GEORGIA DOT RESEARCH PROJECT 17-25

FINAL REPORT

PREDICTION OF RESILIENT MODULUS FROM THE LABORATORY TESTING OF SANDY SOILS

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16. Abstract:

As Georgia Department of Transportation (GDOT) is moving toward implementing the Mechanistic–Empirical Pavement Design Guide (MEPDG) and utilizing the AASHTOWare Pavement ME Design software, there is a pressing need to develop a subgrade resilient modulus (M_R) database considering Georgia-specific soil conditions in order to achieve a reliable pavement design. Developing a reliable subgrade M_R database is key to accurate pavement structure designs. However, establishing a database requires dedicated time and effort for extensive laboratory testing.

To meet GDOT's immediate needs, the researchers built a subgrade M_R prediction model based on available GDOT resources (i.e., local soil index properties and existing M_R data, etc.). The developed model uses the optimum moisture content as the soil predictor of the resilient modulus. The strength of this variable was confirmed by a random forest model and machine learning analysis.

In addition, this study laid the groundwork to develop a performance-based specification (PBS) for subgrade materials. The Indiana Department of Transportation (INDOT) was chosen as an example of a state DOT that has incorporated a PBS for embankment and subgrade construction. A brief discussion of INDOT's process and test methods is presented with a recommendation to use INDOT as a general model for developing a GDOT PBS for embankment and subgrade construction.

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Final Report

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EXECUTIVE SUMMARY

As Georgia Department of Transportation (GDOT) is moving toward implementing the Mechanistic–Empirical Pavement Design Guide (MEPDG) and utilizing the American Association of State Highway and Transportation Officials' AASHTOWare Pavement ME Design software, there is a pressing need to develop a subgrade resilient modulus (M_R) database considering Georgia-specific soil conditions in order to achieve a reliable pavement design. Developing a reliable subgrade M_R database is key to accurate pavement structure designs. However, establishing a database requires dedicated time and effort for extensive laboratory testing.

To meet GDOT's immediate needs, the researchers built a subgrade M_R prediction model based on available GDOT resources (i.e., local soil index properties and existing M_R data, etc). The developed model uses the optimum moisture content as the soil predictor of the resilient modulus. The strength of this variable was confirmed by a random forest model and machine learning analysis.

In addition, this study laid the groundwork to develop a performance-based specification (PBS) for subgrade materials. The Indiana Department of Transportation (INDOT) was chosen as an example of a state DOT that has incorporated a PBS for embankment and subgrade construction. A brief discussion of INDOT's process and test methods is presented with a recommendation to use INDOT as a general model for developing a GDOT PBS for embankment and subgrade construction.

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SI CONVERSION FACTORS

SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^{o}F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^{o}C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^{o}C	Celsius	1.8C+32	Fahrenheit	^{o}F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

1 INTRODUCTION

1.1 Background

The Georgia Department of Transportation (GDOT) currently uses the "AASHTO Interim Guide for Design of Pavement Structures, 1972" for its flexible pavement design procedure. From this guide, GDOT provides the pavement designer with soil classifications and a single strength parameter, based on soaked California Bearing Ratio (CBR) tests to represent the subgrade soils used in construction.

GDOT is in the process of evaluating the Mechanistic–Empirical Pavement Design Guide (MEPDG) in preparation for the replacement of the soil support value and modulus of subgrade reaction with the subgrade resilient modulus (M_R). This new soil parameter is more representative of the behavior of soil under traffic loading. The cyclic loading test procedure AASHTO T 307: *Standard Method for Determining the Resilient Modulus of Soils and Aggregates* is the current test procedure for determining resilient modulus for soils and aggregate materials, but it is a complex test that few state agencies plan to conduct regularly.

Development of correlations between resilient modulus and soil index properties that are routinely tested for or with back-calculated in situ test measurements seems to be the typical approach employed by state agencies to provide design values to pavement designers. The reason for this correlation strategy is that it provides the least disruption to existing procedures while moving toward possible adoption of the MEPDG. Therefore, GDOT has elected to follow this approach of developing correlations.

1.2 Objectives

The primary objectives of this study were to:

(1) develop a simple method to estimate the resilient modulus based on available GDOT resources; and

(2) lay the groundwork to develop a performance-based specification (PBS) approach for subgrade materials.

The results of this study will enable GDOT and its consultants to design pavements that will reliably perform for the design period of roadways by selecting subgrade resilient moduli for use with the MEPDG methodology.

2 LITERATURE REVIEW

2.1 Laboratory Resilient Modulus Test Methods

During the period from 1982 to 2004, there have been six versions of the AASHTO resilient modulus test procedure. Each version has been an attempt to simplify and/or improve some aspect of the test procedure. Some of the improvements that each new revision sought to resolve were reduced test complexity and shorter test durations. The requirement for expensive equipment is also cited as problematic for state agencies (Nguyen and Mohajerani, 2017; Lee et al., 1997; Dione et al., 2014). Due to the frequent iterations of the test method and the uncertainties that are introduced with each change, some state agencies have developed reservations about the test methods (Puppala, 2008). One of these changes was the location of the linear variable differential transducer (LVDT) position when it moved from the platen[1] within the triaxial cell to a mounted position outside of the cell (Ping et al., 2003, Mohammad et al., 1994).

Mohammad et al. (1994) compared the AASHTO T 292: *Standard Method of Test for Resilient Modulus of Subgrade Soils and Untreated Base/Subbase Materials* and T 294: *Standard Method of Test for Resilient Modulus of Unbound Granular Base/Subbase Materials and Subgrade Soils - SHRP Protocol P46* to study the effect of test procedures and the measurement systems. It observed that the resilient moduli of sands were influenced by the test methods because the stress sequences used varied between the two methods. A significant difference was not found between the two test methods for clays, which was attributed to the lower confining stress levels used. However, no significant

[1] A flat plate, especially one that exerts or receives pressure. Merriman Webster website (https://www.merriam-webster.com/dictionary/platen).

conclusions could be drawn from the test results on clays because of the limited amount of data. In addition, the authors found that the deformation measurement system used affected the clays more than the sands tested.

While Kim (2013) used AASHTO T 307: *Standard Method of Test for Determining the Resilient Modulus of Soils and Aggregate Materials* in an earlier study for GDOT, NCHRP 1-28 A: *Harmonized Test Methods for Laboratory Determination of Resilient Modulus for Flexible Pavement Design* is a more recent method, which recommends an internal LVDT system, as opposed to the external system recommended by AASHTO T 307. Should GDOT adopt another test method, the inherent effects of measurement locations, stresses, or other changes should be investigated to quantify their impact on pavement design.

Puppala (2008) decided to gain a better perspective on the practices and views of state agencies in their determination of resilient modulus properties. He conducted a survey of the 50 states from which he received 41 responses; however, not all questions were answered. Of the 22 respondents that use resilient modulus for pavement design, 11 states used resilient modulus on more than 20 projects annually. Twelve DOTs used laboratory resilient modulus testing from geotechnical materials (8 states) and external/university (4 states) laboratories. Nine responses indicated that resilient modulus testing was conducted with repeated load testing (RLT) equipment using AASHTO T 307 (4 responses), NCHRP 1-28 A (2 responses), or other methods (3 responses). Eleven responses indicated that impact (4 responses), static (3 responses), kneading (2 responses), or vibratory (2 responses) compaction methods were used to prepare the lab specimens.

In addition, Puppala (2008) found that 3 respondents out of 41 indicated that the falling weight deflectometer (FWD) was used to verify that laboratory and field modulus values were in agreement. Five responses suggested that there was no correlation between laboratory and field modulus values. While addressing problems related to resilient modulus tests, a majority out of six responses questioned if laboratory resilient modulus values were true resilient modulus values representative of what occurs during subgrade construction. However, four respondents supported the idea that laboratory testing is a better method than others for determining resilient modulus.

2.2 Factors Affecting Resilient Behavior

In a state-of-the-art review, Lekarp et al. (2000) concluded that the behavior of unbound granular materials was not understood very well. It was noted that researchers did not always agree on the influence that commonly used variables had on the resilient behavior of soils and even developed conflicting ideas about what effect some parameters had. However, a consensus was found that the resilient response of granular soils was most affected by stress states and moisture contents. Density, gradation, fines content, maximum grain size, aggregate type, particle shape, stress history, and number of load applications were other factors that they found to affect the resilient behavior of granular soils more than others. Lekarp et al. (2000) found that the plastic strain of granular soils was affected by stress, principle stress reorientation, number of load applications, moisture content, stress history, density, grading, fines content, and aggregate type. It was noted that most research seemed to focus on investigation of the resilient behavior of soils rather than permanent deformation. This gap in the research likely exists because permanent deformation testing requires much time and many test specimens.

After analyzing the Long-Term Pavement Performance (LTPP) database, Yau and Von Quintus (2002) found that there was not one property that was common to all predictive models, and that soil properties correlating to resilient modulus depended on the soil type. Fitting the *k* coefficients of the constitutive models, 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. For higher-strength materials, moisture content and density were determined to be important. The clay content, moisture content, or density seemed to be important to all soil groups. Except for gravel, the silt content was also important.

Malla and Joshi (2008) likewise did not find variables that were common to all models. Their models were based on fine-grained and coarse-grained soil types according to the Unified Soil Classification System (USCS, *ASTM D-2487: Standard Practice for Classification of Soils for Engineering Purposes*). Data from the LTPP database were recovered for 259 samples from 19 states in the United States and 2 provinces in Canada. Using a general constitutive model, they found correlations for *k* coefficients with R^2 values varying from 0.32 to 0.62. Therefore, they found only poor to moderate correlations for the properties examined.

Stress, method of compaction, compaction parameters (moisture content and dry unit weight), degree of saturation, and soil moisture suction were noted by Lee et al. (1997) as factors that affected resilient modulus after their review of the literature. In their testing of 11 soils collected across the state of Tennessee, Drumm et al. (1997) examined moisture with laboratory testing and found it affected the resilient modulus of fine-grained subgrades. Soils classified according to AASHTO as A-7-5 and A-7-6 were affected to a greater extent than A-4 and A-6 soils.

2.3 Behavior of Soils Under Traffic Loading

The goal in selecting a design resilient modulus during the pavement design phase is to characterize the subgrade soil according to its physical properties and to understand its behavior during the design life of the pavement. Therefore, laboratory testing of the soil is typically performed at the density, moisture content, and stresses that it will experience during the life of a pavement. Consideration to its plastic and resilient behavior is also necessary to understand the behavior of the subgrade, which can result in pavement deterioration.

Kim and Kim (2007) tested 11 soils in Indiana, of which four were sandy-silty-clay and seven were silty-clay subgrades, to find that the resilient modulus increased with increasing confining pressure. In the sandy-silty-clay subgrades, they observed that the resilient modulus was higher for the soils compacted at moisture contents less than optimum than for the soils compacted above the optimum moisture content. In the silty-clay soils, the resilient modulus values for the drier samples were greater than those of the optimum moisture samples. The difference in behavior between the soil types was attributed to the decrease in effect of soil suction on silty-clay soils. A higher degree of saturation for both soil types that were wet of optimum was attributed as the reason for the much lower resilient moduli than those moduli at optimum moisture and drier.

In a case study on a low-volume road in north Texas over a two-year period, Hedayati and Hossain (2015) found that the seasonal in situ moisture varied by 5% of the average moisture content. The road was a two-lane flexible pavement overlying homogenous highly plastic clay. Temporary swings were observed as high as 12% of the seasonal average, due to rainfall events. The net increase in the water content of the soils was not found to be strongly affected by rainfall. One millimeter of rainfall on average generated a 0.06% increase in water content. As moisture variations can affect the resilient modulus of subgrade soils, they should be considered in pavement design.

Burczyk et al. (1994) investigated resilient modulus log relationships between moisture content, optimum moisture content, AASHTO soil classification, and group index for nine test sites in Wyoming with undisturbed and remolded cohesive soils (A-4, A-6, and A-7). The authors observed that the resilient modulus for type A-4 and A-6 subgrade soils decreased when the moisture content increased. The A-7 soils were not significantly affected by a change in water content.

Nguyen and Mohajerani (2015) tested several fine-grained soils from different locations in Victoria, Australia. They found that resilient modulus decreased as the deviator stress increased and the resilient modulus increased at varying rates for different soil types as the confining stress increased. In addition, it was observed that the resilient modulus decreased as the moisture content increased.

Consideration of accumulated plastic strain under repeated traffic loading is necessary to design a long-lasting pavement structure that resists rutting. Yang and Huang (2007) noted that cohesive soils with high water contents were found to develop excessive plastic strain under repeated loading. They reported that accumulated excessive plastic strain under repeated loading can be prevented as long as the pavement remains under the critical stress, which defines the state between a stable and unstable stress condition.

For six different soil types from different suburbs in China, Liu et al. (2019) tested these samples at varying moisture contents, compaction percentages, and stress levels. The soils were identified as two of each class: low plasticity clays (CL), silty sands (SM), and low plasticity silts (ML) according to USCS classification. They found that the influences of these factors had similar effects on both the static and dynamic resilient moduli. As the moisture content and deviator stress increased, the static resilient modulus decreased. Greater compaction and confining stresses increased the static resilient modulus. While the effect of the studied factors was the same, the resulting dynamic resilient modulus values were much less than the corresponding static resilient modulus.

