DEVELOPMENT OF DETERIORATION MODELS FOR STREET PAVEMENT IN DALLAS-FORT WORTH METROPLEX

By:

MLADJAN JOHN GRUJICIC

DISSERTATION

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Supervising Committee:

Dr. Stefan Romanoschi, P.E.
Dr. Xinbao Yu, P.E
Dr. Suyun Ham
Dr. Victoria Chen

MLADJAN JOHN GRUJICIC 2020

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Abstract

Development of Deterioration Models for Street Pavement

in the Dallas-Fort Worth Metroplex

Mladjan John Grujicic, PhD, PE

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Supervising professor: Dr. Stefan Romanoschi

Accurate prediction of pavement deterioration is vital for an efficient and cost-effective allocation of available budgets for keeping an agency's road networks operating at a desirable level.

Currently, most cities in the Dallas-Fort Worth Metroplex area are using the software PAVER™ and the associated performance models to predict future conditions as they do not have available reliable prediction models. However, the problem with this type of modeling is that the models are not calibrated to local conditions.

The Pavement Deterioration Prediction models that have been developed in this research will help any pavement management agencies within DFW Metroplex area to identify and predict the future pavement performance for any planning period. The models were developed based on the available data collected by the city's pavement management department for the DFW Metroplex area.

In this research, a family modeling approach has been used as this method reduces the number of independent variables in performance modeling to a single variable (age in this research) by enabling the development of models in each pavement family. Separate models are

also developed for areas with expansive and non-expansive subgrade soil. A total of eleven models are developed for the areas non-expansive subgrade soil area and nine models for the areas with expansive subgrade soil.

Deterministic models that are developed are applicable to cities with available historical data on PCI or IRI. The developed probabilistic models are applicable to cities with a current pavement condition data, but no less than the last two consecutive years.

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Chapter 1. Introduction, Research Rationale and Objective

1.1 Introduction

A road pavement continuously deteriorates under the combined actions of traffic loading and the environment. AASHTO (1993) defines the pavement performance as the ability of a pavement to satisfactorily serve traffic over time (AASHTO, 1993). The change in the value of these performance indicators over time is referred to as pavement deterioration. Pavement performance models, or deterioration models, refer to mathematical expressions used for predicting the future condition(s) of pavement from their present condition. Also, the models may aid in discerning some of the factors that are likely to contribute to changes in the conditions of pavement. Therefore, reliable models are very valuable to pavement managers and engineers.

Accurate prediction of pavement deterioration is vital for an efficient and cost-effective allocation of available budget for keeping an agency's road network operating at a desirable level. Many scholarly investigations affirm that a profound understanding of the pattern of pavement deterioration in urban regions has yet to be achieved. According to Abaza (2016), this lack of understanding arises from traffic pattern complexity and from a variety of pavement structures that are developed in urban roads. Anastasopoulos, McCullouch and Gkritza et al. (2010), further stated that "when a suitable deterioration model is not developed, especially in the case of urban pavements, the possibility of achieving a scientific model for cost-effectiveness and repairs is limited". As stated by Arambula, et al. (2011), "the understanding of the condition of pavements is the best way for deriving effective predictive models for pavement conditions".

While being an essential component under pavement management systems, prediction models have been documented to play crucial roles in estimating the time and type of rehabilitation or maintenance to support decisions in multi-year improvement programs, predicting the duration until the lowest limits of acceptable pavement conditions might be reached (or determining the remaining service life of a pavement), and ensuring that the combination of timing and treatment is optimized in a manner that leads to the accomplishment of an agency's goals.

The common method to measure pavement deterioration relies on the collection of type, severity, and extent of common pavement distresses. For example, three major flexible pavement distresses are rutting, fatigue cracking, longitudinal & transverse cracking. Major distresses for rigid pavement are cracking, corner breaks, shrinkage cracking, and punchouts. They constitute the main factors that reflect the performance and ride quality of pavements.

A very important factor that affects pavement deterioration is the presence of expansive subgrade soil. According to Consoli, et al. (2011), expansive subgrade soils refer to soils with high contents of expansive minerals that are modified by the formation of deep cracks during drier seasons. Indeed, expansive subgrade soils can be concluded to be typical clays demonstrating extensive strength and volume changes with the amount of moisture content. The latter trend is linked to the chemical composition of the soils. Through time, the changes in the volume of the clays lead to significant foundation damages, with pavements undergoing extensive deterioration (Dang, et al. 2016).

Pavement Condition Indices

A great effort has been put into developing a pavement condition index as an indicator to overall pavement health and to ease the characterization of the pavement condition. The condition index combines all measures of pavement distress into a single number. This number can be used at the network-level to define the condition state of each road segment, to identify when treatments are needed, to rank or prioritize, and to forecast pavement condition (FHWA, 2003). Several types of pavement condition indicators have been used by road and street network agencies.

Present Serviceability Index (PSI)

The Present Serviceability Index (PSI) was developed in the early 1960s and is the first comprehensive effort to establish performance standards while considering riding quality (Carey and Irick, 1960). The PSI was based on the values of pavement smoothness, rutting, cracking, and patching. A panel of highway users from different backgrounds evaluated several flexible pavement sections and rated them on a five-point discrete scale (0 for poor, 5 for excellent). An average value of these provided by the raters is computed. The PSI has been related later to the extent of cracking and roughness using regressing models (Yogesh U. Shah, et, all 2011).

Pavement Condition Index (PCI)

The PCI survey methodology was developed by the U.S. Army Corps of Engineers, it uses a very comprehensive condition index (Shahin and Kohn, 1979). The PCI method is based on a visual examination of the pavement distress type, extent, and severity (ASTM, 2007). The PCI provides a measure of the current condition of the pavement based on the distress observed on the surface of the pavement. It may also indicate the surface operational condition (roughness and safety). The PCI scale, shown in *Figure 1.1* is 0 – 100. Sections with 100 represent the best possible condition, and 0 represents the worst possible condition. One PCI survey procedure and calculation method were standardized by ASTM for roads and parking lots pavements (ASTM, 2007). The pavement condition rating consisted of the following steps:

1. Divide pavement section in manageable sizes
2. Identify pavement distress, severity and extend guidelines that have been developed on how to carry out pavement distress evaluation
3. Deduction values were assigned for each distress type, severity, and extent level
4. Add the total number of deducting values

5. Corrected deduction value is determined based on the number of observed distresses
6. Determine the pavement condition rating on a scale from 0-100 by subtracting the deducted value from 100

The PCI has been widely used in the network-level pavement management and has been adapted for the pavement management system PAVER TM software (Shahin and Walter, 1990).

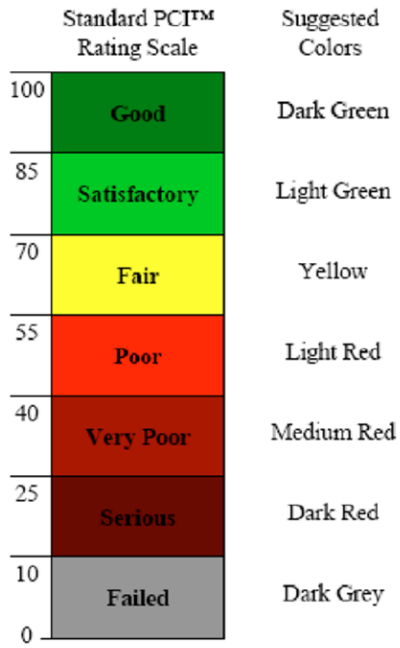

Figure 1.1 Standard PCI Rating Scale by ASTM (Source: ASTM, 2007)

International Roughness Index (IRI)

Another measure of the quality of a road section is the roughness of the longitudinal profile since it significantly affects the comfort of the user and user costs. The IRI is the roughness index obtained from measuring longitudinal road profiles by road meters installed on vehicles or trailers. The IRI was originally developed by the World Bank to be used in the Highway Development Model. The IRI roughness is usually reported in inches per mile (in/mi) or meter per kilometer (m/km) (1 m/km = 63.36 in/mi) on an increasing boundless scale. *Figure 1.2* shows the typical ranges for the IRI. A perfectly smooth pavement (not possible even right after construction) would have an IRI of 0. FHWA specifies an IRI value of 95-170 in/mi as the boundary between acceptable and unacceptable interstate pavement. For the roads with a lower operating speed such as arterial, collector, and residential streets, higher IRI values typically would be allowed before the road section is selected for rehabilitation.

Due to the importance of the roughness of the longitudinal profile, evaluation models have been developed from the IRI. The accurate prediction of the evaluation of IRI allows the estimation of future vehicle operating costs which are important components of the life-cycle cost analysis.

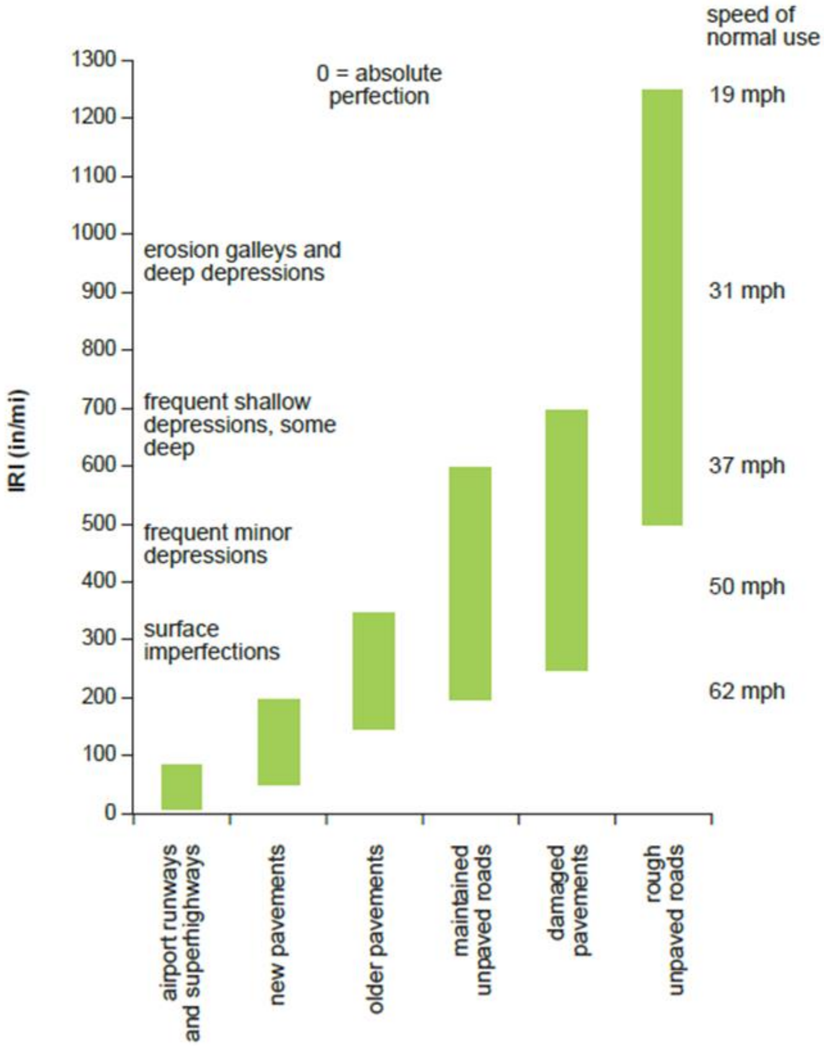

Figure 1.2 IRI Range by Roadway Type (Adapted from Sayers and Karamihas 1998)

Pavement Performance Models

Pavement performance models are the main element in any Pavement Maintenance Management System (PMMS). Pavement performance models can be divided into two major groups: deterministic and probabilistic models.

- *Deterministic models* - These models are developed from a regression analysis in which a statistical relationship between two or more variables is established. The statistical relationships in these models are not exact and include prediction errors. The magnitude of the errors depends on factors such as the quality of the data, the appropriateness of the selected independent variables to predict the dependent variables, and the range of data in the data set. Because the correlation between the independent and dependent variables is not exact, an approach for determining the best statistical fit of the data must be used. A common approach is to use the least squares regression technique, which minimizes the sum of the squared differences between the predicted and the measured points. Deterministic models may take many forms (e.g., shapes) depending on the type of equation used (e.g., linear, quadratic, or sigmoid). For the sake of simplicity and due to the lack of complete datasets to develop more complex models, it is common in pavement management to use a single independent variable to predict the dependent variable (e.g., pavement condition). Pavement age is the most commonly used independent variable and refers either to the number of years since construction or the last major rehabilitation. A typical example of a deterministic model in pavement deterioration would be the sigmoidal model, i.e. a model given by: $y = a * \left[\frac{t^b}{c+t^b}\right]$ where a, b, and c are constant numbers and t represents the time elapsed since the last major rehabilitation.

- *Probabilistic models* – Probabilistic models differ from deterministic models in that instead of predicting a single value for pavement condition, they predict the likelihood of a pavement changing into one of several condition states, or categories, when the current condition state is known. They are typically used more for other asset management systems such as bridge or pipeline management systems. The Markov probabilistic approach assumes that the probability of changing from one condition state to another is independent of the past condition. The Semi-Markov approach is designed to overcome the independence of time assumption used when changing from one pavement condition state to another. Semi-Markov models allow transition probability matrices to be created and used together to provide piecewise increments of time. Since Markov models depend only on the current condition state, there is no opportunity to include other variables such as traffic loading or environmental factors. Since traffic and environmental factors contribute to performance and they are changing over time, the families are created and separate transition matrices are developed for each family. According to Shahin (2005), probabilistic modeling is particularly useful for predicting individual distresses. As an example, Wang et al. (1994) developed the Markov transition-probability matrices for the Arizona DOT by using a comprehensive set of observed pavement performance historical data with several initial pavement condition states. The pavement probabilistic behavior is as follows (Wang et al. 1994):

$$P_{ij}^{(n)} = \sum_{k=0}^{M} P_{ik}^{(1)} P_{kj}^{(n-1)} \qquad \forall n \leq \nu$$

$$P_{ij}^{(n)} = \sum_{i=0}^{M} \sum_{k=0}^{M} (P_{ik}^{(\nu)} P_{kl}^{(1)a}) P_{lj}^{(n-\nu-1)} \qquad \forall n > \nu$$

where $Pij(^{n})$ is the n-step transition probability from condition state i to j for the entire design period (N), M+1 is the total number of pavement condition states, ν is the period when the rehabilitation is applied; $Pik^{(\nu)}$ is the ν-step transition probability from condition state i to k under the routine maintenance; $Pkl^{(1)a}$ is the one-step transition probability from condition k to l at period ν; and $Plj^{(n-\nu-1)}$ is the (n-v-1) step transition probability from condition l to j under the routine maintenance (Wang et al. 1994).

Pavement Prediction Models for Dallas-Fort Worth

Dallas-Fort Worth Metroplex is located in northern Texas, in Zone 1, as shown in *Figure 1.3*. It covers wet-cold climate, poor, and very poor or mixed subgrade. Most of the Metroplex area has Expansive subgrade soil.

The Dallas-Fort Worth Metroplex is made up of one city with over one million inhabitants (Dallas (1,286,380)), another city with 500,000-1,000,000 inhabitants (Fort Worth (829,560)), four other cities between 200,000 – 500,000 inhabitants (Arlington (383,950), Plano (281,390), Irving (237,490), Garland (236,030)), eight cities between 100,000-200,000 inhabitants (Grand Prairie (189,430) McKinney (179,970), Frisco (172,940), Mesquite (143,350), Carrollton (132,330), Denton (130,990), Richardson (110,140) Lewisville (104,780)) and fifty-six cities between 10,000 - 100,000 inhabitants (per North Central Texas Council of Governments (as of January 1, 2018)). In the Dallas-Fort Worth Metroplex, the road network operation and maintenance falls under the jurisdiction of each individual city. The size of the street network in each major city in Dallas-Fort Worth Metroplex is given in *Table 1.1*:

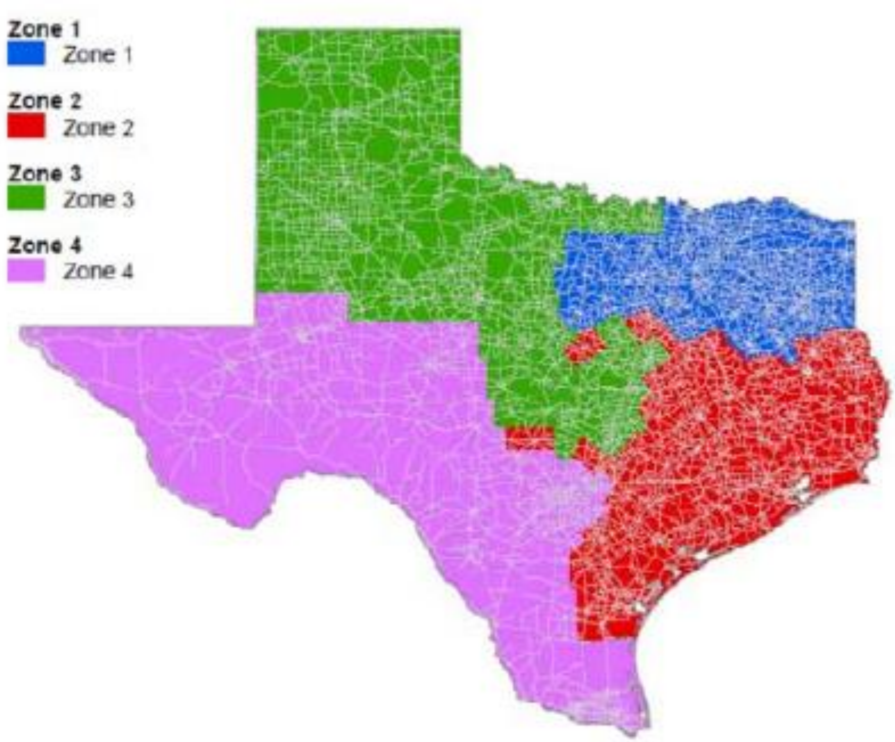

Figure 1.3 Climate and Subgrade Zones for Deterioration Models (TxDOT, Analysis Report 2018)

City	Lane Miles
Dallas	11,775
Fort Worth	7,518
Arlington	3,000
Plano	2,294
Garland	2,361
Irving	1,400

Table 1.1 Major cities in DFW's area – Road Lane Miles

Currently, most cities in the Dallas-Fort Worth Metroplex are using the software PAVER^{TM} and the associated performance models to predict future conditions. However, the models are not calibrated to local conditions. Only the city of Dallas has attempted to develop specific models from its street network.

PCI and IRI Data collection practice

Most cities in the Dallas Fort Worth Metroplex rely on specialized contractors to survey the condition of their street network. Automated survey vehicles are the most used today. As an example, for PCI data collection of each roadway section in the cities of Arlington and Plano, a Mobile Asset Collection (MAC) vehicle is used to gather street-level right of way photos and downward pavement photos (*Figure 1.4*). Similar equipment is used by other cities.

The automated distress data collection is performed in general accordance with ASTM D6433 (Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys) and ASTM Standard E1656 (Standard Guide for Classification of Automated Pavement Condition Survey Equipment), utilizing a Class 1 device as defined by the specifications. MAC vehicles combine multiple engineered technologies to collect real-time pavement data, right-of-way data, and images at posted speed limits. This effectively eliminates the need to place pavement inspection technicians in the field and in close proximity to vehicle traffic, ensuring human health and safety. Some components of the MAC vehicle are (City of Arlington, TX, 2018):

- Navigation System. Inertial Measurement Unit generates a true representation of vehicle motion in all three axes; producing continuous, accurate position and orientation information. A POS Computer System enables raw GPS data from as few as one satellite to be processed directly into the system, to compute accurate positional information in areas of intermittent, or no GPS reception. Embedded GPS receivers provide heading which aides to supplement the inertial data. Two GPS antennas generate raw observables data. The system is rated to get 0.3 m accuracy in the X, Y position and 0.5 m in the Z position.

- Distance Measuring Indicator (DMI) allows for the collection of high-resolution imagery at posted speeds. The Distance Measurement Indicator computes wheel rotation information to aid vehicle positioning.
- High-definition cameras with precision lenses allow for accurate asset extraction and video log recording at a frame rate of 15 images per second, with 1936 x 1456 color resolution.
- A Pavement Imaging System consists of two line-scan cameras and lasers configured to image 4m transverse road sections with 1 mm resolution (4000 pixel) at speeds that can reach 100 km/h. It allows fully illuminated pavement image collection even in heavy shadow/canopy areas.

Figure 1.4 MAC Vehicle (2018 Pvmt Management Services Executive Summary, city of Arlington, TX

In small cities, PCI information is gathered manually per standard practice for roads and parking lots pavement condition index surveys guidelines (ASTM D6433). However, many cities are transitioning to automated distress survey due to their better accuracy, speed, cost, and safety to personnel.

1.2 Research Rationale

The goal of this research is to develop deterioration models that are applicable to the street network conditions in the DFW Metroplex because currently, some cities in the Metroplex are using deterioration performance models which are not calibrated to local conditions. Furthermore, most of the smaller cites do not have prepared deterioration models due to the absence of historical data.

Through establishment of a pavement deterioration prediction model, it will provide models for engineers to predict the timing of pavement treatments and the type of treatment needed by individual streets in the Dallas-Fort Worth Metroplex area. The newly developed models will contribute to a cost reduction in future street maintenance and rehabilitation. The models will also consider the different soil types (Expansive/non-Expansive) which have a major impact on pavement deterioration rates.

In addition, the quality of pavement deterioration prediction models is very much affected by the available data. In the Dallas-Fort Worth Metroplex only major cities have historical data. Many large cities and most small cities do not have enough records to build their own models. For most of the Metroplex, data collection has just recently begun. The deterioration models that will be developed will not only benefit pavement managers and engineers in larger cities, but also those in smaller cities as well. The cities that do not have enough historical records of Pavement Condition Index (PCI) and the International Roughness Index (IRI) will be able to use these models since the soil, environment, materials, traffic, and age are very similar across the Metroplex.

The development of the model will consider the main variables that could affect the behavior of pavements in the Dallas-Fort Worth Metroplex and might shape the models. As such, the prediction models will be developed by ensuring that pavements are grouped into "families". The selected families are expected to constitute groups of street sections with common features, such as surface layer type, functional class, soil type, etc.

1.3 Research Objective

The accurate prediction of pavement network conditions and performance is significant for an effective and well-organized management of the road-street network. The objective of this research is to develop network level deterministic and probabilistic deterioration models that will predict the changes in overall PCI or IRI for streets in the DFW Metroplex.

In this research, deterioration models will be developed for a new flexible (asphalt) and rigid (concrete) pavement structures in the Dallas-Fort Worth Metroplex area using the historical records of the PCI and the IRI.

The question of if different deterioration models are needed for streets built on Expansive and non-Expansive subgrade soil will be investigated.

1.4 Research Approach

In order to achieve the research objectives, this dissertation is organized into six chapters. Chapter 1 covers the introduction, rationale and objective of research. Chapter 2 includes a literature review that outlines the previous work done to develop the pavement deterioration model. The main emphasis was on research modeling techniques that were useful for pavement data in the DFW Metroplex region. More precisely, the literature review was used to identify the best deterministic and probabilistic models for pavement deterioration.

A literature review was conducted to gather information from previous studies that developed pavement deterioration prediction models in regions with structural pavement types similar to those used in the Dallas-Fort Worth Metroplex area. Chapter 3, Data Collection and Management describes how historical data and shape files have been collected from pavement asset management services in the DFW Metroplex area. This chapter also outlines the requirements for organizing, removing, and filtering data. In addition, this chapter clarifies the family approach to creating reliable deterministic and probabilistic models.

Chapter 4, Development of deterministic models, provides a detailed explanation for the development of deterministic models using a regression approach for eleven pavement families in the DFW Metroplex area with non-expansive subgrade soil and nine models in the area with expansive subgrade soil.

Chapter 5, explains the development of probabilistic models using Markovian chain approach for eleven pavement families in the DFW Metroplex area with non-expansive subgrade soil and nine models in the expansive subgrade soil area.

Finally, Chapter 6 presents the summary, conclusions, and recommendations that arise from this research. *Figure 1.5* illustrates the flow chart of the thesis.

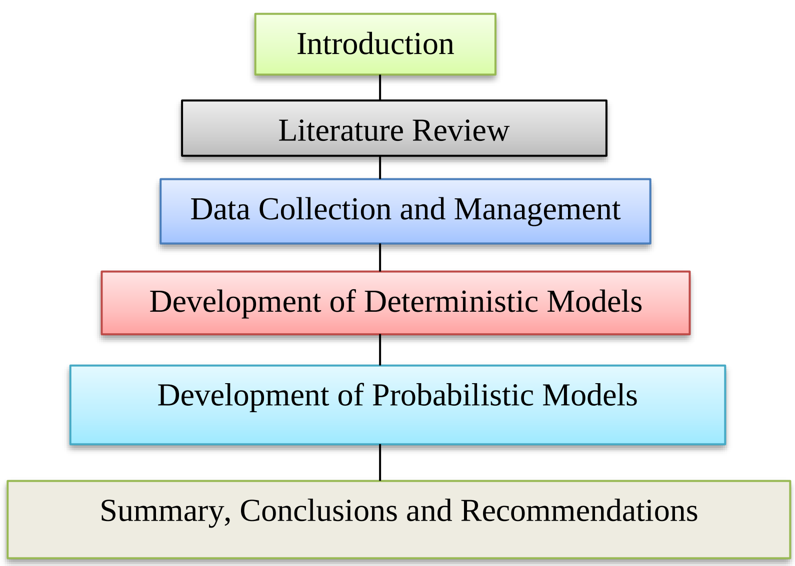

Figure 1.5 Thesis Organization

Chapter 2: Comprehensive Literature Review

Accurate predictions of pavement deterioration are very important for the efficient and cost-effective allocation of the available budget to keep an agency's street network operating at a desirable level. While being an essential component under pavement management systems, prediction models have been documented to play very important roles in estimating the time and type of rehabilitation or maintenance to support decisions in multi-year improvement programs, predicting the duration until the lowest limits of acceptable pavement conditions might be reached (or determining the remaining service life of a pavement), and ensuring that the combination of timing and treatment is optimized in a manner that leads to the accomplishment of agency's goals. Pavement prediction models are the main element in any Pavement Maintenance Management System (PMMS). The prediction models can be divided into two major groups: deterministic and probabilistic models.

De la Garza et al. (2010) developed a regression prediction model by calculating pavement deterioration rates based on historical data; however, the pavement deterioration rates are often "uncertain" (Butt et al. 1994). Therefore, the probabilistic model based on the Markov chain is the most often in use (Bako et al. 1995; Chen et al. 1996; Golabi et al. 1982; Abaza 2007). Pavement prediction influences the quality of other components of pavement management such as rehabilitation years, types of treatment, and selecting cost-effective maintenance alternatives (Li et al., 1996). Figure 2.1 shows that the decline of the pavement condition can be measured by distress parameters such as Present Serviceability Index (PSI). Over time, the pavement will deteriorate due to many factors including traffic load, weather condition, quality of construction, lack of regular maintenance, and aging (Gini Arimbi 2015).

At this stage, the best form of pavement treatment can be determined to improve the condition of the pavement and to extend its life.

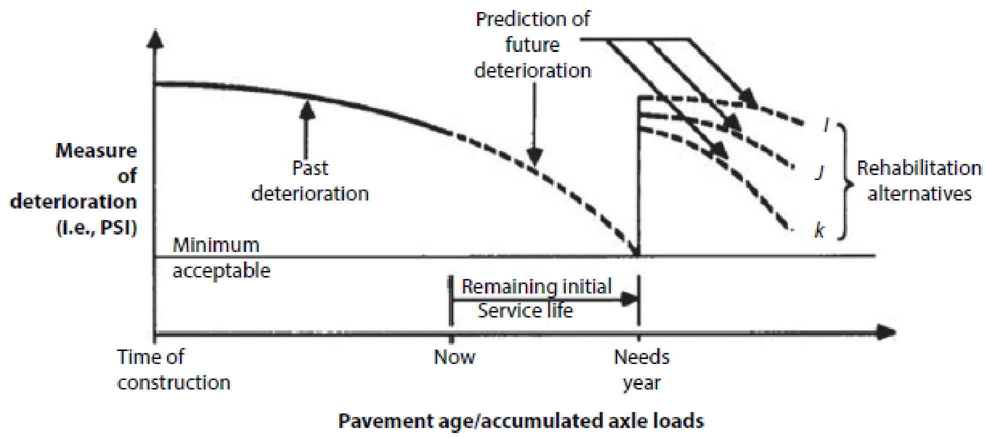

Figure 2.1 The deterioration process of pavement (Haas & Hudson, 2015)

2.1 Method of Prediction Models

A prediction model can be developed by one of the following methods (FHWA 1990):

- Empirical Method
- Mechanistic Method
- Mechanistic-Empirical Method
- Probabilistic Method
- Bayesian Method

  - *Empirical Method*

The empirical approach is based on mathematical models. Empirical models rely on the statistical analysis of locally observed deterioration patterns. This model could not be transferred to other pavements with different pavement conditions. The empirical approach was used for this research as a large amount of data was obtained from cities in the DFW Metroplex region.

- *Mechanistic Method*

The mechanistic models use engineering theories for pavement behavior to predict deterioration models that could be used for the different pavement conditions. Mechanistic method in pavement analysis includes layered elastic and finite element methods (Mubaraki, M, 2010). These types of methods require extensive structural information that restricts the precise calculation of stresses, strains, and deflections to sections for which detailed data is available. Mechanistic approaches are based on mechanical theory.

- *Mechanistic – Empirical Method*

Mechanistic-empirical models are the combination of both mechanistic and empirical models. They can produce models with moderate data requirements and can be applicable to other pavements with different conditions and changed calibration parameters (Harvey, 2012). The analytical – empirical or mechanistic approach has been widely used in the design of flexible pavements. This approach involves two segments: the estimation of the response of the pavement materials to the load applied and the prediction of the output of the pavement from these responses.

- *Probabilistic Method*

Probabilistic models distinguish from deterministic models in that, instead of predicting a single value for the condition of the pavement, the probability of a pavement being in one of many condition states (or categories) is predicted. Probabilistic models are not widely used as deterministic models in pavement management, possibly because most pavement management software programs are not designed to input these types of models without converting them to one of the deterministic model forms.

- *Bayesian Method*

This method allows the integration of current information into the forecast so that past experience can be used instead of ignored. (Zellner, 1971). While this approach commonly uses both objective and subjective data to forecast results, models can only be built using subjective data. The regression analysis methods are used to construct the models but the random and related probability distribution is assumed in each of the variables (AASHTO, 2012). Because subjective data can be used to supplement objective data, Bayesian regression can be useful for agencies that have recently began the implementation of pavement management, that have changed their pavement condition rating procedures (e.g., no historical data are available), or that have introduced new designs or materials into their network. It also offers a way to override the influence of data of poor quality, or to supplement field data with expert models as they become available. The Bayesian approach relies on the use of Bayesian regression techniques to combine observed data and expert experience, mainly based on a popular paper published by the Rev. Thomas Bayes (1702-1761). The theorem of Bayes can be mathematically described as (Thomas 1993):

$$P(p|: x) = \frac{P(x|p).\, x\, P(p)}{\Sigma[P(x|p).\, x\, P(p)]}$$

where,

P(x) = distribution of variants over all possible fraction variants

P(p) = prior distribution

P($x|p$) = sampling distribution

P($p|x$) = posterior distribution

2.2 Types of Prediction Models

In general, there are three main models in the pavement management system that have been developed: Deterministic models, Probabilistic models and Bayesian models. According to García, Costello, Snaith, 2006, a deterministic model is a model for which the condition is projected as a precise value based on the mathematical functions of the deterioration observed. Probabilistic models predict the pavement condition as the probability of occurrence over a range of possible outcomes (Ortiz-García et al., 2006). Pavement management at a network-level uses probabilistic models since network-level analysis involves a high number of variables and variations. Classification of prediction models has been suggested by Mahoney (1990). Table 2.1 shows that deterministic model could be used for the structural distress as specified by PCI for the state / provincial network level as well as for project level but not for national network, while the probabilistic models could be used for any level.

Level of Pavement Management	Types of Performance Models						
	Deterministic Models				Probabilistic Models		
	Primary Response	Structural	Functional	Damage	Survivor Curves	Transition Process Model	
	Deflection, Stress, Strain, Temperature, Thermal Stress, Moisture, Energy Frozen and Unfrozen, Water Content	Distress, Pavement Condition Index (PCI)	Serviceability Index, Skid Loss, Wet Weather Safety Index	Load Equivalence, Marginal Load Equivalence		Markov	Semi - Markov
National Network				●	●	●	●
State / Provincial Network		●	●	●	●	●	●
District Network		●	●	●	●	●	●
Project	●	●	●	●	●	●	●

Table 2.1 Classification of Prediction Models (Mahoney 1990, Haas, 1994)

2.1.1 Deterministic Models

Deterministic models are classified into four types (Lytton, 1987 & Arnibi 2015):

(i) Primary response models - Predicts primary response of pavement to imposed loads and climatic conditions such as deflection, stress, strain, thermal stress, temperature

(ii) Structural performance models - Predicts pavement distress and composite measures of pavement condition such as the pavement condition index

(iii) Functional performance models - Predicts the present serviceability index, pavement surface friction, and wet-weather safety index

(iv) Damage model - Predicts the load equivalence and marginal load equivalence and is obtained from either functional or structural performance models

Equations for Models based on Regression Analysis

Based on their basic behavior, nonlinear regression models can be categorized into families such as exponential models, power models, sigmoid models, etc. (Ratkowsky and Giles, 1989). At present, most of the current deterioration models use the types of regression models described below in their general form.

Exponential Growth

The exponential growth model is used when the growth rate of the mathematical equation is equal to the current value of the function (Ercisli, 2015). This model is commonly applied in many fields such as biology, physics, engineering, and economics. The common form of the exponential growth curve is the following:

$y = a - (a - d) * e^{-st}$

Where

a = Upper asymptote

d = Lower asymptote

t = Time

m = Time of maximum growth

s = Growth rate

Sigmoidal

This model has been used on a regular basis in the development of pavement deterioration models since it can adjust to boundary conditions and provide various parameters. Various experiments in many applications have resulted in the discovery and adaptation of nonlinear S-shaped curves. This form includes the Logistic curve, Verhulst-Pearl equation, Pearl curve, Richard's curve (Generalized Logistic), Growth curve, Gompertz curve, S-curve, S-shaped pattern, Saturation curve, Sigmoid curve, Weibull curve, Foster's curve, Bass model, and many others (Rowe et al., 2009).

Below is a simple S-curve equation:

$$y = a * \left[\frac{t^b}{c + t^b}\right]$$

Where a, b and c are the regression coefficients.

Weibull

Weibull (1951) defined the non-symmetric sigmoidal model as a continuous statistical probability distribution that is commonly used in the modeling of survival rates. The cumulative distribution function for Weibull to be used for modeling can be defined as follows:

$y = a - (a - d) * e(-(st)m)$

Where

a = Upper asymptote

d = Lower asymptote

t = Time

m = Parameter that controls the x-ordinate for the point of inflection

s = Growth rate

It should be noted that, when the parameter "m" equals 1.0, the Weibull equation is basically an exponential growth curve.

Logistic

Logistic function is one of the most common modeling equations and is used in many different fields. The drawback of the model is that it can calculate "t" over a small range of real numbers. The simple logistic function can be defined as the following equation:

$$y = \frac{1}{1 + e^{-\,t}}$$

The cumulative distribution function of continuous logistic probability distribution is the logistic function as follows:

$$y = \frac{a}{1 + e^{-\frac{t-m}{d}}} + d$$

Where

a = Upper asymptote

d = Lower asymptote

t = Time

m = Time of maximum growth

s = Growth rate

Gompertz

Gompertz (1825) suggested a sigmoid function as a type of mathematical model for time series, where growth is slowest at the beginning and end of the time span. The equation is commonly used in biology and medicine to identify aging or spread of cancer cells, or in demographics to describe population in confined spaces, birth rates, etc. (Rowe et al., 2008). The basic equation of a Gompertz curve is as seen below:

$$\mathrm{y} = \mathrm{a}e^{-be^{-ct}} + d$$

Where

a = Upper asymptote

d = Lower asymptote

t = Time

b, *c* = Positive coefficients (c sets the growth rate)

Richards

A flexible sigmoid function was developed by Richards (1959), which is also referred to as the generalized logistic curve. It is widely used for modeling growth and easily matches different S-shaped curves (Mubareki and Sallam, 2014). The general representation of a Richards' curve is:

$$y = \frac{a - d}{(1 + \lambda e^{-st})^{1/m}} + d$$

Where

a = Upper asymptote

d = Lower asymptote

t = Time

m = Sets asymptote near which maximum growth

s = Growth rate

λ = Related to initial y value

Polynomial

The Polynomial model is given by

$$\mathrm{y} = \mathrm{a_n} t^n + a_{n-1} t^{n-1} + \cdots + a_1 t + a_0$$

where t is the time and $\mathrm{a_n}, a_{n-1}, \ldots, a_1, a_0$ are constant numbers that need to be estimated. The Polynomial model can be used for modeling pavement deterioration (Mubaraki 2010), but the choice of how many coefficients to estimate depends on the significance of adding an extra variable. In this model, the Polynomial model of best fit is of third degree, as given by:

$$\mathrm{y} = \mathrm{a_3} t^3 + a_2 t^2 + a_1 t + a_0$$

where $\mathrm{a_3}, a_2, a_1,$ and $\mathrm{a_0}$ need to be estimated from the regression.

Negative Binomial

Negative binomial is an extension of the Poisson sequence that causes the predicted result to be different from the mean μ of the Poisson distribution parameter. Thus, this generalization of Poisson allows the mean and variance to be different (over-dispersion) by adding a disturbance or error term. (Byers et al., 2003). It is commonly used in cases of over-dispersion and frequent-zero counts where linear models lack the distributional properties to properly represent the data and Poisson distribution cannot account for over-dispersion. (Poch and Mannering, 1996). The range of its applications includes driving accidents, neurologic lesions, leukocytes, healthcare utilization, and counts of rare animals (Byers et al., 2003). The negative binomial distribution probability mass function is as follows: $f\ (k, r, p) \equiv \Pr\ (X = k) = \binom{k+r-1}{k} p^k\ (1-p)^r \qquad for\ k = 0,1,2,\ldots.$

2.1.2 Probabilistic Models

The probabilistic models for pavement prediction that are currently in use are survivor curves, Markov chains, and semi-Markov.

2.1.2.1 *Survivor Curve*

Survivor Curve represent a graph for probability and the time that is used to determine a pavement prediction model, Figure 2.2. Developing survivor curves requires an observational time series of data consisting of construction, maintenance, and rehabilitation histories recorded by the road agencies (Austroads, 2012; Lytton, 1987). A probability distribution function (PDF) is usually defined by a Weibull distribution especially when the pavement conditions are approaching failure. The probability density curve for survival may be constructed from historical data by determining the percentage of pavements that must be maintained or rehabilitated each year after its most current major rehabilitation or new construction (Lytton, 1987). The PDFs can be used as input for other probabilistic approaches in performance prediction modelling (Austroads, 2012).

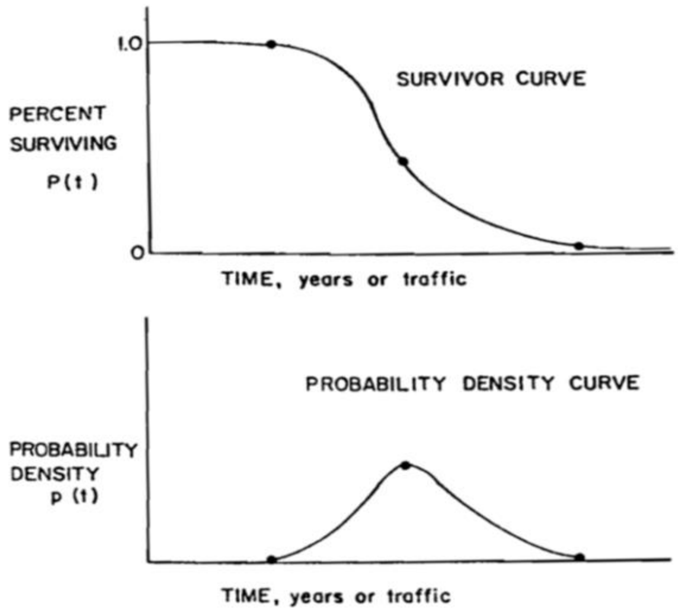

Figure 2.2 Survivor Curve (Lytton, 1987)

2.1.2.2 Markov Chains

Markovian Chain is the probabilistic model that has been very often used to build pavement deterioration models. The Markov process describes a probable "before" and "after" condition of the pavement. The probabilities are shifted downward to lower condition states that are described by ranges of a serviceability index (Arimbi, 2015). Figure 2.3, shows that the probability of pavement sections in state 4 in the "before" condition equals to 0.1. In the "after" condition, the number is reduced to 0 and probability in new states appear. Therefore, it creates a shift in the PDF. A Markov TPM expresses the probability that a group of pavements of similar age or traffic level will transition from one state of distress to another within a specified time period (Lytton, 1987). The most important aspect is to determine the probability of changing from one condition state to another. Theoretically, TPM is used to predict future performance without any explanatory power and thus contain inherent inaccuracy (Austroads, 2012).

In Markov chains, the condition of a pavement is based on its existing condition. The Markov approach assumes that the probability of changing from one state to another is independent of an item's earlier condition history (Austroads, 2012; Black, Brint, & Brailsford, 2005). In addition, performance prediction models from Markov chains are also able to integrate both deterioration rates and improvement rates (Abaza, Ashur, & Al-Khatib, 2004). Markov transition matrices can be constructed for any process of pavement and, especially if the assumptions that are made for the Markov processes are valid, can be used reliably to simulate the overall performance of a network of pavements of similar types with similar weather and traffic patterns (Lytton, 1987). However, in some cases, the assumption of time independence on Markov chains creates a disadvantage since it ignores non-load or environmental effects. In this case, a semi-Markov approach is used. As this model is practical and reliable to simulate the overall performance of a network of pavements of similar types with similar weather and traffic conditions, it is practical use in family pavement modeling.

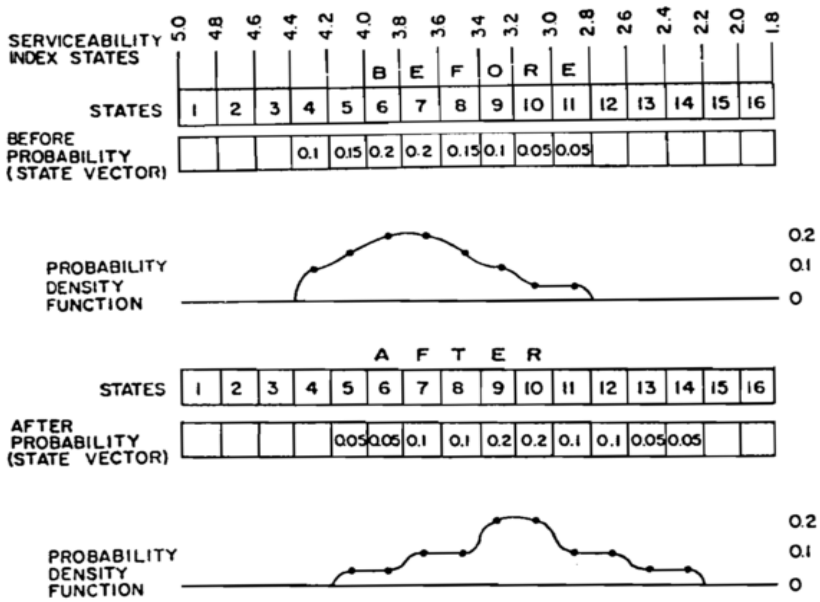

Figure 2.3 Markov Process (Lytton, 1987)

2.1.2.3 Semi-Markov

Semi-Markov is a modification to the Markov approach to overcome the independence of time assumption used when changing from one pavement condition state to another (Lytton, 1987). It recognizes that changing conditions (weather, traffic) creates a variation in the transition process. Semi- Markov allows a state's transition probability to depend on the time spent in that state (Black et al., 2005). In the prediction of pavement performance, the transition process in TPMs is typically implemented at one-year time intervals to compensate for time-related and other unforeseen impacts on pavement performance. This model is more feasible to simulate the performance of the pavement section at the project level, as it may include factors that affect the condition of the pavement, such as the weather and traffic conditions of particular streets, as a family modeling approach grouping similar pavement sections, taking into account a number of factors that affect the performance of the pavement.

2.1.3 Prediction Models Developed in Texas

The modeling system accounts for a broad network spanning various environments in Texas that enables separate models to be used under different circumstances. The prediction models developed by TXDOT are divided into categories based on the following factors (Feng Hong, 2017):

- Climate subgrade zones: Zone 1, Zone 2, Zone 3, and Zone 4 across the state of Texas. Zone 1 covers wet-cold climate and poor, very poor, or mixed subgrade. Zone 2 covers wet-warm climate and poor, very poor, or mixed subgrade. Zone 3 covers dry-cold climate and good, very good, or mixed subgrade. Zone 4 covers dry-warm climate and good, very good, or mixed subgrade.
- Pavement families: asphalt pavement, Continuous Reinforced Concrete Pavement (CRCP), Jointed Concrete Pavement (JCP). The asphalt pavement is further divided into subgroups of A, B, and C mainly based on the structural capacity.
- Treatment types: Preventive Maintenance (PM), Light Rehabilitation (LR), Medium Rehabilitation (MR), and Heavy Rehabilitation (HR).
- Traffic loading levels: low, medium, and heavy traffic based on the 1 predicted 20 years of Equivalent Single Axle Loads (ESALs).

Within each of the families identified by the criteria above, a sigmoidal curve is used to project the conditions of the pavement. The specification of the model adopted for each model category is as follows:

$$Li = \alpha e^{\wedge} - (\frac{\rho}{t})^{\beta}$$

Where,

Li is the dependent variable, which refers to the level of distress or ride quality loss for all pavement types including alligator cracking, transverse cracking, longitudinal cracking, and rutting for asphalt pavement, spalled cracking, and punchout for CRCP, finally slabs with longitudinal cracking and failed slabs for JCP.

t is the age of pavement since last treatment; and α, β and ρ are the model coefficients. These parameters were recently calibrated for each model group respectively.

The Texas Transport Institute in cooperation with the Texas State Department of Highways and Public Transportation also investigated appropriate curve fitting of actual pavement performance data, for use in serviceability prediction (Garcia-Diaz 1985). The proposed model represents an improvement over the form of the original AASHO Road Test performance equation in that it predicts more realistic long-term behavior. This is achieved using a sigmoid or S-shaped curve that recognizes the ability of a pavement to reduce its rate of deterioration as the traffic level approaches the service life of the pavement. The shape that a functional performance curve should take can be deduced from the boundary conditions placed on the serviceability index scale as well as the long term. The following equation with subsequent parameters has been developed by Texas

Department of Transportation (Robinson et al. 1996, and Dossey and Hudson 1994). The Stannard and Shute equations (Zwietering et al. 1990) are sigmoid functions that measure the growth rate. They have a complex structure and more than 3 parameters and are written respectively as follows:

$$\mathrm{y(t)} = a\{1 + \exp[-\frac{l + kt1b}{p}]\}^{-p}$$

$$y\ (t) = \{y1^b + (y2^2 - y1^b)\frac{1 - \exp[-a(t - \lambda)]}{1 - \exp[-a(\lambda b - \lambda 1)]}\}^{1/b}$$

The Morgan-Mercer-Flodin model has the following formula (Rowe et al. 2008)

$$y = a - \frac{a - \beta}{1 + \lambda t^t}$$

The (a) parameter controls the upper asymptote

The (β) parameter at t=0,

The (λ) parameter controls the growth rate

The (a) parameter controls the point of inflection α

Another study was carried out by Christopher (Robinson et al. 1996). The main objective of the study was to establish models for rigid pavement distress levels versus pavement age. For the Pavement Management Information System (PMIS) for the Texas Department of Transportation, a distress prediction model for Portland cement concrete pavements in Texas has been developed. The research quantitatively predicts the level of distress versus the age of pavement on the basis of data on pavement condition maintained by the Center for Transportation Research (CTR) at the University of Texas at Austin. The following models are available in Continuously Reinforced

Concrete Pavement (CRCP) for the following types of distress: Portland concrete patches, asphalt patches, loss of serviceability as calculated by loss of ride score, transverse crack spacing, and crack spelling. Preliminary models are available for the following distresses in the Jointed Concrete Pavement (JCP) and Jointed Reinforced Concrete Pavement (JRCP): patches, corner breaks, broken joints and cracks, transverse crack spacing, and longitudinal crack slabs. A sigmoid regression equation has been used for all forms of distress. These models are applicable only to Portland cement concrete pavements that are not overlaid and are based on a fifteen-year upper limit for CRCP and sixteen years for JCP. Using the sigmoid equation with the available data, the models represent the most accurate regression possible. In both rigid and flexible pavements, the Texas PMIS utilizes the sigmoid equation to predict all forms of distress. Most of the JCP distress models showed considerable dispersion, suggesting that pavement age is not the only significant factor in predicting distress, and perhaps not the most critical one. However, as a function of age, all the models represent rational patterns of growing distress. They stressed the need for frequent data collection in order to better track pavement behavior over time. Some models for urban roads were developed in a study performed by Shiyab (2007) for the use of PMS. The study showed that the exponential function and polynomial function were found to fit well with general data trends with enough accuracy to satisfy the general boundary conditions that were specified in the methodology chapter for the deterioration of the pavement system. Some of the developed model is as follows:

Local Residential:

$$PQI = 100e^{-0.011\,Age}$$

$$PQI = 100 - 0.276\,Age - 0.030\,Age^2$$

Where *PQI* = pavement quality Index

Local Commercial:

$$PQI = 100e^{-0.015\,Age}$$

$$PQI = 100 - 0.408\,Age - \ 0.035\,Age^2$$

Where *PQI* = pavement quality Index

Another study that used sigmoid and power functions for modelling overlaid sections was carried out by Adel et al (1996), as follows.

The power form is:

$$DMR = 100 - 5.17\ (Age)^{\ 0.58}$$

Where *DMR* = Distress Maintenance Rating

The sigmoid Form is:

$$DMR = 100 - 43.96\ e^{\left(\frac{-2.49}{Age^{\wedge}-0.56}\right)}$$

Chapter 3: Data Collection and Management

The objective of this chapter was to collect historical data to develop reliable models that take into consideration the local conditions in the Dallas-Fort Worth Metroplex. The historical pavement condition data and shape files have been obtained from the pavement asset management services of five cities in the Dallas-Fort Worth Metroplex area as follows: Dallas, Fort Worth, Arlington, Burleson, and Garland. Other cities that responded positively to the request for data did not have any historical records or had pavement condition data only for a period of one year. *Figure 3.1* shows the road network in the DFW area for major cities that provided PCI and IRI data for this research. Raw data received from the cities was organized and summarized by asset ID, street name, install / reconstruction year, speed limit, traffic count, pavement type, functional class, PCI, and IRI per year. Samples of the dataset are given in *Tables 3.1*, *3.2*, and *3.3*. The data was summarized by using a pivot table as shown in *Tables 3.4, 3.5,* and *3.6.*

Information regarding the location of Expansive subgrade soil for the Dallas-Fort Worth Metroplex was obtained from the Web Soil Survey site. The data was obtained as a geodatabase file. Using Arch Map GIS software, the data was imported and analyzed. It had a soil boundary that shows the frequency of the presence of expansive subgrade soil as high, medium, low, and extremely limited levels of expansive subgrade soil as shown in *Figure 3.2.* After the raw data was received from the cities, they were organized by pavement section identification number, age, and PCI or IRI as shown in *Tables 3.1, 3.2, & 3.3.* Since raw data may have some errors, it is necessary to clean the data and remove bad data points in order to perform the statistical analysis.

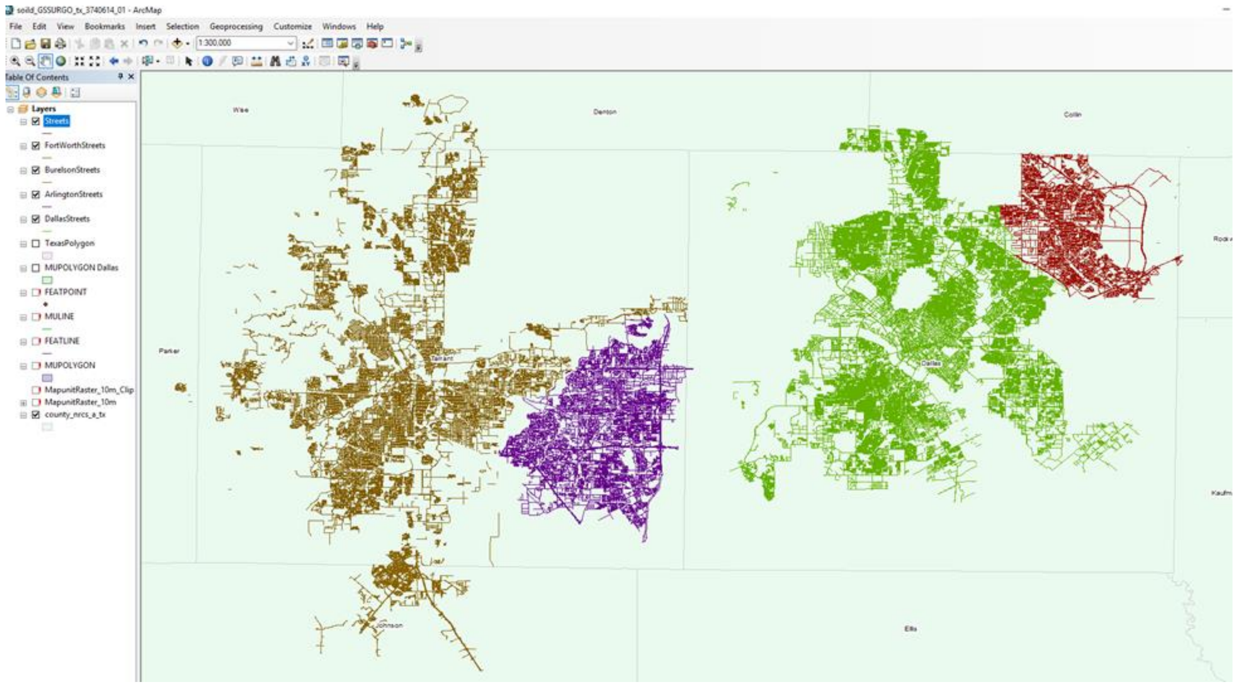

Figure 3.1 Roads network in DFW's area (GIS)

Asset ID	Street Name	Pavement Type	Functional Class	Expansive Soil	Latest Rehab/Reconst Year	PCI 2007	PCI 2008	PCI 2009	PCI 2010	PCI 2011	PCI 2012	PCI 2013	PCI 2014	PCI 2015	PCI 2016	PCI 2017	PCI 2018
49246	FORT WORTH AVE	AC	ART	Yes	2002		72			66				61	58		
50002	W DAVIS ST	AC	ART	Yes	2002		70							59			
53079	S BECKLEY AVE	AC	ART	Yes	2002		75		67				44				
54756	S LEDBETTER DR	AC	ART	Yes	2002		72		68	64	55						
54844	W LEDBETTER DR	AC	ART	Yes	2002		71		63	52	32						
59180	CANADA DR	AC	ART	Yes	2002		74	72		68					63		60
60653	OAK LAWN AVE	AC	ART	Yes	2002		71	60									47
61405	W JEFFERSON BLVD	AC	ART	Yes	2002		73	66						49	49		
61824	OAK LAWN AVE	AC	ART	Yes	2002		73		57								54
61918	W RED BIRD LN	AC	ART	Yes	2002		74	70		68			68		59		
62243	S MARSALIS AVE	AC	ART	Yes	2002		72					43					
68551	E ILLINOIS AVE	AC	ART	Yes	2002		72	70		58	48		45			39	
68659	W ILLINOIS AVE	AC	ART	Yes	2002		72	60	59					50	40		
82996	MILITARY PKWY	AC	ART	Yes	2002		74	70	62				59				47
83519	MCKINNEY AVE	AC	ART	Yes	2002		73	69		66							51
85855	S LAMAR ST	AC	ART	Yes	2002								60				47
86260	S LAMAR ST	AC	ART	Yes	2002		73						71			53	
86790	W RED BIRD LN	AC	ART	Yes	2002		74	68		67			62		59		
86791	W RED BIRD LN	AC	ART	Yes	2002		70	70		68			68		60		
86792	W RED BIRD LN	AC	ART	Yes	2002		70	68		68			63		56		
86796	W RED BIRD LN	AC	ART	Yes	2002		73	71		68			67		63		
88562	S FITZHUGH AVE	AC	ART	Yes	2002		73	71		66			66				60
88564	S FITZHUGH AVE	AC	ART	Yes	2002		72	64		55			50				38
89659	MARSH LN	AC	ART	Yes	2002		74	72		72					59		54

Table 3.1 Sample for PCI data for the streets built on Expansive subgrade soil

Asset id	STREET NAME	PAVEMENT TYPE	FUNCTIONAL CLASS	Expansive Soil	Latest Rehab/Reconstruction Year	PCI 2014	PCI 2015	PCI 2016	PCI 2017	PCI 2018	PCI 2019
PST0000004	TAXCO RD	AC	LR	No	1999	52	50	48	45	42	41
PST0000007	BROADMOOR DR	AC	LR	No	2006	67	64	63	61	58	56
PST0000008	EASTVIEW ST	AC	LR	No	2014	98	94	89	87	84	76
PST0000009	ALBERMARLE DR	AC	LR	No	2008	60	59	56	54	51	49
PST0000010	WINDY HILL LN	AC	LR	No	2015	59	100	94	88	87	83
PST0000011	WIND CHIME DR	AC	LR	No	2004	62	61	58	57	54	51
PST0000012	STAFFORD DR	AC	LR	No	2012	88	87	80	79	71	69
PST0000013	PINEY POINT ST	AC	LR	No	2002	59	57	54	52	50	46
PST0000014	WESTMERE LN	AC	LR	No	2015	53	95	94	88	85	81
PST0000015	COLDSTREAM DR	AC	LR	No	2014	97	93	88	85	80	78
PST0000016	DIRKS RD	AC	LR	No	2012	89	86	83	76	74	69
PST0000017	DIRKS RD	AC	LR	No	2012	89	87	83	78	72	69
PST0000018	JENNIE DR	AC	LR	No	2012	89	86	83	77	74	69
PST0000019	WHITEWOOD DR	AC	LR	No	2015	55	100	92	89	87	82
PST0000070	CAMPBELL ST	AC	LR	No	2012	88	85	82	77	74	68
PST0000202	OCEAN CT	AC	LR	No	2014	100	92	88	87	82	75
PST0000203	KESWICK DR	AC	LR	No	2013	91	89	87	82	76	73
PST0000217	GRAND AVE	AC	LR	No	2001	57	55	52	50	46	45
PST0000226	RANCHO VERDE PKWY	AC	LR	No	2015	60	95	94	89	86	82
PST0000227	GLASGOW RD	AC	LR	No	2009	75	74	69	67	65	62
PST0000228	BILGLADE RD	AC	LR	No	2002	58	56	54	52	49	46
PST0000229	5TH ST, NE	AC	LR	No	2015	63	98	92	89	87	80
PST0000238	WILTON DR	AC	LR	No	2012	89	85	83	77	71	68
PST0000289	HORIZON PL	AC	LR	No	2014	99	91	89	85	80	76
PST0000291	DUBLIN DR	AC	LR	No	2013	92	89	86	83	77	74
PST0000300	RANCHO DIEGO LN, W	AC	LR	No	2012	88	87	82	75	74	69
PST0000301	VEGA DR	AC	LR	No	2008	60	58	57	55	52	49
PST0000302	WINESANKER WAY	AC	LR	No	2001	56	55	53	49	46	45
PST0000303	PERSHING AVE	AC	LR	No	1999	53	49	48	44	42	40
PST0000304	MADRID DR	AC	LR	No	2001	56	55	52	49	48	44
PST0000329	CANTEY ST, W	AC	LR	No	2013	91	89	86	80	78	74
PST0000330	WINDWILLOW DR	AC	LR	No	2002	59	57	54	52	49	46
PST0000336	EDGEHILL RD	AC	LR	No	2008	61	58	56	54	53	49
PST0000340	SOUTH DR, W (COURT	AC	LR	No	2014	100	92	88	86	83	78
PST0000346	LIMERICK DR	AC	LR	No	2008	60	59	56	54	51	50

Table 3.2 Sample of PCI data for the streets built on non-Expansive subgrade soil

Asset ID	Street Name	Pavement Type	Functional Class	Expansive Soil	Latest Rehab/Reconst Year	IRI 2007	IRI 2008	IRI 2009	IRI 2010	IRI 2011	IRI 2012	IRI 2013	IRI 2014	IRI 2015	IRI 2016
28958	PASTEUR AVE	PCC	LR	Yes	1988				469		493	507			
28962	CARTAGENA PL	PCC	LR	Yes	1993			304	314		335	349			
28972	HIBISCUS DR	COM	LR	Yes	1995		249	262	275			303			
29020	MEADOW WAY CT	AC	LR	Yes	2006			345	362		393	408			
29053	LAKELAND DR	PCC	COL	Yes	1993		333		357				402		
29117	HOMEWAY CIR	AC	LR	Yes	1989			332	349		375	390			
29124	JOHN WEST RD	PCC	COL	Yes	1997		165	179	190				240		
29134	CHART DR	PCC	LR	Yes	1988		324	337	350		369	379			
29138	LAKELAND DR	PCC	COL	Yes	1993		332	343	356				399		
29163	LAKELAND DR	PCC	COL	Yes	1993		263	274	283				328		
29178	TWINLAWN DR	PCC	LR	Yes	1993		418	428	439		463	475			
29223	BRETSHIRE DR	PCC	LR	Yes	1993		331	344	355						
29295	JOHN WEST RD	PCC	COL	Yes	1995		255	265	279				318		
29358	ROCKYGLEN DR	AC	LR	Yes	2003		227	244			284	297			
29390	PETUNIA ST	PCC	LR	Yes	2007			205	218			254			
29400	DORRINGTON DR	AC	LR	Yes	1998		276	289	306		335	349			
29419	ST FRANCIS AVE	PCC	LR	Yes	1995		410	419	432		451	461			
29421	SWEETWATER DR	AC	LR	Yes	1998		253	268	283		314	327			
29431	JOHN WEST RD	PCC	COL	Yes	1995		231		253				294		
29520	LA PRADA DR	PCC	ART	Yes	1997		173	186	197				242		
29540	JOHN WEST RD	PCC	COL	Yes	1997		234		257				298		
29544	JOHN WEST RD	PCC	COL	Yes	1995		211		233				278		
29547	ANGIER WAY	PCC	LR	Yes	1993		311	325		351	363	377			
29661	JOHN WEST RD	PCC	COL	Yes	1997			215	225				277		
29693	FENESTRA DR	COM	LR	Yes	1998		231	242	254		276	290			
29723	BELLINGHAM DR	PCC	LR	Yes	1995			322	335		363	373			
29762	OHARE CT	PCC	LR	Yes	2007		191	201	214		234	243			
29769	PINEBLUFF DR	PCC	LR	Yes	1994		273	286			322	336			
29775	DORRINGTON DR	COM	LR	Yes	1988		212	223	237		258	270			
29816	GRAYCLIFF DR	COM	LR	Yes	1993		230	239	248		269				
29836	HUNNICUT RD	AC	LR	Yes	2003			188	204		234	249			
29875	ST THOMAS CIR	AC	LR	Yes	2007		195	211	224		254				
29937	BANQUO DR	AC	LR	Yes	1998		326	340	356		383	395			
29943	BAUMGARTEN DR	PCC	LR	Yes	2002		270	283			319				
29973	CHENAULT ST	AC	COL	Yes	2007		173	185	201		229				

Table 3.3 Sample of IRI data for the streets built on Expansive subgrade soil

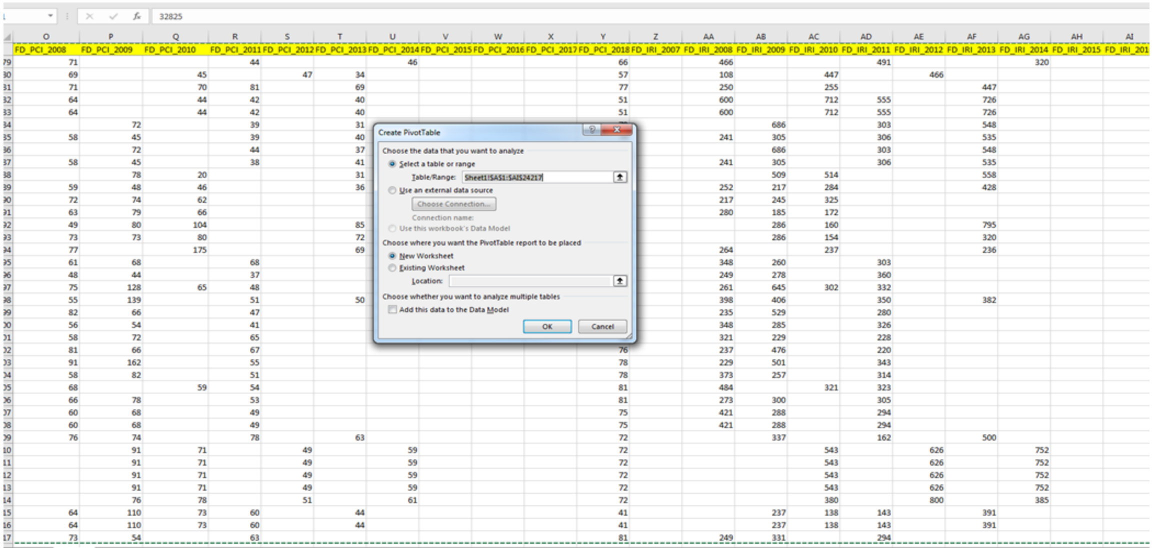

Table 3.4 Sample for Creating Pivot Table

Count of FD_SB_ID	Column Labels							
Row Labels	Alley	Arterial	Collector Improved	Collector Unimproved	Local Improved	Local Unimproved	Unknown	Grand Total
Asphalt	57	1,421	390	218	5,529	1,514	5	9,134
Asphalt Over Concrete	1	1,414	387	14	1,997	40		3,853
Concrete	174	3,139	1,311	18	6,493	54	1	11,190
Gravel	6				3	15		24
Other						1		1
Unknown							14	14
Grand Total	**238**	**5,974**	**2,088**	**250**	**14,022**	**1,624**	**20**	**24,216**

Table 3.5 Summary of information for streets built on Expansive subgrade soil

Count of Asset id	Column Labels				
Row Labels	Arterial	Collector	Local Residential	Rural Road	Grand Total
Brick	67		25		92
Composite	808	67	531		1,406
Hot Mix	776	1,039	11,311	302	13,428
Rigid - PCC	1,663	465	10,205	10	12,343
Surface Treated	85	101	2,932	80	3,198
Unknown/Undefined			28	3	31
Grand Total	**3,399**	**1,672**	**25,032**	**395**	**30,498**

Table 3.6 Summary of information for streets built on non-Expansive subgrade soil

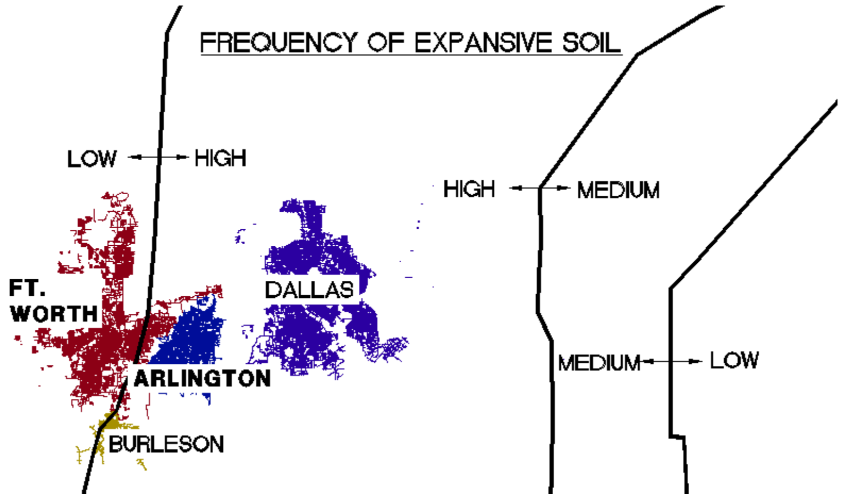

Figure 3.2 Frequency of Expansive subgrade soil

The criteria for removing and filtering data were as follows:

1. Only the age of the pavement section and the measured PCI/IRI values were extracted from the raw dataset for the development of performance models.
2. Each pavement section has PCI recorded each year. If the PCI makes a sudden jump, and immediately falls to the previous trend, then the PCI record of that year was removed. Similarly, for the IRI, this approach was adopted and values were removed when sudden drops occurred.
3. If the year of construction or last major rehabilitation of the pavement section occurred before the first recorded year in the data, and the pavement section saw an increase in PCI, then only data recorded after this increased point was retained. This approach was used for IRI data also where only data after decreased IRI values were retained.
4. Further examination of the data for statistical removal of extreme points was performed by the outlier analysis. The data was sorted to highlight unusual values. After it was sorted, data with unusually high or low values were removed.

5. Furthermore, the data was analyzed to eliminate the street sections that were older than 10 years for AC and COM pavement families, and 15 years for the PCC pavement family from the first recorded PCI record in the 2007 research for Expansive subgrade soil, and 2014 for non-expansive subgrade soil. The reason why 10 and 15 years were chosen is because the life expectancy for the pavements is roughly as follows: AC flexible pavement 20-25 years, and for PCC rigid pavement 30-35 years. It is assumed that for AC and PCC pavements, they reach half of their service life after 10 and 15 years respectively.

The final dataset that results from the data cleaning were used to construct the deterioration models. The dependent variables were PCI and IRI. It is typical to use deterministic models when given the full historical data; however, the Markovian probabilistic prediction model can be constructed from either the historical data or even limited data, but on at least two consecutive years. *Table 5.2* shows the states which were used for the Markovian prediction model.

The development of accurate performance models requires all significant variables to be included in the model's development. Since the type, functional class of the pavement, and the type of subgrade soil that the pavement was built on are categorical in nature, these factors are difficult to include in the deterioration models themselves. Therefore, the family modeling approach was used. To reflect the effect of traffic volume on the condition deterioration each of the asphalt/concrete/composite-surfaced families were further separated into families for arterial, collector, residential/local roads and rural roads. This subsequent separation provides a way to take differences of traffic into account without requiring the accurate traffic counts in the database. This method reduces the number of independent variables in the performance model to a single independent variable (age in this study) by allowing the development of models in each family. The pavement performance model developed for the family will be used in the cities pavement management system to represent the rate of deterioration for all the pavement sections that meet the family definition. It is expected that the definition of pavement families is comprehensive enough that each pavement section in the pavement management database falls into one, and only one pavement family.

From *Tables 3.1, 3.2* and *3.3*, pavement families were defined as a category of pavement sections with the families defined based on pavement type [asphalt concrete (AC) , Portland cement concrete (PCC), and composite (COM)], functional class [arterial (ART), collector (COL), residential/local (LR) and rural (RU)], and soil type (Expansive and non-Expansive) as shown in the *Figure 3.3*. A total of twenty-four different families result from the family definition. Since the data obtained from the pavement asset management departments of the cities had no record for rural roads (RU) in the area with expansive subgrade soil, these models could not be developed. Furthermore, the deterioration model for the COM-RU pavement family could not be developed for the non-expansive subgrade soil area as data was not available. As a result, a total of eleven deterioration models were developed for streets with non-expansive sub-grade soil as well as nine street deterioration models with expansive sub-grade soil. For each of these twenty pavement families, the deterioration models were developed using the SAS statistical software. The deterministic models which were used will predict a single dependent value PCI/IRI from the age as an independent variable. Probabilistic models were also developed from the twenty families using consecutive years of PCI data from the Markovian Chain approach.

The model development procedure had the following steps:

- Data recovery and sorting by pavement family

- Data error filtering
- Outlier identification
- Development of Deterministic model
- Development of Markov model

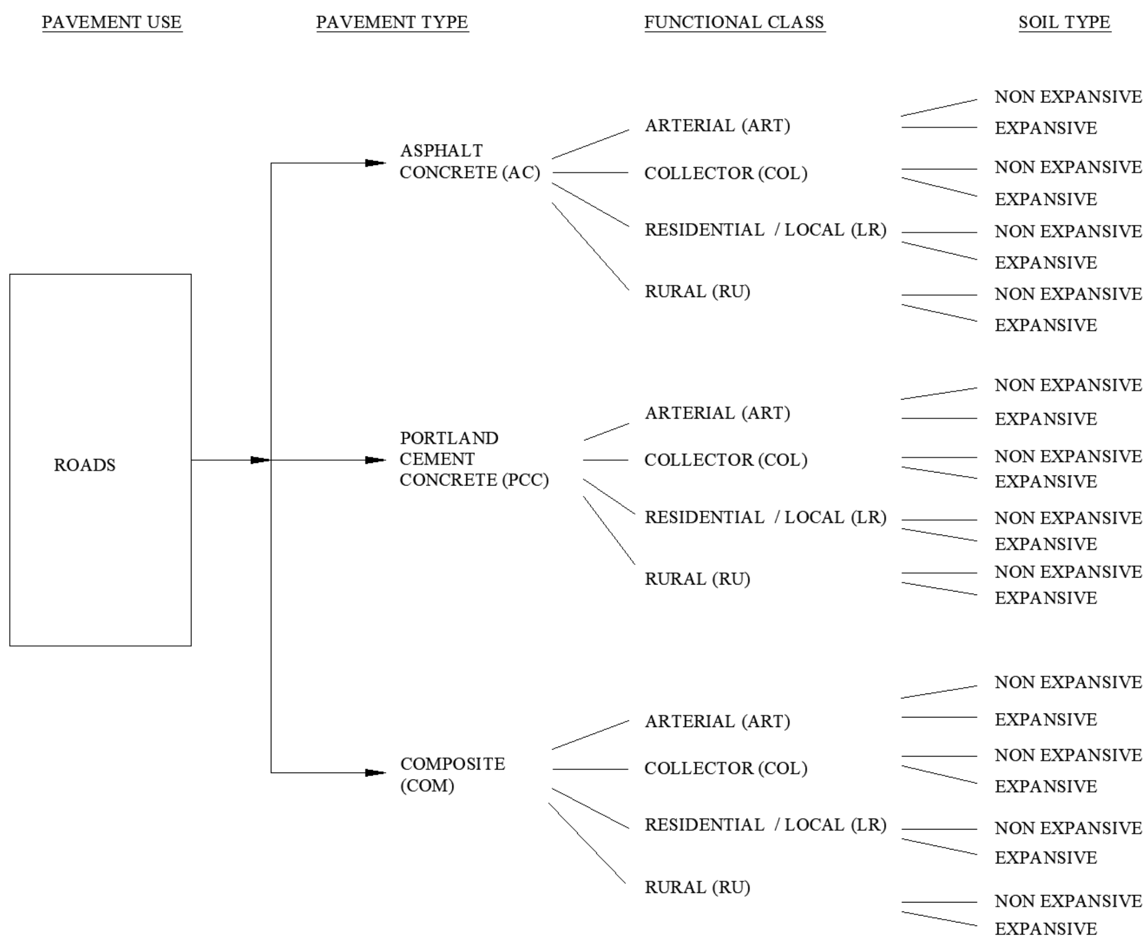

Figure 3.3 Pavement Family Definition

Chapter 4: Development of Deterministic Street Deterioration Models

Model Variables

For the development of pavement performance prediction models, the dependent and independent variables should be chosen carefully. The dependent variable should be an index that reflects the pavement condition at a given time. As mentioned in data collection, the dependent variables are Pavement Condition Index (PCI) and International Roughness Index (IRI). Since the family modeling approach is used, the independent variable will be age, defined as the time in years since the construction or last major rehabilitation.

Model Development

Multiple model formulations were explored to find the best deterioration model for the streets in the Dallas-Fort Worth Metroplex area. Seven functional forms for the deterioration model were studied: Cubic Polynomial, Gompertz model, Logistic model, Stantec (also known as Adjusted Stantec) model, Exponential Curve model, Second Polynomial model, and Sigmoidal model (*Table 4.1*). All these models were fitted to the data using nonlinear regression by minimizing the sum of squares, i.e. minimizing SS_{err} with respect to the given functional form. The models will be fit to each of the families shown in *Figure 3.3*, so a performance model will be developed for each of the twenty families. The statistics reported in the following models include coefficient estimates for each functional form, their 95 percent confidence intervals, the SS_{err} (reported as SSE), the coefficient of determination (R^2), and the root mean squared error ($RMSE = \sqrt(\frac{SS_{err}}{n-p})$ where n is the number of observations and p is the number of estimated coefficients in the functional form. A low SS_{err}, a high R^2 and a low $RMSE$ are desired when evaluating the models.

After fitting all the models, a procedure using the goodness of fit measures such as the R^2 and RMSE will be used to find the best model. The model that has the highest R^2 and lowest RMSE will be chosen as the final selected model. This procedure was repeated for each family member shown in *Figure 3.3.* The model fitting procedure will be used for both PCI and IRI data.

The summarized models that will be used for the development of deterministic deterioration models for PCI and IRI is shown in *Table 4.1*.

	Model	**Equation (PCI/IRI = y)**	**Coeff.**	**Start value (@ t=0) V**
1	Cubic Polynomial Safak Ercisli (2015)	$y = dt^3 + ct^2 + bt + a$	a, b, c, d	a a=V
2	Gompertz *Safak Ercisli (2015)*	$y = ae^{-be^{-ct}}$	a, b, c	ae^{-b} $a=V/e^{-b}$
3	Logistic Kaur, D., and Pulugurta, H. (2008)	$y = \frac{a}{1 + e^{-\frac{t}{c}}} + b$	a, b, c	a/2 + b a = 2*(V- b)
4	Adjusted Stantec – *Stantec (2007),*	$y = 100 - e^{a(1-b^t)}$	a, b	99
5	Exponential Safak Ercisli (2015)	$y = b - (b - a) * e^{-ct}$	a, b	a a=V
6	Second Polynomial Safak Ercisli (2015)	$y = ct^2 + bt + a$	a, b, c	a a=V
7	Sigmoidal *Han Jun; Moraga (1995),*	$y = a * \left[\frac{t^b}{c + t^b}\right]$	a, b, c	a/(c+1) for t=1 a=V*(c+1) for t=1

Table 4.1 Summarized deterministic models

After the data was sorted and cleaned as described in Chapter 3, the data was analyzed to eliminate the street sections for which the first measured PCI was recorded more than 10 years prior for AC and COM pavement families, and 15 years for PCC pavement family after the construction or latest major rehabilitation.

Table 4.2, shows a summary of all the data with the percent of good data for modeling after elimination of the data that are not reliable for development of prediction models. Good data is data which has been cleaned and organized as described in Chapter 3.

Table 4.3 shows a sample of PCI data obtained by the city asset management departments between 2007 and 2018 for streets constructed on expansive subgrade soil. *Table 4.18* displays the sample data for the PCI historical record from 2014 to 2019 for streets built on non-expansive subgrade soil.

