DEVELOPMENT OF RESILIENT MODULUS PREDICTION MODELS FOR LOUISIANA SUBGRADE SOILS

Munir D. Nazzal, Ph.D.
Materials Research Associate
Louisiana Transportation Research Center
Louisiana State University
Baton Rouge, LA 70808

Louay N. Mohammad, Ph.D., Corresponding Author
Professor
Department of Civil and Environmental Engineering
Louisiana Transportation Research Center
Louisiana State University
Baton Rouge, LA 70808
Ph. (225) 767-9126. E-mail: Louaym@Lsu.Edu

Kevin Gaspard, P.E.
Pavement Research Engineer Manager
Louisiana Transportation Research Center
Baton Rouge, LA 70808

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Abstract

Field and laboratory testing programs were conducted to develop an efficient methodology for estimating resilient modulus (M_r) values of subgrade soils for use in the design of pavement structures. The field testing program consisted of obtaining Shelby tube samples of subgrade soils from different pavement projects throughout Louisiana. The laboratory program included conducting Repeated Load Triaxial (RLT) M_r tests as well as physical property tests on the collected samples. The validity of correlation equations developed by the Long Term Pavement Performance (LTPP) to predict the $M_{r,}$ were examined. In general, the LTPP model underestimated the values of M_r coefficients obtained in this study. A comprehensive regression analysis was conducted to develop models that predict the M_r coefficients of different subgrade soils in Louisiana using different physical properties. A good agreement was observed between the measured and predicted M_r coefficient values. Furthermore, the developed models had a better prediction of measured M_r coefficient values than the LTTP models. Finally, a catalog of resilient modulus of subgrade soils at different moisture content levels was developed.

INTRODUCTION

The Resilient Modulus (M_r) has widely been recognized by the pavement community as a good property that describes the stress-dependent elastic modulus of different soil materials under traffic loading. The ASSHTO 1993 (1) pavement design procedure and the Mechanistic Empirical Pavement Design Guide (MEPGD) (2) has also adopted the resilient modulus of subgrade soils as a material property in characterizing pavements for their structural analysis and design. Many studies that were conducted to investigate the effect of the material's M_r on the design of a pavement structure, also showed that the input value of M_r has a dramatic effect on the designed thickness of the base course and asphalt layers.

The resilient modulus is defined as the ratio of the maximum cyclic stress (σ_{cyc}) to the recoverable resilient (elastic) strain (ε_r) in a repeated dynamic loading, as shown in Equation 1. The resilient modulus can be more simply described as the unloaded phase of the stress-strain slope developed during the impulse loading that occurs as vehicles passes over the pavement.

$$M_r = \frac{\sigma_{cyc}}{\varepsilon_r} \tag{1}$$

Three different approaches have been used to estimate the M_r of subgrade soils, namely, conducting Repeated Load Triaxial (RTL) laboratory tests, back-calculation from in-situ test devices measurements, and estimation using correlations with physical properties of tested soils. Generally, the RLT test requires well-trained personnel and expensive laboratory equipment; it is also considered relatively time-consuming. Therefore, different state agencies were hesitant to conduct them and instead used other approaches to estimate the M_r. Another alternative for estimating the M_r of subgrade soils is the use of in-situ test devices. Different devices have been proposed and used during the last decades. However, such an alternative requires the development of reliable correlation between laboratory and field test measurements, which has not been created yet.

The resilient modulus can also be obtained from the correlation equations from soil physical properties. For over four decades, many researchers have studied the characteristics of M_r for various soils and attempted to relate it to engineering properties, so as to reduce costs and time associated with laboratory testing (i.e., 4, 5, 6, etc.). A potential benefit of estimating the M_r from physical properties is that seasonal variations in resilient modulus can be estimated from seasonal changes in the material's physical properties. Seasonal variations are critical for determining the design M_r for a particular project. The concept being used in development of the new MEPDG under NCHRP Project 1-37A (2) is to apply the Enhanced Integrated Climatic Model (EICM) to predict changes in the physical properties of unbound pavement materials and soils and to estimate the effect those changes have on the resilient modulus.

Determining the M_r from physical properties of cohesive materials can capture the effect of the seasonal variations of the M_r, but it does not capture the effect of stress sensitivity. Therefore, to capture the effects of stress sensitivity on M_r, a correct constitutive model should be employed first. During the past two decades, several constitutive models have been proposed by many researchers for modeling resilient moduli of pavement soils (7-10). The MEPDG adopted the generalized M_r constitutive model shown in Equation 5. This model has the ability to capture the effect of the stress state of the material under traffic loading, in which the normal and shear stresses change.

$$\frac{M_r}{P_a} = k_1\left(\frac{\theta}{P_a}\right)^{k_2}\left(\frac{\tau_{oct}}{P_a}+1\right)^{k_3} \tag{2}$$

where,

M_r = resilient modulus

θ = bulk stress = $\sigma_1+\sigma_2+\sigma_3$

σ_1 = major principal stress

σ_2 = intermediate principal stress= σ_3

σ_2 = minor principal stress/ confining pressure

τ_{oct} = $\frac{1}{3}\sqrt{(\sigma_1-\sigma_2)^2+(\sigma_1-\sigma_3)^2+(\sigma_2-\sigma_3)^2}$

P_a = normalizing stress (atmospheric pressure) = 14.7 psi (101.35 kPa), and

k_1, k_2, k_3 = material M_r coefficients.

