	0.000	-0.225	0.000	1.387

Regression Models by Pavement Type

Pavement Type	Model Equation	R^2	Adj. R^2	ANOVA		t- Statistic		RMSE
				F - value	*p*-value	β_1	*p*-value	
Asphalt	$log(PCI_{ASP}) = -0.115[log(IRI_{ASP})] + 2.131$	0.013	0.013	67.623	0.000	-0.115	0.000	1.304
Composite	$log(PCI_{COM}) = -0.056[log(IRI_{COM})] + 1.986$	0.006	0.006	35.875	0.000	-0.056	0.000	1.227
Concrete	$log(PCI_{CON}) = -0.222[log(IRI_{CON})] + 2.431$	0.053	0.051	29.134	0.000	-0.222	0.000	1.288

In addition, predicting segment level PCIs using the model yielded unacceptable level of variances between the predicted and observed values. Thus, it does not appear that the regression models (developed using the OLS method) can be applied in practice. Further research can be conducted to determine whether a more sophisticated prediction tool, such as artificial neural networks, can be used to accurately predict PCI from IRI.

2.0 INTRODUCTION

The District Department of Transportation (DDOT) conducts pavement condition assessments each year to determine the physical status of the roadway network. DDOT uses the compiled data to program improvements such as maintenance, resurfacing, rehabilitation and reconstruction. The type of pavement improvement is dictated by the extent of the distress severity. The annual condition assessment is typically conducted using specialized field equipment to collect distress and ride quality data. The specialized equipment comprises of a custom-designed camera mounted at the back of the survey vehicle, which takes photographs of the pavement at speeds no greater than 50 mph. The distress photographs are reviewed by trained pavement engineers and technicians who classify the distress (if any) of each section of the pavement by type, severity and extent. The pavement condition index (PCI) ranges from zero to one hundred, with zero indicating a very poor pavement condition and one hundred a very good one. Using an established equation, and based on the engineers' (or technicians') subjective evaluations, the distresses found on the sections of pavement within a city block are combined to determine the overall PCI for that block.

In addition to distress data collection, the specialized equipment is used to obtain road profile data that serves as an input to computer algorithms for calculating the pavement smoothness or roughness: the resultant calculation is known as the International Roughness Index (IRI). IRI is measured in in/mi or m/km, where a high IRI value indicates a rougher ride quality. IRI values may be categorized as shown in Table 1.

Table 1: IRI Condition Criteria

IRI scale (in/mi)	Description
<=60	Very Smooth
61 – 120	Smooth
121 – 170	Fair
171 – 220	Rough
>=220	Very Rough

PCI and IRI are very important since they collectively provide to an extent a comprehensive indication of the structural and functional conditions of the pavement. Only IRI is required as part of the Highway Performance Monitoring System (HPMS) reporting required by the Federal Highway Administration (FHWA).

The literature suggests that distresses in pavement surface (PCI) influence the smoothness (IRI) of a pavement. As a result, in order to eliminate the subjectivity in determining PCI, some jurisdictions have modeled relationships between IRI and PCI with the aim of predicting PCI from IRI. The aim of this research is to develop a model that would enable PCI to be predicted from IRI records for roadways in District of Columbia.

3.0 OBJECTIVE AND POTENTIAL BENEFITS

The objective of this project is to use previously obtained distress (PCI) and smoothness data (IRI) of sections of roadways in the District to establish a relationship between PCI and IRI for various roadway classifications and pavement types. It is anticipated that the outcome of this research may reduce the time for collecting, reviewing and processing distress photographs for PCI determination and thereby eliminating the annual routine subjective rating of pavement distress. In addition, the expense for obtaining and analyzing the field data for determining the PCI could be eliminated, except for specific purpose of upgrading established relationships.

Finally, if successful, this research aimed to develop a predictive tool or model that could reduce the need to collect PCI data as frequently. Under the assumption of a 4-year cycle for data revalidation, for the first three years of the cycle only IRI data would need to be collected; in the fourth year, both IRI and PCI data would be collected and analyzed. By reducing the required data collection and the labor hours for obtaining PCI values once every four years, this research project could potentially save DDOT an estimated $750,000 over a four year cycle (in 2014 dollars, assuming no cost escalation). This is a savings of almost 30 percent over the current collection schedule.

4.0 LITERATURE REVIEW

Pavement smoothness or roughness can be expressed as the extent of the non-existence or existence of surface irregularities that affect the ride quality of road users. Research has shown that smooth roads, on the whole, cost highway agencies less over the life of the pavement resulting in decreased highway user operating costs, delay costs, fuel consumption and maintenance costs. Pavement roughness is measured by various automatic multifunctional measuring instruments or devices and is quantified using the International Roughness Index (IRI), an internationally accepted parameter. IRI was first defined in the late 70's by the National Cooperative Highway Research Program (NCHRP) Report 228 and was adopted by the World Bank (Gillespie 1980) as a universal scale. IRI is one of several pavement indices required for annual reporting to FHWA by each state on the annual HPMS report.

IRI is measured by automation using a road profiler, which produces a series of numbers to represent the profile of the road by combining a reference elevation, height relative to the reference, and longitudinal distance. Examples of road profilers include the Profilograph, Dipstick Auto-Read Road, and Inertial Profilers (Sayer et. al.1996). Response-type road roughness meters or profilers are typically used to collect IRI data and are usually mounted on specialized vehicles with computer technology to monitor pavement roughness as shown in Figure 1. The device records the displacement of the vehicle chassis relative to the rear axle per unit distance traveled, usually in terms of counts per mile or foot (Shalfizaden et al. 2002). Other instruments measure pavement roughness in terms of the number of inches per mile that a laser, mounted on a vehicle, jumps as it is driven across roads at speeds of over 30 mph. These instruments are connected to calibrated computer models which are used to calculate and report a corresponding number indicating the roughness or smoothness of the roadway driven. This ensures that the IRI values reported are comparable and repeatable, regardless of the test vehicle (Shalfizaden et al. 2002).

FHWA recommends a threshold of 170 in/mi (2.7 m/km) for acceptable ride quality in its 2006 strategic plan for the National Highway System. The lower the IRI value, the smoother the ride and vice versa. Table 2 provides the pavement condition criteria for all functional road classifications in the national highway system (Dewan, 2012).

Figure 1: Specialized Van for IRI Data Collection

Table 2: FHWA Pavement Condition Criteria

Road Quality Terms	IRI Threshold (in/mi)
Good	< 95
Acceptable	< 170

Source: Dewan, 2012

Park et al. (2007) established a power relationship between PCI and IRI using data from nine states and provinces in Northern America. The IRI-PCI data set used in the study used were extracted from the DataPave program for the regions of Delaware, Maryland, New Jersey, New York, Vermont, Virginia, Ontario, Quebec and Prince Edward Island and spanned the period from 1991 through 2000. The power model proposed was

$$PCI = K_1 * IRI^{K2}$$

which led to a transformed linear regression model as follows:

$$\log PCI = 2 - 0.436 \log(IRI)$$

The R^2 value of the model was determined to be 59%. The plots of the residuals and normal scores were used to confirm the normality and homoscedasticity of the model's distribution.

In 2012, Shahnazri et al. (2012) estimated PCI values from other pavement indices (other than IRI) based on different types of distresses and severity levels using two optimization techniques: artificial neural networks (ANN) and genetic programming (GP). The models were developed based on PCI data gathered from more than 1,250 km of highways in Iran. A feed forward ANN was used with the network being trained using the back propagation method. In addition, the root-mean square error (RMSE) fitness function was used for the GP approach. From the results, the ANN- and GP-based projected values were determined to be in good agreement with the field-measured PCI values. The reported R^2, RSME and mean absolute error (MAE) for the ANN-based models were respectively 0.9986, 0.99, and 0.49, whereas they were equal to 0.9898, 2.63, and 1.79 respectively for the GP-based model.

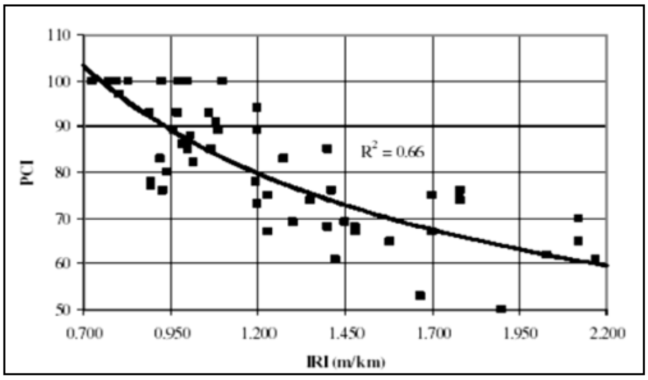
Another model for IRI as a function of PCI was developed for the Bay Area cities and counties in California with the intent of using the model in estimating user costs/benefits in their pavement management system. SAS statistical software was used for the modeling and regression validation resulting in the following equation:

$$IRI = 0.0171(153 - PCI)$$

where IRI is in m/km. The model's R^2 value was 0.53 with a coefficient of variation of 28 percent. The actual and predicted values of IRI were compared graphically to depict the dispersion of data and for model validation (Dewan 2012).

A 2002 study conducted using data from varied roadway pavement sections from the North Atlantic region in the United States and Canada resulted in the development of a relationship between the PCI and IRI. The model confirms the acceptability of the IRI as a predictor variable of the PCI based on the existence of the resulting strong correlation between the two variables (from the ANOVA) and an R^2 value of 0.66 for the model. In addition, the results showed acceptable corresponding *p*-values from the ANOVA and *t*-tests for this model which also suggest the acceptability of IRI as a predictor variable of PCI at a 99% significance level. The model is depicted in Figure 2 (Dewan and Smith 2002).

Figure 2: PCI – IRI Model



Source: Dewan, 2012

Concerned about its inability to make pavement repair and maintenance decisions that are supported by motorists' perception, DDOT launched an exploratory study in March 2007 (Noel and Arhin 2007). Three roadway classifications were considered in the study: freeways, arterials and collectors. The study utilized IRI averages for both directions of travel on the selected segments of roadways. The perception of subjects who traveled in one direction was also observed. The correlation between IRI and motorist perception for freeways and arterials, based on the R^2 statistic, were 0.56 and 0.63 respectively. The R^2 value for collectors was determined to be 0.24, which is considered to be relatively low. Although the exploratory study showed some promise from a statistical perspective, the report recommended an expanded study, with more segments where direction of travel would be considered for the specific lanes selected for each road segment.

In 2013, a neural network model was developed to estimate IRI from PCI. The model was however only based on data obtained for construction work zones. The predicted IRI values from the model were compared with the actual IRI values measured using MERLIN (Machine for Evaluating Roughness using Low-cost Instrumentation) along the construction work zones. The researchers used Levenberg-Marquardt back-propagation for the estimation of IRI from PCI. The neural network model developed was trained and tested resulting in an R^2 value of 0.86 and MSE of 0.041 which indicate that the performance of neural network is satisfactory and feasible for the prediction IRI (Vidya et al. 2013).

The literature review uncovered a variety of statistically significant models or relationships between the IRI and PCI (and other pavement indices). Most of the studies reviewed indicate the acceptability of IRI as a predictor variable of PCI with variations in the confidence level. IRI, which is a profile-based statistic, is shown to be an ideal predictor (or independent variable) since it has the advantage of being repeatable, reproducible, and stable with time. More importantly, IRI is not a subjective measure, compared to PCI. The statistical significance of some of these relationships or models developed also suggest that one variable can be predicted or estimated from the other, depending on data availability and quality.

Several relationships involving other pavement indices have been developed by several jurisdictions whose environmental conditions differ. The following is a summary of the models previously mentioned in the literature review:

Jurisdiction	Model	R^2	MSE
US Mid-Atlantic States and Canada	log(PCI)=2-0.436.log(IRI)	0.59	-
California	IRI=0.0171*(153 - PCI)	0.53	-
Washington, DC	$ln(IRI_{Freeways})= 6.672 – 0.42.PSR$	0.55	-
India	Artificial Neural Networks (Vydia)	0.86	0.041
Iran	Artificial Neural Networks (Shahnazri)	0.99	0.99
Iran	Genetic Programming	0.98	2.63

In addition, some of these models may have been developed based on data compiled in suburban areas, and data from dense areas within that jurisdiction and may or may not have been included. As a result, a model developed for one jurisdiction is often inappropriate for another jurisdiction, especially the District of Columbia, which is a dense urban city. As a result, unique IRI-PCI prediction models for the District of Columbia are justified.

5.0 RESEARCH METHODOLOGY

5.1 IRI-PCI Data Acquisition

Recent PCI and IRI data for years 2009, 2010 and 2012 were provided by DDOT for this study. The IRI-PCI data sets for pavement types and functional classifications for each year were sufficiently large (>30) and were classified according to the following scenarios for each year:

By Pavement Type

Concrete Pavement		Asphalt Pavement		Composite Pavement	
PCI	*IRI*	*PCI*	*IRI*	*PCI*	*IRI*
Y_1	X_1	Y_1	X_1	Y_1	X_1
Y_2	X_2	Y_2	X_2	Y_2	X_2
…	…	…	…	…	…
Y_n	X_n	Y_n	X_n	Y_n	X_n

By Functional Classification

Freeways		Arterials		Collectors		Local	
PCI	*IRI*	*PCI*	*IRI*	*PCI*	*IRI*	*PCI*	*IRI*
Y_1	X_1	Y_1	X_1	Y_1	X_1	Y_1	X_1
Y_2	X_2	Y_2	X_2	Y_2	X_2	Y_2	X_2
…	…	…	…	…	…	…	…
Y_n	X_n	Y_n	X_n	Y_n	X_n	Y_n	X_n

In all, 7,920 data points were used for each of the years. It was ensured that the IRI-PCI data sets for the same street segments were used in each of the years.

5.2 Statistical Analysis

Standard statistical regression methods were employed in the development of the PCI-IRI model for Washington DC. The statistical analysis was conducted using SPSS and confirmed with Microsoft Excel based on the OLS method. The statistical significance of the regression coefficients of the resulting model were tested at 5% level of significance. In addition, the overall statistical significance of each regression model for each roadway classification was tested using the *F*-test (ANOVA) at 5% level of significance.

5.3 Regression Model Validation Methods

The following were employed to validate the models developed for each category.

Three statistics are used in OLS regression to evaluate model fit: R^2, the overall F-test, and the Root Mean Square Error (RMSE). All of these measures are based on two sums of squares: Sum of Squares Total (SST) and Sum of Squares Error (SSE). SST measures how far the data are from the mean and SSE measures how far the data are from the model's predicted values. Different combinations of these two values provide different information about how the regression model compares to the mean model.

R^2 and Adjusted R^2: The difference between SST and SSE is the improvement in prediction from the regression model, compared to the mean model. Dividing that difference by SST gives R^2. It is the proportional improvement in prediction from the regression model, compared to the mean model. It indicates the goodness of fit of the model.

R^2 has the useful property that its scale is intuitive: it ranges from zero to one, with zero indicating that the proposed model does not improve prediction over the mean model and one indicating perfect prediction. Improvement in the regression model results in proportional increases in R^2.

One pitfall of R^2 is that it can only increase as predictors are added to the regression model. This increase is artificial when predictors are not actually improving the model's fit. To remedy this, a related statistic, Adjusted R^2, incorporates the model's degrees of freedom. Adjusted R^2 will decrease as predictors are added if the increase in model fit does not make up for the loss of degrees of freedom. Likewise, it will increase as predictors are added if the increase in model fit is worthwhile. Adjusted R^2 should always be used with models with more than one predictor variable. It is defined as the proportion of total variance that is explained by the model.

F-test: The F-test evaluates the null hypothesis that all regression coefficients are equal to zero versus the alternative that at least one does not. An equivalent null hypothesis is that R^2 equals zero. A significant F-test indicates that the observed R^2 is reliable, and is not a spurious result of oddities in the data set. Thus, the F-test determines whether the proposed relationship between the response variable and the set of predictors is statistically reliable. This is useful particularly when the research objective is to develop a predictive model.

Residual Plots: The regression model was checked for homoscedasticity (constant variance) using residual plots. The residuals from a fitted model are the differences between the observed variables and the corresponding predicted values using the regression function developed. Mathematically, the definition of the residual for the i^{th} observation in the data set is defined as:

$$e_i = y_i - f(x_i, \hat{\beta})$$

with y_i denoting the i^{th} response in the data set and x_i the vector of explanatory variables, each set at the corresponding values found in the i^{th} observation in the data set. If the model fit to the data were correct, the residuals would approximate the random errors that make the relationship between the explanatory variables and the response variable a statistical relationship. Therefore, if the residuals appear to behave randomly, it suggests that the model fits the data well. On the other hand, if non-random structure is evident in the residual plots, it is a clear sign that the model fits the data poorly.

Normal Probability Plots: The normal probability plot was also used to validate the model which is a graphical technique for normality testing: assessing whether or not a data set is approximately normally distributed. In a normal probability plot, if all the data points fall near the line, an assumption of normality is reasonable. Otherwise, the points will curve away from the line, and an assumption of normality is not justified.

Root Mean Square Error: The Root Mean Square Error (RMSE; also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modeled. These individual differences are called the residuals, and the RMSE serves to aggregate them into a single measure of predictive power. The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of the mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}$$

where X_{obs} is observed values and X_{model} is modelled values at time/place *i*.

The RMSE indicates the absolute fit of the model to the data indicating how close the observed data points are to the model's predicted values. Whereas R^2 is a relative measure of fit, RMSE is an absolute measure of fit. The RMSE can be interpreted as the standard deviation of the unexplained variance, and has the useful property of being in the same units as the response variable. Lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response, and is the most important criterion for fit if the main purpose of the model is prediction. A perfect model fit will result in a RMSE value of 0. The smaller the RMSE value, the better the model.

5.4 Model Development

After a series of data transformations within the generalized regression model was determined to assume the following form:

$$\log PCI = A \log(IRI) + K + \varepsilon$$

where IRI is the independent variable and PCI is the dependent variable with A and *k* being constants. The model was assumed to have an associated error of ε [$\varepsilon \sim N(0, \sigma^2)$].

6.0 RESULTS

6.1 Descriptive Statistics

The summaries of the descriptive statistical analyses are presented by year, by functional classification and by pavement type. The detailed results of the descriptive statistics are presented in Appendix 2. The key descriptive statistics are the means, standard deviations and 95% confidence intervals.

6.1.1 Overall Descriptive Statistics

This section provides the summary of the descriptive statistics of the IRI-PCI data for the combined 3-year datasets (2009, 2010 and 2012) by functional classification and pavement type.