Family	Pvmt Type	Func. Class	Expsnsive Soil	Total No.	Last Rehab before 1997/2004* (AC - 10 Yrs.)	Last Rehab before 1997/2004* (COM -10 Yrs.)	Last Rehab before 1992/1999* (PCC - 15 Yrs.)	Good Data for Modeling	% of Good Data
1	AC	ART	YES	1,421	98	N/A	N/A	**1,323**	93%
2	AC	COL	YES	608	101	N/A	N/A	**507**	83%
3	AC	LR	YES	7,043	1,237	N/A	N/A	**5,806**	82%
4	PCC	ART	YES	3,139	N/A	N/A	134	**3,005**	96%
5	PCC	COL	YES	1,329	N/A	N/A	84	**1,245**	94%
6	PCC	LR	YES	6,547	N/A	N/A	1,015	**5,532**	84%
7	COM	ART	YES	1,414	N/A	475	N/A	**939**	66%
8	COM	COL	YES	401	N/A	174	N/A	**227**	57%
9	COM	LR	YES	2,037	N/A	1,299	N/A	**738**	36%
10	AC	ART	NO	776	216	N/A	N/A	**560**	72%
11	AC	COL	NO	1,039	338	N/A	N/A	**701**	67%
12	AC	LR	NO	11,316	6,856	N/A	N/A	**4,460**	39%
13	AC	RU	NO	302	**126**	N/A	N/A	**176**	58%
14	PCC	ART	NO	1,663	N/A	N/A	192	**1,471**	88%
15	PCC	COL	NO	465	N/A	N/A	80	**385**	83%
16	PCC	LR	NO	10,205	N/A	N/A	780	**9,425**	92%
17	PCC	RU	NO	10	N/A	N/A	-	**10**	100%
18	COM	ART	NO	808	N/A	**111**	N/A	**697**	86%
19	COM	COL	NO	67	N/A	**7**	N/A	**60**	90%
20	COM	LR	NO	531	N/A	160	N/A	**371**	70%
PCI - Data			**Total:**	**51,121**	**8,972**	**2,226**	**2,285**	**37,638**	

Table 4.2 PCI Data for Expansive and Non-Expansive subgrade soil

* - Data for Non-Expansive subgrade soil

4.1 Development of Deterministic PCI Deterioration Models for Streets with Expansive Subgrade Soil

All seven models shown in *Table 4.1* have been used to select the best deterministic deterioration model for streets in the DFW Metroplex area with expansive subgrade soil. Every model had to comply with the following requirements:

- The slope of the deterioration curve must always be negative
- The initial PCI values were set to 99 right after construction or major rehabilitation
- The PCI value cannot be less than zero.

Asset ID	Street Name	Pavement Type	Functional Class	Expansive Soil	Latest Rehab/Reconst Year	PCI 2007	PCI 2008	PCI 2009	PCI 2010	PCI 2011	PCI 2012	PCI 2013	PCI 2014	PCI 2015	PCI 2016	PCI 2017	PCI 2018
49246	FORT WORTH AVE	AC	ART	Yes	2002		72			66				61	58		
50002	W DAVIS ST	AC	ART	Yes	2002		70							59			
53079	S BECKLEY AVE	AC	ART	Yes	2002		75		67				44				
54756	S LEDBETTER DR	AC	ART	Yes	2002		72		68	64	55						
54844	W LEDBETTER DR	AC	ART	Yes	2002		71		63	52	32						
59180	CANADA DR	AC	ART	Yes	2002		74	72		68					63		60
60653	OAK LAWN AVE	AC	ART	Yes	2002		71	60									47
61405	W JEFFERSON BLVD	AC	ART	Yes	2002		73	66						49	49		
61824	OAK LAWN AVE	AC	ART	Yes	2002		73		57								54
61918	W RED BIRD LN	AC	ART	Yes	2002		74	70		68			68		59		
62243	S MARSALIS AVE	AC	ART	Yes	2002		72					43					
68551	E ILLINOIS AVE	AC	ART	Yes	2002		72	70		58	48		45			39	
68659	W ILLINOIS AVE	AC	ART	Yes	2002		72	60	59					50	40		
82996	MILITARY PKWY	AC	ART	Yes	2002		74	70	62				59				47
83519	MCKINNEY AVE	AC	ART	Yes	2002		73	69		66							51
85855	S LAMAR ST	AC	ART	Yes	2002								60				47
86260	S LAMAR ST	AC	ART	Yes	2002		73						71			53	
86790	W RED BIRD LN	AC	ART	Yes	2002		74	68		67			62		59		
86791	W RED BIRD LN	AC	ART	Yes	2002		70	70		68			68		60		
86792	W RED BIRD LN	AC	ART	Yes	2002		70	68		68			63		56		
86796	W RED BIRD LN	AC	ART	Yes	2002		73	71		68			67		63		
88562	S FITZHUGH AVE	AC	ART	Yes	2002		73	71		66			66				60
88564	S FITZHUGH AVE	AC	ART	Yes	2002		72	64		55			50				38
89659	MARSH LN	AC	ART	Yes	2002		74	72		72					59		54
89662	MARSH LN	AC	ART	Yes	2002		74	65							65		48
89663	MARSH LN	AC	ART	Yes	2002		71	54		53					48		46
89673	MARSH LN	AC	ART	Yes	2002		74	74		74					73		67
89677	MARSH LN	AC	ART	Yes	2002		71	69		60					57		38
89678	MARSH LN	AC	ART	Yes	2002		75	69							65		57
89679	MARSH LN	AC	ART	Yes	2002		71	62		57							46
89681	MARSH LN	AC	ART	Yes	2002		72	64		58					57		51
89686	MARSH LN	AC	ART	Yes	2002		72	69							65		57
89687	MARSH LN	AC	ART	Yes	2002		71	71		58					57		46
89688	MARSH LN	AC	ART	Yes	2002		72	69		62					57		51
89912	MILITARY SERV N	AC	ART	Yes	2002		71	67		59	47		44				
89913	MILITARY SERV N	AC	ART	Yes	2002		70	69		65	61		56				
89957	N FITZHUGH AVE	AC	ART	Yes	2002		71	65		63			63				56
89958	N FITZHUGH AVE	AC	ART	Yes	2002		71	61		55			49				31
89959	N FITZHUGH AVE	AC	ART	Yes	2002		73	71		64			52				47
90094	S LAMAR ST	AC	ART	Yes	2002		73						71			63	
90104	S POLK ST	AC	ART	Yes	2002					67	55						
90110	S POLK ST	AC	ART	Yes	2002					65	33						
90390	W ILLINOIS AVE	AC	ART	Yes	2002		73	57	50						40		
90415	W JEFFERSON BLVD	AC	ART	Yes	2002		73	66						48	43		
90979	S BECKLEY AVE	AC	ART	Yes	2002		75		69				36				
91297	ABRAMS RD	AC	ART	Yes	2002		73	64	62			58				12	
91298	ABRAMS RD	AC	ART	Yes	2002		74	70	57			52				15	
91302	ABRAMS RD	AC	ART	Yes	2002		70	65	51			46				22	
91306	ABRAMS RD	AC	ART	Yes	2002		71	66	64	57		51				46	
91307	ABRAMS RD	AC	ART	Yes	2002		71	66	64	55		51				46	
91917	GREENVILLE AVE	AC	ART	Yes	2002		72	59	56				52				29
92073	S LAMAR ST	AC	ART	Yes	2002		73	63								40	
92904	ABRAMS RD	AC	ART	Yes	2002		70	69	68			63					45
92905	ABRAMS RD	AC	ART	Yes	2002		70	68	60			54					33
95172	S ZANG BLVD	AC	ART	Yes	2002		73	65						58			
101113	W RED BIRD LN	AC	ART	Yes	2002		70	68		67			64		47		
103647	S BECKLEY AVE	AC	ART	Yes	2002		74		72	63	63		59				

Table 4.3 PCI Sample Data for Expansive subgrade soil

Since the data obtained from cities with expansive subgrade soil was unbalanced (did not have the same number of PCI for each street section, *Figure 4.2*) an Excel macro script was used to calculate the street regression coefficient for each of the models shown in *Table 4.1*. For PCI models, it was a necessity to implement interactive non-linear least squares fitting method. To find the suitable PCI prediction model (best fit), initial regression coefficient values were assumed. Then using these initial values and proposed models' equations from *Table 4.1*, the square of difference between calculated values by the model and recorded PCI's square errors were calculated. The next step in finding the appropriate model was to minimize the value of the Sum of Square Error (SSE) defined in the following equation:

$$SSE = \Sigma\, (y - y_{fit})^2$$

Where y represents data point, and y_{fit}, is the value of the curve at point y. Further, the Excel Solver is used to minimize the final SSE by changing the initial regression values (a, b, c and d). Then, the Total Sum of Square and (TSS) is calculated to find R^2. The following formula was used to calculate TSS:

$$TSS = \Sigma(y - y_{\text{mean}})^2$$

Where y_{mean} is the average value of data points. The TSS depends on the numbers of measured data points. After SSE and TSS were calculated, a R^2 was calculated using following formula:

$$R^2 = 1 - \frac{SSE}{TSS}$$

At the end, the Solver determined regression coefficients (a, b, c and d) and R^2 for all street sections of all models. *Table 4.5* shows an example of the model output. The Excel macro script used is given in Appendix A.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
4																				
5	**ID**	**NAME**	**TYPE**	**CLASS**	**Exp_Soil**	**Latest_Rehab**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	a1	b1	c1
6	PST00306	DORAL DR	AC	LR	No	1998	50	46	45	43	41	39						99	-3.06211	-0.04177
7																				
8																				
9																				
10																				
11							Age													
12		**a**	**b**	**c**	**d**	**1**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	SSE	TSS	R2
13						99	50	46	45	43	41	39	0	0	0	0	0			
14		a1=V	b1	c1	d1															
15	Model 1	99	-3.06211	-0.04177	0.002474	95.89859	49.44695	47.02784	44.77758	42.71099	40.84294	39.18827	37.76182	36.57843	35.65297			1.555437	76	0.979534
16		a2=V/[exp(-b2)]	b2	c2																
17	Model 2	8.1915E+109	248.4898	-0.0002		94.27751	77.5279	73.82612	70.30042	66.94245	63.74426	60.69828	57.7973	55.03443	52.40313	49.897161	47.51057	11.38627		0.911962
18		a3=2*(V-b3)	b3	c3																
19	Model 3	99644.96696	-49723.5	-8401.1		96.03476	51.55625	48.59101	45.62578	42.66055	39.69532	36.73009	33.76486	30.79963	27.8344			16.49678		0.782937
20		a4	b4																	
21	Model 4	4.260772191	0.853827			98.13584	49.55774	46.98792	44.69037	42.65003	40.84847	39.26552	37.88048	36.67292	35.62331			1.483387		0.980482
22		a5=V	b5	c5																
23	Model 5	99	-9.87399	0.038145		94.92525	49.26422	47.05089	44.92041	42.86966	40.89566	38.99554	37.16653	35.40598	33.71132			1.679986		0.977895
24		a6=V*C6	b6	c6																
25	Model 6	-81253228.49	-0.27857	-820741		99	45.73078	44.96497	44.25469	43.59315	42.97469	42.39457	41.84872	41.33372	40.84657			35.62735		0.531219
26		a1=V	b1	c1																
27	Model 7	99	-2	0.005		98.8764	91.66667	88	83.89831	79.51807	75	70.46263	66	61.68224	57.55814	53.658537	50	177.4138	1.4634	-120.234
28																				

Figure 4.1 Excel Calculation using Macro script for all models – PCI - Expansive subgrade soil

Table 4.4 shows an example of an Excel macro where the initial value of 99 is set. This value was assumed to be the PCI after construction or major rehabilitation.

		Dialog Box		Value after last major rehab =			99															
										Run Macro												
ID	**NAME**	**TYPE**	**CLASS**	**Exp_Soil**	**Latest_Rehab**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
270	OLD MILL RD	AC	LR	Yes	1988		53	49		41												
288	OLD MILL RD	AC	LR	Yes	1991		57	56	44													
289	OLD MILL RD	AC	LR	Yes	1996		64	63	57													
290	OLD MILL RD	AC	LR	Yes	1984		45	44	40													
315	OLD MILL RD	PCC	LR	Yes	1988		65	65	37													
316	OLD MILL RD	PCC	LR	Yes	1993		71	70	45													
346	OLD MILL RD	AC	LR	Yes	1984		45	44	39													
347	OLD MILL RD	AC	LR	Yes	2003		78	77	76													
348	OLD MILL RD	AC	LR	Yes	2003		79	79	77													
397	OLD MILL RD	PCC	LR	Yes	1981		52	52	40													
2231	BELT LINE RD	PCC	ART	Yes	1995		75	51	38			24										
2317	BELT LINE RD	PCC	COL	Yes	1995		78		72			57										
3365	WALNUT ST	PCC	COL	Yes	1995		78	63	59													
3663	FOREST LN	PCC	COL	Yes	1995		77	74	70				68									
3716	FOREST LN	PCC	COL	Yes	1995		77	72	57													
6073	PLANO PKWY	AC	LR	Yes	2005		88	83		59												
7167	WILLARD DR	COM	LR	Yes	1988		67	67		53												
7395	BOEDEKER ST	AC	LR	Yes	2004		80	74		74												
15241	COOLWATER CV	PCC	LR	Yes	2003			86		76		63										
15789	BELT LINE RD	PCC	ART	Yes	1997		80		79			61										
15790	BELT LINE RD	PCC	ART	Yes	1997		83		77			71										
15791	BELT LINE RD	PCC	ART	Yes	1995		79		77			66										
15795	BELT LINE RD	PCC	ART	Yes	1995		79					71										
15814	BELT LINE RD	PCC	ART	Yes	1995		79		79			74										
15872	BELT LINE RD	PCC	ART	Yes	2002		88		78			74										
15874	BELT LINE RD	PCC	ART	Yes	1995		75					61										
15877	BELT LINE RD	PCC	ART	Yes	2002		86		77			66										
15880	BELT LINE RD	PCC	ART	Yes	1995		77	76	71			58										
15886	BELT LINE RD	PCC	ART	Yes	1997		83		78			69										
15888	BELT LINE RD	PCC	ART	Yes	2002		87		78			69										
15891	BELT LINE RD	PCC	ART	Yes	2002		88		77			69										
17588	PRESTON RD	COM	ART	Yes	1995		78			78	64											
17785	PRESTON RD	AC	ART	Yes	2003		75	70			64											
17825	PRESTON RD	AC	ART	Yes	2004		80	73			72											
18437	PRESTON RD	AC	ART	Yes	2004		82	81			72											
18438	PRESTON RD	AC	ART	Yes	2004		80	79			77											
18488	DARIA DR	PCC	LR	Yes	1993		71	68			60											

Table 4.4 PCI Sample Data for Macro (Expansive subgrade soil)

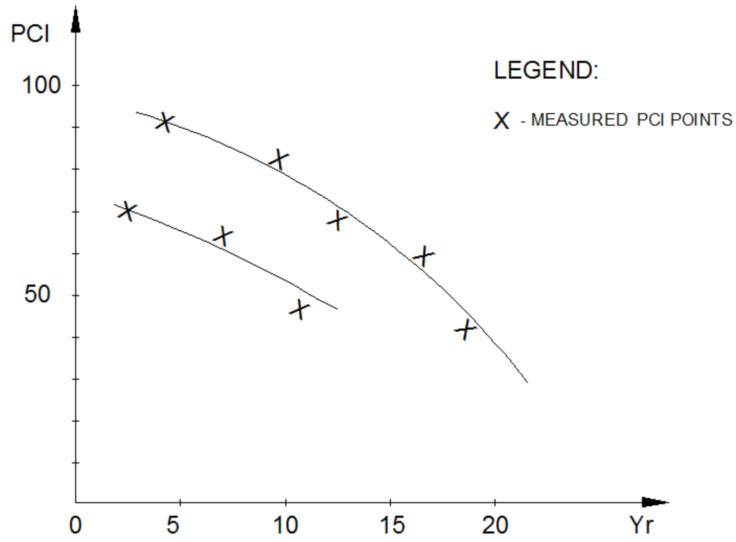

Figure 4.2 Unbalanced PCI data - Expansive subgrade soil

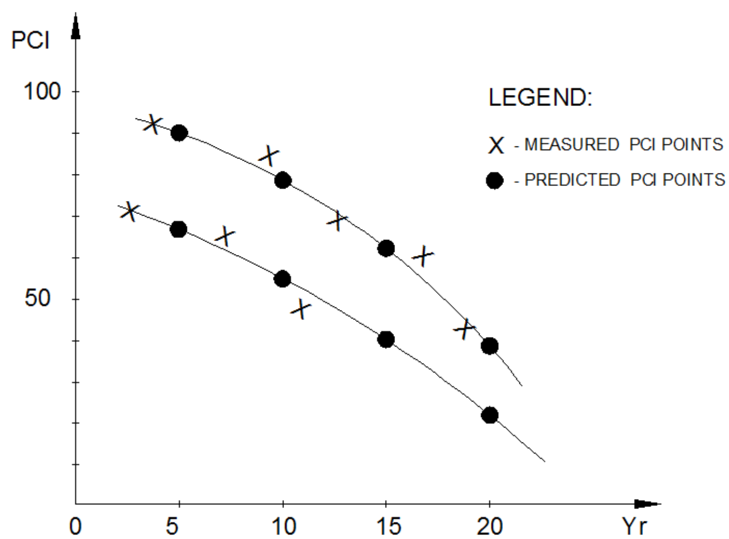

Figure 4.3 Balanced PCI data - Expansive subgrade soil

The regression coefficients obtained by the Excel macros were used to predict the PCI values for the same number of years of all streets sections so that the data set for the model development would be balanced, *Figure 4.3*. *Table 4.5* gives an example of the calculated output for the regression parameters a, b and c, and R^2 for Model 2 as well as the predicted PCI values for 5, 10, 15, and 20 years. This process was performend for all seven models in *Table 4.1*.

										5	10	15	20
ID	NAME	TYPE	CLASS	Exp_Soil	Latest_ Rehab	a2	b2	c2	R-Squared 2	Predicted PCI model 2			
61567	HARRY HINES BLVD	AC	ART	Yes	2004	1E+306	699.9965	-4.5E-05	0.50001377	85	72	62	53
61731	S MARSALIS AVE	AC	ART	Yes	2003	5.94E+16	34.02807	-0.00118	0.50002337	81	66	54	44
64281	PRESIDIO AVE	COM	LR	Yes	1999	1.1E+141	320.145	-0.00013	0.50005231	80	65	53	43
88817	VILBIG RD	COM	COL	Yes	1993	3.97E+35	77.37501	-0.00029	0.50028321	88	79	70	63
101621	BONNIE VIEW RD	PCC	ART	Yes	1989	2.9E-238	-551.547	6.53E-05	0.50028921	83	69	58	48
87795	JASON DR	AC	LR	Yes	2003	1.2E+256	585.0177	-7.4E-05	0.50038613	80	64	52	42
32472	POWER DR	COM	LR	Yes	1993	1.8E+74	166.3841	-0.00021	0.50044459	83	70	59	50
98539	S WESTMORELAND RD	PCC	ART	Yes	1987	1.06E-75	-177.229	0.000156	0.50054396	86	75	65	57
59958	INGERSOLL ST	PCC	LR	Yes	1981	2.8E+242	553.6758	-6.7E-05	0.50069993	82	68	57	47
58871	N WESTMORELAND RD	COM	ART	Yes	1991	1.7E+297	679.7973	-3.7E-05	0.50084377	87	77	68	60
90395	W ILLINOIS AVE	AC	ART	Yes	2004	1E+306	700	-5.4E-05	0.50108034	82	68	56	47
98856	THACKERY ST	COM	LR	Yes	1985	3.97E-36	-86.1086	0.000353	0.50138123	85	73	63	54
97225	FERNALD AVE	PCC	LR	Yes	1997	9.8E-303	-700	5.77E-05	0.5015632	81	66	54	44
104323	MCNEIL ST	COM	LR	Yes	1995	4.3E-204	-472.865	5.84E-05	0.50183328	86	75	65	57
87805	ASH LN	AC	LR	Yes	2000	7.1E+264	605.2474	-6.7E-05	0.50191815	81	66	54	44
91118	WILBARGER DR	PCC	LR	Yes	1993	2.5E+297	680.2007	-5.3E-05	0.502084	83	69	58	48
88285	MICHAEL LN	COM	LR	Yes	1985	3E+74	166.8962	-0.00017	0.50221583	86	74	64	56
62352	E LOUISIANA AVE	AC	LR	Yes	2004	5.12E+44	98.35126	-0.00048	0.50231115	78	61	48	38
98618	SHADOW WAY	COM	LR	Yes	1993	2.9E-193	-447.94	7.83E-05	0.50284615	83	70	59	49
87668	WYOMING ST	AC	LR	Yes	2000	1.26E+57	126.8869	-0.00034	0.50287146	80	65	52	42
100967	STRAIT LN	PCC	LR	Yes	1996	44.75768	-0.79386	0.0426	0.50301982	85	75	68	63
100966	STRAIT LN	PCC	LR	Yes	1996	44.75768	-0.79386	0.0426	0.50301982	85	75	68	63

Table 4.5 Example of PCI Data predicted with parameters calculated by the Excel Macro

After calculating the prediction model values for 5, 10, 15, and 20 years, these PCI values were analyzed and if the predicted PCI value were not continuously decreasing, the model would be considered unreasonable. By applying the criteria described above, models 2, 3, 5 and 7 are the best models within these seven models. Models 1, 4 and 6 have been excluded from further consideration in the development of deterioration models since the predicted PCI values did not decrease over time. *Table 4.6* shows summarized information for R^2 and the numbers of the data used for model development for each of the pavement families. It should be noted that data for all streets with $R^2 < 0.5$ and data that did not decrease over time were removed in order to create better and more reliable prediction models.

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works	Expansive Soil
1	AC	ART	Yes	**1,398**	1	1,397	100%	2	1,396	100%	142	1,256	90%	No	Yes
2	AC	COL	Yes	**601**	-	601	100%	-	601	100%	75	526	88%	No	Yes
3	AC	LR	Yes	**6,993**	3	6,990	100%	25	6,968	100%	816	6,177	88%	No	Yes
4	PCC	ART	Yes	**3,125**	1	3,124	100%	30	3,095	99%	604	2,521	81%	No	Yes
5	PCC	COL	Yes	**3,126**	-	3,126	100%	14	3,112	100%	265	2,861	92%	No	Yes
6	PCC	LR	Yes	**6,535**	4	6,531	100%	33	6,502	99%	958	5,577	85%	No	Yes
7	COM	ART	Yes	**1,408**	1	1,407	100%	24	1,384	98%	301	1,107	79%	No	Yes
8	COM	COL	Yes	**398**	-	398	100%	3	395	99%	55	343	86%	No	Yes
9	COM	LR	Yes	**2,028**	-	2,028	100%	13	2,015	99%	274	1,754	86%	No	Yes

Table 4.6 Model 1 (Cubic Polynomial) – Summarized Results (PCI data used)

Tables for other models with summarized results are shown in Tables B1 to B6 in Appendix B.

PCI - EXPANSIVE SOIL	a	b	c
2	100.6190759	0.016222011	-0.2559421748
3	1878876.822	-939339.411	-127777.0337709460
5	99	-42691.72207	0.0000827639
7	99	-2	0.0050000000

Table 4.7 PCI – Starting parameters for SAS

After selecting four of these seven models, the next step was to prepare the data set to be used by the SAS program to develop the PCI prediction models. As shown in *Table 4.8*, the data had to be reorganized for use in the SAS program. The following data has been extracted from *Table 4.3*: Asset ID, Surface type, Class, Age, and PCI. In order to achieve the best results, the SAS program was run separately for each of the pavement families shown in *Figure 3.3*. Appendix I gives an example of the SAS program. The SAS statistical program has used the starting parameters shown in *Table 4.7* to calculate the best fit parameters: X_2, X_3, R^2 and Standard Error (SE).

The following equation was used by the SAS software to calculate a standard error (SE) which represent the accuracy of the prediction model:

$$SE = \sqrt{\frac{\Sigma(y - yfit)^2}{df}}$$

Where df is the degree of freedom, y is the data point and, $yfit$ is the value of the curve at point y. The number of data points minus the number of parameters in the function is known as the degrees of freedom, df. Models with a highest R^2 and lowest Standard Error (SE) were selected as the best models.

ID	SURF	CLASS	AGE	PCI
61567	AC	ART	5	85
61731	AC	ART	5	81
90395	AC	ART	5	82
85436	AC	ART	5	81
33078	AC	ART	5	77
61567	AC	ART	10	72
61731	AC	ART	10	66
90395	AC	ART	10	68
85436	AC	ART	10	66
33078	AC	ART	10	60
61567	AC	ART	15	62
61731	AC	ART	15	54
90395	AC	ART	15	56
85436	AC	ART	15	53
33078	AC	ART	15	46
61567	AC	ART	20	53
61731	AC	ART	20	44
90395	AC	ART	20	47
85436	AC	ART	20	43
33078	AC	ART	20	36

Table 4.8 PCI – Sample data organized for SAS

Tables 4.9, 4.10, 4.11 and *4.12* show the parameters calculated by the SAS program. All tables with the final outputs have been evaluated to verify that the models meet the minimum criteria which are high R^2 and low SE.

Model 2 - PCI - Expansive Soil

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	3,480	10,942,899	365,696	33.0712	-0.00156	0.9677	10.25
AC	COL	1,456	4,348,353	122,194	2.7020	-0.01810	0.9727	9.16
AC	LR	20,144	60,322,681	2,415,134	8.5326	-0.00617	0.9615	10.95
COM	ART	3,688	19,171,042	304,103	1.2803	-0.01860	0.9844	9.08
COM	COL	980	5,191,885	98,875	0.7953	-0.02720	0.9813	10.04
COM	LR	4,708	23,695,564	590,172	0.7429	-0.03100	0.9757	11.20
PCC	ART	8,480	43,973,998	865,251	1.4632	-0.01660	0.9807	10.10
PCC	COL	3,496	18,331,255	341,949	3.1706	-0.00799	0.9817	9.89
PCC	LR	19,316	101,590,000	1,966,411	0.7513	-0.02890	0.9810	10.09

Table 4.9 SAS results for Model 2 (Gompertz) – Expansive subgrade soil

Model 3 - PCI - Expansive Soil

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	3,196	9,440,739	239,440	-881.1	-124.1	0.9753	8.66
AC	COL	1,516	4,383,872	84,604	-14430.3	-1811.8	0.9811	7.47
AC	LR	14,840	43,562,988	959,480	-1128.2	-154.7	0.9784	8.04
COM	ART	3,576	17,968,879	259,994	-1206.3	-278.0	0.9857	8.53
COM	COL	1,000	5,307,839	52,525	-6979.6	-1628.6	0.9902	7.25
COM	LR	3,176	15,757,872	267,140	-1081.9	-247.3	0.9833	9.17
PCC	ART	10,672	54,621,433	693,791	-1748.1	-403.4	0.9875	8.06
PCC	COL	4,388	22,812,574	214,404	-7206.3	-1631.1	0.9907	6.99
PCC	LR	19,812	103,000,000	1,189,218	-951.4	-234.5	0.9886	7.75

Table 4.10 SAS results for Model 3 (Logistic) – Expansive subgrade soil

Model 5 - PCI - Expansive Soil

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	3,472	10,952,371	423,518	-111.6	0.0202	0.9628	11.04
AC	COL	1,548	4,676,938	147,948	-243.9	0.0122	0.9693	9.78
AC	LR	15,704	47,383,071	1,484,689	-221.2	0.0131	0.9696	9.72
COM	ART	3,372	17,339,594	270,354	-138.5	0.0103	0.9846	8.95
COM	COL	828	4,426,194	68,042	-3841.4	0.0006	0.9849	9.07
COM	LR	828	4,438,098	56,138	-209.1	0.0073	0.9875	8.23
PCC	ART	9,120	47,875,482	735,046	-206.3	0.0076	0.9849	8.98
PCC	COL	3,704	19,695,434	242,360	-161.1	0.0089	0.9878	8.09
PCC	LR	17,452	92,107,370	1,179,127	-297.1	0.0058	0.9874	8.22

Table 4.11 SAS results for Model 5 (Exponential) – Expansive subgrade soil

Model 7 - PCI - Expansive Soil								
Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	3,856	13,727,600	546,881	-1.2505	0.0337	0.9617	11.91
AC	COL	1,260	4,184,070	167,036	-1.3368	0.0303	0.9616	11.51
AC	LR	13,796	45,960,688	1,845,471	-1.3009	0.0330	0.9614	11.57
COM	ART	3,924	20,391,602	531,471	-1.2499	0.0173	0.9746	11.64
COM	COL	948	5,181,605	90,895	-1.4022	0.0104	0.9828	9.79
COM	LR	3,296	17,092,771	384,277	-1.3618	0.0130	0.9780	10.80
PCC	ART	9,528	51,410,171	1,044,261	-1.2735	0.0150	0.9801	10.47
PCC	COL	3,928	21,373,978	365,678	-1.2515	0.0156	0.9832	9.65
PCC	LR	16,104	88,542,003	1,480,032	-1.3246	0.0126	0.9836	9.59

Table 4.12 SAS results for Model 7 (Exponential) – Expansive subgrade soil

All the models shown in *Tables 4.9 to 4.12* have low SE and high R^2, therefore they were further retained for the model selection process. After all the models were analyzed, the next step was to create a chart for each pavement family to display the predicted curves for the selected four models. As can be seen in *Figure 4.4* and *Table 4.13*, all models for the AC-ART pavement family are grouped together and evaluated. The predicted PCI values calculated by the excel macro were used to draw all predicted models as shown in *Figure 4.4* for AC-ART pavement family and Figures D1 to D6 in Appendix D for the rest of the AC pavement families. By drawing all the models in one graph, it was much easier to compare the behavior of each model, and this also helps with the selection of the best models. The same technique has been extended to all pavement families.

4.1.1 Deterministic Prediction model for AC Pavement Family (Exp. Soil) – PCI

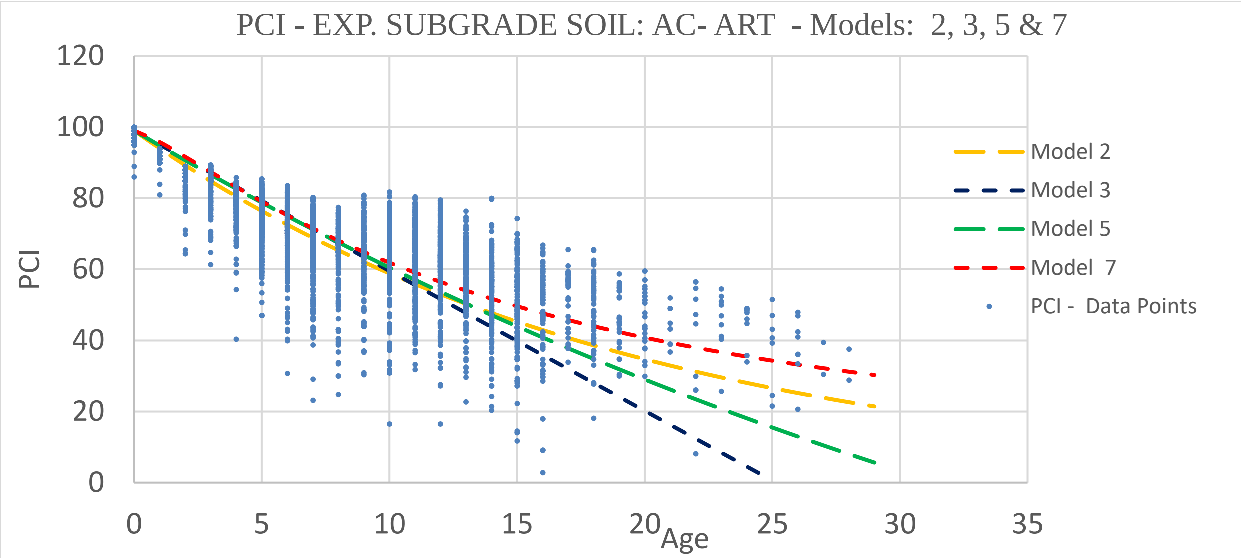

Figure 4.4 Chart for Models 2, 3, 5 & 7 – AC-ART Pvmt Family (Exp. subgrade soil)

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)	Model
AC	ART	3,480	10,942,899	365,696	33.0712	-0.00156	0.96766	**10.25**	2
AC	ART	3,196	9,440,739	239,440	-881.1000	-124.10000	0.97526	8.66	3
AC	ART	3,472	10,952,371	423,518	-111.6000	0.02020	0.96277	11.04	5
AC	ART	3,856	13,727,600	546,881	-1.2505	0.03370	0.96169	11.91	7
AC	COL	1,456	4,348,353	122,194	2.7020	-0.01810	0.97267	**9.16**	2
AC	COL	1,516	4,383,872	84,604	-14430.3000	-1811.80000	0.98107	7.47	3
AC	COL	1,548	4,676,938	147,948	-243.9000	0.01220	0.96934	9.78	5
AC	COL	1,260	4,184,070	167,036	-1.3368	0.03030	0.96161	11.51	7
AC	LR	20,144	60,322,681	2,415,134	8.5326	-0.00617	0.9615	**10.95**	2
AC	LR	14,840	43,562,988	959,480	-1128.2000	-154.70000	0.9784	8.04	3
AC	LR	15,704	47,383,071	1,484,689	-221.2000	0.01310	0.9696	9.72	5
AC	LR	13,796	45,960,688	1,845,471	-1.3009	0.03300	0.9614	11.57	7

Table 4.13 Summarized SAS results for AC-ART, AC-COL & AC-LR pavement family

For AC-ART, AC-COL and AC-LR street pavement families, Model 2 is recommended despite Model 3 having the lowest SE and highest R^2, see *Table 4.13*, since the curves for Model 3 are approaching zero (0) at twenty five years for all AC pavement families, (*Figure 4.4*, D1 and D2).

The prediction curves for Model 2 are reasonable for all pavement families as they are in the center of the measured PCI-data points.

4.1.2 Deterministic Prediction model for COM Pavement Family (Exp. Soil) – PCI

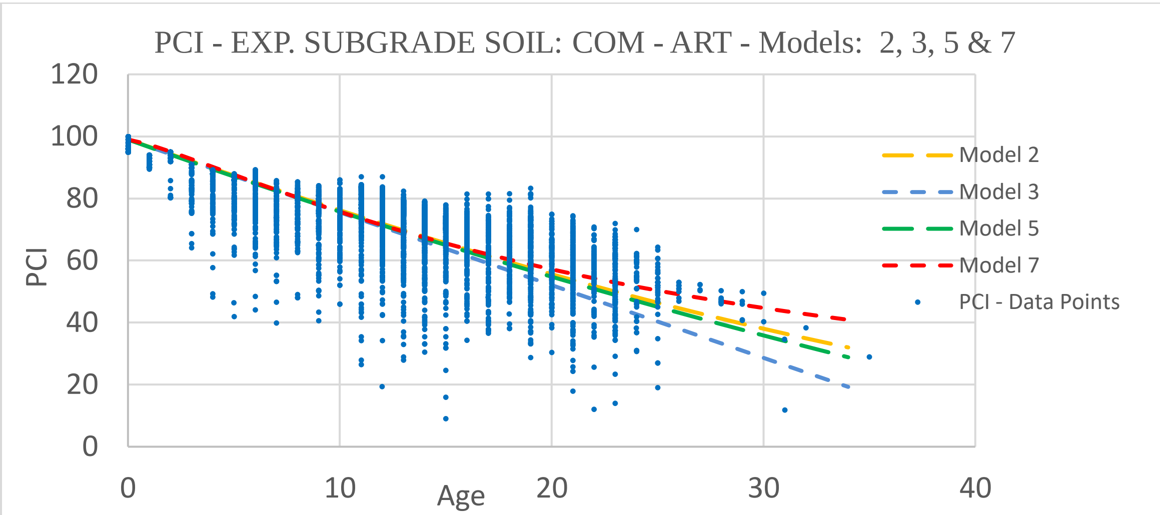

Figure 4.5 Chart for Models 2, 3, 5 & 7 – COM-ART Pvmt Family (Exp. subgrade soil)

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)	Model
COM	ART	3,688	19,171,042	304,103	1.2803	-0.0186	0.9844	9.08	2
COM	ART	3,576	17,968,879	259,994	-1206.3000	-278.0000	0.9857	**8.53**	3
COM	ART	3,372	17,339,594	270,354	-138.5000	0.0103	0.9846	8.95	5
COM	ART	3,924	20,391,602	531,471	-1.2499	0.0173	0.9746	11.64	7
COM	COL	980	5,191,885	98,875	0.7953	-0.0272	0.9813	10.04	2
COM	COL	1,000	5,307,839	52,525	-6979.6000	-1628.6000	0.9902	**7.25**	3
COM	COL	828	4,426,194	68,042	-3841.4000	0.0006	0.9849	9.07	5
COM	COL	948	5,181,605	90,895	-1.4022	0.0104	0.9828	9.79	7
COM	LR	4,708	23,695,564	590,172	0.7429	-0.0310	0.9757	11.20	2
COM	LR	3,176	15,757,872	267,140	-1081.9000	-247.3000	0.9833	9.17	3
COM	LR	828	4,438,098	56,138	-209.1000	0.0073	0.9875	**8.23**	5
COM	LR	3,296	17,092,771	384,277	-1.3618	0.0130	0.9780	10.80	7

Table 4.14 Summarized SAS results for COM-ART, COL & LR pvmt family (Exp. subgrade soil)

Model 3 is recommended for the COM-ART and COM-COL street pavement families and Model 5 is recommend for the COM-LR street pavement family as these modes have the lowest

SE and the highest R^2, (*Table 4.14*). The prediction curve for the recommended model shown in *Figure 4.5* have reasonable trends for the COM-ART pavement family. For pavement families COM-COL and COM-LR shown in Figure D3 & D4, the recommended models show good prediction curves. The curve for Model 3 is positioned in the middle of the measured PCI data points.

4.1.3 Deterministic Prediction models for PCC Pvmt Family (Exp. Subgrade Soil) – PCI

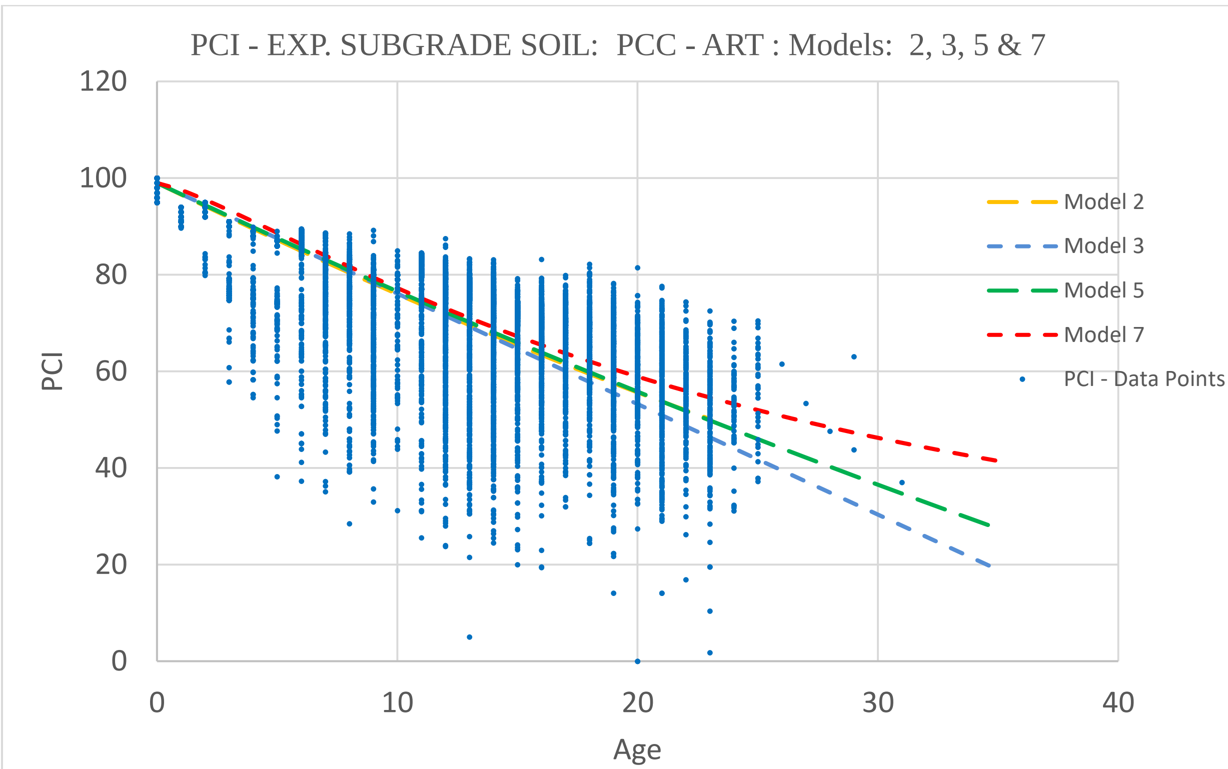

Figure 4.6 Chart for Models 2,3,5 & 7 – PCC-ART Pvmt. Family (Exp. subgrade soil)

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)	Model
PCC	ART	8,480	43,973,998	865,251	1.4632	-0.0166	0.9807	10.10	2
PCC	ART	10,672	54,621,433	693,791	-1748.1000	-403.4000	0.9875	**8.06**	3
PCC	ART	9,120	47,875,482	735,046	-206.3000	0.0076	0.9849	8.98	5
PCC	ART	9,528	51,410,171	1,044,261	-1.2735	0.0150	0.9801	10.47	7
PCC	COL	3,496	18,331,255	341,949	3.1706	-0.0080	0.9817	9.89	2
PCC	COL	4,388	22,812,574	214,404	-7206.3000	-1631.1000	0.9907	**6.99**	3
PCC	COL	3,704	19,695,434	242,360	-161.1000	0.0089	0.9878	8.09	5
PCC	COL	3,928	21,373,978	365,678	-1.2515	0.0156	0.9832	9.65	7
PCC	LR	19,316	101,590,000	1,966,411	0.7513	-0.0289	0.9810	10.09	2
PCC	LR	19,812	103,000,000	1,189,218	-951.4000	-234.5000	0.9886	**7.75**	3
PCC	LR	17,452	92,107,370	1,179,127	-297.1000	0.0058	0.9874	8.22	5
PCC	LR	16,104	88,542,003	1,480,032	-1.3246	0.0126	0.9836	9.59	7

Table 4.15 Summarized SAS results for PCC-ART, PC-COL & PCC-LR pvmt. family (Exp. subgrade soil)

For the PCC-ART, PCC-COL and PCC-LR pavement families, Model 3 is recommended, as this model has the lowest SE and highest R^2, see *Table 4.15*. The prediction curve for the selected model shown in *Figures 4.6* for the PCC-ART pavement family has a good trend.

Figures D5 & D6 for PCC-COL and PCC-LR pavement families show that the recommended models have a good trend as well, as they are positioned toward the middle of the PCI data points.

4.1.4 Summarized Best Deterministic PCI Deterioration Models for Street with Exp. subgrade Soil

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X_1	X_2	X_3	R^2	Stand. Error (SE)	Model
AC	ART	3,480	10,942,899	365,696	2.28E+16	33.07	-0.002	0.96766	10.25	2
AC	COL	1,456	4,348,353	122,194	1,476.0	2.70	-0.018	0.97267	9.16	2
AC	LR	20,144	60,322,681	2,415,134	502,685.4	8.53	-0.006	0.9615	10.95	2
COM	ART	3,576	17,968,879	259,994	2,610.6	-1206.3	-278.000	0.986	8.53	3
COM	COL	1,000	5,307,839	52,525	14,157.2	-6979.6	-1628.600	0.990	7.25	3
COM	LR	828	4,438,098	56,138	99.0	-209.1	0.007	0.988	8.23	5
PCC	ART	10,672	54,621,433	693,791	3,694.2	-1748.1	-403.400	0.987	8.06	3
PCC	COL	4,388	22,812,574	214,404	14,610.6	-7206.3	-1631.100	0.991	6.99	3
PCC	LR	19,812	103,000,000	1,189,218	2,100.8	-951.4	-234.500	0.9886	7.75	3

Table 4.16 Summarized best Models for all pavement families (PCI) – Exp. Soil

Models	**Pavement Family**	**Equation (PCI/IRI = y)**
2	AC-ART	$y = 2.28179\text{E} + 16e^{-33.0712*e^{-(-0.00156t)}}$
2	AC-COL	$y = 1476.042576e^{-2.702e^{-(-0.0181t)}}$
2	AC-LR	$y = 502685.4221e^{-8.5326\, e^{-(-0.0062t)}}$
3	COM-ART	$y = \dfrac{2610.6}{1 + e^{-\frac{t}{278}}} - 1206.3$
3	COM-COL	$y = \dfrac{14157.2}{1 + e^{-\frac{t}{1628.6}}} - 6979.6$
5	COM-LR	$y = -209.1 - (-209.1 - 99) * e^{-0.007t}$
3	PCC-ART	$y = \dfrac{3694.2}{1 + e^{-\frac{t}{-403.4}}} - 1748.1$
3	PCC-COL	$y = \dfrac{14610.6}{1 + e^{-\frac{t}{-1631.1}}} - 7206.3$
3	PCC-LR	$y = \dfrac{2100.8}{1 + e^{-\frac{t}{-234.5}}} - 951.4$

Table 4.17 Summarized Eq. for Best Models for all pavement families (PCI)

The parameters estimated by the non-linear regression analysis performed using SAS program are summarized in *Table 4.16*. They are also shown in the formulas for the selected models in *Table 4.17*.

The residuals for models 2, 3, 5 & 7 for all pavement families built on expansive subgrade soil are shown in Appendix L.

4.1.4 Comparison of Deterioration curves PCC vs AC Pvmt Family (Exp. Soil) – PCI

The two deterioration curves fitted to both PCC and AC data are presented together in *Figure 4.7*. In this graph, local residential streets with concrete (PCC) surface layer deteriorate slower than the streets with asphalt (AC) curve surface layer.

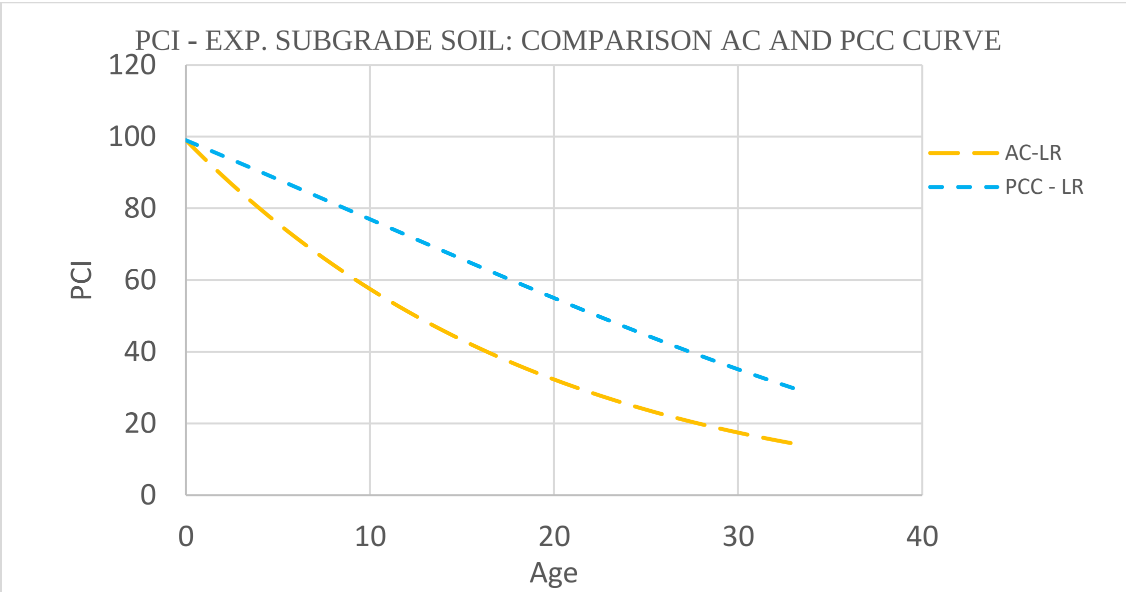

Figure 4.7 Comparison of Deterioration curve PCC-LR vs AC – LR family (Exp. subgrade soil)

4.2 Development of Deterministic PCI Deterioration Models for Street with Non-Exp. Sub. Soil

The seven models given in *Table 4.1* were also used to select the best deterministic deterioration model for the DFW Metroplex area with non-expansive subgrade soil. These models had to also comply with the following conditions:

- The PCI must decrease with time
- The PCI value immediately after construction or major rehabilitation was set to 99
- The PCI value must always be positive

Table 4.18 shows the sample of PCI data for non-expansive subgrade soil collected for the period from 2014 to 2019. The data were sorted and cleaned as described in Chapter 3.

Asset id	STREET NAME	PAVEMENT TYPE	FUNCTIONAL CLASS	Expansive Soil	Latest Rehab/Reconstruction Year	PCI 2014	PCI 2015	PCI 2016	PCI 2017	PCI 2018	PCI 2019
PST0000004	TAXCO RD	AC	LR	No	1999	52	50	48	45	42	41
PST0000007	BROADMOOR DR	AC	LR	No	2006	67	64	63	61	58	56
PST0000008	EASTVIEW ST	AC	LR	No	2014	98	94	89	87	84	76
PST0000009	ALBERMARLE DR	AC	LR	No	2003	60	59	56	54	51	49
PST0000010	WINDY HILL LN	AC	LR	No	2015	59	100	94	88	87	83
PST0000011	WIND CHIME DR	AC	LR	No	2004	62	61	58	57	54	51
PST0000012	STAFFORD DR	AC	LR	No	2012	88	87	80	79	71	69
PST0000013	PINEY POINT ST	AC	LR	No	2002	59	57	54	52	50	46
PST0000014	WESTMERE LN	AC	LR	No	2015	53	95	94	88	85	81
PST0000015	COLDSTREAM DR	AC	LR	No	2014	97	93	88	85	80	78
PST0000016	DIRKS RD	AC	LR	No	2012	89	86	83	76	74	69
PST0000017	DIRKS RD	AC	LR	No	2012	89	87	83	78	72	69
PST0000018	JENNIE DR	AC	LR	No	2012	89	86	83	77	74	69
PST0000019	WHITEWOOD DR	AC	LR	No	2015	55	100	92	89	87	82
PST0000070	CAMPBELL ST	AC	LR	No	2012	88	85	82	77	74	68
PST0000202	OCEAN CT	AC	LR	No	2014	100	92	88	87	82	75
PST0000203	KESWICK DR	AC	LR	No	2013	91	89	87	82	76	73
PST0000217	GRAND AVE	AC	LR	No	2001	57	55	52	50	46	45
PST0000226	RANCHO VERDE PKWY	AC	LR	No	2015	60	95	94	89	86	82
PST0000227	GLASGOW RD	AC	LR	No	2009	75	74	69	67	65	62
PST0000228	BILGLADE RD	AC	LR	No	2002	58	56	54	52	49	46
PST0000229	5TH ST, NE	AC	LR	No	2015	63	98	92	89	87	80
PST0000238	WILTON DR	AC	LR	No	2012	89	85	83	77	71	68
PST0000289	HORIZON PL	AC	LR	No	2014	99	91	89	85	80	76
PST0000291	DUBLIN DR	AC	LR	No	2013	92	89	86	83	77	74
PST0000300	RANCHO DIEGO LN, W	AC	LR	No	2012	88	87	82	75	74	69
PST0000301	VEGA DR	AC	LR	No	2003	60	58	57	55	52	49
PST0000302	WINESANKER WAY	AC	LR	No	2001	56	55	53	49	46	45
PST0000303	PERSHING AVE	AC	LR	No	1999	53	49	48	44	42	40
PST0000304	MADRID DR	AC	LR	No	2001	56	55	52	49	48	44
PST0000329	CANTEY ST, W	AC	LR	No	2013	91	89	86	80	78	74
PST0000330	WINDWILLOW DR	AC	LR	No	2002	59	57	54	52	49	46
PST0000336	EDGEHILL RD	AC	LR	No	2003	61	58	56	54	53	49
PST0000340	SOUTH DR, W (COURT	AC	LR	No	2014	100	92	88	86	83	78
PST0000346	LIMERICK DR	AC	LR	No	2003	60	59	56	54	51	50
PST0000347	THE LANDING ALLEY #8	AC	LR	No	2003	61	59	57	55	53	50
PST0000348	WINDING PASSAGE W	AC	LR	No	2004	62	60	58	56	54	52
PST0000361	RANCHO VERDE PKWY	AC	LR	No	2014	96	92	88	87	80	77
PST0000368	SPRINGER AVE	AC	LR	No	2001	56	54	53	49	47	45
PST0000369	WOOTEN DR	AC	LR	No	2003	61	58	57	55	53	49
PST0000371	ODELL DR	AC	LR	No	2003	60	59	56	54	53	50
PST0000372	RAND ST	AC	LR	No	2015	63	95	91	88	85	81
PST0000388	CREEKWOOD LN	AC	LR	No	2015	51	95	90	88	85	83
PST0000389	RENDON RD	AC	LR	No	2015	57	98	94	89	87	80
PST0000390	CREEKWOOD LN	AC	LR	No	2016	61	59	96	94	89	85
PST0000401	CHALK KNOLL RD	AC	LR	No	2001	56	54	52	50	48	45
PST0000402	CREEKWOOD LN	AC	LR	No	2013	92	89	87	84	75	74
PST0000403	REVERE DR	AC	LR	No	2009	78	74	68	67	65	63
PST0000407	ARBOR GATE	AC	LR	No	2003	61	58	57	54	52	49
PST0000409	WEDGWORTH RD S	AC	LR	No	2003	61	59	56	54	53	50

Table 4.18 PCI Sample Data for Non-Expansive subgrade soil

For the streets built on non-expansive subgrade soil, the PCI values were available for every year from 2014 to 2019 for all streets. Therefore the PCI data set is balanced and SAS statistical software could be used to perform the non-linear regression analysis without the need of the Excel macro. The data shown in *Table 4.18* was formatted as shown in *Table 4.19* so that it could be used by the SAS statistical software. As shown in *Table 4.19*, the following data was extracted from *Table 4.18*: Asset ID, Surface type, Class, Age, and PCI. The age was determined by subtracting the year of construction or major rehabilitation from the year of the PCI record.

Asset id	SURF	CLASS	Age	PCI
PST0018698	AC	ART	0	98
PST0018698	AC	ART	1	91
PST0018698	AC	ART	2	89
PST0018698	AC	ART	3	85
PST0018698	AC	ART	4	80
PST0018698	AC	ART	5	75
PST0018699	AC	ART	1	92
PST0018699	AC	ART	2	88
PST0018699	AC	ART	3	85
PST0018699	AC	ART	4	80
PST0018699	AC	ART	5	79
PST0018699	AC	ART	6	70
PST0018700	AC	ART	0	98
PST0018700	AC	ART	1	92
PST0018700	AC	ART	2	89
PST0018700	AC	ART	3	85
PST0018700	AC	ART	4	84
PST0018700	AC	ART	5	75

Table 4.19 PCI – Sample data organized for SAS

The SAS statistical program was used to calculate the best fit regression parameters: X_2, X_3, R^2 and Standard Error (SE). Models with highest R^2 and lowest standard Error (SE), as stated earlier are considered the best models. All data in the tables was evaluated to verify that the models meet the minimum requirements mentioned above. All of these models shown in *Tables 4.20* to *4.23* have low SE and high R^2 . The best four models selected for expansive subgrade soil (Models 2, 3, 5 &7) were also used for non-expansive subgrade soil since models 1, 4 and 6 did not have reasonable prediction curves.

Model 2 - PCI - Non-Expansive Soil								
SURFACE	CLASS	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	4,656	25,253,633	38,379	155.3000	-0.00028	0.9985	2.87
AC	COL	6,234	31,928,782	42,144	134.7000	-0.00033	0.9987	2.60
AC	LR	67,758	306,660,000	374,621	104.3000	-0.00042	0.9988	2.35
AC	RU	1,746	8,074,249	11,106	102.7000	-0.00043	0.9986	2.52
COM	ART	4,848	33,955,950	40,464	252.4000	-0.00011	0.9988	2.89
COM	COL	402	2,820,522	4,402	260.0000	-0.00010	0.9984	3.31
COM	LR	3,184	20,081,934	25,939	144.0000	-0.00019	0.9987	2.85
PCC	ART	9,978	57,470,198	45,961	43.4795	-0.00062	0.9992	2.15
PCC	COL	2,778	14,664,017	12,715	1.8982	-0.01310	0.9991	2.14
PCC	LR	61,230	333,060,000	194,544	18.5737	-0.00144	0.9994	1.78
PCC	RU	60	363,655	275	90.8567	-0.00031	0.9992	2.14

Table 4.20 SAS results for Model 2 (Gompertz) – Non-Expansive subgrade soil

Model 3 - PCI - Non- Expansive Soil								
SURFACE	CLASS	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	4,656	25,186,103	105,909.0	-694.4	-127	0.9958	4.77
AC	COL	6,234	31,836,903	134,023.0	-696.7	-127	0.9958	4.64
AC	LR	67,758	305,680,000	1,359,333.0	-688.2	-127	0.9956	4.48
AC	RU	1,746	8,050,029	35,325.7	-678.8	-127	0.9956	4.50
COM	ART	4,848	33,910,650	85,764.4	-425.0	-127	0.9975	4.21
COM	COL	402	2,816,684	8,240.3	-389.9	-127	0.9971	4.53
COM	LR	3,184	20,057,125	50,747.8	-432.3	-127	0.9975	3.99
PCC	ART	9,978	57,427,642	88,517.2	-447.8	-127	0.9985	2.98
PCC	COL	2,778	14,659,432	17,300.5	-448.6	-127	0.9988	2.50
PCC	LR	61,230	332,910,000	347,335.0	-452.6	-127	0.9990	2.38
PCC	RU	60	363,297	633.2	-482.5	-127	0.9983	3.25

Table 4.21 SAS results for Model 3 (Logistic) – Non-Expansive subgrade soil

Model 5 - PCI - Non-Expansive Soil								
SURFACE	CLASS	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	4,656	25,263,572	28,440.4	26.16	0.0694	0.9989	2.47
AC	COL	6,234	31,937,988	32,938.1	21.88	0.0643	0.9990	2.30
AC	LR	67,758	306,720,000	322,958.0	15.79	0.0575	0.9989	2.18
AC	RU	1,746	8,075,568	9,787.2	15.70	0.0574	0.9988	2.37
COM	ART	4,848	33,977,463	18,950.7	46.23	0.0657	0.9994	1.98
COM	COL	402	2,822,858	2,065.8	47.81	0.0686	0.9993	2.27
COM	LR	3,184	20,090,440	17,432.9	41.19	0.0571	0.9991	2.34
PCC	ART	9,978	57,470,625	45,534.3	6.30	0.0296	0.9992	2.14
PCC	COL	2,778	14,573,790	102,942.0	55.51	0.1060	0.9930	6.09
PCC	LR	61,230	333,060,000	193,741.0	-6.79	0.0249	0.9994	1.78
PCC	RU	60	363,705	225.4	30.84	0.0452	0.9994	1.94

Table 4.22 SAS results for Model 5 (Exponential) – Non-Expansive subgrade soil

Model 7- PCI - Non-Expansive Soil								
SURFACE	CLASS	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	4,656	25,260,163	31,848.8	-1.0451	0.0547	0.9987	2.62
AC	COL	6,234	31,933,221	37,705.0	-1.0733	0.0518	0.9988	2.46
AC	LR	67,758	306,660,000	382,817.0	-1.1123	0.0473	0.9988	2.38
AC	RU	1,746	8,073,772	11,583.4	-1.1154	0.0471	0.9986	2.58
COM	ART	4,848	33,977,819	18,595.0	-0.8782	0.0469	0.9995	1.96
COM	COL	402	2,822,928	1,995.5	-0.8539	0.0495	0.9993	2.23
COM	LR	3,184	20,090,642	17,231.3	-0.922	0.042	0.9991	2.33
PCC	ART	9,978	57,462,075	54,083.9	-1.1085	0.0253	0.9991	2.33
PCC	COL	2,778	14,655,963	20,769.1	-1.2955	0.0153	0.9986	2.73
PCC	LR	61,230	333,010,000	246,106.0	-1.1479	0.0222	0.9993	2.00
PCC	RU	60	363,705	224.5	-0.9669	0.0372	0.9994	1.93

Table 4.23 SAS results for Model 7 (Exponential) – Non-Expansive subgrade soil

After evaluating all models, the next step was to develop a chart for each pavement family to display the predicted curves for the selected four models.

As can be seen in *Figure 4.8* and *Table 4.24*, the predicted PCI values calculated by Excel were used to draw all predicted models as shown in *Figure 4.8* for AC-ART and Figures E1 to E6, for the rest of the pavement families in Appendix E. By drawing all the models in one graph, it was much easier to compare the behavior of each model, and it also helps with the selection of the best models. The same technique has been extended to all pavement families.

4.2.1 Deterministic Prediction model for AC Pvmt Family (Non-Exp. Soil) – (PCI)

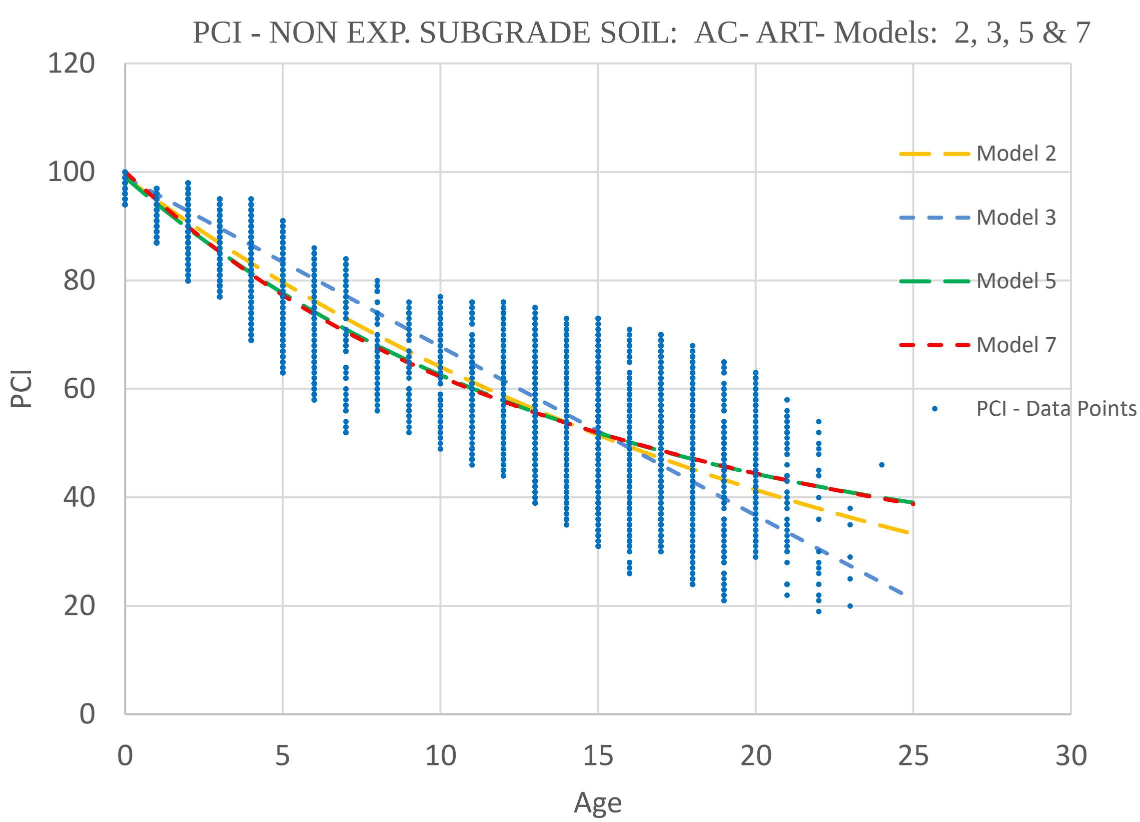

Figure 4.8 Chart for Models 2, 3, 5 & 7 – AC-ART Pavement Family (Non-Exp. subgrade soil)

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)	Model
AC	ART	4,656	25,253,633	38,378.7	155.3000	-0.0003	0.9985	2.87	2
AC	ART	4,656	25,186,103	105,909.0	-694.4000	-127.0000	0.9958	4.77	3
AC	ART	4,656	25,263,572	28,440.4	26.1553	0.0694	0.9989	**2.47**	5
AC	ART	4,656	25,260,163	31,848.8	-1.0451	0.0547	0.9987	2.62	7
AC	COL	6,234	31,928,782	42,143.6	134.7000	-0.0003	0.9987	2.60	2
AC	COL	6,234	31,836,903	134,023.0	-696.7000	-127.0000	0.9958	4.64	3
AC	COL	6,234	31,937,988	32,938.1	21.8810	0.0643	0.9990	**2.30**	5
AC	COL	6,234	31,933,221	37,705.0	-1.0733	0.0518	0.9988	2.46	7
AC	LR	67,758	306,660,000	374,621.0	104.3000	-0.0004	0.9988	2.35	2
AC	LR	67,758	305,680,000	1,359,333.0	-688.2000	-127.0000	0.9956	4.48	3
AC	LR	67,758	306,720,000	322,958.0	15.7866	0.0575	0.9989	**2.18**	5
AC	LR	67,758	306,660,000	382,817.0	-1.1123	0.0473	0.9988	2.38	7
AC	RU	1,746	8,074,249	11,105.7	102.7000	-0.0004	0.9986	2.52	2
AC	RU	1,746	8,050,029	35,325.7	-678.8000	-127.0000	0.9956	4.50	3
AC	RU	1,746	8,075,568	9,787.2	15.6969	0.0574	0.9988	**2.37**	5
AC	RU	1,746	8,073,772	11,583.4	-1.1154	0.0471	0.9986	2.58	7

Table 4.24 Summarized SAS results for AC-ART, COL, LR & RU pvmt family (Non-Expansive)

Models 5 are recommended for the AC-ART, AC-COL and AC-LR pavement families as they have the lowest SE and highest R^2, (*Table 4.24*).

The predicted curves for the AC-ART pavement family are shown in *Figure 4.8*. Figures E1, E2, and E3 for AC-COL, AC-LR and AC-RU in Appendix E indicate the predicted curves for the remaining AC pavement families. As they are located in the middle of the measured PCI, data points, all recommended models are reasonable for all pavement families. It should also be noticed that Model 7 could be used as well as that it has similar prediction curve as Model 5 shown on the charts.

4.2.2 Deterministic Prediction model for COM Pvmt Family (Non-Exp. Sub. Soil) – (PCI)

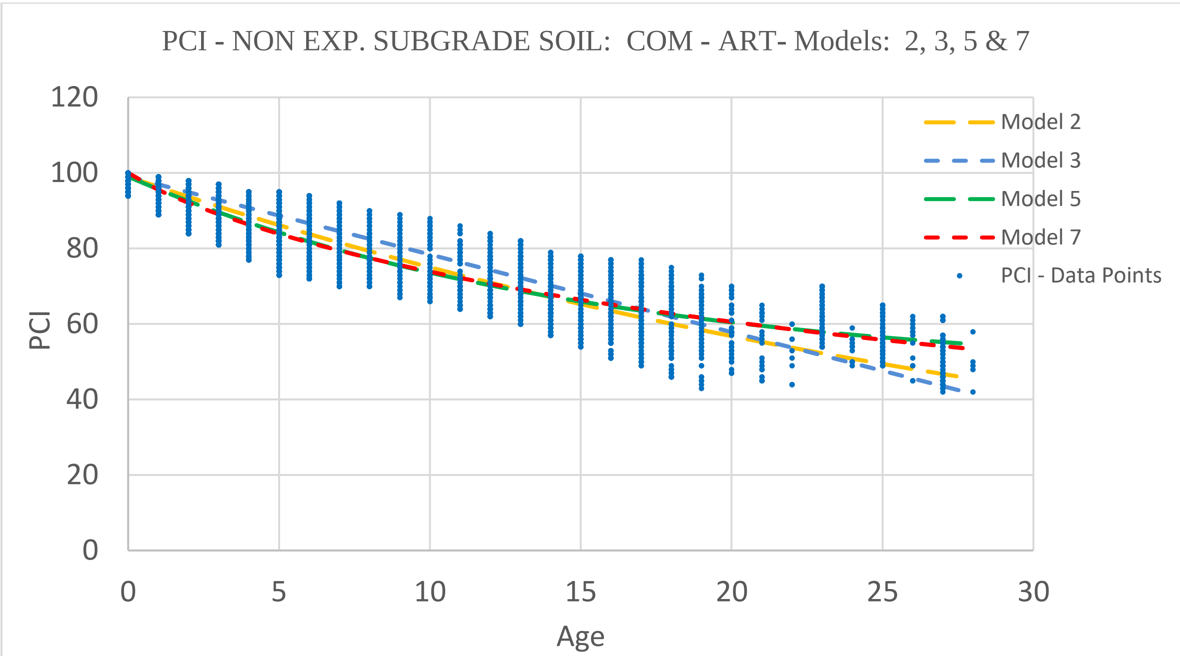

Figure 4.9 Chart for Models 2, 3, 5 & 7 – COM - ART Pvmt Family (Non-Exp. subgrade soil)

Surface	CLASS	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)	Model
COM	ART	4,848	33,955,950	40,463.6	252.4000	-0.0001	0.9988	2.89	2
COM	ART	4,848	33,910,650	85,764.4	-425.0000	-127.0000	0.9975	4.21	3
COM	ART	4,848	33,977,463	18,950.7	46.2305	0.0657	0.9994	**1.98**	5
COM	ART	4,848	33,977,819	18,595.0	-0.8782	0.0469	0.9995	**1.96**	7
COM	COL	402	2,820,522	4,401.8	260.0000	-0.0001	0.9984	3.31	2
COM	COL	402	2,816,684	8,240.3	-389.9000	-127.0000	0.9971	4.53	3
COM	COL	402	2,822,858	2,065.8	47.8146	0.0686	0.9993	**2.27**	5
COM	COL	402	2,822,928	1,995.5	-0.8539	0.0495	0.9993	**2.23**	7
COM	LR	3,184	20,081,934	25,938.7	144.0000	-0.0002	0.9987	2.85	2
COM	LR	3,184	20,057,125	50,747.8	-432.3000	-127.0000	0.9975	3.99	3
COM	LR	3,184	20,090,440	17,432.9	41.1905	0.0571	0.9991	**2.34**	5
COM	LR	3,184	20,090,642	17,231.3	-0.9218	0.0423	0.9991	**2.33**	7

Table 4.25 Summarized SAS results for COM-ART, COL, LR & RU pvmt family (Non-Exp.)

Models 7 are recommended for COM-ART, COL and LR pavement families because they have the lowest SE and highest R^2, (*Table 4.25*).

In *Figure 4.9*, the predicted curves for the AC-ART pavement family are shown. Figures E4, and E5 for COM-COL, and COM-LR in Appendix E shows the predicted curves for the remaining COM pavement families.

As they are in the middle of the measured PCI data points, all recommended models have a reasonable trend. Also, it needs to be noted that Model 5 could be use as well as it has almost an identical prediction curve.

4.2.3 Deterministic Prediction model for PCC Pvmt Family (Non-Exp. Soil) – (PCI)

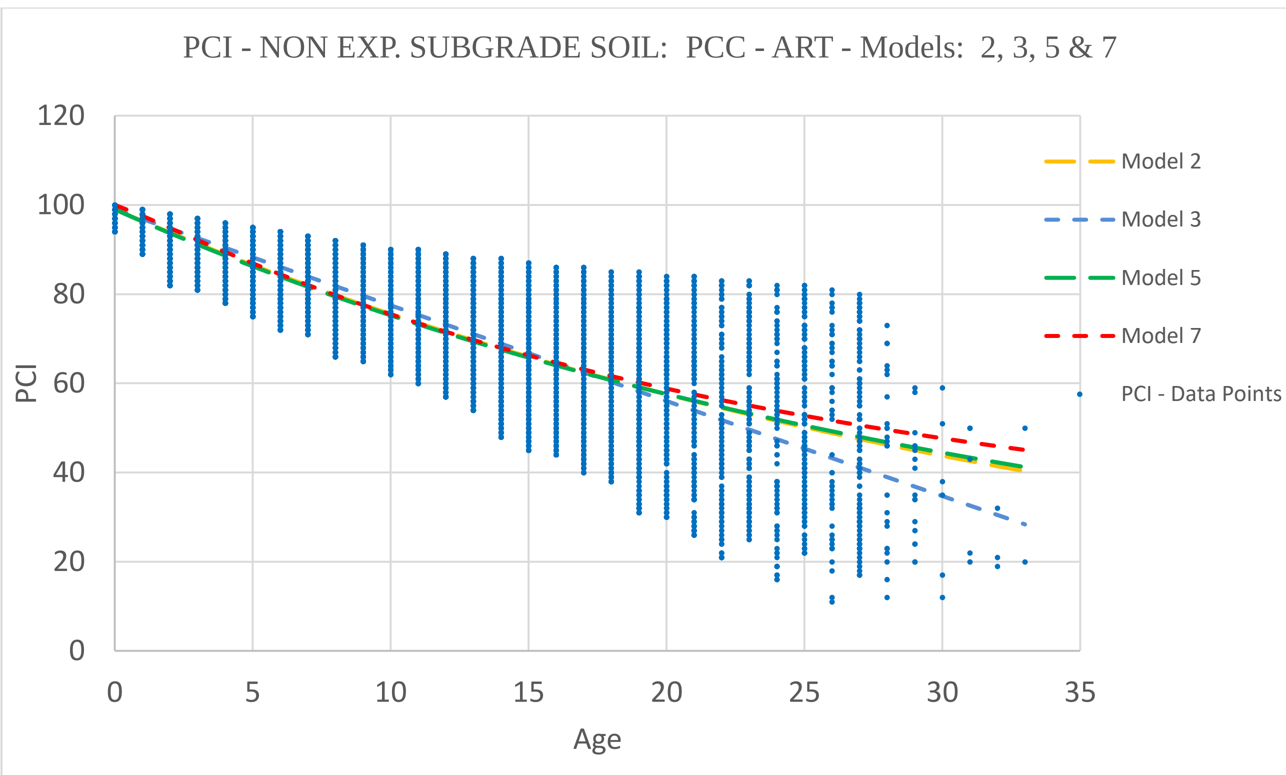

Figure 4.10 Chart for Models 2, 3, 5 & 7 – PCC-ART pvmt Family (Non-Exp. subgrade soil)

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)	Model
PCC	ART	9,978	57,470,198	45,961.4	43.4795	-0.00062	0.9992	**2.15**	2
PCC	ART	9,978	57,427,642	88,517.2	-447.80	-127.00	0.9985	2.98	3
PCC	ART	9,978	57,470,625	45,534.3	6.30	0.0296	0.9992	**2.14**	5
PCC	ART	9,978	57,462,075	54,083.9	-1.1085	0.0253	0.9991	2.33	7
PCC	COL	2,778	14,664,017	12,715.2	1.8982	-0.01310	0.9991	**2.14**	2
PCC	COL	2,778	14,659,432	17,300.5	-448.60	-127.00	0.9988	2.50	3
PCC	COL	2,778	14,573,790	102,942.0	55.51	0.1060	0.9930	6.09	5
PCC	COL	2,778	14,655,963	20,769.1	-1.2955	0.0153	0.9986	2.73	7
PCC	LR	61,230	333,060,000	194,544.0	18.5737	-0.00144	0.9994	**1.78**	2
PCC	LR	61,230	332,910,000	347,335.0	-452.60	-127.00	0.9990	2.38	3
PCC	LR	61,230	333,060,000	193,741.0	-6.79	0.0249	0.9994	**1.78**	5
PCC	LR	61,230	333,010,000	246,106.0	-1.1479	0.0222	0.9993	2.00	7
PCC	RU	60	363,655	274.6	90.8567	-0.00031	0.9992	2.14	2
PCC	RU	60	363,297	633.2	-482.50	-127.00	0.9983	3.25	3
PCC	RU	60	363,705	225.4	30.84	0.0452	0.9994	**1.94**	5
PCC	RU	60	363,705	224.5	-0.9669	0.0372	0.9994	**1.93**	7

Table 4.26 Summarized SAS results for PCC-ART, COL, LR & RU pavement family

For the PCC-ART and PCC-LR pavement families, Models 5 and 2 are recommended as they have the lowest SE and the highest $R^{2,}$. It should be noted that R^2 and SE are almost identical for these two models, as shown in *Table 4.26*.

For the PCC-COL pavement family, Model 2 is recommended because it has the lowest SE and the highest R^2, (*Table 4.26*).

Models 7 and 5 are recommended for the PCC-RU pavement family as they have the lowest SE and the highest R^2.

The predicted curve for the PCC-ART pavement family is shown in *Figure 4.10*. Figures E6 and E7 for PCC-COL and PCC-LR in Appendix E shows the predicted curves for the remaining PCC pavement families. Since they are in the middle of the measured PCI data points, all recommended models have reasonable trend.

4.2.4 Summarized Best Deterministic PCI Deterioration Models for Street with Non-Exp. sub. Soil

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X_1	X_2	X3	R^2	Stand. Error (SE)	Model
AC	ART	4,656	25,263,572	28,440.4	99.0	26.1553	0.0694	0.9989	2.47	5
AC	COL	6,234	31,937,988	32,938.1	99.0	21.8810	0.0643	0.9990	2.30	5
AC	LR	67,758	306,720,000	322,958.0	99.0	15.7866	0.0575	0.9989	2.18	5
AC	RU	1,746	8,075,568	9,787.2	99.0	15.6969	0.0574	0.9988	2.37	5
COM	ART	4,848	33,977,819	18,595.0	99.0	-0.8782	0.0469	0.9995	1.96	7
COM	COL	402	2,822,928	1,995.5	99.0	-0.8539	0.0495	0.9993	2.23	7
COM	LR	3,184	20,090,642	17,231.3	99.0	-0.9218	0.0423	0.9991	2.33	7
PCC	ART	9,978	57,470,625	45,534.3	99.0	6.2994	0.0296	0.9992	2.14	5
PCC	COL	2,778	14,664,017	12,715.2	660.7	1.8982	-0.0131	0.9991	2.14	2
PCC	LR	61,230	333,060,000	194,544.0	1.15E+10	18.5737	-0.0014	0.9994	1.78	2
PCC	RU	60	363,705	224.5	99.0	-0.9669	0.0372	0.9994	1.93	7

Table 4.27 Summarized Best Models for Non-Exp. subgrade soil pvmt families

The parameters estimated by the non-linear regression analysis performed using the SAS program are summarized in *Table 4.27*. They are also shown in the formulas for selected models in *Table 4.28*.

Selected Models	Pavement Family	Equation (PCI = y)
5	AC-ART	$y = 26.1553 - (26.1553 - 99) * e^{-0.0694t}$
5	AC-COL	$y = 21.881 - (21.881 - 99) * e^{-0.0643\,t}$
5	AC-LR	$y = 15.7866 - (15.7866 - 99) * e^{-0.0575t}$
5	AC-RU	$y = 15.6969 - (15.6969 - 99) * e^{-0.0574t}$
7	COM-ART	$y = 99 * \left[\frac{t^{-0.8782}}{0.0469 + t^{-0.8782}}\right]$
7	COM-COL	$y = 99 * \left[\frac{t^{b-0.8539}}{0.0495 + t^{-0.8539}}\right]$
7	COM-LR	$y = 99 * \left[\frac{t^{-0.9218}}{0.0423 + t^{-0.9218}}\right]$
5	PCC-ART	$y = 6.2994 - (6.2994 - 99) * e^{-0.0296\,t}$
2	PCC-COL	$y = 660.713195 * e^{-1.8982 * e^{-(-0.0131t)}}$
2	PCC-LR	$y = 11536939445 * e^{-18.5737 * e^{-(-0.00144t)}}$

7	PCC-RU	$y = 99 * \left[\frac{t^{-0.9669}}{0.0372 + t^{-0.9669}}\right]$

Table 4.28 Summarized Eq. for Best Models for non-exp. soil all pvmt. families (PCI)

The residuals for models 2, 3, 5 & 7 for all pavement families built on non-expansive subgrade soil are shown in Appendix M.