2.4 Resilient Modulus Correlations

A direct or indirect approach to developing resilient correlations can be taken by researchers when faced with the task of predicting a resilient modulus for pavement design. In the direct approach, correlations are developed with soil properties or in situ test results. With the indirect approach, the laboratory resilient modulus is correlated to a stress-based model to determine the values of the constant model parameters, which is followed by development of correlations between constant model parameters and soil properties (Puppala, 2008).

A selection of correlations developed using both approaches is presented in this section. The correlations were developed using a variety of test methods, sample preparation techniques, testing conditions, and soils. Therefore, these correlations are not necessarily transferrable to Georgia for use with the 1993 AASHTO Design Guide or the MEPDG.

2.4.1 Correlations Using the Direct Approach

In the past, the search for a correlation of resilient modulus to California Bearing Ratio was one of the most common plans of attack taken by researchers. The most recognized correlation, Eq. (2.1) of this type was developed by Heukelom and Klomp in 1962. The data used for developing it resulted in coefficients that ranged in value from 750 to 3000 times the Corps of Engineer's CBR. The equation has been used for fine-grained soils when the CBR is less than or equal to 10% (George, 2004; Puppala, 2008).

$$M_R(psi) = 1500 \times CBR \tag{2.1}$$

George (2004), Dione et al. (2014), and Drumm et al. (1990) have suggested that although CBR has been used to characterize subgrade soils, it is a measure of shear strength, which may not correlate well to stiffness. George (2004) recommended that simple correlations, such as Eq. (2.1), should be used with caution. Other studies have shown that the use of the Heukelom and Klomp correlation over-predicts resilient modulus when the CBR is greater than 5%, and under-predicts when the CBR is less than 5%. Dione et al. (2014) reported that the use of these types of correlations is the cause of road deterioration when an under-prediction of resilient modulus is made. The study concluded that the M_R–CBR relationship was not suitable for predicting the resilient modulus of unbound granular materials in Senegal. The Virginia Department of Transportation considers the M_R–CBR correlation in the MEPDG software to be poor (Hossain and Kim, 2014; Hossain, 2009). Smart and Humphrey (1999) also found that CBR does not correlate well to resilient modulus.

Lee et al. (1997) developed an Eq. (2.2) (R^2=0.97) using test results from laboratory resilient modulus and conventional unconfined compressive strength testing on three clayey soils. AASHTO T 274-82: *Standard Method of Testing for Resilient Modulus of Subgrade Soils* was used for resilient modulus testing and conventional unconfined compressive strength testing was conducted at a strain rate of 1%/minute. In addition, the authors concluded that an M_R–$S_{u1\%}$ correlation could be developed with a resilient modulus test series of four to five specimens.

$$M_R = 695.4 * S_{u1\%} - 5.93 * (S_{u1\%})^2 \tag{2.2}$$

Where,

M_R = Resilient modulus at maximum axial stress of 41.4 kPa (6 psi) and a confining stress of 20.7 kPa (3 psi)

$S_{u1\%}$ = Stress causing 1% strain in a conventional unconfined compressive strength test

Smart and Humphrey (1999) developed correlations using the soil index properties of six Maine granular soils that were tested using the Strategic Highway Research Program (SHRP) Protocol P46. The soil properties were retrieved from the LTPP database. Law Engineering, which conducted the laboratory testing in 1992, provided the resilient modulus test results.

The correlation with the greatest R^2 (0.991) and lowest standard error of the estimates (2003 psi, 13.8 MPa), which included a bulk stress parameter is presented in Eq. (2.3).

$$M_R = -6350\,\Delta\gamma_{dmax} + 170\,S - 280P_{25mm} + 730P_{2mm} + 330\theta \tag{2.3}$$

Where,

M_R = Resilient modulus of Type I soils (granular soils) (psi)

$\Delta\gamma_{dmax}$ = Difference between maximum dry density and dry density at the time of testing (pcf)

S = Saturation (%)

P_{25mm} = Percent passing 25 mm (1-inch) sieve (%)

P_{2mm} = Percent passing 2 mm (No. 10) sieve (%)

θ = Bulk stress (psi)

In addition, Smart and Humphrey (1999) developed correlations using eight Maine cohesive soils to include an investigation of the effect of deviator and confining stresses. The model for cohesive soils with the greatest R^2 (0.996) and lowest standard errors of the estimates (950 psi, 6.6 MPa) is presented in Eq. (2.4).

$$M_R = 263\,\Delta\gamma_{dmax} - 234\,W_{opt} + 31S + 165P_{76mm} - 34P_{0.8mm} + 190\sigma_d - 1215\sigma_3 \tag{2.4}$$

Where,

M_R = Resilient modulus of Type 2 soils (cohesive soils) (psi)

$\Delta\gamma_{dmax}$ = Difference between maximum dry density and dry density at the time of testing (pcf)

W_{opt} = Optimum moisture content

S = Saturation (%)

P_{76mm} = Percent passing 76 mm (3-inch) sieve (%)

$P_{0.8mm}$ = Percent passing 0.08 mm (No. 200) sieve (%)

σ_d = Deviator stress (psi)

σ_3 = Confining pressure (psi)

For a study in Virginia, Hossain and Kim (2014) tested fine-grained soils for: (1) resilient modulus (AASHTO T 307), (2) quick shear (AASHTO T 307 at 5 psi or 34.7 kPa confining pressure at the end of testing, rate of axial deviator loading was 1% strain/minute), and (3) unconfined compressive strength (UCS; AASHTO T 208). The rate of loading for the UCS test was 1% strain/minute, which was similar to the quick shear tests.

Only the simplest models with the greatest R^2 values and all parameters reported as significant are presented (Eq. 2.5 and 2.6).

$$M_R = 4283 + 143Q \quad (R^2 = 0.73) \tag{2.5}$$

$$M_R = 657(S_{u1\%}) - 6.75(S_{u1\%})^2 \quad (R^2 = 0.97) \tag{2.6}$$

Where,

M_R = Resilient modulus (psi)

Q = Ultimate compressive strength (psi)

$S_{u1\%}$ = Stress at 1% strain (psi)

2.4.2 Correlations Using the Indirect Approach

Numerous models correlate resilient modulus to the constant model coefficients k_1, k_2, and k_3, using any one of the available constitutive models with varying strengths of correlation. The results of two studies are presented in this section as examples.

Using soils collected from eight road sections across the different districts of Mississippi, George (2004) conducted resilient modulus testing using AASHTO TP 46 Protocol (repeated load triaxial test). With these results he evaluated the prediction models from seven research studies, including a Mississippi DOT study, which was discussed earlier. He determined that the LTTP Eqs. (2.8) to (2.16) from Yau and Von Quintus (2002) with the constitutive Eq. (2.7) could be used for predicting the resilient modulus of the subgrades for Mississippi road projects.

$$M_R = k_1 P_a \left(\frac{\theta}{P_a}\right)^{k_2} \left(\frac{\tau_{oct}}{P_a} + 1\right)^{k_3} \tag{2.7}$$

Yau and Von Quintus (2002) developed the following correlations for the coefficients k_1, k_2, and k_3 with 2014 quality-control checked resilient modulus test results following LTPP Test Protocol P46. These equation sets for the different soil types are presented below as referenced by George (2004) in his report.

<u>For coarse-grained soils:</u>

$$k_1 = 3.2868 - 0.0412 P_{3/8} + 0.0267 P_4 + 0.0137(\%Clay) + 0.0083 LL - 0.0379 w_{opt} - 0.0004 \gamma_s \tag{2.8}$$

$$k_2 = 0.5670 + 0.0045P_{3/8} - 2.98x10^{-5}P_4 - 0.0043(\%Silt) - 0.0102(\%Clay)$$
$$-0.0041LL + 0.0014w_{opt} - 3.41x10^{-5}\gamma_s - 0.4582\left({\gamma_s}/{\gamma_{opt}}\right) + 0.1779\left({w_c}/{w_{opt}}\right) \quad (2.9)$$

$$k_3 = -3.5677 + 0.1142P_{3/8} - 0.0839P_4 - 0.1249P_{200} + 0.1030(\%Silt) +$$
$$0.1191(\%Clay) - 0.00691LL - 0.0103w_{opt} - 0.0017\gamma_s + 4.3177\left({\gamma_s}/{\gamma_{opt}}\right) -$$
$$1.1095\left({w_c}/{w_{opt}}\right) \quad (2.10)$$

<u>For fine-grained silt soils:</u>

$$k_1 = 1.0480 + 0.0177(\%Clay) + 0.0279PI - 0.0370w_c \quad (2.11)$$

$$k_2 = 0.5097 - 0.0286PI \quad (2.12)$$

$$k_3 = -0.2218 + 0.0047(\%Silt) + 0.0849PI - 0.1399w_c \quad (2.13)$$

<u>For fine-grained clay soils:</u>

$$k_1 = 1.3577 + 0.0106(\%Clay) - 0.0437w_c \quad (2.14)$$

$$k_2 = 0.5193 - 0.0073P_4 + 0.0095P_{40} - 0.0027P_{200} - 0.003LL - 0.0049w_{opt} \quad (2.15)$$

$$k_3 = 1.4258 - 0.0288P_4 + 0.0303P_{40} - 0.0521P_{200} + 0.0251(\%Silt) + 0.0535LL -$$
$$0.0672w_{opt} - 0.0026\gamma_{opt} + 0.0025\gamma_s - 0.6055\left({w_c}/{w_{opt}}\right) \quad (2.16)$$

Where,

$P_{3/8}$ = Percent of material passing the No. ⅜ (9.5 mm) sieve, by weight

P_4 = Percent of material passing the No. 4 (4.75 mm) sieve, by weight

P_{200} = Percent of material passing the No. 200 (0.08 mm) sieve, by weight

w_c = Moisture content of the specimen (%)

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

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

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

PI = Plasticity index

LL = Liquid limit

Mehrotra et al. (2018) developed two sets of correlations using the universal constitutive Eq. (2.7) and the M_R-matric constitutive model Eq. (2.17) using four different fine-grained soils tested according to AASHTO T 307.

$$M_R = k_1 P_a \left(\frac{\theta + \Theta^k \Psi}{P_a}\right)^{k_2} \left(\frac{\tau_{oct}}{P_a}\right)^{k_3} \tag{2.17}$$

Where,

P_a = Atmospheric pressure

Θ = Bulk stress

τ_{oct} = Octahedral shear stress

k_1, k_2, k_3 = Model regression constants

ψ = Matric suction

$\Theta = (\theta - \theta_r)/(\theta_s - \theta_r)$, the normalized water content

$\theta =$ Volumetric water content

$\theta_r =$ Water content at residual condition

θ_s= Water content at saturated condition

k = 1/n

n = Rate of change of matric suction with respect to water content

Mehrotra et al. (2018) developed the following set of regression models to include matric suction because matric suction affects the stress state of unsaturated soils. (Their regression equations for the k coefficients in the universal constitutive model are not included. The authors stated that this model could not represent the effect of varying moisture contents on M_R because it only considers the stress state.) The regression models for k coefficients in the M_R-matric constitutive model are as follows:

$$\ln k_1 = 2.449 + 0.3546 s_a + 0.3540 P_{200} - 0.1222 w_{wc} \quad (R^2 = 0.88) \tag{2.18}$$

$$k_2 = 1.756 - 0.08682 s_a - 0.5348 s_{sc} - 0.1932 P_{200} + 0.01311(PI) \quad (R^2 = 0.92) \tag{2.19}$$

$$k_3 = 5.5654 + 0.1337 s_a - 7.801 M_{opt} + 0.01649(PI) \quad (R^2 = 0.69) \tag{2.20}$$

Where,

$s_a = (S - S_{opt}) \times A$

S = Degree of saturation

S_{opt} = Degree of saturation at optimum moisture

$A = PI/P_{200}$

PI = Plasticity index

P_{200} = Percent of material passing the No. 200 (0.08 mm) sieve, by weight

$w_{wc} = ((w - w_{opt})/w_{opt}) \times (\%Clay)$

$s_{sc} = (S - S_{opt}) / (\%Clay)$

2.5 Light Weight Deflectometers and Dynamic Cone Penetrometers

White et al. (2007) noted that plate size, contact stress, type and location of deflection transducer, usage of load transducer, loading rate, and buffer stiffness were some of the key factors that influence the light weight deflectometer's (LWD) estimation of resilient modulus. They compared devices manufactured by Zorn Stendal of Germany and Dynatest of Denmark. The Dynatest device (Keros) measured resilient modulus that was on average 1.8 to 2.2 times the modulus of the ZFG 2000. The main reason for this difference is in the measured deflections. The Zorn device measured deflections were approximately 1.5 times greater than the Dynatest device using the same plate size, drop height, and drop weight.

Kessler (2009) reported that South Africa and Germany use dynamic cone penetrometers (DCPs) and LWDs for quality control and their roads last 20 to 25 years before resurfacing is required. That observation is in contrast to the experiences of agencies that use maximum dry density for quality assurance/quality control (QA/QC) and resurface every 5 to 10 years. Therefore, the use of maximum dry density does not ensure a quality road, and can be a poor indicator of performance when compared to stiffness and strength. Additional benefits of using these devices are that they do not require special handling, safety training, or certification. These devices also provide timely, direct verification of construction requirements. Kessler (2009) also reported that the Minnesota DOT found density specifications imprecise, so they began to use LWDs for quality control. In Germany, where contractors guarantee the roads they build, the LWD is used for QA/QC. In South Africa, contractors produce virtually perpetual pavements with the use of LWDs and DCPs. Its Ministry of Transportation attributes this success to the construction of quality base courses and subgrades.

