DEVELOPMENT OF A SOIL CLASSIFICATION SCHEME FOR FINE-GRAINED SOILS BASED ON THEIR RESILIENT PROPERTIES

by

STEVE VALDEZ PAHNO

(Under the Direction of SUNG-HEE ‘SONNY’ KIM)

ABSTRACT

A soil classification scheme for fine-grained subgrade soils was developed using resilient modulus data extracted from the Long-Term Pavement Performance (LTPP) database. This classification scheme categorizes soils based on resilient properties defined in this study. By employing the rpart library in an R programming environment, a decision tree model with a good correlation was developed between resilient modulus test data and various soil index properties. Based on a statistical analysis of the decision tree output, clearly defined ranges for poor, fair, and stiff resilient properties based on average resilient modulus values were established for the purpose of creating three soil classes. These newly defined soil classes provide engineers with a valuable tool for determining the suitability of fine-grained soils in subgrade construction for pavement structures designed using the Mechanistic-Empirical Pavement Design Guide (MEPDG). This classification scheme aims to align the current pavement design method from the American Association of State Highway and Transportation Officials (AASHTO) with the properties of fine-grained soils that influence their resilient behavior under repeated traffic loadings. In addition, the resilient modulus-based scheme can aid engineers in identifying problematic soils, so that testing resources and remediation efforts can be effectively directed to improve the capacity of the pavement to support the overlying pavement structure and design traffic.

INDEX WORDS: Soil Classification, Fine-Grained Soils, Subgrade Soils, Resilient Modulus, Decision Tree Model, Machine Learning, *rpart*

DEVELOPMENT OF A SOIL CLASSIFICATION SCHEME FOR FINE-GRAINED SOILS BASED ON THEIR RESILIENT PROPERTIES

By

STEVE VALDEZ PAHNO

B.C.E, Georgia Institute of Technology, Atlanta, Georgia 1984

M.S., Georgia State University, Atlanta, Georgia 2004

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2024

DEVELOPMENT OF A SOIL CLASSIFICATION SCHEME FOR FINE-GRAINED SOILS BASED ON THEIR RESILIENT PROPERTIES

by

STEVE VALDEZ PAHNO

Major Professor: S. Sonny Kim
Committee: Stephan Durham
Mi Geum Chorzepa
Ernest (Bill) Tollner
Jidong Yang

Electronic Version Approved:
Ron Walcott
Dean of the Graduate School
The University of Georgia
December 2024

DEDICATION

This dissertation is dedicated to my parents, John Valdez, George Pahno, and Constantia Pahno, for their love and support, which I appreciate more with each passing day.

ACKNOWLEDGEMENTS

First of all, I would like to thank Dr. Sonny Kim for the opportunity and freedom to research this topic, which was of great interest to me; I am very grateful to Dr. Stephan Durham, Dr. Bill Tollner, and Dr. Mi Geum Chorzepa for serving on my committee and for adding to my engineering education through their wisdom and classroom lectures. I am especially grateful to Dr. Jidong Yang, who was also a member of my committee, for teaching me and spending many hours with me inside and outside of the classroom to aid me in understanding machine learning and the R programming language, which played a significant part of my research.

I am also grateful to Dr. John Morelock and Dr. Kyle Johnsen for their support and guidance during my fellowship year.

I would like to thank my former bosses, Rick Deaver, Bill Webb, Warren Bailey, Thomas Scruggs, and A.J. Jubran, for teaching me to be a better researcher, geotechnical engineer, and pavement engineer.

In addition, I would like to thank my family and friends for their support and patience during my doctoral studies and in all the other times when I needed them.

Finally, I would like to thank Ann Marie Hormeku and Margaret Sapp for taking care of all their graduate students, including me.

TABLE OF CONTENTS

Page

ACKNOWLEDGEMENTS V

TABLE OF FIGURES X

TABLE OF TABLES XIV

CHAPTER 1: INTRODUCTION 1

1.1: Background 2

1.2: Problem statement 3

1.3: Research objectives 4

1.4: Significance of the study 4

1.5: Organizations of the remainder of the study 5

CHAPTER 2: LITERATURE REVIEW 6

2.1: Current soil classification systems 6

2.2: Subgrade Construction 9

2.3: Subgrade resilient modulus 10

2.4: Factors influencing resilient modulus 12

2.5: Behavior of fine-grained soils under traffic loading 14

2.6: Correlations for estimating resilient modulus 15

CHAPTER 3: METHODOLOGY 22

3.1: Decision Tree Algorithm 22

3.2: The Long-Term Pavement Performance Program 26

3.3: The Pavement Performance Database 28

3.4: Software tools for data analysis 33

3.5: Assumptions and limitations 37

3.6: Summary 38

CHAPTER 4: STATISTICAL EXPLORATION OF THE LTPP DATA 39

4.1: Fine-grained Soil Criterion 39

4.2: LTPP Protocol P-46 42

4.3: Development of the Base Dataset 45

4.4: Data Cleaning and Review 57

4.5: Plots for Fine-Grained Subgrade Soils in the Base Dataset 58

4.6: Summary 73

CHAPTER 5: DEVELOPMENT OF SOIL CLASSIFICATION SCHEME 74

5.1: Model development procedure 75

5.2: Model for all fine-grained subgrade soils and all stress conditions 76

5.3: Summary 95

CHAPTER 6: CONCLUSIONS 97

6.1: The LTPP database 98

6.2: About the behavior of resilient modulus of fine-grained soils 99

6.3: About the decision tree model and proposed soil classification scheme 100

CHAPTER 7: RECOMMENDATIONS 101

7.1: Recommendations for future research 101

7.2: Recommendations for future practice 101

REFERENCES 102

APPENDIX A 108

APPENDIX B 112

APPENDIX C **123**

APPENDIX D **134**

APPENDIX E **145**

TABLE OF FIGURES

Page

Figure 3-1: Decision tree example ... 25

Figure 3-2: AASHTO M-145 for non-granular soils in a decision tree format ... 26

Figure 3-3: LTPP test sites with fine-grained subgrade soils ... 29

Figure 4-1: Distribution of specimens in the raw dataset by cap height ... 50

Figure 4-2: Distribution of specimens in the raw dataset by mold diameter ... 50

Figure 4-3: Granular and non-granular specimens by AASHTO soil class ... 50

Figure 4-4: Granular and non-granular specimens by initial specimen length ... 50

Figure 4-8: Number of fine-grained specimens by cap height ... 57

Figure 4-9: Number of fine-grained specimens by diameter ... 57

Figure 4-10: Number of fine-grained specimens by specimen length ... 58

Figure 4-11: Distribution of FG specimens by AASHTO soil class ... 59

Figure 4-12: MR ranges by AASHTO soil classes (FG soils) ... 59

Figure 4-13: Deviator stress by AASHTO class for FG soils ... 60

Figure 4-14: Strain by AASHTO class for FG soils ... 60

Figure 4-15: Maximum dry density by AASHTO class for FG soils ... 61

Figure 4-16: Optimum moisture content by AASHTO classes for FG soils ... 61

Figure 4-17: M_R vs Initial Diameters ... 62

Figure 4-18: M_R vs Initial Lengths ... 62

Figure 4-19: M_R vs Strain ... 63

Figure 4-20: M_R vs Deviator Stress 63

Figure 4-21: M_R vs confining stress 64

Figure 4-22: M_R vs Octahedral Stress 64

Figure 4-23: M_R vs OMC 65

Figure 4-24: M_R vs OMC.RATIO2 65

Figure 4-25: M_R vs MDD 66

Figure 4-26: M_R vs Compaction 66

Figure 4-27: M_R by PI 67

Figure 4-28: M_R by LL 67

Figure 4-29: M_R by PL 68

Figure 4-30: M_R by P3d8 68

Figure 4-31: M_R by PN4 69

Figure 4-32: M_R by PN10 69

Figure 4-33: M_R by PN80 70

Figure 4-34: M_R by PN200 70

Figure 4-35: M_R by CLAY 71

Figure 4-36: M_R by SILT 71

Figure 4-37: M_R by cSAND 72

Figure 4-38: M_R by fSAND 72

Figure 5-1: Unpruned decision tree model 80

Figure 5-2: Cross-validation error versus cost complexity factor 81

Figure 5-3: R^2 versus number of theoretical splits in the decision tree model 81

Figure 5-4: Pruned decision tree regression model. 82

Figure 5-5: Ranking of most important features ... 83

Figure 5-6: Plot of estimated versus observed MR using testing data ... 84

Figure 5-7: M_R ranges for M classes (testing dataset) ... 90

Figure 5-8: M_R ranges for AASHTO soil classes (testing dataset) ... 94

Figure A-1: Anaconda Navigator layout ... 111

Figure A-2: Jupyter Notebook screenshot ... 111

Figure B-9: T-test for MR of non-granular soils versus use of caps ... 113

Figure B-10: M_R versus use of test caps ... 114

Figure B-11: T-test for Maximum dry density of non-granular soils versus use of caps ... 115

Figure B-12: Maximum dry density versus use of caps ... 116

Figure B-13: T-test for compaction of non-granular soils versus use of caps ... 117

Figure B-14: Compaction versus use of test caps ... 118

Figure B-15: T-test for labOMC of non-granular soils versus use of caps ... 119

Figure B-16: Optimum moisture content versus use of caps ... 120

Figure B-17: T-test for OMC.RATIO2 of non-granular soils versus use of caps ... 121

Figure B-18: Optimum moisture content ratios versus use of test caps ... 122

Figure C-19: T-test for the M_R of the non-granular soil fractions ... 124

Figure C-20: M_R versus soil fractions ... 125

Figure C-21: T-test for labMDD of non-granular soil fractions tested without caps ... 126

Figure C-22: labMDD versus non-granular soil fractions ... 127

Figure C-23: T-test for compaction of non-granular soils tested without caps ... 128

Figure C-24: Compaction of non-granular soil fractions tested versus use of caps ... 129

Figure C-25: T-test for labOMC of non-granular soil fractions tested without caps ... 130

Figure C-26: Optimum moisture contents versus non-granular soil fractions 131

Figure C-27: T-test for OMC.RATIO2 of non-granular soil fractions versus use of caps 132

Figure C-28: Optimum moisture content ratios versus non-granular soil fractions 133

Figure D-29: T-test for M_R of the fine-grained soil fraction versus use of caps 135

Figure D-30: M_R of the fine-grained soil fraction versus use of caps 136

Figure D-31: T-test for labMDD of fine-grained versus use of caps 137

Figure D-32: labMDD based on the fine-grained soil fraction versus the use of caps 138

Figure D-33: T-test for compaction of the fine-grained fraction versus use of caps 139

Figure D-34: Compaction of the fine-grained soil fraction versus use of caps 140

Figure D-35: T-test for labOMC of the fine-grained soil fraction versus use of caps 141

Figure D-36: OMC of FGF versus the use of caps 142

Figure D-37: T-test for OMC.RATIO2 of the fine-grained soil fraction versus use of caps 143

Figure D-38: OMC ratios of the fine-grained soil fraction versus use of caps 144

TABLE OF TABLES

Page

Table 2-1: Examples of pavement structures 10

Table 3-1: AASHTO group classification scheme for silt-clay materials 25

Table 3-2: Fine-grained subgrade soils in the base dataset 30

Table 3-3: LTPP data tables with data of interest 32

Table 4-1: P-46 M_R laboratory testing sequence 44

Table 4-2: Initial potential list of features (variables) from the base dataset 47

Table 4-3: Calculated features 48

Table 4-5: T-test summary for all non-granular subgrade soils with and without caps 54

Table 4-6: T-test summary for non-granular fractions without caps 55

Table 4-7: T-test summary for FGF subgrade soils with and without caps 56

Table 5-1: Summary statistics on M_R for the no-capped specimens of fine-grained soils ... 77

Table 5-2: MR resilient quality (RQ) levels and M classes for fine-grained soils 85

Table 5-3: Leaf node statistics using the training dataset 88

Table 5-4: M_R statistics for M classes from training dataset 89

Table 5-5: M_R statistics for M classes from testing dataset 90

Table 5-6: One-way ANOVA for M classes 91

Table 5-7: Tukey results on proposed M classes 92

Table 5-8: M_R statistics for fine-grained specimens (testing dataset) 93

Table 5-9: Classification scheme for fine-grained soils with silt content ≥ 41% 95

Table 5-10: Classification scheme for fine-grained soils with silt content < 41%................ 95

Table A-1: Data tables downloaded from InfoPave website.. 108

Table A-2: Data tables downloaded from InfoPave website.. 109

Table A-3: Data tables downloaded from InfoPave website.. 110

CHAPTER 1: INTRODUCTION

The purpose of soil classification systems is to provide a convenient method for engineers to group soils with common properties that are expected to exhibit similar behaviors when supporting design traffic loads (Reale, Librić, & Jurić-Kaćunić, 2018). These classification systems generally reflect the current state of knowledge about soils and should be upgraded as more knowledge about these materials is gained (Arnold, 2001) (Gerasimova, 2019). Therefore, keeping classification systems static while other innovations, such as the Mechanistic-Empirical Pavement Design Guide (MEPDG), are incorporated into the pavement design practice, hinders the progression of knowledge on subgrade soil behavior. It also fails to support engineers in identifying and understanding the quality and expected behavior of the materials they are tasked with using to construct the subgrade layer that supports the overlying pavement structure.

In the field of pavement design, the resilient modulus (M_R) has become the soil property that represents the behavior of the subgrade soils since the release of the 1986 AASHTO Pavement Design Guide (AASHTO, 1986). The challenge for engineers is that no revisions to the AASHTO soil classification system have been made to assist engineers in identifying the physical properties of soils that reflect their resilient behavior and suitability for use in construction that are consistent with the MEPDG methodology.

Some researchers have taken an approach to develop M_R predictive models by separating data into coarse-grained and fine-grained soil groupings (Smart & Humphrey, 1999) (Kutner, Nachtsheim, Neter, & Li, 2005). The reason is that this segregation produces better results in correlation development (Elias & Titi, 2006). Therefore, this strategy was adopted for the current study with the focus on the more problematic fine-grained soils, which in general have lower M_R values than coarse-grained soils (Elias & Titi, 2006). To accomplish the goal of developing soil classes based on the resilient behavior of fine-grained subgrade soils, the application of a decision tree algorithm was used to demonstrate that a soil classification scheme for fine-grained subgrade soils can be developed that reflect the resilient behavior of these soils using the Long-Term Pavement Performance (LTPP) data. Using the resulting decision tree diagram, different leaf nodes with similar average M_R values were grouped together to form proposed soils classes. It will be demonstrated that the grouping process is flexible and can produce useful results supportable with traditional statistical techniques.

1.1: Background

Since the release of the 1986 AASHTO Pavement Design Guide, the American Association of State Highway and Transportation Officials has replaced the soil support value (SSV) parameter with the resilient modulus (AASHTO, 1986). The resilient modulus has been promoted as a property that more accurately represents the response of the subgrade soil to traffic loadings. The SSV was a concept that was developed to allow state agencies to apply the results of the American Association of State Highway Officials (AASHO) Road Test for local use (AASHTO, 1974). AASHTO recommended that state agencies develop their own correlations to the SSV, using parameters such as the California Bearing Ratio (CBR) and even resilient modulus (M_R), to translate the use of the AASHTO pavement design equation to the states that chose to adopt the design guide (AASHTO, 1974).

The AASHTO and Unified Soil Classification Systems have not been proven to provide a reliable indication of the soil strength or resilience (Thompson & Robnett, 1979) (Webb, 1990).

Therefore, some states developed supplemental materials to aid themselves in identifying soil strength (Webb, 1990).

1.2: Problem statement

Determining how soils will behave is a challenging task as no two soils are alike (Baldwin, Kellogg, & Thorp, 1938). They are formed from the deterioration of igneous, sedimentary, and metamorphic rocks under a variety of natural conditions (Dumbleton, 1968). The decomposition of rock produces a wild range of materials that engineers attempt to group with a limited set of properties, which has led to the many efforts of developing correlation models to estimate subgrade resilient modulus (Puppala, 2008). Researchers have developed models using the soils from their localities by collecting their own soil samples or by utilizing of the LTPP database (Smart & Humphrey, 1999) (Elias and Titi, 2006).

With the inability of the AASHTO and Unified Soil Classification Systems to assess the resilient behavior of subgrade soils, there is a pressing need to address this issue. The continued use of the resilient modulus in the design of pavement structures highlights this need (AASHTO, 2015). Field engineers require tools to aid them in understanding the resilient behavior of fine-grained subgrade materials so that they can determine how to manage these materials on the job site. However, there is a disconnect with the current soil classification systems, as these systems do not support the field engineer in making decisions that ensure quality materials are used in subgrade construction. Consequently, the use of poor-quality subgrade soils can lead to failures in the overlying pavement structure, wasting valuable resources.

Using the freely available LTPP database that contains pavement data collected from test sites across the United States and Canada, a soil classification scheme for fine-grained soils can be developed and converted into a format suitable for construction specification manuals. With an easy-to-understand table as an aid, engineers can identify problem soils and use other guidelines to address the handling of potential problems that are flagged during the design and construction phases of a roadway project.

1.3: Research objectives

The primary objectives of this study were:

(1) To identify a suitable source of resilient modulus test data,

(2) To develop a correlation model for the resilient modulus of fine-grained subgrade soils using the Long-Term Pavement Performance (LTPP) database and a decision tree algorithm, and

(3) To provide a table using the decision tree model results that can be used to a draft soil classification specification that demonstrates the application of the preliminary findings of this study.

1.4: Significance of the study

This research effort is a first step in developing a soil classification system that more accurately represents the resilient properties of subgrade soils used in highway construction. It is only a first step because of the challenge of developing a correlation model for resilient modulus (M_R) for fine-grained and coarse-grained soils. Therefore, the results of this study can only be described of as a scheme and not a complete soil classification system. However, development of a soil classification scheme for fine-grained subgrade soils will serve as an aid to engineers in identifying the more problematic soils and properly directing resources to ensure that the pavement system that will last for its design life.

1.5: Organizations of the remainder of the study

The remaining chapters of this dissertation are divided into the following six (6) chapters to provide sufficient background and information to support the analyses and to satisfy the objectives of this study:

- Chapter 2 supplies a literature review of previous work that supports the premises and methods of this work.
- Chapter 3 presents the methodology and tools used to develop a soil classification scheme for fine-grained soils.
- Chapter 4 describes the LTPP Program and the dataset used in this study.
- Chapter 5 discusses the procedure used to correlate resilient modulus to LTPP data using a decision tree algorithm.
- Chapter 6 provides conclusions based on the analyses and findings of this work.
- Chapter 7 provides the recommendations based on this work.

CHAPTER 2: LITERATURE REVIEW

The subject of determining the resilient modulus for subgrade soils has pre-occupied the minds of many engineers over the years, and it is a challenge that still continues. Although the list of relevant topics regarding this subject could be much longer, the items in the following list were seen as the most important ones in developing the understanding of this researcher:

(1) Current soil classification systems

(2) Subgrade Construction

(3) Subgrade resilient modulus

(4) Factors influencing resilient modulus

(5) Behavior of fine-grained soils under traffic loading

(6) Correlations for estimating resilient modulus

2.1: Current soil classification systems

AASHTO M-145 and ASTM D-2487 are the most commonly used soil classification systems by state transportation agencies within the United States (Webb, 1990). Both systems use the 75 µm (No. 200) sieve, plastic index (PI), liquid limit (LL), and/or plastic limit (PL) in their classifications of finer grained inorganic soils. Other transportation agencies have designed their own systems that include other properties such as maximum dry density, clay content, and/or California Bearing Ratio (CBR) (Georgia DOT, 2013) (SANRAL, 2013). In whatever form these systems take, the ultimate goal of them is to aid engineers in identifying suitable soils for use and unsuitable soils for removal or remediation.

Webb (1990) found that transportation agencies in the United States tended to use the AASHTO and/or Unified soil classification systems. A majority of these agencies required the use of supplemental methods for determining soil strength and suitability for subgrade construction. These additional methods were needed because the existing classification systems did not effectively group soils by strength.

With the adoption of the 1986 AASHTO pavement design guide, the design parameter representing subgrade behavior was changed from the soil support value to the resilient modulus (M_R) (AASHTO, 1974) (AASHTO, 1986). The use of M_R has been maintained with the adoption of the subsequent 1993 AASHTO Design Guide and the current Mechanistic-Empirical Pavement Design Guide (MEPDG) (AASHTO, 1993) (AASHTO, 2015).

In a study of 50 fine-grained soils, Thompson & Robnett (1979) found that neither the AASHTO or Unified soil classes were reliable for grouping finer grained soils on the basis of resilient behavior. Therefore, none of these classification systems provide anything but general guidance in identifying suitable soils for subgrade construction. Only AASHTO M-145 provided general ratings for granular materials as good and for silt-clay (non-granular) materials as fair to poor.

In order to understand the primary classification systems used in the United States, a brief review of them was conducted. Both the AASHTO and ASTM (Unified) classification systems use a combination of gradation and Atterberg limits. In addition, both systems divide soils into two broad, general classifications or divisions based on the material passing the 75 µm (No. 200) sieve. AASHTO M-145 divides soils into granular and silt-clay materials (non-granular) general classifications based on the breakpoint of 35% of the material passing the 75 µm (No. 200) sieve. Granular soils have less than 35% passing the 75 µm (No. 200) sieve, and non-granular soils have more than 35%. When the material passing the No. 200 (75 µm) sieve exceeds 35%, the voids in the soil are commonly filled with fines and coarse-grained soils begin to behave more like a fine-grained soils because the coarse particles lose contact with each other (Liu, 1970).

The ASTM system divides soils into coarse-grained and fine-grained divisions based on the breakpoint of 50% of the material passing the 75 µm (No. 200) sieve. Coarse-grained soils have less than 50% of a soil's material passing the 75µm (No. 200) sieve, and fine-grained soils have more than 50%. ASTM D-2487 included a division for peat materials, which is not suitable for subgrade construction. Therefore, further discussion about these materials will not be made.

Beyond these very broad categories, the group classifications of both systems do not provide reliable estimates of M_R to aid the field engineer in identifying the quality of subgrade materials (Thompson & Robnett, 1979). However, it has been found that coarse-grained soils have M_R values that are generally greater than those of fine-grained soils (Elias & Titi, 2006).

The tests used to classify soils are generally straight-forward and inexpensive to perform, which satisfy two basic classification principles (Baldwin, Kellogg, & Thorp, 1938). The disadvantage of these systems is that they lack the robustness needed to effectively classify materials formed from a variety of parent materials and through numerous deterioration methods. Determining how soils will behave is a challenging task as no two soils are alike (Baldwin, Kellogg, & Thorp, 1938). Soils are formed from the deterioration of igneous, sedimentary, and metamorphic rocks under a variety of natural conditions (Dumbleton, 1968). The decomposition of rock produces a wild range of materials that engineers attempt to describe with a limited set of properties . This situation has led to ongoing and independent efforts to develop reliable correlation models for estimating resilient modulus (Puppala, 2008).

2.2: Subgrade Construction

The subgrade is the top six (6) inches of compacted roadbed materials upon which the overlying pavement structure rests (Huang, 2004). In Table 2-1, a visualization of a pavement structure demonstrates the placement of the subgrade beneath two of several possible combinations of subbase, base course, and/or surface course layers (Colorado DOT, 2017). The necessary layers are selected by transportation agencies based on the materials available and their specific requirements to support the design traffic.

The subgrade material may be in-situ soils, or soils that have been hauled in from cut areas of the roadway project, or from approved borrow pits. This layer is often compacted between 95% to 100% of its maximum dry density (Georgia DOT, 2013) (Arizona DOT, 2021) (Indiana DOT, 2018). The target moisture contents for subgrade construction can range from 3% below optimum moisture to optimum moisture, but in-situ moisture contents can be equal to or greater than 2% above optimum before some type of remediation treatment is required (Pennsylvania DOT, 2016) (Indiana DOT, 2018).

Many state agencies conduct soil classifications on the materials that are used for subgrade construction (Webb, 1990). The range of acceptable materials can be established by a state agency based on its own specifications. For instance, the Indiana DOT requires that subgrade materials have a maximum dry density greater than 100 pcf (1602 kg/m^3), a liquid limit (LL) less than 50, and an organic content of less than 3% among other requirements. The Georgia DOT uses a soil classification system that it developed for identifying suitable subgrade materials. In addition to the No. 60 and No. 200 sieves, clay content percentage, volume change percentage, and maximum dry density are used by the Georgia DOT to classify soils that are acceptable for roadway projects.

Table 2-1: Examples of pavement structures

Asphaltic Concrete Pavement
Unbound Base Layer
Compacted Subgrade Layer
Natural Subgrade Layer
Embankment

Concrete Pavement
Base Course
Subbase Course
Compacted Subgrade Layer
Natural Subgrade
Embankment

This brief subgrade construction review revealed that there appears to be some relationship between LTPP Protocol P-46 for resilient modulus laboratory testing and state roadway specifications. The minimum test specimen length is 6 inches (152 mm), which is the same thickness as is typically specified for the subgrade layer. The target moisture and compaction requirements for testing are intended to represent the construction specifications conditions discussed earlier. When this information is not available to the testing laboratory, the optimum moisture contents and maximum dry densities are used instead.

2.3: Subgrade resilient modulus

The resilient modulus (M_R) is a measure of subgrade stiffness which quantifies the response of a soil to rebound after applied loads, such as traffic loads from passing vehicles, have been removed. It became an important parameter in pavement design when it replaced the soil support value as the parameter that represented the behavior of subgrade soil underlying the pavement structure (AASHTO, 1986). It was incorporated into the 1986 AASHTO Design Guide and continues to be used to model the subgrade layer in the Mechanistic-Empirical Pavement Design Guide (MEPDG) (AASHTO, 1993) (AASHTO, 2015). It is defined by the following equation (Huang, 2004):

$$M_R = \frac{\sigma_d}{\epsilon_r} \qquad \textbf{Eq. 2.1}$$

where,

M_R = Resilient modulus of subgrade soil (ksi or MPa),

σ_d = Deviator stress (psi or kPa), and

ε_r = Recoverable strain (in/in or mm/mm)

Since the introduction of M_R into the AASHTO pavement design methodology, the laboratory work needed to test for this property was likely seen as a disruption to the normal way of doing business. This perspective can be attributed to the 1972 Interim Design Guide, which had been in use for about 14 years before the 1986 Guide was introduced. Established infrastructures and protocols for testing, designing, and constructing pavements were already in place, and the introduction of a new soil property inevitably would lead to changes in a familiar system. Resilient modulus testing has also been considered as time-consuming, requiring specialized equipment, and highly trained staff (Puppala, 2008) (Lee, Bohra, Altschaeffl, & White, 1997). Therefore, many state agencies have taken the approach of developing correlation equations to estimate the resilient modulus instead of conducting laboratory or field M_R testing. Some of these correlations are discussed later in this chapter.

The resilient modulus test data in the LTPP database were collected by state agencies, contractors, and various commercial laboratories (FHWA, 2015). The laboratories followed LTTP Protocol P-46 for all testing (FHWA, 1996). The protocol standards for defining material types, sample preparation techniques depending on material types, and various testing conditions are based on whether the materials were subgrade or subbase soils. The variables or features collected from using the test protocol are discussed in Chapter 4.

What has been recognized about this property is that the M_R of coarse-grained and fine-grained soils are different, which complicates the efforts in understanding this soil property. From the calculation equation (Eq 2.1), it can be determined that M_R is stress dependent by definition, so the findings by researchers that stresses are important factors that influence resilient modulus are understandable. However, understanding the influence of other features on M_R has proven to be more challenging.

2.4: Factors influencing resilient modulus

When identifying factors that influence the resilient behavior of fine-grade subgrade soils, researchers generally have three types of data readily available to them from the LTPP database: (1) soil index properties (2) laboratory test conditions, and (3) testing measurements (Elkins & Ostrom, 2021). These types of data are recorded to document details about the in-situ pavement layers, traffic loadings, and subgrade reactions to those field conditions. With these data, engineers have the ability to search for a better understanding about the nature of pavements and how to extend their design lives. Since the resilient modulus (M_R) has become an important parameter to pavement designers and field engineers, recognizing the factors that influence the resilient modulus has become an essential task for every researcher to understand the reactions of the subgrade to traffic loadings.

In general, understanding the behavior of soils has been a challenge to this day. In a state-of-the-art study about granular soils, Lekarp, Isacsson, and Dawson (2000) concluded that the behavior of unbound granular materials was not understood very well. If the authors had extended their study to non-granular or fine-grained soils, they would have likely reached the same conclusion. The reasonableness of this assumption can be supported with the host of research that has been conducted and continues to be conducted over the years (Mitchell, Shen, & Monismith, 1965) (Thompson & Robnett, 1979) (Puppala (2008) (Liu, Zhang, Wang, & Jiang, 2019). This lack of full understanding about the resilient behavior of all subgrade soils has been an obstacle that engineers have striven to overcome in designing and constructing long-life pavements.

In fact, the literature reveals some researchers have generally divided soils into two general soil types: coarse-grained and fine-grained soils (Yau and Von Quintus, 2002) (Rahim, 2005) (Elias & Titi, 2006) . This separation has uncovered different levels of influence that some factors have on the resilient behavior of fine-grained soils. After analyzing the Long-Term Pavement Performance (LTPP) database, Yau and Von Quintus (2002) and Malla and Joshi (2008) were not able to find one property that was common to all their predictive models. Yau and Von Quintus (2002) concluded that correlating soil properties to resilient modulus was dependent on soil type after analyzing the LTPP data at the time of their study. Fitting the *k*-coefficients within a constitutive model, they found that liquid limit, plasticity index, and the percentage of material passing the finer sieves were important factors relating to the resilient modulus to lower strength materials. Malla and Joshi (2008) also used fitted *k*-coefficients of a constitutive model with a larger LTPP dataset, but found that resilient modulus was only weakly influenced by optimum moisture content, maximum dry density, Atterberg limits, stress state, and gradation. While other researchers may not agree on the level of influence, there seemed to be agreement that these factors are influential (Li & Selig, 1994) (Drumm, Reeves, Madgett, and Trolinger, 1997) (Rahim, 2005).

2.5: Behavior of fine-grained soils under traffic loading

The subgrade resilient modulus (M_R) is a complex parameter that may be influenced by many factors. Some of these factors were identified in the previous section. In this section, the findings of some research about the behavior of M_R with respect to some of the more significant factors are discussed. This review was necessary to gain a better understanding of how M_R was affected by these factors. For the purpose of this study, identifying the effects of some of these factors can be useful in reviewing the features that were included in the proposed soil classification scheme. Burczyk, Ksaibati, Anderson-Sprecher, and Farrar (1994) and Kim and Kim (2007) found that resilient modulus decreased with increasing moisture content with soils from different regions of the United States. Burczyk, Ksaibati, et al. (1994) tested undisturbed and remolded cohesive Wyoming soils (A-4, A-6) to make this determination, but also found that A-7 soils were not significantly affected by moisture. Whereas Kim and Kim (2007) discovered that the resilient modulus was higher for Indiana sandy-silty-clay soils at moisture contents less that optimum. They also found that resilient modulus increased with increasing confining pressure.

With the understanding that moisture effected resilient modulus, a case study on a low-volume road in north Texas, Hedayati and Hossain (2015) found that the seasonal in-situ moisture varied as much as 5% from the average moisture content over a two-year period. Temporary moisture swings as high as 12% from the seasonal average for homogenous highly plastic clay were recorded. This number is far greater than the allowable 0.5% deviation from the in-situ moisture content established in Protocol P-46 as the primary moisture condition for the testing of Type 2 soils.

As noted above, moisture content has been reported in the United States as influencing the resilient modulus of subgrade soils, but researchers in other countries have recorded similar results. For instance, Nguyen and Mohajerani (2015) tested several fine-grained soils from different locations in Victoria, Australia and reported that resilient modulus decreased as the deviator stress increased, which were the same results that Liu, Zhang, Wang, & Jiang (2019) found in China with low plasticity clays (CL) and low plasticity silts (ML), which are non-granular soils using AASHTO M-145. Not surprisingly, both groups of researchers observed that resilient modulus increased as the confining stress increased and decreased as moisture content increased.