Previous studies developed relationships between the soil properties and the regressed k-coefficients of the constitutive model (i.e., 10, 11, 12, etc.). Those relationships that have good statistics were generally confined to specific soil types (10). Other studies that have used a wide range of soil types and conditions have generally resulted in poor correlations (14). One of the most well known M_r coefficient prediction models were developed by the LTPP-FHWA study program (12), which were based on a wide range of the resilient modulus test data measured on pavement materials and soils recovered from the LTPP test sections. The models were developed for various types of pavement materials. Equations 3-5 show the models proposed to predict the k coefficients for fine grain clay soils. One problem that affects the reliability of these models is that they did not incorporate soils from all states and regions; therefore, these models have to be recalibrated or modified to account for the local soils in the different states.

$$k_1 = 1.3577 + 0.0106\,(\%Clay) - 0.0437\,wc \quad (3)$$

$$k_2 = 0.5193 - 0.0073\,P4 + 0.0095\,P40 - 0.0027\,P200 - 0.003\,LL - 0.0049\,wopt \quad (4)$$

$$k_3 = 1.4258 - 0.0288\,P4 + 0.0303\,P40 - 0.0521\,P200 + 0.0251\,(\%Silt) + 0.0535\,LL - 0.0672\,wopt - 0.0026\,\gamma opt + 0.0025\,\gamma s - 0.6055\,(wc / wopt) \quad (5)$$

Where,

P3/8 = percentage passing sieve #3/8

P4 = percentage passing #4 sieve

P40 = percentage passing #40 sieve

wc = moisture content of the specimen, %

wopt = optimum moisture content of the soil, %

γs = dry density of the sample, kg/m3

γopt = optimum dry density, kg/m3

This paper examines the validity of correlation equations developed by the Long Term Pavement Performance (LTPP), and proposes an improved model to predict M_r coefficients of different subgrade soils in Louisiana. To achieve this, field and laboratory testing programs were conducted. The field testing program consisted of obtaining Shelby tube samples of subgrade soils from different existing pavement structures throughout Louisiana. The laboratory program included conducting (RLT) M_r tests as well as physical property tests on the collected samples. A comprehensive statistical analysis was conducted on the collected data.

TESTING PROGRAM

The testing program in this study included obtaining subgrade soils samples from different sections in ten pavement projects within the state of Louisiana, namely LA333,

LA347, US171, LA991, LA22, LA28, LA344, LA182, LA15, and LA652. The tested sections covered the common subgrade soil types found in Louisiana (A-4, A-6, A-7-5, and A-7-6 soils types). Figure 1 presents the locations of projects considered.

Three sets of testing (A, B, and C) were conducted at each pavement project. Each testing set was approximately 500-ft apart unless field conditions dictated otherwise. Each set contained nine points (1 to 9). Shelby tubes samples were obtained at three points for each test section, as shown in Figure 6. To obtain Shelby tube samples, a six-inch diameter hole was first augered with a core rig through the asphaltic concrete layer, the base course layer, and six inches into the subgrade. The core rig was then used to shove the three-inch diameter Shelby tube into the subgrade. Although the Shelby tubes were 30 inches long and were fully pushed into the subgrade, only a 5.8-inch long specimen could be obtained from the tube. The obtained specimen was representative of the subgrade soil layer within 6 to 18 inches from the base course.

Once the tube was removed from the ground, the soil specimen was extracted from the tube using the extrusion device mounted on the truck. The soil specimens were then trimmed and wrapped in plastic and aluminum foil. They were then stored in Styrofoam containers and transported to the LTRC laboratory. The samples were kept in a 95 percent relative humidity-controlled room until they were tested.

The laboratory testing program in this study consisted of conducting RLT resilient modulus tests as well as tests to determine the physical properties of tested soils, such as the Standard Proctor test, Sieve Analysis, and Atterberg limits.

The RLT M_r tests were conducted on the 5.6 inches in height and 2.8 inches in diameter specimens obtained from Shelby tube samples collected in the field. All tests

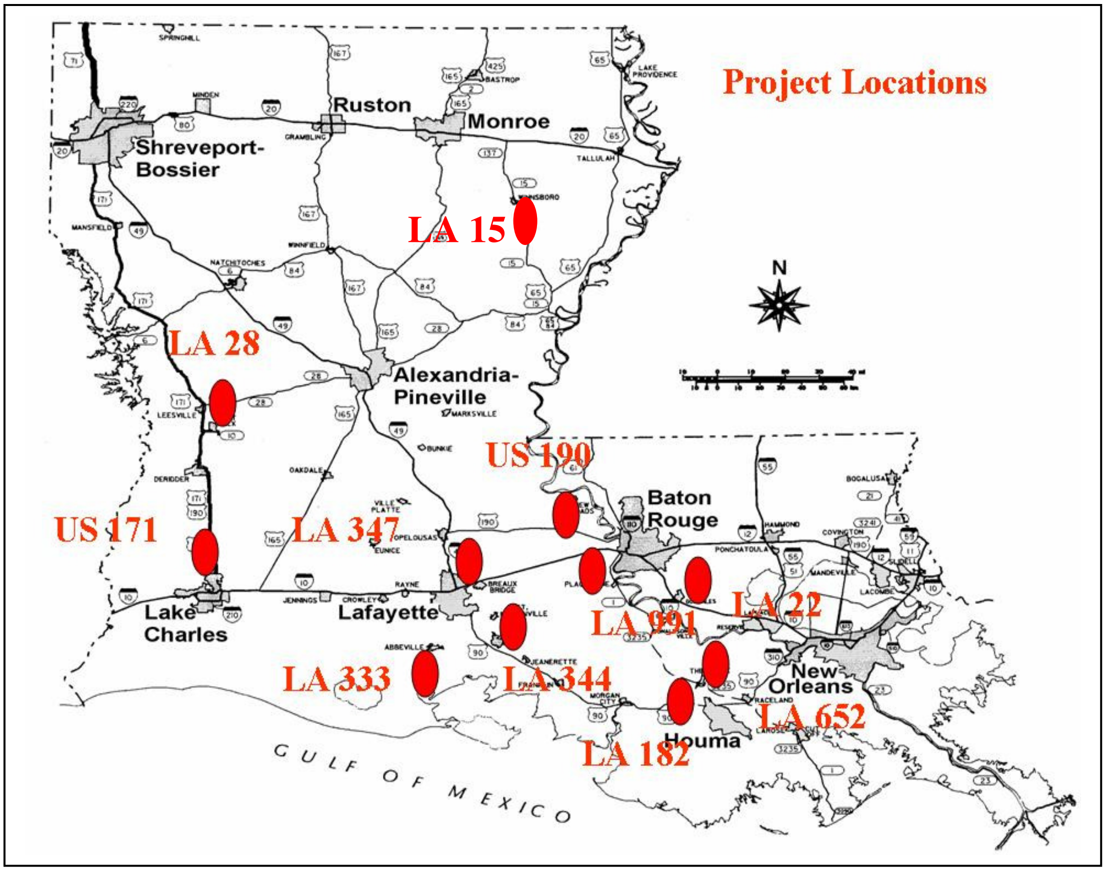
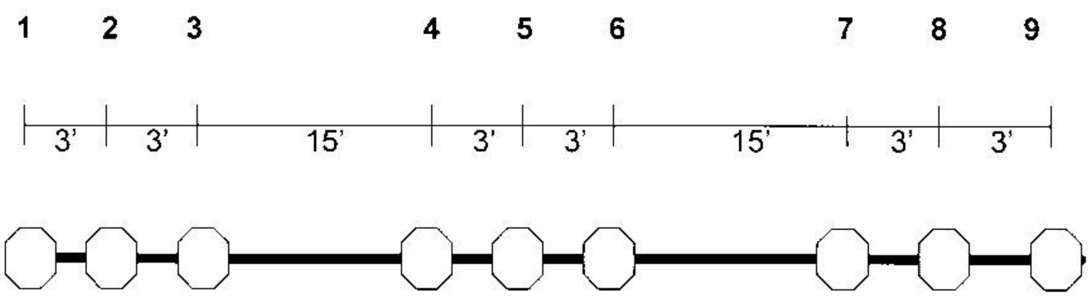