Siekmeier et al. (2009) proposed to the Minnesota DOT to use the grading number and in situ moisture content to target values for the DCP and LWD for granular materials. The plastic limit and in situ moisture content were proposed to set target values for fine-grained soils. The plastic limit was also proposed to be used for classifying soils and estimating optimum moisture contents for compaction. The DCP and LWD would estimate the strength and modulus of compacted materials. Together these testing devices were recommended to improve compaction uniformity and lower life cycle pavement costs, in addition to other benefits.

Hossain and Apeagyei (2010) did not recommend that the Virginia DOT use of the GeoGauge, LWD, or DCP for quality control during construction because of the high variability between the estimated resilient moduli of these three devices. The authors referenced correlations between resilient modulus and other parameters to use as their frame of reference and recommended that these devices not be used until the high variability could be reconciled.

Fleming, Frost, and Lambert (2007) and Vennapusa and White (2009) found that besides LWD type, the plate size, plate rigidity, and buffer stiffness affect the measured LWD modulus. In order to effectively compare LWD test results to the results from other types of in situ tests, it is necessary to include the effect of water content in the data interpretation. This means that multivariate regression is necessary for these types of comparisons. For those DOTs that want to use LWDs for compaction control, a restriction on the time of LWD testing after compaction has occurred or an allowable change in water content should be included in the compaction control specifications, to prevent dryinginduced higher modulus values from “passing” a lift that might not have otherwise met the specified performance criteria.

The influence depth based on the stress criterion was found to lie between 2 and 2.5 times the diameter of the LWD plate, decreasing as the geomaterial becomes stiffer and more granular. The depth of influence based on strain varied between 2 and 3.5 times the diameter of the plate while depth of influence based on deflection varied between 3 and 4 times the plate diameter, both decreasing as the geomaterial becomes less granular and more clayey. These depths of influence are greater than those reported in the literature because the dynamic nature of the load applied was considered. The influence depths of the Dynatest LWD appear to be more sensitive to the geomaterial nonlinear parameters than the Zorn LWD.

Some researchers found that the influence depth of LWD lies between 2 and 2.5 times the LWD plate based on stress criterion. Based on strain, the influence depth is between 2 and 3.5 times the plate diameter. Based on deflection, it is 3 to 4 times the diameter. These numbers are greater than is reported in the literature (Tirado et al. 2015).

3 MATERIALS AND RESILIENT MODULUS TESTING

For the purpose of developing correlations between subgrade resilient modulus and soil index properties, this study analyzed laboratory test data from an earlier GDOT-sponsored research project (Kim, 2013). The soils tested from that study were recovered from nine borrow pits located across the state of Georgia. Table 3.1 displays that all nine soils were classified as sands (SC, SM, or SP).

The physical properties were determined from AASHTO T 89 (*Standard Method of Test for Determining the Liquid Limit of Soils*), and AASHTO T 90 (*Standard Method of Test for Determining the Plastic Limit and Plasticity Index of Soils*). The standard proctor test was conducted in accordance with AASHTO T 99: *Standard Method of Test for Moisture-Density Relations of Soils Using a 2.5-kg (5.5-lb) Rammer and a 305-mm (12-in.) Drop* to obtain optimum moisture content and maximum dry density. The soils were also classified according to the GDOT Soil Classification System (*Section 810 of Georgia Standard Specifications, 2013 Edition*), Unified Soil Classification System (*ASTM D-2487: Standard Practice for Classification of Soils for Engineering Purposes*), and AASHTO Soil Classification System (AASHTO M 145: *Standard Specification for Classification of Soils and Soil-Aggregate Mixtures for Highway Construction Purposes*).

TABLE 3.1

Subgrade Sources and Properties (Kim, 2013)

Subgrade No.	Location (County)	Percent Passing (%)				% Clay	% Volume Change	Max. Dry Density (pcf)	Opt. Moisture Content (%)	LL (%)	PI (%)	GA Soil Class	USCS Soil Class	AASHTO Soil Class
		#10 (2 mm)	#40 (0.42 mm)	#60 (0.25 mm)	#200 (0.08 mm)									
1	Lincoln	99.3	96.8	93.8	48.9	40.7	24.5	93.4 (1496.1 kg/m^3)	23.5	39.9	8.6	IIB4	SC	A-4
2	Washington	99.8	84.6	56.1	23.8	20.6	4.7	117.8 (1887.0 kg/m^3)	11.0	23.0	6.6	IIB2	SM	A-2-4
3	Coweta	89.5	64.6	48.9	28.3	24.0	12.2	105.3 (1686.7 kg/m^3)	16.7	42.5	11.0	IIB3	SC	A-2-7
4	Walton	89.4	61.5	50.5	36.3	28.3	4.0	104.8 (1678.7 kg/m^3)	16.8	40.5	12.7	IIB4	SC	A-7-6
5	Chatham	99.9	97.4	93.5	3.6	1.8	0.0	97.4 (1560.2 kg/m^3)	12.7	0.0	0.0	IIB4	SM	A-2-4
6	Lowndes	99.0	74.9	52.9	12.2	4.5	0.0	113.1 (1811.7 kg/m^3)	4.7	0.0	0.0	IA2	SP	A-2-4
7	Franklin	97.3	89.4	70.9	31.1	19.6	5.2	105.1 (1683.5 kg/m^3)	22.6	39.3	9.8	IIB3	SC	A-2-4
8	Cook	79.9	66.4	46.6	25.0	18.4	0.6	113.1 (1811.7 kg/m^3)	9.9	0.0	0.0	IIB2	SM	A-2-4
9	Toombs	84.2	37.8	17.6	6.2	4.6	1.1	119.3 (1911.0 kg/m^3)	11.9	0.0	0.0	IA1	SP	A-1-b

Figure 3.1 presents the particle size distributions for each of the nine subgrade soils tested by Kim (2013). AASHTO T 307-99 (Standard Method of Test for Determining the Resilient Modulus of Soils and Aggregate Materials) was followed to determine the laboratory resilient modulus of the soils. Three replicates for each of the nine subgrade soils were prepared for a total of 27 test specimens. The cylindrical test specimens were fabricated to be 100 mm (3.94 inches) in diameter by 200 mm (7.87 inches) high and were compacted using impact methods. To remove the effects of initial permanent deformation, the specimens were conditioned at a deviator stress of 4 psi (27.6 kPa) and confining pressure of 6 psi (41.4 kPa) for 500 load repetitions. Next, 100 load repetitions were applied to the specimens for a loading sequence that ranged from 2 to 6 psi (13.8 to 41.4 kPa) for the confining stress and from 2 to 10 psi (13.8 to 68.8 kPa) for the deviator stress. The mean deviator stress and mean recovered strain were then used to calculate the mean resilient modulus at each stress state. The results are presented in Table 3.2.

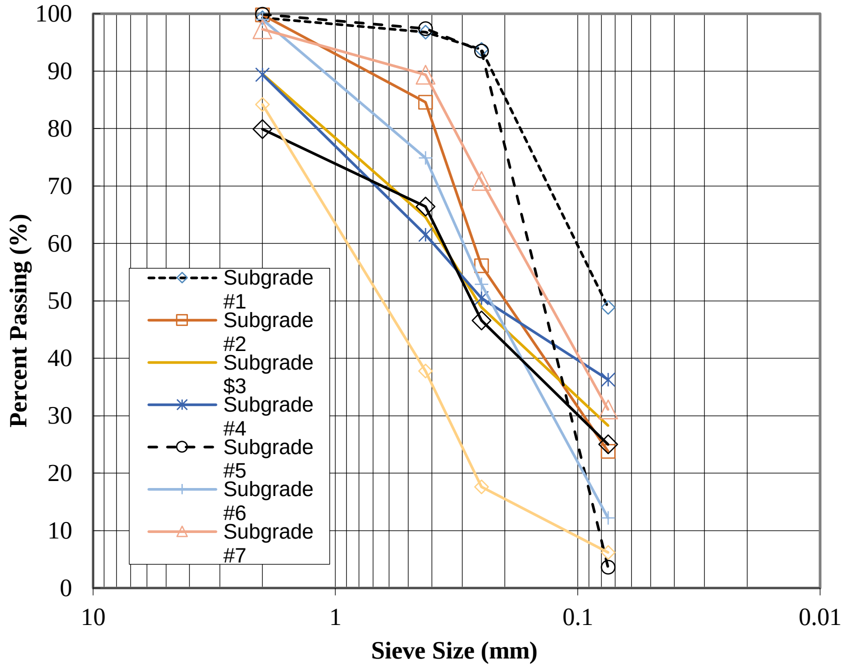


FIGURE 3.1

Subgrade Gradations (Kim, 2013)

TABLE 3.2
Measured Subgrade Resilient Moduli (Kim, 2013)

Subgrade No.	Source Location	GA Soil Class	USCS Class	AASHTO Soil Class	Statistics	*k*-values		
						k1	k2	k3
1	Lincoln	IIB4	SC	A-4	Maximum	634	0.327	-1.884
					Minimum	559	0.026	-3.350
					Average	618	0.164	-2.831
2	Washington	IIB2	SM	A-2-4	Maximum	1209	0.542	-0.123
					Minimum	1079	0.182	-1.061
					Average	1156	0.330	-0.508
3	Coweta	IIB3	SC	A-2-7	Maximum	681	0.306	-1.724
					Minimum	578	0.231	-2.048
					Average	619	0.257	-1.836
4	Walton	IIB4	SC	A-7-6	Maximum	1217	0.352	-2.278
					Minimum	906	0.196	-2.906
					Average	1031	0.285	-2.679
5	Chatham	IIB4	SM	A-2-4	Maximum	1241	0.352	-2.852
					Minimum	1241	0.352	-2.852
					Average	1241	0.352	-2.852
6	Lowndes	IA2	SP	A-2-4	Maximum	1298	0.535	-0.148
					Minimum	1288	0.509	-0.438
					Average	1293	0.522	-0.293
7	Franklin	IIB3	SC	A-2-4	Maximum	495	0.419	-2.773
					Minimum	357	0.341	-3.407
					Average	426	0.380	-3.090
8	Cook	IIB2	SM	A-2-4	Maximum	1153	0.255	-0.369
					Minimum	1153	0.255	-0.369
					Average	1153	0.255	-0.369
9	Toombs	IA2	SP	A-1-b	Maximum	1468	0.316	-2.476
					Minimum	1285	0.240	-2.521
					Average	1386	0.277	-2.499

4 STATISTICAL ANALYSIS OF RESILIENT MODULUS TESTING

One of the objectives of this study is to determine if a linear relationship exists between the subgrade resilient modulus and one or more soil properties, which can be used in the MEPDG. Such a linear relationship will be useful for pavement designers who need to estimate a design resilient modulus when no resilient modulus test data are available. As shown earlier in Table 3.1, the nine soils Kim (2013) used in his study were sandy materials. Therefore, the correlation developed in this study will only be valid for sandy materials.

4.1 List of Potential Resilient Modulus Predictors

Apart from resilient modulus testing, the laboratory test results for most of the following soil properties are routinely collected by GDOT to classify the soils according to Section 810 of the GDOT Standard Specifications. Therefore, these properties were available for consideration as predictor variables in the modeling of the response variable (resilient modulus, M_R). GDOT does not typically run Atterberg limits (liquid limit, LL, and plasticity index, PI) for soils with clay contents less than 25%. Therefore, Atterberg limits were eliminated from consideration, as zero values for some soils are likely assumed values.

(1) *P10*: Percentage of sample material (by weight) passing through the No. 10 (2 mm) sieve.

(2) *P60*: Percentage of sample material (by weight) passing through the No. 60 (0.25 mm) sieve.

(3) *P200*: Percentage of sample material (by weight) passing through the No. 200 (0.08 mm) sieve.

(4) *Clay*: Percentage of clay (by weight) of the soil sample.

(5) *VC*: Percentage of volume change of the soil sample as the material passes from a dry to soaked state.

(6) *SW*: Percentage of swell of a soil

(7) *SH*: Percentage of shrinkage of a soil

(8) *MDD*: Maximum dry density (lb/ft^3) is the dry density of the soil sample at the peak of its parabolic relationship with moisture content.

(9) *OMC*: Optimum moisture content is the moisture percentage (by weight) of the soil sample at its MDD.

(10) *LL*: Liquid limit

(11) *PI*: Plasticity index

(12) *s1*: Principal vertical stress (lb/in^2) at which testing was conducted.

(13) *s3*: Confining pressure (lb/in^2) at which testing was conducted.

(14) *theta*: Bulk stress (lb/in^2) is calculated as follows:

$$theta = s1 + 2(s3)$$

(15) τ_{oct}: Octahedral shear stress (lb/in^2) is calculated as follows for axisymmetric stress conditions:

$$\tau_{oct} = \frac{1}{3}\sqrt{(s1 - s3)^2 + (s3 - s1)^2}$$

(16) *dev*: Deviator stress (lb/in^2) is calculated as follows:

$$dev = s_1 - s_3$$

(17) M_R: Resilient modulus (lb/in^2) of the soil sample.

4.2 Overview of the Data

The average subgrade resilient modulus for the 270 tests Kim (2013) conducted was 11,400 psi (78.6 MPa) (Table 4.1). About 68% of the data is in the range between 5895 and 16,906 psi (40.6 to 116.6 MPa). The median of the M_R data is 10,460 psi (72.1 MPa) (Table 4.2).

Figure 4.1 shows that the resilient modulus decreases as the optimum moisture content increases. In Figure 4.2, the resilient modulus generally increases with increasing confining pressure (s3).

