A study on the variability of pavement foundation properties

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A study on the variability of pavement foundation properties

by

Jia Li

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University
Ames, Iowa
2017

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ABSTRACT

Variations in resilient modulus ($M_r$) values of unbound materials as determined in accordance with AASHTO T307 are studied. Three different granular materials and an elastic polyurethane (control) sample were tested using commercially available laboratory test equipment. A field test bed was also constructed to measure vehicle (Class 3) induced loading conditions at the bottom of an unbound granular layer underlying new hot-mix asphalt pavement to determine stress-pulse duration as a function of vehicle speed. Various interpretation issues were identified within the framework of the testing methods and equipment including: (1) insufficient laboratory sensor sampling rate (per standard); (2) the laboratory specified 0.1 second load-pulse duration and haversine shape are not matching the field stress-pulse duration and shape; (3) the need for careful tuning of the load system gain settings; (4) the number of LVDTs used in the vertical strain calculation; (5) limiting quality control and quality assurance to deformation ratio values in the preconditioning sequence; (6) limiting the load step calculations to the last 5 of 100 load cycles; and (7) the $k_3$ coefficient used in the MEPDG suggested generalized universal model function generally not being statistically significant.

Detailed geostatistical analysis procedures are presented in this study to provide a guide for pavement engineers to study spatial variability of pavement foundation properties with consideration of choosing the best fit semivariogram model and characterization of anisotropy. Measurements from two densely gridded pavement reconstruction sites are presented in studying the geostatistical modelling parameters that characterize spatial variability of stiffness and compaction properties. Preliminary study on anisotropy in spatial variability of pavement foundation properties is performed, but different major and minor anisotropic directions were identified in the two small square study sections. Comparisons of three theoretical
semivariogram models (i.e., spherical, exponential, and Matérn with k=1) in studying different pavement foundation properties shows that there is no single best fit model. The isotropic semivariogram model works as well as the anisotropic semivariogram model in estimating the data at unsampled locations across the studied small square area. The range that indicates the spatial correlation length is less than 5 m in all studied properties of both test sections, without considering anisotropy behavior. When anisotropy behavior is considered, longer spatial correlation length, up to about 11 m, can be expected in the major direction.

The second objective of this study is to investigate variability of pavement foundation properties (e.g., $E_{LWD-Z3}$, $\gamma_d$, and $w$) that are determined from four major in-situ tests (i.e., FWD, LWD, NG, and DCP) over 18 test sections of 6 project sites. Change in variation of in-situ measured properties has been studied in relationship to the number of compaction passes. Univariate statistics of pavement foundation properties is documented for providing references to pavement engineers and researchers to know the range of variability that in-situ measured properties can have. In addition to univariate statistics, spatial analysis was performed on selected sites that contain relatively large data sets for spatial analysis. The difference in spatial variation can be expected in longitudinal and transverse direction. The correlation length of about 2 m to 3 m in the minor or less uniform direction was quantified for spatial variability of dense gridded data on the base layer. The spatial variability of in-situ measured properties along the longitudinal direction could be expected to be 15 m to 23 m in the CTB layer. This study on spatial variability shows that the correlation length can be different in different pavement foundation layers and materials.
CHAPTER 1. INTRODUCTION

Stiffness is an important input parameter in pavement design and laboratory determined resilient modulus values can be used as an input for the stiffness present in the whole pavement foundation layer. Uniform support is desired for pavement structures to have longer service life, but the variability of in-situ measurements on pavement foundations reveals nonuniform support to the pavement surface. This chapter discusses the importance of studying variability of pavement foundation properties, presents the research goal and objectives of this study, and details the organization of the dissertation.

1.1. Problem Statement

Pavement foundation structures are constructed to provide uniform support for upper pavement layers and traffic load. However, material properties of existing pavement foundation structures are generally non-homogeneous. Non-uniform subbase/subgrade stiffness will induce fatigue cracking and other types of pavement distresses and shorten the pavement service life (Titi et al. 2014; White et al. 2004). Dilip abd Babu (2014) concluded that critical strains will be underestimated without considering spatial variability of resilient moduli. Roesler et al. (2016) showed peak concrete slab tensile stresses increases up to 39% in nonuniform compared to uniform support conditions. However, pavement design assumes that uniform layers are achieved and uses a single modulus of subgrade reaction to represent the whole layer.

Resilient modulus ($M_r$) is a pavement foundation input value used in the mechanistic-empirical pavement design method and is often measured using laboratory equipment in accordance with AASHTO T307 (2007). Pavement foundation stress conditions are simulated in the laboratory test by applying transient cyclic load pulses for a series of deviator and confining stress conditions. AASHTO T307 (2007) specifies cyclic loading with each cycle having a
haversine-shaped load pulse with a 0.1 s pulse duration (load time) and 0.9 s rest period (dwell time). \( M_r \) values are well studied by many researchers, but the testing standard and testing system should be assessed for obtaining accurate resilient modulus. According to Witczak (2004), “inaccurate determination of the resilient modulus of the unbound materials in the pavement structure will contribute to erroneous predictions of overall pavement response and pavement performance.”

To achieve a reliable pavement design, variability of engineering properties should be properly quantified. Phoon and Kulhawy (1999) suggested estimating the variability of soil parameters to develop and apply reliability-based design. Otake and Honjo (2013) also suggested evaluating the effects of spatial variability of material properties on pavement structures.

Variability was identified in constructed pavement foundations. Allen and Graves (1994) obtained falling weight deflectometer (FWD) and Road Rater deflection measurements data at 25 foot intervals along a 500 ft long test section and observed a 75% coefficient of variation in subgrade moduli within the section. Yoder (1975) reported a range of standard deviation of layer thickness from 0.6 to 0.72 with 9749 tests on cement treated base, 0.72 to 0.84 with 7046 on aggregate base, and 0.96 to 1.44 with 10758 tests on aggregate subbase. Yoder (1975) reported that a typical range for the standard deviation of percent compaction on embankment/subgrade went from 2.0 to 7.0 percent and on subbase/base went from 2.0 to 3.5 percent. Siddharthan et al. (1992) studied layer moduli that were determined from back calculation of FWD tests performed on asphalt concrete pavement and reported the layer moduli vary in a range of 5 to 65 percent for the coefficient of variation.

However, the nonuniformity of pavement foundation (subbase/subgrade) layers has not been well studied. The univariate statistical analysis of pavement foundation properties shows a range
of the property can vary within the studied area, but it does not describe the spatial uniformity. Several previous studies (Facas et al. 2010; Lea and Harvey 2015a; Lea and Harvey 2015b; Vennapusa 2004; Vennapusa et al. 2010; White et al. 2004) performed spatial variability analysis on pavement related properties (i.e., stiffness, layer thickness, intelligent compaction measurement values), and anisotropy in the studied properties was observed that roller-integrated compaction measurements (Facas et al. 2010; Vennapusa et al. 2010) varied with longer correlation length in the longitudinal direction than in the transverse direction.

Geostatistical methods have been well studied in other fields (i.e., mining, geology, soil science) and details in understanding general spatial variation had appeared in many books (Clark and Harper 2002; Cressie 1993; Deutsch and Journel 1998; Goovaerts 1997; Isaaks and Srivastava 1989; Journel and Huijbregts 1978; Olea 2006). Lea and Harvey (2015b) introduced model types with analysis on pavement layer thickness. However, the details in using geostatistical analysis methods on charactering pavement foundation properties with closer spacing (about 0.6 m) was not studied.

Although variation of in-situ properties in pavement construction has been noticed, there is no documentation of pavement foundation properties variability for people to have ideas on how variable the pavement foundation properties could be. Selective sampling by the inspector, often as ordered by the engineer has played an important part in the failure to recognize the magnitude of the actual variations occurring in embankment and base construction.

Pavement foundation properties are studied by investigating the results $E_{LWD-Z3}$, $y_d$, $W$, $DCP_{subbase}$, and $DCP_{subgrade}$ that are obtained from the light weight deflectometer (LWD) test, nuclear gauge (NG) test, and dynamic cone penetrometer (DCP) test. Following the pavement construction process that the material was spread on the ground and then roller compacted to the
target density, the data on pavement foundation properties may not be statistically independent. Data values that at locations that are closer together tend to be more similar than data values collected at locations that are farther apart. However, how much the pavement foundation properties can vary, univariate and spatially, has not been reported sufficiently. Therefore, in this research, the assessment of testing method in obtaining the design stiffness input, characterization and quantification of variability of in-situ measured pavement foundation properties will be discussed.

1.2. Research Goal and Objectives

The main goals of this research are to provide assessment procedures for verifying the reliability of laboratory determined $M_r$ values that will be used in pavement design and to study variability of in-situ pavement foundation properties after pavement construction. To address these goals, the objectives of the research are to:

- Assess the laboratory testing standard and system for improving the reliability of obtaining $M_r$ values with simulated in-situ conditions,
- Provide the detailed procedures for performing spatial variability analysis on pavement foundation properties using a geostatistical method,
- Document univariate and spatial variability of pavement foundation properties as a reference for pavement engineers.

1.3. Organization of the Dissertation

This dissertation consists of five chapters: a general introduction, three research articles, and conclusions and recommendations for further research.

Following this general introduction, Chapter 2 explains equipment related considerations on differences between the lab and field conditions that can lead to variations in resilient modulus
(M_r) values of unbound materials as determined in accordance with AASHTO T307. Chapter 3 demonstrates detailed geostatistical analysis procedures to provide a guide for pavement engineers to study spatial variability of pavement foundation properties with consideration of choosing the best fitted semivariogram model and characterization of anisotropy. Two densely gridded test sections are studied to characterize the behavior of spatial correlation of pavement foundation properties in both longitudinal and transverse directions within a small study area. Chapter 4 documents the variability of pavement foundation properties by analyzing data collected from 6 project sites and provides a reference for pavement engineers and researchers to know how variable the in-situ measured pavement foundation properties can be. Chapter 5 summarizes the conclusions and outcomes derived from this study, and offers several suggestions and directions for future research.
CHAPTER 2. CONSIDERATIONS FOR LABORATORY RESILIENT MODULUS TESTING OF UNBOUND MATERIALS

A paper submitted to Geotechnical Testing Journal

Jia Li, David J. White, and W. Robert Stephenson

2.1. Abstract

This paper explains equipment related considerations on differences between the lab and field conditions that can lead to variations in resilient modulus (M_r) values of unbound materials as determined in accordance with AASHTO T307. Three different granular materials and an elastic polyurethane (control) sample were tested using commercially available laboratory test equipment. A field test bed was also constructed to measure vehicle (Class 3) induced loading conditions at the bottom of an unbound granular layer underlying new hot-mix asphalt pavement to determine stress-pulse duration as a function of vehicle speed. Various interpretation issues were identified within the framework of the testing methods and equipment including: (1) insufficient laboratory sensor sampling rate (per standard); (2) the laboratory specified 0.1 second load-pulse duration and haversine shape are not matching the field stress-pulse duration and shape; (3) the need for careful tuning of the load system gain settings; (4) the number of LVDTs used in the vertical strain calculation; (5) limiting quality control and quality assurance to deformation ratio values in the preconditioning sequence; (6) limiting the load step calculations to the last 5 of 100 load cycles; and (7) the k_3 coefficient used in the MEPDG suggested generalized universal model function generally not being statistically significant. The goal of this paper is to provide equipment users and specification developers with user knowledge concerning laboratory resilient modulus determination.
2.2. Introduction

Resilient modulus ($M_r$) is a pavement foundation input value used in the state-of-the-art AASHTOWare™ pavement design software based on the mechanistic empirical design principles (2015) and is often measured using laboratory equipment in accordance with AASHTO T307 (2007). Pavement foundation stress conditions are simulated in the laboratory test by applying transient cyclic load pulses for a series of deviator and confining stress conditions. By using a selected portion of the laboratory data, results are then used to develop a nonlinear stress-dependent model of resilient modulus.

AASHTO T307 (2007) specifies cyclic loading with each cycle having a haversine-shaped load pulse with a 0.1 s pulse duration (load time) and 0.9 s rest period (dwell time). The specified minimum sampling rate is 200 Hz. Following an initial 500 to 1000 cycles conditioning phase, 15 different load sequences are specified with 100 load cycles each. There are two different load sequence schedules followed depending on whether the material is an unbound granular material (high stress sequence) or a subgrade soil (low stress sequence). The average $M_r$ of the last five in the 100 cycles is calculated to represent $M_r$ of the specimen under the specified stress state.

Further, AASHTO T307 (2007) requires two externally mounted spring-loaded linear variable differential transducers (LVDTs) to measure vertical axial deformation for determining resilient strain.

This paper discusses practical considerations that affect interpretation of results from a commercially available laboratory $M_r$ test system. Laboratory $M_r$ tests were conducted on three unbound granular materials and one polyurethane control specimen (representing an elastic material). For comparison to the laboratory load pulse duration and shape, a pavement test bed was instrumented and then trafficked with a Class 3 vehicle with two axles (Hallenbeck et al.)
According to Witczak (2004), “inaccurate determination of the resilient modulus of the unbound materials in the pavement structure will contribute to erroneous predictions of overall pavement response and pavement performance.”

Laboratory related equipment factors were studied and characterized including, stress-pulse shape and duration, sensor sampling rates, control system proportional and integral gain factors, an equipment/software error issue that resulted in an examination of differences between deformation measurements of one versus two LVDTs, and criteria used for quality control and quality assurance in \( M_r \) tests. Considering several test parameters, statistical analyses were performed to characterize how the test method and materials influence the calculated \( M_r \) values and development of the non-linear universal stress-dependent resilient modulus model.

### 2.3. Background

Although AASHTO T307 (2007) is widely used to obtain \( M_r \) values for unbound materials, research on many factors affecting pavement foundation stress conditions and alternative concepts for \( M_r \) testing have been studied for years. Barksdale (1971) and Brown (1973) reported that the equivalent stress pulse shapes changed from sinusoidal to triangular with increased depth beneath pavement surfaces and that the stress pulse duration increases with depth and decreases with increasing vehicle speed. Seed et al. (1967) reported that 20% greater \( M_r \) values were obtained by decreasing load application duration that correspond to a vehicle’s travel speed. Allen and Thompson (1974) reported that the \( M_r \) of well-graded granular materials under moving wheel loads between about 24 and 113 km/h is independent of stress pulse duration and used 0.15 s stress pulse duration for further \( M_r \) tests.

In contrast to AASHTO T307, the NCHRP 1-28A method (2004) requires that each load cycle have a haversine-shaped load pulse with 0.2 s pulse duration and 0.8 s rest period for
subgrade soils and 0.1 s pulse duration and 0.9 s rest period for base and subbase materials and a special provision allows for a 0.15 s load pulse and 0.4 s rest period for non-plastic granular materials. Irwin (2009) suggested that load pulse durations of 0.2 s for base course and 0.25 s for subgrade materials would more accurately represent in situ conditions.

AASHTO T307 (2007) uses the average deformation measurements of two LVDTs mounted outside the pressure chamber, while the NCHRP 1-28A method (2004) requires internally mounted LVDTs. Although average values of two outside mounted LVDTs measured deformations are used in calculating $M_r$ values to reduce the effects of imperfect top specimen surfaces, Groeger et al. (2003) suggested that, with careful inspection (e.g., prevent LVDTs from slipping), more accurate deformation values can be obtained with LVDTs mounted inside the pressure chamber. Camargo et al. (2012) compared $M_r$ results determined from internal and external LVDTs deformation measurements and reported that internal $M_r$ values are generally higher than external $M_r$ values. However, the ratio of internal to external $M_r$ values increases with increasing internal $M_r$ values and this ratio is related to material types. Based on Camargo et al. (2012) results, ratios of internal to external $M_r$ values ranges from 1.0 to 2.2 and have a median value of 1.5 for tested base and recycled aggregate materials. Bozyurt et al. (2012) also found that ratios of internal to external were greater than 1.0 (ratio equal to about 3.6 for two recycled aggregate materials).

The NCHRP 1-28A method (2004) and AASHTO T307 (2007) require quality assurance/quality control (QA/QC) checks on deformation measurements of two LVDTs. Both standard methods specify an acceptable value for the vertical deformation ratio ($R_v$) that is the ratio of $Y_{\text{max}}$ to $Y_{\text{min}}$ where the largest deformation measurement of the two LVDTs is $Y_{\text{max}}$ and smallest is $Y_{\text{min}}$. NCHRP 1-28A defines an acceptable maximum defamation ratio of 1.1 and the
test should be stopped if an unacceptable ratio is obtained during the preconditioning (PC) sequence. Per AASHTO T 307 (2007) the desired $R_v$ value is 1.1 and the load sequence contains $R_v$ values larger than 1.3 should be withdrawn. Kim et al. (2007) suggests to have three QA/QC criteria including angle of rotation, signal to noise ratio (SNR) and coefficient of variation ($c_v$) for checking measured $M_r$ values. Angle of rotation is a criteria for checking uniformity of three deformation measurements but this check cannot be done with only two deformation measurements.

AASHTO T307 (2007) specified a loading schedule with 500 to 1000 load cycles for conditioning the specimen and 100 load cycles for each load sequence. Setting the number of cycles to 100 assumes that a representative $M_r$ values can be obtained at 100 load cycles. Seed et al. (1967) reported that increases in $M_r$ values with increasing number of load cycles could be 50% to 100% for specimens with different moisture contents and dry densities. Moore et al. (1970) also reported that $M_r$ increased with the number of load cycles. Morgan (1966) tested two sandy materials and reported that constant $M_r$ values were often obtained only after about 10,000 load cycles. Both Moore et al. (1970) and Morgan (1966) examined results from about one million load cycles and moisture loss may have been a contributing factor to the $M_r$ increase. In other studies such as Hicks and Monismith (1971) test results show that $M_r$ values obtained after 50 to 100 load cycles are reasonable estimates for some granular materials. Allen and Thompson (1974) also reported that the “representative” values $M_r$ can be obtained after 25 to 100 cycles. Boyce et al. (1976) found that steady resilient strain values can be reached after 200 to 1000 load cycles if no substantial permanent strain occurs. Based on testing a subgrade material, Elliott and Thornton (1988) reported that $M_r$ values only differed by about 6% when 50 instead of 200 load cycles was applied instead.
AASHTO T307 (2007) and NCHRP 1-28A (2004) require a minimum sampling rate of 200 Hz. Groeger et al. (2003), however, suggested that 200 readings/second is not sufficient to fully characterize the true shape of a load pulse cycle and that 500 Hz should be implemented.

Given the range of recommendations in the literature concerning load pulse time, deformation measurement, and loading cycles, this study set out to examine these issues for the specific equipment purchased for this study. AASHTO T307 was selected as the reference testing method as this was being used by several state agencies for unbound materials and was specified for the equipment purchased for the experiments.

2.4. Materials and Methods

2.4.1. Laboratory Test Specimens

AASHTO T307 (2007) M_r tests were conducted on three granular materials: crushed limestone, recycled asphalt pavement (RAP), and recycled portland cement concrete with RAP particles (RPCC/RAP), and one polyurethane control specimen. Fines contents and moisture contents were determined for each material according to ASTM D422 (2007) and ASTM D2216 (2010) respectively. A total of thirty-six 101.6 mm diameter by 203.2 mm high specimens were compacted in five equal lifts using a vibration hammer in a split mold. For granular materials, AASHTO T307 (2007) requires vibratory compaction to prepare test specimens with 5 lifts and height and mass of each lift were carefully controlled to ensure the test specimens resulted in uniform density. Samples were compacted to target densities for each lift and then the total sample density measured. Three specimens of each material with the same fines content were compacted to different dry unit weights (i.e., 85 %, 90 %, 95 % relative density). Table 2.1 summarizes properties for all test specimens.
Table 2.1. Properties of the test specimens.

<table>
<thead>
<tr>
<th>Material</th>
<th>Fines Content, %</th>
<th>Dry Unit Weight, kN/m³</th>
<th>Moisture content, %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>Crushed limestone</td>
<td>2.2</td>
<td>19.28</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>5.8</td>
<td>19.76</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>7.9</td>
<td>17.76</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>12.6</td>
<td>20.58</td>
<td>0.19</td>
</tr>
<tr>
<td>RAP</td>
<td>1.6</td>
<td>15.94</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>2.0</td>
<td>15.13</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>5.6</td>
<td>17.19</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>12.5</td>
<td>17.86</td>
<td>0.16</td>
</tr>
<tr>
<td>RPCC/RAP</td>
<td>0.8</td>
<td>15.49</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>3.5</td>
<td>16.22</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>6.0</td>
<td>16.98</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>12.4</td>
<td>17.77</td>
<td>0.16</td>
</tr>
<tr>
<td>Polyurethane</td>
<td>—</td>
<td>11.53</td>
<td>—</td>
</tr>
</tbody>
</table>

Note: Only one polyurethane specimen was tested.

Fourteen tests were performed on the polyurethane specimen to study the effects of proportional gain (P) and integral gain (I) values and to study the effects of stress and strain sampling rates on the resulting calculated $M_r$ values. P and I values are generally only adjusted in the PC sequence when $M_r$ test equipment with proportional-integral (PI) control parameters are used. This adjustment minimizes the difference between the actual applied and target stresses. However, adjustments on P and I values are controlled by operators without specification.

Only two external LVDTs were used to measure vertical deformations of each specimen. The uniformity ratio ($R_v$) of $Y_{\text{max}}$ to $Y_{\text{min}}$ was calculated for all load sequences in addition to the PC sequence. The desired $R_v$ value is 1.1 (AASHTO 2007) and if the load sequence contains $R_v$ values larger than 1.3 they should be withdrawn. In addition to $R_v$ quality criteria during testing, coefficient of variation ($c_v$) and signal to noise ratio (SNR) were calculated for checking measured $M_r$ values. According to Kim and Labuz (2007), $c_v$ is calculated as the ratio of the standard deviation ($s_d$) to the average of the last five $M_r$ values and load sequences. The SNR value is determined by comparing the peak load or displacement to the standard deviation ($s_d$) of
the noise. Kim and Labuz (2007) recommend that $c_v$ values exceeding 10% and SNR values less than 3 for each LVDT and 10 for load at each of the last five cycles used to calculate average $M_r$ at each stress level should be withdrawn. SNR is calculated as a ratio of peak load or displacement to three times the baseline $s_d$ using Eq 2.1 while $s_d$ of baseline is calculated using Eq 2.2.

$$SNR = \frac{\text{Peak}}{3 \times s_d(\text{baseline})}$$  

(2.1)

$$s_d(\text{baseline}) = \sqrt{\frac{\sum_{n=1}^{N}(Y(n)-\mu)^2}{N-1}}$$  

(2.2)

where

$\mu$ = mean value of baseline readings,

$Y(n)$ = stress or displacement reading at point $n$ of baseline, and

$N$ = total data points of baseline.

For this study on the effects of P and I values and sampling rates, a polyurethane specimen was used to mitigate the differences among the specimens. Also, three $M_r$ tests were conducted on RPCC/RAP material to study differences in $M_r$ values using different load-pulse durations. Loading period was controlled as 0.1 s, 0.5 s, and 1.0 s for each test separately while the rest period was controlled as 0.9 s for all tests. The specimens were compacted to the values as listed in Table 2.2.

### Table 2.2. Properties of the RPCC/RAP specimens for loading duration test.

<table>
<thead>
<tr>
<th>Test</th>
<th>Fines Content, %</th>
<th>Dry Unit Weight, kN/m³</th>
<th>Moisture content, %</th>
<th>Loading Time, s</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4</td>
<td>16.38</td>
<td>5.8</td>
<td>0.1</td>
</tr>
<tr>
<td>2</td>
<td>0.4</td>
<td>16.41</td>
<td>5.8</td>
<td>0.5</td>
</tr>
<tr>
<td>3</td>
<td>0.4</td>
<td>16.40</td>
<td>5.8</td>
<td>1.0</td>
</tr>
</tbody>
</table>
2.4.2. Instrumented Pavement Foundation

In situ drive tests were performed on a newly constructed asphalt pavement to study the relationship between driving speed and stress-pulse duration and to determine the in situ stress-pulse shape. A one-half ton truck (Class 3 vehicle) was used for the drive test with tire pressures of 290 kPa. The test pavement has a nominal 152.4 mm pavement surface, a 152.4 mm aggregate base, and a 304.8 mm silty clay subgrade. A triangular aperture geogrid was placed between the subgrade and the base layer. Details for the test section are presented in White et al. (2013).

Three piezoelectric earth pressure cells were installed at the unbound aggregate base/subgrade interface. Figure 2.1 shows the field installation of the earth pressure cells (EPC) embedded in a thin layer of silica sand. Stress-time recording were made at controlled speeds in 16.1 km/h increments from 32.2 km/h to 96.6 km/h. The sampling rate was set at 2500 Hz and a low pass filter (100 Hz finite impulse response) was used to produce the final stress-time plots.

Figure 2.1. Field installation of (a) individual EPC embedded in thin layer of silica sand, and (b) transverse trench with array of three EPCs.
2.5. Results and Analysis

Statistical analyses of variations in $M_r$ were conducted to determine effects of material type, stress level, and load cycle selection. Moreover, nonlinear regression analyses were performed on 36 granular material specimens to study the significance of the three regression coefficients of the universal model.

2.5.1. Characterization of Stress Pulse

The laboratory stress-time pulse shape and duration and influences from sensor sampling rate and P and I gain settings were studied and compared. Results were also compared to the measured in situ trafficking test results. Note that the cross-section area of the specimen is considered constant according to AASHTO T307 for purposes of calculating stress and results are presented in terms of stress and not load.

Stress pulse shape and duration

The laboratory and field stress-pulse shape and duration is compared with the in situ stress pulse in Figure 2.2. Results show that the stresses measured from the drive test are small in comparison to the laboratory test sequences. The peaks of the in situ front tire and one laboratory test stress pulse were matched for comparison in terms of the stress-pulse time history. From the piezoelectric earth pressure cells, the initial front tire stress-pulse is followed by a smaller amplitude stress-pulse for the rear tire (corresponding to heavier front axle). The shapes of the lab and field results are similar. Here the in situ dwell time between front and rear tires is comparatively short (e.g., about 0.14 sec when the test truck traveled at 96.6 km/h), as would be expected for all vehicles traveling at highway speeds. In general, longer stress pulse durations and different pulse shapes were observed with the in situ drive tests compared to the laboratory
test. Note that the commercially available laboratory test system sampling intervals result in closely spaced groups of two to four points per the equipment manufacturer’s setup.

The theoretical haversine cyclic load pulse shape as specified in AASHTO T307 (2007) was compared with the laboratory and in situ stress pulses. Results show that the laboratory stress pulses do not merge with the haversine shape in the regions of the stress-pulse initialization and dissipation (Figure 2.2). The haversine curve shape is described using equation \( \frac{(1 - \cos\theta)}{2} \) with target peak stress and loading duration. The haversine model was fitted to the data obtained from the in situ test for the 96.6 km/h test using 0.1 s pulse duration and the same peak stress obtained in the lab test. This exercise demonstrated that a haversine cyclic stress-pulse shape does not match the initialization and dissipation regions.