2.6: Correlations for estimating resilient modulus

Many studies have been conducted over the years to predict the resilient modulus (M_R) from soil index properties, which are routinely collected for classifying soils using one or both of the current soil classification systems. Despite these efforts, no conclusive relationship between M_R and predictive features has been discovered to date as is demonstrated in the sampling of correlations collected in this chapter. Therefore, it seems a reasonable assumption that these efforts will continue without an actual prediction model and with only correlation models resulting if the same collection of feature variables are used. This explanation may be the reason for the cautionary recommendations from some researchers because there may be a missing feature or features that are not collected using the current sampling and laboratory testing routines. These researchers have recommended that transportation agencies develop their own regional correlations to estimate a M_R for pavement design (Hossain, 2009) (Soliman & Shalaby, 2014). Nevertheless, if an adequate number of representative soil specimens are gathered, useful information may still be gathered that allows for a growing understanding of the expected resilient behavior of fine-grained soils with the use of a correlation model. As will be shown in Chapters 3 and 4, the available dataset of fine-gained soils from the LTPP database consists of data for only 64 soil samples that do not uniformly cover the North American continent.

Elias & Titi (2006) found that by separating their M_R test data into coarse-grained and fine-grained datasets their correlation models improved. Other researchers referenced in this chapter have taken the same approach of separating data into coarse-grained and fine-grained soil datasets, which was also adopted in this study to concentrate on classifying the more problematic fine-grained soils and leaving the task of classifying coarse-grained soils for another time.

There are two approaches that haven been taken by engineers to develop equations for estimating the subgrade M_R. The first one, the direct approach, correlates the modulus to the soil index properties and/or testing conditions. The indirect approach, correlates modulus to a stress-based (constitutive) model to determine the model's constant parameter values, typically *k*-constants. Then correlations are developed between these parameter constants and available soil properties (Puppala, 2008).

Within this chapter, a sample of five correlation models using these approaches are presented. The purpose for this examination was to demonstrate the different features that have been found to estimate the M_R of subgrade soils. While there is a general similarity in the features used, these similarities may be due to the use of the same collection of features and nothing more.

2.6.1: Direct methods

The most recognized correlation (Eq. 2.2) to resilient modulus (M_R) was developed by Heukelom and Klomp in 1962 (Dione et al., 2014). The equation has been used for fine-grained soils when the California Bearing Ratio (CBR) is less than or equal to 10% (George, 2004). There have been several critics of this correlation that have suggested CBR is a measure of shear strength and may not correlate to stiffness (Thompson & Robnett, 1979) (E. C. Drumm, Boateng-Poku, & Pierce, 1990) (Smart and Humphrey, 1999) (Dione et al., 2014). A couple of key criticisms of the CBR model are that it is based on a soaked test procedure and its stress conditions have not been taken into account, whereas the specimens for resilient modulus testing are tested at more restrictive conditions (Smart and Humphrey, 1999) (AASHTO, 2015). In addition, modulus testing is conducted over a range of stress combinations to account for the estimated field conditions while CBR testing are conducted at stress levels do not match in-situ conditions (Smart and Humphrey, 1999).

$$M_r(psi) = 1500\ x\ CBR \qquad \textbf{Eq 2.2}$$

Eq 2.3 was developed with data that was independent of the LTPP database (Rahim, 2005). For M_R testing, Shelby tube samples were collected from sites in the state of Mississippi. Seven (7) of these non-granular test specimens classified as AASHTO A-4, A-6, and/or A-7. The results for Eq 2.3 provided an R^2 of 0.70 and S_e/Sy of 0.204. Its RMSE was 32.5 MPa (4,714 psi). The laboratory M_R ranged from 31 MPa (4,436 psi) to 269 MPa (38,986 psi), which seemed greater than the range for the M_R data on bulk soil samples, which is discussed in Chapter 4.

$$M_R = 17.29\left[\left(\frac{LL}{(w_c+1)} \times \gamma_{dr}\right)^{2.18} + \left(\frac{\#200}{100}\right)^{-0.609}\right] \qquad \textbf{Eq 2.3}$$

where,

M_R = resilient modulus (MPa)

LL = Liquid Limit

w_c = Moisture content (%)

$\gamma_{dr} = \gamma_d / \gamma_{max}$

γ_d = dry density (kN/m^3)

γ_{max} = maximum dry density (kN/m^3)

#200 = Percent of material passing the No. 200 sieve (%)

Although the Rahim model used parameters commonly acknowledged as influencing the M_R, it did not contain a stress variable. The absence of a stress parameter would suggest a relatively constant modulus value regardless of the overlying pavement structure and level of traffic, as long as the moisture and density conditions remain stable.

2.6.2: Indirect methods

As with the direct approach, numerous regression equations have been developed using the indirect approach. Yau and Von Quintus (2002) fit the following constitutive equation (Eq. 2.4) for resilient modulus (M_R) to the LTPP data for fine-grained silty and fine-grained clayey subgrade materials with two separate sets of *k*-coefficients:

$$M_R = k_1 P_a \left(\frac{\theta - 3k_6}{P_a}\right)^{k_2} \left(\frac{\tau_{oct}}{P_a} + 1\right)^{k_3} \qquad \textbf{Eq 2.4}$$

where,

P_a = Atmospheric pressure

θ = Bulk stress

τ_{oct} = Octahedral shear stress

k_1, k_2, k_3, k_6 = Regression constants

During the regression process, the k- coefficients in Eq. 2.4 were determined using resilient modulus and stress conditions. Afterwards, the k- coefficients in the equations below were regressed using soil features. Researchers found that k_6 was zero in more than 50% of the tests. Consequently, they set k_6 to zero and reran the regressions, which did not significantly alter the results. Therefore, the process was followed for the subsequent two sets of regression equations.

The first set of k-coefficients (Eq. 2.5 to Eq 2.7) estimates the resilient modulus of fine-grained silts. A mean square error of 193.0 and S_e/S_y of 0.5622 were reported. In addition, the authors determined that fair to good correlations were found between the LTPP data and the M_R test results based on the k- coefficient equations.

$$k_1 = 1.0480 + 0.0177(\%Clay) + 0.0279PI - 0.0370w_s \quad \textbf{Eq 2.5}$$

$$k_2 = 0.5097 - 0.0286PI \quad \textbf{Eq 2.6}$$

$$k_3 = -0.2218 + 0.0047(\%Silt) + 0.0849PI - 0.1399w_s \quad \textbf{Eq 2.7}$$

For fine-grained clay soils, Eq. 2.8 to 2.10 were used to estimate the resilient modulus for fine-grained clay soils with the constitutive equation (Eq. 2.4). A mean square error of 557.9 and S_e/S_y of 0.8082 were reported.

$$k_1 = 1.3577 + 0.0106(\%Clay) - 0.0437w_c \qquad \textbf{Eq 2.8}$$

$$k_2 = 0.5193 - 0.0073P_4 + 0.0095P_{40} - 0.0027P_{200} - 0.003LL - 0.0049w_{opt} \qquad \textbf{Eq 2.9}$$

$$\begin{aligned} k_3 = 1.4258 &- 0.0288P_4 + 0.0303P_{40} - 0.0521P_{200} + 0.0251(\%Silt) \\ &+ 0.0535LL - 0.0672w_{opt} - 0.0026\gamma_{opt} + 0.0025\gamma_s \\ &- 0.6055\left({}^{w_c}/_{w_{opt}}\right) \end{aligned} \qquad \textbf{Eq 2.10}$$

where,

$\%Clay$ = Clay content of the specimen, %

w_c = Moisture content of the specimen, %

P_4 = Percent of material passing the No. 4 sieve, by weight

P_{40} = Percent of material passing the No. 40 sieve, by weight

P_{200} = Percent of material passing the No. 200 sieve, by weight

LL = Liquid Limit

w_{opt} = Optimum moisture content of the specimen, %

$\%Silt$ = Silt content of the specimen, %

γ_{opt} = Optimum dry density of the sample, kg/m^3

γ_s = Dry density of the sample, kg/m^3

Elias and Titi (2006) used the following constitutive model, which substitutes σ_b for the more commonly used θ symbol for bulk stress in Eq 2.11.

$$M_R = k_1 P_a \left(\frac{\sigma_b}{P_a}\right)^{k_2} \left(\frac{\tau_{oct}}{P_a} + 1\right)^{k_3}$$ **Eq 2.11**

where,

σ_b = Bulk stress

Eqs. 2.12 to 2.14 were developed using four (4) fine-grained Wisconsin soils with 72% or more material passing the No. 200 (75 μm) sieve. The R^2 values for those equations were 0.84, 0.65, and 0.76, respectively. The *k* models from this study were unique in that all three (3) models used the plastic index (PI), dry density (γ_d), and optimum moisture ratio (w/w_{opt}) in this set of correlations. The k_2 model included the maximum dry density (γ_{dmax}).

$$k_1 = 404.166 + 42.933(PI) + 52.260\gamma_d - 987.353\left({}^{w}/_{w_{opt}}\right)$$ **Eq 2.12**

$$k_2 = 0.25113 - 0.0292PI + 0.5573\left({}^{w}/_{w_{opt}}\right)\left({}^{\gamma_d}/_{\gamma_{d\,max}}\right)$$ **Eq 2.13**

$$k_3 = -0.20772 + 0.23088PI + 0.00367\gamma_d - 5.4238\left({}^{w}/_{w_{opt}}\right)$$ **Eq 2.14**

where,

PI = Plastic Index

γ_d = Dry unit weight, kN/m^3

γ_{dmax} = Maximum dry unit weight, kN/m^3

w = Moisture content of the specimen, %

CHAPTER 3: METHODOLOGY

This discussion will continue with explanations about the methods, database, and software tools used to meet the objectives of this study, as provided below. This effort was made to support the decisions made in conducting this study.

(1) To identify a suitable source of resilient modulus test data,

(2) To develop a correlation model for the resilient modulus of fine-grained subgrade soils using the Long-Term Pavement Performance (LTPP) database and a decision tree algorithm, and

(3) To provide a table using the decision tree model results that can be used to a draft soil classification specification that demonstrates the application of the preliminary findings of this study.

3.1: Decision Tree Algorithm

Decision tree modeling was selected for use in developing the soil classification scheme for fine-grained subgrade soils because it offered the following benefits:

(1) a simple and straight-forward tree modelling procedure that was easy to interpret and translate into a soil classification table,

(2) a decision tree hierarchy that can provide engineers with a general understanding of the resilient behavior of this soil type by identifying features and their general level of importance, and

(3) a similar classification structure to the current AASHTO soil classification system.

To implement the use of the decision tree algorithm, a decision tree prediction model had to be created to begin the process. Then the average M_R values within each leaf node prediction at the bottom of the tree were grouped with other leaf nodes that that had similar average M_R values to create proposed soil classes (Figure 3-1). The features in the decision tree diagram were identified as being most influential in predicting M_R and would be used to create criteria to separate the soil into any proposed soil class groupings.

Using the R programming language, the *rpart* function of the *rpart* library was used to construct decision tree regressions to predict laboratory M_R values. This function used a recursive splitting procedure, which began by arranging the values of the target feature (M_R) for each predictive feature from the lowest to highest. From that point, the algorithm searched for a binary split point for each predictive feature that minimized the prediction squared error (Rokach and Maimon, 2005). The predictive feature that minimized the error the most was selected as the root node. Then the process was repeated for each succeeding lower-level child node until a stopping criterion was met (Suthaharan, 2016). The splitting process has been described as "greedy" because it does not evaluate the global effect of each nodal split, just the immediate benefit resulting from the split (Bi, Goodman, Kaminsky, & Lessler, 2019). This procedure was practical because programming the algorithm to consider every possible split and its global consequences could consume a considerable amount of computational resources and slow down the development of the decision tree model.

There are a number of stopping criteria for tree development that can be used to end the splitting process. For instance, the maximum number of levels of the tree, or a minimum required number of M_R test results within a leaf node can be used to stop model development and control the size of the decision tree. It was decided to use the default stopping criteria to end the tree building process.

The result of executing the algorithm was a decision tree model that looked like an upside-down tree with the root node at the top of the diagram and the leaf nodes at the bottom (see Figure 3-1). The root node indicated the silt content (SILT) feature that was the most important one in predicting the target feature, which is the M_R in this study and example diagram. In between the root and leaf nodes were intermediate (child) nodes with features that represented lower levels of feature importance compared to the features at the higher levels. The intermediate node labelled CLAY was the only intermediate node in Figure 3-1. Model developers can simply assess that it was of secondary importance to the root node (SILT) in predicting M_R. If there were child nodes emanating from the CLAY node, these nodes would have indicated features of lower importance to the CLAY feature. In the leaf node depictions are displayed the average values of M_R (target feature) of the nodal contents that resulted from following the hierarchy of conditional statements.

The final reason for applying a decision tree algorithm to develop a new soil classification scheme was because the current AASHTO soil classification scheme already has a structure that is similar to a decision tree (compare Table 3-2 and Figure 3-4) even though it may not be seen as such at first glance. Therefore, modifying the current classification structure to a newer tree with parameters that are more reflective of the resilient properties of fine-grained soils may aid in overcoming any natural resistance to altering the status quo, which is essential for users in accepting a revision to the current soil classification system (Jick, 1991) (Mento, Jones, & Dirndorfer, 2002).

The current AASHTO scheme is essentially composed of a series of “yes” or “no” decisions as displayed in Figure 3-4. The decision condition splitting the soils into granular and non-granular general classifications is based on the material by weight passing the 75µm (No. 200) sieve. A minimum of 36% passing the 75µm (No. 200) sieve is required for the soil to be classified as a non-granular soil (75µm or No. 200, PN200 sieve ≥ 36%). If the condition is false, then the soil is a granular soil and would not be used in this study.

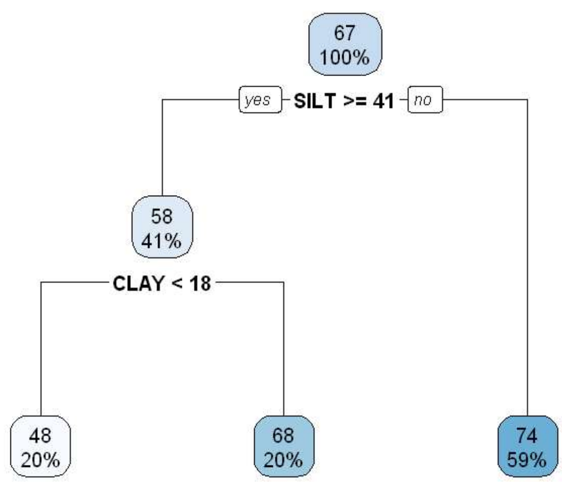

Figure 3-1: Decision tree example

Table 3-1: AASHTO group classification scheme for silt-clay materials

Group Classification	A-4	A-5	A-6	A-7-5	A-7-6
75 µm (No. 200)	36 min	36 min	36 min	36 min	36 min
Liquid Limit (LL)	40 max	41 min	40 max	41 min	41 min
Plasticity Index (PI)	10 max	10 max	11 min	11 min & PI ≤ LL-30	11 min & PI > LL-30

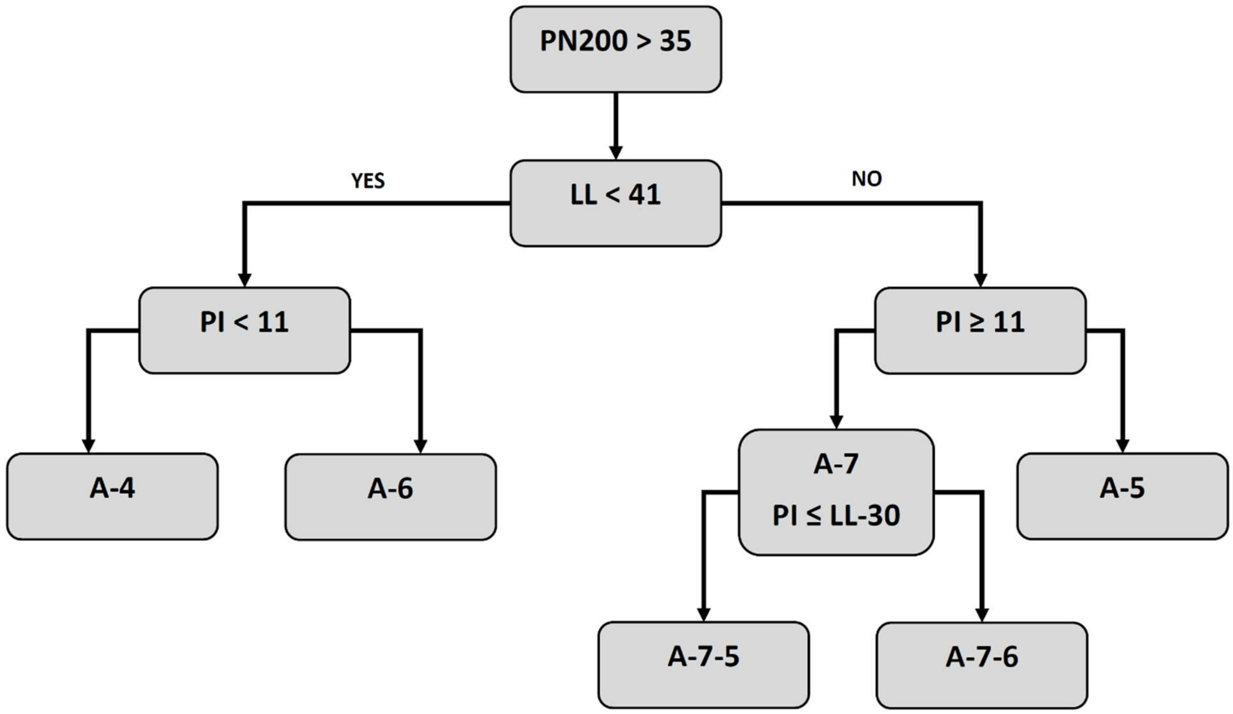

Figure 3-2: AASHTO M-145 for non-granular soils in a decision tree format

Using a more advanced machine learning algorithm can produce a better predictive accuracy, but cannot be more easily interpreted than a decision tree model (James, Witten, Hastie, & Tibshirani, 2013). Random forest algorithms can result in hundreds of smaller decision trees to determine a final prediction (Maindonald, 2021). The output for this type model can produce many pages of output that would be difficult to review and understand. XGBoost algorithms can also produce hundreds of trees that correct the errors of earlier tree iterations (Chen & Guestrin, 2015). Again, this type model would be more difficult to review and understand that a decision tree model.

3.2: The Long-Term Pavement Performance Program

Before explaining the database used in this study, it was necessary to discuss the origins of the data collection effort, which began with the Long-Term Pavement Performance (LTPP) Program.

It is one of the largest and most comprehensive pavement monitoring efforts in the world (FHWA, 2015). Its test sites are located throughout the United States and Canada. The program was carefully developed for seven years by the Federal Highway Administration (FHWA), American Association of State Highway and Transportation (AASHTO), the Road and Transportation Association of Canada, and the Transportation Research Board (TRB). Part of the development included a pilot study that was conducted in eight states beginning in 1982. This initial study was intended to address the issues that are involved with building a database that could be used to improve various aspects of managing a multi-faceted research program.

After the program beginning in 1987, the data collected was intended to be used to better understand the long-term behavior of pavements and the variables that influence them. Some of the variables that were acknowledged as being influential fall into the general categories of climate, materials, maintenance practices, and various others. To ensure that research-quality data was collected, many guidelines and tools have been developed for use in the program. The following list provides a very small sample of the guidelines that have been developed for collecting high-quality research data:

- Guidelines for the Collection of Long-Term Pavement Performance Data,
- LTPP Information Management System (IMS) Quality Control Checks,
- LTPP Traffic Analysis Software, and
- LTPP Protocol P46: Resilient Modulus of Unbound Granular Base/Subbase Materials and Subgrade Soils.

The approach taken by the LTPP Program has been a departure from the earlier methods of conducting research (Elkins & Ostrom, 2021). Previous approaches concentrated on studying specific interests with a limited scope and within a limited timeframe. This strategy was used in the AASHO Road Test that was conducted over a 2-year period on a pavement structure that was devoted to the research project. The truck loadings eventually exceeded those from the study by the mid 1980's. The LTPP began data collection in 1987 and continues to collect data on in-service roadways to gain a better understanding of pavement behavior. Another difference from previous research approaches is that data from studies like AASHO Road Test were not freely and easily assessable. The LTPP data is easily and freely available to the public for anyone to conduct pavement research. Needless to say, the LTPP strives to produce high-quality data by establishing standards for data collection, quality control checks, and testing from which all researchers can benefit.

3.3: The Pavement Performance Database

One of the challenges that researchers face is developing a set of conclusions based on sample data and applying those inferences to a larger population (Tintle, et.al). The attempt to achieve this goal involves gathering and describing representative sample data so that these generalizations can be developed. The LTPP database was selected as the source of the sample data for this study, as it is one of the most comprehensive pavement performance databases in the world (FHWA, 2015). The data in the LTPP database was collected from test sites across the United States and Canada (Figure3-3). These sites were established to investigate a wide range of research questions about materials, construction practices, and rehabilitation techniques for example. Therefore, the soil data may or may not necessarily be representative of all fine-grained subgrade soils of interest that are generally used in highway construction in the United States and Canada. The data did span a wide range of geographic locations and geological formations that may be able to provide some insight into the resilient behavior of fine-grained subgrade soils that could lead to the characterizing these soils into a classification scheme that could be useful in identifying soils that are suitable for highway construction whenever they are encountered on the job site.

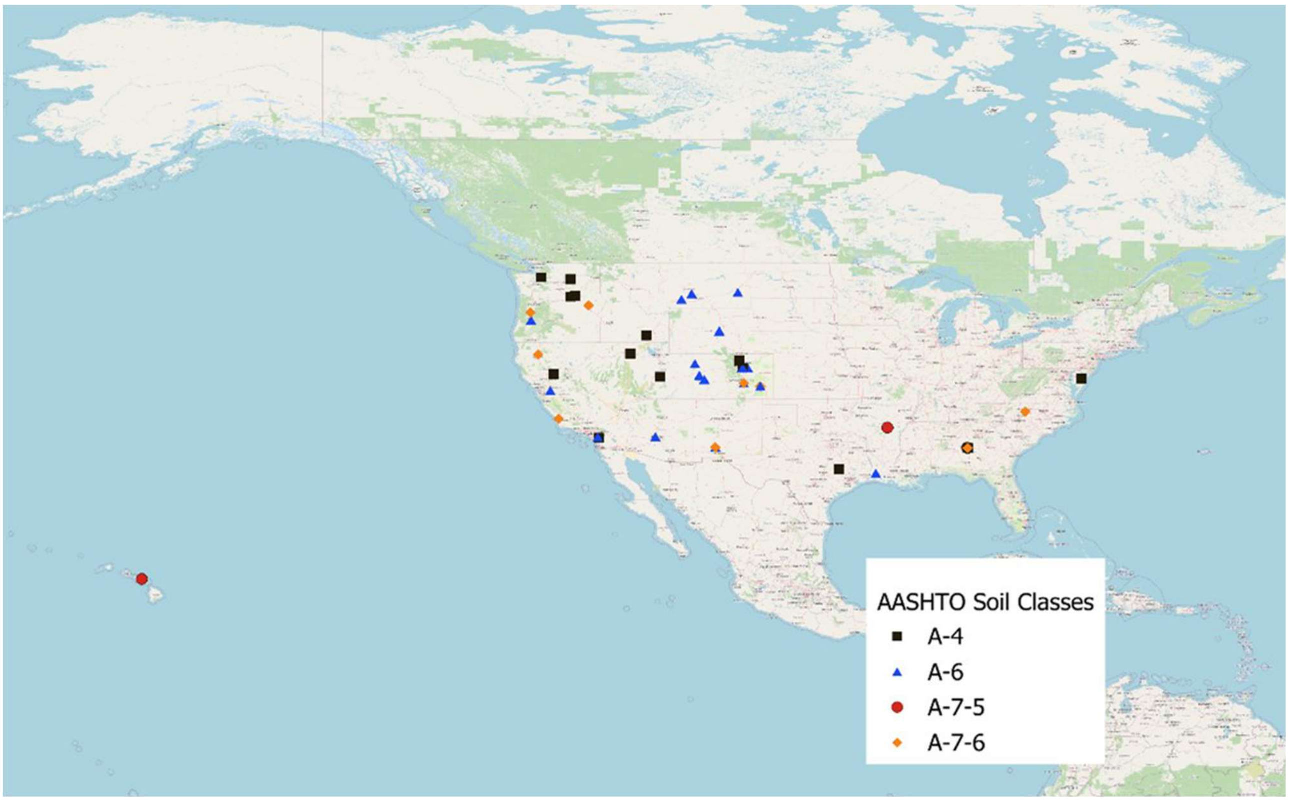

Figure 3-3: LTPP test sites with fine-grained subgrade soils

Table 3-2 provides a tabular representation of the LTPP test site map from where the fine-grained soils originated. It unmasks the clumping of the data from test sites that were located very close to each other. The main purpose for providing Figure 3-3 and Table 3-2 was to provide a visual aid to demonstrate that the fine-grained soil data was not evenly spread out across the United States and Canada. In fact, there were no test sites/ fine-grained soils from Canada in the dataset that was used to develop the decision tree model in Chapter 5. Despite the apparent data gaps with respect to geographic location, some useful decision tree models were developed.

Table 3-2: Fine-grained subgrade soils in the base dataset

State	Number of Soil Specimens	State	Number of Soil Specimens	State	Number of Soil Specimens
Alabama	7	**Hawaii**	1	**North Carolina**	1
Arizona	2	**Idaho**	2	**Oregon**	3
Arkansas	2	**Louisiana**	1	**Texas**	3
California	8	**Montana**	5	**Utah**	1
Colorado	15	**Nevada**	1	**Washington**	4
Delaware	1	**New Mexico**	5	**Wyoming**	2

As has been discussed in Chapter 2, predicting the M_R of any subgrade soil type has been a very challenging task, as can be surmised by the continued efforts to develop more M_R correlations after so many that have already been developed throughout the years (Puppala, 2008). Some researchers have used the strategy of segregating regional soils into unique sets of independent variables that can be used for correlating subgrade M_R (Hossain, 2009) (Smart & Humphrey, 1999). In addition, the literature revealed that researchers have developed stronger correlations by separating the distinction of fine-grained and coarse-grained soils (Yau and Von Quintus, 2002).

The data used in this study was downloaded from the InfoPave website, which served as the public interface to the Information Management System (IMS) that was composed of three components: (1) Products, (2) Pavement Performance Database, and (3) Ancillary Information Management System (AIMS). The component of interest for this study was the Pavement Performance Database (PPDB) which housed the data of interest. Table 4-1 lists the tables and descriptions of these tables from which the all-subgrade data was contained. The data in these tables provided details about sample type, locations of the test sites, test site designations, layer identifications, soil index properties, laboratory testing conditions, resilient modulus test results, and AASHTO soil classifications.

The soil data used in this study were selected from the tables associated with bulk soil samples. Bulk soil samples are more likely to be collected during the preliminary field investigation of a roadway project as this type of sample is quicker and more economical to collect. The thin-walled (Shelby) tube samples are more likely to be selectively used in areas that are potentially unstable. Because "pushing" tubes takes more time to set up and to focus on the changes in the underlying strata changes, this procedure would not be practical to use during the investigation of a proposed construction alignment. In addition, because of differences in sample test dimensions, test procedures, and test results, the data from these two groups cannot be combined.

The descriptions of the data tables were provided in the IMS User Guide and other PPDB tables (Table Reference and Field Reference). Although table TST_SS02_UG03 was described as containing gradations for "unbound fine-grained granular base, subbase and subgrade materials", it included gradation data for all non-granular subgrade soils. Therefore, the data for non-granular soils was used as the starting point for cleaning the raw dataset. This starting point also served as a means for understanding the differences between the coarse-grained (CGF) and fine-grained (FGF) fractions of the non-granular soil general classification.

The subgrade soil data was organized into a group of relatable tables, which required merging into a single base dataset using primary keys within an R programing environment. The LTPP Information Management System User Guide provided the guidance needed for identifying the set of features that served as primary keys. Examples of these keys are SHRP ID code, layer number, and location number. More details about the data tables and primary keys are provided in Appendix A.

Table 3-3: LTPP data tables with data of interest

Table Name	Description of Relevant Data
SECTION_COORDINATES	Longitude/Latitude of test site locations
TST_SS02_UG03	Gradations of fine-grained soil samples
TST_UG04_SS03	Atterberg limits of soil samples
TST_UG05_SS05	Maximum dry density and optimum moisture content
TST_UG07_SS07_A	Testing details on molded bulk soil samples
TST_UG07_SS07_WKSHT_SUM	Average resilient modulus and stress/strain conditions for the testing sequences for bulk soil samples
TST_SS04_UG08	AASHTO soil classifications
TST_L05B	Identification code of subgrade layer
EXPERIMENT_SECTION	Identification codes for GPS and SPS sections

By identifying the data tables that contained the subgrade data of interest, the relevant data was merged into a single dataset that could be examined for areas of concern in the following sections. These issues were related to limiting the sample data to fine-grained subgrade soils, adherence to LTPP Protocol P-46 for M_R testing, samples not achieving a record status of “E”, and removal of test results that exhibited anomalous behavior. The record status of “E” indicated that the individual test results had undergone all available quality control checks. The researcher was cautioned that records in the PPDB with an “E” status may still have errors that have not been flagged by the current quality control procedures (FHWA, 2015).

3.4: Software tools for data analysis

In this section, several software applications used to examine the PPDB (LTPP database) and conduct the analyses of the data in this study. These tools are briefly described in this section to understand the benefits of their selection for use.

3.4.1: Anaconda and Anaconda Navigator

The Anaconda software distribution was selected for use in this study because it was freely available from its website (https://www.anaconda.com) and provided many tools that were suitable for educational research. It included an environment manager, a graphical user interface (GUI), many automatically installed packages, and a large public repository of freely available data science and machine learning packages (Anaconda Software Distribution, 2020).

The conda package manager made it easy to install, update, and remove the packages that were used to perform a variety of tasks. Packages to create plots, conduct t-tests, and conduct decision tree analyses were among some of the packages that were used in this study.

The conda environment manager allowed the creation of multiple programming environments that could be established to perform various tasks. While R programming was used exclusively in this study, the option to use Python or another programming language was also available. A benefit of using different programming environments when using only the R programming language was that R and the R packages are constantly in a state of being updated. While it was easy enough to create an environment for using R version 3.6.3, the challenge occurred when adding new packages that were not compatible with previously installed packages. The strategy that was followed was to use R version 3.6.3 for all programming environments because most of the same basic packages were needed for all tasks. However, when installing new packages that were developed for higher versions of R, a new environment was created to experiment with the new package. Needless to say, this strategy was only developed after some time-consuming mishaps.

Another tool that was provided in the distribution was Anaconda Navigator, which was a graphical user interface (see Appendix A, Part 2) that made performing many functions easier than having to type commands at a command prompt. Some of the actions that were performed with Navigator were the environment and package management tasks mentioned earlier in this section in addition to launching Jupyter Notebooks in the environment to be used for coding.

3.4.2: Jupyter Notebook

Jupyter Notebook is a web-based application that was also available within the Anaconda software distribution. It uses the default web browser to create computational documents that can be annotated to remind the programmer of the purpose of coding blocks, which can help during debugging process and to inform members of a coding collaboration team about the function of the code (Kluyver, et al, 2016).

The Google Chrome and Mozilla Firefox web browsers were used at different times. Each browser worked equally well with Jupyter Notebooks. A screenshot is provided while using the Firefox browser to provide a visual representation of the application layout (see Appendix A, Part 2). Having two monitors to work with, it was decided to use Google Chrome for any UGA library and non-school-related internet searches and to use Firefox for Jupyter Notebooks. By assigning these functions to different browsers, it was simpler to move the browsers to different monitors.

