Improving Pavements With Long-Term Pavement Performance: *Products for Today and Tomorrow*

Winning Papers From the 2001–2002 International Contest on Long-Term Pavement Performance Data Analysis.

Sponsored by the Federal Highway Administration and the American Society of Civil Engineers.

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Federal Highway Administration

FOREWORD

In 1998, the Federal Highway Administration (FHWA), Long-Term Pavement Performance (LTPP) Program and the Highway Division Pavements Committee of the American Society of Civil Engineers (ASCE) initiated a program to organize an international contest on the use of LTPP data. The competition was designed to promote the use of LTPP data and involve the future pavement engineers in university in the analysis of data from the LTPP database. The program has been in operation for 4 years with three contests. The papers contained in this document are the results of the 2001–2002 contest.

Gary L. Henderson
Director, Office of Infrastructure
Research and Development

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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)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		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)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		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)

TABLE OF CONTENTS

Page

TABLE OF CONTENTS—*Continued*

Page

TABLE OF CONTENTS—*Continued*

Page

LIST OF FIGURES

Page

PAPER 1

Page

LIST OF FIGURES—*Continued*

Page

LIST OF FIGURES—*Continued*

Page

LIST OF FIGURES—*Continued*

Page

PAPER 5

LIST OF TABLES

LIST OF TABLES—*Continued*

Page

PAPER 3

Page

LIST OF TABLES—*Continued*

Page

PAPER 5

INTRODUCTION

BACKGROUND

In 1998, the Federal Highway Administration (FHWA), Long-Term Pavement Performance (LTPP) Program, and the Highway Division Pavements Committee of the American Society of Civil Engineers (ASCE) initiated a program to organize an international contest on the use of LTPP data. The competition was designed to promote the use of LTPP data and involve the future pavement engineers in university in the analysis of data from the LTPP database. The program has been in operation for 4 years with three contests. The papers contained in this document are the results of the 2001–2002 contest.

DATA ANALYSIS CONTEST

The contest has been expanded to cover four categories:

- Category 1, Undergraduate Students (individual or team entry).
- Category 2, Graduate Students (individual or team entry).
- Category 3, Partnership.
- Category 4, Curriculum.

The contest now expands to other key experts, including State departments of transportation, consultants, and industry as well as the universities. The Transportation and Development Institute continues to provide oversight of the contest with strong support from FHWA.

For the 2001–2002 contest, a total of 11 papers were submitted, and experts from academia, industry, and highway agencies reviewed these papers. Awards were given for the best paper from each of the four categories. The winners for 2001–2002 are listed in table 1.

Table 1. Data Analysis Contest winners for 2001–2002

Prize	Name	Faculty Advisor
Category 1—Undergraduate Students: No entries		
Category 2—Graduate Students		
1st Place	Hassan M. Aly Salem	Fouad M. Bayomy, P.E. Professor of Civil Engineering University of Idaho
1st Place	Yuhong Wang	Donn E. Hancher Department of Civil Engineering University of Kentucky
2nd Place	Shameem Dewan	Roger E. Smith, Ph.D., P.E. Associate Professor CE/TTI, 503G Texas A&M University
2nd Place	Mohammed Zulyaminayn	Roger E. Smith, Ph.D., P.E. Associate Professor Department of Civil Engineering Texas A&M University
3rd Place	Christopher Raymond	Ralph Haas, Ph.D., Susan L. Tighe, Ph.D., and Leo Rothenburg, Ph.D. Department of Civil Engineering University of Waterloo
Category 3—Partnership: No entries		
Category 4—Curriculum		
1st Place	Neeraj Buch and Karim Chatti	

For more information on the contest, please visit the LTPP Data Analysis contest Web site at http://www.fhwa.dot.gov/pavement/ltpp/contest2002.cfm.

PAPER 1 THE USE OF THE LONG-TERM PAVEMENT PERFORMANCE DATABASE IN THE PAVEMENT ENGINEERING CURRICULUM AT MICHIGAN STATE UNIVERSITY

Neeraj Buch[1] and Karim Chatti[2]

ABSTRACT

The authors describe the inclusion of the Long-Term Pavement Performance (LTPP) data in the pavement engineering curriculum at Michigan State University (MSU) using two examples: one from an undergraduate course on pavement rehabilitation, and one from a graduate course on pavement analysis and design. The design examples illustrate the use of LTPP data in computing pavement responses, predicting traffic, developing rehabilitation strategies, and predicting pavement performance for both rigid and flexible pavements.

INTRODUCTION

Pavement engineering curriculum in the Department of Civil and Environmental Engineering (CEE) at Michigan State University (MSU) consists of a suite of five courses, two at the undergraduate level (4XX series senior level) and three at the graduate level (8XX series). First-year graduate students are allowed to enroll in the 4XX design courses if they lack the necessary background in pavement analysis and design. The two undergraduate courses are titled “CE431—Pavement Design and Analysis-I,” and “CE432—

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Pavement Rehabilitation." The three graduate courses are titled "CE831—Pavement Design and Analysis-II," "CE835—Pavement Management," and "CE837—Infrastructure Materials." Three pavement engineering faculty members share the load of teaching these five courses.

UNDERGRADUATE PAVEMENT DESIGN AND REHABILITATION COURSES

Course CE431 is offered twice a year (fall and summer semesters). The average fall enrollment is 30 and 15 during the summer. The prerequisites for this course are a required junior-level course in construction materials and a course in soil mechanics. The course description reads as follows: "The students will be exposed to pavement structural design, evaluation of performance measures, failure mechanisms, thickness design procedures (state-of-the-practice), and design considerations for surface friction, pavement joints, and drainage." The assessment is based on homework assignments (20 percent of the grade), two design projects (30 percent), two exams (30 percent) and weekly quizzes (20 percent). The text is *Pavement Analysis and Design*, by Yang H. Huang (1993).

Course CE432 is offered once a year (spring semester), with average enrollment of 25. The course description reads as follows: "The students will be exposed to techniques in pavement evaluation, distress identification, pavement rehabilitation strategies, life cycle cost analysis, and strategy selection." The assessment is based on homework assignments (10 percent of the grade), two design projects (40 percent), two exams (40 percent), and weekly quizzes (10 percent). The course uses the *Techniques for Pavement Rehabilitation* (Reference Manual), Federal Highway Administration, as a textbook.

GRADUATE PAVEMENT DESIGN COURSE

Course CE831 is offered once a year during the spring semester and uses the Huang (1993) text. The average enrollment is seven people. The course description reads as follows, "This course deals with advanced pavement analysis and design. The students will be exposed to theoretical models, numerical models, performance characterization and damage models for pavements." The main objectives of the course are to expose students to advanced pavement analysis techniques. As such, they learn about the different pavement response and performance prediction models. The course is divided into two parts dealing with flexible and rigid pavements, respectively. The, students learn to use pavement analysis programs such as KENLAYER (Huang, 1993), MICHPAVE, MICHBACK, (Buch, et al., 1999) and Stet 2000 (ERES Consultants, 2000). The assessment is based on homework assignments (40 percent of the grade), two exams (50 percent) and weekly quizzes (10 percent). The homework assignments were divided into two categories: Type I comprises the conventional assignment where questions are directly related to the lectures, assigned reading, and class notes, purpose being to measure "short-term transfer" of knowledge. Type II assignments consist of open-ended questions and required students to access data from the DataPave 3.0 software to conduct the analysis.

The use of DataPave 3.0 in CE835 and CE837 is under development; hence, these courses will not be discussed further in this paper.

EXAMPLES OF DATAPAVE 3.0 APPLICATION

CE432—PAVEMENT REHABILITATION

Traditionally, this course consists of two design projects, one for rigid pavement and one for flexible pavement rehabilitation. During the first few offerings of this course, the distress data were obtained from local and county roads; the pavement cross sections and traffic distributions were assumed; and little or no deflection information was available. Because the sites selected were from local and county roads, the distress types were very restricted. The disadvantage of these projects was that many assumptions had to be made to complete the analysis. Moreover, the absence of time-series data did not adequately demonstrate the idea of pavement deterioration. With these shortcomings in mind, the instructors decided to explore the use of DataPave 2.0/3.0 as a source for extracting real-time series pavement distress and deflection data. The database also provides information on traffic growth (in terms of average daily traffic (ADT), equivalent standard axle loads in thousands (KESALS), and axle distribution), pavement inventory, and climate.

It was envisioned that after completing the project the students would:

- Be familiar with the LTPP database.
- Be able to extract information from the database.
- Be able to synthesize traffic, distress and deflection data.
- Be able to use the synthesized data for pavement analysis and determine remaining life of the pavement.
- Be able to develop preventative and rehabilitation strategies for the repair of distressed pavements.

The class received entire project statement with the tasks and the data on the first day. Because the class was large and students had varying pavement experience backgrounds, the instructors extracted the raw data from the master database and gave it to the groups rather than providing access to the entire database. Students were introduced to typical data, definitions of terms, and data layout through a series of tutorial sessions held after regular class hours. As part of the project deliverables, each group was to develop:

- Graphical relationships among time, distress, and severity level for the assigned LTPP section.
- Graphical relationships between time and traffic (for some groups this was time versus ADT, for some it was time versus KESALs, and for others it was time versus axle growth) for the assigned LTPP section.

- Graphical relation between International Roughness Index (IRI) and distress deterioration (if any).
- Analysis of the deflection data to quantify load transfer efficiency (LTE) for rigid pavements, backcalculated layer parameters (for both pavement types), void potential and lateral support (for rigid pavements), and to relate this analytical data to the observed pavement performance.
- The rehabilitation strategy/strategies to "fix" the problems and extend pavement life, selection of final strategy would be based on engineering and economic considerations.
- Sketch of the pavement section indicating the distress type, severity, and locations.

Reports were graded on format, technical content, and group interviews.

Inventory Data

To illustrate the deliverables (for rigid pavements), the authors have chosen examples from Strategic Highway Research Program (SHRP) ID 1-4084-1, General Pavement Study-4 (GPS) Jefferson County, AL. This section was assigned to a group of three students. The original surface layer is 266.7 millimeters (mm) (10.5 inches) of portland cement concrete (PCC) jointed reinforced concrete pavement (JRCP); the base layer is 142.24 mm (5.6 inches) of gravel (uncrushed); the subbase layer is 347.98 mm (13.7 inches) of soil aggregate mixture (predominantly coarse grained); and the subgrade layer is clayey sand. The original construction date of the pavement is June 1, 1970. The inside and outside shoulder is asphalt. There is no subsurface drainage. The average joint spacing is 17.575 meters (m) (57.5 feet (ft)). Round dowels were used for load transfer and the longitudinal steel content is 0.1 percent. The freezing index is –2.94 degrees Celsius (^{o}C) (27.3 degrees Fahrenheit (^{o}F)) days, and the climatic region is wet-no freeze. This region experiences 375 m (1476.4 inches) of precipitation, and 63 days above 36.25 ^{o}C (90 ^{o}F). Climatic data was available for 27 years. In 1995, the annual average daily traffic

(AADT) was 13,057, and the average daily truck traffic (ADTT) was 639. The pavement inventory and cross section information is summarized in figure 1, which is a screen capture from DataPave 3.0.

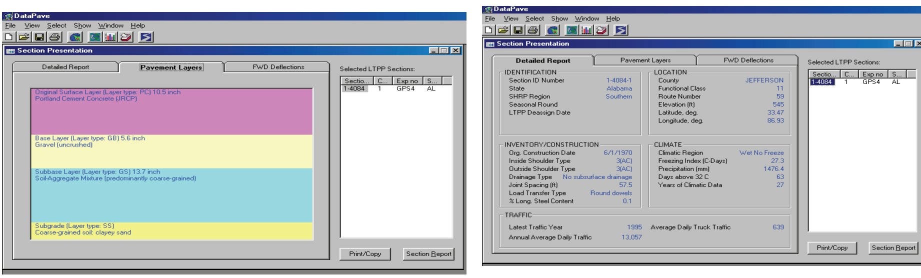
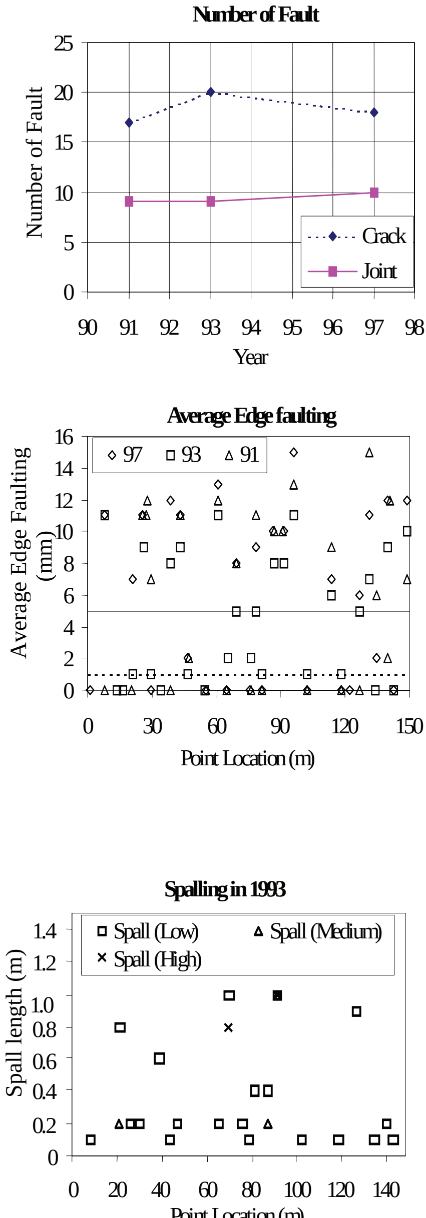


Figure 1. Pavement inventory and cross section information for SHRP ID 1-4084-1

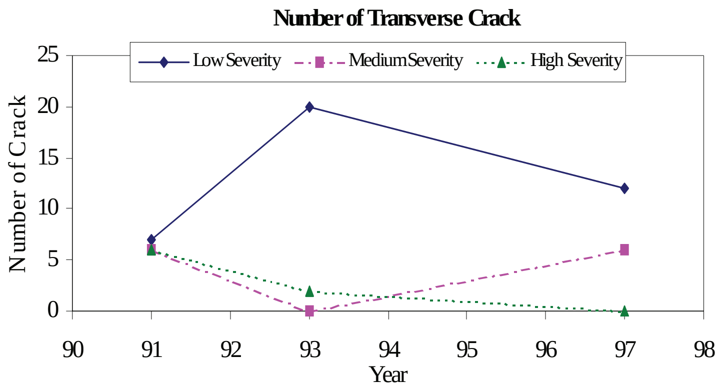
Distress Evaluation

The distress data were extracted from DataPave 3.0 tables MON_DIS_JPCC_REV and MON_DIS_JPCC_REV. In summary, the distresses included medium-to-high-severity faulting, low-to-medium-severity transverse cracks, low-to-high-severity spalling, sealant damage, polished aggregates, scaling, and map cracking. Figures 2 and 3 illustrate the magnitude and severity of distresses as a function of time and location (where available).



1 mm = 0.039 inches
1 m = 3.28 ft

Figure 2. Distress progression as a function of time



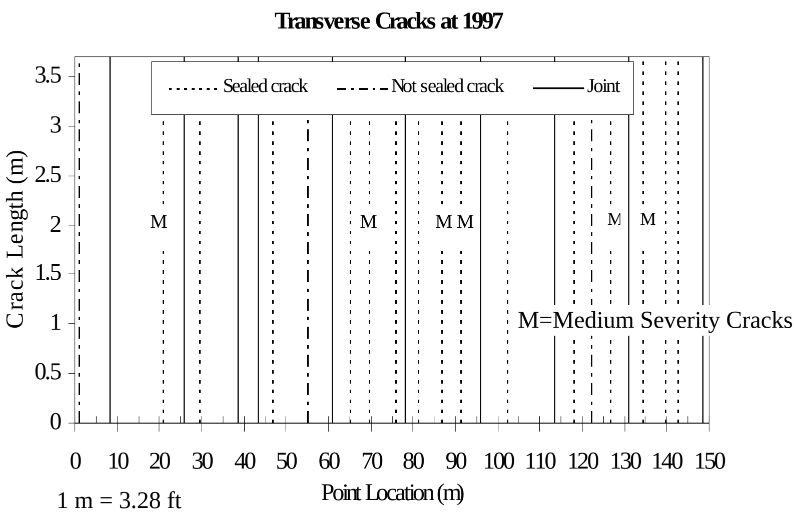


Figure 3. Progression of distress as a function of time

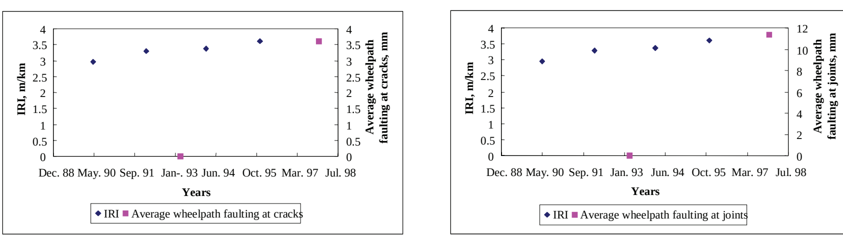
The other distresses observed for this SHRP ID are summarized in table 1.

Table 1. Other distresses found in this section

Year	Low-Severity Longitudinal Joint Seal Damage (m)	Low-Severity Longitudinal Joint Spalling (m)	Scaling (square meter $(m^{2)})$	Polished aggregate (m^2)	Map Cracking (m^2)
1991	–	–	557.4	–	–
1993	305	10	–	366	559.6
1997	–	–	–	305	–

Dashes in cells represent “no data available” or “zero” distress.
1 m = 3.28 ft
1 m^2 = 10.8 ft^2

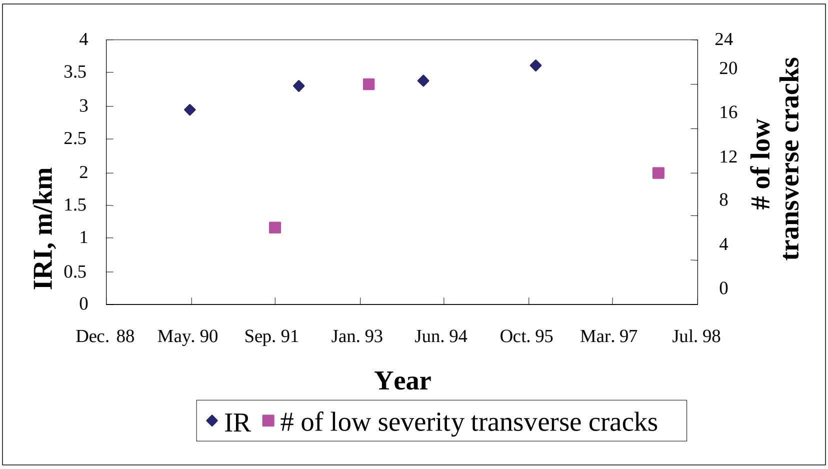
A review of the relationship between pavement roughness and distress shows that as the distresses increase in magnitude the pavement appears to get rougher. Interestingly, it can be hypothesized that the roughness precedes the manifestation of distress. These relationships are summarized in figures 4 and 5.



(a) (b)

1 meter per kilometer (m/km) = 63.36 inches per mil (inches/mi)
1 mm = 0.039 inches

Figure 4. Relationship between IRI and joint and crack faulting



1 m/km = 63.36 inches/mi

Figure 5. Relationship between IRI and transverse cracking

Functional Evaluation

The functionality of a pavement can be described in many forms, such as the International Roughness Index (IRI), (as reported in DataPave 3.0) and the Present Serviceability Index (PSI) as characterized by American Association of State Highway and Transportation Officials (AASHTO). Using the relationship between PSI and IRI reported by Hall and Correa (1999), the PSI was calculated to be between 2.0 to 2.5.

Structural Evaluation

For the structural evaluation, the design groups extracted deflection and temperature gradient information from the data tables labeled MON_DEFL_DROP DATA, MON_TEMP_DEPTH DATA, and MON_TEMP_VALUES_ DATA.

The deflection at the midslab (J1) was used to compute the modulus of elasticity of concrete (E_c) and the modulus of subgrade reaction (k). Moreover, the data were used to subdivide the project into three distinct subsections based on the magnitudes of the deflections. The variation in deflection as a function of project length is summarized in figure 6. Deflection data at the corner of the slab (J2) were used for calculating the void potential underneath the corner of PCC slabs; the deflection from the slab edge (J3) was used to compute the lateral support provided by the shoulder; and the data from positions J4 and J5 were used to compute approach and leave load transfer efficiencies (LTE) respectively. Figure 7 illustrates the various falling weight deflectometer (FWD) test locations.

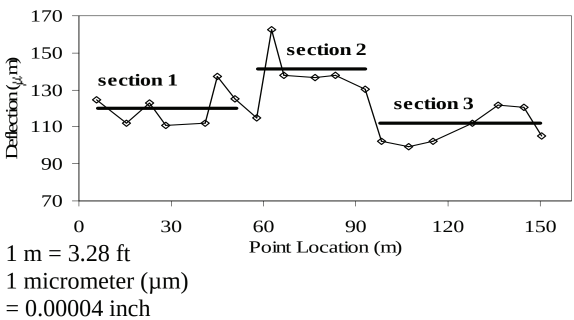


Figure 6. Deflection profile as function of distance

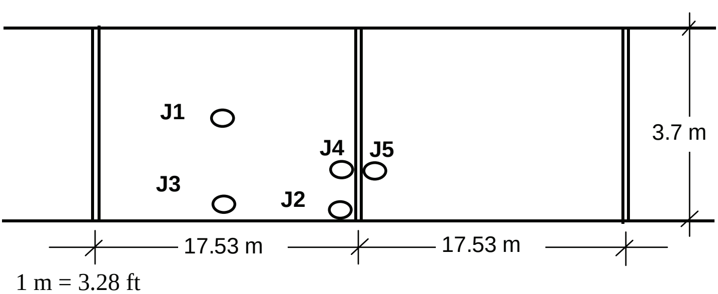
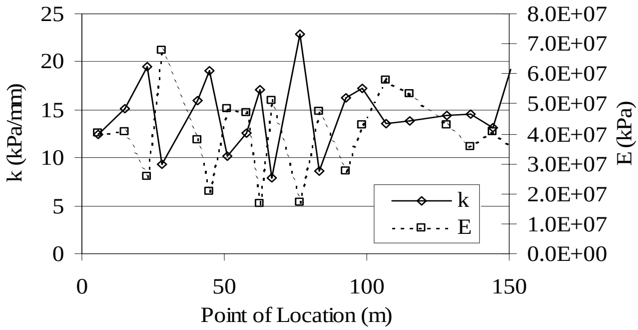


Figure 7. LTPP FWD positions

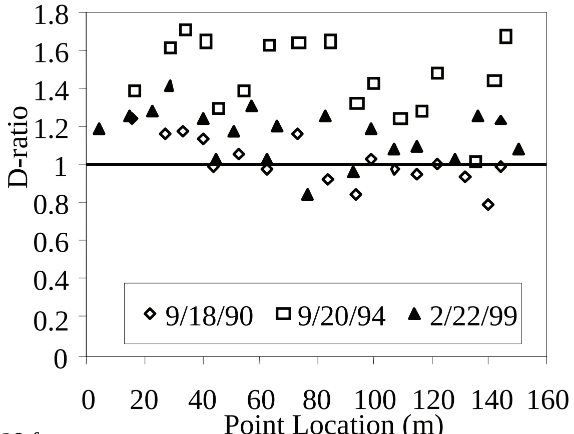
The backcalculated layer parameters for this example section are summarized in figure 8.



1 m = 3.28 ft

Figure 8. Backcalculated layer parameters

The deflection ratio (D-ratio), which is a good indicator of lateral support along the edge of the slab, was calculated. The results are summarized in figure 9. If the slab has a uniform adequate support, this ratio should be close to 1. The lack of lateral support results in D-ratio values significantly greater than 1.



1 m = 3.28 ft

Figure 9. D-ratio versus point location for years 1990, 1994, and 1999

Figure 10 shows the LTE calculated from J4 for the 3 years at each point location.

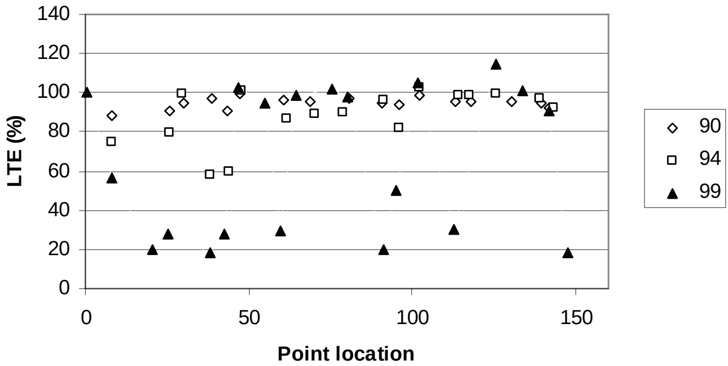


Figure 10. LTE versus point location (J4)

The group further investigated the relationship between void potential and load transfer efficiency. The results from this investigation are summarized in figure 11.