TABLE 4.1
Summary Statistics of M_R

Mean	11,400
Std Dev	5,506
Std Err Mean	335
Upper 95% Mean	12,060
Lower 95% Mean	10,741
N	270
Maximum	25,887
Median	10,460
Mode	18,647
Range	22,713
Interquartile Range	9,373

TABLE 4.2
Quartiles for M_R

100.0%	maximum	25,887
75.0%	quartile	16,068
50.0%	median	10,460
25.0%	quartile	6,694
0.0%	minimum	3,174

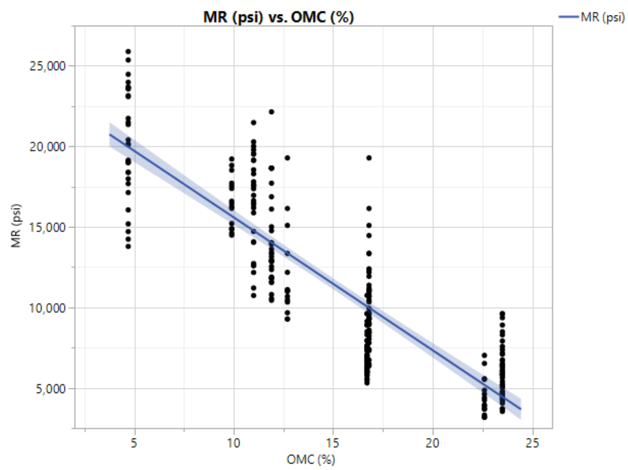


FIGURE 4.1

Resilient Modulus versus Optimum Moisture Content

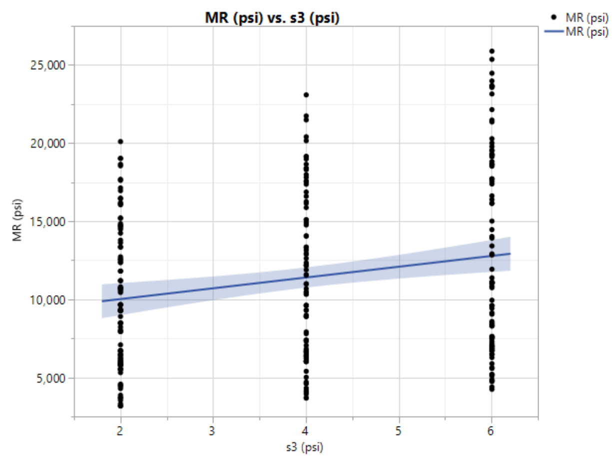


FIGURE 4.2

Resilient Modulus versus Confining Pressure

4.3 Linear Regression Analysis Methodology

This linear regression analysis began with an examination of the correlations (*R*'s) between the initial list of potential predictor variables and the response variable (resilient modulus) in Table 4.3. The purpose of this step was to simplify the model fitting process by removing variables that did not individually correlate well to the subgrade resilient modulus.

Therefore, variables with the weakest R's, approximately −0.2 to 0.2, were removed from consideration during this initial screening process.

TABLE 4.3
Correlations Between Predictor Variables and Resilient Modulus (M_R)

Predictor Variables	M_R	Predictor Variables	M_R
*P10**	−0.019	*MDD*	0.679
P60	−0.403	*OMC*	−0.858
P200	−0.617	*s1**	−0.021
Clay	−0.632	*s3**	0.205
VC	−0.652	*theta**	0.107
SW	−0.616	*toct**	−0.143
SH	−0.648	*dev**	−0.143

*Removed as useful predictors of M_R during the initial screening.

Next, each pair of predictor variables in Table 4.4 was examined to remove variables that could cause multicollinearity in the final model. If a pair of variables exhibited a high level of correlation ($R \geq 0.8$ or $R \leq -0.8$), the variable with the lower correlation to resilient modulus was removed from further consideration. For instance, there is a strong, positive, linear relationship between *VC* and *SW* ($R = 0.98$). *P60*, *P200*, *SH*, and *Clay* were also removed following a similar process, which left *VC*, *MDD*, and *OMC* as the final list of potential predictor variables for consideration.

TABLE 4.4
Correlations (R) Among the List of Potential Predictors After Initial Screening

	P60	P200	Clay	VC	SW	SH	MDD	OMC
P60	**1.00**	0.56	0.53	0.63	0.67	0.47	-0.83	0.55
P200	0.56	**1.00**	0.99	0.80	0.71	0.85	-0.70	0.81
Clay	0.53	0.99	**1.00**	0.84	0.76	0.82	-0.68	0.82
VC	0.63	0.80	0.84	**1.00**	0.98	0.71	-0.74	0.79
SW	0.67	0.71	0.76	0.98	**1.00**	0.59	-0.74	0.73
SH	0.47	0.85	0.82	0.71	0.59	**1.00**	-0.72	0.85
MDD	-0.83	-0.70	-0.68	-0.74	-0.74	-0.72	**1.00**	-0.77
OMC	0.55	0.81	0.82	0.79	0.73	0.85	-0.77	**1.00**

Note: $|R| \geq 0.80$ between predictor variables indicate a high level of correlation.

A manual step-by-step process was then followed to remove variables from the overall model based on two criteria: (1) *p-values* greater than an *α-level* of 0.05, which would indicate an insignificant parameter estimate for the variable; and (2) parameter estimates with a variance inflation factor (VIF) greater than 5, which would indicate issues with multicollinearity.

These variables were removed during the model fitting process in the following order: (a) MDD (*p-value = 0.1414*) and (b) VC (*p-value = 0.1355*), leaving OMC as the final predictor variable.

4.4 Statistical Conclusions

The null hypothesis that the grand mean (M_R = 11,400 psi or 78.6 MPa) from Table 4.5 can be used to model subgrade soils can be rejected because the final model is significant (*p-value* <0.0001 in Table 4.6) is lower than the *α-level* of significance (0.05). Eq. (4.1) with an R^2 of 0.7369 (Table 4.5) can be used to predict the resilient modulus of coarse-grained subgrade materials.

$$M_R = 23{,}850.435 - 825.7241(OMC) \tag{4.1}$$

Where,

OMC = Optimum moisture content percentage by weight

M_R = Subgrade resilient modulus (lb/in^2)

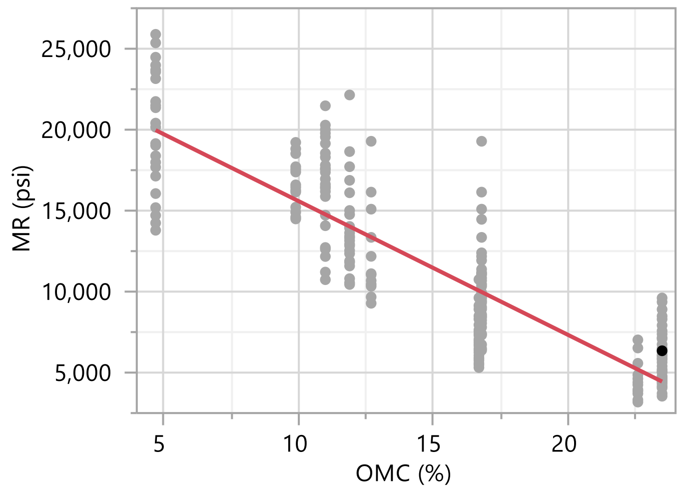


FIGURE 4.3

Resilient Modulus (M_R) by Optimum Moisture Content

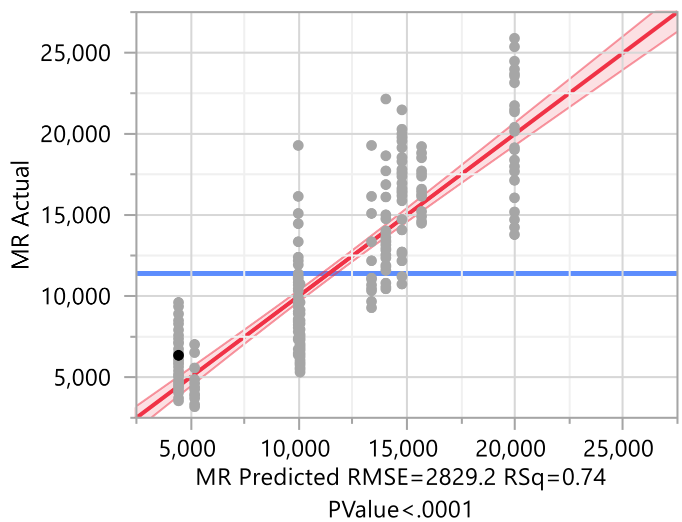


FIGURE 4.4

Actual M_R versus Predicted M_R

TABLE 4.5

Summary of Fit

RSquare	0.736913
RSquare Adj	0.735931
Root Mean Square Error	2,829.15
Mean of Response	11400.35
Observations (or Sum Wgts)	270

TABLE 4.6

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	6008450924	6.0085e+9	750.6726
Error	268	2145096145	8004090.1	**Prob > F**
C. Total	269	8153547069		<.0001*

TABLE 4.7

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	23850.435	485.9346	49.08	<.0001*	.
OMC	-825.7241	30.13767	-27.40	<.0001*	1

5 PREDICTING RESILIENT MODULUS OF SUBGRADE WITH MACHINE LEARNING USING RANDOM FORESTS

Many state agencies plan to adopt the Mechanistic–Empirical Pavement Design Guide. However, there is a large gap between the current pavement design practices and MEPDG implementation. MEPDG uses resilient modulus, M_R, to reflect the behavior of soil under traffic loading due to its cyclic loading test procedure (AASHTO T 307: *Standard Method of Test for Determining the Resilient Modulus of Soils and Aggregate Materials*). Provided the complexity of the M_R test, few agencies plan to conduct it on a regular basis. Instead, many state agencies start developing correlations between M_R and other routinely measured soil properties or back-calculated in situ test measurements. As described in Chapter 4, M_R can be conveniently estimated based on the correlations, resulting in the least disruption to the state's current pavement design procedures while moving toward the adoption of the MEPDG. In Chapter 5, a versatile machine learning framework, random forest, was applied to correlate M_R with soil characteristic metrics obtained from routinely conducted tests. The results demonstrate the superiority of the random forest model to the conventional multiple linear regression model in terms of accuracy and robustness.

5.1 Introduction

The goal in selecting a design resilient modulus during the pavement design phase is to characterize the subgrade soil according to its physical properties and its behavior within the pavement structure. Therefore, laboratory testing of the soil at the density, moisture content, and stresses that it will experience during the lifespan of a pavement is recommended. When subjected to dynamic loading (e.g., traffic), subgrade soil typically exhibits both resilient and plastic behavior, whereas the latter will result in settlement and cracking of the pavement. To be able to reliably predict M_R, it is important to understand the key factors that govern the behavior of subgrade. In general, a higher confining stress will increase the resilient modulus of the soil, and a lower stress will decrease the resilient modulus. A higher deviator stress will result in a lower resilient modulus.

5.2 Laboratory Test and Data Set

The laboratory test data from GDOT RP 12-07 project (Kim, 2013) was utilized to establish correlation between M_R and a number of influential variables. The soils tested in GDOT RP 12-07 project were recovered from nine borrow pits located across the state of Georgia. Those soils were selected by GDOT as being representative of materials used in subgrade construction. As seen in Table 3.1, all nine soils are classified as sands (SC, SM, or SP).

The physical properties were determined based on AASHTO T 89 (Standard Method of Test for Determining the Liquid Limit of Soils) and AASHTO T 90 (Standard Method of Test for Determining the Plastic Limit and Plasticity Index of Soils). The standard proctor test was conducted in accordance with AASHTO T 99: *Standard Method of Test for Moisture-Density Relations of Soils Using a 2.5-kg (5.5-lb) Rammer and a 305-mm (12-in.) Drop* to obtain optimum moisture content and maximum dry density. The soils were also classified according to the GDOT Soil Classification System (*Section 810 of Georgia Standard Specifications, 2013 Edition*), Unified Soil Classification System (*ASTM D-2487: Standard Practice for Classification of Soils for Engineering Purposes*), and AASHTO Soil Classification System (AASHTO M 145: *Standard Specification for Classification of Soils and Soil-Aggregate Mixtures for Highway Construction Purposes*)..

AASHTO T 307-99 was followed to determine the laboratory resilient modulus of the soil samples. It uses repeated load testing equipment designed to simulate traffic wheel loading at a dynamic cyclic load rate of 0.1 second for every rest period of 0.9 second. The testing sequence included applying a range of deviator stresses for a set of confining pressures. For each confining pressure, the resilient modulus was determined by averaging the resilient deformation for the last five deviator stress cycles. Based on the averages using this method, a design resilient modulus was determined to represent the expected subgrade condition in the constructed pavement structure.

Three replicates for each of the nine subgrade soils were prepared for a total of 27 test specimens. The cylindrical test specimens were fabricated to be 4-inch (102 mm) in diameter by 8-inch (203 mm) high and were compacted using impact methods. To remove the effects of initial permanent deformation, the specimens were conditioned at a deviator stress of 4 psi (27.6 kPa) and confining pressure of 6 psi (41.4 kPa) for 500 load repetitions. Next, 100 load repetitions were applied to the specimens for a loading sequence that ranged from 2 to 6 psi (13.8 to 41.3 KPa) for the confining stress and from 2 to 10 psi (13.8 to 68.9 KPa) for the deviator stress. The mean deviator stress and mean recovered strain were then used to calculate the mean resilient modulus at each stress state.

The M_R test results and the soil properties test data routinely collected by GDOT were pooled together to form a data set for modeling purposes. The variables included in the data set are presented in Table 5.1.