As can also be observed in Figure 3-2, Jupyter Notebooks allowed for incremental coding and annotation with the use of cells without having to re-run each line of code, which could be over 400 lines, depending on the task being performed. While this capability was seen as a benefit, others have criticized Jupyter Notebooks as leading to poor coding behaviors that resulted in irreproducible results (Perkel, 2018) (Pimentel, Murta, Braganholo, & Freire, 2019). However, it seemed like these issues were more likely a problem with inexperienced programmers. As long, as the programmer understands basic programming principles, annotates his/her code properly, and understands the effects of the code being written, these reported problems can be managed, as they were during this study with a little effort.

3.4.3: R programing environment and language

In order to use the capabilities of the R programming language, a programming environment for it was created using Anaconda Navigator. The R environment consisted of the R language in addition to the many packages for statistical analysis, data visualization, data manipulation (Albert & Rizzo, 2012) (R Core Team, 2023a). The robustness of R was apparent from its open-source status and its supportive community that has developed over 20 thousand packages to conduct a variety of functions (de Micheaux, Drouilhet, & Liquet, 2013) (R Core Team, 2024). The primary drawback to using R was the steep learning curve (Zuur, Ieno, & Meesters, 2009).

The R programming language (version 3.6.3) was used for the analysis of the LTPP data and model development for this study (R Core Team, 2020). Version 3.6.3 was the one that was provided during the original installation of the distribution. Throughout the process of learning more about Anaconda environments and the R programming language, it was decided to keep using this version because of various issues that resulted from incompatibility with some R packages by updating R language versions. The benefit of this course of action became apparent after the various software/package updates and reinstallations necessary because of unsuccessful experimentation with the software and virus infections. Some of these mishaps were another reason why creating new environments or cloning existing environments for experimentation was seen as necessary. More experience or understanding of Anaconda Navigator and the R programming language would have been useful in avoiding these setbacks.

Although the R software was freely provided with the Anaconda Navigator, it was also freely available from the R project website (https://www.r-project.org/), which provided useful references to help with understanding and programming in the language (R Core Team, 2000) (R Core Team, 2000a) (R Core Team, 2020).

There were many packages, or library functions, that were available for use with the R language. Some were installed during the initial creation of the R environment and others required manual installation. If the packages were pre-installed, the *install.packages()* function updated the specified package library. After the installations, the commands were commented out, so that they would not be re-executed and kept for future use in a new programming environment.

The primary library packages that were used were as follows:

(1) rpart: training decision tree models (Therneau & Atkinson, 2019),

(2) rpart.plot: plotting decision tree models (Milborrow, 2024), and

(3) ggplot2: creating graphical plots (Wickham, 2016).

3.4.4: Miscellaneous commercial software applications

While most of the work in this study was performed using freely available software, there were several commercial applications that were used because of personal familiarity with their functions and because of possession of licenses for their use. These applications and how they were used are given below. No other description of their use was deemed necessary.

- Microsoft (MS) Access was only used to export the relevant data tables from the MS Access bucket file that was downloaded from the InfoPave website to MS Excel. Having the data in an Excel format made manipulating the data simpler with the R programming language.

- MS Excel was used to manually examine the contents of the exported data tables. The datasets created with R were written into Excel files for review of the dataset contents. In addition, some tables in this document were created with Excel and pasted into MS Word for editing.
- Affinity Photo was used to format some of the images in this document.
- Microsoft Word was used to prepare this document.
- Microsoft Publisher was used to draw some of the diagrams in this document.

3.5: Assumptions and limitations

The following assumptions were necessary in order to conduct this study:

- Use of the Long-Term Pavement Performance (LTPP) Protocol P-46 provided an accurate and stable method for measuring the resilient modulus properties of fine-grained subgrade soils in the laboratory that could be applied to pavement design using the Mechanistic-Empirical Pavement Design Guide (MEPDG). Should the protocol be revised or replaced with a new protocol, the effect upon the resilient modulus test results should be analyzed.

- The subgrade resilient modulus testing data in the PPDB (LTPP database) were representative of the true populations of ASTM-defined fine-grained subgrade soils that have been used in highway construction of the LTPP test sections.

The following were limitations of the database used in this study:

- Because not all AASHTO soil group classifications were represented in the PPDB, it was unclear if the unbalanced distribution of subgrade soil classifications was because the imbalance was representative of the construction materials actually used, or because the selection of the test sites did not properly consider the various AASHTO group classifications.
- Without a complete and representative database of all fine-grained subgrade soils that have been used in highway construction in the United States and Cananda, it was unclear if the imbalance of AASHTO group classifications were meaningful.

3.6: Summary

Based on the methodology detailed in this chapter, the appropriate database, tools, and analysis procedure have been selected to develop a classification scheme for fine-grained subgrade soils that reflect their resilient behavior. The PPDB (LTPP database) from the LTPP Program was used because it was identified as the largest research-quality database of its kind, which satisfied one of the objectives of this study. The freely available Anaconda, Jupyter Notebook, and R programming provided a manageable programming environment to develop the decision tree models. The use of Microsoft Office Suite and Affinity Photo were useful and relatively simple software packages to prepare this study.

CHAPTER 4: STATISTICAL EXPLORATION OF THE LTPP DATA

With a source of research-quality resilient modulus (M_R) test results, the next logical step was to review the raw dataset before conducting the decision tree analyses to develop the soil classification scheme for fine-grained subgrade soils. ASTM D-2487, AASHTO M-145, and LTPP Protocol P-46 were the documents used to process and review the raw data.

The data processing consisted of creating smaller datasets that could be used to compare various groupings, such as capped and uncapped specimens, against each other. The first part of the data review consisted of confirming the test specimens were prepared and tested per the standards established by LTPP Protocol P-46. Test results that did not conform to that protocol were removed from the raw dataset. The second part of the review consisted of searching for possible data anomalies, which would be removed if encountered. The third and final part of the data review consisted of plotting the resilient modulus (M_R) versus each of the predictor features to check if the LTPP data mimicked the responses documented in the literature review. Even though decision trees are nonparametric models and the trendlines in the plots represent linear relationships, it still was of interest to see how and where the data would fall within the plots.

4.1: Fine-grained Soil Criterion

As was noted in the literature, good correlations for resilient modulus (M_R) were not found when using a single dataset for both coarse-grained and fine-grained soil types. However, good models could be developed when using separate datasets for these soil types (Elias and Titi, 2006). Therefore, that approach was adopted for this study while focusing only on fine-grained soils in order to keep the work more manageable because developing correlation models has continued to be a challenge for research engineers for many years (Puppala, 2008) (Yau & Von Quintus, 2002). Another reason for limiting the scope of this study was to concentrate on the more problematic fine-grained soils, which would be more useful for design and field engineers to identify the properties that could contribute to a soil's resilient behavior (AASHTO, 2000).

Elias and Titi (2006) followed ASTM D-2487 for distinguishing coarse-grained and fine-grained soils. The need for making this distinction in defining soil types became evident due to the inherent confusion that arose from reviewing the PPDB (LTPP database), which included AASHTO group classifications and "fine-grained material" descriptions in the database. These fine-grained descriptions applied to all soils that had group classifications of A-4, A-5, A-6, and A-7, which are under the AASHTO general classification of silt-clay (non-granular) materials. AASHTO M-145 states that silt-clay materials are fine soil particles that will pass the 75µm (No. 200) sieve, but it sets the criterion for the silt-clay (non-granular) general classification as having greater than 35% of its material passing the 75 µm (No. 200). While this confusion may simply be a personal challenge, it seemed necessary to address it. With all this being said, the definitions for ASTM D-2487 and AASHTO M-145 have been presented below, as the broad categories from each classification system were examined for differences in M_R results later in this chapter to further support the decision to use the ASTM standard.

Before examination of the M_R values between the broad categories in the AASHTO and ASTM standards could begin, it was necessary to separate the soils into the appropriate subgrade soil datasets using the R programming language. For ASTM D-2487, datasets for the soil divisions of coarse-grained and fine-grained were created. The highly organic soil type was not encountered in the PPDB, so it was not included in the M_R comparison. The ASTM standard defined the soil divisions as follows:

(1) Coarse-grained soils: more than 50% of material by weight retained on the No. 200 (75µm) sieve,

(2) Fine-grained soils: more than 50% of material by weight passing the No. 200 (75µm) sieve, and

(3) Highly organic soils: primarily organic matter, dark in color, and with an organic odor.

Using AASHTO M-145 subgrade soil datasets were created for the two general classifications of soils, using the following criteria:

(1) Granular materials: if 35% or less of the material passes the 75 µm (No. 200) sieve and

(2) Silt-clay materials (non-granular): if greater than 35% of material passing the 75 µm (No. 200) sieve.

The LTPP database (PPDB) did not include ASTM group symbols, and these group labels were not added with R programming code to identify them in the analyses. However, the database did include the group classifications from AASHTO M-145, so datasets for these group classes were created. The caveat being that the plots later in this chapter and analyses in Chapter 5 were prepared with the primary intention of evaluating ASTM fine-grained soils, which are the same as the fine-grained fraction (FGF) of the silt-clay (non-granular) general classification of the AASHTO specification. With the FGF being defined using the 50% of material by weight passing the No. 200 (75 µm) criterion from ASTM.

4.2: LTPP Protocol P-46

LTPP Protocol P-46 is the laboratory testing procedure for the LTPP Program to test soil samples for resilient modulus (M_R). It provided a consistent procedure with guidelines for sample type, specimen dimensions, and test conditions. This data was stored in the database with measured physical dimensions and stress conditions that varied slightly from those prescribed in the protocol. A review of the database was conducted using Protocol P-46 to verify that the testing followed the established procedure.

The soil samples in the bulk soil tables consisted of bulk soil samples and remolded thin-walled tube samples. The thin-walled samples included were remolded and tested in the same manner as bulk soil samples.

The test specimens were compacted to the in-situ moisture and density conditions when that information was available. If these conditions were not known, the specimens were compacted to the optimum moisture content at 95% of the maximum dry density. The plots based on these criteria were reviewed later in this chapter, but none of the data were removed if these conditions were not met. Although subgrade construction specifications typically specify a 95 to 100% compaction range, the actual compaction range can vary beyond the specification limits and cannot always be identified without extensive testing. Therefore, removal from the final analysis dataset was not conducted based on compaction results.

Materials were defined as being either Type 1 or 2. This distinction was made to determine the mold size to use in specimen preparation. Fine-grained subgrade soils fell into the Type 2 category, which were prepared in 71-mm (2.8-inch) diameter molds. Type 1 soils were prepared with 152-mm (6-inch) diameter molds. Therefore, test specimens that varied significantly from 71 mm were targeted for removal from the basic analysis dataset. Because the specimen length was required to be at least twice the specimen diameter, specimen lengths were reviewed to ensure that the lengths were at least 142 mm. None of the test results from these specimens were removed as long as the specimen lengths were at least 142 mm long.

Fine-grained soils were categorized as Type 2 because they did not meet the following criteria for Type 1 soils:

a) Untreated soils with less than 70% passing the 2.00 mm (No. 10) sieve,

b) Less than 20% passing the 75mm (No. 200) sieve, and

c) With PI values less than or equal to 10%.

Sub-section 8.1: *Resilient Modulus Test for Subgrade Soils* of the protocol did not specify the use of test caps. The use of test caps was only specified for base materials in Sub-section 8.2: *Resilient Modulus Test for Base/Subbase Materials*. Therefore, specimens identified as being tested with caps were targeted for removal from the base analysis dataset. A significant number of records were eventually removed because of this criterion. Contact with the InfoPave support staff was made to learn the reason for this deviation from the protocol. No explanation could be determined from the InfoPave staff, who generously spent some time researching the issue. However, they did provide documents that could resolve this issue. Although the documents were reviewed briefly, an in-depth analysis was believed to be necessary to answer the question. As the specimens that were tested with test caps failed the criterion of not using test caps, the investigation into their use was postponed to a future, undefined study. As by chance, a possible explanation for the use of test caps on these Type 2 soils was found. It seems that these materials were tested for use as subbase materials, which would necessitate these specimens be tested as Type 1 soils, i.e.

with test caps (Smart and Humphrey, 1999). In any case, the testing of these capped specimens were removed from the dataset.

The P-46 Protocol specified testing at three levels of confining stresses and five levels of axial stresses, as given in Table 4-1. The prepared test specimens are tested in decreasing levels of confining pressures and decreasing levels of maximum axial stresses for each confining pressure level, excluding the conditioning sequence (Sequence No. 0). Therefore, there are 15 testing sequences with 15 resulting M_R test values. In theory, the stress combinations result in 15 unique M_R test results with the soil properties repeated 15 times. The actual number of soils used to prepare the test specimens was determined by using the stress conditions from Sequence Number 1. This determination was conducted by coding with the R programming language to match each combination of stress conditions to the resulting M_R test result. Simply dividing the total number of M_R tests by 15 did not guarantee a correct number count of tests because not all specimens survived the full testing sequence.

Table 4-1: P-46 M_R laboratory testing sequence

Sequence No.	**Confining Pressure, S3**		**Maximum Axial Stress, MAS**		**Cyclic Stress, DEV**		**Contact Stress, CS**	
	kPa	**psi**	**kPa**	**psi**	**kPa**	**psi**	**kPa**	**psi**
0	41.4	6	27.6	4	24.8	3.6	2.8	0.4
1	41.4	6	13.8	2	12.4	1.8	1.4	0.2
2	41.4	6	27.6	4	24.8	3.6	2.8	0.4
3	41.4	6	41.4	6	37.3	5.4	4.1	0.6
4	41.4	6	55.2	8	49.7	7.2	5.5	0.8
5	41.4	6	68.9	10	62.0	9.0	6.9	1.0
6	27.6	4	13.8	2	12.4	1.8	1.4	0.2
7	27.6	4	27.6	4	24.8	3.6	2.8	0.4
8	27.6	4	41.4	6	37.3	5.4	4.1	0.6
9	27.6	4	55.2	8	49.7	7.2	5.5	0.8
10	27.6	4	68.9	10	62.0	9.0	6.9	1.0
11	13.8	2	13.8	2	12.4	1.8	1.4	0.2
12	13.8	2	27.6	4	24.8	3.6	2.8	0.4

Sequence No.	Confining Pressure, S3		Maximum Axial Stress, MAS		Cyclic Stress, DEV		Contact Stress, CS	
	kPa	**psi**	**kPa**	**psi**	**kPa**	**psi**	**kPa**	**psi**
13	13.8	2	41.4	6	37.3	5.4	4.1	0.6
14	13.8	2	55.2	8	49.7	7.2	5.5	0.8
15	13.8	2	68.9	10	62.0	9.0	6.9	1.0

In summary, the only samples that were eventually removed from the base dataset were due to being tested with test caps. The analyses that support this decision are discussed in Section 4.3.4. No test results were removed because of unprescribed stress conditions or sample dimensions.

4.3: Development of the Base Dataset

4.3.1: Data Processing

Some of the data downloaded from the InfoPave website required processing in order to make it useable in the analyses in this study. The need for this processing related to renaming feature names, unit conversion, recalculation of the plastic index (PI), and the calculation of new features that are acknowledged in the literature as having potential influence on the resilient behavior of soils.

The field names in the PPDB data tables were long and not practical for use in writing the code to analyze the subgrade testing data. For example, the AASHTO soil classification data was given in the AASHTO_SOIL_CLASS_EXP field which was shortened to AASHTO. Most feature names were shortened to the symbols given in Table 4.3 in the next section.

Although the subgrade testing data was downloaded in SI units, the maximum dry density values were in English units. Therefore, these values were converted to kg/m3 (SI units) by multiplying them by 16.0184684.

The plastic index (PI) values in the PPDB were stored as character values because some soils were non-plastic as indicated by their PI values of "NP". Therefore, the PI values were recalculated as numeric ones using the liquid limit (LL) and plastic limit (PL) with Equation 4.1. When the soils were non-plastic, they were assigned a PI value of zero (0).

$$PI = PL - LL \qquad \textbf{Eq. 4.1}$$

The features listed in Table 4.4 were added to the dataset for inclusion in the analyses. These features have been noted as being influential on M_R behavior. However, the values for the features had to be calculated and inserted into the dataset using the following list of equations. A description of these calculated features can be found in Tables 4.3 and 4.4.

$$\theta = \sigma_1 + 2\sigma_3 \qquad \textbf{Eq. 4.2}$$

$$\tau_{oct} = \frac{1}{3}\sqrt{(\sigma_1 - \sigma_3)^2 - (\sigma_3 - \sigma_1)^2} \qquad \textbf{Eq. 4.3}$$

$$OMC.RATIO2 = \frac{CMC}{labOMC} \qquad \textbf{Eq. 4.4}$$

$$MDD.RATIO2 = \frac{CDD}{labMDD} \qquad \textbf{Eq. 4.5}$$

4.3.2: Potential Features

The list of the features (independent variables) in Tables 4.3 and 4.4 are many of the variables that are commonly considered for use when attempting to correlate soil index properties to subgrade resilient modulus (M_R). The features in Table 4.3 came directly from the PPDB. The feature symbols were abbreviated from the lengthy ones in the database to simplify the R code that was written for analyzing the data, plotting the data, and modeling.

Table 4-2: Initial potential list of features (variables) from the base dataset

Symbol Used	Feature Description
DIA	Diameter of laboratory test specimen (mm)
LENGTH	Initial length of laboratory test specimen (mm)
CAP_HT	Cap height used in M_R testing (mm)
AASHTO	AASHTO soil class of the test specimen
P3IN	Percent material passing the 3-inch sieve by weight (%)
P2IN	Percent material passing the 2-inch sieve by weight (%)
P1p5	Percent material passing the 1.5-inch sieve by weight (%)
P1IN	Percent material passing the 1-inch sieve by weight (%)
P3d4	Percent material passing the ¾-inch sieve by weight (%)
P1d2	Percent material passing the ½-inch sieve by weight (%)
P3d8	Percent material passing the ⅜-inch sieve by weight (%)
PN4	Percent material passing the No. 4 sieve by weight (%)
PN10	Percent material passing the No. 10 sieve by weight (%)
PN40	Percent material passing the No. 40 sieve by weight (%)
PN80	Percent material passing the No. 80 sieve by weight (%)
PN200	Percent material passing the No. 200 sieve by weight (%)
cSAND	Percentage of coarse sand by weight (%)
fSAND	Percentage of fine sand by weight (%)
SILT	Percentage of silt by weight (%)
CLAY	Percentage of clay by weight (%)
LL	Liquid limit of soil sample (%)
PL	Plastic limit of soil sample (%)
PI*	Plastic index of soil sample (%)
CDD	Compacted dry density of test specimen during M_R testing (kg/m^3)
CMC	Compacted moisture content of test specimen during M_R testing (%)
labMDD*	Maximum dry density of soil sample (kg/m^3)
labOMC	Optimum moisture of soil sample (%)
S3 (σ_3)	Confining stress (kPa)
DEV (σ_{dev})	Deviator stress (kPa)
STRAIN	Recoverable strain (mm/mm)
MR	Resilient modulus (MPa)

* *Required some processing*

The use of MDD.RATIO2 and OMC.RATIO2 feature names stemmed from the maximum dry density (labMDD) and optimum moisture content (labOMC) properties being measured and recorded twice. One set of density and moisture measurements was made for M_R testing and was not used in this analysis. A second set of testing was conducted during a separate operation and was stored in a different database table. This second set of measurements was used in this study. These two sets of measurements were plotted and visually compared against each other. The two sets of data appeared to be virtually equal.

Table 4-3: Calculated features

Symbol Used	Feature Description
S1 (σ_1)	Principle stress (kPa)
TOCT (τ_{oct})	Octahedral stress (kPa)
THETA (θ)	Bulk stress (kPa)
OMC.RATIO2	Ratio of CDD to labOMC
MDD.RATIO2	Ratio of CMD to labMDD

4.3.3: Raw Dataset

The raw dataset was composed of 6603 resilient modulus (M_R) test results for 442 ASTM coarse- and fine-grained soils, or 442 AASHTO granular and non-granular soils. The specimen count was determined by totaling the number of records tested at a single confining stress condition of 41.4 kPa and deviator stress of 61 kPa. Each record in this total represented one M_R result of the 15 stress conditions that each specimen was tested at using LTPP Protocol P-46. It should be noted that some specimens did not complete the full set of stress conditions, which prohibited the simple division of the total number of test results by 15. This initial discussion about the raw dataset will continue with all granular/non-granular or coarse-/fine-grained soil data.

With the establishment of the total number of raw data records, the first consideration taken to clean the dataset was to remove data that had not passed all the quality control checks (Yau & Von Quintus, 2002). This step of the cleaning process was conducted during the reading of the data into individual datasets for each Microsoft Excel tables, which were exported from the downloaded Microsoft Access database. When a table had the feature RECORD_STATUS, it was reviewed to ensure that it had achieved the status of "E". Out of the five tables with this status feature, two of the tables had a total of 1525 records that had not passed all quality checks. However, the combined dataset was only reduced by 100 records.

Although this study is focused on fine-grained soils, all contents of the raw dataset will be reviewed with respect to Protocol P-46 to understand the complete contents of the database with respect to M_R laboratory testing. In Figure 4.1, it can be seen that 253 test specimens were tested with caps, which does not comply with the P-46 Protocol for Type 2 subgrade soils (fine-grained soils). Therefore, these capped specimens were scheduled for removal from the dataset. In Figure 4.2, the ten specimen diameters of 76, 152, and 153 mm were much greater than the 71 mm specified for Type 2 soils; therefore, these specimens were removed without further consideration.

In Figure 4.3, it can be seen that there were 170 granular soils with AASHTO classifications of A-1, A-2, and A-3. These soils were targeted for immediate removal. The 272 non-granular soils (A-4 to A-7-6) would be retained for further examination to determine their suitability for this study, but the initial prejudice was to remove the coarse-grained fractions of every non-granular soil type. This prejudice will be supported with t-tests in a later section.

Another filter that was applied is related to the specimen diameters presented in Figure 4.4. The initial specimen lengths were required to be twice those diameters. Therefore, lengths less than 142 to 144 mm, depending on the actual specimen diameter were scheduled for removal. The lengths that were 307 mm and greater were related to the 152 mm (6-inch) diameter molds for Type 1 soils, which are typically coarse-grained soils. These soils were also marked for removal.

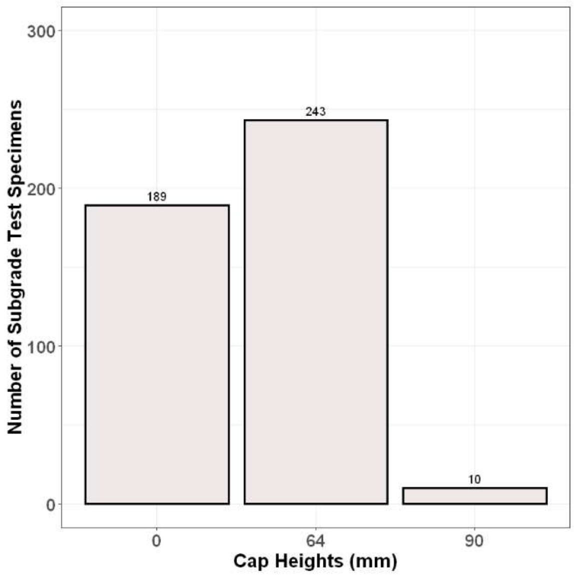

Figure 4-1: Distribution of specimens in the raw dataset by cap height

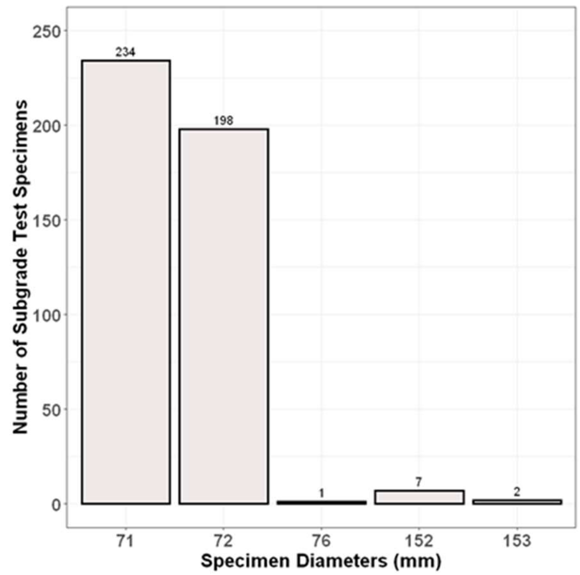

Figure 4-2: Distribution of specimens in the raw dataset by mold diameter

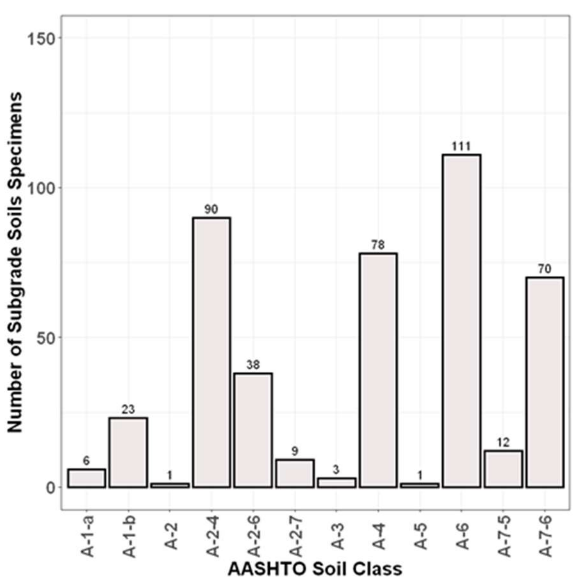

Figure 4-3: Granular and non-granular specimens by AASHTO soil class

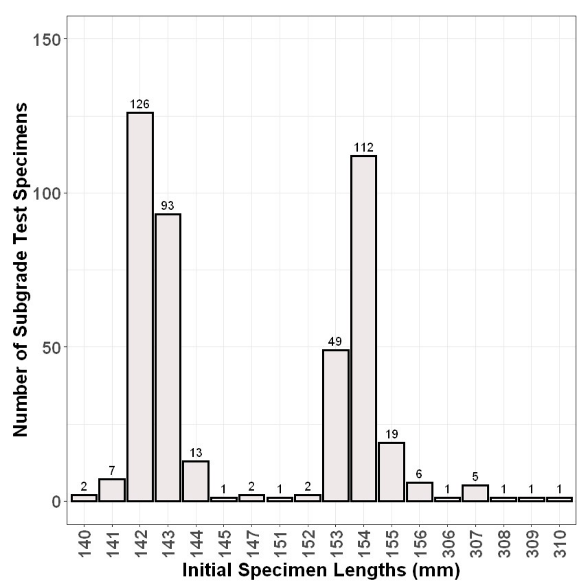

Figure 4-4: Granular and non-granular specimens by initial specimen length

4.3.4: T-tests for Data Cleaning

In this section, two issues presented themselves during the review of the dataset and the current literature that will be discussed. The first issue was in regards to the presence of data features that indicated a significant portion of the M_R testing was performed using test caps, contrary to the procedure outlined in LTPP Protocol P-46. The second issue dealt with the handling of the AASHTO silt-clay (non-granular) materials.

The first inclination was to exclude the test results that were collected during the testing of soil specimens using test caps because Section 8.1 *Resilient Modulus Test for Subgrade Soils* does not discuss the use of test caps. However, Sub-Section 8.2.1 *Assembly of the Triaxial Chamber* (Resilient Modulus Test for Base/Subbase Materials) does mention the use of test (sample) caps. By removing the specimens tested with sample caps, the number of specimens decreased from a total of 442 granular and non-granular specimens to 189 specimens tested without sample caps in the raw dataset. This estimated 57.2% reduction in useable test data was a concern to the development and application of the findings to be made in this study.

The decision was made to conduct an in-depth review of the test specimens using t-tests to investigate whether the uncapped and capped specimens were different, so that the dataset. If no difference was detected based on this laboratory test condition, then the option to include the capped specimens with the uncapped specimens or to perform an additional analysis with the capped specimens would be reasonable. The t-test analyses included a review of the following:

- Laboratory resilient modulus (MR),
- Maximum dry density (labMDD),
- Maximum dry density ratio or compaction (MDD.RATIO2),

- Optimum moisture content (labOMC), and
- Optimum moisture content ratio (OMC.RATIO2).

These properties were considered as relevant because of their use in the AASHTO pavement design guides and/or subgrade construction specifications. In addition to the latest pavement design guide (Mechanistic-Empirical Pavement Design Guide), the 1986 and 1993 AASHTO guides use the resilient modulus (M_R) as the property to represent the behavior of the subgrade soil layer. Therefore, this property was the primary one to investigate. The other properties were included because state agency specifications often include them in their construction specifications for quality control. In addition, the contractor is often required to prepare the subgrade at specified compaction (maximum dry density ratio) levels depending on the site conditions. The optimum moisture contents are associated with the maximum dry density, so both forms of this soil property were included in the t-tests.

The second issue concerning the handling of non-granular soils requires addressing because the literature has found that correlations to M_R improve when separating the independent variables into coarse-grained and fine-grained datasets. However, the AASHTO soil classification does not use coarse-grained and fine-grained soil divisions. Instead, granular and silt-clay (non-granular) material general classifications are used to broadly divide soils. It seemed that some consideration to the AASHTO M-145: *Classification Soils and Soil-Aggregate Mixtures for Highway Construction Purposes* was necessary. The main reasons being that the MEPDG is an AASHTO product, the PPDB contains AASHTO soil classifications, and this AASHTO Standard Specification was developed for highway construction. Ignoring AASHTO M-145 needed addressing. After all, the only difference between the systems was that the silt-clay (non-granular) general classification included soils with more than 35% of its material passing the 75 µm (No. 200) sieve by weight. The fine-grained fraction of the non-granular soils is the same as the fine-grained soil division because both broad categories include materials with more 50% or more material passing the 75 µm (No. 200) sieve by weight. It was decided that t-tests could also help to resolve this conundrum.

Therefore, these two issues will be addressed with a series of t-tests that will compare the soil properties discussed earlier of the:

- Capped and non-capped soil specimens, and
- Coarse- and fine-grained fractions of the non-granular general classification.

The next logical step was that all five (5) properties would have to be the same for each comparison of the specimen groupings to be the same. The following is a list of the three (3) null hypotheses that will be addressed with t-test analyses:

(1) There is no difference in the mean resilient modulus (M_R), maximum dry density, maximum dry density ratio (compaction), optimum moisture content, and optimum moisture content ratios between the non-granular specimens tested with and without test caps.

(2) There is no difference in the mean resilient modulus (M_R), maximum dry density, maximum dry density ratio (compaction), optimum moisture content, and optimum moisture content ratios between the uncapped specimens of coarse-grained and fine-grained soils, and

(3) There is no difference in the mean resilient modulus (M_R), maximum dry density, maximum dry density ratio (compaction), optimum moisture content, and optimum moisture content ratios between the fine-grained specimens tested with and without test caps.

4.3.4.1: Non-granular Specimens Tested with and without Test Caps

The given series of null hypotheses were presented in the same general order that the questions came to the researcher. While the first hypothesis may not be the most logical one based on the primary objective of this study, it was the first set that presented itself during the initial coding process. The results from the first null hypothesis series in Table 4-5 supported the decision to remove the capped specimens from this research study. The low p-values (> 0.05) provided the evidence that there was enough evidence to reject the null hypothesis that the soil properties were the same. Therefore, the alternate hypothesis that these soils were different was supportable. The complete t-test output for this first series of t-test hypotheses are given in Appendix B.

Table 4-5: T-test summary for all non-granular subgrade soils with and without caps

	Average Values		p-value	Conclusion
	Cap (No)	Caps (Yes)		
M_R	67.7	88.0	$< 2.2 \times 10^{-16}$	Reject null
labMDD	1787.9	1821.7	1.316×10^{-13}	Reject null
MDD.RATIO2	0.9586	0.9470	$< 2.2 \times 10^{-16}$	Reject null
labOMC	15.3	14.9	0.0049	Reject null
OMC.RATIO2	0.9938	1.0048	1.31×10^{-8}	Reject null

4.3.4.2: Uncapped specimens of coarse-grained and fine-grained fractions

The next series of t-tests were conducted to determine if the coarse-grained fraction (CGF) and fine-grained fraction (FGF) of the non-granular general classification were significantly different based on the non-use of test caps. Table 4-6 presented a summary of a mixed set of t-test results with the complete set of output in Appendix C.