FIGURE 1 Location of The Pavement Projects



Points 2,5, 8 Shelby Tube Samples

FIGURE 2 Field-Testing Layout For Each Set

were performed using the Material Testing System (MTS) 810 machine with a closed loop and a servo hydraulic loading system. The applied load was measured using a load cell installed inside the triaxial cell. Placing the load cell inside the triaxial chamber eliminate the push-rod seal friction and pressure area errors which will results in reducing the testing equipment error. An external load cell is affected by changes in confining pressure and by load rod friction, and the internal load cell; therefore, gives more accurate readings. The capacity of the load cell used was ± 4.45 kN (±1000 lbf.). The axial displacement measurements were made using two Linearly Variable Differential Transducers (LVDT) placed between the top platen and base of the cell to reduce the amount of extraneous axial deformation measured compared to external LVDTs. Air was used as the confining fluid to the specimens. Figure 10 depicts a picture of the testing setup used in this study.

Resilient modulus tests were performed in accordance with AASHTO procedure T 307 standard method (15). In this test method, the samples are first conditioned by applying 1,000 load cycles to remove most of the irregularities on the top and bottom surfaces of the test sample and also to suppress most of the initial stage of permanent deformation. The conditioning of the samples is followed by a series of steps consisting of applying 100 cycles with haversine shaped load-pulse at different levels of confining and deviatoric stresses such that the resilient modulus is measured at varying normal and shear stresses. The load pulse used in this study had a 0.2 sec load duration and 0.8 sec rest period.

FIGURE 3 MTS Machine Used in This Study

RESULTS AND ANALYSIS

Resilient Modulus Test Results

The average value of the resilient modulus for the last ten cycles of each stress sequence was first calculated; a regression analysis was then carried out to fit the data of each test to the generalized constitutive model given in Equation 2 and to determine the k_{1-3} coefficients for the different tested samples. Figure 4 compares the M_r calculated using the regressed k-coefficients of the constitutive model in Equation 2 to the measured M_r for the samples tested in this study. As shown, the constitutive equation provides an excellent fit to the M_r test data.

Figures 5a-c show the k_{1-3} coefficients for the different soils considered at the tested in-situ moisture conditions, respectively. It is noted that the tested samples were categorized into four moisture content groups (Level I-IV), which are chosen based on the stiffness behavior that unsaturated soils experience at different moisture contents. Level I represents the soils that are on the lower end of the dry side of the optimum

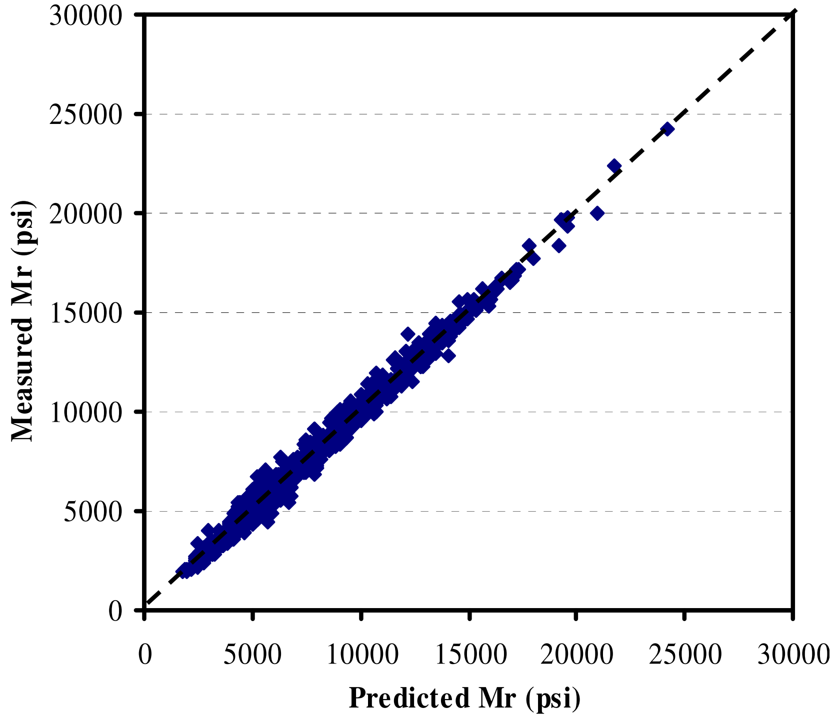


FIGURE 4 Comparison of M_r Values Predicted Using the Universal Constitutive Model to the Measured M_r for the Tested Subgrade Soils

moisture content (OMC). Level II is used for soils that have higher moisture content than in Level-I, but are still on the dry side of the optimum moisture content. While Level III represents the soils that are at or close to the OMC. Finally, Level IV is for soils with moisture content that is on the wet side of the OMC.