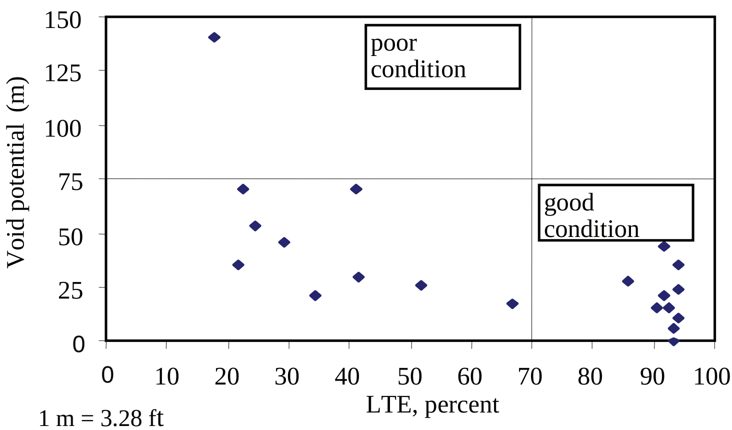


Figure 11. Relationship between LTE and void ratio

The traffic data for this section were available as annual KESALs between 1976 and 1989. Based on this information the group computed the growth rate and subsequently was able to predict future ESALs for the year 2011. Figure 12 summarizes the ESAL information for this project.

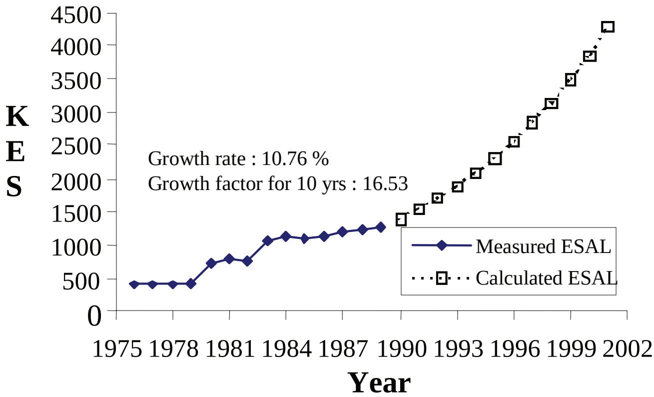


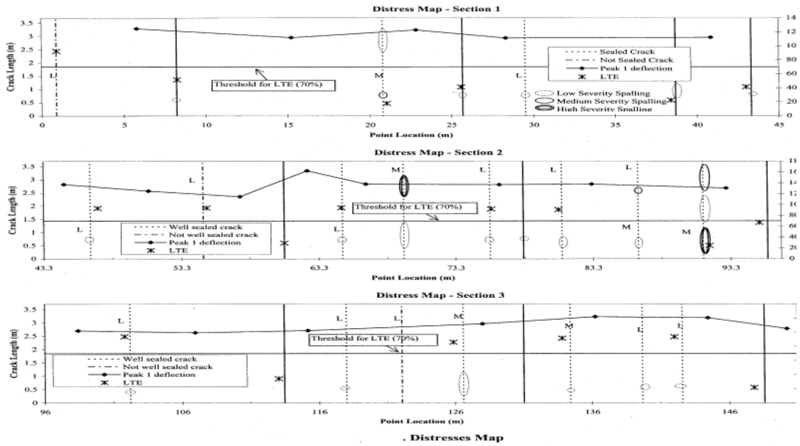
Figure 12. Measured ESAL and predicted ESAL

Once the individual pieces of the project were analyzed, the next task was to synthesize this information, rank the distresses, and suggest rehabilitation strategies. The ranking was based on backcalculated layer parameters, severity levels of distresses, magnitude of void potential, and LTE magnitudes. Table 2 summarizes ranking information, and figure 13 illustrates the distress map.

Table 2. Ranking based on distress and computed responses

At Cracks and Joints						At mid Slab and Edge				
Point Location (m)	Average Edge Faulting	LTE (J5)%	LTE (J4)%	Void Potential	Spall	Point Location J1 (m)	Peak Deflection	Average K	Average E	D ratio
0.9	18	15	15	16	–	5.8	7	5	9	11
8.2	14	9	10	11	L	15.2	13	12	11	4
20.8	18	1	4	1	L,M	22.9	9	19	4	3
25.7	17	7	6	2	L	28.3	16	3	20	1
29.5	18	–	–	–	L	–	–	–	–	–
38.7	18	3	1	3	L	40.8	13	13	8	7
43.3	13	8	5	9	L	44.8	4	17	3	17
46.7	18	16	18	19	L	50.9	7	4	16	12
54.9	18	18	12	12	–	57.6	12	6	14	2
60.8	10	5	7	5	–	62.5	1	15	1	16
65.0	10	20	14	7	L	66.8	2	1	17	9
69.5	18	–	–	–	L,H	–	–	–	–	–
75.8	18	14	17	6	L	76.5	4	20	2	20
78.2	18	–	–	–	L	–	–	–	–	–
81.0	16	12	13	16	L	83.2	2	2	15	5
86.6	17	–	–	–	L,M	–	–	–	–	–
91.3	3	4	3	4	L,M,H	93.0	6	14	5	19
96.0	18	10	9	15	–	98.5	18	16	12	10
102.2	6	19	19	18	L	107.0	20	8	19	14
113.5	6	6	8	13	–	115.2	18	9	18	13
118.0	3	–	–	–	L	–	–	–	–	–
122.1	6	–	–	–	–	–	–	–	–	–
126.6	2	11	20	10	L	128.0	13	10	13	18
131.0	12	–	–	–	–	–		–	–	–
134.4	1	13	16	13	L	136.2	10	11	6	6
139.7	14	–	–	–	L	–	–	–	–	–
142.6	6	17	11	–	L	144.5	11	7	10	8
148.6	3	2	2	7	–	150.3	17	18	7	15

1 m = 3.28 ft



1 m = 3.28 ft

Figure 13. Example of a distress map

Based on the overall distress condition and the ride quality of the pavement section, the group recommended the construction of an unbounded concrete overlay, whose design was done in accordance with the AASHTO 1993 procedure. It was also suggested that pre-overlay repairs be conducted prior to the construction of the overlay.

Similar design projects were done by other student groups, but space limitations prohibit presenting flexible pavement rehabilitations projects. The subsequent sections will describe the use of DataPave 3.0 in CE831 and the example(s) described deal with flexible pavements.

CE831—PAVEMENT ANALYSIS AND DESIGN II

Traditionally, the course includes several assignments dealing with pavement analysis and a comprehensive design project using the mechanistic-empirical approach. A main shortcoming of the assignments and project was the lack of "real" performance data that could be used to evaluate the accuracy of the mechanistic predictions. Accordingly, the instructors decided to explore the use of the LTPP DataPave 3.0 data as a source for extracting "real" pavement response and performance data, which the students could use to evaluate existing performance prediction models. The database also provides information on traffic growth (in terms of ADT, KESALS, and axle distribution), pavement inventory, and climate.

The reports were graded according to similar criteria to those in the CE432 class. These criteria were handed out to the students along with the problem statement.

The overall objectives of the LTPP-based assignment are similar to those in CE432, with the specific objectives being:

- To select 3 sections from the assigned SPS-1 sites.
- To synthesize the inventory, deflection, roughness, distress and traffic data.
- To investigate the relationships between pavement performance and response
- To provide an engineering discussion summarizing the findings.

Each student had to select three sections from the assigned SPS-1 site, each representing a dense-graded aggregate base (DGAB), asphalt-treated base (ATB) and permeable-asphalt-treated base (PATB) with external drainage. To illustrate the deliverables for flexible pavements, the authors have chosen an example from the SPS-1 site in the State of Louisiana (State Code 22).

The following tasks were assigned as a starting point to assist students in satisfying the assignment objectives:

TASK 1: Selection of Sections from SPS-1 Sites

Each SPS-1 site consists of 12 sections, with varying asphalt concrete (AC) thickness, base thickness, and base type. The last four sections are provided with some drainage to study drainage impact on pavement performance. All the 12 SPS-1 sections for the State of Louisiana were examined for the following characteristics:

- The pavement cross-section, including the subgrade.
- The type of base: whether granular, cement treated, or asphalt treated.
- The most important aspect of this data inspection was to observe the amount and quality of the performance data available in LTPP.

Three sections were selected for this example, as shown in table 3.

Table 3. The LTPP section report

Section No.	Layer Thicknesses (inches)	Drainage Type
22-0114-1	AC Layers: 1.4+8.1 = 9.5 Crushed Gravel, Granular Base (GB): 11.4 Granular Subbase (GS): 12 Fine-grained soil, lean inorganic clay	None
22-0116-1	AC Layers: 2+2.8 +11 = 15.8 Granular Subbase (GS): 18” Fine-grained soil, lean inorganic clay	None
22-0124-1	AC Layers: 1.3+5.9 +10.6+3.2 = 21 Granular Subbase (GS): 30 Fine-grained soil, lean inorganic clay	Blanket w/long drains

1 inch = 25.4 millimeters

An example of the layer cross section is illustrated in the screen capture in figure 14.

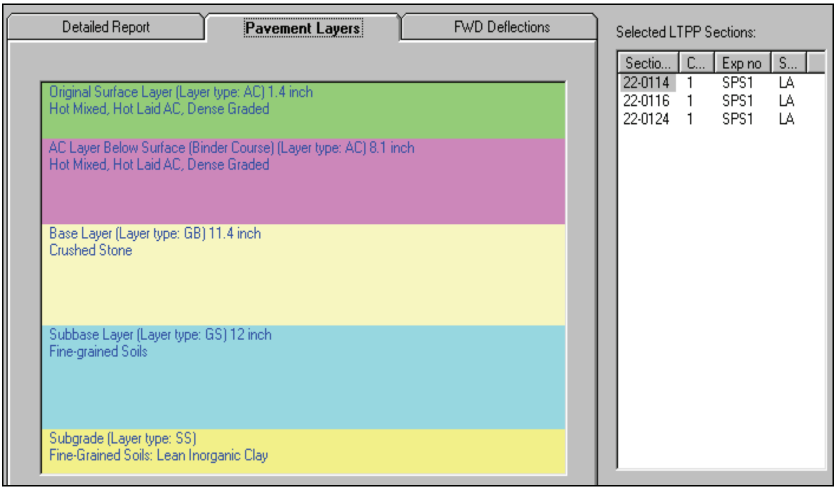


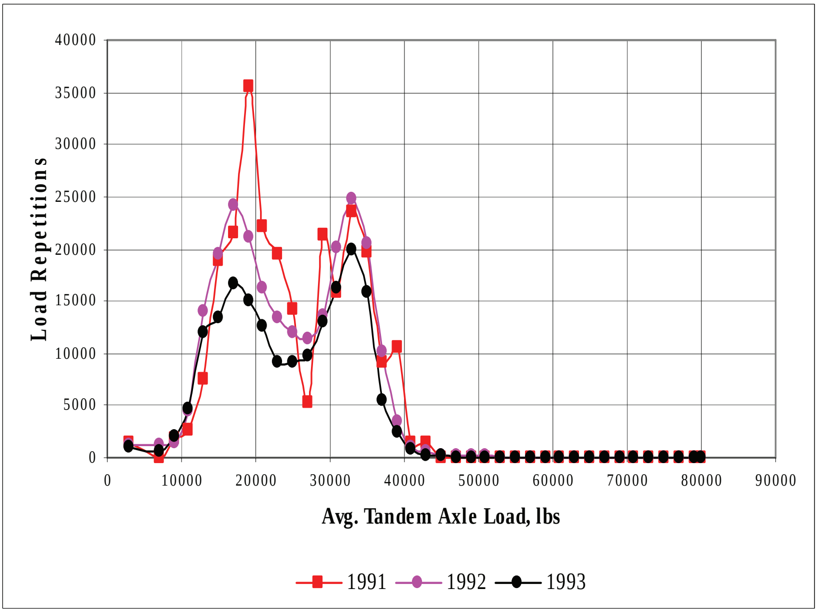
Figure 14. The pavement structure details for Section 22-0114

TASK 2: Data for Selected SPS-1 Sites

The relevant data for the selected sites in the assignment were:

- Various performance measures (fatigue cracking, transverse cracking, rutting and IRI).
- Environmental data (temperatures, etc.).
- Inventory data (layer thicknesses, base type, and drainage, etc.).
- Traffic data with time (axle load spectrum for various axle types, etc.).

During the search for traffic data for SPS-1 sites in Louisiana, no traffic data were found for enough number of years to ascertain the growth rate and cumulative ESALs and axle load repetitions. Therefore, traffic data available for the GPS sections in Louisiana from 1991 to 1993 were used. The load spectra for single, tandem, and tridem, axle loads for the selected sites were extracted and used in the analysis to calculate ESALs. Figure 15 shows an example of load spectra distribution for tandem axles.



1000 pounds (lbs) = 454 kilograms (kg)

Figure 15. Tandem axle load spectrum

Because actual KESAL data were available for more years (1991–1996) in the monitoring data for the same GPS section, these data were used to ascertain the traffic growth rate. A growth rate of 9 percent was assumed based on the past trend of the traffic data.

Figure 16 shows the actual monitored trend of the KESAL on this road section for the past 6 years and predicted ESALs for future years based on 9 percent growth rate. The details of ESALs and growth rate calculation are not provided in this paper. Because the three sections are adjacent to each other, the same traffic is assumed for all of them. From the given traffic data, it was found that the sections have sustained about 3.5 million ESALs between 1991 and 2002.

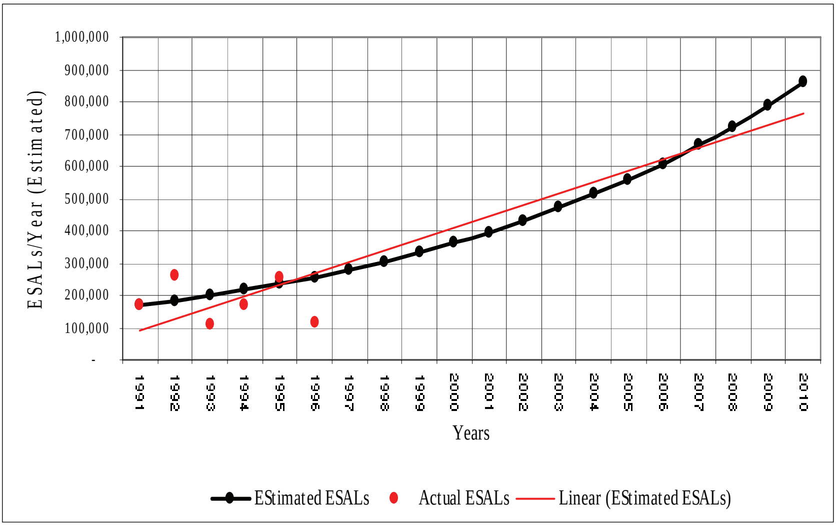


Figure 16: Actual and predicted ESALs

TASK 3: Pavement Performance and Response for Selected SPS-1 Sites

This task shows the actual versus predicted pavement performance for the three selected sections, which have different characteristics but are subjected to the same environmental and loading conditions. The following sections summarize the analysis conducted.

Material Characterization

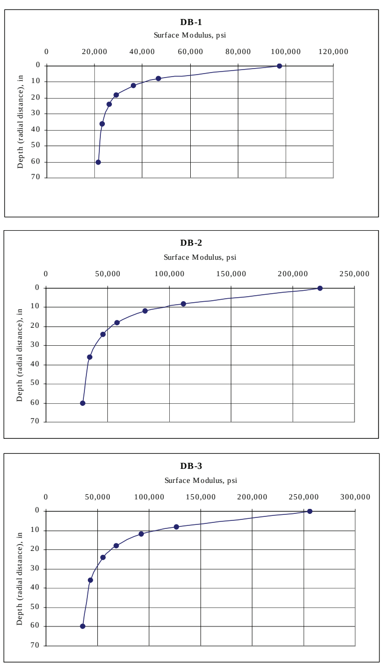
In situ layer moduli for different layers were backcalculated by using the FWD deflection data for each section. Three representative deflection basins (one for each section) were selected. The new version of MICHBACK (MFPDS) software was used for the backcalculation. The students also investigated the presence of a stiff layer.

The backcalculation of the layer moduli is very sensitive to the presence of a stiff layer below the roadbed. A simple equation based on Boussinesq's equation for a point load was used to estimate the modulus from the surface deflections.

$$E = P * (1 - \mu^2)/[\pi * r * d_o(r)] \tag{1}$$

where P is the applied load and $d_o(r)$ is the surface deflection at distance r from the center of the load.

The above equation was used to calculate the moduli for the various deflections as a check on the linearity of the subgrade. The results are shown in figure 17. Based on this plot, it was concluded that there is no stiff layer or ground water table close to the surface of the pavement.



1 inch = 25.4 millimeters
1 psi = 145 MPa

Figure 17. The average surface moduli plot with depth for three selected sections

Various AC layers (surface course, binder course, and ATB course) and granular materials (base and subbase) were combined to eliminate complications with the backcalculation. The summary of the backcalculated layer moduli for different sections is given in table 4 below. Details of the results and the deflection profile for each section are not shown in this paper.

Table 4. Summary results for material properties based on backcalculation, September, 1998

Section Number	Backcalculated Moduli, psi		
	Asphalt Layers	Granular Material Layers	Subgrade
22-0114-1	315,321	46,658	20,562
22-0116-1	841,822	116,570	28,100
22-0124-1	629,161	68,053	31,880

1 psi = 145 MPa

Pavement Response

The layer thickness data along with the backcalculated moduli of the various layers were used for the analysis of the layered system for the selected section using the KENLAYER computer program. The summary results are presented in table 5 below:

Table 5. Summary of the pavement response

Section Number	Pavement Response			
	Deflection[1] (mils)	Tensile Strain[2] (microns)	Vertical Strain[3] (microns)	Vertical Stress[4] (psi)
22-0114-1	9.10	113.0	83.0	2.210
22-0116-1	3.75	23.6	28.7	1.210
22-0124-1	3.50	20.5	23.0	0.764

1 = Surface deflection. 1 mils = .001 inch
2 = Tensile strain at the bottom of asphalt layer. 1 psi = 145 MPa
3 = Vertical strain at the top of subgrade.
4 = Vertical stress at the top of subgrade.

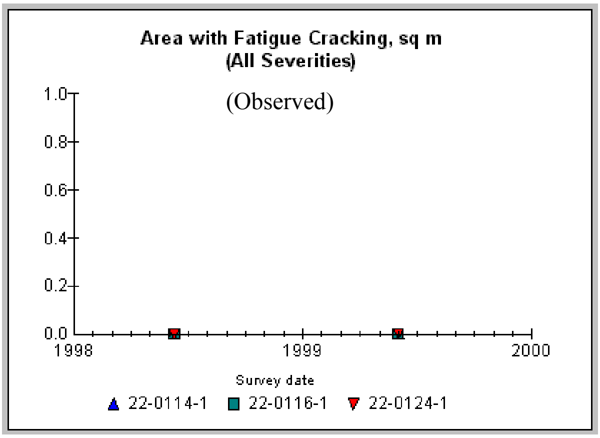
The analysis was based on a dual wheel load of 4086 kg (9000 pounds); the critical response was calculated at the center of the tire, edge of the tire, and between the wheels. The maximum response was found between the wheels, which were subsequently used in the performance models. Given the low stress levels, a linear analysis was used to calculate the pavement response. The seasons were considered in the analysis were fall (August, September, October; 3 months); winter (November–March; 5 months); and spring and summer (April–July; 4 months).

The seasonal analysis was carried out by assuming various material properties and average ESALs in a particular season.

Pavement Performance

Three performance measures were analyzed:

- Fatigue Cracking. Figure 18 shows the fatigue cracking observed in the field since the opening of these sections (from 1991–2000). Seven models were used to calculate the allowable number of ESALs (N_f) for the selected sections.



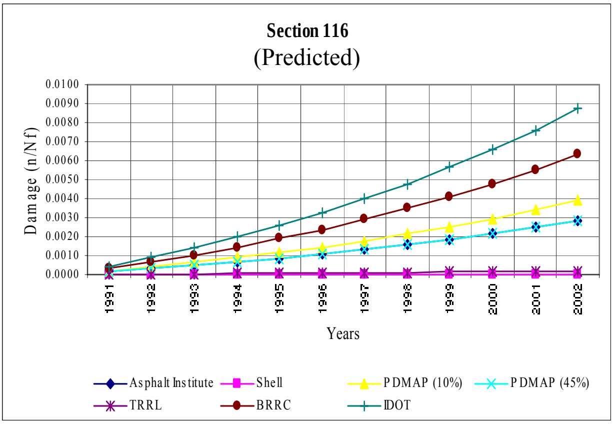


Figure 18. Example of observed and predicted fatigue cracking

All models predicted a sufficient remaining life for fatigue (n/N < 0.01), except for the Belgian Road Research Center (BRRC) model for section 22-0114-1. Hence, the prediction by the majority of these models was deemed as representative of the actual field performance data.

- Rutting in the wheel path. Rutting can be defined as the permanent deformation in the wheel path in transverse plane along the direction of the traffic. Rutting is a load-associated distress and can be caused in the subgrade (wide rut channel), base, or subbase layers and asphalt layers only (narrow rut channel). The field performance data for the selected section show some signs of rut, as shown in figure 19.

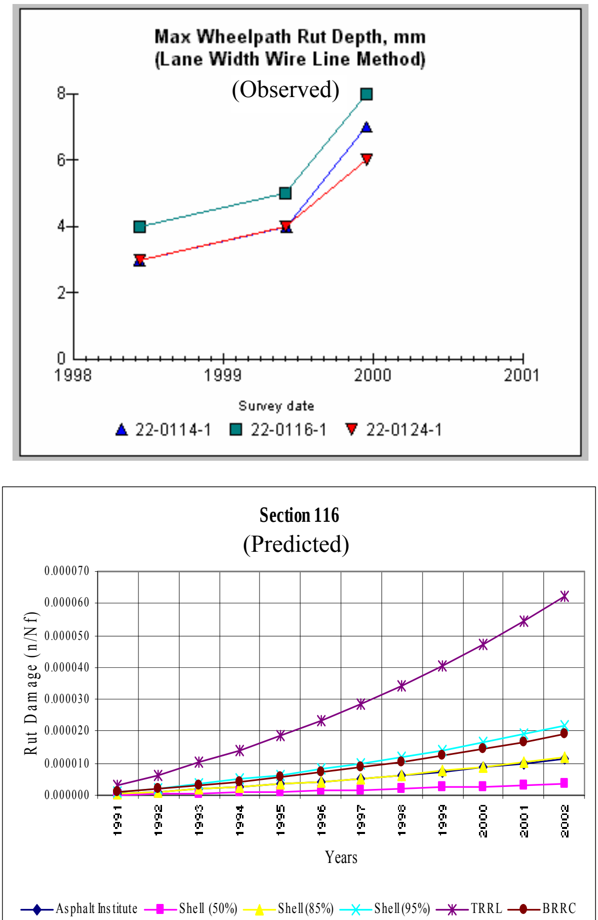
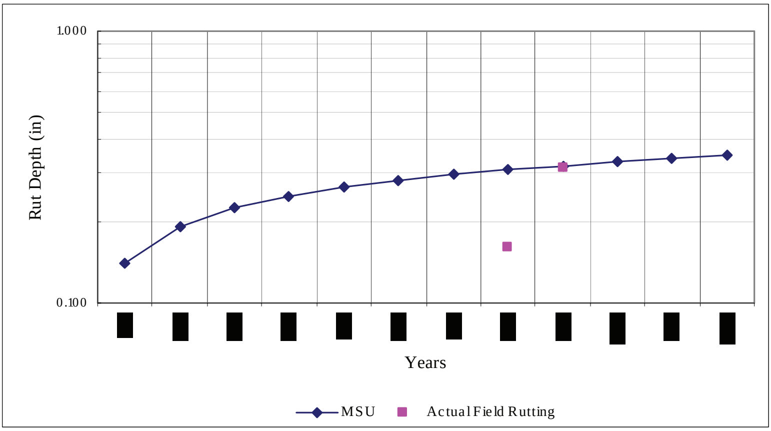


Figure 19. Example of observed and predicted rutting

All the above models predicted a low rutting damage (n/N). The results from the MSU rut models are shown in figure 20.



1 inch = 25.4 millimeters

Figure 20. Predicted rut depth for section 116

- Transverse cracking. No transverse cracking was observed.

TASK 4: Engineering Discussion and Summary of Findings

Most of the analysis and evaluation presented in tasks 1 to 3 can be summarized as follows:

- Three sections from LTPP SPS-1 sites for Louisiana were selected based on the various base types and drainage characteristics.
- Various critical distresses for these selected sections along with the inventory, material, traffic, and environmental data were extracted from the LTPP DataPave 3.0.
- If any missing or insufficient data were found in SPS-1 sites, then reasonable data were extracted for GPS sites within the same state in the close vicinity of these SPS-1 sites. In the worst case, i.e., no required data available, reasonable data were assumed.
- The actual critical distresses extracted were plotted against the predicted distresses. It was found that the predicted distress levels agreed reasonably with the actual levels. However, there were some discrepancies; these can be

attributed to the empirical nature of these models and data assumptions.

- From the traffic analysis (load spectrum), it was found that single and tandem axles load repetitions occupy about 40 percent and 59 percent shares, whereas tridem axles only have 1–2 percent of the share. This trend is consistent over time.
- The fatigue analysis for all sections shows that there should be no sign of this distress for the next 5–10 years.
- The fatigue life for the section with ATB and drainage was found to be infinite.
- The only load-associated distress observed in the selected pavement sections was rutting; the MSU rut model seems to predict this distress with reasonable accuracy considering overall rutting in all pavement layers.
- All subgrade-strain based models were predicting a high number of repetitions to rut failure; therefore, it can be assumed that the rutting in these pavement sections pertains to permanent deformations within the pavement structure.
- The analysis showed that a simple analysis with appropriate material properties and traffic estimates could be used to give reasonable predictions of the performance of new flexible pavement structures.