Examination of the t-test results reveals that the average M_R of the CGF and FGF were equal which is interesting. This finding supports the AASHTO general rating of non-granular soils (CGF and FGF) as fair to poor. Using the CGF as the reference point, the labMDD was 6.4% lower for the FGF, and the labOMC was 25.1% higher for the FGF. The similarity in compaction (MDD.RATIO2) and OMC ratios could simply reflect that the quality control during the laboratory testing was good because these values did not vary greatly.

Table 4-6: T-test summary for non-granular fractions without caps

	Average Values		**p-value**	**Conclusion**
	CGF	**FGF**		
M_R	67.9	67.6	0.7987	Cannot Reject
labMDD	1867.8	1748.0	$< 2.2 \times 10^{-16}$	Reject null
MDD.RATIO2	0.9593	0.9595	0.7431	Cannot Reject
labOMC	13.1	16.4	$< 2.2 \times 10^{-16}$	Reject null
OMC.RATIO2	0.9987	0.9913	0.0761	Cannot Reject

4.3.4.3: Fine-grained Fraction Tested with and without Caps

While this series of hypotheses may appear to be a repeat of the first series, the first series of hypotheses was performed on the non-granular soils as a whole to document the learning progression of the data in the PPDB. Additionally, the information from the first set of hypotheses could be of use to researchers that may come across this study in the future. As expected, this final series of t-tests determined that the soil properties of the capped and uncapped fine-grained soil fraction (FGF) specimens were significantly different from each other.

Table 4-7 provides a summary of the t-test outputs that can be found in Appendix D. The average M_R and maximum dry density (labMDD) of the capped fine-grained fraction specimens were found to be greater than the uncapped specimens. Thes findings were identical to those of the non-granular soils as a single group. The only property that was the same for the capped and uncapped FGF specimens was the optimum moisture content (labOMC). The use of the test cap appeared to provide an additional compaction effort during the M_R testing process, but this conclusion will require additional investigation. The similarity in labOMC between the capped and uncapped specimens was not totally unexplainable. There would not be any reason for the average labOMC to be different between these testing conditions unless one method was able to dry out the sample more than the other.

Table 4-7: T-test summary for FGF subgrade soils with and without caps

	Average Values		p-value	Conclusion
	NO Cap	YES Cap		
M_R	67.6	86.8	$< 2.2 \times 10^{-16}$	Reject null
labMDD	1748.0	1762.3	0.0059	Reject null
MDD.RATIO2	0.9595	0.9475	$< 2.2 \times 10^{-16}$	Reject null
labOMC	16.4	16.6	0.3026	Cannot Reject
OMC.RATIO2	0.9913	1.0051	5.498×10^{-10}	Reject null

4.3.4.4: Summary

The t-tests for the hypotheses presented supported the decisions to remove the M_R and associated tests performed on capped soil specimens. The t-tests also supported the decision to disregard the fine-grained fraction (CGF) of the AASHTO non-granular general classification. With these conundrums resolved, only the uncapped specimens as prescribed for M_R testing by LTPP Protocol P-46 will be used in this study from this point forward, and the soils of the FGF will be referred to as simply fine-grained soils.

4.4: Data Cleaning and Review

Records in the raw dataset were purged using the criteria discussed earlier in this chapter. As a review of these criteria, records were removed for the following:

- Not having undergone all quality control checks;
- Not conforming to the LTPP Protocol P-46; and
- Not conforming to the ASTM D-2487 description for fine-grained soils.

The plots in this section were prepared using the cleaned raw dataset, i.e. the base dataset. Figure 4-8 confirms that the dataset consists of specimens tested without a test (sample) cap. Figure 4-9 displays the rounded average specimen diameter of 72 mm, despite the fact that 71 mm diameter molds were used for specimen preparation.

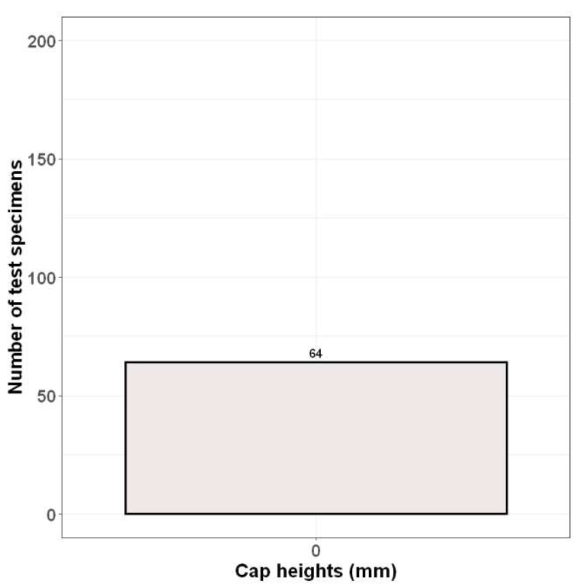

Figure 4-8: Number of fine-grained specimens by cap height

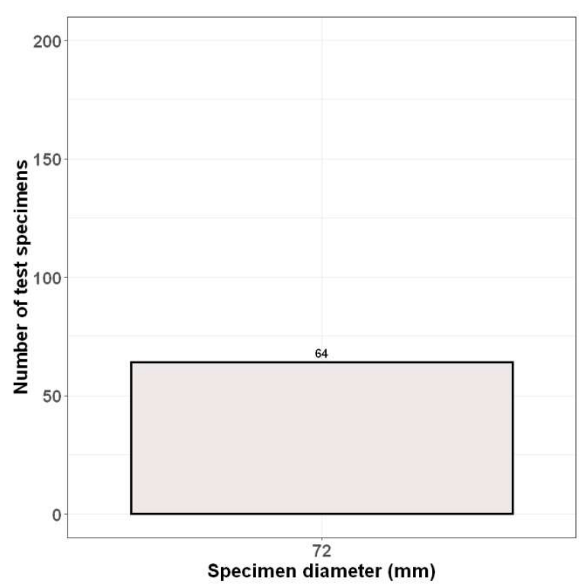

Figure 4-9: Number of fine-grained specimens by diameter

Figure 4-10 displays the lengths of the soil specimens. These lengths were greater than twice the specimen diameters, which satisfies the length requirement in Protocol P-46.

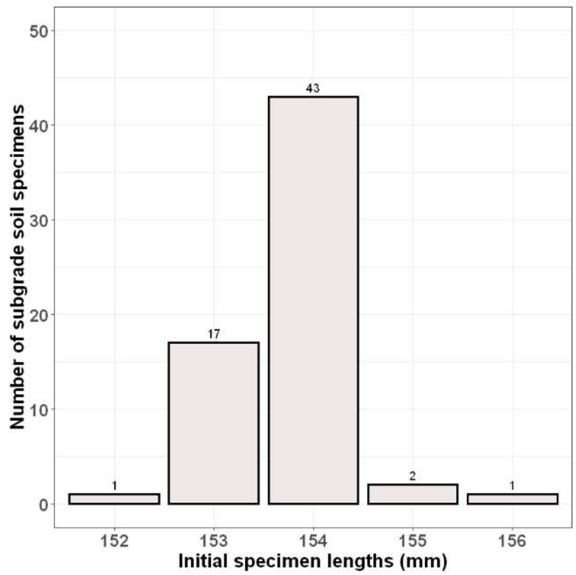

Figure 4-10: Number of fine-grained specimens by specimen length

4.5: Plots for Fine-Grained Subgrade Soils in the Base Dataset

The analysis of the data within the base dataset continued with a review of the distribution of the fine-grained (FG) subgrade soils among the AASHTO soil classes. As a reminder, the use of the AASHTO soil classifications was done as a matter of convenience instead of using ASTM soil classes, as the AASHTO classes were provided in the LTPP database. All references to AASHTO classifications in the base dataset were made with the understanding that only fine-grained soils were discussed.

4.5.1: Plots of Basic Properties of Fine-Grained Soils by AASHTO Soil Class

Figure 4-11shows that the distribution of the 64 fine-grained (FG) soil specimens among the AASHTO soil classifications was unbalanced. The A-6 class was best represented with 26 soil samples. The A-5 was not represented at all with no soil samples. The A-7-5 soil class was the next least represented class with five (3) soils. In Figure 4-12, the generally A-4 silty soils had median M_R values that were typically less than those of the generally clayey soils (A-6, A-7). The A-4 and A-6 soils also had M_R test values that fluctuated more than the clayey soils.

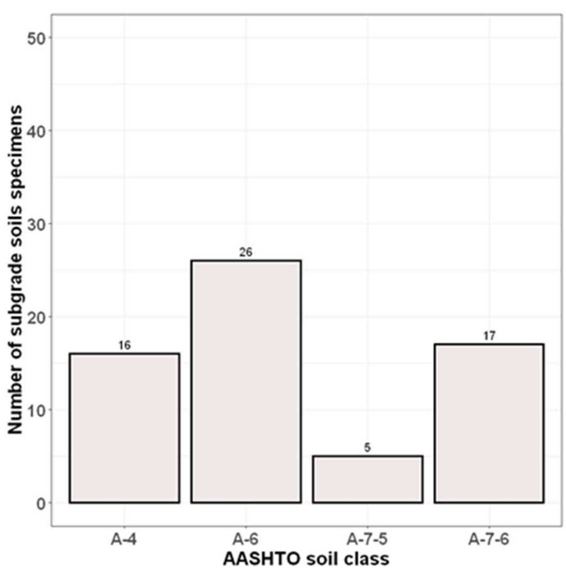

Figure 4-11: Distribution of FG specimens by AASHTO soil class

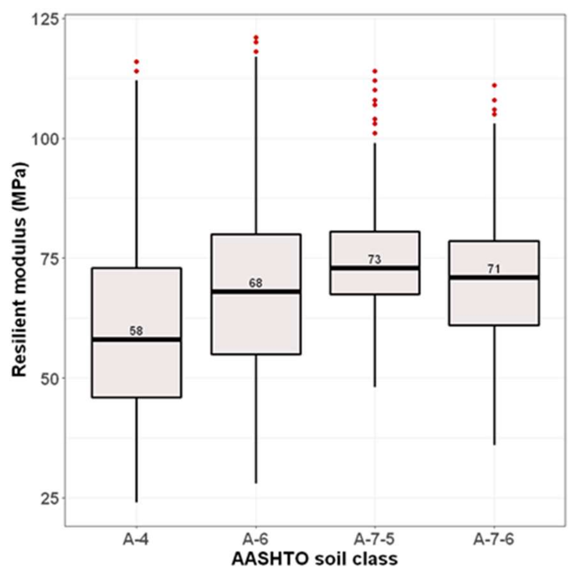

Figure 4-12: MR ranges by AASHTO soil classes (FG soils)

The deviator stress and strain for FG soils were selected for discussion because these parameters are used to define M_R. Therefore, reviewing the plots of these parameters versus the AASHTO soil classifications was deemed necessary. As expected, the plot in Figure 4-13 depicts the deviator stresses used in M_R laboratory testing as being consistent for all soil classes. This consistency supported the expectation that testing was consistent among the laboratories that conducted these tests and followed the P-46 Protocol. In Figure 4-14, the median strain (0.000615 mm/mm) for the A-4 soils was the greatest and were consistent with that class having the lowest median values (58 MPa) of M_R. Also, the A-7-5 soil class had a median strain that was the lowest of the four soil classes and expectedly the highest median M_R values (73 MPa).

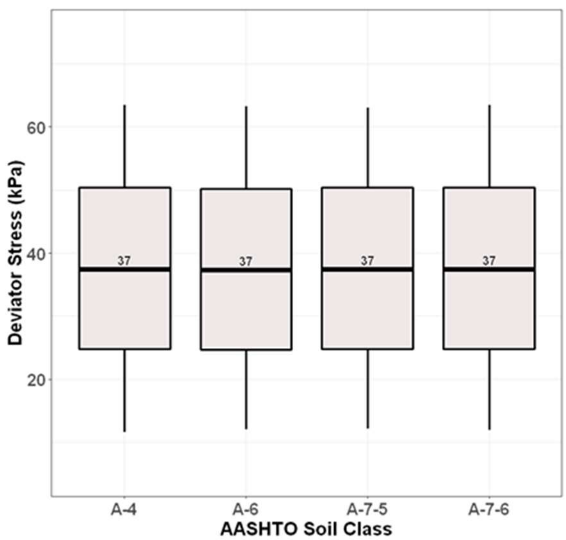

Figure 4-13: Deviator stress by AASHTO class for FG soils

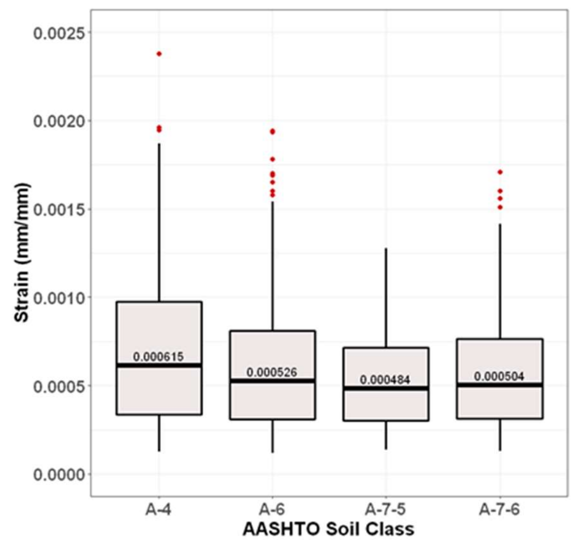

Figure 4-14: Strain by AASHTO class for FG soils

In Figures 4-15 and 4-16, distinct breaks in maximum dry densities (MDDs) and optimum moisture contents (OMCs) were noticeable between the A-4/A-6 grouping of soils and the A-7-5/A-7-6 grouping. The MDDs were generally greater in the first grouping of silty soils while the OMCs were generally lower when compared to the second group of clayey soils.

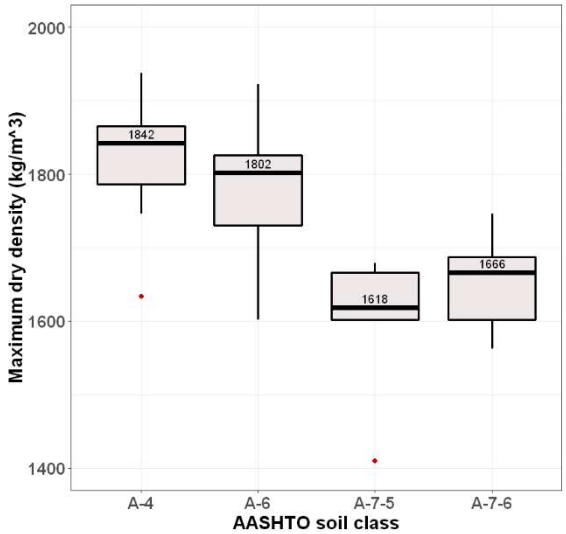

Figure 4-15: Maximum dry density by AASHTO class for FG soils

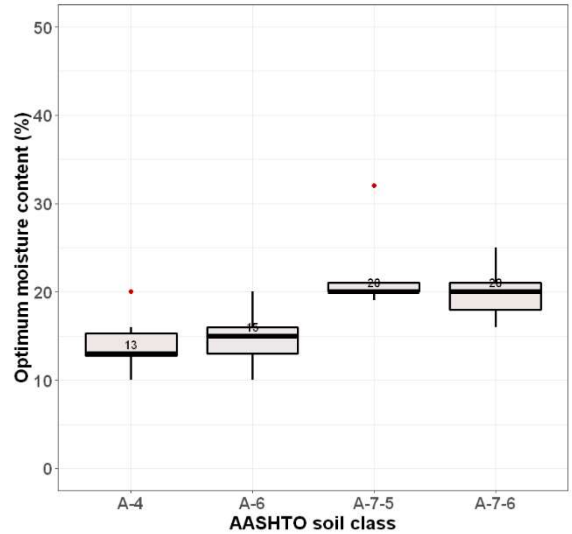

Figure 4-16: Optimum moisture content by AASHTO classes for FG soils

4.5.2: Review of resilient modulus (M_R) values by features

The following and final set of plots for data analysis depict the relationships between the M_R and each potential predictive feature in the base dataset. The purpose of this exercise was to confirm that the data was successfully imported from the downloaded LTPP database that was hosted on the InfoPave website. This confirmation took the form of plots that reflected some of the same general relationships that were reported in the literature. Although a decision tree algorithm was used to develop the predictive model for M_R that was necessary to develop a soil classification scheme for fine-grained soils (FG), it should be remembered that the algorithm does not rely on linear relationships. When the lines are drawn on the plots, they are an aid to visualize the relationships that are typically drawn for linear regressions.

As Figure 3-1 shows, the decision tree algorithm creates nodes that divides the data into clumps based on the conditional statement given in the nodes. Therefore, the following plots were presented as a familiar representation of the data. Notes are provided for the figures to identify noticeable characteristics of the plots.

Figure 4-17 Notes: The diameters of the specimens prepared with the 71-mm mold ranged from 71.80 to 72.30 mm. The larger diameters represent a 1.13% to 1.83% increase from the inside diameter of the mold with a resulting increase in top surface area of 2.27% to 3.70%.

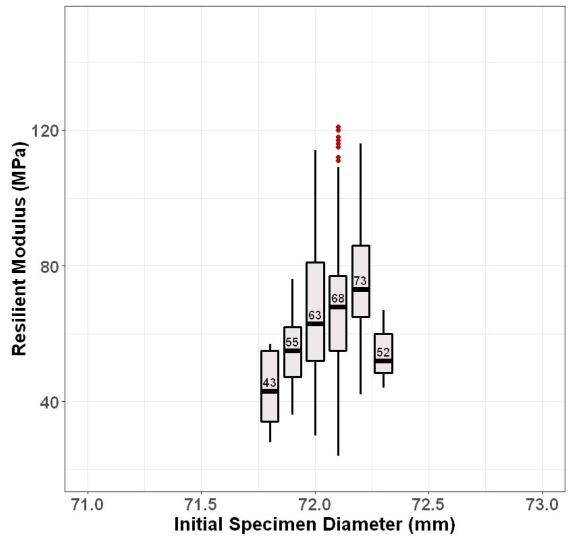

Figure 4-17: M_R vs Initial Diameters

Figure 4-18 Notes: The initial specimen lengths ranged from 152 to 156 mm. Protocol P-46 specifies the specimen lengths be twice the diameter (143.6 to 144.6 mm), which these fine-grained specimens met.

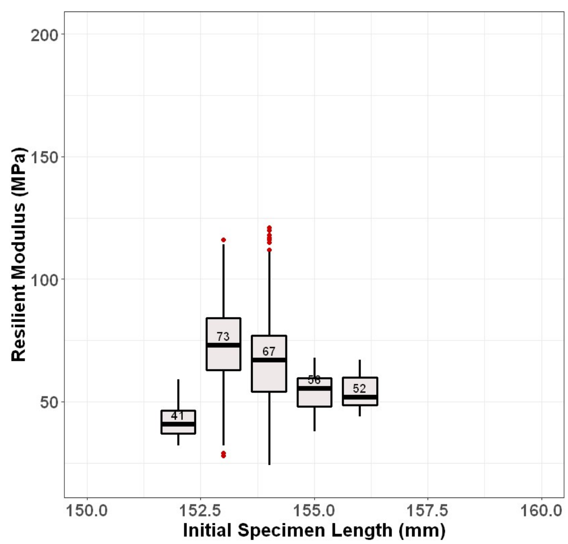

Figure 4-18: M_R vs Initial Lengths

Figure 4-19 Notes: The M_R decreased as the strain increased.

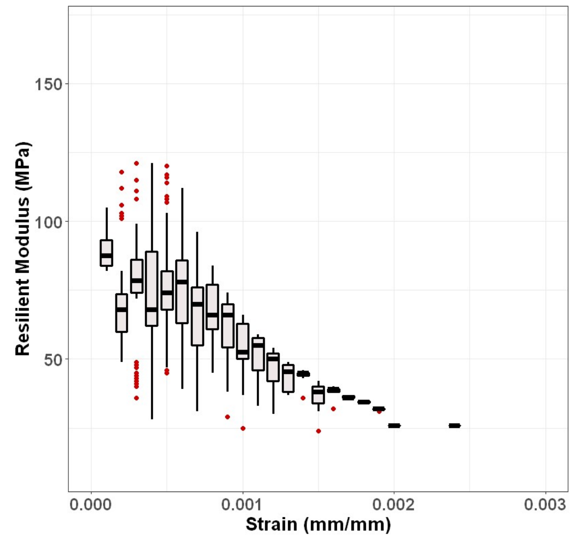

Figure 4-19: M_R vs Strain

Figure 4-20 Notes: By visual inspection of the trendline, M_R did not indicate a significant negative linear relationship with deviator stress. The deviator stress data was not rounded, which led to the multiple bars at each deviator stress level. In addition, the bar groups in other stress plots resulted from the same reason.

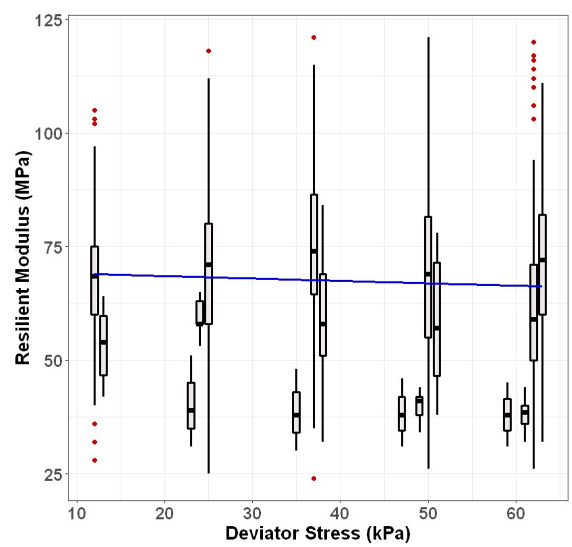

Figure 4-20: M_R vs Deviator Stress

Figure 4-21 Notes: The M_R increased as the confining stress increased. The median M_R increased 7.9% when the confining stress increased from 13.8 to 27.6 kPa. The median M_R increased 7.4% when the confining stress increased from 27.6 to 41.4 kPa.

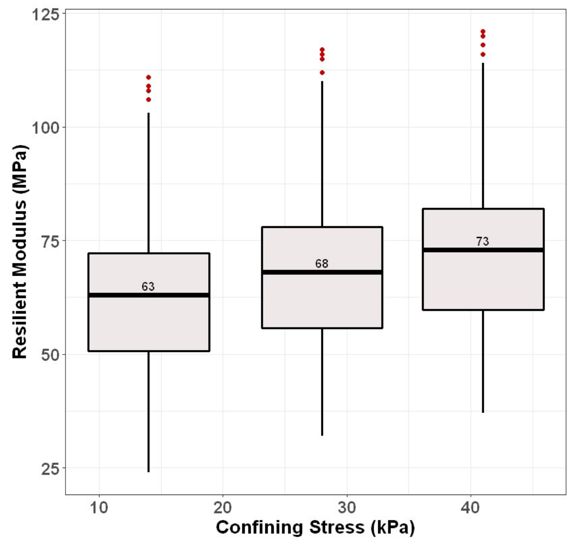

Figure 4-21: M_R vs confining stress

Figure 4-22 Notes: Based on a visual inspection of the trendline, the M_R did not appear to decrease significantly as the octahedral stress increased.

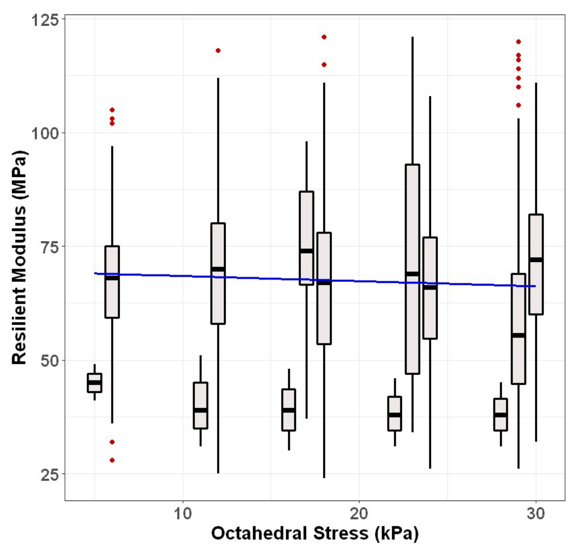

Figure 4-22: M_R vs Octahedral Stress

Figure 4-23 Notes: Based on a visual inspection of the trendline, the M_R decreased as the optimum moisture content (OMC) increased.

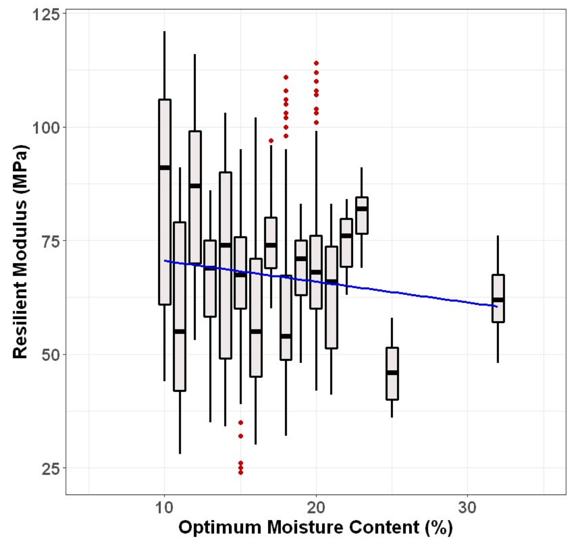

Figure 4-23: M_R vs OMC

Figure 4-24 Notes: Based on a visual inspection of the trendline, the M_R increased as the optimum moisture content ratio increased. Based on a visual inspection of the plot, the ratio of most specimens were prepared within 10% of the OMC. More than 92% of the test specimens were prepared within 10% of the optimum moisture content.

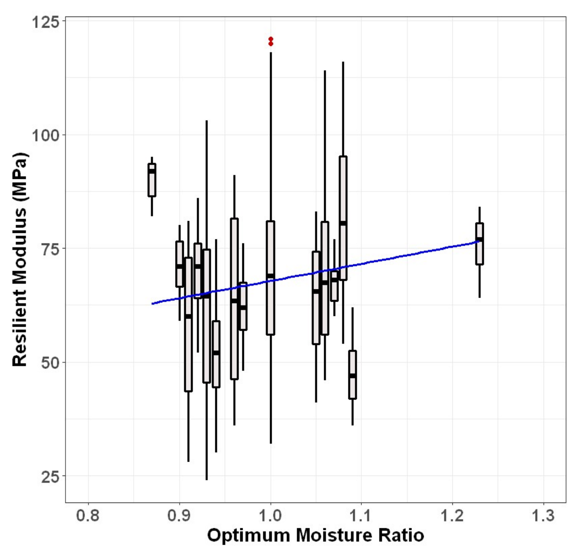

Figure 4-24: M_R vs OMC.RATIO2

Figure 4-25 Notes: Based on a visual inspection of the trendline, there was a gradual increase in M_R as the maximum dry density increased.

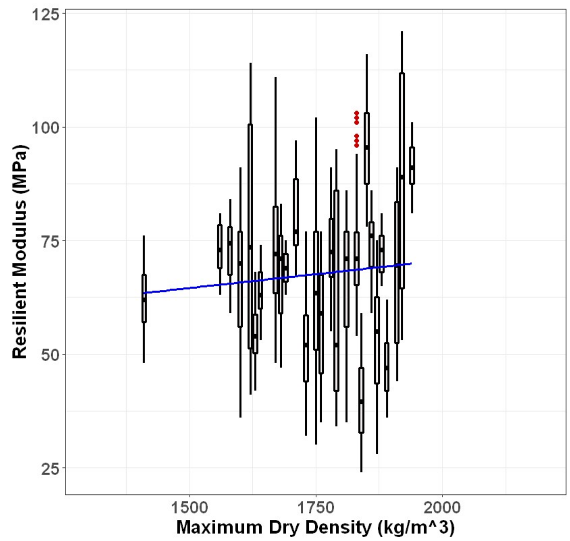

Figure 4-25: M_R vs MDD

Figure 4-26 Notes: Based on a visual inspection of the trendline, there was a decrease in M_R as the maximum dry density ratio (compaction) increased. More than 82% of the test specimens were prepared between 95 and 97.5% of the maximum dry density.

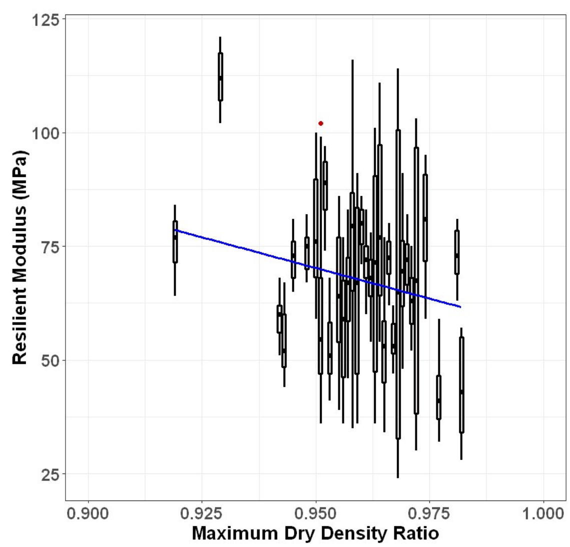

Figure 4-26: M_R vs Compaction

Figure 4-27 Notes: Based on a visual inspection of the trendline, there did not appear to be any effect on M_R as the plastic index increased.

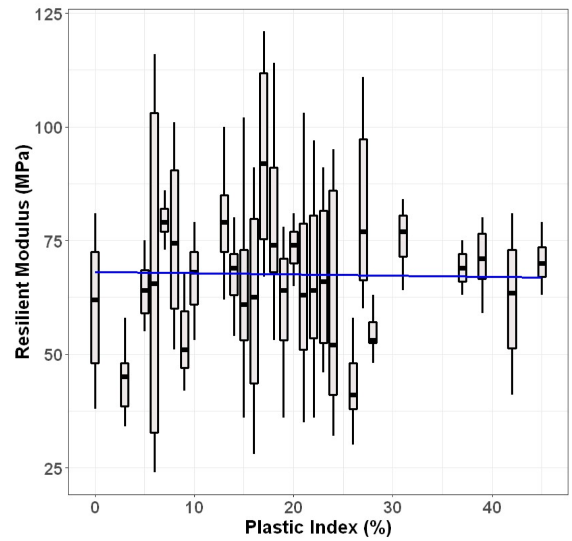

Figure 4-27: M_R by PI

Figure 4-28 Notes: Based on a visual inspection of the trendline, there was an increase in M_R as the liquid limit (LL) increased.

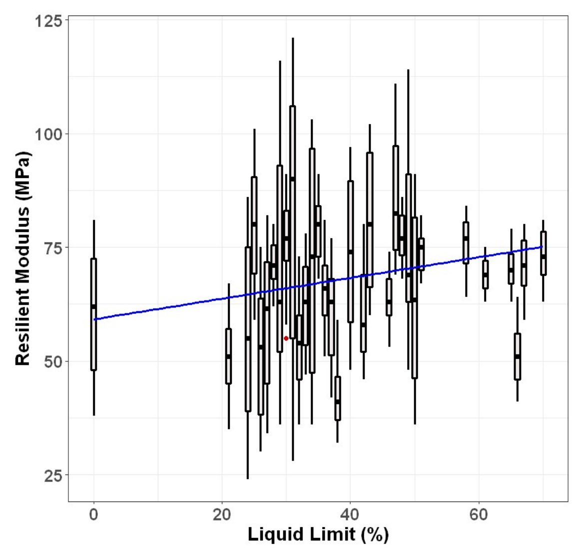

Figure 4-28: M_R by LL

Figure 4-29 Notes: Based on a visual inspection of the trendline, there was an increase in M_R as the plastic limit (PL) increased.