![Figure 2.2. Comparison of laboratory and in situ measured stress pulse shape and duration.](image-url)
Through investigation of several alternative shapes, it was determined that a modified Gaussian pulse shape fits both the laboratory and field data. Eq 2.3 shows the parameters for this model.

\[ \sigma = \sigma_0 + ae^{-0.5\left(\frac{|t-t_0|}{b}\right)^c} \]  

(2.3)

where

\( \sigma = \) laboratory deviator stress or in situ vertical total stress,

\( \sigma_0 = \) minimum stress at initialization,

\( t = \) time,

\( t_0 = \) time at peak stress, and

\( a, b, \) and \( c = \) regression coefficients.

An example of the modified Gaussian model fit to the in situ test data for both front and rear tire stress pulses is provided in Figure 2.3. Although the modified Gaussian model fits the in situ data better than the haversine model, comparison of the actual and modeled results shows that the model may slightly over-predict the maximum stress. The actual peak stresses can be matched by changing values of the modified Gaussian model coefficients and/or by adjusting the low pass filtering parameters to process the raw EPC measurements. The peak stress occurs at time \( t_0 \) and parameter \( a \) indicates the peak stress from the modified Gaussian model fit, parameter \( b \) and \( c \) may be adjusted to change the width of the peak curve that affect stress pulse duration.

The examples of the modified Gaussian fit to the measured in situ stress shows that the minimum stress in initialization (\( \sigma_0 \) in Eq 2.3) is zero for the front tire but 0.043 for the rear tire. The reason is that the short period between the front and rear peak stress (e.g., about 0.16 s for drive tests at 80.5 km/h) will not allow the full stress to be dissipated before the rear tire stress is
initiated and dissipation of the stress is not a sudden decrease but is slowly decreased to zero (e.g., a rate of decrease of about 0.45 kPa/s for the rear tire stress for drive tests at 80.5 km/h).

Consequently, the modified Gaussian model was used to determine the in situ stress pulse durations for all of the in situ drive tests and the relationship between stress pulse duration and driving speed was also studied. The modified Gaussian model was fitted to front and rear tire stress pulses separately by non-linear regression analysis. The stress pulse duration is calculated as the time difference when stress $\sigma - \sigma_0$ is equal to 0.05 kPa at stress initialization and dissipation using Eq 3. The duration of rear tire stress pulse at a given speed was slightly longer than the stress pulse duration of front tire. The average stress pulse duration of front and rear tires decreased from 0.50 s to 0.15 s as drive speed increased from 32.2 km/h to 96.6 km/h. Eq 2.4 describes the relationship between stress pulse durations and vehicle driving speeds:

$$\Delta t = t_0 + \frac{a}{v}$$  \hspace{1cm} (2.4)
Where: $\Delta t =$ the stress-pulse duration (s), $t_0 =$ time correction for model fit (s), $v =$ vehicle velocity (km/h), and $a =$ a regression coefficient.

Analysis of stress pulse duration vs. drive speed shows that to achieve the AASHTO T307 specified 0.1 s stress-pulse duration at the in situ sensor location (152.4 mm beneath the bottom of pavement), the vehicle speed would need to be about 128 km/h (Figure 2.4). However, considering that the in situ test response is a composite response of the pavement foundation layers, including the underlying subgrade layer, the non-linear nature of the stress-pulse vs. vehicle speed suggests that the rebound rate of the subgrade may influence the in situ test results.

![Figure 2.4. Stress pulse duration at varied drive speeds.](image)

To investigate the influence of stress pulse duration on the laboratory $M_r$ test results, laboratory specimens were prepared using the RPCC/RAP material. The stress-pulse duration was set at 0.1 s, 0.5 s or 1.0 s. Figure 2.5 shows the resilient modulus plotted as a function of the bulk stress. The raw data and the Mechanistic-Empirical Pavement Design Guide (MEPDG) suggested generalized model (NCHRP 2004) curves are presented. Results show that the
specimen loaded with the 0.5 s stress-pulse duration produced higher $M_r$ values than the specimen tested at 0.1 s for most of the applied bulk stresses. Lower $M_r$ values were obtained with the 1.0 s stress-pulse duration compared to the 0.5 s duration at most bulk stresses. A definite relationship between stress pulse duration and $M_r$ values needs to be studied further in respect to the fact that the in situ response is a composite response, not just one layer or material. Previously, Marr et al. (2003) suggested that a simpler and less expensive $M_r$ test could be conducted with loading period of 0.5 s.

![Graph showing resilient modulus values for different stress pulse durations.](image)

**Figure 2.5. $M_r$ values from laboratory tests with varied pulse duration.**

*Influence of Laboratory Sampling Rate*

AASHTO T307 requires a 200 Hz minimum sampling rate. An experiment was performed on a uniform polyurethane specimen to investigate the effects of 200 Hz, 500 Hz, 1000 Hz, and 1250 Hz sampling rates on peak load values. The polyurethane specimen was used to minimize effects of different specimen properties on the resulting $M_r$ values. Figure 2.6 shows an example
of the load-time history at the 200 Hz sample rate. The sampling rate and pattern results in an obvious miss in terms of peak value determination with characteristic aliasing effect from under sampling. This observation confirmed that the sampling pattern and rate at 200 Hz is not sufficient to quantify the peak load.

**Figure 2.6. Example of M_r test on the polyurethane specimen with 200 Hz sampling rate.**

With increasing sampling rate, variation in the maximum load was reduced along with a reduction in variation of the minimum applied load during the dwell period. Improvement by reduced variability was observed at all stress levels. Figure 2.7 shows a frequency plot of peak loads and the differences in recorded peak loads with the selected sampling rates. Although a higher sampling rate means more data could be recorded to identify the actual peak load, the test with 1250 Hz target sampling rate had lower consistency in peak loads than the test with 1000 Hz target sampling rate. The reason could be that the actual recorded data is less than 1250
points per load cycle as the result of capability of the data acquisition system used to collect a large amount of data points in a short period of time. However, based on the results presented herein, a minimum sampling rate of 500 Hz would provide a significant improvement relative to the existing minimum rate of 200 Hz.

![Graph showing frequency plot for maximum applied loads within a load sequence with different sampling rates.](image)

**Figure 2.7. Frequency plot for maximum applied loads within a load sequence with different sampling rates.**

**P and I Gain Settings**

P and I gain settings are tuned during the PC load sequence to minimize the difference between the applied and target maximum load. The effect of selected gain settings, within a narrow range of optimal settings per the equipment manufacturer, were studied by conducting several laboratory $M_r$ tests on the polyurethane specimen per the details provided in Figure 2.8 (see legend notes). This study demonstrated that the differences among $M_r$ values of the
A polyurethane specimen are about 6% of the maximum $M_r$ value at each stress level for varied initial P and I settings. Each point in Figure 2.8 shows the average $M_r$ values of the last five load cycles in each load sequence. Compared to the I value, the P value was considered the more dominate parameter for the range of values selected. Careful adjustment of P and I signal values are necessary for each $M_r$ test.

Figure 2.8. $M_r$ values of a polyurethane specimen with varied P and I signal values.

Although P and I values are varied in a small range for seven $M_r$ tests on the polyurethane specimen, differences in the determined $M_r$ values are obvious. Three selected load sequences that have different deviator and confining stresses were studied for determining relationships between P or I values and the average peak load or displacement of the last five load cycles in the given load sequence. Although changes in response associated with the I values are much smaller compared to P values, signal I is adjusted by multiplying the I value by the sum of the
previous load errors and signal P is adjusted by multiplying the P value by the load error. The P and I values were estimated only in the PC sequence for the target deviator stress of 103.4 kPa and confining pressure of 103.4 kPa, so the P and I values are not always giving the closest actual load to the target load that varied in different load sequences.

Figure 2.9. $M_r$ values of a polyurethane specimen at selected load sequences with varied P and I signal values.
Figure 2.9 shows that the average peak load at the same P and I values is close, undershooting, and overshooting the target load for different load sequences. Increases in P and I values generally give higher actual peak load and displacement, except the actual peak load and displacement decreased about 0.5% when the I value increased from 0.001 to 0.002 at P equal to 0.4. To get the best possible control, P and I values should be adjusted during the first few load cycles in each load sequence that has deviator stress changed from 20.7 kPa to 275.8 kPa.

2.5.2. Influence of Deformation Measurements

Vertical deformations were measured using two outside mounted LVDTs according to AASHTO T307 (2007). Figure 2.10 shows an example dataset comparing results using one LVDT versus the average of two LVDTs measurements. Surprisingly, the commercially available equipment was programmed to read only from LVDT1. This suggests that new users should carefully study how the sensors are integrated into the data collection and analysis software provided by the manufacturer. Based on the results presented in Figure 2.10, the differences between $M_r$ values determined using LVDT1 and LVDT2 deformation measurements are up to about 60% of the $M_r$ values calculated with average deformation measurements of LVDT1 and LVDT2. If one LVDT is used, the determined $M_r$ values will overestimate or underestimate the actual resilient properties of the test specimen. Because the top surface of the specimen may rotate during loading, one or even two LVDTs may not be sufficient to characterize the rotation and check uniformity of the test specimen. (see, Ping et al. (2003), Bozyurt et al. (2012), Camargo et al. (2012)).
2.5.3. Quality Control and Quality Assurance

Variation of the calculated $M_r$ values cannot be eliminated but needs to be maintained below a maximum value that reflects the quality of the test. Therefore, quality verification was done by checking the signal to noise ratio (SNR), deformation ratio ($R_v$), and coefficient of variation ($c_v$) for the last five $M_r$ values in a load sequence.

SNR is calculated for each load cycle using Eq 2.1 and Eq 2.2, and Kim et al. (2007) suggested that the minimum SNR of 10 for each load is acceptable. Figure 2.11 shows an example of SNR values for checking the peak load to the noise of 90% baseline data of a polyurethane specimen with varied sampling rate and three granular materials with target 85% RD. All measurements met the minimum SNR value of 10 for each load, except the first load sequence at the first (lowest) peak loading sequence. SNR values of load for the polyurethane specimen with 200 Hz sampling rate varied in a relatively constant range for the last 14 load
sequences. But for aggregate specimens, the SNR values increase with the number of load sequences. This can be explained as the standard deviation ($s_d$) is not increasing significantly with increasing bulk stress.

![SNR Graph](image1)

**Figure 2.11.** Average SNR for load measurements of last five cycles at all load sequences

![Deformation Ratio Graph](image2)

**Figure 2.12.** $R_v$ for all deformation measurements at each load sequence of one $M_r$ test on crushed limestone.
As described previously, AASHTO T307 (2007) requires quality verification assessment of the deformation ratio ($R_v$). It is desired that $R_v \leq 1.1$ and it is considered unacceptable if $R_v > 1.30$ during the PC phase of the test. However, the comparative checks might be conducted for all load sequences not only the PC sequence as an additional measure of quality testing. Two examples of $R_v$ values for $M_r$ tests on crushed limestone and RPCC/RAP are shown by box-plots in Figure 2.12 and Figure 2.13, respectively. All box plots in this paper are plotted to show the 10% and 90% quartile with boundary of the upper and lower whiskers, the 25% and 75% quartile with the upper and lower boundary of the box, the median with the horizontal line inside the box, and the values that are out of the range (10% to 90% quartile) with single points. Results show that all load sequences, except the PC sequence, have $R_v$ values less than the desired limit of 1.1. In general, the results for both test samples show that the $R_v$ values are highest during the PC sequence and that virtually all the $R_v$ values meet the desired limit of 1.1 for the subsequent 15 loading cycles.

**Figure 2.13.** $R_v$ for all deformation measurements at each load sequence of one $M_r$ test on RPCC/RAP.
In addition to the comparison of paired $R_v$ values, the resilient strain ($\varepsilon_r$) for each load cycle that is calculated from the deformation measurement of each LVDT was compared. Figure 2.14 shows an example of the resilient strain ratio ($R_{\varepsilon_r}$) calculated as the ratio of resilient strain determined from LVDT1 to LVDT2 on the same RPCC/RAP specimen that was used for calculating $R_v$ values in Figure 2.13. $R_{\varepsilon_r}$ varied from 0.7 up to 1.9 for all load cycles, and values of $R_{\varepsilon_r}$ varied differently from $R_v$ values for all load sequences. Figure 2.13 shows that the PC sequence is the only load sequence that has $R_v$ values exceeding 1.1, but Figure 2.14 shows that the first load sequence where the lowest stresses were applied has the highest $R_{\varepsilon_r}$.

Large differences between LVDT1 and LVDT2 measured resilient strains result in larger errors in $M_r$ calculation. Both deviator stress and confining pressure applied in the first load sequence are lower than stresses applied in the PC sequence, but they all have deviator stress to confining pressure ratio of one. During the transition between the PC sequence and the first load sequence, stresses at a lower stress level are applied. Per the raw data obtained in several $M_r$ tests, the displacements that were measured by both LVDTs decrease with increasing number of load cycles in the first load sequence. This analysis suggests that cyclic densification and/or particle rearrangement leading to non-uniform vertical strain might contribute to differences in all paired resilient strains in the first load sequence.
Figure 2.14. $R_{tr}$ for all load cycles at each load sequence of one $M_r$ test on RPCC/RAP.

In addition to the observation of variation of $M_r$ values in a load sequence, the variation of $M_r$ values within the last five load cycles was also studied based on the suggestion of Kim et al. (2007) for quality verification of the test results that $c_v$ for the last five $M_r$ values should be below the limit of 10%. In this present study, all 36 $M_r$ tests on granular soils have $c_v$ less than 10% at all load sequences. The distribution of $c_v$ values for each test was presented in box-plots and summarized in Figure 2.15. Properties of each test specimen are noted above each box-plot. Figure 2.15 shows that all tests that were performed on crushed limestone material have 50% of the $c_v$ values less than 4% and 75% of the $c_v$ values less than 5%. The tests that were performed on RPCC and RAP materials agreed with the results summarized from tests on crushed limestone, except the first RAP test. However, this $c_v$ value only shows variation among the last five load cycle that cannot identify the variation of $M_r$ values of the entire 100 load cycle of each load sequence that shows if the average $M_r$ of the last five load cycles is representative for that load sequence.
Further study on variation of $M_r$ values was accomplished by comparing the average $M_r$ of the last 5 load cycles to the average maximum $M_r$ and the average minimum $M_r$ separately. The average maximum $M_r$ is calculated using the maximum and 4 adjacent $M_r$ values.

### 2.5.4. Statistical Analysis of $M_r$ Variation and Model Coefficients

All 36 $M_r$ test results were used to study the variation in $M_r$ values as a function of the different stress levels. Analysis was performed to characterize the statistical importance of factors that influence $M_r$ values. Coefficients fit to the universal prediction model were also determined using non-linear regression analysis. Moreover, the significance of each coefficient was determined from the statistical analysis.

**Figure 2.15.** $c_v$ of last five $M_r$ values for all $M_r$ tests on crushed limestone.
$M_r$ variation

Morgan (1966) and Moore et al. (1970) reported that $M_r$ values generally increased with number of load cycles, so the average $M_r$ of the last 5 load cycles should be nearly the same as the maximum $M_r$ value. However, observation of variation in $M_r$ values within each load sequence indicates that the average $M_r$ of the last 5 load cycles is not always the maximum value nor representative of the load sequence.

Figure 2.16 shows an example where the $M_r$ values decrease near the end of the 100 load cycles and the minimum $M_r$ value was obtained at the last load cycle. Another example (Figure 2.17) shows that the $M_r$ value decreased first and then increased. Consequently, the variation of $M_r$ values within each 100 load cycle sequence was identified by comparing the average $M_r$ of the last 5 load cycles to the average 5-pt. maximum and the average 5-pt. minimum $M_r$ values. By observation, the first 10 load cycles were excluded because these cycles often result in significant changes.

![Graph showing variation in $M_r$](image)
By plotting the ratio of the average maximum of 5 consecutive values to the average of the last 5 $M_r$ cycles (FIG. 18) it can be seen that the RAP specimens have larger ratios than crushed limestone and RPCC/RAP specimens, and the ratio is up to 1.45 which means the average maximum $M_r$ is up to 45 % higher than the average $M_r$ of the last 5 load cycles. Studying all tests on crushed limestone, 78.3 % of the load sequences have an average maximum $M_r$ larger than the average $M_r$ of the last 5 load cycles. A similar result was found for 86.1 % of the load sequences for RAP and 82.2 % of the load sequences for RPCC/RAP. This finding suggests that selection of the last five load cycles does not necessarily provide a representative maximum $M_r$ value for the load sequence.

In addition, the average minimum $M_r$ was not necessarily obtained at the beginning of the load sequence (examples are shown in Figure 2.16 and Figure 2.17), so ratios of the average minimum $M_r$ to the average $M_r$ of the last 5 load cycles for each load sequence were calculated and summarized (Figure 2.18). Studying all tests and materials, less than 5 % of the load
sequences have an average minimum $M_r$ at the end of the load sequence. The ratios larger than one indicate large variation among the five points, because the average minimum $M_r$ was calculated using the minimum $M_r$ from five consecutive points. Results show that the RAP specimens have larger ratios than crushed limestone and RPCC/RAP specimens, and the ratio is up to 1.04.

![Figure 2.18. Ratios of the average maximum $M_r$ to average $M_r$ of last 5 load cycles for 36 granular specimens.](image)

Statistical analysis was performed on test results to determine the significance of material types, load sequence number, and 5-point average $M_r$ value (considering average maximum/minimum/last 5 load cycles). P-values less than 0.05 were used to indicate significant effects of the tested factors. Results summarized in Table 2.3 show that material type, load sequence, and 5-point $M_r$ values all have significant effects. The least square means of $M_r$ values (Figure 2.19) showed that the deviator stress ($\sigma_d$) and confining pressure ($\sigma_c$) have positive effects on $M_r$ values and $M_r$ values of crushed limestone are very different from that of RAP and...
Tukey HSD (honest significant difference) tests were also performed to study statistical differences in average $M_r$ values among levels of a factor.

Figure 2.19. Least square means plot for $M_r$ tests on 3 base/subbase materials.

Table 2.3. Tests for fixed and random effects of analysis of variance.

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Material</td>
<td>4361301</td>
<td>2180650</td>
<td>2</td>
<td>23.40</td>
<td>&lt;.0001**</td>
</tr>
<tr>
<td>Test No.[Material]&amp;Random</td>
<td>3075393</td>
<td>93194</td>
<td>33</td>
<td>94.59</td>
<td>&lt;.0001**</td>
</tr>
<tr>
<td>Load Sequence #</td>
<td>16052914</td>
<td>1146637</td>
<td>14</td>
<td>1163.84</td>
<td>&lt;.0001**</td>
</tr>
<tr>
<td>Material*Load Sequence #</td>
<td>1302376</td>
<td>46513</td>
<td>28</td>
<td>47.21</td>
<td>&lt;.0001**</td>
</tr>
<tr>
<td>$M_r$ Calculation</td>
<td>111770</td>
<td>55885</td>
<td>2</td>
<td>56.72</td>
<td>&lt;.0001**</td>
</tr>
<tr>
<td>Material*$M_r$ Calculation</td>
<td>26717</td>
<td>6679</td>
<td>4</td>
<td>6.78</td>
<td>&lt;.0001**</td>
</tr>
<tr>
<td>Load Sequence #*$M_r$ Calculation</td>
<td>26036</td>
<td>930</td>
<td>28</td>
<td>0.94</td>
<td>0.5498</td>
</tr>
<tr>
<td>Material<em>Load Sequence #</em>$M_r$ Calculation</td>
<td>15516</td>
<td>277</td>
<td>56</td>
<td>0.28</td>
<td>1.0000</td>
</tr>
<tr>
<td>Error</td>
<td>1430532</td>
<td>985</td>
<td>1452</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: * = interaction of factors; ** = significant at $\alpha = 0.01$; p-value = probability that larger than F ratio

Tukey’s HSD test compares all possible pairs of factor level means by first computing the pairwise differences in mean $M_r$ values. Each pairwise difference is compared to a critical value (HSD) to determine the statistical significance of all pairwise differences. The critical HSD value
uses a value from the studentized range distribution. Values of the studentized range are based on Type I error rate (\(\alpha\)), number of groups or factor levels (k), and degrees of freedom (df) for error.

In JMP, a statistical program, the critical HSD value is calculated as \(Q \sqrt{\text{MS}_{\text{error}} \left(\frac{1}{n_i} + \frac{1}{n_j}\right)}\) where \(\text{MS}_{\text{error}}\) is mean square error, \(n_i\) and \(n_j\) are numbers of observations for factor levels i and j and Q is derived from the distribution of the studentized range. If the absolute value of the pairwise difference between two factor level means is less than the HSD value, these two factor levels are not significantly different and marked by the same letter. Otherwise, the factor level means are significantly different and marked by different letters.

Table 2.4 shows results of two Tukey HSD tests that were performed on material type and \(M_r\) calculation separately, each set of alphabetically listed letters indicates the statistical significance of the difference between mean \(M_r\) values of any two levels of each factor. The Tukey HSD test on material type shows that the differences in mean \(M_r\) between recycled materials (RAP, RPCC/RAP) and virgin materials (crushed limestone) are statistically significant while the difference in mean \(M_r\) between the two recycled materials is not. Moreover, the differences in the mean \(M_r\) values calculated using each of the three \(M_r\) calculation methods are significantly different from the other two.

**Table 2.4. Tukey HSD test on material type and \(M_r\) calculation method.**

<table>
<thead>
<tr>
<th>Factors</th>
<th>Levels</th>
<th>Letter</th>
<th>Least Square Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Material</td>
<td>Limestone</td>
<td>A</td>
<td>323.2401</td>
</tr>
<tr>
<td></td>
<td>RAP</td>
<td>B</td>
<td>232.9138</td>
</tr>
<tr>
<td></td>
<td>RPCC/RAP</td>
<td>B</td>
<td>200.6457</td>
</tr>
<tr>
<td>(M_r)</td>
<td>Avg (M_r) of max and adjacent 4 load cycles</td>
<td>A</td>
<td>261.9112</td>
</tr>
<tr>
<td>Calculation</td>
<td>Avg (M_r) of last 5 load cycles</td>
<td>B</td>
<td>253.2517</td>
</tr>
<tr>
<td></td>
<td>Avg (M_r) of min and adjacent 4 load cycles</td>
<td>C</td>
<td>241.6368</td>
</tr>
</tbody>
</table>

Note: Levels that are not connected by same letter are significantly different and \(\alpha=0.05\).
Coefficients of $M_r$ prediction model

Values of universal prediction model coefficients are determined from non-linear regression analysis as the direct inputs for the AASHTOWare design software (AASHTO 2015). This model predicts $M_r$ values based on the bulk stress ($\sigma_B$) and octahedral stress ($\tau_{oct}$) with three coefficients, $k_1$, $k_2$, $k_3$, as given by Eq 2.5, in which $P_a$ is atmosphere pressure.

$$M_r = k_1 P_a \left(\frac{\sigma_B}{P_a}\right)^{k_2} \left(1 + \frac{\tau_{oct}}{P_a}\right)^{k_3} \quad (2.5)$$

$M_r$ values are positive, so values of $k_1$ are positive. Values of $k_2$ are also positive, because $k_2$ is the exponent coefficient of bulk stress and $M_r$ is positively related to bulk stress. Strain hardening of the material is caused by increasing bulk stress, so a higher $M_r$ value is obtained. In addition, negative values of $k_3$ should be obtained to account for strain softening effects of increasing octahedral shear stresses. Negative values for $k_3$ are generally obtained for fine-grained soils, but not always for coarse-grained or granular materials. Strain softening of granular materials generally occurs at high stress levels where volumetric strains are increasing. $M_r$ testing is normally limited to strains $< 5\%$. Therefore, it is not surprising that 33 of the 36 $M_r$ tests resulted in positive values of $k_3$. In addition, all 36 $M_r$ tests have positive values for $k_1$ and $k_2$ coefficients.

The significance of $k_1$, $k_2$, and $k_3$ coefficients was determined for all 36 $M_r$ tests at a significance level of 0.001. Results show that $k_1$ and $k_2$ are significant for all 36 tests, but only 13 of the 36 tests produce a statistically significant $k_3$ value. Figure 2.20 shows the p-values for all 36 $k_3$ coefficients. As indicated, the RAP specimens produced least significant $k_3$ coefficients compared to crushed limestone and RPCC/RAP. The insignificant $k_3$ coefficients indicate that octahedral shear stress is not a significant factor in controlling resilient modulus for the materials.
tested. Examining the data with respect to statistical significance in lieu of just a curve fitting exercise thus reveals useful information about the material properties.

![Figure 2.20. P-values for coefficient k₃ of 36 Mᵣ tests on granular materials.](image)

### 2.6. Conclusions

This paper characterizes sources of error associated with laboratory Mᵣ tests conducted with a commercially available Mᵣ system. Laboratory Mᵣ tests conducted on three unbound granular materials and one polyurethane specimen and in situ drive tests performed on a flexible pavement revealed some sources of error related to strain and stress measurements for granular materials.

The errors related to stress measurements were characterized by identifying the difference between in situ and laboratory stress pulse shape and duration, studying the effects of sampling
rates, and P and I signal values. A comparison of randomly selected raw data of a AASHTO T307 test with the required theoretical haversine-shaped stress pulse and in situ stress pulses revealed inadequate simulation of in situ stress pulse shapes and fast stress pulse durations in laboratory tests. The haversine-shaped stress pulse does not simulate the actual slow stress initialization and dissipation that in situ stress pulse experienced. A modified Gaussian model with 5 parameters can better simulate in situ stress pulses. Stress pulse duration of 0.1 s is too fast compared to in situ stress pulse duration of 0.14 s at 304.8 mm beneath the pavement surface and base layer when the test vehicle was driving at 96.6 km/h. In addition, a 0.1 s stress pulse duration might be obtained at the same position when the test vehicle is driving at 128 km/h. Although Mr values varied with different stress pulse durations, three laboratory tests are not sufficient to conclude effects of stress pulse duration on Mr values. Therefore, the effects of the inadequate simulation on Mr values needs to be studied further to determine if a revision is needed for the laboratory tests. Further, the specified 200 Hz sampling rate for laboratory tests is insufficient to fully characterize the true shape of stress pulses, especially the applied peak stresses. After tests with different sampling rates, rates of 500 Hz or greater can capture applied peak stresses better than the 200 Hz rate and result in less variation in Mr values. However, the different Mr test appliance may perform better or worse with the same sampling rate. Different sampling rates during the loading and rest period might be used with capable software to save computer storage and time for processing data. Initial adjustments of P and I signal values and automatic adaptation with time within the PC sequence is good when applying the target load in the PC sequence but not for achieving target loads for subsequent sequences where different stress levels are required. Therefore, careful adjustments of P and I signal values in each load sequence might be suggested when Mr test equipment with a PID controller is used.
The differences between deformation measurements of two LVDTs were studied. In some cases, large differences were observed perhaps because top surfaces of the test specimens were not perfectly flat and the unit weights of the specimens were not uniform. In some cases, large differences in two LVDTs measurements were not observed in the PC sequence but in other load sequences. The larger the difference in two LVDTs measurements, the lower the accuracy in $M_r$ values. Therefore, quality control and quality assurance (QC/QA) are needed to determine the reliability of the $M_r$ tests results. SNR values of loads, the AASHTO T307 required displacement ratio $R_v$ in the PC sequence, a proposed resilient strain ratio $R_{εr}$ of LVDT1 to LVDT2, and $c_v$ of the last five $M_r$ values in each load sequence were studied for QC/QA. Most of the SNR values met the requirement except for the first load sequence. The first load sequence has most SNR values less than 10, the minimum criteria. A possible reason for this is particle rearrangement in the specimen. Values of $R_v$ in the PC sequence are not representative of $R_v$ values for all load sequences, so $R_v$ values should be checked for all load sequences. The highest $R_{εr}$ values were obtained in the first load sequence not the PC sequence this suggests a possible particle rearrangement might have occurred in that load sequence. Therefore, $R_{εr}$ should be studied to check the uniformity of the specimen response. However, two LVDTs may not be sufficient for checking the uniformity of the specimen response and more LVDTs are suggested. In addition, $c_v$ was calculated for the last five load cycles of selected $M_r$ tests and all the values met the requirement. However, this only shows that variations within the last five load cycles were acceptable and that the average of the last five $M_r$ values is used to represent the $M_r$ at the given stress for the tested material.