4.2.5 Comparison of Deterioration curves for Exp. vs Non-Exp. Subgrade Soil and AC vs PCC

The primary classification of the pavement is flexible and rigid. The phrase "flexible and rigid" describes how the surface of the pavement reacts to loads and to the environment. The flexible pavement has the capability to withstand applied stress without cracking. Flexible pavement is a pavement made of asphalt. It is a thin asphalt surface, which is constructed over a gravel base and a sub-base. These layers are rest on the subgrade, which are normally the native soil and is usually compacted to nine-five percent. On the other hand, the rigid pavement is made of Portland cement concrete that rests on the base of the compacted subgrade. The rigid pavement, due to the hardness and stiffness of the concrete, tends to spread the load over a relatively broad subgrade area. *Figure 4.11* illustrates a typical load transfer for asphalt and concrete pavements.

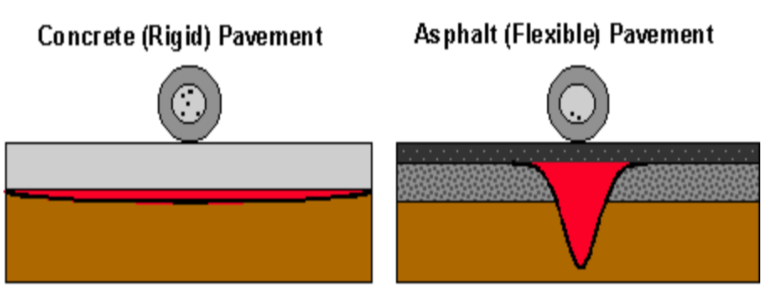

Figure 4.11 Typical Load Transfer PCC (Concrete Pavement) &AC (Asphalt) Pavement (ACPA)

The concrete slab itself gives a significant part of the structural capacity of the rigid pavement. Flexible pavement, made of a weaker and less rigid material, does not distribute loads as well as concrete. Flexible pavements therefore usually need more layers and more thickness for efficient load transfer to the subgrade. Based on the environment, traffic, and maintenance, the life expectancy of asphalt and concrete pavements varies. The life expectancy of the flexible pavement is 20-25 years, while the rigid pavement could last 30 to 35 years (ACPA), but this depends on how strong the base is, the types of soil underneath, how well these soils drain and how paved the street is.

According to *Figure 3.2* in this research, most of the streets in the DFW metropolitan area are built on expansive subgrade soil. Expansive subgrade soil is one of the most common causes of pavement degradation in the streets. Depending on the moisture content, expansive subgrade soils will undergo changes in volume due to seasonal variations in moisture. For the streets that are constructed on expansive subgrade soil, sub - grade preparation is carried out in order to prevent early degradation. The most common treatments for expansive subgrade soil for paved roads are over-excavation, cement treated foundation, lime, and fly ash treatment. Charts 4.12, 4.13 and 4.14 were constructed in order to compare the rate of deterioration of the PCC and AC pavement families and the rate of deterioration of the streets built on expansive and non-expansive sub-grade soil.

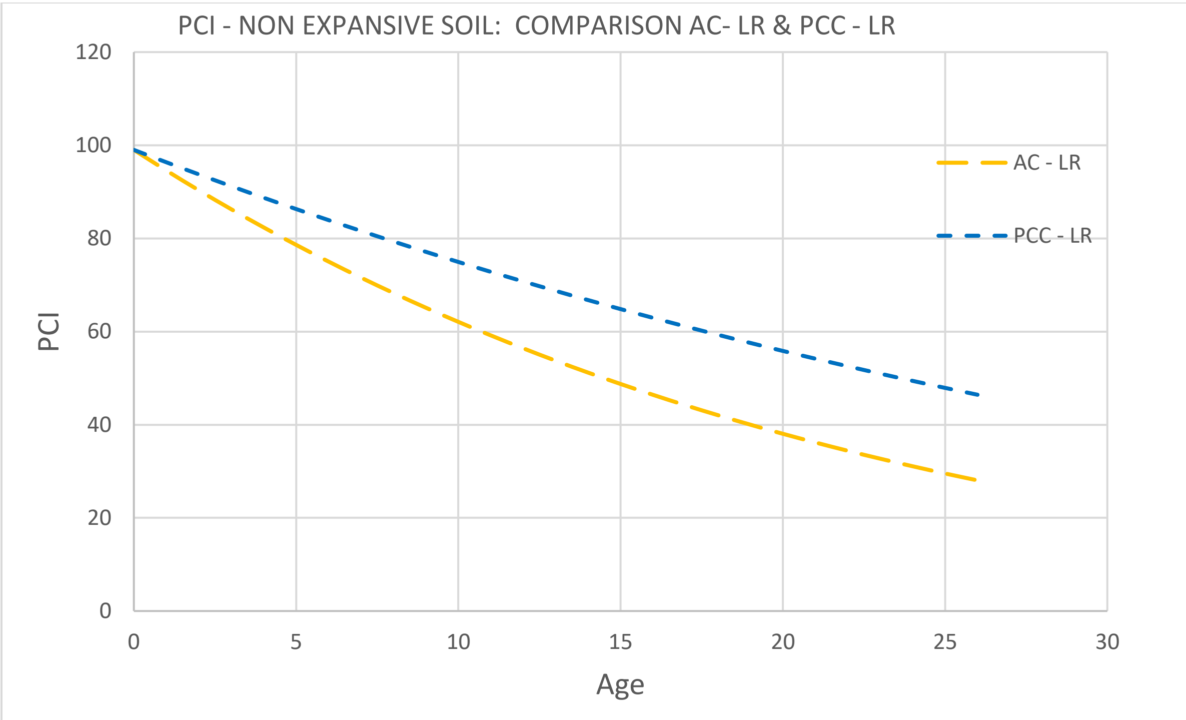

Figure 4.12 Comparison of Deterioration curve PCC vs AC – LR family (Non-Exp. subgrade soil)

The two deterioration curves fitted to both PCC and AC data are shown together in the chart above, *Figure 4.12*. In this graph, it can be seen that local residential streets with concrete (PCC) surface layer deteriorate slower than the streets with asphalt (AC) curve surface layer. Four deterioration curves for both PCC and AC data are presented together for expansive vs. non-expansive subgrade soil in the charts below, *Figures 4.13* and *4.14*. The blue line defines the deterioration curve of the expansive subgrade soil dataset, while the red curve reflects the deterioration curve of the non-expansive subgrade soil dataset for the AC-LR pavement family (*Figure 4.13*). The green line illustrates the deterioration curve of the expansive subgrade soil dataset, while the orange curve shows the deterioration curve of the non-expansive subgrade soil dataset for the PCC-LR pavement family (*Figure 4.13*). These charts show that the pavement resting on non-expansive subgrade soil deteriorates slower than the pavement resting on expansive subgrade soil. This outcome is expected when considering the behavior of the expansive subgrade soil. The charts shown in *Figure 4.14* are constructed to verify whether there is a difference in the rate of degradation of PCC-ART and AC-ART pavement families vs. PCC-LR and AC-LR pavement families built on expansive subgrade soil. As can be seen in the graph AC-ART pavement families have almost the same behavior as AC-LR families, while PCC-ART pavement families have the same rate of degradation for the first 15 years regardless of whether or not the streets are built on expansive subgrade soil. This could be explained by the concrete behavior and preparation of subgrade soil during the construction within the area with expansive subgrade soil as mentioned above.

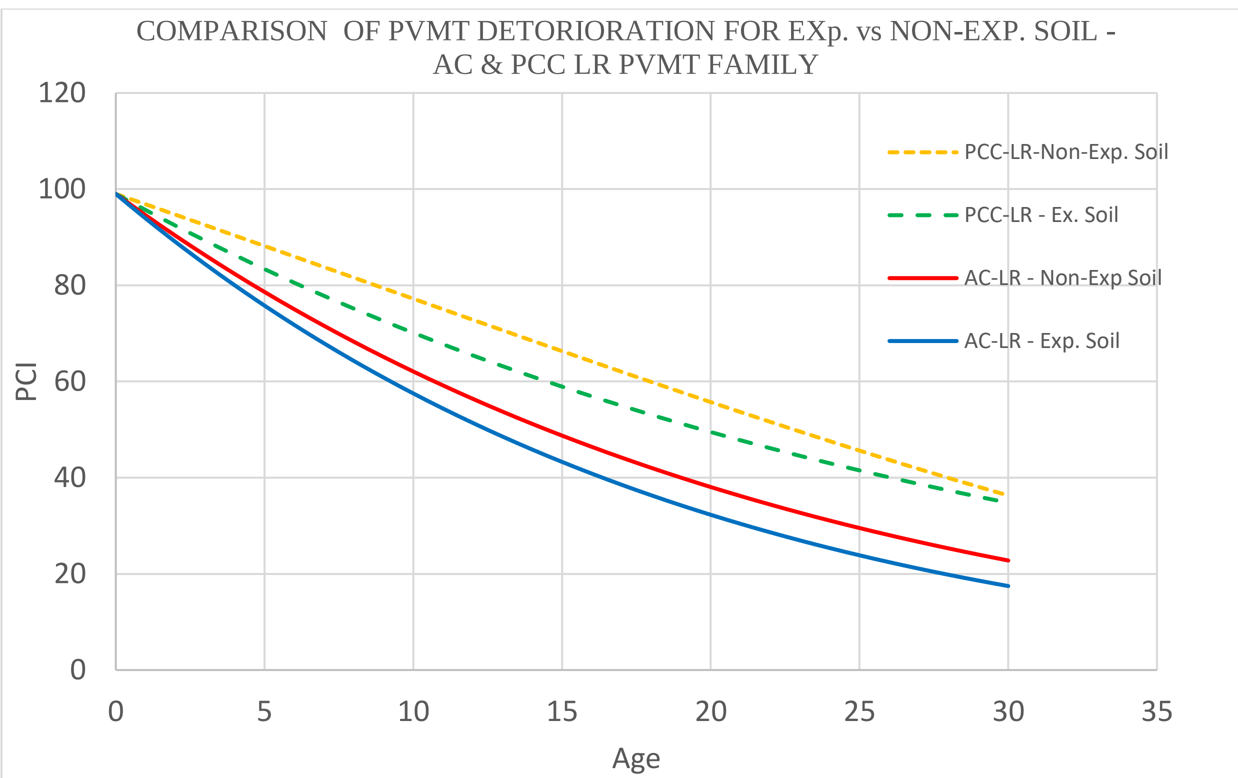

Figure 4.13 Comparison of Deterioration curve - Exp. vs Non-Exp. Soil AC & PCC-LR pvmt family

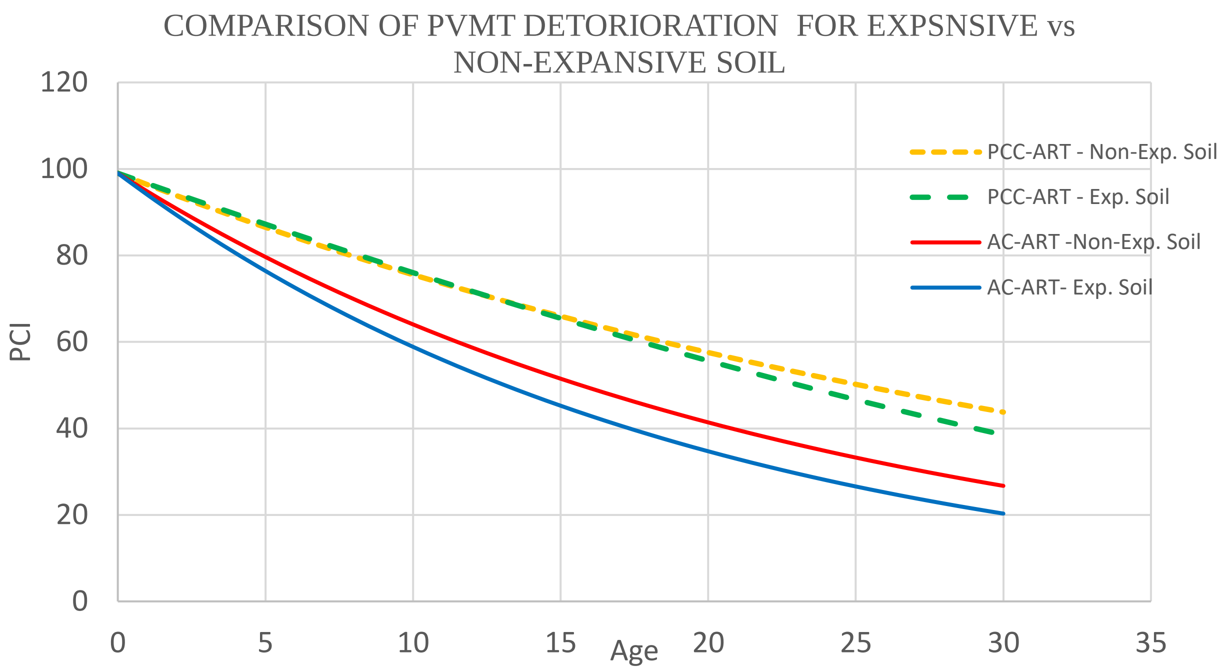

Figure 4.14 Comparison of Deterioration curve - Exp. vs Non-Exp. Soil AC & PCC-ART pvmt family

4.3 Development of Deterministic IRI Deterioration Models for Streets with Exp. Sub. Soil

The development of deterministic deterioration models for IRI followed the same process used for PCI models. The seven models shown in *Table 4.1* were also used to select the best deterministic street deterioration model in the DFW Metroplex area with expansive subgrade soil using IRI data. *Table 4.30* displays the sample data for the historical record of IRI collected by the city's asset management departments for the years 2007 to 2018 on expansive subgrade soil. After the data was sorted and cleaned as described in Chapter 3, the data was removed for streets which had the first IRI measured value recorded more than 10 years for AC and COM pavement families and more than 15 years for the PCC pavement family.

Table 4.29, provides a summary of all data with the percent of good data for modeling after elimination of the data that is not reliable for development of prediction models. Good data is data which has been cleaned and organized as described in Chapter 3.

Family	Pavement Type	Functional Class	Expsnsive Soil	Total No.	Last Rehab before 1998 (AC - 10Yrs.)	Last Rehab before 1998 (COM -10Yrs.)	Last Rehab before 1993 (PCC - 15 Yrs.)	Good Data for Modeling	% of Good Data
1	AC	ART	YES	1,323	3	N/A		**1,320**	100%
2	AC	COL	YES	503	3	N/A		**500**	99%
3	AC	LR	YES	5,781	75	N/A		**5,706**	99%
4	PCC	ART	YES	3,005	N/A	N/A	1	**3,004**	100%
5	PCC	COL	YES	1,245	N/A	N/A	2	**1,243**	100%
6	PCC	LR	YES	5,532	N/A	N/A	253	**5,279**	95%
7	COM	ART	YES	1,089	N/A	166	N/A	**923**	85%
8	COM	COL	YES	207	N/A	49	N/A	**158**	76%
9	COM	LR	YES	882	N/A	117	N/A	**765**	87%
IRI - Data			**Total:**	**19,567**	**81**	**332**	**256**	**18,898**	

Table 4.29 Summarized IRI Data for Expansive subgrade soil

These models should also comply with the following conditions:

• The initial IRI values right after a construction or major rehabilitation was considered as 160 for Arterial and Collector and 180 for Local Roads

• The IRI must increase with time

Asset ID	Street Name	Pavement Type	Functional Class	Expansive Soil	Latest Rehab/Reconst Year	IRI 2007	IRI 2008	IRI 2009	IRI 2010	IRI 2011	IRI 2012	IRI 2013	IRI 2014	IRI 2015	IRI 2016
28958	PASTEUR AVE	PCC	LR	Yes	1988				469		493	507			
28962	CARTAGENA PL	PCC	LR	Yes	1993			304	314		335	349			
28972	HIBISCUS DR	COM	LR	Yes	1995		249	262	275			303			
29020	MEADOW WAY CT	AC	LR	Yes	2006			345	362		393	408			
29053	LAKELAND DR	PCC	COL	Yes	1993		333		357				402		
29117	HOMEWAY CIR	AC	LR	Yes	1989			332	349		375	390			
29124	JOHN WEST RD	PCC	COL	Yes	1997		165	179	190				240		
29134	CHART DR	PCC	LR	Yes	1988		324	337	350		369	379			
29138	LAKELAND DR	PCC	COL	Yes	1993		332	343	356				399		
29163	LAKELAND DR	PCC	COL	Yes	1993		263	274	283				328		
29178	TWINLAWN DR	PCC	LR	Yes	1993		418	428	439		463	475			
29223	BRETSHIRE DR	PCC	LR	Yes	1993		331	344	355						
29295	JOHN WEST RD	PCC	COL	Yes	1995		255	265	279				318		
29358	ROCKYGLEN DR	AC	LR	Yes	2003		227	244			284	297			
29390	PETUNIA ST	PCC	LR	Yes	2007			205	218			254			
29400	DORRINGTON DR	AC	LR	Yes	1998		276	289	306		335	349			
29419	ST FRANCIS AVE	PCC	LR	Yes	1995		410	419	432		451	461			
29421	SWEETWATER DR	AC	LR	Yes	1998		253	268	283		314	327			
29431	JOHN WEST RD	PCC	COL	Yes	1995		231		253				294		
29520	LA PRADA DR	PCC	ART	Yes	1997		173	186	197				242		
29540	JOHN WEST RD	PCC	COL	Yes	1997		234		257				298		
29544	JOHN WEST RD	PCC	COL	Yes	1995		211		233				278		
29547	ANGIER WAY	PCC	LR	Yes	1993		311	325		351	363	377			
29661	JOHN WEST RD	PCC	COL	Yes	1997			215	225				277		
29693	FENESTRA DR	COM	LR	Yes	1998		231	242	254		276	290			
29723	BELLINGHAM DR	PCC	LR	Yes	1995			322	335		363	373			
29762	OHARE CT	PCC	LR	Yes	2007		191	201	214		234	243			
29769	PINEBLUFF DR	PCC	LR	Yes	1994		273	286			322	336			
29775	DORRINGTON DR	COM	LR	Yes	1988		212	223	237		258	270			
29816	GRAYCLIFF DR	COM	LR	Yes	1993		230	239	248		269				
29836	HUNNICUT RD	AC	LR	Yes	2003			188	204		234	249			
29875	ST THOMAS CIR	AC	LR	Yes	2007		195	211	224		254				
29937	BANQUO DR	AC	LR	Yes	1998		326	340	356		383	395			
29943	BAUMGARTEN DR	PCC	LR	Yes	2002		270	283			319				
29973	CHENAULT ST	AC	COL	Yes	2007		173	185	201		229				

Table 4.30 IRI Sample Data for Expansive subgrade soil

New Pavement IRI Limits	Road Types		
	Freeways	Arterials/ Collectors	Local Roads
IRI_c (Good)	≤80	≤160	≤180
IRI_f (Acceptable)	81-160	161-300	181-350

Table 4.31 DDOT's IRI Thresholds for New Pvmt and Rah. Pvmt (Stephen A. Arhin, 2015)

Since the data obtained from cities with expansive subgrade soil was unbalanced (did not have equal number of a IRI data for each street section) in order to develop deterministic models for all families shown in *Figure 3.3*, the macro script was used to determine the regression coefficients for each of the seven models shown in *Table 4.1*, as it was done for the development of PCI models. The Excel macro incorporated the Solver process to find model parameters such that the value of the Sum of the Square Error (SSE) is minimized. Then, TSS is calculated to find R^2. At the end, the Solver determined the best regression coefficients (a, b, c and d) and R^2 for all street sections of all models. See *Table 4.33* for an example of the model output.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1													
2	ID	NAME	TYPE	CLASS	Exp_Soil	Latest_ Rehab	2007	2008	2009	2010	2011	2012	2013
3	113493	VISALIA DR	PCC	LR	Yes	1985		555		576	587		610
4													
5							Age						
6		a	b	c	d	1	22	23	24	25	26	27	28
7						180	0	554.9	0	576	587	0	610
8		a1=V	b1	c1	d1								
9	Model 1	180	-11.3043	1.857109908	-0.04839	170.5044	314.8788	313.6384	309.4343	301.976	290.9733	276.1358	257.1732
10													
11	Model 2	1330.030098	2	0.05		198.4422	683.4918	706.0481	728.1947	749.9055	771.158	791.9326	812.2132
12													
13		a3=2*(V-b3)	b3	c3									
14	Model 3	-2.49209E+11	1.25E+11	-1.0776E+10		185.7814	307.1903	312.9717	318.7531	324.5344	330.3158	336.0972	341.8786
15													
16		a4	b4	c4									
17	Model 4	160	2	0.5		162.7183	157.8583	158.6976	159.2088	159.5196	159.7085	159.8231	159.8927
18													
19		a5=V	b5	c5									
20	Model 5	180	-119635	-4.8256E-05		185.7819	307.2671	313.0552	318.8435	324.6322	330.4211	336.2103	341.9998
21													
22		a6	b6	c6									
23	Model 6	418.3639279	1.768393	0.181357506		420.3137	454.1836	459.7605	465.7001	472.0025	478.6675	485.6953	493.0857
24													
25		a1	b1	c1									
26	Model 1	160	4	0.1		159.9984	159.9984	159.9989	159.9992	159.9994	159.9996	159.9997	159.9998

	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA
1														
2	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	a1	b1	c1
3												180	-11.3043	1.85711
4														
5														
6	29	30	31	32	33	34	35	36	37	38	39	SSE	TSS	R2
7	0	0	0	0	0	0	0	0	0	0	0			
8														
9	233.7951	205.7111	172.63103	134.2644	90.32087	40.51013	-15.4582	-77.8744	-147.029	-223.212	-306.714	345414.8	1579.408	-217.699
10														
11	831.9865	851.2421	869.97189	888.1706	905.8349	922.9636	939.5574	955.6188	971.1515	986.161	1000.654	127893.2		-79.9755
12														
13														
14	347.6599	353.4413	359.22269	365.0041	370.7854	376.5668	382.3482	388.1296	393.911	399.6923	405.4737	259540.1		-163.328
15														
16														
17	159.9349	159.9605	159.97605	159.9855	159.9912	159.9947	159.9968	159.998	159.9988	159.9993	159.9996	157323		-42.2821
18														
19														
20	347.7895	353.5796	359.36988	365.1605	370.9513	376.7425	382.5339	388.3256	394.1176	399.9099	405.7025	259331.5		-163.195
21														
22														
23	500.8389	508.9548	517.43345	526.2748	535.4788	545.0456	554.9751	565.2673	575.9222	586.9398	598.3202	62381.84		-16.1622
24														
25														
26	159.9998	159.9998	159.99988	159.9999	159.9999	159.9999	159.9999	160	160	160	160	156594.8	3634.83	-42.0817

Figure 4.15 Macro with all models – IRI (Expansive subgrade soil)

The initial IRI values of 160 and 180 values were set, as shown in *Table 4.32*. *Table 4.33* shows an example of the macro calculation output for Model 2 (Gompertz), the calculated parameters a, b, and c, as well as R^2 are given for each street section. These parameters were used to predict the IRI values at 5, 10, 15, and 20 years for Model 2 formula ($y = ae^{-be^{-ct}}$). After calculating predicted values for the same number of years of all streeet sections, the data set for models developent was balanced.

Dialog Box	Value after last major rehab for	LR	180	
	Value after last major rehab for	ART	160	Run Macro
		COL	160	

ID	NAME	TYPE	CLASS	Exp_Soil	Latest_Rehab	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
270	OLD MILL RD	AC	LR	Yes	1988		383	399		424													
288	OLD MILL RD	AC	LR	Yes	1991		120	132	148														
289	OLD MILL RD	AC	LR	Yes	1996		201	213	229														
290	OLD MILL RD	AC	LR	Yes	1984		241	255	268														
315	OLD MILL RD	PCC	LR	Yes	1988		385	395	409														
316	OLD MILL RD	PCC	LR	Yes	1993		407	420	431														
346	OLD MILL RD	AC	LR	Yes	1984		265	281	297														
347	OLD MILL RD	AC	LR	Yes	2003		243	255	271														
348	OLD MILL RD	AC	LR	Yes	2003		236	252	266														
397	OLD MILL RD	PCC	LR	Yes	1981		264	275	285														
2231	BELT LINE RD	PCC	ART	Yes	1995		249		274			312											
2317	BELT LINE RD	PCC	COL	Yes	1995		236		262			293											
3365	WALNUT ST	PCC	COL	Yes	1995		232	241	252														
3663	FOREST LN	PCC	COL	Yes	1995		198	209	218														
3716	FOREST LN	PCC	COL	Yes	1995		188	202	215														
6073	PLANO PKWY	AC	LR	Yes	2005		297	310		341													
7167	WILLARD DR	COM	LR	Yes	1988		220	229		251													
7395	BOEDEKER ST	AC	LR	Yes	2004		256	273		300													
15241	COOLWATER CV	PCC	LR	Yes	2003			279		301		321											
15789	BELT LINE RD	PCC	ART	Yes	1997		166		192			227											
15790	BELT LINE RD	PCC	ART	Yes	1997		185		209			247											
15791	BELT LINE RD	PCC	ART	Yes	1995		185		210			239											
15795	BELT LINE RD	PCC	ART	Yes	1995		160		184			215											
15814	BELT LINE RD	PCC	ART	Yes	1995		160		178			210											
15872	BELT LINE RD	PCC	ART	Yes	2002		188		209			248											
15874	BELT LINE RD	PCC	ART	Yes	1995		185		206			237											
15877	BELT LINE RD	PCC	ART	Yes	2002		166		188			220											
15880	BELT LINE RD	PCC	ART	Yes	1995		179		200			230											
15886	BELT LINE RD	PCC	ART	Yes	1997		176		196			232											
15888	BELT LINE RD	PCC	ART	Yes	2002		139		159			192											
15891	BELT LINE RD	PCC	ART	Yes	2002		170		189			221											
17588	PRESTON RD	COM	ART	Yes	1995		183			221	230												
17785	PRESTON RD	AC	ART	Yes	2003		202	217			260												
17825	PRESTON RD	AC	ART	Yes	2004		168	184			227												
18437	PRESTON RD	AC	ART	Yes	2004		159	174			217												
18438	PRESTON RD	AC	ART	Yes	2004		193	206			252												
18488	DARIA DR	PCC	LR	Yes	1993		182	191			227												
18512	PRESTON RD	AC	ART	Yes	2008		159	172			216												
18579	PRESTON RD	AC	ART	Yes	2003		238	253			298												
18607	PRESTON RD	AC	ART	Yes	2008		158	174			218												
18620	DARIA DR	PCC	LR	Yes	1995		182	191			226												
18889	AVERILL WAY	PCC	LR	Yes	1981		384		408		436												
19295	PRESTON RD	AC	ART	Yes	2003		187	200			242												
19322	PRESTON RD	AC	ART	Yes	1998		254	270			314												
19572	PRESTON RD	AC	ART	Yes	2004		167	181			226												

Table 4.32 IRI Sample Data for Macro (Expansive subgrade soil)

										5	10	15	20
ID	NAME	TYPE	CLASS	Exp_Soil	Latest_Rehab	a2	b2	c2	R-Squared 2	Predicted IRI model 2			
102491	S BELT LINE RD	PCC	ART	Yes	1993	4661.192	3.371853	0.005302	0.50006441	175	190	207	225
95538	N HAMPTON RD	COM	ART	Yes	1998	1508412	9.151394	0.002039	0.50030488	176	192	211	231
85813	GOOCH ST	AC	COL	Yes	2003	2292763	9.570094	0.002426	0.50032281	180	201	225	252
108736	S MARSALIS AVE	COM	ART	Yes	1993	3701	3.141185	0.005479	0.50048082	174	189	205	222
96695	BUNCHE DR	COM	LR	Yes	1995	848.7028	1.550752	0.01106	0.50050462	196	212	228	245
90767	GAYLORD DR	PCC	LR	Yes	1997	2348.482	2.568568	0.006863	0.50052922	196	213	231	250
96734	CAPELLA PARK AVE S	PCC	LR	Yes	1997	16733.92	4.532236	0.003582	0.50078941	195	211	228	246
92316	LAKELAND DR	AC	LR	Yes	1991	3337.973	2.920162	0.006305	0.50081673	197	215	234	254
62277	S MARSALIS AVE	COM	ART	Yes	1993	86224.06	6.289531	0.002794	0.5009092	175	190	207	225
66557	SONATA LN	AC	LR	Yes	2003	2036968	9.334016	0.002458	0.50092995	202	226	252	282
52993	S MARSALIS AVE	AC	ART	Yes	2003	1.07E+08	13.41418	0.001743	0.50111289	180	202	226	253
96922	COOLMEADOW LN	COM	LR	Yes	1995	780.0729	1.466431	0.013061	0.50123921	197	215	234	252
107104	FRANKFORD RD	PCC	ART	Yes	1995	3611.726	3.116767	0.006563	0.50190509	177	195	214	235
91096	W CLARENDON DR	COM	COL	Yes	1995	1566.378	2.281347	0.007297	0.50252347	174	188	203	218
61426	S CORINTH ST RD	PCC	ART	Yes	1997	13018.9	4.398984	0.004221	0.50259735	175	192	210	228
96265	WRIGHT ST	AC	COL	Yes	1988	1011.569	1.844084	0.012152	0.50278474	178	198	218	238
59815	S MARSALIS AVE	COM	ART	Yes	1995	22670.94	4.953666	0.00356	0.50280075	175	190	207	225
105752	S BELT LINE RD	PCC	ART	Yes	1993	1633.877	2.323537	0.007637	0.50317196	175	190	206	222
26011	DIXON BRANCH DR	PCC	LR	Yes	1995	786.4647	1.474591	0.013	0.50327712	198	215	234	252
61580	S EWING AVE	AC	LR	Yes	1996	19329.28	4.676419	0.004125	0.50341959	198	217	238	261
35788	BODINE LN	PCC	LR	Yes	1997	5463.227	3.412838	0.005007	0.50342993	196	213	230	249
82899	BICKERS ST	PCC	COL	Yes	1993	1231.574	2.040874	0.010043	0.50346752	177	194	213	232
90435	W KIEST BLVD	PCC	ART	Yes	1983	1282.636	2.081499	0.009466	0.50364352	176	193	211	229
93944	PLEASANT DR	PCC	LR	Yes	1995	5532.992	3.425527	0.004959	0.5036566	196	212	230	249
66128	HIGHCREST DR	PCC	LR	Yes	1997	2501.33	2.631621	0.006163	0.50441916	195	211	227	244
96332	ALADDIN DR	COM	LR	Yes	1997	82.56878	-0.77933	-0.01427	0.50458091	191	203	217	233

Table 4.33 IRI Sample Data with parameters calculated by Macro (Expansive subgrade soil)

The predicted of IRI at 5, 10, 15, and 20 years, was done to inspect if the IRI values are always increasing with time. The data for which the $R^2 < 0.5$ were removed. The results are summarized in Tables C1 to C6 in Appendix C. By applying the criteria described above, models 2, 3, 5 and 6 are the best models within these seven models. Models 1, 4 and 7 have been excluded from further consideration in the development of deterioration models since the predicted IRI values did not increase over time. *Table 4.34* shows summarized information for R^2 and the numbers of the data used for model development for each of the pavement families.

Family	**Pvmt Type**	**Func. Class**	**Expansive Soil**	**Total Data**	**Criteria $R^2 < 0.5$**	**Good Data $R^2 > 0.5$**	**Good Data (%) $R^2 > 0.5$**	**Criteria $R^2 < 0.7$**	**Good Data $R^2 > 0.7$**	**Good Data (%) $R^2 > 0.7$**	**Criteria $R^2 < 0.9$**	**Good Data $R^2 > 0.9$**	**Good Data (%) $R^2 > 0.9$**	**Prediction Model works**
1	AC	ART	Yes	**1,421**	-	1,421	100%	-	1,421	100%	-	1,421	100%	Yes
2	AC	COL	Yes	**608**	1	607	100%	2	606	100%	2	606	100%	Yes
3	AC	LR	Yes	**6,728**	5	6,723	100%	10	6,718	100%	38	6,690	99%	Yes
4	PCC	ART	Yes	**3,139**	-	3,139	100%	-	3,139	100%	1	3,138	100%	Yes
5	PCC	COL	Yes	**1,329**	1	1,328	100%	2	1,327	100%	2	1,327	100%	Yes
6	PCC	LR	Yes	**6,516**	2	6,514	100%	7	6,509	100%	11	6,505	100%	Yes
7	COM	ART	Yes	**1,414**	-	1,414	100%	2	1,412	100%	2	1,412	100%	Yes
8	COM	COL	Yes	**401**	-	401	100%	-	401	100%	1	400	100%	Yes
9	COM	LR	Yes	**2,011**	2	2,009	100%	2	2,009	100%	2	2,009	100%	Yes

Table 4.34 IRI - Model 1 (Cubic Polynomial) – Summarized Results

SAS statistical program has used the parameters shown in *Table 4.35* to calculate the best fit parameters: X_2, X_3, R^2 and Standard Error (SE). As shown in *Table 4.36*, the data had to be reorganized for use by the SAS program. The SAS statistical program was run separately for each pavement family.

IRI EXPANSIVE SOIL	a	b	c
2	1330.030098	2	0.05000000
4	-331295233.2	0.99	
5	180.00000000	-119635.2312	-0.00004826
6	418.36392794	1.768392874	0.181357506

Table 4.35 Starting parameters for SAS - IRI Models (Expansive subgrade soil)

Models with a high R^2 values and low Standard Error (SE) are the best fit. *Tables 4.37* to *4.40* list the parameters determined by the SAS program. All models shown have low SE and high R^2, so the models were retained for further selection. All tables with the final outputs have been evaluated to verify that the models meet the minimum criteria set out above.

ID	SUFT	CLASS	AGE	IRI
19322	AC	ART	5	212
58026	AC	ART	5	209
89693	AC	ART	5	213
109816	AC	ART	5	250
88328	AC	ART	5	211
19322	AC	ART	10	263
58026	AC	ART	10	259
89693	AC	ART	10	265
109816	AC	ART	10	339
88328	AC	ART	10	262
19322	AC	ART	15	315
58026	AC	ART	15	308
89693	AC	ART	15	318
109816	AC	ART	15	429
88328	AC	ART	15	313
19322	AC	ART	20	367
58026	AC	ART	20	357
89693	AC	ART	20	370
109816	AC	ART	20	518
88328	AC	ART	20	363

Table 4.36 IRI – Sample data organized for SAS statistical software

Model 2 - IRI - Expansive Soil								
Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	3,892	438,770,000	12,040,731	1.3325	0.0638	0.9733	55.62
AC	COL	1,564	185,090,000	5,230,851	1.2076	0.0809	0.9725	57.83
AC	LR	17,380	2,455,900,000	85,623,777	0.9754	0.1212	0.9663	70.19
COM	ART	2,428	221,510,000	6,106,518	1.1957	0.0599	0.9732	50.15
COM	COL	464	39,939,222	960,456	1.1008	0.0638	0.9765	45.50
COM	LR	1,640	182,150,000	8,167,259	0.8867	0.1000	0.9571	70.57
PCC	ART	10,908	919,610,000	25,597,080	1.1646	0.0566	0.9729	48.44
PCC	COL	4,484	382,610,000	11,381,329	1.1405	0.0595	0.9711	50.38
PCC	LR	19,972	2,112,000,000	80,223,397	1.0442	0.0672	0.9634	63.38

Table 4.37 SAS results for Model 2-IRI (Gompertz) – Expansive subgrade soil

Model 3 - IRI - Expansive Soil								
Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	3,620	399,670,000	10,624,242	-41451.1	1585.1	0.9741	54.17
AC	COL	1,416	167,810,000	4,155,658	-43556.9	1559.3	0.9758	54.17
AC	LR	14,224	1,990,000,000	52,000,957	-46766.2	1587.7	0.9745	60.46
COM	ART	2,312	205,790,000	3,739,448	-35728.7	1694.0	0.9822	40.22
COM	COL	436	37,685,413	889,741	-29559.9	1447.3	0.9769	45.17
COM	LR	1,340	132,680,000	3,050,934	-31586.6	1535.3	0.9775	47.72
PCC	ART	10,160	850,870,000	19,401,205	-28988.0	1468.8	0.9777	43.70
PCC	COL	4,180	351,320,000	7,989,005	-29052.2	1466.3	0.9778	43.72
PCC	LR	17,852	1,798,600,000	42,982,926	-31838.0	1517.3	0.9767	49.07

Table 4.38 SAS results for Model 3-IRI (Logistic) – Expansive subgrade soil

Model 5 - IRI - Expansive Soil								
Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	3,480	416,340,000	11,760,564	19702.4	0.00073	0.9725	58.13
AC	COL	1,384	176,390,000	4,156,349	21317.4	0.00071	0.9770	54.80
AC	LR	13,388	2,042,500,000	328,150,000	46702.5	0.00035	0.8616	156.56
COM	ART	2,312	216,250,000	4,120,459	37554.4	0.00030	0.9813	42.22
COM	COL	444	42,104,558	3,798,784	72904.2	0.00016	0.9172	92.50
COM	LR	1,644	185,020,000	12,408,781	839.1	0.02110	0.9371	86.88
PCC	ART	9,920	879,170,000	21,874,667	25176.8	0.00042	0.9757	46.96
PCC	COL	3,992	358,660,000	7,972,311	26498.0	0.00041	0.9783	44.69
PCC	LR	19,012	1,971,600,000	59,166,026	1563.2	0.00840	0.9709	55.79

Table 4.39 SAS results for Model 5- IRI (Exponential) – Expansive subgrade soil

Model 6 - IRI - Expansive Soil								
Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)
AC	ART	3,944	624,960,000	25,843,362	11.212	0.4193	0.9603	80.95
AC	COL	1,592	244,090,000	8,041,550	14.0092	0.2171	0.9681	71.07
AC	LR	18,820	3,289,400,000	118,460,000	18.4627	-0.0281	0.9652	79.34
COM	ART	2,500	268,120,000	8,641,476	9.3692	0.2116	0.9688	58.79
COM	COL	544	56,229,556	2,004,764	6.9880	0.3319	0.9656	60.71
COM	LR	1,848	239,890,000	15,943,189	12.289	0.0901	0.9377	92.88
PCC	ART	11,264	1,054,600,000	46,773,765	8.7469	0.1506	0.9575	64.44
PCC	COL	4,628	444,610,000	21,420,141	9.3502	0.1311	0.9540	68.03
PCC	LR	21,012	2,416,300,000	150,930,000	11.2955	0.0529	0.9412	84.75

Table 4.40 SAS results for Model 6-IRI 2-nd Polynomial) – Expansive subgrade soil

After all models were analyzed, the next step was to construct a chart for each model. *Figure 4.16* for AC-ART and Figures F1 to F6 for the rest of the pavement families. By drawing all the models in one graph, the behavior of and model was much easier to compare. The same was done for all pavement families, the charts are shown in Appendix F. All models are grouped together as shown in *Figure 4.16* and *Table 4.41*.

4.3.1 Deterministic Prediction model for AC Pvmt Family (Exp. Soil) – IRI

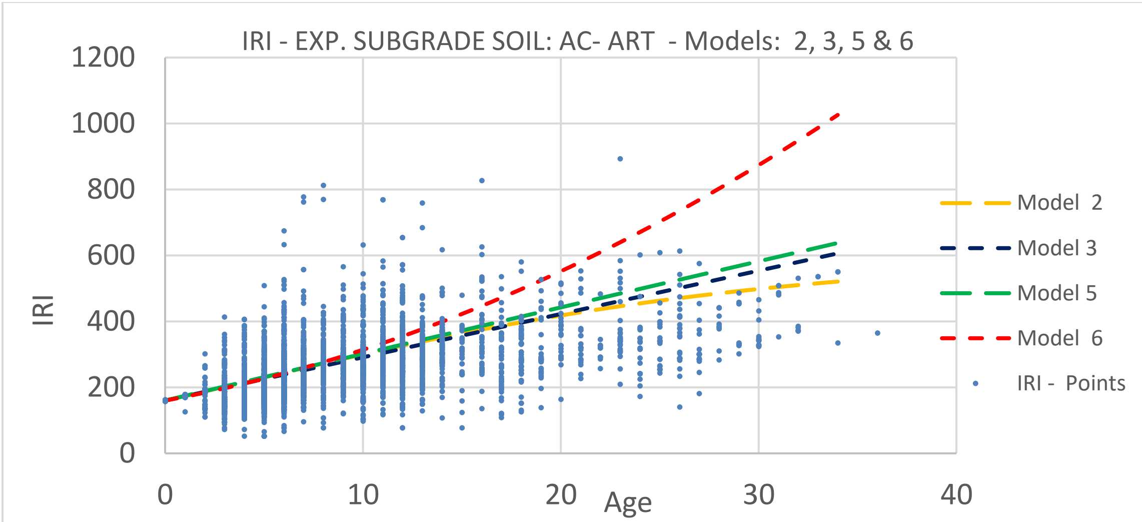

Figure 4.16 Chart for Models 2,3,5 & 6 – AC-ART Pavement Family (Exp. subgrade soil)

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)	Model
AC	ART	3,892	438,770,000	12,040,731	1.3325	0.0638	0.9733	55.62	2
AC	ART	3,620	399,670,000	10,624,242	-41451.1000	1585.10	0.9741	**54.17**	3
AC	ART	3,480	416,340,000	11,760,564	19702.4000	0.00073	0.9725	58.13	5
AC	ART	3,944	624,960,000	25,843,362	11.2120	0.4193	0.9603	80.95	6
AC	COL	1,564	185,090,000	5,230,851	1.2076	0.0809	0.9725	57.83	2
AC	COL	1,416	167,810,000	4,155,658	-43556.9000	1559.30	0.9758	**54.17**	3
AC	COL	1,384	176,390,000	4,156,349	21317.4000	0.00071	0.9770	54.80	5
AC	COL	1,592	244,090,000	8,041,550	14.0092	0.2171	0.9681	71.07	6
AC	LR	17,380	2,455,900,000	85,623,777	0.9754	0.1212	0.9663	70.19	2
AC	LR	14,224	1,990,000,000	52,000,957	-46766.2000	1587.70	0.9745	**60.46**	3
AC	LR	13,388	2,042,500,000	328,150,000	46702.5000	0.00035	0.8616	156.56	5
AC	LR	18,820	3,289,400,000	118,460,000	18.4627	-0.0281	0.9652	79.34	6

Table 4.41 Summarized SAS results for AC-ART, COL & LR pavement family

Models 3 are recommended for AC-ART, AC-COL and AC-LR pavement families because they have the lowest SE, as can be seen in *Table 4.41*.

The predicted curve for the AC-ART pavement family is shown on the graph in *Figure 4.16*. Figures F1 and F2 for AC-COL and AC-LR in Appendix F shows the predicted curves for the remaining AC pavement families. As they are in the middle of the PCI, data points, all recommended models are reasonable.

4.3.2 Deterministic Prediction model for COM Pavement Family (Exp. Soil) – IRI

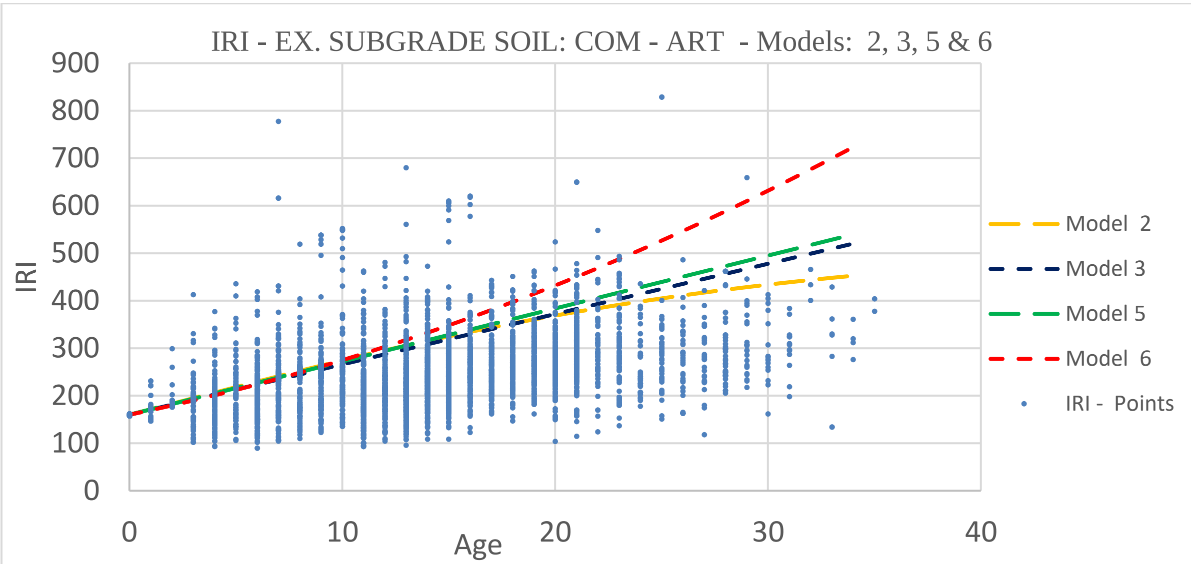

Figure 4.17 Chart for Models 2, 3, 5 & 6 – COM-ART Pavement Family (Expansive subgrade soil)

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)	Model
COM	ART	2,428	221,510,000	6,106,518	1.1957	0.0599	0.9732	50.15	2
COM	ART	2,312	205,790,000	3,739,448	-35728.70	1694.00	0.9822	**40.22**	3
COM	ART	2,312	216,250,000	4,120,459	37554.40	0.00030	0.9813	42.22	5
COM	ART	2,500	268,120,000	8,641,476	9.3692	0.2116	0.9688	58.79	6
COM	COL	464	39,939,222	960,456	1.1008	0.0638	0.9765	45.50	2
COM	COL	436	37,685,413	889,741	-29559.90	1447.30	0.9769	**45.17**	3
COM	COL	444	42,104,558	3,798,784	72904.20	0.00016	0.9172	92.50	5
COM	COL	544	56,229,556	2,004,764	6.9880	0.3319	0.9656	60.71	6
COM	LR	1,640	182,150,000	8,167,259	0.8867	0.1000	0.9571	70.57	2
COM	LR	1,340	132,680,000	3,050,934	-31586.60	1535.30	0.9775	**47.72**	3
COM	LR	1,644	185,020,000	12,408,781	839.10	0.02110	0.9371	86.88	5
COM	LR	1,848	239,890,000	15,943,189	12.289	0.0901	0.9377	92.88	6

Table 4.42 Summarized SAS results for COM-ART, COM & LR pavement family

Models 3 are recommended for COM-ART, COM-COL and COM-LR pavement families as they have the lowest SE and the highest R^2 (*Table 4.42*).

The predicted curve for the COM-ART pavement family is shown in *Figure 4.17*. Figures F3 and F4 for COM-COL and COM-LR in Appendix F give the model curves for the remaining COM pavement families. Since the curves are located in the middle of the PCI, data points, all recommended models are reasonable.

4.3.3 Deterministic Prediction model for PCC Pavement Family (Exp. Soil) – IRI

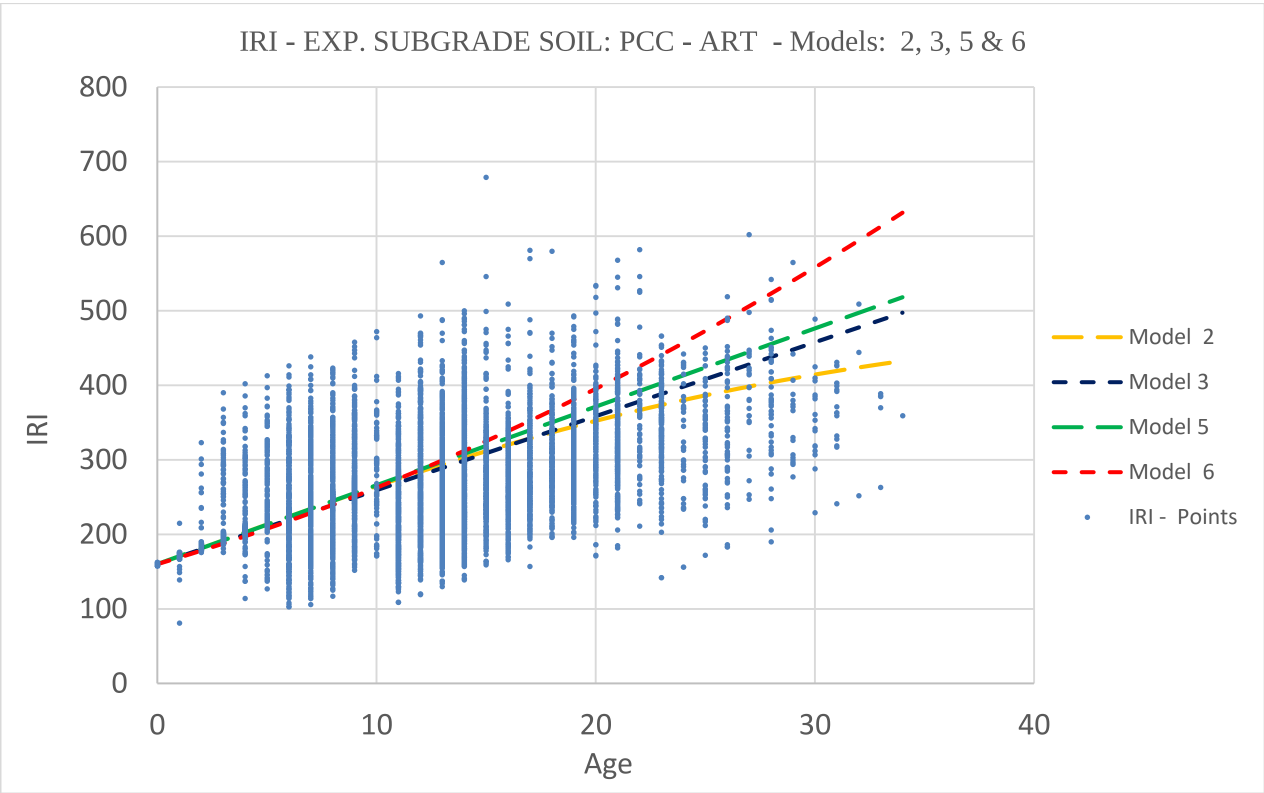

Figure 4.18 Chart for Models 2,3,5 & 6 – PCC-ART Pavement Family (Expansive subgrade soil)

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X2	X3	R^2	Stand. Error (SE)	Model
PCC	ART	10,908	919,610,000	25,597,080	1.1646	0.0566	0.9729	48.44	2
PCC	ART	10,160	850,870,000	19,401,205	-28988.00	1468.80	0.9777	**43.70**	3
PCC	ART	9,920	879,170,000	21,874,667	25176.80	0.00042	0.9757	46.96	5
PCC	ART	11,264	1,054,600,000	46,773,765	8.7469	0.1506	0.9575	64.44	6
PCC	COL	4,484	382,610,000	11,381,329	1.1405	0.0595	0.9711	50.38	2
PCC	COL	4,180	351,320,000	7,989,005	-29052.20	1466.30	0.9778	**43.72**	3
PCC	COL	3,992	358,660,000	7,972,311	26498.00	0.00041	0.9783	44.69	5
PCC	COL	4,628	444,610,000	21,420,141	9.3502	0.1311	0.9540	68.03	6
PCC	LR	19,972	2,112,000,000	80,223,397	1.0442	0.0672	0.9634	63.38	2
PCC	LR	17,852	1,798,600,000	42,982,926	-31838.00	1517.30	0.9767	**49.07**	3
PCC	LR	19,012	1,971,600,000	59,166,026	1563.20	0.00840	0.9709	55.79	5
PCC	LR	21,012	2,416,300,000	150,930,000	11.2955	0.0529	0.9412	84.75	6

Table 4.43 Summarized SAS results for PCC-ART, COL & LR pavement family

Models 3 are recommended for PCC-ART, COL and LR pavement families, as they have the lowest SE, (*Table 4.43*). The predicted curve for the PCC-ART pavement family is shown in *Figure 4.18*. Figures F5 and F6 for PCC-COL and PCC-LR in Appendix E depict the predicted curves for the remaining PCC pavement families. As the curves are located in the middle of the PCI data points, all recommended models are reasonable.

4.2.4 Summarized Best Deterministic IRI Deterioration Models for Streets with Expansive Subgrade Soil

Surface	Class	Degree of Freedom (DF)	Sum of Square (SS)	Error Sum of Square (SSE)	X1	X2	X3	R^2	Stand. Error (SE)	Model
AC	ART	3,620	399,670,000	10,624,242	83,222.2	-41451.1	1585.1	0.9741	54.17	3
AC	COL	1,416	167,810,000	4,155,658	87,433.8	-43556.9	1559.3	0.9758	54.17	3
AC	LR	14,224	1,990,000,000	52,000,957	93,892.4	-46766.2	1587.7	0.9745	60.46	3
COM	ART	2,312	205,790,000	3,739,448	71,777.4	-35728.7	1694.0	0.9822	40.22	3
COM	COL	436	37,685,413	889,741	59,439.8	-29559.9	1447.3	0.9769	45.17	3
COM	LR	1,340	132,680,000	3,050,934	63,533.2	-31586.6	1535.3	0.9775	47.72	3
PCC	ART	10,160	850,870,000	19,401,205	58,296.0	-28988.0	1468.8	0.9777	43.70	3
PCC	COL	4,180	351,320,000	7,989,005	58,424.4	-29052.2	1466.3	0.9778	43.72	3
PCC	LR	17,852	1,798,600,000	42,982,926	64,036.0	-31838.0	1517.3	0.9767	49.07	3

Table 4.44 Summarized best Models for Expansive subgrade soil pavement families (IRI)

The parameters obtained in the non-linear regression analysis using the SAS program are summarized in *Table 4.44* and models are given in *Table 4.45*.

Models	**Pavement Family**	**Equation (IRI = y)**
3	AC-ART	$y = \frac{83222.2}{1 + e^{-\frac{t}{1585.1}}} - 41451.1$
3	AC-COL	$y = \frac{87433.8}{1 + e^{-\frac{t}{1559.3}}} - 43556.9$
3	AC-LR	$y = \frac{93892.4}{1 + e^{-\frac{t}{1587.7}}} - 46766.2$
3	COM-ART	$y = \frac{71777.4}{1 + e^{-\frac{t}{1694}}} - 35728.7$
3	COM-COL	$y = \frac{59439.8}{1 + e^{-\frac{t}{1447.3}}} - 29559.9$
3	COM-LR	$y = \frac{63533.2}{1 + e^{-\frac{t}{1535.3}}} - 31586.6$
3	PCC-ART	$y = \frac{58296}{1 + e^{-\frac{t}{1468.8}}} - 28988$
3	PCC-COL	$y = \frac{58424.4}{1 + e^{-\frac{t}{1466.3}}} - 29052.2$
3	PCC-LR	$y = \frac{64036}{1 + e^{-\frac{t}{1517.3}}} - 31838$

Table 4.45 Summarized Eq. for Best Models for Exp. soil all pvmt. families (IRI)

The residuals for models 2, 3, 5 & 6 for all pavement families built on expansive subgrade soil are shown in Appendix N.

4.2.5 Comparison of Deterioration curves for PCC vs AC Pvmt Family (Exp. Soil) – IRI

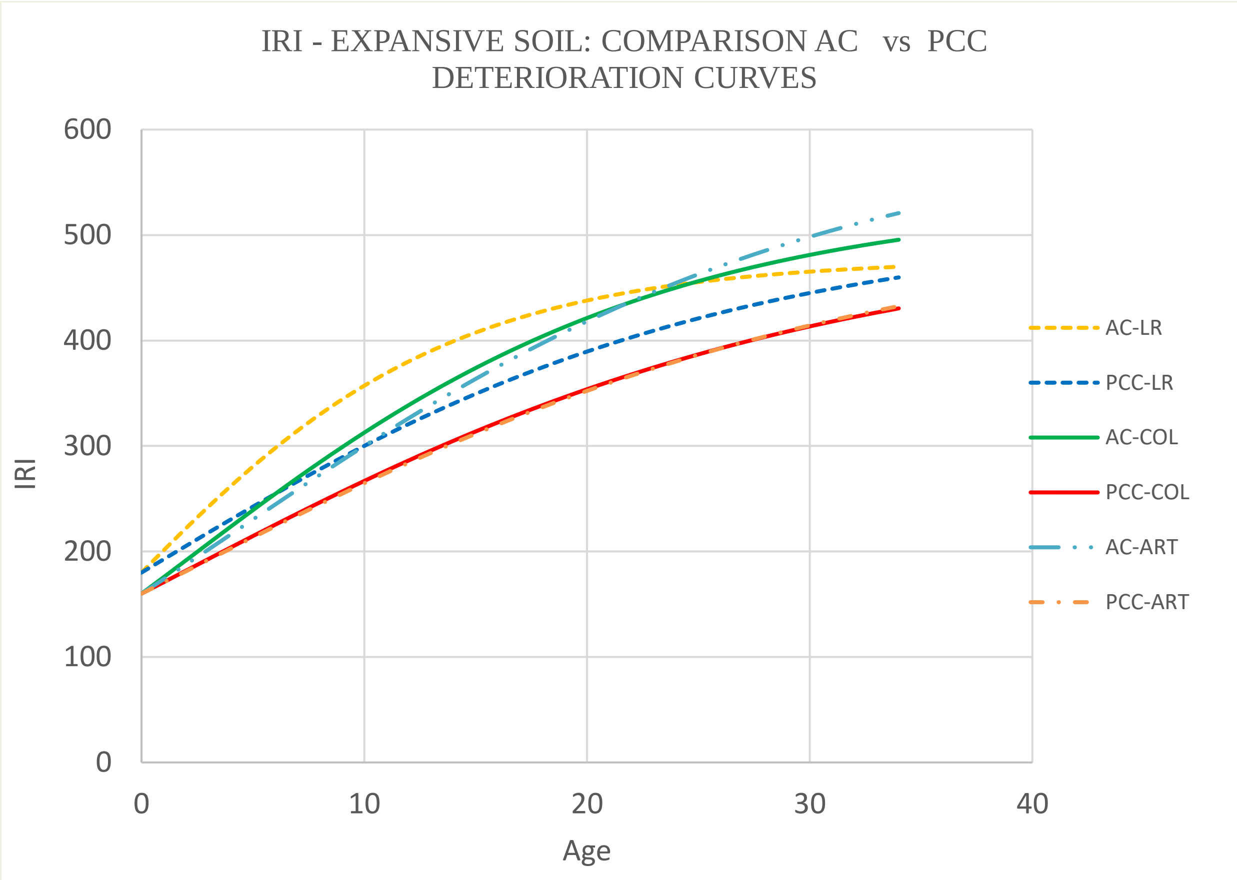

Figure 4.19 Comparison of Deterioration curve PCC vs AC family (IRI Exp. subgrade soil)

The six deterioration curves fitted to both PCC and AC data are shown together in the chart above, *Figure 4.19.* In this graph, streets with a concrete (PCC) surface layer deteriorate slower than the streets with asphalt (AC) curve surface layer, which is expected. It should be noted that PCC-ART and PCC-COL pavement families have almost identical deterioration curves, the explanation for this outcome may be the strength of the concrete pavement structure.

Chapter 5: Development of Probabilistic Deterioration Models

The probability – based Markov model was first developed for the Arizona Pavement Management System to describe pavement condition changes (Polhemus, N.W. 1980). Markovian models are the most common stochastic techniques used extensively in modeling the deterioration of infrastructure facilities (Butt et al 1987; Jiang et al. 1988).

The Markovian technique is a probabilistic model that accounts for the uncertainty associated with the future pavement condition. These models use the Markov Decision Process (MDP) that predicts the deterioration of a component by defining discrete condition states and using the probability of transition from one condition state to another over multiple discrete time intervals (Lounis et al. 1998).

The idea of a Markov prediction model centers on a mathematical structure known as a Markov Chain. This is used to model the condition of the road with a discrete number of states, say 1, 2, … n. In the case presented in this research, condition states are divided into bins determined by the PCI (Pavement Condition Index) values, as shown in *Table 5.2*. The first assumption for this model is that time is considered discrete, i.e. $t = 0, 1, 2, \dots$ Secondly, it is assumed that pavement deterioration follows the Markov property, i.e. pavement condition in the next year only depends on the current state. Given a starting vector $a_0 = (\alpha_1, \alpha_2, \dots, \alpha_n)$, which represents the initial state of the process, the goal of the Markov prediction model is to find the transition probability matrix (TPM), M which will model all of the probabilities of moving from state i to state j, for example.

$$M = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1n} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2n} \\ p_{31} & p_{32} & p_{33} & \cdots & p_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & p_{n3} & \cdots & p_{nn} \end{bmatrix}$$

Assuming that this Markov Chain is time-homogeneous, or that the transition probability matrix is constant at every time *t*, then the Markov prediction model will be able to determine the distribution of the states a_t at each time *t* in the following way:

$$a_1 = a_0 M$$

$$a_2 = a_0 M^2$$

$$\vdots$$

$$a_t = a_0 M^t$$

where a_0 is the initial distribution of states at time $t = 0$ and M^t represents the transition probability matrix raised to the power of *t*.

The form of M can be adjusted by making several observations. Firstly, it is assumed that $i > j$ has 0.0 probability because pavement conditions cannot improve without reconstruction/rehabilitation. Hence, $p_{ij} = 0$ for $1 \leq i < j \leq n$. Secondly, once the poorest state is reached (when the state is n), then it must stay in that state indefinitely until rehabilitation. This means that $p_{nn} = 1$. The TPM is now given by:

$$M = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1n} \\ 0 & p_{22} & p_{23} & \cdots & p_{2n} \\ 0 & 0 & p_{33} & \cdots & p_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}$$

Furthermore, it is assumed that any state cannot jump more than one state, e.g. there can be no jumps directly from “good” to “poor” without transitioning first from “good” to “satisfactory”, etc. This leads to the final form of the TPM:

$$M = \begin{bmatrix} p_{11} & p_{12} & 0 & \dots & 0 \\ 0 & p_{22} & p_{23} & \dots & 0 \\ 0 & 0 & p_{33} & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \end{bmatrix}$$

From here, it is important to be able to estimate the transition probabilities p_{ij} from the data. These can only be estimated provided that consecutive years of PCI are reported, i.e. historical data is available. The minimal sufficient quantity of data needed for estimation is only two years. The transition probabilities are typically estimated using the Maximum Likelihood Estimator (Jiang et al. (1988); Morcous et al. (2002); Garcia et al. (2006)):

$$p_{ij} = \frac{N_{ij}}{N_i}$$

Where N_i represents the number of roads that start at condition i and N_{ij} represents the number of transitions out of condition i to condition j in 1 year.

There were certain assumptions made in generating a transition probability matrix for the pavements, which are as follows (Kamalesh 2009):

- Pavement conditions are expressed in a finite number of states.
- The transition probabilities depend only on the present condition state.
- The transition process is stationary, that is, the probability of transition from one condition state to another does not change with time.

- Condition ratings will always remain constant or decrease with time. Increase in condition rating is not considered for pavement that is left to deteriorate on its own.

5.1 Development of Probabilistic Deterioration Models for street pavements built on Non-Exp. subgrade soil (PCI)

For this research, historical records of PCI data collected in the DFW Metroplex area for non-expansive subgrade soil was used to develop a probabilistic model for all pavement families specified in *Figure 3.3*. At this time, no systematic research has been conducted to develop probabilistic models for the street network in the DFW Metroplex area.

Table 5.1, shows sample data for the historical record of PCI collected by the city's asset management departments from 2014 to 2019. After the data was sorted and cleaned as previously described in Chapter 3, the data then was categorized in order to develop the Markovian probabilistic models. The data was categorized per *Table 5.2*, using the excel "IF" function.

E	F	G	H	I	J	K	L	M	N	O	P	Q	R
Expansive Soil	Latest Rehab/Reconstruction Year	PCI 2014	PCI 2015	PCI 2016	PCI 2017	PCI 2018	PCI 2019	PCI 2014 category	PCI 2015 category	PCI 2016 category	PCI 2017 category	PCI 2018 category	PCI 2019 category
No	2015	60	95	91	89	85	83	3	1	1	1	2	2
No	2015	60	95	94	88	87	83	3	1	1	1	1	2
No	2015	58	95	90	89	85	80	3	1	1	1	2	2
No	2012	88	86	83	76	70	68	1	1	2	2	3	3
No	2013	91	88	87	81	77	71	1	1	1	2	2	2
No	2012	88	86	81	78	74	68	1	1	2	2	2	3
No	2013	94	88	86	82	77	71	1	1	1	2	2	2
No	2012	89	86	81	76	73	69	1	1	2	2	2	3
No	2013	94	89	87	81	77	70	1	1	1	2	2	3
No	2014	98	93	89	85	80	75	1	1	1	2	2	2
No	2014	98	91	89	85	80	75	1	1	1	2	2	2
No	2013	92	88	85	80	79	70	1	1	2	2	2	3
No	2014	98	92	89	85	84	75	1	1	1	2	2	2
No	1998	50	48	45	42	41	38	4	4	4	4	4	5
No	2000	54	53	49	46	44	42	4	4	4	4	4	4
No	2002	58	57	54	53	49	48	3	3	4	4	4	4
No	1999	53	50	48	44	42	41	4	4	4	4	4	4
No	1999	53	50	48	44	43	41	4	4	4	4	4	4
No	2002	58	57	54	52	49	47	3	3	4	4	4	4
No	2000	54	51	49	48	45	42	4	4	4	4	4	4
No	2009	79	74	68	66	64	63	2	2	3	3	3	3
No	1998	50	47	44	42	41	38	4	4	4	4	4	5
No	1998	49	48	44	43	40	38	4	4	4	4	5	5
No	2015	52	99	94	88	85	82	4	1	1	1	2	2
No	2000	54	53	49	47	44	43	4	4	4	4	4	4
No	2006	67	65	63	61	58	57	3	3	3	3	3	3
No	2014	95	93	89	85	84	76	1	1	1	2	2	2
No	2003	61	59	57	55	53	50	3	3	3	4	4	4
No	2013	90	89	85	83	77	72	1	1	2	2	2	2
No	2013	92	88	85	80	76	70	1	1	2	2	2	3

Table 5.1 Sample data for probabilistic modeling

After the data was sorted according to the family definition and categorized per *Tables 5.2*, the Transition State to State Count table was created in order to count each state. *Table 5.3* shows an example for the AC-ART streets. The Appendix G contains the transition state to state tables for all other pavement families.

Proposed Rating	PCI values	State
Very Good (VG)	85-100	1
Good (G)	71-85	2
Satisfactory (S)	56-70	3
Poor (P)	41-55	4
Very Poor (VP)	0-40	5

Table 5.2 Standard PCI rating

AC-ART	
Transition State	**Count**
1-1 (VG-VG)	**1,063**
1-2 (VG-G)	**428**
1-3 (G-S)	-
1-4 (VG-P)	-
1-5 (VG-VP)	-
2-1 (G-VG)	-
2-2 (G-G)	**498**
2-3 (G-S)	**103**
2-4 (G-P)	-
2-5 (G-VP)	-
3-1 (S-VG)	161
3-2 (S-G)	-
3-3 (S-S)	**479**
3-4 (S-P)	**164**
3-5 (S-VP)	-
4-1 (P-VG)	82
4-2 (P-G)	-
4-3 (P-S)	-
4-4 (P-P)	**802**
4-5 (P-VP)	**54**
5-1 (VP-VG)	-
5-2 (VP-G)	-
5-3 (VP-S)	-
5-4 (VP-P)	-
5-5 (VP-VP)	**46**
SUM	**3,880**

Table 5.3 Transition State to State Transition Matrix (2014 – 2019)

In this research, it is assumed that the pavement condition will not be decreased by more than one state in one year, so that the pavement will remain in its current state or transit to the next lower state. All other transitions are not included in the final transition matrix.

Tables 5.3 indicate that between 2014-2019 there were 428 pavement sections which transitioned from Very Good (1) to a Good state (2). In addition, 103 pavement sections went from a Good (2) to a satisfactory state (3).

Furthermore, 164 pavement sections transitioned form Satisfactory to Poor state (4), and 54 pavement sections transitioned from Poor (4) to Very Poor State (5). After counting pavement sections that transitioned from one to another state the next step was to create a Transition Matrixes. Transition Matrix for AC-ART pavement family is shown in *Table 5.4*. These tables were created for each pavement family following the same procedure. After the Transition Matrix table was created, a Transition Probability Matrix (TPM) was created for each pavement family. The TPM for AC–ART pavement family is shown in *Table 5.5*.

The numbers in the TPM matrix were calculated by taking the number of observations transitioning from a particular state to the current state, the value was then divided by the total number of observations in the previous state (i.e.: The count in a cell divided by the total count in a row). For example, to calculate the probability of a transiting from Very Good to a Good state, the number of transitions from Very Good transitioning to Good were divided by the total number in the row, i.e. $\frac{1063}{1063+428} = 0.7129$, (*Table 5.5*). All transition probabilities were estimated in this manner.

5.1.1 Probabilistic Street Deterioration Model for AC-ART Pvmt Family - PCI (Non-Exp. subgrade soil)

The total number of street sections for AC-ART pavement family was 3,637, which were used to create a TPM. These sections were the final set of data after being cleaned and filtered as discussed in Chapter 3. *Table 5.4* displays the transition matrix for the AC-ART pavement family .

TM for AC-ART (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	1,063	428	0	0	0
Good (2)	0	498	103	0	0
Satisfactory (3)	0	0	479	164	0
Poor (4)	0	0	0	802	54
Very Poor (5)	0	0	0	0	46

Table 5.4 Transition Matrix for AC-ART pavement family (non-expansive subgrade soil)

Table 5.5 shows the final transition probability matrix representing the road conditions of the AC-ART pavement family within five years between 2014 and 2019.

TPM for AC-ART (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.7129	0.2871	0	0	0
Good (2)	0	0.8286	0.1714	0	0
Satisfactory (3)	0	0	0.7449	0.2551	0
Poor (4)	0	0	0	0.9369	0.0631
Very Poor (5)	0	0	0	0	1

Table 5.5 Transition Probability Matrix for AC-ART (non-expansive subgrade soil)

The transition matrix (TM) and transition probability matrix (TPM) for the rest of the pavement families are given in Appendix J.

5.1.2 Predicted Street Deterioration for all pavement families in 15 years - PCI (Non-Exp. subgrade soil)

A utilization of probability transfer matrices is used to estimate what would be the state of a newly constructed or rehabilitated street section 15 years after this action. Fifteen years is a typical design life for a street section. If the initial state of a Very Good pavement section is given by $a_0 = (1, 0, 0, 0, 0)$,

the forecasted probability distribution of states after 15 years are given in *Table 5.6* for all pavement families.

The numbers in each row come from the matrix multiplication $a_1 = a_0 * M$ for the current state and $a_{15} = a_0 * M^{15}$ respectively for deterioration after fifteen years.

According to *Table 5.6*, fifteen years after construction or major rehabilitation, the percent of streets that may stay in Very Good condition varies from 0.34 percent for the AC-LR to 30.82 percent for the COM-COL pavement family.

Pavement Family	Very Good (1)	Good (2)	Satisfactory	Poor (4)	Very Poor (5)
AC - ART	0.62%	13.24%	16.42%	50.06%	19.66%
AC - COL	0.43%	15.12%	17.26%	44.36%	22.84%
AC - LR	0.34%	9.55%	15.43%	42.17%	32.52%
AC - RU	0.54%	12.78%	24.31%	34.06%	28.31%
COM - ART	8.82%	28.74%	46.69%	15.75%	0%
COM - COL	30.82%	22.97%	38.29%	7.92%	0%
COM - LR	10.05%	15.96%	45.76%	28.24%	0%
PCC - ART	3.43%	24.32%	45.70%	22.41%	4.14%
PCC - COL	2.43%	18.63%	48.88%	21.55%	8.50%
PCC - LR	2.20%	16.51%	62.88%	15.15%	3.26%
PCC - RU	3.52%	50.13%	46.35%	0%	0%

Table 5.6 Predicted Street's Condition after 15 years after construction or major rehabilitation

In addition, *Table 5.6* shows that 15 years after the construction of major rehabilitation, the percentage of streets that may deteriorate in Very Poor condition varies from 0 percent for the

COM-ART, COM-COL, COM-LR and PCC-RU pavement families to 32.52 percent for the AC-LR pavement family. It should be noted that *Table 5.6* shows that fifteen years after the construction or significant rehabilitation of the COM-ART, COM-COL, COM-LR and PCC-RU pavement families will not have a street in Very Poor condition, while the rest of the pavement families will have street sections in that condition. After fifteen years, the COM-COL pavement family could have 30.82 percent of the streets in Very Good condition.

The PCC-RU pavement family fifteen years later may have 50.13 percent of the streets in Good condition and 46.35 percent of the streets in Satisfactory condition, the reason for this outcome could be the strength of the concrete pavement structures and low traffic load at the rural streets. This table has confirmed that the deterioration rate of the AC pavement families is higher than the estimated deterioration rate of the PCC pavement family, which is expected. After 15 years , the percentage of streets in Very Poor condition for AC pavement families ranges from 19.66 percent for AC - ART pavement family to 32.52 percent for AC - LR pavement family, while the percentage of streets in Very Poor condition for PCC pavement families varies from 0 percent for PCC-RU pavement family to 8.50 percent for PCC-COL pavement family.

As this table shows, AC pavement families may have a high percentage of streets in Poor and Very Poor condition, AC-ART pavement family may have 69.71 percent, AC-COL pavement family may have 67.19 percent and AC-LR pavement family may have 74.69 percent. This shows that the life of AC pavement families are approaching the minimum acceptable rating, and will require a major rehabilitation after fifteen years.

5.2 Development of Probability PCI Deterioration Models for street with exp. subgrade soil

The procedure described for the development of probability deterioration models for street pavements built on non-expansive subgrade soil is the same as the procedure for the development of probability models for the street pavements built-on expansive subgrade soil. Developed probabilistic models are provided in Appendix H and K.

5.2.2 Predicted Street Deterioration for all pavement families in 15 years - PCI (Exp. subgrade soil)

Table 5.7 shows the probability distribution for all pavement families fifteen years after construction or major rehabilitation. It is also assumed that the pavement section is in Very Good condition after construction or major rehabilitation.

According to *Table 5.7*, fifteen years later the percent of the streets that may be in Very Good condition ranges from 0.25 percent for the AC-COL to 4.47 percent for the PCC–COL pavement family.

Pavement Family	Very Good (1)	Good (2)	Satisfactory (3)	Poor (4)	Very Poor (5)
AC - ART	0.79%	6.17%	25.45%	19.08%	48.51%
AC - COL	0.25%	1.63%	32.80%	17.57%	47.75%
AC - LR	0.83%	1.78%	25.31%	15.49%	56.59%
COM - ART	2.79%	28.90%	20.75%	17.43%	30.13%
COM - COL	0.80%	25.11%	14.56%	59.53%	0.00%
COM - LR	3.57%	11.11%	22.68%	12.55%	50.09%
PCC - ART	2.18%	27.34%	13.60%	17.75%	39.13%
PCC - COL	4.47%	26.20%	13.09%	38.32%	17.93%
PCC - LR	2.10%	22.01%	19.76%	16.26%	39.87%

Table 5.7 Predicted Street's Condition 15 years after construction or major rehabilitation

According to this table, after 15 years, the highest percent of streets in Very Good condition should have PCC - COL pavement family, 4.47 percent and the lowest percent should have AC - COL pavement family, 0.25 percent, at the same time PCC - COL pavement family should have 17.93 percent of the streets in Very Poor condition and AC - COL could have 47.75 percent in the same state. This table also confirms that the deterioration rate of the AC pavement families is much higher than the estimated deterioration rate of the PCC pavement family, what is anticipated. After 15 years , the percentage of streets in Very Poor condition for AC pavement families ranges from 47.75 percent for AC – COL pavement family to 56.59 percent for AC-LR pavement family, while the percentage of streets in Very Poor condition for PCC pavement families varies from 17.93 percent for PCC-COL pavement family to 39.87 percent for PCC-LR pavement family. As these tables show, AC pavement families have high percent of streets in Poor and Very Poor condition, AC-ART pavement family has 67.59 percent, the AC-COL pavement family has 65.32 percent and AC-LR pavement family has 72.07 percent. This shows that AC pavement life for AC families are approaching the minimum acceptable rating, and will require a major rehabilitation after fifteen years.

5.2.3 **Comparison of probabilistic models for Expansive versus Non-Exp. subgrade soil**

Table 5.8 was created in order to compare the rate of deterioration of the streets built on expansive versus non-expansive subgrade soil based on the fifteen-year probability distribution defined above. As shown in this table, pavement families built on expansive and non-expansive subgrade soils are grouped together to make comparison easier. It should be noted that the difference in percentage between streets that may be in Very Good condition built on expansive and non-expansive subgrade soil, fifteen years later, is not significant for this pavement family, whereas differences in percentage of streets that will be in Very Poor condition is much higher. The streets constructed on expansive subgrade soils deteriorate much faster. This is true for all pavement families. *Table 5.8* confirms that expansive subgrade soils reduce pavement efficiency for all surface types and street categories. Also, concrete pavements typically perform much better than asphalt pavements for all categories and all soil types.

Pavement Family	Very Good (1)	Good (2)	Satisfactory (3)	Poor (4)	Very Poor (5)	Expansive Soil
AC - ART	0.79%	6.17%	25.45%	19.08%	48.51%	Yes
AC - ART	0.62%	13.24%	16.42%	50.06%	19.66%	No
AC - COL	0.25%	1.63%	32.80%	17.57%	47.75%	Yes
AC - COL	0.43%	15.12%	17.26%	44.36%	22.84%	No
AC - LR	0.83%	1.78%	25.31%	15.49%	56.59%	Yes
AC - LR	0.34%	9.55%	15.43%	42.17%	32.52%	No
COM - ART	2.79%	28.90%	20.75%	17.43%	30.13%	Yes
COM - ART	8.82%	28.74%	46.69%	15.75%	0%	No
COM - COL	0.80%	25.11%	14.56%	59.53%	0%	Yes
COM - COL	30.82%	22.97%	38.29%	7.92%	0%	No
COM - LR	3.57%	11.11%	22.68%	12.55%	50.09%	Yes
COM - LR	10.05%	15.96%	45.76%	28.24%	0%	No
PCC - ART	2.18%	27.34%	13.60%	17.75%	39.13%	Yes
PCC - ART	3.43%	24.32%	45.70%	22.41%	4.14%	No
PCC - COL	4.47%	26.20%	13.09%	38.32%	17.93%	Yes
PCC - COL	2.43%	18.63%	48.88%	21.55%	8.50%	No
PCC - LR	2.10%	22.01%	19.76%	16.26%	39.87%	Yes
PCC - LR	2.20%	16.51%	62.88%	15.15%	3.26%	No

Table 5.8 Comparison of Predicted Street's Cond. after 15 years for Exp. vs Non-Exp Sub. Soil

Chapter 6: Summary, Conclusions and Recommendations

The main objective of this research was to develop PCI and IRI deterioration models for streets pavements in the Dallas Forth Worth Metroplex area. Historical records of pavement conditions were used to develop deterministic and probabilistic deterioration models. A total of eleven deterministic and probabilistic deterioration models were developed for streets built on non-expansive subgrade soil and nine deterministic and probabilistic models for streets built on expansive subgrade soil. These models can be used by any city's pavement managements department or engineers in the DFW Metroplex area. In order to determine which model will be used, it is important to use the first soil map given in *Figure 3.2*. It shows the borderline map for the frequency of the expansive subgrade soil for all cities in DFW area. The Pavement Deterioration Prediction models developed in this research will enable all pavement management agencies to identify and predict future pavement performance for any planning period.