Figure 5a shows that the $k_1$coefficient had positive values in all cases. In general, the $k_1$coefficients had the lowest values at the lower end of the dry side and the wet side of the OMC, i.e., Level I and IV, while it had the maximum value at Level II moisture content, which is on the dry side of OMC. Finally, intermediate values of k_1 were obtained at the OMC. This behavior is expected since the coefficient k_1 is proportional to the stiffness of a material. Therefore, k_1 will increase with the increase in the effective stress. The effective stress of partially saturated soils can be determined using the expression proposed by Bishop (16) that is shown in Equation 6. In this equation the

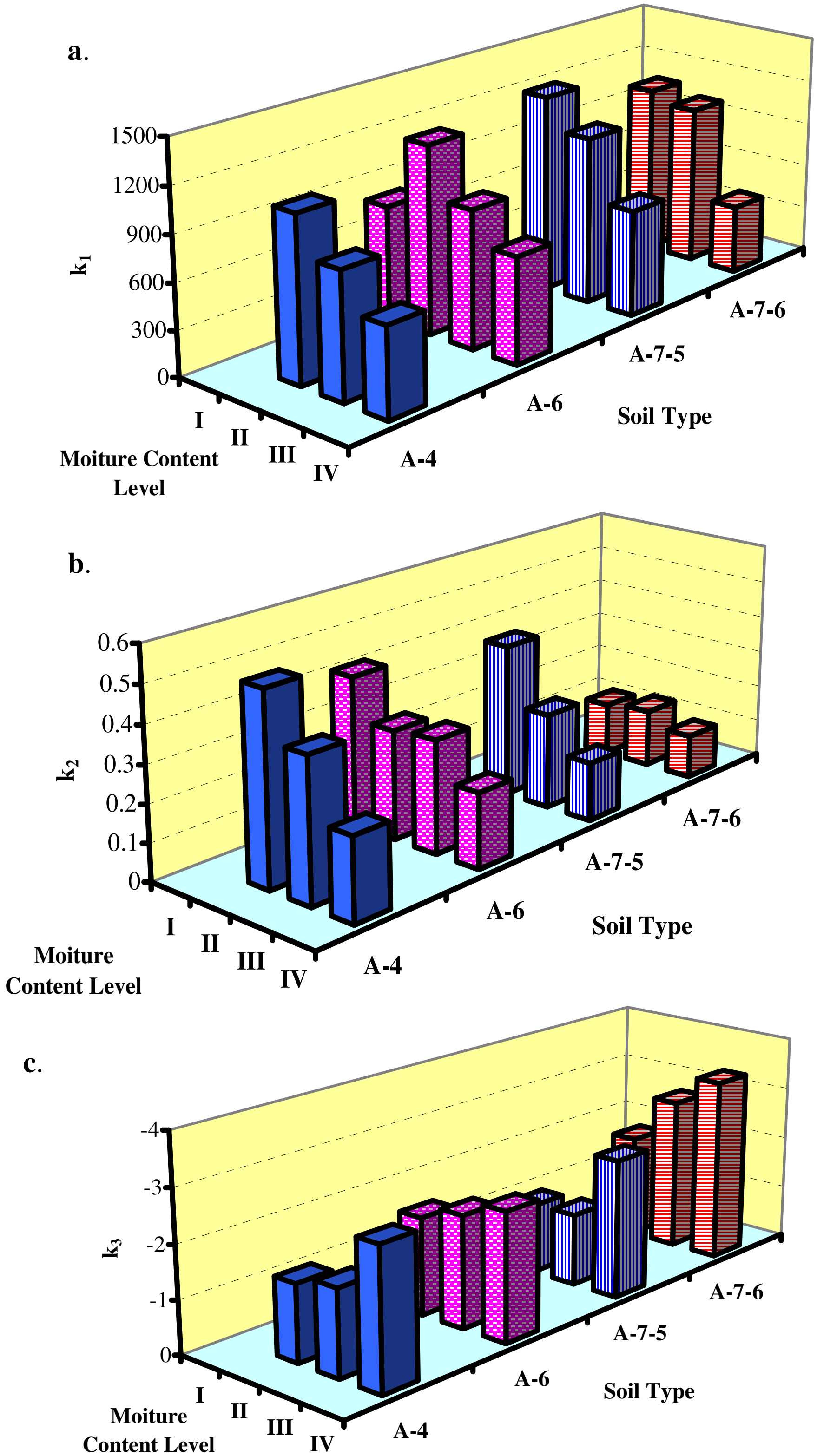


FIGURE 5 Resilient Modulus Coefficients for Tested Soils: a. k_1 ; b. k_2; c. k_3

effective stress is governed by the matric suction (u_a – u_w) and the effective stress parameter (χ). Those variables have different relations with the increase of moisture content. χ is zero for dry soils and increases to unity for saturated soils, which explains the low values of stiffness obtained at the lower side of the dry of optimum. While the matric suction is extremely high at low water contents, and it decreases to zero for saturated soils, which results in significant decrease in stiffness at wet side of the OMC. Although the two variable have opposite trends, there exists a moisture content value at which their combined effect is maximum; consequently, the stiffness peaks. This moisture content value at which the combined effect reaches a maximum value differs with type of cohesive soils considered. However, this value occurs at the dry side of the optimum moisture content.

$$\sigma_v^{'} = \sigma_v - u_a + \chi (u_a - u_w) \qquad (6)$$

Where

σ_v = total stress

u_a = pore air pressure , u_w = pore water pressure , and matric suction= (u_a – u_w)

χ = effective stress parameter.