However, $M_r$ values varied in different ways than the average of the last five $M_r$ values, they could be higher than the maximum or lower than the minimum $M_r$ values. This suggests steady
Mr values were not obtained at the end of the 100 load cycles. According to the statistical analysis on all 36 Mr tests on three granular materials, variations among the average of the last five Mr values, the average of the maximum and adjacent four Mr values, and the average of the minimum and adjacent four Mr values are statistically different. In addition, crushed limestone specimens had higher average Mr than RAP and RPCC/RAP specimens, and material type is a statistically significant factor affecting Mr values. Although increasing use of recycled materials can help environmental sustainability and reduce costs, careful investigation of the properties of the recycled materials should be conducted. Moreover, regression coefficient k3 is not necessary for granular materials because the effects of shear stress that k3 interprets in the universal model can be negative or positive.

Assessments of testing errors are necessary to ensure accurate Mr values. Practitioners who perform AASHTO T307 Mr tests with similar equipment can use these findings to evaluate their equipment and identify possible sources of error.

2.7. Acknowledgements

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CHAPTER 3. STUDYING SPATIAL VARIATION OF PAVEMENT FOUNDATION PROPERTIES WITH GEOSTATISTICAL ANALYSIS METHOD

A paper submitted to Journal of Geotechnical and Geoenvironmental Engineering

Jia Li, David J White, Philip M Dixon, and Pavana Vennapusa

3.1. Abstract

Geostatistical analysis procedures are presented in this study to provide a guide for geotechnical and pavement engineers to quantify spatial variability of pavement foundation properties with consideration of choosing the best fitted semivariogram model and characterization of anisotropy. Characterization of spatial variability of stiffness and compaction properties are presented from two Interstate projects sites in Michigan (I-94 and I-96).

Geospatial analysis of anisotropy for the geotechnical measurements shows different major and minor anisotropic directions for densely tested spatial areas. Comparisons of three theoretical semivariogram models (i.e., spherical, exponential, and Matérn with k=1) using elastic modulus, moisture/density, and penetration resistance show that there is no single best fitted model for all measurement types. The isotropic semivariogram model works as well as the anisotropic semivariogram model in estimating the data at unsampled locations across the studied areas. The range values (indicating the spatial correlation length) are almost all less than 5 m for all measurements without considering the anisotropic behavior. When anisotropy is considered, longer spatial correlation lengths up to 11 m were determined in the longitudinal direction of the road alignment. The importance of this research is that with high quality field measurements, different anisotropic behaviors were observed and therefore careful assessment of geospatial modeling is required to adequately characterize spatial variability of pavement foundation layer properties.
3.2. Introduction

Non-uniform subbase/subgrade stiffness can accelerate fatigue cracking and other types of pavement distresses and shorten the pavement service life (Titi et al. 2014; White et al. 2004). Dilip abd Babu (2014) concluded that critical strains will be underestimated without considering the spatial variability of resilient moduli. Roesler et al. (2016) showed peak concrete slab tensile stresses increase up to 39% in nonuniform compared uniform support conditions. However, there have been very limited studies that documented the fundamental aspects of nonuniformity modeling of the foundation layer properties. In part, the lack of study in this area is due to the state of practice that relies on sparse data collected. The univariate statistical analysis of pavement foundation properties shows a range of engineering parameters values can vary within the studied area, but it does not describe the spatial variability. Several previous studies (Facas et al. 2010; Lea and Harvey 2015a; Lea and Harvey 2015b; Vennapusa 2004; Vennapusa et al. 2010; White et al. 2004) performed spatial variability analysis on pavement foundation layer properties (i.e., stiffness, layer thickness, intelligent compaction measurement values). Anisotropy in engineering parameters has been observed and characterized using roller-integrated compaction measurements (Facas et al. 2010; Vennapusa et al. 2010) where longer correlation lengths were observed in the longitudinal direction compared to the transverse direction.

Geostatistical methods have been well studied in other fields (i.e., mining, geology, soil science) and details of understanding general spatial variation have been introduced in many books (Clark and Harper 2002; Cressie 1993; Deutsch and Journel 1998; Goovaerts 1997; Isaaks and Srivastava 1989; Journel and Huijbregts 1978; Olea 2006). Lead and Harvey (2015b) introduced model types with analysis of pavement layer thickness. However, the details in using
geostatistical analysis methods for charactering pavement foundation properties with closer spacing (about 0.6 m) was not studied.

Herein pavement foundation properties were studied by investigating the in-situ stiffness, penetration resistance, and compaction properties. Stiffness properties include elastic modulus \(E_{LWD-Z3}\) determined from the light weight deflectometer (LWD) test. Penetration resistance was determined from the dynamic cone penetration index (DCPI) (ASTM D6951-03) of subbase layer and subgrade layers (DCPI_{subbase, and DCPI_{subgrade}). Compaction properties include dry unit weight \((\gamma_d)\) and moisture content \((w)\), as determined from the nuclear gauge (NG) test method (ASTM D6938-10). In-situ testing was performed shortly after pavement foundation construction process was completed. Observation of the construction processes were noted in terms of how the materials were placed, spread, and compacted.

The in-situ measurements were taken at several test locations with consideration for the depth of measurement that the values represent. For example, the LWD test is a spot test where the \(E_{LWD-Z3}\) values represent stiffness for the composite subgrade and subbase layers at the test location. Other measurements were interpreted to represent the target layer, like DCP and the NG tests results. Interpretation of the in-situ test results is important for further interpretation of the geospatial results.

This paper focuses on quantifying spatial variability using a geostatistical method, comparing efficiency of different theoretical semivariogram models in fitting the semivariogram of studied properties, describing different methods in identifying anisotropic spatial variance, and comparing isotropic and anisotropic semivariogram models in describing the spatial variability. The interpretation and modelling of experimental measures of spatial variability are discussed and demonstrated using data collected at two projects MI I-94 and MI I-96 in Michigan. This
paper introduces researchers and engineers to quantifying spatial variability, examines how the correlation of the pavement foundation properties could be in different directions, and guides readers to plan future sampling programs for studying the spatial variability of the pavement foundation sections.

3.3. Geostatistical Analysis

The semivariogram $\gamma(h)$ is a tool in geostatistical studies to describe and quantify spatial variability of studied variables. A semivariogram $\gamma(h)$ measures the average dissimilarity of paired data separated by a vector $h$ (Goovaerts 1997). The semivariogram $\gamma(h)$ is defined as half of the average squared differences between a number, $N(h)$, of data values pairs separated at a distance $h$ as calculated in Eq. 3.1 (Isaaks and Srivastava 1989).

$$\gamma(h) = \frac{1}{2N(h)} \sum_{(i,j)|h_{ij}=h} (Z(s_i)-Z(s_j))^2$$ (3.1)

The random function $Z(s)$ where $s$ denotes spatial location is second order stationary, which means that the mean value ($\mu$) is a constant and the covariance between any pair of data values separated by the vector with vector distance $h$ is the same across the study area. Although semivariance, variance, semivariogram, and variogram have been used in different studies (Bachmaier and Backes 2011), the semivariogram, $\gamma(h)$ given in Eq. 3.1, will be used in this study.

A semivariogram plot is composed of sill (C) that includes nugget effect ($C_0$) and partial sill ($C_s$), and range (a) or effective range ($a'$) for a single semivariogram model with nugget effect. Figure 3.1 shows a typical spherical semivariogram fitted to the experimental semivariogram data.
Three major semivariogram parameters are the nugget effect ($C_0$), the sill ($C=C_0+C_s$), and the range ($a$). The brief description of each parameter will be summarized from geostatistical books (Goovaerts 1997; Isaaks and Srivastava 1989).

The nugget effect ($C_0$) is the sudden increase in the semivariogram value as the separation distance goes from 0 m at the origin to an extremely small distance. This nugget effect can be the result of sampling error and short scale variability. The nugget effect can be determined by fitting the straight line through the first few semivariogram values to the intercept with the vertical axis. The relative nugget effect tends to increase with the lag ($h$) tolerance and data sparsity. Data sparsity or measurement errors may lead to a semivariogram with noisy values and can only be presented with a pure nugget effect. In general, the nugget effect is modelled as an isotropic component, but it could be modeled as an anisotropic spatial structure if the range value is smaller than the shortest sampling distance.
The sill (C=C₀+Cₘ) is the value of semivariogram that no longer increases with increasing separation distance, that is the semivariogram reaches a plateau with value C₀. The sill of the semivariogram may not be equal to the sample variance (Barnes 1991; Goovaerts 1997) and so forcing the sill to be equal to the sample variance (s²) is a questionable practice.

The range (a) is the separation distance at which the semivariogram reaches the sill plateau. In most models, the effective range (a′) is determined as the semivariogram reaches 95% of the sill plateau. More and better data tends to produce a semivariogram with longer range.

Some properties of a semivariogram are that the semivariogram values are identical when computed on opposite directions, the omnidirectional semivariogram is computed on the data pairs in all directions that have an angular tolerance (∆θ) greater than or equal to 90°, the directional semivariogram is computed when ∆θ less than 90°, and semivariogram values are sensitive to extreme data or outlier values (Goovaerts 1997). The ∆θ extend the vector h angle θ to include all distance vector falls in the direction θ±∆θ.

The appropriate lag or separation distance should be chosen according to the average minimum spacing among the sampling locations. The lag tolerance is commonly one half of the lag spacing. The default setting in the statistical program R is to study the semivariogram values of the data pairs separated at a distance up to 1/3 of the maximum length of the studied area. In general, 10 to 15 bins is desired at separation distance up to ½ of the maximum distance over the sampling area, but the number of data pairs within each bin is more important.

The discrepancies in semivariogram values reflect experimental fluctuation that result from the small number of data pairs available for each lag. Generally, the minimum of 30 and preferred 50 or more data pairs is desired within each bin (Journel and Huijbregts 1978). Erratic behaviors could be found in experimental semivariogram for data that is skewed or has
extremely high or low values (outliers). If the sampled data is highly skewed (skewness is out the range of -1 to 1), the data may be transformed before performing spatial analysis. If the experimental semivariogram keeps increasing with increasing separation distance between data pairs, there could be a trend in the sampled data that should be removed before spatial analysis (Gringarten and Deutsch 2001). The reason for this is that it is unreasonable to expect a constant mean value over the study area, as is assumed in spatial analysis, if a significant trend is identified.

3.4. Project Overview

Two dense gridded test sections with the minimum spacing of about 0.6 m were studied for investigating and quantifying the spatial variability of the pavement foundation properties. The in situ test data used in this study were collected from one test section from each of the MI I-94 and the MI I-96 reconstruction projects.

3.4.1. Test section

The first dense gridded test section (TS1b) is part of the MI I-94 project which involved pavement reconstruction. The new pavement was constructed with a 280 mm (11 in.) thick JCPC pavement surface and a 406 mm (16.0 in.) thick OGDC base layer that sat on the subgrade layer of silty clay which was classified as ML in the USCS classification system with a geotextile layer in between. TS1b involved testing a 7 m × 7 m area in a dense grid pattern with 121 test points on the newly constructed trimmed OGDC base layer. The second dense gridded test section (TS1) is part of the MI I-96 project which also involved pavement reconstruction. The new pavement was constructed with a 292 mm (11.5 in.) thick jointed PCC pavement, 127 mm (5 in.) cement treated base (CTB) layer with recycled PCC (RPCC) material and 279 mm (11 in.) of existing or new sand subbase with a geotextile separator at the CTB/subbase interface. TS1 involved
testing an 8.5 m × 8.5 m area in a dense grid pattern with 73 test points on the final compacted and trimmed sand subbase layer. Soil properties of these two test sections determined by laboratory tests, are summarized in Table 3.1.

### Table 3.1. Soil properties summary for studied test sections

<table>
<thead>
<tr>
<th>Pavement Foundation Layer</th>
<th>Project Site</th>
<th>MI I-94</th>
<th>MI I-96</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base/subbase</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( r_{d_{\text{max}}} ) (kN/m³) (ASTM D4253-00)</td>
<td>16.23</td>
<td>20.06</td>
<td></td>
</tr>
<tr>
<td>( r_{d_{\text{min}}} ) (kN/m³) (ASTM D4254-00)</td>
<td>14.05</td>
<td>14.98</td>
<td></td>
</tr>
<tr>
<td>AASHTO Classification</td>
<td>A-1-a</td>
<td>A-1-b</td>
<td></td>
</tr>
<tr>
<td>USCS Classification</td>
<td>GP</td>
<td>SP-SM</td>
<td></td>
</tr>
<tr>
<td>Subgrade</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( r_{d_{\text{max}}} ) (ASTM D698-07)</td>
<td>18.58</td>
<td>20.1</td>
<td></td>
</tr>
<tr>
<td>( w_{\text{opt}} ) (ASTM D698-07)</td>
<td>13.8</td>
<td>9.5</td>
<td></td>
</tr>
<tr>
<td>AASHTO Classification (ASTM D3282-09)</td>
<td>A-4(0)</td>
<td>A-4</td>
<td></td>
</tr>
<tr>
<td>USCS Classification (ASTM D2487-00)</td>
<td>ML</td>
<td>SC</td>
<td></td>
</tr>
</tbody>
</table>

#### 3.4.2. In-situ tests

The following in situ tests were conducted on test sections MI I-94 TS 1b and MI I-96 TS1 to evaluate the variability in properties of pavement foundation systems: real-time kinematic global positioning system (RTK-GPS); Zorn light weight deflectometer (LWD); dynamic cone penetrometer (DCP); and Humboldt nuclear gauge (NG).

**Real-Time Kinematic Global Positioning System**

RTK GPS system was used to obtain global spatial coordinates (i.e., northing, easting, and elevation) of in situ test locations and tested pavement layers. The local spatial coordinates (x, y, and z) were determined for all tested sections from their global coordinates. A Trimble SPS 851 was established on site to provide base station correction for a Trimble SPS 851 receiver. This system has manufactured accuracies of < 10 mm in the horizontal direction and < 20 mm in the vertical direction.
Zorn Light Weight Deflectometer

Zorn LWD tests were performed according to manufacturer’s recommendations (Zorn G. 2003) on base and subbase layers to determine elastic modulus. These LWD tests were set up with a 300-mm diameter plate and a 71 cm drop height. Elastic modulus ($E_{LWD-Z3}$) from LWD results were determined using Eq. 3.2 where $E$ is elastic modulus (MPa); $D_0$ is measured deflection under the plate (mm); $\eta$ is Poisson’s ratio (0.4); $\sigma_0$ is applied stress (MPa); $r$ is radius of the plate (mm); and $F$ = shape factor = 8/3 per Vennapusa and White (2009).

$$E = \frac{(1 - \eta^2)\sigma_0 r}{D_0} \times F$$

(Nuclear gauge)

A nuclear moisture-density gauge (NG) device was calibrated and used to measure in situ soil dry unit weights ($\gamma_d$) and moisture contents ($w$) in the base and subbase materials. Tests were performed according to ASTM D6938-10 (2010) at each test location. The average values of $\gamma_d$ and $w$ are reported for spatial analysis.

Dynamic Cone Penetrometer

DCP tests were performed following ASTM D6951-03 (2003) to evaluate the in situ strength of compacted base, subbase, and subgrade materials, and dynamic penetration index (DCPI) and penetration depth were determined at each test point. The weighted average DCPI was calculated for each identified subbase and subgrade layer at each test point to evaluate variability of the in-situ strength at different pavement foundation layers. The first reading of the DCPI from the beginning of the test was excluded from the calculation of the weighted average DCPI. The reason is that the initial large DCPI value was obtained at the near surface of the subbase. After compaction of the subgrade and subbase, the lack of confining pressure of the unbound layer will
have less resistance to penetration. Since the pavement surface will be constructed on the top of the subbase layer that will provide confining pressure, the exclusion of the first reading will result in a more accurate average DCPI value for the subbase layer. By evaluating the test results, MI I-94 DCPI was calculated into the weighted average value for base and subgrade layers, and MI I-96 DCPI was calculated into the weighted average value for subbase and subgrade layers.

### 3.4.3. Test plan

The test point locations of MI I-94 TS1b and MI I-96 TS1 are shown in Figure 3.2 and Figure 3.3. All three LWD, NG, DCP tests were conducted at all test points in MI I-94 TS1b (Figure 3.2). Both LWD and NG tests were conducted at all tests points in MI I-96 TS1 and DCP tests were conducted at fewer test points as shown in Figure 3.3.

![Figure 3.2. Test points in MI I-94 TS1b](image-url)
Spatial analysis of pavement foundation properties was performed using the statistical analysis program R (Bivand et al. 2013; Pebesma 2001). The R program calculates the experimental semivariogram efficiently, fits a theoretical semivariogram model with statistical criteria to obtain the best fit to the calculated semivariogram values, and uses ordinary kriging to visualize the fitted semivariogram prediction results over the studied area.

The basic steps are summarized below:

- Calculate the omnidirectional experimental semivariogram values with adjustment on lag distance (h), angle tolerance (Δθ), and the maximum distance.
- Plot the variogram map as a preliminary study of anisotropy of the experimental semivariogram values of the studied variable.
• Calculate the semivariogram values in four major directions with azimuth angle (θ) is equal to 0°, 45°, 90°, 135° separately to identify existence and type of anisotropy (geometric, zonal, or both), and investigate major and minor anisotropy directions that are generally perpendicular to each other.

• Fit a theoretical model to the omnidirectional experimental semivariogram if isotropic or directional semivariogram if anisotropy is identified, and record values of a, C₀, Cₛ and sum of square errors (SSErr).

• Perform cross-validation with the fitted semivariogram model and calculate the mean square of the prediction error (MSPE).

• Use ordinary kriging with the fitted model to predict the values at unsampled locations among the sampled points and use contour plotting to present the results.

The calculation of an omnidirectional semivariogram is useful in starting the spatial analysis for investigating the distance parameters to produce a clearer structure without having insufficient bins or amount of data pairs in each bin. The omnidirectional semivariogram can indicate an erratic directional variogram when it exists. Several tolerances (Δθ) should be tried to use the smallest tolerance value that still provide good results (Isaaks and Srivastava 1989).

Although several commercially available geostatistical analysis software are available for calculating and plotting experimental semivariograms and fitting theoretical semivariogram models, the R program allows fitting theoretical semivariograms with a weighted least square method that can provide a better statistically fitted model and allow comparison between different theoretical models.

The maximum cutoff length is controlled to be 1/3 to ½ of the maximum distance of the studied area to exclude the effect of fewer data pairs at larger separation distances when studying
the spatial variability over the test area. Figure 3.4 shows an example of calculating experimental semivariogram of the variable \( E_{L,WD-Z3} \) calculated from LWD tests performed on MI I-94 TS1b. The example shows fewer data pairs were obtained with increasing separation distances, the variance of the semivariogram values is larger at larger separation distance, and semivariogram values start to decrease at about 2/3 of the maximum distance of the studied area when number of data pairs is smaller.

![Graph](image)

**Figure 3.4. Illustration of choosing the maximum cutoff length (MI I-94 TS1b)**

Extreme values or outliers should be identified and removed before calculating the experimental semivariogram, because the semivariogram values are sensitive to these extreme values that can introduce errors in studying the spatial continuity. For example, univariate statistical analysis of DCPI values on the subbase layer indicate there might be an outlier value. Figure 3.5 clearly shows the location where the extreme value, 22.648 blows/mm, was obtained.
The extreme value will significantly affect the calculation of semivariance. A bubble plot, like the one in Figure 3.5, is useful in visually identifying the location of extreme values.

![Bubble plot of DCPI values of subbase layer](image)

**Figure 3.5. Bubble plot of DCPI values of subbase layer**

### 3.5.1. Model types

Although the experimental semivariogram summarized the mean semivariogram for each lag distance (h), it does not give the value of correlation length that should be obtained by fitting the theoretical semivariogram models. The most important characteristic for the choice of the variogram model is the interpretation of the behavior at the origin. The objective of fitting theoretical semivariogram models to the experimental semivariogram is to capture the major spatial features of the studied variable (Goovaerts 1997). Webster and Oliver (2007) summarized several semivariogram models and there are selected model types is summarized in Table 3.2.
Table 3.2. Semivariogram models

<table>
<thead>
<tr>
<th>Model</th>
<th>R code</th>
<th>Equation</th>
<th>Parameter note</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nugget</td>
<td>Nug</td>
<td>( \hat{\gamma}(h) = \begin{cases} 0 &amp; h=0 \ \frac{C_s}{h} &amp; h \neq 0 \end{cases} )</td>
<td></td>
</tr>
<tr>
<td>Spherical</td>
<td>Sph</td>
<td>( \hat{\gamma}(h) = \begin{cases} \frac{C_s}{2} \left( \frac{3}{2} h - \frac{1}{2} h^3 \right) &amp; 0 \leq h \leq r \ \frac{C_s}{h^2} &amp; h &gt; r \end{cases} )</td>
<td>( a = r ) (range reaches 100% of ( C_s ))</td>
</tr>
<tr>
<td>Gaussian (Matérn, ( k=\infty ))</td>
<td>Gau</td>
<td>( \hat{\gamma}(h) = \begin{cases} 0 &amp; h=0 \ C_s \left( 1 - e^{-\frac{h}{r}} \right)^2 &amp; h &gt; 0 \end{cases} )</td>
<td>( a' = \sqrt{3} r ) (effective range reaches 95% of ( C_s ))</td>
</tr>
<tr>
<td>Exponential (Matérn, ( k=0.5 ))</td>
<td>Exp</td>
<td>( \hat{\gamma}(h) = \begin{cases} 0 &amp; h=0 \ C_s \left( 1 - e^{-\frac{h}{r}} \right) &amp; h &gt; 0 \end{cases} )</td>
<td>( a' = 3r ) (effective range reaches 95% of ( C_s ))</td>
</tr>
<tr>
<td>Whittles (Matérn, ( k=1 ))</td>
<td>Bes</td>
<td>( \hat{\gamma}(h) = \begin{cases} 0 &amp; h=0 \ C_s \left( 1 - \frac{1}{2^k \Gamma(k)} \left( \frac{h}{r} \right)^k K_k \left( \frac{h}{r} \right) \right) &amp; h &gt; 0 \end{cases} )</td>
<td>( a' = 4r ) (effective range reaches 95% of ( C_s ))</td>
</tr>
<tr>
<td>Matérn</td>
<td>Mat</td>
<td>( \hat{\gamma}(h) = \begin{cases} 0 &amp; h=0 \ C_s \left( 1 - \frac{1}{2^{k-1} \Gamma(k)} \left( \frac{h}{r} \right)^k K_k \left( \frac{h}{r} \right) \right) &amp; h &gt; 0 \end{cases} )</td>
<td>( k ) (smoothness parameter)</td>
</tr>
</tbody>
</table>

Note: \( \Gamma(k) \) and \( K_k(h/r) \) are Gamma function and modified Bessel function of the second kind with order \( k \) respectively, \( r \) is the range parameter obtained in R program.

Goovaerts (1997) suggested that models with parabolic behavior at the origin (i.e., Gaussian model) should be used for highly continuous properties (i.e., Ground water level) and

Wackernagel (2003) said that the Gaussian model is “pathological”. The Gaussian model is not suggested (Wackernagel 2003; Webster and Oliver 2007) for describing the spatial variability of general properties that are not highly continuous. Pavement foundation properties are not expected to be highly continuous variable, so a Gaussian model will not be used in this paper.

This paper will instead consider application of a spherical (Sph) model, an exponential (Exp) model, and Matérn (Mat, \( k=1 \)) models in describing spatial variability of pavement foundation properties.
The Matérn model class has a smoothness parameter \( k \) to describe the behavior of the semivariogram at the origin. The exponential model, Whittle’s model, and Gaussian model are particular cases of the Matérn model with \( k \) equal to 0.5, 1, and infinity, respectively. With \( k=\infty \) the Gaussian model describes the most continuous origin behavior.

An experimental semivariogram is meaningless with only a pure nugget effect model fitted that indicates the studied properties lack spatial continuity within the studied area (Olea 2006). Therefore, the nugget model is generally nested with other models. Nested models are combinations of different models where properties of the original models are not changed. There are many possible combinations of semivariogram models. A combination of basic models is generally required to satisfactorily fit the directional experimental semivariogram, but overfitting the semivariogram with complicated a model that consists of three or more basic models usually will not result in more accurate estimates than using the simpler models.

Olea (2006) reported that nested models are often a combination of two simple models and one pure nugget effect model as shown in Eq. 3.3.

\[
\hat{\gamma}(h) = \sum_{i=0}^{k} C_i \gamma_i(h)
\]

Equation 3.4 shows a nested model consisting of a nugget effect model, an exponential model, and a Gaussian model:

\[
\hat{\gamma}(h) = \begin{cases} 
0 & h=0 \\
C_0 + C_{s1} \left( \frac{h}{a_1} - \frac{1}{2} \left( \frac{h}{a_1} \right)^3 \right) + C_{s2} \left( 1 - e^{-3 \left( \frac{h}{a'_2} \right)^2} \right) & h \neq 0
\end{cases}
\]

\[\text{(3.4)}\]

Figure 3.6 shows semivariogram plots of these four models with values assigned to \( C \) and \( a \) and \( a' \) where sill = 1.
3.5.2. Model selection

The theoretical model can be fit to the experimental semivariogram to describe the spatial variability of the data with quantified parameters. The theoretical model can be selected based on one of two methods; one method chooses the model that best fits the calculated experimental semivariogram values, another method chooses the model that gives the best predictions. Four statistical criteria are discussed here. Three methods for defining the “best fit” use either the squared errors (SSErr), Akaike information criterion (AIC), or Cressie goodness of fit (GoF). The mean squares prediction error (MSPE) can be used to choose the model that give the “best” predictions.