By Functional Classification

The summary of the means of the IRI values in the years 2009, 2010 and 2012 by functional classification is presented in Figure 3. From the figure, the highest mean IRI was 361.77 in/mi on local roads, with the lowest being 211.73 in/mi on freeways. This indicates that the ride quality on freeways was better than on arterials, followed by collectors and finally local roads.

Figure 3: Overall Mean IRI Values (in/mi) by Functional Classification

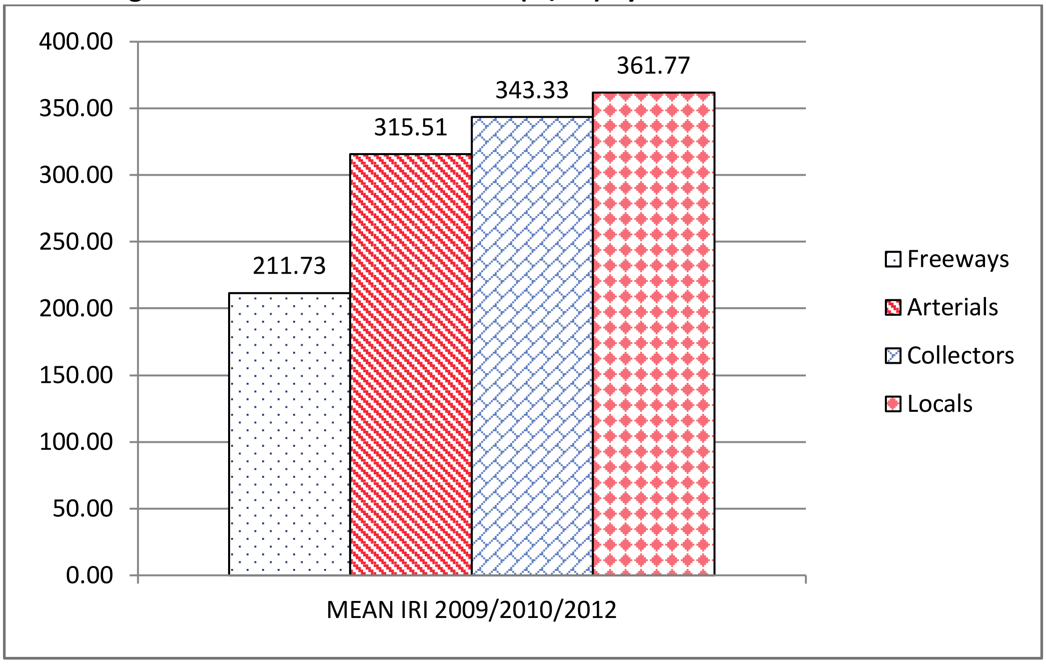
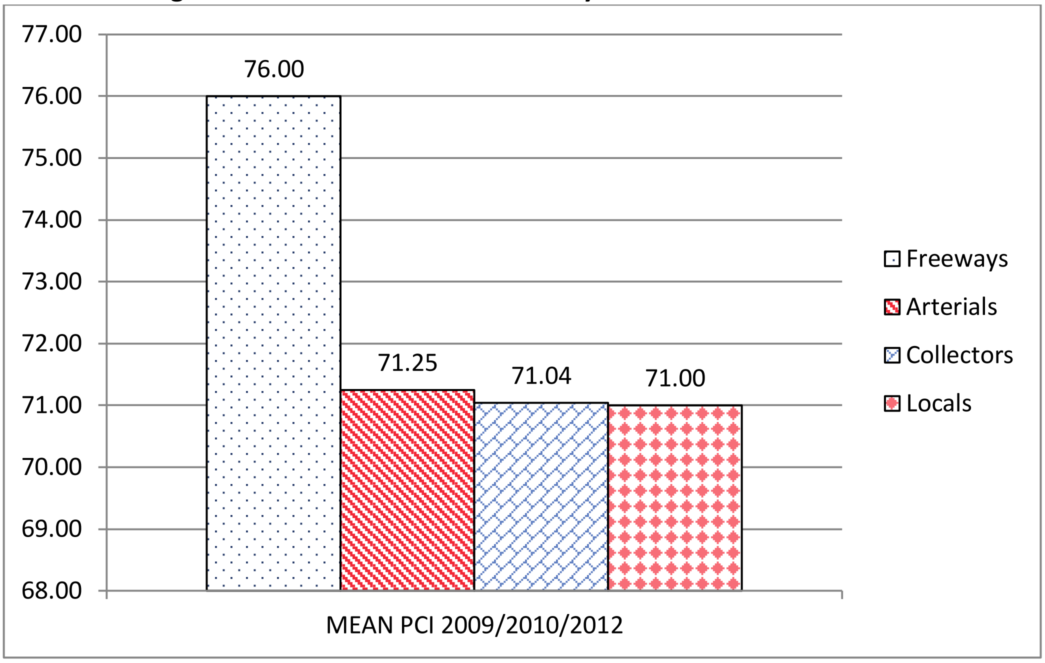


Figure 4 shows the mean PCI values by functional classification in 2009, 2010 and 2012. From the figure, the lowest mean PCI value was 71 on local roads, while the highest mean PCI (76) was recorded on freeways. This indicates that freeways had lower irregularities than arterials, collectors and local roads.

Figure 4: Overall Mean PCI Values by Functional Classification



By Pavement Type

The summary of the means of the IRI values in the years 2009, 2010 and 2012 by pavement type is presented in Figure 5. The results showed that the highest mean IRI was 284.32 in/mi for asphalt pavement, with the lowest being 271.14 in/mi for concrete pavement. This indicates that the ride quality of concrete pavement was better than that of asphalt or composite pavement.

Figure 6 shows the summary of the mean PCI values by pavement type in 2009, 2010 and 2012. The figure shows that the lowest mean PCI value was 72.03 for composite pavement, while the highest mean PCI was recorded for concrete pavement with 80.79. This indicates that, on average, concrete pavement had lower irregularities than asphalt and composite pavement when all the years are considered.

Figure 5: Overall Mean IRI Values (in/mi) by Pavement Type

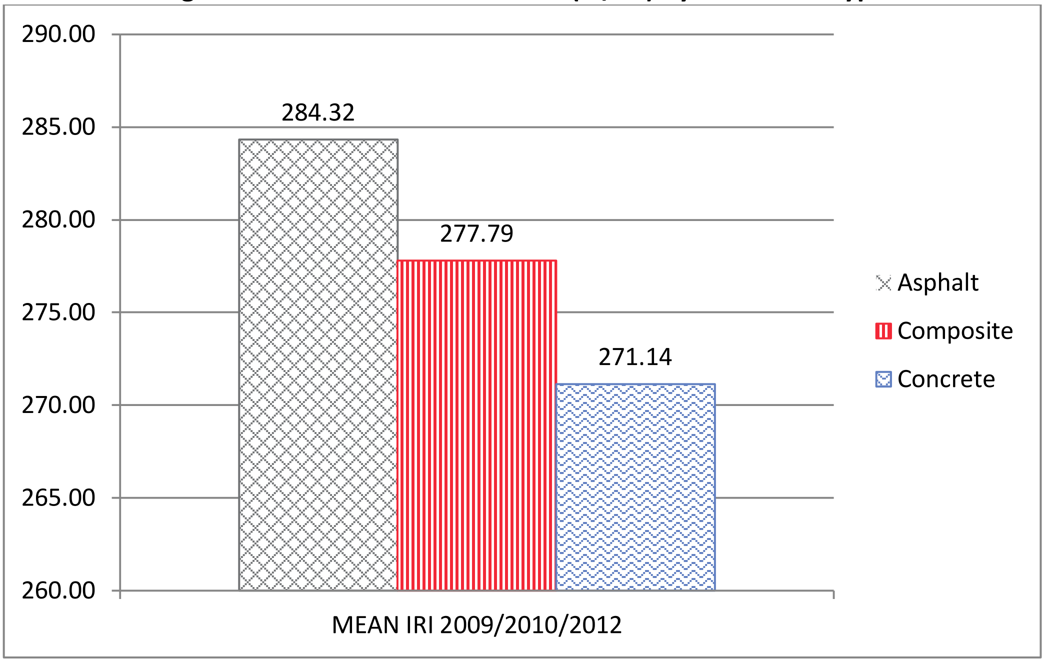
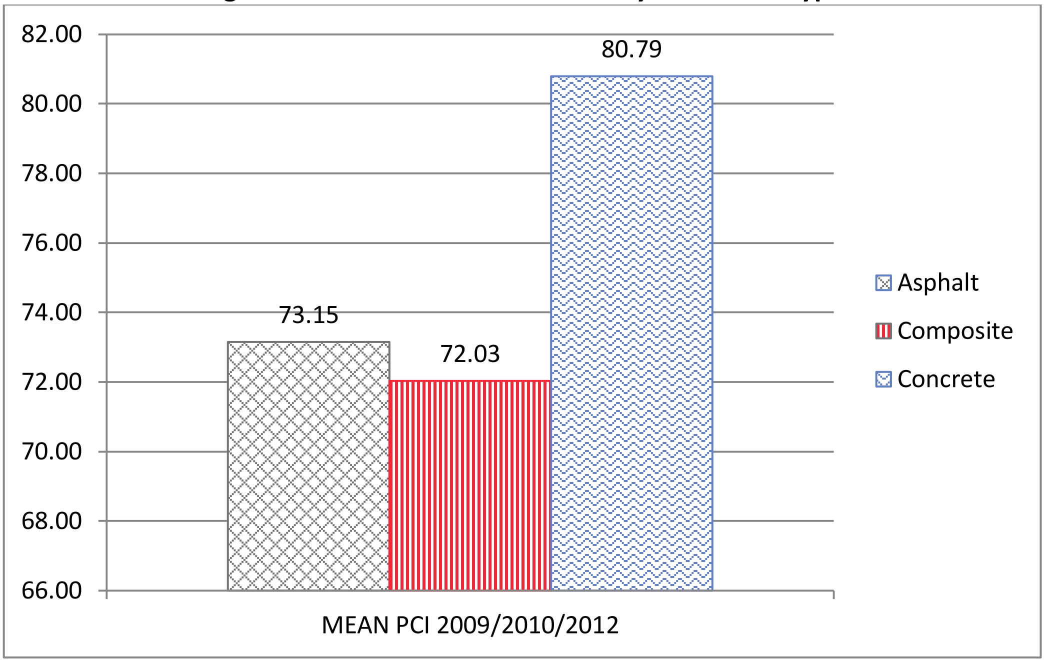


Figure 6: Overall Mean PCI Values by Pavement Type



6.1.2 Descriptive Statistics by Year

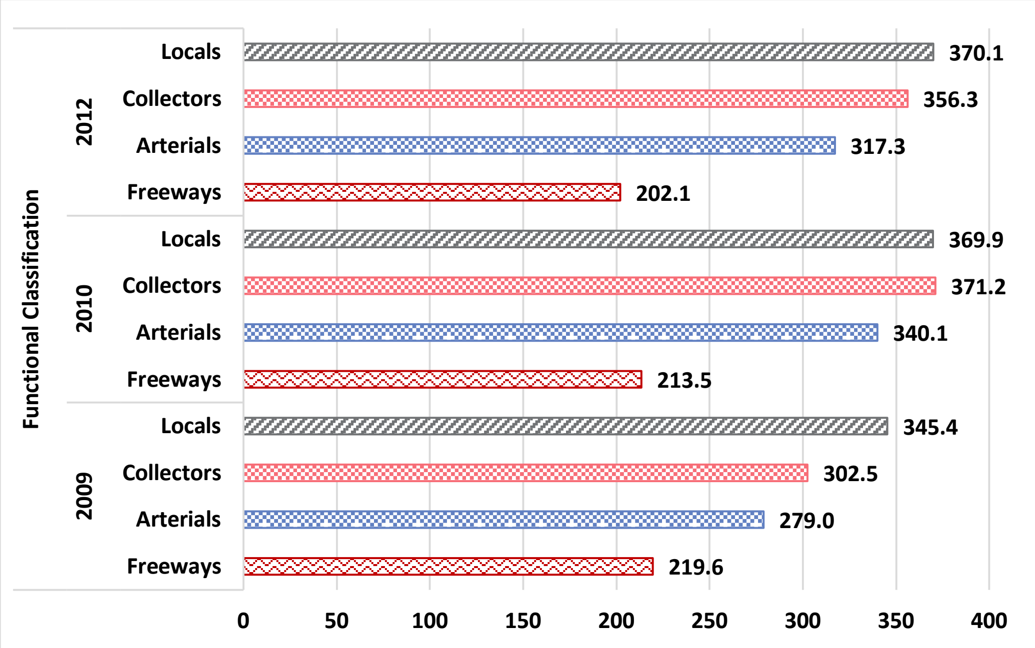
This section provides the summary of the descriptive statistics of the IRI-PCI data by year (2009, 2010 and 2012). For each year, the analysis was conducted by functional classification and pavement type.

Summaries for the Years 2009, 2010 and 2012

By Functional Classification

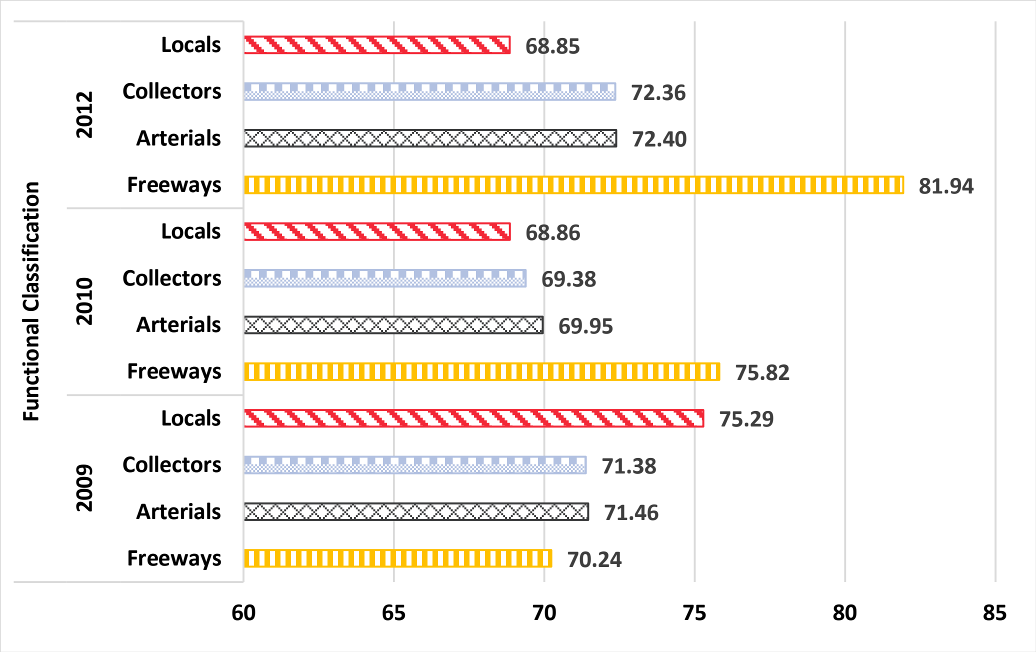
Figure 7 presents the mean IRI values by functional classification for the years 2009, 2010 and 2012. From the figure, it can be observed that the ride quality on freeways was better than on arterials, followed by collectors and finally local roads. Thus, it can be said that freeways were smoother than the remaining functional classes over the three years. On the other hand, arterials and collectors showed deterioration in ride quality from 2009 to 2010, while locals showed a continuous decline over the three years. Finally, freeway segments showed a consistent improvement trend in ride quality over the 3 years.

Figure 7: Mean IRI Values (in/mi) by Functional Classification for 2009, 2010 and 2012



The summary of the mean PCI values by functional classification for years 2009, 2010 and 2012 is presented in Figure 8. From the figure, it can be observed that most of the PCI values are consistent with the IRI values previously presented. Also, freeways were the only category that showed gradual improvement along the three years. Arterials and collectors showed some deterioration from 2009 to 2010, and then a small improvement from 2010 to 2012. Finally, local roads showed a continuous deterioration trend over the three years.

Figure 8: 2009-2010-2012 Mean PCI Values by Functional Classification



By Pavement Type

Figure 9 presents the mean IRI values by pavement type in the years 2009, 2010 and 2012. From the figure it can be observed that values for concrete, composite and asphalt did not differ much from each other from year to year. In addition, for the three years analyzed, all the three pavement types showed some deterioration from 2009 to 2010, with modest improvements in ride quality from 2010 to 2012.

