Geostatistical Analysis for Spatially Referenced Roller-Integrated Compaction Measurements

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Keywords
Statistics, Geostatistics, Soil compaction, quality control, earthwork, intelligent compaction, semivariogram, measurement

Disciplines
Geotechnical Engineering | Statistics and Probability

Comments
This is a post-print of an article from Journal of Geotechnical and Geoenvironmental Engineering 136, no. 6 (2010): 813–822, doi:10.1061/(ASCE)GT.1943-5606.0000285.
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Manuscript submitted for review to the
Journal of Geotechnical and Geoenvironmental Engineering
ASCE

Revised October 2009 (original submitted July 2008)

Word Count

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Geostatistical Analysis for Spatially Referenced Roller-Integrated Compaction Measurements

By: Pavana K R. Vennapusa¹, David J. White², Max D. Morris³

Abstract: An approach to quantify non-uniformity of compacted earth materials using spatially referenced roller-integrated compaction measurements and geostatistical analysis is discussed. Measurements from two detailed case studies are presented in which univariate statistical parameters are discussed and compared to geostatistical semivariogram modeling parameters and analysis. The univariate and geostatistical parameter values calculated from the roller-integrated measurements are also compared to traditional spot test acceptance criteria. Univariate statistical parameter values based on roller-integrated measurement values provide significantly more information than traditional point measurements, while geostatistics can be used to identify regions of non-compliance and prioritize areas for rework. (96 words)

CE Database subject headings: geostatistics, semivariogram, soil compaction, quality control, earthwork, intelligent compaction.

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INTRODUCTION

Roller-integrated compaction monitoring (RICM) technologies for earth materials provide spatially referenced compaction measurements in real time with 100% coverage, which is a significant improvement over conventional spot test density measurements. This is accomplished by instrumenting the roller with sensors (e.g., accelerometer, torque sensor) that evaluate machine-ground interactions, a global positioning system (GPS) for mapping, and a computer to record, analyze, and output the data. There are at least six RICM measurement values: *omega value* ($\omega$), *compaction meter value* (CMV), *compaction control value* (CCV), roller-determined stiffness ($k_v$) and vibration modulus ($E_{vib}$), and *machine drive power* (MDP) (see Mooney and Adam 2007, White et al. 2005). Measurements are commonly recorded every 0.1 to 0.5 m and are integrated over the width of the roller drum. GPS coordinates are assigned to create spatially referenced maps of the measurements. RICM measurements have been correlated to a variety of in-situ spot test measurements (Floss et al. 1983, Samaras et al. 1991, Brandl and Adam 1997, White and Thompson 2008, Thompson and White 2008). Spatial comparisons between in-situ spot test measurements and roller-integrated measurements are documented by Thompson and White (2007) and White et al. (2008b).

The ability to view compaction data in real time offers an opportunity to improve process control, construct more uniform foundation layers, and reduce rework and overwork in areas that have already met the specification. Although there are several identified benefits of implementing this technology, challenges exist with interpreting data and developing suitable specifications for acceptance (White 2008). White et al. (2008b) reviewed five different RICM specifications which showed that univariate statistics (i.e., mean and standard deviation) are typically used for quality control criteria (ZTVE-StB 1994, RVS 8S.02.6 1999, ATB Väg 2004, ISSMGE 2005, Mn/DOT 2006). Univariate statistics, however, do not address the issue of spatial uniformity. Two datasets with identical frequency distributions of the data can have significantly different spatial characteristics. Geostatistical analysis tools, such as a semivariogram model (Fig. 1), in combination with univariate statistics could potentially
be utilized to quantify spatial uniformity, identify poorly compacted areas, and improve process control during earthwork operations.

Geostatistical analysis could also be beneficial in evaluating the performance of geotechnical structures like shallow foundations and pavement layers. Generally, pavement design considers the foundation as a layered medium with uniform material properties in each layer. In reality, soil engineering parameters generally show significant spatial variation. Spatial variation of strength, stiffness, and permeability properties of pavement foundation layers are documented by Vennapusa (2004) and White et al. (2004). Results based on average layer values may vary considerably from actual performance (White et al. 2004, Griffiths et al. 2006). Better understanding the influence of spatial variability on the performance of geotechnical structures is increasingly being studied for a wide range of geotechnical applications (e.g., Mostyn and Li 1993, Phoon et al. 2000, White et al. 2004, Griffiths et al. 2006). One challenge in this area has been collecting enough information to make use of geostatistics. Dense sampling and spatially referenced RICM data overcomes this obstacle. If the data can be linked to suitable analytical/numerical models, new insights into spatial load-deformation analysis can be developed and is a subject of on-going research.