Fitting a semivariogram model by eye relies on the averaged semivariance values at each lag distance and ignores the number of pairs of data spaced at that lag distance. A weighted least squares method as Cressie (1985) suggested will be used for this study. The weighted least
squares method gives the most weight to the early lags and less weight to those lags that have fewer data pairs. Therefore, the weighted least squares method allows fitting the theoretical model to capture the major spatial characteristics of the variable, rather than not to be the closest to the experimental values.

There are several methods for calculating the weight \((w_i)\) for the weighted least squares fit, the weight calculation method used in this study is presented in Eq. 3.5 with \(N_i\) is the number of data pairs that are separated by a distance \(h_i\).

\[
w_i = \frac{N_i}{h_i^2}
\]  

(3.5)

In this study, exponential, spherical, and Matérn \((k=1)\) model will be fitted to the experimental semivariogram and the nested model of more than one structure might be used to better describe the anisotropic experimental semivariogram. The sum of square errors \((\text{SSErr})\) is calculated for each fitted theoretical semivariogram to describe how well the model fits the experimental semivariogram. In calculation of \(\text{SSErr}\) (Eq. 3.6), \(\hat{\gamma}(h_i)\) is the predicted semivariogram value with the fitted theoretical model and \(\gamma(h_i)\) is the average experimental semivariogram value at a set of lag distance \(h_i\).

\[
\text{SSErr} = \sum_{i=1}^{n} w_i [\hat{\gamma}(h_i) - \gamma(h_i)]^2
\]  

(3.6)

Akaike information criterion (AIC) can also be used to assess the goodness of fit as well as the parsimony of the model (Jian et al. 1996; Webster and Oliver 2007). Equation 3.7 is used to calculate AIC where \(n\) is the number of experimental semivariogram values and \(p\) is the number of parameters in that theoretical model. Since the three models (i.e., spherical, exponential, Matérn with \(k=1\)) have the same \(p\) is equal to three, using the AIC criteria is not different from using \(\text{SSErr}\).

\[
\hat{AIC} = n \ln \left( \frac{\text{SSErr}}{n} \right) + 2p
\]  

(3.7)
Clark and Harper (2002) suggested a modified Cressie goodness of fit (GoF) criteria to measure how well the model fits the data. Smaller GoF indicates better fit of the theoretical semivariogram model to the experimental semivariogram values. GoF is calculated with Eq. 3.8 that \( N_h \) is the number of data pairs used to calculate the average experimental semivariogram \( \gamma(h) \) at lag or separation distance \( h \), and \( \hat{\gamma}(h) \) is the fitted theoretical semivariogram at \( h \).

\[
\text{GoF} = \frac{1}{\sum_h N_h} \sum_h N_h \left( \frac{\hat{\gamma}(h) - \gamma(h)}{\gamma(h)} \right)^2
\]  

(3.8)

SSErr, AIC and GoF are used to measure how well the theoretical model fits the experimental semivariogram values. However, they may not measure the goodness of using the fitted model to describe the spatial variability of the studied variable. Therefore, the mean squared prediction error (MSPE) using the fitted model to predict the variable values at unsampled locations, calculated from cross-validation, can be used to evaluate the better semivariogram model for that variable.

The objective of fitting the experimental semivariogram is to describe the spatial continuity of the studied variable and ultimately to estimate the variable values at the unsampled locations. The impacts of different models on interpolating experimental semivariogram results can be compared through cross-validation (Isaaks and Srivastava 1989). The cross-validation process involves removing the first data value \( Z(s_i) \) at location \( s_i \) (\( i=1 \) to \( N \)) and using the rest (\( N-1 \)) of the data values sampled over the study area to fit the theoretical semivariogram model and predicted \( \hat{Z}(s_i) \) and calculating the squared error for the first data value. The cross-validation process is repeated for all data values sampled at all \( N \) locations \( s_i \), and the average squared error in the cross-validation process is calculated as the mean squared prediction error (MSPE) in Eq. 3.9.

\[
\text{MSPE} = \frac{1}{N} \left[ Z(s_i) - \hat{Z}(s_i) \right]^2
\]  

(3.9)
The idea consists of removing one datum at a time from the data set and re-estimating this value from the remaining data using the different semivariogram models. Interpolated and actual values are compared, and the model that yields the most accurate predictions is retained.

3.5.3. Anisotropy

Anisotropy is the phenomenon that the spatial variability is a function of the magnitude and the direction of the separation distance vector \( h \). Two types of two-dimensional anisotropy are defined as geometric anisotropy and zonal anisotropy (Goovaerts 1997) and shown in Figure 3.7. Eriksson and Siska (2000) clarified the details in calculations of modelling anisotropy in spatial analysis with defining the types of anisotropy to be nugget anisotropy, range anisotropy, and sill anisotropy. Isaaks and Srivastava (1989) and Goovaerts (1997) presented the concept of geometric and zonal anisotropy in spatial analysis.

Geometric anisotropy can be identified when the directional semivariograms have the same shape and sill values \((C_0 \text{ and } C_s)\) but different range values and the rose diagram or plot of range values versus the azimuth \( \theta \) of the direction is an ellipse (Goovaerts 1997). Azimuth angle \( \theta \) is counted clockwise from the north. The anisotropy ratio \((\lambda<1)\) is the ratio of the minor range \((a_\phi)\) to the major range \((a_\delta)\) of the directional semivariograms that are generally perpendicular to each

![Figure 3.7. Types of anisotropy: geometric anisotropy (left); zonal anisotropy (right)](image-url)
other. Zonal anisotropy can be identified when the directional semivariograms have different partial sill values.

Geometric anisotropic semivariogram can be modeled by clockwise rotating the coordinate system to make the major direction \( (\delta) \) that has the longer range to be aligned with an axis and rescale the anisotropic range to be the minor range \( a_\phi \) (Eq. 3.10).

\[
\gamma(h) = \gamma(h^*) \quad \text{with} \quad h^* = \begin{bmatrix} 1 & 0 \\ 0 & \lambda \end{bmatrix} \begin{bmatrix} \cos \delta \\ \sin \delta \\ -\sin \delta \\ \cos \delta \end{bmatrix} h
\] (3.10)

Zonal anisotropic semivariogram can be modeled by clockwise rotating the coordinate system to have the direction that shows the maximum continuity (lowest \( C_s \)) aligned with an axis and set the range \( (a_\delta) \) in that direction to be a very large value towards infinity \( (\lambda) \) is very small towards zero) (Eq. 3.11).

\[
\gamma(h) = \gamma_1(h) + \gamma_2(h^*) \quad \text{with} \quad h^* = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \cos \delta \\ \sin \delta \\ -\sin \delta \\ \cos \delta \end{bmatrix} h
\] (3.11)

**Figure 3.8. Methodology of plotting semivariogram map**

Semivariogram maps (Goovaerts 1997; Isaaks and Srivastava 1989) can be used as a tool that can detect anisotropy directions. The computation of a semivariogram map requires considering
many directions and lags. A semivariogram map can be a useful tool in the preliminary study of the major and minor spatial continuity directions. However, the spatial resolution of the semivariogram map will be largely reduced when sparse and irregular spaced data are collected (Facas et al. 2010). Figure 3.8 shows the process of plotting the semivariogram map and also shows semivariogram values are the same in the opposite direction.

Another tool that can quickly reveal anisotropy is a semivariogram contour map (Isaaks and Srivastava 1989) which is similar to the semivariogram map but the average values calculated in each area cell will be used for the contour plot. We don’t know the actual population mean of the studied variable, so we will use ordinary kriging to estimate the value at unsampled locations. Simple kriging requires input of the population mean that means we know the actual mean value, but we cannot say the sample mean is the population mean.

### 3.5.4. Kriging

The word kriging means optimal prediction (Cressie 1993). Kriging is used to make prediction on values of a continuous variable Z at unsampled locations using the observed value at sampled locations of the study area. Kriging makes no distributional assumptions and the variates are statistically correlated. Ordinary kriging and the minimum mean squared prediction error will be used in this study to present the fitted semivariogram model. The two assumptions in ordinary kriging are that the local mean is unknown but constant and the sum of the coefficients of the linear predictor is equal to one. The assumptions guarantee that the mean of the predicted values is the same as the observed values over the study area (Cressie 1993; Goovaerts 1997; Journel and Huijbregts 1978). The brief description of ordinary kriging is only to introduce the basics of understanding how the kriged contour map is created. The ordinary
kriging estimator \( Z_{OK}^*(s) \) at location \( s \) is written as a linear combination of the \( n(s) \) random variables \( Z(s_i) \) with the kriging weights forced to be equal to 1 (Eq. 3.12).

\[
Z_{OK}^*(s) = \sum_{i=1}^{n(s)} \varepsilon_i^{OK}(s)Z(s_i) \quad \text{with} \quad \sum_{i=1}^{n(s)} \varepsilon_i^{OK}(s) = 1
\]  

(3.12)

### 3.6. Univariate statistical analysis

The univariate statistics of pavement foundation properties \( E_{LWD-Z3}, \gamma_d, w, \text{DCPI}_{\text{subbase}}, \) and \( \text{DCPI}_{\text{subgrade}} \) of both test sections MI I-94 TS1a (Figure 3.2) and MI I-96 TS1 (Figure 3.3) are summarized in Table 3.3. Each variable was studied by plotting a histogram, examining skewness, and identifying outliers. The collected data for each property variable do not show extremely skewed and no transformation of the data was made for spatial variability analysis.

One extreme value or outlier of \( \text{DCPI}_{\text{subbase}} \) was identified at a sample location in MI I-94 TS1b (Figure 3.5) and removed for spatial variability analysis.

#### Table 3.3. Soil properties summary for studied test sections

<table>
<thead>
<tr>
<th>Project Test Section</th>
<th>Univariate Statistics</th>
<th>( E_{LWD-Z3} ) (MPa)</th>
<th>( \gamma_d ) (kN/m(^3))</th>
<th>( w ) (%)</th>
<th>( \text{DCPI}_{\text{subbase}} ) (mm/blow)</th>
<th>( \text{DCPI}_{\text{subgrade}} ) (mm/blow)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MI I-94 TS1b</td>
<td>Mean (( \bar{x} ))</td>
<td>58.5</td>
<td>20.00</td>
<td>2.3</td>
<td>7</td>
<td>43</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>58.6</td>
<td>20.00</td>
<td>2.3</td>
<td>7</td>
<td>43</td>
</tr>
<tr>
<td></td>
<td>Variance (( s^2 ))</td>
<td>50.5</td>
<td>0.38</td>
<td>0.1</td>
<td>1.3</td>
<td>61.3</td>
</tr>
<tr>
<td></td>
<td>Std Dev (( s ))</td>
<td>7.1</td>
<td>0.61</td>
<td>0.3</td>
<td>1.1</td>
<td>7.8</td>
</tr>
<tr>
<td></td>
<td>COV</td>
<td>12</td>
<td>3</td>
<td>14</td>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>121</td>
<td>121</td>
<td>121</td>
<td>120</td>
<td>121</td>
</tr>
<tr>
<td></td>
<td>Skewness</td>
<td>0.43</td>
<td>-0.13</td>
<td>-0.70</td>
<td>0.48</td>
<td>-0.07</td>
</tr>
<tr>
<td>MI I-96 TS1</td>
<td>Mean (( \bar{x} ))</td>
<td>30.9</td>
<td>20.16</td>
<td>7.8</td>
<td>19</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>31.3</td>
<td>20.15</td>
<td>7.7</td>
<td>19</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Variance (( s^2 ))</td>
<td>124.1</td>
<td>0.34</td>
<td>1.0</td>
<td>20.7</td>
<td>6.3</td>
</tr>
<tr>
<td></td>
<td>Std Dev (( s ))</td>
<td>11.1</td>
<td>0.59</td>
<td>1.0</td>
<td>4.5</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>COV</td>
<td>36</td>
<td>3</td>
<td>13</td>
<td>24</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>73</td>
<td>73</td>
<td>73</td>
<td>57</td>
<td>57</td>
</tr>
<tr>
<td></td>
<td>Skewness</td>
<td>-0.20</td>
<td>-0.03</td>
<td>0.47</td>
<td>0.37</td>
<td>0.92</td>
</tr>
</tbody>
</table>
The overall sample mean ($\bar{x}$) of $E_{\text{LWD-Z3}}$ determined LWD test is higher in MI I-94 TS1b than in MI I-96 TS1, the reason could be that the LWD tests were performed on top of the base layer in MI I-94 TS1b and on top of the subbase layer in MI I-96 TS1 while $E_{\text{LWD-Z3}}$ presents the stiffness of the composite pavement foundation layers not a single layer. However, the coefficient of variation (COV) is higher in MI I-96 TS1 than in MI I-94 TS1b. This indicates there are some possible soft spots that could be identified in MI I-96 TS1.

Histograms of each variable are created as shown in Figure 3.9 to Figure 3.13. Univariate statistics show that dry unit weight ($\gamma_d$) and moisture content ($w$) that determined NG test at a desired point within the base/subbase layer are less variable in both test sections than the other variables. DCPI of both subbase and subgrade layer determined from DCP tests shows high COV and higher COV was obtained in MI I-96 TS1. The sample mean value of DCPI is lower in the subgrade layer than the base layer of MI I-94 TS1b. This means the subbase layer could be stiffer than the subgrade layer, on average. However, the sample mean value of DCPI is higher in the subgrade layer than the subbase layer of MI I-96 TS1. This means the subbase layer could be insufficiently compacted in some areas. The preliminary analysis of the pavement foundation properties with univariate statistics should be further studied with spatial variability analysis.

![Histograms](image_url)

**Figure 3.9. Histogram of $E_{\text{LWD-Z3}}$ on MI I-94 TS1b (left) and MI I-96 TS1 (right)**
Figure 3.10. Histogram of $\gamma_d$ on MI 194 TS1b (left) and MI 196 TS1 (right)

Figure 3.11. Histogram of $w$ on MI 194 TS1b (left) and MI 196 TS1 (right)

Figure 3.12. Histogram of DCPI$_{subbase}$ on MI 194 TS1b (left) and MI 196 TS1 (right)
3.7. Spatial variability analysis

Spatial variability analysis is used to characterize and quantify the spatial continuity of the five studied pavement foundation property variables $E_{l,WD-Z3}$, $\gamma_d$, $w$, DCPI$_{subbase}$, and DCPI$_{subgrade}$. The omnidirectional semivariogram which neglects the directions is the isotropic semivariogram modelling. The omnidirectional semivariogram and directional semivariogram will be studied to explore the anisotropy of each variable over each of the studied test sections and to examine the need of modeling the possible anisotropy.

3.7.1. Omnidirectional semivariogram

The experimental semivariogram of each property variable was calculated as omnidirectional, the spatial variability is only investigated with the distance $h$ that data pairs are apart and assumes isotropic spatial correlation. Three theoretical semivariogram models, spherical, exponential, and Matérn ($k=1$), are used to fit the experimental semivariogram using weighted least square methods. The model parameters are estimated and the statistical criteria of choosing the better fitted model that including SSErr, GoF, and MSPE are summarized in Table 3.4.
Table 3.4. Summary of spatial analysis with omnidirectional semivariogram

<table>
<thead>
<tr>
<th>Project Site</th>
<th>MI I-94 TS1b</th>
<th>Sph</th>
<th>Exp</th>
<th>Mat, $k=1$</th>
<th>MI I-96 TS1</th>
<th>Sph</th>
<th>Exp</th>
<th>Mat, $k=1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Properties</td>
<td>$\hat{\gamma}(h)$ estimation parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$E_{LWD-Z3}$</td>
<td>$C_0$</td>
<td>11.45</td>
<td>4.145</td>
<td>12.52</td>
<td>0</td>
<td>0</td>
<td>12.18</td>
<td></td>
</tr>
<tr>
<td>(MPa)</td>
<td>$C_S$</td>
<td>41.54</td>
<td>54.644</td>
<td>44.04</td>
<td>146.6</td>
<td>212.2</td>
<td>161.43</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r$</td>
<td>3.167</td>
<td>1.45</td>
<td>0.9489</td>
<td>3.437</td>
<td>2.772</td>
<td>1.247</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$a$ or $a'$</td>
<td>3.167</td>
<td>4.35</td>
<td>3.7956</td>
<td>3.437</td>
<td>8.316</td>
<td>4.988</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SSEr</td>
<td>15829</td>
<td>15555</td>
<td>16009</td>
<td>159196</td>
<td>170814</td>
<td>164420</td>
<td></td>
</tr>
<tr>
<td></td>
<td>GoF</td>
<td>0.0050</td>
<td>0.0055</td>
<td>0.0054</td>
<td>0.0412</td>
<td>0.0442</td>
<td>0.0417</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MSPE</td>
<td>22.84</td>
<td>22.77</td>
<td>23.08</td>
<td>46.25</td>
<td>44.74</td>
<td>43.72</td>
<td></td>
</tr>
<tr>
<td>$\gamma_d$</td>
<td>$C_0$</td>
<td>0.1522</td>
<td>0.1283</td>
<td>0.1635</td>
<td>0.05901</td>
<td>0.03935</td>
<td>0.08359</td>
<td></td>
</tr>
<tr>
<td>(kN/m$^3$)</td>
<td>$C_S$</td>
<td>0.2088</td>
<td>0.2818</td>
<td>0.2256</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r$</td>
<td>3.412</td>
<td>1.885</td>
<td>1.121</td>
<td>6.891</td>
<td>2.966</td>
<td>2.238</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$a$ or $a'$</td>
<td>3.412</td>
<td>5.655</td>
<td>4.484</td>
<td>6.891</td>
<td>8.898</td>
<td>8.952</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SSEr</td>
<td>0.1845</td>
<td>0.1702</td>
<td>0.1723</td>
<td>0.1156</td>
<td>0.189</td>
<td>0.1293</td>
<td></td>
</tr>
<tr>
<td></td>
<td>GoF</td>
<td>0.0024</td>
<td>0.0022</td>
<td>0.0022</td>
<td>0.0104</td>
<td>0.0170</td>
<td>0.0117</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MSPE</td>
<td>0.2106</td>
<td>0.2107</td>
<td>0.2115</td>
<td>0.135</td>
<td>0.1327</td>
<td>0.1362</td>
<td></td>
</tr>
<tr>
<td>$w$ (%)</td>
<td>$C_0$</td>
<td>0.06975</td>
<td>0.04562</td>
<td>0.07216</td>
<td>0.07296</td>
<td>0.01137</td>
<td>0.1771</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$C_S$</td>
<td>0.27523</td>
<td>0.98209</td>
<td>0.3576</td>
<td>1.00653</td>
<td>1.48051</td>
<td>1.1507</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r$</td>
<td>48.46</td>
<td>128.3</td>
<td>12.34</td>
<td>3.757</td>
<td>2.69</td>
<td>1.484</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$a$ or $a'$</td>
<td>48.46</td>
<td>384.9</td>
<td>49.36</td>
<td>3.757</td>
<td>8.07</td>
<td>5.936</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SSEr</td>
<td>0.02271</td>
<td>0.0784</td>
<td>0.01504</td>
<td>5.168</td>
<td>5.39</td>
<td>5.277</td>
<td></td>
</tr>
<tr>
<td></td>
<td>GoF</td>
<td>0.0031</td>
<td>0.0021</td>
<td>0.002</td>
<td>0.0399</td>
<td>0.0427</td>
<td>0.0421</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MSPE</td>
<td>0.0807</td>
<td>0.08903</td>
<td>0.0811</td>
<td>0.3937</td>
<td>0.4124</td>
<td>0.4085</td>
<td></td>
</tr>
<tr>
<td>DCPI$_{subbase}$</td>
<td>$C_0$</td>
<td>0.5344</td>
<td>0.3036</td>
<td>0.51</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>(mm/blow)</td>
<td>$C_S$</td>
<td>0.6974</td>
<td>0.9745</td>
<td>0.7569</td>
<td>26.57</td>
<td>46.05</td>
<td>30.95</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r$</td>
<td>58.87</td>
<td>81.7</td>
<td>60.18</td>
<td>3.8</td>
<td>3.923</td>
<td>1.232</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$a$ or $a'$</td>
<td>2.197</td>
<td>2.451</td>
<td>2.4072</td>
<td>3.8</td>
<td>11.769</td>
<td>4.928</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SSEr</td>
<td>5.364</td>
<td>5.565</td>
<td>5.31</td>
<td>23.87</td>
<td>2608</td>
<td>2302</td>
<td></td>
</tr>
<tr>
<td></td>
<td>GoF</td>
<td>0.0027</td>
<td>0.0025</td>
<td>0.0024</td>
<td>0.0728</td>
<td>0.0737</td>
<td>0.0702</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MSPE</td>
<td>0.9048</td>
<td>0.8679</td>
<td>0.8701</td>
<td>11.76</td>
<td>11.97</td>
<td>11.95</td>
<td></td>
</tr>
<tr>
<td>DCPI$_{subgrade}$</td>
<td>$C_0$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2.11</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>(mm/blow)</td>
<td>$C_S$</td>
<td>57.61</td>
<td>58.79</td>
<td>58.61</td>
<td>3.995</td>
<td>5.954</td>
<td>5.551</td>
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<tr>
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<td>$r$</td>
<td>8.48</td>
<td>0.3019</td>
<td>0.211</td>
<td>4.091</td>
<td>1.101</td>
<td>0.5887</td>
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<tr>
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<td>$a$ or $a'$</td>
<td>8.48</td>
<td>0.9057</td>
<td>0.844</td>
<td>4.091</td>
<td>3.303</td>
<td>2.3548</td>
<td></td>
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<td>SSEr</td>
<td>16893</td>
<td>21970</td>
<td>19925</td>
<td>179.5</td>
<td>170.2</td>
<td>169.4</td>
<td></td>
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<tr>
<td></td>
<td>GoF</td>
<td>0.0022</td>
<td>0.0022</td>
<td>0.0021</td>
<td>0.0390</td>
<td>0.0424</td>
<td>0.0461</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MSPE</td>
<td>60.3</td>
<td>60.41</td>
<td>60.48</td>
<td>3.455</td>
<td>3.514</td>
<td>3.56</td>
<td></td>
</tr>
</tbody>
</table>

The estimated model parameters for each variables summarized in Table 3.4 show that there is no single best model type that can better fit the experimental semivariogram than the other two
models. The exponential $\hat{\gamma}(h)$ model estimates the largest range or effective range value, $a$, in most of the cases while the Matérn ($k=1$) model estimates the largest nugget effect, $C_0$, in all cases. The better fitted model is chosen according the statistical criteria to present the results in characterizing and quantifying the isotropic or omnidirectional spatial variability. The smaller value of each of three statistical criteria SSErr, GoF, and MSPE is desired and indicate a better fitted model. Since the range value of the studied variables is close to or larger than the 1/3 of the maximum distance that data pairs are apart over the study area, the difference of three models in the initial part of the semivariogram cannot be identified for the experimental semivariogram without $\gamma(h)$ values at distance smaller than 0.5 m in MI I94 TS1b and 0.7 m in MI I96 TS1.

**MI I94 TS1b**

The sill of the omnidirectional experimental semivariogram of $E_{LWD-Z3}$ is higher than the sample variance slightly (Figure 3.14) which indicates a possible trend or an anisotropic semivariogram.

![Figure 3.14. Omnidirectional $\gamma(h)$ of $E_{LWD-Z3}$ with fitted $\hat{\gamma}(h)$ on MI I94 TS1b](image)

Figure 3.14. Omnidirectional $\gamma(h)$ of $E_{LWD-Z3}$ with fitted $\hat{\gamma}(h)$ on MI I94 TS1b
Figure 3.15 shows the contour plot of the ordinary kriging values with the selected exponential model has smaller MSPE in the three studied models. A less variable $E_{\text{LWD-Z3}}$ with distance in the transverse direction is presented in Figure 3.15 and further analysis with directional variability should be performed to identify correlation length in different directions.

**Figure 3.15. Ordinary kriging of $E_{\text{LWD-Z3}}$ with fitted omnidirectional exponential $\hat{\gamma}(h)$ on MI I94 TS1b**

Omnidirectional $\gamma(h)$ of $\gamma_d$ is calculated and fitted with three models that shows increasing $\gamma(h)$ with separation distance and close to the sample variance (Figure 3.16), but the nugget values of $\hat{\gamma}(h)$ is relatively larger compared to its sill value. The measurement error or insufficient sampling at smaller spacing might be the cause for the relatively high nugget value. The ordinary kriging values of $\gamma_d$ with the selected spherical model plotted in Figure 3.17 that less compacted area can be observed at the upper left portion of the studied area.
Figure 3.16. Omnidirectional $\gamma(h)$ of $\gamma_d$ with fitted $\hat{\gamma}(h)$ on MI I94 TS1b

Figure 3.17. Ordinary kriging of $\gamma_d$ with fitted omnidirectional spherical $\hat{\gamma}(h)$ on MI I94 TS1b
Figure 3.18. Omnidirectional $\gamma(h)$ of $w$ with fitted $\hat{\gamma}(h)$ on MI I94 TS1b

Omnidirectional $\gamma(h)$ of moisture content as shown in (Figure 3.18) shows a very large nugget effect compared to the sample variance and a trend can be observed in the fitted
semivariogram with range estimated as about 50 m. The experimental omnidirectional \( \gamma(h) \) calculated in this study area is close to a straight line, this could be caused by a leaking water tank in the study area during the pavement base construction except a leaking of water tank at the study area. The raw data should be examined for reliability. The ordinary kriging plot of \( w \) with all three models, like the example with the fitted Matérn \((k=1)\) model (Figure 3.19) shows clear trend that \( w \) is higher in upper left triangle portion than the lower right portion of the studied area. However, with knowledge of in-situ measured \( w \) values, the raw data could have possible mistakes.