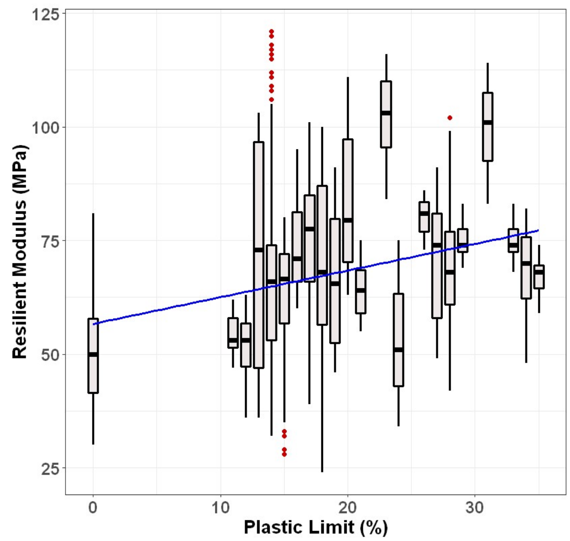

Figure 4-29: M_R by PL

Figure 4-30 Notes: Based on a visual inspection of the trendline, there did not appear to be a significant change in M_R as the material passing the ⅜-inch sieve (P3d8) increased.

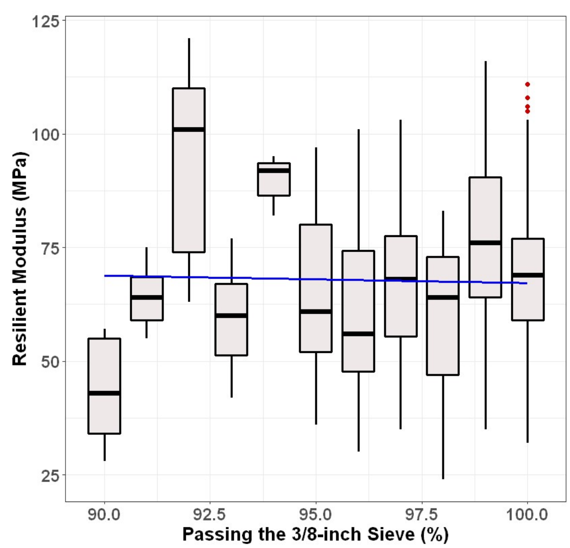

Figure 4-30: M_R by P3d8

Figure 4-31 Notes: Based on a visual inspection of the trendline, there did not appear to be a significant change in M_R as the material passing the No. 4 sieve (PN4) increased.

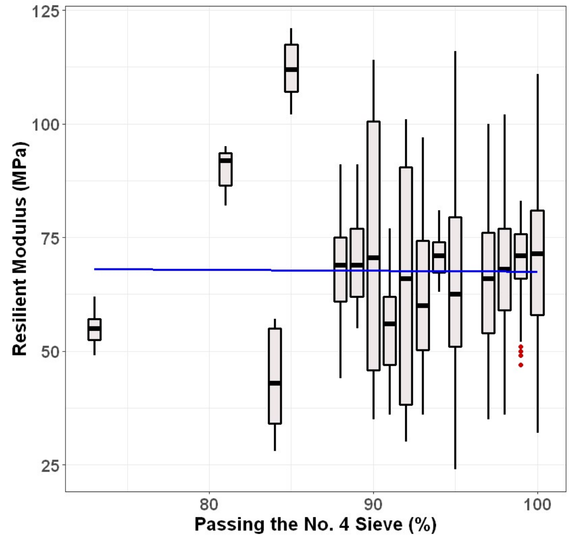

Figure 4-31: M_R by PN4

Figure 4-32 Notes: Based on a visual inspection of the trendline, there did not appear to be a significant change in M_R as the material passing the No. 10 sieve increased.

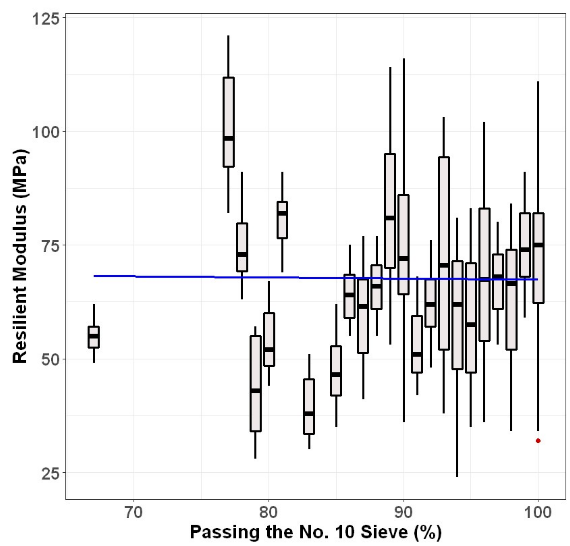

Figure 4-32: M_R by PN10

Figure 4-33 Notes: Based on a visual inspection of the trendline, the M_R gradually increased as the material passing the No. 80 sieve increased.

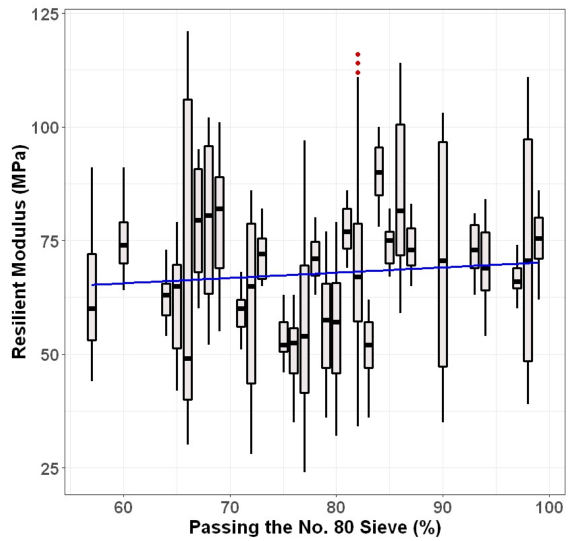

Figure 4-33: M_R by PN80

Figure 4-34 Notes: Based on a visual inspection of the trendline, the M_R did not change significantly as the material passing the No. 200 sieve increased.

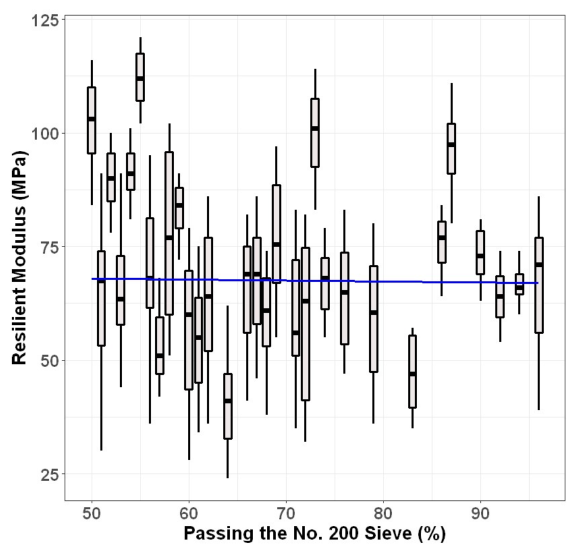

Figure 4-34: M_R by PN200

Figure 4-35 Notes: Based on a visual inspection of the trendline, the M_R increased as the clay content increased.

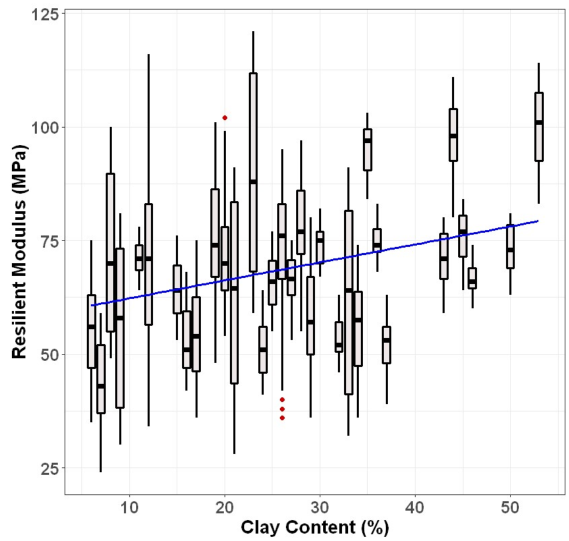

Figure 4-35: M_R by CLAY

Figure 4-36 Notes: Based on a visual inspection of the trendline, the M_R decreased as the silt content increased.

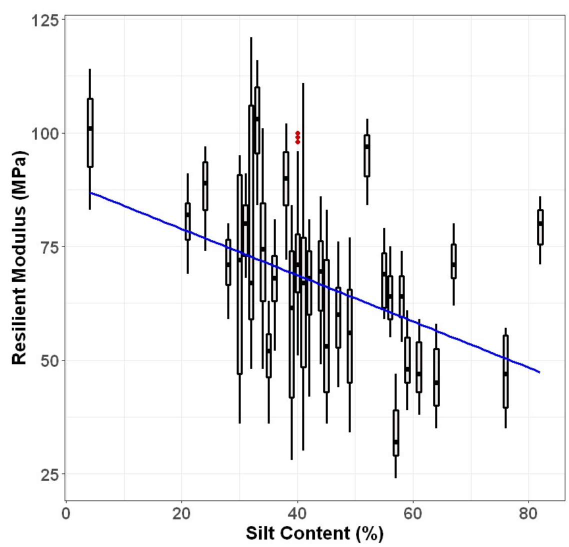

Figure 4-36: M_R by SILT

Figure 4-37 Notes: Based on a visual inspection of the trendline, the M_R does not appear to be influenced by the coarse sand content (cSAND).

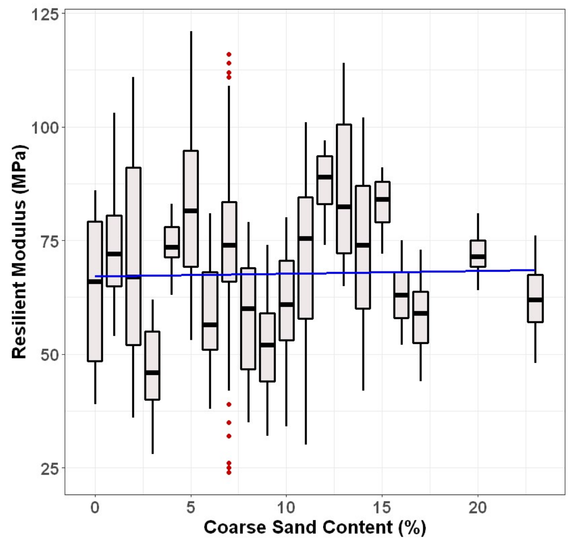

Figure 4-37: M_R by cSAND

Figure 4-38 Notes: Based on a visual inspection of the trendline, the M_R increases as the fine sand content (fSAND) increases.

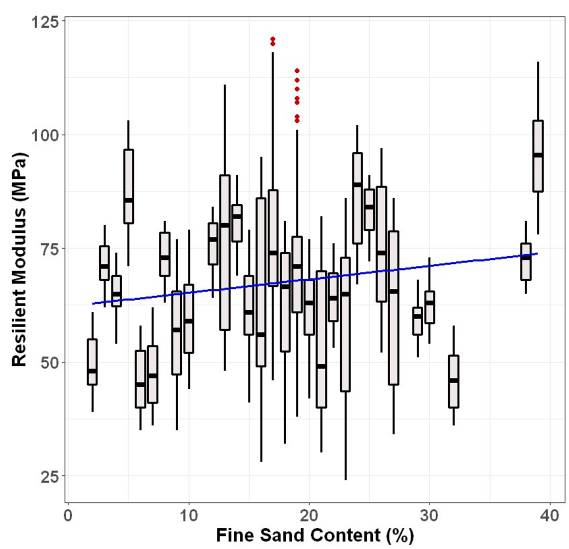

Figure 4-38: M_R by fSAND

4.6: Summary

In Chapter 4, the case has been made for using PPDB as a data source for resilient modulus test data for fine-grained subgrade soils. Although some Type 2 specimens were found to have been tested with caps, contrary to P-46, they were easily identifiable during the review process. ASTM D-2487 was used as the criterion for separating the coarse-grained and fine-grained soils. The capped soils and coarse-grained fraction of the non-granular soils were removed based on t-tests. Plots of the resilient modulus versus the potential features were made to provide additional support for the findings of other researchers and to verify that the base dataset developed in this study was composed properly.

CHAPTER 5: DEVELOPMENT OF SOIL CLASSIFICATION SCHEME

In this chapter the development of a soil classification scheme that would reflect the resilient behavior of fine-grained subgrade soils using the methodology discussed in Chapter 3. The scheme produced from the analyses was described as such because it was not a full classification system, which would also need to include classifications for coarse-grained soils. However, even with better correlation results, predicting M_R has been a challenge for engineers since before the AASHO Road Test, which ended in 1960. Only fine-grained soils were included in this study because separating soils into coarse-grained and fine-grained subsets had been found to produce better correlations to resilient modulus than a single dataset that combined all soils together. In addition, identifying the more problematic fine-grained soils would be of a more immediate benefit to engineers during subgrade construction, so this challenge was approached first.

Because the current AASHTO soil classification system resembled a decision tree, it seemed a suitable strategy to use a decision tree algorithm to develop a soils classification scheme. As the tree would not only correlate M_R to soil index properties and testing parameters, but it would also provide the framework that would easily translate to a table that could be inserted into a complete soil classification standard. The tree model provided a good R^2, despite the cautions from multiple studies that recommended segregating soils into regional datasets. This suggestion was probably to account for unknown soil properties that were not typically measured (Hossain, 2009) (Soliman & Shalaby, 2014). The modulus-based classes were found to be significant and the process of supporting their use was also discussed.

The main benefit of the decision tree model is that it was easy to understand. The primary disadvantage is that the model can change with the addition of even a few more data records. Therefore, the small collection of records using the 64 soil samples from 18 states would likely lead to further modifications to the system with the addition of more test data.

5.1: Model development procedure

The primary reasons for using decision tree modeling as the basis for developing a soil classification scheme were (1) the transparency of decision tree models that can provide correlations similar in accuracy to those of multiple linear regression models (Pahno, Yang, & Kim, 2021) and (2) the conversion of the decision tree model to a classification table that has a structure similar to the current AASHTO soil classification table.

As was seen in Figure 3.3, the decision tree example model provided the binary split conditions that was readily available for review. There was no need to sift through multiple pages of output to determine how the model was constructed, as would be necessary with the better predictive XGBoost or random forest models. Therefore, the model resulting from using decision tree modeling was easy to understand and easily revealed the features that were most influential in finding a correlation between the predictive features and M_R.

The following eight (8) steps were used to develop a decision tree correlation model for predicting the M_R of fine-grained subgrade soils. The conditional statements in the decision tree would later be transformed into a tabular format. These steps only applied to specimens that were compliant with the P-46 Protocol and any testing results identified as being non-anomalous in Chapter 4.

(1) Create training and testing datasets.

(2) Create a decision tree regression model that correlated M_R to most influential soil properties and/or stress conditions using the training dataset.

(3) Review statistics of leaf node contents using the training dataset of the decision tree model to create a criterion for grouping soils. Evaluate the pruned decision tree model

(4) Group leaf nodes with similar average M_R values based on resilient quality levels of fine-grained soils

(5) Conduct t-test and one-way ANOVA analyses to establish the statistical significance of the new classification scheme using the results from the testing dataset. Apply resilient quality property criteria to leaf nodes

(6) Compare new fine-grained classes to AASHTO soil classes from the fine-grained fraction of the non-granular (silt-clay materials) general classification. T-tests to support the M class groupings

(7) Create a table that could be applied as a specification for classifying fine-grained subgrade soils with the new classification scheme. Compare M classes to AASHTO soil classes for fine-grained soils

(8) Convert decision tree into a table format

5.2: Model for all fine-grained subgrade soils and all stress conditions

As a reminder, the decision tree model was trained on the features identified in Tables 4-2 and 4-3. The three primary requirements of the specimens and data are that:

(1) they conform to LTPP Protocol P-46,

(2) they were identified as subgrade materials in the PPDB,

(3) they passed all LTPP quality control checks to achieve a record status of “E”, and

(4) they meet the definition of fine-grained soils according to ASTM D-2487.

5.2.1: STEP 1 - Create training and testing datasets

The first step in the decision tree development process was to create training and testing datasets with the features in Tables 4-2 and Table 4-3. These two datasets would be used to develop the decision tree model and to test the model for accuracy. The base dataset consisting of resilient modulus (M_R) testing records for fine-grained subgrade soil specimens was the source from which the training and testing datasets were created with a user-specified split of 80-20 (Table 5-1). The splitting of the test results was based on random selection of records from the base dataset.

The larger training dataset (*ds_train*) comprising 80% of the 960 test records was used to develop the decision tree model, and the smaller testing dataset (*ds_test*) with the remaining 20% of the records was used to test the accuracy of the model. The summary statistics on the 960 M_R tests for the 64 soil specimens indicated that the training and testing datasets were representative of the base dataset.

Table 5-1: Summary statistics on M_R for the no-capped specimens of fine-grained soils

	Training Dataset	**Testing Dataset**	**Base Dataset**
Number of Observations	768	192	960
Average M_R	67.8 MPa	66.9 MPa	67.6 MPa
Standard Deviation	18.1 MPa	18.2 MPa	18.1 MPa
Coefficient of Variation	26.7%	27.2%	26.8%

5.2.2: STEP 2 - Create decision tree regression model

The decision tree regression model that was developed in this study was trained using the *rpart* library in a Jupyter notebook (Kluyver, T. et al., 2016). The R programming environment was created and managed with Anaconda Navigator (R Core Team, 2020) (Therneau, T. & Atkinson, B., 2019). The *rpart* function presented in Eq. 5.1 was used to train the decision tree model (*tree.MR*) to estimate M_R. The equation required only a minimum number of inputs, which demonstrated the ease of applying this machine learning algorithm to develop prediction models.

tree.MR ← rpart(MR~., ds_train[dt.list], method="anova") **Eq 5-1**

The arguments used in the equation are explained as follows:

- *tree.MR*: dataset that stored the components of the resulting decision tree model.
- *MR~.*: formula that predicted the resilient modulus (*MR*), is the target feature. The "~." indicated that all features within the features list (*dt.list*) will be used to train the model for M_R.
- *ds_train*: the training dataset that contained the features and feature values used to train the model.
- *dt.list* : a list of features that was used to store the features used in conjunction with the training dataset. The list argument was created to more easily prepare a long list of features that could be edited once and applied to numerous equations. This programming strategy allowed for experimentation with different combinations of features while only having to type the feature list once.

- *anova*: the method that was required to conduct a regression model analysis.

Running Eq 5.1 produced the *tree.MR* dataset, which was used to plot the unpruned decision tree in Figure 5-1 with the *rpart.plot* function from the *rpart.plot* library. The diagram displays the root node at the top of the tree with the binary split condition of *SILT>=41*. The root node identifies the silt content (SILT) of fine-grained soils as the most important feature with respect to reducing the mean square error (MSE) of the average nodal M_R by splitting the ordered data with the given condition (Greenwell, 2022). The lower leveled internal nodes were established using the same recursive process that also reduced the MSE for their contents with respect to M_R. The 21 leaf nodes at the bottom of the decision tree provided the average M_R values and percentages of the 768 test records of the training dataset that were contained within them.

The concern with the model in its current state was with overfitting the training dataset, which could result in an ineffective model for estimating the M_R of the testing dataset and independent soil data. To remedy this potential, the decision tree was pruned using a cost complexity factor (c_p) of 0.013 from Figure 5-2 that minimized the corresponding error to generalize the model.

The plot in Figure 5-3 displayed the relationship between the theoretical R^2 and the number of splits used to create a tree model. The maximum theoretical R^2 for the model was approximately 0.8 using the training dataset. Therefore, any model produced from the selected data was evaluated as being useful in estimating M_R. It should be noted that editing the number of features used in the model can result in a different model with different results.

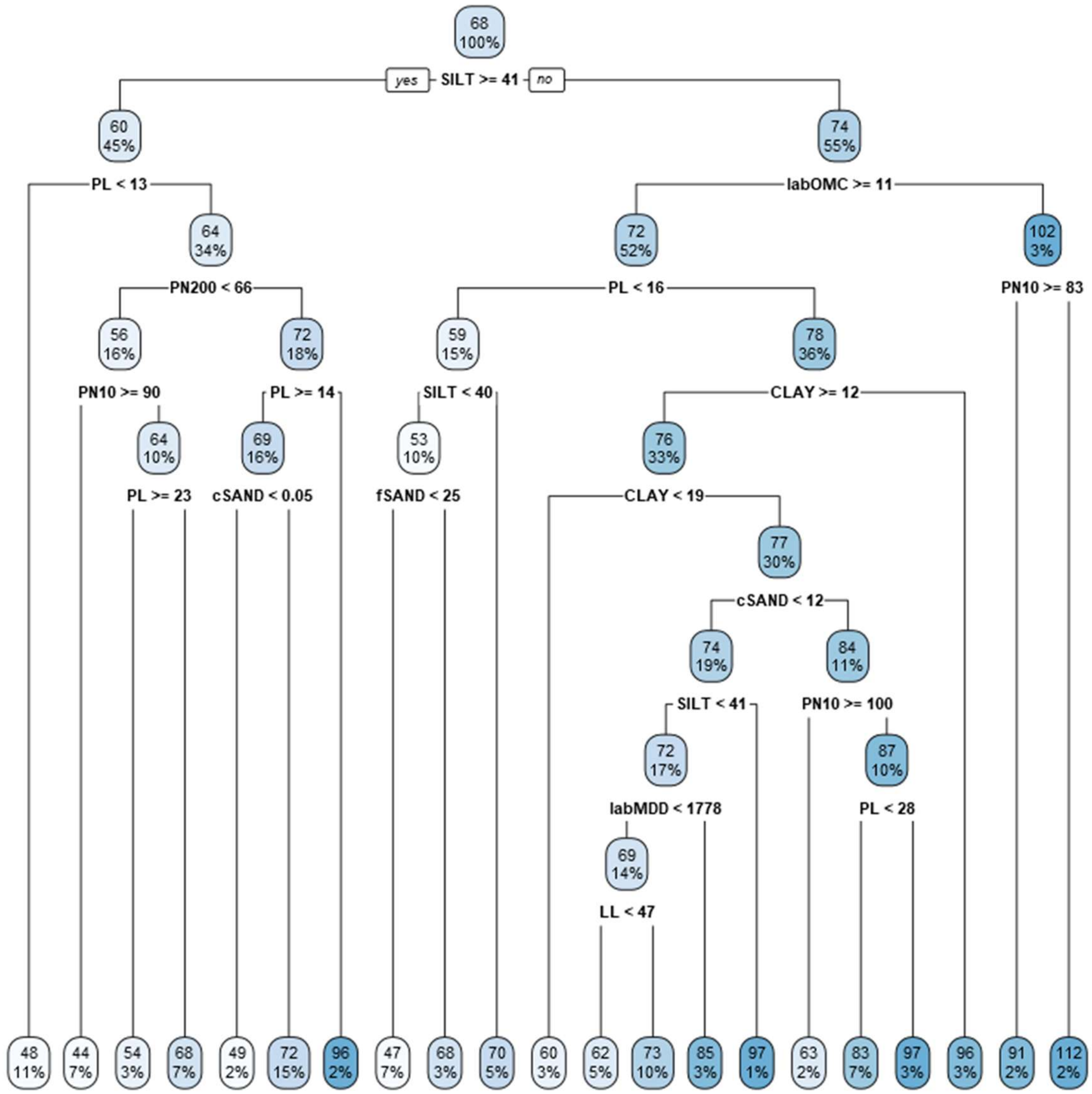

Figure 5-1: Unpruned decision tree model

From examination of the unpruned and pruned decision trees in Figures 5-1 and 5-4, it can be seen that two intermediate nodes (*with conditional statements of LL<47 and PL<28*) near the bottom were removed from the unpruned tree. The resulting pruned tree had 9 levels using 9 unique features: (1) SILT, (2) PL, (3) labOMC, (4) PN200, (5) PN10, (6) CLAY, (7) cSAND, (8) fSAND, and (9) labMDD.

In comparison, the AASHTO soil classification system used an equivalent of 4 levels to classify non-granular soils with only 2 unique features (LL and PI), neglecting the PN200, which was also neglected in the count for the decision tree models. Interestingly, neither set of predictive features has any in common. The reason being that the decision tree model was developed to predict M_R while the AASHTO M-145 was not.

Returning to the pruned decision tree regression model in Figure 5-4, it can be seen that the 18 leaf nodes at the bottom of the tree were manually labelled “A” to “R” from left to right to make referencing these nodes easier in later sections.

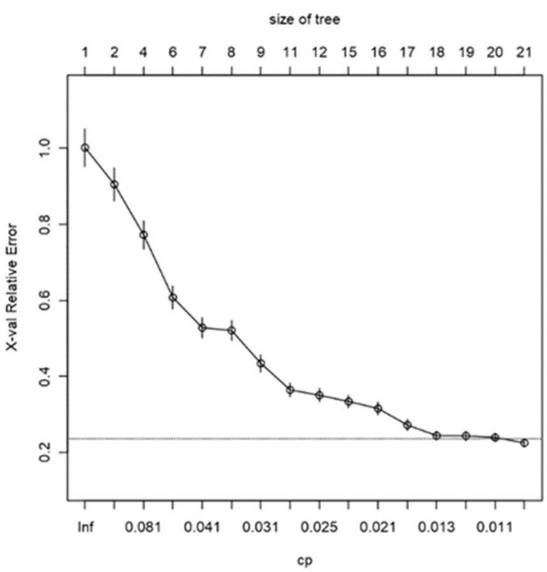

Figure 5-2: Cross-validation error versus cost complexity factor

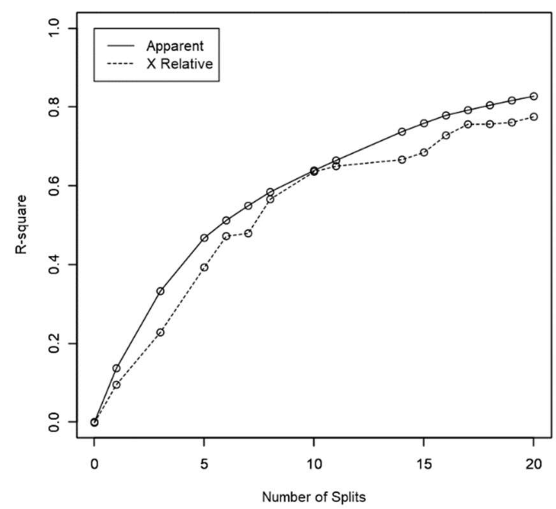

Figure 5-3: R^2 versus number of theoretical splits in the decision tree model

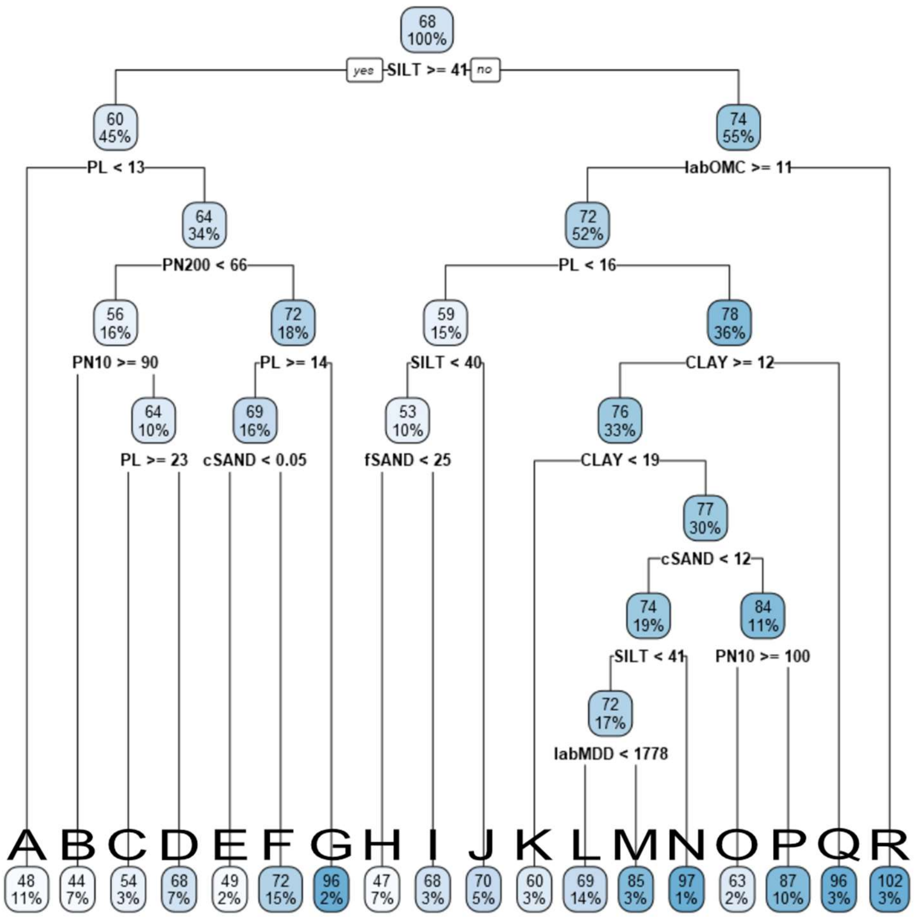

Figure 5-4: Pruned decision tree regression model.

The root node at the top of the tree indicated that the silt content (SILT) was the most important variable for predicting M_R. At each subsequent lower level, the next most important features can be detected. For example, the plastic limit (PL) and optimum moisture content (labOMC) were the next most important features at level 2. The recursive search process allows for a feature to be re-identified as important at lower tree levels. The following five features were repeated multiple times with the repeat count given in parenthesis: SILT (3), PL (4), PN10 (2), cSAND (2), and CLAY (2).

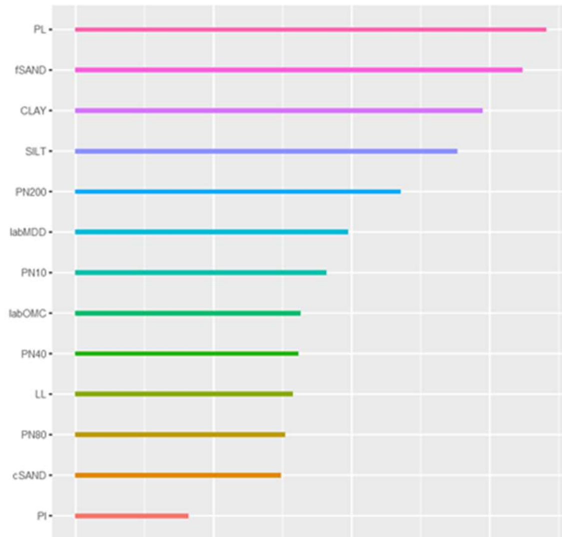

Figure 5-5: Ranking of most important features

The difference between the findings from the tree model and the variable importance plot was because the most important feature plot considers surrogate splits when determining importance. Surrogate splits are created by the algorithm to be used as an alternate means of determining an average leaf node value in the event there is missing data. While it was not immediately apparent from the tree diagram what the surrogate features and split conditions could be substituted at each node, the surrogate features were available using the *summary* function from the *rpart* library (Appendix E).

5.2.3: STEP 3 - Evaluate the pruned decision tree model

Next, the testing dataset was used to test the decision tree model. The plot of the estimated versus the observed M_R showed that the R^2 of the tree model was 0.772 with a root mean squared error (RMSE) of 8.67 MPa. The RMSE provides an estimate of the model's prediction error and is related to the standard deviation of the residuals (Judd, McClelland, & Ryan, 2009).