CONCLUSIONS

In the author's opinion, the use of DataPave 3.0 as a source of "real" pavement data has considerably enhanced the quality of the pavement rehabilitation, design, and analysis courses. The initial offerings proved to be a challenge both for the instructors and for the students, because the learning curve is rather steep. As instructors, the authors had to commit considerable time to prepare the project statements, hold tutorials, and respond to questions on the use of the database. The hope is that the time commitment will diminish after multiple offerings as the instructors become more comfortable with the database. It is hoped that the LTPP database, and more specifically the DataPave 3.0 (and subsequent future versions), will be incorporated into the other pavement management and material courses at Michigan State University.

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DISCLAIMER

The paper presents results obtained by student groups and does not represent the opinions of the authors or Michigan State University. The sole purpose of this paper is to demonstrate the use of DataPave 3.0; it does not constitute a standard or specification.

PAPER 2 TRANSFORMING LTPP DISTRESS INFORMATION FOR USE IN MTC-PMS

By Shameem A. Dewan[1]

ABSTRACT

The severities, types, and definitions of surface distresses used in the Strategic Highway Research Program (SHRP) database for Long-Term Pavement Performance (LTPP) sites are not the same as those used in the Metropolitan Transportation Commission Pavement Management System (MTC-PMS) system. Therefore, to use the LTPP distress data as inputs in the MTC-PMS software, the LTPP data must be transformed to match the MTC-PMS distress definitions. The objective of this paper is to describe a method to complete such transformations. Data conversion and use of converted data as inputs in the MTC-PMS were performed to develop a model for International Roughness Index (IRI) as a function of pavement condition information (the IRI model is intended for use in estimating user costs/benefits in the pavement management system). The condition information includes all MTC distress-severity combinations transformed from LTPP data, and corresponding deducts, percent load related deducts, percent nonload related deducts, and pavement condition index (PCI) values calculated using MTC-PMS software. The paper first presents the differences in definitions of distresses and severities in the two systems. It describes the selection of appropriate LTPP distress types to be transformed to generate required MTC distress data. Then the data transformation techniques for different distress types and severities from the LTPP system to the MTC system are explained. It was found that several types of manipulations were required to conduct the transformation of different distresses. These manipulations were performed based on the differences in definition for distresses and severities in the two systems. An IRI

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model was eventually developed using the transformed distress data and the output from MTC-PMS software.

INTRODUCTION

The MTC-PMS of Oakland, CA, does not consider road user costs in producing decision support recommendations (MTC, 1999). Management system capabilities can be improved by incorporating models that estimate road user costs and/or user benefits attributable to different management strategies. Because the road user cost is a function of pavement roughness (Gillespie, 1981), it will be helpful to estimate pavement roughness to incorporate user cost models in the pavement management system. However, the MTC-PMS system uses only distress information to estimate and predict pavement conditions, so it was necessary to establish a correlation between IRI and pavement distresses. The objective was to estimate road user costs for the streets in the cities and counties of the San Francisco Bay area directly from MTC pavement distress information and incorporating additional models for user costs relating IRI. The distress information used all MTC distress-severity combinations, deduct values, and PCI values calculated from all distress-severity combinations using MTC-PMS.

The distresses types, along with their severities, used in MTC-PMS software, are defined in MTC's distress identification manual (MTC, 1986). The cities and counties of the San Francisco Bay area do not generally have IRI data available for their city and local streets, but the distress and IRI data for State highways and freeways of California's LTPP sites are available in the SHRP database. In the future, it would be more appropriate to use data for the model from the city streets instead of using LTPP site's data. However, the current effort to develop an IRI model using the LTPP distress data can be considered as a starting point, and the intended model will need refinements in future using data from city streets.

This study requires the MTC-PMS system to use SHRP's LTPP distresses as inputs to calculate PCI values and deducts prior to the use of these data in the statistical analysis to develop the intended IRI model. But the severities, types, and definitions of surface distresses used in the SHRP database for LTPP sites are not the same as those used in the MTC-PMS. The definitions of distress types and extents of severities in the two systems differ in several respects. For asphalt concrete surfaces, the LTPP database uses 15 types of distresses (SHRP, 1993), while MTC-PMS uses only 7 distress types to define road conditions. Because of the differences in the two systems for distress types, severities, and definitions, the LTPP distress information had to be transformed to MTC distress information before being used as inputs in the MTC-PMS software.

To achieve the intended IRI model using LTPP distress data, the following major activities were required:

- Extraction of SHRP distress data and IRI data from the SHRP database for California LTPP sites.
- Transformation of the SHRP distress data into MTC distress data based on the differences in distress definitions and severities in the two systems.
- Calculation of PCI values and deducts for all distress type-severity combinations using MTC-PMS software.
- Statistical analysis on the converted distress data, PCI values, and deducts along with corresponding IRI values.

DATA EXTRACTION FROM LTPP DATABASE

The extracted data for distress, transverse profile, and IRI values from the LTPP database were found in IMS Modules: Monitoring and Tables: MON_DIS_AC_REV, MON_T_PROF_PROFILE, and MON_PROFILE_MASTER, respectively (FHWA, 2001). The data were extracted to Microsoft® Excel® spreadsheets for further evaluation, conversion, and analysis.

The desired IRI model was a proof-of-concept model for the cities and counties of the San Francisco Bay area. Because of the lack of IRI data for Bay area city and county streets, SHRP data for California LTPP sites were used in this pilot study. The LTPP data for pavements with asphalt concrete on granular base (general pavement study GPS-1) and asphalt concrete on bound base (GPS-2) were extracted form LTPP DataPave 3.0 released in September 2001 (Federal Highway Administration (FHWA), 2001). Only 39 sets of data were available in the database September 2001 in the specific categories GPS-1 and GPS-2 in California and for which the profile dates of IRI data match survey dates of distress and transverse profile data. The profile dates of IRI were not exactly the same as the survey dates of distresses because the roughness measurements and the distress measurements were made on different dates. Reasonably close dates were considered in selecting these 39 data sets for conducting further analysis.

LTPP DISTRESSES VERSUS MTC DISTRESSES

MTC uses seven types of distresses with three severity levels that are slight modifications of the PAVER distress definitions (Shahin and Walters, 1990). The MTC distress types are (MTC, 1986):

- Alligator cracking.
- Block cracking.
- Distortions.
- Longitudinal and transverse cracking.
- Rutting and depression.
- Patching and utility cut patch.
- Weathering and raveling.

The three severity levels of the distresses are “Low,” “Medium,” and “High.” Considering the similarities between the MTC distress types and the LTPP distress types, the set of LTPP distresses used in this study includes:

- Fatigue cracking.
- Block cracking.
- Longitudinal cracking (wheel path and non-wheel path).
- Transverse cracking.
- Patch/patch deterioration.
- Shoving.
- Raveling.
- Transverse profile data (used to estimate rutting).

The MTC definitions of distress types and severities are different, in several cases, from the LTPP definitions of distress types and severities. Table 1 briefly describes the differences in definitions for severities between the two systems for the MTC distress types (MTC, 1986; FHWA, 2001). One difference between the LTPP system and MTC system not included in table 1 is that LTPP longitudinal cracking in the wheel path of any severity level is considered as a part of the low severity alligator cracking in the MTC system.

Table 1. Differences in definitions between MTC and LTPP for MTC distresses-severities (MTC, 1986; SHRP, 1993)

MTC Distress Type	Distress Severity	LTPP Definition	MTC Definition
Alligator Cracking	Low	Both definitions are similar for all severity levels.	
	Medium		
	High		
Block Cracking	Low	Crack width < 6 millimeter (mm)	Crack width < 10 mm
	Medium	6mm ≤ Crack width ≤ 19 mm	10mm ≤ Crack width ≤ 76 mm
	High	Crack width > 19 mm	Crack width > 76 mm
Distortions	Low	Both definitions are similar for all severity levels.	
	Medium		
	High		

Table 1. Differences in definitions between MTC and LTPP for MTC distresses-severities (MTC, 1986; SHRP, 1993)—*Continued*

MTC Distress Type	Distress Severity	LTPP Definition	MTC Definition
Longitudinal and Transverse Cracking	Low	Crack width < 6 mm	Crack width < 10 mm
	Medium	6mm ≤ Crack width < 19 mm	Crack width 10 mm to 76 mm
	High	Crack width > 19 mm	Crack width > 76 mm
Patching and Utility Cut Patch	Low	Both definitions can be considered similar for all severity levels.	
	Medium		
	High		
Rutting and Depression	Low	Rutting data are not available. Transverse profile data are available in LTPP database.	13 mm ≤ Rut depth < 25 mm
	Medium		25 mm ≤ Rut depth < 50 mm
	High		Rut depth ≥ 50 mm
Weathering and Raveling	Low	Both definitions are similar for all severity levels.	
	Medium		
	High		

1 mm = 0.039 inches

DATA TRANSFORMATION TECHNIQUES

It was necessary to transform several of the LTPP distress data types and severities to equivalent MTC distress types and severities. Table 2 shows which distresses in LTPP system were used to calculate which distresses in MTC system. First, the data in the LTPP database are stored in metric units (mm, etc.) were converted to English units (inch, etc.) to match the units system used in the MTC PMS software. Moreover, several manipulations were required to calculate MTC distress quantities in three severity levels from LTPP distress types and severities.

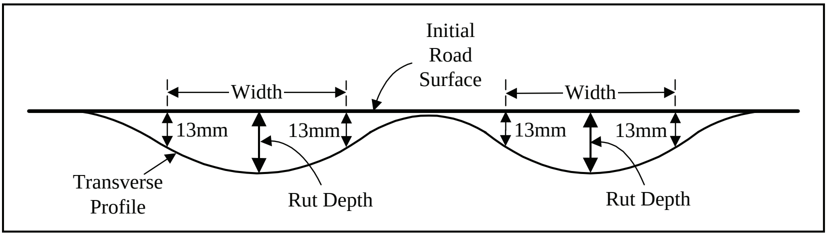
Table 2. Distress quantities in LTPP system used to obtain distress quantities in MTC system

MTC Distresses	Low Severity	Medium Severity	High Severity
Alligator Cracking	Add LTPP low severity alligator cracking and the portion converted from LTPP longitudinal cracking in wheel path	Use LTPP medium severity alligator cracking	Use LTPP high severity alligator cracking
Block Cracking	Use the distribution of LTPP block cracking quantities given in equation (1)	Use the distribution of LTPP block cracking quantities given in equation (1)	Use the distribution of LTPP block cracking quantities given in equation (1)
Distortions	Use LTPP shoving	Use LTPP shoving	Use LTPP shoving
Longitudinal and Transverse Cracking	Add LTPP low severity longitudinal cracking in non-wheel path and LTPP low severity transverse cracking	Add LTPP medium severity longitudinal cracking in non-wheel path and LTPP medium severity transverse cracking	Add LTPP high severity longitudinal cracking in non-wheel path and LTPP high severity transverse cracking
Rutting and Depression	Multiply low severity rutted width in LTPP system by distance between two profile measurements	Multiply medium severity rutted width in LTPP system by distance between two profile measurements	Multiply high severity rutted width in LTPP system by distance between two profile measurements
Patching and Utility Cut Patch	Use LTPP low severity patch/patch deterioration	Use LTPP medium severity patch/patch deterioration	Use LTPP high severity patch/patch deterioration
Weathering and Raveling	Use LTPP low severity raveling	Use LTPP medium severity raveling	Use LTPP high severity raveling

LTPP TRANSVERSE PROFILE DATA TO MTC RUTTING DATA

Transverse profile data from the LTPP database were used to calculate MTC rutting quantities. MTC measures rut depths and quantities by laying a 3-meter (m) (10-feet (ft)) straightedge across the rut. Rut depths are the maximum depths found in the wheel paths and rutted widths are the parts of the widths in the wheel paths rutted more than 13 mm (0.5 inches). The rutted widths were divided into three severity levels according to the definitions given in table 1. A rutting quantity (area) in a specific severity level was calculated multiplying the rutted width portion in that severity level by the length of the test section between the transverse profile measurements.

In the LTPP database, transverse profile data are stored for 152.4 m (500 ft) long by 3.66 m (12 ft) wide; sections are collected at an interval of 15.2 m (50 ft). For the current study, all transverse profile data sets that were selected for the study were plotted. Rut depths and rutted widths in different severity levels for both wheel paths were recorded from the plots. An Excel-Visual Basic® macro was written and used to facilitate this. Figure 1 shows a typical transverse profile plotted with LTPP transverse profile data and the measurement of rutted widths and rut depths for calculating MTC rutting quantities and severities.



1 mm = 0.039 inches

Figure 1. A schematic diagram for the measurement of rutted widths and rut depths from LTPP transverse profile data

LTPP BLOCK CRACKING TO MTC BLOCK CRACKING

According to the definitions of severities for block cracking, the ranges defining the boundaries of severity levels in the LTPP system are different from those in MTC system (see table 1). Figure 2 provides a graphic comparison of the definitions in two systems. This figure was used to develop ratios of quantities based on the width of the cracks to convert LTPP block cracking quantities in different severity levels to MTC block cracking quantities. The following equations were developed based on these relationships and used for the conversions.

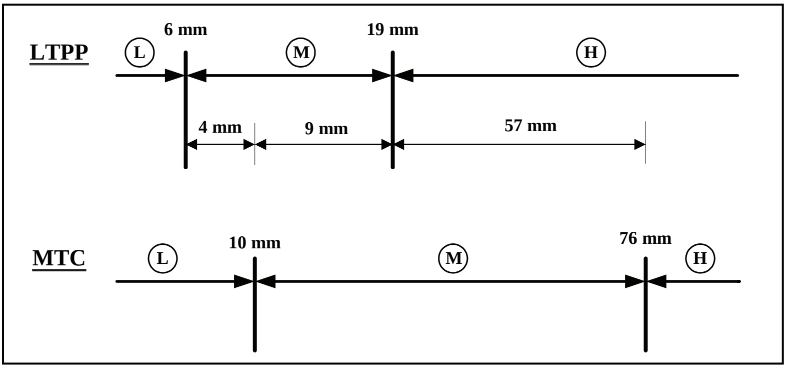
$$\begin{aligned} L_{MTC} &= L_{LTPP} + (4/13)\, M_{LTPP} \\ M_{MTC} &= (9/13)\, M_{LTPP} + (0.7)\, H_{LTPP} \\ H_{MTC} &= (0.3)\, H_{LTPP} \end{aligned} \qquad (1)$$

Where:

L_{MTC}, M_{MTC}, H_{MTC} = Low, medium, and high severity block cracking quantities respectively in the MTC system

L_{LTPP}, M_{LTPP}, H_{LTPP} = Low, medium, and high severity block cracking quantities respectively in the LTPP system

The high severity distress quantity in LTPP system was distributed into 70 percent and 30 percent of the medium and high severity, respectively, in MTC system. This distribution was selected because of the high coverage of MTC medium severity (57 mm in figure 2) on the LTPP high severity region.



1 mm = 0.039 inches

Figure 2. A comparison between SHRP and MTC definitions for block cracking severities, and conversion of LTPP quantities to MTC quantities

LTPP ALLIGATOR CRACKING TO MTC ALLIGATOR CRACKING

The LTPP system records the portions for wheel path and non-wheel path of the longitudinal cracking in three severity levels in two separate columns. Since LTPP longitudinal cracking in the wheel path at any severity level is considered as a part of the low severity alligator cracking in the MTC system, MTC low severity alligator cracking incorporates both LTPP low severity alligator cracking and LTPP longitudinal cracking in the wheel path of any severity. LTPP longitudinal cracking quantity (in length) in the wheel path was converted to MTC low severity alligator cracking quantity (in area) by multiplying the crack length by a unit width of 1 foot (0.305 m). The medium and high severity alligator cracking figures in the MTC system were obtained from the medium and high severity alligator cracking, respectively, in the LTPP system.

LTPP Longitudinal and Transverse Cracking to MTC Longitudinal and Transverse Cracking

The differences in definitions of the three severity levels of longitudinal and transverse cracking in the two systems are the same as the differences for severity levels in block cracking. The conversion technique used to convert LTPP longitudinal and transverse cracking quantities in three severity levels to MTC longitudinal and transverse cracking quantities was similar to that used for converting (equation (1)) block cracking quantities, except that MTC longitudinal cracking includes LTPP longitudinal cracking only from the non-wheel path (because MTC assigns the portion in the wheel path to low severity alligator cracking, according to the definition). Moreover, the quantities in LTPP longitudinal cracking in non-wheel path and LTPP transverse cracking are added together after the conversions to MTC system to obtain MTC longitudinal and transverse cracking quantities in different severities.

LTPP Patching, Shoving, and Raveling to MTC Patching, Distortions, Weathering, and Raveling

During conversions of these distresses, it was assumed, based on their definitions, that there is no difference between LTPP shoving and MTC distortion. Similarly, LTPP patch/patch deterioration was considered the same as MTC patching and utility cut patch, and LTPP raveling was considered the same as MTC weathering and raveling (see table 2).

PCI AND DEDUCTS FROM MTC-PMS

When appropriate data conversions were complete, the converted data were used as inputs in the MTC-PMS software version 7.5 (MTC, 1999) to calculate PCI values, deducts associated with each of the distress type-severity combinations, percent-load related deducts, and percent-nonload related deducts. Each of the selected 39 data sets was considered as if it were from an individual inspection unit. A database was first developed for the inspection units using the MTC-PMS software's "Road Inventory" and "Section Description" modules, and distress information was provided as input distresses using its "Inspection Units" module. The "Calculations" module was used to calculate "PCI from Inspection Units." All necessary data for statistical analysis were extracted from the report "PCI Calculation—Deduct Values" produced by the software (MTC, 1999). The software calculates deduct values for all distress type-severity combinations based on the pavement surface type. It combines all deducts to a single value, corrects for multiple occurrences, and subtracts the corrected value from 100 to determine PCI value (MTC, 1999). This process is a modification of the PAVER PCI calculation process (Shahin and Walters, 1990). The percent-load related and nonload related deducts are calculated based on the severity levels of distress types related to the cause of deterioration. Table 3 shows the severity levels of distress types related to cause of deterioration (Smith, 1999). The report titled "PCI Calculation—Deduct Values" provides deducts for each of the distress-severity combinations, total deduct amount, percent load related deduct, percent-nonload related deduct, and PCI for each inspection unit.

Table 3. Severity levels of distress types related to cause of deterioration for asphalt and surface treatment pavements (Smith, 1999)

Distress Type	Cause of Deterioration		
	Load	**Environment**	**Other**
Alligator Cracking	Low, medium, high	–	–
Block Cracking	High	Low, medium	–
Distortions	–	–	Low, medium, high
Longitudinal and Transverse Cracking	High	Low, medium	–
Patching and Utility Cuts	(Low, medium, high)/2	–	(Low, medium, high)/2
Rutting and Depressions	Low, medium, high	–	–
Weathering and Raveling	–	Low, medium, high	–

Partial results are shown in table 4 with the IRI values associated with each data set.

Table 4. Partial results from MTC-PMS and corresponding IRI values

Data Number	MTC PCI	MTC % Load Deduct	MTC % Nonload Deduct	IRI (m/km)
1	63	30.58	69.42	1.7228
2	26	75.34	24.66	2.1024
3	93	0.00	100.00	1.3832
4	92	0.00	100.00	1.4360
5	60	75.09	24.91	1.9102
6	70	85.73	14.27	1.2492
7	76	33.68	66.32	1.2060
8	56	58.23	41.77	2.0114
9	100	0.00	100.00	1.0108
10	53	78.40	21.60	1.5092
11	100	0.00	100.00	1.5694
12	36	77.47	22.53	1.4498
13	77	21.12	78.88	0.8844
14	51	38.92	61.08	1.1076
15	79	7.29	92.71	1.5756
16	76	12.25	87.75	1.9334
17	56	60.50	39.50	1.8020
18	66	63.45	36.55	1.5766
19	27	84.86	15.14	3.2080
20	100	0.00	100.00	0.7514
21	83	41.70	58.30	0.8644
22	68	51.35	48.65	0.7314
23	100	0.00	100.00	0.6540
24	100	0.00	100.00	0.6800
25	79	43.22	56.78	0.9900
26	66	33.85	66.15	1.4342
27	67	54.12	45.88	1.5474
28	46	94.25	5.75	1.6496

Table 4. Partial results from MTC-PMS and corresponding IRI values—*Continued*

Data Number	MTC PCI	MTC % Load Deduct	MTC % Nonload Deduct	IRI (m/km)
29	70	94.43	5.57	0.7586
30	46	53.43	46.57	1.7088
31	6	88.09	11.91	2.2162
32	91	0.00	100.00	1.3686
33	78	0.00	100.00	1.5440
34	62	55.99	44.01	2.2574
35	28	69.94	30.06	2.3558
36	99	0.00	100.00	0.7332
37	89	14.46	85.54	0.7952
38	100	0.00	100.00	0.7804
39	100	0.00	100.00	0.7816

STATISTICAL ANALYSIS AND ESTABLISHING IRI MODEL

A statistical analysis was conducted in an effort to establish a model of IRI as a function of PCI, all distress-severity combinations, deducts from each distress-severity combination, percent-load related deducts, and percent-nonload related deducts. A total of 45 predictor variables was considered in the statistical analysis, which came from 21 distress-severity combinations (7 distress types times 3 severity levels), 21 deducts from 21 distress type-severity combinations, 1 PCI, 1 percent load deduct, and 1 percent nonload deduct. These 45 predictor variables, data for 16 variables were zero for all 39 data sets. These 16 predictors thus were removed from further consideration in the analysis. The removed predictor variables were: medium and high severity rutting and their deducts; high severity block cracking and its deduct; low, medium, and high severity distortions and their deducts; high severity patching and its deduct; and high severity weathering and raveling and its deduct.

A multilinear regression analysis was conducted using the remaining 29 predictor variables. SAS statistical software was used for all statistical validation and modeling (SAS, 2000). The final model for IRI from this statistical analysis was:

$$IRI = 0.0171\,(153 - PCI) \qquad (2)$$

where, IRI is in m/km

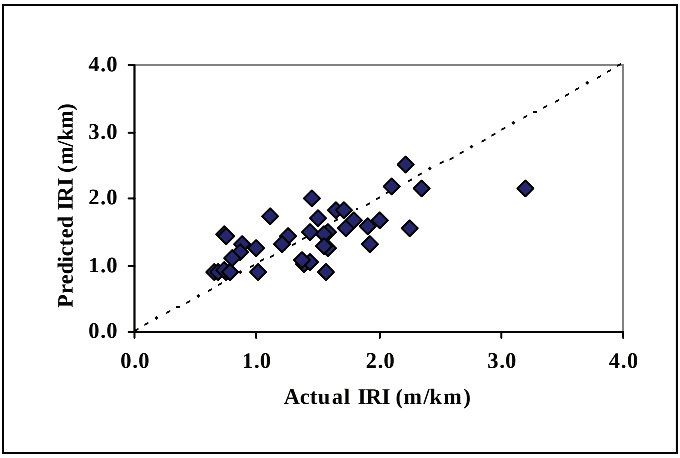
The model in equation (2) has a correlation coefficient (R2) of 0.53, coefficient of variation (CV) of 28 percent, and a root mean square error of 0.39. Figure 3 compares graphically the actual and the predicted values of IRI from correlation with PCI (equation (2)) and gives a graphical view of the dispersion of data that leads to the R2 value. Equation (2) can be used to estimate pavement roughness for the highways in California, and it needs only the quantities of distress-severity combinations as inputs. Because of the lack of roughness data for the local streets, this correlation should only be used as a starting point, and should be refined using data on city streets. The Bay area agencies need established correlations between user costs and pavement roughness, valid for Bay area cities and counties, to couple with equation (2) to estimate user costs.

CRITICAL REMARKS

A major problem encountered working with the SHRP distress data from LTTP sites was that some distress type-severities were all zeros because those distress-severities were not present on the road surface during distress surveys. It is now evident from the previous discussion that most of these absent distress-severities were associated with high severities and with distortions of all severities. All of these absent distress-severity combinations and distortions should have a significant influence on the values of IRI. The reason for the absence of these distress-severity combinations is that LTPP data are collected from the State highways, and these high distresses or distress-severity combinations are generally quickly repaired on State highways, but common on city streets.

There was no way to incorporate these highly influential distress-severity combinations and associated deducts in the statistical analysis because of the use of LTPP data. City streets are generally found with more distress quantities and higher severities than are highways. An IRI model developed using data from city streets would have more applicability.

Some agencies in the cities and counties of the San Francisco Bay area need to collect, at least once, IRI data, along with the distress data from a representative sample of their city streets, and then establish a more appropriate IRI model for their streets by using the data transformations similar to the ones described above. The initial model developed should be refined at reasonable time intervals, for example once in every 5 years, using the most current data from the city streets to maintain the IRI model's reliability.



1 m/km = 63.36 inches/mi

Figure 3. Actual versus predicted values of IRI

SUMMARY

Using the LTPP distress data as inputs in the MTC-PMS system requires transformations to match the data with MTC-PMS definitions because of the differences between the distress definitions and severities used in the LTPP database and in the MTC-PMS system. A model for IRI as a function of pavement condition information was developed using the MTC data, and this IRI model is intended for use in calculating user costs/benefits in the management system. Several manipulations were required to conduct the transformation of different LTPP distresses and severities to obtain MTC distress quantities in three severity levels. Manipulations were performed based on the differences in definition for distresses and severities in the two systems.