The main objectives of this paper are to: (a) provide an overview of geostatistical analysis procedures for spatially referenced RICM to characterize and model spatial variability using semivariogram analysis, (b) identify challenges involved in performing the analysis, (c) compare spatial statistics with univariate statistics in characterizing non-uniformity, and (d) demonstrate the practical significance of the analysis results. Detailed measurements from two case studies are analyzed for these purposes and presented in this paper. The analysis approach is applicable to any of the RICMs referenced above.

BACKGROUND

Roller-Integrated Compaction Measurement Values

Caterpillar’s CS-533E and CS-563E smooth drum soil compaction rollers equipped with RICM technology were used in the two field studies documented in this paper. These rollers simultaneously
calculate the vibratory-based compaction meter value (CMV) and resonant meter value (RMV), and the static or vibratory-based machine drive power (MDP). A brief description of these technologies is provided below.

CMV is a dimensionless compaction parameter developed by Geodynamik that depends on roller dimensions (i.e., drum diameter and weight) and roller operation parameters (e.g., frequency, amplitude, and speed) and is determined using the dynamic roller response (Sandström 1994). It is calculated as

\[
CMV = C \cdot \frac{A_{2\Omega}}{A_\Omega}
\]

(1)

where \(C\) is a constant (300), \(A_{2\Omega}\) is the acceleration of the first harmonic component of the vibration, \(A_\Omega\) is the acceleration of the fundamental component of the vibration (Sandström and Pettersson 2004). Correlation studies relating CMV to soil dry unit weight, strength, and stiffness are documented in the literature (e.g., Floss et al. 1983, Samaras et al. 1991, Brandl and Adam 1997, Thompson and White 2008, White and Thompson 2008).

RMV provides an indication of the drum behavior (e.g., continuous contact, partial uplift, double jump, rocking motion, and chaotic motion) and is calculated as

\[
RMV = C \cdot \frac{A_{0.5\Omega}}{A_\Omega}
\]

(2)

where \(A_{0.5\Omega}\) is the subharmonic acceleration amplitude caused by jumping.

According to Adam and Kopf (2004), RMV = 0 theoretically indicates that the drum is in a continuous contact or partial uplift mode. When RMV > 0, the drum enters double jump mode and transitions to rocking and chaotic modes. Based on numerical studies, Adam (1997) showed that as the soil stiffness increases CMV increases almost linearly for the roller drum in a continuous or partial uplift mode. With increasing soil stiffness, the drum behavior transitions to double jump mode where RMV increases and CMV decreases rapidly. With further increase in ground stiffness, CMV decreases to a minimum value and then increases again. This relationship between drum operation mode, RMV, and ground stiffness is identified as a distinctive feature of CMV (Adam 1997 and Sandström 1994).
CMV measurements must therefore be interpreted in conjunction with the RMV measurements. Although this effect has been identified by several researchers, to the authors’ knowledge, it has lacked attention in the literature concerning specification/quality assurance criteria (data analysis using RMV measurements is presented in Case Study II later in this paper). New developments in RICM technology with variable feedback control systems, referred to as intelligent compaction (IC) help control the drum behavior to prevent double jump by automatically adjusting the frequency and/or amplitude of vibration (Adam and Kopf 2004).

MDP is a machine power-based technology that monitors and empirically relates mechanical performance of the roller during compaction to the properties of the compacted soil. It is calculated as

\[
MDP = P_g - WV \left( \sin \theta + \frac{A'}{g} \right) - (mV + b)
\]  

(3)

where \( P_g \) is the gross power needed to move the machine (kJ/s), \( W \) is the roller weight (kN), \( A' \) is the machine acceleration (m/s²), \( g \) is the acceleration of gravity (m/s²), \( \theta \) is the slope angle (roller pitch), \( V \) is the roller velocity (m/s), and \( m \) (kJ/m) and \( b \) (kJ/s) are machine internal loss coefficients specific to a particular machine. The use of roller machine power for indicating soil compaction is documented in the literature (e.g., White et al. 2005, White et al. 2006, Thompson and White 2008). MDP measurements can be made in static or vibratory mode.