TABLE 5.1

Summary of Variables

Variable	Description	Unit	Min	Max	Mean
P10	Percentage of sample material (by weight) passing through the No. 10 sieve.	%	79.9	99.9	93.2
P60	Percentage of sample material (by weight) passing through the No. 60 sieve.	%	17.6	93.8	58
P200	Percentage of sample material (by weight) passing through the No. 200 sieve.	%	3.6	48.9	26.9
Clay	Percentage of clay (by weight) of the soil sample.	%	1.8	40.7	21.0
VC	Percentage of volume change of the soil sample as the material passes from a dry to soaked state.	%	0.0	24.5	7.8
SW	Percentage of swell of a soil	%	0.0	20.5	6.4
SH	Percentage of shrinkage of a soil	%	0.0	4.0	1.6
MDD	Maximum dry density is the dry density of the soil sample at the peak of its parabolic relationship with moisture content.	lb/ft^3	93.4	119.3	107.0
OMC	Optimum moisture content is the moisture percentage (by weight) of the soil sample at its MDD.	%	4.7	23.5	15.1
LL	Liquid limit	%	0.0	42.5	25.2
PI	Plasticity index	%	0.0	12.7	6.7
theta	$theta = S1 + 2(S3)$	lb/in^2	55.2	193.1	124.2
T_{oct}	$Toct = \frac{1}{3}\sqrt{(S1 - S3)^2 + (S3 - S1)^2}$	lb/in^2	6.5	32.5	19.5
M_R	Resilient modulus of soil samples	lb/in^2	21885.2	178484.8	78602.5

5.3 Random Forest Models

Random forest is an ensemble machine learning method, typically used for classification or regression. A random forest is often consdiered as a “meta” estimator that fits a number of classification or regression trees on various subsamples of a dataset and then uses averaging to improve the predictive accuracy and robustness. To minimize correlation among the trees, two techniques are commonly used: (1) bootstrap for resampling, and (2) randomization of split variables. A benefit of the bootstrap resampling is to have an out-of-bag sample to approximate test error. All trees in the forest are constructed independently using a bootstrap sample of the data. By averaging the predictions from those trees in the forest, the risk of overfitting is reduced (Hastie et al., 2008).

To construct a random forest model, a number of hyperparameters need to be carefully selected. This process is referred to as hyperparameters tuning. The typical hyperparameters include: the number of trees in the random forest model, the number of variables to randomly sample at each split, the number of samples for training, minimum number of samples within the terminal nodes, and maximum number of terminal nodes. The H2O package (LeDell et al., 2019) was used to choose hyperparameters. The resulting random forest model is summarized in Table 5.2. The estimated random forest model contains 350 trees and the resampling rate is 70%. The number of variables to randomly sample at each split is 5.

TABLE 5.2
Summary of Random Forest Model

Random Forest Model	
Mtries[1]	5
Sample Rate[2]	0.7
Number of Trees	350
Min Depth	8
Max Depth	13
Mean	10.8
Min Leaves	45
Max Leaves	112
Mean Leaves	86.3
Out-of-Bag Errors	
RMSE[3]	11704
MAE[4]	8741

[1] Mtries: the number of variables to randomly sample at each split
[2] Sample Rate: the percent of sample for training
[3] RMSE: root mean square error
[4] MAE: mean absolute error

The variables are sorted by their importances, which are measured by accumulated reduction in MSE (Mean Squared Error) each time a variable is selected as a node split in a tree for the entire forest. The variable importances were sorted in decending order, as shown in Figure 5.1. The top three most important variables are OMC, P200, and MDD.

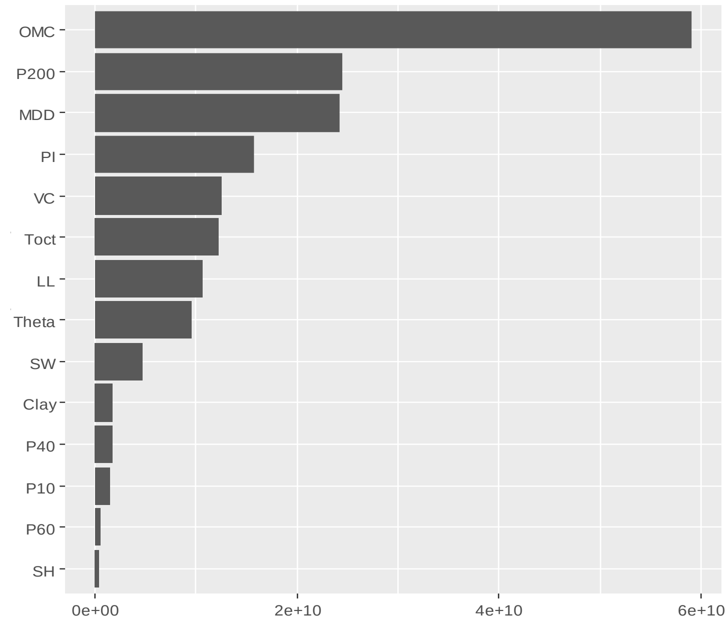


FIGURE 5.1

Importance of Variables

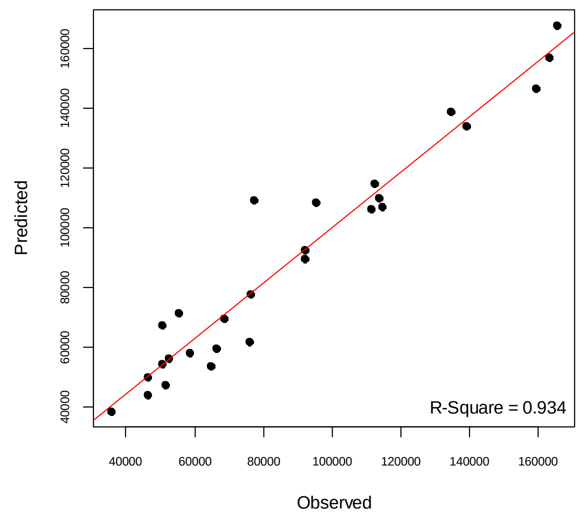
For comparison purposes, a multiple linear regression (MLR) model was also estimated using the same training data set. The model estimation results are shown in Table 5.3. The backward elimination method was used for the selection of variables based on their signficance and overall contribution to variance reduction. Note that some variables were excluded in the MLR model due to collinearity. For example, Clay has nearly perfect correlation with P200, and the same is true for LI and PI. As a result, only P200 and PI were retained in the model specification.

TABLE 5.3
Multiple Linear Regression Model Estimation

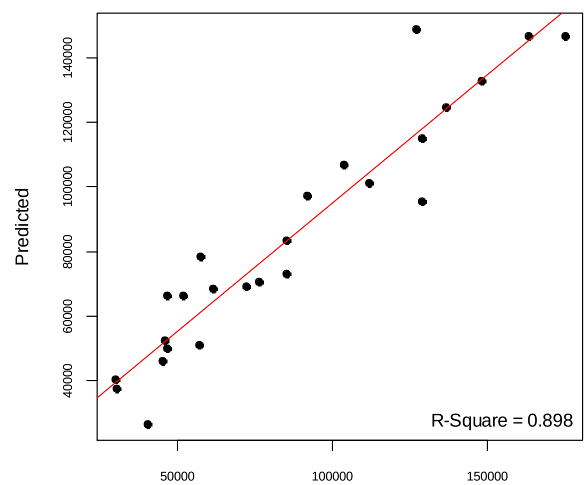
Variable	Estimate	Std. Err	t-value	p-value	Sig.
(Intercept)	62278.81	23077.57	2.699	0.00746	**
P200	1109.88	136.05	8.158	2.03E-14	***
MDD	749.11	181.71	4.123	5.19E-05	***
OMC	−5771.02	331.55	−17.406	2.00E-16	***
PI	−2094.52	309.34	−6.771	1.01E-10	***
Theta	234.68	27.88	8.418	3.72E-15	***
T_{oct}	−1112.98	118.22	−9.414	2.00E-16	***
	R square = 0.8519				
	Residual Std. Err. = 14730				
	F statistic = 226.3 (p-value < 2.2e−16)				

Significance: *** < 0.001; ** < 0.001; * < 0.05

To evaluate the random forest (RF) and MLR models, an independent data set was utilized. By applying both models to this data set, the predicted M_R were plotted against the observed M_R in Figure 5.2. The predictions of the RF model fit the observations better (R^2 = 0.934) than the MLR model (R^2 = 0.898).



a) RF model



b) MLR Model

FIGURE 5.2

Predicted M_R versus Observed M_R

5.4 Summary of Machine Learning Approach

M_R is a critical input parameter for MEPDG. However, the M_R test is complex and time-consuming. Instead of conducting M_R tests on a regular basis, many state agencies start developing correlations between M_R and other routinely measured soil properties or back-calculated in situ test measurements. In this chapter, the researchers propose a generic machine learning method, random forests, to correlate M_R with soil properties test data routinely collected by state agencies. As a case study, the test data from GDOT was used for model estimation. To demonstrate the superiority of the random forest model, a conventional multiple linear regression model was also developed using the same training data set. An independent data set was used for model evaluation, and the predictions from both models were compared. It showed that the random forest model outperforms the multiple linear regression model in terms of accuracy and robustness. Random forest is a flexible modeling framework, which does not require the strict assumptions imposed by the classic regression models, such as error normality and homogeneity. The ensemble nature of random forest helps to improve accuracy and reduce variance, as well. By controlling the risk of overfitting through bootstrap for resampling and randomization of split variables, random forest provides an effective approach to data-driven modeling.

6 EXAMPLE OF PERFORMANCE-BASED SPECIFICATION

6.1 Indiana Department of Transportation

The Indiana Department of Transportation adopted MEPDG in January 2009. Section 207: *Subgrade* of INDOT's current Standard Specifications (2018) provides detailed guidance to the department's engineers and contractors to construct a subgrade with properties that are more representative of the MEPDG methodology. The following series of Indiana test methods (ITMs) and manual provide additional detailed guidance to the QA/QC aspects of construction:

(a) ITM 506-16T: Field Determination of Moisture Content of Soils

(b) ITM 508-18: Field Determination of Deflection Using Light Weight Deflectometer

(c) ITM 509-18: Field Determination of Strength Using Dynamic Cone Penetrometer

(d) ITM 512-16T: Field Determination of Maximum Dry Density and Optimum Moisture Content of Soil

(e) ITM 513-17T: Determination of Soil Target Values

(f) ITM 802-18: Random Sampling

(g) Manual for Frequency of Sampling and Testing and Basis of Use of Materials (Revised January 2019)

6.2 Overview of Subgrade and Embankment Construction

A thorough and complete discussion of the subgrade and embankment construction processes by INDOT is outside the scope of this study because of the variety and complexity of scenarios that can occur in the field that are addressed in INDOT's Standard Specifications. Therefore, only a general discussion of the most basic subgrade construction scenario that will aid the understanding of the pavement designer will be provided. A brief discussion about embankment construction is included as this type of construction has many elements in common with subgrade construction.

For this overview, the focus will be on construction with clayey, silty, and sandy materials meeting the requirements of Section 203: *Excavation and Embankment* and Section 207: *Subgrade*. Whereas GDOT identifies suitable and unsuitable embankment materials using its soil classification system and GDOT Section 208: *Embankments*, INDOT identifies suitable and unsuitable materials by description with similar considerations in its specifications. For subgrade soils, INDOT identifies unacceptable soils by organic content, maximum dry density, liquid limit, and soluble sulfate content under INDOT Section 207.

INDOT requires a minimum compaction of 95% for embankments and 100% compaction for subgrades, which is similar to GDOT specifications. The embankment and subgrade are constructed in lifts of 6 inches (152 mm) with acceptance testing performed every 6 inches (152 mm) for clayey materials and every 12 inches (305 mm) for silty, sandy, or granular materials.

Compaction on embankment materials is determined using a dynamic core penetrometer (ITM 509). Stoves, hot plates, moisture probes, or microwaves are allowed to check moisture contents (ITM 506) depending on the soil type. These data with the textural soil classification (ITM 512) can be used to select target DCP values from Table 6.1 (Section 203.23) for compaction control. Granular and modified materials used in embankments are tested for stiffness (deflection) with a light weight deflectometer per ITM 508-18. The target values for deflection are established from a test area.

Preparation of the test area is quite simple in that it should be level, so that the undersurface of the load plate is in contact with the material to be tested. If the test area is uneven, fine sand can be used to level it out. The test area should be 1.5 times larger than the LWD plate diameter. Three seating drops are conducted, which are followed by three test drops. The operator is required to catch the drop, so it does not rebound against the plate. If the plate rebounds, then the test is invalid and the LWD is to be moved at least 2 feet (610 mm) from the invalid test location. The average deflection must equal to less than the maximums allowed in Table 6.2 and must not be 10% or greater for any two consecutive drops. Otherwise, the materials should be re-compacted before testing is resumed. Three LWD tests are performed for every 800 tons (725.8 Metric tons) of compacted aggregate and every 1400 yd^3 (1070 m^3) of chemically modified soil.

Compaction requirements for most subgrade materials are established from a test section. Clayey, silty, and sandy subgrade materials are not tested for stiffness. Table 6.1 (Section 203.23) may be used to select DCP targets for granular soils (structural backfill, A-1, A-2, and A-3) without the need of a test section.