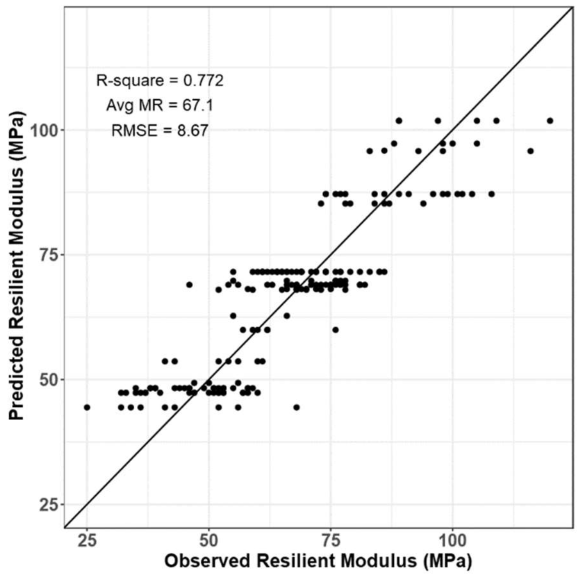

Figure 5-6: Plot of estimated versus observed MR using testing data

Although there was not a substantial difference between the average predicted MR (67.1 MPa) and the average laboratory M_R (67.6 MPa), the pruned tree produced an RMSE of 8.67 MPa. This RMSE was approximately 52% lower than the standard deviation of the laboratory M_R values (18.1 MPa), highlighting the model's precision. With an R^2 of 0.772, the tree model demonstrated a strong fit and was subsequently used to advance this research study.

5.2.4: STEP 4 - Resilient quality levels for fine-grained soils

A soil classification system that provides design values was not a practical expectation for this research effort due to the complexity of soils, which vary widely in parent materials and deterioration histories. However, it seemed feasible to develop a scheme representing M_R values that were below average, average, and above average based on their laboratory test results. These three ranges of M_R values were categorized as poor, fair, and stiff resilient quality (RQ) levels to create a new soil classification scheme for fine-grained soils.

The new categorical descriptions adapted the AASHTO general rating of fair to poor for non-granular subgrade soils, taking into account the statistical analysis of the test data. These RQ levels and the assigned M classes in Table 5-2 serve as a guide for field engineers to identify soils suitable or unsuitable for subgrade construction. Using the RQ levels/M classes, field engineers can order targeted field and/or laboratory testing to confirm that the resilient behavior of the subgrade soil is as expected.

The first RQ established was the fair level (Class M-2), representing an average fine-grained subgrade soil. It was defined using the average MR (67.1 MPa) and RMSE (8.7 MPa) from the plot of the estimated versus the observed M_R (Figure 5-6). Because the RMSE estimates the average prediction error and is related to the standard deviation of the residuals, it was used to define the fair quality level, which initially ranged from 58 to 76 MPa. However, these limits were later adjusted to 55 MPa and 75 MPa, as the adjusted range limits were considered easier to remember and still yielded acceptable results, as demonstrated in Step 6. The statistics in Table 5-4 were not used because the standard deviations from the M_R laboratory test data (18.1 MPa) were approximately 2.1 times greater than the RMSE from the correlation model. The decision was made to utilize the precision of the correlation model by using the RMSE, which provided a more accurate measure of the model's prediction error compared to the larger standard deviations from the M_R laboratory test data. Subsequently, the poor and stiff RQ levels were easily established as being less than and greater than the fair RQ range, respectively.

Table 5-2: MR resilient quality (RQ) levels and M classes for fine-grained soils

Resilient Quality	**M_R (MPa)**	**M_R (ksi)**	**M Class**
Poor	< 55	< 8	M-1
Fair	55 to 75	8 to 11	M-2
Stiff	> 75	> 11	M-3

5.2.5: STEP 5 - Apply resilient quality property criterion to leaf nodes

With the information in Table 5-2, the associated M classes were generally assigned to the leaf nodes in the decision tree in Figure 5-4 based on their average M_R values. However, some class assignments were made based on the average M_R values of higher-level parent nodes. The parent nodes were used in some cases to reduce the number of M_R prediction nodes. There were four cases where parent nodes of adjacent leaf nodes were used, which will be discussed later. The disadvantage of using the parent nodes was that the variability in the M_R averages increased from those of the individual leaf nodes. The parent nodes selected are identifiable by the nodal condition in the tree that divided that parent node into the lower-level child nodes or leaf nodes. The following list of nodal condition statements identifies the parent nodes, which were assigned the M classes instead of the leaf nodes, with a brief explanation of their selection:

- Node condition cSAND<0.05 with an average M_R of 69 MPa was used to assign leaf nodes E and F to class M-2. Leaf node E contained only 2% of the training data, and leaf node F contained 15% of the data.
- Node condition SILT<40 with an average M_R of 59 MPa was used to assign leaf nodes H, I, and J to class M-2. Leaf node H contained only 7% of the data, leaf node I contained 3%, and leaf node J contained 5%. Use of this parent node resulted in a relatively balanced combination of poor and fair RQ soils; However, it was the most volatile combination of soils because of the range of M_R values and the possible consequences of not identifying the poor RQ constituent during construction. Nevertheless, using the parent node in this case was still shown to work in segregating the soils into meaningful M classes later in this chapter.

- Node condition SILT<41 with average M_R of 74 MPa was used to assign leaf nodes L, M, and N to class M-2. Leaf node L contained only 14% of the data, leaf node M contained 3%, and leaf node N contained 1%. Use of this parent node resulted in a majority of fair RQ soils with only 1% having a stiff RQ. There does not seem to be a downside to using this parent node.
- Node condition PN10>100 with average M_R of 84 MPa was used to assign leaf nodes O and P to class M-3. Leaf node O contained only 2% of the training data, and leaf node P contained 10% of the data. Use of this parent node resulted in a majority of the soils having a stiff RQ with a subset of fair RQ soils. There did not seem to be a downside to using this parent node either.

The decision to use the parent nodes with poor RQ soil constituents is a concern that can be addressed with additional notes or a suffix appended to the M class. For instance, M-2 soils that sifted into leaf node E could have a note that would caution the engineer to confirm the RQ of the soils with a cSAND of zero percent (0%). A similar note can be made for soils that sifted into leaf node H and classified as a M-2 soil. For example, a caution would be made to confirm the RQ of soils with a soil content (SILT) of less than 40% and a fine sand content (fSAND) of less than 25%.

Table 5-3 provides the statistics for the leaf nodes and the used parent nodes using the training dataset. The statistics for the training dataset was selected for this review instead of the testing dataset because it was used to create the tree model. Therefore, the goal was to gain a better understanding of the data used to create the decision tree model. The italicized text designated the leaf nodes that were constituents of the parent nodes combining the same leaf node designations.

For example, intermediate parent node EF contained the testing data of leaf nodes E and F. The asterisked nodal combinations and corresponding statistics were calculated and presented for comparison.

The following observations were noted:

- As expected, individual leaf nodes typically had lower CVs (6.0 to 21.1%) than the parent nodes used for classification (14.2 to 22.7%).
- The poor RQ soils (nodes A, B, C, E, and H) had CVs ranging from 10.0 to 21.1%.
- The fair RQ soils (nodes D, F ,I , J , K, L, and O) had CVs ranging from 8.1 to 12.0%.
- The stiff RQ soils (nodes G, M, N, P, Q, and R) had CVs ranging from 6.0 to 12.3%.

Table 5-3: Leaf node statistics using the training dataset

Leaf Node	Number of Tests	Mean M_R (MPa)	Std Dev (MPa)	CV (%)	M Class
A	85	48.3	8.7	18.1	M-1
B	51	44.4	9.4	21.1	M-1
C	23	53.7	5.4	10.0	M-1
D	51	68.1	7.3	10.7	M-2
E	*12*	*49.3*	*7.3*	*14.8*	---
F	*112*	*71.6*	*7.2*	*10.1*	---
EF*	124	69.4	9.8	14.1	M-2
G	14	95.9	5.8	6.0	M-3
H	*55*	*47.4*	*8.8*	*18.6*	---
I	*23*	*68.0*	*7.8*	*11.5*	---
J	*38*	*69.8*	*5.6*	*8.1*	---
HIJ*	116	58.8	13.3	22.7	M-2
K	23	60.0	7.2	11.9	M-2
L	*110*	*69.0*	*8.3*	*12.0*	---
M	*23*	*85.3*	*6.5*	*7.7*	---
N	*11*	*97.3*	*9.7*	*10.0*	---
LMN*	144	73.7	12.1	16.4	M-2
O	*13*	*62.8*	*5.5*	*8.7*	---
P	*74*	*87.2*	*10.1*	*11.6*	---
OP*	87	83.5	12.9	15.5	M-3

Leaf Node	Number of Tests	Mean M_R (MPa)	Std Dev (MPa)	CV (%)	M Class
Q	26	95.8	10.2	10.6	M-3
R	24	101.8	12.5	12.3	M-3

** Higher-level intermediate parent node that combined the leaf nodes*

Table 5-4 provides a summary of the M classes with respect to the target feature of M_R from the training dataset. It can be seen that the average M_R increased moving from the M-1 class to the M-3 class. In addition, the coefficient of variation (CV) of the M-1 and M-2 classes were greater than the M-3 class.

Table 5-4: M_R statistics for M classes from training dataset

M Class	Number	Average (MPa)	Std Dev (MPa)	CV (%)
M-1	159	47.8	9.0	18.8
M-2	458	67.5	12.7	18.8
M-3	151	89.7	14.0	15.6

Note: CV= Coefficient of variation

As expected, the data from Table 5-4 reflected the same tendencies as the data from the training dataset. The data from the testing dataset was used to create the plot in Figure 5-7 because the testing dataset provides the confirming support that the tree model reflected the RQ qualities defined in the previous section. The boxplot indicates that there are clear separation of interquartile ranges (IQR) of the M classes that comprises 50% of the M_R correlation data. This finding is in contrast to Figure 4-12, which does not depict any meaningful separation among the AASHTO classes of the complete set of fine-grained subgrade soils. Therefore, the M classes should provide more useful information to the engineer than the AASHTO classes do.

Table 5-5: M_R statistics for M classes from testing dataset

M Class	Number	Average (MPa)	Std Dev (MPa)	CV (%)
M-1	36	47.4	9.6	20.2
M-2	127	66.9	13.6	20.3
M-3	29	91.1	14.8	16.3

Note: CV= Coefficient of variation

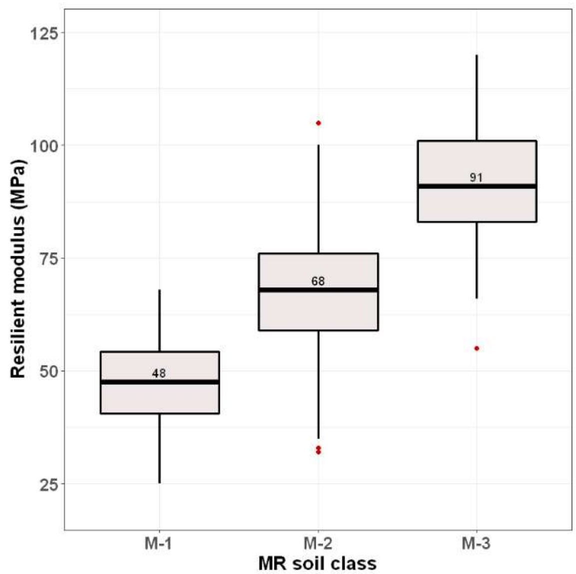

Figure 5-7: M_R ranges for M classes (testing dataset)

5.2.6: STEP 6 - One-way ANOVA and Tukey testing

Next, one-way ANOVA and Tukey tests were performed on the average M_R values from the M classes. The one-way ANOVA was run to determine if there were significant differences in the mean M_R values of at least one of the M classes. As will be demonstrated, the ANOVA test did support the alternative hypothesis that were was at least one class group with a different average M_R. Because the one-way ANOVA only indicated that is a difference and not where the difference or differences were, a Tukey test was conducted. The Tukey test performs a pairwise comparison of each combination of average M_R values to identify which classes are different from each other.

To introduce the ANOVA analysis, the null and alternative hypotheses are presented as follows:

- **Null hypothesis (H_o)**: There is no difference among the average resilient moduli of the M soil classes, i.e.

  H_o: $\mu_{M1} = \mu_{M2} = \mu_{M3}$

- **Alternate hypothesis (H_a)**: There is at least one M class with an average resilient modulus that is different from averages of the other M classes, i.e.

  H_a: $\mu_{M1} \neq \mu_{M2}$ *and/or* $\mu_{M1} \neq \mu_{M3}$ *and/or* $\mu_{M2} \neq \mu_{M3}$

In Table 5-6, the p-value (<2e-16) from the one-way ANOVA analysis, which is less than the significance level of 0.05, indicated that there is enough evidence to reject the null hypothesis that there are no differences in average M_R values among the proposed M classes. Therefore, there is at least one M class with an average M_R that is different from the other M classes.

Table 5-6: One-way ANOVA for M classes

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
classMR	2	30741	15371	89.37	<2e-16 ***
Residuals	189	32507	172	---	---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					

With evidence that there is at least one M class with an average M_R that is different from the other M classes, a Tukey test was run to pairwise comparisons of the M classes. It is an post hoc test used after an ANOVA provides evidence that there is at least one group mean that is different from the other group means. The Tukey test provided where the group mean differences in M_R were found. The test results are introduced with the following null and alternate hypotheses:

- **Null hypothesis (H_o)**: The M_R means of all M class groups are equal, i.e.

  H_o: $\mu_{M1} = \mu_{M2} = \mu_{M3}$

- **Alternate hypothesis (H_a)**: There is at least one M class with an average resilient modulus that is different from averages of the other M classes, i.e.

  H_a: $\mu_{M1} \neq \mu_{M2}$ *and/or* $\mu_{M1} \neq \mu_{M3}$ *and/or* $\mu_{M2} \neq \mu_{M3}$

From Table 5-7, the p-values (p adj) of each pairwise comparison were equal to zero (0). From these results, there is evidence to reject the null hypothesis. Reviewing each comparison, it can be determined that all M classes have M_R averages that are different from each other. Therefore, the conclusions from the ANOVA and Tukey tests support the proposed M classes and the criteria used to establish them.

Table 5-7: Tukey results on proposed M classes

Tukey multiple comparisons of means 95% family-wise confidence level				
	diff	**lwr**	**upr**	**p adj**
M-2-M-1	19.51662	13.66687	25.36637	0
M-3-M-1	43.74904	36.01862	51.47946	0
M-3-M-2	24.23242	17.85628	30.60856	0

5.2.7: STEP 7 - Testing dataset statistics for AASHTO soil classes

For comparison, some basic statistics on the testing dataset were prepared with respect to the AASHTO soil classes. The statistics in Table 5-8 are presented in contrast to Table 5-5, which contains statistics with the same testing dataset, but with respect to the M classifications. Based on the standard deviations (Std Dev), the variability in the AASHTO classification was greater than that for the M classifications. The A-7-6 soils had the lowest standard deviation at 15.1 MPa versus the M-3 with a standard deviation of 14.8 MPa.

The average M_R for the M classes methodically increase from the lowest class (M-1) to the highest one (M-3). The M_R values for the AASHTO classes also increase from the A-4 to the A-7 class. However, the A-7-5 subgroup has a higher M_R than the A-7-6.

Table 5-8: M_R statistics for fine-grained specimens (testing dataset)

AASHTO	Number	Average (MPa)	Std Dev (MPa)	CV (%)
A-4	44	59.4	18.7	31.5
A-6	79	66.4	18.3	27.5
A-7-5	17	80.5	16.8	20.8
A-7-6	52	69.5	15.1	21.8

Note: CV= Coefficient of variation

Besides the lower standard deviations with the M classes, another difference between the two classes can be seen in comparing Figure 5-7 and Figure 5-8. The M classes indicate more distinct separations among their constituents while the IQRs of the AASHTO classes overlap each other.

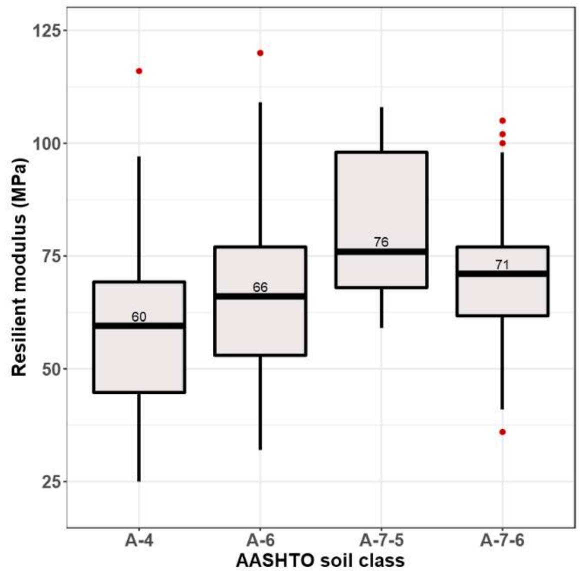

Figure 5-8: M_R ranges for AASHTO soil classes (testing dataset)

5.2.8: STEP 8 - Convert decision tree into a table format

The pruned decision tree in Figure 5-4 was converted into Tables 5-11 and 5-12 to demonstrate how the tree diagram would appear in a format that would be accessible to design and field engineers. In both tables, the root node (SILT≥41) appears in the leftmost column with either the true (SILT≥41) or false (SILT<41) condition. Table 5-11 presents the true condition of the root node, and Table 5-12 presents the false condition of the root node. Although the decision tree works from top to bottom, the tables work from left to right.

In order to use these tables, the engineer would need possession of a soils report with at least the features given in the column headings. For instance, a fine-grained soil with a silt content of 45% would use Table 5-11 to classify the soil. With the other feature values of 15% for plastic limit, 45% for material passing the No. 200 sieve, and 100% for material passing the No. 10 sieve, the soil would be classified as an M-1 soil. With this data, a field engineer would then be alerted to the presence of a possibly problematic soil on his/her project site. Therefore, localized testing such as proof-rolling or light-weight deflectometer (LWD) testing could be set up to verify the resilient properties of this material and decide on the appropriate course of action.

Table 5-9: Classification scheme for fine-grained soils with silt content ≥ 41%

<table>
<tr><th>SILT</th><th>PL</th><th>PN 200</th><th>PN 10</th><th>PL</th><th>M Class</th></tr>
<tr><td rowspan="6">≥ 41</td><td>< 13</td><td>---</td><td>---</td><td>---</td><td>M-1</td></tr>
<tr><td rowspan="5">≥ 13</td><td rowspan="3">< 66</td><td>≥ 90</td><td>---</td><td>M-1</td></tr>
<tr><td rowspan="2">< 90</td><td>≥ 23</td><td>M-1</td></tr>
<tr><td>< 23</td><td>M-2</td></tr>
<tr><td rowspan="2">≥ 66</td><td rowspan="2">---</td><td>≥ 14</td><td>M-2a*</td></tr>
<tr><td>< 14</td><td>M-3</td></tr>
</table>

***Note**: For M-2 soils with an "a" suffix, check the materials for their resilient behavior.*

Table 5-10: Classification scheme for fine-grained soils with silt content < 41%

<table>
<tr><th>SILT</th><th>labOMC</th><th>PL</th><th>CLAY</th><th>cSAND</th><th>M Class</th></tr>
<tr><td rowspan="6">< 41</td><td rowspan="5">≥ 11</td><td>< 16</td><td>---</td><td>---</td><td>M-2b</td></tr>
<tr><td rowspan="4">≥ 16</td><td>< 12</td><td>---</td><td>M-3</td></tr>
<tr><td>≥ 12 to 19</td><td>---</td><td>M-2</td></tr>
<tr><td rowspan="2">≥ 19</td><td>< 12</td><td>M-2</td></tr>
<tr><td>≥ 12</td><td>M-3</td></tr>
<tr><td>< 11</td><td>---</td><td>---</td><td>---</td><td>M-3</td></tr>
</table>

***Note**: For M-2 soils with a "b" suffix, check the materials for their resilient behavior.*

5.3: Summary

Using the data collected for the LTPP Program from test sites across the United States, a decision tree model was developed to correlate the M_R of fine-grained subgrade soils to soil index properties and laboratory test conditions of LTPP Protocol P-46. A soil classification scheme was devised using groupings of the leaf nodes. These groupings were based on the average M_R values in the leaf nodes and a basic statistical analysis of these nodes.

The statistical analysis was conducted as a means to define the resilient qualities (RQ) of poor, fair, and stiff subgrade soils with the fair RQ representing a fine-grained soil within an average M_R range. These RQs also served as the foundation for establishing three M (modulus) classes of subgrade soils that would act as a tool for engineers to identify the expected resilient behavior of these materials. For instance, if a field engineer received a report with M-1 (poor RQ) soils on it, he/she could set up targeted field and/or laboratory testing to verify the resilient behavior of those soils. If M-3 (stiff RQ) materials were reported, then more limited testing could be set up for those areas so as to more efficiently assign testing efforts to more problematic areas. Finally, the statistical significance of the M classes was established with one-way ANOVA and Tukey tests, which supported the analyses in this chapter that each M soil class had an M_R range that clearly separated it from the other M soil classes.

CHAPTER 6: CONCLUSIONS

In this study, a soil classification scheme was successfully developed for fine-grained subgrade soils based on their resilient properties, utilizing resilient modulus data extracted from the Long-Term Pavement Performance (LTPP) database. This new classification scheme categorizes soils based on their resilient properties as defined in this study, using statistical analysis of outputs from the decision tree model that correlated resilient modulus to soil index properties. The decision tree model was used to create a table that provides soil classes based on the resilient properties of fine-grained soils that can be easily interpreted and incorporated into construction specifications for subgrade materials.

The analysis in this study was conducted in an R programming environment using the rpart library within a Jupyter notebook to develop a decision tree model. Decision tree modeling was selected because it can provide models with predictive strengths comparable to linear regression analysis. The rpart library was chosen for decision tree modeling because of its recursive partitioning function, ease of use, transparency with respect to the model's structure and feature importance, and integration with other R packages.

These newly defined soil classes align more closely with the Mechanistic-Empirical Pavement Design Guide than the current portion of the AASHTO soil classification system that includes fine-grained soils. Moreover, the resilient modulus-based scheme serves as a valuable tool for identifying potentially problematic soils, thereby aiding engineers in efficiently directing testing resources and remediation efforts. The redirection of resources and identification of areas that require remediation ultimately enhance the capacity of the pavement to support the overlying structure and design traffic in the most economical way possible.

The following conclusions summarize the observations and limitations encountered in this study:

6.1: The LTPP database

(1) Approximately 56% of the fine-grained subgrade soil specimens were tested with test (sample) caps. Therefore, only 960 (44%) of the M_R test results on fine-grained subgrade soils were tested according to the LTPP Protocol P-46 for Type 2 soils and were available for analysis.

(2) Not all granular and silt-clay materials group classifications from AASHTO M-145 are equally represented in the LTPP database. It is uncertain if this unbalance was significant.

(3) The A-6 group based on AASHTO M-145 was the most predominate group of fine-grained subgrade soils in this study with more than 50% of its material passing the No. 200 (75 μm) sieve. The A-5 group was not represented in the base dataset.

(4) The average and median resilient moduli of the A-4 and A-6 soils are generally lower than those of the A-7-5 and A-7-6 soils.

(5) The average and median maximum dry densities of the A-4 and A-6 soils are generally higher than those of the A-7-5 and A-7-6 soils.

(6) The average and median optimum moisture contents of the A-4 and A-6 soils are generally lower than those of the A-7-5 and A-7-6 soils.

6.2: About the behavior of resilient modulus of fine-grained soils

Despite the trendlines in the figures from Chapter 4, the resilient modulus in these plots did not consistently increase or decrease based on the slopes of the trendlines. When considering the effects of each feature, the range of the resilient modulus test results was compared across the value ranges of these features. If the individual boxplots did not rise or fall consistently with the trendline, those features were not considered influential on the resilient behavior of fine-grained soils as a collective group. Examining test data from individual soil specimens might have led to different conclusions. However, this study aimed to classify the resilient behavior of the fine-grained division of soils in the LTPP database. Therefore, data from all fine-grained subgrade soils were analyzed as a whole.

(7) The resilient modulus of fine-grained subgrade soils increased with increasing confining stress.

(8) The plastic index of fine-grained subgrade soils did not appear to influence the resilient modulus of fine-grained soils.

(9) The amount of material passing the No. 200 (75 μm) sieve of fine-grained subgrade soils did not appear to influence the resilient modulus of fine-grained soils.

(10) The average laboratory resilient modulus of uncapped fine-grained subgrade soil specimens had a significantly lower average resilient modulus values than specimens tested with caps.

(11) There is no statistical difference in the average resilient modulus values of the fine-grained and coarse-grained fractions of the silt-clay (non-granular) general classification of AASHTO M-145.

6.3: About the decision tree model and proposed soil classification scheme

(12) The decision tree model, which correlated the features in the dataset to the resilient modulus target feature, yielded a good model that was easily converted to a classification table for fine-grained soils.

(13) The silt content of fine-grained soils was found to be the most influential feature on resilient modulus based on the decision tree model. The plastic limit, optimum moisture content, and the material passing the No. 200 (75 µm) sieve are the next most important features.

(14) The plastic limit of fine-grained soils was found to be the most influential on resilient modulus based on the ranking of most important features, which considered surrogate split data. The fine sand content, clay content, silt content, the material passing the No. 200 (75 µm) sieve are the next most important features.

CHAPTER 7: RECOMMENDATIONS

7.1: Recommendations for future research

(1) Create a separate and independent database of subgrade soils and resilient modulus data that follows the same quality control measures without the restrictions of adding and maintaining a limited number of LTPP test sites. Soil samples can be retrieved during preliminary field investigations and from construction sites. Although the ultimate goal is to create a database that covers the North American continent, this strategy can also be applied on a state-by-state basis for states interested in creating their own database without depending on a national effort.

(2) Prepare a soil classification scheme for coarse-grained soils using the same procedures outlined in this study.

(3) Conduct a study to research other soil properties that may affect the resilient behavior of fine-grained (and coarse-grained) subgrade soils.

7.2: Recommendations for future practice

(4) Strategically grow the LTPP database by including more fine-grained soils from the eastern United States and all of Canada to more evenly cover the continent.

(5) The proposed soil classification table for fine-grained soils should only be used with caution by states that are represented in the LTPP database.

REFERENCES

Albert, J., & Rizzo, M. (2012). *R by Example*. Springer Science & Business Media.

American Association of State Highway Officials. (1974). AASHTO interim guide for design of pavement structures, 1972. Washington, D.C.: American Association of State Highway and Transportation Officials.

American Association of State Highway and Transportation Officials. (1986). AASHTO guide for design of pavement structures, 1986. Washington, D.C.: American Association of State Highway and Transportation Officials.

American Association of State Highway and Transportation Officials. (1993). AASHTO guide for design of pavement structures, 1993. Washington, D.C.: American Association of State Highway and Transportation Officials.

American Association of State Highway and Transportation Officials. (2000). AASHTO M 145. Classification of soils and soil-aggregate mixtures for highway construction purposes.

American Association of State Highway and Transportation Officials. (2015). Mechanistic-empirical pavement design guide: A manual of practice. Washington, D.C.: American Association of State Highway and Transportation Officials.

Anaconda Software Distribution. (2020). Anaconda Documentation. Anaconda Inc. Retrieved from https://docs.anaconda.com/

Arizona Department of Transportation. (2021). Standard specifications for road and bridge construction (2021 ed.). Arizona Department of Transportation.

Arnold, R. W. (2001). Soil classification principles. In Soil classification 2001: contributions to the International symposium "Soil Classification 2001", 8-12 October 2001, Velence, Hungary (pp. 3-8).

American Society for Testing and Materials (2017). ASTM D2487-17e1: Standard Practice for Classification of Soils for Engineering Purposes (unified Soil Classification System). ASTM.

Baldwin, M., Kellogg, C. E., & Thorp, J. (1938). Soil classification (pp. 979-1001). Indianapolis: Bobbs-Merrill.

Bi, Q., Goodman, K. E., Kaminsky, J., & Lessler, J. (2019). What is machine learning? A primer for the epidemiologist. American journal of epidemiology, 188(12), 2222-2239.

Burczyk, J. M., K. Ksaibati, R. Anderson-Sprecher and M. J. Farrar (1994). "Factors influencing determination of a subgrade resilient modulus value." Transportation Research Record (1462).

Chen, T., & Guestrin, C. (2015). Xgboost: Reliable large-scale tree boosting system. In Proceedings of the 22nd SIGKDD Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA (pp. 13-17).

Colorado Department of Transportation. (2017). Standard Specifications for Road and Bridge Construction. Colorado Department of Transportation.

de Micheaux, P. L., Drouilhet, R., & Liquet, B. (2013). The R software. *Fundamentals of Programming and Statistical Analysis*, 978-1.

Dione, A., Fall, M., Berthaud, Y., Benboudjama, F., & Michou, A. (2014). Implementation of resilient modulus–CBR relationship in mechanistic pavement design. Sciences Appliquées et de l'Ingénieur, 1(2), 65-71.

Drumm, E. C., Boateng-Poku, Y., & Johnson Pierce, T. (1990). Estimation of subgrade resilient modulus from standard tests. Journal of Geotechnical Engineering, 116(5), 774-789.

Drumm, E. C., Reeves, J. S., Madgett, M. R., and Trolinger, W. D. (1997). "Subgrade resilient modulus correction for saturation effects." Journal of Geotechnical and Geoenvironmental Engineering 123(7): 663-670.

Dumbleton, M. J. (1968). The classification and description of soils for engineering purposes: a suggested revision of the British system. Rrl Reports, Road Research Lab/UK/.

Elias, M. B., & Titi, H. H. (2006). Evaluation of resilient modulus model parameters for mechanistic–empirical pavement design. Transportation research record, 1967(1), 89-100.

Elkins, G. E., & Ostrom, B. (2021). Long-term pavement performance information management system user guide (No. FHWA-HRT-21-038). United States. Federal Highway Administration. Office of Infrastructure Research and Development.

Federal Highway Administration (FHWA). (1996). Long-term pavement performance protocol P46: Resilient modulus of unbound granular base/subbase materials and subgrade soils. U.S. Department of Transportation.

Federal Highway Administration (FHWA). (2015). The Long-Term Pavement Performance Program.

George, K. P. (2004). Prediction of resilient modulus from soil index properties (No. FHWA/MS-DOT-RD-04-172). University of Mississippi.

Georgia Department of Transportation (GDOT). (2013). Standard Specifications for Construction of Transportation Systems. Department of Transportation, State of Georgia.

Gerasimova, M. I. (2019). Russian soil classification system: towards the next approximation. Eurasian Soil Science, 52, 25-33.

Greenwell, B. M. (2022). Tree-based methods for statistical learning in R. CRC Press.

Hossain, M. S. (2009). Estimation of subgrade resilient modulus for Virginia soil. Transportation Research Record, 2101(1), 98-109.

Hossain, M. S., & Kim, W. S. (2014). Estimation of subgrade resilient modulus using the unconfined compression test (No. FHWA/VCTIR 15-R12). Virginia Center for Transportation Innovation and Research.

Hossain, M. S. and A. K. Apeagyei (2010). Evaluation of the lightweight deflectometer for in-situ determination of pavement layer moduli, Virginia Transportation Research Council.

Huang, Y. H. (2004). Pavement analysis and design (Second Edition). Upper Saddle River, NJ: Pearson Prentice Hall.

Indiana Department of Transportation. (2018). Standard specifications for road and bridge construction (2018 ed.). Indiana Department of Transportation.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112, p. 18). New York: Springer.

Jick, T. (1991) Note on the Recipients of Change, Note 9-491-039, Harvard Business School Press, Boston.

Judd, C. M., McClelland, G. H., & Ryan, C. S. (2009). Data analysis: A model comparison approach, 2nd ed. Routledge/Taylor & Francis Group.

Kluyver, T.; Ragan-Kelley, B.; Perez, F.; Granger, B.; Bussonnier, M.; Frederic, J., et al. (2016). Jupyter Notebooks-a publishing format for reproducible computational workflows. UC Berkeley. http://dx.doi.org/10.3233/978-1-61499-649-1-87 Retrieved from https://escholarship.org/uc/item/08b3d4s2.

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). Applied linear statistical models. McGraw-hill.

Lee, W., Bohra, N. C., Altschaeffl, A. G., & White, T. D. (1997). Resilient modulus of cohesive soils. Journal of Geotechnical and Geoenvironmental Engineering, 123(2), 131-136.

Lekarp, F., Isacsson, U., & Dawson, A. (2000). State of the art. II: Permanent strain response of unbound aggregates. Journal of transportation engineering, 126(1), 76-83.