6.1 Conclusions

The development of performance models requires all significant variables to be included in the development of the model. Since the type, functional class of the pavement and the type of subgrade soil on which the pavement was constructed are categorical in nature, it is difficult to include these variables in the deterioration models themselves. The family modeling approach was therefore used.

Eleven deterministic street pavement deterioration models have been developed for the DFW Metroplex area with non-expansive subgrade soil as well as nine deterministic street deterioration models for the area with expansive subgrade soil using the PCI historical record.

Nine deterministic IRI models have been developed for DFW Metroplex area with expansive subgrade soil only, since no historical IRI data was found for streets built on non-expansive soils. Eleven probabilistic models were also developed for streets built on non-expansive subgrade soil, as well as nine probabilistic models for streets built on expansive subgrade soil. Both deterministic and probabilistic models confirmed that the streets constructed on expansive subgrade soils deteriorate much faster than the streets built on non-expansive subgrade soils, no matter the type of pavement structure. In addition, the research confirmed that concrete pavements typically perform much better than asphalt pavements for all categories and all soil types.

6.2 Recommendations

The following recommendations were drawn from the work conducted in this research:

• The dataset used for the model development in this research should be updated periodically and it should include data for other cities as well, so that these models can be reviewed and updated periodically.

• All cities across DFW area should start collecting data of pavement condition on regular basis. It is desirable if the data is assembled in a uniform format, to ease further development of PCI and IRI models.

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Abbreviation

AC - Asphalt Concrete

AASHTO - American Association of State Highway and Transportation Officials

ACPA – American Concrete Association

ASTM - American Society for Testing and Materials

ART – Arterial

COM – Composite

COL- Collector

DMI – Distance Measuring Indicator

GPS - Global Positioning System

EXP – Expansive

FHWA - Federal Highway Administration

IRI – International Roughness Index

LR – Local Residential

MAC – Mobile Asset Collection

RU - Rural

PCC - Portland Cement Concrete

PCI Pavement Condition Index

PMS Pavement Management System

PSI – Pavement Serviceability Index

PSR Present Serviceability Rating

APPENDIX A: Excel Macro Script

```
Sub Macro()
' Macro
' Keyboard Shortcut: Ctrl+Shift+M
i = 1
Do While Cells(7, 1) <> ""
   Sheets("Data").Select
   Range("A7:Q7").Select
   Selection.Copy
   Sheets("Calculations").Select
   Range("A6").Select
   ActiveSheet.Paste
   ' Solve Model #1
   SolverReset
   SolverOptions Assumenonneg:=False
   SolverOk SetCell:="$R$20", MaxMinVal:=2, ValueOf:=0, ByChange:="$C$20:$E$20", _
      Engine:=1, EngineDesc:="GRG Nonlinear"
   SolverSolve True
   Range("A6:F6").Select
   Selection.Copy
   Sheets("Output").Select
   Range("A2").Select
   Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
      :=False, Transpose:=False
   Sheets("Calculations").Select
   Range("R6:AK6").Select

   Selection.Copy
   Sheets("Output").Select
   Range("G2").Select
   Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
      :=False, Transpose:=False
   Rows("2:2").Select
   Application.CutCopyMode = False
   Selection.Insert Shift:=xlDown, CopyOrigin:=xlFormatFromLeftOrAbove
   Sheets("Data").Select
   Rows("7:7").Select
   Selection.Delete Shift:=xlUp
   i = i + 1
   Loop
End Sub
```

APPENDIX B: Summarized Results for Models 2 to 7 (Exp. subgrade soil) – PCI

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works	Expansive Soil
1	AC	ART	Yes	**1,186**	249	937	79%	357	829	70%	649	537	45%	Yes	Yes
2	AC	COL	Yes	**465**	62	403	87%	92	373	80%	242	223	48%	Yes	Yes
3	AC	LR	Yes	**4,886**	819	4,067	83%	1,275	3,611	74%	2,671	2,215	45%	Yes	Yes
4	PCC	ART	Yes	**2,400**	193	2,207	92%	579	1,821	76%	1,500	900	38%	Yes	Yes
5	PCC	COL	Yes	**992**	62	930	94%	217	775	78%	601	391	39%	Yes	Yes
6	PCC	LR	Yes	**3,263**	144	3,119	96%	442	2,821	86%	1,742	1,521	47%	Yes	Yes
7	COM	ART	Yes	**1,149**	135	1,014	88%	314	835	73%	734	415	36%	Yes	Yes
8	COM	COL	Yes	**302**	29	273	90%	63	239	79%	187	115	38%	Yes	Yes
9	COM	LR	Yes	**730**	87	643	88%	172	558	76%	435	295	40%	Yes	Yes

Table B1: PCI - Model 2 (Gompertz) – Summarized Results

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works	Expansive Soil
1	AC	ART	Yes	**1,399**	422	977	70%	579	820	59%	960	439	31%	Yes	Yes
2	AC	COL	Yes	**602**	119	483	80%	174	428	71%	413	189	31%	Yes	Yes
3	AC	LR	Yes	**7,004**	1,787	5,217	74%	2,615	4,389	63%	5,061	1,943	28%	Yes	Yes
4	PCC	ART	Yes	**3,125**	309	2,816	90%	853	2,272	73%	2,390	735	24%	Yes	Yes
5	PCC	COL	Yes	**1,326**	133	1,193	90%	356	970	73%	1,010	316	24%	Yes	Yes
6	PCC	LR	Yes	**6,541**	623	5,918	90%	2,044	4,497	69%	5,192	1,349	21%	Yes	Yes
7	COM	ART	Yes	**1,408**	239	1,169	83%	454	954	68%	1,040	368	26%	Yes	Yes
8	COM	COL	Yes	**396**	45	351	89%	126	270	68%	306	90	23%	Yes	Yes
9	COM	LR	Yes	**2,029**	276	1,753	86%	751	1,278	63%	1,713	316	16%	Yes	Yes

Table B2: PCI - Model 3 (Logistic) – Summarized Results

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works	Expansive Soil
1	AC	ART	Yes	**1,387**	35	1,352	97%	130	1,257	91%	530	857	62%	Yes	Yes
2	AC	COL	Yes	**599**	7	592	99%	37	562	94%	230	369	62%	Yes	Yes
3	AC	LR	Yes	**6,879**	80	6,799	99%	436	6,443	94%	2,616	4263	62%	Yes	Yes
4	PCC	ART	Yes	**3,082**	44	3,038	99%	273	2,809	91%	1,333	1749	57%	Yes	Yes
5	PCC	COL	Yes	**1,307**	10	1,297	99%	110	1,197	92%	544	763	58%	Yes	Yes
6	PCC	LR	Yes	**6,311**	35	6,276	99%	337	5,974	95%	2,625	3686	58%	Yes	Yes
7	COM	ART	Yes	**1,374**	26	1,348	98%	170	1,204	88%	635	739	54%	Yes	Yes
8	COM	COL	Yes	**387**	5	382	99%	23	364	94%	153	234	60%	Yes	Yes
9	COM	LR	Yes	**1,337**	8	1,329	99%	125	1,212	91%	878	459	34%	Yes	Yes

Table B3: PCI - Model 4 (Stantec) – Summarized Results

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works	Expansive Soil
1	AC	ART	Yes	**1,398**	392	1,006	72%	557	841	60%	915	483	35%	Yes	Yes
2	AC	COL	Yes	**602**	126	476	79%	191	411	68%	418	184	31%	Yes	Yes
3	AC	LR	Yes	**7,004**	1,829	5,175	74%	2,671	4,333	62%	5,013	1,991	28%	Yes	Yes
4	PCC	ART	Yes	**3,125**	720	2,405	77%	1,299	1,826	58%	2,491	634	20%	Yes	Yes
5	PCC	COL	Yes	**1,326**	317	1,009	76%	545	781	59%	1,060	266	20%	Yes	Yes
6	PCC	LR	Yes	**6,541**	1,376	5,165	79%	2,789	3,752	57%	5,413	1,128	17%	Yes	Yes
7	COM	ART	Yes	**1,408**	364	1,044	74%	604	804	57%	1,087	321	23%	Yes	Yes
8	COM	COL	Yes	**396**	108	288	73%	179	217	55%	323	73	18%	Yes	Yes
9	COM	LR	Yes	**2,029**	510	1,519	75%	979	1,050	52%	1,765	264	13%	Yes	Yes

Table B4: PCI - Model 5 (Exponential) – Summarized Results

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works	Expansive Soil
1	AC	ART	Yes	**1,398**	12	1,386	99%	72	1,326	95%	385	1,013	72%	Yes	Yes
2	AC	COL	Yes	**602**	2	600	100%	17	585	97%	182	420	70%	Yes	Yes
3	AC	LR	Yes	**7,004**	32	6,972	100%	410	6,594	94%	2,383	4,621	66%	Yes	Yes
4	PCC	ART	Yes	**3,124**	17	3,107	99%	177	2,947	94%	900	2,224	71%	Yes	Yes
5	PCC	COL	Yes	**1,326**	11	1,315	99%	86	1,240	94%	427	899	68%	Yes	Yes
6	PCC	LR	Yes	**6,540**	53	6,487	99%	430	6,110	93%	2,325	4,215	64%	Yes	Yes
7	COM	ART	Yes	**1,408**	13	1,395	99%	110	1,298	92%	478	930	66%	Yes	Yes
8	COM	COL	Yes	**396**	1	395	100%	22	374	94%	133	263	66%	Yes	Yes
9	COM	LR	Yes	**2,029**	18	2,011	99%	182	1,847	91%	848	1,181	58%	Yes	Yes

Table B5: PCI - Model 6 (2-nd Polynomial) – Summarized Results

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works	Expansive Soil
1	AC	ART	Yes	**1,398**	3	1,395	100%	36	1,362	97%	292	1,106	79%	Yes	Yes
2	AC	COL	Yes	**602**	1	601	100%	10	592	98%	133	469	78%	Yes	Yes
3	AC	LR	Yes	**7,004**	10	6,994	100%	110	6,894	98%	1,476	5,528	79%	Yes	Yes
4	PCC	ART	Yes	**3,125**	12	3,113	100%	112	3,013	96%	801	2,324	74%	Yes	Yes
5	PCC	COL	Yes	**1,326**	3	1,323	100%	61	1,265	95%	349	977	74%	Yes	Yes
6	PCC	LR	Yes	**6,541**	19	6,522	100%	200	6,341	97%	1,994	4,547	70%	Yes	Yes
7	COM	ART	Yes	**1,408**	12	1,396	99%	90	1,318	94%	480	928	66%	Yes	Yes
8	COM	COL	Yes	**396**	1	395	100%	12	384	97%	115	281	71%	Yes	Yes
9	COM	LR	Yes	**2,029**	5	2,024	100%	87	1,942	96%	732	1,297	64%	Yes	Yes

Table B6: PCI - Model 7 (Sigmoidal) – Summarized Results

APPENDIX C: Summarized Results for Models 2 to 7 (Non-Exp. Soil) - IRI

IRI - MODEL 2 - Gompertz

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works
1	AC	ART	Yes	**1,421**	95	1,326	93%	224	1,197	84%	394	1,027	72%	Yes
2	AC	COL	Yes	**608**	51	557	92%	91	517	85%	159	449	74%	Yes
3	AC	LR	Yes	**6,728**	298	6,430	96%	521	6,207	92%	1,301	5,427	81%	Yes
4	PCC	ART	Yes	**3,139**	176	2,963	94%	359	2,780	89%	803	2,336	74%	Yes
5	PCC	COL	Yes	**1,329**	74	1,255	94%	158	1,171	88%	328	1,001	75%	Yes
6	PCC	LR	Yes	**6,516**	456	6,060	93%	785	5,731	88%	1,565	4,951	76%	Yes
7	COM	ART	Yes	**1,414**	222	1,192	84%	525	889	63%	626	788	56%	Yes
8	COM	COL	Yes	**401**	95	306	76%	380	21	5%	218	183	46%	Yes
9	COM	LR	Yes	**2,011**	245	1,766	88%	145	1,866	93%	872	1,139	57%	Yes

Table C1: IRI - Model 2 (Gompertz) – Summarized Results

IRI - MODEL 3 - Logistic

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works
1	AC	ART	Yes	**1,421**	221	1,200	84%	400	1,021	72%	628	793	56%	Yes
2	AC	COL	Yes	**608**	113	495	81%	175	433	71%	274	334	55%	Yes
3	AC	LR	Yes	**6,728**	1,516	5,212	77%	2,103	4,625	69%	3,448	3,280	49%	Yes
4	PCC	ART	Yes	**3,139**	426	2,713	86%	762	2,377	76%	1,379	1,760	56%	Yes
5	PCC	COL	Yes	**1,329**	175	1,154	87%	308	1,021	77%	553	776	58%	Yes
6	PCC	LR	Yes	**6,516**	1,054	5,462	84%	1,647	4,869	75%	3,063	3,453	53%	Yes
7	COM	ART	Yes	**1,414**	330	1,084	77%	559	855	60%	823	591	42%	Yes
8	COM	COL	Yes	**401**	128	273	68%	205	196	49%	275	126	31%	Yes
9	COM	LR	Yes	**2,011**	417	1,594	79%	727	1,284	64%	1,242	769	38%	Yes

Table C2: IRI - Model 3 (Logistic) – Summarized Results

IRI - MODEL 4 - Stantec

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works
1	AC	ART	Yes	**1,421**	70	1,351	99%	99	1,322	93%	197	1,224	86%	Yes
2	AC	COL	Yes	**608**	31	577	95%	45	563	93%	91	517	85%	Yes
3	AC	LR	Yes	**6,728**	203	6,525	97%	344	6,384	95%	1,047	5,681	84%	Yes
4	PCC	ART	Yes	**3,139**	62	3,077	98%	99	3,040	97%	274	2,865	91%	Yes
5	PCC	COL	Yes	**1,329**	48	1,281	96%	65	1,264	95%	119	1,210	91%	Yes
6	PCC	LR	Yes	**6,516**	232	6,284	96%	316	6,200	95%	526	5,990	92%	Yes
7	COM	ART	Yes	**1,414**	96	1,318	93%	146	1,268	90%	231	1,183	84%	Yes
8	COM	COL	Yes	**401**	48	353	88%	63	338	84%	94	307	77%	Yes
9	COM	LR	Yes	**2,011**	102	1,909	95%	139	1,872	93%	236	1,775	88%	Yes

Table C3: IRI - Model 4 (Stantec) – Summarized Results

IRI - MODEL 5 - Exponential

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works
1	AC	ART	Yes	**1,421**	216	1,205	85%	340	1,081	76%	518	903	64%	Yes
2	AC	COL	Yes	**608**	95	513	84%	144	464	76%	223	385	63%	Yes
3	AC	LR	Yes	**6,728**	1,360	5,368	80%	1,850	4,878	73%	3,010	3,718	55%	Yes
4	PCC	ART	Yes	**3,139**	337	2,802	89%	630	2,509	80%	1,107	2,032	65%	Yes
5	PCC	COL	Yes	**1,329**	166	1,163	88%	268	1,061	80%	465	864	65%	Yes
6	PCC	LR	Yes	**6,516**	973	5,543	85%	1,450	5,066	78%	2,641	3,875	59%	Yes
7	COM	ART	Yes	**1,414**	275	1,139	81%	438	976	69%	650	764	54%	Yes
8	COM	COL	Yes	**401**	118	283	71%	183	218	54%	255	146	36%	Yes
9	COM	LR	Yes	**2,011**	376	1,635	81%	625	1,386	69%	1,071	940	47%	Yes

Table C4: IRI - Model 5 (Exponential) – Summarized Results

IRI - MODEL 6 - 2nd Polynomial

Family	Pvmt Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works
1	AC	ART	Yes	**1,421**	4	1,417	100%	6	1,415	100%	14	1,407	99%	Yes
2	AC	COL	Yes	**608**	-	608	100%	-	608	100%	1	607	100%	Yes
3	AC	LR	Yes	**6,728**	5	6,723	100%	12	6,716	100%	47	6,681	99%	Yes
4	PCC	ART	Yes	**3,139**	1	3,138	100%	3	3,136	100%	5	3,134	100%	Yes
5	PCC	COL	Yes	**1,329**	2	1,327	100%	4	1,325	100%	5	1,324	100%	Yes
6	PCC	LR	Yes	**6,516**	6	6,510	100%	10	6,506	100%	27	6,489	100%	Yes
7	COM	ART	Yes	**1,414**	2	1,412	100%	4	1,410	100%	11	1,403	99%	Yes
8	COM	COL	Yes	**401**	2	399	100%	4	397	99%	8	393	98%	Yes
9	COM	LR	Yes	**2,011**	2	2,009	100%	12	1,999	99%	29	1,982	99%	Yes

Table C5: IRI - Model 6 (2-nd Polynomial) – Summarized Results

IRI - MODEL 7 - Sigmoidal

Family	Pavement Type	Func. Class	Expansive Soil	Total Data	Criteria $R^2 < 0.5$	Good Data $R^2 > 0.5$	Good Data (%) $R^2 > 0.5$	Criteria $R^2 < 0.7$	Good Data $R^2 > 0.7$	Good Data (%) $R^2 > 0.7$	Criteria $R^2 < 0.9$	Good Data $R^2 > 0.9$	Good Data (%) $R^2 > 0.9$	Prediction Model works
1	AC	ART	Yes	**1,421**	-	1,421	100%	-	1,421	100%	-	1,421	100%	Yes
2	AC	COL	Yes	**608**	-	608	100%	-	608	100%	3	605	100%	Yes
3	AC	LR	Yes	**6,728**	2	6,726	100%	8	6,720	100%	33	6,695	100%	Yes
4	PCC	ART	Yes	**3,139**	1	3,138	100%	1	3,138	100%	7	3,132	100%	Yes
5	PCC	COL	Yes	**1,329**	-	1,329	100%	1	1,328	100%	7	1,322	99%	Yes
6	PCC	LR	Yes	**6,516**	1	6,515	100%	3	6,513	100%	21	6,495	100%	Yes
7	COM	ART	Yes	**1,414**	1	1,413	100%	1	1,413	100%	8	1,406	99%	Yes
8	COM	COL	Yes	**401**	1	400	100%	2	399	100%	5	396	99%	Yes
9	COM	LR	Yes	**2,011**	-	2,011	100%	3	2,008	100%	19	1,992	99%	Yes

Table C6: IRI - Model 7 (Sigmoidal) – Summarized Results

APPENDIX D: Charts for expansive subgrade soil – Models 2, 3, 5 & 7 (PCI)

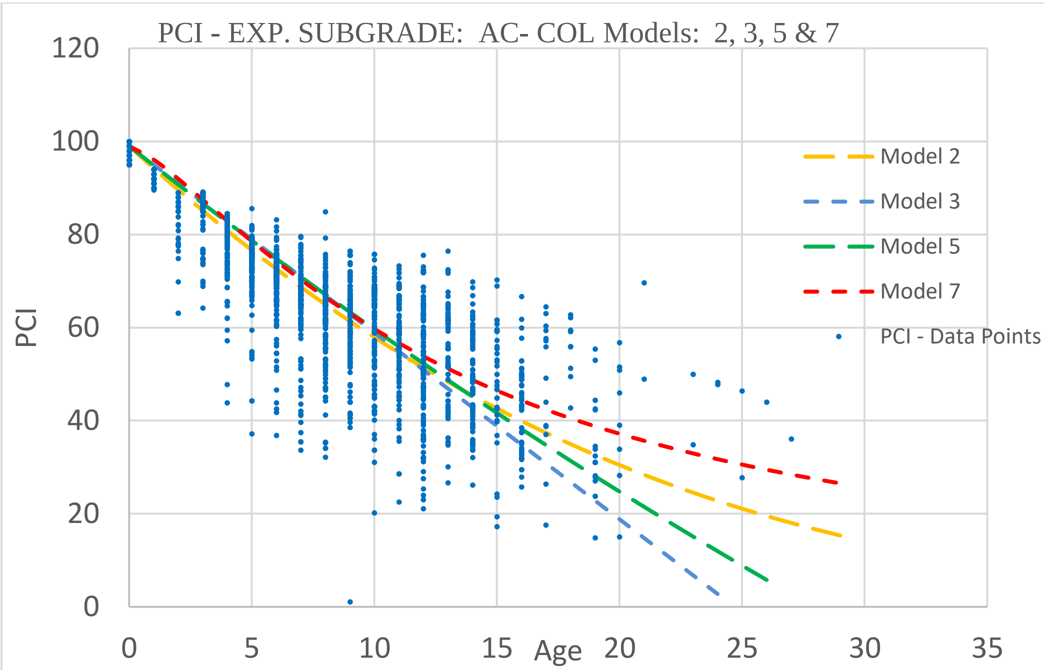

Figure D1. Chart for Models 2,3,5 & 7 – AC-COL Pavement Family (Expansive subgrade soil)

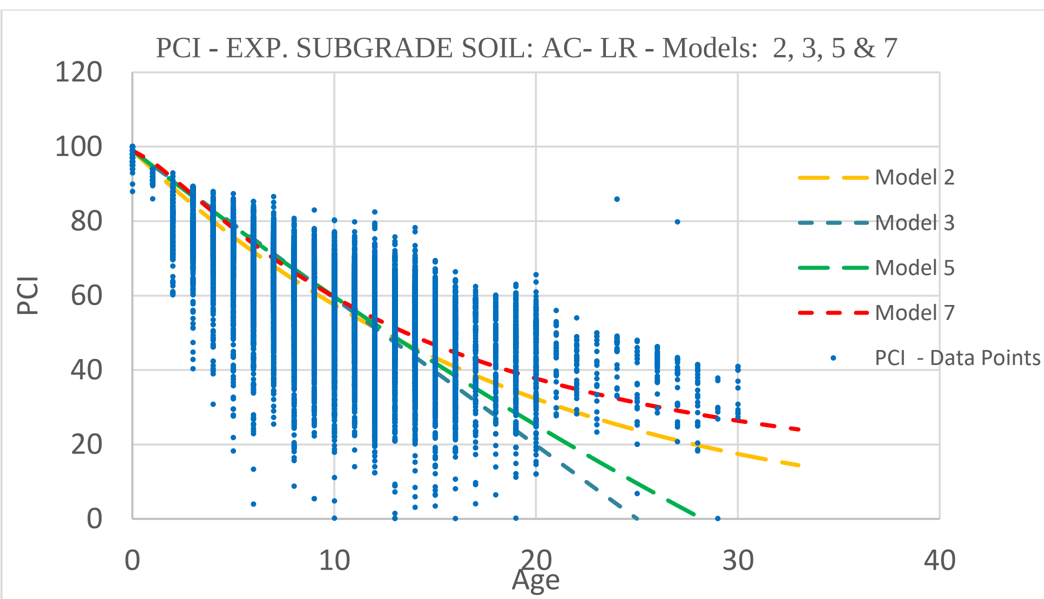

Figure D2. Chart for Models 2,3,5 & 7 – AC-LR Pavement Family (Expansive subgrade soil)

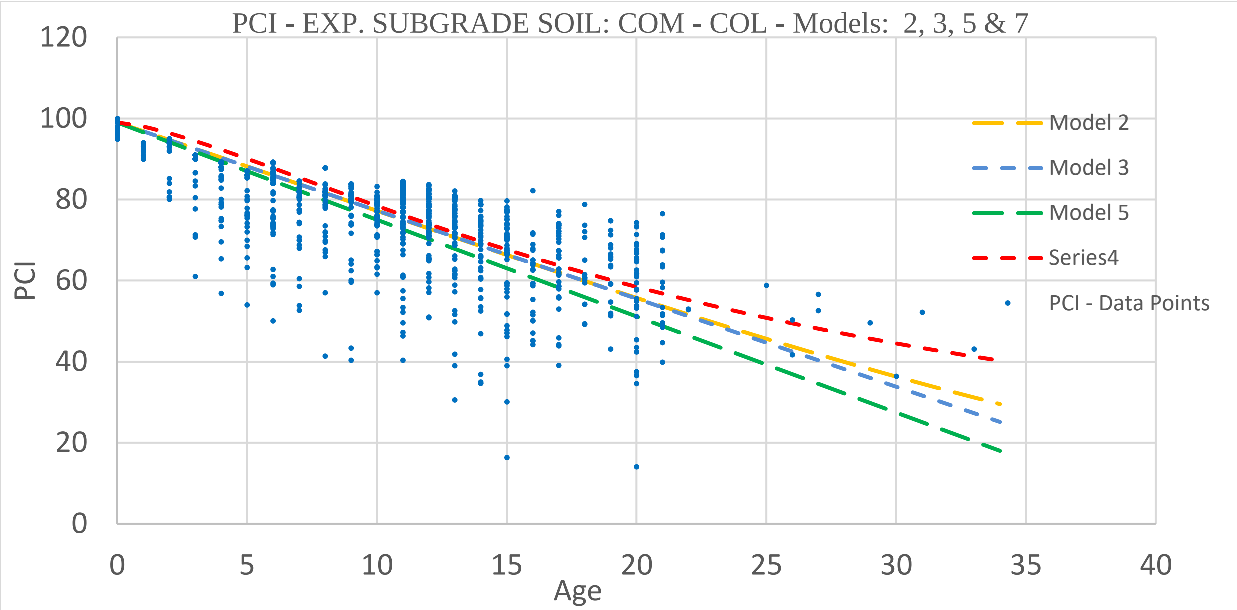

Figure D3. Chart for Models 2,3,5 & 7 – COM-COL Pavement Family (Expansive subgrade soil)

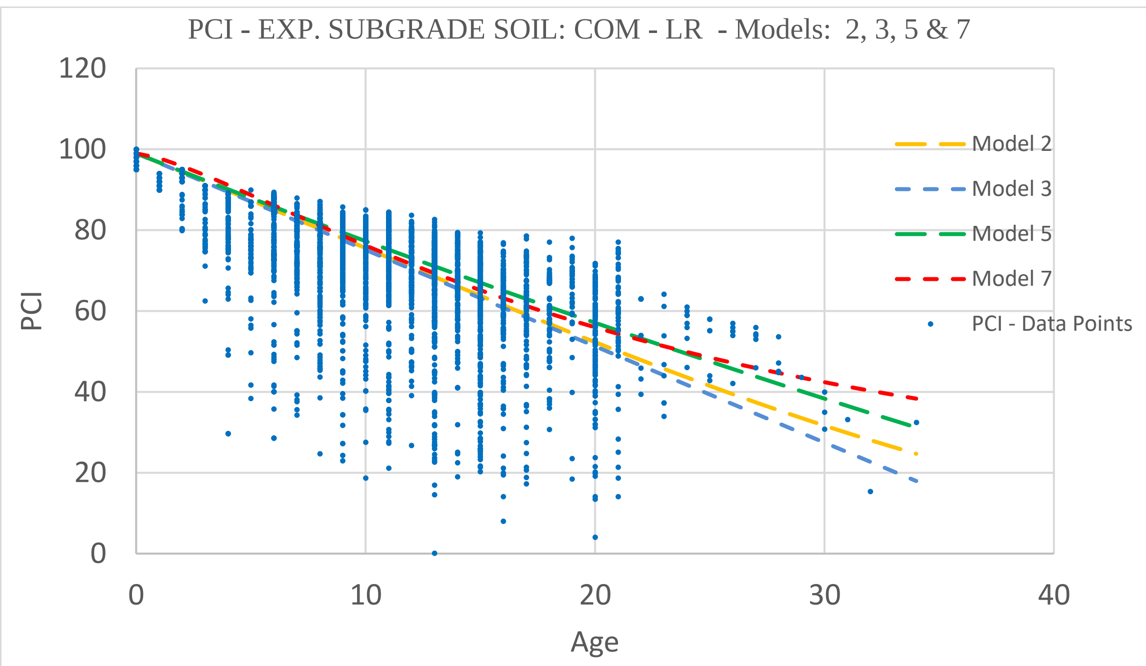

Figure D4. Chart for Models 2,3,5 & 7 – COM-LR Pavement Family (Expansive subgrade soil)

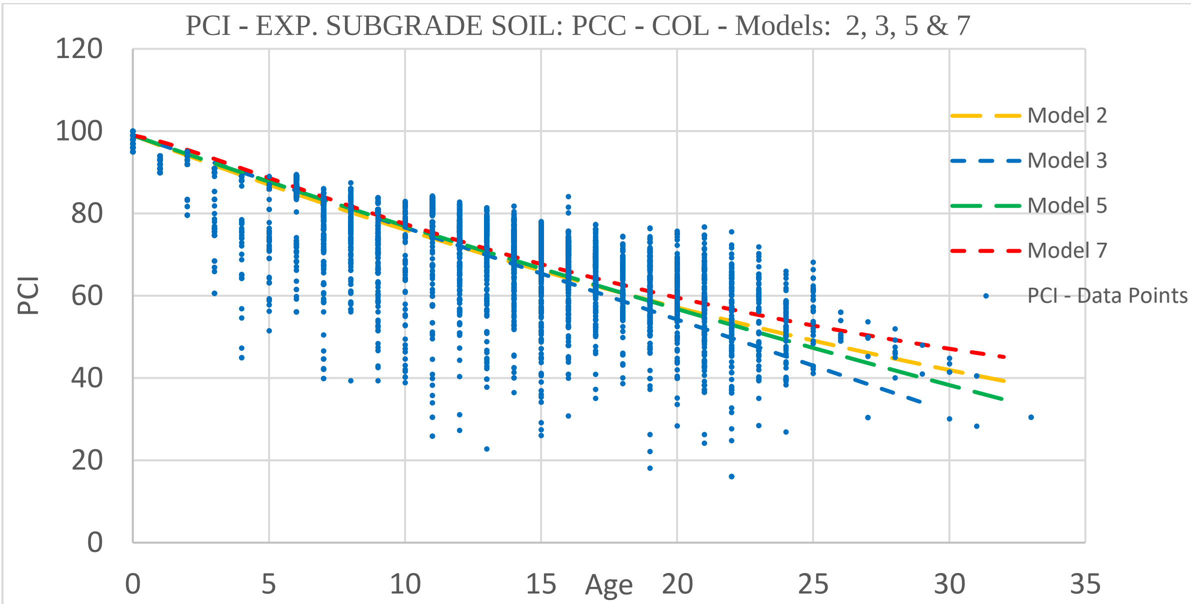

Figure D5. Chart for Models 2,3,5 & 7 – PCC-COL Pavement Family (Expansive subgrade soil)

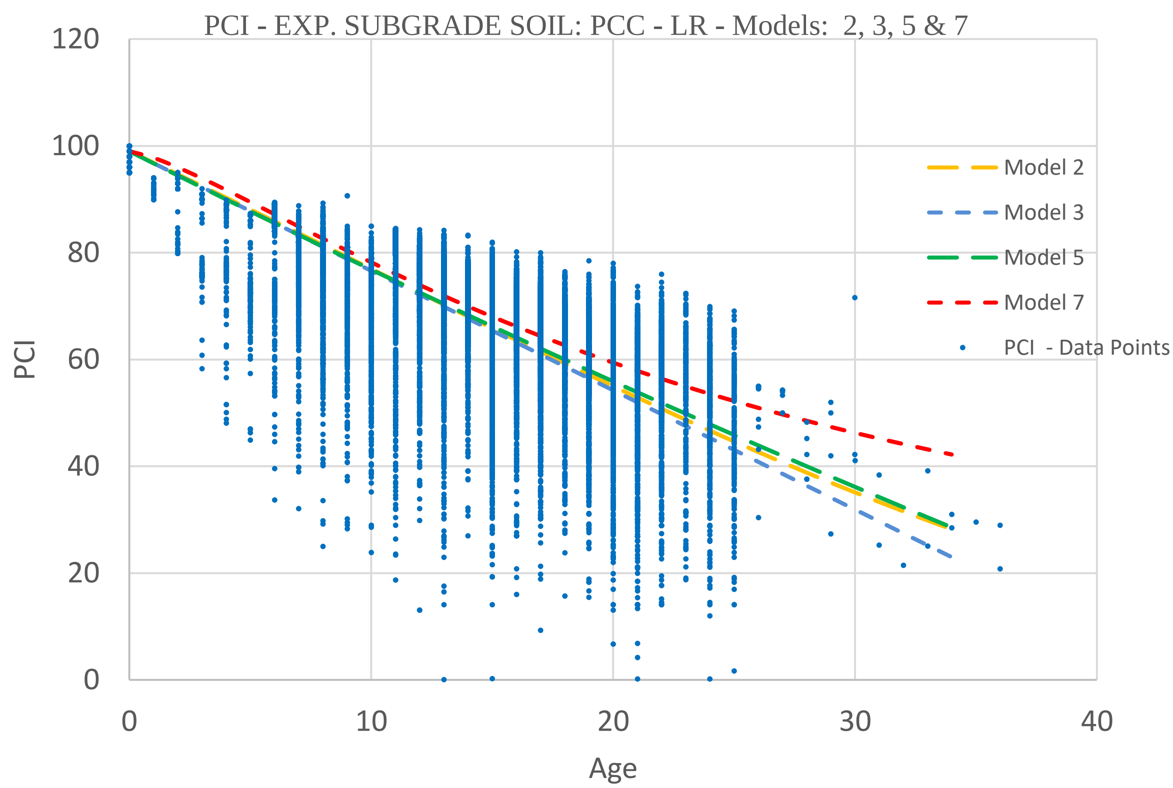

Figure D6. Chart for Models 2,3,5 & 7 – PCC-LR Pavement Family (Expansive subgrade soil)

APPENDIX E: Charts for Non–Exp. subgrade soil – Models 2, 3, 5 & 7 (PCI)

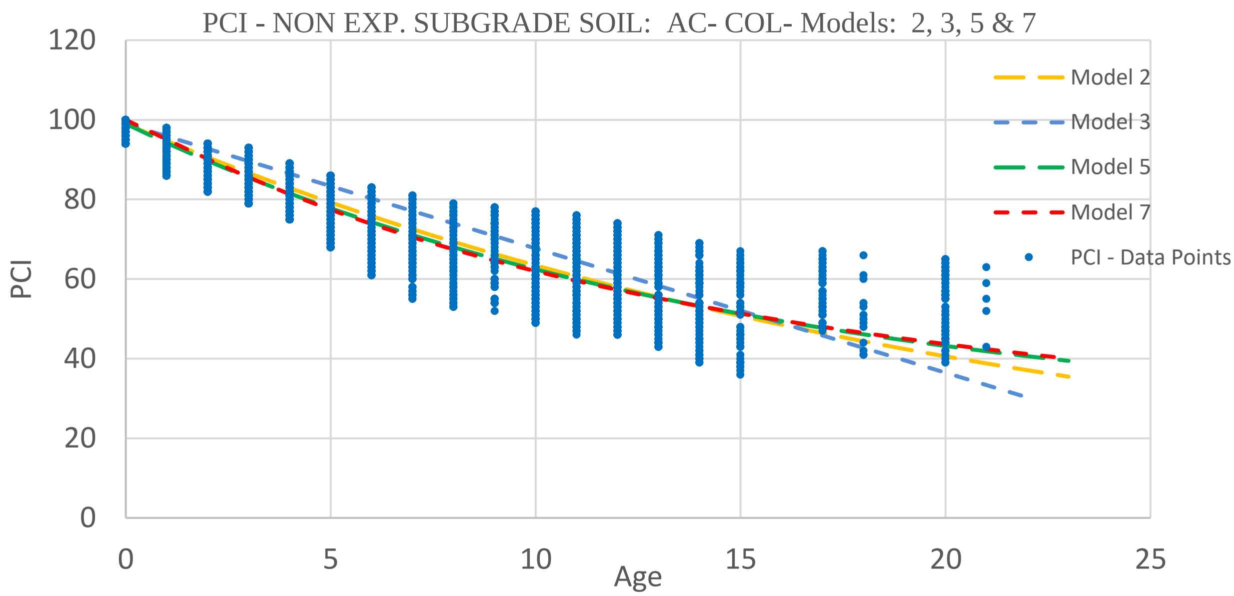

Figure E1. Chart for Models 2,3,5 & 7 – AC-COL Pavement Family (Non-Exp. subgrade soil)

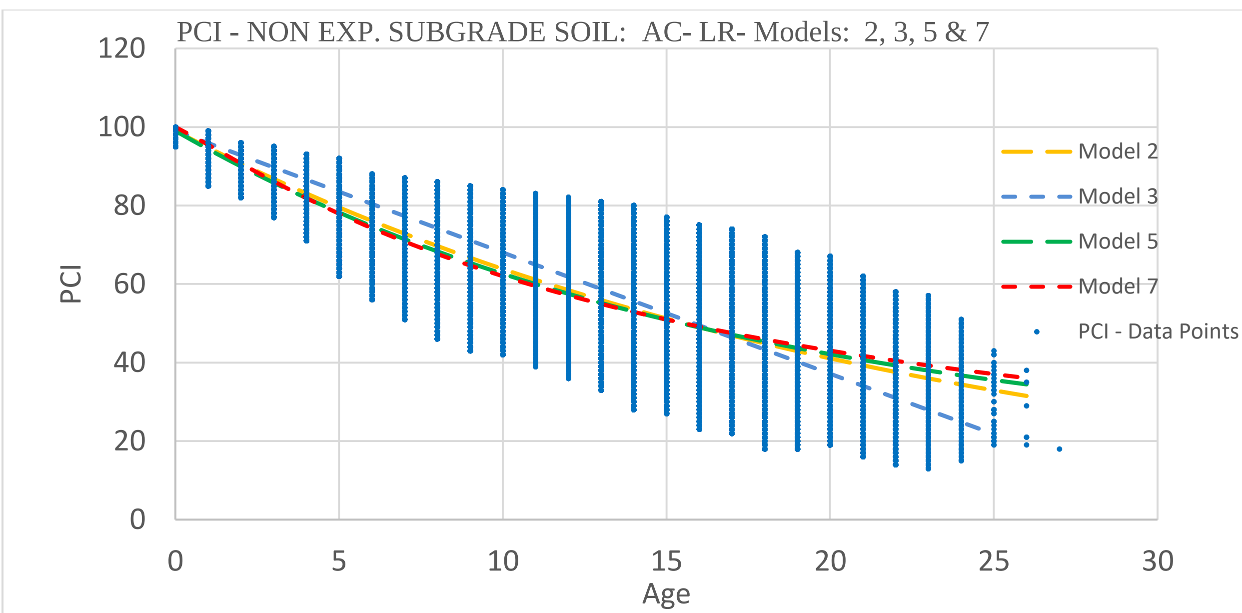

Figure E2. Chart for Models 2,3,5 & 7 – AC-LR Pavement Family (Non-Expansive subgrade soil)

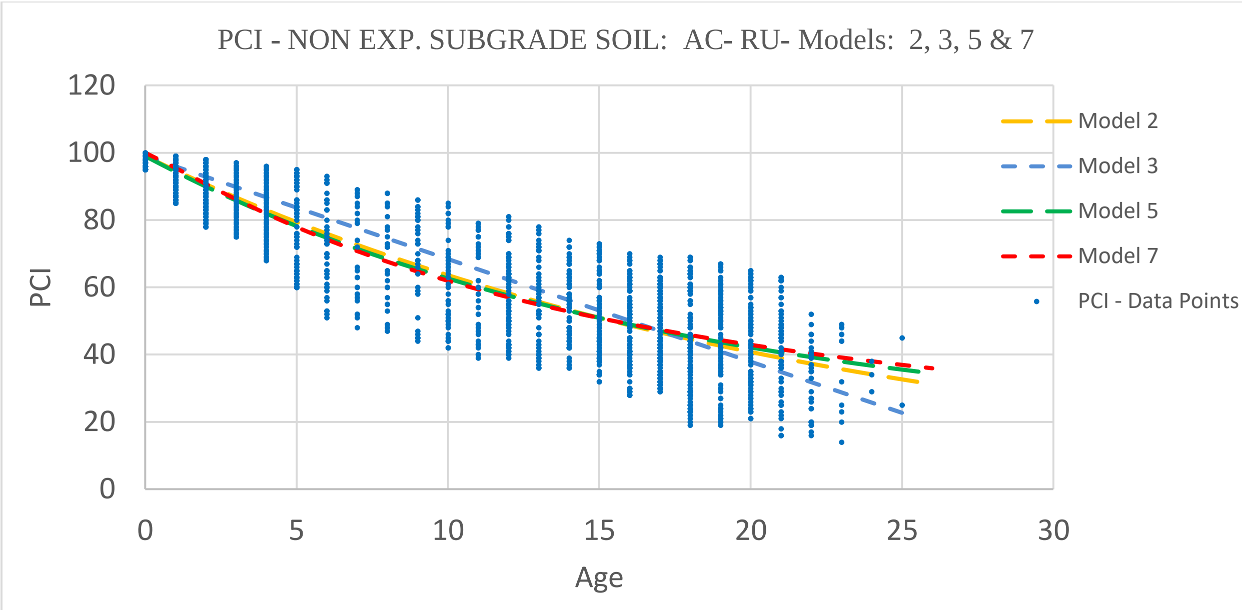

Figure E3. Chart for Models 2,3,5 & 7 – AC-RU Pavement Family (Non-Expansive subgrade soil)

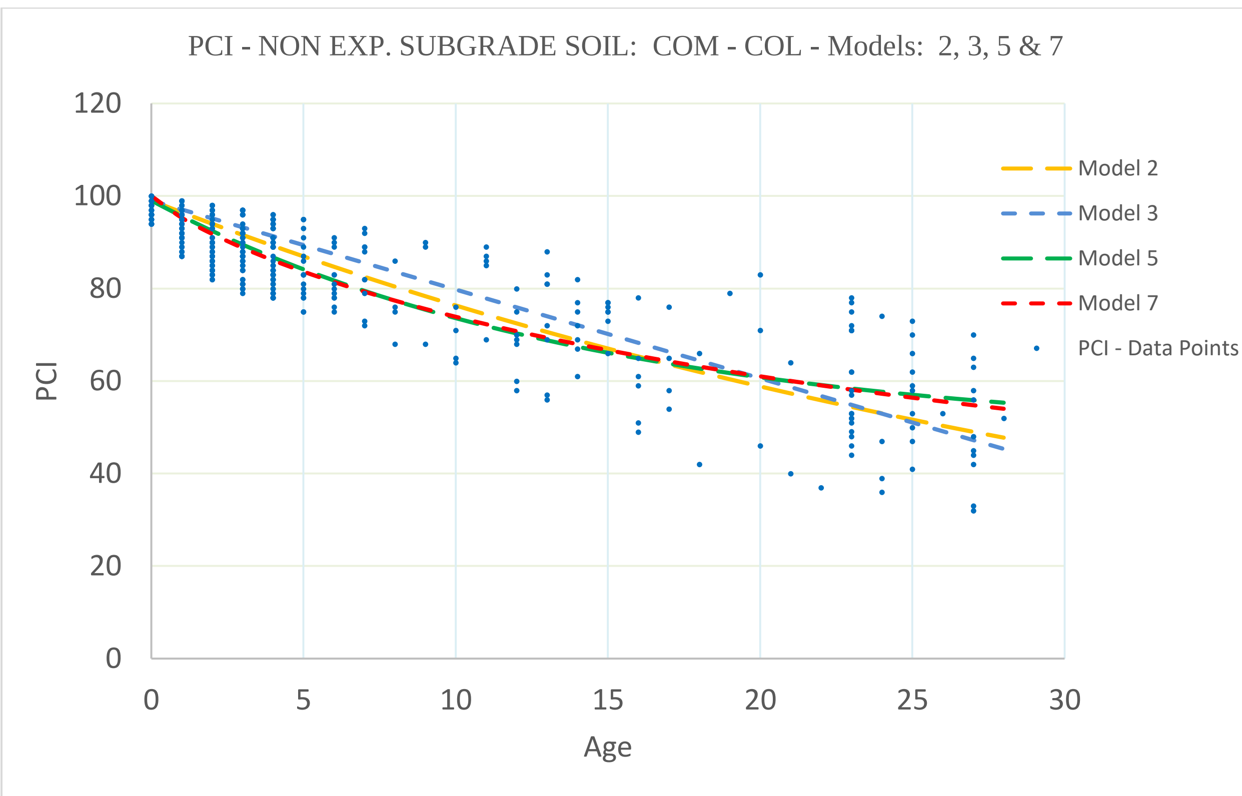

Figure E4. Chart for Models 2,3,5 & 7 – COM-COL Pavement Family (Non-Exp. subgrade soil)

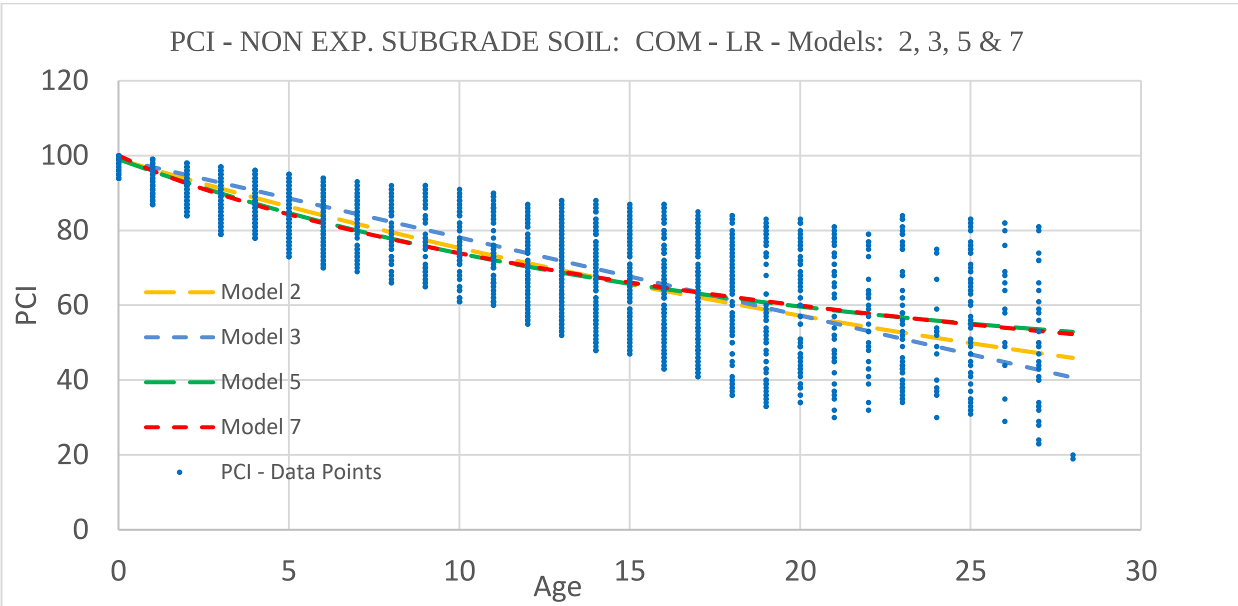

Figure E5. Chart for Models 2,3,5 & 7 – COM-LR Pavement Family (Non-Exp. subgrade soil)

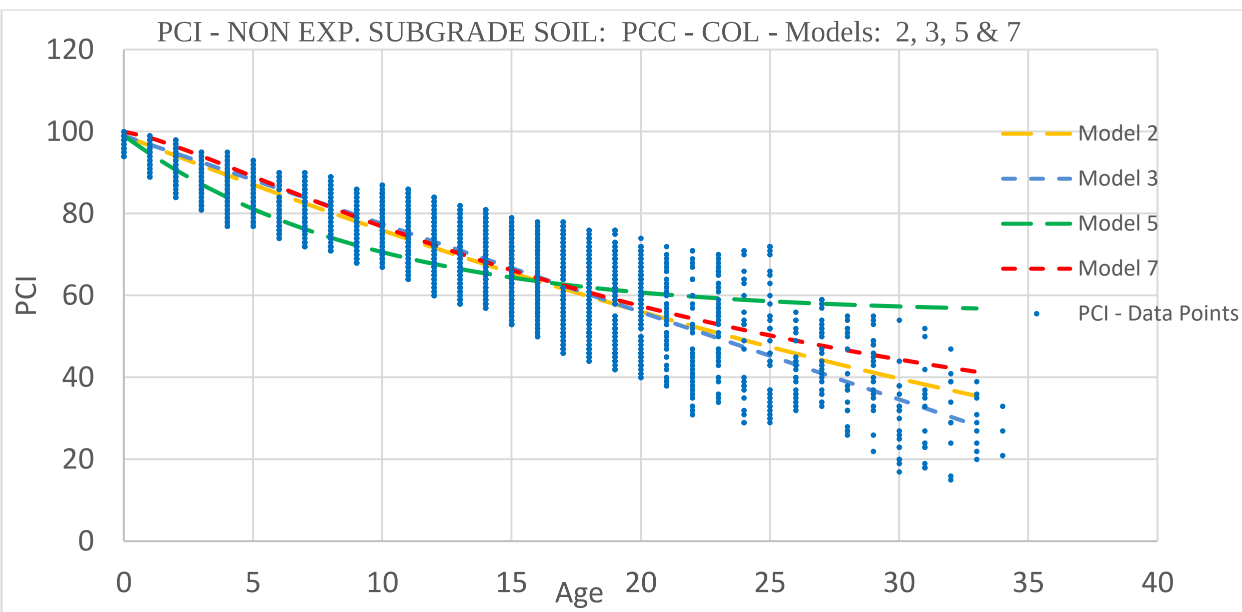

Figure E6. Chart for Models 2,3,5 & 7 – PCC - COL Pavement Family (Non-Exp. subgrade soil)

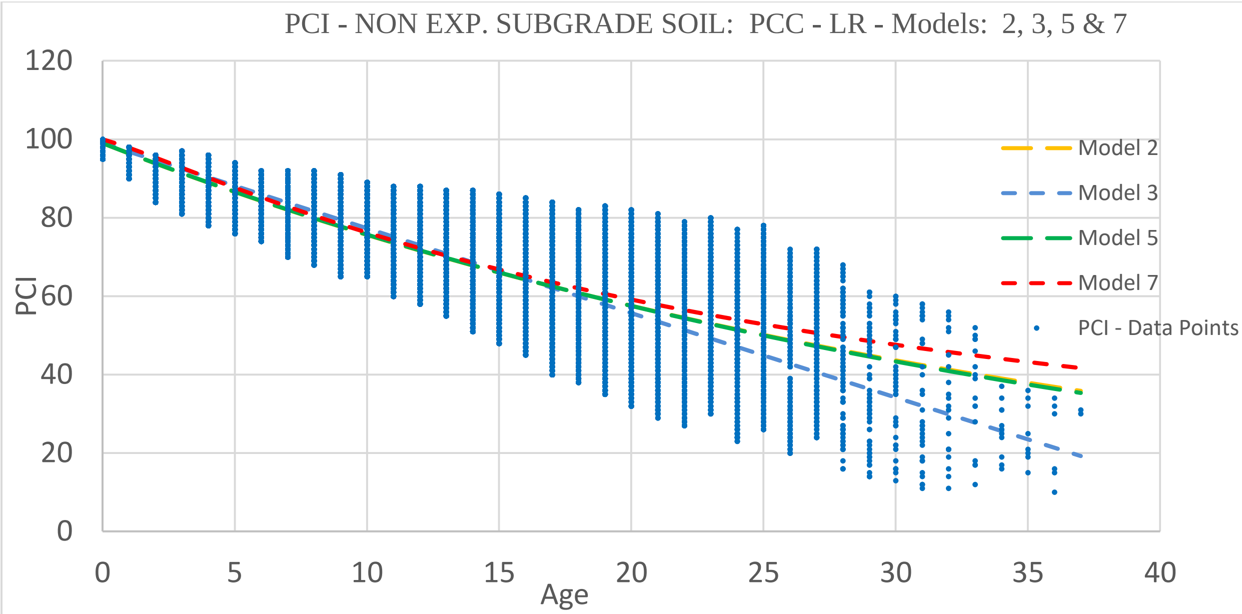

Figure E7. Chart for Models 2,3,5 & 7 – PCC - LR Pavement Family (Non-Exp. subgrade soil)

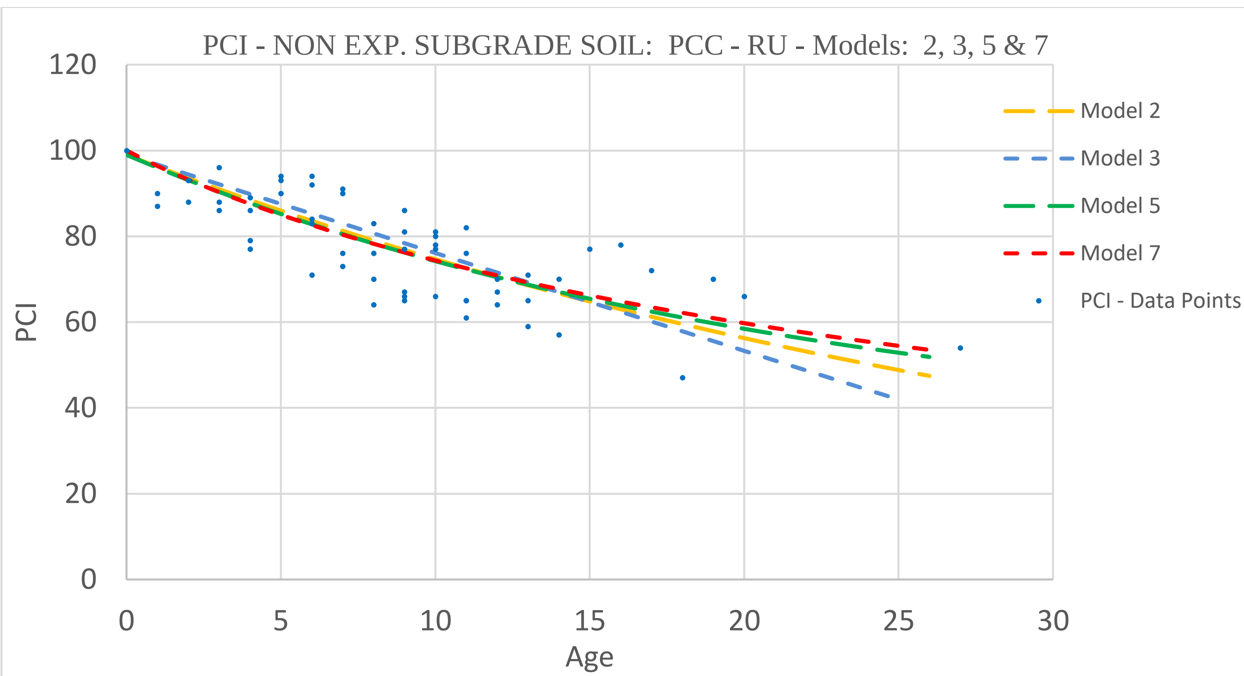

Figure E8. Chart for Models 2,3,5 & 7 – PCC-RU Pavement Family (Non-Exp. subgrade soil)

APPENDIX F: Charts for Expansive subgrade soil – Models 2, 3, 5 & 6 (IRI)

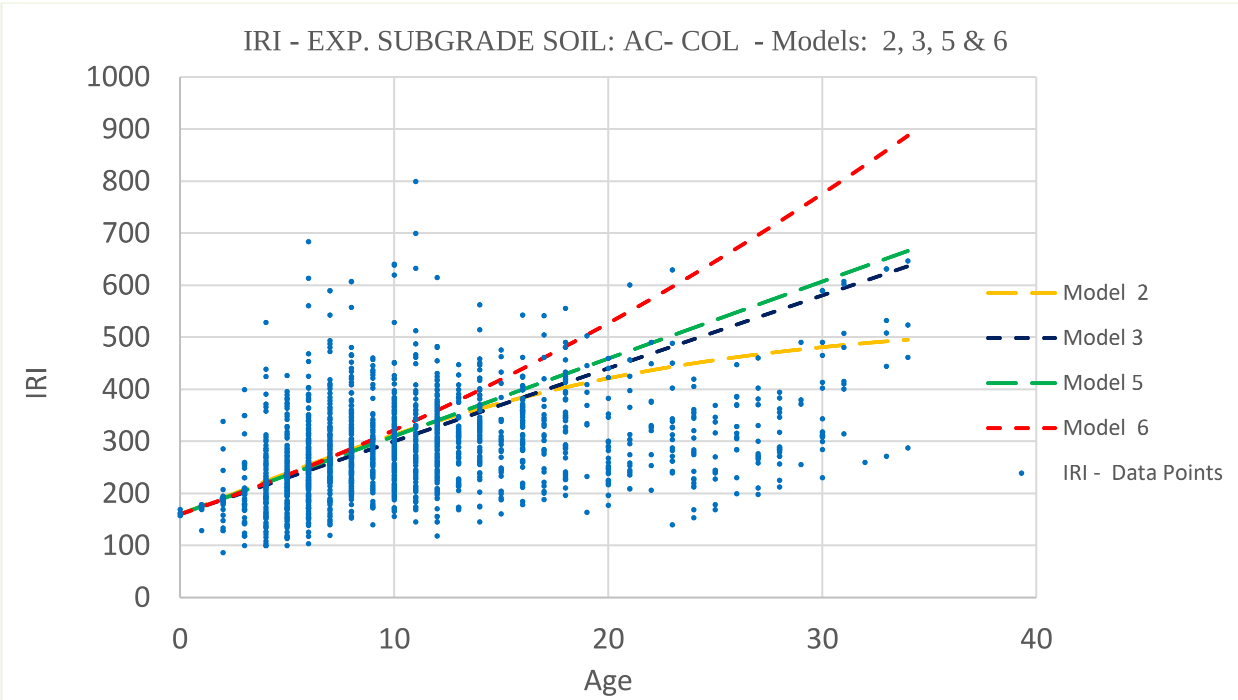

Figure F1. Chart for Models 2,3,5 & 6 – AC-COL Pavement Family (Expansive subgrade soil)

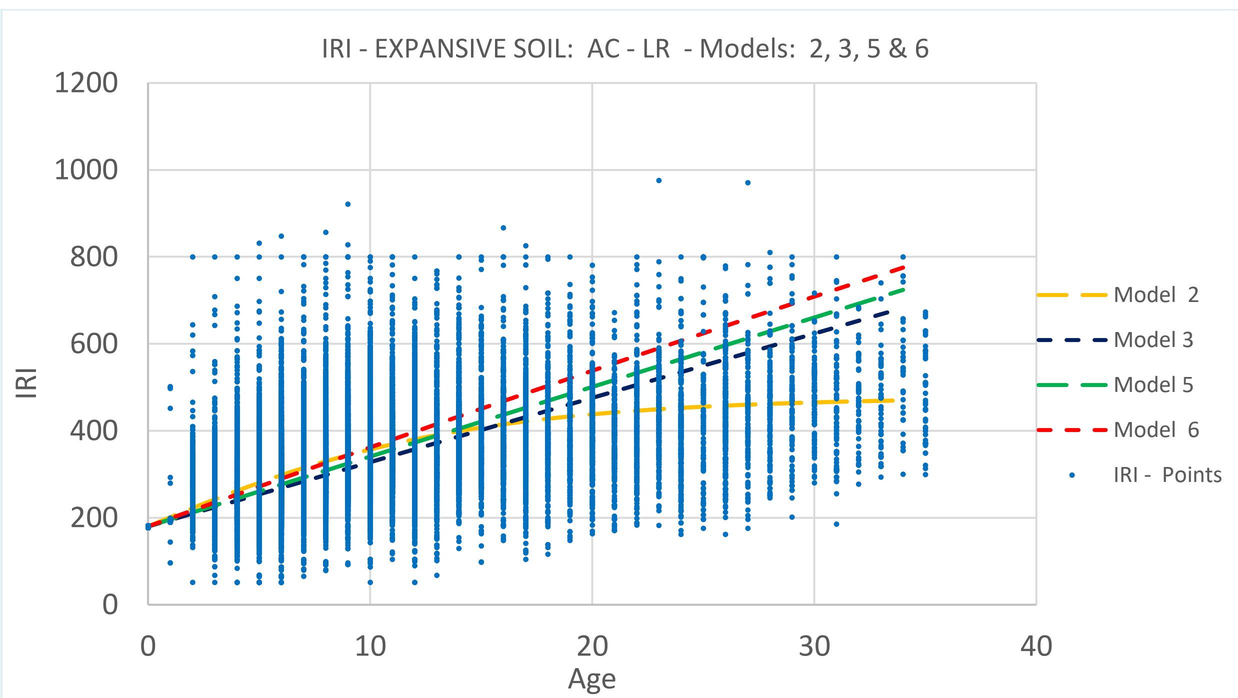

Figure F2. Chart for Models 2,3,5 & 6 – AC-LR Pavement Family (Expansive subgrade soil)

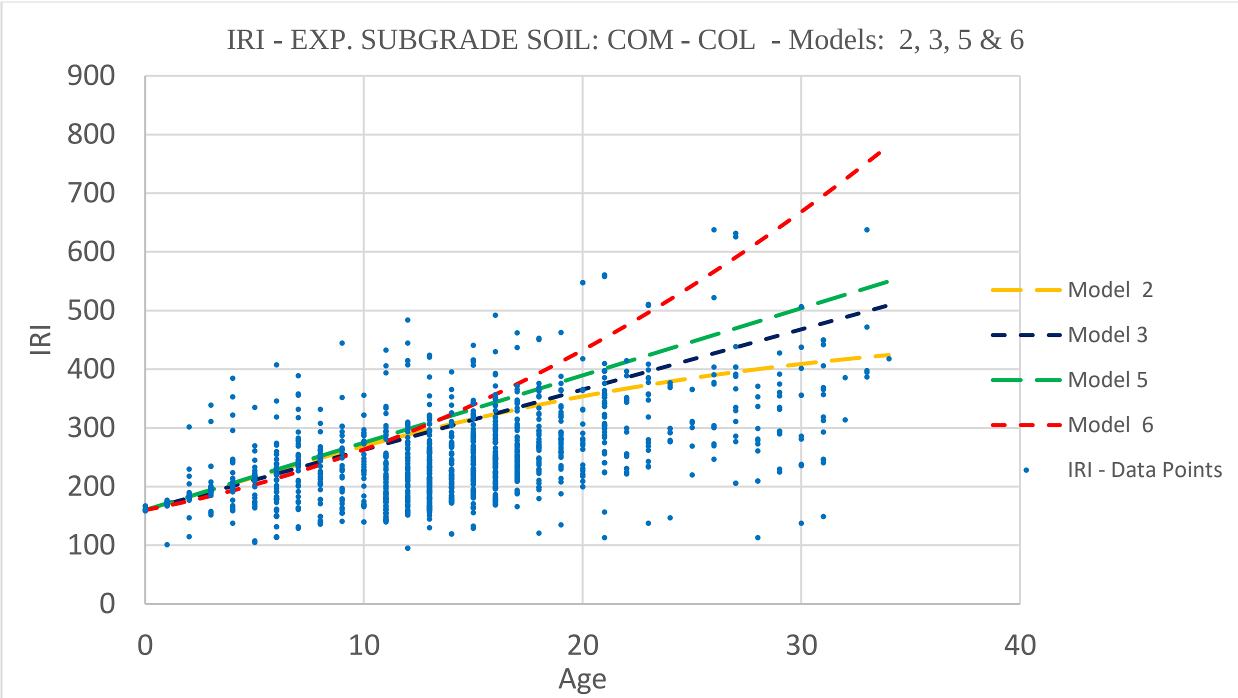

Figure F3. Chart for Models 2,3,5 & 6 – COM-COL Pavement Family (Expansive subgrade soil)

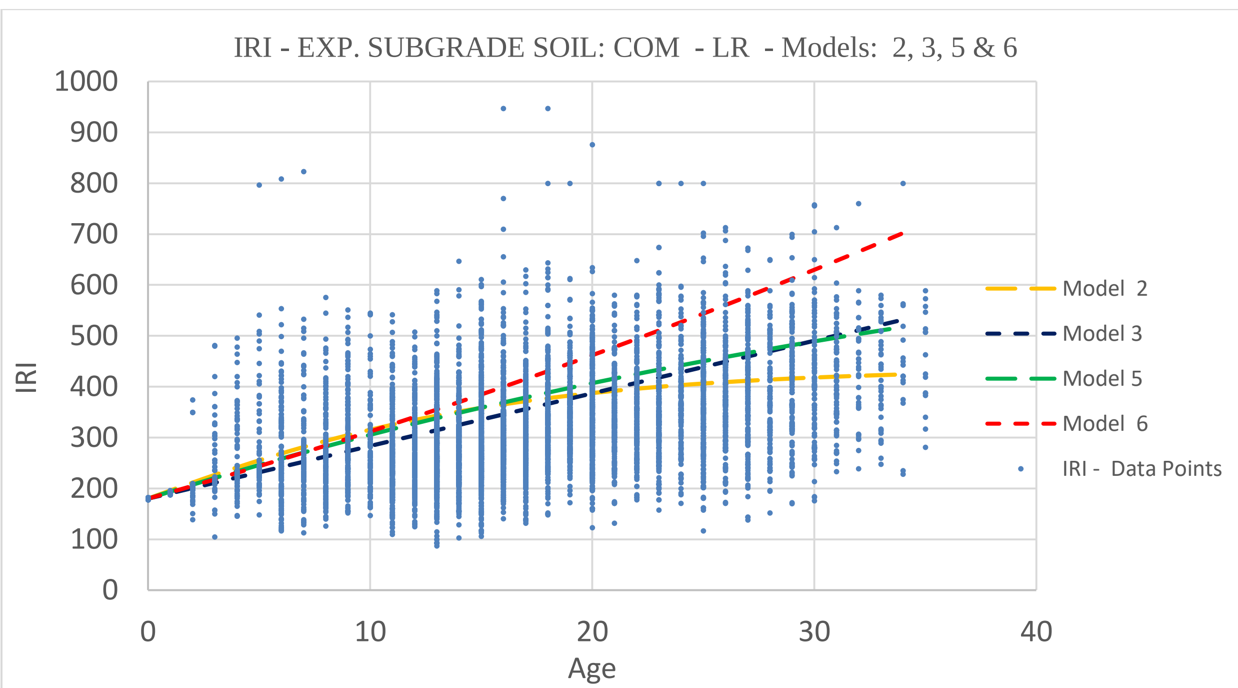

Figure F4. Chart for Models 2,3,5 & 6 – COM-LR Pavement Family (Expansive subgrade soil)

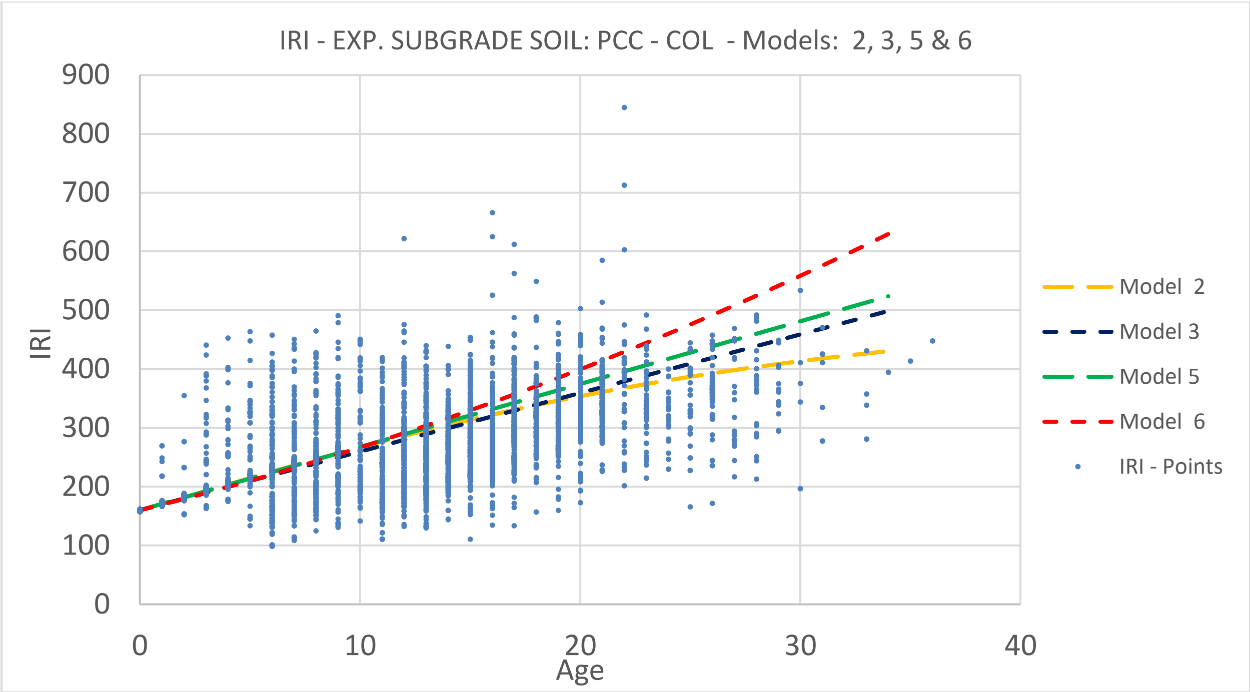

Figure F5. Chart for Models 2,3,5 & 6 – PCC-COL Pavement Family (Expansive subgrade soil)

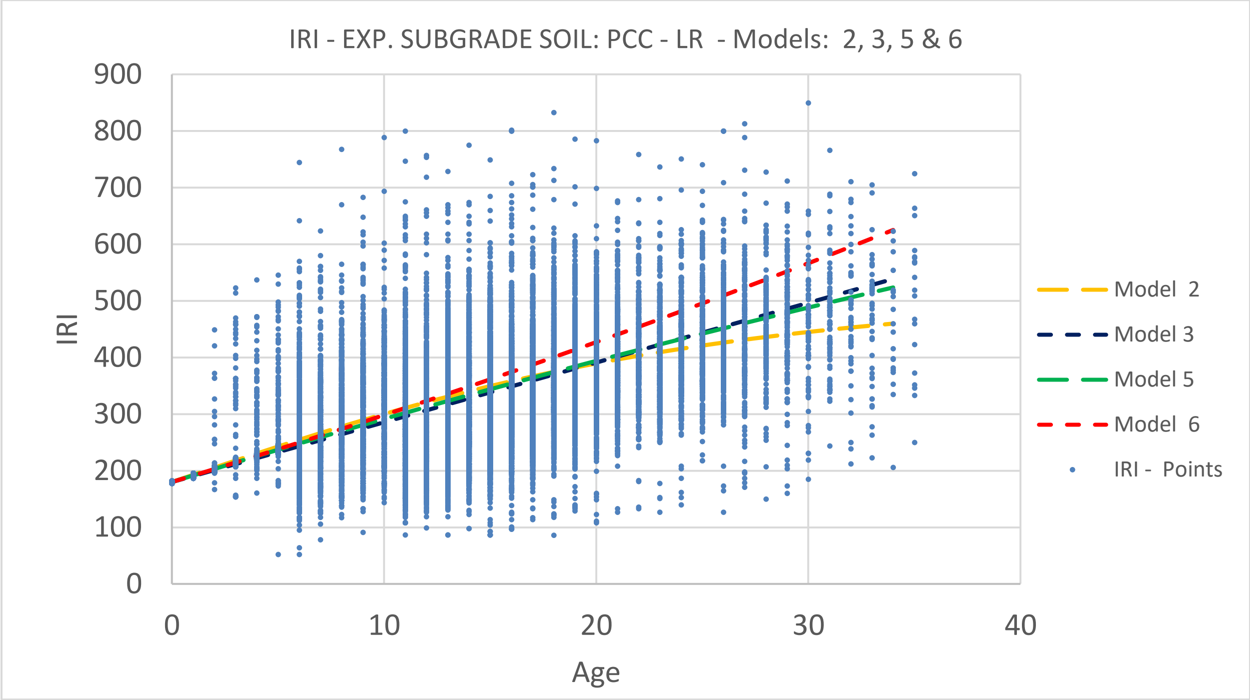

Figure F6. Chart for Models 2,3,5 & 6 – PCC-LR Pavement Family (Expansive subgrade soil)

APPENDIX G: Transition State to State Count Tables – Non-Exp. subgrade Soil (2014-2019)

AC-COL

Transition State	Count
1-1	**1,205**
1-2	**529**
1-3	-
1-4	-
1-5	-
2-1	-
2-2	**701**
2-3	**130**
2-4	-
2-5	-
3-1	147
3-2	-
3-3	**729**
3-4	**237**
3-5	-
4-1	87
4-2	-
4-3	-
4-4	**1,215**
4-5	**107**
5-1	-
5-2	-
5-3	-
5-4	-
5-5	**108**
SUM	**5,195**

AC-LR

Transition State	Count
1-1	**9,858**
1-2	**4,553**
1-3	2
1-4	-
1-5	3
2-1	-
2-2	**6,399**
2-3	**1,521**
2-4	1
2-5	2
3-1	1,138
3-2	-
3-3	**8,451**
3-4	**2,876**
3-5	9
4-1	665
4-2	-
4-3	-
4-4	**16,339**
4-5	**1,957**
5-1	-
5-2	-
5-3	-
5-4	-
5-5	**2,801**
SUM	**56,575**

AC-RU

Transition State	Count
1-1	**305**
1-2	**127**
1-3	-
1-4	-
1-5	7
2-1	4
2-2	**134**
2-3	**28**
2-4	-
2-5	-
3-1	49
3-2	-
3-3	**187**
3-4	**42**
3-5	4
4-1	25
4-2	-
4-3	3
4-4	**440**
4-5	**64**
5-1	-
5-2	-
5-3	-
5-4	-
5-5	**91**
SUM	**1,510**

Table G.1 Transition State to State Transition Matrix– for AC-COL. AC–LR & AC-RU

COM-ART

Transition State	Count
1-1	**2,163**
1-2	**380**
1-3	-
1-4	-
1-5	-
2-1	-
2-2	**627**
2-3	**89**
2-4	-
2-5	-
3-1	164
3-2	-
3-3	**473**
3-4	**24**
3-5	-
4-1	94
4-2	-
4-3	-
4-4	**26**
4-5	**-**
5-1	-
5-2	-
5-3	-
5-4	-
5-5	**-**
SUM	**4,040**

COM-COL

Transition State	Count
1-1	**196**
1-2	**16**
1-3	-
1-4	-
1-5	-
2-1	-
2-2	**41**
2-3	**7**
2-4	-
2-5	-
3-1	29
3-2	-
3-3	**29**
3-4	**1**
3-5	-
4-1	11
4-2	-
4-3	-
4-4	**5**
4-5	**-**
5-1	-
5-2	-
5-3	-
5-4	-
5-5	**-**
SUM	**335**

COM-LR

Transitio n State	Count
1-1	**1,051**
1-2	**174**
1-3	-
1-4	1
1-5	-
2-1	-
2-2	**435**
2-3	**109**
2-4	3
2-5	2
3-1	92
3-2	-
3-3	**633**
3-4	**51**
3-5	-
4-1	49
4-2	4
4-3	-
4-4	**51**
4-5	**-**
5-1	-
5-2	-
5-3	-
5-4	-
5-5	**-**
SUM	**2,655**

Table G.2 Transition State to State Transition Matrix– for COM-ART, COM–LR & COM-LR

PCC-ART		**PCC-COL**		**PCC-LR**		**PCC-LR**	
Transition State	**Count**	**Transition State**	**Count**	**Transition State**	**Count**	**Transition State**	**Count**
1-1	**1,745**	**1-1**	**327**	**1-1**	**6,172**	**1-1**	**8**
1-2	**440**	**1-2**	**92**	**1-2**	**1,788**	**1-2**	**2**
1-3	-	1-3	-	1-3	-	1-3	-
1-4	-	1-4	-	1-4	-	1-4	-
1-5	-	1-5	-	1-5	-	1-5	-
2-1	-	2-1	-	2-1	-	2-1	-
2-2	**2,866**	**2-2**	**797**	**2-2**	**19,335**	**2-2**	**30**
2-3	**443**	**2-3**	**148**	**2-3**	**3,886**	**2-3**	**2**
2-4	-	2-4	-	2-4	-	2-4	-
2-5	-	2-5	-	2-5	-	2-5	-
3-1	124	3-1	21	3-1	425	3-1	-
3-2	-	3-2	-	3-2	-	3-2	-
3-3	**1,967**	**3-3**	**640**	**3-3**	**16,843**	**3-3**	7
3-4	**152**	**3-4**	**49**	**3-4**	**641**	**3-4**	**-**
3-5	-	3-5	-	3-5	-	3-5	-
4-1	95	4-1	15	4-1	250	4-1	1
4-2	-	4-2	-	4-2	-	4-2	-
4-3	-	4-3	-	4-3	-	4-3	-
4-4	**435**	**4-4**	**146**	**4-4**	**1,441**	**4-4**	**-**
4-5	**19**	**4-5**	**13**	**4-5**	**73**	**4-5**	**-**
5-1	-	5-1	-	5-1	-	5-1	-
5-2	-	5-2	-	5-2	-	5-2	-
5-3	-	5-3	-	5-3	-	5-3	-
5-4	-	5-4	-	5-4	-	5-4	-
5-5	**29**	**5-5**	**67**	**5-5**	**171**	**5-5**	**-**
SUM	**8,315**	**SUM**	**2,315**	**SUM**	**51,025**	**SUM**	**50**

Table G.3 Transition State to State Transition Matrix– for PCC-ART, PCC–LR & PCC-LR

APPENDIX H: Transition State to State Count Tables – Exp. subgrade soil (2007-2018)

AC-ART			AC-COL			AC-LR	
Transition State	**Count**		**Transition State**	**Count**		**Transition State**	**Count**
1-1	**415**		**1-1**	**118**		**1-1**	**1,213**
1-2	**158**		**1-2**	**58**		**1-2**	**457**
1-3	2		1-3	1		1-3	20
1-4	0		1-4	-		1-4	-
1-5	0		1-5	-		1-5	1
2-1	31		2-1	13		2-1	117
2-2	**973**		**2-2**	**232**		**2-2**	**2,080**
2-3	**315**		**2-3**	**120**		**2-3**	**1,338**
2-4	27		2-4	9		2-4	23
2-5	2		2-5	1		2-5	2
3-1	30		3-1	17		3-1	-
3-2	6		3-2	-		3-2	-
3-3	**423**		**3-3**	**207**		**3-3**	**2,067**
3-4	**86**		**3-4**	**28**		**3-4**	**367**
3-5	5		3-5	5		3-5	9
4-1	48		4-1	24		4-1	-
4-2	14		4-2	-		4-2	-
4-3	1		4-3	2		4-3	-
4-4	**55**		**4-4**	**15**		**4-4**	**246**
4-5	**22**		**4-5**	**6**		**4-5**	**124**
5-1	11		5-1	5		5-1	-
5-2	11		5-2	7		5-2	-
5-3	7		5-3	3		5-3	-
5-4	2		5-4	1		5-4	-
5-5	**12**		**5-5**	**4**		**5-5**	**111**
SUM	**2656**		**SUM**	**876**		**SUM**	**8,175**

Table H.1 Transition State to State Transition Matrix– for AC-ART, AC-COL. & AC–LR

COM-ART

Transition State	Count
1-1	**486**
1-2	**131**
1-3	1
1-4	-
1-5	-
2-1	45
2-2	**594**
2-3	**77**
2-4	10
2-5	1
3-1	48
3-2	4
3-3	**78**
3-4	**21**
3-5	3
4-1	7
4-2	8
4-3	2
4-4	**32**
4-5	**11**
5-1	1
5-2	-
5-3	5
5-4	-
5-5	**3**
SUM	**1,568**

COM-COL

Transition State	Count
1-1	**71**
1-2	**27**
1-3	1
1-4	-
1-5	-
2-1	3
2-2	**231**
2-3	**31**
2-4	1
2-5	-
3-1	7
3-2	-
3-3	**22**
3-4	**9**
3-5	-
4-1	-
4-2	-
4-3	-
4-4	**2**
4-5	**-**
5-1	1
5-2	-
5-3	-
5-4	-
5-5	**-**
SUM	**406**

COM-LR

Transition State	Count
1-1	**221**
1-2	**55**
1-3	-
1-4	-
1-5	-
2-1	11
2-2	**442**
2-3	**125**
2-4	11
2-5	4
3-1	28
3-2	2
3-3	**119**
3-4	**30**
3-5	2
4-1	10
4-2	5
4-3	1
4-4	**20**
4-5	**15**
5-1	8
5-2	-
5-3	3
5-4	-
5-5	**6**
SUM	**1,118**

Table H.2 Transition State to State Transition Matrix– for COM-ART, COM–LR & COM-LR

PCC-ART		PCC-COL		PCC-LR	
Transition State	**Count**	**Transition State**	**Count**	**Transition State**	**Count**
1-1	**1,553**	**1-1**	**643**	**1-1**	**1,637**
1-2	**451**	**1-2**	**148**	**1-2**	**481**
1-3	39	1-3	1	1-3	-
1-4	7	1-4	-	1-4	-
1-5	-	1-5	-	1-5	-
2-1	-	2-1	4	2-1	-
2-2	**1,769**	**2-2**	**703**	**2-2**	**2,426**
2-3	**237**	**2-3**	**104**	**2-3**	**390**
2-4	24	2-4	5	2-4	14
2-5	1	2-5	-	2-5	-
3-1	4	3-1	47	3-1	-
3-2	-	3-2	-	3-2	-
3-3	**117**	**3-3**	**46**	**3-3**	**306**
3-4	**54**	**3-4**	**23**	**3-4**	**91**
3-5	6	3-5	3	3-5	4
4-1	-	4-1	8	4-1	-
4-2	-	4-2	6	4-2	-
4-3	-	4-3	2	4-3	-
4-4	**34**	**4-4**	**23**	**4-4**	**44**
4-5	**13**	**4-5**	**2**	**4-5**	**20**
5-1	-	5-1	7	5-1	-
5-2	-	5-2	-	5-2	-
5-3	-	5-3	4	5-3	-
5-4	-	5-4	1	5-4	-
5-5	**5**	**5-5**	**1**	**5-5**	**13**
SUM	**4,314**	**SUM**	**1,781**	**SUM**	**5,426**

Table H.3 Transition State to State Transition Matrix– for PCC-ART, PCC–LR & PCC-LR

APPENDIX I: Example for SAS results

The SAS System

The NLIN Procedure
Dependent Variable PCI
Method: Newton

SURF=AC CLASS=ART

Iterative Phase			
Iter	x2	x3	Sum of Squares
0	2.0000	3.0000	1.5905E9
1	1.5193	3.0000	5.4988E8
2	1.0514	3.0000	1.8247E8
3	0.6046	3.0000	56599197
4	0.1930	3.0000	15821103
5	-0.1602	3.0000	3990645
6	-0.4217	2.8627	1278008
7	-0.5603	2.8627	913578
8	-0.5953	2.8627	899104
9	-0.5972	2.8627	899065
10	-0.5972	2.8627	899065

NOTE: Convergence criterion met but a note in the log indicates a possible problem with the model.