TABLE 6.1

Blow Counts for Compaction Control from INDOT Section 203.23

Textural Classification	Maximum Dry Density (pcf)	Optimum Moisture Content Range (%)	Acceptable Minimum DCP Value for 6 in. and 95% Compaction	Acceptable Minimum DCP Value for 12 in. and 95% Compaction	Acceptable Minimum DCP Value for 6 or 12 in. and 100% Compaction
CLAY SOILS					
Clay	< 105 (< 1682 kg/m^3)	19 – 24	6		*
Clay	105 – 110 (1682 – 1762 kg/m^3)	16 – 18	7		*
Clay	111 – 114 (1778 – 1826 kg/m^3)	14 – 15	8		*
SILTY SOILS					
Silty	115 – 116 (1842 – 1858 kg/m^3)	13 – 14		9	*
Silty	117 – 120 (1874 – 1922 kg/m^3)			11	*
SANDY SOILS					
Sandy	121 – 125 (1938 – 2002 kg/m^3)	8 – 12		12	*
Sandy	> 125 (> 2002 kg/m^3)			15	*
GRANULAR SOILS – STRUCTURAL BACKFILL and A-1, A-2, A-3 SOILS					
No. 30				6	9
No. 4				7	10
½ inch				11	14
1 inch				16	19
Note: * Test section required in accordance with ITM 513.					

TABLE 6.2

Maximum Allowable Deflections for Embankment Materials

Material Type	Maximum Allowable Deflection (mm)
Lime Modified Soil	0.30 (0.012 inch)
Cement Modified Soil	0.27 (0.011 inch)
Aggregate over Lime Modified Soil	0.30 (0.012 inch)
Aggregate over Cement Modified Soil	0.27 (0.011 inch)

6.3 Test Sections for Subgrade Construction

Test section construction is covered in ITM 513-17T: *Determination of Soil Target Values*. From this ITM, the procedures listed below are covered. Although the use of intelligent compaction (IC) is available, it is not required for construction; therefore, this topic will not be discussed. Only Items (c) and (d) will be discussed.

(a) Determination of target intelligent compaction measurement values (IC-MV) of soils

(b) Determination of the number of passes of rollers to obtain the IC-MV

(c) Determination of the number of passes for verification of the DCP requirements for QA/QC

(d) Determination of the number of blow counts for 100% compaction.

A test section area of 225 feet (68.6 m) long by 24 feet (7.3 m) wide is required. The test method prescribes a test section for a construction area of 10,000 ft^2 to 75,000 ft^2 (929.0 m^2 to 6967.7 m^2) to determine a target IC-MV. However, for Items (c) and (d), which do not require IC rollers, an explicitly prescribed construction area is not given.

To begin preparing the test section, the natural ground is proof-rolled with a roller that will be used in construction. DCP and moisture requirements are verified until the final grade of the test section is achieved. An initial four applications of a compaction roller are made on top of the test section. Then, 10 random and uniformly spaced DCP tests are conducted until the 95% compaction requirement of Section 203.23 is met.

To determine the target for 100% compaction, the subgrade is tested for maximum dry density and optimum moisture content (ITM 512). Additional rolling is performed, which is followed by sand cone testing (AASHTO T 191: *Standard Method of Test for*

Density of Soil In-Place by the Sand-Cone Method). The average of these density values are required to fall within tolerance and precision stated in AASHTO T 191. Once the AASHTO requirement is met, the average density is compared to the maximum dry density (ITM 512) to determine if the 100% compaction level is achieved. If so, the test section is completed. The acceptable minimum DCP value is the average of the 10 DCP tests or 2 DCP values more than the minimum required for 95% compaction. If that value is not achieved, then the test section is reworked until the desired compaction is achieved.

6.4 Subgrade Construction

Subgrade construction is covered under Section 207: *Subgrade* of the Indiana Department of Transportation's Standard Specifications. INDOT uses a textural soil classification for the field classification of clayey, silty, or sandy soils based on the maximum dry density using the charts in the appendix of ITM 512-16T. The soil's moisture content is determined using ITM 506-16T. During the performance of IMT 512-16T, the moisture content is checked to verify that it lies within −3% to +1% of the optimum moisture content from the charts. Table 6.3 (Section 203.23) also establishes moisture compaction ranges for all soil types. If the moisture content lies outside that range, moisture is added or the soil sample is dried to bring it within range. Then the adjusted maximum dry density and adjusted optimum moisture content is determined from charts.

In accordance with Section 203.23, the compaction of the subgrade is checked with DCP using ITM 509-18 at every completed lift of 6 or 12 inches (152 or 305 mm), which is based on the textural soil classification, until subgrade construction is complete. Even if the subgrade has been accepted, it is retested at the time of paving for final compliance with the specifications. In addition, proof-rolling the subgrade is required before placing the base material.

TABLE 6.3
Moisture Compaction Range for All Soil Types

Soil Type	Moisture Compaction Range
Clay (<105 lb/cu ft or <1682 kg/m^3)	−2 to +2% of optimum moisture content
Clay (105 to 114 lb/cu ft or 1682 to 1826 kg/m^3)	−2 to +1% of optimum moisture content
Silty and Sandy (>114 lb/cu ft or > 1826 kg/m^3)	−3 to +1% of optimum moisture content
Granular	5 to 8%

6.5 INDOT Research Efforts

INDOT has sponsored many research projects in its progression toward adoption of the MEPDG and performance-based specifications. Copies of the completed reports are available on the Joint Transportation Research Program website of Purdue University. A selection of these studies with brief and relevant findings, regarding the MEPDG and performance-based specification implementation, is discussed below:

(a) An investigation into the adoption of intelligent compaction was conducted to provide INDOT with recommendations for action. The researchers concluded that at the time of the study it was too early for adoption of IC. However, adoption of IC was determined to be likely in the future (Zambrano et al., 2006).

(b) A total of four sites in Indiana were selected to conduct FWD, LWD, and DCP tests in addition to laboratory resilient modulus testing. The study found that LWD and DCP testing can be used to assess the quality and uniformity of the subgrade but do not provide reliable estimates of the subgrade stiffness (Park et al., 2018).

(c) For clayey sands classified according to the Unified Soil Classification System, a prediction equation was developed for dry density using the penetration index (PI) from DCP testing. Predictions using the DCP testing are not reliable and require use with more conventional test methods for compaction control (Salgado & Yoon, 2003).

(d) This study aimed to refine the DCP-based quality assurance and quality control correlations that were developed in earlier studies. The foci of the study were on: (a) grouping soils according to their mechanical response to the DCP impact loading, and (b) limiting the moisture range of in situ soils used for the development of correlations to −2% of the optimum moisture content. Soils were grouped into coarse-grained or fine-grained categories. For fine-grained soils, DCP test results had good correlations with the PI. Coarse-grained soils had good correlations with the optimum moisture content (Ganju et al., 2015).

(e) A follow-up to an earlier study on Intelligent Compaction, this study recommended additional work to pursue the incorporation of IC mapping for the QA/QC of embankment construction. It seems that, at a minimum, IC could be used to reduce the number of DCP tests required for QA/QC. The long-term goal for pursuing IC is for the implementation of specifications and test methods, which can alleviate some of the need for DCP testing while assuring the construction of quality embankments (Dunston et al., 2018).

(f) In INDOT study, four accelerated pavement test (APT) sections were constructed to study permanent deformation in asphaltic concrete pavements. The researchers found that permanent deformation within the asphalt layers does not increase once an adequately thick structure has been constructed. They learned that most rutting occurred in the asphaltic concrete layers. Half of this deformation occurred within the top 4 inches (102 mm) of the pavement, and about 10% occurred in the subgrade. From these findings, guidelines were developed to calibrate the MEPDG prediction models using data from APT and field sections (Nantung et al., 2018).

(g) This study found that from laboratory resilient modulus test results it may be possible to simplify the complex procedures of AASHTO T307. The simplified procedure compared favorably with the existing M_R testing procedure (Kim & Siddiki, 2006).

7 LABORATORY LWD TESTING

7.1 Background

Modern construction of roads and pavements involves the use and compaction of unbound geomaterials under unsaturated conditions. Conventional QA and QC practices utilize nuclear density gauges (NDGs) in a density-based method. Recent developments in modulus-based compaction QA/QC, coupled with the drawbacks of NDG use, has resulted in the increased use of the LWD in compaction QA/QC. The primary impediment for universal implementation of the modulus-based QA/QC is attributed to the absence of a general standard for interpreting the recorded stiffness data.

However, Schwartz et al. (2017) outline their findings in a draft test method for LWD testing in the field and laboratory LWD target modulus verification. In the study, three different LWDs (Zorn ZGF 3000, Dynatest 3031, and Olson's LWD-1) were used to represent the variety of common LWD models used in the field with the understanding that different LWDs measure soil deflection and modulus values differently. In addition, the study evaluates and compares the use of two different moisture content measuring devices (i.e., Ohaus MB45 moisture analyzer and Decagon GS-1 volumetric water content sensor) to traditional means of measuring water content due to the effect of moisture on the measured modulus of compacted geomaterials. Their findings establish the framework with which state DOTs are able to develop cost-efficient modulus-based QA/QC specifications that eliminate the negative consequences associated with the current use of NDG in compaction QA/QC.

7.2 M_R Predictive Models and Failure

The use of LWDs in modulus-based QA/QC is dependent on the ability to determine a target modulus. This process is further complicated by the unpredictability of the soil modulus at varying stress conditions and ranging moisture contents. Resilient modulus tests were performed in accordance with AASHTO T 307: *Standard Method of Test for Determining the Resilient Modulus of Soils and Aggregate Materials* on the soils that were used for the test pit construction, which is discussed in the next section. Due to the impracticality of iterative M_R testing, a predictive model was used in an effort to estimate modulus values at varying soil conditions. Table 7.1, Table 7.2, and Table 7.3 display the average results of the universal constitutive model for the three different materials used in the test pits. Though the results presented below are the best of nine models, they display a level of accuracy considered insufficient to be used in estimating the field LWD target modulus. This failure resulted in the subsequent investigation of determining an LWD target modulus from using the LWD in the laboratory by testing soil samples in a proctor mold.

TABLE 7.1

ALF M_R Test Results (Schwartz et al., 2017)

Sample ID	[-]	OPT	Pit 2	~Pit 1
Achieved MC	[%]	11.9%	14.6%	9.4%
Matric Suction	[kPa]	30	20	200
Achieved DD	[pcf]	118.9	116.5	110.6
	[kg/m3]	1904.3	1867.0	1771.2
Pa	[kPa]	101.3	101.3	101.3
k1	[-]	1437.4	177.6	793.9
k2	[-]	0.429	0.485	0.601
k3	[-]	-3.717	0.000	-2.023
SSE	[MPa^2]	131.6	384.1	1635.8
Sqr(SSE)	[MPa]	11.5	19.60	40.44
R^2	[MPa^2]	98.1%	58.7%	66.2%
R^2_adj	[MPa^2]	97.6%	52.8%	61.4%
Max Sample-to-Sample COV of M_R at different stress states	[%]	32.5%	27.9%	5.0%
Average Sample-to-Sample COV of M_R at different stress states	[%]	16.2%	13.2%	1.8%

TABLE 7.2

HPC[2] M_R Test Results (Schwartz et al., 2017)

Test Condition/ Material	[-]	OPT	Pit 3
Achieved MC	[%]	24.5	30.8
Matric Suction	[kPa]	180	50
Achieved DD	[pcf]	93.6	89.4
	[kg/m3]	1499.2	1432.1
Pa	[kPa]	101.3	101.3
k1	[-]	888.8	583.4
k2	[-]	0.378	0.095
k3	[-]	-0.843	-1.789
SSE	[MPa^2]	2261.6	259.0
Sqr(SSE)	[MPa]	47.56	16.09
R^2	[MPa^2]	26.8	81.0
R^2_adj	[MPa^2]	16.4	78.3
Max Sample-to-Sample COV of M_R at different stress states	[%]	6.4	18.7
Average Sample-to-Sample COV of M_R at different stress states	[%]	2.4	5.3

[2] HPC = High plasticity clay

TABLE 7.3
VA21a[3] M_R Test Results (Schwartz et al., 2017)

Sample ID	[-]	VA21a__Ave OMC
Achieved MC	[%]	3.7
Matric Suction	[kPa]	1.5
Achieved DD	[pcf]	153.4
	[kg/m3]	2458.0
Pa	[kPa]	101.3
k1	[-]	590.6
k2	[-]	0.824
k3	[-]	0.000
SSE	[MPa2]	2765.0
Sqr(SSE)	[MPa]	52.58
R2	[MPa2]	96.6
R2_adj	[MPa2]	95.7
Max Sample-to-Sample COV of MR at different stress states	[%]	47.9
Average Sample-to-Sample COV of MR at different stress states	[%]	17.6

7.3 Test Pits, LWD Testing on Proctor Molds & Results

The test pits portion of the study consisted of the construction of three 4.5 m × 4.5 m (14.8 ft x 14.8 ft) test pits, which were utilized to simulate scenarios of acceptable and failing construction quality. The materials used in the test pits include two different cohesive high-plasticity clays, a non-cohesive–locally sourced–subgrade soil, and one type of granular aggregate base. LWD tests were conducted on the final layer of each pit, and the results from said tests were used to assess the spatial variability measured by the various LWD models. Additionally, static plate load tests were performed on the test pits for the purpose of determining the static modulus during loading ($E_{S\text{-}load}$), static modulus during unloading ($E_{S\text{-}unload}$), permanent soil deformation (d_P), and resilient soil deflection (d_R). Thereafter, the ratio of $E_{S\text{-}unload}$-to-$E_{S\text{-}load}$ ($E_{S\text{-}unload}/E_{S\text{-}load}$) was calculated and graphed against the pit

[3] VA21a = a well graded aggregate base commonly used in the state of Virginia

number and test number. Higher ratios of $E_{S\text{-unload}}$-to-$E_{S\text{-load}}$ were observed in the first test in the under-compacted accelerated load facility (ALF) material in pit 1, which was subsequently followed by a lower $E_{S\text{-unload}}$-to-$E_{S\text{-load}}$ ratio, indicating that the material condensed significantly from test one to test two.