The weighted average DCPI values of subbase and subgrade indication average ability of that layer to resist penetration and higher DCPI indicates less stiffness would be expected at that location. The omnidirectional \( \gamma(h) \) of DCPI\textsubscript{subbase} and DCPI\textsubscript{subgrade} are shown in Figure 3.20 and Figure 3.22 separately. A longer range value was observed in DCPI\textsubscript{subbase} than DCPI\textsubscript{subgrade} which indicates higher spatial correlation could be observed in weighted average DCPI of the subbase layer than the subgrade layer. The experimental semivariogram calculated for DCPI\textsubscript{subbase} shows a nearly zero nugget effect, only a few \( \gamma(h) \) values within the first 1 m separation distance show a possible correlation of DCPI\textsubscript{subgrade} with spacing distance. The zero nugget effect and short range value modelled in DCPI\textsubscript{subgrade} predicted values at unsampled location around the sampled location with variation equal to the sill value which shows up as a small circle areas with similar values in the ordinary kriging plot of DCPI\textsubscript{subgrade} shown in Figure 3.23. The longer range value indicated correlation of DCPI\textsubscript{subbase} with longer spacing distance up to 2 m is presented with the ordinary kriging contour plot (Figure 3.21) that larger area of unsampled locations around the sampled locations have similar values.
Figure 3.20. Omnidirectional $\gamma(h)$ of DCPI\textsubscript{subbase} with fitted $\hat{\gamma}(h)$ on MI I94 TS1b

Figure 3.21. Ordinary kriging of DCPI\textsubscript{subbase} with fitted omnidirectional spherical $\hat{\gamma}(h)$ on MI I94 TS1b
Figure 3.22. Omnidirectional $\gamma(h)$ of DCPI_{subgrade} with fitted $\hat{\gamma}(h)$ on MI I94 TS1b

Figure 3.23. Ordinary kriging of DCPI_{subgrade} with fitted omnidirectional spherical $\hat{\gamma}(h)$ on MI I94 TS1b
MI I96 TS1

Omnidirectional experimental semivariogram $\gamma(h)$ of $E_{LWD-Z3}$ increases with separation distance and exceeds the sample variance before the fitted model predicted range is reached (Figure 3.24). This $\gamma(h)$ behavior shows a possible trend or anisotropy behavior in the collected $E_{LWD-Z3}$ values through the study area. There could be an insufficiently compacted roller pass in compacting the study area in MI I96 TS1 as shown in Figure 3.25, because the roller width is about two meters and there are consistently lower $E_{LWD-Z3}$ values obtained in the transverse direction while the roller travels along the longitudinal direction in compacting materials. Anisotropy of the directional semivariogram should be investigated for this data.

![Graph](image)

**Figure 3.24. Omnidirectional $\gamma(h)$ of $E_{LWD-Z3}$ with fitted $\hat{\gamma}(h)$ on MI I96 TS1**

The calculated experimental semivariogram of $\gamma_d$ measurements shows a possible trend with long spatial correlation. The range value, estimated as 6.891 m with spherical model, is larger than the maximum semivariogram study distance of 4 m (Figure 3.26). The ordinary kriging contour plot (Figure 3.27) of $\gamma_d$ shows two sections with consistently higher predicted values at
the upper portion of the plot and consistently lower value at the lower portion. This indicates that anisotropy should be investigated for the collected $\gamma_d$ values.

**Figure 3.25.** Ordinary kriging of $E_{\text{LWD-Z3}}$ with fitted omnidirectional Matérn (k=1) $\hat{\gamma}(h)$ on MI 196 TS1

**Figure 3.26.** Omnidirectional $\gamma(h)$ of $\gamma_d$ with fitted $\hat{\gamma}(h)$ on MI 196 TS1
Figure 3.27. Ordinary kriging of $\gamma(h)$ with fitted omnidirectional spherical $\hat{\gamma}(h)$ on MI I94 TS1b

The calculated experimental semivariogram of $w$ measurements shows a possible trend because $\gamma(h)$ tends to be larger than the sample variance after about 3 m in separation distance (Figure 3.28). The ordinary kriging contour plot (Figure 3.29) of $w$ also shows two sections with consistently higher predicted values at the lower portion of the plot and consistently higher values at the upper portion which is with the reverse of the kriging contour plot of $\gamma_d$. Investigating anisotropy is advised for the collected $w$ values.

The calculated experimental semivariogram of $\text{DCPI}_{\text{subbase}}$ also shows a possible trend that $\gamma(h)$ tends to be larger than the sample variance after about 2 m in separation distance (Figure 3.30). The ordinary kriging contour plot (Figure 3.31) of $\text{DCPI}_{\text{subbase}}$ also shows an approximate 2.5 m wide strip along the longitudinal direction possibly due to insufficient compacted. This is similar to what the ordinary kriging plot of $E_{\text{LWD-Z3}}$ shows.
Figure 3.28. Omnidirectional $\gamma(h)$ of $w$ with fitted $\hat{\gamma}(h)$ on MI 196 TS1

Figure 3.29. Ordinary kriging of $w$ with fitted omnidirectional spherical $\hat{\gamma}(h)$ on MI 196 TS1
Figure 3.30. Omnidirectional $\gamma(h)$ of DCPI_{subbase} with fitted $\hat{\gamma}(h)$ on MI I96 TS1

Figure 3.31. Ordinary kriging of DCPI_{subbase} with fitted omnidirectional spherical $\hat{\gamma}(h)$ on MI I96 TS1
The erratic experimental semivariogram values of DCPI<sub>subgrade</sub> does not show clear correlation of DCPI<sub>subgrade</sub> measurements with separation distance. The overall weighted average DCPI of the subgrade layer is higher than that of the subbase layer as shown in ordinary kriging.
contour plots in Figure 3.31 and Figure 3.33. The difference could be the result of the material used in construction of the subbase and subgrade layers having similar maximum dry unit weight but less confinement in the subbase layer which is exposed to air while it providing confinement to the underlying subgrade layer. Another possible reason could be more fines in the subgrade material may result in a larger contact area between aggregate particles making it harder to penetrate.

3.7.2. Directional semivariogram anisotropy study

Directional experimental semivariograms can be studied in order to identify anisotropic behavior of variables throughout the study area. A rose diagram, semivariogram map, semivariogram contour map, and plotting the directional semivariogram in several directions on the plot could help in identifying anisotropic behavior. The ordinary kriging contour plots with omnidirectional experimental semivariogram of some pavement foundation properties studied on MI I94 TS1b and MI I96 TS1 revealed the need for directional semivariograms. The obvious anisotropic $\gamma(h)$ will be modelled by fitting the theoretical semivariogram model with identified anisotropy ratio ($\lambda$), major direction ($\delta$) for both geometric and zonal anisotropy, and a nested model for zonal anisotropy.

Directional $\gamma(h)$ is calculated in four major directions ($\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$) and the major and minor directions are generally at $\theta$ equals to $0^\circ$ and $90^\circ$ which aligns with transverse and longitudinal directions of pavement sections. One exception is the study on the moisture content measurements on MI I-94 TS1b where a possible error was identified in omnidirectional semivariogram study. All three theoretical models (i.e., spherical, exponential, and Matérn with $k=1$) are fitted to the $\gamma(h)$ in major and minor direction individually, and the best fitted model of the three are selected based on the smallest SSErr value and summarized in Table 3.5.
Table 3.5. Summary of theoretical model fitted to major and minor directional $\gamma(h)$

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<tr>
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<th>MI I-96 TS1</th>
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<td>Transverse Direction, $y$, $0=0^\circ$</td>
<td>Longitudinal Direction, $x$, $0=90^\circ$</td>
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<td>Mat, $k=1$</td>
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<td>Exp</td>
<td>Sph</td>
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<td>2.993</td>
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<td></td>
<td>a or $a'$</td>
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<td>2.993</td>
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<td>GoF</td>
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<td>0.0087</td>
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<td>$r_d$ (kN/m$^3$)</td>
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<td>Sph</td>
<td>Sph</td>
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<td></td>
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<td>a or $a'$</td>
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<td>$w$ (%)</td>
<td>Model</td>
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<td>Mat, $k=1$ ($0=135^\circ$)</td>
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<td>SSErr</td>
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<td>GoF</td>
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<td>DCPI$_{su}$</td>
<td>Model</td>
<td>Sph</td>
<td>Mat, $k=1$</td>
</tr>
<tr>
<td>bbase (mm/b low)</td>
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<td></td>
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<tr>
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<td>$Cs$</td>
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<td></td>
<td>$r$</td>
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<td>SSErr</td>
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<td>GoF</td>
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<td>DCPI$_{subgrade}$</td>
<td>Model</td>
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<td>(mm/b low)</td>
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<td>Spherical</td>
<td>Spherical</td>
</tr>
<tr>
<td></td>
<td>$C_0$</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>$Cs$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>a or $a'$</td>
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<tr>
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<td>SSErr</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>GoF</td>
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</tr>
</tbody>
</table>

Note: *directional experimental semivariogram of DCPI$_{subgrade}$ on MI I94 TS1b shows close pure nugget effect, no directional semivariogram was modelled.
Figure 3.34. Directional $\gamma(h)$ of $E_{LWD-Z3}$ on MI 194 TS1b
The detailed study process for constructing directional semivariograms of all studied pavement foundation properties for both study test sections are not provided, but examples of procedures in studying the anisotropy behavior will be shown in this section. Three types of plots, a rose diagram, a semivariogram map, and a semivariogram contour map for preliminary examination of the directional variation of sill and range parameters are presented for $E_{LWD-Z3}$ collected on MI I94 TS1b.

A rose diagram of range values is created by identifying the range values at each directional $\gamma(h)$ with a selected $\gamma(h)$ that is not the initial value nor the constant $\gamma(h)$ in all directions. Range values are determined and recorded at each directional $\gamma(h)$ plot, as Figure 3.34 shows. Then, the rose diagram is created with ranges as distance from the center to the end point along each axial direction as shown in Figure 3.35. An ellipse that indicates geometric anisotropy is closely fitted to the end points of range values along the axial directions (Figure 3.35). Note that possible zonal anisotropy could be expected at larger $\gamma(h)$.

![Rose diagram of $E_{LWD-Z3}$ on MI I94 TS1b](image-url)

**Figure 3.35.** Rose diagram of $E_{LWD-Z3}$ on MI I94 TS1b
A semivariogram map is created by setting a lag distance and calculating the average value of all $\gamma(h)$ falling into the area cell with the side distance the same as the lag distance which was discussed in the method section. The lag distance should be chosen as a value not smaller than the minimum spacing that point pairs are apart. Figure 3.36 is the semivariogram plot using a color scheme to represent the value of the average $\gamma(h)$ in each area cell and Figure 3.37 is the semivariogram contour map that plots the same values in a contour line. Both of these two plot a show zonal anisotropy that $E_{LWD-Z3}$ is less variable in transverse direction compared to the longitudinal direction. The reason could be the dense gridded sampling test section, MI I94 TS1b, is sampled from a small area that may not catch the variance in the longitudinal direction. According the ordinary kriging contour plot (Figure 3.15) of the same data, $E_{LWD-Z3}$ on MI I94 TS1b, the consistently low $E_{LWD-Z3}$ values were estimated along the transverse direction at an approximate range from 2 m to 5 m that may indicate insufficient compaction in that area.

![Figure 3.36. Semivariogram map of $E_{LWD-Z3}$ on MI I94 TS1b](image)

Figure 3.36. Semivariogram map of $E_{LWD-Z3}$ on MI I94 TS1b
The three models fitted to transverse (y) direction and longitudinal (x) direction separately as Figure 3.38 shows and the fitted $\hat{\gamma}(h)$ in the longitudinal direction exceed the sample variance while the fitted $\hat{\gamma}(h)$ in transverse direction is reach a constant value that below the sample variance at a small range value. However, the experimental semivariogram $\gamma(h)$ tends to increase at separation distances over 3 m which may indicate a possibly higher variation could be observed in the transverse direction.

**Figure 3.37. Semivariogram contour map of $E_{LWD Z3}$ on MI I94 TS1b**

**Figure 3.38. Fitted $\hat{\gamma}(h)$ for $E_{LWD Z3}$ on MI I94 TS1b, transverse direction (left) and longitudinal (right)**
With the fitted $\hat{\gamma}(h)$ $E_{LWD-Z3}$ on MI 194 TS1b in both transverse and longitudinal directions, the best fitted model could be selected with the smaller SSErr and GoF values. The first isotropic part of zonal anisotropy is modelled with the selected model for the transverse direction $\hat{\gamma}_1(h)$ that has the lower sill than the longitudinal direction, and the second part of zonal anisotropy $\hat{\gamma}_2(h)$ is modelled with the model selected for the longitudinal direction that sill is the difference between the fitted $\hat{\gamma}(h)$ in transverse and longitudinal direction and range is set to be extremely large (e.g., $10^9$) with zonal anisotropy ratio ($\lambda$) that $\lambda \times 10^9$ will be same as the selected fitted $\hat{\gamma}(h)$ in longitudinal direction.

![Figure 3.39. Modelling $\gamma(h)$ with zonal anisotropy for $E_{LWD-Z3}$ on MI 194 TS1b](image)

The nested model with zonal anisotropy fitted $\hat{\gamma}(h)$ is shown as a continuous curve with the experimental semivariogram of $E_{LWD-Z3}$ shown as black dots which clearly shows the zonal anisotropic model describing the variation of $E_{LWD-Z3}$ in different directions (Figure 3.39), but the quality of prediction using the zonal anisotropic model should be verified using the cross-validation MSPE value. The ordinary kriging plot using the zonal anisotropic model for $E_{LWD-Z3}$
on MI I-94 TS1a is shown in Figure 3.40 which is similar to the ordinary kriging plot using the omnidirectional model shown in Figure 3.15.

![Figure 3.40. Ordinary kriging contour plot of $E_{LWD-Z3}$ on MI I94 TS1b](image)

The detailed study on anisotropic behavior of $E_{LWD-Z3}$ on MI I96 TS1 is also discussed. The semivariogram map of $E_{LWD-Z3}$ on MI I96 TS1 (Figure 3.41) shows that $E_{LWD-Z3}$ is more uniform and continuously varied along the longitudinal direction which is similar to what the literature study suggests. Directional semivariograms calculated in all four directions with angle tolerance ($\Delta\theta$) equal to 45° (Figure 3.42) tend to reach the same sill at separation distance equal to 4 m. However, the zonal anisotropy as semivariogram map (Figure 3.41) indicates can be observed when angle tolerance decreased to 25° (Figure 3.42) to narrow the searching angle that less data pairs will be counted. Therefore, a different tolerance angle should be studied to accurately characterize the spatial anisotropic variability.
Figure 3.41. Semivariogram map of $E_{LWD-Z3}$ on MI I96 TS1

Figure 3.42. Directional $\gamma(h)$ of $E_{LWD-Z3}$ on MI I96 TS1b with $\Delta \theta = 45^\circ$
Figure 3.43. Directional $\gamma(h)$ of $E_{LWD-Z3}$ on MI I96 TS1b with $\Delta \theta = 25^\circ$

The zonal anisotropy behavior of $E_{LWD-Z3}$ on MI I96 TS1 is modelled using the same process as that used on $E_{LWD-Z3}$ on MI I94 TS1b. The nested semivariogram that modelled zonal anisotropy with major direction along the longitudinal direction is shown in Figure 3.44. Besides fitting the theoretical model, the pattern of the experimental semivariogram can also tell some characteristics of how the data varied at the study area. Both of $\hat{\gamma}(h)$ and $\gamma(h)$ in longitudinal direction ($\theta = 90^\circ$) tends to increase at the end the studied maximum separation distance of 4 m as shown in Figure 3.44. This could be an indication of a longer range or correlation length could be obtained in longitudinal direction. Moreover, the experimental semivariogram in the transverse direction ($\theta = 0^\circ$) shows a cyclic behavior which may indicate stripes of lower and higher data along the longitudinal direction. The ordinary kriging contour plot with the fitted zonal anisotropic model shown in Figure 3.44 predicts the lower $E_{LWD-Z3}$ values more precisely and the continuity of estimated data along the longitudinal direction is increased.
Figure 3.44. Modelling $\gamma(h)$ with zonal anisotropy for $E_{LWD-Z3}$ on MI I96 TS1

Figure 3.45. Ordinary kriging contour plot of $E_{LWD-Z3}$ on MI I94 TS1b

The MSPE value should be used as the statistical criteria for comparing the ability of selected omnidirectional semivariogram model and anisotropic semivariogram models to predict the data at the missing location. The omnidirectional semivariogram model will be chosen for describing
the spatial variation for the studied variable if a similar MSPE value is obtained. Comparing the fitted semivariogram models for omnidirectional semivariograms and directional semivariograms with anisotropy behavior, the isotropic semivariogram models show similar accuracy as anisotropic semivariogram models in predicting the pavement foundation properties at unknown locations across the studied area. The MSPE of each fitted semivariogram for both isotropic and anisotropic experimental semivariogram are summarized in Table 3.6.

Table 3.6. Summary of fitted isotropic and anisotropic semivariogram model parameters

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<th>MI I-96 TS1</th>
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<td>(MPa)</td>
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<td>γ_d (kN/m^3)</td>
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Note: — means not available
Table 3.6 Continued. Summary of fitted isotropic and anisotropic semivariogram model parameters

<table>
<thead>
<tr>
<th>Project Site</th>
<th>MI I-94 TS1b</th>
<th>MI I-96 TS1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Properties</td>
<td>( \hat{\gamma}(h) ) estimation parameters</td>
<td>Anisotropic</td>
</tr>
<tr>
<td>Anisotropy</td>
<td>Zonal</td>
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</tr>
<tr>
<td>Model 1</td>
<td>Matern, k=1</td>
<td>Spherical</td>
</tr>
<tr>
<td>Model 2</td>
<td>Matern, k=1</td>
<td>—</td>
</tr>
<tr>
<td>( w ) (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( C_0 )</td>
<td>0.06748</td>
<td>0.06975</td>
</tr>
<tr>
<td>( C_{s1} ) or ( C_s )</td>
<td>0.01381</td>
<td>0.27523</td>
</tr>
<tr>
<td>( C_{s2} )</td>
<td>512.36918</td>
<td></td>
</tr>
<tr>
<td>( a_{s1} ) or ( r )</td>
<td>0.2965</td>
<td>48.46</td>
</tr>
<tr>
<td>( a_{s2} )</td>
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<td>—</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>6.667E-07</td>
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</tr>
<tr>
<td>( \delta )</td>
<td>45°</td>
<td>—</td>
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<tr>
<td>MSPE</td>
<td>0.08006</td>
<td><strong>0.0807</strong></td>
</tr>
<tr>
<td>DCPI\textsubscript{subbase} (mm/blow)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anisotropy</td>
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<td>—</td>
</tr>
<tr>
<td>Model 1</td>
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</tr>
<tr>
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</tr>
<tr>
<td>( C_0 )</td>
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<td>0.3036</td>
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<td>( C_{s2} )</td>
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<td>—</td>
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<tr>
<td>( a_{s1} ) or ( r )</td>
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<td>0.817</td>
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<tr>
<td>( \lambda )</td>
<td>0.5</td>
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</tr>
<tr>
<td>( \delta )</td>
<td>90°</td>
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<td>MSPE</td>
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<td>0.8701</td>
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<td>DCPI\textsubscript{subgrade} (mm/blow)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anisotropy</td>
<td>—</td>
<td>Zonal</td>
</tr>
<tr>
<td>Model 1</td>
<td>Spherical</td>
<td>Spherical</td>
</tr>
<tr>
<td>Model 2</td>
<td>—</td>
<td>Spherical</td>
</tr>
<tr>
<td>( C_0 )</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( C_{s1} ) or ( C_s )</td>
<td>57.61</td>
<td>4.152</td>
</tr>
<tr>
<td>( C_{s2} )</td>
<td>—</td>
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</tr>
<tr>
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</tr>
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</tr>
<tr>
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<td>—</td>
<td>1.068E-09</td>
</tr>
<tr>
<td>( \delta )</td>
<td>—</td>
<td>90°</td>
</tr>
<tr>
<td>MSPE</td>
<td><strong>60.3</strong></td>
<td><strong>2.335</strong></td>
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Note: — means not available
Table 3.7. Summary of spatial variability estimates

<table>
<thead>
<tr>
<th>In-situ properties</th>
<th>Directions</th>
<th>MI I-94 TS1b</th>
<th>MI I-96 TS1</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Sill (C+C₀)</td>
<td>Range (a or a’), m</td>
<td>Sill (C+C₀)</td>
</tr>
<tr>
<td>E₇₆₋₃₋₃ (MPa)</td>
<td>Omnidirection</td>
<td>58.789</td>
<td>4.35</td>
</tr>
<tr>
<td></td>
<td>Transverse Direction (y)</td>
<td>59.08</td>
<td>11.022</td>
</tr>
<tr>
<td></td>
<td>Longitudinal Direction (x)</td>
<td>63.019</td>
<td>2.993</td>
</tr>
<tr>
<td>γₐ (kN/m⁴)</td>
<td>Omnidirection</td>
<td>0.361</td>
<td>3.412</td>
</tr>
<tr>
<td></td>
<td>Transverse Direction (y)</td>
<td>0.3488</td>
<td>2.328</td>
</tr>
<tr>
<td></td>
<td>Longitudinal Direction (x)</td>
<td>0.6244</td>
<td>9.86</td>
</tr>
<tr>
<td>w (%)</td>
<td>Omnidirection</td>
<td>0.34498</td>
<td>48.46*</td>
</tr>
<tr>
<td></td>
<td>Transverse Direction (y)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>Longitudinal Direction (x)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>DCPIsubbase (mm/blow)</td>
<td>Omnidirection</td>
<td>1.2781</td>
<td>2.451</td>
</tr>
<tr>
<td></td>
<td>Transverse Direction (y)</td>
<td>1.1952</td>
<td>1.732</td>
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<tr>
<td></td>
<td>Longitudinal Direction (x)</td>
<td>1.2961</td>
<td>2.1792</td>
</tr>
<tr>
<td>DCPIsubgrade (mm/blow)</td>
<td>Omnidirection</td>
<td>57.61</td>
<td>0.848</td>
</tr>
<tr>
<td></td>
<td>Transverse Direction (y)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>Longitudinal Direction (x)</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

Note: * possible measurement error

A summary of sill and range values estimated by weighted least squares fitted theoretical semivariogram models are summarized in Table 3.7. The fitted semivariogram model estimated range values that indicates the separation distance that the data pairs are no longer correlated. $E_{LWD-Z3}$ is spatially correlated within 4.35 m in the test point in MI I-94 TS1b test section and about 5 m in MI I-96 TS1 test section without considering the directions. The anisotropic behavior of $E_{LWD-Z3}$ in MI I-94 TS1b is different from MI I-96 TS1 that $E_{LWD-Z3}$ is more spatially correlated in the transverse direction in MI I-94 TS1b and is more spatially correlated in the
longitudinal direction in MI I-96 TS1. Since the sample variance is relatively small in MI I-94 TS1b in the smaller sampling area, the different anisotropic behavior might be expected in the larger sampling area. The spatial correlation length or range of dry unit weight in MI I-96 TS1 is about twice as in MI I-94 TS1b without considering anisotropy. The similar anisotropic behavior of $E_{LWD-Z3}$ is observed in $\gamma_d$. Anisotropic behavior of the questioned moisture content data in MI I-94 TS1b is not reported, but the anisotropic behavior of $w$ in MI I96 TS1 is similar to $E_{LWD-Z3}$ and $\gamma_d$. Spatial variability of weighted average DCPI in subbase and subgrade layer is almost the same in all directions. The reason could be the weighted average DCPI value averaged the difference in vertical direction to present as a point for horizontal direction analysis.

### 3.8. Conclusions

Detailed geostatistical analysis procedures are presented in this study to provide a guide for pavement engineers to study spatial variability of pavement foundation properties with consideration of choosing the best fitted semivariogram model and characterization of anisotropic behavior. Isotropic semivariogram modelling indicates that the studied measurement values has the same spatial correlation between data pairs separated at distance $h$ in all directions, but anisotropic semivariogram modelling shows that the spatial correlation between data pairs separated at distance $h$ is different in different directions. Measurements obtained in a relatively dense grid pattern from two sections of pavement reconstructions sites (MI I-94 and MI I-96) are presented in studying the geostatistical modelling parameters that characterize spatial variability of stiffness and compaction properties. Preliminary study on anisotropy of spatial variability of pavement foundation properties is allowed with the dense gridded measurements, but different anisotropic behavior was identified in two test sections that may
only represent the local sample area. More data in the longitudinal direction should be provided for further anisotropy analysis.

Experimental semivariogram of layer averaged DCPI values are nearly isotropic with possible anisotropic behavior in the horizontal direction on both subbase and subgrade layers. Zonal anisotropy with the major anisotropic axis along the longitudinal direction indicates greater continuity in the longitudinal direction is present in the experimental semivariogram of $E_{LWD-Z3}$, moisture content ($w$), and dry unit weight ($\gamma_d$) measured in dense gridded test locations in project MI I-96. Therefore, the univariate statistical analysis should be analyzed to assist in correctly describing spatial variability of pavement foundation properties and identifying possible trends.

Comparison of three theoretical semivariogram models reveals that no obviously best fitted model of the three models (i.e., spherical, exponential, Whittle or Matern with k=1) are found to describe the experimental semivariogram of dense gridded measurements of pavement foundation properties as the spatial variation at distances smaller than the smallest sampling distance were not determined. A nested model with an anisotropy ratio helps in estimating the data at unsampled locations with consideration of the correlation of data sampled at different locations. However, in most cases for this study on a small test area, the isotropic or omnidirectional semivariogram model works as well as an anisotropic semivariogram model. Correctly calculating an experimental semivariogram is more important than fitting different models. The MSPE from cross-validation on $E_{LWD-Z3}$ in MI I-96 TS1 decreased from 46.28 with angle tolerance of 45° to 33.3 with 25°.

Further study on spatial variability of pavement foundation properties is suggested with measurements at test locations in different spacing and across the pavement width. A smaller
spacing which is less than 0.6 m is suggested for research on identifying the initial spatial correlation characteristics.

3.9. Acknowledgements

This study was sponsored by the Federal Highway Administration under agreement No. DTFH61-06-H-00011 and the Iowa Department of Transportation under Transportation Pooled Fund Program TPF-5(183).