Estimation Summary	
Method	Newton
Iterations	10
R	1.59E-10
PPC	7.87E-11
RPC(x2)	9.376E-6
Object	3.59E-10
Objective	899065.4
Observations Read	3468
Observations Used	3468
Observations Missing	0

Note: An intercept was not specified for this model.

Source	DF	Sum of Squares	Mean Square	F Value	Approx Pr > F
Model	1	10295128	10295128	39700.3	<.0001
Error	3467	899065	259.3		
Uncorrected Total	3468	11194193			

Note: The (approximate) Hessian is singular.

Parameter	Estimate	Approx Std Error	Approximate 95% Confidence Limits	
x2	-0.5972	0.00502	-0.6070	-0.5874
x3	2.8627	.	.	.

Approximate Correlation Matrix		
	x2	x3
x2	1.0000000	.
x3	.	.

The SAS System

The NLIN Procedure
Dependent Variable PCI
Method: Newton

SURF=AC CLASS=LR

Iterative Phase			
Iter	x2	x3	Sum of Squares
0	2.0000	3.0000	8.0152E9
1	1.5194	3.0000	2.7708E9
2	1.0515	3.0000	9.1936E8
3	0.6047	3.0000	2.8515E8
4	0.1933	3.0000	79726499
5	-0.1598	3.0000	20155833
6	-0.4209	2.8528	6509824
7	-0.5592	2.8528	4680594
8	-0.5939	2.8528	4608302
9	-0.5958	2.8528	4608111
10	-0.5958	2.8528	4608111

NOTE: Convergence criterion met but a note in the log indicates a possible problem with the model.

Estimation Summary	
Method	Newton
Iterations	10
R	1.51E-10
PPC	7.54E-11
RPC(x2)	9.186E-6
Object	3.38E-10
Objective	4608111
Observations Read	17480
Observations Used	17480
Observations Missing	0

Note: An intercept was not specified for this model.

Source	DF	Sum of Squares	Mean Square	F Value	Approx Pr > F
Model	1	52032391	52032391	197364	<.0001
Error	17479	4608111	263.6		
Uncorrected Total	17480	56640502			

Note: The (approximate) Hessian is singular.

Parameter	Estimate	Approx Std Error	Approximate 95% Confidence Limits	
x2	-0.5958	0.00225	-0.6002	-0.5914
x3	2.8528	.	.	.

Approximate Correlation Matrix		
	x2	x3
x2	1.0000000	.
x3	.	.

The SAS System

The NLIN Procedure
Dependent Variable PCI
Method: Newton

SURF=AC CLASS=RU

Iterative Phase			
Iter	x2	x3	Sum of Squares
0	2.0000	3.0000	1.7956E8
1	1.5195	3.0000	62041413
2	1.0518	3.0000	20565978
3	0.6054	3.0000	6365887
4	0.1946	3.0000	1770968
5	-0.1576	3.0000	441145
6	-0.4173	2.8817	137862
7	-0.5540	2.8817	97618.8
8	-0.5878	2.8817	96064.3
9	-0.5896	2.8817	96060.4
10	-0.5896	2.8817	96060.4

NOTE: Convergence criterion met but a note in the log indicates a possible problem with the model.

Estimation Summary	
Method	Newton
Iterations	10
R	1.28E-10
PPC	6.19E-11
RPC(x2)	8.363E-6
Object	2.99E-10
Objective	96060.39
Observations Read	392
Observations Used	392
Observations Missing	0

Note: An intercept was not specified for this model.

Source	DF	Sum of Squares	Mean Square	F Value	Approx Pr > F
Model	1	1181443	1181443	4808.89	<.0001
Error	391	96060.4	245.7		
Uncorrected Total	392	1277503			

Note: The (approximate) Hessian is singular.

Parameter	Estimate	Approx Std Error	Approximate 95% Confidence Limits	
x2	-0.5896	0.0144	-0.6180	-0.5613
x3	2.8817	.	.	.

Approximate Correlation Matrix		
	x2	x3
x2	1.0000000	.
x3	.	.

The SAS System

The NLIN Procedure
Dependent Variable PCI
Method: Newton

SURF=COM CLASS=ART

Iterative Phase			
Iter	x2	x3	Sum of Squares
0	2.0000	3.0000	5.3124E8
1	1.5233	3.0000	1.8117E8
2	1.0620	3.0000	58693678
3	0.6262	3.0000	17429594
4	0.2330	3.0000	4483580
5	-0.0907	3.0000	969307
6	-0.3089	3.0997	274675
7	-0.4026	3.0997	208363
8	-0.4177	3.0997	207135
9	-0.4181	3.0997	207135

NOTE: Convergence criterion met but a note in the log indicates a possible problem with the model.

Estimation Summary	
Method	Newton
Iterations	9
R	9.061E-7
PPC(x2)	4.377E-7
RPC(x2)	0.000836
Object	2.994E-6
Objective	207134.6
Observations Read	1196
Observations Used	1196
Observations Missing	0

Note: An intercept was not specified for this model.

					Approx

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	5080281	5080281	29309.1	<.0001
Error	1195	207135	173.3		
Uncorrected Total	1196	5287415			

Note: The (approximate) Hessian is singular.

Parameter	Estimate	Approx Std Error	Approximate 95% Confidence Limits	
x2	-0.4181	0.00584	-0.4295	-0.4066
x3	3.0997	.	.	.

Approximate Correlation Matrix		
	x2	x3
x2	1.0000000	.
x3	.	.

The SAS System

The NLIN Procedure
Dependent Variable PCI
Method: Newton

SURF=COM CLASS=LR

Iterative Phase			
Iter	x2	x3	Sum of Squares
0	2.0000	3.0000	2.9837E8
1	1.5234	3.0000	1.0174E8
2	1.0621	3.0000	32954505
3	0.6265	3.0000	9784764
4	0.2335	3.0000	2518727
5	-0.0898	3.0000	548105
6	-0.3075	3.1067	159389
7	-0.4007	3.1067	122454
8	-0.4156	3.1067	121777
9	-0.4159	3.1067	121777

NOTE: Convergence criterion met but a note in the log indicates a possible problem with the model.

Estimation Summary	
Method	Newton
Iterations	9
R	8.478E-7
PPC(x2)	4.201E-7
RPC(x2)	0.000821
Object	2.744E-6
Objective	121777.1
Observations Read	672
Observations Used	672
Observations Missing	0

Note: An intercept was not specified for this model.

					Approx

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	2866567	2866567	15795.0	<.0001
Error	671	121777	181.5		
Uncorrected Total	672	2988344			

Note: The (approximate) Hessian is singular.

Parameter	Estimate	Approx Std Error	Approximate 95% Confidence Limits	
x2	-0.4159	0.00796	-0.4316	-0.4003
x3	3.1067	.	.	.

Approximate Correlation Matrix		
	x2	x3
x2	1.0000000	.
x3	.	.

The SAS System

The NLIN Procedure
Dependent Variable PCI
Method: Newton

SURF=PCC CLASS=ART

Iterative Phase			
Iter	x2	x3	Sum of Squares
0	2.0000	3.0000	2.0938E9
1	1.5253	3.0000	7.0924E8
2	1.0671	3.0000	2.2708E8
3	0.6367	3.0000	65987223
4	0.2525	3.0000	16273264
5	-0.0569	3.0000	3240165
6	-0.2556	3.3566	859598
7	-0.3318	3.3566	669945
8	-0.3416	3.3566	667595
9	-0.3418	3.3566	667594

NOTE: Convergence criterion met but a note in the log indicates a possible problem with the model.

Estimation Summary	
Method	Newton
Iterations	9
R	1.886E-7
PPC(x2)	9.262E-8
RPC(x2)	0.000425
Object	7.491E-7
Objective	667594.5
Observations Read	4788
Observations Used	4788
Observations Missing	0

Note: An intercept was not specified for this model.

					Approx

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	23690536	23690536	169873	<.0001
Error	4787	667594	139.5		
Uncorrected Total	4788	24358130			

Note: The (approximate) Hessian is singular.

Parameter	Estimate	Approx Std Error	Approximate 95% Confidence Limits	
x2	-0.3418	0.00243	-0.3465	-0.3370
x3	3.3566	.	.	.

Approximate Correlation Matrix		
	x2	x3
x2	1.0000000	.
x3	.	.

The SAS System

The NLIN Procedure
Dependent Variable PCI
Method: Newton

SURF=PCC CLASS=LR

Iterative Phase			
Iter	x2	x3	Sum of Squares
0	2.0000	3.0000	1.226E10
1	1.5256	3.0000	4.1482E9
2	1.0680	3.0000	1.3256E9
3	0.6384	3.0000	3.8384E8
4	0.2556	3.0000	93978023
5	-0.0516	3.0000	18417252
6	-0.2472	3.4147	4792689
7	-0.3210	3.4147	3738818
8	-0.3301	3.4147	3726586
9	-0.3302	3.4147	3726584

NOTE: Convergence criterion met but a note in the log indicates a possible problem with the model.

Estimation Summary	
Method	Newton
Iterations	9
R	1.474E-7
PPC(x2)	7.222E-8
RPC(x2)	0.000382
Object	6.073E-7
Objective	3726584
Observations Read	28104
Observations Used	28104
Observations Missing	0

Note: An intercept was not specified for this model.

					Approx

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	1.423E8	1.423E8	1073144	<.0001
Error	28103	3726584	132.6		
Uncorrected Total	28104	1.4603E8			

Note: The (approximate) Hessian is singular.

Parameter	Estimate	Approx Std Error	Approximate 95% Confidence Limits	
x2	-0.3302	0.000965	-0.3321	-0.3283
x3	3.4147	.	.	.

Approximate Correlation Matrix		
	x2	x3
x2	1.0000000	.
x3	.	.

The SAS System

The NLIN Procedure
Dependent Variable PCI
Method: Newton

SURF=PCC CLASS=RU

Iterative Phase			
Iter	x2	x3	Sum of Squares
0	2.0000	3.0000	17570099
1	1.5247	3.0000	5963022
2	1.0657	3.0000	1915524
3	0.6337	3.0000	559949
4	0.2469	3.0000	139603
5	-0.0666	3.0000	28280.1
6	-0.2707	3.2688	7471.6
7	-0.3517	3.2688	5724.0
8	-0.3628	3.2688	5699.7
9	-0.3630	3.2688	5699.7

NOTE: Convergence criterion met but a note in the log indicates a possible problem with the model.

Estimation Summary	
Method	Newton
Iterations	9
R	3.037E-7
PPC(x2)	1.45E-7
RPC(x2)	0.000516
Object	1.168E-6
Objective	5699.692
Observations Read	40
Observations Used	40
Observations Missing	0

Note: An intercept was not specified for this model.

					Approx

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	189683	189683	1297.90	<.0001
Error	39	5699.7	146.1		
Uncorrected Total	40	195383			

Note: The (approximate) Hessian is singular.

Parameter	Estimate	Approx Std Error	Approximate 95% Confidence Limits	
x2	-0.3630	0.0278	-0.4191	-0.3069
x3	3.2688	.	.	.

Approximate Correlation Matrix		
	x2	x3
x2	1.0000000	.
x3	.	.

APPENDIX J: TM & TPM – Non-Expansive Subgrade Soils

TM for AC-COL (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	1,205	529	0	0	0
Good (2)	0	701	130	0	0
Satisfactory (3)	0	0	729	237	0
Poor (4)	0	0	0	1,215	107
Very Poor (5)	0	0	0	0	108

Table J1 Transition Matrix for AC-COL pavement family (non-expansive subgrade soil)

TPM for AC-COL (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.6949	0.3051	0	0	0
Good (2)	0	0.8436	0.1564	0	0
Satisfactory (3)	0	0	0.7547	0.2453	0
Poor (4)	0	0	0	0.9191	0.0809
Very Poor (5)	0	0	0	0	1

Table J2 Transition Probability Matrix for AC-COL (non-expansive subgrade soil)

TM for AC-LR (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	9,858	4,553	0	0	0
Good (2)	0	6,399	1,521	0	0
Satisfactory (3)	0	0	8,451	2,876	0
Poor (4)	0	0	0	16,339	1,957
Very Poor (5)	0	0	0	0	2,801

Table J3 Transition Matrix for AC-LR pavement family (non-expansive subgrade soil)

TPM for AC-LR (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.6841	0.3159	0	0	0
Good (2)	0	0.8080	0.1920	0	0
Satisfactory (3)	0	0	0.7461	0.2539	0
Poor (4)	0	0	0	0.8930	0.1070
Very Poor (5)	0	0	0	0	1

Table J4 Transition Probability Matrix for AC-LR (non-expansive subgrade soil)

TM for AC-RU (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	305	127	0	0	0
Good (2)	0	134	28	0	0
Satisfactory (3)	0	0	187	42	0
Poor (4)	0	0	0	440	64
Very Poor (5)	0	0	0	0	91

Table J5 Transition Matrix for AC- RU pavement family (non-expansive subgrade soil)

TPM for AC-RU (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.7060	0.2940	0	0	0
Good (2)	0	0.8272	0.1728	0	0
Satisfactory (3)	0	0	0.8166	0.1834	0
Poor (4)	0	0	0	0.8730	0.1270
Very Poor (5)	0	0	0	0	1

Table J6 Transition Probability Matrix for AC-RU (non-expansive subgrade soil)

TM for COM-ART (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	2,163	380	0	0	0
Good (2)	0	627	89	0	0
Satisfactory (3)	0	0	473	24	0
Poor (4)	0	0	0	26	0
Very Poor (5)	0	0	0	0	0

Table J7 Transition Matrix for COM-ART pavement family (non-expansive subgrade soil)

TPM for COM-ART (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.8506	0.1494	0	0	0
Good (2)	0	0.8757	0.1243	0	0
Satisfactory (3)	0	0	0.9517	0.0483	0
Poor (4)	0	0	0	1	0
Very Poor (5)	0	0	0	0	0

Table J8 Transition Probability Matrix for COM-ART (non-expansive subgrade soil)

TM for COM-COL (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	196	16	0	0	0
Good (2)	0	41	7	0	0
Satisfactory (3)	0	0	26	1	0
Poor (4)	0	0	0	5	0
Very Poor (5)	0	0	0	0	0

Table J9 Transition Matrix for COM-COL pavement family (non-expansive subgrade soil)

TPM for COM-COL (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.9245	0.0755	0	0	0
Good (2)	0	0.8542	0.1458	0	0
Satisfactory (3)	0	0	0.9630	0.0370	0
Poor (4)	0	0	0	1	0
Very Poor (5)	0	0	0	0	0

Table J10 Transition Probability Matrix for COM-COL (non-expansive subgrade soil)

TM for COM-LR (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	1,051	174	0	0	0
Good (2)	0	435	109	0	0
Satisfactory (3)	0	0	633	51	0
Poor (4)	0	0	0	51	0
Very Poor (5)	0	0	0	0	0

Table J11 Transition Matrix for COM-LR pavement family (non-expansive subgrade soil)

TPM for COM-LR (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.8580	0.1420	0	0	0
Good (2)	0	0.7996	0.2004	0	0
Satisfactory (3)	0	0	0.9254	0.0746	0
Poor (4)	0	0	0	1	0
Very Poor (5)	0	0	0	1	0

Table J12 Transition Probability Matrix for COM-LR (non-expansive subgrade soil)

TM for PCC-ART (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	1,745	440	0	0	0
Good (2)	0	2,866	443	0	0
Satisfactory (3)	0	0	1,967	152	0
Poor (4)	0	0	0	435	19
Very Poor (5)	0	0	0	0	29

Table J13 Transition Matrix for PCC-ART pavement family (non-expansive subgrade soil)

TPM for PCC-ART (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.7986	0.2014	0	0	0
Good (2)	0	0.8661	0.1339	0	0
Satisfactory (3)	0	0	0.9283	0.0717	0
Poor (4)	0	0	0	0.9581	0.0419
Very Poor (5)	0	0	0	0	1

Table J14 Transition Probability Matrix for PCC-ART (non-expansive subgrade soil)

TM for PCC-COL (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	327	92	0	0	0
Good (2)	0	797	148	0	0
Satisfactory (3)	0	0	640	49	0
Poor (4)	0	0	0	146	13
Very Poor (5)	0	0	0	0	67

Table J15 Transition Matrix for PCC-COL pavement family (non-expansive subgrade soil)

TPM for PCC-COL (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.7804	0.2196	0	0	0
Good (2)	0	0.8434	0.1566	0	0
Satisfactory (3)	0	0	0.9289	0.0711	0
Poor (4)	0	0	0	0.9182	0.0818
Very Poor (5)	0	0	0	0	1

Table J16 Transition Probability Matrix for PCC-COL (non-expansive subgrade soil)

TM for PCC-LR (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	6,172	1,788	0	0	0
Good (2)	0	19,335	3,886	0	0
Satisfactory (3)	0	0	16,843	641	0
Poor (4)	0	0	0	1,441	73
Very Poor (5)	0	0	0	0	171

Table J17 Transition Matrix for PCC-LR pavement family (non-expansive subgrade soil)

TPM for PCC-LR (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.7754	0.2246	0	0	0
Good (2)	0	0.8327	0.1673	0	0
Satisfactory (3)	0	0	0.9633	0.0367	0
Poor (4)	0	0	0	0.9518	0.0482
Very Poor (5)	0	0	0	0	1

Table J18 Transition Probability Matrix for PCC-LR (non-expansive subgrade soil)

TM for PCC-RU (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	8	2	0	0	0
Good (2)	0	30	2	0	0
Satisfactory (3)	0	0	7	0	0
Poor (4)	0	0	0	0	0
Very Poor (5)	0	0	0	0	0

Table J19 Transition Matrix for PCC-RU pavement family (non-expansive subgrade soil)

TPM for PCC-RU (2014-2019)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.8	0.2	0	0	0
Good (2)	0	0.9375	0.0625	0	0
Satisfactory (3)	0	0	1	0	0
Poor (4)	0	0	0	0	0
Very Poor (5)	0	0	0	0	0

Table J20 Transition Probability Matrix for PCC-RU (non-expansive subgrade soil)

APPENDIX K: TM & TPM– Expansive Subgrade Soils

TM for AC--COL (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	118	58	0	0	0
Good (2)	0	232	120	0	0
Satisfactory (3)	0	0	207	28	0
Poor (4)	0	0	0	15	6
Very Poor (5)	0	0	0	0	4

Table K1 Transition Matrix for AC-COL pavement family (expansive subgrade soil)

TPM for AC-COL (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.6705	0.3295	0	0	0
Good (2)	0	0.6591	0.3409	0	0
Satisfactory (3)	0	0	0.8809	0.1191	0
Poor (4)	0	0	0	0.7143	0.2857
Very Poor (5)	0	0	0	0	1

Table K2 Transition Probability Matrix for AC-COL (expansive subgrade soil)

TM for AC-LR (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	1,213	457	0	0	0
Good (2)	0	2,080	1,338	0	0
Satisfactory (3)	0	0	2,067	367	0
Poor (4)	0	0	0	246	124
Very Poor (5)	0	0	0	0	111

Table K3 Transition Matrix for AC-LR pavement family (expansive subgrade soil)

TPM for AC-LR (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.7263	0.2737	0	0	0
Good (2)	0	0.6085	0.3915	0	0
Satisfactory (3)	0	0	0.8492	0.1508	0
Poor (4)	0	0	0	0.6649	0.3351
Very Poor (5)	0	0	0	0	1

Table K4 Transition Probability Matrix for AC-LR (expansive subgrade soil)

TM for COM-ART (2007-2018)					
Rating Value	Very Good (1)	Good (2)	Satisfactory (3)	Poor (4)	Very Poor (5)
Very Good (1)	486	131	0	0	0
Good (2)	0	594	77	0	0
Satisfactory (3)	0	0	78	21	0
Poor (4)	0	0	0	32	11
Very Poor (5)	0	0	0	0	3

Table K5 Transition Matrix for COM-ART pavement family (expansive subgrade soil)

TPM for COM-ART (2007-2018)					
Rating Value	Very Good (1)	Good (2)	Satisfactory (3)	Poor (4)	Very Poor (5)
Very Good (1)	0.7877	0.2123	0	0	0
Good (2)	0	0.8852	0.1148	0	0
Satisfactory (3)	0	0	0.7879	0.2121	0
Poor (4)	0	0	0	0.7442	0.2558
Very Poor (5)	0	0	0	0	1

Table K6 Transition Probability Matrix for COM-ART (expansive subgrade soil)

TM for COM-COL (2007-2018)					
Rating Value	Very Good (1)	Good (2)	Satisfactory (3)	Poor (4)	Very Poor (5)
Very Good (1)	71	27	0	0	0
Good (2)	0	231	31	0	0
Satisfactory (3)	0	0	22	9	0
Poor (4)	0	0	0	2	0
Very Poor (5)	0	0	0	0	0

Table K7 Transition Matrix for COM-COL pavement family

TPM for COM-COL (2007-2018)					
Rating Value	Very Good (1)	Good (2)	Satisfactory (3)	Poor (4)	Very Poor (5)
Very Good (1)	0.7245	0.2755	0	0	0
Good (2)	0	0.8817	0.1183	0	0
Satisfactory (3)	0	0	0.7097	0.2903	0
Poor (4)	0	0	0	1	0
Very Poor (5)	0	0	0	0	0

Table K8 Transition Probability Matrix for COM-COL (expansive subgrade soil)

TM for COM-LR (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	221	55	0	0	0
Good (2)	0	442	125	0	0
Satisfactory (3)	0	0	119	30	0
Poor (4)	0	0	0	20	15
Very Poor (5)	0	0	0	0	6

Table K9 Transition Matrix for COM-LR pavement family (expansive subgrade soil)

TPM for COM-LR (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.8007	0.1993	0	0	0
Good (2)	0	0.7795	0.2205	0	0
Satisfactory (3)	0	0	0.7987	0.2013	0
Poor (4)	0	0	0	0.5714	0.4286
Very Poor (5)	0	0	0	0	1

Table K10 Transition Probability Matrix for COM-LR (expansive subgrade soil)

TM for PCC-ART (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	1,553	451	0	0	0
Good (2)	0	1,769	237	0	0
Satisfactory (3)	0	0	117	54	0
Poor (4)	0	0	0	34	13
Very Poor (5)	0	0	0	0	5

Table K11 Count Table for expansive PCC-ART pavement family

TPM for PCC-ART (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.7750	0.2250	0	0	0
Good (2)	0	0.8819	0.1181	0	0
Satisfactory (3)	0	0	0.6842	0.3158	0
Poor (4)	0	0	0	0.7234	0.2766
Very Poor (5)	0	0	0	0	1

Table K12 Transition Probability Matrix for PCC-ART (expansive subgrade soil)

TM for PCC-COL (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	643	148	0	0	0
Good (2)	0	703	104	0	0
Satisfactory (3)	0	0	46	23	0
Poor (4)	0	0	0	23	2
Very Poor (5)	0	0	0	0	1

Table K13 Transition Matrix for PCC-COL pavement family (expansive subgrade soil)

TPM for PCC-COL (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.8129	0.1871	0	0	0
Good (2)	0	0.8711	0.1289	0	0
Satisfactory (3)	0	0	0.6667	0.3333	0
Poor (4)	0	0	0	0.9200	0.0800
Very Poor (5)	0	0	0	0	1

Table K14 Transition Probability Matrix – PCC-COL (expansive subgrade soil)

TM for PCC-LR (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	1,637	481	0	0	0
Good (2)	0	2,426	390	0	0
Satisfactory (3)	0	0	306	91	0
Poor (4)	0	0	0	44	20
Very Poor (5)	0	0	0	0	13

Table K15 Transition Matrix for PCC-LR pavement family (expansive subgrade soil)

TPM for PCC-LR (2007-2018)					
Rating Value	**Very Good (1)**	**Good (2)**	**Satisfactory (3)**	**Poor (4)**	**Very Poor (5)**
Very Good (1)	0.7729	0.2271	0	0	0
Good (2)	0	0.8615	0.1385	0	0
Satisfactory (3)	0	0	0.7708	0.2292	0
Poor (4)	0	0	0	0.6875	0.3125
Very Poor (5)	0	0	0	0	1

Table K16 Transition Probability Matrix for PCC-LR (expansive subgrade soil)

APPENDIX L: Residuals – Expansive Soil (PCI)

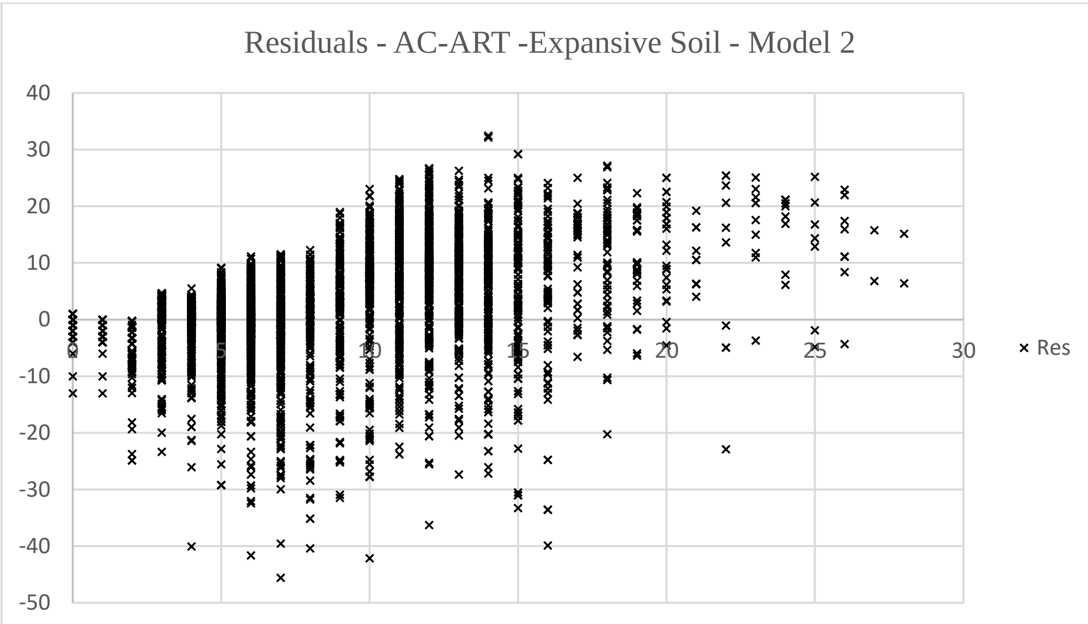

Figure L1 Residuals AC-ART – Model 2 (Selected)

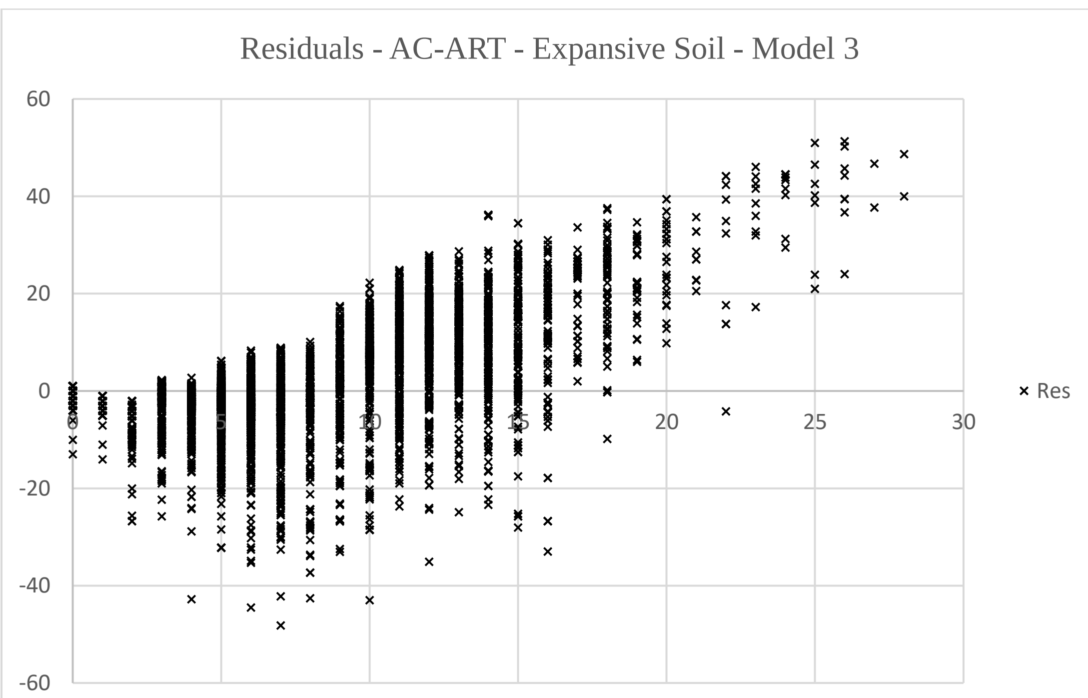

Figure L2 Residuals AC-ART – Model 3

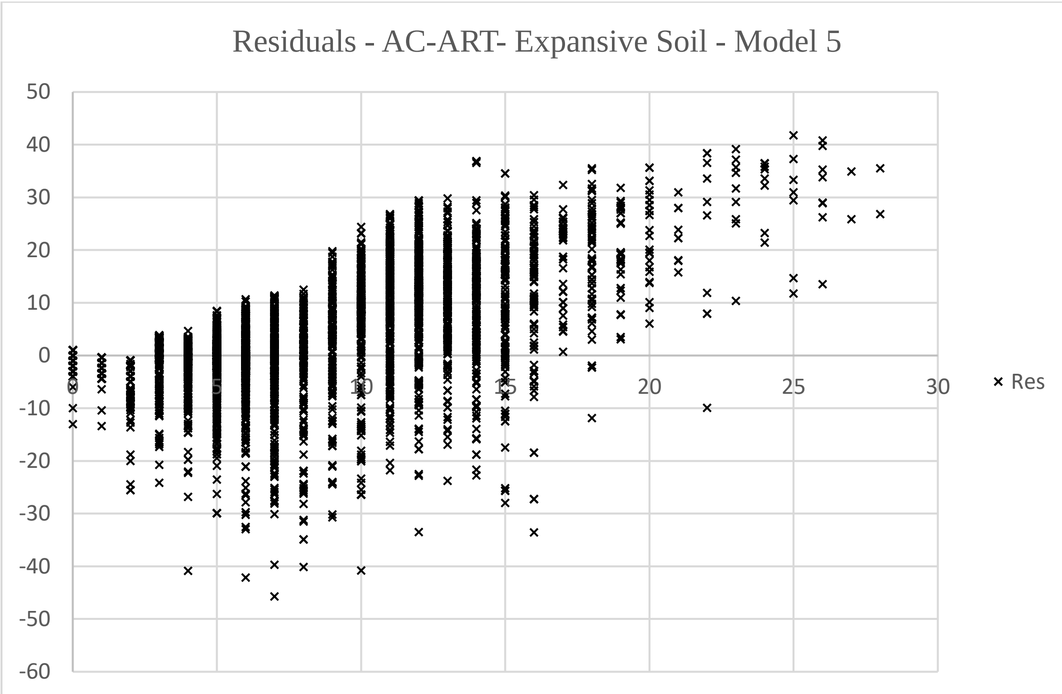

Table L3 Residuals AC-ART – Model 5

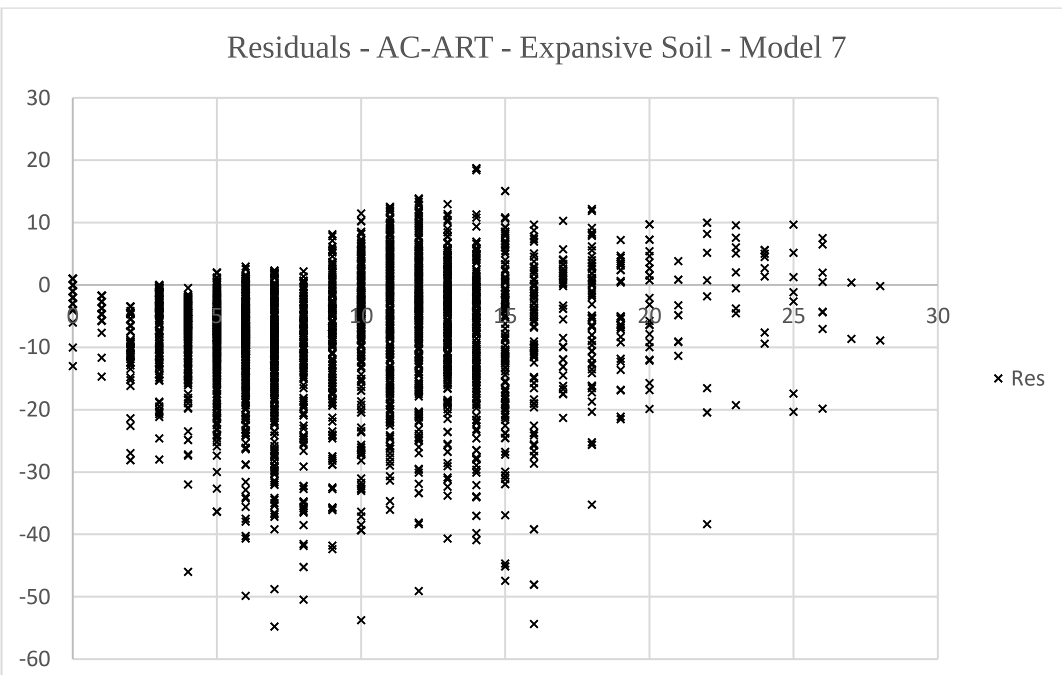

Figure L4 Residuals AC-ART – Model 7

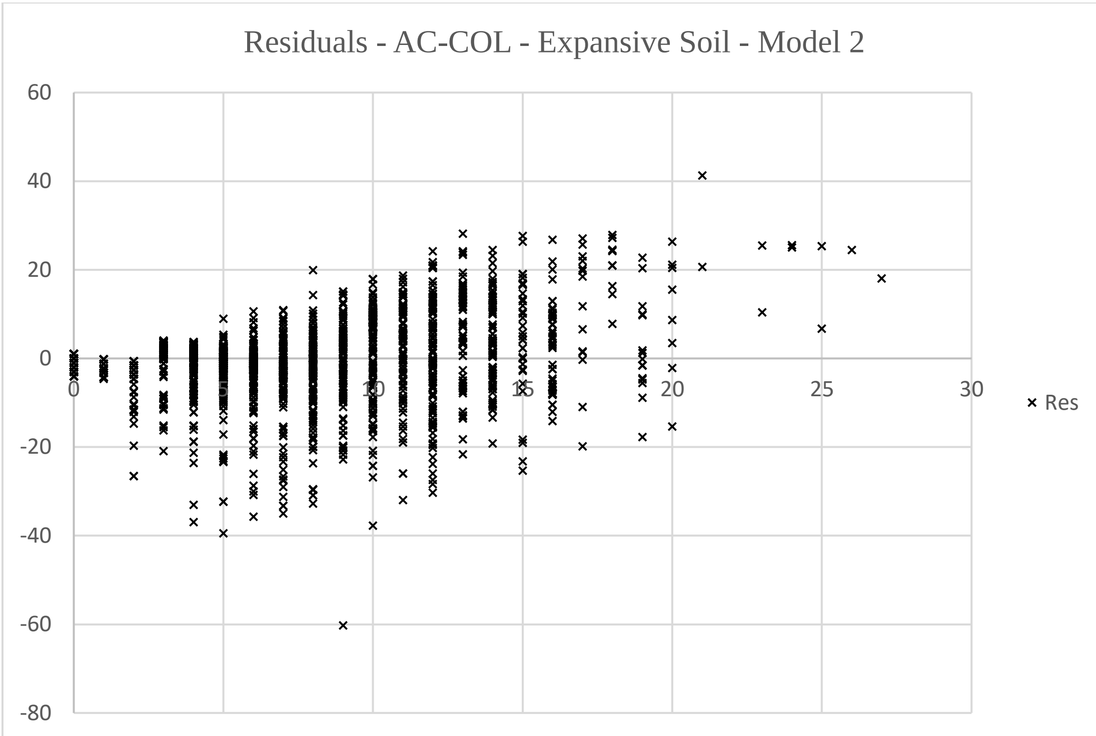

Figure L5 Residuals AC-COL – Model 2 (Selected)

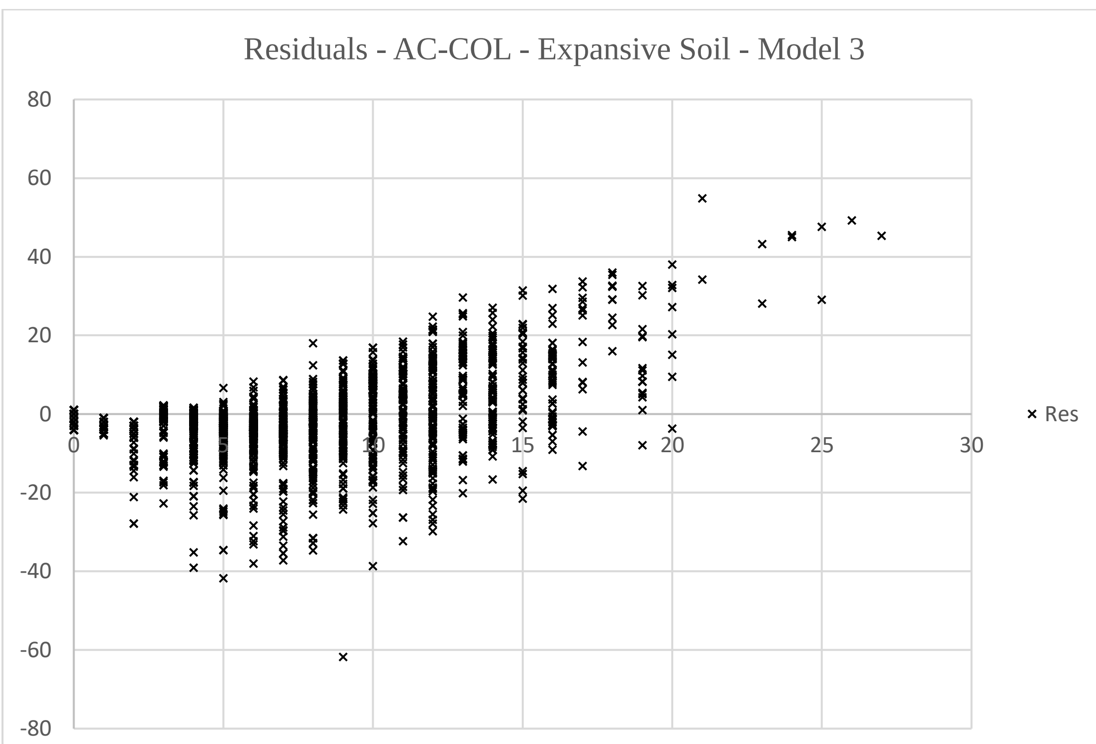

Figure L6 Residuals AC-COL – Model 3

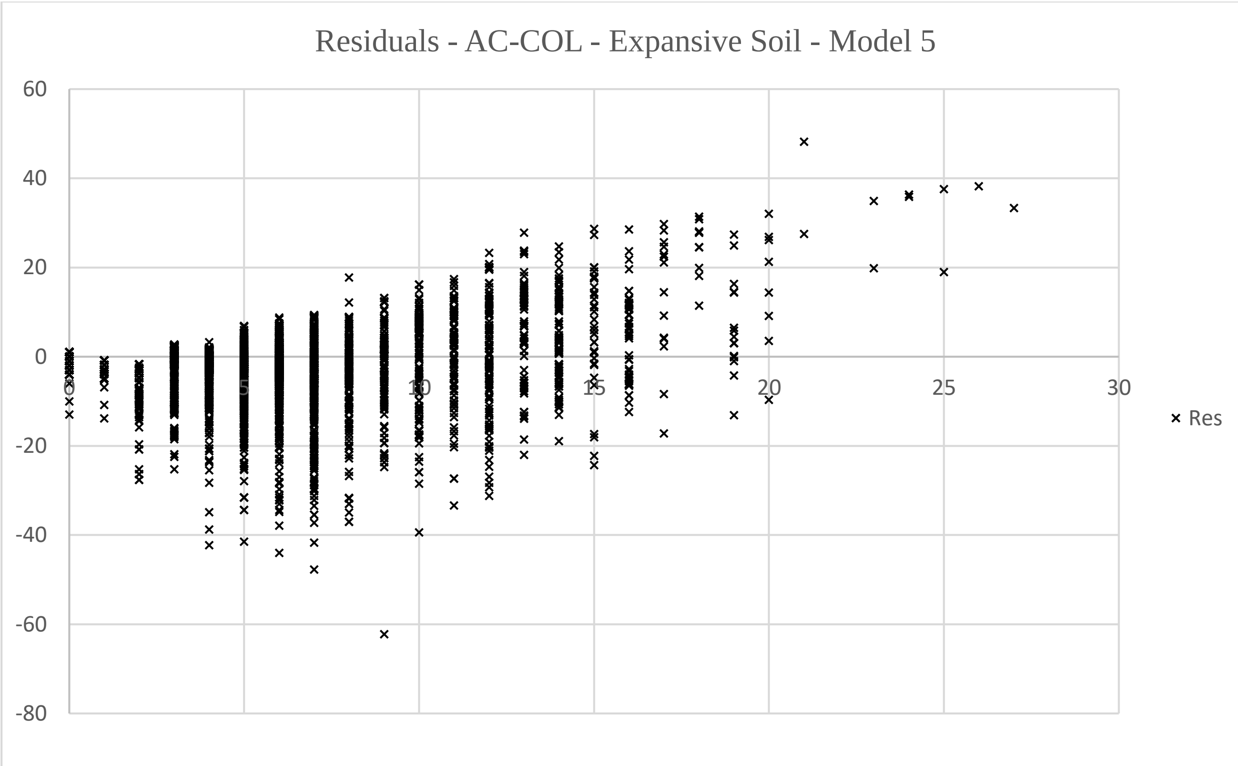

Figure L7 Residuals AC-COL – Model 5

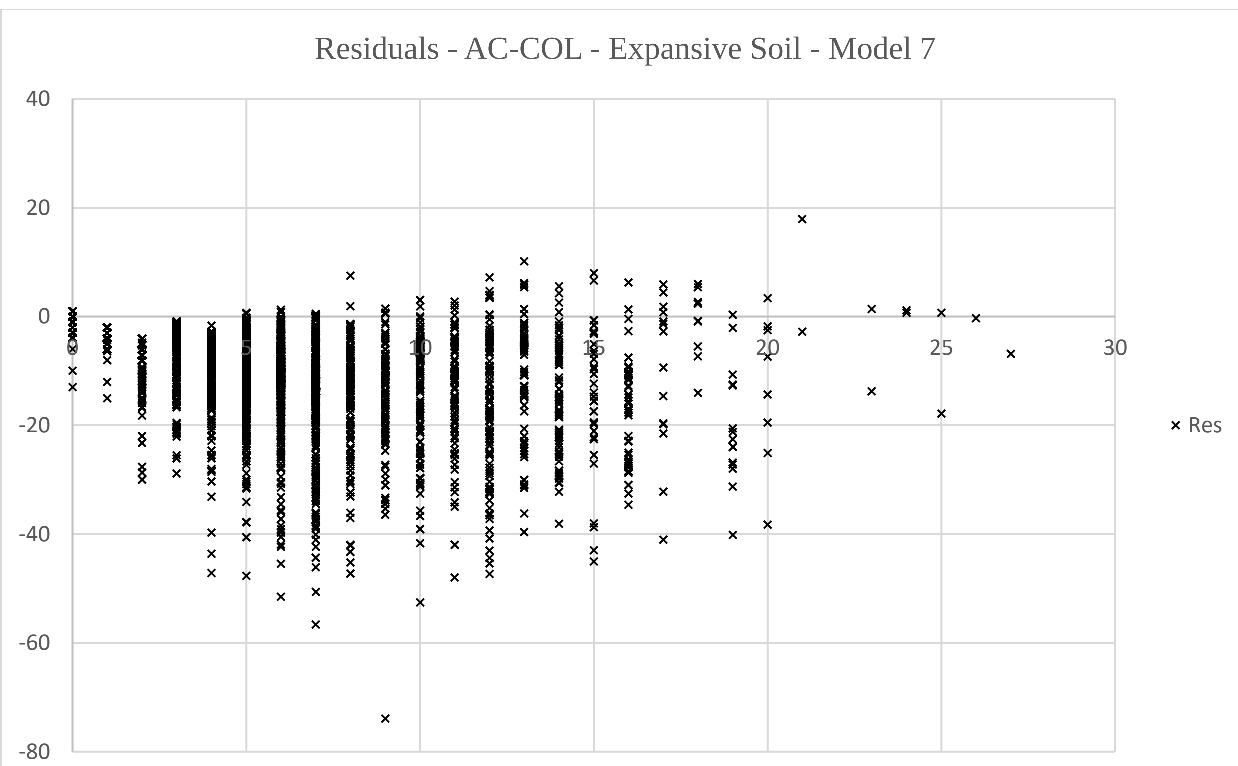

Figure L8 Residuals AC-COL – Model 7

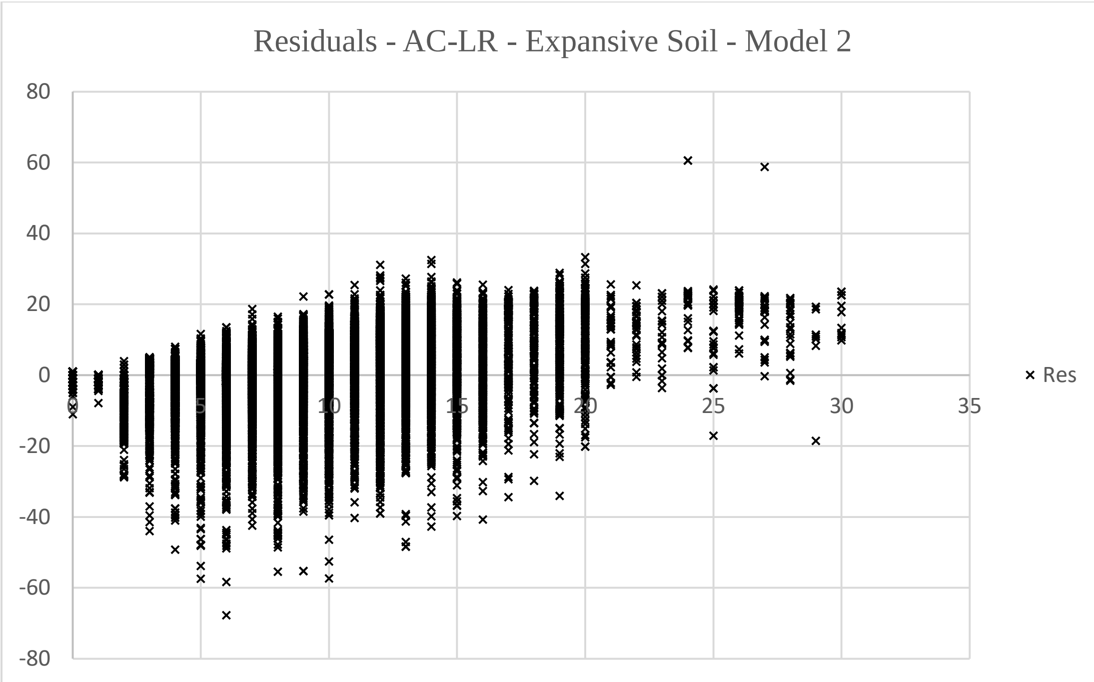

Figure L9 Residuals AC-LR – Model 2 (Selected)

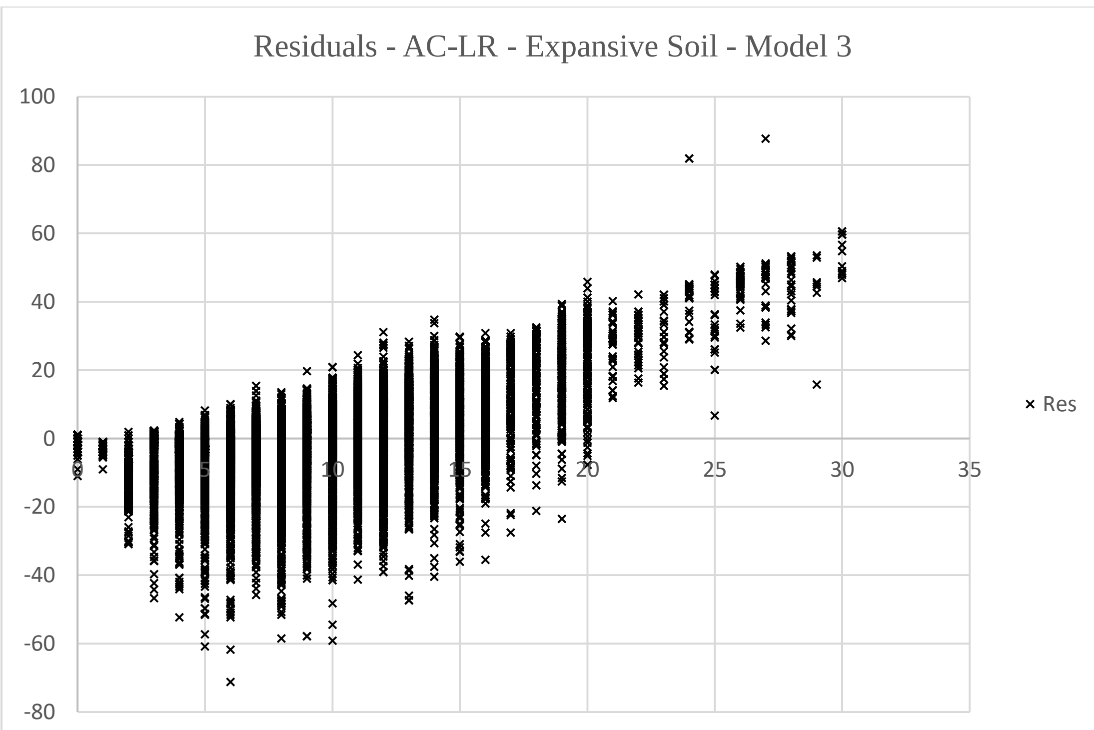

Figure L10 Residuals AC-LR – Model 3

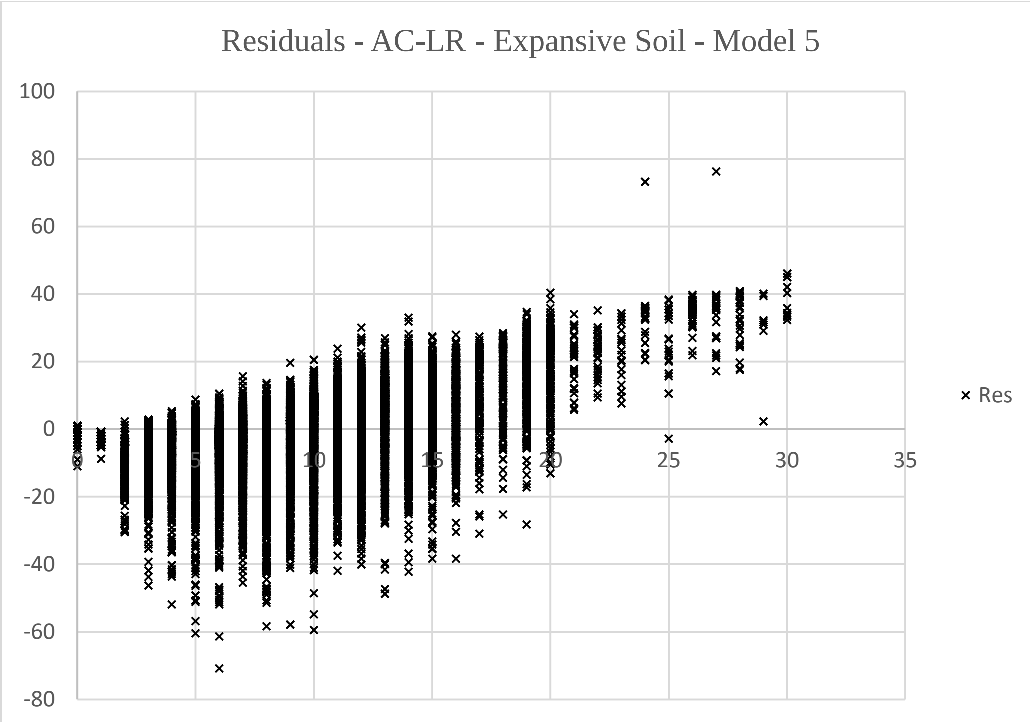

Figure L11 Residuals AC-LR – Model 5

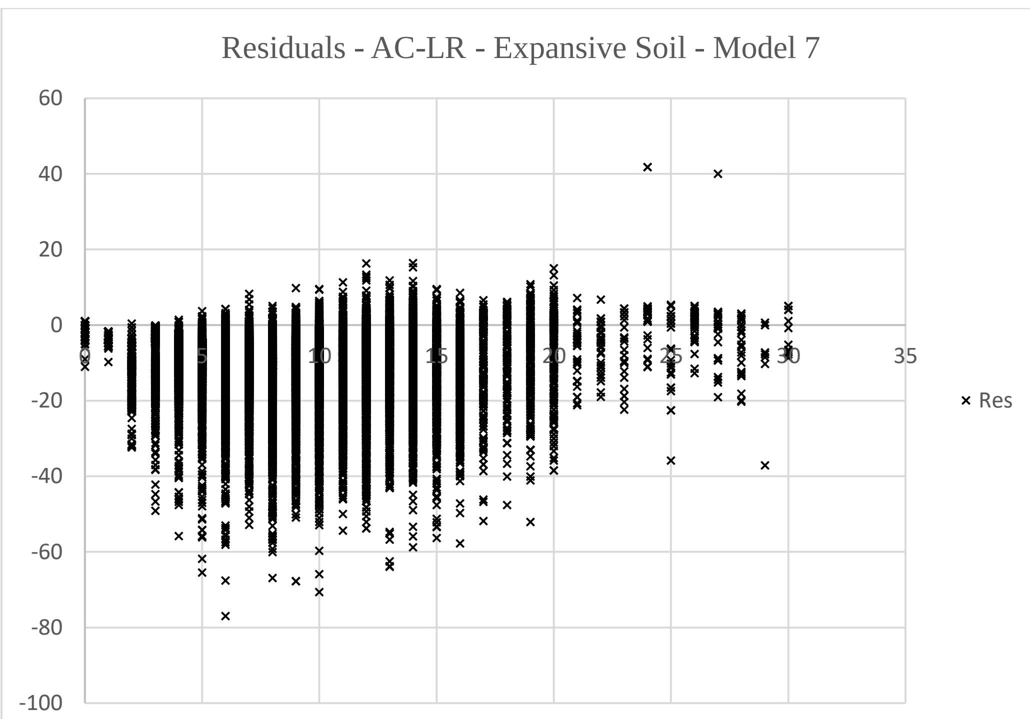

Figure L12 Residuals AC-LR – Model 7

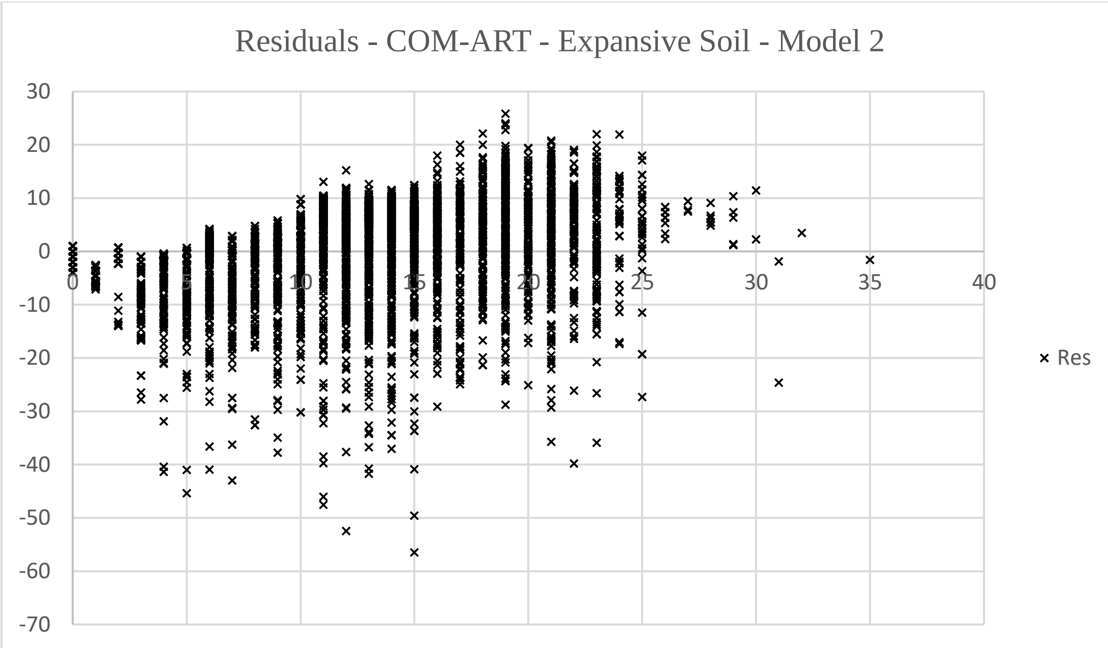

Figure L13 Residuals COM-LR – Model 2

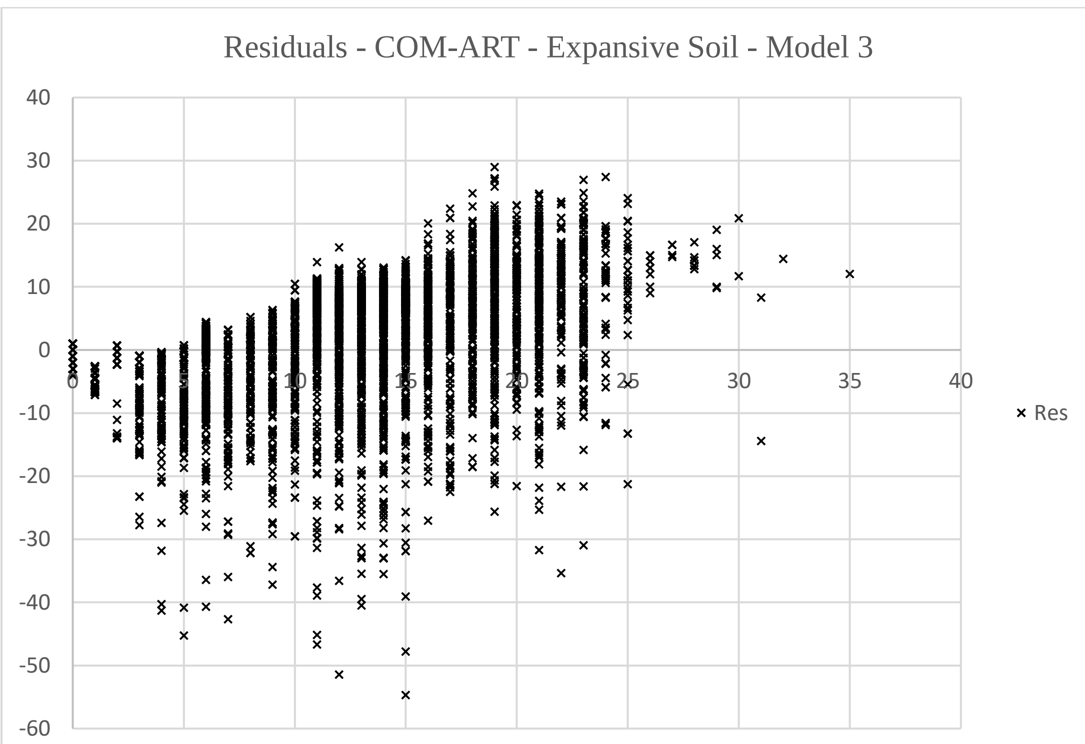

Figure L14 Residuals COM-LR – Model 3 (Selected)

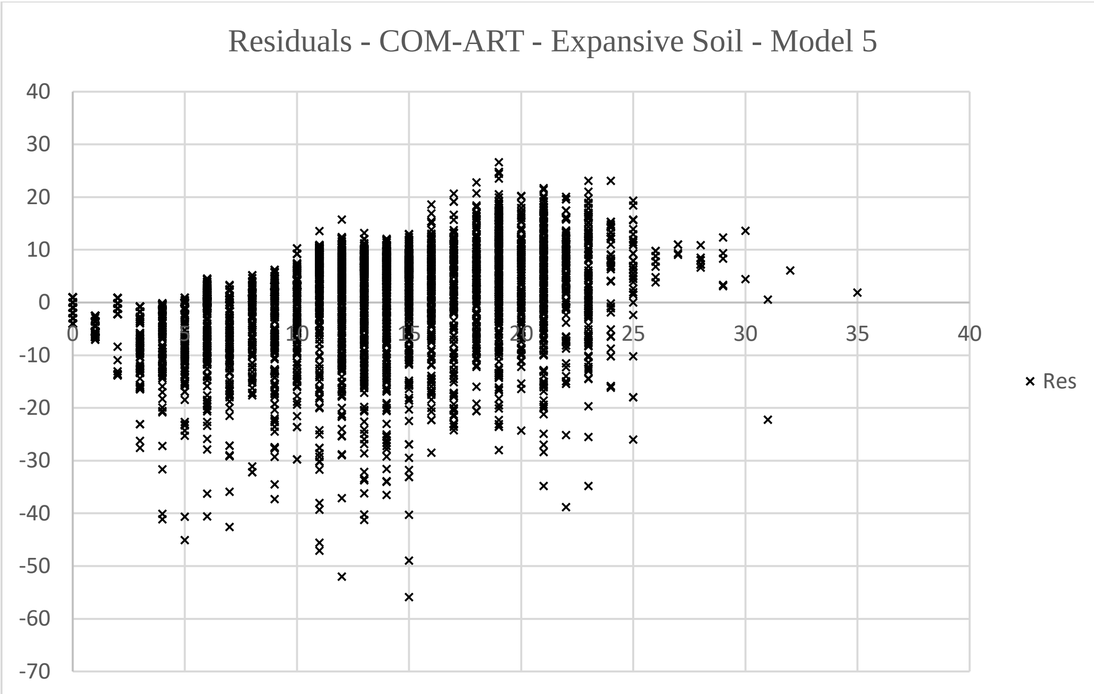

Figure L15 Residuals COM-LR – Model 5

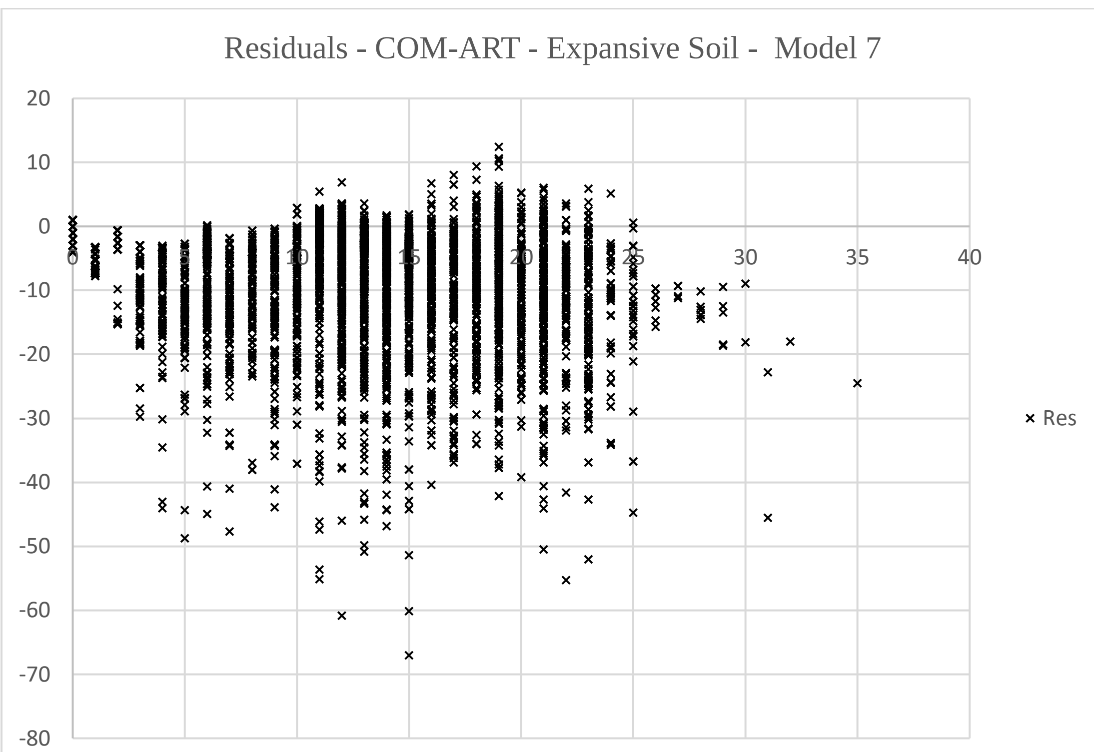

Figure L16 Residuals COM-LR – Model 7

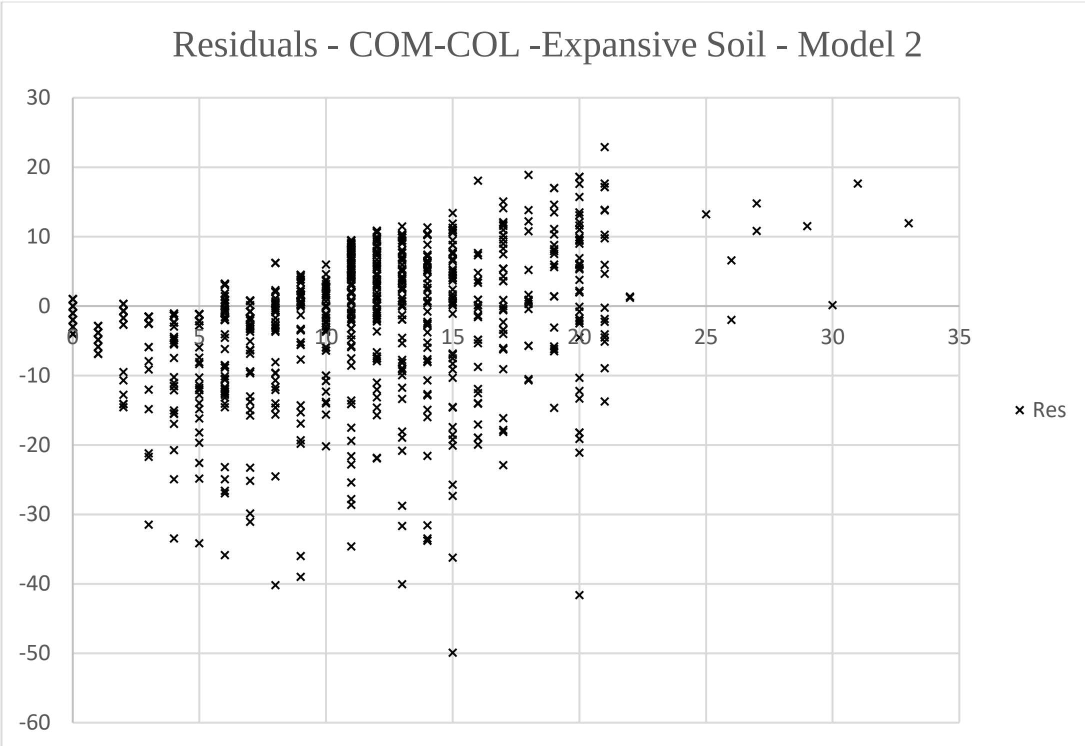

Figure L17 Residuals COM-COL – Model 2

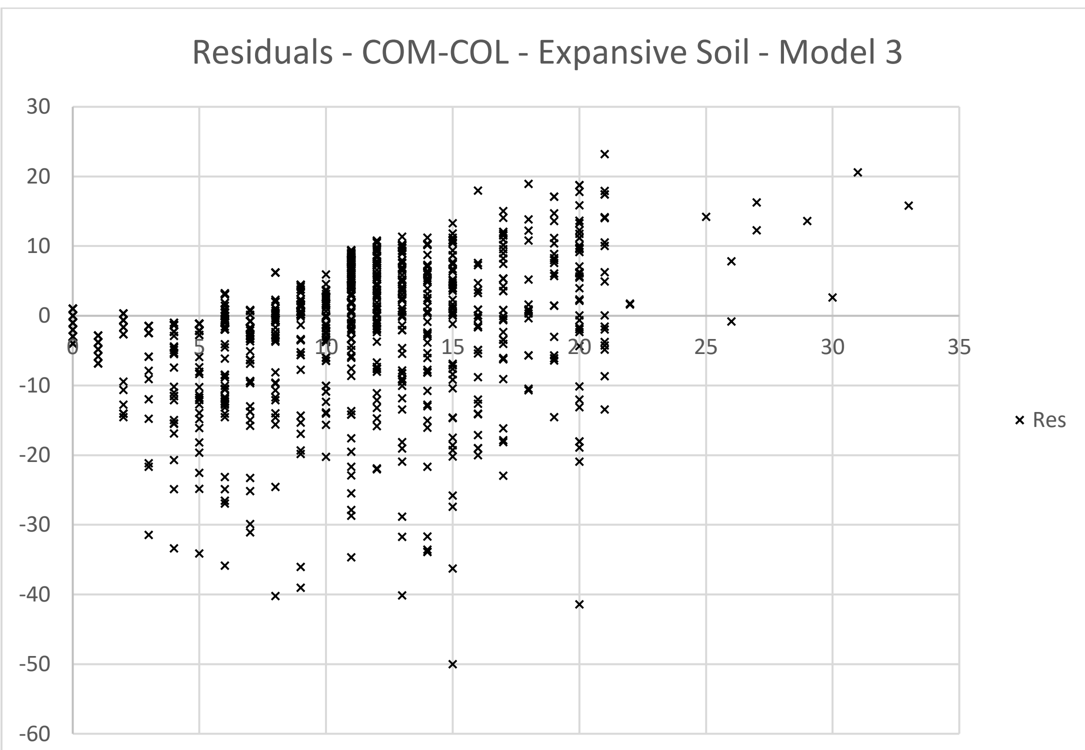

Figure L18 Residuals COM-COL – Model 3 (Selected)