LWD testing on Proctor molds using the test pit soils was also conducted in an effort to derive target moduli at various moisture conditions. The LWD on Proctor mold test results were interpolated at the desired stress level and compaction water content in an effort to derive the appropriate target LWD modulus. After excluding the initial modulus determined from the over-saturated base material in pit 2, a strong correlation between the LWD moduli determined in the lab and in the field for pits 2 and 3 was observed with R^2 values of 1, 0.94, and 0.73 for the Dynatest, Zorn, and Olson LWDs, respectively. The results support the use of laboratory LWD testing on mold specimens as a potential way to establish the target modulus values for the field at a given water content and density condition.

7.4 Field Validation

Schwartz et al. (2017) proceeded with verifying their findings in the subsequent field validation phase. During a field validation of the results to determine the practicality and applicability of the test method for developing a set of specifications, field and laboratory LWD testing was performed on soil samples obtained from eight projects in six states. Additionally, NDG measurements were taken at each site when available. It is important to note that none of the evaluated sites contained fine-grained subgrade soils. This leaves a great opportunity for further validation of the method whereby sites with cohesive soils are assessed in addition to sites with coarser materials. Using the results from the laboratory

LWD tests, target moduli were estimated at the appropriate field water content and plate pressure and subsequently compared to measured moduli in the field by calculating the field-to-target modulus ratio (E_{field}/E_{target}). It was observed that the well-compacted material exhibited both a passing percent compaction (PC) and passing E_{field}/E_{target} criteria; however, the sites with inadequate compaction exhibited a failing PC and E_{field}/E_{target} criteria, thus legitimizing the merit and applicability of LWD on mold method for field QA/QC.

The moisture measurement devices were evaluated during the test pits and field validation phases. During the test pits phase, it was determined that the use of the Decagon sensor is impractical when soils are densely compacted or when base soils contain a large nominal maximum aggregate size (NMAS). This is attributed to the need to insert the prongs of the sensor adequately into the material, and, in the case of densely packed material or material with a large NMAS, requires the use of pre-drilled holes. Therefore, it was removed from further consideration. As a result, only the Ohaus moisture analyzer was evaluated against the NDG and the traditional oven drying method during the field evaluation phase. A strong correlation (R^2 = 0.9446) between the Ohaus moisture analyzer and the NDG results was observed following the application of a 1.11 correction factor to the Ohaus moisture analyzer; this was determined from a laboratory calibration.

7.5 Proposed Draft Test Methods

The LWD testing procedure was improved throughout the field verification phase, which leads to the development of two draft test methods: (1) for LWD testing in the field, and (2) for target modulus determination in the laboratory. The specifications are written generally so that an agency or DOT could augment them in such a way that local material and equipment conditions are accounted for. Although methods for determining the appropriate sampling frequency and acceptance criteria are provided for both the LWD laboratory testing and field LWD testing, the results should be used with a degree of caution as a large variety of materials, such as unbound aggregate sources and cohesive soils, were not included in the field validation portion of the study. The proposed test methods are provided in the Appendix.

7.6 Study Synopsis

The laboratory LWD method for estimating target moduli provides a viable alternative to the traditional density-based QA/QC methods. This comprehensive method is applicable to a large range of geomaterials, including chemically treated material. Schwartz et al. (2017) contend the method is cost efficient and does not increase field work significantly as it can be viewed as a simple add-on to the routine proctor test. It is recommended that each agency or DOT calibrate the specification by means of existing projects in conjunction with density-based methods using NDGs as performed in the study. The somewhat complex process of collecting and analyzing the LWD data necessitates the employment of qualified and trained personnel. Moreover, the primary equipment required for proposed test methods are delineated in their work and primarily consists of: (1) an LWD and its associated components, (2) a means of measuring soil moisture content, and (3) a Proctor mold. The affordability and practicality of this innovative, modulus-based QA/QC method provides an excellent alternative to traditional methods that require the use of less convenient equipment.

8 CONCLUSIONS

The following conclusions are based on this work:

(1) The results from laboratory resilient modulus testing can vary because of location of the measurement system, testing stress sequences, and compaction methods, which vary among the test methods available for use. Therefore, correlations developed by other researchers may not produce similar results.

(2) The correlation model developed in this study can be used to predict resilient modulus for coarse-grained soils, with the caution that it should be compared to available test data before a resilient modulus is selected for pavement design with the MEPDG.

$$M_R\ (psi) = 23{,}850.435 - 825.7241(\%OMC)$$

(3) The Indiana DOT has a performance-based specification for using DCPs to measure the compaction of soils and LWDs to measure the compaction of chemically modified soils and coarse aggregates. This specification can be used as a model for GDOT to follow in developing its performance-based specification.

9 RECOMMENDATIONS

We recommend the Georgia Department of Transportation consider the following steps as it proceeds toward adoption of the Mechanistic–Empirical Pavement Design Guide:

- Use the subgrade resilient predictive model presented in this study in a process to select design values for subgrades constructed of coarse-grained materials. The predictive values should be compared to available laboratory and/or field test results until a level of comfort with its use can be attained. Refinement of the model with additional research is recommended.
- Use the Indiana DOT's specifications, test methods, and research efforts as a model to create a program for developing performance-based specifications for use in Georgia. In addition, continue the investigation into how other DOT's have developed and implemented performance-based specifications.
- Develop a simple laboratory test method or adopt another simple test method that produces results that correlate well to resilient modulus values. In this study, simplification of the existing AASHTO test method can be examined by reducing the number of stress sequences, for example, to become more practical for pavement design. It can also include the correlation between resilient modulus and unconfined compressive strength test results.
- After selecting a simple test method for determining resilient modulus, conduct a study to develop a correlation between laboratory resilient modulus test results and soil index properties for fine-grained and coarse-grained soils.
- Develop a plan to grow the materials library for subgrade soils that could involve the collection of soil samples recovered during soil survey investigations conducted

by GDOT or its consultant. Reserving this sample could be on a frequency of one sample of the most predominant material per project that is greater than a minimum length to be determined. These soils should be tested for developing new correlation models and/or refining existing models.

- Develop a requirement for consultants to perform at least one laboratory resilient modulus test per project with a simple test method that is greater than a minimum length to be determined. All results from routine testing of other soil properties that are conducted by consultants should be submitted electronically to GDOT for inclusion in its material database. Such data are needed for statistical reasons in determining representative soil types and properties.
- Develop a correlation between dynamic cone penetrometer test results on in situ soils and the density of subgrade soils. In addition, develop a correlation between light weight deflectometer test results on in situ soils and other soil properties to improve the understanding of soil stiffness. The information from this work can be used in the development of performance-based specifications.

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APPENDIX A: CONVERTED RESILIENT MODULUS FOR USE WITH THE 1993 AASHTO DESIGN GUIDE

During the course of this research project, the Georgia Department of Transportation (GDOT) began to consider a progressive stepped adoption toward the Mechanistic–Empirical Pavement Design Guide (MEPDG), which meant that the 1993 AASHTO Guide for Design of Pavement Structures is being considered as the next accepted pavement design method for use on roadway projects in the state. This stepped approach would allow for all stakeholders to become more familiar with some of the new concepts that were introduced in the 1993 Guide. Reliability, standard deviation, and subgrade resilient modulus are design parameters that replaced the regional factor and soil support value of the 1972 AASHTO Design Guide. These new design parameters are also used in the MEPDG. In addition to allowing the stakeholders within Georgia to become more familiar with these concepts and their effects, this strategic move will also allow more time for growth of the materials library and a well-planned adoption of the MEPDG.

Although this research project proposes a resilient modulus correlation to the optimum moisture content for granular soils, there is no predictive model for fine-grained soils until a sufficient number of fine-grained soils can be tested with AASHTO T 307: *Standard Method for Determining the Resilient Modulus of Soils and Aggregates*. The test data from this testing could then be used to develop a predictive model for fine-grained soils for use with the MEPDG. However, until the testing and model development for fine-grained soils can be conducted, there is a gap in design values for resilient modulus.

A temporary method of providing resilient modulus designs only for use with the 1993 AASHTO Guide is available. The method will provide a resilient modulus for the

1993 Guide that results in a pavement thickness equivalent to a thickness that is determined with the 1972 Guide by equating the two design equations in a method that is described later in this appendix.

AASHTO Guide for Design of Pavement Structures, 1972

When designing a flexible pavement, the GDOT uses the 1972 AASHTO Pavement Design Guide to determine the required structural number (*SN*) based on the total design period ESALs (W_{t18}) and other design factors using Eq. (A1). The inputs for the pavement thickness design equation are as follows:

W_{t18} = Total design period ESALs

SN = Structural number

p_t = Terminal serviceability

R = Regional factor

S_i = Soil support value (based on a soaked California Bearing Ratio test, CBR)

$$\log W_{t_{18}} = 9.36 \log(SN+1) - 0.20 + \frac{\log\left[\frac{(4.2-p_t)}{(4.2-1.5)}\right]}{0.40+\frac{1094}{(SN+1)^{5.19}}} + \log\frac{1}{R} + 0.372(S_i - 3.0) \qquad \text{(A1)}$$

GDOT uses Eq. A2 to determine what is termed the proposed structural number ($SN_{proposed}$) of a structure being analyzed for inclusion in a roadway construction project. Then, GDOT adjusts the thicknesses of the individual layers (D_i) with consideration to their SuperPave Mix Guidelines until the $SN_{proposed}$ is within the target under-design percentage range of the required *SN*.

$$SN_{proposed} = \sum_{i=1}^{n} a_i D_i \qquad \text{(A2)}$$

AASHTO Guide for Design of Pavement Structures, 1993

The inputs for the 1993 AASHTO design equation (A3) are:

W_{t18} = Total design period ESALs

Z_R = Reliability

S_o = Standard deviation

SN = Structural number

p_t = Terminal serviceability

M_R = Subgrade resilient modulus (psi)

Although GDOT is not currently using the 1993 Guide, it is considering using reliability levels of 95% ($Z_R = -1.645$), 90% ($Z_R = -1.282$), and 75% ($Z_R = -0.674$) for designing the various types of roads within the state. A standard deviation of 0.40 is also under evaluation. These values were recommended in the GDOT MEPDG User Guide, which has not been approved for use in the design of pavement structures in the state. Nevertheless, these values will be used for developing a converted M_R from the S_i (soil support value) of the 1972 pavement design methodology.

The idea behind this conversion is that if GDOT approves the 1993 AASHTO Guide, it will be able to design pavements that are at least equivalent in structure to the 1972 AASHTO Guide. A converted resilient modulus can be used until GDOT can conduct enough resilient modulus testing on fine-grained soils to develop a prediction model. A converted M_R should not be used with the MEPDG.

$$\log W_{t_{18}} = Z_R S_o + 9.36\log(SN+1) - 0.20 + \frac{\log\left[\frac{(4.2-p_t)}{(4.2-1.5)}\right]}{0.40+\frac{1094}{(SN+1)^{5.19}}} + 2.32\log M_R - 8.07 \qquad \text{(A3)}$$

$$SN_{proposed} = a_1 D_1 + \sum_{i=2}^{n} a_i D_i \, m_i \tag{A4}$$

Resilient Modulus Conversion Methodology

A conversion of the soil support value (S_i) to a converted resilient modulus value (M_R) was developed by equating the total design ESALs from the 1972 AASHTO Interim Guide to the total design ESALs from the 1993 Guide as shown in Eq. (A5) and then simplifying it to Eq. (A6). It is understood that the design ESAL calculation method will not change with the adoption of the 1993 AASHTO Design Guide. Also, the calculation of the $SN_{proposed}$ will not change, as the drainage coefficients (m_i) for each subsurface layer will equal 1 in Eq. (A4), thus making the $SN_{proposed}$ calculation for the 1972 Guide and 1993 Guide the same.