Another reason that explains having the peak values of the k_1 coefficient on the dry side of OMC is the structure of the cohesive soils particles, since at given compaction effort, cohesive soils tend to be more flocculated for compaction on the dry side of their optimum moisture content. However, as the water content increases, the soil inter-particle repulsions increases; thus the soil structure becomes more dispersed. The soil particles tend to orient themselves in an edge-to-face configuration in a flocculated structure, mainly since the edges are positively charged and the faces are negatively charged. The resulting electrostatic attractive forces bond the soil particles together; therefore, it results in a higher stiffness on the dry side (17).

Figure 5b shows the k_2 coefficient variation for the considered soils at the different tested moisture content levels. The k_2 coefficient describes the stiffening or hardening (higher modulus) of the material with increase in the bulk stress. In general, it is noted that the k_2 coefficients decreased with the increase in the moisture content. Furthermore, values of the k_2 coefficients were small for A-7-6 soils compared to other soil types. This indicates that the effect of confining stress is less pronounced for this soil type compared to other subgrade soils types.

Figure 5c shows that all k_3 coefficients were negative. This is expected since this parameter describes the softening of the material (lower modulus) with the increase in the shear stress. It is noted that, in general, k_3 values were high at the dry side of OMC and decreased with the increase in the moisture content; however, this decrease was dependent on the soil type. This suggests that the softening cohesive material experience as the shear stresses is magnified as the moisture content increase, which is reasonable since the moisture content affects the soil structure through the destruction of the cementation between soil particles (2).

Prediction of M_r from LTPP Equations

LTPP correlation Equations 3-5 were employed to predict the resilient modulus coefficients of tested subgrade soils based on soil index properties. Figures 6a-c show the predicted and measured resilient modulus coefficients k_{1-3}, respectively. It is noted that there is a large discrepancy between measured and predicted coefficients. The largest difference was observed in the k_3 values. The figures also show that the prediction

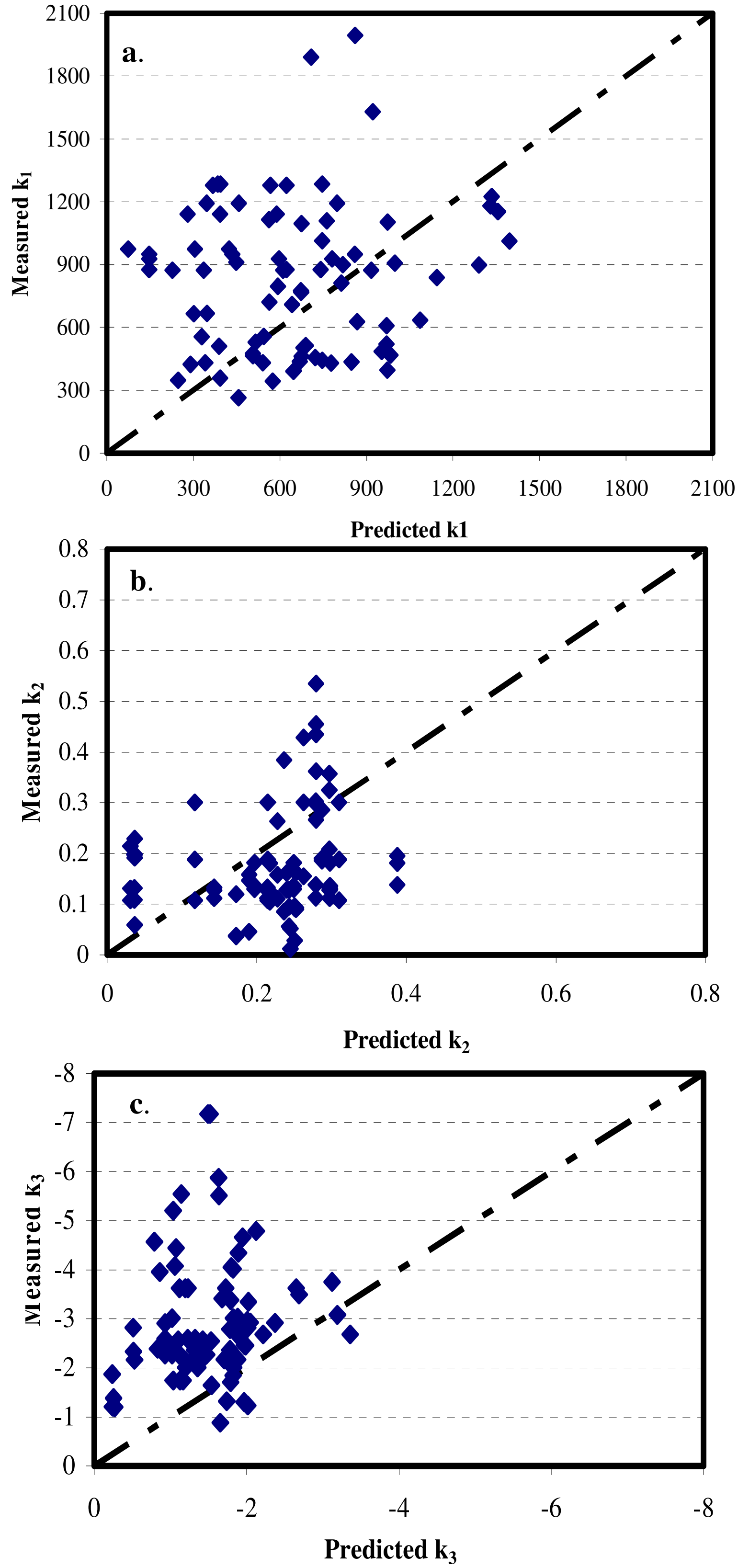


FIGURE 6 LTPP Models Prediction of M_r k_1 Coefficients of Tested Subgrade soils: a. k_1 ;b. k_2; c. k_3

models underestimated the measured k_2 and k_3 values. This result can be explained by the fact that none of the data used in the development of LTTP models were collected from sections in Louisiana. Therefore, the empirically based LTPP models are only reliable for the soils properties used in developing the model. This suggests that there is a need for validation and calibration of these models for local soils in each region.