3.10. Notation

The following symbols are used in this paper:

\( a \) = Range
\( a_{s1} \) = Range in first part of anisotropic semivariogram model
\( a_{s2} \) = Range in second part of anisotropic semivariogram model
\( a' \) = Effective range where 95\% \( C_s \) reached
\( \hat{\alpha} \) = Variable component of AIC
\( \text{AIC} \) = Akaike Information Criterion
\( C \) = Sill
\( C_0 \) = Nugget effect
\( C_s \) = Partial sill that obtained in variogram model
\( C_{s1} \) = Partial sill in first part of anisotropic semivariogram model
\( C_{s2} \) = Partial sill in second part of anisotropic semivariogram model
\( \text{COV} \) = Coefficient of variation
\( D_0 \) = measured deflection under the plate (mm)
\( \text{DCPI} \) = Dynamic cone penetration index (mm/blow)
\( E \) = elastic modulus (MPa)
\( E_{LWD-Z3} \) = Elastic modulus (Zorn LWD test with 300 mm dia. plate) (MPa)
\( F \) = Shape factor for LWD
\( G_s \) = Specific gravity
\( h \) = Vector indicates distance and direction of two points apart
\[ h_i = \text{Average distance of all } N_i \text{ point pairs separated by distance } h \text{'s.} \]
\[ k = \text{Smoothness parameter in the Matérn model} \]
\[ k = \text{Stiffness estimated from a static plate load test} \]
\[ n = \text{Number of points on the experimental variogram} \]
\[ N = \text{Number of tests} \]
\[ N_i = \text{Number of point pairs that separated at distance } h \]
\[ p = \text{Number of model parameters} \]
\[ P = \text{Applied load at surface} \]
\[ r = \text{Range number obtained in R program} \]
\[ r = \text{radius of the plate (mm)} \]
\[ s = \text{Spatial location} \]
\[ s^2 = \text{Sample variance} \]
\[ \text{SSErr} = \text{Sum of squares of error or residuals} \]
\[ w_j = \text{Weight in weighted least squares fit} \]
\[ w = \text{Moisture content} \]
\[ w_{\text{opt}} = \text{Optimum moisture content} \]
\[ \gamma_d = \text{Dry unit weight} \]
\[ \gamma_{d\text{max}} = \text{Maximum dry unit weight} \]
\[ \gamma_{d\text{min}} = \text{Minimum dry unit weight} \]
\[ \gamma(\text{h}) = \text{experimental semivariogram at distance } h \]
\[ \hat{\gamma}(\text{h}) = \text{fitted theoretical semivariogram at distance } h \]
\[ \delta = \text{major anisotropy direction} \]
\[ \eta = \text{Poisson’s ratio (0.4)} \]
\[ \theta = \text{semivariogram direction (azimuth angle)} \]
\[ \lambda = \text{anisotropy ratio} \]
\[ \sigma = \text{standard deviation} \]
\[ \sigma_0 = \text{applied stress} \]
\[ \Delta \theta = \text{angular tolerance} \]
\[ \phi = \text{angular tolerance direction} \]
CHAPTER 4. CHARACTERIZATION OF VARIABILITY IN PAVEMENT FOUNDATION PROPERTIES

A paper submitted to *International Journal of Pavement Engineering*

Jia Li, David J. White, and Pavana Vennapusa

4.1. Abstract

This study investigates variability of pavement foundation properties (e.g., $E_{\text{LWD-Z3}}$, $\gamma_d$, and $w$) that were determined from four major in-situ tests (i.e., FWD, LWD, NG, and DCP) over 18 test sections of 6 project sites. Change in variation of in-situ measured properties is studied in relationship to the number of compaction passes. Univariate statistics of pavement foundation properties is documented to provide references to pavement engineers and researchers to know the range of variability that in-situ measured properties can vary. In addition to univariate statistics, spatial analysis is performed on selected sites that contain relatively large data sets. The difference in spatial variation can be expected in longitudinal and transverse directions. The correlation length of 2 m to 3 m in the minor or less uniform direction is quantified for spatial variability of dense gridded data on the base layer. The spatial variability of in-situ measured properties along the longitudinal direction can be expected to be 15 m to 23 m in the CTB layer. This study on spatial variability indicates that the correlation length can be different in different pavement foundation layers and materials.

4.2. Introduction

Pavement foundation structures are constructed to provide uniform support for upper pavement layers and traffic load. However, material properties of existing pavement foundation structures are generally non-homogeneous. Non-uniform pavement foundation structures may cause stress concentration and then reduce pavement service life according to White et al.
To achieve a reliable pavement design, variability of engineering properties should be properly quantified. Phoon and Kulhawy (1999) suggested estimating the variability of soil parameters to develop and apply reliability-based design. Otake and Honjo (2013) suggested to evaluating the effects of spatial variability of material properties on pavement structures. However, pavement design assumes that uniform layers are achieved and uses a single modulus of subgrade reaction to represent the whole layer.

Pavement foundation properties with less variability indicate better quality of construction. Factors that may affect this variability include the sampling pattern, distance between sampling locations, area of test section, and quantity of tests over the test sections where the variability is measured. It is likely that the decrease in variability of processes can be attributed to one or more of the following: contractor quality control, specifications that require a measurement of variability, improved industrial technology, and improved test methods (Hughes 1996).

Variability has been identified in constructed pavement foundations. Allen and Graves (1994) obtained falling weight deflectometer (FWD) and Road Rater deflection measurements data at 25 foot intervals along a 500 ft long test section and observed a 75% coefficient of variation in subgrade moduli within the section. Yoder (1975) reported a range in standard deviations of layer thickness from 0.6 to 0.72 with 9749 tests on cement treated base, 0.72 to 0.84 with 7046 on aggregate base, and 0.96 to 1.44 with 10758 tests on aggregate subbase. Yoder reported that a typical range for the standard deviation of percent compaction on embankment/subgrade varied from 2.0 to 7.0 percent and on subbase/base varied from 2.0 to 3.5 percent. Siddharthan et al. (1992) studied layer moduli that were determined from back calculation of FWD tests performed on asphalt concrete pavement and they reported the layer moduli has coefficient of variation in a range of 5 to 65 percent.
Dilip and Babu (2014) studied the effect of the variance and correlation length on pavement responses to loading. The variation in the correlation length was found to have a marginal effect on the mean values of the critical strains and a noticeable effect on the standard deviation which decreases with decreases in correlation length. The pavement performance is adversely affected by the presence of spatially varying layers. The study also confirmed that the higher the variability in the pavement layer moduli, introduced through a higher value of coefficient of variation (COV), the higher the variability in the pavement response. The study concludes that ignoring spatial variability by modeling the pavement layers as homogeneous with very short correlation lengths can result in the underestimation of the critical strains and thus an inaccurate assessment of the pavement performance.

Although variation of in-situ properties in pavement construction has been noticed, there is no documentation of variability in pavement foundation properties so that people have an idea of how variable the pavement foundation properties could be. Selective sampling by the inspector, often as ordered by the engineer, has played an important part in the failure to recognize the magnitude of the actual variations occurring in embankment and base construction.

This study will focus on documenting the variability on 18 test sections over 6 projects on either the base/subbase layer or subgrade layer to provide a reference for pavement engineers or researchers to know how variable some pavement foundation properties can be within a small distance of the test section compared to the single design value that is used to represent the properties of a whole pavement foundation layer across the project. The variability of pavement foundation properties is also studied in relation to the number of roller compaction passes to see how the variability of pavement foundation properties could be reduced with the number of passes. Spatial variability of pavement foundation properties is a growing interest for more
researchers, but cost and time restraints limited the quality of data that can be used for spatial analysis. This study also investigates the spatial variability of pavement foundation properties in both longitudinal and transverse directions for identifying the difference in spatial variation as related to pavement geometry.

4.3. Background

4.3.1. Project information

The variability of pavement foundation properties is studied by statistical analysis on the in-situ test data that were collected on base, subbase, or subgrade layers from six project sites across five states (Figure 4.1).

Figure 4.1. Test sites map

The MI I-96 reconstruction project used 65% of the existing sand subbase layer and about 35% of newly constructed sand subbase layer. In situ testing data were obtained from two test
sections (TS). TS1 involved tests performed on the sand subbase and TS2 involved tests performed on the cement treated base (CTB) that was constructed with recycled portland cement concrete (RPCC). The pavement structure was reconstructed with a twenty-year design life jointed PCC pavement that was composed of a 292 mm (11.5 in.) thick PCC pavement at 4.3 m (14 ft) joint spacing, a 127 mm (5 in.) cement treated base (CTB) layer with recycled PCC (RPCC) material and a 279 mm (11 in.) existing or new sand subbase with a geotextile separator at the CTB/subbase interface.

The MI I-94 reconstruction project used a 20-year design life jointed PCC pavement that was composed of a 280 mm (11 in.) thick jointed PCC pavement, and undercutting the existing foundation layers to a depth of about 686 mm (27 in.) for placement of a layer of open-graded drainage course (OGDC) that was composed of recycled steel slag over the subgrade with a geotextile separation layer at the subgrade/OGDC layer interface. Field testing was conducted on TS1 and TS3 that were the newly constructed ODGC base layer.

The IA US-30 reconstruction project used a pavement that was composed of a nominal 254 mm (10 in.) thick JPCP pavement surface and a 152 mm (6 in.) thick RPCC underlain by a 254 mm (10 in.) thick mixture of RPCC/RAP modified subbase layer over the existing subgrade.

The WI US-10 new construction project used a pavement that was composed of a 254 mm (10 in.) thick plain PCC with dowels surface, underlain by a 152 mm (6 in.) thick dense aggregate base layer that was on top of a 610 mm (24 in.) thick Grade 1 granular subbase layer over the subgrade.

The NC Hwy-218 and FL I-10 projects studied the correlation of roller-integrated compaction monitoring measurements with in-situ testing methods measured pavement foundation properties. The NC Hwy-218 project tests were performed on base and subgrade
layers after construction of 102 mm (4 in.) of granular base material and 203 mm (8 in.) of subgrade materials. The FL I-10 project tests were performed on base and subgrade layers after construction of 152 mm (6 in.) of granular base material and 305 mm (12 in.) of stabilized subgrade materials or natural subgrade materials.

In-situ test sampling plans are different in all test sections, the major sampling patterns that were used for collecting data in this study are shown in Figure 4.2 to Figure 4.5. Only test sections with more than 70 data values collected with small spacing (<1 m) will be considered as dense gridded sampling sites. The dense gridded data will be used for spatial variability analysis. The other test sections are all said to be sparse sampling sites, but the test sections with more than 30 data values collected in one direction may be used for studying the large spacing spatial variability behavior.

![Figure 4.2. Sparse random linear test sampling on NC Hwy-218 TS3b](image)
Figure 4.3. Dense square test sampling on MI I94 TS1b

Figure 4.4. Sparse systematic linear test sampling on MI I96 TS2

Figure 4.5. Sparse linear cross test sampling on WI US-10 TS1
The soil index properties of the layer that in-situ tests were performed on are summarized in Table 4.1 with approximate sampling rate calculated as the number of in-situ tests that were performed per unit length in the longitudinal direction of the pavement. The approximate sampling rate is calculated with the maximum number of tests over the maximum longitudinal distance of the test section, but it could be lower for certain types of tests that were not performed at certain points.

Two dense sampling sites, MI I-94 TS1b and MI I96 TS1, are used for quantifying the spatial variability of pavement foundation properties using geostatistical methods (Chapter 2). Sparse data does not allow correct quantification of the correlation length, but some features of anisotropic behavior that different spatial variability could be expect in the sparse data collected in both transverse and longitudinal directions with more than 40 points were collected in each direction. Oliver and Webster (2015) suggest a target of 150 data values and a minimum of 100 data values should be collected for spatial analysis on a variable that has isotropic variation while more than 150 data values should be collected for identifying anisotropic variation. However, limited data can be studied to characterize the spatial variability and to explore the number of data values that should be collected to properly study the spatial variability of pavement foundation properties.

Moreover, univariate statistics are used to relate the change of studied pavement foundation properties with the number of passes of roller compaction using the data from NC Hwy-218 and FL I-10 projects. However, these data were collected from the calibration test area are not presented for studying the overall variability of pavement foundation properties, only data collected in the production area will be used.
Table 4.1. Soil index properties and sampling rate summary

<table>
<thead>
<tr>
<th>Site</th>
<th>Test Section (TS)</th>
<th>Layer</th>
<th>Soil index properties and classification</th>
<th>Sampling rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$\gamma_{\text{dmax}}$ (kN/m$^3$)$^a$</td>
<td>$\gamma_{\text{dmin}}$ (kN/m$^3$)$^b$</td>
</tr>
<tr>
<td>MI I-94</td>
<td>TS1a</td>
<td>Base</td>
<td>16.23</td>
<td>4.05</td>
</tr>
<tr>
<td></td>
<td>TS1b</td>
<td>Base</td>
<td>16.23</td>
<td>4.05</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Base</td>
<td>16.23</td>
<td>4.05</td>
</tr>
<tr>
<td>MI I-96</td>
<td>TS1</td>
<td>Sand subbase</td>
<td>20.06</td>
<td>14.98</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>CTB</td>
<td>13.61</td>
<td>12.26</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Sand subbase</td>
<td>20.06</td>
<td>14.98</td>
</tr>
<tr>
<td>WI US-10</td>
<td>TS1</td>
<td>Sandy Subbase</td>
<td>18.19</td>
<td>15.07</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Subgrade</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>NC Hwy-218</td>
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<tr>
<td></td>
<td>TS6</td>
<td>Stabilized Subgrade</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>IA US-30</td>
<td>TS1</td>
<td>RPCC modified Subbase</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>RPCC modified Subbase</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

Note: $^a$ASTM D4253-00; $^b$ASTM D4253-00; $^c$ASTM D698-07 (AASHTO T180 for FL I-10); $^d$ASTM D3282-09; $^e$ASTM D2487-00.
4.3.2. In Situ Testing Methods

The following in situ tests were conducted on 18 test sections of 6 project sites with real-time kinematic global positioning system (RTK-GPS) for positioning each test point to evaluate the variability in properties of pavement foundation systems (Table 4.2): Zorn light weight deflectometer (LWD); Kuab falling weight deflectometer (FWD); dynamic cone penetrometer (DCP); and Humboldt nuclear gauge (NG).

Table 4.2. In-situ tests summary

<table>
<thead>
<tr>
<th>Field site</th>
<th>TS</th>
<th>Tests performed on</th>
<th>FWD (E_{FWD-k3})</th>
<th>LWD (E_{LWD-Z3})</th>
<th>NG (γ_d and w)</th>
<th>DCP (DCPI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MI I-94</td>
<td>TS1a</td>
<td>Base</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>TS1b</td>
<td>Base</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Base</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>MI I-96</td>
<td>TS1</td>
<td>Sand subbase</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>CTB</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Sand subbase</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>WI US-10</td>
<td>TS1</td>
<td>Subbase</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Subgrade</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>NC Hwy-218</td>
<td>TS1</td>
<td>Subgrade</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Subgrade</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>TS3a</td>
<td>Base</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>TS3b</td>
<td>Base</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>FL I-10</td>
<td>TS1</td>
<td>Base1</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Base2</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>TS5</td>
<td>Subgrade</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>TS6</td>
<td>Stabilized Subgrade</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>IA US-30</td>
<td>TS1</td>
<td>RPCC modified Subbase</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>RPCC modified Subbase</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
</tbody>
</table>

Note: Y = test was performed on all test locations; N = test was not performed.
Real-Time Kinematic Global Positioning System

An RTK GPS system was used to obtain global spatial coordinates (i.e., northing, easting, and elevation) of in situ test locations and tested pavement layers. The local spatial coordinates (x, y, and z) were determined for all tested sections from their global coordinates. A Trimble SPS 851 was established on site to provide base station correction for a Trimble SPS 851 receiver. This system has manufactured accuracies of $< 10$ mm in horizontal direction and $< 20$ mm in vertical direction.

Zorn Light Weight Deflectometer

Zorn LWD tests were performed according to manufacturer’s recommendations (Zorn G. 2003) on base and subbase layers to determine elastic modulus. These LWD tests were set up with a 300 mm diameter plate and a 71 cm drop height. Elastic modulus ($E_{\text{LWD-Z3}}$) from LWD results was determined using Eq. 4.1:

$$E = \frac{(1-\eta^2)\sigma_0 r}{D_0} \times F$$

(4.1)

where: $E$ = elastic modulus (MPa);
$D_0$ = measured deflection under the plate (mm);
$\eta$ = Poisson’s ratio (0.4);
$\sigma_0$ = applied stress (MPa);
$r$ = radius of the plate (mm); and
$F$ = shape factor = $8/3$ per Vennapusa and White (2009).

Kuab Falling Weight Deflectometer

Kuab FWD tests were conducted by applying one seating drop using a nominal force of 24.5 kN (5500 lb) followed by test drops. The number of test drops and nominal forces varied for
each project. In every test, a load cell recorded actual applied forces, and deflections were recorded using seismometers mounted on the device according to ASTM D4694-09 (2009). A 300 mm diameter loading plate and 7 deflection sensors were set up. All deflection measurements were normalized to 40 kN to compare deflection values at different test locations. Composite modulus values ($E_{FWD,K3}$) were calculated using Eq. 4.1 with the measured deflection at the center of the plate and corresponding applied contact force. However, the plate used in Kuab FWD tests is a four-segmented plate that, according to the FWD manufacturer results in a uniform stress distribution. Therefore, a shape factor $F = 2$ was used in Eq. 4.1 instead of $8/3$ according to Vennapusa and White (2009).

**Nuclear gauge**

A nuclear moisture-density gauge (NG) device was calibrated and used to measure in situ soil dry unit weights ($\gamma_{d}$) and moisture content ($w$) in the base and subbase materials. Tests were performed according to ASTM D6938-10 (2010) at each test location. The average values of $\gamma_d$ and $w$ are reported for spatial analysis.

**Dynamic Cone Penetrometer**

DCP tests were performed following ASTM D6951-03 (2003) to evaluate the in situ strength of compacted base, subbase, and subgrade materials, and to determine the dynamic penetration index (DCPI) and penetration depth at each test point. Weighted average DCPI is calculated for each layer to evaluate variability of the in-situ strength at different pavement foundation layers. The calibrated California bearing ratio (CBR), back calculated from DCPI is also studied.

Several test sampling grids were studied to characterize the spatial variability of pavement foundation properties, and the fundamental assumption of this spatial analysis is that sample population of the variable values has an approximate normal distribution. Histograms, box with
whiskers plots, and normal quantile plots of the sampled values are analyzed to verify the normal distribution assumption. If the values are normally distributed, the values will be used for semivariogram analysis. However, if the values are not normally distributed and highly skewed in their distribution, an appropriate transformation will be made based on format of the original distribution.

4.3.3. Statistical analysis on variability

Univariate statistics are used in this study to quantify the variability of pavement foundation properties as determined using limited in-situ tests. Spatial variability analysis is performed with the statistical program R (Bivand et al. 2013; Pebesma 2001) to characterize and quantify the spatial variability of pavement foundation properties in longitudinal and transverse directions.

*Univariate statistics*

The box plot is an efficient graphical method for displaying the distribution of the data (Figure 4.6) and will be used to present variation of pavement foundation properties determined from different test sections.

![Box plot illustration](image)

**Figure 4.6. Illustration of box plot of $E_{LWD-Z3}$ measured in MI I-94 TS3**
The coefficient of variation (COV) will be used as the primary way of quantifying the variability with respect to the mean of the sample. The ratio of standard deviation (σ) to mean (μ) in Eq. 4.2 is the COV where σ is calculated as Eq. 4.3 where n is the number of data values, x.

\[
\text{COV} = \frac{\sigma}{\mu} \quad (4.2)
\]

\[
\sigma = \sqrt{\frac{\sum(x-\mu)^2}{n-1}} \quad \text{and} \quad \mu = \frac{\sum x}{n} \quad (4.3)
\]

**Spatial variability analysis**

Semivariogram γ(h) is a tool in geostatistical studies to describe and quantify spatial variability of studied variables. Semivariogram γ(h) measures the average dissimilarity of paired data separated by a vector h (Goovaerts 1997). The semivariogram γ(h) is defined as half of the average squared differences between number of pairs N(h) data values separated at a distance h as calculated in Eq. 4.4 (Isaaks and Srivastava 1989).

\[
\gamma(h) = \frac{1}{2N(h)} \sum_{|h_{ij}|=h}(Z(s_i)-Z(s_j))^2 \quad (4.4)
\]
A semivariogram plot is composed of a sill ($C$) that includes a nugget effect ($C_0$) and partial sill ($C_s$), and a range ($a$) or effective range ($a'$). Figure 4.7 shows a typical spherical semivariogram model fitted to the experimental semivariogram values.

Three major semivariogram parameters are nugget the effect ($C_0$), the sill ($C=C_0+C_s$), and the Range ($a$). A brief description of each parameter is summarized below using information from geostatistical books (Goovaerts 1997; Isaaks and Srivastava 1989).

The nugget effect ($C_0$) is the sudden increase of the semivariogram value as the separation distance goes from 0 m at the origin to an extremely small distance. This nugget effect can be the result of sampling error or short scale variability. The nugget effect can be determined by fitting a straight line through first few semivariogram values to intercept with the vertical axis. The relative nugget effect tends to increase with the lag ($h$) tolerance and data sparsity. Data sparsity or measurement errors may lead to a semivariogram with noisy values and can only be represented with a pure nugget effect. In general, the nugget effect is modeled as an isotropic component, but it can be modeled as an anisotropic spatial structure when the range value is smaller than the shortest sampling distance.

The sill ($C=C_0+C_s$) is the value of the semivariogram when the average squared difference between pairs of values no longer increases with increasing separation distance, that is the semivariogram reaches a plateau. The sill of the semivariogram may not be equal to the sample variance (Barnes 1991; Goovaerts 1997) and so forcing the sill to be equal to the sample variance ($s^2$) is a questionable practice.

The range ($a$) is the distance at which the semivariogram reaches the sill plateau. In most models, the effective range ($a'$) is determined as the distance at which the semivariogram reaches
95% of the sill plateau. More and better data tends to produce a longer range for the experimental semivariogram.

The discrepancies in semivariogram values reflect experimental fluctuations that result from the small number of data pairs available for each lag. Generally, the minimum of 30 and preferred 50 or more data pairs is desired within each bin (Journel and Huijbregts 1978). Erratic behaviors can be found in experimental semivariograms for data that are skewed or have extremely high or low values (outliers). If the sampled data is highly skewed (skewness is out the range of -1 to 1), the data may be transformed before performing spatial analysis. If the experimental semivariogram keeps increasing with increasing separation distance between data pairs, there could be a trend in the sampled data that should be removed before spatial analysis (Gringarten and Deutsch 2001). If a significant trend is identified this violates the assumption for spatial analysis that the mean is constant.

Three theoretical semivariogram models (Table 4.3) are used in this study to describe the experimental semivariogram values and the best fitted model is chose using statistical criteria.

### Table 4.3. Semivariogram models

<table>
<thead>
<tr>
<th>Model</th>
<th>R code</th>
<th>Equation</th>
<th>Parameter note</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nugget</td>
<td>Nug</td>
<td>( \hat{\gamma}(h) = \begin{cases} 0 &amp; h=0 \ C_0 &amp; h \neq 0 \end{cases} )</td>
<td></td>
</tr>
<tr>
<td>Spherical</td>
<td>Sph</td>
<td>( \hat{\gamma}(h) = \begin{cases} \frac{3}{2} \frac{h}{r} \left( \frac{h}{r} - \frac{1}{2} \left( \frac{h}{r} \right)^{\frac{3}{2}} \right) &amp; 0 \leq h \leq r \ C_s &amp; h &gt; r \end{cases} )</td>
<td>( a = r ) (range reaches 100% of ( C_s ))</td>
</tr>
<tr>
<td>Exponential (Matérn, ( k=0.5 ))</td>
<td>Exp</td>
<td>( \hat{\gamma}(h) = \begin{cases} 0 &amp; h=0 \ C_s \left( 1 - e^{\frac{h}{r}} \right) &amp; h &gt; 0 \end{cases} )</td>
<td>( a' = 3r ) (effective range reaches 95% of ( C_s ))</td>
</tr>
<tr>
<td>Whittles (Matérn, ( k=1 ))</td>
<td>Bes</td>
<td>( \hat{\gamma}(h) = \begin{cases} 0 &amp; h=0 \ C_s \left( 1 - \frac{h}{r} \right) K_1 \left( \frac{h}{r} \right) &amp; h &gt; 0 \end{cases} )</td>
<td>( a' = 4r ) (effective range reaches 95% of ( C_s ))</td>
</tr>
</tbody>
</table>

Note: \( K_1(h/r) \) is modified Bessel function of the second kind with order \( k=1 \), \( r \) is the range parameter obtained in R program.
In this study, model is fit to the The calculated experimental semivariogram using a weighted least squares method as Cressie (1985) suggested. The weight calculation method is presented in Eq. 4.5 where \( N_i \) is the number of data pairs that are an average distance, \( h_i \), apart.

\[
w_i = \frac{N_i}{h_i^2}
\]

(4.5)

The sum of square errors (SSErr) is calculated for each fitted theoretical semivariogram to describe how well the model fits the experimental semivariogram. SSErr is calculated using Eq. 4.6 where \( \hat{\gamma}(h_i) \) is the predicted semivariogram value using the fitted theoretical model and \( \gamma(h_i) \) is the average experimental semivariogram value at a lag distance \( h_i \).

\[
SSErr = \sum_{i=1}^{n} w_i [\hat{\gamma}(h_i) - \gamma(h_i)]^2
\]

(4.6)

### 4.4. Results and Discussion

Variability of pavement foundation properties are studied in three sections, the first is to investigate how the variability changes with the number of roller compaction passes, second is to summarize the univariate statistical analysis of different in-situ tests measurements, and third is to introduce the spatial variability analysis.

#### 4.4.1. Variation of pavement foundation properties to number of compaction passes

The relationship between in-situ measured pavement foundation properties and the number of compaction roller passes is studied on NC Hwy-218 with 21 tests performed after every target number of passes. The results are presented in box plots and COVs are calculated to see how variation changes with the number of passes for two subgrade and two base sections as Figure 4.8 to Figure 4.11 show.
Figure 4.8. Variation of pavement foundation properties with number of compaction pass
(NC Hwy-218 TS1 subgrade)
Figure 4.9. Variation of pavement foundation properties with number of compaction pass (NC Hwy-218 TS2 subgrade)
Figure 4.10. Variation of pavement foundation properties with number of compaction pass (NC Hwy-218 TS3a base)
Figure 4.11. Variation of pavement foundation properties with number of compaction pass (NC Hwy-218 TS3b base)

Figure 4.8 shows the LWD test and NG test results with number of passes. The mean value of both $E_{LWD-Z3}$ and $\gamma_d$ increase to a relative constant value after three passes while there is no
obvious change in the mean value of moisture content. The COV of both $E_{LWD-Z3}$ and $\gamma_d$ reaches the lowest value at the third pass, but increases in COV values for $E_{LWD-Z3}$ are observed with more compaction passes. Figure 4.10 shows relative lower COV value at the first two passes than after more passes in $E_{LWD-Z3}$ and $\gamma_d$ while the constant decreasing COV value is observed in the collected $\gamma_d$ values.

The overall mean value of $E_{LWD-Z2}$ significantly decreases after more passes compaction after 8 passes on TB3a and 4 passes on TB3b (Figure 4.10 and Figure 4.11).

Figure 4.10 shows variation of two stiffness measurements and dry unit weight decreases with increasing number of passes. Figure 4.11 shows variation of $E_{LWD-Z2}$ and $E_{LWD-D2}$ initially decreases with up to 4 passes, but variation increases about 4% with more passes after 8 and 4 passes for $E_{LWD-Z2}$ and $E_{LWD-D2}$ respectively. The mean value of $\gamma_d$ increases and COV decreases with number of passes.

The relationship between in-situ measured pavement foundation properties and the number of compaction roller passes is studied on FL I-10 with 20 tests on two base sections and 10 tests on two subgrade sections after every target number of passes. The results are presented in box plots and COVs are calculated to see variation change with number of passes for two subgrade and two base sections as Figure 4.12 to Figure 4.16 show.