The calculations using the equations in this appendix were used to prepare the maps in Figures A.1 through A.3. These maps are similar to the Soil Support Value map that GDOT currently uses with the 1972 AASHTO Design Guide. The new maps can be used to select design resilient modulus values without the need for calculations based on the appropriate reliability level to provide a 1993 design that is equivalent to the 1972 Design Guide.

$$9.36 \log(SN+1) - 0.20 + \frac{\log\left[\frac{(4.2-p_t)}{(4.2-1.5)}\right]}{0.40+\frac{1094}{(SN+1)^{5.19}}} + \log\frac{1}{R} + 0.372(S_i - 3.0) = Z_R S_o + 9.36 \log(SN+1) - 0.20 + \frac{\log\left[\frac{(4.2-p_t)}{(4.2-1.5)}\right]}{0.40+\frac{1094}{(SN+1)^{5.19}}} + 2.32 \log M_R - 8.07 \tag{A5}$$

$$\log M_R = \frac{1}{2.32} * \left(0.372 * SSV + 6.954 + log\frac{1}{R} - Z_R S_o\right) \tag{A6}$$

Converted Resilient Modulus Values for 75% Reliability

ONLY for use with the 1993 AASHTO Pavement Design Guide

Assumptions:

1. $W_t(1972) = W_t(1993)$
2. Drainage Coefficients = 1.0
3. Standard Deviation (S_o) = 0.40
4. Reliability = 75% (Z_R = -0.674)

Converted Resilient Modulus (M_R) [psi]			
COLOR	MIN.	AVG.	MAX.
(white)	2,000	2,484	3,000
(yellow)	3,000	3,445	4,000
(green)	4,000	4,639	5,000
(orange)	5,000	5,587	6,000

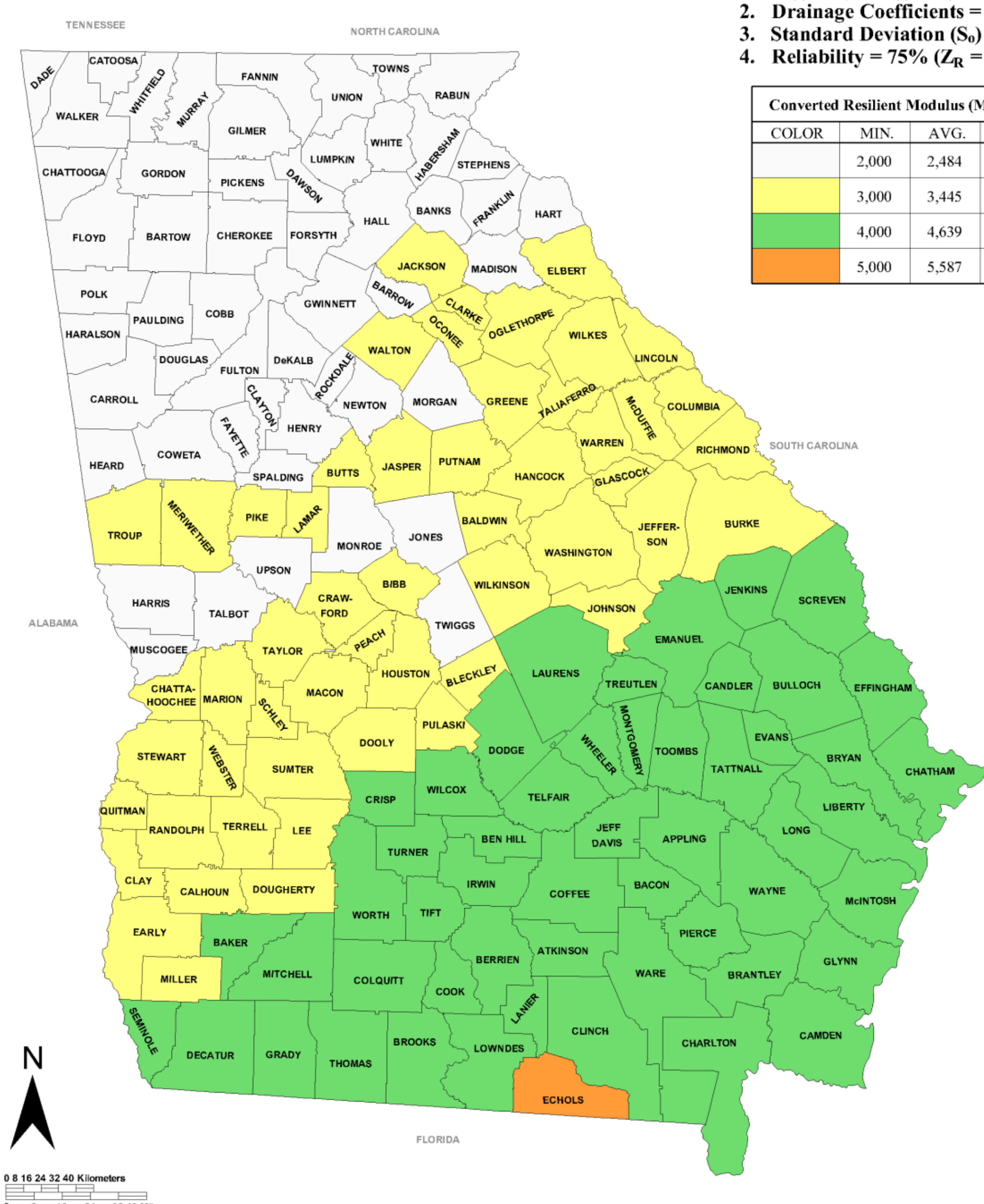

FIGURE A.1

Converted Resilient Modulus Values for 75% Reliability

Converted Resilient Modulus Values for 90% Reliability

ONLY for use with the 1993 AASHTO Pavement Design Guide

Assumptions:

1. **$W_t(1972) = W_t(1993)$**
2. **Drainage Coefficients = 1.0**
3. **Standard Deviation (S_o) = 0.40**
4. **Reliability = 90% (Z_R = -1.282)**

Converted Resilient Modulus (M_R) [psi]			
COLOR	MIN.	AVG.	MAX.
(white)	2,000	2,838	3,000
(yellow)	3,000	3,419	4,000
(green)	4,000	4,263	5,000
(orange)	5,000	5,488	6,000
(purple)	6,000	6,239	7,000
(blue)	7,000	7,112	8,000

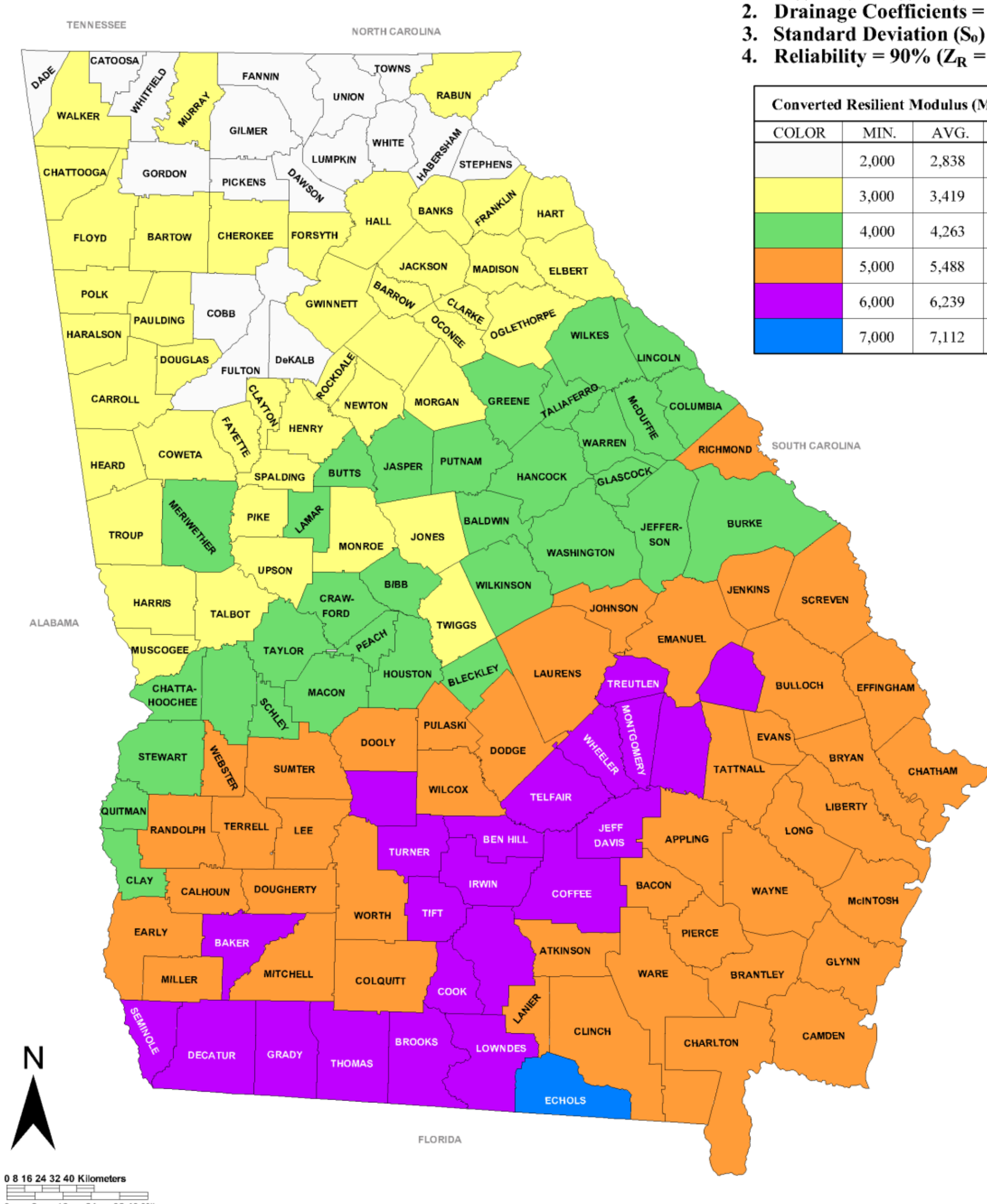

FIGURE A.2

Converted Resilient Modulus Values for 90% Reliability

Converted Resilient Modulus Values for 95% Reliability

ONLY for use with the 1993 AASHTO Pavement Design Guide

Assumptions:

1. $W_t(1972) = W_t(1993)$
2. Drainage Coefficents = 1.0
3. Standard Deviation (S_o) = 0.40
4. Reliability = 95% (Z_R = -1.645)

Converted Resilient Modulus (M_R) [psi]			
COLOR	MIN.	AVG.	MAX.
(yellow)	3,000	3,577	4,000
(green)	4,000	4,629	5,000
(orange)	5,000	5,786	6,000
(purple)	6,000	6,539	7,000
(blue)	7,000	7,206	8,000
(black)	8,000	8,215	9,000

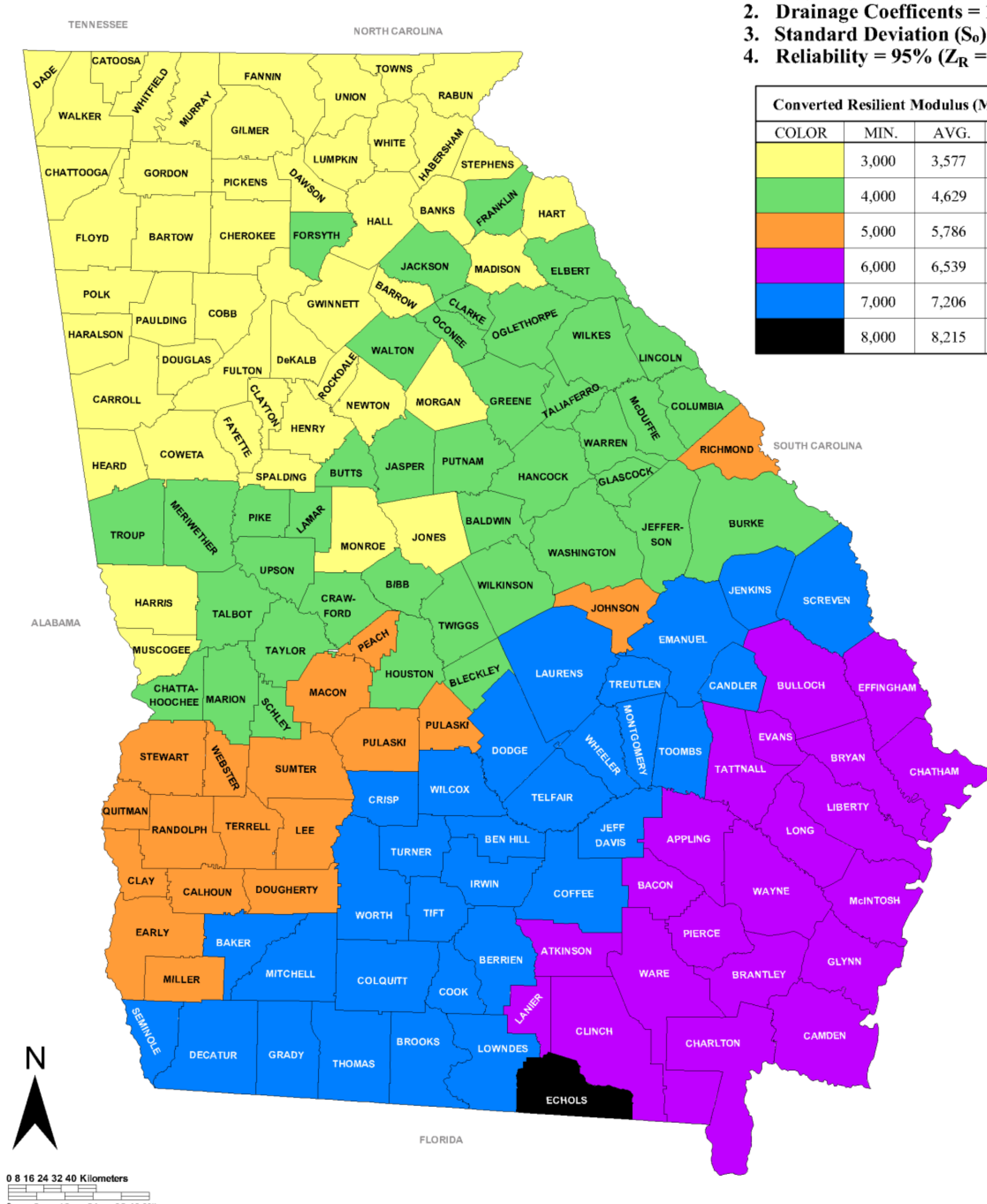

FIGURE A.3

Converted Resilient Modulus Values for 95% Reliability