Figure 9: 2009-2010-2012 Mean IRI Values (in/mi) by Pavement Type

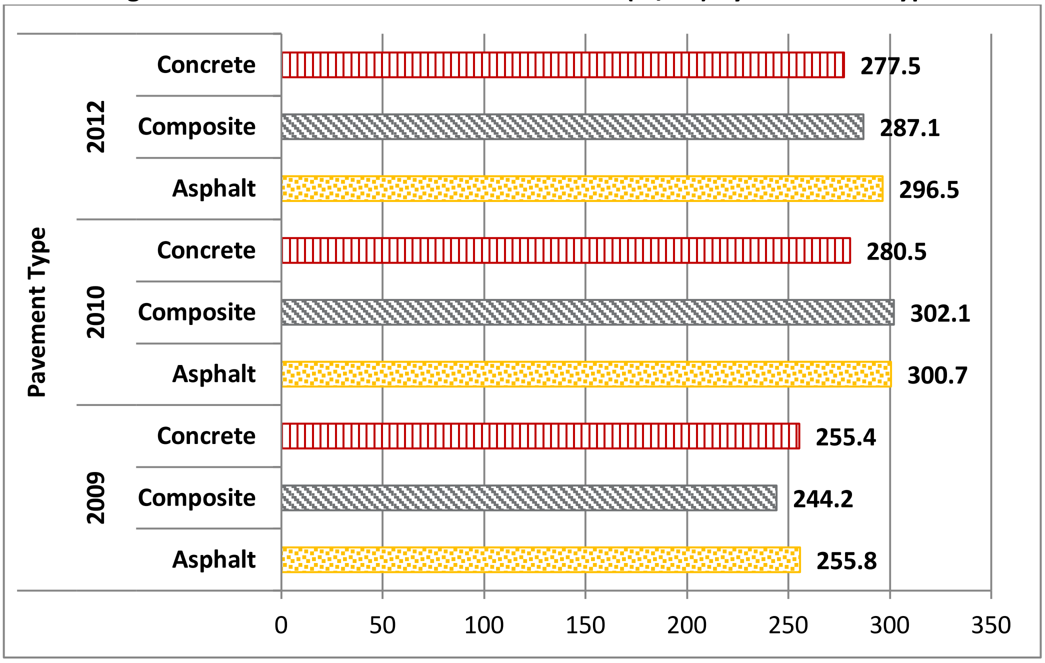
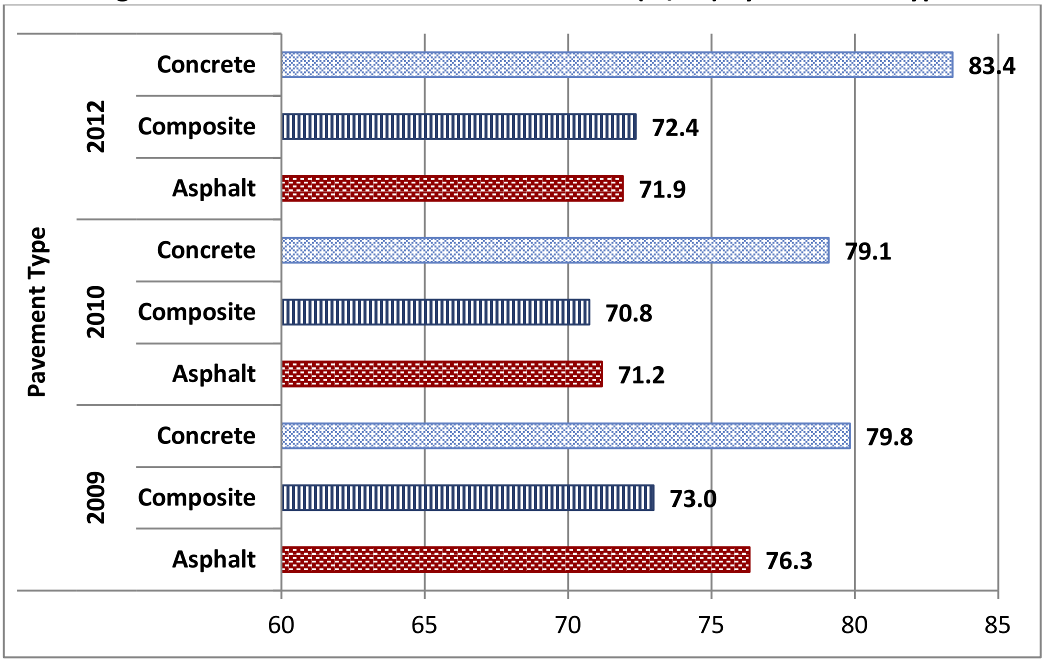


Figure 10 presents the mean PCI values by pavement type in the years 2009, 2010 and 2012. From the figure, concrete pavement had lower irregularities than asphalt and composite pavement during all three years. From 2009 to 2010, all pavement types showed deterioration. Finally, the PCI values improved in 2012 from 2010.

Figure 10: 2009-2010-2012 Mean PCI Values (in/mi) by Pavement Type



6.2 Regression Analysis

Regression models were developed by functional classification and by pavement type using the combined data for 2009, 2010 and 2012. The regression models for four functional classifications were developed: freeways, arterials, collectors and locals. Those developed by pavement type were asphalt, concrete and composite. The adequacy and significance of the regression models were all tested at 5% level of significance. The summary of the regression analysis indicators by functional classification and pavement type are respectively presented in Tables 3 and 4. In addition, regression models were also developed by functional classification and by pavement type for each of the years, the results of which are presented in Appendix 3.

The results shown in the tables indicate that the regression models could explain very low percentages of the variations in the data, based on the R^2 values (7% or less). The RMSEs for the models were also relatively high (greater than 1) indicating that there is a wide variance between the observed and predicted PCI values. On the other hand, the *p*-values for the *F*-statistics for the regression models were determined to be less than 0.05 (except for freeways), indicating that the coefficients of the regression models are not equal to zero, at 5% level of significance.

Table 3: Summary of Regression Analysis by Functional Classification

Functional Class	Model Equation	R^2	Adj. R^2	ANOVA		*t*- Statistic		RMSE
				F - value	*p*-value	β_1	p-value	
Freeways	$log(PCI_{FWY})$= -0.202[$log(IRI_{FWY})$]+ 2.336	0.073	0.054	3.8561	0.055	-0.202	0.055	1.250
Arterials	$log(PCI_{ART})$= -0.101[$log(IRI_{ART})$]+ 2.092	0.021	0.020	184.641	0.000	-0.101	0.000	1.243
Collectors	$log(PCI_{COL})$= -0.077[$log(IRI_{COL})$] + 2.030	0.008	0.008	37.507	0.000	-0.077	0.000	1.321
Locals	$log(PCI_{LOC})$= -0.225[$log(IRI_{LOC})$]+ 2.404	0.035	0.035	365.835	0.000	-0.225	0.000	1.387

Table 4: Summary of Regression Analysis by Pavement Type

Pavement Type	Model Equation	R^2	Adj. R^2	ANOVA		*t*- Statistic		RMSE
				F - value	*p*-value	β_1	p-value	
Asphalt	$log(PCI_{ASP})$= -0.115[$log(IRI_{ASP})$]+ 2.131	0.013	0.013	67.623	0.000	-0.115	0.000	1.304
Composite	$log(PCI_{COM})$= -0.056[$log(IRI_{COM})$]+ 1.986	0.006	0.006	35.875	0.000	-0.056	0.000	1.227
Concrete	$log(PCI_{CON})$= -0.222[$log(IRI_{CON})$]+ 2.431	0.053	0.051	29.134	0.000	-0.222	0.000	1.288

6.3 Residual and Normal Probability Plots

For a valid regression model, the residuals would approximate the random errors that establish the relationship between the explanatory variables and the response variables. Therefore, if the residuals appear to behave randomly, it suggests that the model fits the data well. The normal probability plots were also used to determine the validity of the models. If all the data points fall near the line, an assumption of normality is reasonable, otherwise, the points will curve away from the line. Figures 11 and 12 are the respective residual plots and normal probability plots for the regression model for freeways. The remaining plots by year are presented in Appendix 3.

By Functional Classification

Figure 11: Residual Plot for Freeways

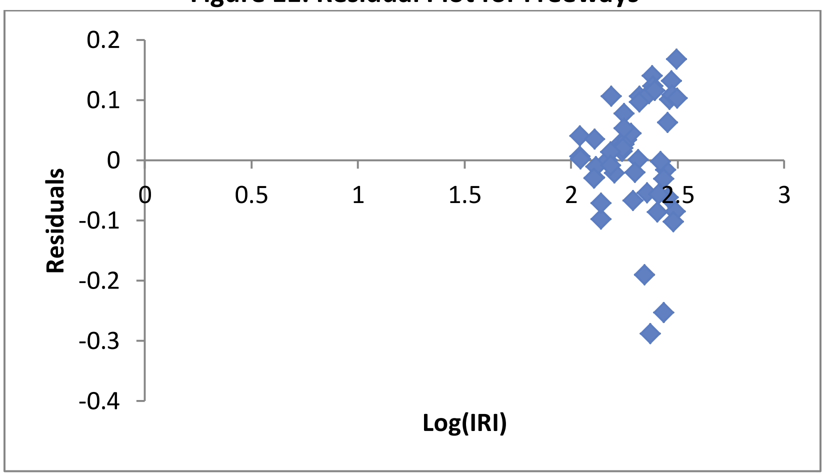
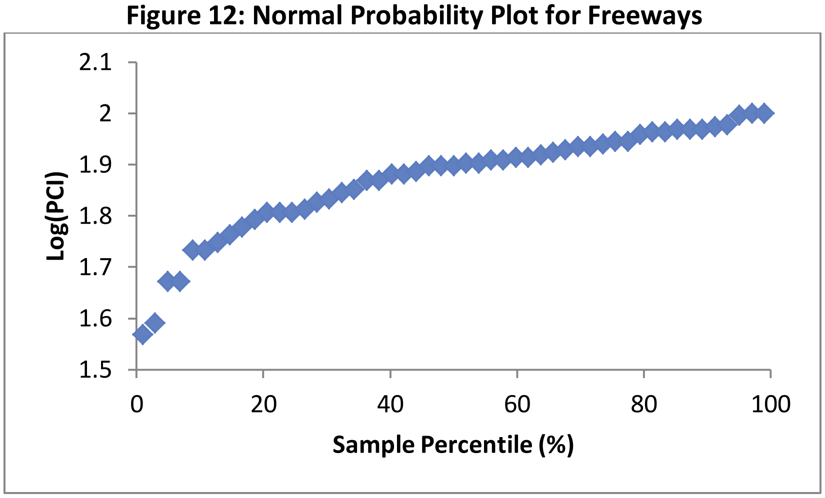


Figure 12: Normal Probability Plot for Freeways



For each functional classification and pavement type, the residual plots did not show evenly distributed random plots about the zero line which confirms that the models do not fit the data sets well. Also, the normal probability plots do not generally show a line along the all points, thus an assumption of normality would not be necessarily reasonable for the data sets. From the figures, it can be concluded that the models do not adequately predict PCI using IRI.

7.0 DISCUSSION

From the literature review, a variety of statistically significant models or relationships between the IRI and PCI (and other pavement indices) were identified for various jurisdictions. The studies also reveal the notion that it is acceptable to use IRI as a predictor variable of PCI. IRI, which is a profile-based statistic, is shown to be an ideal predictor (or independent variable) since it has the advantage of being repeatable, reproducible, and stable with time. The vast variations of models developed between IRI and PCI is a strong indication that models can only be developed exclusively for each jurisdiction. The statistically significant relationships or models developed for these variables also suggests that one variable can be predicted or estimated from the other, depending on the availability of one dataset.

From the results of the analyses, it can be suggested from the mean IRI and PCI values that freeways have a smoother ride than arterials, followed by collectors and local roads. The lowest mean IRI value was 211.73 in/mi for freeways when all the 3-year data was combined with a corresponding mean PCI value of 76. Similarly, when the data was analyzed by pavement type, the results show that Concrete Pavements were smoother than Composite Pavements followed by Asphalt Pavement. Concrete Pavements recorded the least average IRI value (271.14 in/mi) with a corresponding mean PCI value of approximately 80.79 when all the 3-year data was combined.

For the 3-year data considered, the mean IRI values appeared to be declining for freeways for 2009, 2010 and 2012 (219.6, 213.5 and 202.1 in/mi respectively), indicating an improved smoothness of the roadway type. For arterials and collector streets, however, an increase was identified in 2010 compared with 2009, while the 2012 mean IRI values were determined to be less than those in 2010. The average IRI values for local roads showed a continuous increase from 2009 through 2012, indicating a decline in the smoothness of the roadway type. The increases in IRI values could be attributed to the increased number of work zone and roadway rehabilitation projects which commenced in the 2010-2011 timeframe. The average PCI values showed a similar trend as the mean IRI values.

A review of the results of the analysis by pavement type revealed that, overall, concrete pavement had the lowest mean IRI values over the period considered. The mean IRI values ranged from 255.4 to 277.5 in/mi. This was followed by Composite pavement (average ranges between 244.2 and 287.1 in/mi) and then Asphalt pavement (average ranges between 255.8 and 300.7 in/mi). The average PCI values showed a similar trend as the mean IRI values.

The regression models between the IRI and PCI values yielded very low R^2 values with relatively high RMSEs indicating that the regression models do not adequately predict PCI from IRI accurately within the margin of error (5% level of significance). The R^2 and Adjusted R^2 values were no more than 7.3% indicating that the models explain a very low percentage in the variability of the models. The results of the ANOVA tests, however, showed statistically significant F - statistics ($p < 0.05$) for most of the models implying that the models' coefficients are not necessarily equal to zero. The residual plots for all the models also did not show the randomness about the zero line while the normal probability plots showed points near a curve instead of a straight line.

8.0 CONCLUSIONS AND RECOMMENDATIONS

The OLS method used on predicting PCI from IRI did not yield statistically significant regression models. Within the margin of error, the regression models developed could not be adequately used to predict PCI from IRI. A more sophisticated prediction tool, such as artificial neural networks or genetic programming, could be explored to determine if PCI values could be predicted from IRI more accurately (yielding low RMSEs, for example).

A viable prediction model would help to eliminate the need for annual routine subjective determination of the PCI values and reduce or eliminate the need for allocating several man-hours for its determination. Under the assumption of a 4-year cycle for data revalidation, for the first three years of the cycle only IRI data will need to be collected; in the fourth year, both IRI and PCI data will be collected and analyzed. By reducing the required data collection and the labor hours for obtaining the PCI values to once every four years, this research project will potentially save DDOT an estimated $750,000 over a four year cycle (in 2014 dollars, assuming no cost escalation). This is a savings of almost 30 percent over the current collection schedule.

9.0 REFERENCES

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APPENDIX 1

DESCRIPTIVE STATISTICS

2009 IRI-PCI by Functional Clasification

Freeway 2009

	IRI 2009	PCI 2009
Mean	219.588235	70.23529412
Standard Error	14.1143072	4.527310437
Median	210	74
Mode	177	64
Standard Deviation	58.1947794	18.66657913
Sample Variance	3386.63235	348.4411765
Kurtosis	-0.8594014	-1.037156257
Skewness	-0.0794475	-0.42846672
Range	199	57
Minimum	110	37
Maximum	309	94
Sum	3733	1194
Count	17	17
Confidence Level (95.0%)	29.9209946	9.597469386

Collector 2009

	IRI 2009	PCI 2009
Mean	302.5485893	71.38244514
Standard Error	1.793138244	0.462106526
Median	299	71
Mode	278	100
Standard Deviation	71.61337093	18.45535677
Sample Variance	5128.474896	340.6001935
Kurtosis	-0.802640323	-0.330618942
Skewness	0.050407787	-0.336913929
Range	321	90
Minimum	126	10
Maximum	447	100
Sum	482565	113855
Count	1595	1595
Confidence Level (95.0%)	3.51715701	0.906400391

Arterial 2009

	IRI 2009	PCI 2009
Mean	281.16859	71.561863
Standard Error	1.3063105	0.2712348
Median	275	71
Mode	233	100
Standard Deviation	70.854551	14.711833
Sample Variance	5020.3674	216.43803
Kurtosis	-0.662717	-0.068384
Skewness	0.1961334	-0.122374
Range	343	85
Minimum	104	15
Maximum	447	100
Sum	827198	210535
Count	2942	2942
Confidence Level (95.0%)	2.5613756	0.5318294

Local 2009

	IRI 2009	PCI 2009
Mean	345.3743316	75.29174094
Standard Error	1.079109633	0.310653241
Median	350	78
Mode	411	100
Standard Deviation	62.60696129	18.02324329
Sample Variance	3919.631602	324.8372988
Kurtosis	-0.36595248	0.320338412
Skewness	-0.463199036	-0.785325128
Range	320	93
Minimum	127	7
Maximum	447	100
Sum	1162530	253432
Count	3366	3366
Confidence Level (95.0%)	2.11577704	0.609088248

2009 IRI-PCI by Pavement Type

Asphalt 2009

	IRI 2009	PCI 2009
Mean	255.801301	76.33885275
Standard Error	1.021906063	0.412355768
Median	264	77
Mode	306	100
Standard Deviation	42.02258647	16.95679922
Sample Variance	1765.897773	287.5330399
Kurtosis	-0.174312617	-0.187100527
Skewness	-0.724637384	-0.523079312
Range	209	80
Minimum	104	20
Maximum	313	100
Sum	432560	129089
Count	1691	1691
Confidence Level (95.0%)	2.004334549	0.808781691

Composite 2009

	IRI 2009	PCI 2009
Mean	244.2263258	72.98958333
Standard Error	0.931449303	0.314748496
Median	248	73
Mode	239	100
Standard Deviation	42.806151	14.46473964
Sample Variance	1832.366564	209.228693
Kurtosis	-0.306414709	-0.116421456
Skewness	-0.517144909	-0.142494968
Range	212	85
Minimum	101	15
Maximum	313	100
Sum	515806	154154
Count	2112	2112
Confidence Level (95.0%)	1.82665441	0.61724962

Concrete 2009

	IRI 2009	PCI 2009
Mean	255.4375	79.83523
Standard Error	3.551080467	1.303893
Median	266	87
Mode	307	93
Standard Deviation	47.11040604	17.2981
Sample Variance	2219.390357	299.2241
Kurtosis	0.389285543	0.61452
Skewness	-0.967617792	-1.18507
Range	221	76
Minimum	91	24
Maximum	312	100
Sum	44957	14051
Count	176	176
Confidence Level (95.0%)	7.008456663	2.57338

2010 IRI-PCI by Functional Clasification

Freeway 2010

	IRI 2010	PCI 2010
Mean	213.4705882	75.82352941
Standard Error	15.5733836	3.437718222
Median	210	79
Mode	NA	79
Standard Deviation	64.21070554	14.17407534
Sample Variance	4123.014706	200.9044118
Kurtosis	-1.145705401	-0.283651225
Skewness	0.015443517	-0.341007006
Range	202	53
Minimum	110	47
Maximum	312	100
Sum	3629	1289
Count	17	17
Confidence Level (95.0%)	33.01409842	7.287637076

Collector 2010

	IRI 2010	PCI 2010
Mean	371.173	69.38244514
Standard Error	3.66724	0.432191272
Median	345	69
Mode	322	100
Standard Deviation	146.4602	17.26061778
Sample Variance	21450.59	297.9289263
Kurtosis	18.43427	-0.170625373
Skewness	2.751937	-0.222903792
Range	1940	87
Minimum	42	13
Maximum	1982	100
Sum	592021	1100655
Count	1595	1595
Confidence Level (95.0%)	7.193119	0.84723016

Arterial 2010

	IRI 2010	PCI 2010
Mean	340.0649218	69.9503739
Standard Error	2.232479309	0.268443019
Median	321	70
Mode	266	68
Standard Deviation	121.0901387	14.56148958
Sample Variance	14662.82169	212.036958
Kurtosis	3.556376606	-0.005506704
Skewness	1.367455953	-0.023625961
Range	1063	85
Minimum	94	15
Maximum	1157	100
Sum	1000471	205794
Count	2942	2942
Confidence Level (95.0%)	4.377380535	0.526394484

Local 2009

	IRI 2010	PCI 2010
Mean	369.8740345	68.85680333
Standard Error	2.317441374	0.327352696
Median	346.5	70
Mode	289	100
Standard Deviation	134.4515496	18.99209955
Sample Variance	18077.21919	360.6998452
Kurtosis	33.72049667	-0.106694405
Skewness	3.550673418	-0.459449353
Range	2276	95
Minimum	99	5
Maximum	2375	100
Sum	1244996	231772
Count	3366	366
Confidence Level (95.0%)	4.543735966	0.641830355

2010 IRI-PCI by Pavement Type

Asphalt 2010

	IRI 2010	PCI 2010
Mean	300.6587818	71.18864577
Standard Error	2.387534632	0.414752005
Median	281	71
Mode	288	100
Standard Deviation	98.17965093	17.0553367
Sample Variance	9639.243856	290.8845101
Kurtosis	6.359123069	-0.05444742
Skewness	1.849209345	-0.319202401
Range	900	91
Minimum	107	9
Maximum	1007	100
Sum	508414	120380
Count	1691	1691
Confidence Level (95.0%)	4.682835659	0.813481594