The following can also be summarized from the study:

- The data in the LTPP database are stored in metric units (mm, etc.) that needed to be converted to English units (inch, etc.) to match the units system used in the MTC-PMS software.
- Transverse profile data from the LTPP database were used to calculate MTC rutting. MTC measures rut depths and quantities by laying a 3-m (10-ft) straightedge across the rut. Rut depths are the maximum depths found in the wheel paths; rutted widths are the widths of the wheel paths rutted more than 13 mm (0.5 inch).
- According to the definitions of severities for block cracking, the ranges defining the boundaries of severity levels in the LTPP system are different from those in the MTC system. Equations were formulated based on the differences in definitions in the two systems and used to convert data from one system to the other.
- Since LTPP longitudinal cracking in a wheel path at any severity was considered as a part of the low severity alligator cracking in the MTC system, MTC low severity alligator cracking includes LTPP low severity alligator cracking as well as LTPP longitudinal cracking in the wheel path at any severity.
- The transformation technique used to convert LTPP longitudinal and transverse cracking quantities in three

severity levels to MTC longitudinal and transverse cracking quantities was similar to the technique used for the transformation of block cracking quantities except the MTC longitudinal cracking quantities do not include LTPP longitudinal cracking quantities in the wheel path.

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PAPER 3 ANALYSIS OF INFLUENCES ON AS-BUILT PAVEMENT ROUGHNESS IN ASPHALT OVERLAYS

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ABSTRACT

Pavement roughness immediately after construction is a key measure of quality. The use of smoothness specifications requires an understanding of the influences on as-built roughness for both transportation agencies and contractors. This paper uses data from the Long-Term Pavement Performance (LTPP) program to examine four factors and determine their effects on the as-built roughness of a pavement; these factors are: the extent of surface preparation before resurfacing; overlay thickness; type of overlay material; and pavement roughness before resurfacing. Various statistical procedures (including paired data analyses, regression analyses, and a repeated measures analysis) are performed to investigate these effects and any interactive effects. The extent of surface preparation, overlay thickness and pavement roughness before resurfacing are determined to have a statistically significant effect (at a 95 percent significance level) on the as-built roughness of a pavement either directly or interactively with another variable. The overlay mix type is determined not to have an influence on as-built pavement roughness. Data from the Canadian Long-Term Pavement Performance (C-LTPP) program is used to validate the results for overlay thickness and pavement roughness before

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resurfacing. A series of prediction equations are also developed to allow for estimating the as-built roughness of a pavement under various conditions. Pavement designers, construction engineers, and contractors should understand the effects that influence the as-built roughness of a pavement so that they can maximize their designs, smoothness specifications, and/or bidding of contracts with smoothness specifications.

INTRODUCTION

Pavement roughness is the primary measure of public satisfaction with the highway system and, accordingly, the as-built roughness of a pavement immediately after construction is a key quality measure. As-built pavement roughness has also been shown to affect the long-term performance of a pavement (Raymond, 2001; TAC, 2002). Consequently, most transportation agencies have incorporated as-built roughness requirements into their acceptance criteria. These roughness requirements are generally termed "smoothness specifications." Although there has been common acceptance of smoothness specifications in Canada and the United States, the pay adjustments and smoothness requirements vary considerably among transportation agencies (Schmitt et al., 1998; TAC, 1999).

Smoothness specifications are an effective means of improving the as-built smoothness of a pavement (Smith 1997, McGhee 2000). The incentive/disincentive provisions encourage contractors to achieve a smooth pavement surface, which can include purchasing new equipment, improving grade controls and additional training of staff. In developing a smoothness specification, it is important that transportation agencies understand not only the effect of as-built pavement roughness on long-term performance but also the factors that affect as-built pavement roughness. Contractors must also understand the factors that will affect their ability to construct a smooth pavement. This knowledge is important for competitively bidding contracts with payment adjustments based on as-built pavement roughness.

This paper examines four design factors for their effect on the as-built pavement roughness of asphalt overlays constructed over existing asphalt pavements: the degree of surface preparation before overlay; overlay thickness; type of overlay material; and pavement roughness before resurfacing. The influence of these factors on as-built pavement roughness can be an issue of disagreement between transportation agencies and contractors. A number of other factors not considered in the analysis include the use of a material transfer vehicle; the degree of smoothness required by the owner's smoothness specification; the magnitude of incentives and/or disincentives provided in the owner's smoothness specification; the contractor's attitude and capability to achieve a smooth pavement; and the operational constraints related to the project (such as traffic staging, location of intersections, and extent of night paving).

RELATED STUDIES

Previous research has provided different conclusions regarding the influences on as-built roughness. An earlier study sponsored by the Federal Highway Administration (FHWA) was unable to identify any statistical difference in as-built roughness from the four factors mentioned above (surface preparation, overlay thickness, overlay material and roughness before resurfacing) (Perera, Byrum, and Kohn, 1998; Perera, and Kohn, 1999). Research by the Virginia Department of Transportation concluded that as-built pavement roughness is influenced by the pavement roughness before resurfacing, the functional classification of the roadway, and the application of a smoothness specification (McGhee, 2000). The same research also reports that the number of additional structural layers, the surface mix type, and pavement milling before overlay do not influence as-built pavement roughness.

DESCRIPTION OF DATA SOURCES

The data for the analysis is from the LTPP program established as part of the Strategic Highway Research Program (SHRP) that began in 1987. It consists of numerous test sections located throughout the United States and Canada. Of interest to this research are the SPS-5 experiments. Each SPS-5 site consists of nine 150-meter (m) (492-feet (ft)) sections (FHWA, 96). Eight sections are experimental, while one section, section 501, is a control section with no specific treatment except for routine maintenance. Because the control section provides no information related to this examination of as-built roughness, it is not incorporated into the analysis. The eight experimental sections for each project were setup as shown in table 1 with different treatments for extent of surface preparation, type of overlay material, and overlay thickness (not including replacement of milled material). The primary difference between basic and intensive surface preparation is the amount of milling that was performed for the section. Pavement roughness is measured in terms of International Roughness Index (IRI) using a K.J. Law Profilometer. Data for this analysis are from the DataPave 3.0 database. The tables entitled TST_L05A, SPS5_LAYER, and MON_PROFILE_MASTER were used for this research. Validation of SPS-5 analysis was performed based on data from the C-LTPP database supplied by the Canadian Strategic Highway Research Program (C-SHRP).

Table 1. SPS-5 experimental test sections

Section	Surface Preparation	Design Overlay Thickness (mm)*	Overlay Material
502	Basic	50	Recycled
503	Basic	125	Recycled
504	Basic	125	Virgin
505	Basic	50	Virgin
506	Intensive	50	Virgin
507	Intensive	125	Virgin
508	Intensive	125	Recycled
509	Intensive	50	Recycled

1 mm = 0.039 inch

* Design overlay thickness does not include replacement of milled material

AS-BUILT ROUGHNESS PAVEMENT SECTIONS

As-built pavement roughness measurements were taken for each section immediately after resurfacing for the 17 sites and are shown in table 2. Roughness is quantified based on the IRI. The table also provides the average as-built IRI for each site, the average as-built IRI determined for each section treatment, corresponding standard deviations, and coefficients of variations. Five of the as-built IRI values for Maine were missing from the database, requiring extrapolation from the IRI data 2 years following construction. The extrapolation of these as-built roughness values is based on the average change in IRI for the other three sections during this time period.

An examination of the average as-built roughness of the various sections indicates that most averages are close to the overall average of 0.91 m/km (58 inches per mile (inches/mi). Section 502 (basic surface preparation, thin overlay, and recycled material) and section 508 (intensive surface preparation, thick overlay, and recycled material) have the greatest deviation from the overall site average. Section 502 has a high average as-built roughness of 0.97 m/km (61 inches/mile); section 508 has a low as-built roughness of 0.86 m/km (54 inches/mile). The theory that extensive surface preparation and thick overlays provide the smoothest as-built pavements would seem to be consistent with the average roughness values for sections 502 and 508. What remains unexplained is why the corresponding sections with different overlay material do not provide similar as-built roughness values. Because the type of overlay material is not considered to affect as-built roughness, the as-built roughness of sections 505 (basic surface preparation, thin overlay, and virgin material) and 507 (intensive surface preparation, thick overlay, and virgin material) should correspond with the averages for sections 502 and 508. The average as-built roughness for section 505 is slightly greater than the overall average and the average as-built roughness for section 507 is slightly lower than the overall average. The effect of the various treatments on as-built roughness is examined later in this paper.

Table 2. As-built IRI measurements

State/ Province	As-Built IRI (m/km) Test Section Number								Aver-age (m/km)
	502	503	504	505	506	507	508	509	
Alabama	0.77	0.83	0.85	0.82	0.70	0.76	0.93	0.81	0.81
Arizona	1.36	0.95	1.20	1.27	1.02	1.30	0.94	1.03	1.13
California	0.95	1.08	1.02	0.72	0.81	0.83	0.75	1.01	0.90
Colorado	0.94	0.78	0.83	0.78	0.93	0.70	0.78	0.91	0.83
Florida	0.68	0.74	0.64	0.49	0.50	0.55	0.72	0.57	0.61
Georgia	0.52	0.54	0.49	0.56	0.47	0.47	0.66	0.52	0.53
Maine	0.68	0.88	0.84	0.67	0.79	0.82	0.75	0.98	0.80
Maryland	1.39	1.03	0.91	1.01	0.74	0.88	0.79	1.03	0.97
Minnesota	0.85	0.76	1.12	1.08	1.08	0.85	1.00	078	0.94
Mississippi	1.41	1.80	1.20	1.72	1.41	1.26	1.41	1.78	1.50
Montana	0.82	0.99	0.72	0.66	0.67	1.14	0.76	0.69	0.81
New Jersey	0.99	0.67	0.72	0.89	0.73	0.78	0.74	0.75	0.78
New Mexico	0.59	0.45	0.44	0.47	0.44	0.51	0.49	0.50	0.49
Oklahoma	1.13	1.01	1.07	1.02	1.00	0.88	0.94	0.91	1.00
Texas	1.23	1.11	1.54	1.36	1.52	1.45	1.06	1.24	1.32
Alberta	1.04	1.05	1.29	1.14	1.06	1.38	1.04	1.01	1.12
Manitoba	1.20	0.79	0.79	1.08	1.45	0.69	0.81	0.99	0.97
Average	0.97	0.91	0.92	0.92	0.90	0.90	0.86	0.91	0.91
Standard Deviation	0.28	0.30	0.29	0.34	0.33	0.30	0.20	0.30	0.26
Coefficient of Variation	0.29	0.33	0.32	0.36	0.37	0.34	0.24	0.33	0.29

1 m/km = 63.36 inches/mile

PRIOR ROUGHNESS OF PAVEMENT SECTIONS

Roughness measurements for each section before resurfacing are shown in table 3. The table also provides the average prior IRI for each site, the average prior IRI determined for each section treatment, and the corresponding standard deviations and coefficients of variations. Roughness measurements before resurfacing are not available for the Manitoba site. The New Mexico site has prior roughness measurements for only two sections. Because there is considerable variation in the two roughness values (1.74 m/km (110 inches/mile) and 3.04 m/km (193 inches/mile), the measurements were not incorporated into the analyses (i.e., the New Mexico site was evaluated without prior roughness measurements). Two other sites, Colorado and

Minnesota, were missing roughness measurements before resurfacing for at least one section. These sites were evaluated based on the information available, with the average site roughness being substituted for missing values.

Table 3. IRI measurements before resurfacing

State/ Province	As-Built IRI (m/km) Test Section Number								Average (m/km)
	502	503	504	505	506	507	508	509	
Alabama	1.04	0.99	1.03	1.14	1.05	1.24	1.06	1.71	1.16
Arizona	2.01	1.69	1.55	2.56	1.73	1.83	1.55	2.38	1.91
California	3.13	1.78	1.89	1.55	1.81	2.35	2.06	2.13	2.09
Colorado	1.49	1.74	1.51	1.38			1.86		1.60
Florida	1.07	1.03	1.40	1.45	0.97	1.14	1.12	1.07	1.16
Georgia	1.07	0.96	1.11	1.21	1.07	0.88	0.91	0.99	1.03
Maine	1.02	1.21	1.37	1.27	1.16	1.43	1.24	1.10	1.22
Maryland	1.60	2.07	2.02	1.53	1.35	1.41	1.47	1.36	1.60
Minnesota	2.80	2.74	3.17	2.55		2.64	2.49	2.95	2.76
Mississippi	2.58	2.70	2.42	1.75	2.06	2.07	2.33	2.73	2.33
Montana	1.56	1.80	1.39	1.07	1.95	1.03	1.34	0.98	1.39
New Jersey	2.07	2.02	1.61	1.80	1.74	2.05	1.53	2.18	1.88
New Mexico									
Oklahoma	2.51	2.04	2.08	1.07	2.01	2.31	1.76	1.59	1.92
Texas	1.37	1.49	1.38	1.55	1.18	1.46	1.26	1.95	1.45
Alberta	2.06	2.09	2.41	1.38	1.50	1.62	1.80	1.98	1.85
Manitoba									
Average	1.83	1.76	1.76	1.55	1.51	1.68	1.59	1.79	1.68
Standard Deviation	0.69	0.56	0.58	0.46	0.40	0.54	0.46	0.65	0.48
Coefficient of Variation	0.38	0.32	0.33	0.30	0.26	0.32	0.29	0.36	0.29

1 m/km = 63.36 inches/mile

The average roughness before resurfacing for the sites is 1.68 m/km (106 inches/mile). Section 506 has the lowest average roughness before resurfacing of 1.51 m/km (96 inches/mile) and section 502 has the highest, of 1.83 m/km (116 inches/mile). If the IRI before resurfacing is related to the as-built roughness of a pavement, the low prior IRI for sections 505 and 508 may help explain why their average as-built roughness values are lower than for their corresponding sections with different overlay material (i.e., sections 502 and 507). Similarly, the high prior IRI of section 509 may help explain why its average as-built roughness is higher than section 506, the corresponding section with different overlay material.

INVESTIGATION OF INFLUENCES ON AS-BUILT ROUGHNESS

The influences on as-built pavement roughness are investigated using several statistical techniques. The effects of surface preparation, overlay thickness, and overlay material on as-built roughness are investigated based on a series of paired analyses. The paired analyses consider the various effects based on three data sets: pavement sites with a high pavement roughness before resurfacing (i.e., IRI greater than 1.5 m/km (95 inches/mile)); pavement sites with a low pavement roughness before resurfacing (i.e., IRI less than 1.5 m/km (95 inches/mile)); and all sites. Following the paired data analysis, a regression analysis is preformed to examine the influence of pavement roughness before resurfacing on the as-built roughness of a pavement. This analysis is required to examine pavement roughness before resurfacing as a quantitative variable. A third statistical tool, a repeated measures analysis, is used to examine the interactive effects of surface preparation, overlay thickness, overlay material and pavement roughness before resurfacing on the as-built roughness of a pavement. Next, regression analyses are performed on data from the C-LTPP program to validate some of the conclusions reached from the SPS-5 data. Lastly, regression analyses are performed on the SPS-5 data to develop four prediction equations for estimating the as-built roughness of a pavement. A 95 percent statistical significance level was selected for all analyses as the criteria to identify the presence of a significant relationship.

SURFACE PREPARATION

The SPS-5 test sections involved two types of surface preparation, basic and intensive (Perera, Byrum, and Kohn, 1998; Perera, and Kohn, 1999). Intensive surface preparation consists of milling the existing asphalt followed by patching distressed areas and crack sealing. Basic surface preparation is intended to consist of patching severely distressed areas and potholes, and placement of a leveling course for ruts greater than 12 mm (0.47 inches) in depth, although the construction information indicates that 5 of the 17 sites had milling performed for the sections designated for basic surface preparation. Where milling was performed, the depth of replacement material was not counted as the part of the overlay thickness specified for the section (Perera, Byrum, and Kohn, 1998; Perera, and Kohn, 1999). The primary difference in the two extents of surface preparation is whether or not milling of the existing asphalt pavement is performed. Milling is a technique than planes off the existing asphalt to a predetermined depth. The Asphalt Institute (AI) reports that milling can often remove roughness better than an asphalt paver because of its greater ability to remove a variable thickness of material (AI, 1989). A paired comparison of the as-built roughness of pavement sections with different extents of surface preparation is shown in table 4, which is separated into three rows. The first row presents data from pavement sites with a high pavement roughness before resurfacing (i.e., IRI greater than 1.5 m/km (95 inches/mile)); the second row presents data from pavement sites with a low pavement roughness before resurfacing (i.e., IRI less than 1.5 m/km (95 inches/mile)); and the third row presents the complete set of data. The results indicate that there is an overall significant difference (at a two-tailed significance level of 95 percent) in the as-built roughness of pavement sections with basic and extensive surface preparation. This statistical difference is evident with both the complete data set and for the data with a high roughness before resurfacing. No significant statistical difference was found for the data from sites with a low roughness level before resurfacing. In fact, the mean difference in as-built roughness for these sites is essentially zero, indicating no difference in as-built roughness for the different levels of surface preparation. This lack of difference may be because a low prior pavement roughness does not provide an adequate opportunity for the effect of surface preparation to be demonstrated. The paired t-test analyses indicates that on average, there is a 0.040 m/km (2.5 inches/mile) lower as-built IRI for pavements constructed with intensive surface preparation as compared with pavements constructed with basic surface preparation (i.e., intensive surface preparation contributes to smoother as-built pavements). When only pavements with a high level of roughness before resurfacing are examined, the average difference in as-built IRI increases to 0.081 m/km (5.1 inches/mile).

Table 4. Paired data analysis of the effect of surface preparation on as-built IRI

Data Set	Mean Difference (m/km)	Standard Deviation of differences (m/km)	Obser-vations	t-statistic	Statistical Significance (2-tailed)
Data with prior IRI greater than 1.5 m/km	0.081	0.070	9	3.489	0.008
Data with prior IRI less than 1.5 m/km	−0.004	0.045	6	−0.260	0.806
All	0.040	0.070	17	2.385	0.030

1 m/km = 63.36 inches/mile

OVERLAY THICKNESS

Overlay thickness is considered to be a contributing factor to the as-built roughness of a pavement. Thicker overlays provide a contractor more opportunity to reduce the roughness of a pavement section. This improvement can be attributed to the fact that thicker overlays typically involve more lifts, which allow for incremental improvements in pavement smoothness. The opportunity for improving smoothness with more overlay lifts is related to the operational constraints of an asphalt paver. One objective of an asphalt paver is to produce a smooth asphalt mat behind the screed through the use of proper paving techniques and grade controls. Should a perfectly smooth asphalt layer be placed over a previous pavement deviation, the subsequent compaction of the asphalt mix by rollers will "reflect" a portion of the roughness into the new asphalt layer, as illustrated in figure 1. Asphalt behind a paving screed is at approximately 70 to 80 percent of theoretical maximum density, while the final asphalt compaction is generally around 94 percent of theoretical maximum density (USACE, 1991). This additional consolidation can result in approximately 20 percent of the previous deviations being reflected into the new asphalt lift. It should be noted that the overlay thickness values presented earlier do not include the replacement of milled material for sections where pavement milling was performed.

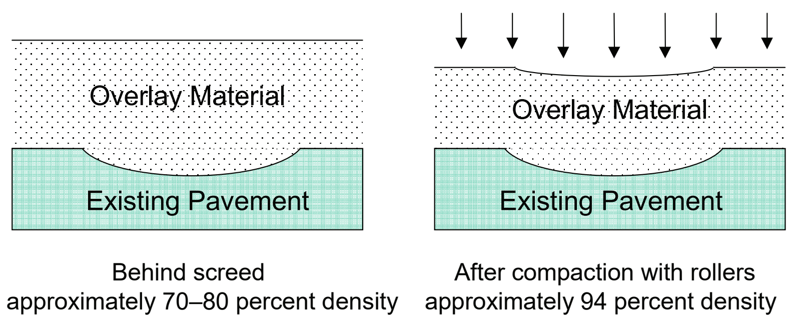


Figure 1. Limitation on achieving a smooth pavement with a single lift of asphalt

A comparison of the as-built roughness of thin overlays in relation to thick overlays is shown in table 5. The results of this analysis indicate no statistically significant differences in as-built roughness compared to overlay thickness. Although the mean difference in IRI between thin and thick overlays is 0.033 m/km (2.1 inches/mile), the two-tailed p-value is 35 percent, which indicates no statistically significant relationship (at a two-tailed significance level of 95 percent) is present. The mean difference in IRI between thin and thick overlays is 0.055 m/km (3.5 inches/mile) for pavements with a high pavement roughness before resurfacing with a two-tailed p-value of 12.1 percent. Although not statistically significant at a two-tailed significance level of 95 percent, when the analysis is considered from a one-sided approach, the p-value becomes 6.05 percent, which is close to being statistically significant at a 95 percent significance level. The mean difference in IRI between thin and thick overlays is −0.063 m/km (−4.0 inches/mile) for pavements with a low pavement roughness before resurfacing. The difference is not statistically significant. However, the fact that pavements with a high pavement roughness before resurfacing have a positive difference in IRI and pavements with a low pavement roughness before resurfacing have a negative difference suggests a possible interactive effect with prior roughness. This interactive effect is examined later in this paper.

Table 5. Paired data analysis of the effect of design overlay thickness on as-built IRI

Data Set	Mean Difference (m/km)	Standard Deviation of Differences (m/km)	Obser-vations	t-statistic	Statistical Significance (2-tailed)
Data with prior IRI greater than 1.5 m/km	0.055	0.095	9	1.736	0.121
Data with prior IRI less than 1.5 m/km	−0.063	0.081	6	−1.906	0.115
All	0.033	0.139	17	0.969	0.347

1 m/km = 63.36 inches/mile

COMPARISON OF OVERLAY MATERIAL

The type of overlay material (i.e., recycled or virgin) has not traditionally been considered an influencing factor in pavement roughness, but is investigated to confirm its lack of effect. The results of a comparison of the effect of overlay material on as-built roughness are shown in table 6. The results indicate that there are essentially no statistical differences in as-built roughness between recycled and virgin mixtures. All of the p-values are close to a value of one, indicating no relationship with as-built roughness.

Table 6. Paired data analysis of the effect of overlay material on as-built IRI

Data Set	Mean Difference (m/km)	Standard Deviation of Differences (m/km)	Obser-vations	t-statistic	Statistical Significance (2-tailed)
Data with prior IRI greater than 1.5 m/km	0.005	0.144	9	0.099	0.924
Data with prior IRI less than 1.5 m/km	0.000	0.155	6	−0.004	0.997
All	0.002	0.135	17	0.060	0.953

1 m/km = 63.36 inches/mile

COMPARISON OF PAVEMENT ROUGHNESS BEFORE RESURFACING

As outlined previously, the SPS-5 experimental sections were setup as a factorial experiment based on extent of surface preparation, overlay thickness, and type of overlay material. Because the effect of pavement roughness before resurfacing cannot be investigated in the same manner as the factorial variables, a regression analysis was performed to determine whether the as-built roughness of a pavement is affected by the pavement roughness before resurfacing. A plot of the regression analysis is shown in figure 2, and the analysis of variance statistics are shown in table 7. The p-value is 3.5 percent, which indicates that the pavement roughness before resurfacing has a statistically significant effect (at a two-tailed 95 percent significance level) on as-built pavement roughness. Pavements with a high pavement roughness before resurfacing will tend to have a higher as-built roughness after resurfacing. The estimate of the regression slope is 0.29, which indicates that for every 1.0 m/km (63 inches/mile) increase in pavement IRI before resurfacing there will be an expected 0.29 m/km (18 inches/mile) increase in as-built IRI. The regression line is based on the average roughness for each site before resurfacing and the average as-built roughness for each site. The data exclude two sites, New Mexico and Manitoba, because limited information is available on the roughness of these sites before resurfacing.

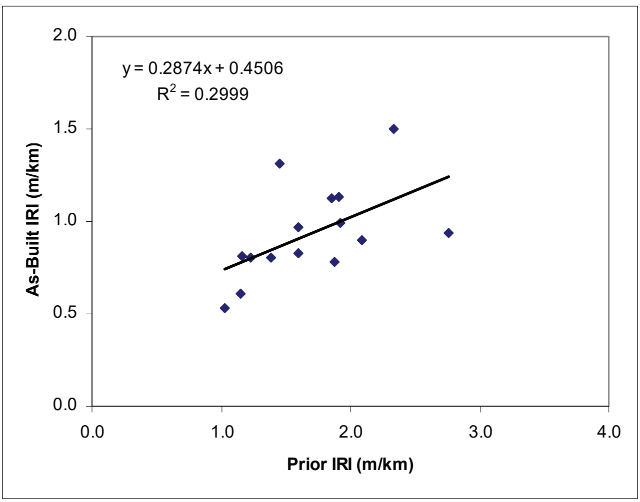


Figure 2. As-built roughness versus prior roughness for SPS-5 data

Table 7. Results of analysis of variance for logarithm of prior roughness for SPS-5 sites

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Statistical Significance
Prior Roughness	0.270	1	0.270	5.569	0.035
Error	0.630	13	0.048	–	–
Total	0.900	14	–	–	–

INVESTIGATION OF INTERACTIVE EFFECTS

As noted earlier in this paper, the effects of surface preparation and pavement roughness before resurfacing statistically influence the as-built roughness of a pavement, and the effect of overlay thickness has a marginally statistical influence on the as-built roughness of a pavement. To fully understand the factors that influence the as-built roughness of a pavement, it is also necessary to investigate the interactive effects. The best method for examining the interactive effects is to perform a repeated-measures analysis on the effects of surface preparation, overlay thickness, overlay material, and pavement roughness before resurfacing. The limited amount of data requires that pavement roughness before resurfacing be categorized into high and low pavement roughness. An IRI level of 1.5 m/km (95 inches/mile) was selected as an appropriate level to separate low and high prior pavement roughness.