Figure 4.12 shows increasing $E_{LWD-Z3}$ with increasing number of passes and COV decreasing from about 15.5% with passes to 10% after 8 passes. Increasing average $\gamma_d$ values were observed with more passes of compaction while there is a slight decrease in $\gamma_d$ is observed. The variation of both $\gamma_d$ and $\gamma$ is relatively small and does not change a lot with increasing number of compaction passes. The similar observation has been found in compaction on second base layer in FL I-10 TS2 (Figure 4.14).
Figure 4.12. Variation of pavement foundation properties with number of compaction pass (FL I-10 TS1 Base)
Figure 4.13. Variation of pavement foundation properties with number of compaction pass (FL I-10 TS2 Base)
Figure 4.14. Variation of pavement foundation properties with number of compaction pass (FL I-10 TS5 subgrade)
Figure 4.15. Variation of pavement foundation properties with number of compaction pass (FL I-10 TS6 Stabilized subgrade)

Figure 4.14 shows that the mean $E_{LWD-Z3}$ value increases from 25 MPa to 40 MPa with COV decreases from 16% to 8.5% after 8 compaction passes on the subgrade. The increase in mean $\gamma_d$
value has been observed with increasing number of compaction passes while moisture content remains nearly the same. The variations in $\gamma_d$ and $w$ are small in comparison with variation of $E_{LWD-Z3}$. Figure 4.15 shows consistent increase in the mean value of $E_{LWD-Z3}$ and $\gamma_d$ with first three passes and then levels off while moisture content remains nearly unchanged. Decrease of variation in $E_{LWD-Z3}$ has been observed with increasing number of compaction passes while no clear relationship between COV and number of passes observed in $\gamma_d$ and $w$ measurements on FL I-10 TS6 stabilized subgrade.

4.4.2. Univariate variability

Univariate statistics are calculated for data measured on each test section on all 6 projects. The LWD test determined $E_{LWD-Z3}$ and NG test determined $\gamma_d$ and $w$ are measured on all test sections, so the univariate statistics of each of these three pavement foundation properties are summarized in a single table (Table 4.4, Table 4.5, and Table 4.6). The rest of the in-situ test results for pavement foundation properties are summarized in Table 4.7.

According to the variability study on LWD tests measurements (Table 4.4), the average ($\mu$) $E_{LWD-Z3}$ on base/subbase layer is generally varying in a range from 12.6 MPa to 98.7 MPa and at maximum of 214.8 MPa on CTB and on subgrade layer is varying from 18.9 MPa to 34.9 MPa in general and the maximum 83.6 MPa is the average measurements on stabilized subgrade. The coefficient of variation (COV) of $E_{LWD-Z3}$ varies from 11% to 39% on 11 base/subbase layers and from 17% to 89% on 5 subgrade layers. The largest COV of 89% is obtained at the NC Hwy-218 TS1 which has the lowest mean value of $E_{LWD-Z3}$, and possible soft area could be expected according to the measured $E_{LWD-Z3}$ cross the study area that shown in Figure 4.16. Higher COV will be expected in stiffness measurements as the stiffness is measured as a composite layer property that not a value measured for a point whining a layer as NG does.
Figure 4.16. Variation of $E_{LWD-Z3}$ in NC Hwy-218 TS1

Table 4.4. Univariate statistics summary of $E_{LWD-Z3}$ (MPa)

<table>
<thead>
<tr>
<th>Field Site</th>
<th>TS</th>
<th>Layer</th>
<th>Mean ($\mu$)</th>
<th>Median</th>
<th>Variance ($s^2$)</th>
<th>Std Dev ($\sigma$)</th>
<th>COV</th>
<th>N</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>MI I-94</td>
<td>TS1a</td>
<td>Base</td>
<td>73.3</td>
<td>73.7</td>
<td>206.0</td>
<td>14.4</td>
<td>20</td>
<td>54</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td>TS1b</td>
<td>Base</td>
<td>58.5</td>
<td>58.6</td>
<td>50.5</td>
<td>7.1</td>
<td>12</td>
<td>16</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Base</td>
<td>49.0</td>
<td>49.6</td>
<td>109.8</td>
<td>10.5</td>
<td>21</td>
<td>16</td>
<td>0.06</td>
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<tr>
<td>MI I-96</td>
<td>TS1</td>
<td>Sand Subbase</td>
<td>30.9</td>
<td>31.3</td>
<td>124.1</td>
<td>11.1</td>
<td>36</td>
<td>73</td>
<td>-0.20</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>CTB</td>
<td>214.8</td>
<td>216.9</td>
<td>7152.4</td>
<td>84.57</td>
<td>39</td>
<td>11</td>
<td>0.29</td>
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<tr>
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<td>TS3</td>
<td>Sand Subbase</td>
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<td>31</td>
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<tr>
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<td>TS1</td>
<td>Sandy Subbase</td>
<td>12.6</td>
<td>12.6</td>
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<td>3.2</td>
<td>25</td>
<td>17</td>
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<td>TS2</td>
<td>Subgrade</td>
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<td>28.3</td>
<td>5.3</td>
<td>17</td>
<td>80</td>
<td>0.62</td>
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<td>TS1</td>
<td>Subgrade</td>
<td>18.9</td>
<td>12.4</td>
<td>285.8</td>
<td>16.9</td>
<td>89</td>
<td>19</td>
<td>1.10</td>
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<tr>
<td></td>
<td>TS2</td>
<td>Subgrade</td>
<td>29.2</td>
<td>26.1</td>
<td>349.8</td>
<td>18.7</td>
<td>64</td>
<td>45</td>
<td>2.06</td>
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<td></td>
<td>TS3a</td>
<td>Base</td>
<td>39.7</td>
<td>40.4</td>
<td>28.7</td>
<td>5.4</td>
<td>13</td>
<td>6</td>
<td>-0.05</td>
</tr>
<tr>
<td>FL I-10</td>
<td>TS1</td>
<td>Base1</td>
<td>98.7</td>
<td>93.8</td>
<td>379.6</td>
<td>19.5</td>
<td>20</td>
<td>27</td>
<td>0.98</td>
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<td>Base2</td>
<td>83.2</td>
<td>84.4</td>
<td>87.8</td>
<td>9.4</td>
<td>11</td>
<td>15</td>
<td>0.39</td>
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<td>Subgrade</td>
<td>34.9</td>
<td>33.6</td>
<td>194.6</td>
<td>14.0</td>
<td>40</td>
<td>40</td>
<td>1.38</td>
</tr>
<tr>
<td></td>
<td>TS6</td>
<td>Stabilized Subgrade</td>
<td>83.6</td>
<td>82.4</td>
<td>263.4</td>
<td>16.2</td>
<td>19</td>
<td>27</td>
<td>0.20</td>
</tr>
<tr>
<td>IA US-30</td>
<td>TS2</td>
<td>RPCC modified Subbase</td>
<td>56.6</td>
<td>57.5</td>
<td>120.6</td>
<td>11.0</td>
<td>19</td>
<td>40</td>
<td>-0.81</td>
</tr>
</tbody>
</table>
Dry unit weight ($\gamma_d$) was measured with NG tests on 15 test sections for 5 of the project sites.

The summarized univariate statistics (Table 4.5) shows that the mean $\gamma_d$ of 10 base/subbase layers varies from 14.6 kN/m$^3$ to 20.3 kN/m$^3$ with the COV varies from 2% to 6%. The mean $\gamma_d$ of 5 subgrade layers varies from 15.7 kN/m$^3$ to 19.84 kN/m$^3$ with the COV varies from 2% to 6%. A lower COV should be expected according to the density control method used in pavement foundation construction. The test area should be evaluated for identifying possible weak area when COV of higher than 10% was obtained.

Table 4.5. Univariate statistics summary of $\gamma_d$ (kN/m$^3$)

<table>
<thead>
<tr>
<th>Field site</th>
<th>TS</th>
<th>Layer</th>
<th>Univariate Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean ($\mu$)</td>
<td>Median</td>
</tr>
<tr>
<td>MI I-94</td>
<td>TS1a</td>
<td>Base</td>
<td>20.08</td>
</tr>
<tr>
<td></td>
<td>TS1b</td>
<td>Base</td>
<td>20.00</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Base</td>
<td>19.21</td>
</tr>
<tr>
<td>MI I-96</td>
<td>TS1</td>
<td>Sand subbase</td>
<td>20.16</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>CTB</td>
<td>14.56</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Sand subbase</td>
<td>20.01</td>
</tr>
<tr>
<td>WI US-10</td>
<td>TS1</td>
<td>Sandy Subbase</td>
<td>16.15</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Subgrade</td>
<td>19.84</td>
</tr>
<tr>
<td>NC Hwy-218</td>
<td>TS1</td>
<td>Subgrade</td>
<td>18.00</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Subgrade</td>
<td>16.98</td>
</tr>
<tr>
<td></td>
<td>TS3a</td>
<td>Base</td>
<td>20.25</td>
</tr>
<tr>
<td>FL I-10</td>
<td>TS1</td>
<td>Base1</td>
<td>17.78</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Base2</td>
<td>17.79</td>
</tr>
<tr>
<td></td>
<td>TS5</td>
<td>Subgrade</td>
<td>16.27</td>
</tr>
<tr>
<td></td>
<td>TS6</td>
<td>Stabilized Subgrade</td>
<td>15.70</td>
</tr>
</tbody>
</table>
Figure 4.17. Variation of in-situ measured $w$ compared to laboratory determined $w_{\text{opt}}$.

Moisture content ($w$) was measured with NG tests on 14 test sections over the 5 project sites. The summarized univariate statistics (Table 4.6) shows that the mean value of $w$ varies from 1.3% to 10.1% over 9 test sections on base/subbase and varies from 7.5% to 14.6% over 5 test sections on subgrade. The large range of $w$ variation could be the result of the length of time after construction that NG tests were performed and the difference in target moisture content which is in a range of $w_{\text{opt}}$ determined with laboratory tests. The mean value of in-situ measured $w$ was compared to laboratory determined $w_{\text{opt}}$ on selected test sections that laboratory tests were performed in determining the compaction curve (Figure 4.17). There is no definite trend of COV with $w_{\text{opt}}$ or difference between in-situ measured $w$ and $w_{\text{opt}}$. 
Table 4.6. Univariate statistics summary of w (%) 

<table>
<thead>
<tr>
<th>Field site</th>
<th>TS</th>
<th>Layer</th>
<th>Univariate Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean (μ)</td>
</tr>
<tr>
<td>MI I-94</td>
<td>TS1</td>
<td>Base</td>
<td>1.8</td>
</tr>
<tr>
<td></td>
<td>TS1</td>
<td>Base</td>
<td>2.3</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Base</td>
<td>1.3</td>
</tr>
<tr>
<td>MI I-96</td>
<td>TS1</td>
<td>Sand subbase</td>
<td>7.8</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>CTB</td>
<td>7.3</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Sand subbase</td>
<td>6.3</td>
</tr>
<tr>
<td>WI US10</td>
<td>TS1</td>
<td>Sandy Subbase</td>
<td>3.7</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Subgrade</td>
<td>7.5</td>
</tr>
<tr>
<td>NC Hwy218</td>
<td>TS1</td>
<td>Subgrade</td>
<td>10.2</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Subgrade</td>
<td>12.1</td>
</tr>
<tr>
<td>FL I-10</td>
<td>TS1</td>
<td>Base1</td>
<td>9.9</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Base2</td>
<td>10.1</td>
</tr>
<tr>
<td></td>
<td>TS5</td>
<td>Subgrade</td>
<td>11.0</td>
</tr>
<tr>
<td></td>
<td>TS6</td>
<td>Stabilized Subgrade</td>
<td>14.6</td>
</tr>
</tbody>
</table>

The in-situ tests in addition to LWD and NG tests were performed on selected test sections and the univariate statistics of variation of DCPI and CBR determined from DCP tests and $E_{FWD-K3}$ determined from FWD tests are summarized in Table 4.7. The average DCPI of base or subbase layer varies from 7 mm/blow to 19 mm/blow with COV varied from 8% to 53% over 8 tests sections of three projects. The high COV value might be expected due to the calculation of DCPI that is the weighted average value across the data analyst identified layer thickness. California bearing ratio (CBR) was calculated from the DCP tests and is not a direct measurements. The mean value of CBR of tests performed on base/subbase layer over 4 test sections of three project sites varies from 11% to 67% with COV varies from 19% to 35%.
Table 4.7. Univariate statistics summary of other pavement foundation properties

<table>
<thead>
<tr>
<th>Field site</th>
<th>TS</th>
<th>Layer</th>
<th>Properties</th>
<th>Univariate Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>MI I-94</td>
<td>TS1 a</td>
<td>Base</td>
<td>DCPI</td>
<td>Mean (μ)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>TS1 b</td>
<td>Base</td>
<td>DCPI</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Base</td>
<td>$E_{FWD,k3}$</td>
<td>44.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>DCPI</td>
<td>8</td>
</tr>
<tr>
<td>MI I-96</td>
<td>TS1</td>
<td>Sand subbase</td>
<td>DCPI</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>TS3</td>
<td>Sand subbase</td>
<td>DCPI</td>
<td>16</td>
</tr>
<tr>
<td>WI US10</td>
<td>TS1</td>
<td>Sandy Subbase</td>
<td>CBR</td>
<td>5.6</td>
</tr>
<tr>
<td></td>
<td>TS2</td>
<td>Subgrade</td>
<td>CBR</td>
<td>15.4</td>
</tr>
<tr>
<td>NC Hwy218</td>
<td>TS2</td>
<td>Subgrade</td>
<td>DCPI</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>TS3 a</td>
<td>Base</td>
<td>DCPI</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>TS3 b</td>
<td>Base</td>
<td>DCPI</td>
<td>14</td>
</tr>
<tr>
<td>FL I-10</td>
<td>TS1</td>
<td>Base1</td>
<td>DCPI</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CBR</td>
<td>32.9</td>
</tr>
<tr>
<td>IA US30</td>
<td>TS1</td>
<td>RPCC Subbase</td>
<td>CBR</td>
<td>11.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RPCC/R AP Subbase</td>
<td>CBR</td>
<td>67.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Subgrade</td>
<td>CBR</td>
<td>12.9</td>
</tr>
</tbody>
</table>

Note: DCPI unit is mm/blow; $E_{FWD,k3}$ unit is MPa; CBR unit is %.

4.4.3. Directional spatial variability

Spatial variability of pavement foundation properties is studied in longitudinal and transverse directions with respect to pavement structure geometry as many researchers have indicated a possible anisotropic spatial variability in pavement structure. Two sections of the total 18 test sections over the 6 project sites are densely gridded samples appropriate for spatial variability analysis study on pavement foundation properties. The detailed procedures of spatial are discussed chapter 3 and will not be provided in this section. Only the directional experimental semivariogram with fitted theoretical semivariogram models are presented for characterizing the
directional spatial variability of pavement foundation properties and these are compared with directional spatial variability of those properties measured in long sparse sampled test sections. Although the in-situ measurements are much more than the required number in pavement construction quality control and quality assurance programs, the amount of data in several test sections is inadequate for spatial variability analysis.

The first dense gridded test section MI I-94 TS1b is inside of the long sparse sampled test section MI I-94 TS1a as shown in Figure 4.18.

![Figure 4.18. Test plan for TS1a and TS1b test sections of MI I94](image)

Semivariograms for directional spatial variability are presented for $E_{LWD-Z3}$, $\gamma_d$, and DCPI$_{subbase}$ in Figure 4.19, Figure 4.20, and Figure 4.21, respectively. The semivariogram in the transverse direction for $E_{LWD-Z3}$ tend to reach the sample variance in larger range distance $>4$ m while the semivariogram in longitudinal direction shows a shorter range $<4$ m. In the longitudinal direction the sill is larger than the sample variance. The transverse $\gamma(h)$ of $\gamma_d$ shows a range of about 2 m while the longitudinal $\gamma(h)$ shows a possible trend. The $\gamma(h)$ of DCPI$_{subbase}$ in both transverse and longitudinal directions show clear sill values with similar range length which may imply isotropic $\gamma(h)$ of DCPI$_{subbase}$. Semivariograms based on the long sparse data from MI I94 TS1a (Figure 4.22, Figure 4.23, and Figure 4.24), show erratic behavior as
separated distance increases beyond 45 m. There is clear relationship between $\gamma(h)$ and separation distance can be identified, so the theoretical model was controlled with sample variation as partial sill ($C_s$) to fit to the experimental $\gamma(h)$. With the controlled sill, the range value are expected to be in a range of 25 m to 40 m that may not be true with no data pairs was obtained within a separation distance of 15 m. According to the spatial analysis on the same test site, the minimum spacing should be about 0.5 m to catch the initial part of the semivariogram from the origin to describe the directional semivariogram with more confidence. If only large spacing data are collected with a limited number of tests, the data may not be useful for spatial variability analysis.

Figure 4.19. Experimental $\gamma(h)$ of $E_{LWD-Z3}$ on MI I-94 TS1b in transverse direction (left) and longitudinal direction (right)

Figure 4.20. Experimental $\gamma(h)$ of $\gamma_d$ on MI I-94 TS1b in transverse direction (left) and longitudinal direction (right)
Figure 4.21. Experimental $\gamma(h)$ of DCPI subbase on MI I-94 TS1b in transverse direction (left) and longitudinal direction (right)

Figure 4.22. Experimental $\gamma(h)$ of $E_{LWD-Z3}$ on MI I-94 TS1a in longitudinal direction

Figure 4.23. Experimental $\gamma(h)$ of $\gamma_d$ on MI I-94 TS1a in longitudinal direction
Figure 4.24. Experimental $\gamma(h)$ of DCPI\textsubscript{subbase} on MI I-94 TS1a in longitudinal direction

Directional spatial variability analysis was performed on the dense gridded data collected on MI I-96 TS1. According to the spatial analysis on $E_{LWD-Z3}$, $\gamma_d$, and $w$ (Figure 4.25, Figure 4.26, and Figure 4.27) shows higher variation within smaller correlation lengths in the transverse direction compared to the longitudinal direction. This indicates more uniform pavement foundation properties ($E_{LWD-Z3}$, $\gamma_d$, and $w$) would be expected in the longitudinal direction than the transverse direction. However, the spatial analysis on DCPI\textsubscript{subbase} and DCPI\textsubscript{subgrade} does not show the same trends as described for $E_{LWD-Z3}$, $\gamma_d$, and $w$. Figure 4.28 shows that higher spatial variation of DCPI\textsubscript{subbase} will be expected in both transverse and longitudinal directions at a correlation distance longer than 4 m. Figure 4.29 shows DCPI\textsubscript{subgrade} is possibly more uniform in the longitudinal direction than the transverse direction with small correlation length <2 m.
Figure 4.25. Experimental $\gamma(h)$ of $E_{LWD-Z3}$ on MI I-96 TS1 in transverse direction (left) and longitudinal direction (right)

Figure 4.26. Experimental $\gamma(h)$ of $\gamma_d$ on MI I-96 TS1 in transverse direction (left) and longitudinal direction (right)

Figure 4.27. Experimental $\gamma(h)$ of $w$ on MI I-96 TS1 in transverse direction (left) and longitudinal direction (right)
With 121 of each FWD and NG test performed on cement treated base on MI I-96 TS2, the spatial analysis is performed to characterize and quantify the spatial variability only in the longitudinal direction as only 4 tests were performed along the transverse direction. Although the data spacing is larger than 2 m which may not be able to use for sampling MI I94 TS1 above to study spatial variability, the higher correlation of $E_{LWD-Z3}$, $\gamma_d$, and $w$ (Figure 4.30, Figure 4.31, and Figure 4.32) allows spatial variability on this CTB layer. A clear relationship between $\gamma(h)$ and separation distance helps with fitting the theoretical semivariogram model to quantify the spatial variability of $E_{LWD-Z3}$, $\gamma_d$, and $w$ that are summarized in Table 4.8.
Figure 4.30. Experimental $\gamma(h)$ of $E_{LWD-Z3}$ on MI I-96 TS2 in longitudinal direction

Figure 4.31. Experimental $\gamma(h)$ of $\gamma_d$ on MI I-96 TS2 in longitudinal direction

Figure 4.32. Experimental $\gamma(h)$ of $w$ on MI I-96 TS2 in longitudinal direction
Table 4.8. Directional spatial variability characteristics summary on four test sections

<table>
<thead>
<tr>
<th>Properties</th>
<th>Sampling type</th>
<th>Small Dense</th>
<th>Long Sparse</th>
<th>Small Dense</th>
<th>Long Sparse</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direction</td>
<td>MI I-94 TS1b</td>
<td>MI I-94 TS1a</td>
<td>MI I-96 TS1</td>
<td>MI I-96 TB2</td>
</tr>
<tr>
<td></td>
<td>Sill (C+Cₐ)</td>
<td>Range (a or a'), m</td>
<td>Sill (C+Cₐ)</td>
<td>Range (a or a'), m</td>
<td>Sill (C+Cₐ)</td>
</tr>
<tr>
<td>Eₑₕₑ₋ₚₑ-3 (MPa)</td>
<td>Transverse</td>
<td>59.0 8</td>
<td>11.022</td>
<td>165.301</td>
<td>2.624</td>
</tr>
<tr>
<td></td>
<td>Longitudinal</td>
<td>63.0 19</td>
<td>2.993</td>
<td>206.3599</td>
<td>38.288</td>
</tr>
<tr>
<td>Eₑₑ₋ₚₑ-K₃ (MPa)</td>
<td>Transverse</td>
<td>6046.3 22.452</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Longitudinal</td>
<td>6046.3 22.452</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>γₜ (kN/m³)</td>
<td>Transverse</td>
<td>0.34 88</td>
<td>2.328</td>
<td>0.67 4</td>
<td>7.482</td>
</tr>
<tr>
<td></td>
<td>Longitudinal</td>
<td>0.62 44</td>
<td>9.86</td>
<td>0.354 1</td>
<td>33.172</td>
</tr>
<tr>
<td>w (%)</td>
<td>Transverse</td>
<td>0.157 294</td>
<td>27.048</td>
<td>0.83 21</td>
<td>5.355</td>
</tr>
<tr>
<td></td>
<td>Longitudinal</td>
<td>0.157 294</td>
<td>27.048</td>
<td>0.83 21</td>
<td>5.355</td>
</tr>
<tr>
<td>DCPIₑₑ₋ₚₑ-base (mm/blow)</td>
<td>Transverse</td>
<td>1.19 52</td>
<td>1.732</td>
<td>30.2 1</td>
<td>4.288</td>
</tr>
<tr>
<td></td>
<td>Longitudinal</td>
<td>1.29 61</td>
<td>2.1792</td>
<td>288.2 45.4</td>
<td>27.9 924</td>
</tr>
<tr>
<td>DCPIₑₑ₋ₚₑ-grade (mm/blow)</td>
<td>Transverse</td>
<td>5.86 5 1.068</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Longitudinal</td>
<td>5.86 5 1.068</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The summarized spatial variability characteristics (Table 4.8) show that the correlation length of around 2 m to 11 m could be expected in small dense gridded area while the long sparse sampling with about 16 m spacing in longitudinal direction does not tell the true estimation of spatial variability. However, with more data collected with about 5 m spacing in longitudinal direction on CTB layer can clearly tell the correlation length of about 22 m for Eₑₑ₋ₚₑ-K₃ and w and about 15 m for γₜ for spatial analysis and is expected to have an erratic experimental semivariogram.
4.5. Conclusions

This study investigates variability of pavement foundation properties that were determined from four major in-situ tests (FWD, LWD, NG, and DCP) over 18 test sections of 6 project sites. Studying the variability of $E_{LWD-Z3}$, $\gamma_d$, and $w$ revealed that 4 passes of compaction could result in a production as good as are compacted with more passes and reduced coefficient of variation could be expected at larger number of passes.

Univariate statistics of in-situ measured data show that the highest variation could be expected in stiffness measurements (e.g., $E_{LWD-Z3}$, $E_{FWD-K3}$, and CBR), the reason could be that the stiffness is measured for the whole pavement foundation while the other can be measured at certain depth of pavement structure. The COV of $E_{LWD-Z3}$ varies from 11% to 39% on studied base/subbase layer and 19% to 89% on subgrade layer that COV of 89% in subgrade stiffness could be questioned for testing weak area. In addition, the lowest COV will be expected as 2% to 6% in dry unit weight of base/subbase or subgrade layer while the moisture content shows high variation. A test section might have a weak spot with $\gamma_d$ varying with COV more than 10%.

Spatial variability analysis on a dense gridded test section suggests that different anisotropic major directions can be expected in different test areas. The dense gridded MI I-94 TS1b shows the transverse direction is more uniform than the longitudinal direction, but the dense gridded MI I-96 TS1 shows the longitudinal direction is more uniform than the transverse direction. The two dense gridded sites suggest that the correlation length is about 2 m to 3 m in the minor direction (less uniform) and the correlation length in the major direction is about 3 to 4 times that of the minor direction. In addition, the longitudinal direction spatial variability of $E_{FWD-K3}$, $\gamma_d$, and $w$ on the CTB layer suggests a 15 m to 23 m correlation length. The spatial variability of pavement foundation properties could be different for different pavement structures and are recommended
with more number of tests (>150 points) with smaller spacing (<0.7 m spacing in 100 m² area and <2 m in large study area).

4.6. Acknowledgements

This study was sponsored by the Federal Highway Administration under agreement No. DTFH61-06-H-00011 and the Iowa Department of Transportation under Transportation Pooled Fund Program TPF-5(183).

4.7. Notation

The following symbols are used in this paper:

- \( a \) = Range
- \( a' \) = Effective range where 95% \( C_s \) reached
- \( C \) = Sill
- \( C_0 \) = Nugget effect
- \( C_s \) = Partial sill that obtained in variogram model
- \( \text{COV} \) = Coefficient of variation
- \( D_0 \) = measured deflection under the plate (mm)
- \( \text{DCPI} \) = Dynamic cone penetration index
- \( E \) = elastic modulus (MPa)
- \( E_{\text{LWD-Z3}} \) = Elastic modulus (Zorn LWD test with 300 mm dia. plate)
- \( E_{\text{FWD-K3}} \) = Elastic modulus (Kuab FWD test with 300 mm dia. plate)
- \( F \) = Shape factor for LWD
- \( G_s \) = Specific gravity
- \( h \) = Vector indicates distance and direction of two points apart
- \( k \) = Smoothness parameter in the Matérn model
- \( k \) = Stiffness estimated from a static plate load test
- \( n \) = Number of points on the experimental variogram
- \( N \) = Number of tests
- \( P \) = Applied load at surface
\[ r \] = Range number obtained in R program
\[ r \] = radius of the plate (mm)
\[ s^2 \] = Sample variance
\[ \text{SSErr} \] = Sum of squares of error or residuals
\[ w_j \] = Weight in weighted least squares fit
\[ w \] = Moisture content
\[ w_{\text{opt}} \] = Optimum moisture content
\[ \gamma_d \] = Dry unit weight
\[ \gamma_{d_{\text{max}}} \] = Maximum dry unit weight
\[ \gamma_{d_{\text{min}}} \] = Minimum dry unit weight
\[ \gamma(h) \] = experimental semivariogram at distance \( h \)
CHAPTER 5. CONCLUSIONS AND RECOMMENDATIONS

This research is composed of three major topics, assessing laboratory determination of $M_r$ values as design input for pavement design, introducing the detailed geostatistical method for characterizing and quantifying spatial variability of pavement foundation properties, and documenting the univariate and spatial variability of in-situ measured pavement foundation properties. The results should be of use to people who want to have knowledge on assessing the variability of pavement foundations for improving the construction of pavement foundation support to extend the pavement service life.