Development of Prediction Models for Resilient Modulus Coefficients

A comprehensive statistical analysis was conducted using the Statistical Analysis System (SAS) program to develop models that predict the resilient modulus regressed coefficients of subgrade soils from the different physical properties. The data used in the development of these models included those collected in this study as well as previous studies conducted by the authors (18, 19). The ranges of variables used in the regression analyses are presented in Table 1.

A stepwise regression analysis was initially performed to identify the important variables (physical properties) that affect the prediction of the resilient modulus coefficient. This analysis included the following variables and their interactions: Liquid Limit, %Passing Sieve No.40, % Passing Sieve No.200, % Clay, % Silt, optimum moisture content, maximum dry unit weight, in-situ moisture content, in-situ dry unit weight. The stepwise regression analysis combines the forward and backward stepwise regression methods. It fits all possible simple linear models, and chooses the best one with largest F-test statistic value. Then, all possible two-variable models that include the first variable are compared, and so on. The significance of each variable included is rechecked at each step along the way and removed if it falls below the significance threshold. The process is completed when no more variables outside the model had a level of significance to enter.

Based on the results of the stepwise regression procedure, multiple regression analysis was conducted to determine the adequacy of the best models that predict the M_r regressed coefficients based on the physical properties of tested soils, examine the significance of independent variables of these models, and detect any multicolinearity (possible correlations among the independent variables). The adequacy of the model is assessed using the coefficient of determination, R^2, and the square root of the mean square errors (RMSE). The R^2 represents the proportion of variation in the dependant variable that is accounted for by the regression model and has values from zero to one. If it is equal to one, the entire observed points lie on the suggested least square line, which means a perfect correlation exists. The RMSE represent the standard error of the regression model. The *t-test* is utilized to examine the significance of each of the independent variables used in the model. The probability associated with the *t-test* is designated with a *p-value*. A *p-value* less than 0.05 indicates that, at 95% confidence level, the independent variable is significant in explaining the variation of the dependent variable. The multicolinearity is detected using the variance inflation factor (VIF). A VIF factor greater than 10, indicate that weak dependencies may be starting to affect the regression estimates.

The multiple regression analysis that was conducted on the data considered in this study yielded the k_1, k_2, and k_3 prediction models presented in Equations 7-9, respectively. The results of this analysis are also presented in Table 2. In general, the models had a relatively high coefficient of determination (R^2), and low RMSE values, especially when

TABLE 1 Ranges of Variables of Tested Subgrade Materials

Property	Range for A-4 soils	Range for A-6 soils	Range for A-7-5 soils	Range for A-7-6 soils
PI (%)	4-6	12-23	27-61	15-43
γ_d (pcf)	100-104	96-118	57-113	84-108
w (%)	15-24	8-27	21-60	18-35
LL (%)	22-28	27-40	46-98	41-62
Sand (%)	7-58	11-35	4-28	3-32
Silt (%)	28-72	37-72	9-62	23-58
Clay (%)	14-23	8-32	27-86	32-53
Passing sieve #200 (%)	42-93	65-89	72-96	68-97

TABLE 2 Results of Multiple Regression Analysis

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation	95% Confidence Limits	
k_1 Coefficient Prediction Models								
Intercept	1	1.3337	0.4636	2.88	0.0045	0.0000	1.2386	3.3229
P200	1	0.0127	0.0015	8.59	<.0001	2.5331	0.0075	0.0142
LL	1	0.0160	0.0016	9.97	<.0001	5.6411	0.0126	0.0200
γdmax	1	0.0362	0.0034	10.69	<.0001	3.2475	0.0214	0.0365
MCCL	1	-0.0110	0.0038	-11.28	<.0001	4.5863	-0.0156	-0.0102
MCDDmaxP	1	0.0010	0.0009	1.09	0.02790	3.2014	0.0003	0.0046
k_2 Coefficient Prediction Models								
Intercept	1	0.7221	0.0443	16.32	<.0001	0.0000	0.6347	0.8094
LL	1	0.0057	0.0007	7.73	<.0001	4.8557	0.0042	0.0071
MCDDmaxPI	1	-0.0045	0.0010	-4.54	<.0001	5.6023	-0.0065	-0.0026
MCDDP	1	0.0003	0.0001	5.4	<.0001	1.4902	0.0002	0.0004
P200	1	-0.0088	0.0006	-14.94	<.0001	1.5643	-0.0099	-0.0076
k_3 Coefficient Prediction Models								
Intercept	1	-7.4789	0.6938	-10.78	<.0001	0.0000	-8.8488	-6.1090
γd/mc	1	0.2354	0.0321	7.33	<.0001	5.3815	0.1720	0.2989
LL	1	0.0380	0.0033	11.64	<.0001	5.0785	0.0316	0.0445
MCPI	1	-0.0008	0.0001	-6.22	<.0001	5.5210	-0.0011	-0.0005
gdmax	1	0.0329	0.0062	5.30	<.0001	2.5358	0.0207	0.0452
MCDDP	1	-0.0016	0.0004	-4.39	<.0001	3.2506	-0.0024	-0.0009

$$\ln(k_1) = 1.334 + 0.01265(P200) + 0.016(LL) - 0.0362(\gamma_{dmax}) - 0.011(MCCL) + 0.001(MCDDmaxP) \quad \left(\mathbf{R^2 = 0.61,\ RMSE = 0.23}\right) \tag{7}$$

$$k_2 = 0.722 + 0.00569(LL) - 0.00454(MCDDmaxPI)^{0.641} + 0.00324(MCDDP)^{1.28} - 0.875(P_{200}) \quad \left(\mathbf{R^2 = 0.74,\ RMSE = 0.1}\right) \tag{8}$$

$$k_3 = -7.48 + 0.235\left(\frac{\gamma_d}{mc}\right) + 0.038(LL) - 0.0008(MCPI) + 0.033(\gamma_{dmax}) -0.016(MCDDP) \quad \left(\mathbf{R^2 = 0.66,\ RMSE = 0.49}\right) \tag{9}$$

where,

$MCCL = (mc - mc_{opt}) \cdot Clay\%$

$MCDDmaxP = P200 \cdot \frac{mc - mc_{opt}}{mc_{opt}} \cdot \frac{\gamma_d}{\gamma_{dmax}}$