The within-subjects effects for repeated measured analysis are presented in table 8 and the between-subjects effects are presented in table 9. The results for the repeated measures analysis confirm the results of the previous paired-data analysis related to the individual effects of surface preparation, overlay thickness, and overlay material. The analysis also indicates that there are statistically significant (at a 95 percent significance level) interactive effects for surface preparation and pavement roughness before resurfacing as well as for overlay thickness and pavement roughness before resurfacing. The p-values for these interactive effects are 1.8 percent and 2.7 percent, respectively. The presence of these interactive effects means that when estimating the effect of surface preparation or overlay thickness on as-built roughness, the effect should be considered in combination with the pavement roughness before resurfacing. No other statistically significant interactive effects are apparent from the analysis.

Table 8. Within-subjects effects of repeated measures analysis

Source of Variation	Sum of Squares	Df	Mean Square	F	Statistical Significance
SP	4.24 E-02	1	4.24 E-02	5.897	0.030
SP, PR	5.22 E-02	1	5.22 E-02	7.268	0.018
Error	9.34 E-02	13	7.18 E-02		
OT	5.23 E-04	1	5.23 E-04	0.033	0.860
DT, PR	0.100	1	0.100	6.228	0.027
Error	0.209	13	1.61 E-02		
OM	1.46 E-04	1	1.46 E-04	0.003	0.955
OM, PR	1.79 E-04	1	1.79 E-04	0.004	0.950
Error	0.574	13	4.41 E-02		
SP, OT	1.42 E-06	1	1.42 E-06	0.000	0.993
SP, OT PR	3.90 E-03	1	3.90 E-03	0.192	0.669
Error	0.265	13	2.04 E-02		
SP, OM	2.68 E-03	1	2.68 E-03	0.229	0.640
SP, OM PR	1.20 E-04	1	1.20 E-04	0.010	0.921
Error	0.152	13	1.17 E-02		
OT, OM	3.42 E-02	1	3.42 E-02	1.805	0.202
OT, OM PR	2.54 E-03	1	2.54 E-03	0.134	0.720
Error	0.246	13	1.90 E-02		
SP, OT, OM	2.60 E-03	1	2.60 E-03	0.119	0.735
SP, OT OM, PR	3.73 E-04	1	3.73 E-04	0.017	0.898
Error	0.283	13	2.18 E-02		

Prior Roughness – PR
Surface Preparation – SP
Overlay Thickness – OT
Overlay Material – OM

Table 9. Between-subjects effects of repeated measures analysis

Source of Variation	Sum of Squares	Df	Mean Square	F	Statistical Significance
Intercept	96.559	1	96.559	210.44	0.000
Prior Roughness (High or Low)	1.233	1	1.233	2.687	0.125
Error	5.965	13	0.459	–	–

The effect of pavement roughness before resurfacing has a p-value of 12.5 percent, which does not indicate a statistically significant relationship (at a 95 percent significance level). Pavement roughness before resurfacing should still be considered as a statistically significant influence on as-built roughness because it was determined to have a statistically significant effect when examined quantitatively instead of qualitatively as high and low roughness. A second reason to consider pavement roughness before resurfacing as a statistical influence is that it has statistically significant interactive effects with surface preparation and overlay thickness.

VALIDATION WITH C-LTPP DATA

To validate the findings of the analyses performed on the SPS-5 sites, data from the C-LTPP program was examined. Regression analyses were performed to validate the individual effects of prior roughness and overlay thickness. Insufficient data were available to validate the effects of surface preparation and overlay material. Average prior roughness and overlay thickness values for each site were analyzed for their relationship with the average as-built roughness for each site. The C-LTPP measurements represent 14 data points.

VALIDATION OF THE EFFECT OF SURFACE PREPARATION

The regression graph for the effect of pavement roughness before resurfacing on as-built roughness is shown in figure 3. This graph is similar to the corresponding SPS-5 graph in that the data indicate a positive relationship between prior roughness and as-built roughness. Pavements with a high roughness before resurfacing correspond to a high as-built roughness. One difference between the data sets is that the C-LTPP data contain generally higher prior roughness and higher as-built roughness measurements than the SPS-5 data. The analysis of variance for the relationship is shown in table 10. The p-value is 5.2 percent and indicates that the relationship is very close to being statistically significant at a 95 percent significance level. Examining the analysis as a validation of the SPS-5 relationship, the p-value becomes 2.6 percent and indicates a statistically significant relationship at a 95 percent confidence level. The results from the C-LTPP data confirm the findings of the LTPP SPS-5 analysis.

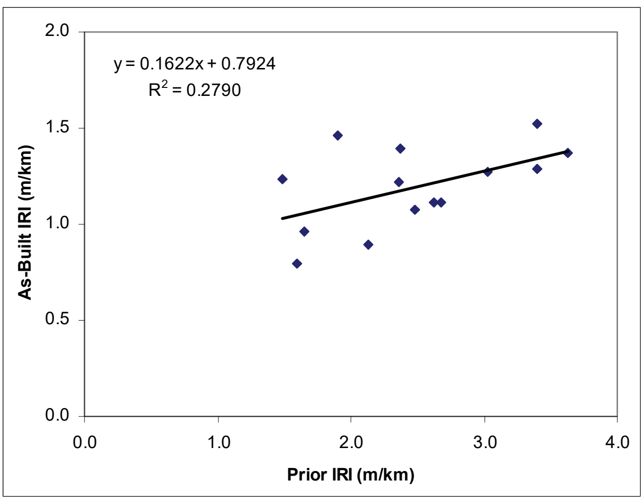


Figure 3. As-built roughness versus prior roughness for C-LTPP data

Table 10. Results of analysis of variance for prior roughness with C-LTPP data

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Statistical Significance
Prior Roughness	0.167	1	0.167	4.643	0.052
Error	0.431	12	0.036	–	–
Total	0.597	13	–	–	–

VALIDATION OF THE EFFECT OF OVERLAY THICKNESS

A regression plot of overlay thickness and as-built roughness for the C-LTPP data is shown in figure 4. The data indicate lower as-built roughness with thicker overlay thickness. This is consistent with the analyses of the SPS-5 data. The analysis of variance for the C-LTPP data is shown in table 11. The p-value for the relationship is 58 percent, indicating a weak relationship. It should be noted that the SPS-5 relationship was also weak and not statistically significant at a 95 percent significance level.

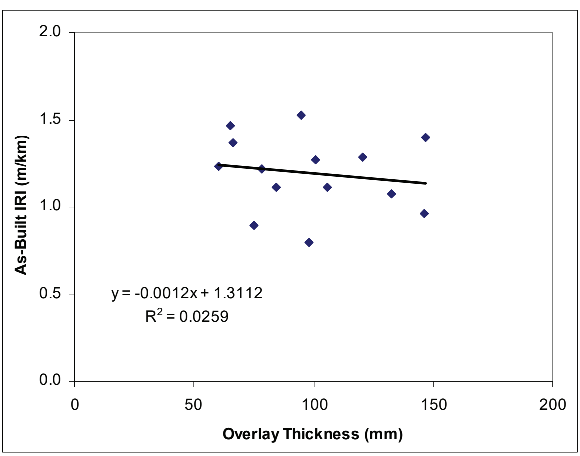


Figure 4. As-built roughness versus overlay thickness for C-LTPP data

Table 11. Results of analysis of variance for overlay thickness with C-LTPP data

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Statistical Significance
Prior Roughness	0.015	1	0.015	0.320	0.582
Error	0.582	12	0.048	–	–
Total	0.597	13	–	–	–

PREDICTION EQUATIONS FOR AS-BUILT ROUGHNESS

The previous analyses have shown that four factors have a statistically significant effect on as-built roughness at a 95 percent significance level:

- Surface preparation.
- Pavement roughness before resurfacing (measured quantitatively).
- The interactive effect of surface preparation and pavement roughness before resurfacing.
- The interactive effect of overlay thickness and pavement roughness before resurfacing.

The presence of these statistical effects identifies the need to quantify the expected as-built roughness that will occur for these factors, thus four regression analyses were performed to determine prediction equations that account for the influence of these factors. These prediction equations can be used by designers to evaluate the effect on as-built roughness of their design alternatives and by contractors to estimate the as-built roughness that will be achieved under a particular combination of design factors. It should be noted that there is a considerable amount of variability in the prediction equations, and the actual as-built roughness of a pavement may be influenced by other factors not incorporated into the equations. The equations are intended to provide typical as-built roughness values for different levels of surface preparation, overlay thickness, and prior pavement roughness and to provide a method of quantifying the expected difference resulting from a change in one or more of these factors. For example, both a designer and contractor could estimate the additional smoothness that would be expected by increasing a pavement overlay thickness. The designer would be interested in the longer pavement life that would result from the lower as-built roughness and the contractor would be interested in the administrative impact related to the achieving the requirements of a smoothness specification. The prediction equations are considered valid for the range of the regression data, which is for a range of prior roughness of approximately 1.0 m/km (63 inches/mile) to 2.75 m/km (174 inches/mile).

BASIC SURFACE PREPARATION AND THIN OVERLAY

The regression graph for basic surface preparation and thin overlays is shown in figure 5 and shows an R-squared of 0.28. The relationship has a p-value of 4.2 percent as shown in table 12. The prediction equation determined for basic surface preparation and a thin overlay is as follows:

$$IRI_{As-Built} = 0.44 + 0.31 \times IRI_{Prior} \qquad (1)$$

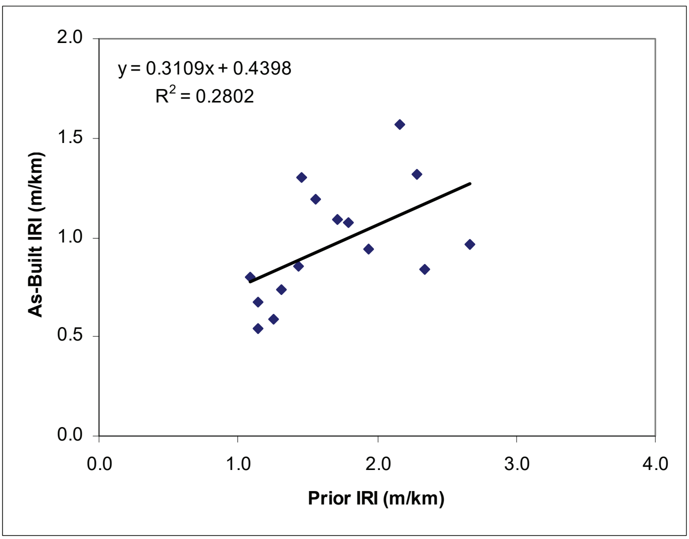
where $\mathrm{IRI}_{\mathrm{As-Built}}$ = as-Built IRI in m/km

and $\mathrm{IRI}_{\mathrm{Prior}}$ = IRI prior to resurfacing in m/km

For example, the expected as-built roughness for a pavement with a prior roughness of 2.00 m/km (127 inches/mile) undergoing basic surface preparation and a thin overlay is 1.06 m/km (67 inches/mile).

Table 12. Results of analysis of variance for basic surface preparation and thin overlay

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Statistical Significance
Prior Roughness	0.334	1	0.334	5.061	0.042
Error	0.859	13	0.066	–	–
Total	1.193	14	–	–	–



1 m/km = 63.36 inches/mi

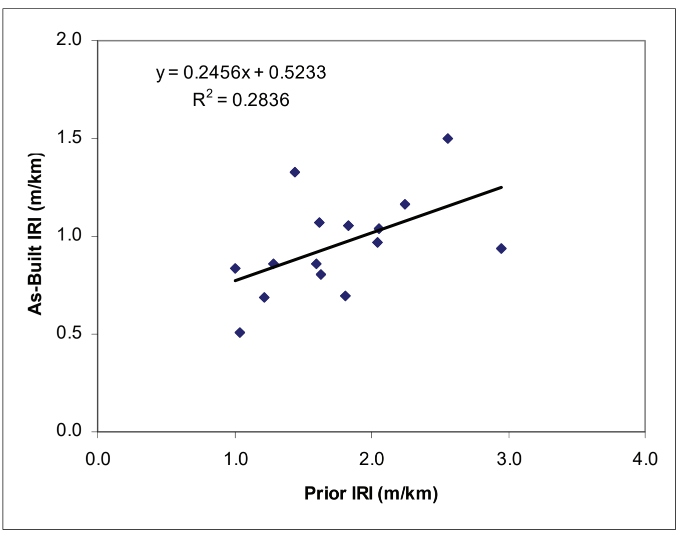
Figure 5. As-built roughness versus prior roughness for SPS-5 data with basic surface preparation and thin overlay

BASIC SURFACE PREPARATION AND THICK OVERLAY

The regression graph for basic surface preparation and thick overlays is shown in figure 6 and shows an R-squared of 0.28. The relationship has a p-value of 4.1 percent as shown in table 13. The prediction equation for basic surface preparation and a thick overlay is as follows:

$$IRI_{As-Built} = 0.52 + 0.25 \times IRI_{\Pr ior} \qquad (2)$$

For example, the expected as-built roughness for a pavement with a prior roughness of 2.00 m/km (127 inches/mile) undergoing basic surface preparation and a thick overlay is 1.01 m/km (64 inches/mile). This value is approximately 0.05 m/km lower than the previous value determined for a basic surface preparation and thin overlay, and is in line with the mean difference determined earlier in the paired data analysis. Another difference in the prediction equation for basic surface preparation and thick overlay is that the constant is larger and the slope is smaller than in the previous equation. The smaller slope is an indication that the thicker overlay reduces the effect of pavement roughness before resurfacing.



1 m/km = 63.36 inches/mi

Figure 6. As-Built roughness versus prior roughness for SPS-5 data with basic surface preparation and thick overlay

Table 13. Results of analysis of variance for basic surface preparation and thick overlay

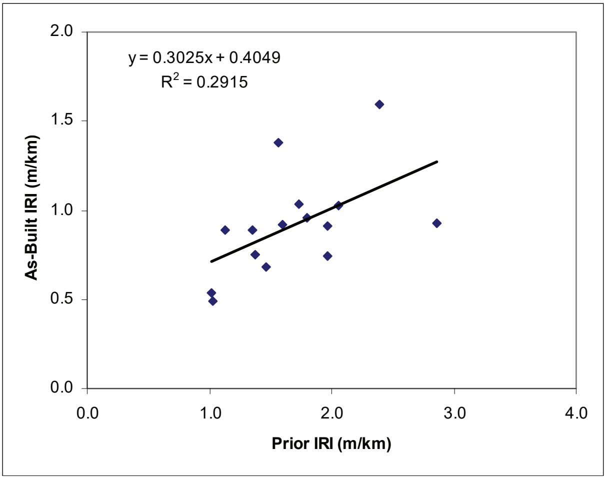
Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Statistical Significance
Prior Roughness	0.256	1	0.256	5.147	0.041
Error	0.648	13	0.050	–	–
Total	0.905	14	–	–	–

INTENSIVE SURFACE PREPARATION AND THIN OVERLAY

The regression graph for intensive surface preparation and thin overlays is shown in figure 7 and shows an R-squared of 0.29. This R-squared value is the highest of the four regression analyses for specific surface preparation and overlay thickness treatments. The relationship has a p-value of 3.8 percent as shown in table 14. This is the strongest statistical relationship of the four regression analyses. The prediction equation for intensive surface preparation and a thin overlay is as follows:

$$IRI_{Initial} = 0.40 + 0.29 \times IRI_{Prior} \qquad (3)$$

For example, the expected as-built roughness for a pavement with a prior roughness of 2.00 m/km (127 inches/mile) undergoing an intensive surface preparation and a thin overlay is 1.01 m/km (64 inches/mile). This value is approximately 0.05 m/km (3.2 inches/mile) lower than the value determined for a basic surface preparation and thin overlay. This value is similar to the mean difference determined earlier in the paired data analyses.



1 m/km = 63.36 inches/mi

Figure 7. As-built roughness versus prior roughness for SPS-5 data with intensive surface preparation and thin overlay

Table 14. Results of analysis of variance for intensive surface preparation and thin overlay

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Statistical Significance
Prior Roughness	0.333	1	0.333	5.349	0.038
Error	0.810	13	0.062	–	–
Total	1.143	14	–	–	–

INTENSIVE SURFACE PREPARATION AND THICK OVERLAY

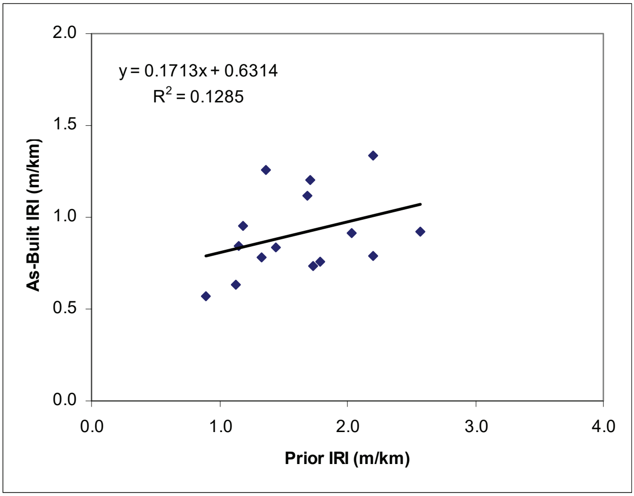
The regression graph for intensive surface preparation and thick overlays is shown in figure 8 and shows an R-squared of 0.13. This is lowest R-squared value of all four regression analyses. The relationship has the lowest statistical strength with a p-value of

18.9 percent as shown in table 15. One possible reason for the weak relationship is the low influence in the relationship of pavement roughness before resurfacing has in the relationship. The slope of the regression line is the lowest of all the regression lines. Although the relationship is weak, the prediction equation for as-built roughness based on pavement roughness before resurfacing with intensive surface preparation and a thick overlay is as follows:

$$IRI_{Initial} = 0.63 + 0.17 \times IRI_{Prior} \tag{4}$$

For example, the expected as-built roughness for a pavement with a prior roughness of 2.00 m/km (127 inches/mile) undergoing intensive surface preparation and a thick overlay is 0.97 m/km (61 inches/mile). As expected, this is the lowest expected as-built roughness of the four combinations. The expected IRI is 0.05 m/km (3.2 inches/mile) lower than the treatment of basic surface preparation and a thick overlay and 0.03 m/km (1.9 inches/mile) less than the value expected for a intensive surface preparation and thin overlay. These values compare well with the expected differences from the paired analyses.

The slope of the prediction equation for basic surface preparation and thick overlay is the lowest of all four prediction equations. The low slope is an indication that as-built roughness is least sensitive to prior roughness when intensive surface preparation and thick overlay treatment are used. This is as expected because this treatment is considered the most extensive for improving the as-built roughness of a pavement.



1 m/km = 63.36 inches/mi

Figure 8. As-built roughness versus prior roughness for SPS-5 data with intensive surface preparation and thick overlay

Table 15. Results of analysis of variance for intensive surface preparation and thick overlay

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Statistical Significance
Prior Roughness	0.092	1	0.092	1.917	0.189
Error	0.627	13	0.048	—	—
Total	0.719	14	—	—	—

CONCLUSIONS

Various statistical analyses, including paired analyses, regression analyses, and a repeated measures analysis, were performed to examine the effects of surface preparation, overlay thickness, type of overlay material, pavement roughness before resurfacing, and the interactive effects of these factors on the as-built roughness of a pavement. The following conclusions are provided based on these analyses:

1. The extent of surface preparation was determined to affect the as-built roughness of a pavement. The extent of surface preparation was also found to have an interactive effect on as-built roughness when considered in combination with the pavement roughness before resurfacing.

2. The overlay thickness was determined to affect the as-built roughness of a pavement. Although the effect was not determined to be statistically significant when considered individually, it was determined to have a statistically significant effect on as-built roughness when considered in combination with the pavement roughness before resurfacing.

3. The pavement roughness before resurfacing was found to have an effect on the as-built roughness of a pavement. In addition, pavement roughness before resurfacing was found to have interactive effects with both the extent of surface preparation and overlay thickness.

4. The type of overlay material (i.e., virgin or recycled) was determined to have essentially no effect on the as-built roughness of a pavement.

5. Prediction equations are provided to estimate the as-built roughness of a pavement for different types of surface preparation, overlay thickness, and pavement roughness before resurfacing.

RECOMMENDATIONS

Based on the findings of this paper, the following recommendations are provided:

1. Transportation agencies and contractors should consider the effects of surface preparation, overlay thickness, and pavement roughness before resurfacing when tendering or bidding asphalt overlay contracts with smoothness specifications.

2. Pavement designers should consider the lower as-built roughness that is achieved by incorporating a thicker pavement overlay and/or intensive surface preparation.

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PAPER 4 EFFECT OF SEASONAL MOISTURE VARIATION ON SUBGRADE RESILIENT MODULUS

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ABSTRACT

It is well known that environmental changes have severe effects on pavement performance. While an asphalt layer may be more sensitive to temperature, a soil or untreated pavement layer might be more affected by the change in moisture. This research aims at quantifying the effect of subgrade moisture variation, caused by environmental changes, on subgrade's resilient modulus and including its effects in the design process for new and rehabilitated pavements. To achieve this objective, data representing different soil types in non-freeze zones at various Long-Term Pavement Performance Seasonal Monitoring Program (LTPP-SMP) sites were downloaded from the DataPave 3.0 software. The downloaded data were analyzed to establish the effect of subgrade moisture variation on subgrade's resilient strength represented by the backcalculated elastic modulus. The analysis indicated that moisture in the subgrade layer is related to the precipitation intensity. The study also revealed that a Seasonal Adjustment Factor (SAF) could be used to shift the subgrade modulus from a normal season to another. The SAF is considered a key input in the mechanistic-based pavement design system. It allows the inclusion of the seasonal effects on the layer moduli for different seasons. In this paper, a method is presented for calculating the SAF for the subgrade soils. Using the collected data, regression analysis was performed and correlation equations were developed. These equations relate the backcalculated subgrade modulus to the subgrade moisture content and to other soil properties. The SAF

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relates the change in the moisture content to the change in the modulus value.

INTRODUCTION AND BACKGROUND

It is well known that high subgrade moisture content, with resulting decrease in subgrade strength and stiffness, is detrimental to roadway pavement performance. Establishing relationships between the highway pavement response and subgrade moisture variation is necessary for efficient pavement design. The backcalculated modulus, or the resilient modulus, of subgrade soil is the key parameter that is considered to represent pavement response. A brief summery of previous work discussing the effect of seasonal variations on soil resilient modulus is presented in the following subsections.

STUDY OBJECTIVE

The primary objective of this study is to examine the impacts of seasonal moisture variation on the subgrade resilient modulus.

MOISTURE EFFECTS ON SOIL RESILIENT MODULUS

Many researchers have investigated the influence of water content on the resilient modulus of fine-grained soils. Seed, Chan, and Lee (1962) studied the influence of “natural” water content on the resilient modulus of undisturbed samples of the silty clay (CL) American Association of State Highway and Transportation Officials (AASHTO) Road Test subgrades soil. The positions of the test points showed that for this soil a decrease in water content of only 3 percent below the T99 optimum doubled the decrease of the resilient modulus (from about 34 megapascal (MPa) (4931.28 poundforce per square inch (psi)) to about 69 MPa (10007.6 psi)). Tests conducted on CL subgrade soil at the San Diego County Experimental Base Project by Jones and Witczak (1977) showed that as its compaction water content was increased from about 11 percent to about 20 percent, the resilient modulus varied from almost 275 MPa (3988.5 psi) to a low of about 52 MPa (7541.96 psi).

Carmichael and Stuart (1985) presented correlations relating resilient modulus to fine-grained soil composition parameters. Using a database representing more than 250 soils (fine and coarse) and 3300 modulus test data points, they developed the following relationship:

$$\begin{aligned} MR = 37.431 - 0.4566\,PI - 0.6179\,w - 0.1424F \\ + 0.1791CS - 0.3248\,\sigma_d + 36.422CH + 17.097MH \end{aligned} \qquad (1)$$

Where MR is resilient modulus in kilopounds per square inch (ksi), PI is plasticity index in percent, w is water content in percent, F is percent passing sieve number 200, CS is the confining stress in psi, and σd is deviator stress in psi. The (CH) term is a material factor that is equal to one for soils classified as CH and is equal to zero for soils classified as inorganic silts (ML), elastic silts (MH), or clay (CL). MH is a material factor equal to 1 for soils classified as MH and equal to zero for soils classified as ML, CL, or CH.

The moisture sensitivity of coarse-grained materials depends on the amount and nature of their fine fraction. Clean gravels and sands classified as well graded gravel (GW), poorly graded gravel (GP), well-graded sand (SW), and poorly graded sand (SP) are not likely to exhibit moisture sensitivity because they lack a sufficient number of the small pores necessary to create significant suction-induced effective stresses, even at low water contents (Hicks and Monismith, 1971). Studies of coarse materials containing larger amounts of fines have shown that increasing degrees of saturation above about 80 to 85 percent can have a pronounced effect on resilient modulus. Rada and Witczak (1981) concluded that changes in water content of compacted aggregates and coarse soils could cause modulus decreases of up to 207 MPa (30,022.8 psi).