Composite 2010

	IRI 2010	PCI 2010
Mean	302.0700758	70.74526515
Standard Error	2.15214692	0.297753911
Median	285	70
Mode	262	68
Standard Deviation	98.90514246	13.68372798
Sample Variance	9782.227205	187.244115
Kurtosis	5.275322693	0.6168469205
Skewness	1.607543839	-0.004051624
Range	896	87
Minimum	72	13
Maximum	968	100
Sum	637972	149414
Count	2112	2112
Confidence Level (95.0%)	4.220550327	0.583921737

Concrete 2010

	IRI 2010	PCI 2010
Mean	280.4943182	79.09659091
Standard Error	6.464985598	1.277672371
Median	277	85
Mode	266	95
Standard Deviation	85.76772601	16.95023943
Sample Variance	7356.102825	287.3106169
Kurtosis	8.87174559	0.373907547
Skewness	2.097966794	-1.070010491
Range	630	73
Minimum	91	27
Maximum	721	100
Sum	49367	13921
Count	176	176
Confidence Level (95.0%)	12.75937614	2.521630113

2012 IRI-PCI by Functional Clasification

Freeway 2012

	IRI 2012	PCI 2012
Mean	202.1176471	81.94117647
Standard Error	16.41844424	3.021334177
Median	175	81
Mode	153	80
Standard Deviation	67.69497983	12.45727994
Sample Variance	4582.610294	155.1838235
Kurtosis	-1.451031953	0.076057854
Skewness	0.30234424	-0.51842812
Range	204	46
Minimum	111	54
Maximum	315	100
Sum	3436	1393
Count	17	17
Confidence Level (95.0%)	34.80554696	6.404942332

Collector 2012

	IRI 2012	PCI 2012
Mean	356.2752351	72.36363636
Standard Error	3.247310199	0.395136619
Median	334	72
Mode	334	100
Standard Deviation	129.6892923	15.78074941
Sample Variance	16819.31253	249.032052
Kurtosis	10.38566057	-0.139802668
Skewness	2.1887189933	-0.220404574
Range	1520	87
Minimum	51	13
Maximum	1571	100
Sum	568259	115420
Count	1595	1595
Confidence Level (95.0%)	6.369447457	0.775042044

Arterial 2012

	IRI 2012	PCI 2012
Mean	317.3031951	72.39496941
Standard Error	1.965061151	0.266907467
Median	300	71
Mode	280	68
Standard Deviation	106.5853226	14.4771161
Sample Variance	11360.43099	209.5868907
Kurtosis	7.033912829	-0.312892852
Skewness	1.755919415	0.107216051
Range	1236	77
Minimum	77	23
Maximum	1313	100
Sum	933506	212986
Count	2942	2942
Confidence Level (95.0%)	3.853034784	0.523344402

Local 2012

	IRI 2012	PCI 2012
Mean	370.0505051	68.85145573
Standard Error	2.322847464	0.327278351
Median	346.5	70
Mode	289	100
Standard Deviation	134.7651961	18.98778624
Sample Variance	18161.65807	360.5360261
Kurtosis	33.42897563	-0.106035315
Skewness	3.539560251	-0.45977489
Range	2276	95
Minimum	99	5
Maximum	2375	100
Sum	1245590	231754
Count	3366	3366
Confidence Level (95.0%)	4.554335521	0.641684588

2012 IRI-PCI by Pavement Type

Asphalt 2012

	IRI 2012	*PCI 2012*
Mean	*296.5162626*	*71.91188646*
Standard Error	*2.311743423*	*0.396547775*
Median	*279*	*72*
Mode	*284*	*100*
Standard Deviation	*95.06298225*	*16.30674655*
Sample Variance	*9036.97093*	*265.9099829*
Kurtosis	*7.424464882*	*0.055286674*
Skewness	*1.971475062*	*-0.343774742*
Range	*956*	*91*
Minimum	*51*	*9*
Maximum	*1007*	*100*
Sum	*501409*	*121603*
Count	*1691*	*1691*
Confidence Level (95.0%)	*4.534181156*	*0.777776387*

Composite 2012

	IRI 2012	*PCI 2012*
Mean	*287.0610795*	*72.36505682*
Standard Error	*1.838739605*	*0.28628283*
Median	*274*	*71*
Mode	*246*	*65*
Standard Deviation	*84.5020388*	*13.15655723*
Sample Variance	*7140.594562*	*173.0949982*
Kurtosis	*6.426223655*	*0.179222342*
Skewness	*1.683721114*	*0.11321016*
Range	*891*	*87*
Minimum	*77*	*13*
Maximum	*968*	*100*
Sum	*606273*	*152835*
Count	*2112*	*2112*
Confidence Level (95.0%)	*3.605930882*	*0.561425933*

Concrete 2012

	IRI2012	*PCI 2012*
Mean	*277.4829545*	*83.42045455*
Standard Error	*6.317518287*	*1.316391249*
Median	*272.5*	*92*
Mode	*285*	*97*
Standard Deviation	*83.8113105*	*17.4639034*
Sample Variance	*7024.342565*	*304.9879221*
Kurtosis	*6.556884829*	*0.033899557*
Skewness	*1.516469651*	*-1.156603061*
Range	*630*	*68*
Minimum	*91*	*32*
Maximum	*721*	*100*
Sum	*48837*	*14682*
Count	*176*	*176*
Confidence Level (95.0%)	*12.46833282*	*2.598046174*

Descriptive Statistics Summaries per Year

By Functional Classification

Functional Classification	Year	Variable	Mean	Standard Deviation	Conf. Level (95%)
Highways	2009	IRI	219.59	58.20	29.92
		PCI	70.24	18.67	9.60
	2010	IRI	213.47	64.21	33.01
		PCI	75.82	14.17	7.29
	2012	IRI	202.12	67.70	34.81
		PCI	81.94	12.46	6.40
Arterials	2009	IRI	279.02	70.78	3.01
		PCI	71.46	14.08	0.60
	2010	IRI	340.06	121.09	4.38
		PCI	69.95	14.56	0.53
	2012	IRI	317.30	106.59	3.85
		PCI	72.40	14.48	0.52
Collectors	2009	IRI	302.55	71.61	3.52
		PCI	71.38	18.46	0.91
	2010	IRI	371.17	146.46	7.19
		PCI	69.38	17.26	0.85
	2012	IRI	356.28	129.69	6.37
		PCI	72.36	15.78	0.78
Locals	2009	IRI	345.37	62.61	2.12
		PCI	75.29	18.02	0.61
	2010	IRI	369.87	134.45	4.54
		PCI	68.86	18.99	0.64
	2012	IRI	370.05	134.77	4.55
		PCI	68.85	18.99	0.64

By Pavement Type

Pavement Type	Year	Variable	Mean	Standard Deviation	Conf. Level (95%)
Asphalt	2009	IRI	255.80	42.02	2.00
		PCI	76.34	0.41	0.81
	2010	IRI	300.66	98.18	4.68
		PCI	71.19	17.06	0.81
	2012	IRI	296.52	95.06	4.53
		PCI	71.92	16.31	0.78
Composite	2009	IRI	244.23	42.81	1.83
		PCI	72.99	14.47	0.62
	2010	IRI	302.07	98.91	4.22
		PCI	70.75	13.68	0.58
	2012	IRI	287.06	84.50	3.61
		PCI	72.37	13.16	0.56
Concrete	2009	IRI	255.44	47.11	7.00
		PCI	79.84	17.30	2.57
	2010	IRI	280.49	85.77	12.76
		PCI	79.10	16.95	2.52
	2012	IRI	277.48	83.81	12.47
		PCI	83.42	17.46	2.60

APPENDIX 2

REGRESSION ANALYSIS

2009 Log (IRI)-Log (PCI) By Functional Classification

Freeways

Regression Statistics	
Multiple R	0.33602538
R Square	0.11291306
Adjusted R Square	0.05377393
Standard Error	0.12529392
Observations	17

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.029972934	0.02997293	1.909278323	0.187277659
Residual	15	0.235478507	0.01569857		
Total	16	0.265451441			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2.64160929	0.588223315	4.49082725	0.000431109	1.387840972	3.895377608	1.387840972	3.895377608
log(IRI 2009)	-0.34898936	0.252567555	-1.3817664	0.187277659	-0.88732436	0.189345645	-0.887324356	0.189345645

Arterials

Regression Statistics	
Multiple R	0.148140818
R Square	0.021945702
Adjusted R Square	0.02161303
Standard Error	0.096219236
Observations	2942

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.610741812	0.61074181	65.9680797	6.67218E-16
Residual	2940	27.21893584	0.00925814		
Total	2941	27.82967765			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2.152753438	0.03798818	56.6690328	0	2.07826731	2.227239567	2.07826731	2.227239567
log(IRI 2009)	-0.1265969	0.015586771	-8.1220736	6.6722E-16	-0.15715899	-0.09603481	-0.15715899	-0.09603481

Collectors

Regression Statistics	
Multiple R	0.11938048
R Square	0.0142517
Adjusted R Square	0.0136329
Standard Error	0.13107184
Observations	1595

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.395671871	0.39567187	23.0311912	1.7432E-06
Residual	1593	27.36746382	0.01717983		
Total	1594	27.76313569			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2.19581941	0.075047437	29.2590861	5.63E-151	2.048617298	2.343021531	2.048617298	2.343021531
log(IRI 2009)	-0.1457988	0.030380563	-4.7990823	1.7432E-06	-0.20538891	-0.086208737	-0.20538891	-0.08620874

Locals

Regression Statistics	
Multiple R	0.178345302
R Square	0.031807047
Adjusted R Square	0.031519237
Standard Error	0.127407924
Observations	3366

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.793949847	1.793949847	110.5140299	1.86776E-25
Residual	3364	54.60706926	0.016232779		
Total	3365	56.40101911			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.541148261	0.064788417	39.22226197	1.9781E-277	2.414119596	2.668176926	2.4141196	2.668176926
log(IRI 2009)	-0.269016179	0.025589965	-10.5125653	1.86776E-25	-0.31918964	-0.21884272	-0.31918964	-0.218842718

2009 Log (IRI)-Log (PCI) By Pavement Type

Asphalt

Regression Statistics	
Multiple R	0.010239
R Square	0.0001048
Adjusted R Square	-0.000487
Standard Error	0.1110809
Observations	1691

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.002185071	0.00218507	0.177087007	0.673942203
Residual	1689	20.84051746	0.01233897		
Total	1690	20.84270253			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.9047626	0.082645439	23.047402	2.022E-102	1.742664405	2.06686088	1.742664405	2.066860884
log (IRI 2009)	-0.014476	0.034398951	-0.4208171	0.673942203	-0.08194472	0.05299339	-0.081944719	0.052993387

Composite

Regression Statistics	
Multiple R	0.048164734
R Square	0.002319842
Adjusted R Square	0.001847007
Standard Error	0.092942676
Observations	2112

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.042381838	0.04238184	4.906247	0.026866162
Residual	2110	18.22689956	0.00863834		
Total	2111	18.26928139			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.98247845	0.058075943	34.1359667	9.9E-204	1.868586365	2.096371	1.868586365	2.09637053
log (IRI 2009)	-0.054009	0.024383241	-2.2150051	0.026866	-0.1018267	-0.00619	-0.101826705	-0.0061913

Concrete

Regression Statistics	
Multiple R	0.27740036
R Square	0.07695096
Adjusted R Square	0.07164608
Standard Error	0.11249189
Observations	176

ANOVA

	df	SS	MS	F	ignificance F
Regression	1	0.183561239	0.183561	14.5056946	0.000194
Residual	174	2.201870117	0.012654		
Total	175	2.385431356			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2.72402618	0.219457749	12.41253	9.5722E-26	2.290884	3.157168052	2.290884311	3.157168052
log (IRI 2009)	-0.3482366	0.091433448	-3.80863	0.00019352	-0.5287	-0.16777515	-0.528697972	-0.16777515

2010 Log (IRI)-Log (PCI) By Functional Classification

Freeways

Regression Statistics	
Multiple R	0.291783807
R Square	0.08513779
Adjusted R Square	0.024146976
Standard Error	0.08556539
Observations	17

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.010220078	0.01022008	1.395911688	0.255802908
Residual	15	0.109821539	0.00732144		
Total	16	0.120041617			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2.290319944	0.35462893	6.45835619	1.07843E-05	1.534446272	3.046193616	1.534446272	3.04619362
log(IRI 2010)	-0.1811295	0.153306375	-1.1814871	0.255802908	-0.507894304	0.145635304	-0.507894304	0.1456353

Arterials

Regression Statistics	
Multiple R	0.116853673
R Square	0.013654781
Adjusted R Square	0.013319289
Standard Error	0.096608565
Observations	2942

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.379869466	0.379869466	40.70081682	2.0538E-10
Residual	2940	27.43965151	0.009333215		
Total	2941	27.81952097			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2.029307181	0.030578308	66.36427289	0	1.969350116	2.089264245	1.96935012	2.08926425
log(IRI 2010)	-0.07769571	0.012178547	-6.37971918	2.0538E-10	-0.10157505	-0.05381636	-0.1015751	-0.0538164

Collectors

Regression Statistics	
Multiple R	0.061860798
R Square	0.003826758
Adjusted R Square	0.003201414
Standard Error	0.12349895
Observations	1595

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.093333696	0.093333696	6.11944356	0.013473867
Residual	1593	24.29642124	0.015251991		
Total	1594	24.38975494			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.95405263	0.052063367	37.53219837	2.044E-221	1.851932715	2.05617254	1.85193272	2.056172545
log(IRI 2010)	-0.05057115	0.020443106	-2.473750908	0.01347387	-0.090669371	-0.01047293	-0.09066937	-0.01047293

Locals

Regression Statistics	
Multiple R	0.182718634
R Square	0.033386099
Adjusted R Square	0.033098758
Standard Error	0.14685669
Observations	3366

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.50585595	2.50585595	116.189967	1.1712E-26
Residual	3364	72.55100964	0.021566888		
Total	3365	75.05686559			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.337579008	0.048408663	48.28844388	0	2.24266562	2.43249239	2.242665625	2.432492391
log(IRI 2010)	-0.204658114	0.018986489	-10.779145	1.17124E-26	-0.24188434	-0.16743189	-0.24188434	-0.167431888

2010 Log (IRI)-Log (PCI) By Pavement Type

Asphalt

Regression Statistics	
Multiple R	0.120621756
R Square	0.014549608
Adjusted R Square	0.013966156
Standard Error	0.120095054
Observations	1691

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.359663544	0.359663544	24.93711315	6.53536E-07
Residual	1689	24.36014636	0.014422822		
Total	1690	24.71980991			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.118983902	0.056435834	37.54678112	7.6508E-225	2.00829238	2.229675423	2.00829238	2.229675423
log (IRI 2010)	-0.11448073	0.022924998	-4.99370736	6.53536E-07	-0.159445121	-0.069516339	-0.15944512	-0.06951634

Composite

Regression Statistics	
Multiple R	0.03640366
R Square	0.00132523
Adjusted R Square	0.00085192
Standard Error	0.08989604
Observations	2112

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.022627134	0.02262713	2.79993795	0.094416185
Residual	2110	17.05153948	0.0080813		
Total	2111	17.07416661			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.9018547	0.036462049	52.1598419	0	1.830349385	1.97336002	1.830349385	1.973360022
log (IRI 2010)	-0.02477085	0.014803576	-1.67330151	0.09441619	-0.05380198	0.00426028	-0.05380198	0.004260282

Concrete

Regression Statistics	
Multiple R	0.217069426
R Square	0.047119136
Adjusted R Square	0.041642809
Standard Error	0.110729216
Observations	176

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.105495129	0.105495129	8.6041497	0.0038059
Residual	174	2.133406906	0.012260959		
Total	175	2.238902035			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.371602287	0.165956035	14.29054563	3.77426E-31	2.04405629	2.69914829	2.044056289	2.699148286
log (IRI 2010)	-0.200040577	0.068196819	-2.93328309	0.003805897	-0.3346401	-0.0654411	-0.33464005	-0.065441101

2012 Log (IRI)-Log (PCI) By Functional Classification

Freeways

Regression Statistics	
Multiple R	0.092619732
R Square	0.008578415
Adjusted R Square	-0.05751636
Standard Error	0.072236252
Observations	17

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.000677252	0.000677252	0.12978961	0.723672798
Residual	15	0.078271141	0.005218076		
Total	16	0.078948394			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.0087795	0.27921071	7.194493016	3.10137E-06	1.41365596	2.60390304	1.41365596	2.603903041
log(IRI 2012)	-0.04398923	0.122103031	-0.36026325	0.723672798	-0.304245685	0.21626722	-0.30424569	0.216267215

Arterials

Regression Statistics	
Multiple R	0.160453983
R Square	0.025745481
Adjusted R Square	0.025414102
Standard Error	0.089467776
Observations	2942

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.621883721	0.621883721	77.69192911	2.02038E-18
Residual	2940	23.53317984	0.008004483		
Total	2941	24.15506356			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.118234955	0.030408432	69.65945943	0	2.058610978	2.177858931	2.058610978	2.177858931
log(IRI 2012)	-0.107916405	0.012243329	-8.81430253	2.02038E-18	-0.131922771	-0.08391004	-0.131922771	-0.083910039

Collectors

Regression Statistics	
Multiple R	0.097596594
R Square	0.009525095
Adjusted R Square	0.008903328
Standard Error	0.105075861
Observations	1595

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.16914047	0.16914047	15.31939513	9.46054E-05
Residual	1593	17.58821195	0.011040937		
Total	1594	17.75735242			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.031980535	0.047130246	43.11415109	8.7792E-270	1.939536713	2.124424357	1.939536713	2.124424357
log(IRI 2012)	-0.072860712	0.01861541	-3.91399989	9.46054E-05	-0.109373987	-0.03634744	-0.10937399	-0.036347437

Locals

Regression Statistics	
Multiple R	0.182368154
R Square	0.033258144
Adjusted R Square	0.032970765
Standard Error	0.146848747
Observations	3366

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.495651635	2.49565164	115.7293385	1.4661E-26
Residual	3364	72.54316153	0.02156455		
Total	3365	75.03881317			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.335748162	0.048337294	48.3218642	0	2.24097471	2.430521615	2.24097471	2.430521615
log(IRI 2012)	-0.203939348	0.018957423	-10.7577571	1.46608E-26	-0.2411086	-0.16677011	-0.24110859	-0.16677011