$MCDDmaxPI = PI \cdot \frac{mc - mc_{opt}}{mc_{opt}} \cdot \frac{\gamma_d}{\gamma_{dmax}}$

$MCDDmaxPI = PI \cdot \frac{mc - mc_{opt}}{mc_{opt}} \cdot \frac{\gamma_d}{\gamma_{dmax}}$

$MCDDP = \frac{P200 \cdot \gamma_d}{mc}$

$MCPI = PI \cdot \frac{mc - mc_{opt}}{mc_{opt}}$

P200= percentage passing sieve #200

Clay%= percentage of clay in the soil, %

LL= liquid limit of the soil, %

PI= plasticity index of clay in the soil, %

mc = moisture content of the soils, %

mc_{opt} = optimum moisture content of the soil, %

γ_d = dry unit weight of the soil, pcf

γ_{dmax} = maximum dry unit weight in standard Proctor test , pcf considering the wide range of soils considered in the model development. The k_2 model had highest R^2 and lowest RMSE, 0.74 and 0.1, respectively, and hence it was the best model. Furthermore, when comparing the Equations 7-9 and LTPP prediction models (Equations 3-5), it is noted that the LTPP prediction models did not account for the dry unit weight variation of tested soils. In addition, the LTPP k_1 and k_2 prediction models used moisture content values; however, the stiffness is more influenced by the deviation of moisture content from OMC rather than the absolute value itself, especially that the OMC value varies from one soil to another. This can also be noticed in Figure 5a.

Table 2 suggests that the index properties such as the liquid limit, plasticity index, and percent passing #200 were influential variables in all of the developed models, as indicated by the t-value. These variables were also included with the LTPP models as well. It is also noted that that the most significant variable affecting the k_1 coefficient prediction was the "MCCL" variable which represents the combined effect of moisture content and clay percentage.

Figures 7a-c compare measured k to those predicted using the models shown in Equations 7-9, respectively. It is noted that there was good agreement between the measured and predicted values. Furthermore, the data were much less scattered about the equality line when compared to Figures 6a-c. This suggests that the proposed models fit the data better than the LTPP prediction models.

Limitation of the Developed Models

The prediction models developed in this study are reliable for the range of independent variables (physical properties) used in the developing the models and shown in Table 1. Therefore, the values of physical properties must be checked before using these models.

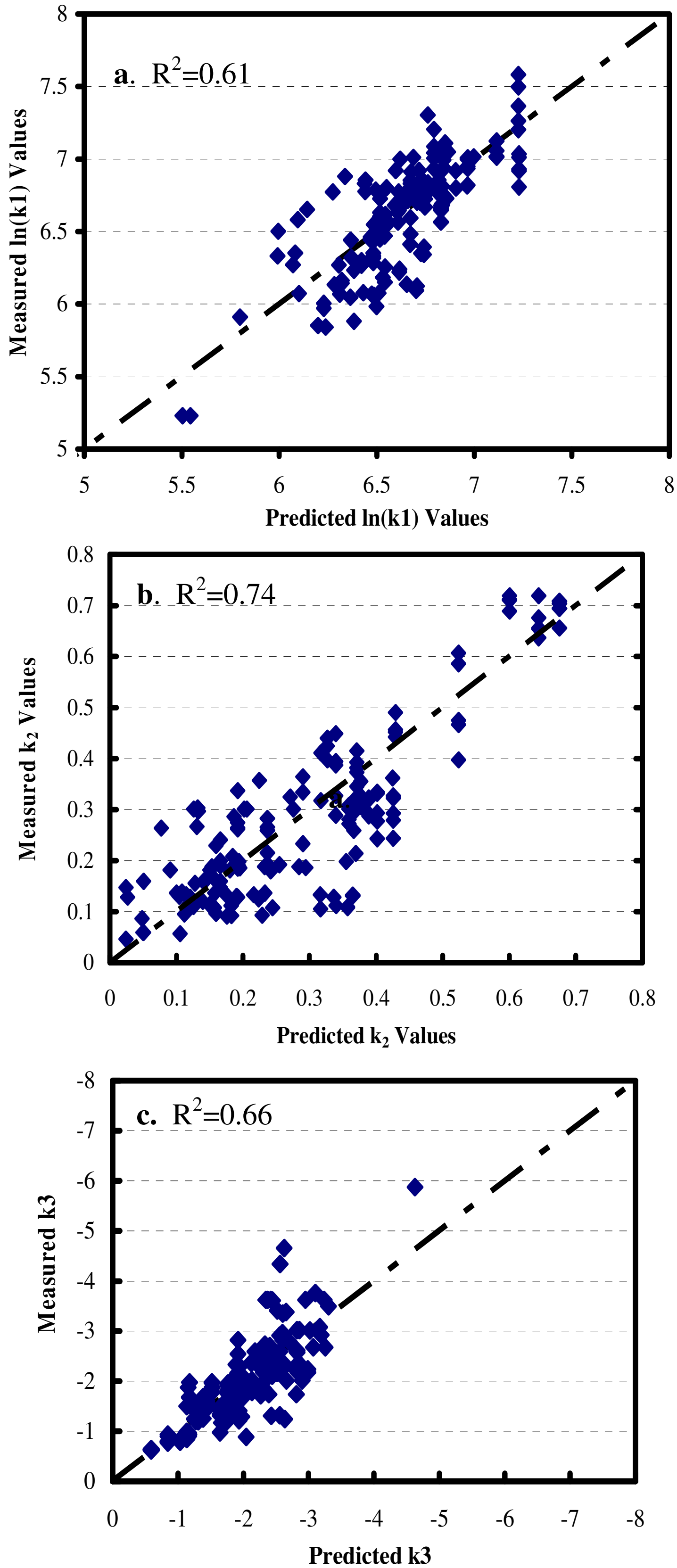


FIGURE 7 Prediction Of The Models Developed In Study: a. k_1 ;b. k_2; c. k_3

Furthermore, these models were developed based on subgrade soils in Louisiana; consequently, the models may need local calibration for soils in other regions.