Several researchers have developed regression relationships between the resilient modulus of granular materials and water content. The general regression relationship for granular materials of Carmichael and Stewart (1985), stated previously as equation (1), contains a water content term that results in an 11.6 MPa (1682.45 psi) decrease in resilient modulus for each 1 percent increase in water content. Lary and Mahoney (1984) found regression relationships for resilient moduli of specific northwest aggregate base materials and predominantly coarse subgrade soils. The regression equations for the materials showed that if the initial modulus is on the order of 140 MPa (20,305.3 psi), a 1 percent increase in moisture content typically results in a resilient modulus decrease from about 4 to 11 MPa (580.15 psi to 1595.42 psi). A reasonable estimate for the influence of water content on reference resilient modulus of coarse soils would be about a 3.4 MPa (493.13 psi) decrease for each 1 percent moisture content increase for uniform or well-graded coarse materials containing little or no nonplastic fines (GW, GP, SW, SP). That value would increase to about 3.8 MPa (551.14 psi) per 1 percent moisture content increase for sands and gravels containing substantial amounts of plastic fines silty gravels (GM), clayey gravels (GC), course grained sands (SM), clayey sands (SC).

TEMPERATURE EFFECTS ON SOIL RESILIENT MODULUS

Temperature has significant effects on soil resilient modulus. The penetration of freezing temperatures into moist pavement subgrade soils can cause more severe effects than the effects of any of the water content changes likely to occur as a result of seasonal variations in precipitation. Freezing of soil moisture can transform a soft subgrade into a material that, at the stress levels existing in pavements, is essentially rigid. Thawing of the same material can produce a softening effect such that the material has a resilient modulus that is only a fraction of its pre-freezing value for some time after thawing, (Hardcastle, 1992).

The effects of an annual cycle of freezing and thawing on the deflections of pavements having coarse and fine-grained subgrades in Illinois and Minnesota were studied by Scrivner et al., (1969). The study showed that freezing results in sharp reductions in surface deflections while thawing produces immediate deflection increase for all of the pavements. The authors also found that pavement deflection changes could occur due to freezing of the structural layers alone, while the largest thaw-induced deflection increases take place when there is deep frost penetration into the fine-grained subgrade soils. Increases in deflection due to deep frost penetration and thawing of the coarse-grained subgrade soil are smaller than those for fine-grained soils. Because the sites included in this study are from the non-freeze zones, the effect of freeze/thaw is not considered in our study.

SEASONAL VARIATION AND SEASONAL ADJUSTMENT FACTORS

In a study on the LTPP data from site 48SA of a non-freeze zone, Ali and Parker, (1996) found that the backcalculated resilient moduli of both subgrade and asphalt concrete (AC) surface could be correlated to the month of the year in a sinusoidal function with reasonable accuracy.

Several research projects were conducted at the University of Idaho to study the effect of seasonal variations on pavement performance (Hardcastle, 1992; Al-Kandari, 1994; Bayomy et al., 1996, 1997; and Abo-Hashema et al., 2002). These projects recommended the use of the Falling Weight Deflectometer (FWD) to evaluate the pavement structure conditions, and provided initial values of subgrade soil resilient modulus for various climatic regions and soil types across the State of Idaho. Based on the study by Hardcastle (1992), Al-Kandari (1994) incorporated the SAF for subgrade soils in an environmental database derived from various climatic zones in Idaho. Abo-Hashema et al. (2002) suggested a general procedure for calculating the seasonal adjustment factor for subgrade soils, but they did not consider the effect of soil type (fine, coarse, plastic, and/or nonplastic). The previous projects demonstrated the need to establish a realistic SAF to be applicable to different soil types and environmental conditions. The SAF is a rationale adopted that incorporates the environmental effects in the design system to adjust subgrade modulus from one season to another.

The Washington State Department of Transportation (WSDOT) uses a mechanistic-empirical (M-E) system developed at the University of Washington and implemented in the computer program EVERPAVE 5.0 (1999). This program uses SAFs as key inputs by users and does not compute the SAF. The Minnesota Department of Transportation (MNDOT) uses an M-E flexible pavement thickness design that is implemented in the computer program ROADENT 4.0 by Timm, Birgisson, and Newcomb (2001). Because ROADENT does not have the SAF to adjust the resilient modulus from one season to another, the user must calculate and enter the resilient modulus values for each season.

APPROACH

The elastic modulus of a pavement layer represents the main parameter that reflects the materials' structural adequacy; the study thus is focused on the determination of the seasonal impacts on the layer moduli, but is limited to the subgrade layer. The elastic modulus of a pavement layer changes in response to environmental changes such as variations in temperature for asphalt layers, and moisture variation for untreated layers such as base and subgrade. To account for the changes in subgrade elastic modulus, a multiplier can be used for adjusting subgrade resilient modulus from one season (reference) to another. This multiplier, Seasonal Adjustment Factor (SAF), is based on soil type and environmental conditions. This study aims at developing a concept for calculating the SAF for subgrade soil layer as well as a model relating the subgrade backcalculated modulus to its moisture content.

MOISTURE AND MODULUS DATA

To address the issue of environmental impacts on pavement at a national level, the Federal Highway Administration (FHWA) launched the SMP as a major component of the LTPP program (Rada et al., 1994). The data used in this study were downloaded from the DataPave 3.0 (2001), a software package that contains most data from the LTPP experiments. Seven different LTPP sites were considered in this study to represent different soil types (sites

35-1112, 28-1016, 48-1122, 48-1077, 13-1005, 48-4143 and 24-1634). The subgrade soils of the sites are sand, coarse silty sand, coarse clayey sand, fine sandy silt, fine sandy clay, clay, and silt, respectively. All selected sites are from the non-freezing zones except the last site, 24-1034, which is considered as a wet-freeze zone, where the minimum average monthly air temperature is 1.7 °C (35 °F), as shown in table 1. Site 24-1034 thus also could be considered to be from the non-freezing zones.

Detailed explanations for the selected sites are shown in table 1, which shows the site location, minimum average monthly air temperature, subgrade soil type, soil classification, soil sieve analysis, Atterberge limits, dry density, and optimum moisture content for each soil type in the selected sites. Downloaded data for each site included the backcalculated elastic moduli for subgrade soil and AC surfaces, the AC layer temperature, and both volumetric and gravimetric moisture content of subgrade soil at different time intervals. For the purpose of this study, only the analyses of the change in subgrade soil moduli with seasonal moisture variation were considered.

Table 1. LTPP site locations and subgrade soil characterization

Sites ID	**35-1112**	**28-1016**	**48-1122**	**48-1077**	**13-1005**	**48-4143**	**24-1634**
State	NM	MS	TX	TX	GA	TX	MD
Surface Type	Flexible	Flexible	Flexible	Flexible	Flexible	Rigid	Flex-ible
Minimum Monthly Air Temperature, Co	5.80	5.00	9.70	3.60	8.70	9.70	1.70
Soil Type	Coarse, poorly graded sand	Coarse, silty sand	Coarse, clayey sand	Fine, sandy silt	Fine, clayey sand	Fine, clay	Fine, silt
Soil Symbol	S	SM-C	SC-C	SM-F	SC-F	C	M

Table 1. LTPP site locations and subgrade soil characterization—*Continued*

Sites ID	35-1112	28-1016	48-1122	48-1077	13-1005	48-4143	24-1634
Unified Soil Classification	SP	SM	SC	SM	SC	CL	ML
AASHTO Soil Classification	A-3	A-2-4	A-2-6	A-4	A-6	A-7-6	A-4
% Passing # 4	100.00	92.00	99.00	94.00	–	–	99.00
% Passing # 10	99.00	91.00	97.00	93.00	–	–	98.00
% Passing # 40	94.00	85.00	75.00	87.00	–	–	98.00
% Passing # 200	2.70	25.70	6.50	51.80	38.40	90.00	97.90
D60, mm	0.18	0.23	0.30	0.10	–	–	–
Liquid Limit, %	–	18.00	26.00	–	27.00	41.00	–
Plasticity Index, %	NP	3.00	12.00	NP	12.00	23.00	NP
Dry Density, gm/cm3	1.698	1.906	1.858	1.906	2.05	1.730	1.746
Optimum Moisture, %	12.00	13.00	8.00	10.00	10.00	15.00	12.00

DATA ANALYSIS

To study the effect of seasonal moisture variation on pavement performance, seven different LTPP sites were considered; they represent different soil types, as explained above. The primary data collected at these sites are the gravimetric moisture content (considered to be the main factor affecting subgrade soil strength) and the backcalculated elastic moduli for different subgrade soils at different seasons. Results are discussed and analyzed in the following subsections.

SEASONAL VARIATION OF MOISTURE AND MODULUS OF SUBGRADE SOIL

Moisture content of soils near the ground surface depends on a variety of climatic and physical factors, including soil type, temperature, precipitation, vegetation, and others. It is widely known that pavement subgrade soils not only experience temporary (seasonal) changes in moisture content but also undergo changes in their long-term average annual moisture content. This section discusses the seasonal variation in both moisture and modulus of subgrade soil.

Moisture and Modulus Variation with Time

Figures 1 through 4 show the relationship between both gravimetric moisture content and subgrade backcalculated modulus with time for different sites from the non-freeze zones. The figures indicate that both moisture content and backcalculated elastic moduli have almost a sinusoidal function with time. The figures also indicate that the backcalculated elastic modulus could be related to moisture content with an opposite fitness function, as the elastic modulus increases when the moisture decreases and vice versa. This behavior could be observed at all sites except site 28-1016, shown in figure 4, and also site 35-1112. The main reason for the different behavior of sites 28-1016 and 35-1112 regarding the direct proportional relationship between their moduli and moisture content is that the subgrade soils at both sites are noncohesive (silty sand and sand, respectively), and the field moisture content at both sites is below the optimum moisture content measured at the lab from a compaction test, as shown in table 1. In this case, increasing soil moisture results in increasing its modulus until the optimum moisture content is reached, then the modulus will reduce with further increase in moisture content. Figures 2 and 3 also indicate that both the maximum modulus values and minimum moisture values are measured through the summer season (July and August), while the minimum modulus values and maximum moisture values are measured through the winter (January and February).

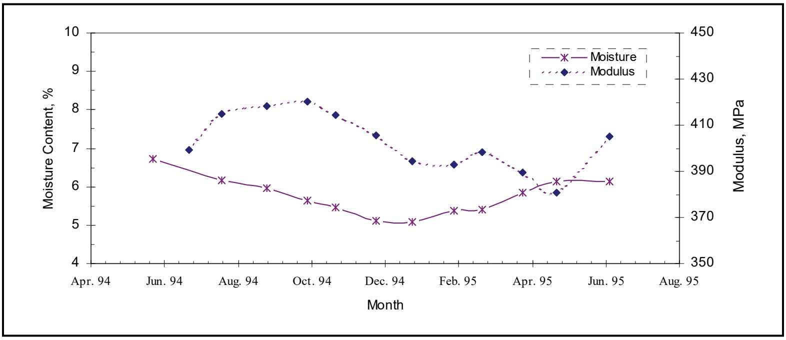


Figure 1. Moisture content and elastic modulus versus season for clayey soil, site 48-1122

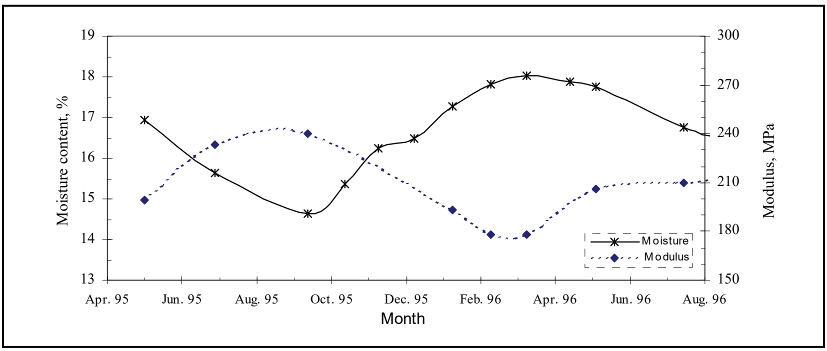


Figure 2. Moisture content and elastic modulus versus season for silty soil, site 24-1634

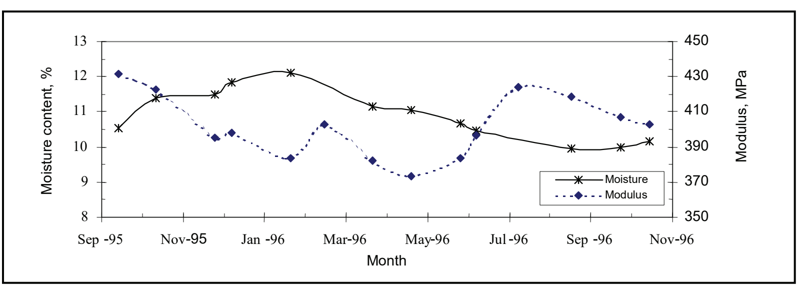


Figure 3. Moisture content and elastic modulus versus season for clayey soil, site 13-1005

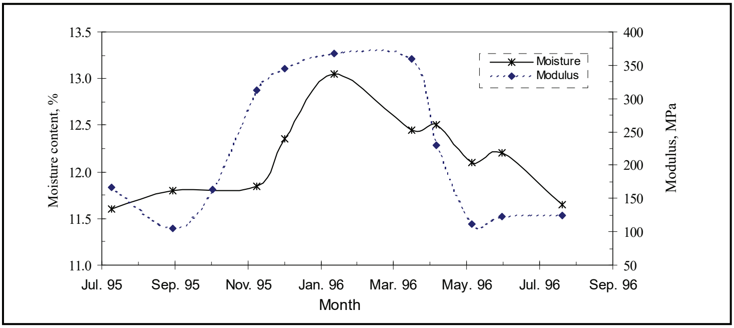


Figure 4. Moisture content and elastic modulus versus season for silty sand, site 28-1016

Relating Moisture Content to Average Precipitation

The average monthly precipitation and the measured moisture content at sites 28-1016, 24-1634, 13-1005 and 48-4143 are shown in figures 5 through 8, respectively. The figures indicate that the moisture increases when the average precipitation increases and decreases with decreasing precipitation. Therefore, the moisture content could be highly related to the average precipitation. Figure 9, for site 48-4143, shows that moisture content could be related to the average precipitation with a liner function having R2 value of 0.48. Similar relationships could be developed for the other sites. It should be noted that the average precipitation is not the only factor that affects subgrade moisture content. There are many other climatic and physical factors such as: soil type, temperature, precipitation, vegetation, and others. Witczak et al., (2000), are extensively studying the use of precipitation in moisture content predictions through the intergraded climatic model (EICM 2.6), for the development of the AASHTO 2002 *Guide for the Design Of New And Rehabilitated Pavement Structures*.

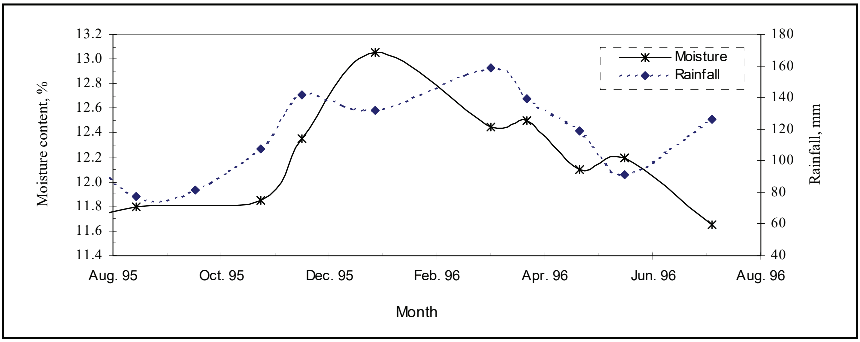


Figure 5. Moisture content and rainfall versus season for silty sand soil, site 28-1016

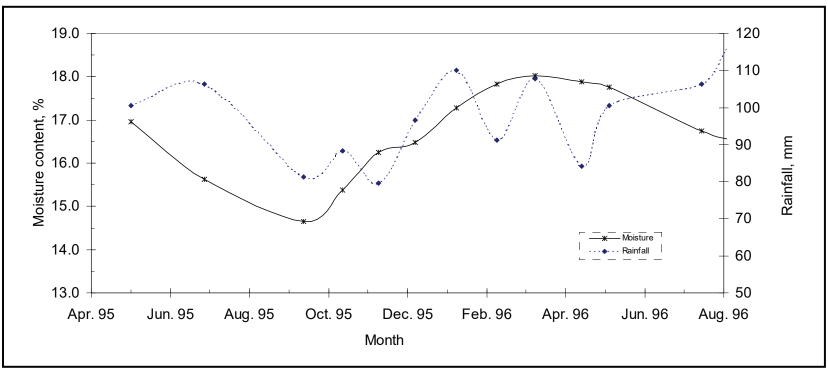


Figure 6. Moisture content and rainfall versus season for silty soil, site 24-1634

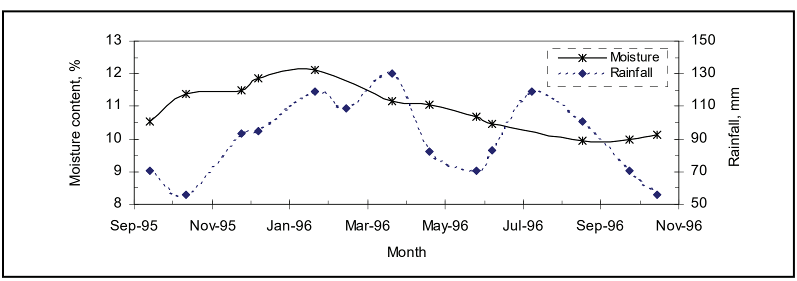


Figure 7. Moisture content and rainfall versus season for clayey soil, site 13-1005

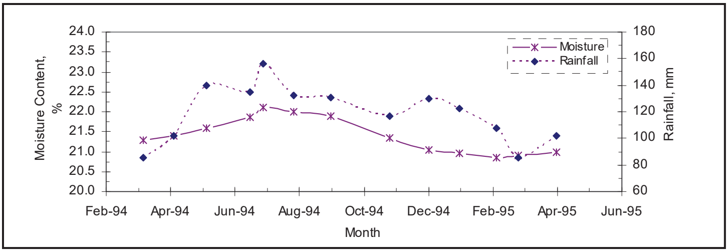


Figure 8. Moisture content and rainfall versus season for clayey soil, site 48-4143

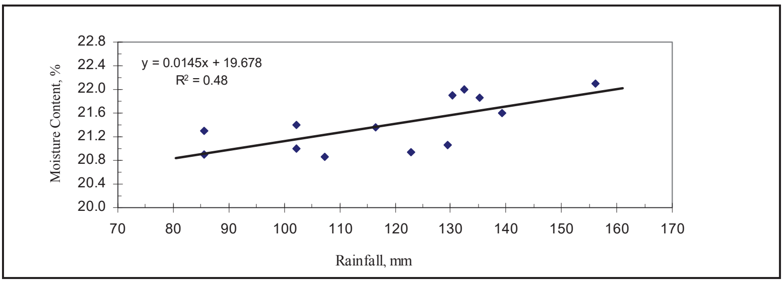


Figure 9. Moisture content versus rainfall for clayey soil, site 48-4143

CORRELATING THE BACKCALCULATED ELASTIC MODULUS TO SUBGRADE SOIL MOISTURE AND OTHER SOIL PROPERTIES

Model Development for Plastic Soils

For the purpose of this study, multiple regression analysis is applied using the SAS program to relate the backcalculated elastic modulus to subgrade moisture content and such other soil properties as: Atterberge limits, percentage passing sieve # 200, D60. Data from three different LTPP sites (48-4143,13-1005 and 48-1122) are used in this analysis. The subgrade soils at these three sites are: clay, fine sandy clay, and coarse sandy clay, respectively. These sites were chosen because their soils have values for plasticity index (PI; plastic soil), while most of the other sites have nonplastic soils. The SAS program output of the regression analysis is shown in table 2, in which:

E = Backcalculated elastic modulus, MPa
E1 = Log (E)
X1 = Log (moisture content, percent)
X2 = 1/(moisture content, percent)
F = Percentage passing sieve # 200, %
PI = Plasticity index, percent

Table 2. The regression procedure using R-square selection method for three sites

SAS program output, dependent variable: E1

Number in Model	R-Square	C(p)	BIC	Root MSE	Variables in Model
1	0.9767	176.6577	-844.4975	0.07112	PI
1	0.7840	2926.776	-491.2373	0.21651	F
1	0.6981	4151.479	-437.8291	0.25593	x1
1	0.5068	6880.904	-359.4122	0.32712	x2
2	0.9795	137.8704	-863.9304	0.06683	F PI
2	0.9768	177.2805	-844.1832	0.07120	x2 PI
2	0.9767	178.3979	-843.6575	0.07132	x1 PI
2	0.9022	1241.671	-617.3199	0.14614	x1 x2
3	0.9884	13.2697	-950.0654	0.05045	x1 F PI
3	0.9871	32.4110	-933.3682	0.05329	x1 F PI
3	0.9781	159.8558	-852.5841	0.06930	x1 x2 PI
3	0.9161	1045.302	-641.4009	0.13579	x1 x2 F
4	0.9891	5.0000	-957.7523	0.04902	x1 x2 F PI

Table 2 indicates that the logarithm of the backcalculated modulus (E1) could be related only to the logarithm of moisture content (X1) with a function having a coefficient of determination (R2) value of 0.698. However, when adding other soil properties, like PI and F to the model, a better model having R-square value of 0.989 could be achieved. The developed model is shown in equation (2).

$$\begin{aligned}\text{Log (E)} = \text{Co} + \text{C1} * \text{Log (moisture)} + \text{C2} \\ * (1/\text{moisture}) + \text{C3} * \text{F} + \text{C4} * \text{PI}\end{aligned} \qquad (2)$$

Where: E, F, and PI are as described before in table 2 and Co, C1, C2, C3 and C4 are model constants.

The estimated values of the model constants and the analysis of variance (ANOVA) for that model are shown in table 3. Table 3 also shows that the sum of squared errors (SSE) for that model is 0.372, the coefficient of variation is 0.859, and the adjusted R2 is 0.989. The last two columns in the bottom of table 3 contain results of the statistical test that evaluates the significance of each regression coefficient. The test results indicate that at a significance level of 95 percent, all estimated model parameters are significant (p-value is less than 0.05). The final model with its estimated constants is shown in equation (3).

$$\text{Log (E)} = 8.82 - 0.673 * \text{Log (moisture)} - 2.44 * (1/\text{moisture}) + 0.0084 * F - 0.11 * PI \tag{3}$$

Table 3. Analysis of variance table and estimated model parameters

(SAS program output, dependent variable: E1)

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value
Model	4	33.90986	8.47747	3528.46
Error	155	0.37240	0.00240	
Corrected Total	159	34.28227		

Root MSE	0.04902	R-Square
Dependent Mean	5.70630	Adj R-Sq
Coeff Var	0.85899	

Estimated Model Parameters

Variable	DF	Parameter Estimate	Standard Error	t Value
Intercept	1	8.81933	0.31794	27.74
X1	1	-0.67276	0.12405	-5.42
X2	1	-2.43912	0.76112	-3.20
F	1	0.00838	0.00066926	12.52
PI	1	-0.11065	0.00343	-32.28

Figures 10 through 12 show the model application on the data collected from sites 48-4143, 13-1005, and 48-1122, respectively. The figures indicate that the model fits the data very well and that the modulus decreases with increasing soil moisture even if the field moisture content is less than the optimum moisture content, as shown in figures 11 and 12 for sites 13-1005 and 48-1122, respectively. The reason is that the subgrade soils at both sites are cohesive soils (sandy clay). Therefore, when the moisture content decreases, the soil becomes harder and its modulus increases, while the modulus deceases when moisture increases. It should be noted that this model could be applied only for plastic (clayey) soils, as there is a term in the model for PI. For nonplastic soils, this model will be modified to account for soil properties other than PI (explained later in this paper).

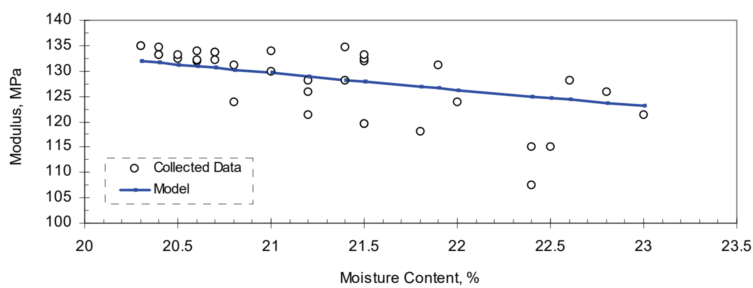


Figure 10. Backcalculated modulus vs. moisture content for clayey soil, site 48-4143

145 MPa = 1 psi

Figure 10. Backcalculated modulus versus moisture content for clayey soil, site 48-4143

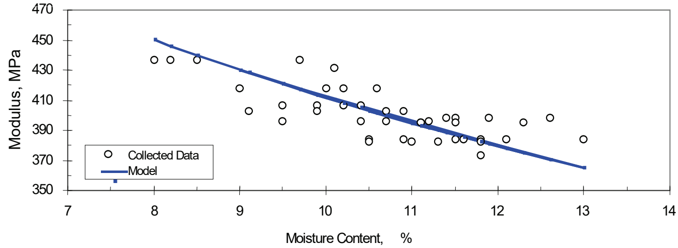


Figure 11. Backcalculated modulus vs. moisture content for fine sandy clay soil, site 13-1005

145 MPa = 1 psi

Figure 11. Backcalculated modulus versus moisture content for fine sandy clay soil, site 13-1005

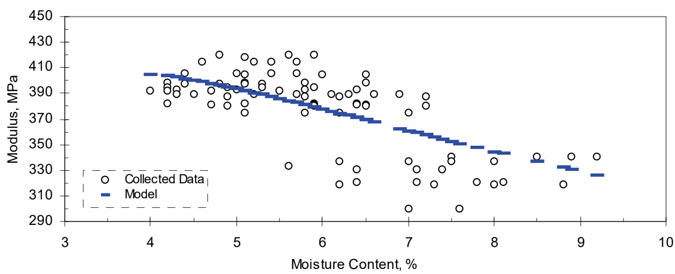


Figure 12. Backcalculated modulus vs. moisture content for coarse sandy clay soil, site 48-1122

145 MPa = 1 psi

Figure 12. Backcalculated modulus versus moisture content for coarse sandy clay soil, site 48-1122

Model Development for Nonplastic Soils

As was described previously, the model shown in equation (3) could not be applied directly for non-plastic soils (sandy and/or silty soils), as there is a term in the model for PI. To generalize the previous model, it is simplified to the generic form shown in equation (4).

$$\text{Log (E)} = C^* + C1 * \text{Log (moisture)} + C2 * (1/\text{moisture}) \quad (4)$$

where:

C*	= Co + C3 * F + C4 * PI	
	= 8.82 + 0.0084 * F - 0.11* PI	(for plastic soils)
C1	= - 0.673	(for plastic soils)
C2	= - 2.44	(for plastic soils)

E, F, and PI are as described before for table 2.