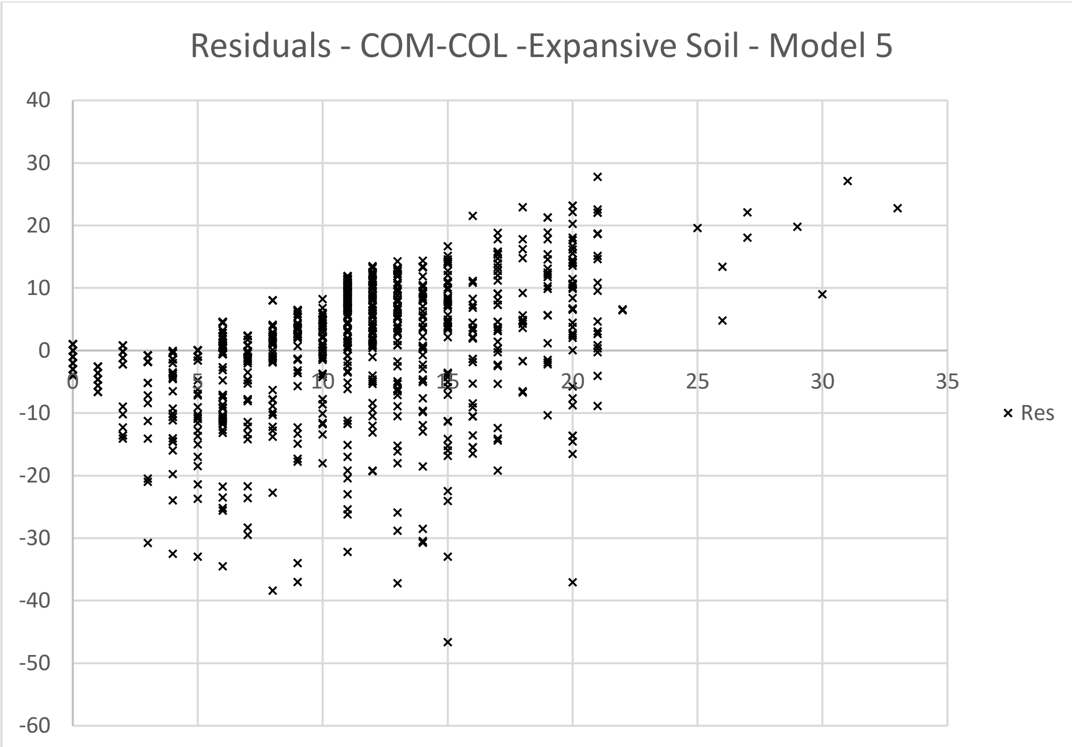

Figure L19 Residuals COM-COL – Model 5

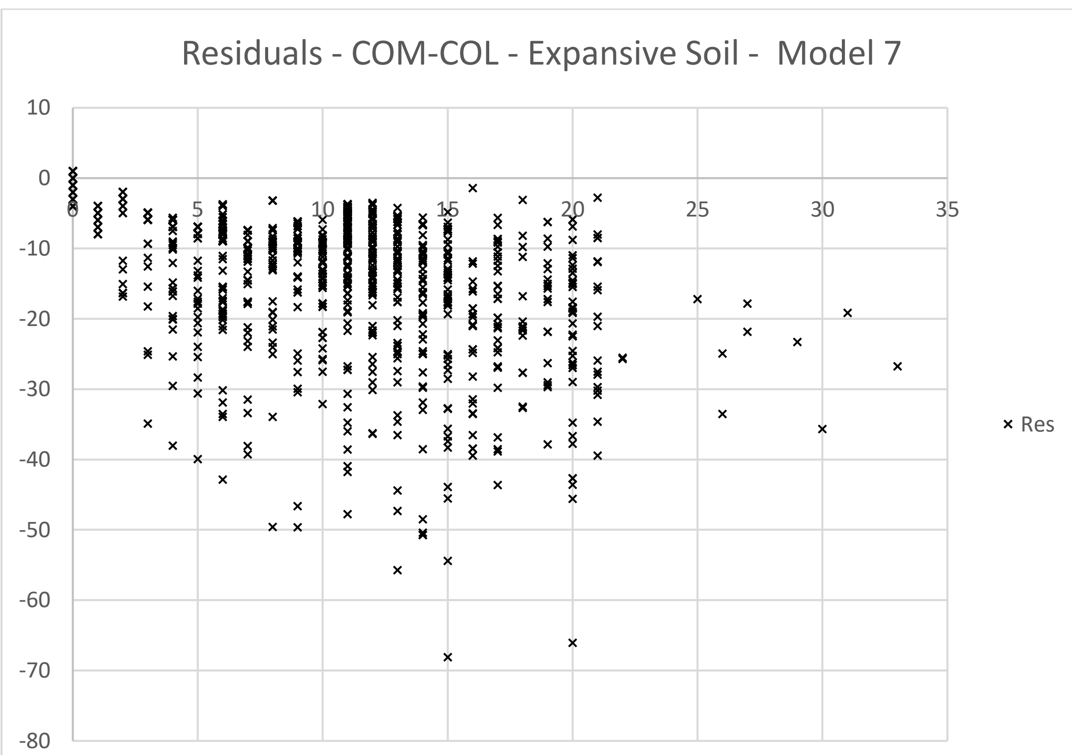

Figure L20 Residuals COM-COL – Model 7

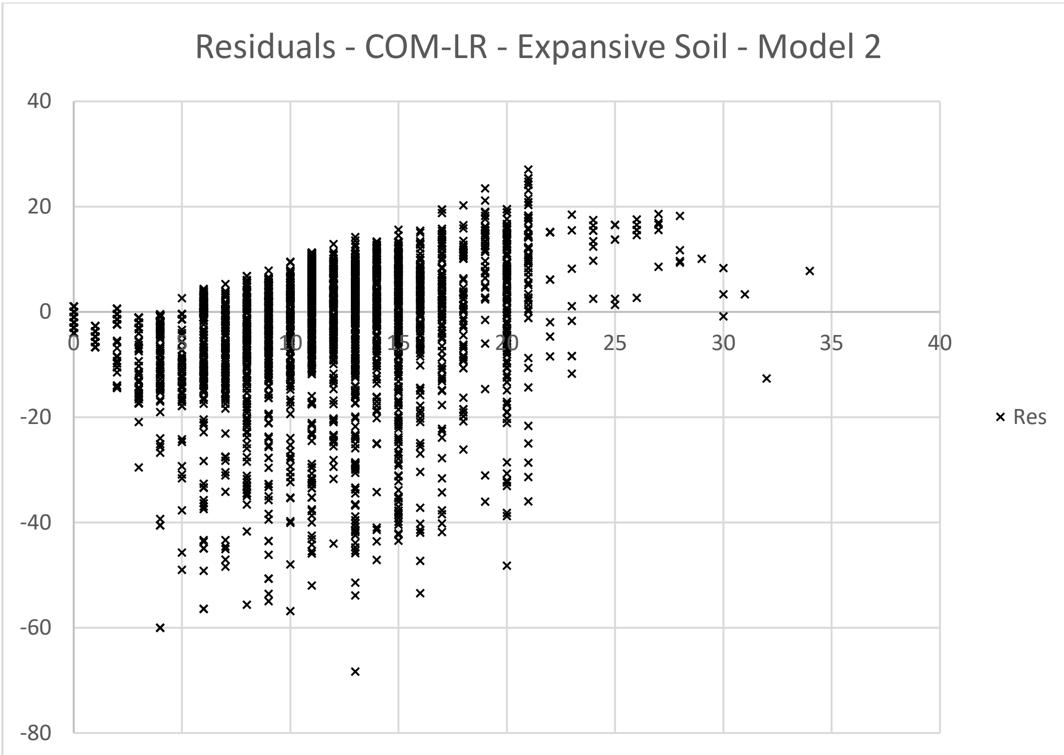

Figure L21 Residuals COM-LR – Model 2

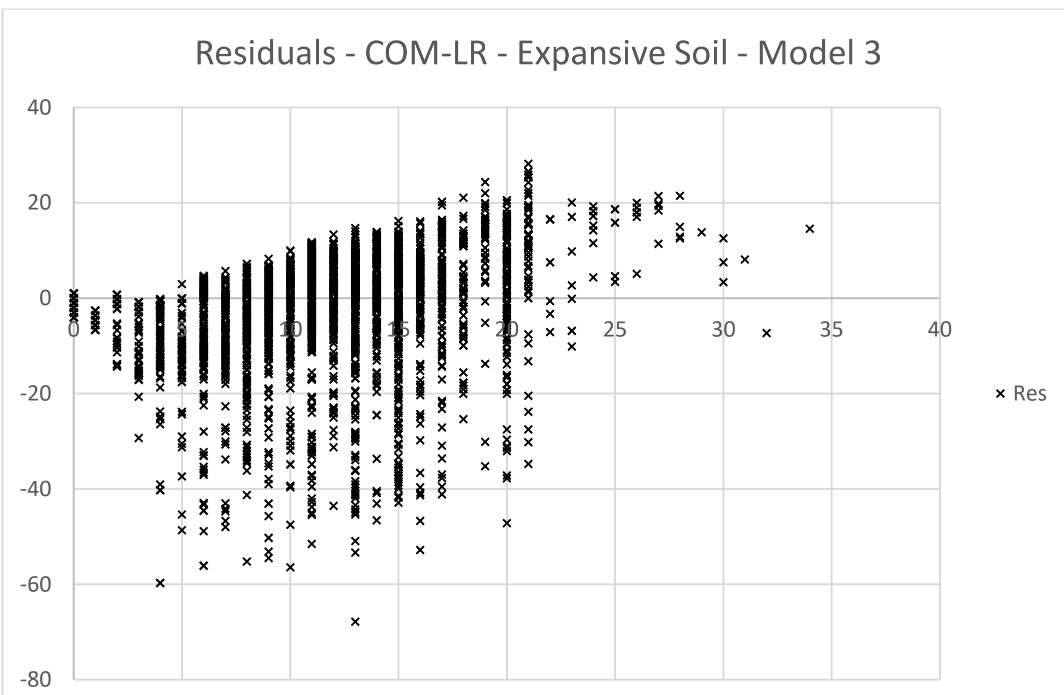

Figure L22 Residuals COM-LR – Model 3

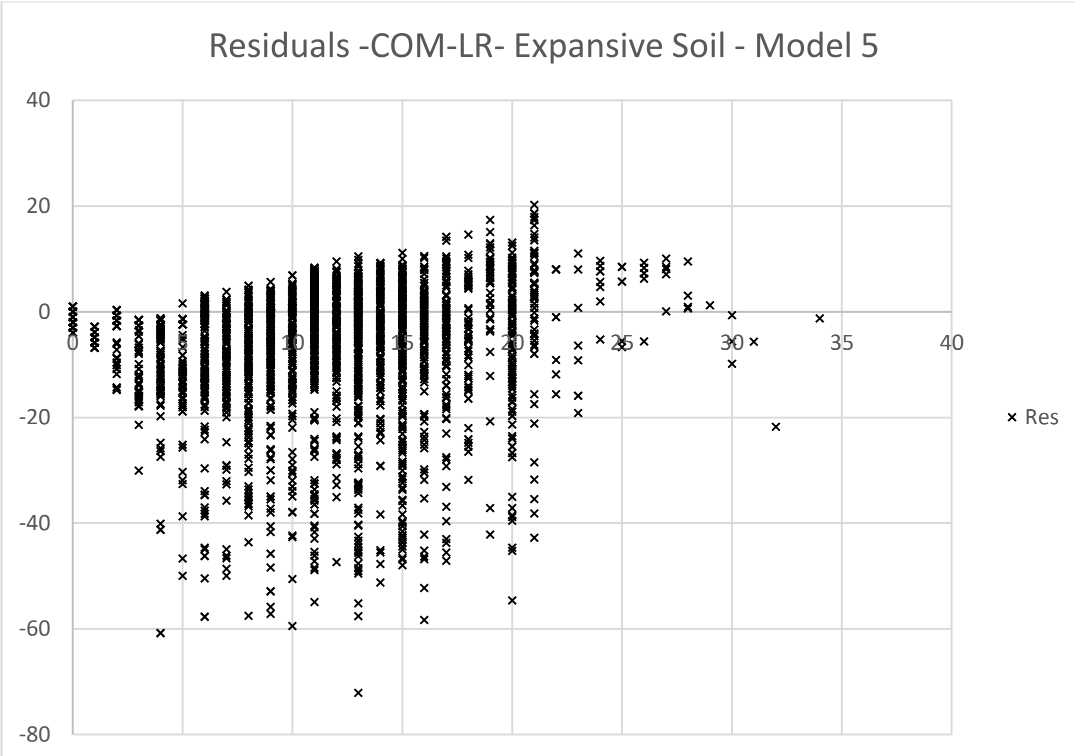

Figure L23 Residuals COM-LR – Model 5 (Selected)

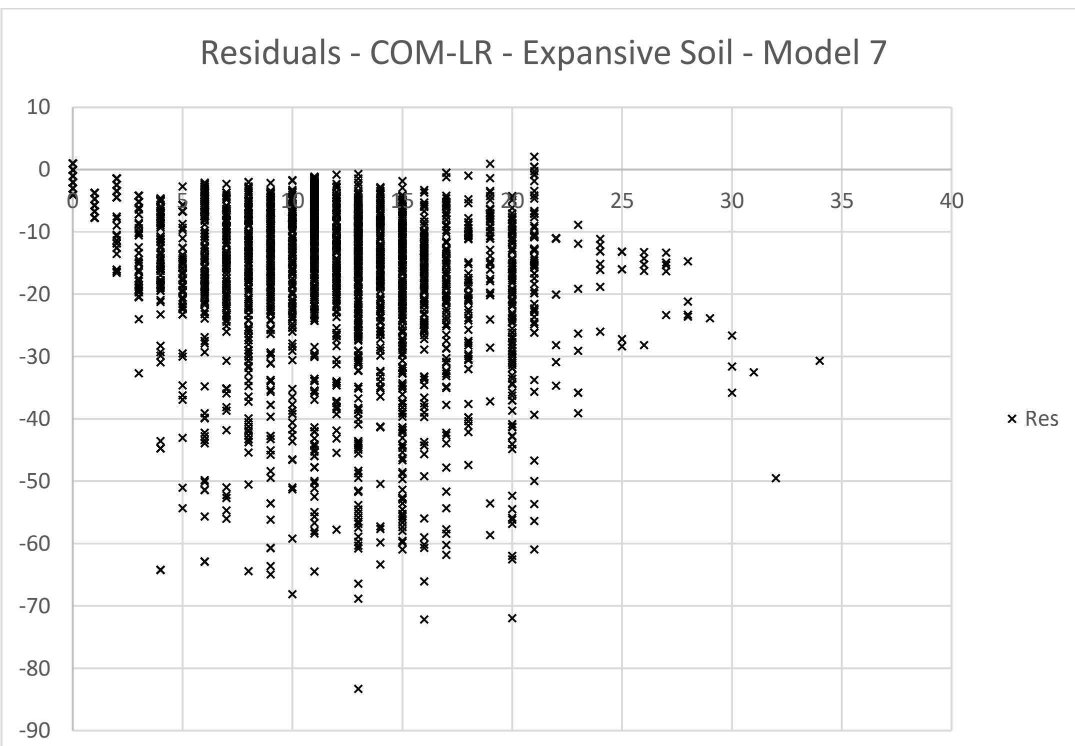

Figure L24 Residuals COM-LR – Model 7

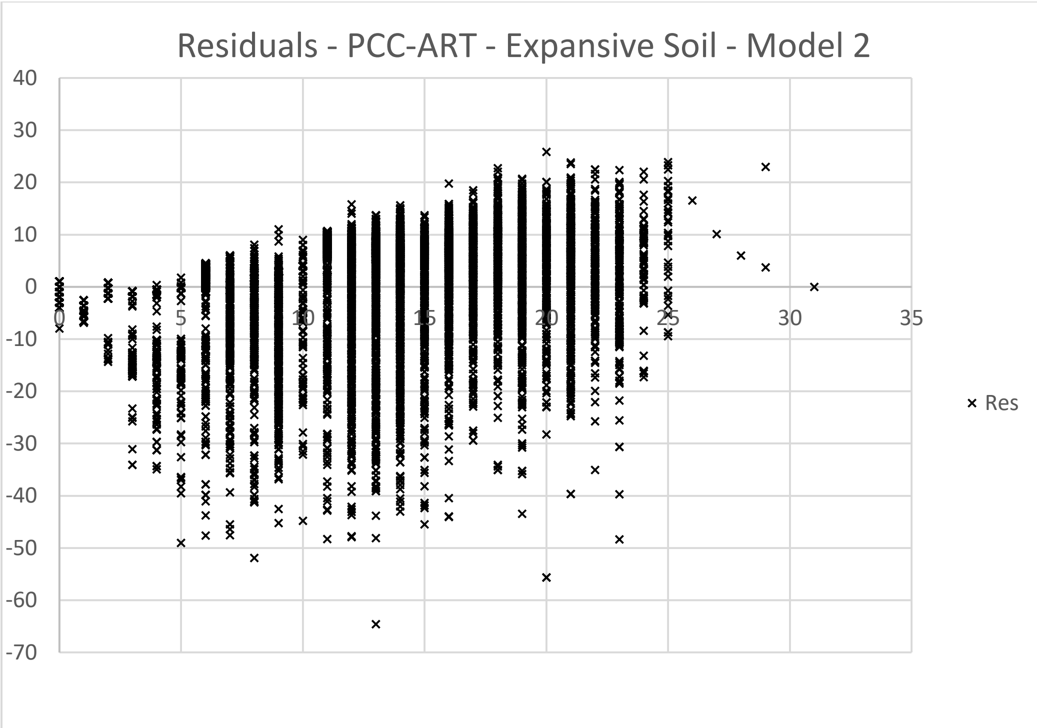

Figure L25 Residuals PCC-ART – Model 2

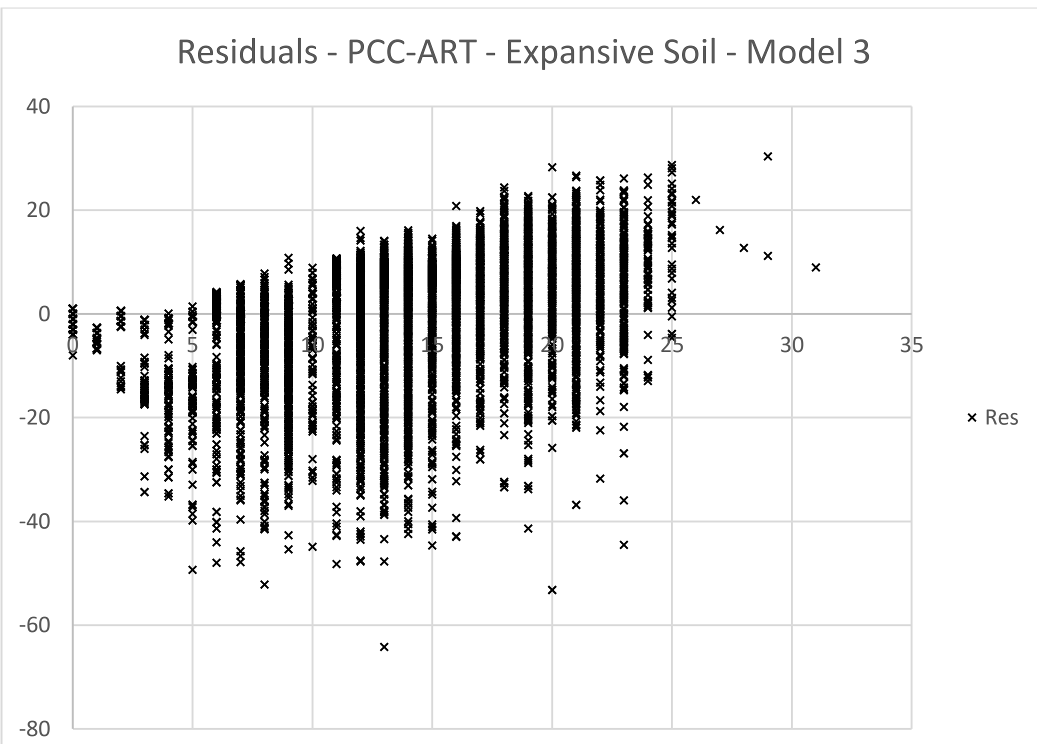

Figure L26 Residuals PCC-ART – Model 3 (Selected)

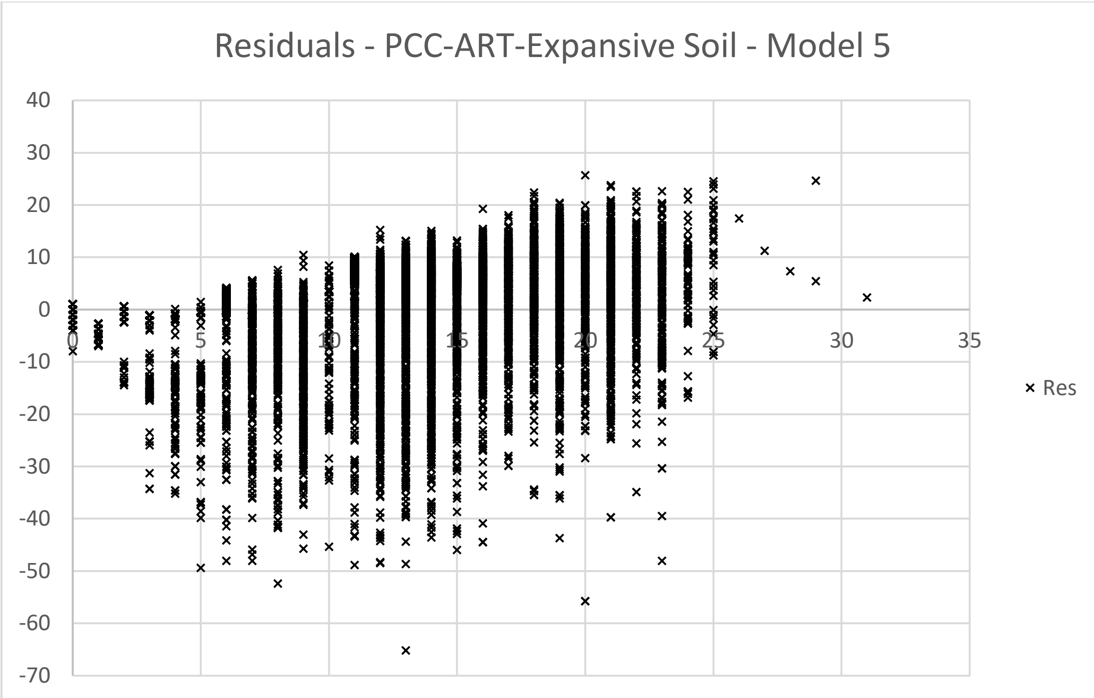

Figure L27 Residuals PCC-ART – Model 5

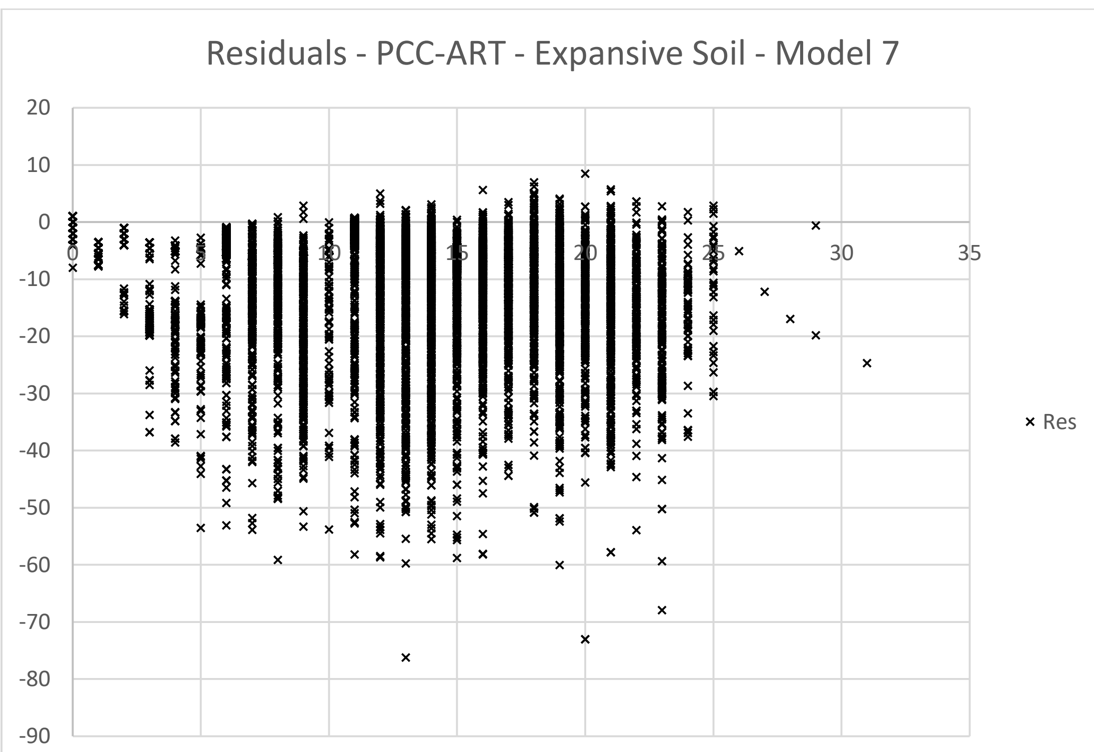

Figure L28 Residuals PCC-ART – Model 7

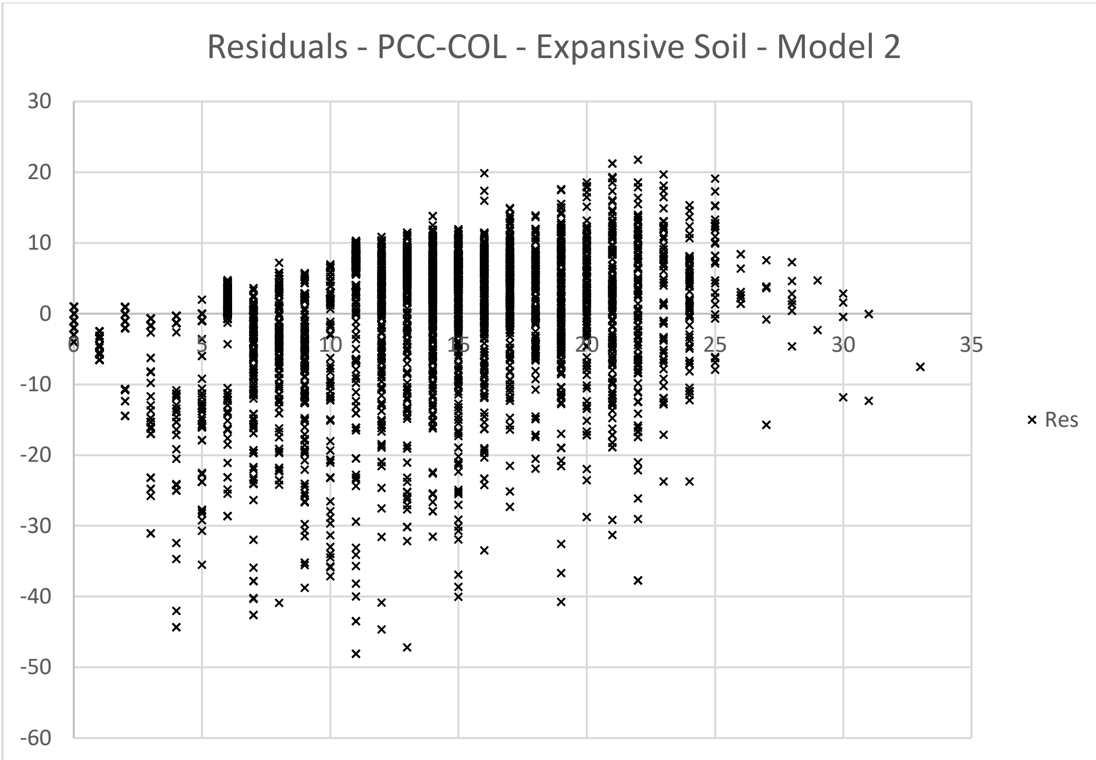

Figure L29 Residuals PCC-COL – Model 2

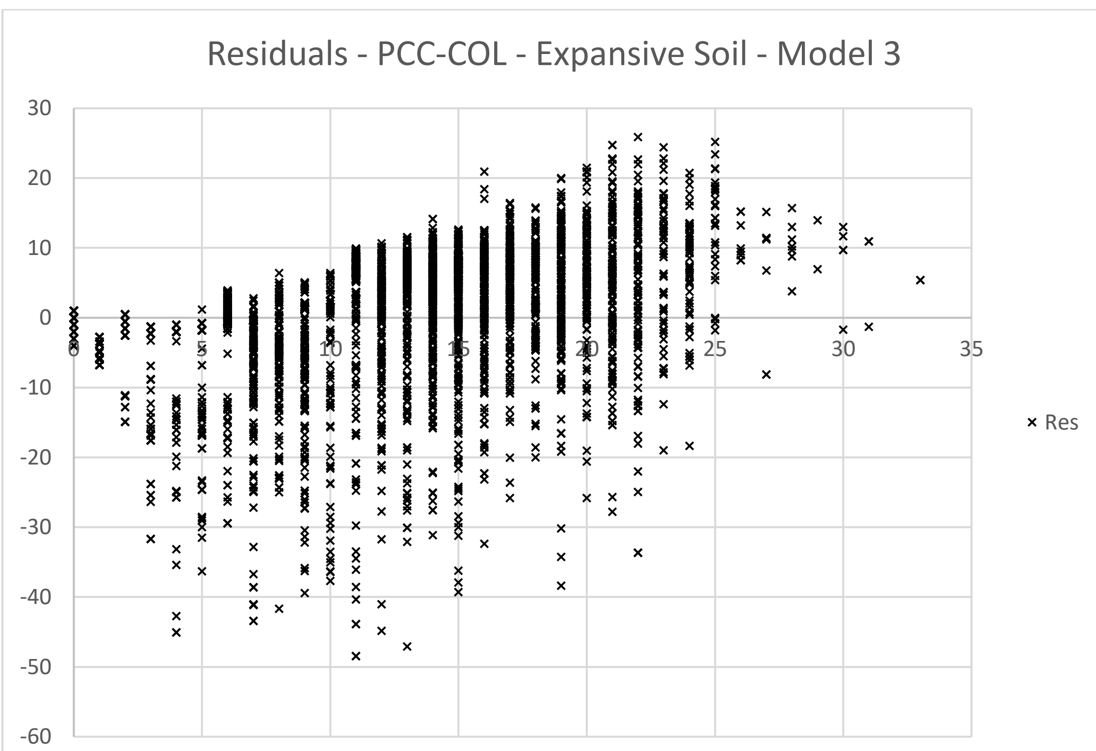

Figure L30 Residuals PCC-COL – Model 3 (Selected)

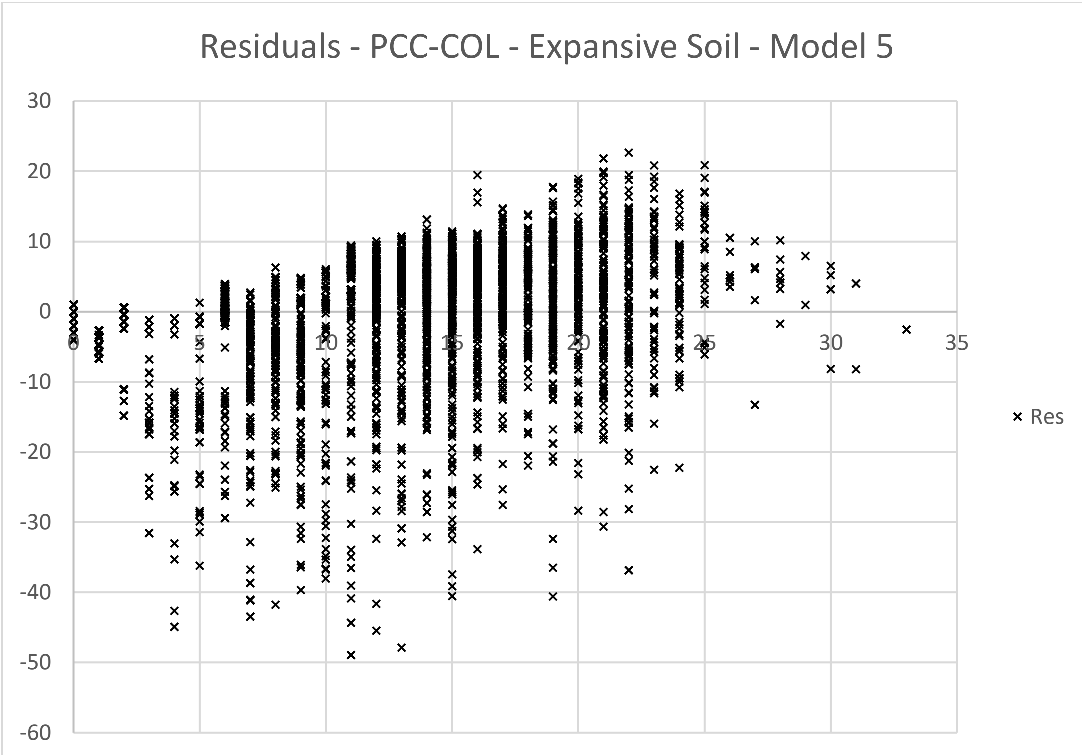

Figure L31 Residuals PCC-COL – Model 5

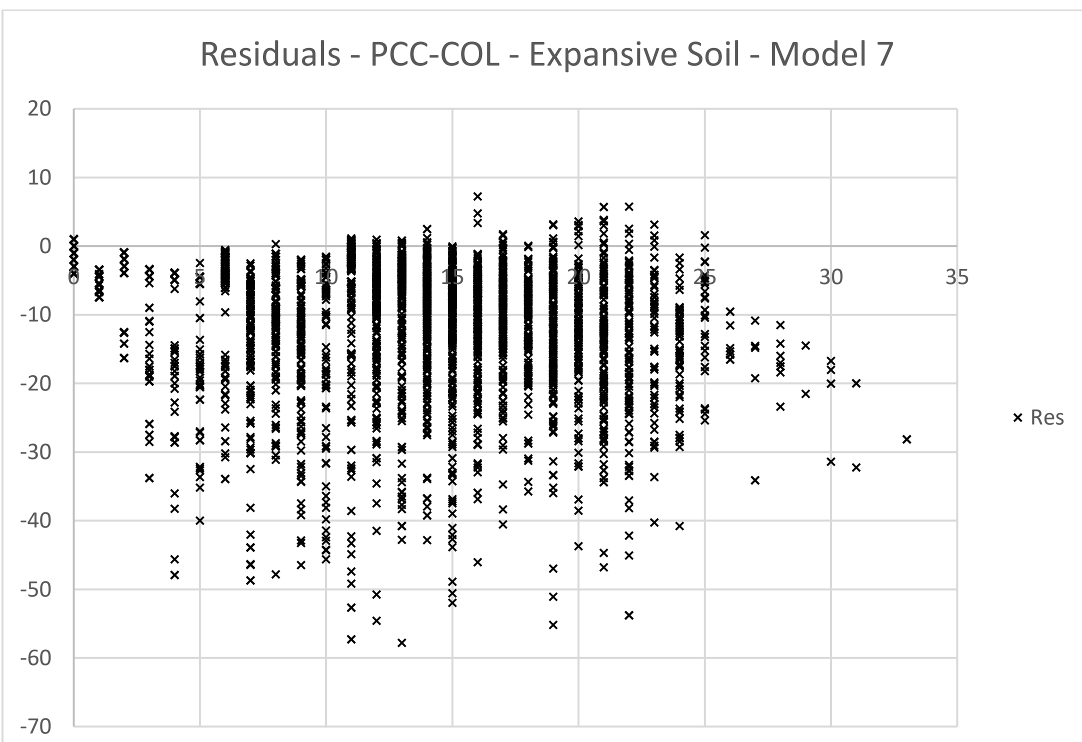

Figure L32 Residuals PCC-COL – Model 7

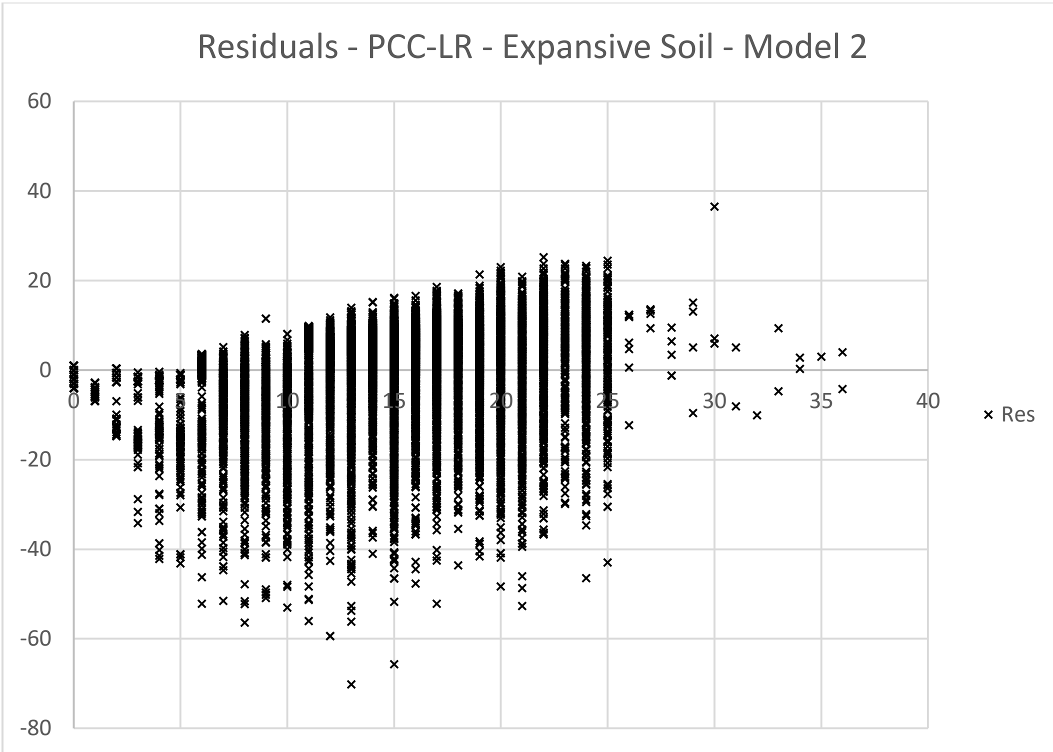

Figure L33 Residuals PCC-LR – Model 2

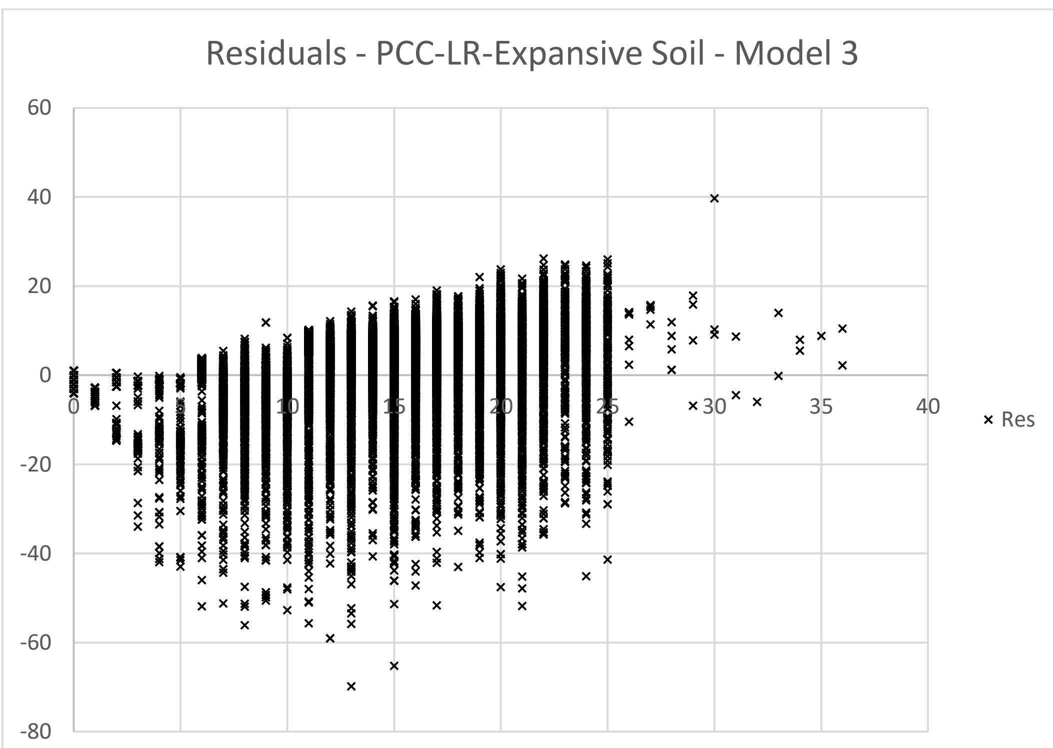

Figure L34 Residuals PCC-LR – Model 3 (Selected)

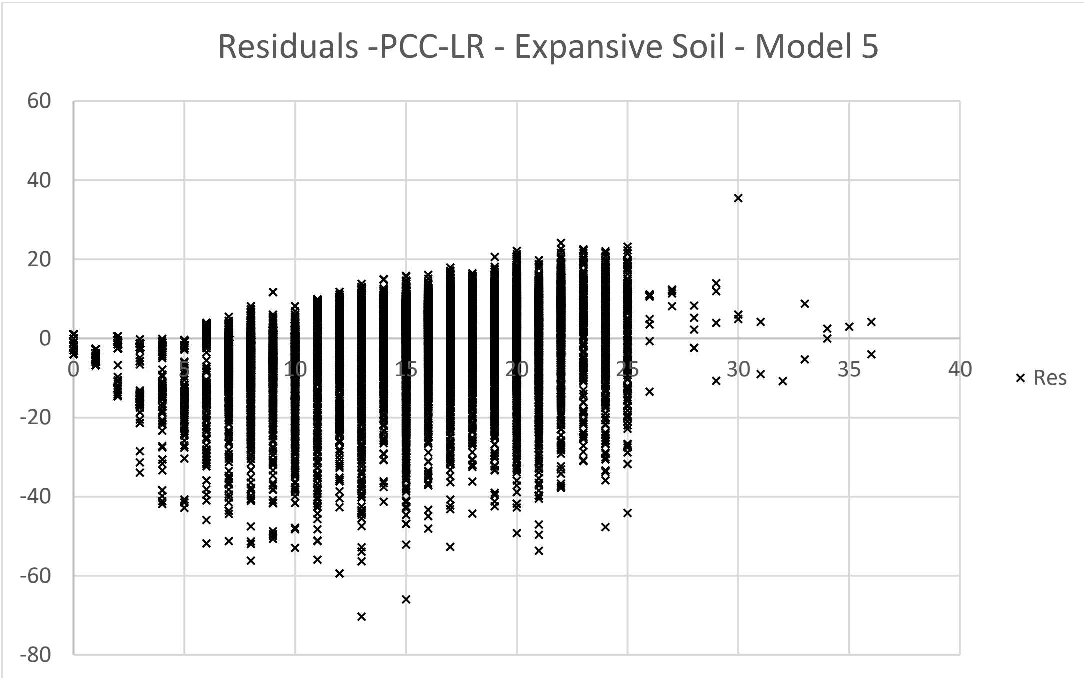

Figure L35 Residuals PCC-LR – Model 5

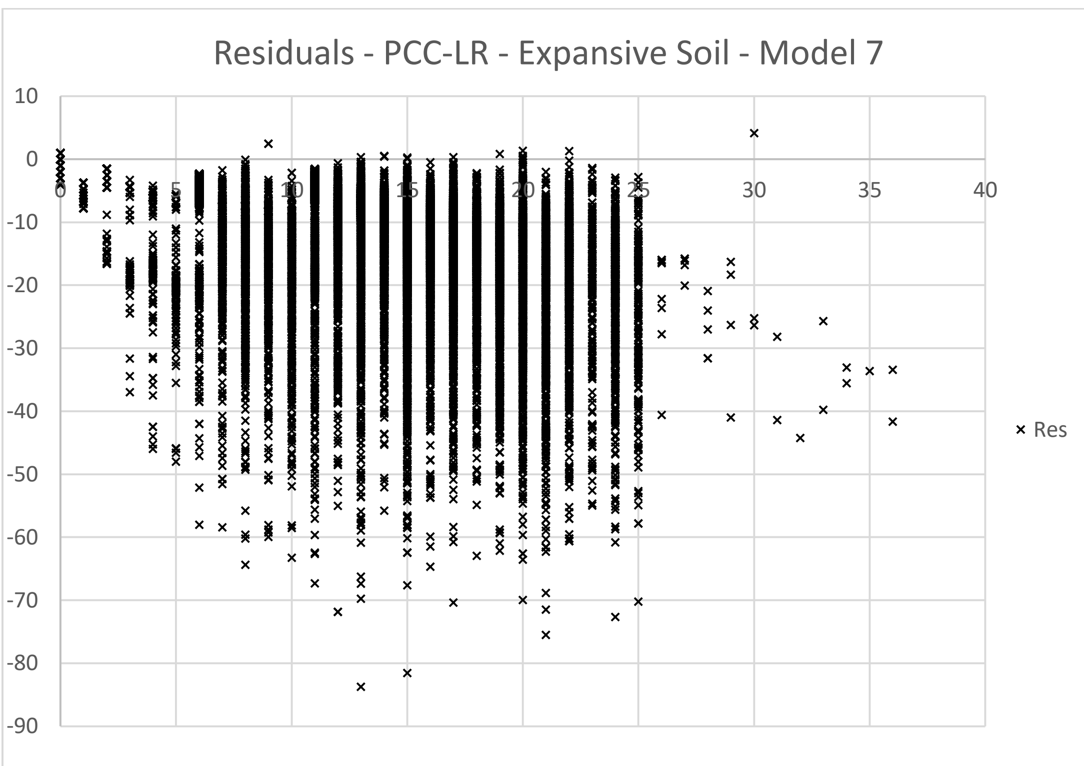

Figure L36 Residuals PCC-LR – Model 7

APPENDIX M: Residuals – Non-Expansive Soil (PCI)

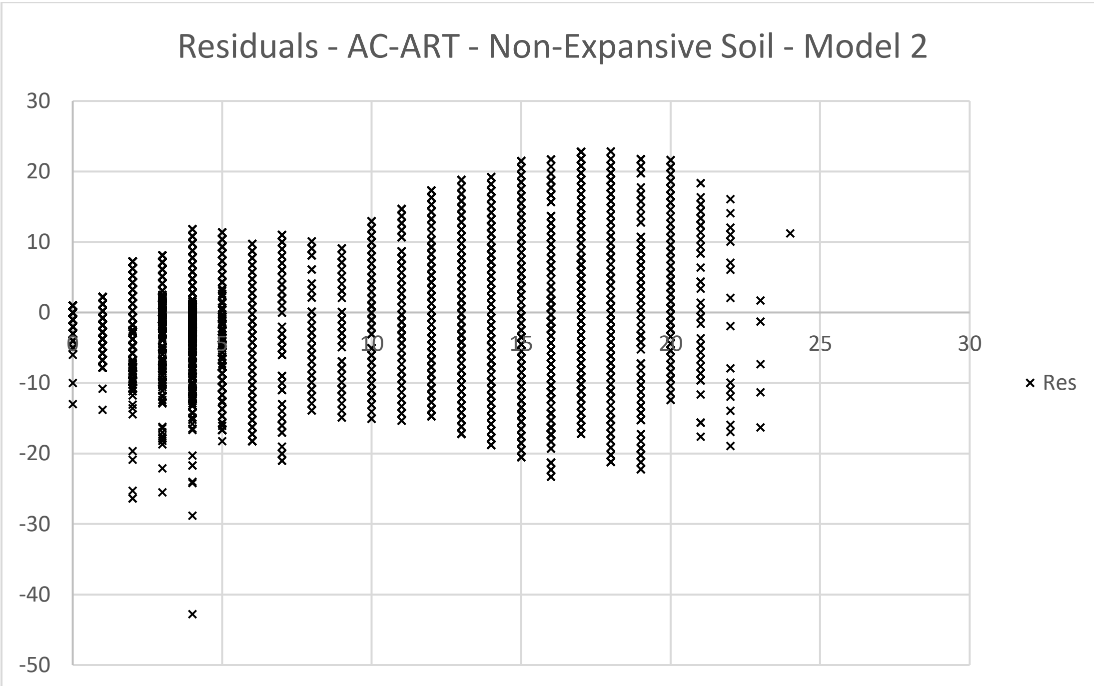

Figure M1 Residuals AC-ART – Model 2

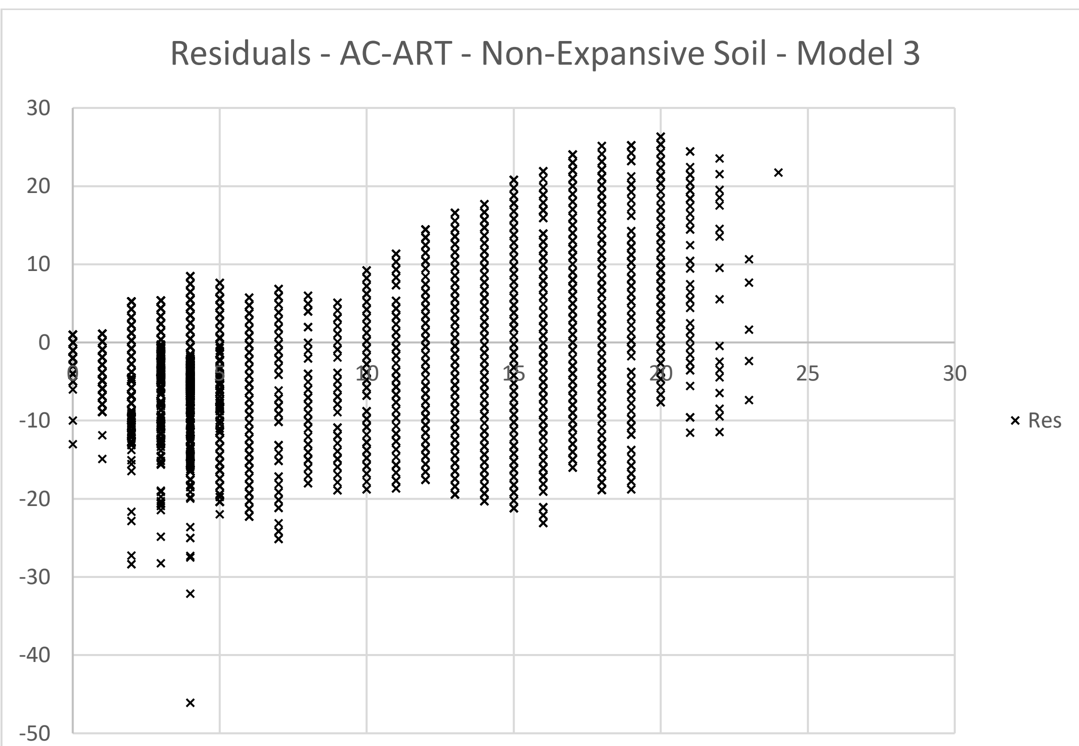

Figure M2 Residuals AC-ART – Model 3

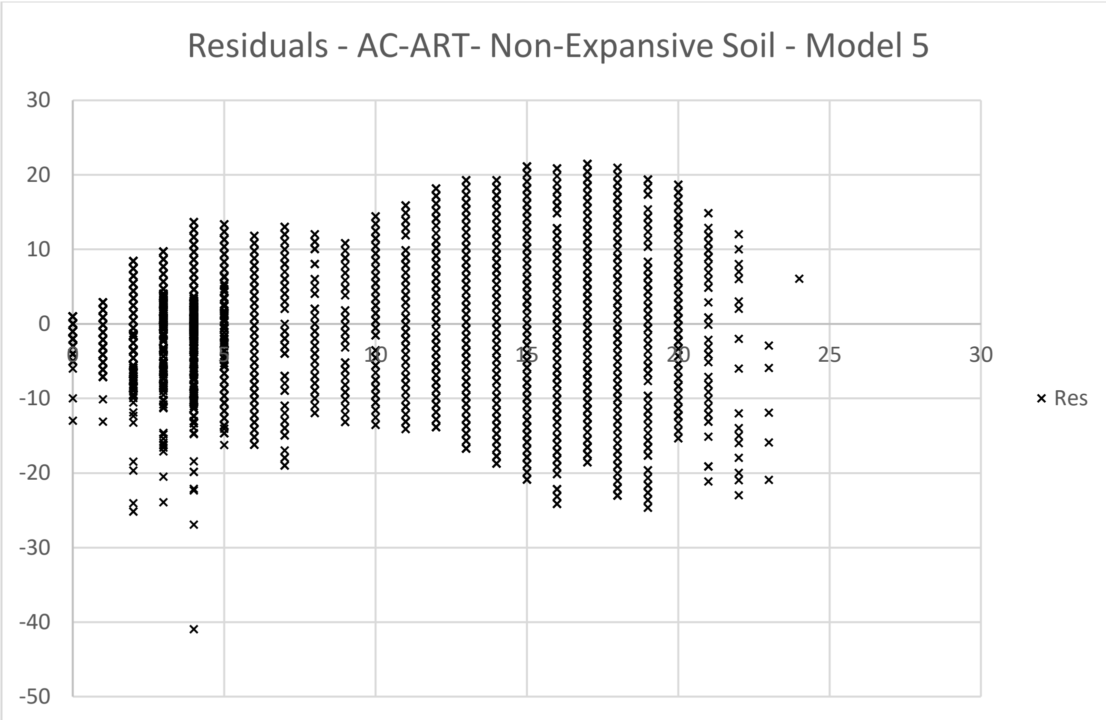

Figure M3 Residuals AC-ART – Model 5 (Selected)

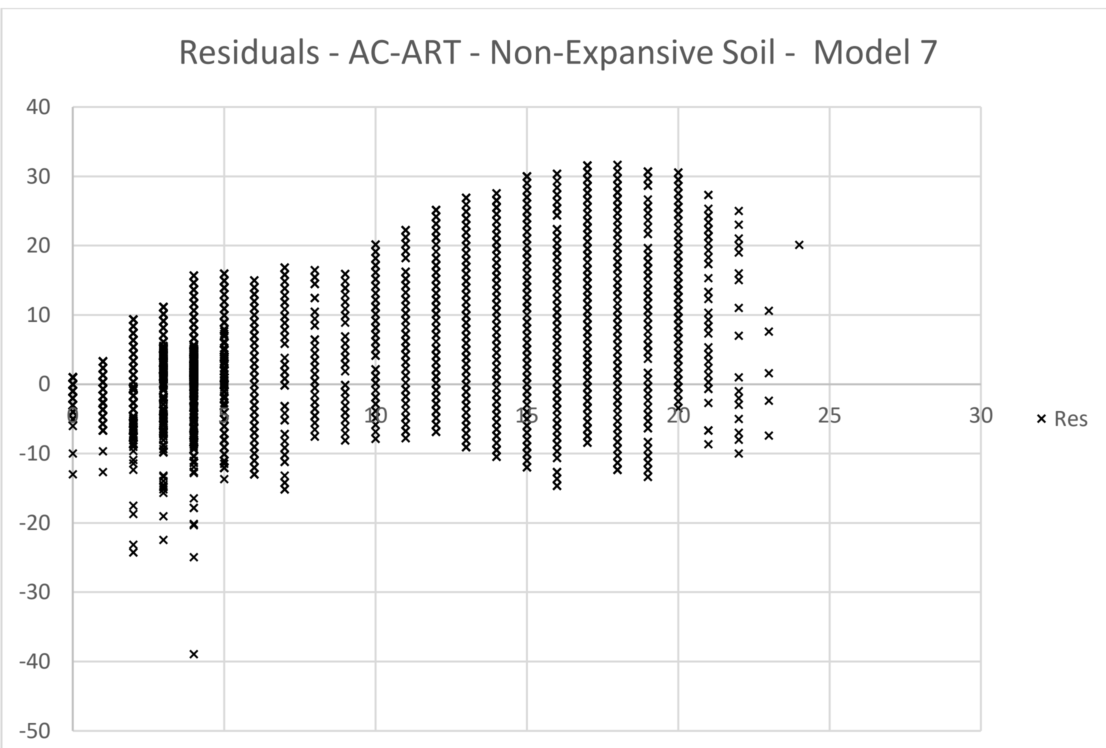

Figure M4 Residuals AC-ART – Model 7

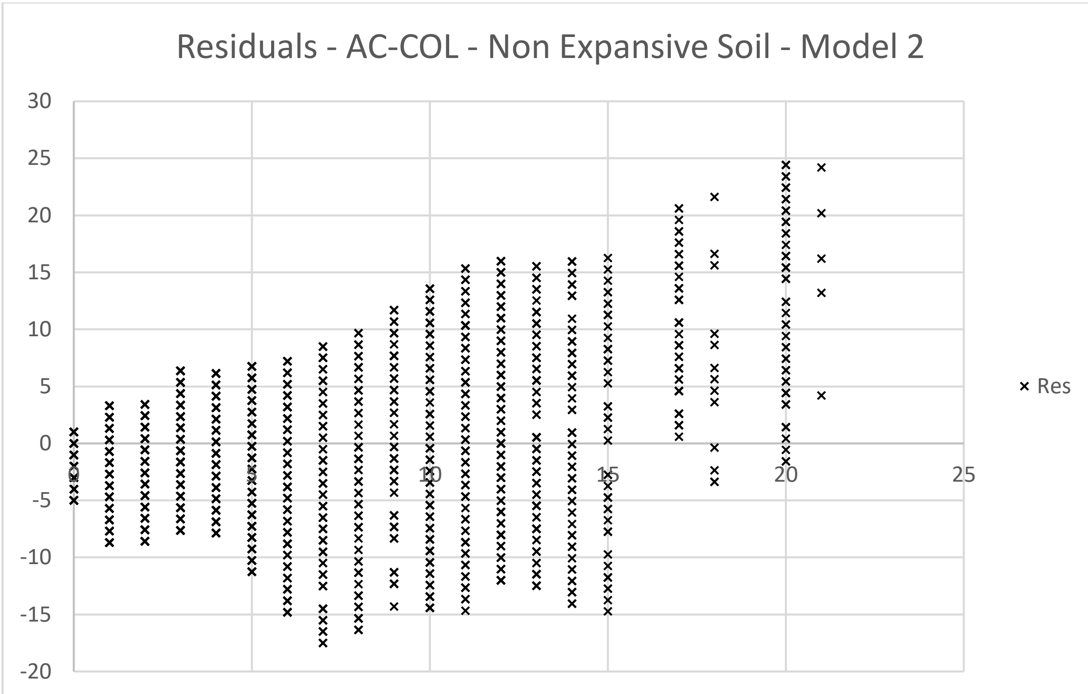

Figure M5 Residuals AC-COL – Model 2

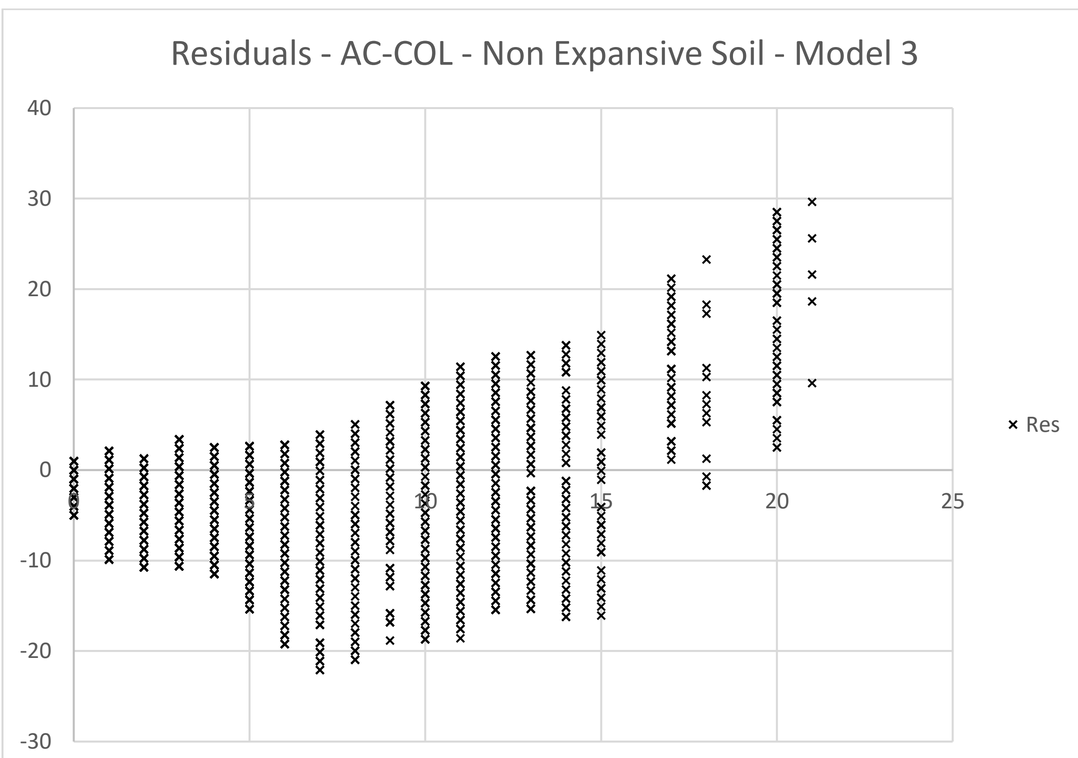

Figure M6 Residuals AC-COL – Model 3

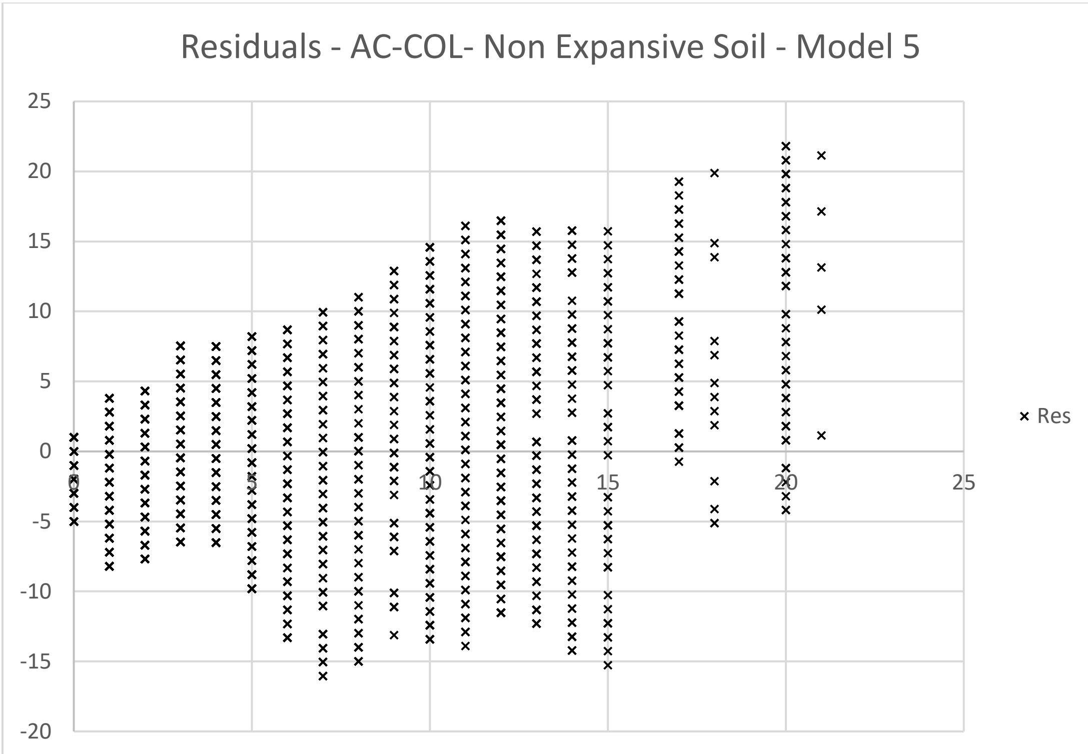

Figure M7 Residuals AC-COL – Model 5 (Selected)

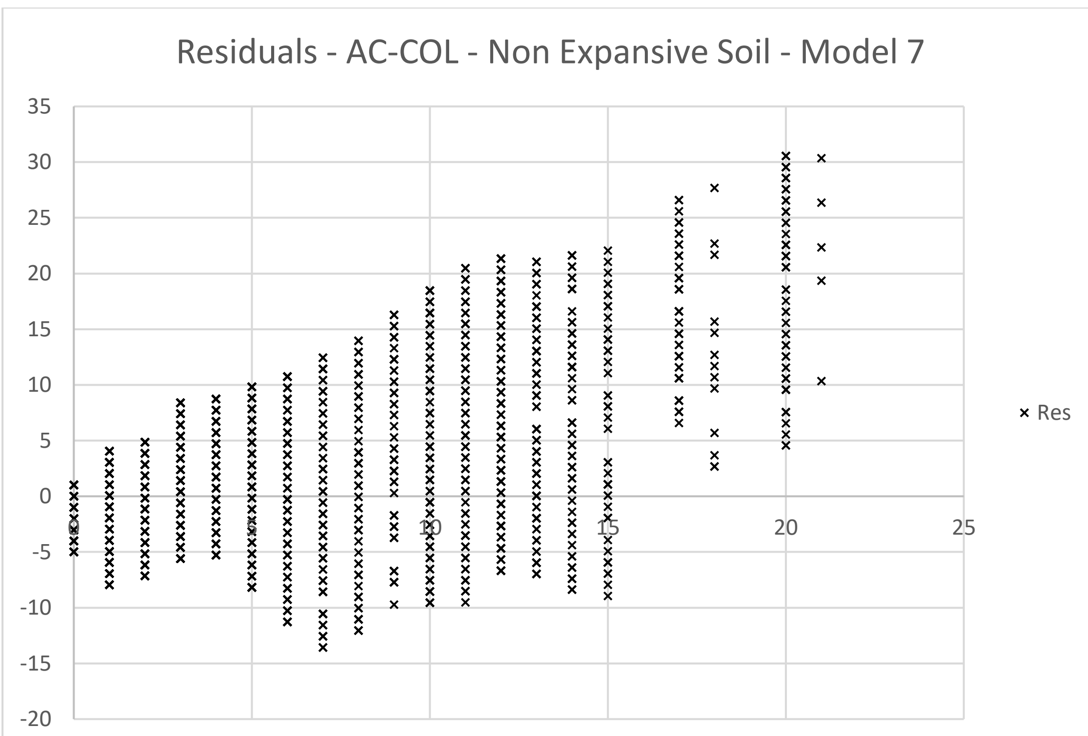

Figure M8 Residuals AC-COL – Model 7

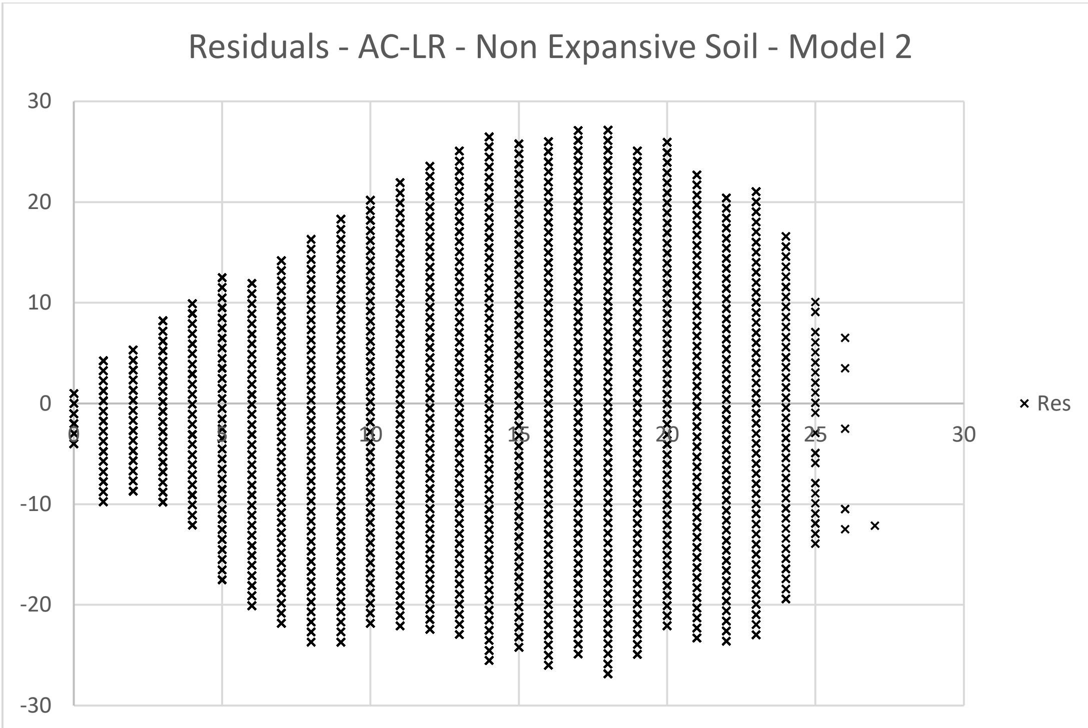

Figure M9 Residuals AC-LR – Model 2

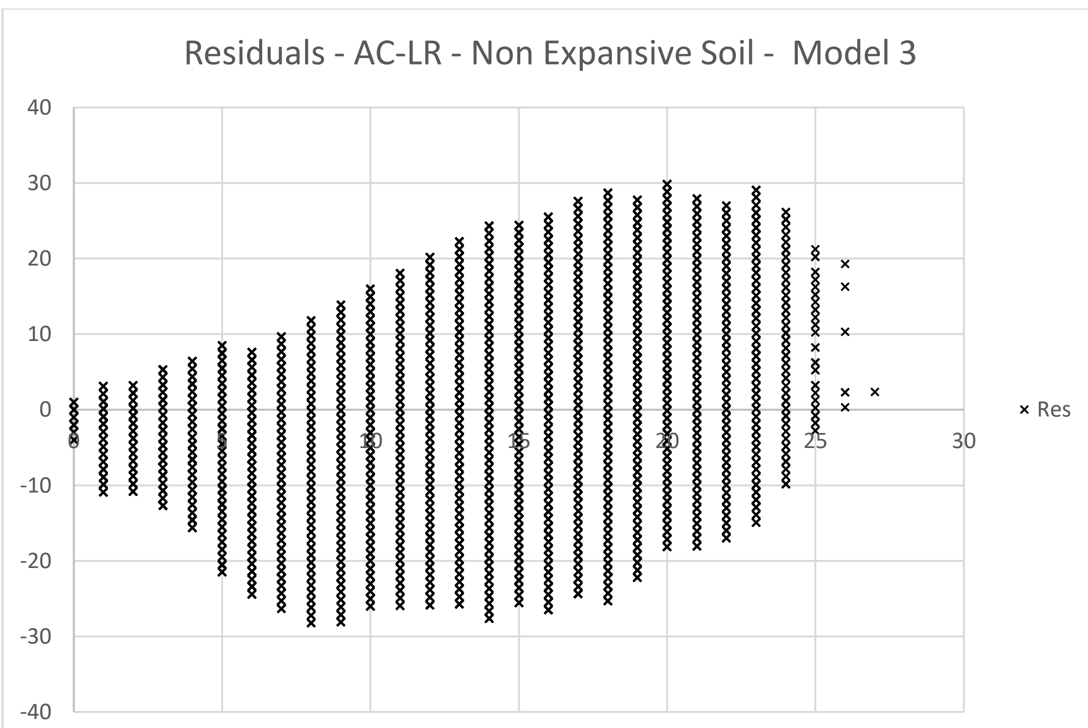

Figure M10 Residuals AC-LR – Model 3

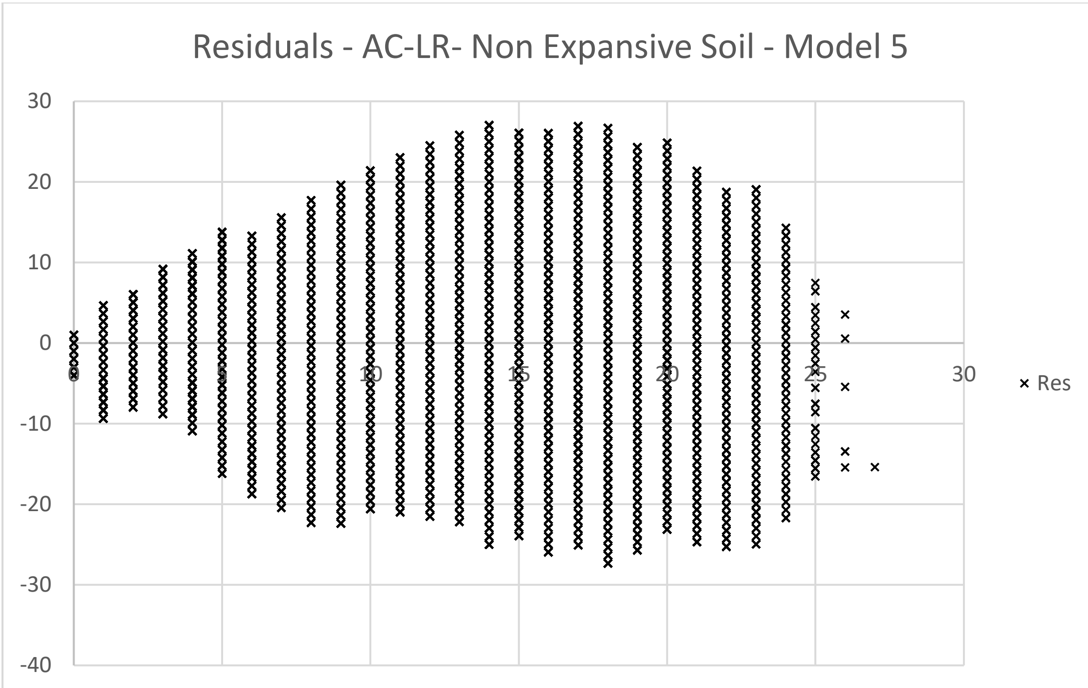

Figure M11 Residuals AC-LR – Model 5 (Selected)

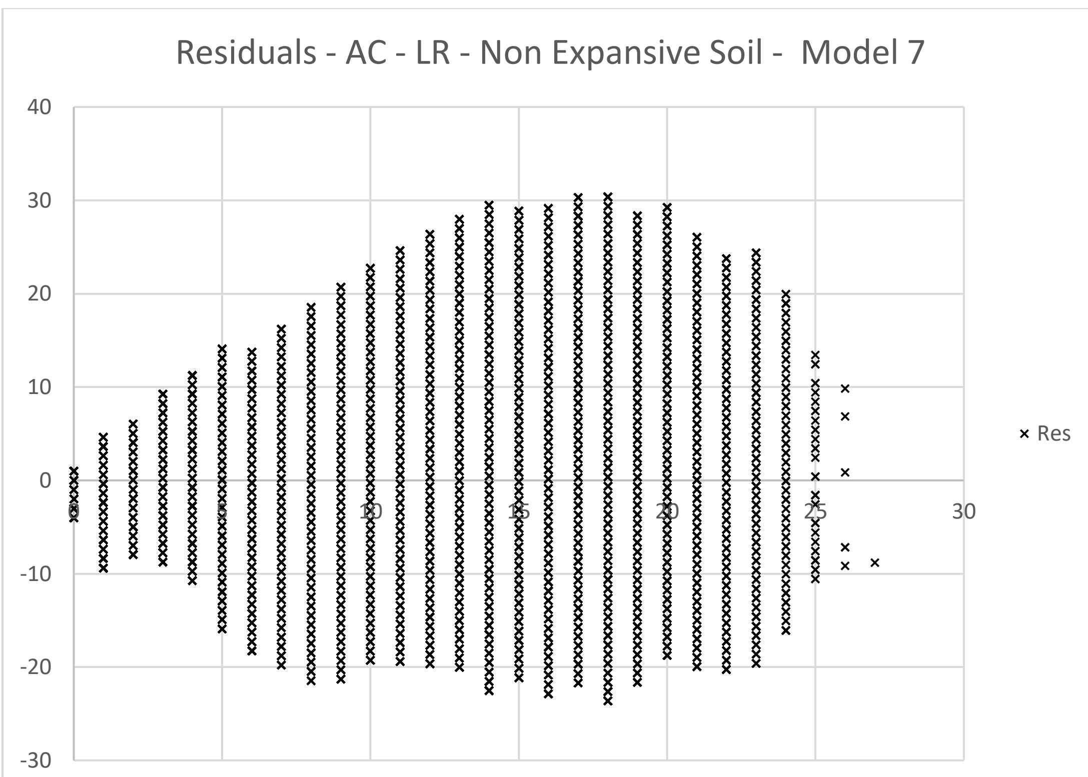

Figure M12 Residuals AC-LR – Model 7

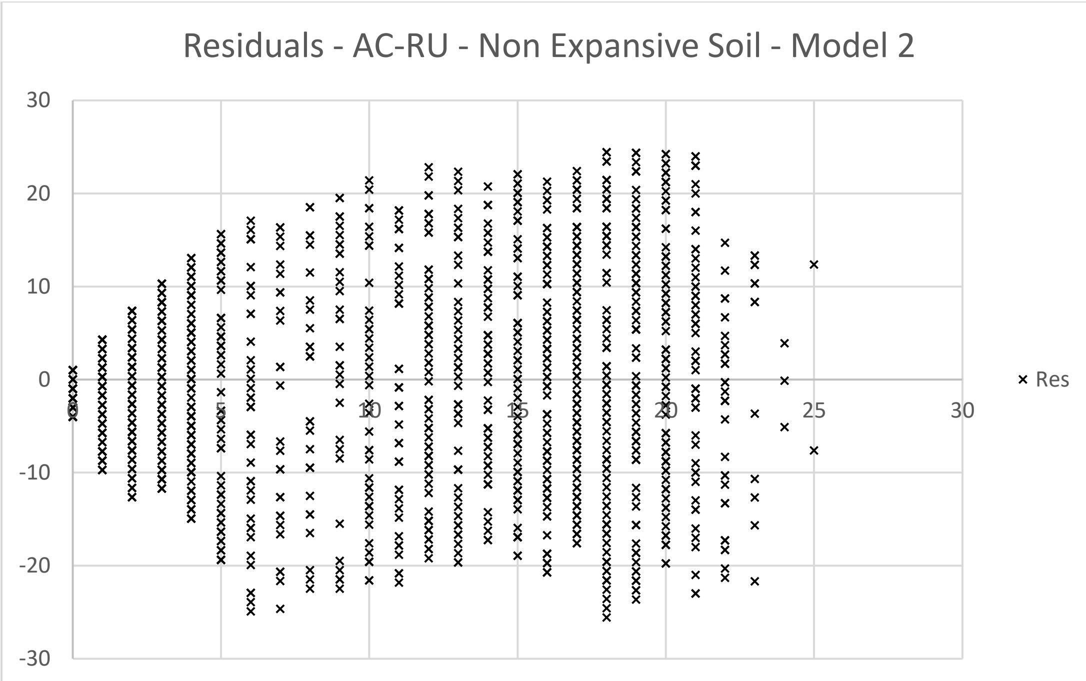

Figure M13 Residuals AC-RU – Model 2

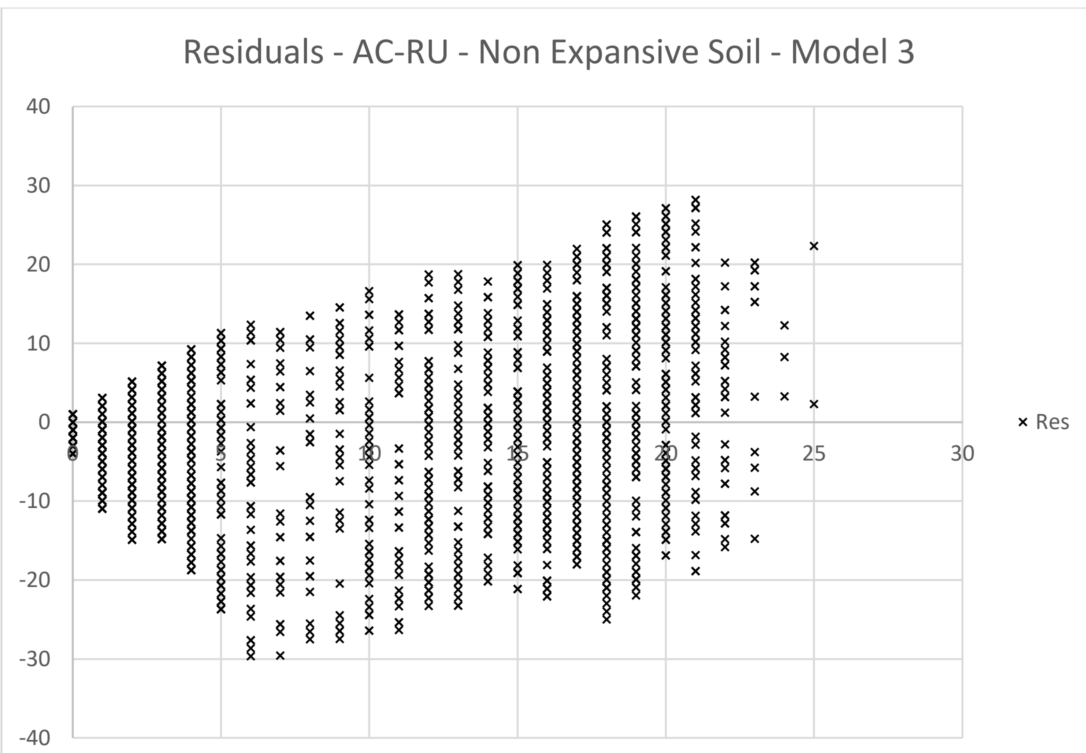

Figure M14 Residuals AC-RU – Model 3

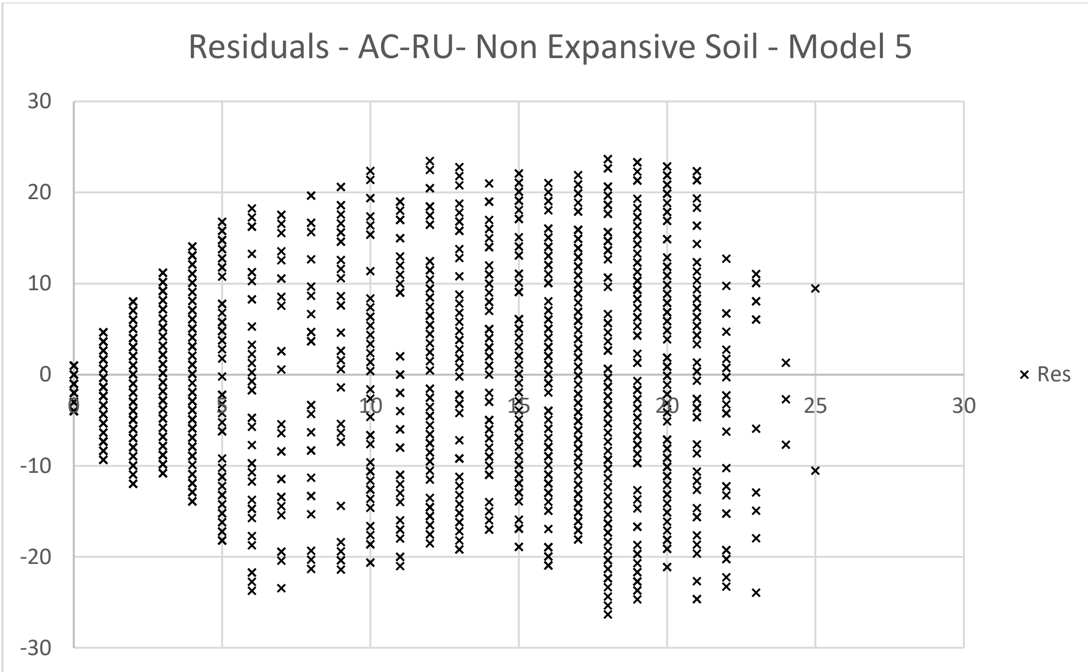

Figure M15 Residuals AC-RU – Model 5(Selected)