Catalog of M_r Values of Subgrade Soils in Louisiana

A catalog for the M_r values is needed so that the different subgrade soils in each state/region can be categorized, and a simplified method may be developed to select an appropriate M_r value for pavement design. Therefore, a database was established for M_r coefficients for all subgrade soils tested in Louisiana, which was reported in previous studies and used in the development of the regression models described above(16,17,18). Table 3 provides typical M_r coefficients and values for typical subgrade soils in Louisiana at the different moisture content levels. It is noted that the M_r values were calculated based on Equation 2 using a cyclic deviotroic stress level of 37.2 kPa (5.4 lbf/in.^{2}) and a confining stress of 14 kPa (2 lbf/in.^{2}), which represents the stress state a subgrade encounters under traffic loading(20). Table 3 also shows the M_r values and ranges recommended in MEPDG for the different soil types considered. It is noted that there is a large discrepancy between the average M_r values reported in this study and those recommended by MEPDG for A-4 and A-6 soils. However, for A-7-5 and A-7-6 soils the two values were comparable.

TABLE 3 Catalog of M_r Values for Subgrade Soil in Louisiana

Soil Type	Moisture Content Level	Parameter	Mean	Range	MEPDG Recommended Value	MEPDG Recommended Range
A-4	II	k_1	1079.25	1027.5-1132.23		
		k_2	0.51	0.40-0.61		
		k_3	-1.44	-1.55 - -1.25		
		M_r (psi)	11073	10649-11671	N/A*	N/A*
	III	k_1	824.05	709.44-950.44		
		k_2	0.38	0.11-0.49		
		k_3	-1.62	-3.76 - -1.11		
		M_r (psi)	8495	5561-10330	24000	21500-2900
	IV	k_1	584.28	390.61-721.66		
		k_2	0.22	0.14-0.3		
		k_3	-2.62	-3.08 - -1.23		
		M_r (psi)	5346	3387-8074	N/A*	N/A*
A-6	I	k_1	869.82	837.86-897.74		
		k_2	0.4	0.3-0.54		
		k_3	-2.05	-0.887- -2.53		
		M_r (psi)	8319	6396-9989	N/A*	N/A*
	II	k_1	1239.28	873.6-1521.2		
		k_2	0.29	0.24-0.33		
		k_3	-1.84	-1.979 - -1.488		
		M_r (psi)	12614	8806-16209	N/A*	N/A*
	III	k_1	906.96	787.94-1284.68		
		k_2	0.29	0.13-0.43		
		k_3	-2.11	-4.34 - -1.1.71		
		M_r (psi)	9115	5598-1287	17000	13500-2400
	IV	k_1	764.14	444.00 -885.16		
		k_2	0.20	0.11-0.3		
		k_3	-2.90	-4.66 - -2.69		
		M_r (psi)	6720	3014-8391.8	N/A*	N/A*
A-7-5	II	k_1	1310.30	1011.07-1964.02		
		k_2	0.41	0.23-0.6		
		k_3	-1.31	-1.977- -1.13		
		M_r (psi)	14070	10219-24276	N/A*	N/A*

TABLE 3 Catalog of M_r Values for Subgrade Soil in Louisiana (Continued)

Soil Type	Moisture Content Level	Parameter	Mean	Range	MEPDG Recommended Value	MEPDG Recommended Range
A-7-5	III	k_1	1104.95	915.05-1346.53		
		k_2	0.25	0.19-0.34		
		k_3	-1.35	-1.72 - -0.98		
		M_r (psi)	12267	9735-15525	12000	8000-17500
	IV	k_1	701.63	264.94-947.00		
		k_2	0.16	0.03-0.29		
		k_3	-2.61	-5.54 - -1.68		
		M_r (psi)	6530	1595-9889	N/A*	N/A*
A-7-6	II	k_1	1122.22	906.65-1225.65		
		k_2	0.14	0.09-0.21		
		k_3	-1.94	-5.52 - -1.2		
		M_r (psi)	11667	5391-14097	N/A*	N/A*
	III	k_1	1050.43	873.85-1284.68		
		k_2	0.15	0.09-0.3		
		k_3	-2.86	-4.06 - -1.74		
		M_r (psi)	9197	6562-13250	8000	6562-13500
	IV	k_1	433.47	186.9-668.04		
		k_2	0.12	0.06-0.38		
		k_3	-3.45	-7.18 - -1.32		
		M_r (psi)	3567	885-7220	N/A*	N/A*

N/A*: MEPDG does not provide M_r Values for this moisture content level.

CONCLUSIONS

Field and laboratory testing programs were conducted to develop an efficient methodology for estimating resilient modulus (M_r) values of subgrade soils for use in the design of flexible pavement structures. The field testing program consisted of obtaining Shelby tube samples of subgrade soils from different existing pavement structures throughout Louisiana. The laboratory program included conducting RLT M_r tests as well as physical property tests on the collected samples. A regression analysis was conducted on the collected data and M_r coefficient prediction models were developed. Based on the results of this study the following conclusions can be drawn:

1. In general, the value of resilient modulus regressed coefficients was affected by the deviation of the moisture content from the optimum moisture content. However, the significance of this effect was dependent on the soil type.
2. A significant difference was observed between the M_r coefficients predicted by the LTTP models, and those measured in this study.
3. The LTTP M_r prediction models should be calibrated to account for local subgrade soils available in the different States.
4. A Good agreement was observed between the measured M_r coefficient values and those predicted using the regression models developed in this study.
5. A catalog of M_r values of commonly found subgrade soils in Louisiana at different moisture content levels was developed.
6. A significant difference was observed between the measured M_r values of A-4 and A-6 soils and those recommended by the MEPDG. However, this difference was not significant for soil types A-7-5 and A-7-6.

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