Li, D., & Selig, E. T. (1994). Resilient modulus for fine-grained subgrade soils. Journal of geotechnical engineering, 120(6), 939-957.

Liu, T. K. (1970). A review of engineering soil classification systems. Special Procedures for Testing Soil and Rock for Engineering Purposes: Fifth Edition.

Liu, X., Zhang, X., Wang, H., & Jiang, B. (2019). Laboratory testing and analysis of dynamic and static resilient modulus of subgrade soil under various influencing factors. Construction and Building Materials, 195, 178-186.

Maindonald, J. H., 2021. "Random Forests with R. Robin Genuer & Jean-Michel Poggi Springer, 2019, x + 99 pp, £49.99, paperback. ISBN: 978-3-030-56484-1," International Statistical Review, International Statistical Institute, vol. 89(2), pages 422-423, August. https://ideas.repec.org/a/bla/istatr/v89y2021i2p422-423.html.

Malla, R. B. & Joshi, S. (2008). Subgrade resilient modulus prediction models for coarse and fine-grained soils based on long-term pavement performance data. International Journal of Pavement Engineering, 9(6), 431-444.

Milborrow, S., (2024). rpart.plot: Plot 'rpart' Models: An Enhanced Version of 'plot.rpart'. R package version 3.1.2. https://CRAN.R-project.org/package=rpart.plot

Mitchell, J. K., Shen, C. K., & Monismith, C. L. (1965). Behavior of Stabilized Soils Under Repeated Loading. Report I. Background, Equipment, Preliminary Investigations, Repeated Compression and Flexure Tests on Cement-Treated Silty Clay. California University, Berkeley Department of Civil Engineering.

Nguyen, B. T., & Mohajerani, A. (2015). The dynamic behaviour of some fine-grained subgrade soils under traffic load. Australian Geomechanics Journal, 50(2), 45-54.

Pahno, S., Yang, J. J., & Kim, S. S. (2021). Use of machine learning algorithms to predict subgrade resilient modulus. *Infrastructures*, *6*(6), 78.

Perkel, J. M. (2018). By Jupyter, it all makes sense. Nature, 563(7729), 145-146.

Pimentel, J. F., Murta, L., Braganholo, V., & Freire, J. (2019). A large-scale study about quality and reproducibility of Jupyter notebooks. In 2019 IEEE/ACM 16th international conference on mining software repositories (MSR) (pp. 507-517). IEEE.

Puppala, A. J. (2008). *Estimating stiffness of subgrade and unbound materials for pavement design* (Vol. 382). Transportation Research Board.

R Core Team (2000). R language definition. Vienna, Austria: R foundation for statistical computing, 3(1). URL https://cran.r-project.org/manuals.html (Accessed on January 26, 2024).

R Core Team (2000a). R data import/export. URL https://cran.r-project.org/manuals.html (Accessed on January 26, 2024).

R Core Team (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://cran.r-project.org/manuals.html (Accessed on January 26, 2024).

R Core Team, (2023). R: A language and environment for statistical computing: Reference Index. URL https://cran.r-project.org/manuals.html (Accessed on January 26, 2024).

R Core Team (2023a). R: A Language and Environment for Statistical Computing. The R Project for Statistical Computing. URL: https://www.r-project.org/about.html (Accessed on January 26, 2024).

R Core Team (2024). The Comprehensive R Archive Network (CRAN). URL: https://cran.r-project.org/ (Accessed on January 26, 2024).

Rahim, A. M. (2005). Subgrade soil index properties to estimate resilient modulus for pavement design. International Journal of Pavement Engineering, 6(3), 163-169.

Reale, C., Gavin, K., Librić, L., & Jurić-Kaćunić, D. (2018). Automatic classification of fine-grained soils using CPT measurements and Artificial Neural Networks. Advanced Engineering Informatics, 36, 207-215.

Rokach, L., & Maimon, O. (2005). Decision trees. Data mining and knowledge discovery handbook, 165-192.

Smart, A. L., & Humphrey, D. N. (1999). *Determination of resilient modulus for Maine roadway soils* (No. Technical Report ME 96-10).

Soliman, H., & Shalaby, A. (2014). Characterising the elastic behaviour of fine-grained subgrade soils under traffic loading. International Journal of Pavement Engineering, 15(8), 698-707.

South African National Roads Agency Ltd. (SANRAL) (2013). South African Pavement Engineering Manual, Chapter 4. South African National Roads Agency Ltd.

Suthaharan, S. (2016). Machine learning models and algorithms for big data classification. Integr. Ser. Inf. Syst, 36, 1-12.

Therneau, T. & Atkinson, B. (2019). rpart: Recursive Partitioning and Regression Trees. R package version 4.1-15. https://CRAN.R-project.org/package=rpart.

Tintle, N., Chance, B. L., Cobb, G. W., Rossman, A. J., Roy, S., Swanson, T., & VanderStoep, J. (2016). Introduction to statistical investigations. John Wiley & Sons.

Thompson, M. R., & Robnett, Q. L. (1979). Resilient properties of subgrade soils. Transportation Engineering Journal of ASCE, 105(1), 71-89.

Webb, William M. (1990). Revision to Georgia's Soil Classification System (FHWA-GA-90-8903). Georgia Department of Transportation.

Wickham, H. (2016). ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York.

Yau, A., & Von Quintus, H. L. (2002). *Study of LTPP laboratory resilient modulus test data and response characteristics* (No. FHWA-RD-02-051; 3032.1). Turner-Fairbank Highway Research Center.

Zuur, A. F., Ieno, E. N., & Meesters, E. H. (2009). *A Beginner's Guide to R* (p. 150). New York: Springer.

APPENDIX A

Part 1: LTPP data tables

Table A-1: Data tables downloaded from InfoPave website

TST_UG07_SS07_A	TST_SS02_UG03	
	Beginning Column	*Column Continuation*
LINKED_LAYER_NO	LINKED_LAYER_NO	NO_80_PASSING
LINKED_SHRP_ID	LINKED_SHRP_ID	NO_200_PASSING
SHRP_ID*	SHRP_ID*	HYDRO_02
STATE_CODE*	STATE_CODE*	HYDRO_002
STATE_CODE_EXP	STATE_CODE_EXP	HYDRO_001
LAYER_NO*	LAYER_NO*	GT_2MM
TEST_NO*	FIELD_SET*	COARSE_SAND
TEST_NO_EXP	TEST_NO_EXP	FINE_SAND
FIELD_SET*	TEST_NO*	SILT
LOC_NO*	LOC_NO*	CLAY
SAMPLE_NO*	CONSTRUCTION_NO	COLLOIDS
MR_MATL_TYPE_EXP	SAMPLE_NO*	HYGRO_MOIST
MR_MATL_TYPE	TEST_DATE	
TOTAL_HT	THREE_PASSING	
IN_SITU_MOIST	TWO_PASSING	
IN_SITU_DENSITY	ONE_AND_HALF_PASSING	
MAX_DRY_DENSITY	ONE_PASSING	
MAX_DRY_DENSITY_95	THREE_FOURTHS_PASSING	
COMP_MOIST_CONT	ONE_HALF_PASSING	
COMP_DRY_DENSITY	THREE_EIGHTHS_PASSING	
MAX_STRENGTH	NO_4_PASSING	
TEST_DATE	NO_10_PASSING	
CONSTRUCTION_NO	NO_40_PASSING	

** Primary key elements used for merging tables into a single dataset*

Table A-2: Data tables downloaded from InfoPave website

TST_UG07_SS07_WKSHT_SUM	**TST_UG04_SS03**
LINKED_SHRP_ID	LINKED_SHRP_ID
LINKED_LAYER_NO	LINKED_LAYER_NO
SHRP_ID*	SHRP_ID*
STATE_CODE*	STATE_CODE*
STATE_CODE_EXP	STATE_CODE_EXP
LAYER_NO*	LAYER_NO*
TEST_NO*	FIELD_SET*
TEST_NO_EXP	TEST_NO*
FIELD_SET*	TEST_NO_EXP
LOC_NO*	LOC_NO*
SAMPLE_NO*	SAMPLE_NO*
CON_PRESSURE	LIQUID_LIMIT
NOM_MAX_AXIAL_STRESS	PLASTIC_LIMIT
CONSTRUCTION_NO	PLASTICITY_INDEX
LAYER_TYPE	TEST_DATE
LAYER_TYPE_EXP	CONSTRUCTION_NO
RES_STRAIN_AVG	
RES_MOD_AVG	
TEST_DATE	

** Primary key elements used for merging tables into a single dataset*

Table A-3: Data tables downloaded from InfoPave website

TST_UG05_SS05	**SECTION_COORDINATES**
LINKED_SHRP_ID	STATE_CODE*
LINKED_LAYER_NO	STATE_CODE_EXP
SHRP_ID*	SHRP_ID*
STATE_CODE*	LATITUDE
STATE_CODE_EXP	LONGITUDE
LAYER_NO*	DATUM
FIELD_SET*	DATUM_EXP
TEST_NO*	DATUM_OTHER
TEST_NO_EXP	ELEVATION
LOC_NO*	
SAMPLE_NO*	
TEST_DATE	
CONSTRUCTION_NO	
MAX_LAB_DRY_DENSITY	
OPTIMUM_LAB_MOISTURE	

** Primary key elements used for merging tables into a single dataset*

Part 2: Software Screenshots

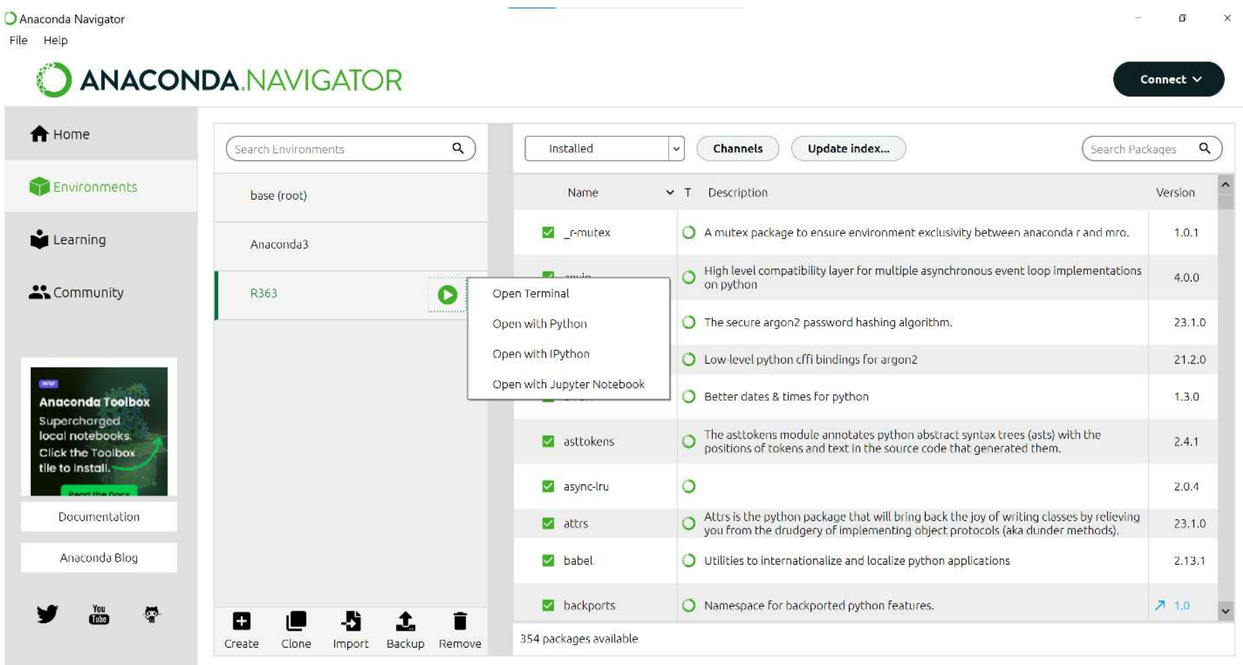

Figure A-1: Anaconda Navigator layout

Filter out non-subgrade soils into dsBase, leaving only subgrade soils

```
[139]: #dsBase$LLDcode
       #str(dsBase)
```

```
[140]: print(paste0("Number of subgrade observations in dsBase (all material types)      = ", nrow(dsBase)))
       #
       dsRemoveNonSubgrade <- dsBase[!(dsBase$LAYER_TYPE=="SS"),]
       dsBase <- dsBase[dsBase$LAYER_TYPE=="SS",]
       #
       print(paste0("Number of non-subgrade observations in dsBase = ", nrow(dsRemoveNonSubgrade)))
       print(paste0("Number of subgrade observations in dsBase (only subgrade soil type) = ", nrow(dsBase)))
       #write.xlsx(dsBase, 'metricData/output/CHECK_dsBase_Subgrade_v1.xlsx')
```

```
[1] "Number of subgrade observations in dsBase (all material types)      = 6377"
[1] "Number of non-subgrade observations in dsBase = 0"
[1] "Number of subgrade observations in dsBase (only subgrade soil type) = 6377"
```

Review of soil specimen dimensions, Cap Heights, MR

```
[141]: summary(dsBase$DIA)
```

Figure A-2: Jupyter Notebook screenshot

APPENDIX B

T-test outputs for non-granular soils tested with and without caps

Series B: A series of t-tests on all non-granular specimens prepared in a 71-mm (2.8-inch) mold and tested with caps (YES) and without caps (NO) using the following soil properties from the raw dataset. The t-test analyses provided supporting evidence to determine if the use of test caps altered the given soil properties from the established test conditions specified by LTPP Protocol P-46. A t-test was conducted for each of these properties to consider the properties that are commonly used during subgrade construction.

(1) M_R

(2) labMDD,

(3) MDD.RATIO2,

(4) labOMC, and

(5) OMC.RATIO2

The following Welch (Student) t-test evaluated the laboratory M_R test results of all non-granular soils tested without and with test caps. The following null and alternate hypotheses were posed to determine if capped and non-capped specimens had equivalent M_R values.

- **Null hypothesis B.1**: The M_R of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are equal.
- **Alternate hypothesis B.1**: The M_R of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are not equal.

Conclusion: There is very strong evidence that the alternate hypothesis is true as supported by the *p-value* (< 2.2e-16) and 95% confidence interval. Therefore, the test data from these two groups are not equal and cannot be combined into a single dataset based on laboratory M_R test results.

```
Welch Two Sample t-test

data:  ds$MR by ds$CAP
t = -27.737, df = 3671.9, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -21.69256 -18.82833
sample estimates:
 mean in group NO mean in group YES
         67.69840          87.95884
```

Figure B-9: T-test for MR of non-granular soils versus use of caps

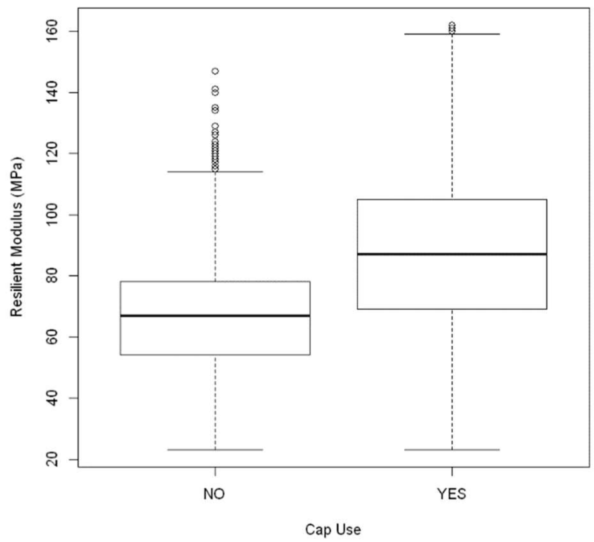

Figure B-10: M_R versus use of test caps

The following Welch (Student) t-test evaluated the maximum dry density (labMDD) of all non-granular soils tested without and with test caps. The following null and alternate hypotheses were posed to determine if capped and non-capped specimens had equivalent maximum dry density values.

- **Null hypothesis B.2**: The maximum dry density of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are equal.
- **Alternate hypothesis B.2**: The maximum dry density of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are not equal.

Conclusion: There is very strong evidence that the alternate hypothesis is true as supported by the *p-value* (= 1.316e-13) and 95% confidence interval. Therefore, the test data from these two groups are not equal and cannot be combined into a single dataset based on their maximum dry densities.

```
Welch Two Sample t-test

data:  ds$labMDD by ds$CAP
t = -7.4328, df = 3664.4, p-value = 1.316e-13
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -42.77720 -24.92012
sample estimates:
 mean in group NO mean in group YES 
         1787.879          1821.728 
```

Figure B-11: T-test for Maximum dry density of non-granular soils versus use of caps

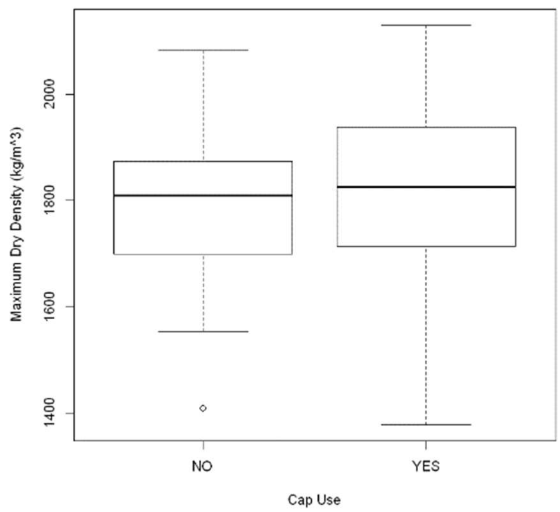

Figure B-12: Maximum dry density versus use of caps

The following Welch (Student) t-test evaluated the soil compaction (MDD.RATIO2) test results of all non-granular soils tested without and with test caps. The following null and alternate hypotheses were posed to determine if capped and non-capped specimens had equivalent compaction values.

- **Null hypothesis B.3**: The compaction values of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are equal.
- **Alternate hypothesis B.3**: The compaction values of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are not equal.

Conclusion: There is very strong evidence that the alternate hypothesis is true as supported by the *p-value* (< 2.2e-16) and 95% confidence interval. Therefore, the test data from these two groups are not equal and cannot be combined into a single dataset based on their compaction values.

```
Welch Two Sample t-test

data:  ds$MDD.RATIO2 by ds$CAP
t = 37.184, df = 5790.6, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.01100562 0.01223067
sample estimates:
 mean in group NO mean in group YES
        0.9585883         0.9469701
```

Figure B-13: T-test for compaction of non-granular soils versus use of caps

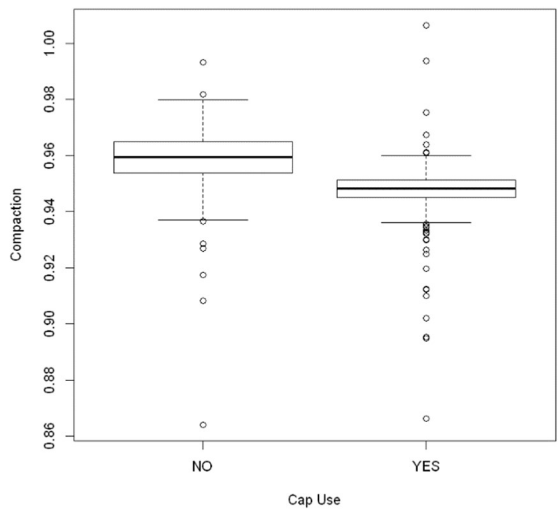

Figure B-14: Compaction versus use of test caps

The following Welch (Student) t-test evaluated the optimum moisture content (labOMC) test results of all non-granular soils tested without and with test caps. The following null and alternate hypotheses were posed to determine if capped and non-capped specimens had equivalent optimum moisture contents.

- **Null hypothesis B.4**: The optimum moisture contents (labOMC) of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are equal.
- **Alternate hypothesis B.4**: The optimum moisture contents (labOMC) of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are not equal.

Conclusion: There is evidence that the alternate hypothesis is true as supported by the *p-value* (0.004923) and 95% confidence interval. Therefore, the test data from these two groups are not equal and cannot be combined into a single dataset based on their optimum moisture contents.

```
Welch Two Sample t-test

data:  ds$labOMC by ds$CAP
t = 2.8139, df = 3420.7, p-value = 0.004923
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.1207475 0.6756988
sample estimates:
 mean in group NO mean in group YES
         15.29256          14.89434
```

Figure B-15: T-test for labOMC of non-granular soils versus use of caps

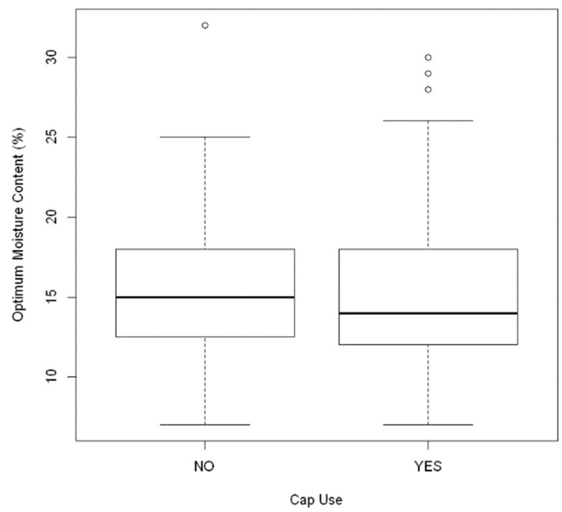

Figure B-16: Optimum moisture content versus use of caps

The following Welch (Student) t-test evaluated the optimum moisture content ratio (OMC.RATIO2) test results of all non-granular soils tested without and with test caps. The following null and alternate hypotheses were posed to determine if capped and non-capped specimens had equivalent optimum moisture content ratios.

- **Null hypothesis B.5**: The optimum moisture content ratios of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are equal.
- **Alternate hypothesis B.5**: The optimum moisture content ratios of soil specimens prepared in a 71-mm (2.8-inch) mold tested with test caps and the soil specimens tested without test caps are not equal.

Conclusion: There is evidence that the alternate hypothesis is true as supported by the *p-value* (= 1.31e-08) and 95% confidence interval. Therefore, the test data from these two groups are not equal and cannot be combined into a single dataset based on their optimum moisture content ratios.

```
Welch Two Sample t-test

data:  ds$OMC.RATIO2 by ds$CAP
t = -5.711, df = 1812, p-value = 1.31e-08
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.014858449 -0.007261872
sample estimates:
 mean in group NO mean in group YES
        0.9937628         1.0048229
```

Figure B-17: T-test for OMC.RATIO2 of non-granular soils versus use of caps

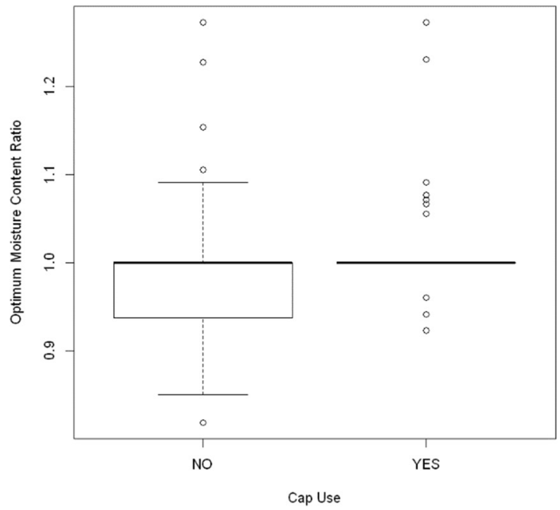

Figure B-18: Optimum moisture content ratios versus use of test caps

APPENDIX C

T-test outputs for non-granular soil fractions

Series C: A series of t-tests on the two non-granular soil fractions (coarse-grained and fine-grained) were conducted. These specimens were prepared in a 71-mm (2.8-inch) mold and tested without caps. The following soil properties from the raw dataset were analyzed using t-tests to determine if the coarse-grained and fine-grained soil fractions were equivalent based on these property values.

(1) M_R,

(2) labMDD,

(3) MDD.RATIO2,

(4) labOMC, and

(5) OMC.RATIO2

The following Welch (Student) t-tests evaluated the coarse- and fine-grained fractions of the non-granular general classification that were tested without caps. The following null and alternate hypotheses were posed to determine if the two non-granular fractions were equivalent based on M_R values.

- **Null hypothesis No. C.1**: The M_R of the coarse- and fine-grained fractions prepared and tested in a 71-mm (2.8-inch) mold without test caps had M_R values that were equal.
- **Alternate hypothesis No. C.1**: The M_R of the coarse- and fine-grained fractions prepared and tested in a 71-mm (2.8-inch) mold without test caps had M_R values that were not equal.

Conclusion: There is not enough evidence to reject the null hypothesis as supported by the *p-value* (= 0.7987) and 95% confidence interval. Therefore, the test data from these two groups are equal based on laboratory M_R test results.

```
Welch Two Sample t-test

data:  ds$MR by ds$Fraction
t = 0.25515, df = 803.87, p-value = 0.7987
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.999573  2.597063
sample estimates:
mean in group CGF mean in group FGF
         67.89770          67.59896
```

Figure C-19: T-test for the M_R of the non-granular soil fractions

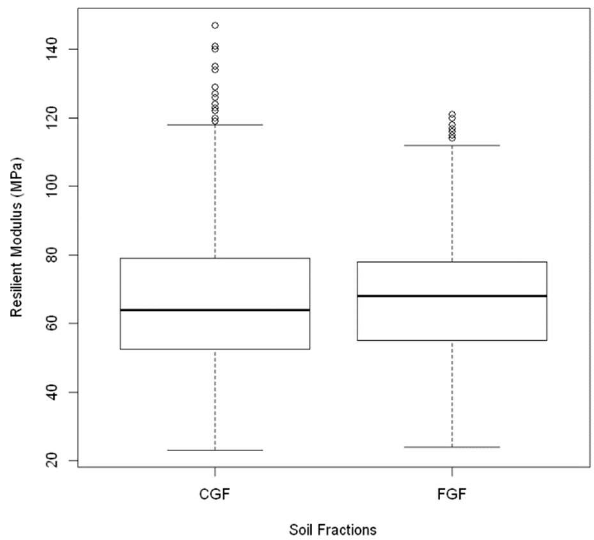

Figure C-20: M_R versus soil fractions

The following Welch (Student) t-tests evaluated the coarse- and fine-grained fractions of the non-granular general classification that were tested without caps. The following null and alternate hypotheses were posed to determine if the two non-granular fractions were equivalent based on their maximum dry densities (labMDD).

- **Null hypothesis No. C.2**: The maximum dry densities of soil specimens prepared in a 71-mm (2.8-inch) mold and tested without test caps are equal.
- **Alternate hypothesis No. C.2**: The maximum dry densities of soil specimens prepared in a 71-mm (2.8-inch) mold and tested without test caps are not equal.

Conclusion: There is very strong evidence that the alternate hypothesis is true as supported by the *p-value* (< 2.2e-16) and 95% confidence interval. Therefore, the test data from these two non-granular soil fractions are not equal based on their maximum dry densities.

```
Welch Two Sample t-test

data:  ds$labMDD by ds$Fraction
t = 19.821, df = 963.4, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 107.9423 131.6653
sample estimates:
mean in group CGF mean in group FGF
         1867.804          1748.000
```

Figure C-21: T-test for labMDD of non-granular soil fractions tested without caps

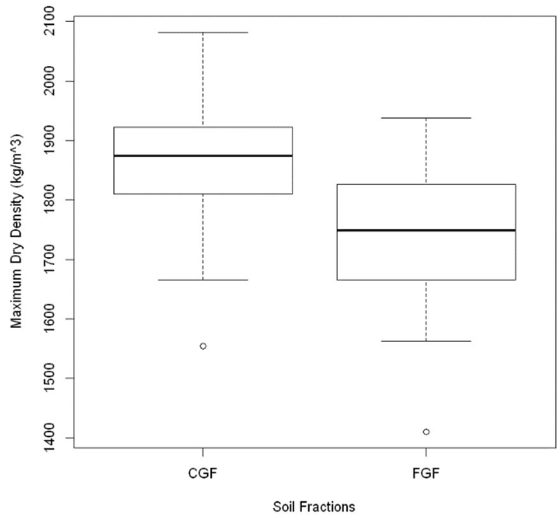

Figure C-22: labMDD versus non-granular soil fractions

The following Welch (Student) t-test evaluated the compaction (MDD.RATIO2) test results of the coarse- and fine-grained soil fractions tested without caps. The following null and alternate hypotheses were posed to determine if the non-granular soil specimens had equivalent compaction values.

- **Null hypothesis No. C.3**: The specimens of the two non-granular soil fractions prepared in a 71-mm (2.8-inch) mold and tested without caps are equal based on compaction values.
- **Alternate hypothesis No. C.3**: The specimens of the two non-granular soil fractions prepared in a 71-mm (2.8-inch) mold and tested without caps are not equal based on compaction values.

Conclusion: There is not enough evidence to reject the null hypothesis as supported by the *p-value* (= 0.7431) and 95% confidence interval. Therefore, the test data from these two groups are equal based on their compaction values.

```
Welch Two Sample t-test

data:  ds$MDD.RATIO2 by ds$Fraction
t = -0.32782, df = 876.93, p-value = 0.7431
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.001498278  0.001069409
sample estimates:
mean in group CGF mean in group FGF
        0.9593215         0.9595359
```

Figure C-23: T-test for compaction of non-granular soils tested without caps

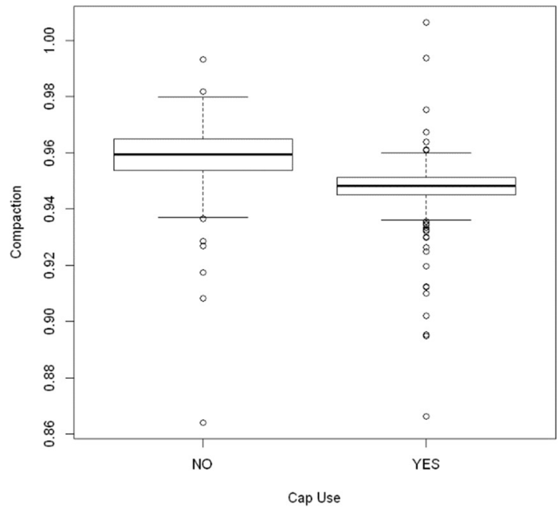

Figure C-24: Compaction of non-granular soil fractions tested versus use of caps

The following Welch (Student) t-test evaluated the optimum moisture contents (labOMC) of the two non-granular soil fractions tested without caps. The following null and alternate hypotheses were posed to determine if coarse- and fine-grained soil specimens had equivalent optimum moisture contents.

- **Null hypothesis No. C.4**: The optimum moisture contents of the coarse- and fine-grained soil specimens prepared in a 71-mm (2.8-inch) mold and tested without caps are equal.
- **Alternate hypothesis No. C.4**: The optimum moisture contents of the coarse- and fine-grained soil specimens prepared in a 71-mm (2.8-inch) mold and tested without caps are not equal.

Conclusion: There is very strong evidence that the alternate hypothesis is true as supported by the *p-value* (< 2.2e-16) and 95% confidence interval. Therefore, these two non-granular soil fractions are not equal based on their optimum moisture contents.

```
Welch Two Sample t-test

data:  ds$labOMC by ds$Fraction
t = -18.209, df = 1275.5, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -3.706175 -2.985240
sample estimates:
mean in group CGF mean in group FGF
         13.06054          16.40625
```

Figure C-25: T-test for labOMC of non-granular soil fractions tested without caps

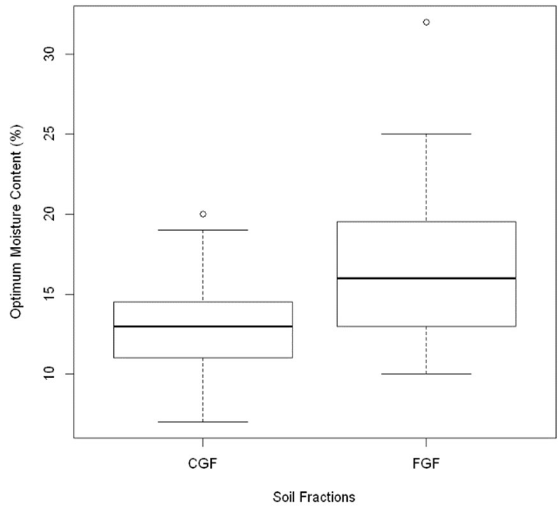

Figure C-26: Optimum moisture contents versus non-granular soil fractions

The following Welch (Student) t-test evaluated the optimum moisture content ratios (OMC.RATIO2) of coarse- and fine-grained soil fractions tested without caps. The following null and alternate hypotheses were posed to determine if the coarse- and fine-grained specimens had equivalent optimum moisture content ratios.