2012 Log (IRI)-Log (PCI) By Pavement Type

Asphalt

Regression Statistics	
Multiple R	0.111384
R Square	0.0124064
Adjusted R Square	0.0118217
Standard Error	0.112961
Observations	1691

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.270740892	0.270740892	21.21762717	4.40679E-06
Residual	1689	21.55195593	0.012760187		
Total	1690	21.82269683			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.0915568	0.053902307	38.80273243	4.9965E-236	1.985834469	2.197279148	1.985834469	2.197279148
log (IRI 2012)	-0.101078	0.021943625	-4.606259564	4.40679E-06	-0.144117591	-0.05803848	-0.144117591	-0.05803848

Composite

Regression Statistics	
Multiple R	0.11256689
R Square	0.0126713
Adjusted R Square	0.01220338
Standard Error	0.08261927
Observations	2112

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.184843706	0.184843706	27.0795855	2.14157E-07
Residual	2110	14.40273967	0.006825943		
Total	2111	14.58758338			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.0433377	0.036821724	55.4927217	0	1.971127026	2.1155484	1.971127026	2.11554837
log (IRI 2012)	-0.0783966	0.015065239	-5.2038049	2.1416E-07	-0.10794084	-0.0488523	-0.10794084	-0.0488523

Concrete

Regression Statistics	
Multiple R	0.226522
R Square	0.051312
Adjusted R Square	0.04586
Standard Error	0.10614
Observations	176

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.10602505	0.10602505	9.41125452	0.00250167
Residual	174	1.96024441	0.01126577		
Total	175	2.06626946			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.370132	0.15042572	15.756164	2.4963E-35	2.07323841	2.6670263	2.07323841	2.667026327
log(IRI 2012)	-0.19007	0.06195576	-3.0677768	0.00250167	-0.312348	-0.0677849	-0.31234802	-0.067784897

Regression Models by Year

By Functional Classification

Functional Classification	Year	Model Equation	R^2	Adj R^2	ANOVA		T- Statistic		RMSE
					F - value	p-value	β_1	p-value	
Freeways	2009	$log(PCI_{hwy09})$= -0.349[$log(IRI_{hwy09})$]+2.642	0.113	0.054	1.909	0.187	-0.349	0.187	1.311
	2010	$log(PCI_{hwy10})$= -0.181[$log(IRI_{hwy10})$]+2.290	0.085	0.024	1.396	0.256	-0.181	0.256	1.203
	2012	$log(PCI_{hwy12})$= -0.044[$log(IRI_{hwy12})$]+2.009	0.009	-0.058	0.130	0.724	-0.044	0.724	1.169
Arterials	2009	$log(PCI_{art09})$= -0.127[$log(IRI_{art09})$]+2.153	0.022	0.022	65.968	0.000	-0.127	0.000	1.248
	2010	$log(PCI_{art10})$= -0.078[$log(IRI_{art10})$]+2.029	0.014	0.013	40.701	0.000	-0.078	0.000	1.249
	2012	$log(PCI_{art12})$= -0.108[$log(IRI_{art12})$]+2.118	0.026	0.025	77.692	0.000	-0.108	0.000	1.229
Collectors	2009	$log(PCI_{col09})$= -0.146[$log(IRI_{col09})$]+2.196	0.014	0.014	23.031	0.000	-0.146	0.000	1.352
	2010	$log(PCI_{col10})$= -0.051[$log(IRI_{col10})$]+1.954	0.004	0.003	6.119	0.014	-0.051	0.014	1.329
	2012	$log(PCI_{col12})$= -0.073[$log(IRI_{col12})$]+2.032	0.010	0.009	15.319	0.000	-0.073	0.000	1.274
Locals	2009	$log(PCI_{loc09})$= -0.269[$log(IRI_{loc09})$]+2.541	0.032	0.032	110.514	0.000	-0.269	0.000	1.341
	2010	$log(PCI_{loc10})$= -0.205[$log(IRI_{loc10})$]+2.338	0.033	0.033	116.190	0.000	-0.205	0.000	1.402
	2012	$log(PCI_{loc12})$= -0.204[$log(IRI_{loc12})$]+2.336	0.033	0.033	115.729	0.000	-0.204	0.000	1.402

By Pavement Type

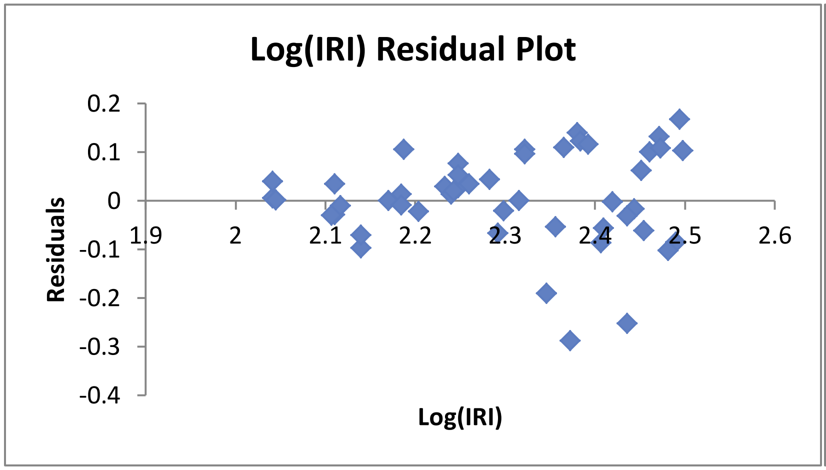
Pavement Type	Year	Model Equation	R^2	Adj R^2	ANOVA		T- Statistic		RMSE
					F - value	p-value	β_1	p-value	
Asphalt	2009	$log(PCI_{asp09})$= -0.015[$log(IRI_{asp09})$]+ 1.905	0.0001	-0.0005	0.177	0.674	-0.015	0.674	1.291
	2010	$log(PCI_{asp10})$= -0.115[$log(IRI_{asp10})$]+ 2.119	0.015	0.0140	24.937	0.000	-0.115	0.000	1.318
	2012	$log(PCI_{asp12})$= -0.101[$log(IRI_{asp12})$]+ 2.092	0.012	0.012	21.218	0.000	-0.101	0.000	1.297
Composite	2009	$log(PCI_{com09})$= -0.054[$log(IRI_{com09})$]+ 1.982	0.002	0.002	4.906	0.027	-0.054	0.027	1.239
	2010	$log(PCI_{com10})$= -0.025[$log(IRI_{com10})$]+ 1.902	0.001	0.001	2.800	0.094	-0.025	0.094	1.230
	2012	$log(PCI_{com12})$= -0.078[$log(IRI_{com12})$]+ 2.043	0.013	0.012	27.080	0.000	-0.078	0.000	1.209
Concrete	2009	$log(PCI_{con09})$= -0.348[$log(IRI_{con09})$]+ 2.724	0.077	0.072	14.506	0.000	-0.348	0.000	1.294
	2010	$log(PCI_{con10})$= -0.200[$log(IRI_{con10})$]+ 2.372	0.047	0.042	8.604	0.004	-0.200	0.004	1.289
	2012	$log(PCI_{con12})$= -0.190[$log(IRI_{con12})$]+ 2.370	0.051	0.046	9.411	0.003	-0.190	0.003	1.275

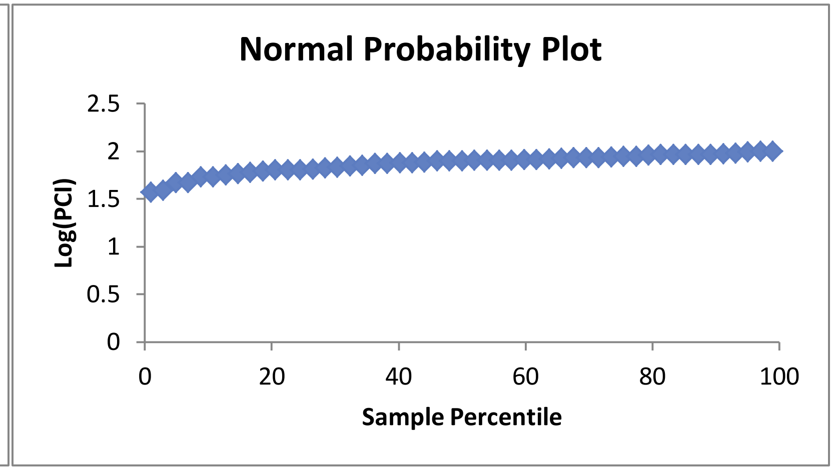
APPENDIX 3

MODEL VALIDATION BY FUNCTIONAL CLASSIFICATION AND PAVEMENT TYPE

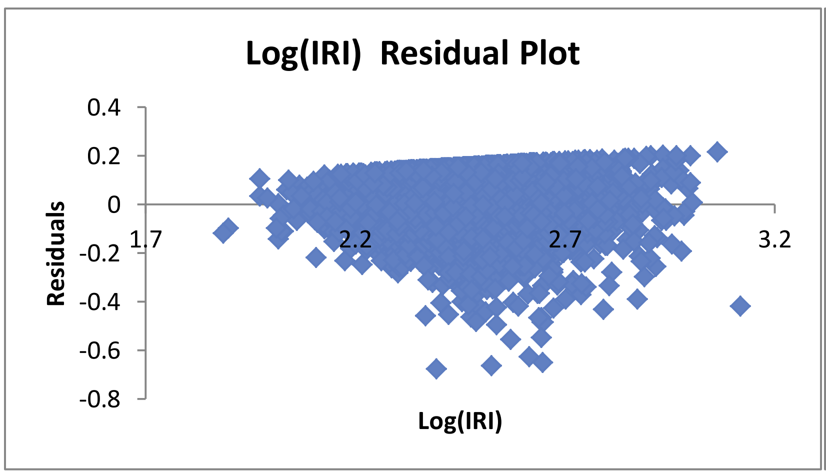
2009-2010-2012 Combined Residual and Normal Probability Plots