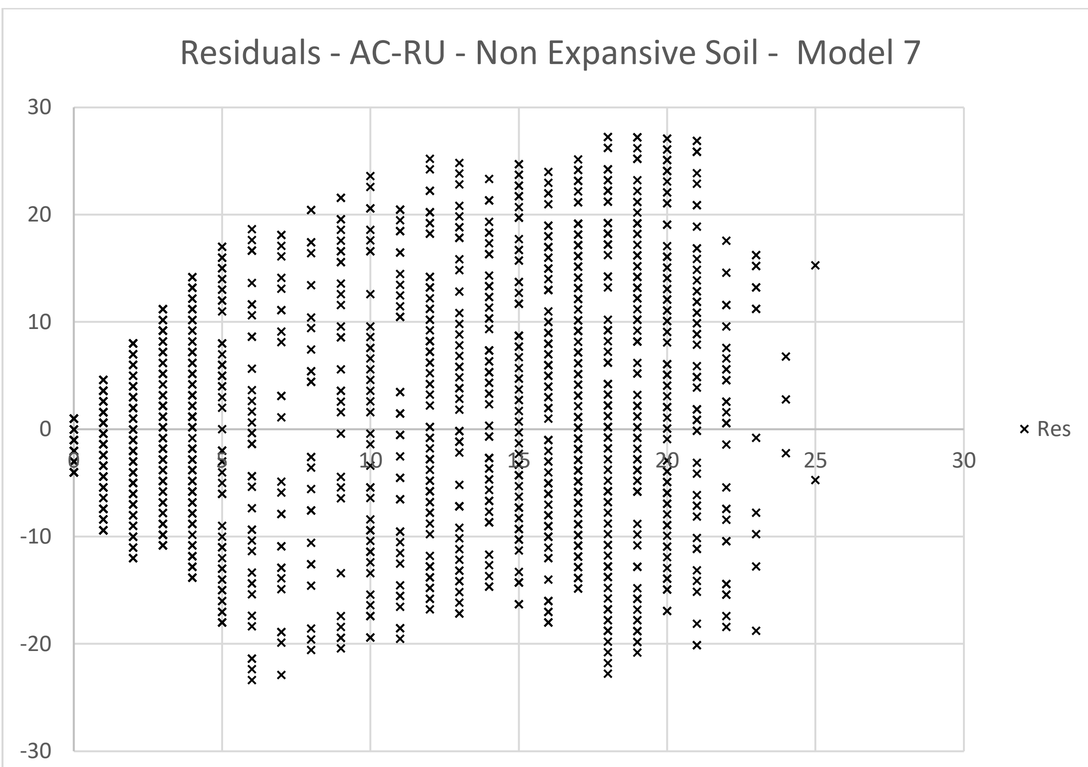

Figure M16 Residuals AC-RU – Model 7

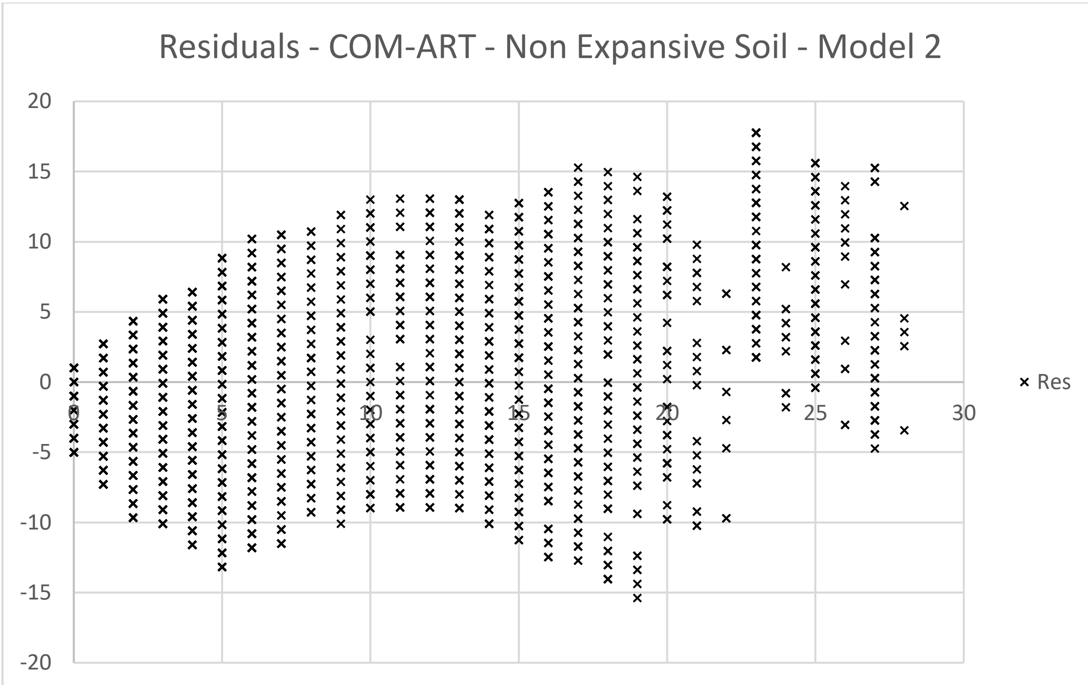

Figure M17 Residuals COM-ART – Model 2

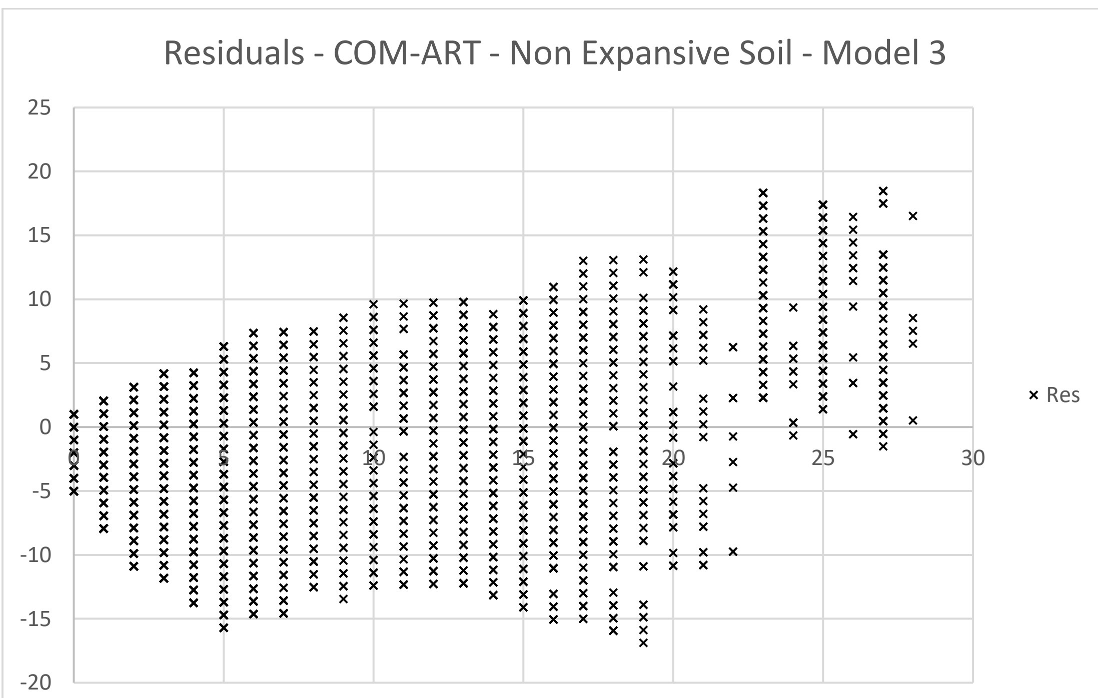

Figure M18 Residuals COM-ART – Model 3

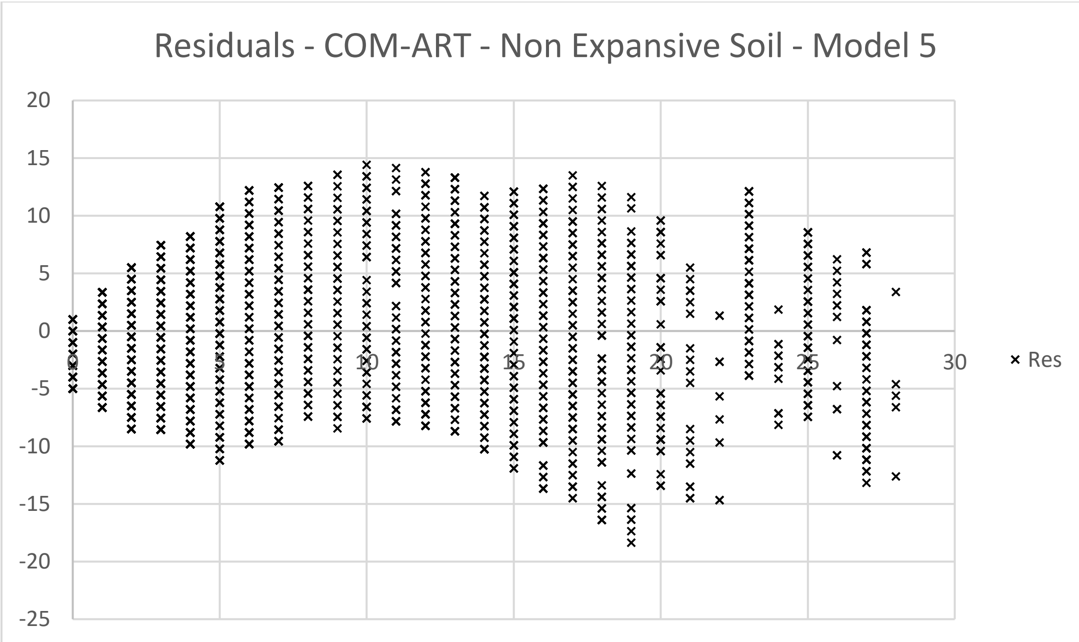

Figure M19 Residuals COM-ART – Model 5

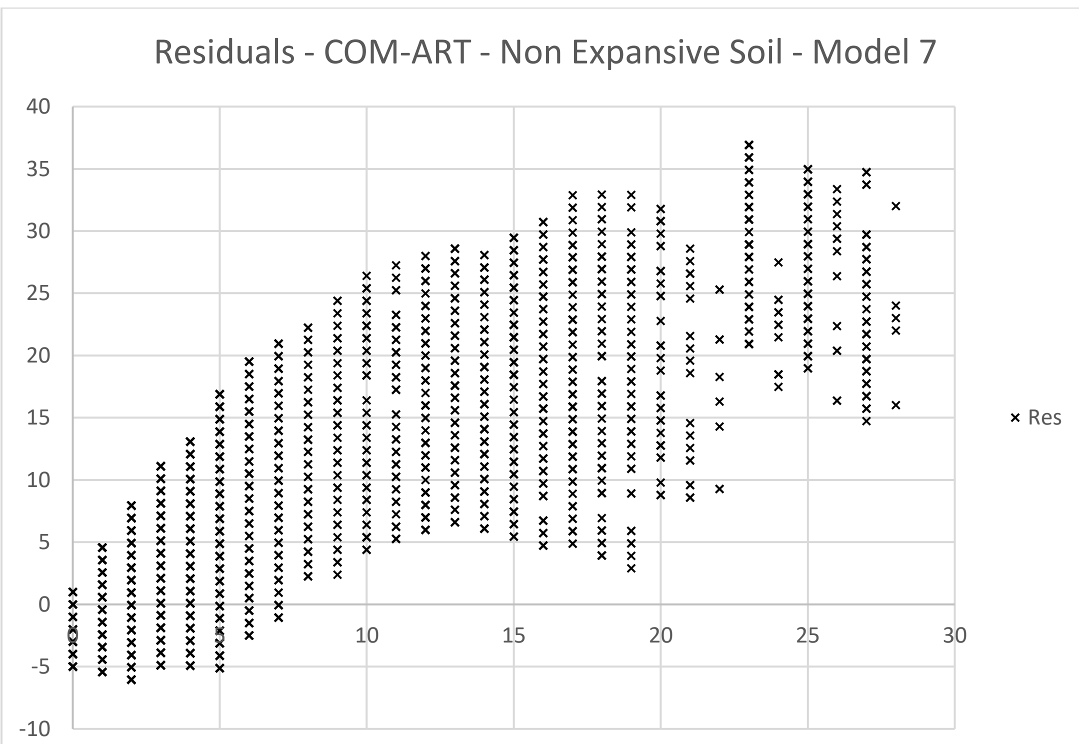

Figure M20 Residuals COM-ART – Model 7 (Selected)

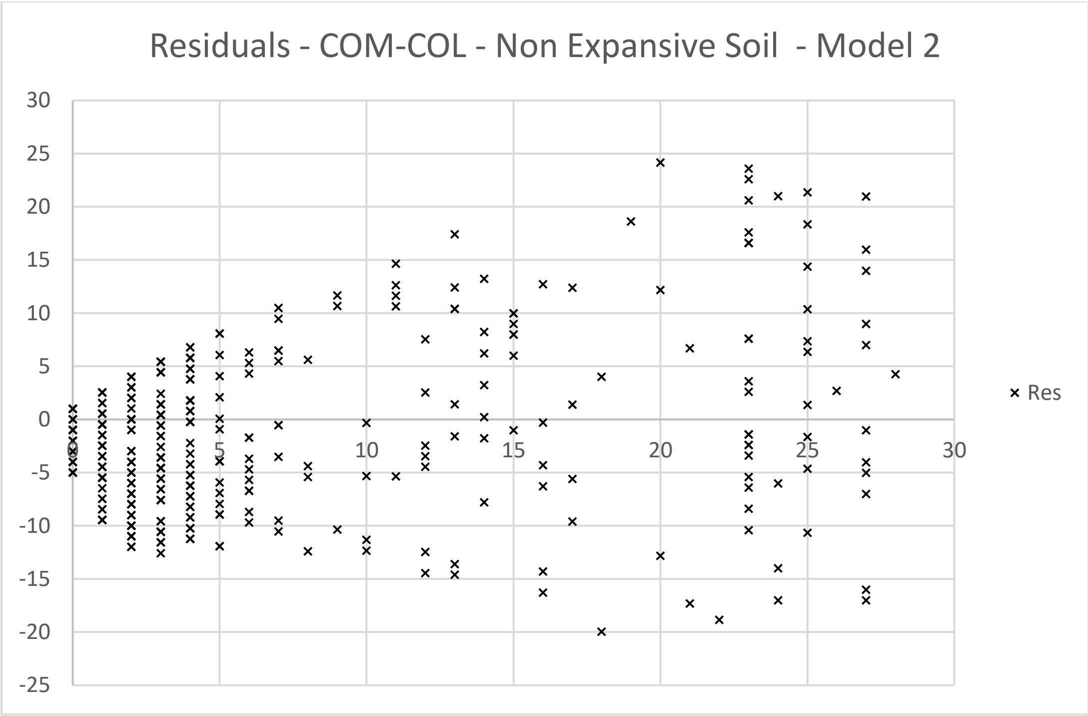

Figure M21 Residuals COM-COL – Model 2

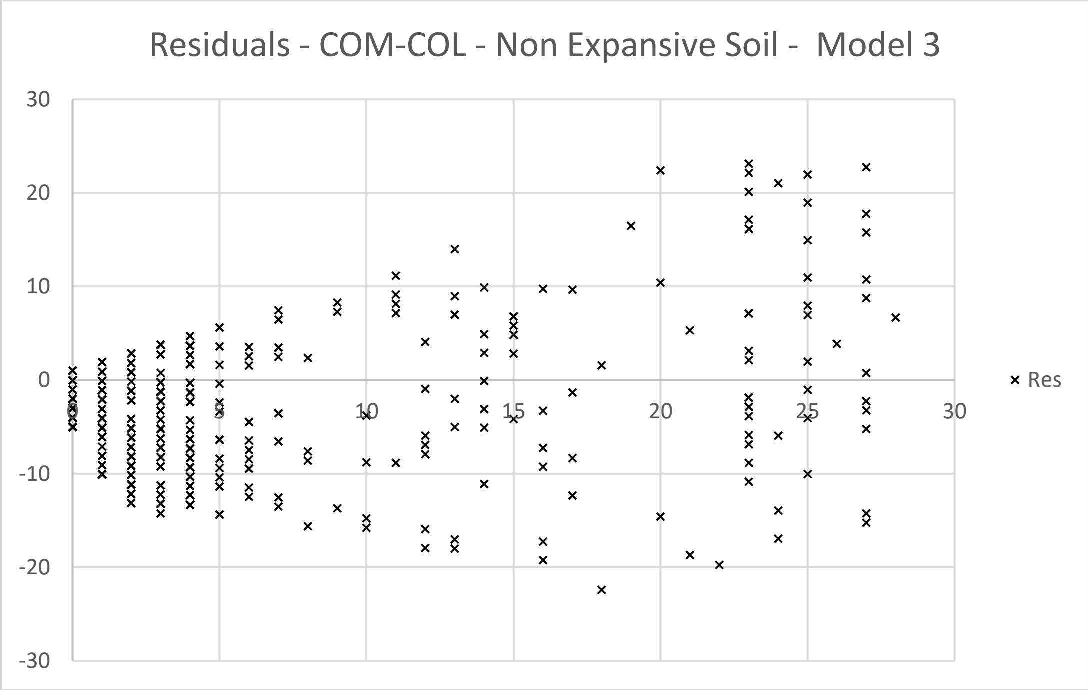

Figure M22 Residuals COM-COL – Model 3

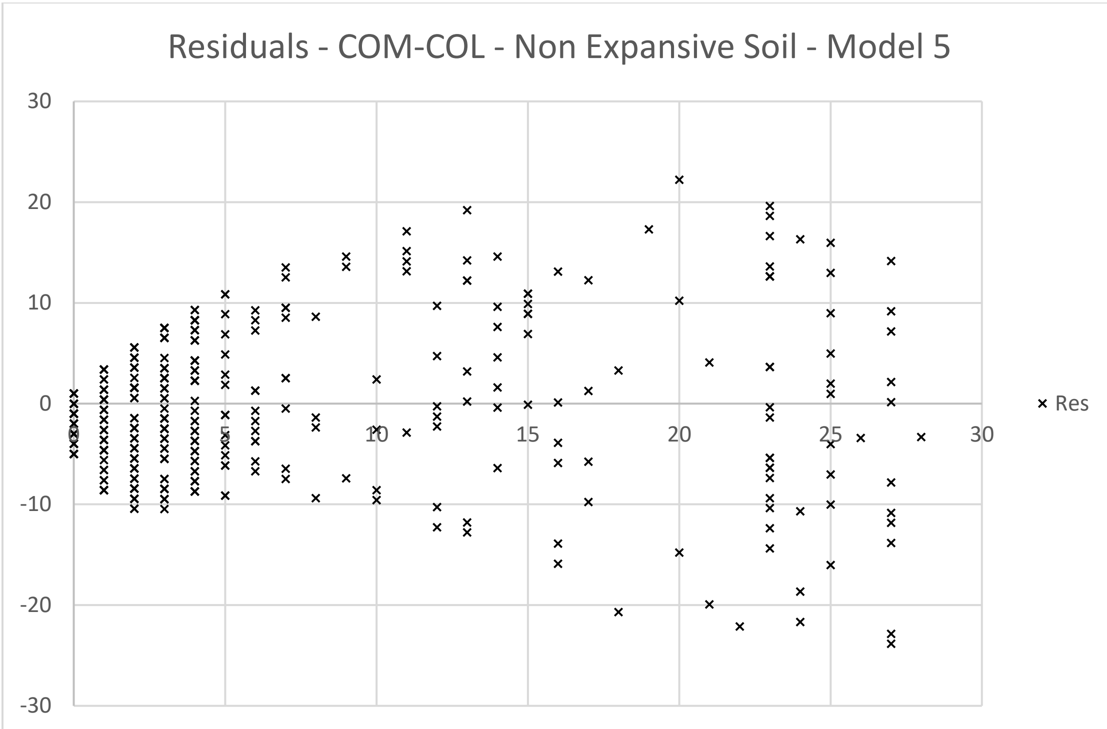

Figure M23 Residuals COM-COL – Model 5

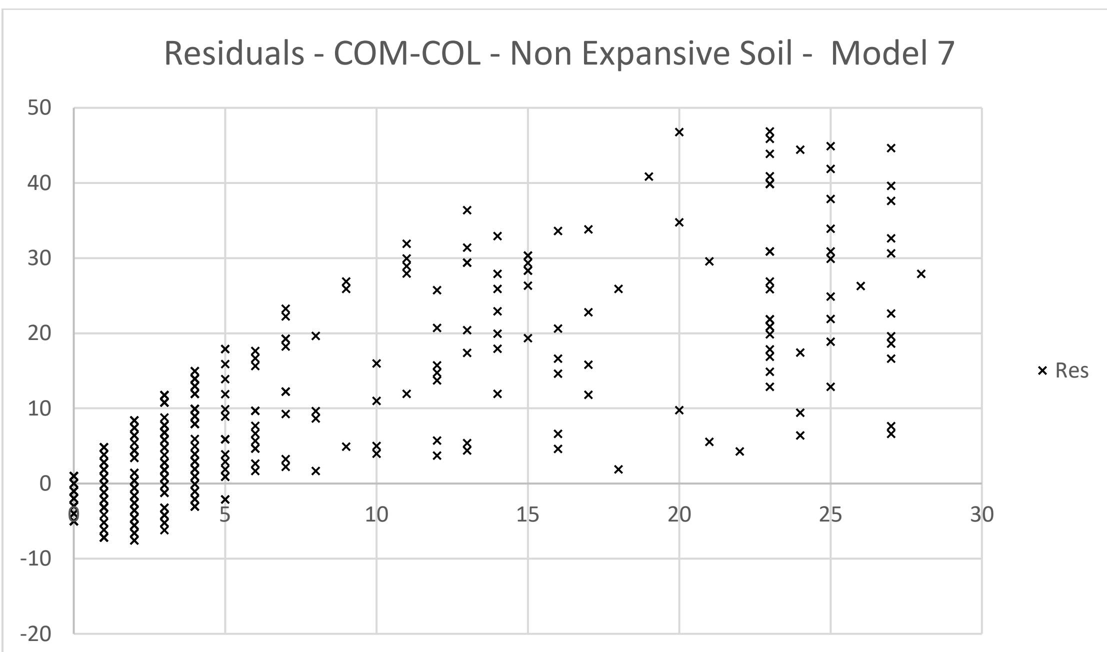

Figure M24 Residuals COM-COL – Model 7 (Selected)

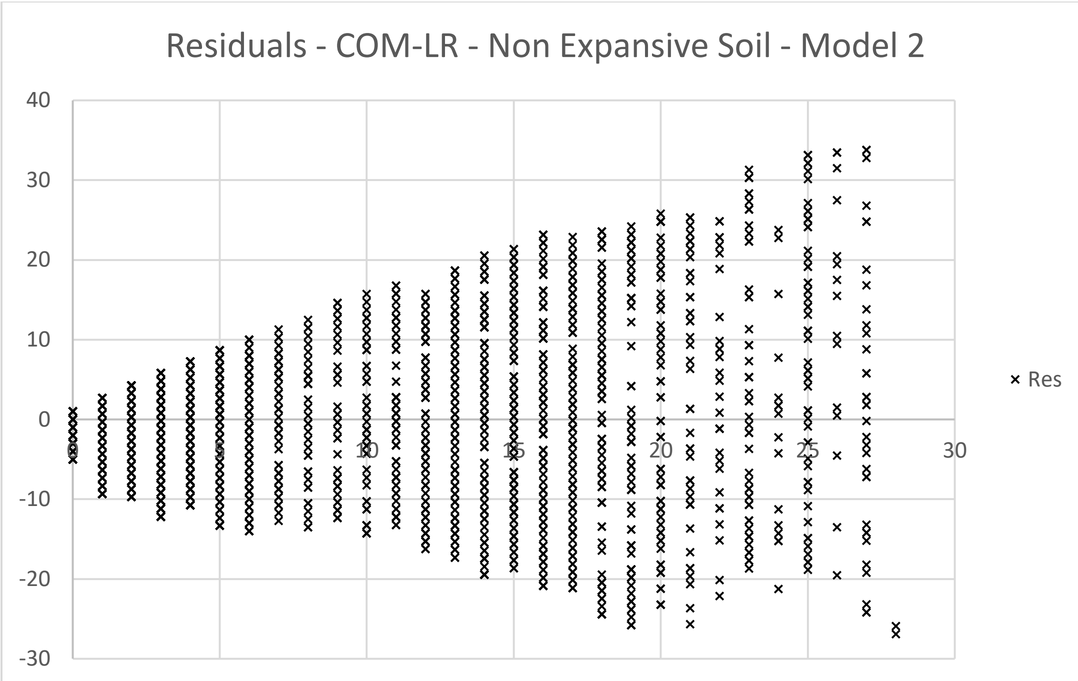

Figure M25 Residuals COM-LR – Model 2

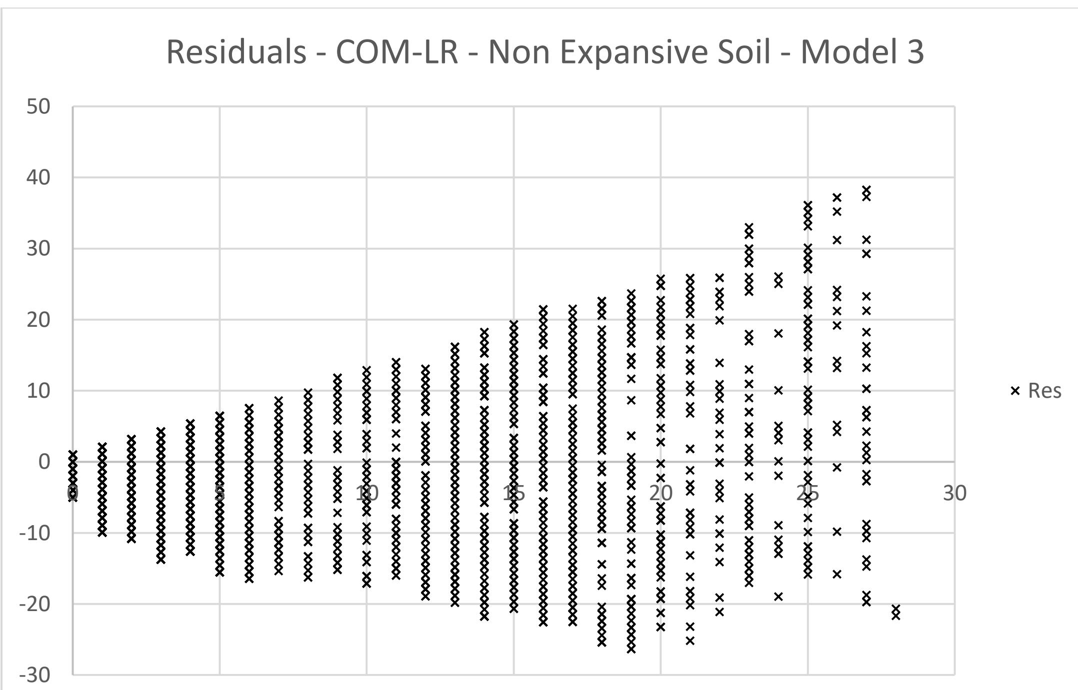

Figure M26 Residuals COM-LR – Model 3

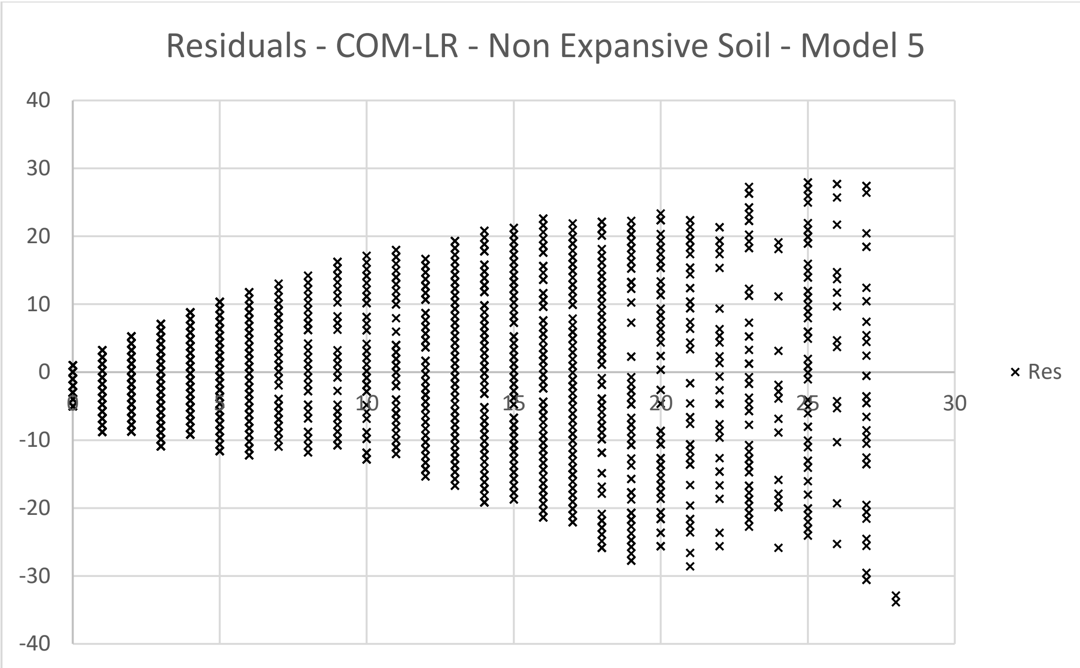

Figure M27 Residuals COM-LR – Model 5

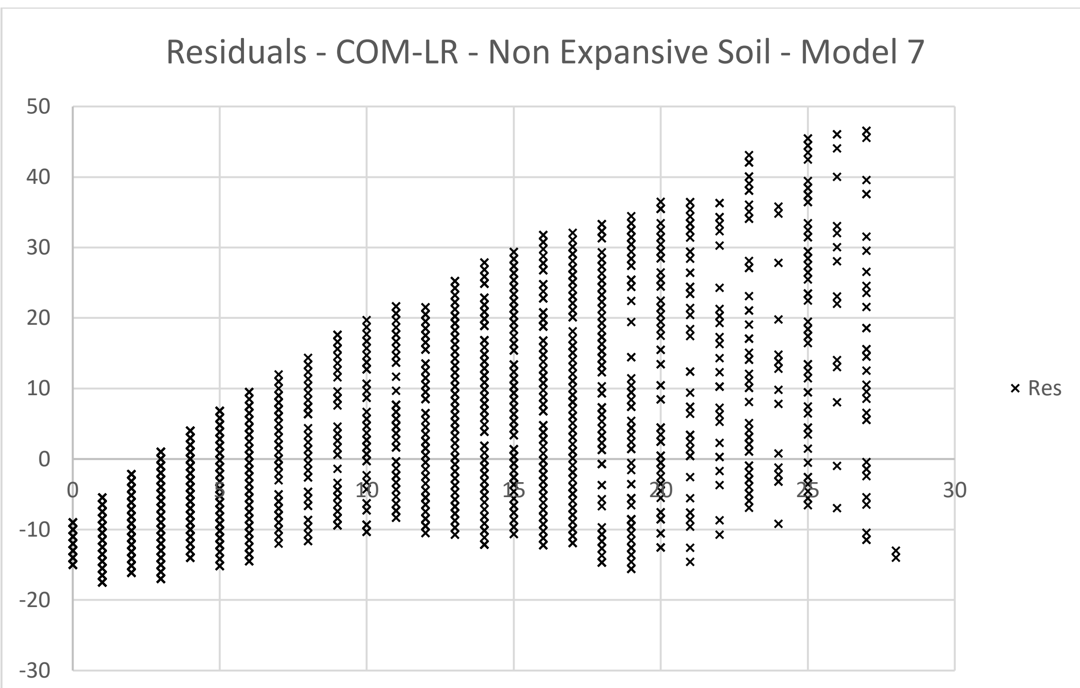

Figure M28 Residuals COM-LR – Model 7 (Selected)

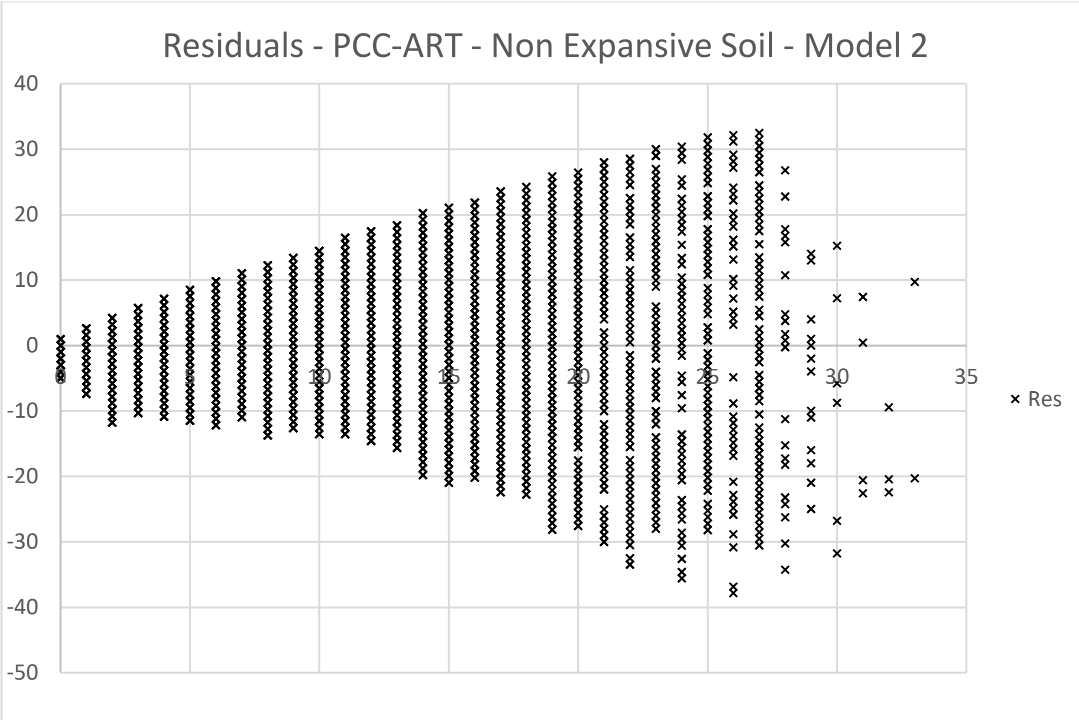

Figure M29 Residuals PCC-ART – Model 2

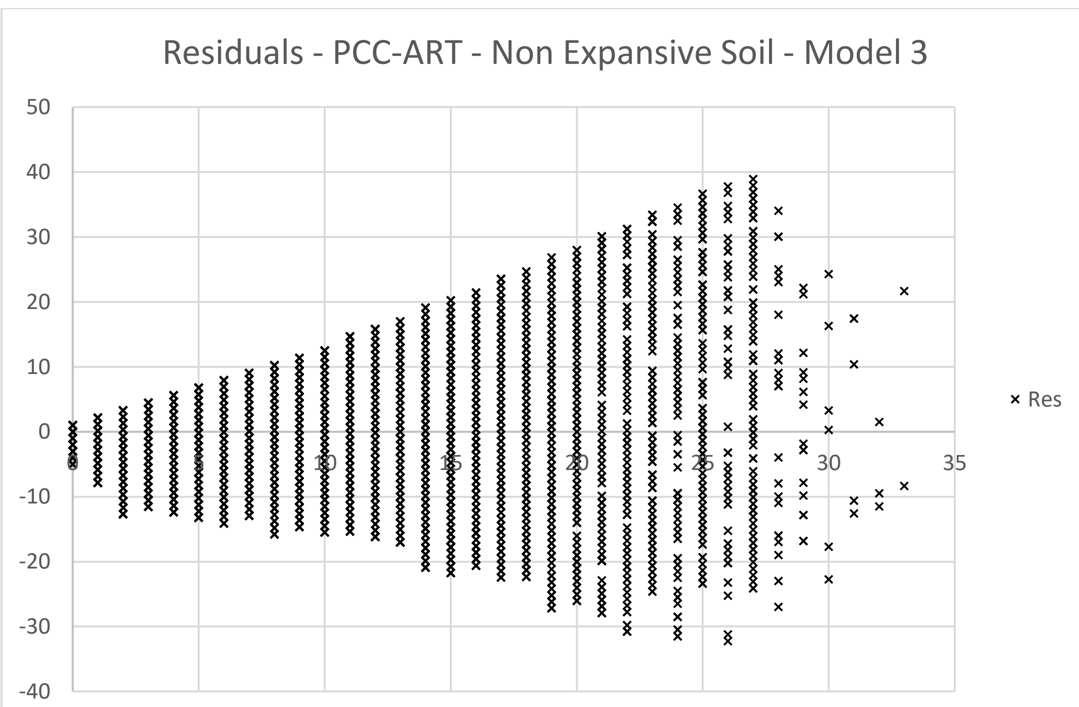

Figure M30 Residuals PCC-ART – Model 3

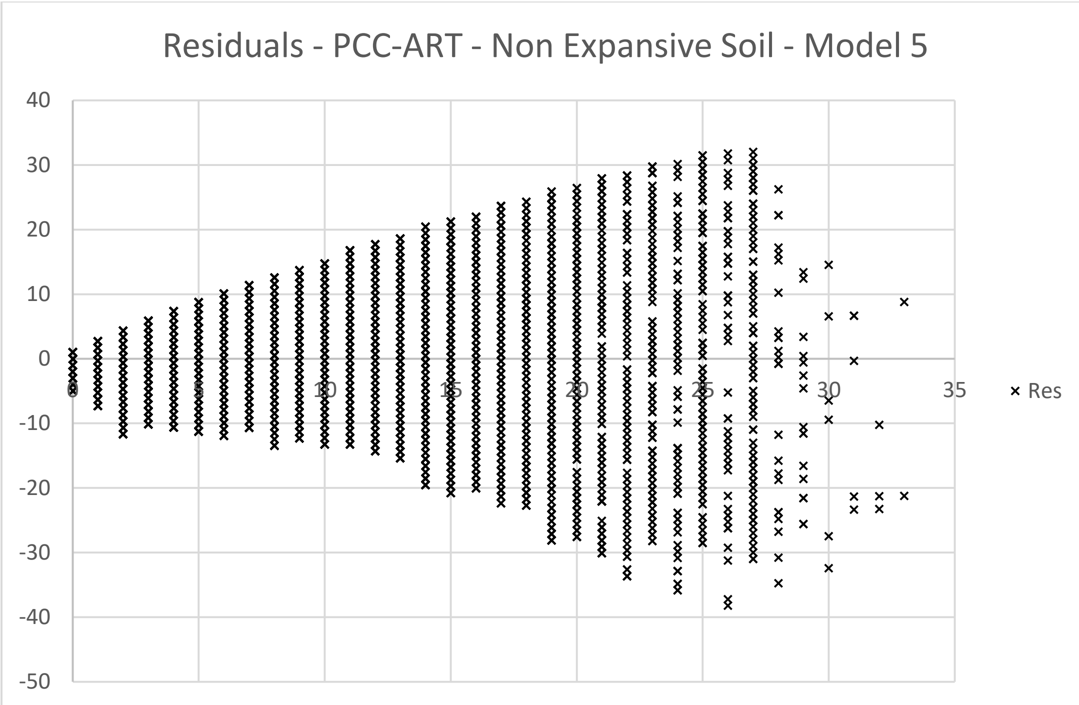

Figure M31 Residuals PCC-ART – Model 5 (Selected)

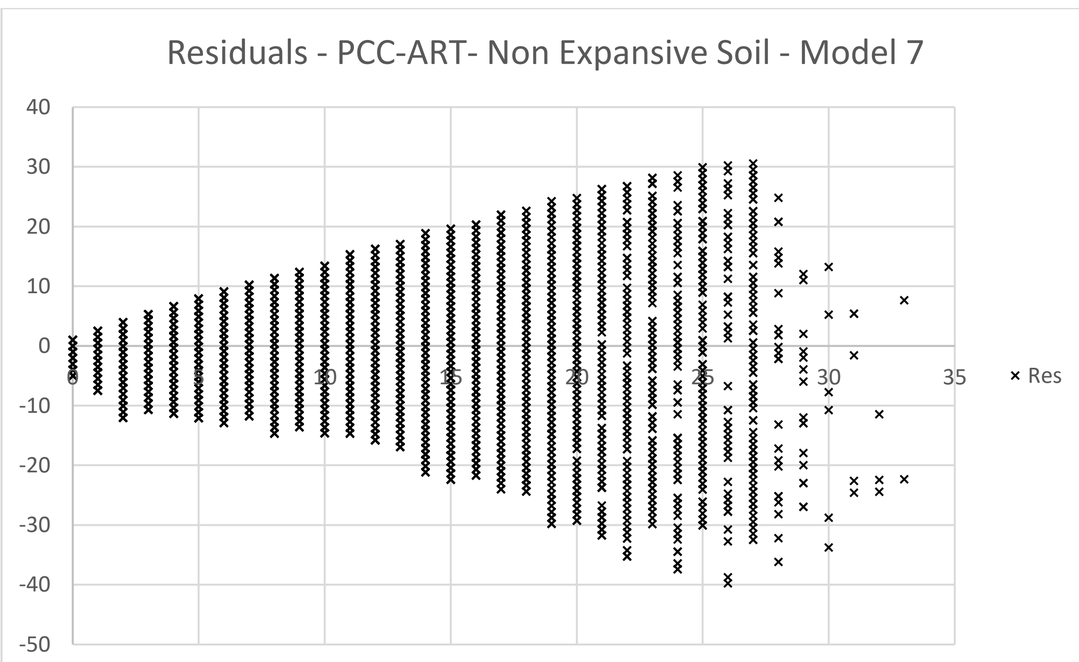

Figure M32 Residuals PCC-ART – Model 7

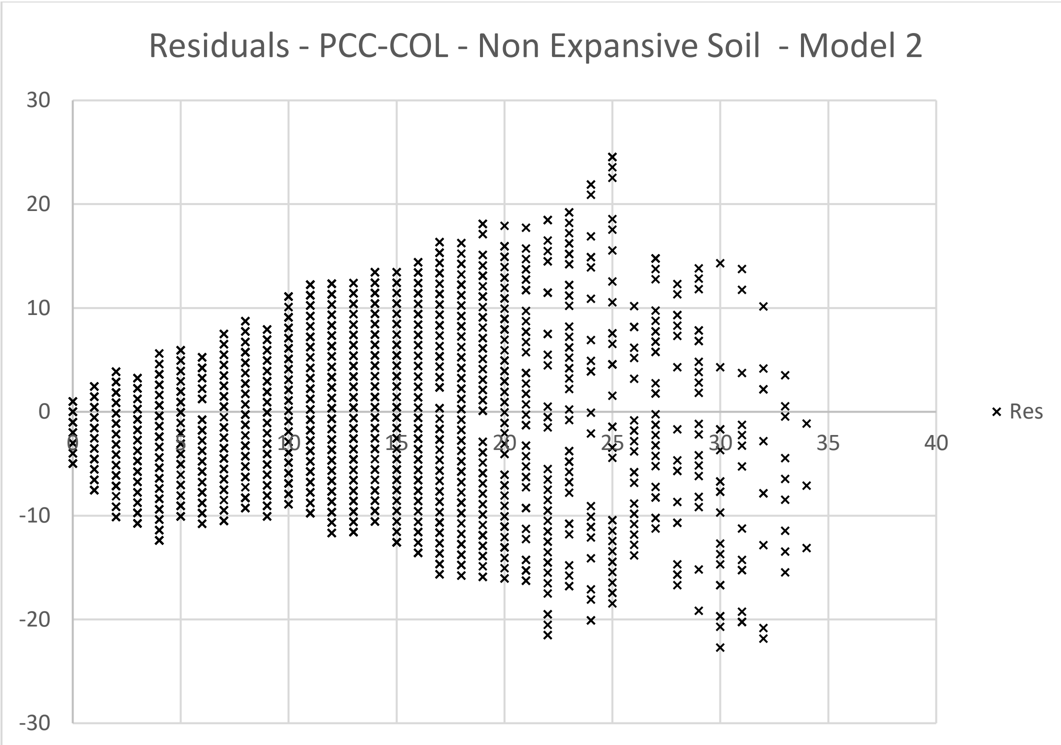

Figure M33 Residuals PCC-COL – Model 2 (Selected)

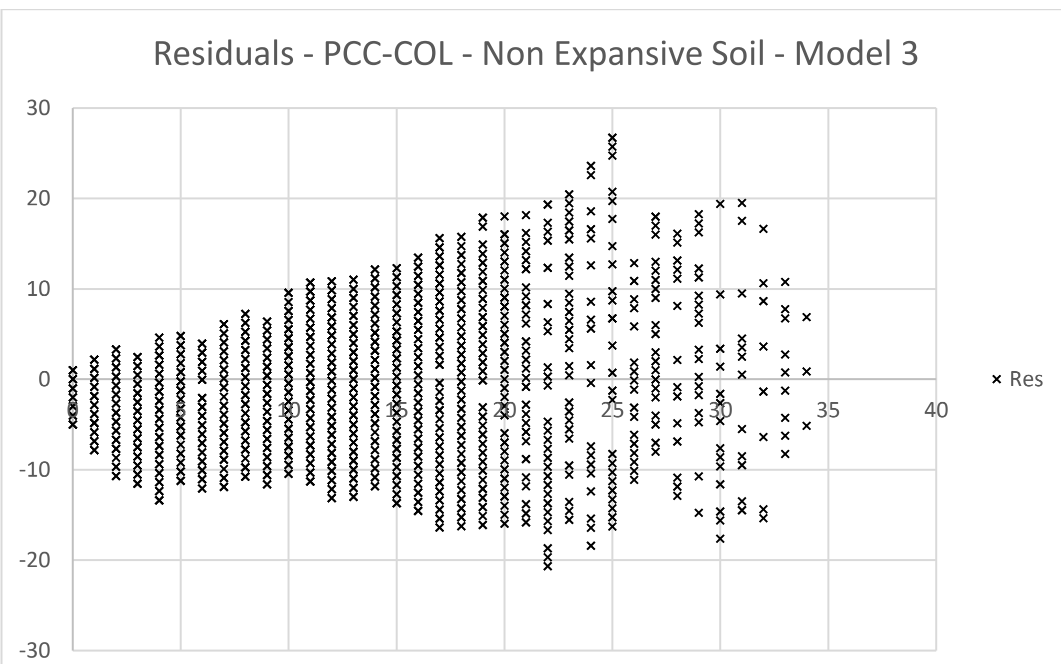

Figure M34 Residuals PCC-COL – Model 3

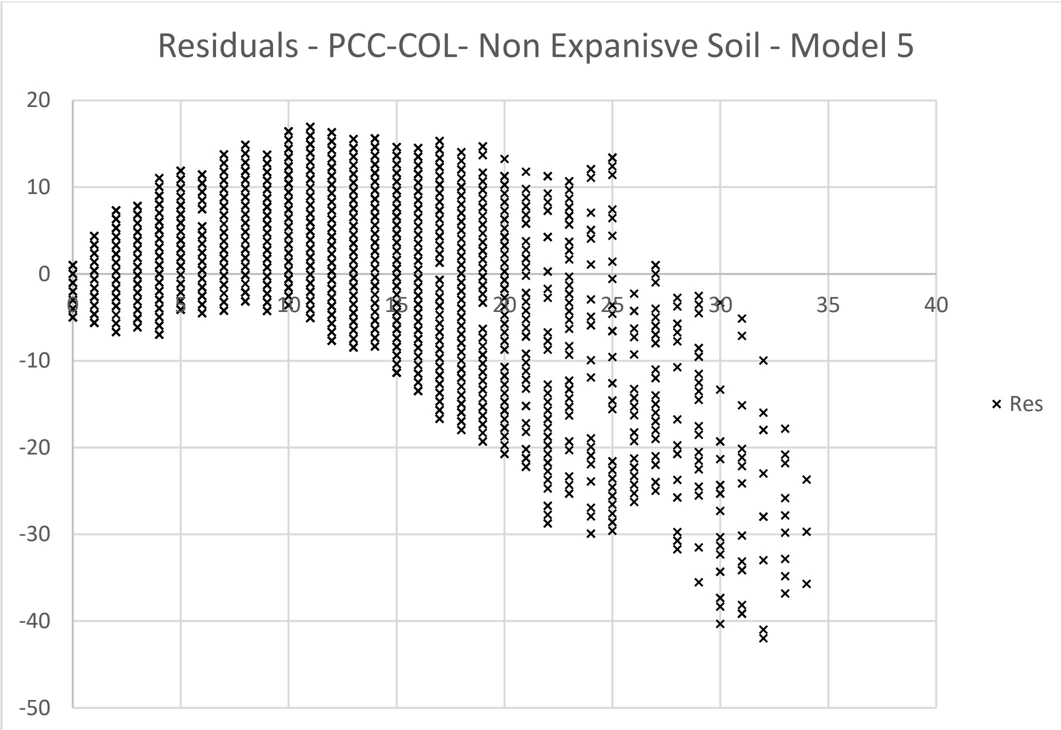

Figure M35 Residuals PCC-COL – Model 5

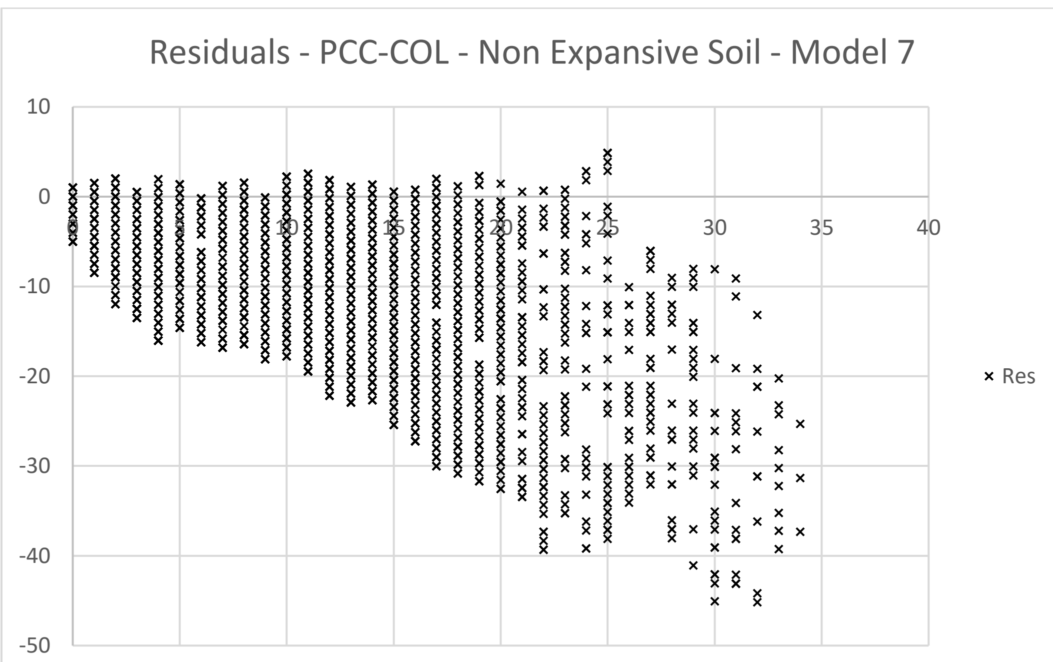

Figure M36 Residuals PCC-COL – Model 7

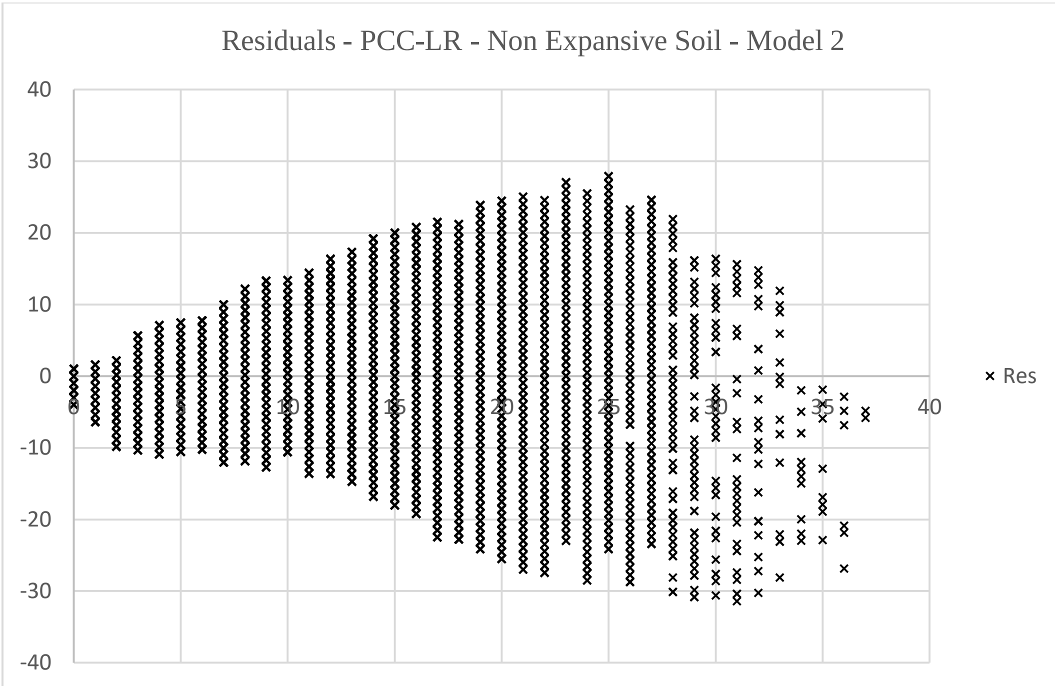

Figure M37 Residuals PCC-LR – Model 2 (Selected)

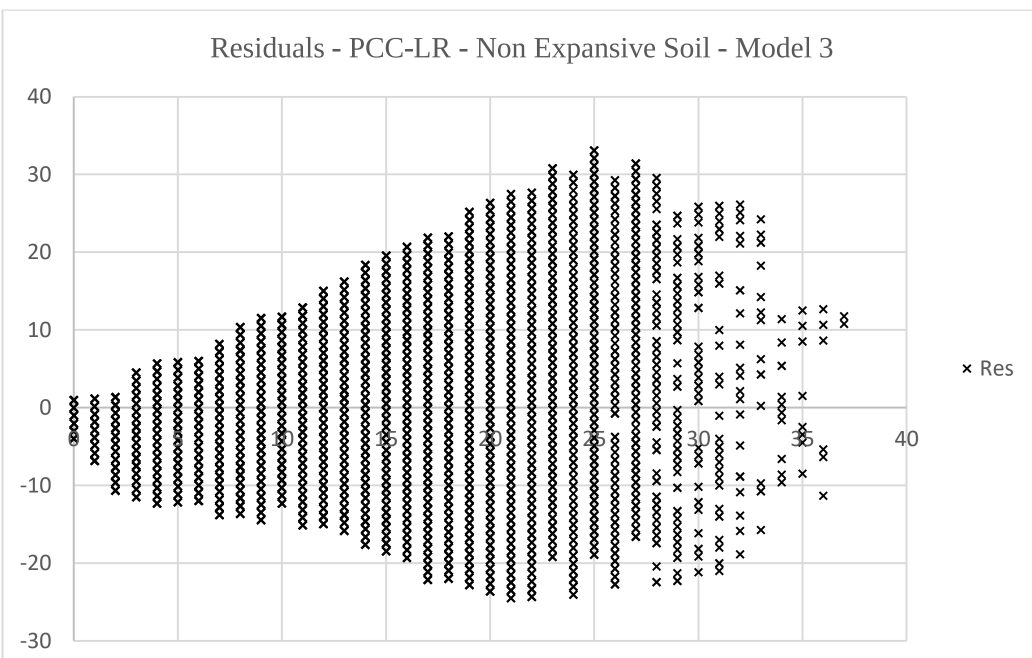

Figure M38 Residuals PCC-LR – Model 3

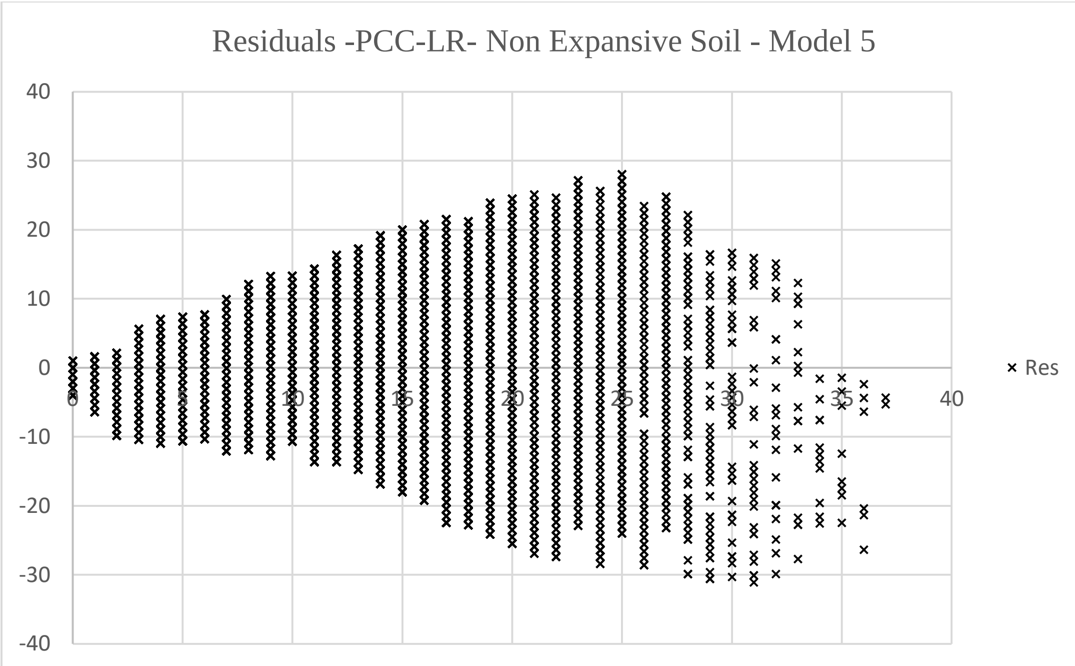

Figure M39 Residuals PCC-LR – Model 5

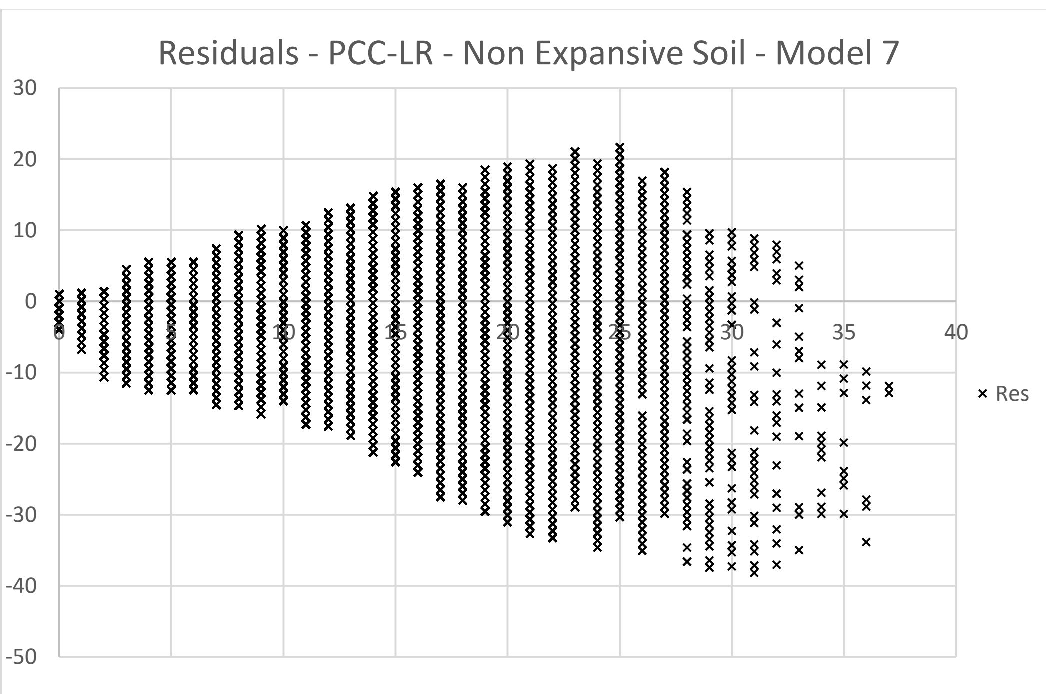

Figure M40 Residuals PCC-LR – Model 7

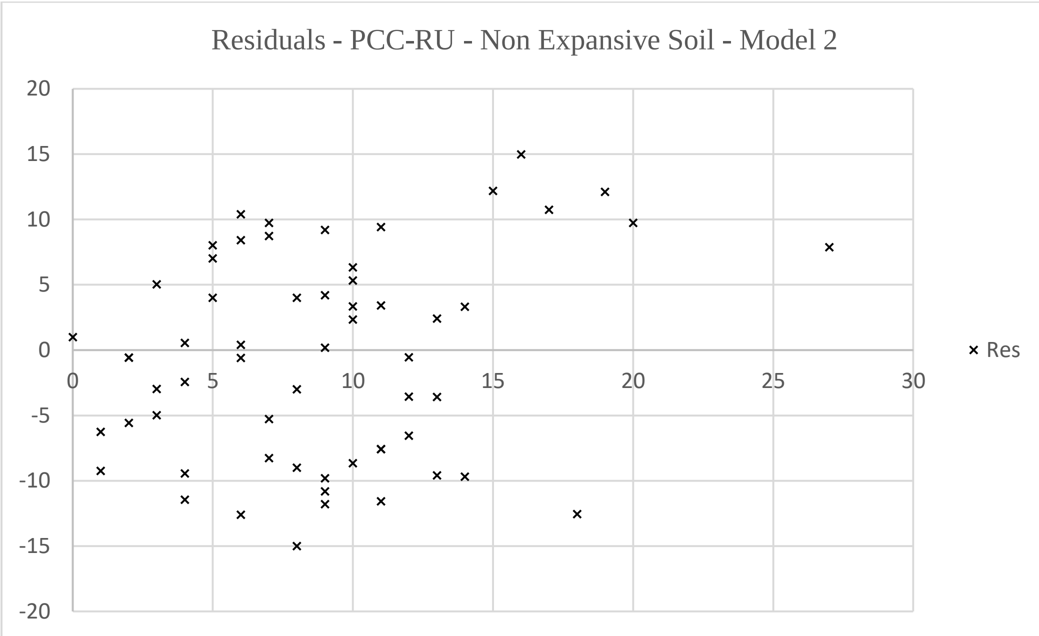

Figure M41 Residuals PCC-RU – Model 2

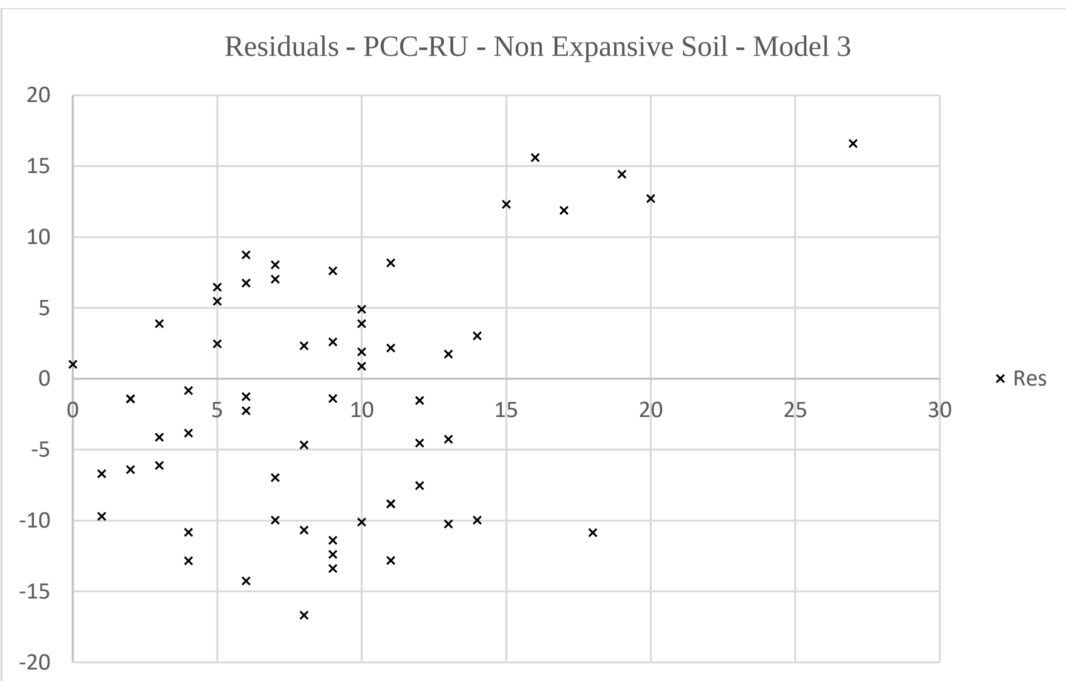

Figure M42 Residuals PCC-RU – Model 3

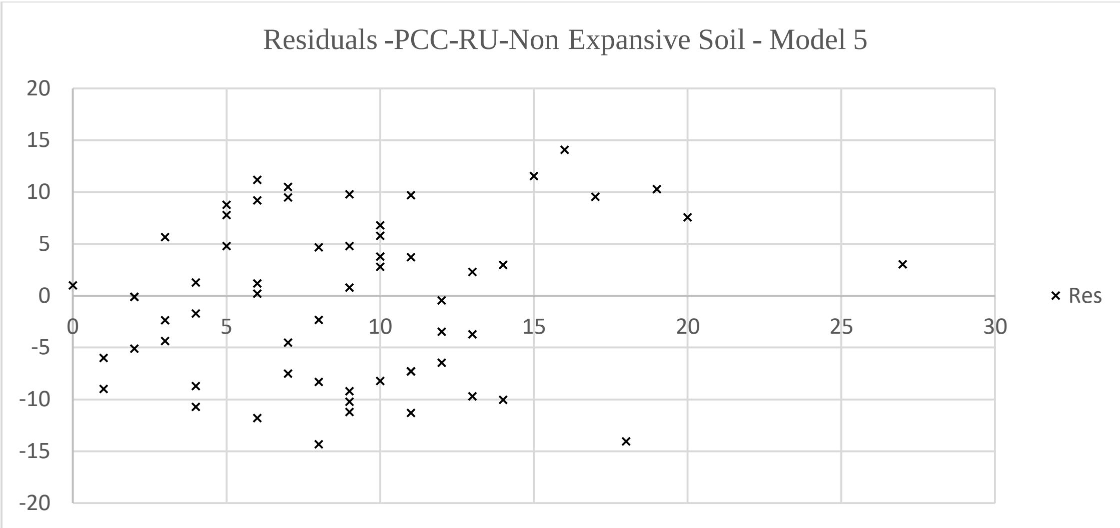

Figure M43 Residuals PCC-RU – Model 5

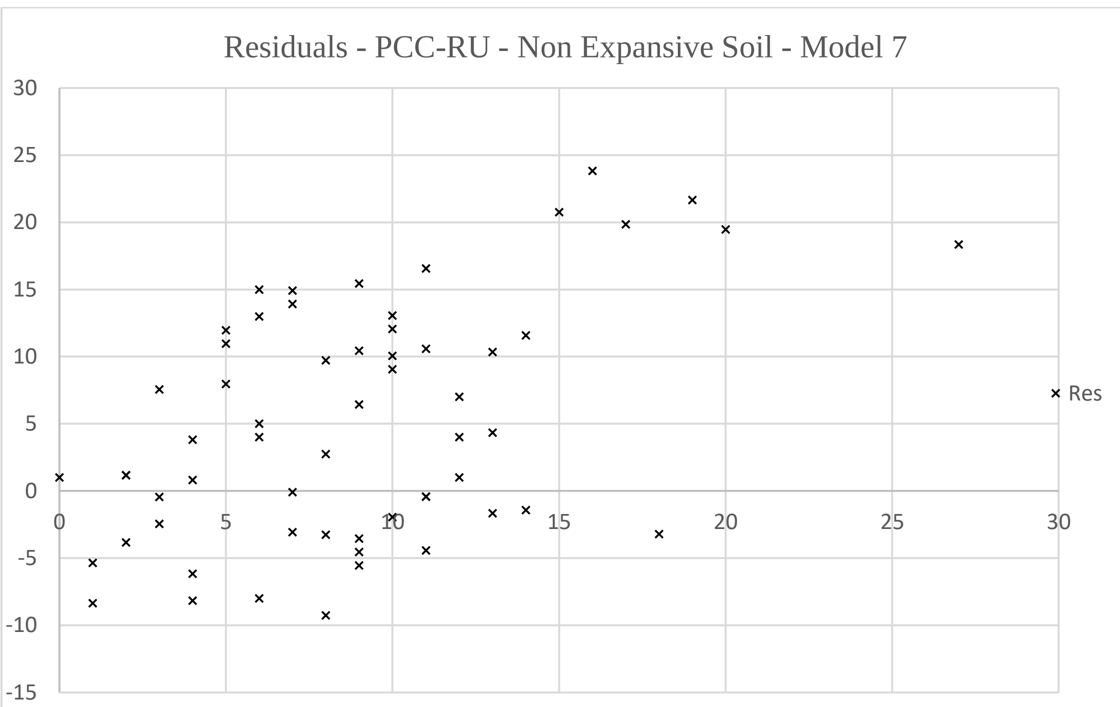

Figure M44 Residuals PCC-RU – Model 7 (Selected)

APPENDIX N: Residuals – Expansive Soil (IRI)

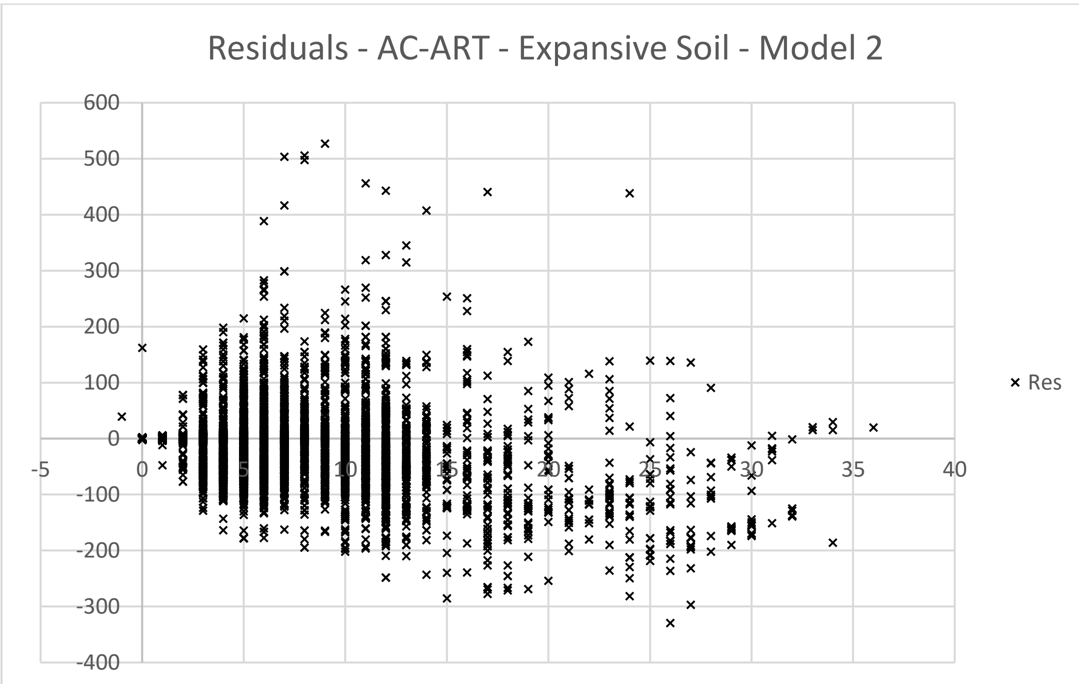

Figure N1 Residuals AC-ART – Model 2

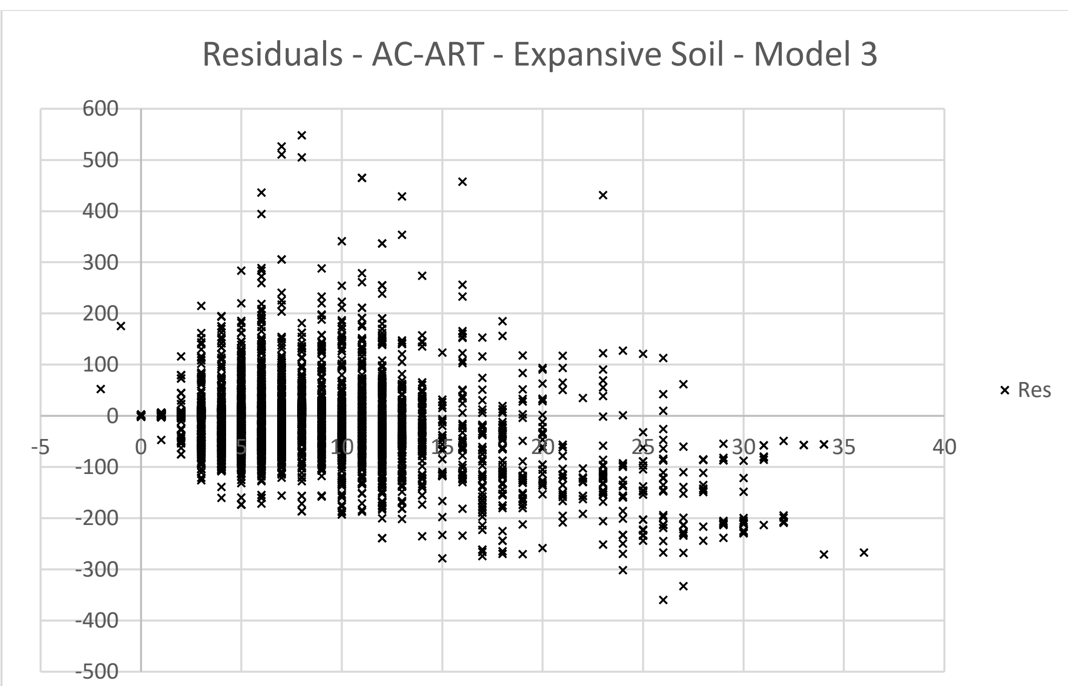

Figure N2 Residuals AC-ART – Model 3 (Selected)

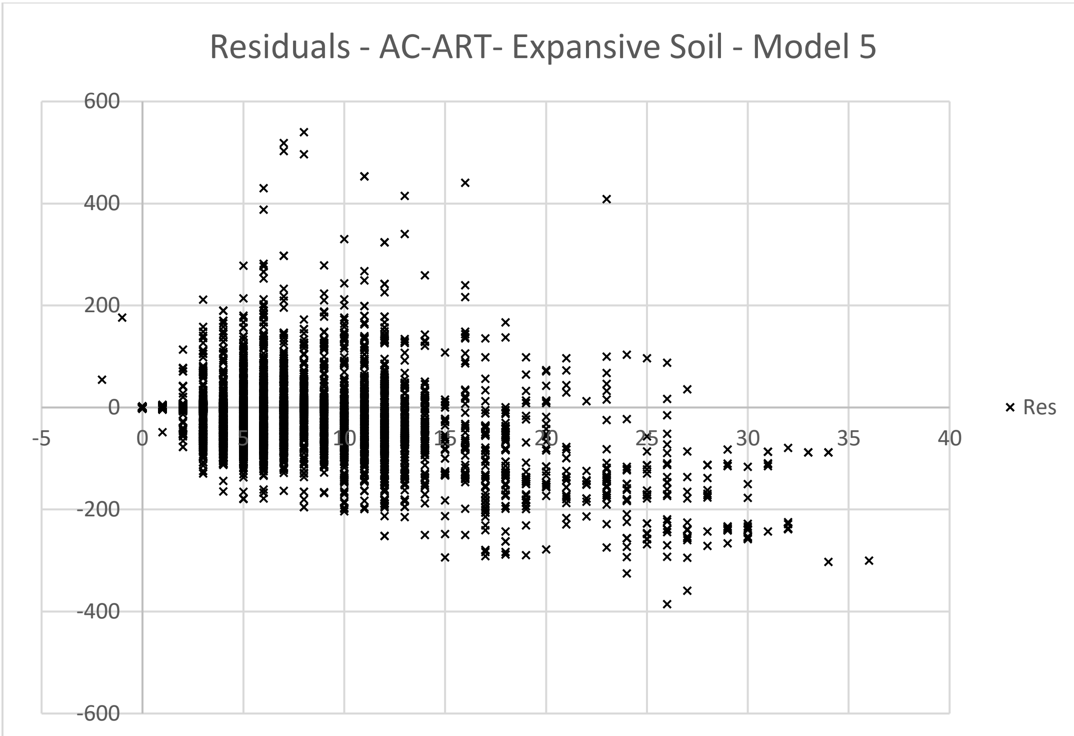

Figure N3 Residuals AC-ART – Model 5

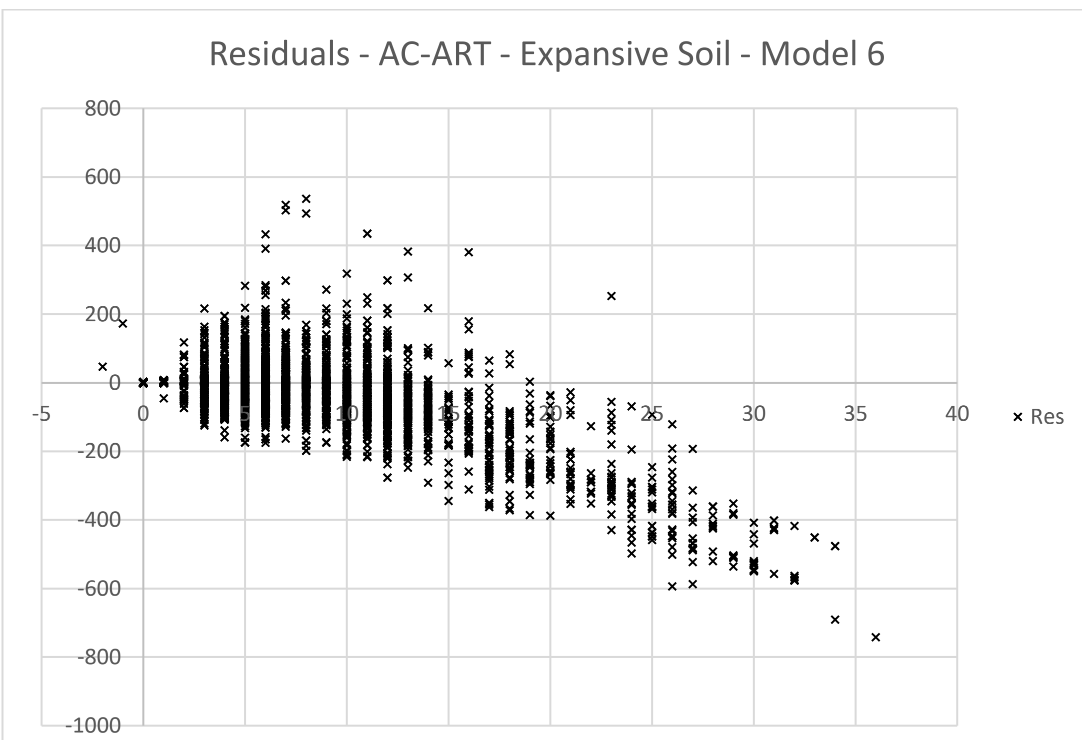

Figure N4 Residuals AC-ART – Model 6

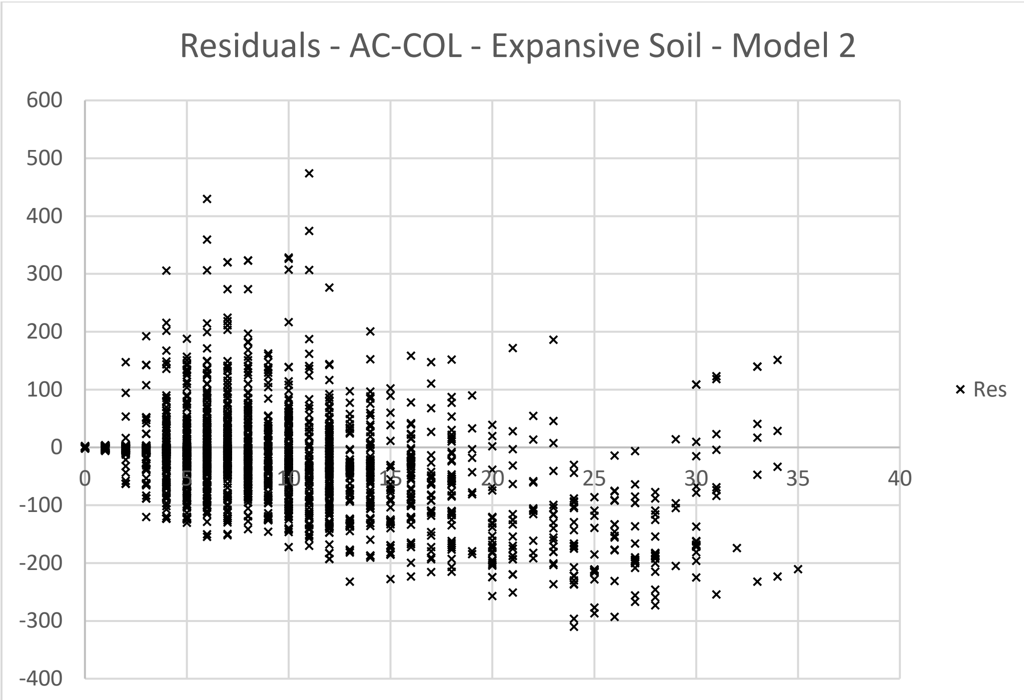

Figure N5 Residuals AC-COL – Model 2

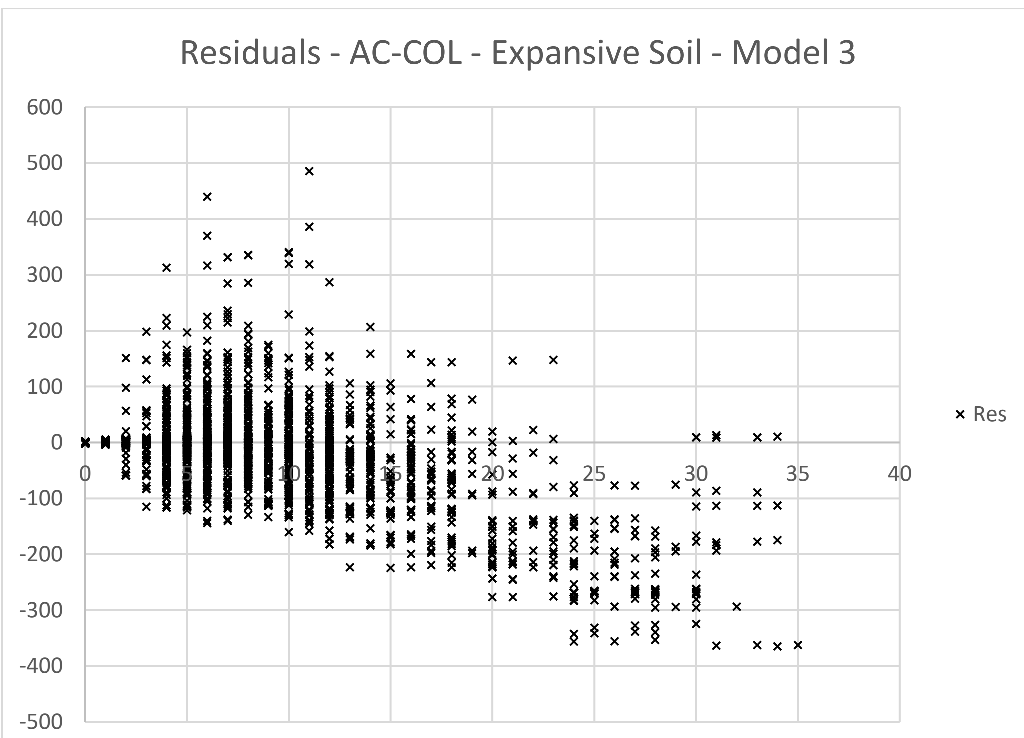

Figure N6 Residuals AC-COL – Model 3 (Selected)