- **Null hypothesis No. C.5**: The optimum moisture content ratios of the coarse- and fine-grained soil fractions of the non-granular general classification that were prepared in a 71-mm (2.8-inch) mold and tested without caps are equal.
- **Alternate hypothesis No. C.5**: The optimum moisture content ratios of the coarse- and fine-grained soil fractions of the non-granular general classification that were prepared in a 71-mm (2.8-inch) mold and tested without caps are not equal.

Conclusion: There is not enough evidence to reject the null hypothesis as supported by the *p-value* (= 0.07605) and 95% confidence interval. Therefore, the coarse- and fine-grained soil fractions of the non-granular general classification are equal based on their optimum moisture content ratios.

```
Welch Two Sample t-test

data:  ds$OMC.RATIO2 by ds$Fraction
t = 1.7764, df = 783.06, p-value = 0.07605
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.0007799028  0.0156333083
sample estimates:
mean in group CGF mean in group FGF
        0.9987173         0.9912906
```

Figure C-27: T-test for OMC.RATIO2 of non-granular soil fractions versus use of caps

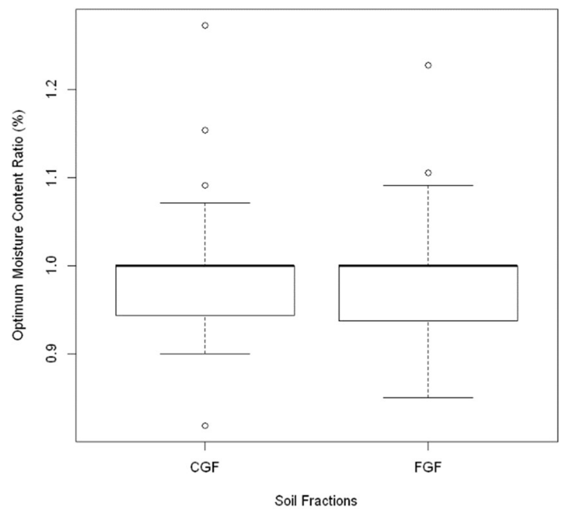

Figure C-28: Optimum moisture content ratios versus non-granular soil fractions

APPENDIX D

T-test outputs for fine-grained soil fraction tested with and without caps

Series D: A series of t-tests on the fine-grained soil fraction from the non-granular general classification was conducted. These specimens were prepared in a 71-mm (2.8-inch) mold and tested with and without caps. The following soil properties from the raw dataset were analyzed using t-tests to determine if the fine-grained soil fraction tested with and without test caps were equivalent based on the following property values. This series is different than Series B because that initial series of t-tests included the coarse- and fine-grained soil fractions in the initial analysis. This series of t-tests were conducted to further validate the use of only the fine-grained soil fraction from AASHTO M-145, which is equivalent to the ASTM D-2487 fine-grained soils.

(1) M_R,

(2) labMDD,

(3) MDD.RATIO2,

(4) labOMC, and

(5) OMC.RATIO2

The following Welch (Student) t-tests evaluated the laboratory M_R test results of the fine-grained soil fraction from the AASHTO non-granular soils tested without and with test caps. The following null and alternate hypotheses were posed to determine if these capped and non-capped specimens had equivalent M_R values.

- **Null hypothesis D.1**: The M_R of the fine-grained soil fraction from the AASHTO non-granular general classification prepared and tested in a 71-mm (2.8-inch) mold without test caps had M_R values that were equal.
- **Alternate hypothesis D.1**: The M_R of the fine-grained soil fraction from the AASHTO non-granular general classification prepared and tested in a 71-mm (2.8-inch) mold without test caps had M_R values that were not equal.

Conclusion: There is very strong evidence to reject the null hypothesis as supported by the *p-value* (< 2.2e-16) and 95% confidence interval. Therefore, the test data from these two groups are not equal based on laboratory M_R test results.

```
Welch Two Sample t-test

data:  ds$MR by ds$CAP
t = -21.886, df = 2376.1, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -20.91565 -17.47585
sample estimates:
 mean in group NO mean in group YES
         67.59896          86.79471
```

Figure D-29: T-test for M_R of the fine-grained soil fraction versus use of caps

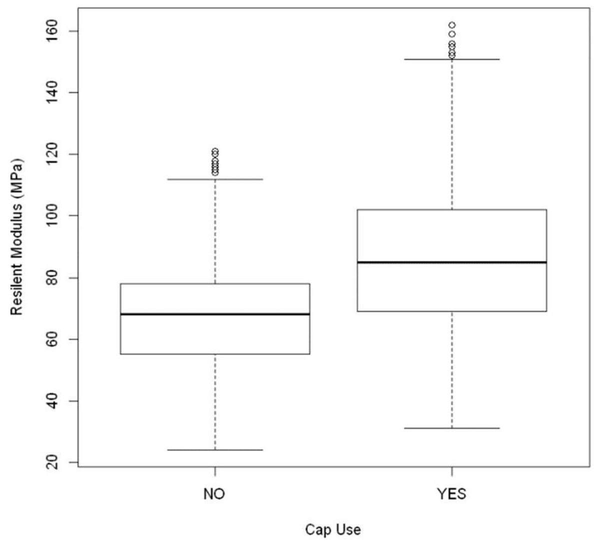

Figure D-30: M_R of the fine-grained soil fraction versus use of caps

The following Welch (Student) t-tests evaluated the maximum dry densities of the fine-grained soil fraction from the AASHTO non-granular soils tested without and with test caps. The following null and alternate hypotheses were posed to determine if these capped and non-capped specimens had equivalent maximum dry densities.

- **Null hypothesis D.2**: The maximum dry densities of the fine-grained soil fraction from the AASHTO non-granular general classification prepared and tested in a 71-mm (2.8-inch) mold without test caps had maximum dry densities that were equal.
- **Alternate hypothesis D.2**: The maximum dry densities of the fine-grained soil fraction from the AASHTO non-granular general classification prepared and tested in a 71-mm (2.8-inch) mold without test caps had maximum dry densities that were not equal.

Conclusion: There is evidence to reject the null hypothesis as supported by the *p-value* (=0.005905) and 95% confidence interval. Therefore, the test data based on the use and non-use of test caps are not equal based on maximum dry densities.

```
Welch Two Sample t-test

data:  ds$labMDD by ds$CAP
t = -2.7555, df = 2363.6, p-value = 0.005905
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -24.483580  -4.124632
sample estimates:
 mean in group NO mean in group YES
         1748.000          1762.304
```

Figure D-31: T-test for labMDD of fine-grained versus use of caps

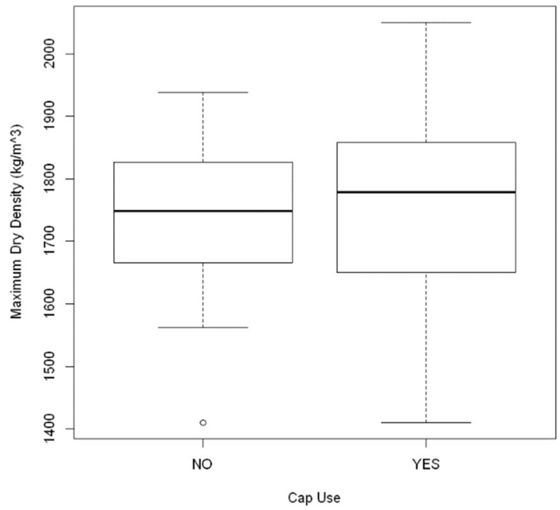

Figure D-32: labMDD based on the fine-grained soil fraction versus the use of caps

The following Welch (Student) t-tests evaluated the compactions (MDD.RATIO2) of the fine-grained soil fraction from the AASHTO non-granular soils tested without and with test caps. The following null and alternate hypotheses were posed to determine if these capped and non-capped specimens had equivalent compaction values.

- **Null hypothesis D.3**: The compaction of the fine-grained soil fraction from the AASHTO non-granular general classification prepared and tested in a 71-mm (2.8-inch) mold with and without test caps had compactions that were equal.
- **Alternate hypothesis D.3**: The compaction of the fine-grained soil fraction from the AASHTO non-granular general classification prepared and tested in a 71-mm (2.8-inch) mold with and without test caps had compactions that were not equal.

Conclusion: There is very strong evidence to reject the null hypothesis as supported by the *p-value* (< 2.2e-16) and 95% confidence interval. Therefore, the test data from these non-capped and capped soil groups are equal based on their compaction values.

```
Welch Two Sample t-test

data:  ds$MDD.RATIO2 by ds$CAP
t = 27.945, df = 1834.6, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.01118799 0.01287693
sample estimates:
 mean in group NO mean in group YES
        0.9595359         0.9475035
```

Figure D-33: T-test for compaction of the fine-grained fraction versus use of caps

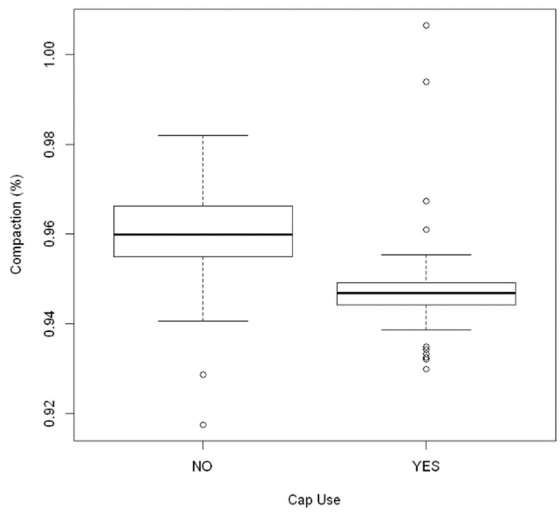

Figure D-34: Compaction of the fine-grained soil fraction versus use of caps

The following Welch (Student) t-test evaluated the optimum moisture contents (labOMC) of the fine-grained soil fractions tested with and without caps. The following null and alternate hypotheses were posed to determine if coarse- and fine-grained soil specimens had equivalent optimum moisture contents.

- **Null hypothesis D.4**: The optimum moisture contents of the fine-grained soil fractions prepared in a 71-mm (2.8-inch) mold and tested with and without caps are equal.
- **Alternate hypothesis D.**: The optimum moisture contents of the fine-grained soil fractions prepared in a 71-mm (2.8-inch) mold and tested with and without caps are not equal.

Conclusion: There is not enough evidence to reject the null hypothesis as supported by the *p-value* (= 0.3026) and 95% confidence interval. Therefore, the capped and non-capped soil specimens are not equal based on their optimum moisture contents.

```
Welch Two Sample t-test

data:  ds$labOMC by ds$CAP
t = -1.031, df = 2208.7, p-value = 0.3026
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.5275243  0.1639630
sample estimates:
 mean in group NO mean in group YES
         16.40625          16.58803
```

Figure D-35: T-test for labOMC of the fine-grained soil fraction versus use of caps

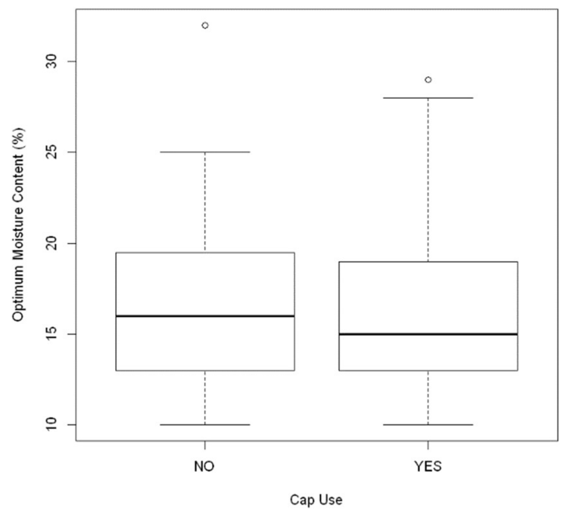

Figure D-36: OMC of FGF versus the use of caps

The following Welch (Student) t-test evaluated the optimum moisture content ratios (OMC.RATIO2) of the fine-grained soil fraction tested with and without caps. The following null and alternate hypotheses were posed to determine if the fine-grained specimens had equivalent optimum moisture content ratios.

- **Null hypothesis D.5**: The optimum moisture content ratios of the fine-grained soil fractions of the non-granular general classification that were prepared in a 71-mm (2.8-inch) mold and tested without caps are equal.
- **Alternate hypothesis D.5**: The optimum moisture content ratios of the fine-grained soil fractions of the non-granular general classification that were prepared in a 71-mm (2.8-inch) mold and tested without caps are not equal.

Conclusion: There is very strong evidence to reject the null hypothesis as supported by the *p-value* (5.498e-10) and 95% confidence interval. Therefore, the fine-grained soil fraction of the non-granular general classification are not equal based on their optimum moisture content ratios.

```
Welch Two Sample t-test

data:  ds$OMC.RATIO2 by ds$CAP
t = -6.2515, df = 1304.5, p-value = 5.498e-10
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.018140457 -0.009474535
sample estimates:
 mean in group NO mean in group YES
        0.9912906         1.0050981
```

Figure D-37: T-test for OMC.RATIO2 of the fine-grained soil fraction versus use of caps

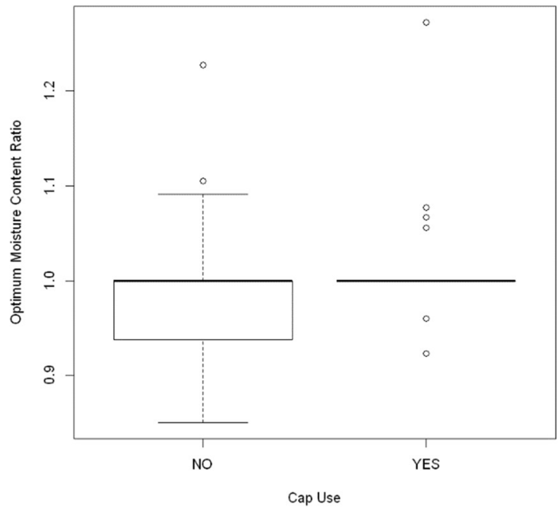

Figure D-38: OMC ratios of the fine-grained soil fraction versus use of caps

APPENDIX E

Decision Tree Primary and Surrogate Splits

This appendix contains the output from the *summary(MR.pruned)* command discussed in Chapter 5. The output was only edited by bolding "section" headers and by shifting some column contents by adding spaces to align them with the column headers to make reading the output easier.

Call:
rpart(formula = MR ~ ., data = ds_train[dt.list], method = "anova")
n= 768

	CP	**nsplit**	**rel error**	**xerror**	**xstd**
1	0.13652517	0	1.0000000	1.0018949	0.04944148
2	0.09792777	1	0.8634748	0.9053202	0.04360083
3	0.06767235	3	0.6676193	0.7724299	0.03677768
4	0.04432653	5	0.5322746	0.6073722	0.02977508
5	0.03728374	6	0.4879481	0.5280192	0.02672805
6	0.03500419	7	0.4506643	0.5207763	0.02628011
7	0.02732880	8	0.4156601	0.4341295	0.02265109
8	0.02540843	10	0.3610025	0.3642837	0.01804610
9	0.02435663	11	0.3355941	0.3500992	0.01742595
10	0.02133889	14	0.2625242	0.3335997	0.01646355
11	0.02006902	15	0.2411853	0.3152389	0.01563206
12	0.01324059	16	0.2211163	0.2718634	0.01401372
13	0.01300000	17	0.2078757	0.2437686	0.01219033

Variable importance

PL	fSAND	CLAY	SILT	PN200	labMDD	PN10	labOMC	PN40	LL	PN80
13	12	11	10	9	7	7	6	6	6	6

cSAND	PI
5	3

Node number 1: 768 observations, complexity param=0.1365252
mean=67.77214, MSE=327.0692
left son=2 (348 obs) right son=3 (420 obs)
Primary splits:
SILT < 41 to the right, improve=0.13652520, (0 missing)
PL < 12.5 to the left, improve=0.12738690, (0 missing)
CLAY < 7.9 to the left, improve=0.11353960, (0 missing)
fSAND < 38.5 to the left, improve=0.08397612, (0 missing)
labMDD < 1914 to the left, improve=0.06849857, (0 missing)

Surrogate splits:
fSAND < 11.25 to the left, agree=0.729, adj=0.402, (0 split)
CLAY < 18.65 to the left, agree=0.691, adj=0.319, (0 split)
LL < 28.5 to the left, agree=0.660, adj=0.250, (0 split)
PN200 < 59.85 to the right, agree=0.645, adj=0.216, (0 split)
PL < 13.5 to the left, agree=0.638, adj=0.201, (0 split)

Node number 2: 348 observations, complexity param=0.06767235
mean=60.43103, MSE=240.0613
left son=4 (85 obs) right son=5 (263 obs)
Primary splits:
PL < 12.5 to the left, improve=0.1983160, (0 missing)
CLAY < 17.9 to the left, improve=0.1974283, (0 missing)
LL < 27.5 to the left, improve=0.1933494, (0 missing)
PN10 < 98.5 to the left, improve=0.1323766, (0 missing)
cSAND < 1.5 to the right, improve=0.1269308, (0 missing)
Surrogate splits:
LL < 22.5 to the left, agree=0.853, adj=0.400, (0 split)
CLAY < 7.6 to the left, agree=0.816, adj=0.247, (0 split)
PN10 < 85.5 to the left, agree=0.796, adj=0.165, (0 split)
PN200 < 50.85 to the left, agree=0.796, adj=0.165, (0 split)
SILT < 60.05 to the right, agree=0.793, adj=0.153, (0 split)

Node number 3: 420 observations, complexity param=0.09792777
mean=73.85476, MSE=317.5099
left son=6 (396 obs) right son=7 (24 obs)
Primary splits:
labOMC < 10.5 to the right, improve=0.14942040, (0 missing)
labMDD < 1914 to the left, improve=0.14942040, (0 missing)
PN10 < 77.5 to the right, improve=0.14364890, (0 missing)
PL < 15.5 to the left, improve=0.13858090, (0 missing)
fSAND < 38.5 to the left, improve=0.09981178, (0 missing)
Surrogate splits:
labMDD < 1914 to the left, agree=1.000, adj=1.000, (0 split)
PN10 < 77.5 to the right, agree=0.945, adj=0.042, (0 split)

Node number 4: 85 observations
mean=48.29412, MSE=75.38408

Node number 5: 263 observations, complexity param=0.06767235
mean=64.35361, MSE=230.2894
left son=10 (125 obs) right son=11 (138 obs)
Primary splits:
PN200 < 66 to the left, improve=0.2877770, (0 missing)
PI < 9.5 to the left, improve=0.2661370, (0 missing)
PL < 13.5 to the right, improve=0.2423110, (0 missing)
CLAY < 17.9 to the left, improve=0.1869367, (0 missing)

fSAND < 25.25 to the right, improve=0.1714114, (0 missing)
Surrogate splits:
PN80 < 77.75 to the left, agree=0.947, adj=0.888, (0 split)
CLAY < 19.1 to the left, agree=0.913, adj=0.816, (0 split)
PN40 < 87.4 to the left, agree=0.859, adj=0.704, (0 split)
PN10 < 92 to the left, agree=0.810, adj=0.600, (0 split)
fSAND < 9.5 to the right, agree=0.776, adj=0.528, (0 split)

Node number 6: 396 observations, complexity param=0.09792777
mean=72.15909, MSE=277.3055
left son=12 (116 obs) right son=13 (280 obs)
Primary splits:
PL < 15.5 to the left, improve=0.2665528, (0 missing)
fSAND < 38.5 to the left, improve=0.1412571, (0 missing)
PN80 < 81 to the left, improve=0.1386855, (0 missing)
PN200 < 50.6 to the right, improve=0.1066891, (0 missing)
SILT < 25.75 to the right, improve=0.0892466, (0 missing)
Surrogate splits:
LL < 34 to the left, agree=0.785, adj=0.267, (0 split)
labMDD < 1866 to the right, agree=0.785, adj=0.267, (0 split)
cSAND < 3.3 to the left, agree=0.740, adj=0.112, (0 split)
PI < 3 to the left, agree=0.735, adj=0.095, (0 split)
labOMC < 11.5 to the left, agree=0.727, adj=0.069, (0 split)

Node number 7: 24 observations
mean=101.8333, MSE=150.6389

Node number 10: 125 observations, complexity param=0.04432653
mean=55.8, MSE=177.392
left son=20 (51 obs) right son=21 (74 obs)
Primary splits:
PN10 < 90 to the right, improve=0.5021350, (0 missing)
PN40 < 85.5 to the right, improve=0.4904696, (0 missing)
fSAND < 22.5 to the right, improve=0.4904696, (0 missing)
PN80 < 73 to the right, improve=0.3098085, (0 missing)
PN200 < 62.2 to the right, improve=0.3048264, (0 missing)
Surrogate splits:
PN40 < 85.5 to the right, agree=0.904, adj=0.765, (0 split)
fSAND < 22.5 to the right, agree=0.904, adj=0.765, (0 split)
PI < 9.5 to the left, agree=0.808, adj=0.529, (0 split)
SILT < 47.85 to the right, agree=0.712, adj=0.294, (0 split)
PL < 22.5 to the right, agree=0.712, adj=0.294, (0 split)

Node number 11: 138 observations, complexity param=0.03500419
mean=72.10145, MSE=151.9028
left son=22 (124 obs) right son=23 (14 obs)
Primary splits:
PL < 14 to the right, improve=0.4194461, (0 missing)

cSAND < 0.05   to the left, improve=0.3250119, (0 missing)
fSAND < 2.5   to the left, improve=0.3250119, (0 missing)
CLAY < 36.05 to the right, improve=0.2715898, (0 missing)
PN200 < 95.75 to the right, improve=0.2025764, (0 missing)

Surrogate splits:

PN10 < 94.1   to the right, agree=0.92, adj=0.214, (0 split)

Node number 12: 116 observations,   complexity param=0.0273288

mean=58.80172, MSE=176.159

left son=24 (78 obs) right son=25 (38 obs)

Primary splits:

SILT < 39.7   to the left, improve=0.3338887, (0 missing)
fSAND < 18.5   to the left, improve=0.3063364, (0 missing)
PI   < 14   to the right, improve=0.2727119, (0 missing)
LL   < 28   to the right, improve=0.2727119, (0 missing)
cSAND < 11.5   to the left, improve=0.2620559, (0 missing)

Surrogate splits:

PN40 < 73   to the right, agree=0.784, adj=0.342, (0 split)

PN80 < 63   to the right, agree=0.784, adj=0.342, (0 split)

PN200 < 51.95 to the right, agree=0.784, adj=0.342, (0 split)
cSAND < 2.5   to the right, agree=0.784, adj=0.342, (0 split)
CLAY < 11.2   to the right, agree=0.784, adj=0.342, (0 split)

Node number 13: 280 observations,   complexity param=0.03728374

mean=77.69286, MSE=214.6699

left son=26 (254 obs) right son=27 (26 obs)

Primary splits:

CLAY   < 12.05 to the right, improve=0.1558084, (0 missing)
fSAND < 34.5   to the left, improve=0.1558084, (0 missing)
labOMC < 12.5   to the right, improve=0.1471994, (0 missing)
PN10   < 90.05 to the right, improve=0.1413185, (0 missing)
LL   < 31.5   to the right, improve=0.1340220, (0 missing)

Surrogate splits:

fSAND < 34.5   to the left, agree=1.000, adj=1.000, (0 split)

PN200 < 50.6   to the right, agree=0.957, adj=0.538, (0 split)
PI   < 6.5   to the right, agree=0.957, adj=0.538, (0 split)
labOMC < 12.5   to the right, agree=0.954, adj=0.500, (0 split)
LL   < 29.5   to the right, agree=0.914, adj=0.077, (0 split)

Node number 20: 51 observations

mean=44.43137, MSE=86.44137

Node number 21: 74 observations,   complexity param=0.01324059

mean=63.63514, MSE=89.61012

left son=42 (23 obs) right son=43 (51 obs)

Primary splits:
PL < 22.5 to the right, improve=0.5015559, (0 missing)
labMDD < 1650 to the left, improve=0.5015559, (0 missing)
cSAND < 7 to the left, improve=0.3766064, (0 missing)
PN200 < 63.8 to the right, improve=0.2678080, (0 missing)
labOMC < 20.5 to the right, improve=0.2678080, (0 missing)
Surrogate splits:
labMDD < 1650 to the left, agree=1.000, adj=1.000, (0 split)
PN200 < 63.8 to the right, agree=0.851, adj=0.522, (0 split)
SILT < 41.4 to the left, agree=0.851, adj=0.522, (0 split)
CLAY < 21.45 to the right, agree=0.851, adj=0.522, (0 split)
LL < 65.5 to the right, agree=0.851, adj=0.522, (0 split)

Node number 22: 124 observations, complexity param=0.02133889
mean=69.41935, MSE=94.66285
left son=44 (12 obs) right son=45 (112 obs)
Primary splits:
cSAND < 0.05 to the left, improve=0.4566374, (0 missing)
fSAND < 2.5 to the left, improve=0.4566374, (0 missing)
CLAY < 31.55 to the right, improve=0.4014985, (0 missing)
PN200 < 95.75 to the right, improve=0.2303929, (0 missing)
PL < 22 to the left, improve=0.1727752, (0 missing)
Surrogate splits:
fSAND < 2.5 to the left, agree=1.000, adj=1.000, (0 split)
PN200 < 95.75 to the right, agree=0.919, adj=0.167, (0 split)
CLAY < 35.6 to the right, agree=0.911, adj=0.083, (0 split)

Node number 23: 14 observations
mean=95.85714, MSE=30.83673

Node number 24: 78 observations, complexity param=0.0273288
mean=53.44872, MSE=159.4012
left son=48 (55 obs) right son=49 (23 obs)
Primary splits:
fSAND < 24.5 to the left, improve=0.5554897, (0 missing)
PN200 < 56 to the right, improve=0.5554897, (0 missing)
CLAY < 18.9 to the right, improve=0.5554897, (0 missing)
PN80 < 83.5 to the left, improve=0.3973801, (0 missing)
LL < 14.5 to the right, improve=0.3973801, (0 missing)
Surrogate splits:
PN200 < 56 to the right, agree=1.000, adj=1.000, (0 split)
CLAY < 18.9 to the right, agree=1.000, adj=1.000, (0 split)
cSAND < 13 to the left, agree=0.859, adj=0.522, (0 split)
PN80 < 83.5 to the left, agree=0.846, adj=0.478, (0 split)
LL < 14.5 to the right, agree=0.846, adj=0.478, (0 split)

Node number 25: 38 observations
mean=69.78947, MSE=31.00831

Node number 26: 254 observations, complexity param=0.02540843
mean=75.84252, MSE=189.55
left son=52 (23 obs) right son=53 (231 obs)
Primary splits:
CLAY < 19 to the left, improve=0.1325626, (0 missing)
SILT < 25.75 to the right, improve=0.1304016, (0 missing)
S3 < 13.9 to the left, improve=0.1303248, (0 missing)
fSAND < 28 to the right, improve=0.1219579, (0 missing)
THETA < 104.05 to the left, improve=0.1177654, (0 missing)
Surrogate splits:
cSAND < 20 to the right, agree=0.957, adj=0.522, (0 split)
labMDD < 1486 to the left, agree=0.957, adj=0.522, (0 split)
labOMC < 27.5 to the right, agree=0.957, adj=0.522, (0 split)

Node number 27: 26 observations
mean=95.76923, MSE=99.86982

Node number 42: 23 observations
mean=53.65217, MSE=27.79206

Node number 43: 51 observations
mean=68.13725, MSE=52.27528

Node number 44: 12 observations
mean=49.33333, MSE=48.55556

Node number 45: 112 observations
mean=71.57143, MSE=51.7449

Node number 48: 55 observations
mean=47.36364, MSE=76.08595

Node number 49: 23 observations
mean=68, MSE=58.34783

Node number 52: 23 observations
mean=59.95652, MSE=48.99811

Node number 53: 231 observations, complexity param=0.02435663
mean=77.42424, MSE=175.9153
left son=106 (144 obs) right son=107 (87 obs)
Primary splits:
cSAND < 11.55 to the left, improve=0.1275015, (0 missing)
SILT < 25.75 to the right, improve=0.1211685, (0 missing)
CLAY < 51.55 to the left, improve=0.1197785, (0 missing)
S3 < 13.9 to the left, improve=0.1175227, (0 missing)
PN80 < 96.15 to the left, improve=0.1119750, (0 missing)

Surrogate splits:
PN80 < 70.5 to the right, agree=0.810, adj=0.494, (0 split)
PN200 < 60.65 to the right, agree=0.810, adj=0.494, (0 split)
PN40 < 84.1 to the right, agree=0.805, adj=0.483, (0 split)
CLAY < 23.5 to the right, agree=0.805, adj=0.483, (0 split)
fSAND < 23.5 to the left, agree=0.792, adj=0.448, (0 split)

Node number 106: 144 observations, complexity param=0.02435663
mean=73.74306, MSE=146.1076
left son=212 (133 obs) right son=213 (11 obs)
Primary splits:
SILT < 40.65 to the left, improve=0.3134007, (0 missing)
PN80 < 96.15 to the left, improve=0.3134007, (0 missing)
PN40 < 97.95 to the left, improve=0.3134007, (0 missing)
fSAND < 16.5 to the right, improve=0.2973903, (0 missing)
cSAND < 5.15 to the right, improve=0.2878716, (0 missing)
Surrogate splits:
PN40 < 97.95 to the left, agree=1, adj=1, (0 split)
PN80 < 96.15 to the left, agree=1, adj=1, (0 split)

Node number 107: 87 observations, complexity param=0.02435663
mean=83.51724, MSE=165.698
left son=214 (13 obs) right son=215 (74 obs)
Primary splits:
PN10 < 99.5 to the right, improve=0.4564018, (0 missing)
cSAND < 16 to the right, improve=0.4564018, (0 missing)
fSAND < 28.2 to the right, improve=0.4564018, (0 missing)
PN80 < 66 to the left, improve=0.4269449, (0 missing)
PN200 < 55.85 to the left, improve=0.4269449, (0 missing)
Surrogate splits:
cSAND < 16 to the right, agree=1, adj=1, (0 split)
fSAND < 28.2 to the right, agree=1, adj=1, (0 split)

Node number 212: 133 observations, complexity param=0.02006902
mean=71.79699, MSE=101.5152
left son=424 (110 obs) right son=425 (23 obs)
Primary splits:
labMDD < 1778 to the left, improve=0.3733743, (0 missing)
PN10 < 82 to the right, improve=0.3061743, (0 missing)
PN40 < 74 to the right, improve=0.3061743, (0 missing)
cSAND < 5.4 to the right, improve=0.2287871, (0 missing)
fSAND < 16.5 to the right, improve=0.1853190, (0 missing)
Surrogate splits:
PN10 < 99.15 to the left, agree=0.917, adj=0.522, (0 split)
fSAND < 25 to the left, agree=0.917, adj=0.522, (0 split)
LL < 30.5 to the right, agree=0.917, adj=0.522, (0 split)
PI < 11 to the right, agree=0.917, adj=0.522, (0 split)
labOMC < 14 to the right, agree=0.917, adj=0.522, (0 split)

Node number 213: 11 observations
mean=97.27273, MSE=85.83471

Node number 214: 13 observations
mean=62.76923, MSE=27.71598

Node number 215: 74 observations
mean=87.16216, MSE=101.0278

Node number 424: 110 observations
mean=68.98182, MSE=68.38149

Node number 425: 23 observations
mean=85.26087, MSE=40.80151