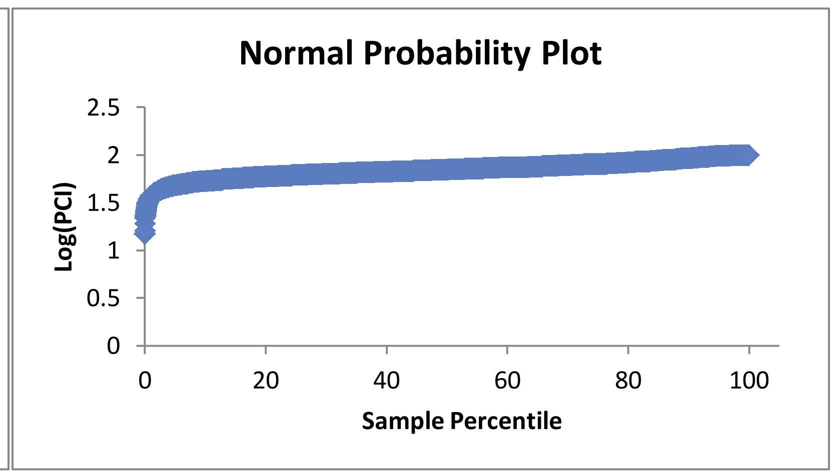
Freeways 2009 2010 2012



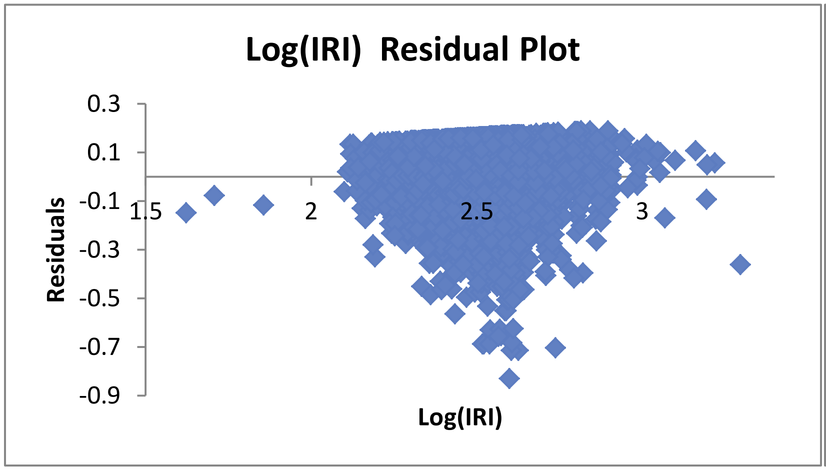


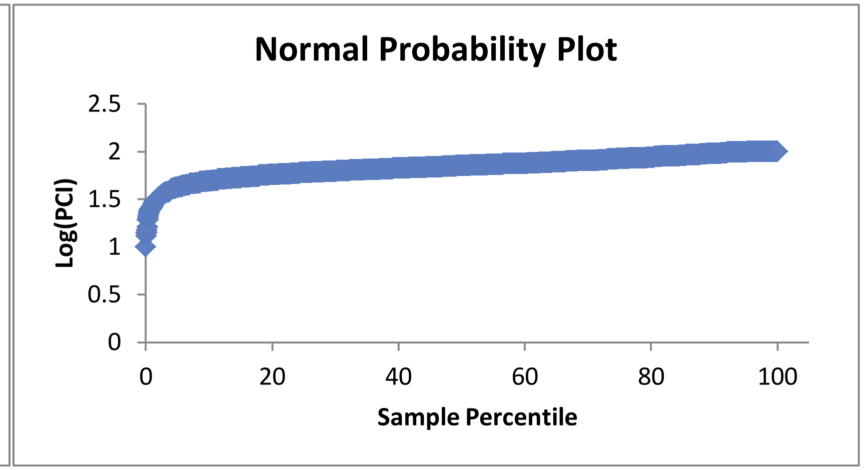
Arterials 2009 2010 2012



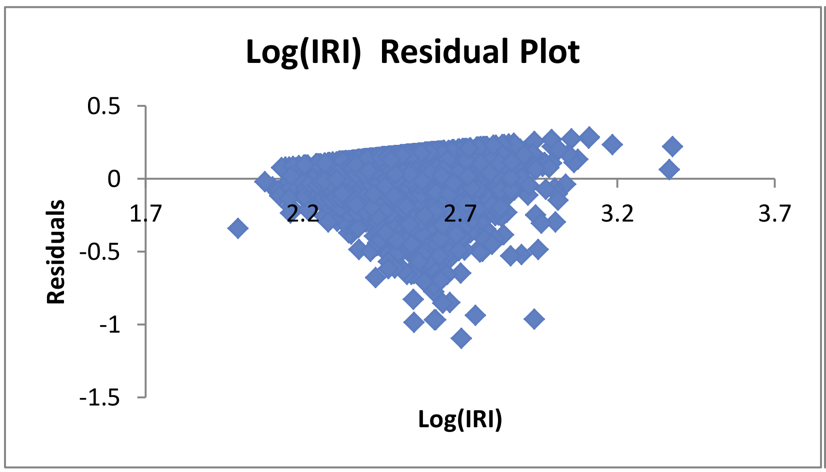


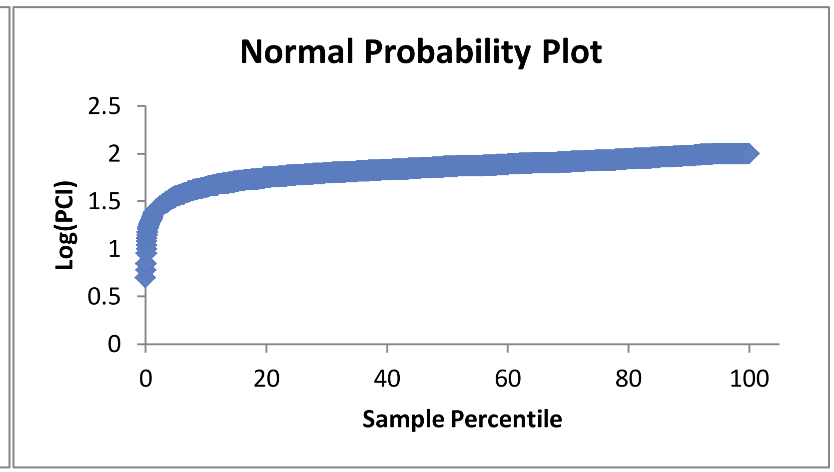
Collectors 2009 2010 2012



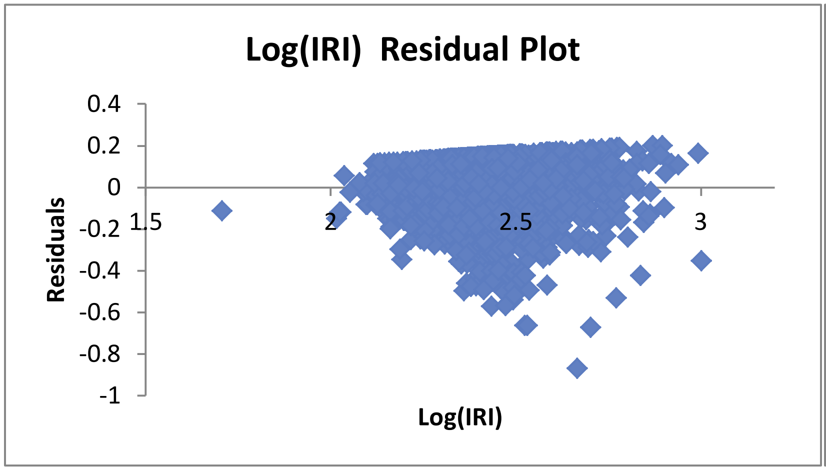


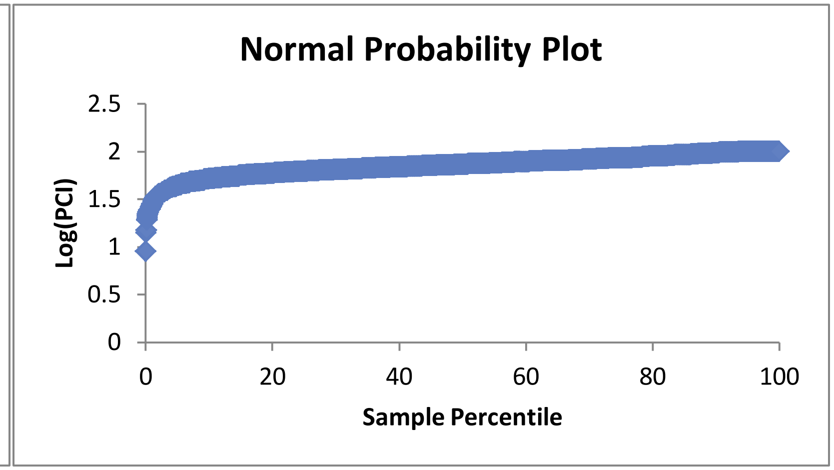
Local 2009 2010 2012



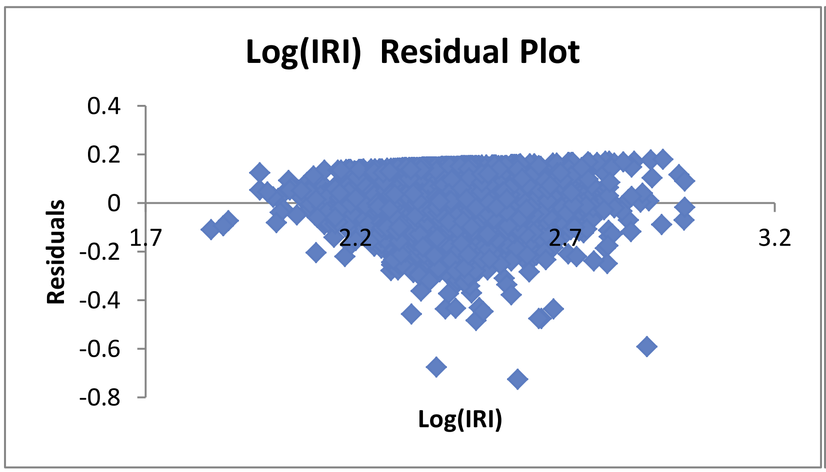


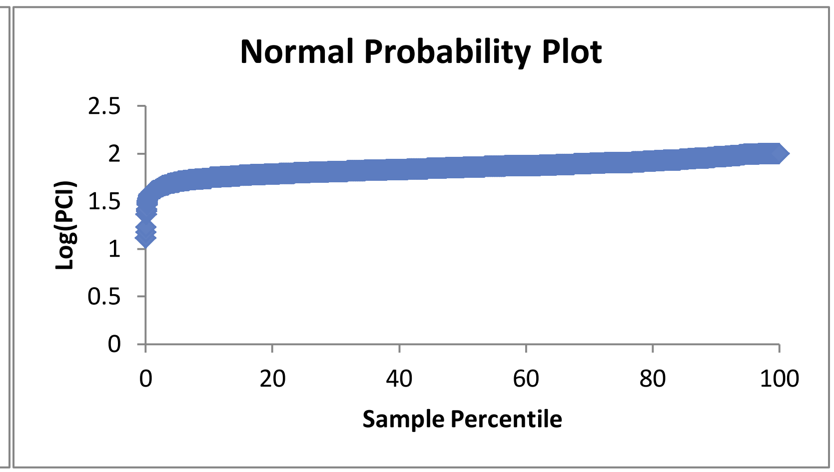
Asphalt 2009 2010 2012



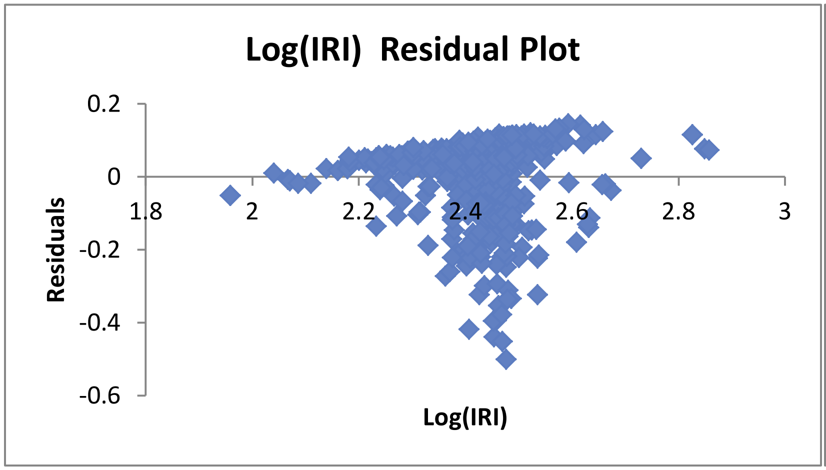


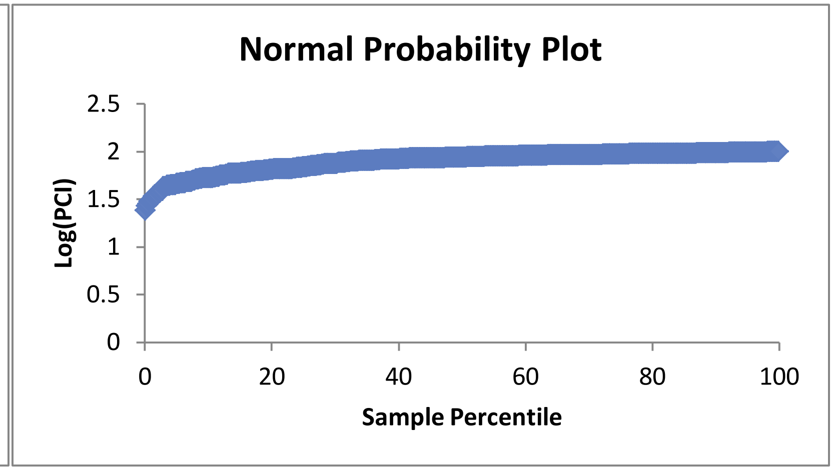
Composites 2009 2010 2012





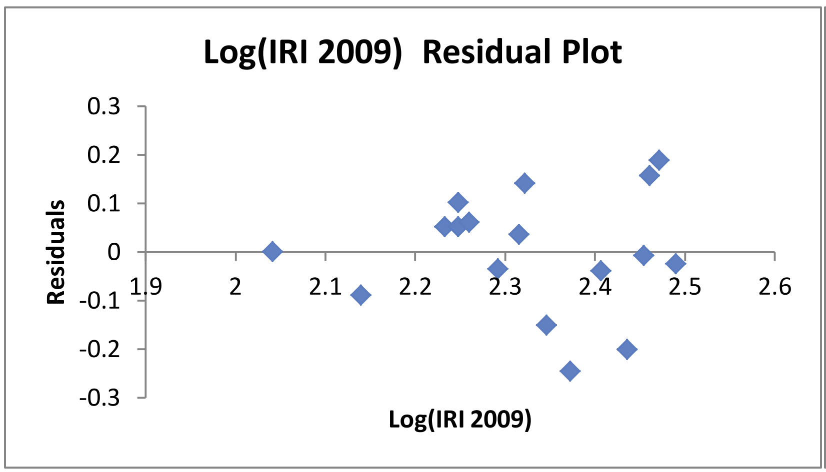
Concrete 2009 2010 2012

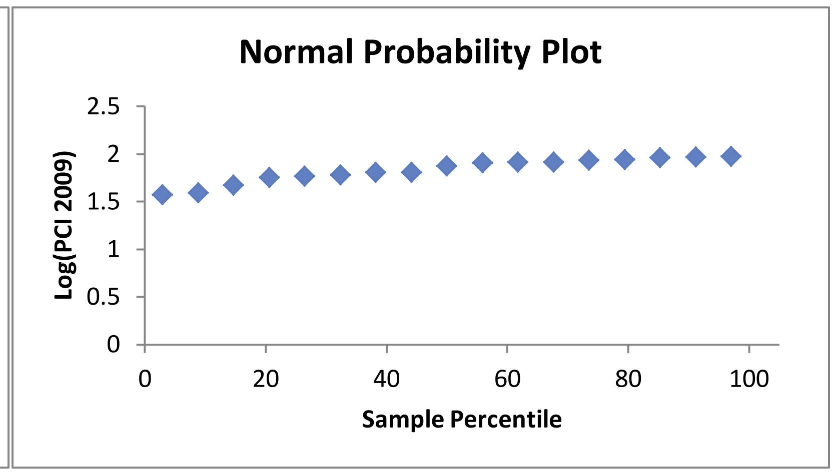




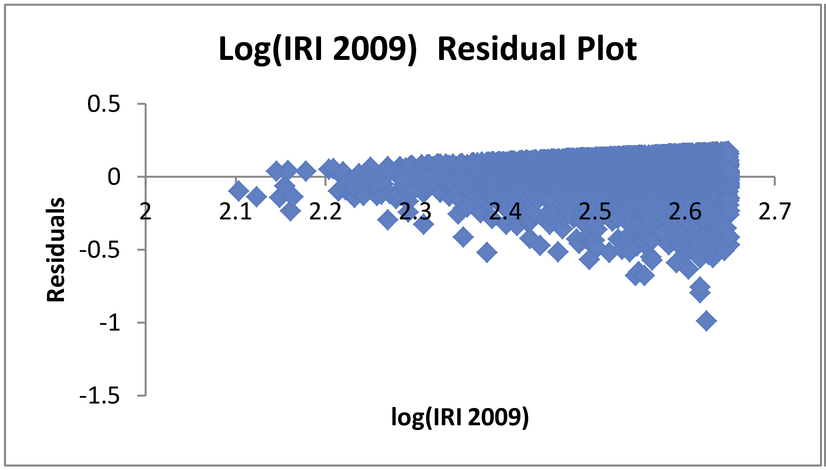
2009 Residual and Normal Probability Plots