Errors related to stress measurements were characterized by identifying the difference between in situ and laboratory stress pulse shape and duration, studying the effects of sampling rates, and P and I signal values. A comparison of randomly selected raw data of a AASHTO T307 test with the required theoretical haversine-shaped stress pulse and in situ stress pulses revealed inadequate modeling of in situ stress pulse shapes and fast stress pulse durations in laboratory tests. The haversine-shaped stress pulse does not model the actual slow stress initialization and dissipation that an in situ stress pulse experienced. A modified Gaussian model with 5 parameters can better model in situ stress pulses. Stress pulse duration of 0.1 s is too fast compared to the observed in situ stress pulse duration of 0.14 s at 304.8 mm beneath the pavement surface and base layer when the test vehicle was driving at 96.6 km/h. In addition, a 0.1 s stress pulse duration might be obtained at the same position when the test vehicle is driving at 128 km/h. Although $M_r$ values varied with different stress pulse durations, three laboratory tests are not sufficient to conclude effects of stress pulse duration on $M_r$ values. Therefore, the effects of the inadequate modeling of $M_r$ values needs to be studied further to determine if a revision is needed for the laboratory tests. Further, the specified 200 Hz sampling rate for
laboratory tests is insufficient to fully characterize the true shape of stress pulses, especially the applied peak stresses. After tests with different sampling rates, rates of 500 Hz or greater can capture applied peak stresses better than the 200 Hz rate and result in less variation in $M_r$ values. However, the different $M_r$ test appliance may perform better or worse with the same sampling rate. Different sampling rates during the loading and rest period might be used with capable software to save computer storage and time for processing data. Initial adjustments of P and I signal values and automatic adaptation with time within the PC sequence is good when applying the target load in the PC sequence but not for achieving target loads for subsequent sequences where different stress levels are required. Therefore, careful adjustments of P and I signal values in each load sequence might be suggested when $M_r$ test equipment with a PID controller is used.

The differences between deformation measurements of two LVDTs were studied. In some cases, large differences were observed perhaps because top surfaces of the test specimens were not perfectly flat and the unit weights of the specimens were not uniform. In some cases, large differences in two LVDTs measurements were not observed in the PC sequence but in other load sequences. The larger the difference in two LVDTs measurements, the lower the accuracy in $M_r$ values. Therefore, quality control and quality assurance (QC/QA) are needed to determine the reliability of the $M_r$ tests results. SNR values of loads, the AASHTO T307 required displacement ratio $R_v$ in the PC sequence, a proposed resilient strain ratio $R_{er}$ of LVDT1 to LVDT2, and $c_v$ of the last five $M_r$ values in each load sequence were studied for QC/QA. Most of the SNR values met the requirement except for the first load sequence. The first load sequence has most SNR values less than 10, the minimum criteria. A possible reason for this is particle rearrangement in the specimen. Values of $R_v$ in the PC sequence are not representative of $R_v$ values for all load sequences, so $R_v$ values should be checked for all load sequences. The highest $R_{er}$ values were
obtained in the first load sequence not the PC sequence this suggests a possible particle rearrangement might have occurred in that load sequence. Therefore, $R_{cr}$ should be studied to check the uniformity of the specimen response. However, two LVDTs may not be sufficient for checking the uniformity of the specimen response and more LVDTs are suggested. In addition, $c_v$ was calculated for the last five load cycles of selected $M_r$ tests and all the values met the requirement. However, this only shows that variations within the last five load cycles were acceptable and that the average of the last five $M_r$ values is used to represent the $M_r$ at the given stress for the tested material.

However, $M_r$ values varied in different ways than the average of the last five $M_r$ values, they could be higher than the maximum or lower than the minimum $M_r$ values. This suggests steady $M_r$ values were not obtained at the end of the 100 load cycles. According to the statistical analysis on all 36 $M_r$ tests on three granular materials, variations among the average of the last five $M_r$ values, the average of the maximum and adjacent four $M_r$ values, and the average of the minimum and adjacent four $M_r$ values are statistically different. In addition, crushed limestone specimens had higher average $M_r$ than RAP and RPCC/RAP specimens, and material type is a statistically significant factor affecting $M_r$ values. Although increasing use of recycled materials can help environmental sustainability and reduce costs, careful investigation of the properties of the recycled materials should be conducted. Moreover, regression coefficient $k_3$ is not necessary for granular materials because the effects of shear stress that $k_3$ interprets in the universal model can be negative or positive.

Spatial variability analysis on dense gridded test section suggests that different anisotropic major directions could be expected in different test areas. The dense gridded MI I-94 TS1b shows the transverse direction is more uniform than the longitudinal direction, but the dense
gridded MI I-96 TS1 shows the longitudinal direction is more uniform than the transverse direction. The two dense gridded sites suggest that the correlation length is about 2 m to 3 m in the minor direction (less uniform) and the correlation length in the major direction is about 3 to 4 times as the minor direction. In addition, the longitudinal direction spatial variability of \( E_{\text{FWD-K3}} \), \( \gamma_d \), and \( w \) on CTB layer suggests a 15 m to 23 m correlation length.

Preliminary study on anisotropy of spatial variability of pavement foundation properties is allowed with the dense gridded measurements, but different anisotropic behavior was identified in two test sections that may only represent the local sample area. More data in the longitudinal direction should be provided for further anisotropy analysis.

Experimental semivariogram of layer averaged DCPI values are nearly isotropic with possible anisotropic behavior in horizontal directions (parallel to pavement surface) with study on both subbase and subgrade layers. Zonal anisotropy with major anisotropic axis along the longitudinal direction which means greater continuity in the longitudinal direction are presented in experimental semivariograms of \( E_{\text{LWD-Z3}} \), moisture content (\( w \)), and dry unit weight (\( \gamma_d \)) measured in dense gridded test locations in project MI I-96. Therefore, the univariate statistical analysis should be analyzed to assist in correctly describing spatial variability of pavement foundation properties and identifying possible trends.

Comparison of three theoretical semivariogram models reveals that no obviously best fitted model of the three models (i.e., spherical, exponential, Whittle or Matern with k=1) are found to describe the experimental semivariogram of dense gridded measurements of pavement foundation properties as the spatial variation at distances smaller than the smallest sampling distance were not determined. A nested model with an anisotropy ratio helps in estimating the values at unsampled locations with consideration of the correlation of data sampled at different
locations. However, in most cases for this study on a small test area, the isotropic or omnidirectional semivariogram model can work as well as an anisotropic semivariogram model. Correctly calculated the experimental semivariogram is more important than fitting different models. For example, the MSPE from cross-validation on $E_{LWD-Z3}$ in MI I-96 TS1 decreased from 46.28 with an angle tolerance of 45° to 33.3 with 25° angle tolerance.

Studying the variability of $E_{LWD-Z3}$, $r_d$, and $w$ revealed that 4 passes of compaction could result in a production as good as are compacted with more passes and a reduced coefficient of variation could be expected at larger number of passes.

Univariate statistics of in-situ measured data shows that the highest variation could be expected in stiffness measurements (e.g., $E_{LWD-Z3}$, $E_{FWD-K3}$, and CBR), the reason could be that the stiffness is measured for the whole pavement foundation while the other can be measured at certain depth of pavement structure. The COV of $E_{LWD-Z3}$ varies from 11% to 39% on studied base/subbase layer and 19% to 89% on subgrade layer that COV of 89% in subgrade stiffness could be questioned for testing weak area. In addition, the lowest COV will be expected as 2% to 6% in dry unit weight of base/subbase or subgrade layer while the moisture content shows high variation. A test section might have a weak spot varying with $\gamma_d$ varied with COV more than 10%.

5.1. Recommendations

There are several ideas for future research related to studying variability of pavement foundation properties.

- The laboratory determined $M_r$ values are always higher than the in-situ measured stiffness, the correlation between laboratory tests and in-situ measurement could be
constructed by testing the composite specimens with variation of combination of soil index properties to simulate the variation of in-situ dry unit weight and moisture content.

- Further study on spatial variability of pavement foundation properties is suggested with measurements at test locations with different spacing and across the pavement width. A smaller spacing which is less than 0.5 m is suggested for research studying for identifying the initial spatial correlation characteristics.

- The spatial variability of pavement foundation properties could be different for different pavement structures and are recommended with a greater number of tests (>150 points) with smaller spacing (<0.7 m spacing in 100 m² area and <2 m in large study area).
BIBLIOGRAPHY


Ping, W. V., Xiong, W., and Yang, Z. (2003). "Implementing resilient modulus test for design of pavement structures in Florida." Florida Department of Transportation, Tallahassee, FL.


APPENDIX A. R PROGRAM CODE FOR SPATIAL SEMIVARIOGRAM ANALYSIS

# Data format: Excel.csv id-x-y-variables (no blank cells allowed)
# x=longitudinal direction and y= transverse direction
# Units of coordinates is "m", modulus is "MPa", and DCPI is "mm/blow"
# analyze each variable separately (be aware of state and test bed that
data was collected in data analysis report)
data is the general name for the studied data file
data<- read.csv(file.choose(), as.is=T)

# Print variable name to make sure that the name of the analyzed variable
# is right in coding.
head(data)
data[1,]

# Plot test locations
plot(data$x, data$y,xlab='longitudinal direction (m)',ylab='transverse
direction (m)')

# Specify axis options within plot()
# plot(x, y, main="title", sub="subtitle",
#     xlab="x-axis label", ylab="y-axis label",
#     xlim=c(xmin, xmax), ylim=c(ymin, ymax))

# Univariate statistics analysis
summary(data)
library(pastecs)
options(scipen=100)
options(digits=4)
stat.desc(data, basic=F)
hist(data$ELWD)
hist(data$rd)
hist(data$w)
hist(data$DCPI_subbase_w.o.1st)
hist(data$DCPI_subgrade)

# Spatial variance analysis
library(sp)
library(gstat)
data.sp<- data
coordinates(data.sp)<- c('x','y')
plot(coordinates(data.sp))

bubble(data.sp,'ELWD', maxsize = 2.5,
scales=list(draw=T),xlab="Longitudinal direction (m)",ylab="Transverse
direction (m)")
bubble(data.sp,'rd', maxsize = 2.5,scales=list(draw=T),xlab="Longitudinal
direction (m)",ylab="Transverse direction (m)"
bubble(data.sp,'w', maxsize = 2.5,scales=list(draw=T),xlab="Longitudinal
direction (m)",ylab="Transverse direction (m)"
```r
bubble(data.sp,'DCPI_subbase_w.o.1st', maxsize = 2.5,scales=list(draw=T),xlab="Longitudinal direction (m)",ylab="Transverse direction (m")
bubble(data.sp,'DCPI_subgrade', maxsize = 2.5,scales=list(draw=T),xlab="Longitudinal direction (m)",ylab="Transverse direction (m")

# define the grid number and size for kriging, can define or adjust later after obtain the semivariogram model
xrange = bbox(data.sp)[1,]
yrange = bbox(data.sp)[2,]
data.grid <- expand.grid(
  x=seq(xrange[1], xrange[2], length=100),
  y=seq(yrange[1], yrange[2], length=100) )
plot(data.grid,main='Specified data grid',xlab='longitudinal direction (m)',ylab='transverse direction (m)')
coordinates(data.grid) <- c('x','y')   # qui
gridded(data.grid) <- T                # and flag as a grid
plot(data.grid, xlab='longitudinal direction(m)',ylab='transverse direction(m)') #view the defined grid

# variogram estimation
# vgm(), show.vgms( par.strip.text=list(cex=0.7) )
# variogram, define alpha is to define the direction of the variogram,
# tol.hor is the tolerance in xy-plane, the default value is =90 degree/number of the alpha defined in the same variogram.

# omni-directional variogram
data.vc <- variogram(ELWD~1, data.sp, cloud=T)
plot(data.vc, main='ELWD', xlab='Seperation Distance (m)',
ylab='Semivariance (MPa^2)')
data.v <- variogram(ELWD~1, data.sp, cutoff=4)
# calculate experimental semi-variogram, assuming constant mean
plot(data.v,main='ELWD')
# the output object from variogram() has three variables of interest:
# dist: average distance for that bin
# gamma: empirical semivariance for that bin
# np: number of points in that bin

# fit theoretical model to experimental variogram calculated in omni-direction
omni.vm <- variogram(ELWD~1, data.sp, cutoff=4)
plot(omni.vm,main='ELWD')
data.omni.vm1 <- fit.variogram(omni.vm, vgm(6, 'Sph', 4, 0)) #fit spherical model
```
data.omni.vm2 <- fit.variogram(omni.vm, vgm(6, 'Exp', 2, 0)) # fit exponential model
data.omni.vm3 <- fit.variogram(omni.vm, vgm(6, 'Mat', 1, 0, k=1)) # fit matern model with k=1
plot(omni.vm, data.omni.vm1, main="ELWD omni-direction Sph")
data.omni.vm1
attr(data.omni.vm1, 'SSErr') # SSErr is sum of square errors in weighted least square fitting the semivariogram
plot(omni.vm, data.omni.vm2, main="ELWD omni-direction Exp")
data.omni.vm2
attr(data.omni.vm2, 'SSErr')
plot(omni.vm, data.omni.vm3, main="ELWD omni-direction Mat k=1")
data.omni.vm3
attr(data.omni.vm3, 'SSErr')

with(omni.vm, plot(dist, gamma, xlim=c(0,4), ylim=c(0,200)))  # plot experimental semivariogram with all three fitted models
lines(variogramLine(data.omni.vm1, maxdist=4), lwd=2)
lines(variogramLine(data.omni.vm2, maxdist=4), col=2, lwd=2)
lines(variogramLine(data.omni.vm3, maxdist=4), col=4, lwd=2)
legend('bottomright', bty='n', lty=1, col=c(1,2,4), lwd=2,
legend=c('Spherical','Exponential','Matern, k=1') )

#-----
# if the plot need to be plotted in the other programs, the line value can be extracted as following
omni.vm.fit1= variogramLine(data.omni.vm1, 4, 40)
omni.vm.fit2= variogramLine(data.omni.vm2, 4, 40)
omni.vm.fit3= variogramLine(data.omni.vm3, 4, 40)
library(xlsx)
library(dplyr)

omni.vmfit <- omni.vm.fit1 %>%
  left_join(omni.vm.fit2, by = "dist", suffix = c("Sph", "Exp")) %>%
  left_join(omni.vm.fit3, by = "dist") %>%
glimpse
write.xlsx(omni.vmfit, "omni.vm.fit.xlsx", sheetName="Sheet1", col.names = TRUE, row.names = TRUE, append = FALSE, showNA = TRUE)

#-----
# choose the suitable model as data.ovm (omni-direction vm)
data.ovm= data.omni.vm1
data.ovm

#------------------------------------
# analysis with anisotropy
# start to look at the directional variogram
# variogram map:
plot(variogram(ELWD~1, data.sp, map=T, cutoff=4, width=1), main='ELWD',
  xlab='dx (Longitudinal)', ylab='dy (Transverse)')
# width is the bin size, dx=dy=width

# directional variograms
data.v4 <- variogram(ELWD~1, data.sp, alpha=c(0,45,90,135),cutoff=4,tol.hor=25, width=0.5) # four major directions
plot(data.v4,type='b', main='ELWD')
write.xlsx(data.v4, "directional_expr_vm_new.xlsx", sheetName="Sheet1", col.names = TRUE, row.names = TRUE, append = FALSE, showNA = TRUE)
# save calculated directional semivariogram into Excel

# direction at alpha=0 along y or transverse direction
data.vT <- variogram(ELWD~1, data.sp, cutoff=4, alpha=c(0), tol.hor=25, width=0.5)
# alpha=direction in plane (x,y), in positive degrees clockwise from positive y (North)
plot(data.vT)
data.vmT1 <- fit.variogram(data.vT, vgm(100, 'Sph', 6, 0), fit.sills=c(FALSE,TRUE))
# if fixed nugget value is desired, add fit.sills=c(FALSE, TRUE) to fit.variogram
data.vmT2 <- fit.variogram(data.vT, vgm(100, 'Exp', 1.3, 0))
data.vmT3 <- fit.variogram(data.vT, vgm(100, 'Mat', 1, 0, k=1))
data.vmT1
attr(data.vmT1, 'SSErr')
data.vmT2
attr(data.vmT2, 'SSErr')
data.vmT3
attr(data.vmT3, 'SSErr')
with(data.vT, plot(dist, gamma, xlim=c(0,4), ylim=c(0,200),main='ELWD along Y direction'))
lines(variogramLine(data.vmT1, maxdist=4), col=1, lwd=2)
lines(variogramLine(data.vmT2, maxdist=4), col=2, lwd=2)
lines(variogramLine(data.vmT3, maxdist=4), col=4, lwd=2)
legend('bottomright', bty='n', lty=1, col=c(1,2,4), lwd=2, legend=c('Spherical','Exponential','Whittle'))

# direction at alpha=90 along x or longitudinal direction
data.vL <- variogram(ELWD~1, data.sp, cutoff=4, alpha=c(90), tol.hor=25, width=0.5)
plot(data.vL)
# if fixed nugget value is desired, add fit.sills=c(FALSE, TRUE) to fit.variogram
data.vmL1 <- fit.variogram(data.vL, vgm(50, 'Sph', 4, 0),fit.sills=c(FALSE,TRUE))
data.vmL2 <- fit.variogram(data.vL, vgm(50, 'Exp', 1.5, 0),fit.sills=c(FALSE, TRUE))
data.vmL3 <- fit.variogram(data.vL, vgm(50, 'Mat', 2, 0, k=1),fit.sills=c(FALSE, TRUE))
data.vmL1
attr(data.vmL1, 'SSErr')
data.vmL2
attr(data.vmL2, 'SSErr')
data.vmL3
attr(data.vmL3, 'SSErr')
plot(data.vL, data.vmL3)
with(data.vL, plot(dist, gamma, xlim=c(0,4), ylim=c(0,20),main='ELWD along X direction'))
lines(variogramLine(data.vmL1, maxdist=4), col=1, lwd=2)
lines(variogramLine(data.vmL2, maxdist=4), col=2, lwd=2)
lines(variogramLine(data.vmL3, maxdist=4), col=4, lwd=2)
legend('bottomright', bty='n', lty=1, col=c(1,2,4), lwd=2,
legend=c('Spherical','Exponential','Whittle') )

# Identify major direction (lowest sill in zonal anisotropy or largest
# range in geometric anisotropy),
# this case is 90 degree (X direction)
# model geometric anisotropy first
v <- variogram_ELWD~1, data.sp, alpha=c(0,45,90,135),cutoff=4, tol.hor=45)
# use the coefficients from the autofitted vargioram values for the major
direction
vm1<- vgm(4.152, 'Sph',2.289,0, anis=c(90,0.8))
# the anisotropy factor =(range at minor direction reach sill, smaller)/(range at major direction, larger)<1
vm1
plot(v, vm1, main = "geometric")
# if only geometric anisotropy exist, then just model geometric anisotropy
vm.final = vm1

# Then, model zonal anisotropy (difference between major and minor
# directions)
zonal= vgm(1.713,'Sph',1e9, anis=c(90,1/9.36e8))
# partial sill=sill in the original minor direction-(nugget and partial
sill from geometric anis model)
# 1e9 is the range, effectively infinity in 90 direction that means model
zonal effect in 0 direction only
# anisotropy ratio 9.36e8= 1e9/1.068 (3.105 is the range from 0
direction)
vm2<- vgm(4.152, 'Sph',2.289,0, add.to=zonal)
plot(v, vm2, main = "zonal")
vm2
vm.final=vm2
plot(v, vm.final)

# extract points' coordinates on the fitted anisotropic variogram
vfit1= variogramLine(vm.final, 4, 40,dir=c(0,1,0))  #in y-direction (0
degrees)
vfit2= variogramLine(vm.final, 4, 40,dir=c(sqrt(2)/2,sqrt(2)/2,0))  #in y-
direction (45 degrees)
vfit3= variogramLine(vm.final, 4, 40,dir=c(1,0,0))  #in x-direction (90
degrees)
vfit4= variogramLine(vm.final, 4, 40,dir=c(-sqrt(2)/2,sqrt(2)/2,0))  #in y-
direction (135 degrees)
library(dplyr)

vfit <- vfit1 %>%
  left_join(vfit2, by = "dist", suffix = c("0", "45")) %>%
  left_join(vfit3, by = "dist") %>%
  left_join(vfit4, by = "dist", suffix = c("90", "135")) %>%
glimpse
write.xlsx(vfit, "fit.xlsx", sheetName="Sheet1", col.names = TRUE,
row.names = TRUE, append = FALSE, showNA = TRUE)
getwd()
kriging

# need four things:
#   model for trend (could be just a mean)
#   data (sp PointsDataFrame object),
#   locations to predict at (sp Points or Pixels (for grid) object)
#   the semivariogram model (est. from empirical SV or specified)

# Keep originally setted data.grid or reset the suitable grid size and
estimation area

tslb.grid <- expand.grid(x=seq(0,8.5,0.1), y=seq(0,8.5,0.1))
coordinates(tslb.grid) <- c('x','y')
gridded(tslb.grid) <- T

#--Omni-directional, without consideration in anisotropy
data.ovm=data.omni.vm3 #the one you chose from the three fitted models
data.ovm #double check if the correct one is chosen
data.k.omni <- krige(ELWD ~ 1, data.sp, tslb.grid, data.ovm)
image(data.k.omni) #visualize the krigged plot
plot(data.k.omni, main="semivariogram omni Mat", xlab="distance",
ylab="semivariance",axes=TRUE) #visualize the krigged plot in another way

#--Consider anisotropy, now, use vm.final
vm.final
data.k.final <- krige(ELWD ~ 1, data.sp, tslb.grid, vm.final)
image(data.k.final)
plot(data.k.final, main="ELWD semivariogram_Anisotropy", axes=T, xlim=c(0,8.5), ylim=c(0,8.5))

#--Omni-directional,
data.cv.omni <- krig.cv(ELWD ~ 1, data.sp, data.ovm)
names(data.cv.omni)
bubble(data.cv.omni, 'residual')
mean(data.cv.omni$residual) # average prediction error
mean(data.cv.omni$residual^2) # mean squared prediction error
plot(data.cv.omni$var1.pred, data.cv.omni$residual)
plot(data.cv.omni$var1.pred, data.cv.omni$observed)

#--Consider anisotropy,
data.cv.final <- krig.cv(ELWD ~ 1, data.sp, vm.final)
names(data.cv.final)
bubble(data.cv.final, 'residual')
mean(data.cv.final$residual) # average prediction error
mean(data.cv.final$residual^2) # mean squared prediction error
plot(data.cv.final$var1.pred, data.cv.final$residual)

#--Save kriged map values into excel file
library(xlsx)
write.xlsx(data.k.omni, "yourfilenamepath_new.omni.xlsx",
sheetName="Sheet1", col.names = TRUE, row.names = TRUE, append = FALSE,
showNA = TRUE)
write.xlsx(data.k.final, "yourfilenamepath_new.anis.xlsx",
sheetName="Sheet1", col.names = TRUE, row.names = TRUE, append = FALSE,
showNA = TRUE)
# the file will be automatically saved into the working directory
# find the working directory to find the file
getwd()
# or we can set the working directory to the target folder that we want to
# saved our files in.
setwd("..")
APPENDIX B. STATISTICAL ANALYSIS PLOTS FOR CHAPTER 2

B.1. MI I-94 TS1a

**Figure B.1. Test plan for MI I-94 TS1a**

**Figure B.2. Histogram of $E_{LWD,Z3}$ for MI I-94 TS1a**

**Figure B.3. Histogram of $\gamma_d$ for MI I-94 TS1a**
Figure B.4. Histogram of \( w \) for MI I-94 TS1a

- \( n = 54 \)
- \( \mu = 1.8 \% \)
- \( \sigma = 0.4 \% \)
- \( \text{COV} = 22 \% \)

Figure B.5. Histogram of DCPI_{subbase} for MI I-94 TS1a

- \( n = 54 \)
- \( \mu = 6 \text{ mm/blow} \)
- \( \sigma = 1.7 \text{ mm/blow} \)
- \( \text{COV} = 27 \% \)

Figure B.6. Histogram of DCPI_{subgrade} for MI I-94 TS1a

- \( n = 54 \)
- \( \mu = 49 \text{ mm/blow} \)
- \( \sigma = 18.3 \text{ mm/blow} \)
- \( \text{COV} = 37 \% \)
Figure B.7. Omnidirectional semivariogram of $E_{LWD-Z3}$ for MI I-94 TS1a

Figure B.8. Omnidirectional semivariogram of $E_{LWD-Z3}$ in three lanes for MI I-94 TS1a

Figure B.9. Omnidirectional semivariogram of $\gamma_d$ for MI I-94 TS1a
Figure B.10. Omnidirectional semivariogram of \( w \) for MI I-94 TS1a

Figure B.11. Omnidirectional semivariogram of DCPI_{subbase} for MI I-94 TS1a

Figure B.12. Omnidirectional semivariogram of DCPI_{subgrade} for MI I-94 TS1a
B.2. MI I-94 TS1b

Figure B.13. Semivariogram cloud for $E_{LWD-Z3}$ in full test section length in MI I-94 TS1b

Figure B.14. Average semivariogram in each bin with number of data pairs for $E_{LWD-Z3}$ in full test section length in MI I-94 TS1b
Figure B.15. Histogram of $E_{LWD-Z3}$ for MI I-94 TS1b

Figure B.16. Histogram of $\gamma_d$ for MI I-94 TS1b

Figure B.17. Histogram of $w$ for MI I-94 TS1b
Figure B.18. Histogram of DCPI_{subbase} (removed one outlier) for MI I-94 TS1b

Figure B.19. Histogram of DCPI_{subgrade} for MI I-94 TS1b
Figure B.20. Omnidirectional semivariogram of $E_{\text{LWD-Z3}}$ for MI I-94 TS1b

Figure B.21. Kriging contour map with spherical model of $E_{\text{LWD-Z3}}$ for MI I-94 TS1b
Figure B.22. Kriging contour map with exponential model of \( E_{\text{LWD-Z3}} \) for MI I-94 TS1b

Figure B.23. Kriging contour map with Matérn \((k=1)\) model of \( E_{\text{LWD-Z3}} \) for MI I-94 TS1b
Figure B.24. Semivariogram map of $E_{LWD-Z3}$ for MI I-94 TS1b

Figure B.25. Semivariogram contour plot of $E_{LWD-Z3}$ for MI I-94 TS1b
Figure B.26. Multiple directional semivariogram of $E_{LWD-Z3}$ for MI I-94 TS1b
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