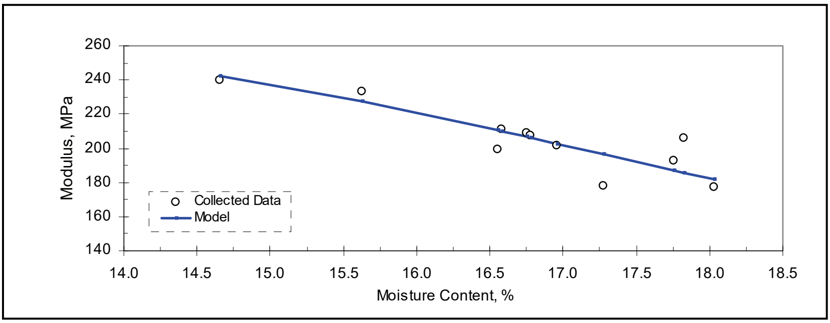
Several trials were made, using Solver in the Microsoft® Excel® program, to fit the moisture-modulus data of nonplastic soils to the model shown in equation (4). Data from sites 24-1634, 48-1077, and 35-1112 were used in these trials. The subgrade soils at these sites are silt, fine silty sand, and sand soils, respectively. The model constants C*, C1, and C2 were calculated for each site using the Solver program, and are shown in table 4. The model was found to fit the data, as shown in figures 13 through 15. The estimated R2 values for the previous figures are 0.72, 0.36, and 0.32 respectively. The higher R2 value was achieved with the silty soil (site 24-1634), while the lower R2 value was achieved with sand (site 35-1112).

Table 4. Estimated model constants for nonplastic soils

Site	Type	C*	C1	C2
24-1634	Silt	30.16	−89.670	−6.910
48-1077	Fine sandy silt	12.40	−24.900	−2.080
35-1112	Sand	5.74	0.043	0.133

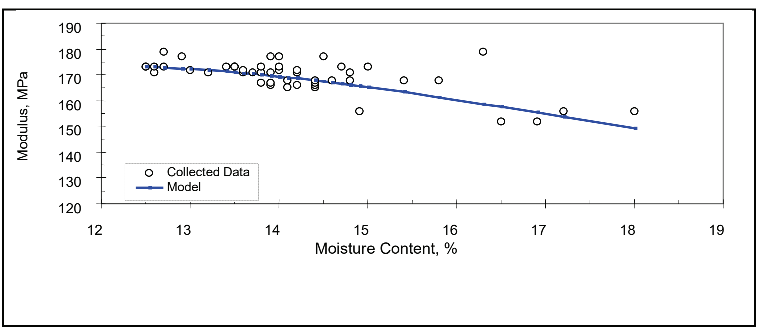
Regression analysis was applied using the SAS program to relate the model constants (C*, C1, and C2), shown in table 4, to other material properties of nonplastic soils like dry density, D60 and percentage passing sieve #200. It was found, with good accuracy (R2 = 1), that the model constants (C*, C1, and C2) could be related to the percentage passing sieve #200 (F) and D60, with a linear function. Therefore, the following equations were developed through regression analysis to estimate the model parameters for nonplastic soils.

$$\left.\begin{aligned} C^* &= 90.63 - 0.618 * F - 462.35 * D60 \\ C1 &= -304.96 + 2.199 * F + 1661.50 * D60 \\ C2 &= -20.14 + 0.135 * F + 110.58 * D60 \end{aligned}\right\} \qquad (5)$$



145 MPa = 1 psi

Figure 13. Backcalculated modulus versus moisture content for silty soil, site 28-1634



145 MPa = 1 psi

Figure 14. Backcalculated modulus versus moisture content for fine sandy silt, site 48-1077

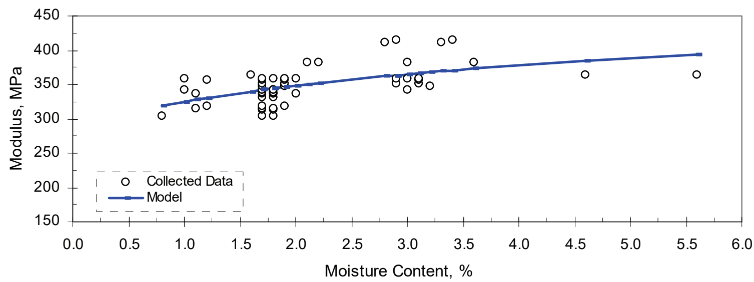


Figure 15. Backcalculated modulus vs. moisture content for sandy soil,

145 MPa = 1 psi

Figure 15. Backcalculated modulus versus moisture content for sandy soil, site 35-1112

In conclusion, as figures 10 through 14 show the backcalculated elastic modulus decreases with increasing soil moisture content for non-freeze sites. Only figure 15 indicated that the elastic modulus increases with increasing moisture content. The reason for the direct relationship shown in figure 15 is the same as described for figure 4 (e.g., noncohesive soil). The soil in figure 4 is sand, and its field moisture is much less than the optimum moisture content for this soil, which is 12.0 percent as shown in table 1. Therefore, increasing moisture content in such cohesionless soils by increases their modulus until the optimum moisture is reached, then the modulus reduces. For cohesive soils (clayey soils), increases in subgrade moisture will be accompanied with a reduction in their moduli, whatever the soil moisture condition is, before or after the optimum, as discussed earlier.

It should be noted that the general model shown in equation (4), could be applied to any soil type. The model constants (C*, C1, and C2) could be estimated either from equation (4) in the case of plastic soils, or equation (5) in the case of nonplastic soils.

ESTIMATING SEASONAL ADJUSTMENT FACTORS

The SAF is considered to account for the changes in subgrade soil modulus due to seasonal change in subgrade moisture content. The SAF reflects both the subgrade soil class and the climate in which the pavement is located. For the purpose of developing a model to measure the subgrade modulus shift factor, regression analysis was applied to the moisture-modulus data of different soil types. The soil types that were included in this study are: silt (M), clay (C), silty sand (SM), fine sandy clay (F-SC) and coarse sandy clay (C-SC). The moisture-modulus data of the previous soil types were downloaded from sites 24-1634 (M), 48-4143 (C), 48-1077 (SM), 13-1005, and 28-1016 (F-SC).

The result of the regression analysis is shown in figure 16. The X-axis of figure 16 shows the moisture increase, which is the seasonal moisture divided by the minimum moisture content measured at this site through the year (usually summer moisture content). The Y-axis shows the modulus shift factor: the seasonal backcalculated modulus at any site divided by the maximum modulus measured throughout the year (usually the summer modulus or the modulus corresponding to the minimum seasonal moisture). The analysis of figure 16 indicates that the shift factor could be related to moisture increase with the model shown in equation (6).

$$SF = k_o * M - k \qquad (6)$$

Where:

SF	= Modulus shift factor (E_{Season}/ E_o)
M	= Moisture increase (M_{Season}/ E_o)
k_o, k	= Model constants, dependent on soil type
M_{Season}, E_{Season},	= Moisture and modulus at any season, respectively

M_o, E_o = Reference moisture and corresponding modulus, usually taken during summer or at the season having the minimum moisture throughout the year.

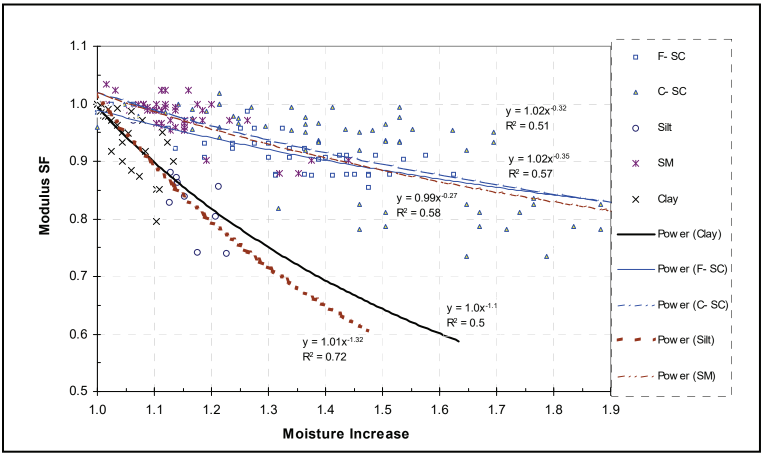


Figure 16. Estimated modulus shift factor for different soil types

The model shown in equation (6) is simple and dimensionless, and was found to fit the data from most sites with reasonable accuracy (R2 ranges from 0.5 to 0.72), as shown in figure 16. The model constant (k_o) was found to be 1.0 for all soils, as shown in the figure, while the constant (k) changes with soil type. The model constant (k) increases with increasing soil sensitivity to moisture increase. The figure indicates that constant (k) ranges from 0.32 for coarse sandy clay to 1.1 for clay and 1.32 for silty soils. The figure indicates also that if the moisture content is increased by 20 percent (factor 1.2), the modulus for silty soils reduces to 0.80 of its value. The corresponding modulus reductions for clay and sandy clay soils are 0.83 and 0.96, respectively. Therefore, the pure silty soils are more sensitive to moisture increase than pure clayey soil and all other soil types. Figure 16 also indicates that water sensitivity for sandy soils (sandy silt, fine sandy clay, and coarse sandy clay) is almost the same and is much less than that of pure silty or clayey soils. Equation (6) and/or figure 16 could be used to estimate the seasonal adjustment factor for a certain season by just knowing soil type and the expected moisture increase in that season with respect to the reference season.

SUMMARY AND CONCLUSION

The data used in this study were downloaded from the LTPP-SMP database, DataPave 3.0 (2001). Through the analysis of these data it was found that both moisture and modulus follow almost a sinusoidal function with different months of the year. While the moisture increases during a season, the modulus decreases during the same season and vice versa. The minimum seasonal subgrade moisture content (higher modulus values) was observed during summer season while the highest moisture (lowest modulus) was observed during winter. However, in some cases for noncohesive soils, increasing moisture content may result in increasing its modulus if the in situ moisture content is below the optimum moisture content. The data showed also that the moisture content profile through the months of the year could be related to the average monthly rainfall.

In this study, the relationship between subgrade modulus (E) and the gravimetric moisture content was determined for different soil types. A general model relating subgrade modulus to soil moisture and other soil properties was developed and applied for different soil types. Also, a simple model for calculating the modulus shift factor of subgrade soil was developed. The modulus shift factor adjusts subgrade modulus from one reference season (usually summer) to another. This allows determination of subgrade resilient modulus at any season by multiplying the reference value by the SAF for that season. The reference value is the modulus value determined by testing during any selected season (summer). The SAF varies according to subgrade soil type and climatic conditions. The results showed also that pure silty soil is more sensitive to moisture variation than are all other soils.

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PAPER 5 DEVELOPMENT OF A PAVEMENT CLIMATE MAP BASED ON LTPP DATA

Yuhong Wang

ABSTRACT

It has long been recognized that climate factors have important influences on pavement performance. To help investigate this influence, the Strategic Highway Research Program (SHRP) Long-Term Pavement Performance (LTPP) research has been using onsite or virtual weather stations to record climate information on test sections. The data will facilitate the study of the quantitative relationship between climate and pavement performance. This paper discusses how to develop a climate map using cluster analysis on performance-related climate data from the LTPP database, which contains nearly 1,000 virtual weather stations recorded for more than 17 years. The aim of developing this map is to help researchers, who are performing data analysis on the LTPP database, to incorporate or separate climate factors in their models. Another potential use of this map is to help highway practitioners get climate pattern information for their geographical areas so that they can apply the same design criteria, construction requirements, and maintenance strategies to those regions with similar climate patterns.

INTRODUCTION

It has long been recognized that the climate factors have important influences on highway pavement performance. They can not only influence pavement structure integrity, but also cause common surface distresses. For example, temperature is widely known to have significant influence on pavement rutting and cracking. To account for its influence, the Superpave® mix design approach has incorporated temperature as an input factor of the mix design process.

If highway practitioners recognize the quantitative relationship between climate factors and road performance, and have sufficient information on local climate conditions, they can reduce the negative influences of these factors through correct practices. To get extensive climate information from across the United States and some areas of Canada, the LTPP program, sponsored by SHRP, constructed a climate database to record climate information on most LTPP test sections. A quality-control check was then conducted on the raw data; these data sometimes were summarized. The database distributed by the DataPave 3.0 software contains climate information on nearly 1,000 test sections recorded from 1980 or even earlier. The aim of this paper, however, is not to examine the quantitative relationship between the climate factors and pavement performance, but to develop a climate map that will partition test sections according to their climate patterns. Test sections that have a similar climate pattern will be assigned to the same group by using a multivariate data analysis technique, cluster analysis. This climate map should help researchers who are using the LTPP data to perform statistical treatment comparison incorporate or separate the climate factors in their models. Without appropriately addressing these climate factors, one cannot get valid inferences from comparison of other controlled parameters. Another potential use of this map is to help highway practitioners get climate pattern information in their geographical areas so that they can apply the same design criteria, construction requirements, and maintenance strategies to those regions with similar climate patterns.

At present, the highway climate regions in the United States and Canada are roughly divided into four major groups:

- Wet freeze.
- Wet no freeze.
- Dry freeze.

- Dry no freeze.

A wet region has an average annual rainfall over 508 millimeters (mm) (20 inches). A freeze region has an average freezing index of more than 83.3 degree-Celsius days (150 degree-Fahrenheit days, e.g., 10-degree days = 10 days with a mean air temperature of 1 degree below freezing or 5 days with a mean air temperature of 2 degrees below freezing).

This categorizing method can be easily followed and thus widely used in practice. However, the drawback of this method is that it may miss other climate parameters that also influence pavement performance. For example, in cold areas, roads with or without a lot of snow will unlikely perform the same way. Even with the same amount of annual rainfall, roads in areas under frequent intense rains should not have the same design criteria as roads in areas with frequent drizzles, because the two precipitation patterns bring different pressures on road drainage systems. Therefore, more parameters should be included in categorizing climate regions. However, the increase of the number of parameters makes it difficult to partition data in an ordinary way. This research uses cluster analysis to group the LTPP test sections based on multiple climate variables, and uses principle components analysis and Geographic Information System (GIS) maps to verify the grouping results.

RESEARCH APPROACH

The climate data in the LTPP database are organized into several tables, most of which contain large amounts of records. For example, the monthly precipitation table alone has 243,237 records with 10 fields for each record. Analysis of this large amount of data was fulfilled through the following steps:

- Selecting tables that contain climate information from the LTPP database.
- Preprocessing and transforming the data.

- Partitioning the virtual weather stations using hierarchical and nonhierarchical clustering methods.
- Verifying and comparing the clustering results using principle components analysis.
- Presenting the clustering results on a GIS map.

At first, this research picked climate tables from the LTPP database that were going to be used for analysis and wrote the Structured Query Language (SQL) commands to get required information from these tables. These data were processed in excel with embedded excel functions, or the researchers wrote Visual Basic Application (VBA) commands.

Cluster analysis was then conducted to group the test sections based on several climate variables (parameters) after the transformation of the data. Of the many different clustering approaches, this research selected both a hierarchical clustering method (average link) and a nonhierarchical clustering method (K-means), and then combined these two methods together. After finishing the cluster analysis, this research employed another multivariate data-analysis technique, principle components analysis, to verify and compare the clustering results by the different clustering techniques. The statistical software packages SAS and SPSS were used for cluster analysis and principle component analysis.

Finally, this research input the clustering results into the GIS provided by the DataPave 3.0 software. After processing by the Arcview™ software, the clustering results were presented on a GIS map, which is not only visually friendly, but can also verify the validity of the cluster results.

CLIMATE DATA PREPROCESSING AND TRANSFORMATION

The climate data used in this research were obtained from the latest update of the LTPP database distributed with the software package, DataPave 3.0. This research did not get the data through the software directly, but employed its underlying database. The climate data stored in the LTPP database can be divided into two categories according to the source of data: directly from onsite weather stations, or calculated from public climate databases. The onsite climate measurements are taken from all Seasonal Monitoring Program (SMP) test sections and Specific Pavement Studies (SPS-1 and -2), and 8 projects (LAW PCS, 1999), which involve 41 unique test sections. Data from the public climate databases, provided by the National Climatic Data Center (NCDC) and the Canadian Climatic Center (CCC), covers more than 1,000 distinctive test sections. However, this part of the data is not observed values; these values are computed by using a distance-weighted average method from up to five nearby public weather stations, so the test sections with such climate records are called “virtual” weather stations. The virtual climate data consist of monthly and annual climate parameter values, from the earliest available records to the most recent. Currently, there are 22 different climatic observation parameters and associated descriptive statistics, including minimum temperature, maximum temperature, mean temperature, precipitation, snowfall, minimum relative humidity, maximum relative humidity, average wind speed, peak gust speed, percent sunshine, and percent sky cover. Also included are derived quantities calculated from the measured data, such as air freezing index, air freeze-thaw cycles, total precipitation, total snowfall, etc. A limited set of annual statistics also is available; these include annual air freezing index, number of air freeze-thaw cycles, and snow coverage data for each of the monthly parameters (LAW PCS, 1999).

Data selection in this research is very important for cluster analysis on the LTPP database. If too few data are included, the analysis results will not be very representative. On the other hand, too many data are difficult to handle and may exceed the capacity of standard software. Because cluster analysis compares the similarity among observations, the variables should also be recorded from the same source (onsite or virtual weather stations), and special attention should be paid to missing values.

The virtual weather stations cover many more test sections than do the onsite weather stations; therefore, this research only selected climate data from this source. The climate tables include both monthly and annual observations. Because the size of the monthly data records is too large and they contain many missing values, this research only uses the annual summary tables.

The earliest virtual climate data recorded in the database are from 1933, while the most recent are from 1996. The number of test sections that have virtual weather records along the time axis is shown in figure 1, which shows most observations concentrated between 1980 and 1996. To make the data comparable, this research preprocessed the annual data in two separate parts. The first part, which includes 867 test sections without missing values, comprises annual weather records from 1980 to 1996. This part of the data is called Type I data in this paper. The second part, which includes 894 test sections, consists of the overall average values of climate parameters for each test section since 1980, called Type II data in this paper. The reason for using Type I data is to keep the pattern of annual climate conditions. Type II data are more concise, thus more workable in data analysis, but the pattern information may be lost. After cluster analysis, a final comparison was conducted to investigate which part of the data yields the best clustering results.

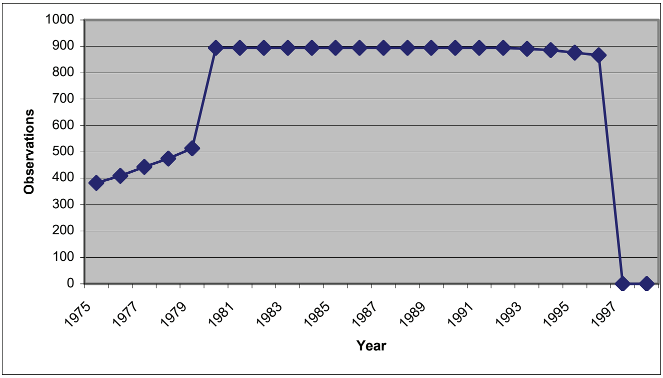

Figure 1. The number of text sections having climate records each year.

This research finally selected the 14 parameters in table 1 as the cluster analysis variables.

Table 1. Final climate parameters in cluster analysis

Field Name	Explanation
TOTAL_ANN_PRECIP	Total annual precipitation
INTENSE_PRECIP_DAYS_YR*	Number of days for which precipitation was greater than 12.7 mm (0.5 inches)
WET_DAYS_YR	Number of days for which precipitation was greater than 0.25 mm (0.01 inches)
TOTAL_SNOWFALL_YR	Total snowfall for year
SNOW_COVERED_DAYS_YR	Number of days for which snow covered data were available for year
MEAN_ANN_TEMP_AVG	Average of daily mean air temperatures for year
MAX_ANN_TEMP_AVG	Average of daily maximum air temperatures for year
MIN_ANN_TEMP_AVG	Average of daily minimum air temperatures for year
MAX_ANN_TEMP	Absolute maximum air temperature for year
MIN_ANN_TEMP	Absolute minimum air temperature for year
DAYS_ABOVE_32_C_YR	Number of days where daily maximum air temperature is above 32.2 °C (90 °F) for year
DAYS_BELOW_0_C_YR	Number of days where daily minimum air temperature is below 0 °C (32 °F) for year
FREEZE_INDEX_YR	Calculated freezing index for year
FREEZE_THAW_YR	Number of freeze/thaw cycles for year

* Where YR appears in the field, it means the unit being measured over the course of one year.

For the Type I data, because each test section contains 17 years' observations, comparing the annual pattern required that the original variables be combined with the year in which they were recorded to create new variables. After this transformation, each climate parameter becomes 17 new variables that not only show the parameter name but also indicate which year it is recorded. The process of transformation is shown in table 2. Finally, 17×14 = 238 new variables generated for each test section.

Table 2. Transformation of the Type I data

Sections	Year	Total Annual Precipitation (mm)	Average Temperature (°C)
Section #1	1996	1325.8	16.7
Section #1	1995	1266.4	17.5
Section #1	–	–	–
Section #1	1980	1384.7	17.1
Section #2	1996	1518.5	14.8

⇩

	Total Annual Precipitation 1996 (mm)	Total Annual Precipitation 1995 (mm)		Total Annual Precipitation 1980 (mm)	Average Temperature 1996 (°C)
Section #1	1325.8	1266.4		1384.7	16.7
Section #2	1518.5	–		–	14.8

1 mm = 0.039 inch
1.8 x °C + 32 = °F

The Type II data are the annual average value of the climate parameters recorded after the year 1980. Each test section contains only 14 calculated variables (table 3).

Table 3. Preprocessing of the Type II data

	Total Annual Precipitation	Annual Average Temperature
Section #1	Average of 16 years	Average of 16 years
Section #2	Average of 17 years	Average of 17 years

CLUSTER ANALYSIS

Cluster analysis is a multivariate data analysis (or data mining) technique to partition original observations into subgroups called clusters so that the observations that belong to the same subgroup have as much similarity as possible with respect to the measured variables (Johnson, 1998).

When one wants to generate clusters, one basic question would be how to measure the "similarity" or "dissimilarity" between two points, or two observations. There are three methods for measuring the distance of similarity: Ruler Distance, Standard Ruler Distance, and Mahalanobis Distance (Johnson, 1998). Suppose the data have three variables, the distance between each of the two observations, A (x1, y1, z1) and B(x2, y2, z2) would be decided by a Euclidean distance. The smaller this distance, the more similar are the two observations. Sometimes the variables have different scales. For example, the annual total amount of precipitation is in thousands (millimeters), while the number of intense rain days is less than one hundred (days). To avoid inflating the impact of variables with larger scales, the first thing that needs to be done in the cluster analysis is to standardize the variables.

This research first standardizes the climate data by replacing them with their Z scores:

$$\mathrm{Z} = \frac{x - \overline{X}}{S} \tag{1}$$

Where: $\overline{X}$ is the average of each variable and S is its standard deviation.

The distance calculated by using each data's Z score is called the Standard Ruler Distance.

The clustering methods can be categorized as nonhierarchical and hierarchical methods. The nonhierarchical method is more computational efficient and faster when running in a computer program. The disadvantage of the nonhierarchical method is that the number of clusters in the data must be known before an analysis can be conducted. Another disadvantage is that it requires initial cluster seeds (initial cluster centers) that may randomly influence the results. The hierarchical clustering method does not have such problems. However, it lacks the "global" view of the analyzed data in comparison with the nonhierarchical method; moreover, once an experimental unit (a test section) enters one group, it cannot change later. Each method has advantages and disadvantages, so some people recommend combining them by using the hierarchical clustering results as the required cluster seeds for the nonhierarchical methods. This research tried all three clustering techniques. Because the size of the data, all calculations are carried out by computer programs.

There are several hierarchical clustering methods with different clustering effects and computational efficiencies. This research chose to use the average linkage clustering method that works in the following steps:

- Step 1: Find the two closest objects (points or existing clusters) by measuring the average distance between each combination pair of observations in different objects (figure 2).