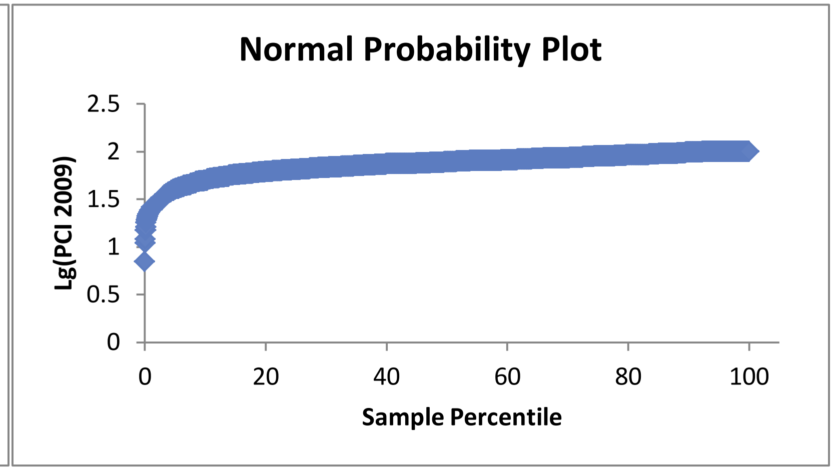
Freeways 2009



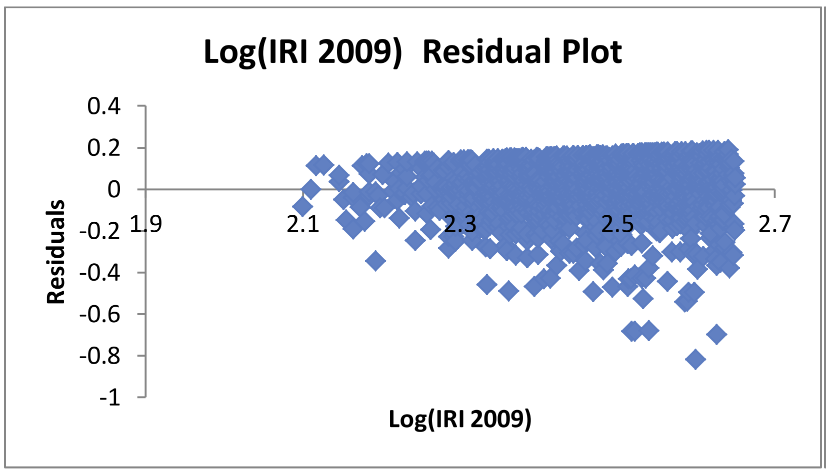


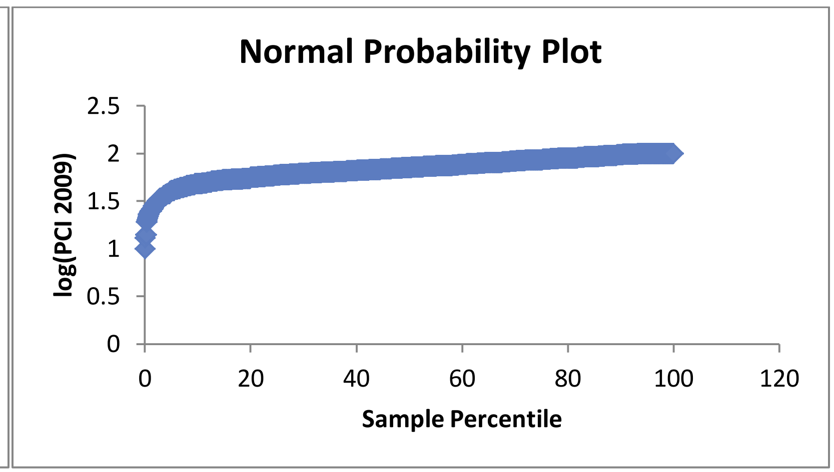
Arterials 2009



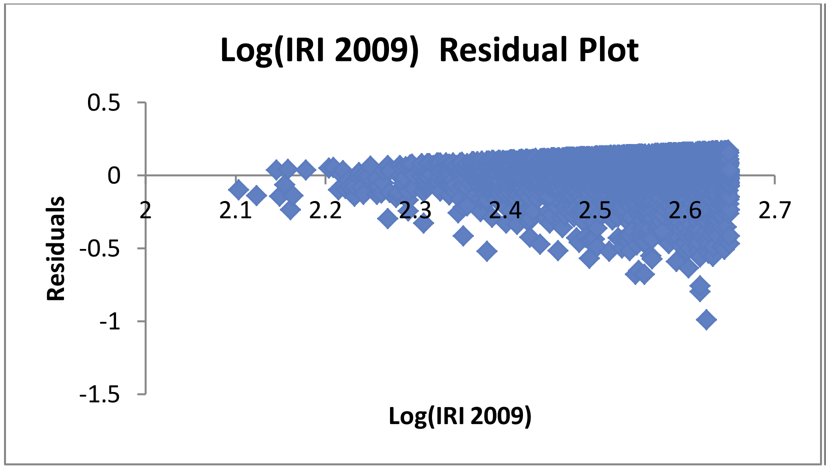


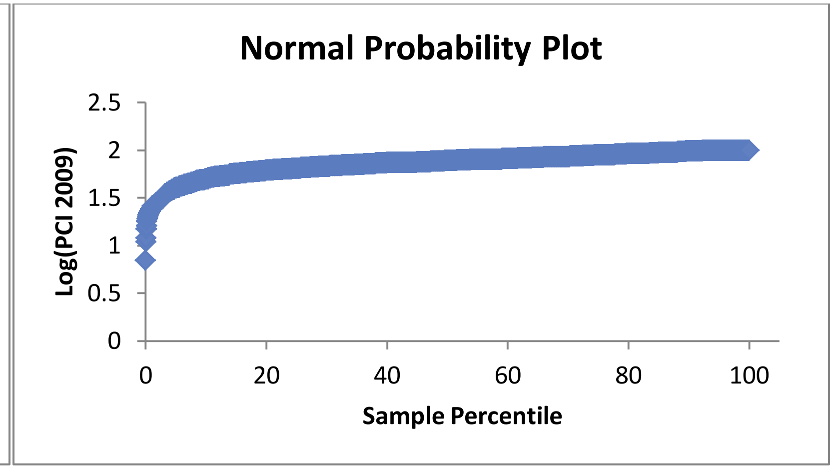
Collectors 2009



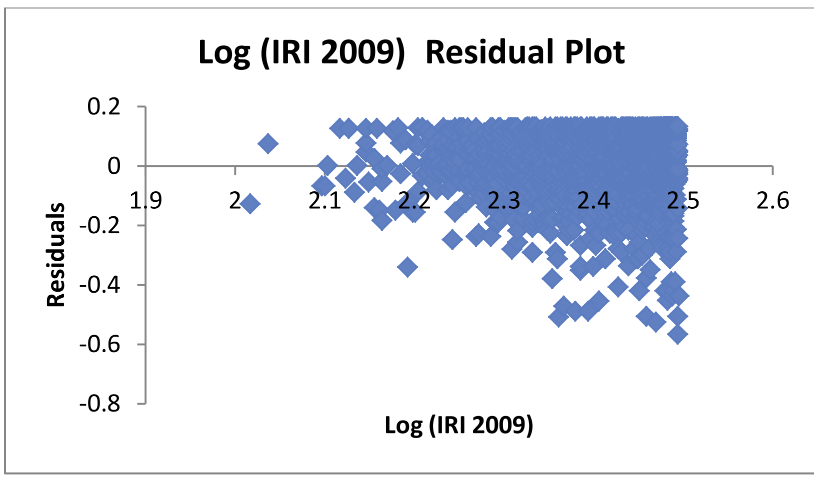


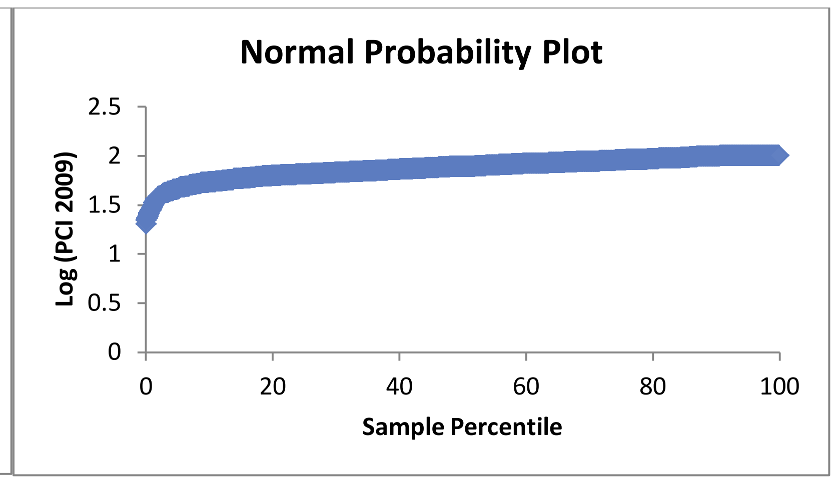
Locals 2009



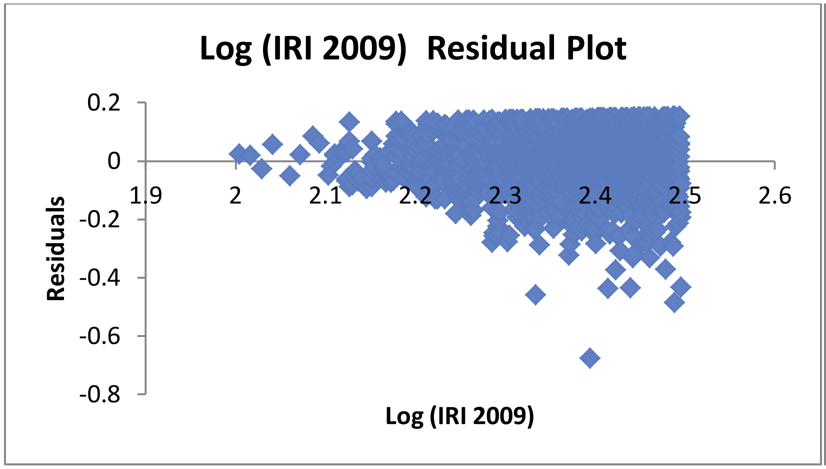


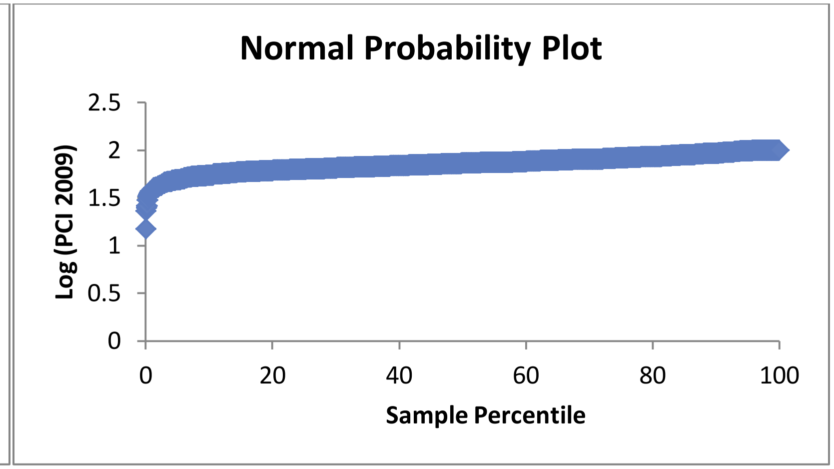
Asphalt 2009



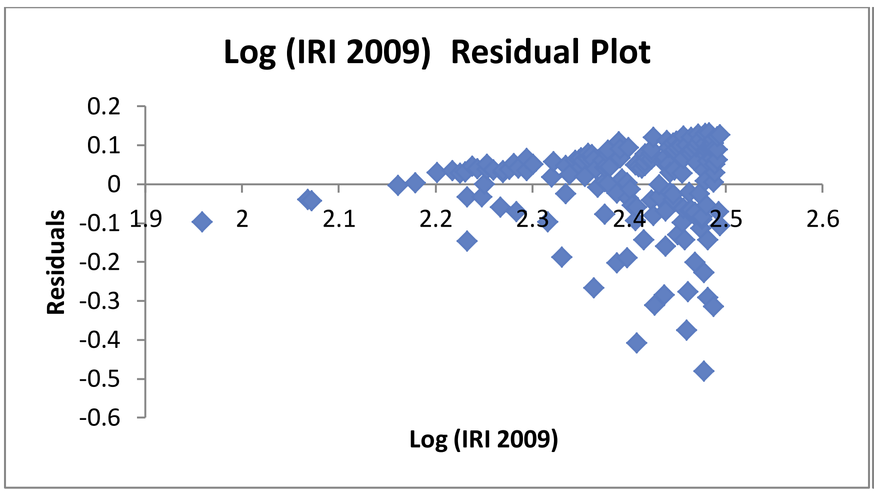


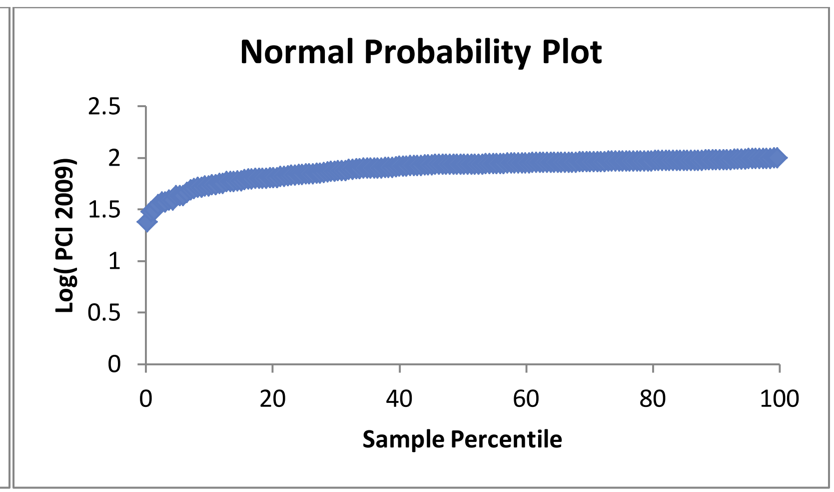
Composite 2009





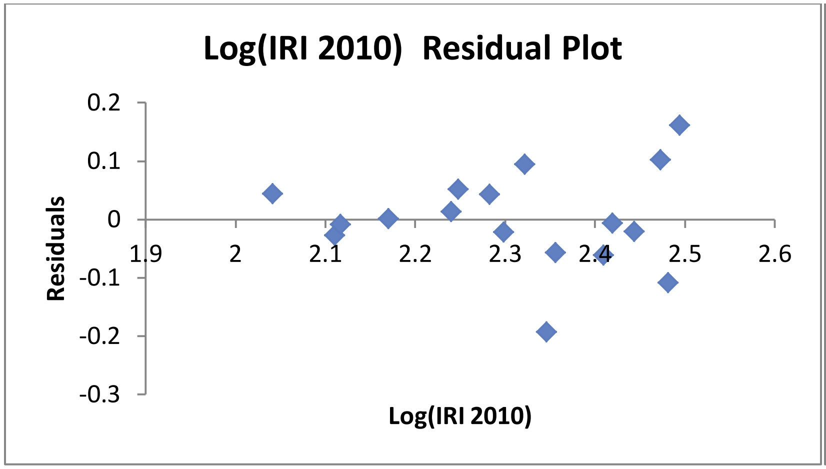
Concrete 2009

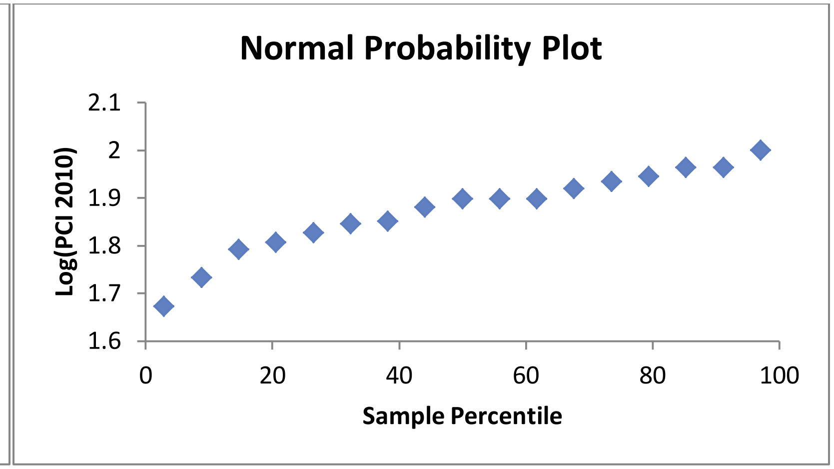




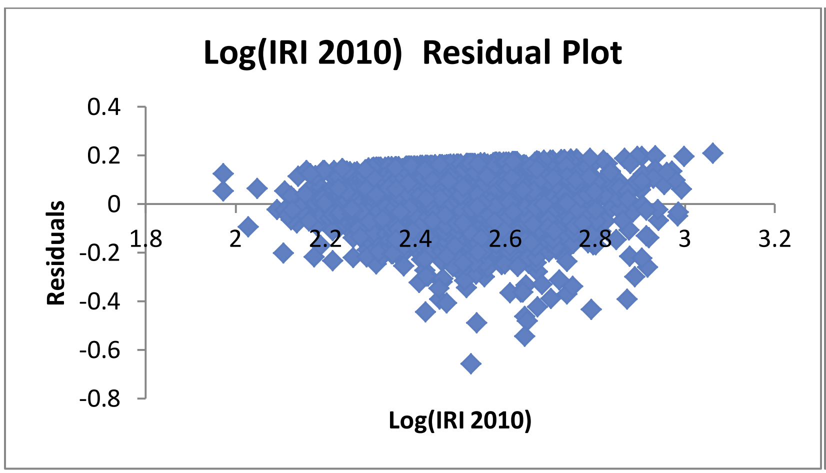
2010 Residual and Normal Probability Plots