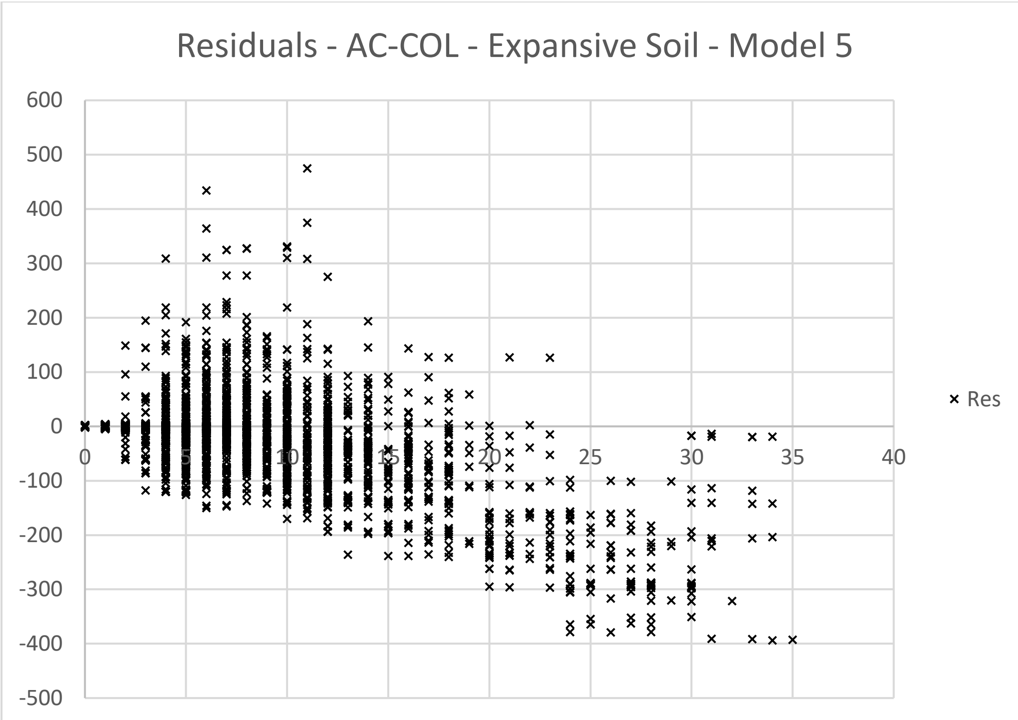

Figure N7 Residuals AC-COL – Model 5

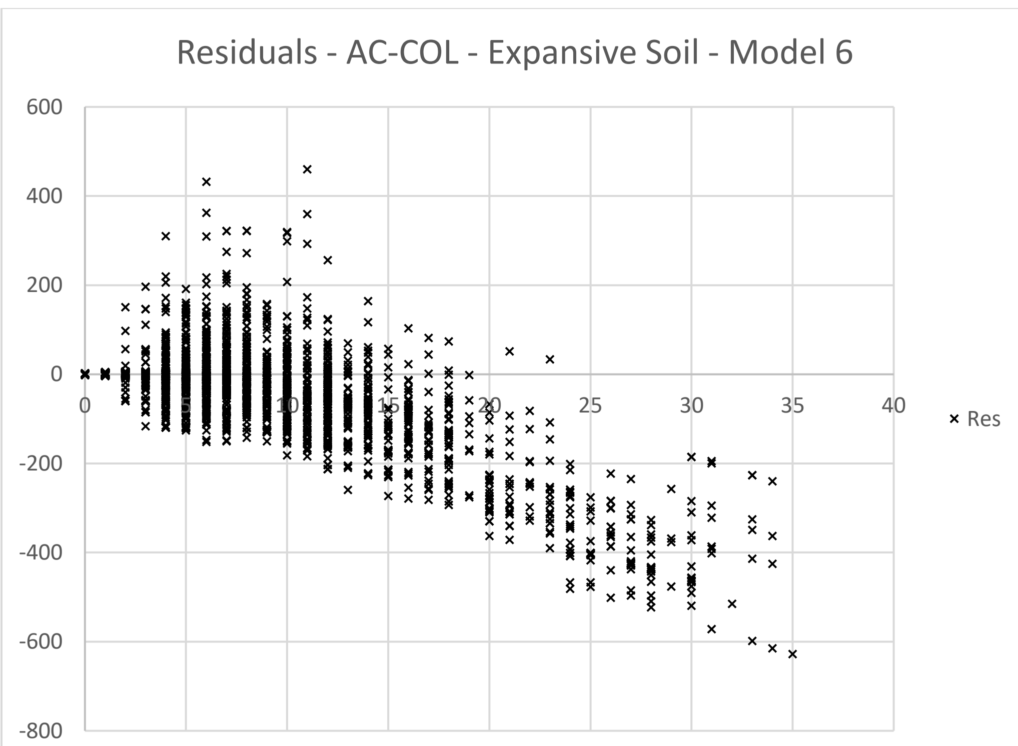

Figure N8 Residuals AC-COL – Model 6

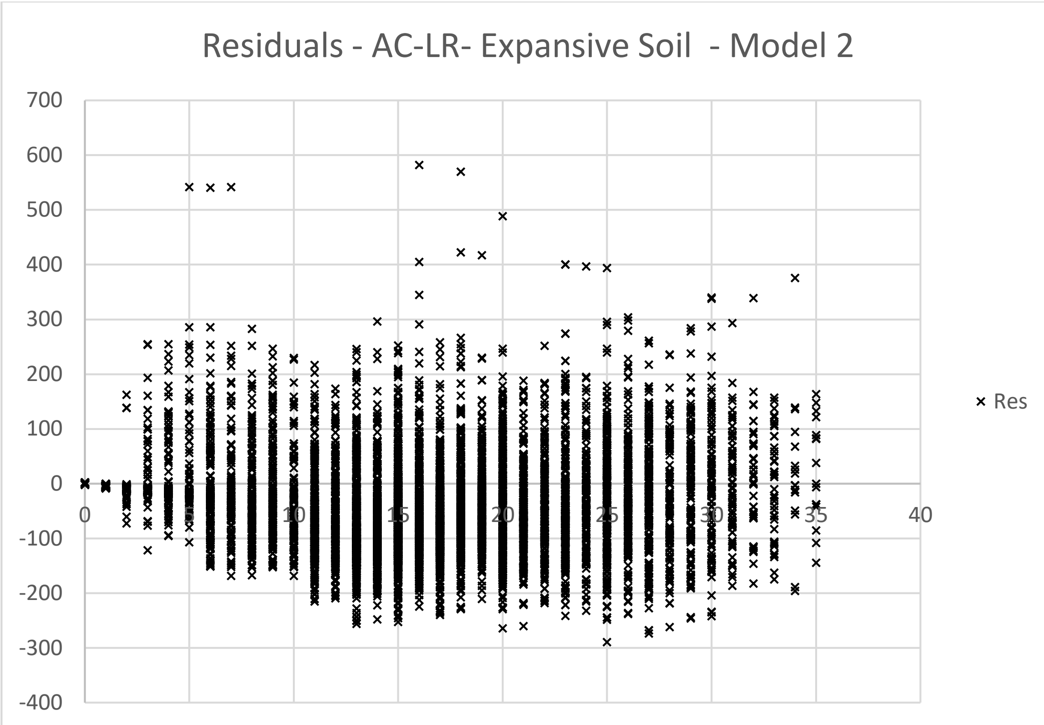

Figure N9 Residuals AC-LR – Model 2

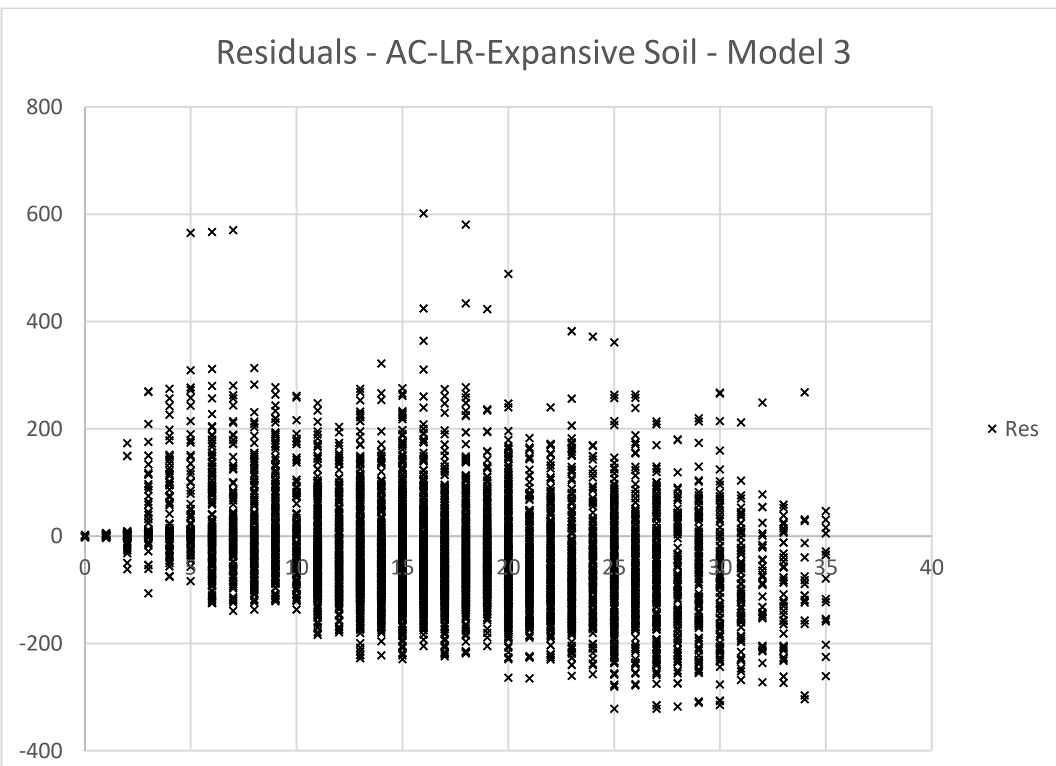

Figure N10 Residuals AC-LR – Model 3 (Selected)

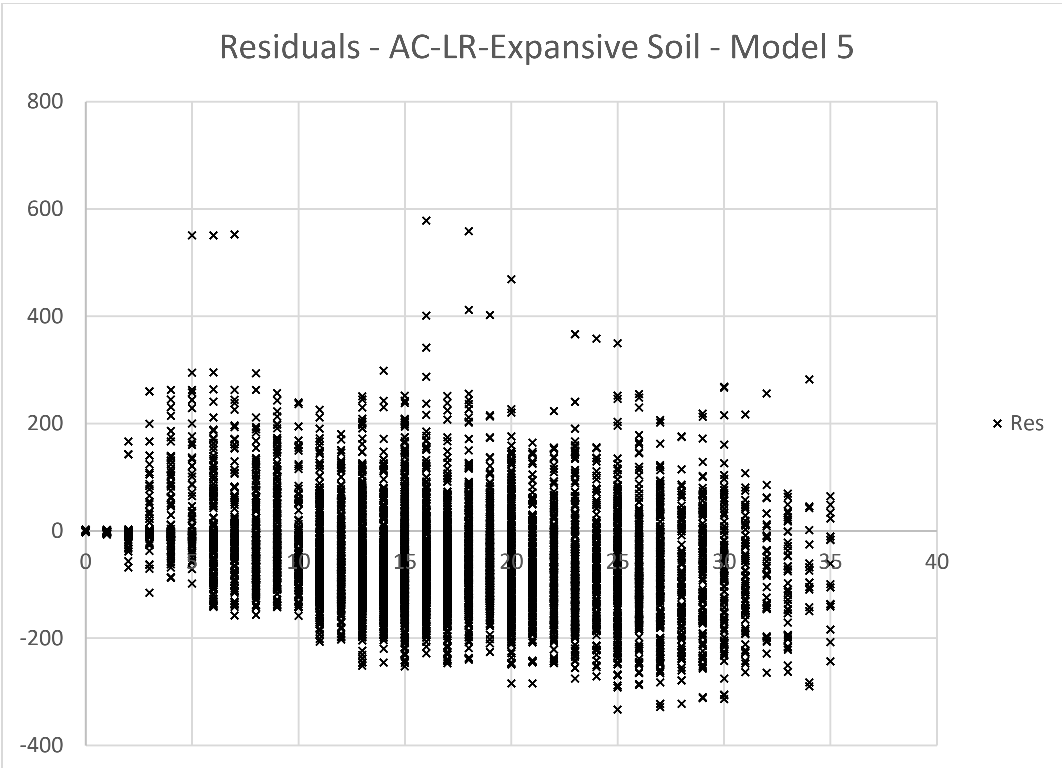

Figure N11 Residuals AC-LR – Model 5

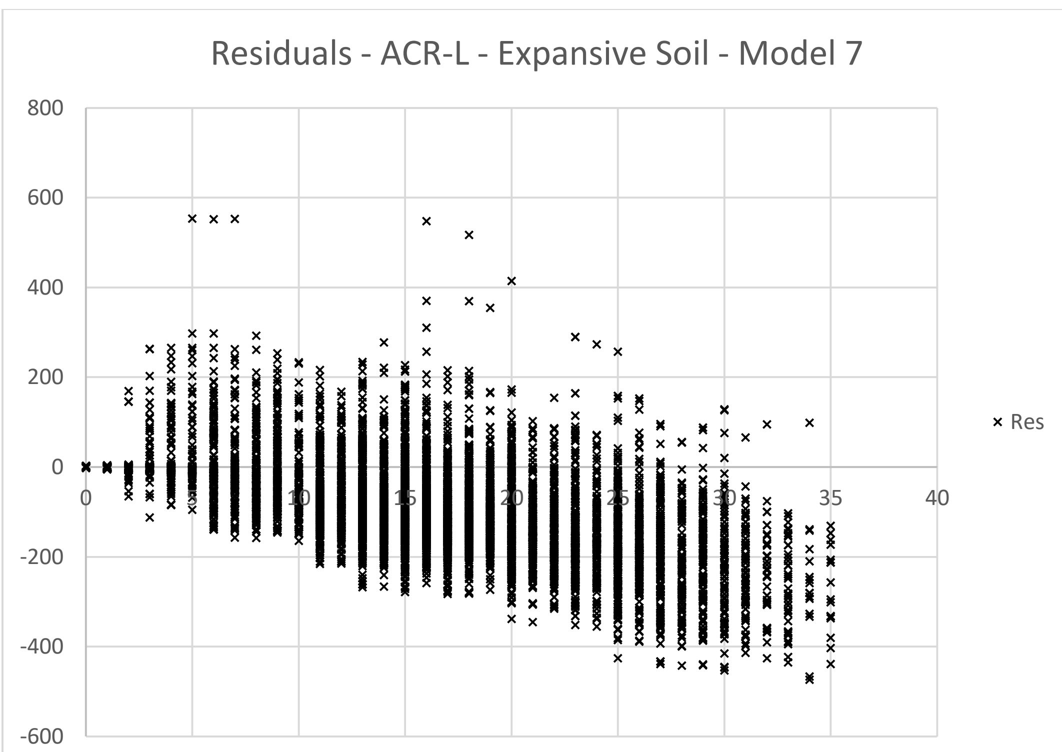

Figure N12 Residuals AC-LR – Model 6

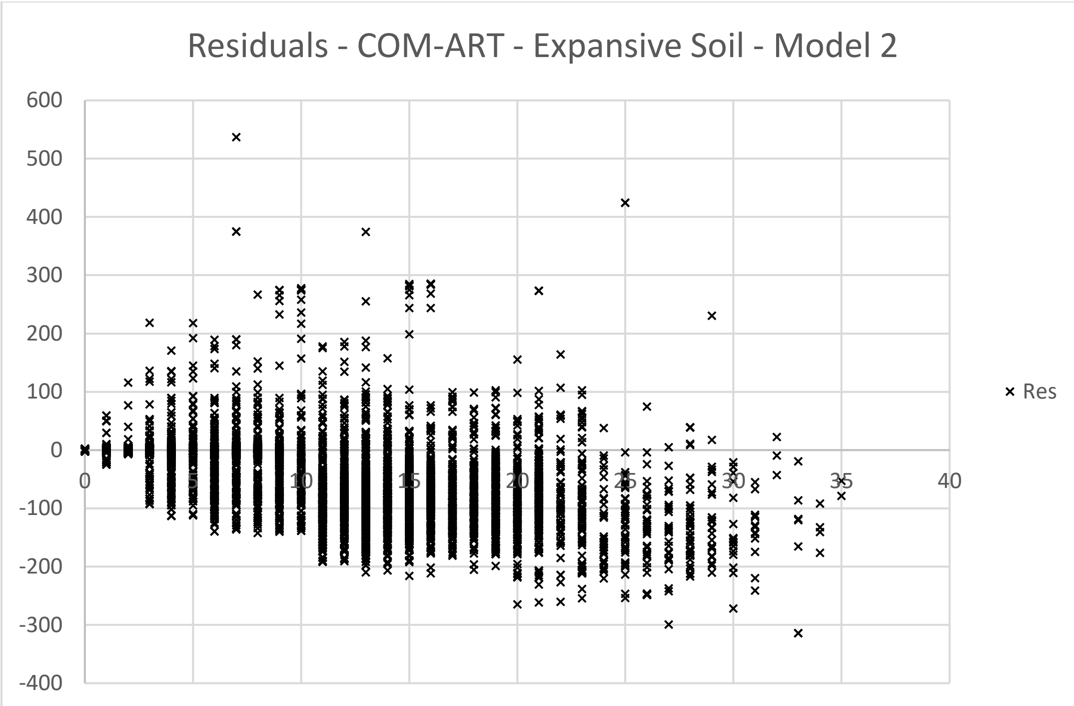

Figure N13 Residuals COM-ART – Model 2

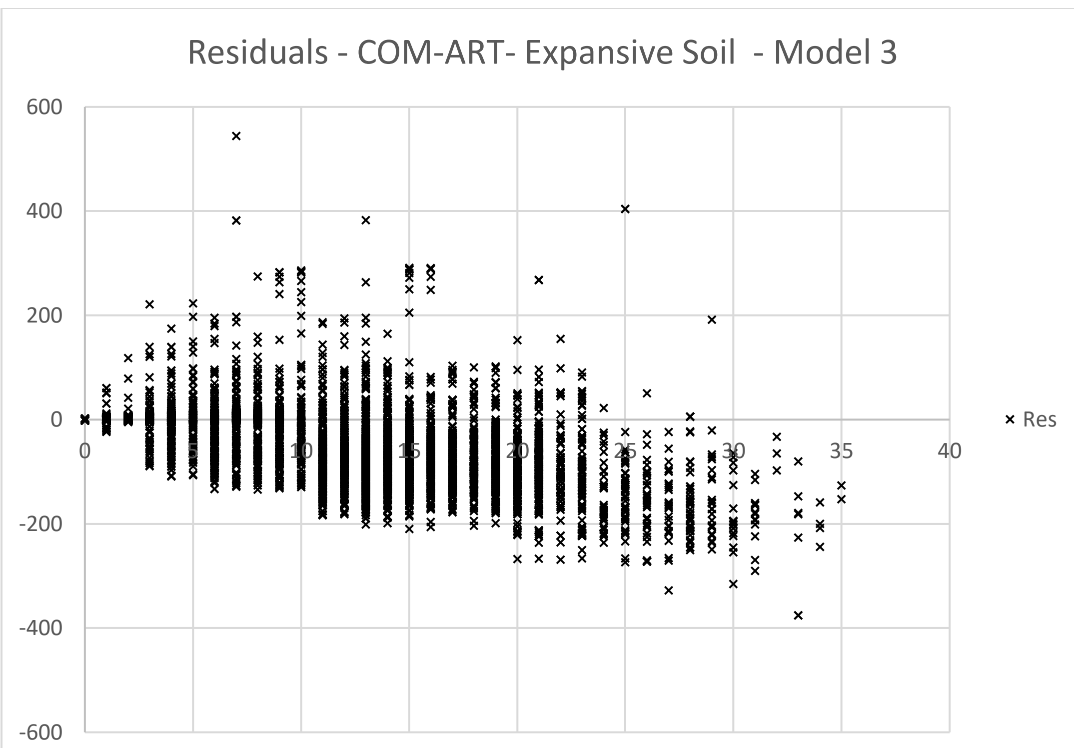

Figure N14 Residuals COM-ART – Model 3 (Selected)

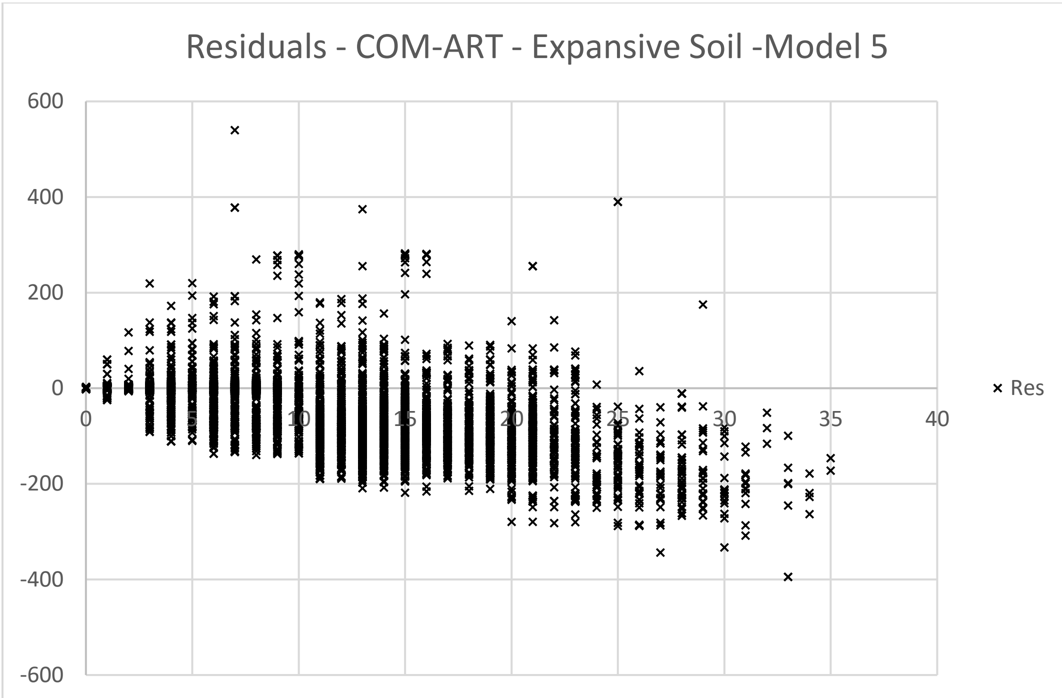

Figure N15 Residuals COM-ART – Model 5

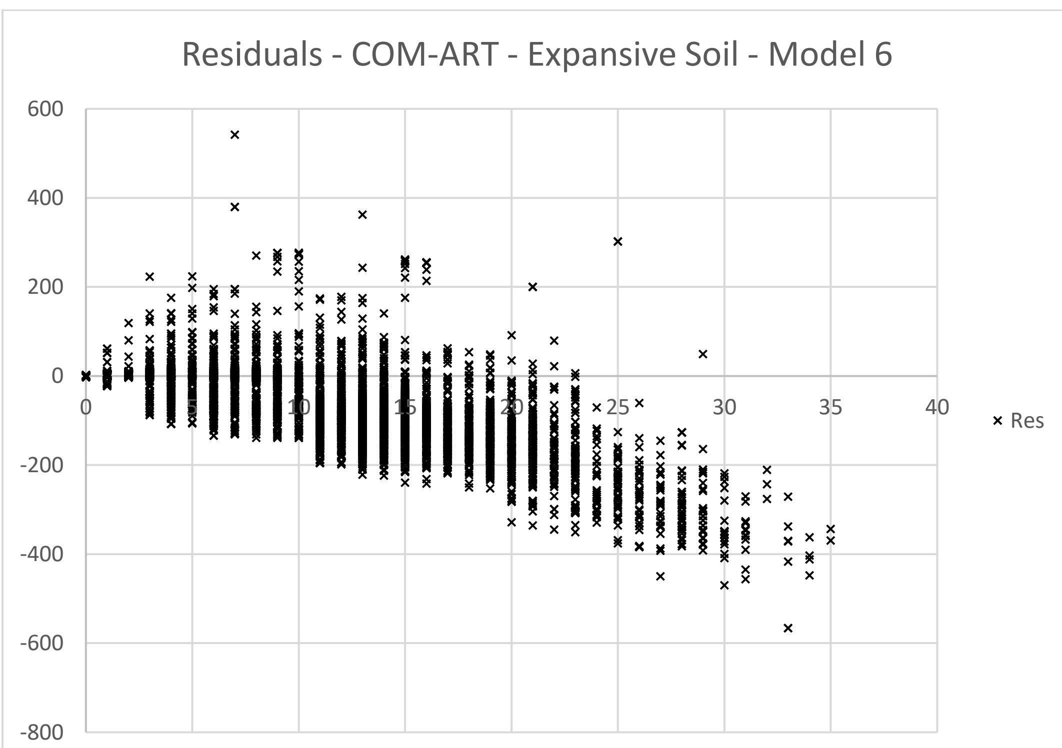

Figure N16 Residuals COM-ART – Model 6

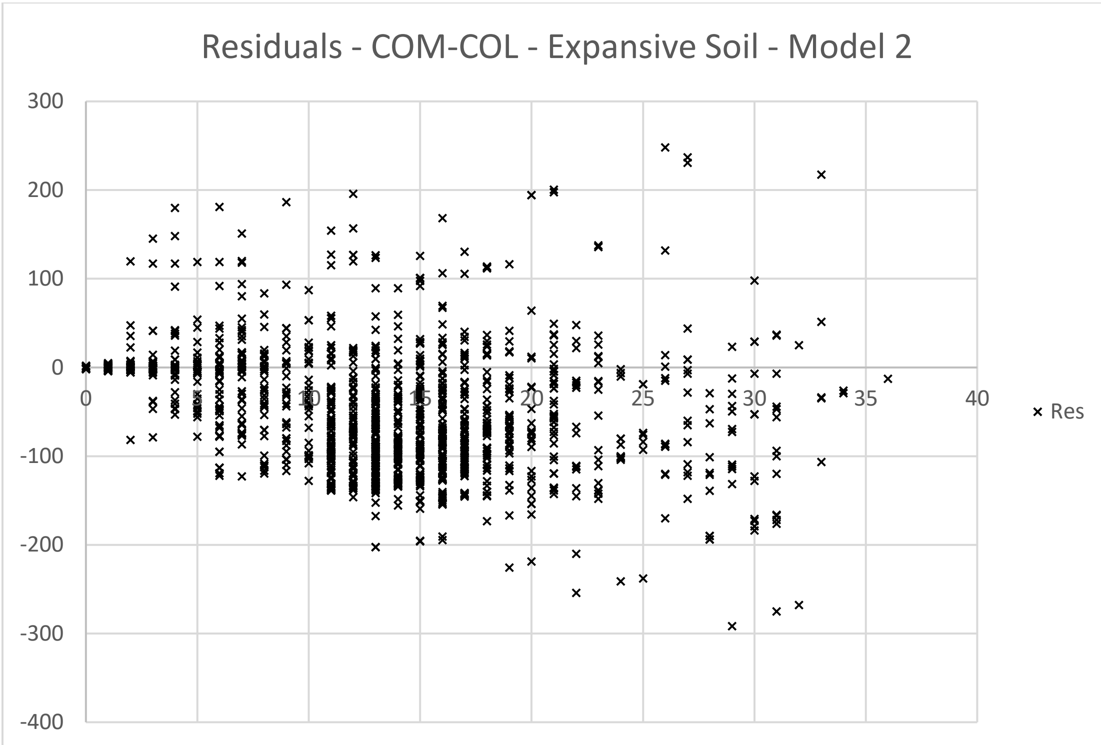

Figure N17 Residuals COM-COL – Model 2

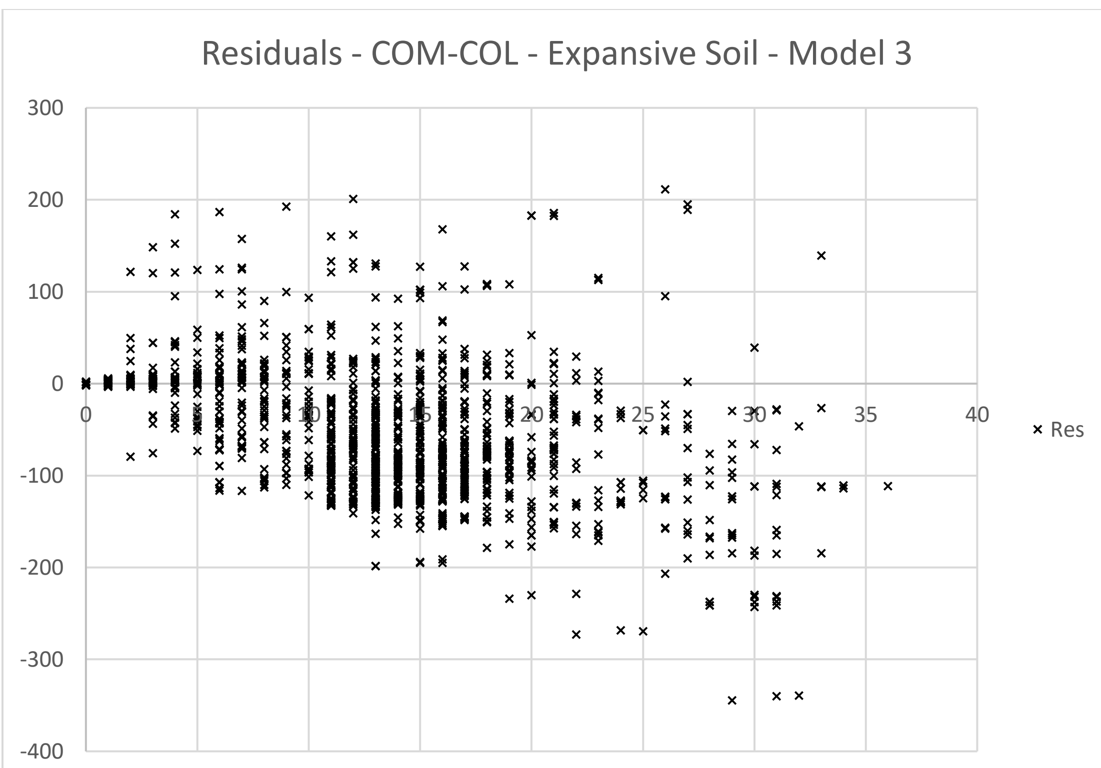

Figure N18 Residuals COM-COL – Model 3 (Selected)

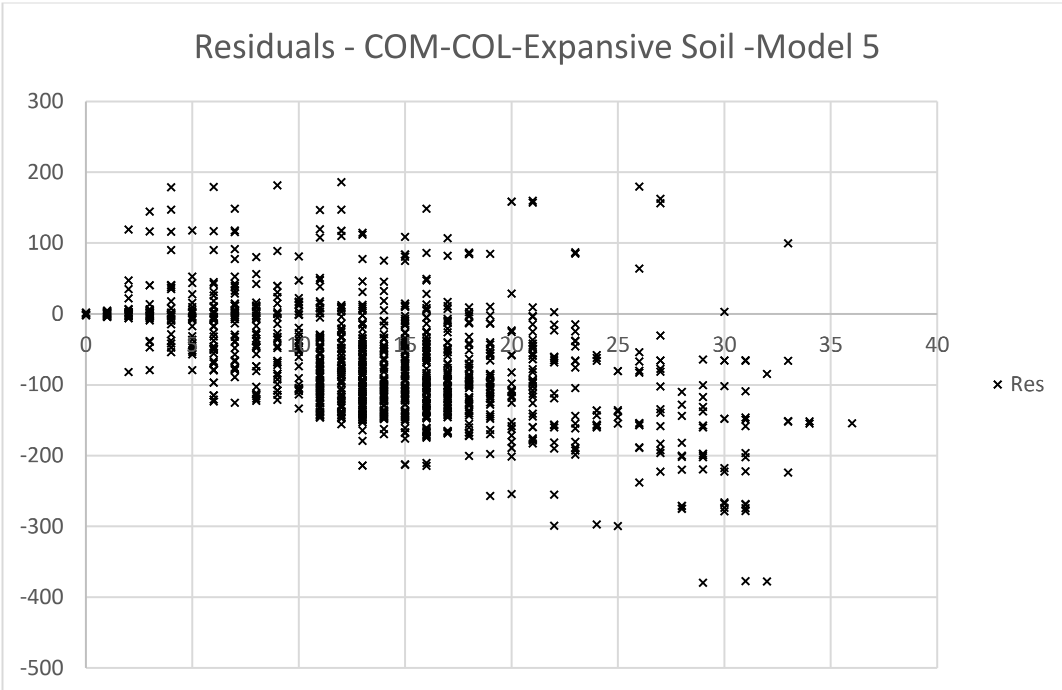

Figure N19 Residuals COM-COL – Model 5

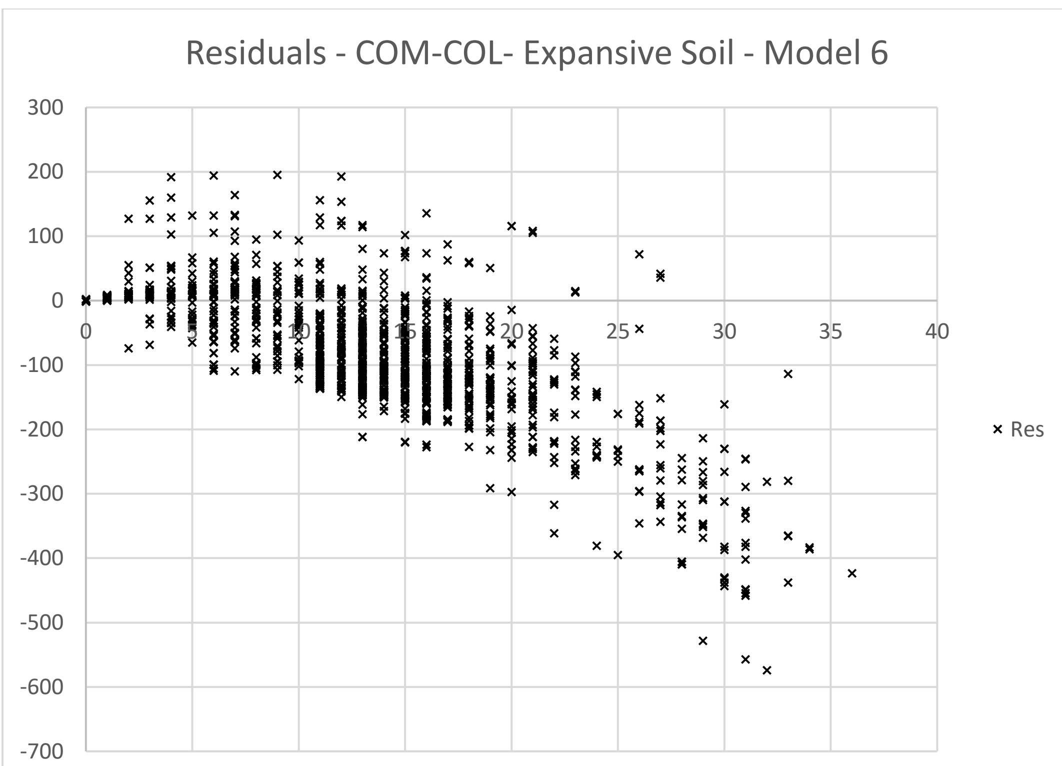

Figure N20 Residuals COM-COL – Model 6

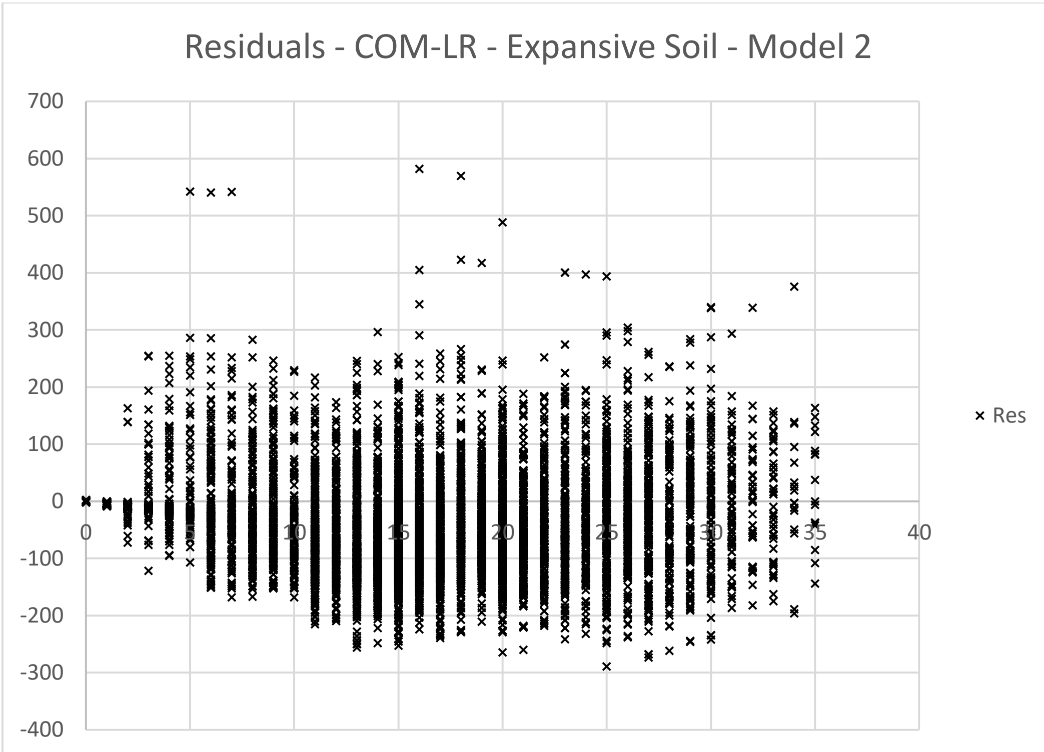

Figure N21 Residuals COM-LR – Model 2

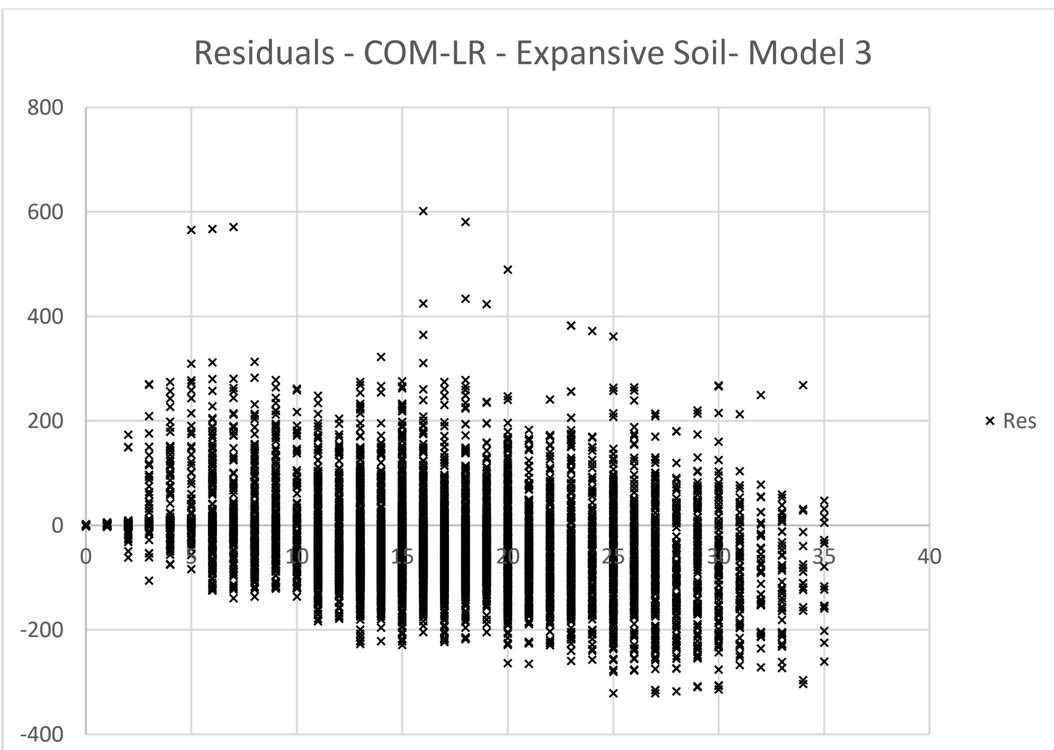

Figure N22 Residuals COM-LR – Model 3 (Selected)

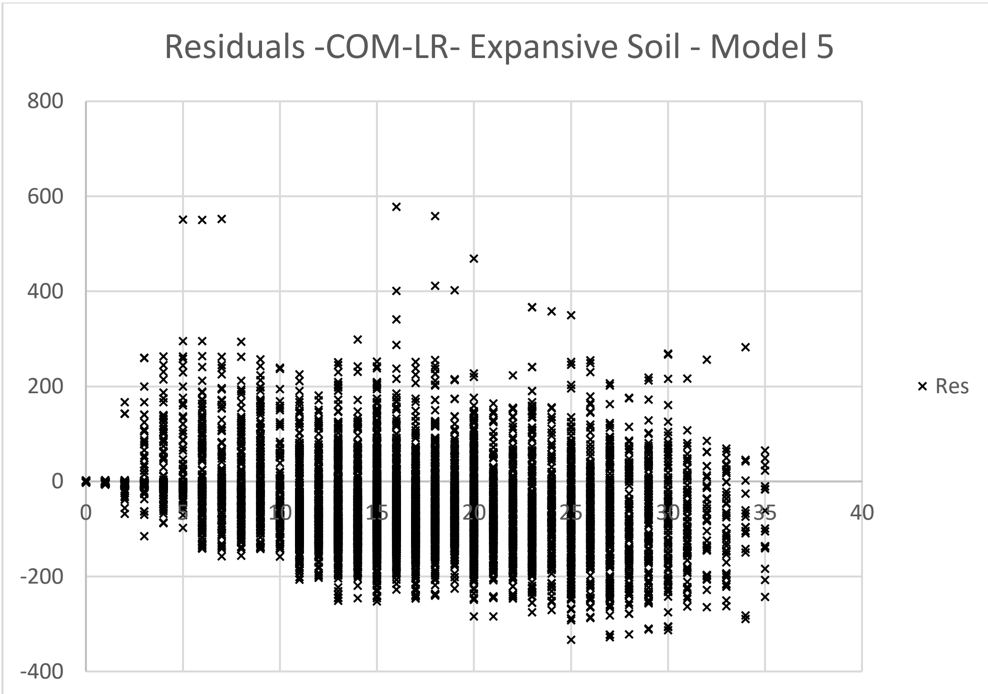

Figure N23 Residuals COM-LR – Model 5

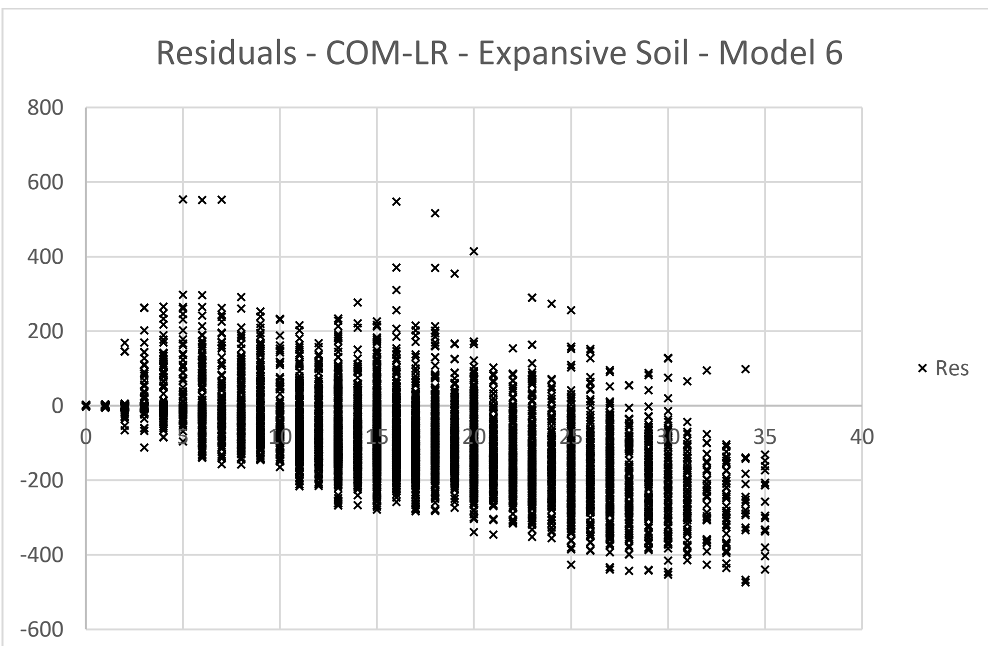

Figure N24 Residuals COM-LR – Model 6

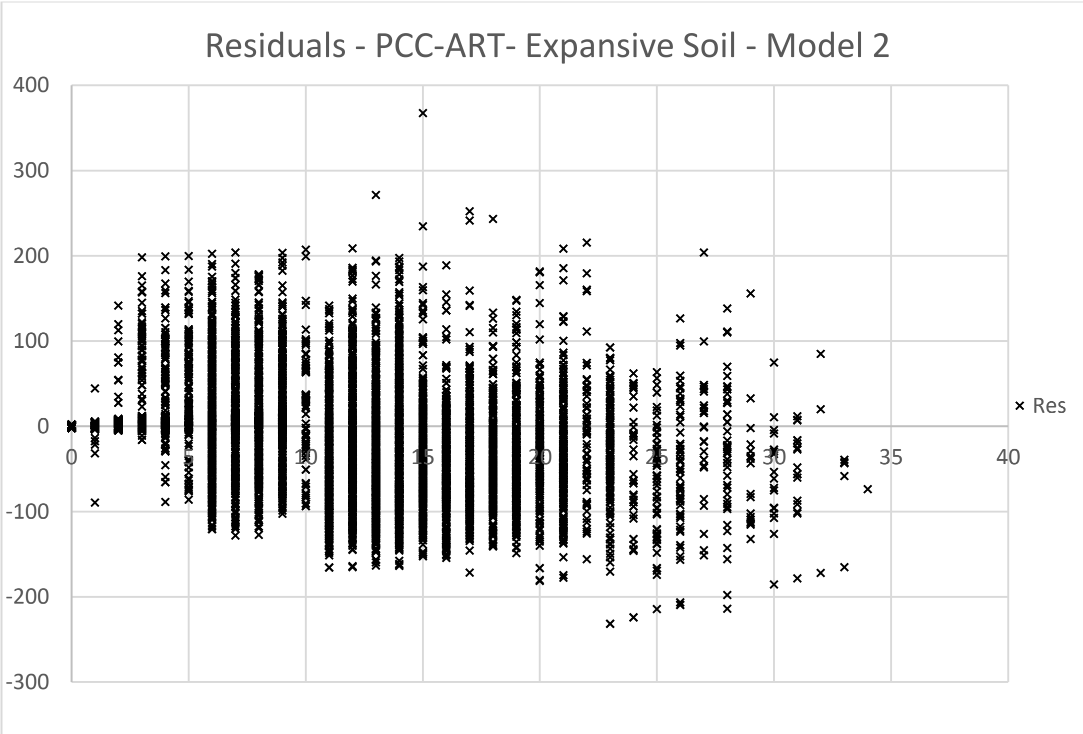

Figure N25 Residuals PCC-ART – Model 2

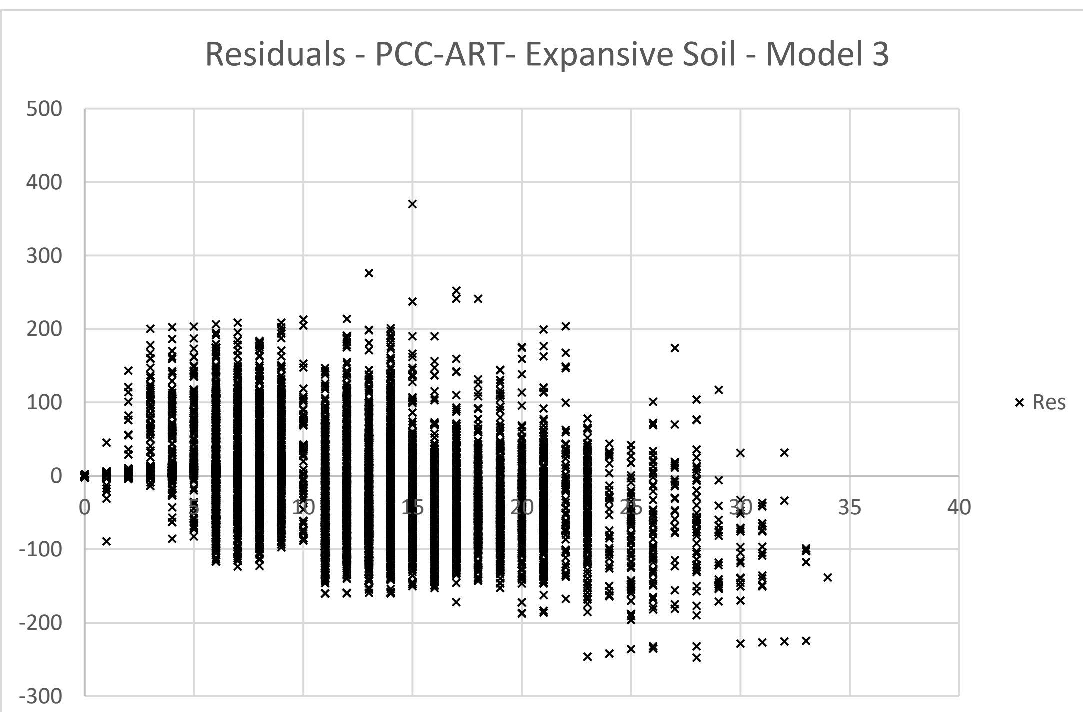

Figure N26 Residuals PCC-ART – Model 3 (Selected)

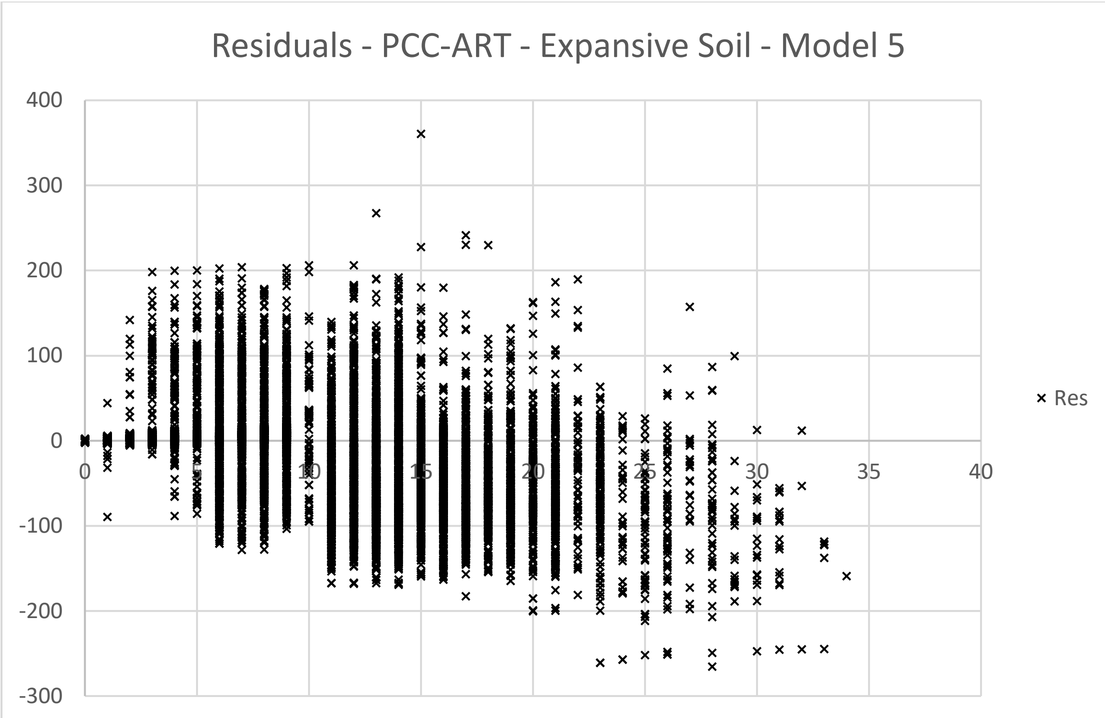

Figure N27 Residuals PCC-ART – Model 5

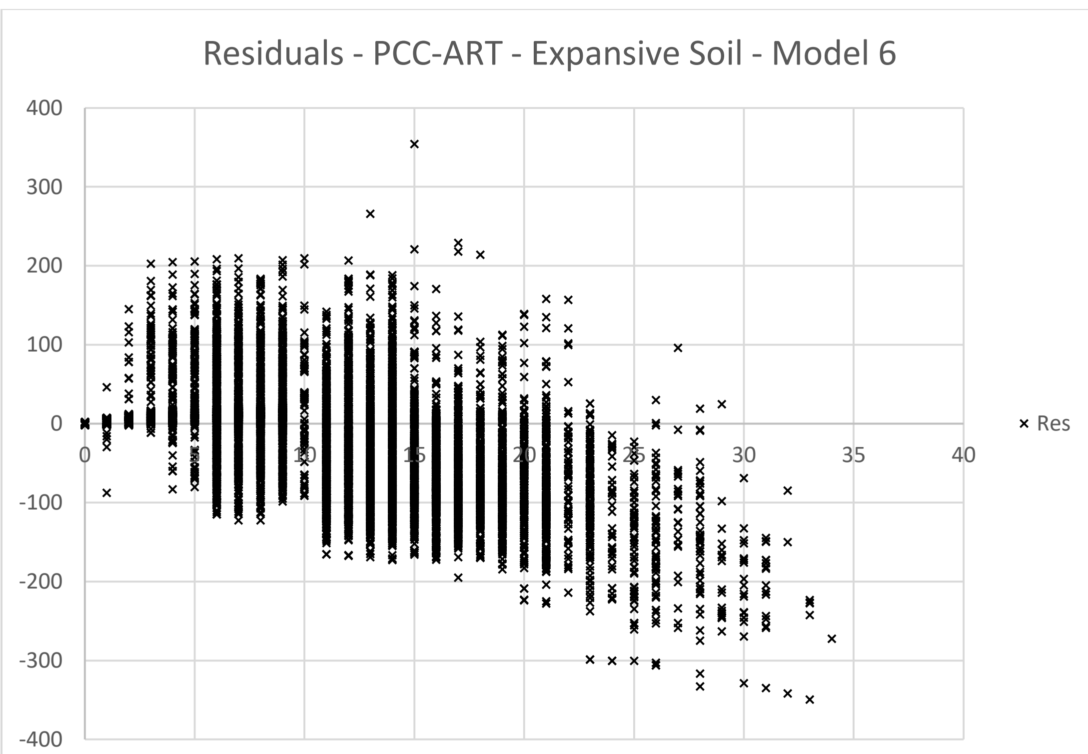

Figure N28 Residuals PCC-ART – Model 6

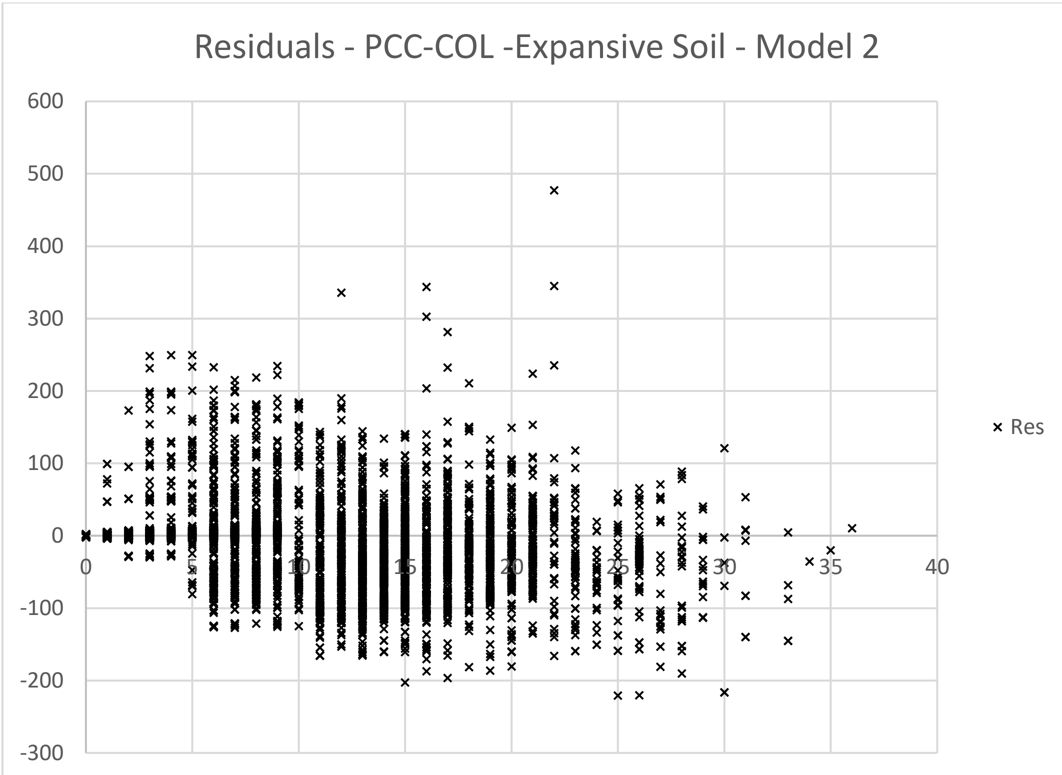

Figure N29 Residuals PCC-COL – Model 2

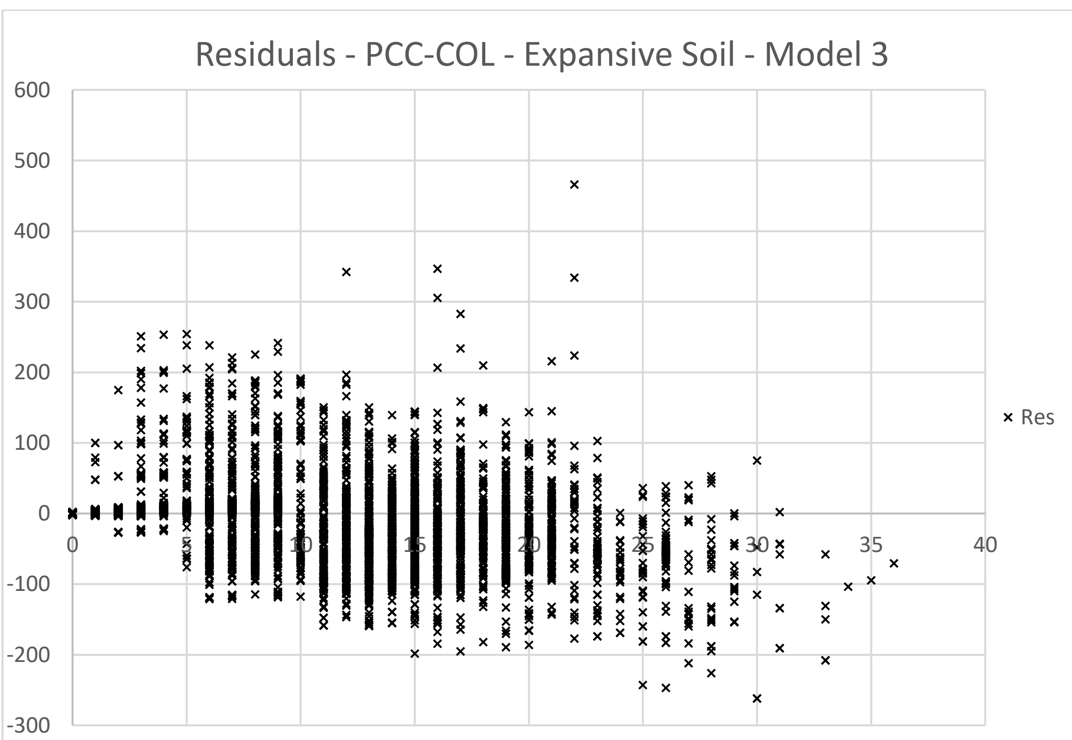

Figure N30 Residuals PCC-COL – Model 3 (Selected)

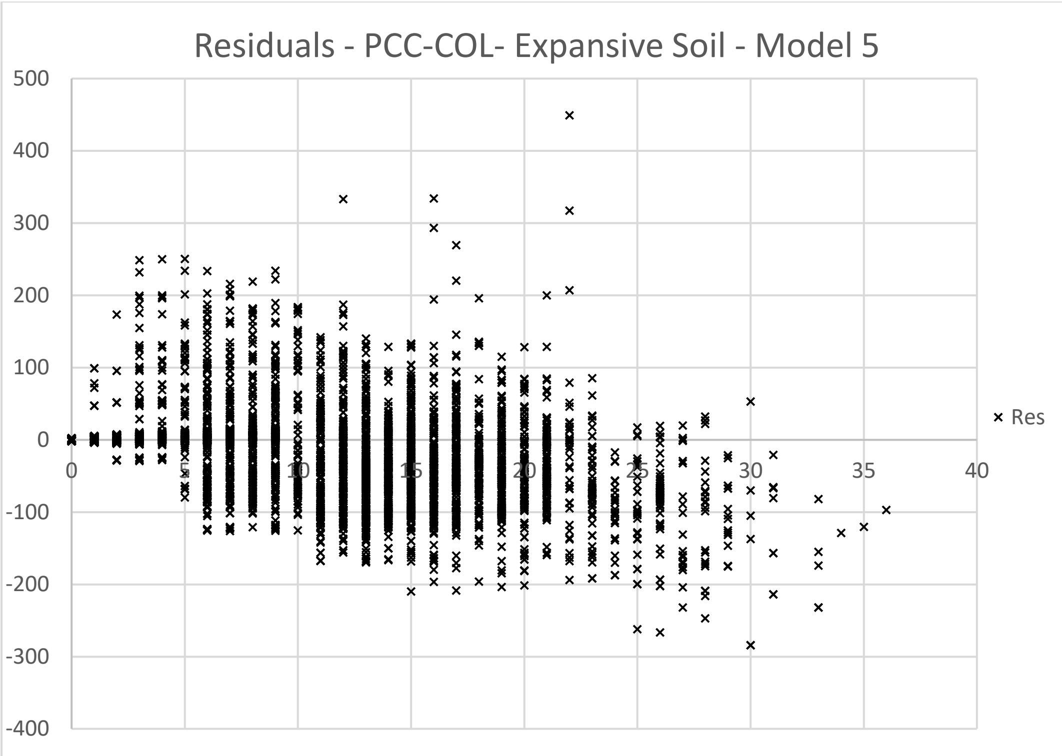

Figure N31 Residuals PCC-COL – Model 5

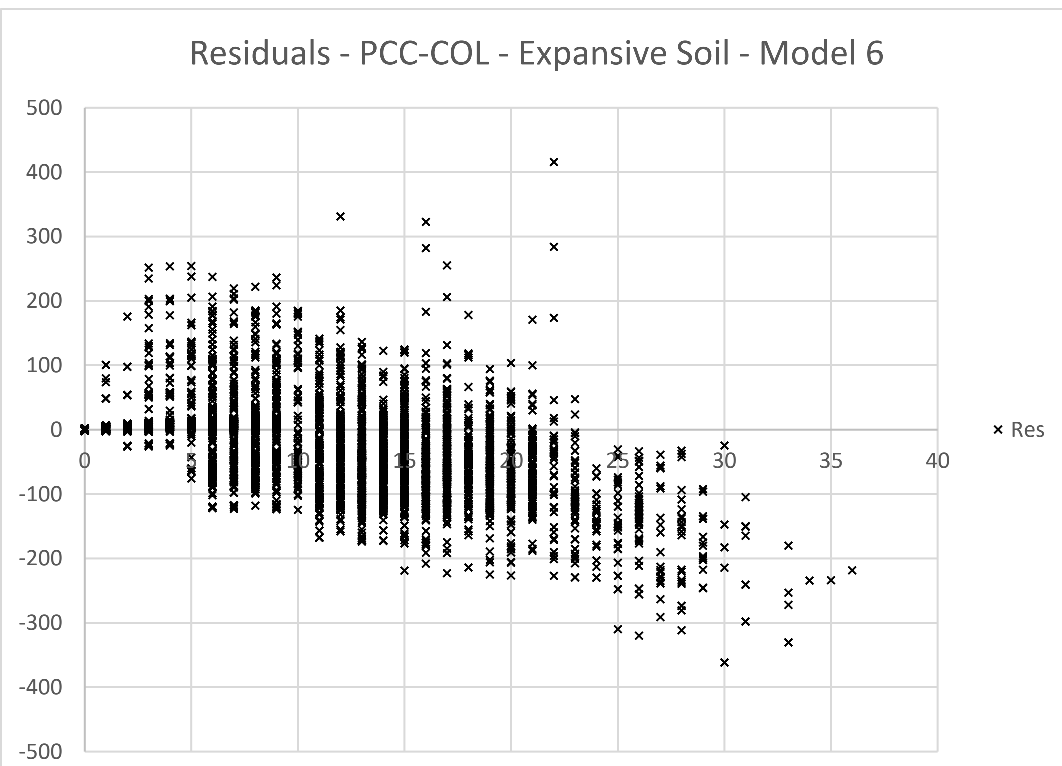

Figure N32 Residuals PCC-COL – Model 6

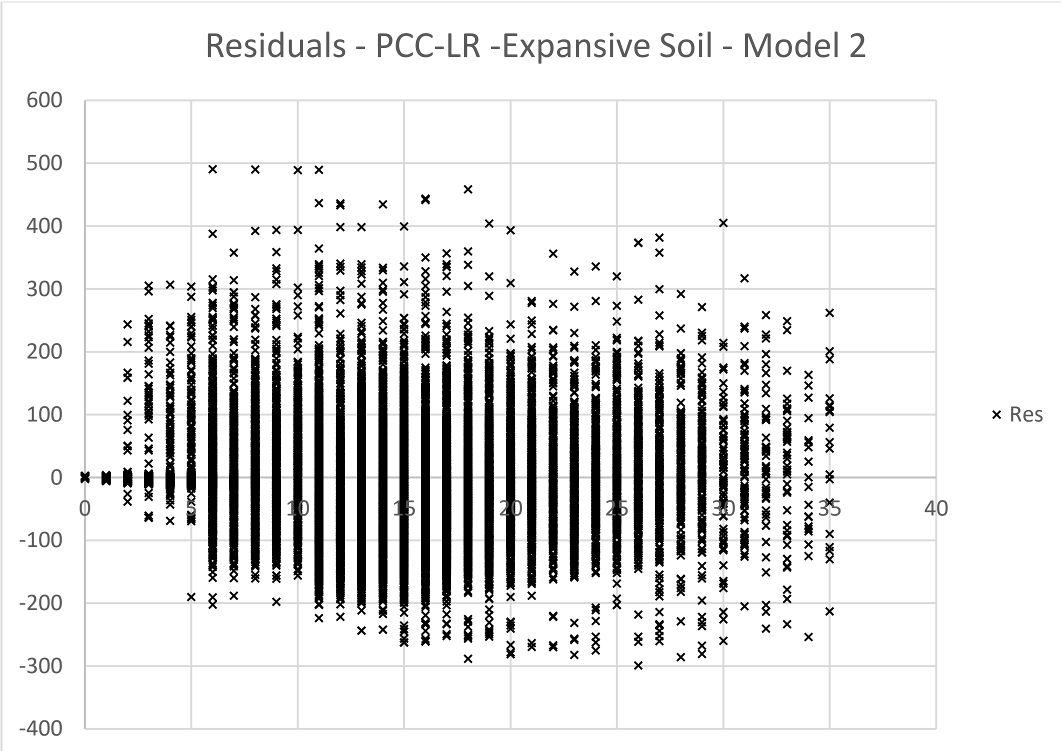

Figure N33 Residuals PCC-LR – Model 2

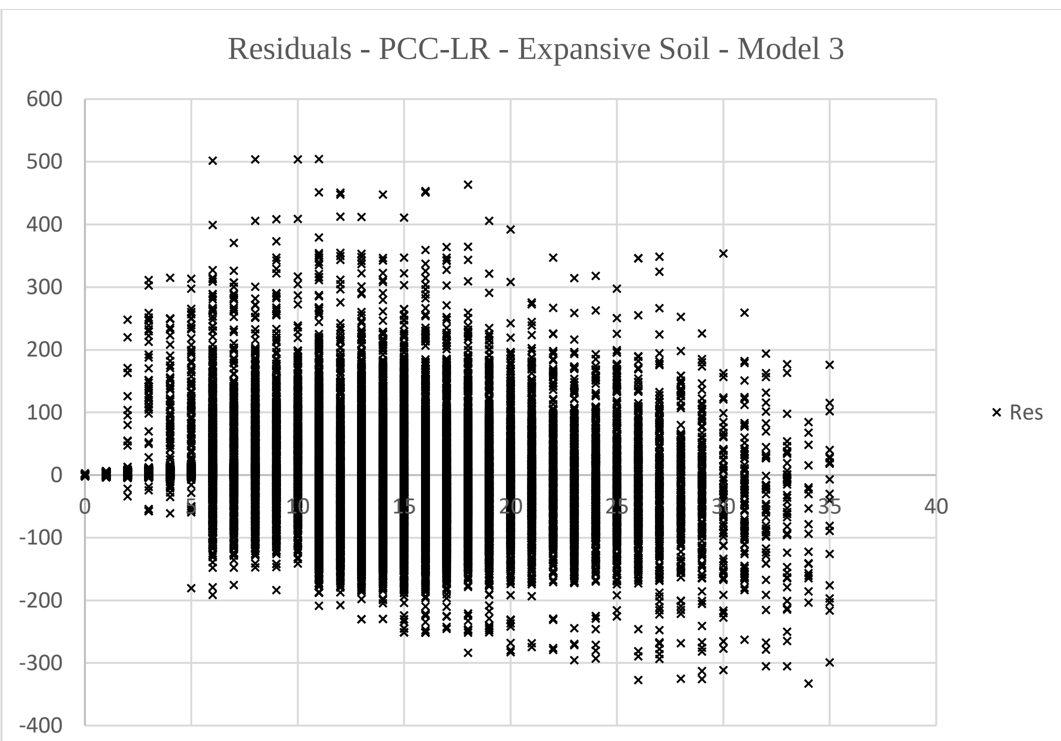

Figure N34 Residuals PCC-LR – Model 3 (Selected)

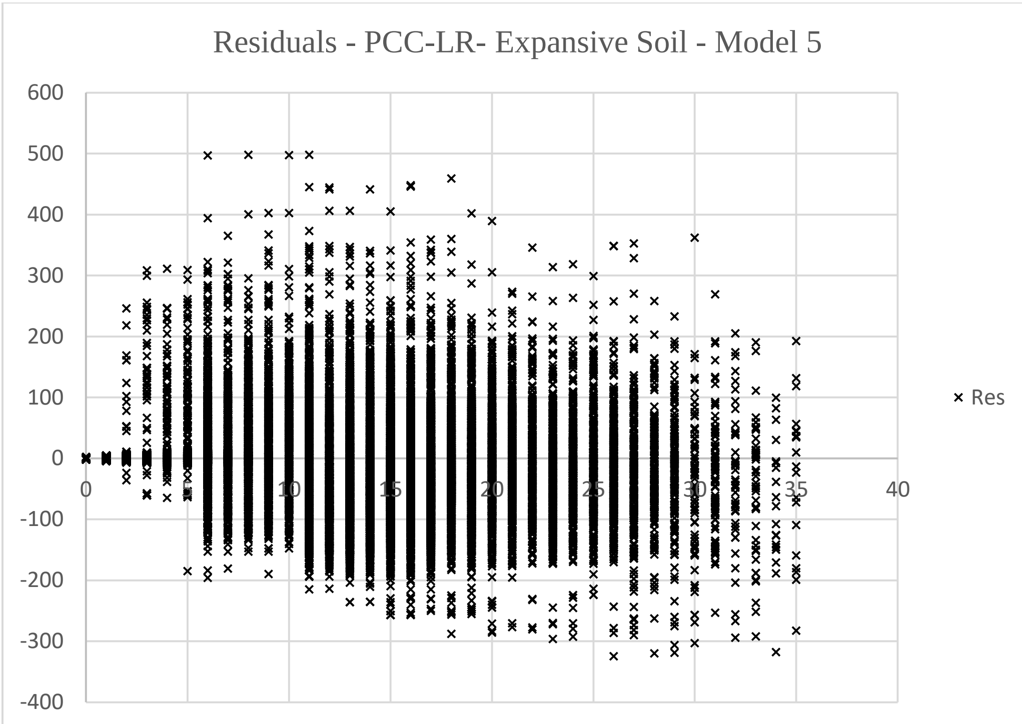

Figure N35 Residuals PCC-LR – Model 5

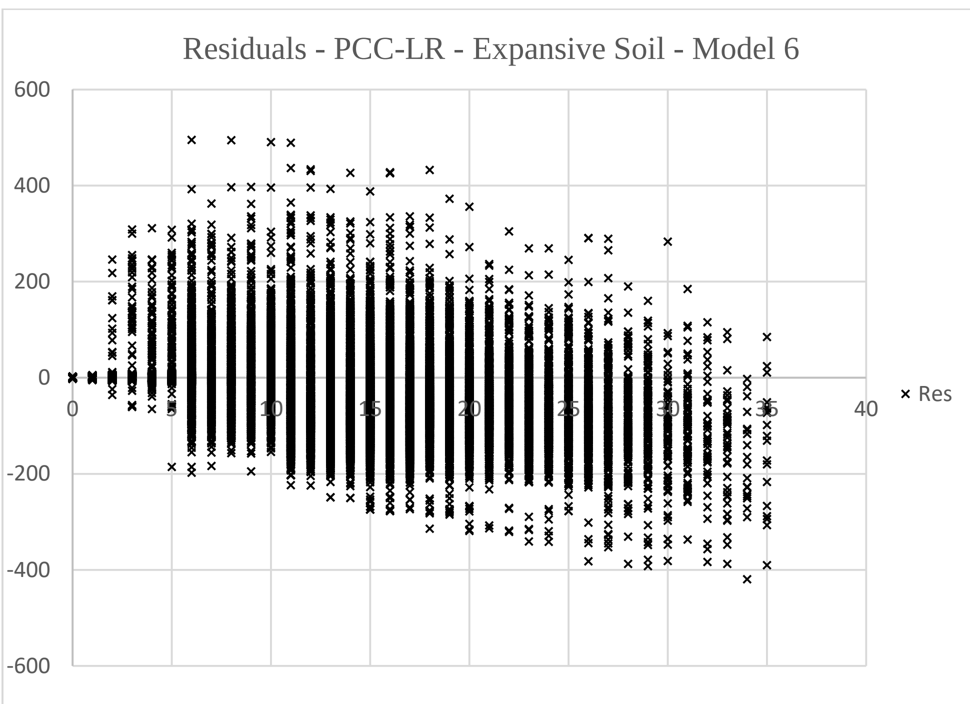

Figure N36 Residuals PCC-LR – Model 6