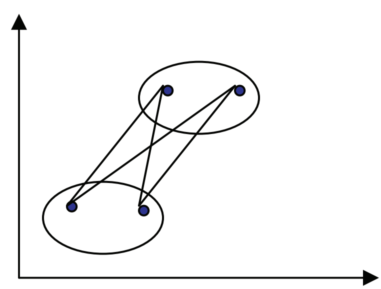

Figure 2. Distance measurement of the average linkage clustering method

- Step 2: Merge them into a cluster.
- Step 3: Keep doing so until all observations are conglomerated into a big cluster.

The true number of clusters will be between 1 and the total number of observations.

The nonhierarchical method used in this research is the K-means method. Using the K-means method, at first the number of clusters (c) needs to be defined. The remaining experimental units are then allocated to the nearest seed, forming an initial set of c clusters. The centroids of these initial clusters are identified, and the experimental units are relocated to the nearest cluster centroid, providing a revised set of clusters. New centroids are then identified for the revised clusters and the process is repeated until no experimental units change clusters (Barnard, 2002).

This research first performs a K-means cluster analysis using SPSS by allowing the software to pick the initial cluster seeds randomly. Then, to reduce the randomness in initial seeds selection and improve clustering accuracy, this research uses the partitioning results from the average link clustering analysis to compute the initial cluster centers for K-means (for convenience, called average link plus K-means method in the latter part of this paper).

DETERMINING THE NUMBER OF CLUSTERS

Cluster analysis performed by computer programs does not recommend the appropriate number of clusters directly, but produces graphs and statistics that can help researchers determine it. However, the amount of data in this research produces very messy graphs that are not usable. The following statistics, produced by including the PSEUDO and CCC options in SAS, is used in deciding the number of clusters: CCC, pseudo T2 statistic, pseudo F statistic, and R square.

The ordinary significance test for testing the differences among clusters, such as analysis of variance F tests, are not valid in cluster analysis. Because clustering methods attempt to maximize the separation among clusters, the assumptions of the usual significance tests, parametric or nonparametric, are drastically violated (SAS Manual, 1992). However, some asymptotic results from the within-cluster sum of the squares can be used to roughly judge the number of clusters. Sarle (1983) introduced a cubic clustering criterion (CCC) in 1983. If the CCC value is plotted against the number of clusters, the peaks on this plot that have CCC>3 are supposed to correspond to an appropriate number of clusters (Johnson, 1998).

NUMBER OF CLUSTERS FOR THE TYPE I DATA

The SAS output and the plot of the CCC shows that the CCC values continue increasing with the number of clusters until 173 clusters. This implies that this many clusters are required, or that the distribution may be grainy, or that the data may have been excessively rounded or recorded with just a few digits (Sarle, 1983). Part of the CCC plot is shown in figure 3, which shows a jump in CCC value from 19.87 to 24.27 when the cluster number increases from 60 to 61. Although there are other small jumps afterwards, because this research just intends to indicate the general climate patterns in these test sections, having 61 clusters is deemed appropriate, according to the CCC criteria. However, if a very detailed climate partition is required, the cluster numbers can be increased.

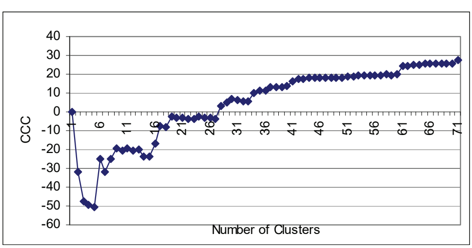

Figure 3. CCC versus number of clusters (Type I data)

When using the pseudo T2 statistic, one needs to start at the top of the SAS printed output and look for the relatively large value, then move back up one cluster (SAS Institute, 2002). Part of the pseudo T2 statistics are reported in table 4. The pseudo T2 statistic for 60 clusters in table 4 is 71.14, which is relatively large compared to numbers around it. Going back to 61 clusters, the pseudo T2 statistic reduces to 8.32. This indicates that having 61 clusters is more appropriate.

Table 4. Pseudo T2 statistic versus number of clusters (Type I data)

Number of Clusters	Pseudo T2 statistic
52	23.99
53	8.85
54	3.60
55	6.09
56	3.93
57	12.87
58	2.18
59	7.96
60	71.14
61	8.32
62	14.64
63	3.33

Another useful statistic is the pseudo F statistic. The relatively large value (table 5) indicates the appropriate number of clusters. Table 5 shows that cluster number 61 corresponds to a regional peak in the pseudo F statistic.

Table 5. Number of clusters versus pseudo F statistic (Type I data)

Number of Clusters	Pseudo F Statistic
52	114.62
53	115.09
54	113.44
55	111.69
56	110.46
57	108.74
58	108.68
59	107.00
60	106.20
61	114.45
62	113.71
63	113.72

The R square does not provide any more information in this research. Considering the CCC, pseudo T2 statistic and pseudo F statistic, the author recommends 61 cluster numbers based on Type I data.

NUMBER OF CLUSTERS FOR THE TYPE II DATA

Similar procedures of deciding the number of clusters are performed for Type II data. The analysis indicates that having 50 clusters is appropriate for Type II data. The cluster process based on Type II data tends to produces fewer clusters compared to Type I data, which is reasonable because the data are the average climate values.

VERIFICATION OF THE CLUSTERING RESULTS

If the data are two dimensional, a scatter plot is enough for validating the cluster results. For example, figure 2 clearly indicates that two clusters are enough. However, when the dimension of the data exceeds three, direct graphic plots are almost inapplicable. Principle components analysis is a multivariate data analysis technique that can reduce the dimension of the data by transforming a set of correlated variables into a new set of uncorrected variables called principle components (Johnson, 1998, p.107). If the first two or three principle components account for most of the variability in the data, their values (principle component scores) can be plotted in a two- or three-dimensional space to help people examine the cluster analysis results. If the principle components of two observations are very close to each other in a scatter plot, they should belong to the same cluster; otherwise they should belong to different clusters. The Eigenvalue is a number indicating the amount of variability accounted for by the new-formed variables that are computed from the correlation matrix of the transformed climate variables. The larger a principle component's Eigenvalue, the more variability is accounted for by it. Principle components having large Eigenvalues can be used to represent the whole variables. Eigenvalues larger than 1 are listed in table 6.

Table 6. Eigenvalues larger than one

Principle Component	Eigenvalues	% of Variance	Cumulative %
1	142.401	59.832	59.832
2	45.501	19.118	78.950
3	12.289	5.163	84.114
4	7.676	3.225	87.339
5	5.801	2.437	89.777
6	3.390	1.424	91.201
7	2.749	1.155	92.356
8	1.684	0.707	93.064
9	1.279	0.537	93.601
10	1.122	0.472	94.073

The first two principle components account for 79 percent of the total variability, while the first three principle components account for 84 percent of the total variability. Although the first three principle component scores are not so overwhelming, they may still give some indication of which clustering method is better. Both the two-dimensional and three-dimensional plots are examined in this research. Because of the paper size and the large amount of the data, the three-dimensional plot is illegible. This paper only presents the scatter plots of the first two principle component scores for Type I data using average link, K-means, and average link plus K-means approaches in figures 4, 5, and 6, respectively.

In the plots, the number labels the cluster membership of a certain observation (test section) whose position is decided by its first two Eigenvalues. These plots reveal some interesting information. When an observation is very different from the others, all three clustering methods correctly assign it a distinctive cluster membership. But when the observations are not so distinctive, especially in the middle of the plots, different methods result in different clusters.

In the upper left corner of these plots, some observations are very closely grouped. Both the average link method (figure 4) and the average link plus K-means method (figure 6) assign them to a distinctive cluster (labeled with “15” in these plots). The difference of these observations in cluster 15 with the others is more evident in a three-dimensional plot (not shown here). But the K-means method assigns more unnecessary observations (figure 5). To compare the effectiveness of the average link method and the average link plus K-means method, the author examines those observations labeled with “24” and “10” in the right corner of figure 4 and figure 6. The plots show that the average link plus K-means method outperforms the average link method by better delimiting the observations belonging to these two clusters.

The plots show that the sequence of three clustering methods, in the order of validity by examining the first two principle component scores, is the average link plus K-means, the average link, and the K-means method. However, because more than 20 percent of the variability is not accounted for by the first two principle components, one cannot judge the effectiveness of these cluster methods solely depending on these scatter plots. Another way to compare is to examine the cluster memberships of the three cluster methods in separate maps and judge them by experience.

The above discussion is based on Type I data. The verification process for the Type II data is also performed the same way, although it is simpler because it contains only 14 variables. The final result of the statistical cluster analysis is a table comprising the test sections and their corresponding cluster memberships. Test sections with the same cluster membership belong to one group with similar climate patterns. Because of the size of the table, it is not shown in this paper.

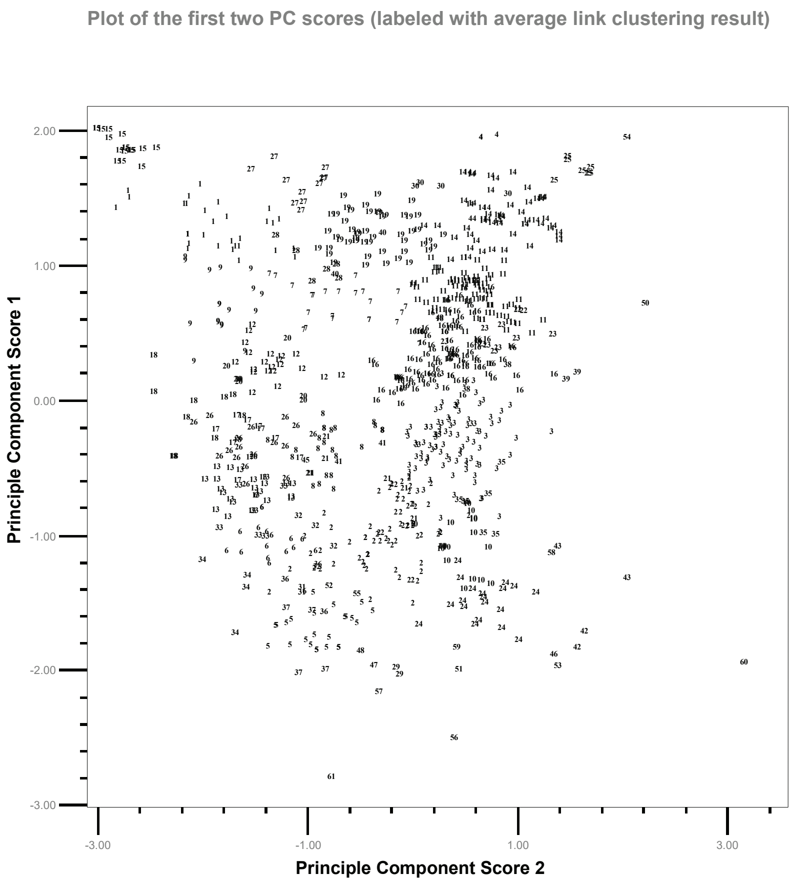

Figure 4. Scatter plot of the first two PC scores labeled with average link cluster analysis results

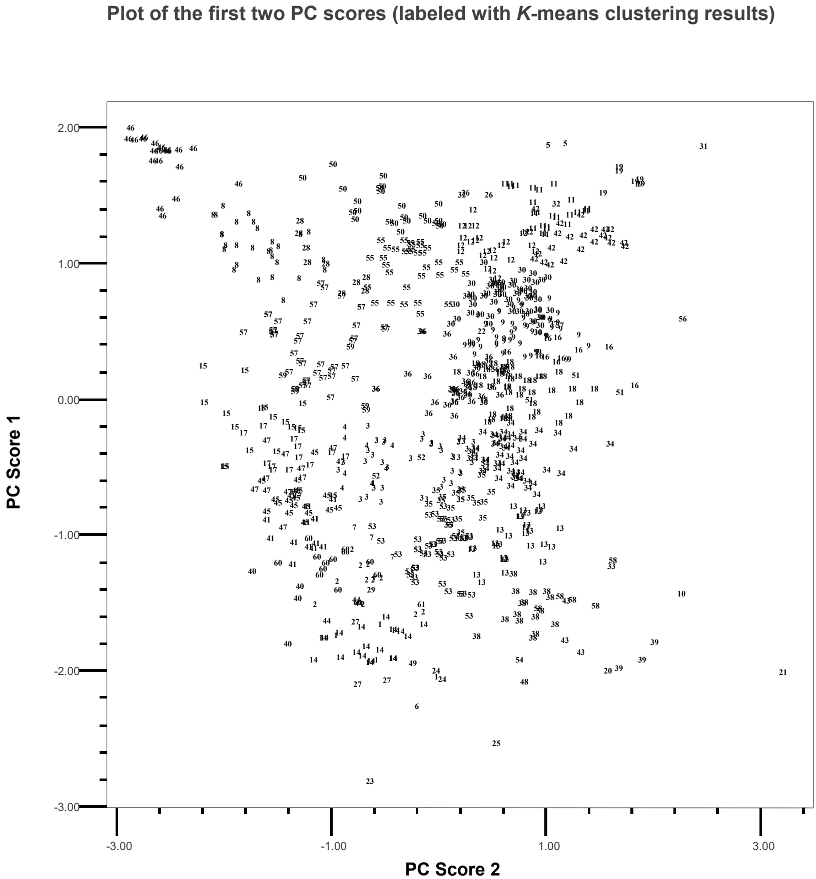

Figure 5. Scatter plot of the first two PC scores labeled with *K*-means cluster analysis results

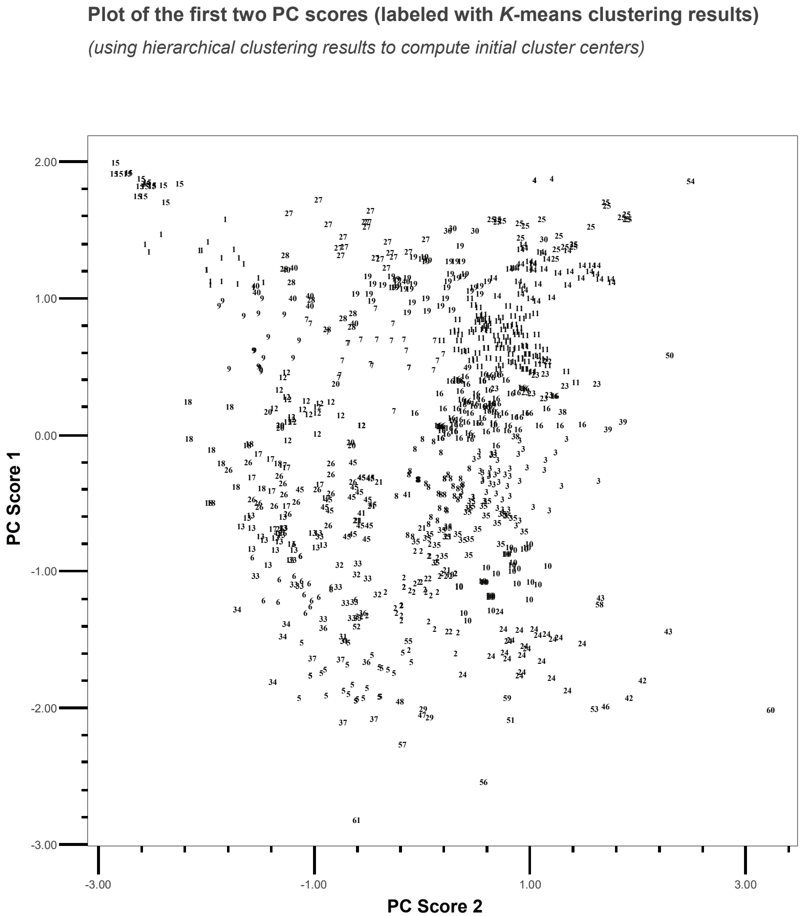

Figure 6. Scatter plot of the first two PC scores labeled with average link plus K-means cluster analysis results

CLUSTER MEMBERSHIPS ON GIS MAPS

Besides being a database, the DataPave 3.0 software also provides geographic information related to each LTPP test section, which includes the States or Provinces in which the test section is located, the major highway systems in the North America, the positions of the test sections in the map, detailed geographic features. The purpose of using GIS in this research is to put the cluster analysis results on a map so that they can be visually verified. And if the clustering result is acceptable, a climate map is more suitable for practical use than a cluster membership table. This research uses Arcview software to perform GIS operations, which is accomplished by the following steps:

1. Selecting the appropriate map themes (features) from the GIS database. This research selects all entire test sections and the States or Provinces in which they are located as map themes.

2. Transforming the cluster membership tables to new Arcview-recognizable tables.

3. Joining the attribute tables in the GIS database with the tables created in Step 2 by using the virtual weather station identifications as combination key words. Because the attribute tables do not have virtual weather stations identifications, this research creates a new column in the original GIS attribute tables.

4. Adding the membership labels to the GIS map and editing the map.

The GIS map labeled with cluster memberships generated by the average link plus K-means cluster analysis on Type I data is presented in figure 7. This research also developed cluster membership maps based on the other cluster analysis approaches and on the Type I data in figures 8 and 9. This paper does not show the cluster membership maps based on Type II data. And due to the limited paper size, maps presented in this paper must exclude some test sections and remove overlapping labels to make them legible. These maps are useful in checking the clustering results. If the test sections are geographically very close to each other, their climate characteristics, in most cases, tend to be similar. Map comparison shows that the average link plus K-means method based on Type I data produces better cluster results, although in general the difference between these methods is not large.

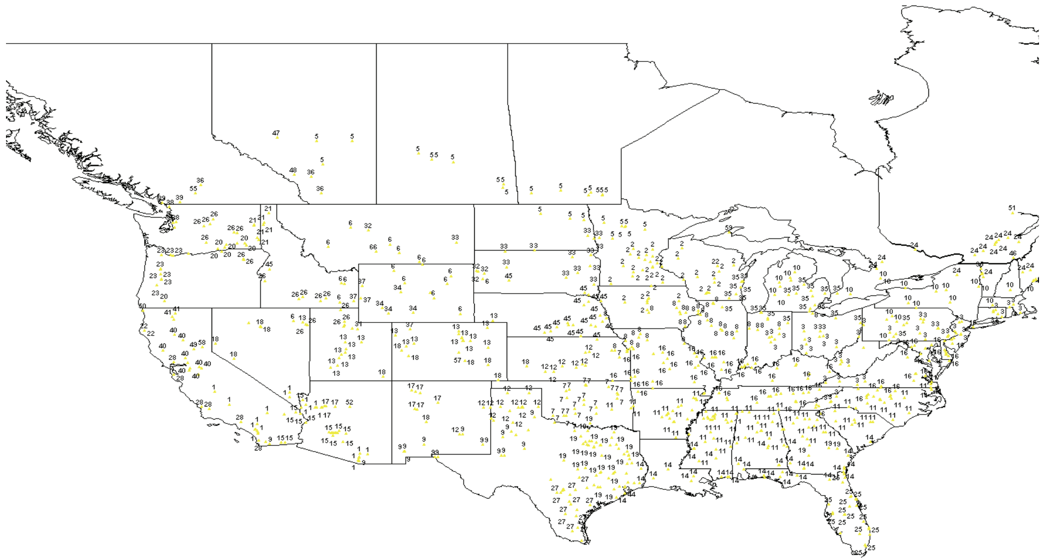

Figure 7. Cluster membership map based on the plus K-means method

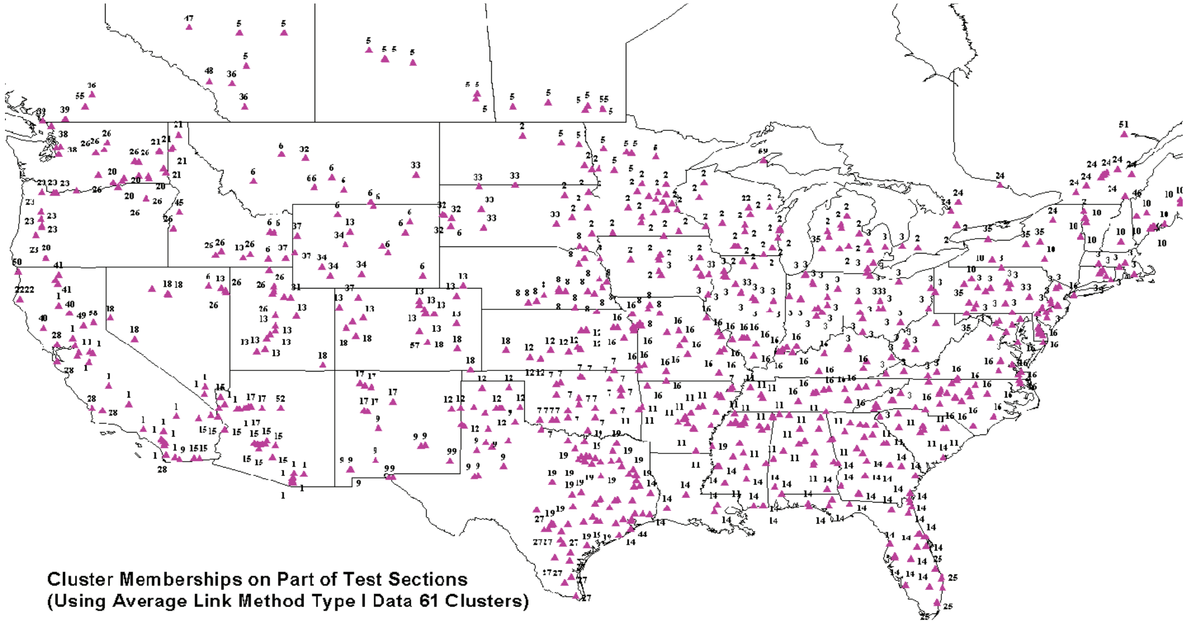

Figure 8. Cluster membership map based on the average link method

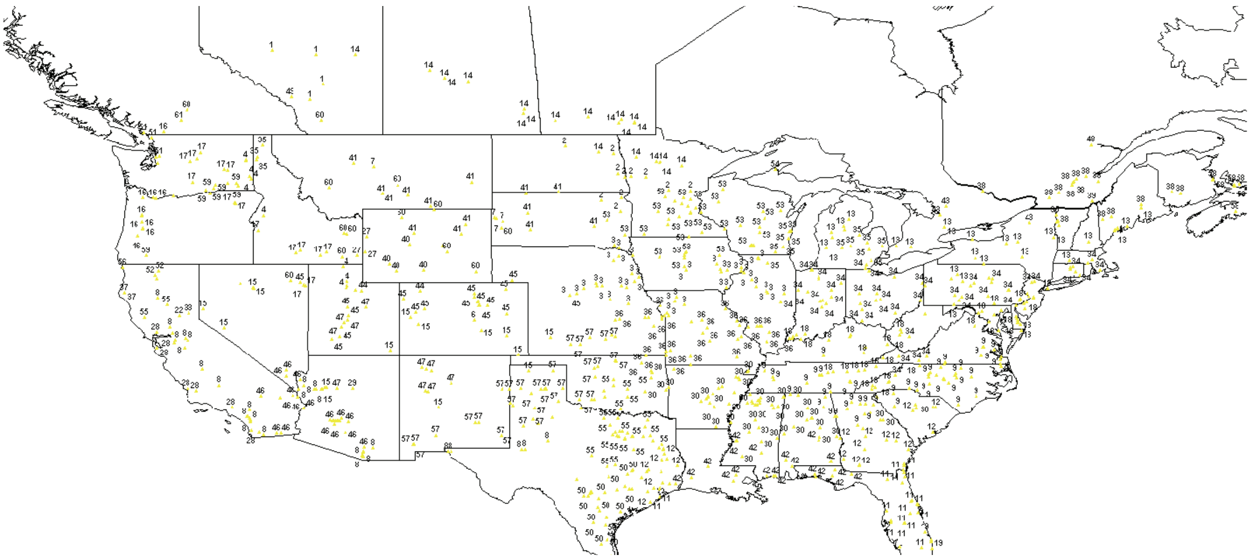

Figure 9. Cluster membership map based on the K-means method

SUMMARY AND CONCLUSTIONS

This paper describes the process of developing a climate map by partitioning LTPP test sections into different groups using the annual climate data recorded in the LTPP database since 1980. The test sections belonging to the same group (cluster), which are labeled with the same cluster membership on the map, have similar climate characteristics. Fourteen climate parameters have been used for comparison.

To reflect the annual climate pattern and the overall climate information, this research preprocessed climate data into two separate parts: Type I data and Type II data. The Type I data comprise annual weather records while the Type II data are made up of the average of the records. Cluster analysis was conducted on both sets of data to partition test sections. Three cluster analysis approaches were employed by this research: the average link, K-means, and the combination of first two methods. The research examined cluster analysis outputs to determine the appropriate number of clusters. Based on the CCC, pseudo T2, and pseudo F statistic, this research recommends 61 clusters for Type I data and 50 clusters for Type II. The statistics also indicate that more detailed partition is possible and the number of clusters can be increased if required in practice.

Scatter plots of principle components were used to verify the cluster results. Based on the plot of the first two- and three-principle component scores, this research found that the combination of average link and K-means method produces the best clustering results for Type I data. However, because about 20 percent of variability in the climate data is not accounted for by the first two principle components, the scatter plots should be assisted by a real cluster membership map to judge the effectiveness of the three cluster approaches.

This research developed GIS climate maps for the test sections, parts of which are presented in this paper. The maps also show that the combination of average link and K-means method generates the most reasonable clustering results, but the difference between these methods is not large.

The cluster membership tables and the climate maps developed in this study can help researchers incorporate or separate climate factors in their models when are using the LTPP data to perform statistical treatment comparison analysis. Another potential use of this map is to help highway practitioners get climate pattern information for their geographical areas so that they can apply the same design criteria, construction requirements, and maintenance strategies to those regions with similar climate patterns.

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