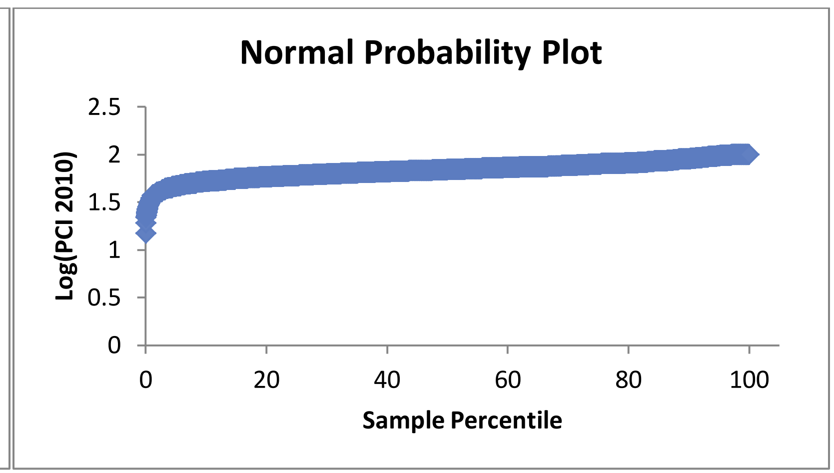
Freeways 2010



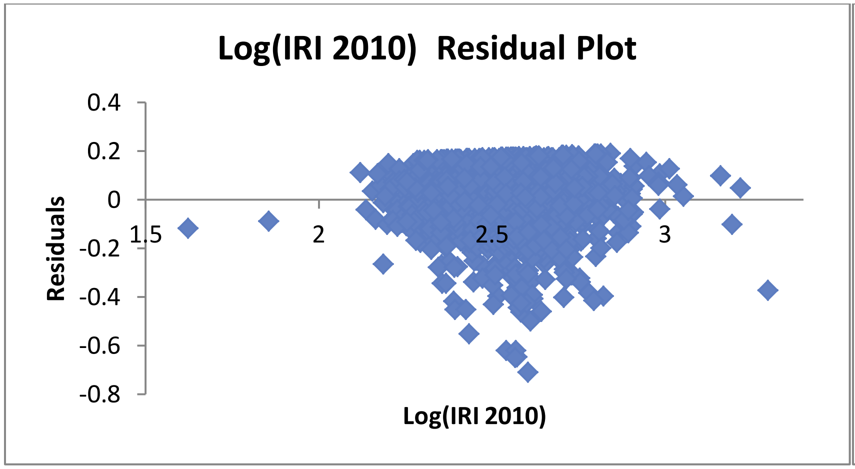


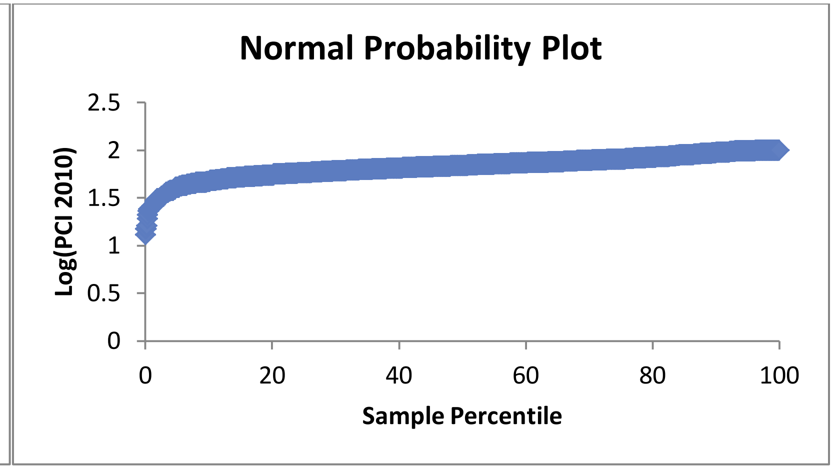
Arterials 2010



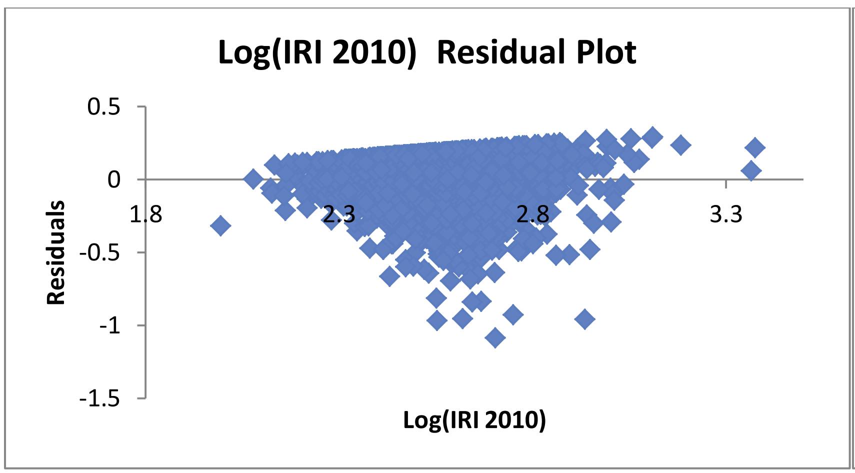


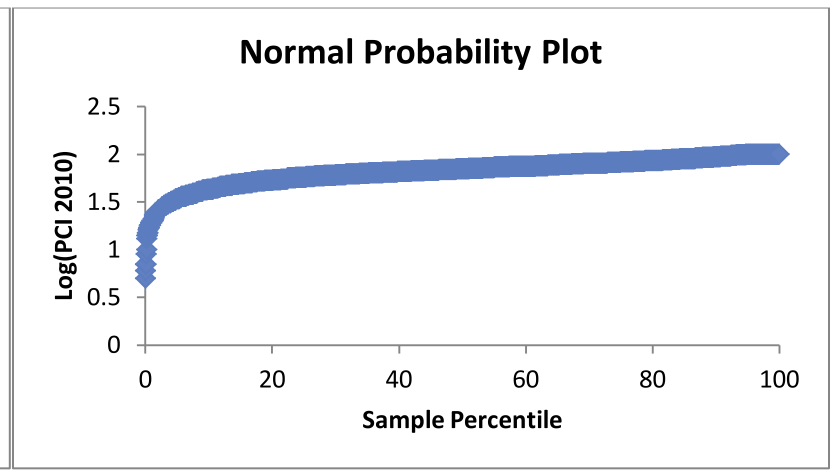
Collectors 2010



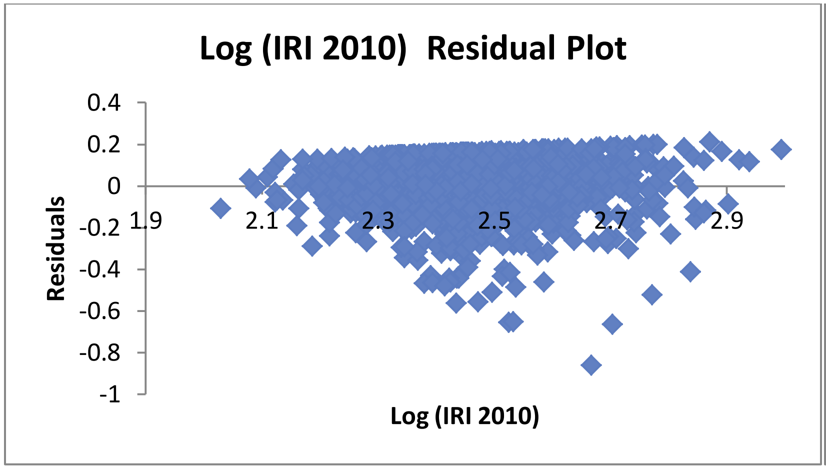


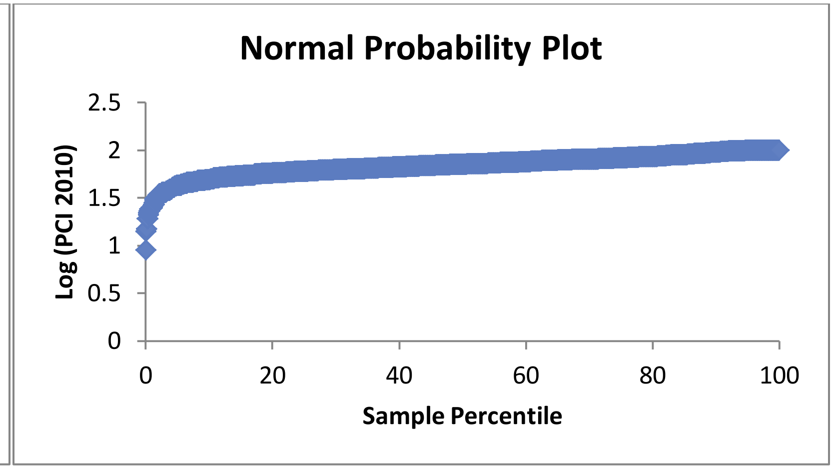
Locals 2010



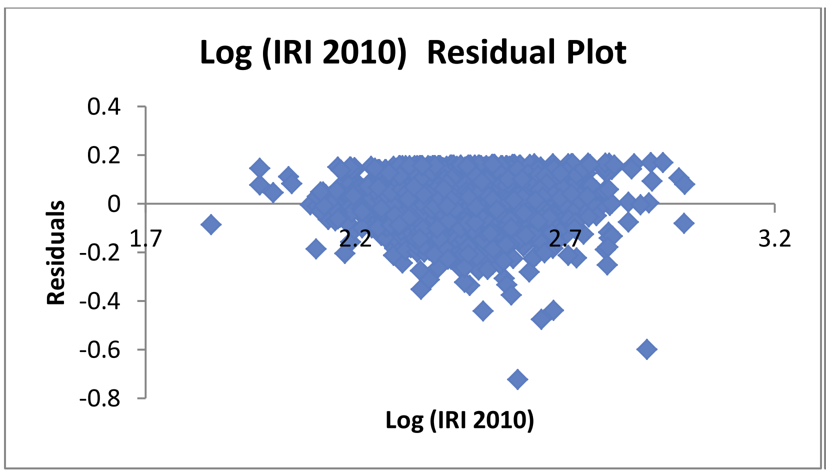


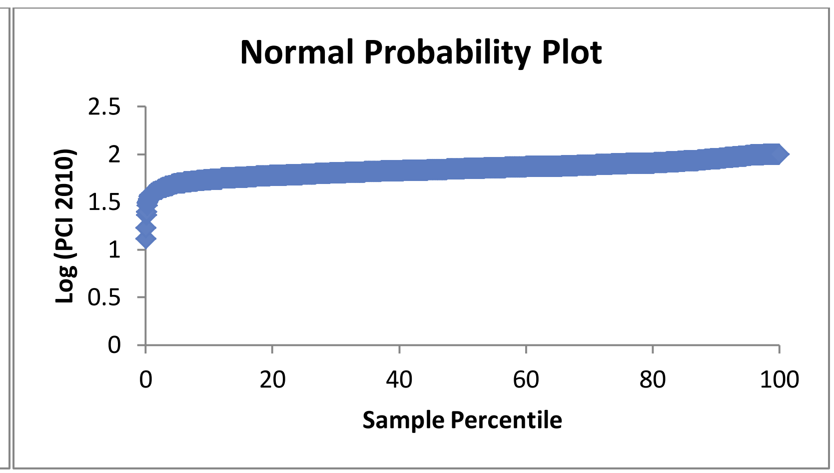
Asphalt 2010



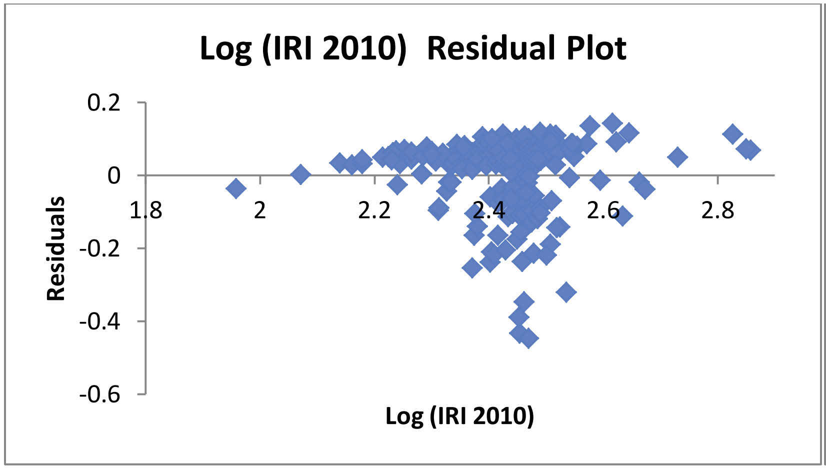


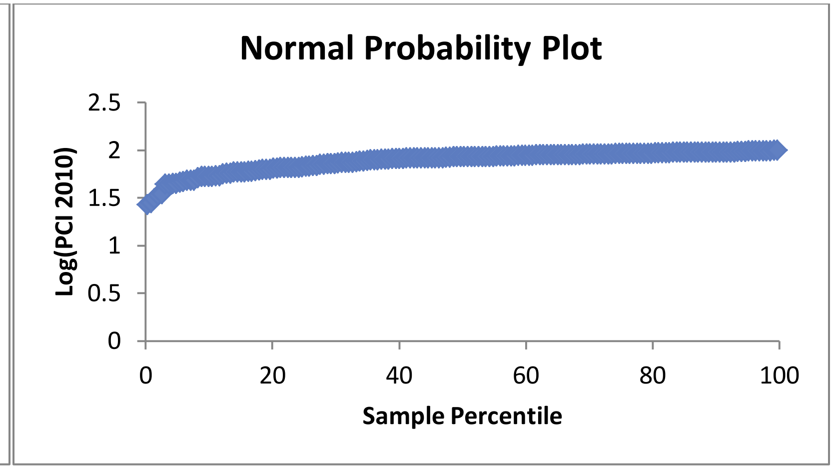
Composite 2010





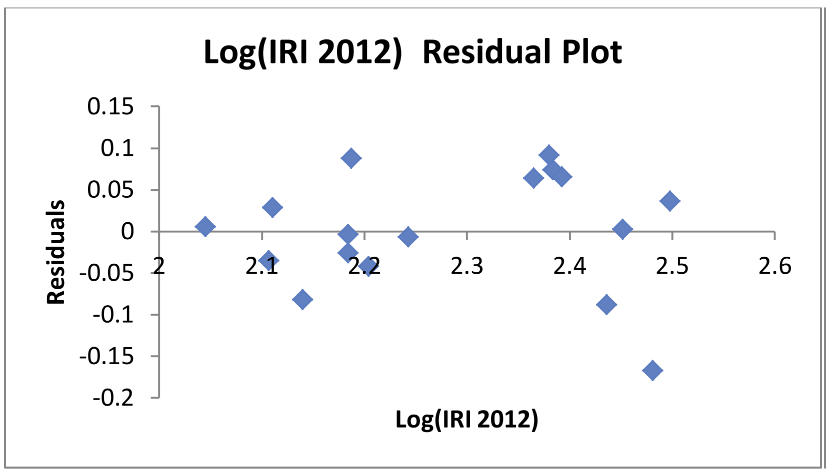
Concrete 2010

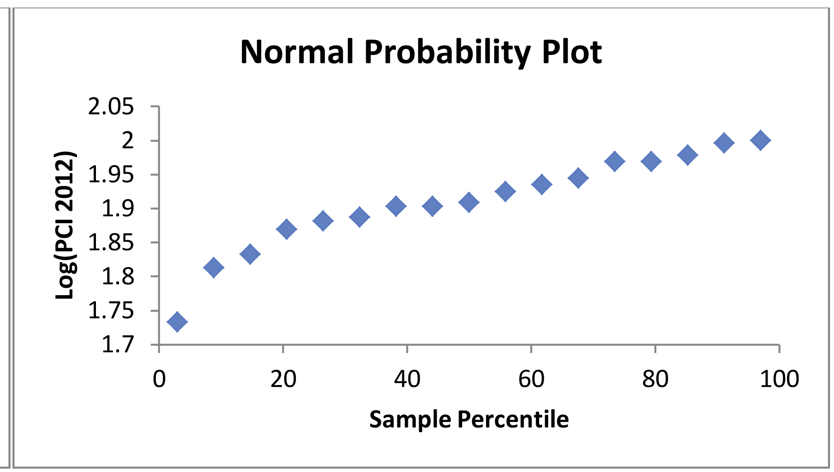




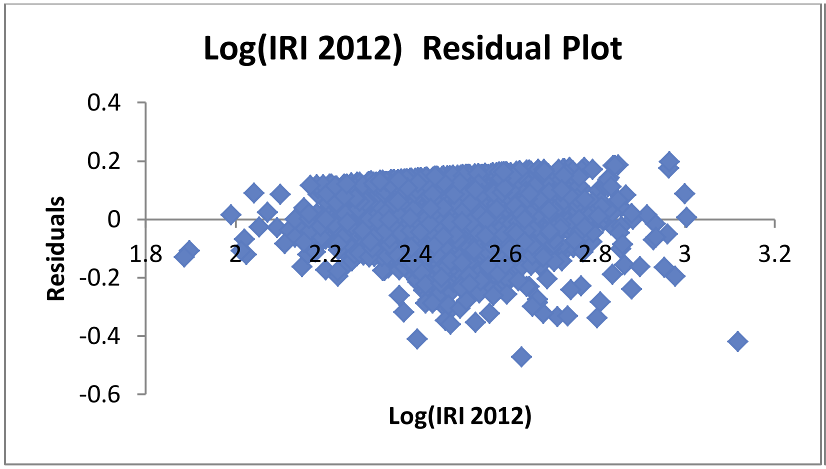
2010 Residual and Normal Probability Plots

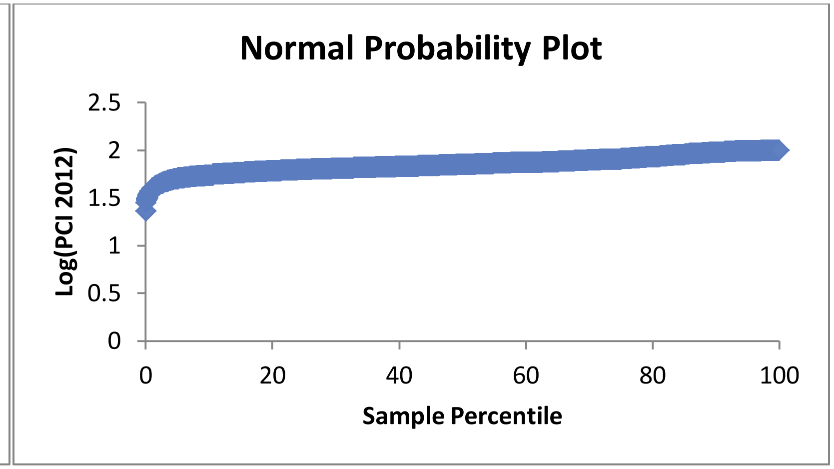
Freeways 2012



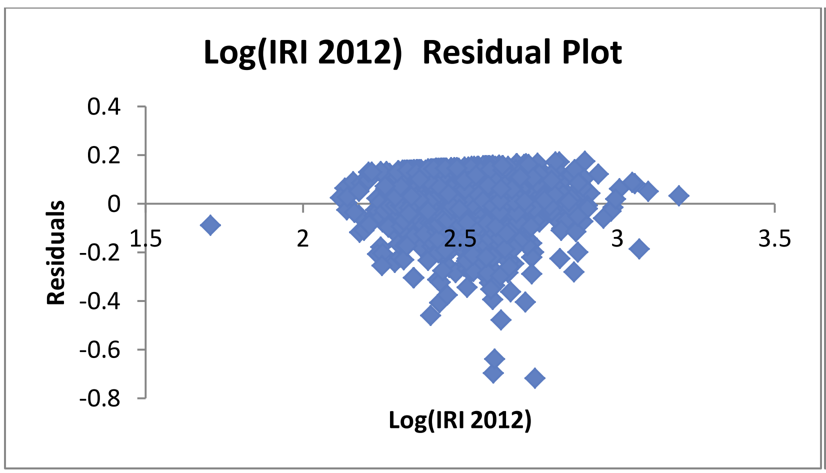


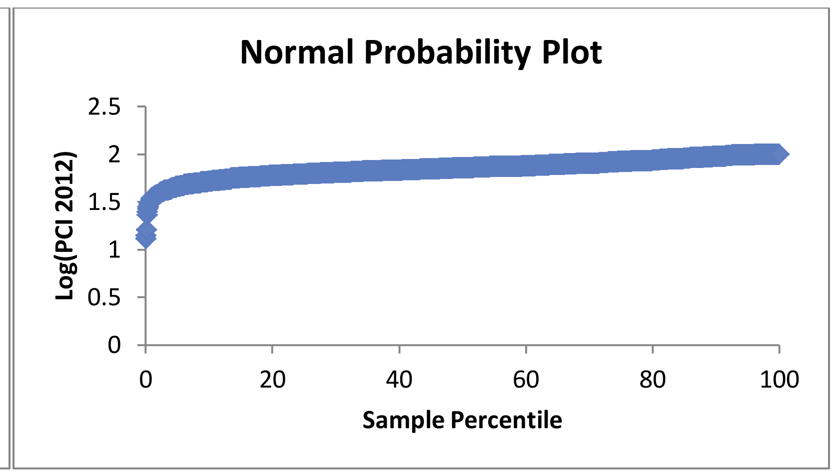
Arterials 2012



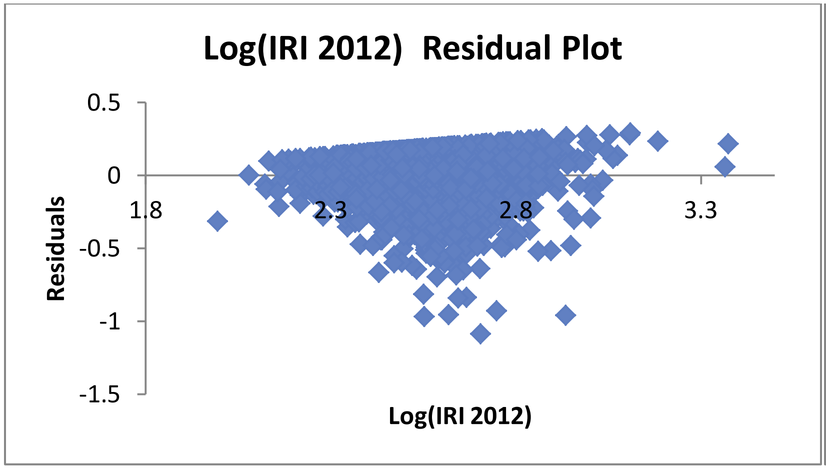


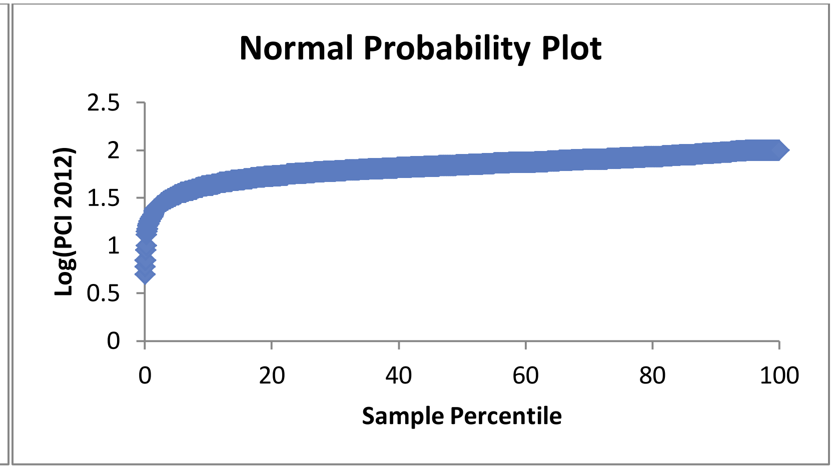
Collectors 2012



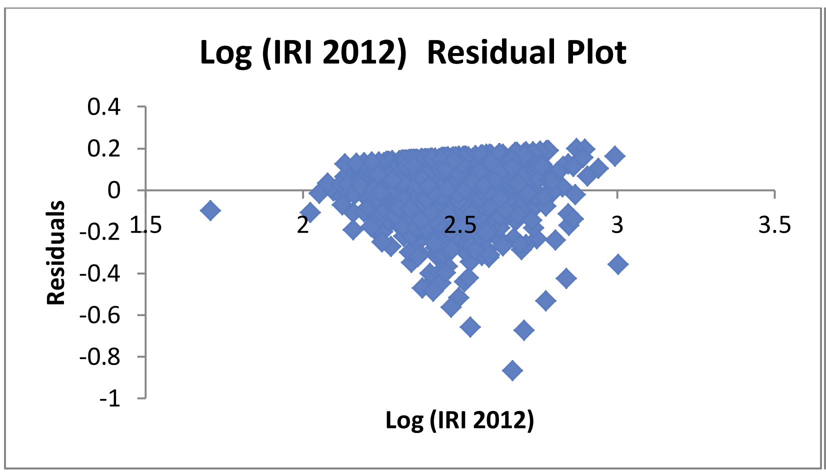


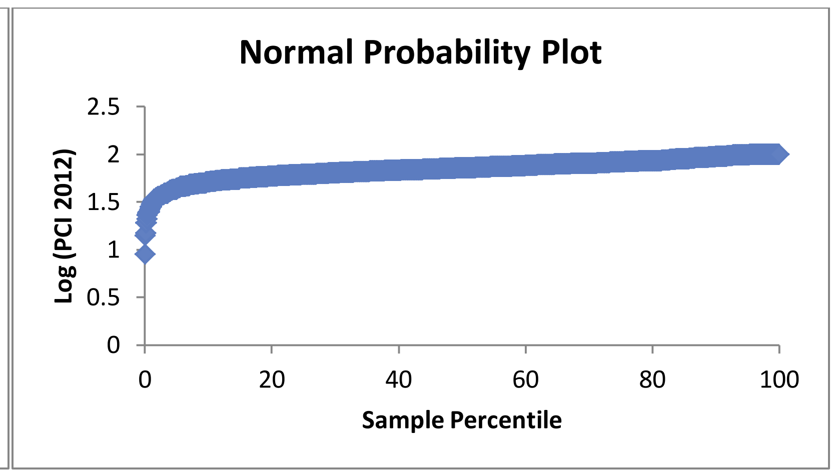
Locals 2012



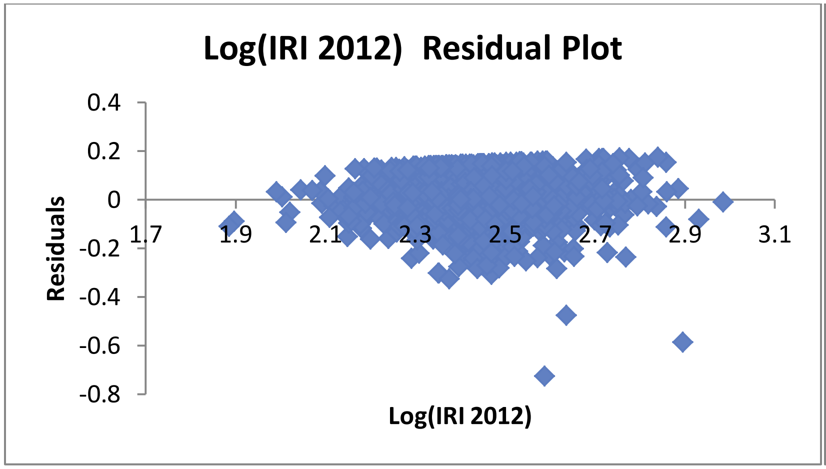


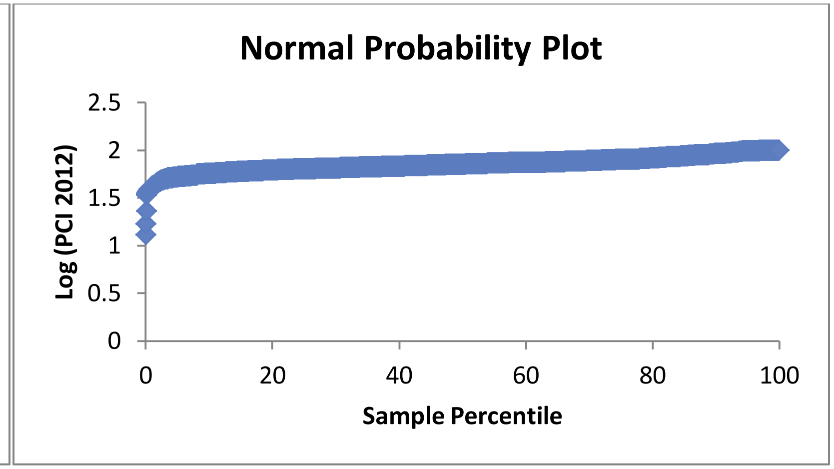
Asphalt 2012





Composite 2012





Concrete 2012