The two rollers used in the case studies presented in this paper were equipped with a GPS system to spatially reference the RICM measurements. The mapped data is viewed in real time using an on-board compaction monitor.

**Geostatistical Analysis**

Geostatistics characterize and quantify spatial variability. The semivariogram \( \gamma(h) \) is a common analysis tool to describe spatial relationships in many earth science applications and is defined as one-half of the average squared differences between data values that are separated at a distance \( h \) (Isaaks and Srivastava 1989). If this calculation is repeated for as many different values of \( h \) as the sample data will support, the result can be graphically presented as shown in Fig. 1 (shown as circles), which constitutes
the experimental semivariogram plot. The mathematical expression to estimate the experimental semivariogram is

\[
\hat{\gamma}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(x_i + h) - z(x_i)]^2
\]

where \(z(x_i)\) is a measurement taken at location \(x_i\), \(n(h)\) is the number of data pairs \(h\) units apart in the direction of the vector, and \(\hat{\gamma}\) is an experimental estimate of the underlying variogram function \(\gamma\) (Olea, 2006).

The three main characteristics by which a semivariogram plot is often summarized include the following (Issaks and Srivastava 1989):

- **Range** \((a)\): As the separation distance between pairs increase, the corresponding semivariogram value will also generally increase. Eventually, however, an increase in the distance no longer causes a corresponding increase in the semivariogram and the semivariogram reaches a plateau. The distance at which the semivariogram reaches this plateau is called the **range**. Longer range values suggest greater spatial continuity or relatively larger (more spatially coherent) “hot spots”.

- **Sill** \((C_0+C)\): The plateau that the semivariogram reaches at the range is called the **sill**. A semivariogram (which is one-half of the variogram) generally has a sill that is approximately equal to the variance of the data (Srivastava 1996).

- **Nugget Effect** \((C_0)\): Though the value of the semivariogram at \(h = 0\) is strictly zero, several factors, such as sampling error and very short scale variability, may cause sample values separated by extremely short distances to be quite dissimilar. This causes a discontinuity at the origin of the semivariogram called the **nugget effect**.

Some important points to note are that a semivariogram model is stable only if the measurement values are stationary over an aerial extent. If the data values are non-stationary, spatial variability should be modeled only after appropriate transformation of the data (Clark and Harper 2002). If the values show
a systematic trend, this trend must be modeled and removed prior to modeling a semivariogram (Gringarten and Deutsch 2001). An example with polynomial trend surface analysis is presented later in this paper.

In addition to quantifying spatial variability, geostatistics can be used as a spatial prediction technique, i.e., for predicting a value at unsampled locations based on values at sampled locations. Kriging is a stochastic interpolation procedure (Kriges 1951) by which the variance of the difference between the predicted and “true” values is minimized using a semivariogram model. Kriging was used to create “smoothed” contour maps of RICM point data for analysis of non-uniformity and comparison to maps of different in-situ spot test measurement values. Results from Kriging are discussed later in this paper.

Fitting a Theoretical Model

The major purpose of fitting a theoretical model to the experimental semivariogram is to give an algebraic formula for the relationship between values at specified distances. There are many possible models to fit an experimental semivariogram. Some commonly used models include linear, spherical, exponential, and Gaussian models. Mathematical expressions for these models are presented in Table 1. Detailed descriptions of these theoretical models can be found elsewhere in the literature (e.g., Isaaks and Srivastava 1989, Clark and Harper 2002).

The range in a spherical model is well defined because it has a definitive sill. This is not true for exponential or Gaussian models that have asymptotic sills. The approximate range for these models is three to five times larger than the range values obtained for closely matched spherical models (Clark and Harper 2002). Some researchers have used $3\sigma$ as an effective range for the exponential semivariogram (e.g., Erickson et al. 2005).

CASE STUDIES

Roller-integrated compaction measurements obtained from two case studies were analyzed using geostatistical methods and are presented in this section. Exponential models were found to fit well with most of the experimental semivariograms, while spherical models fit less frequently. For purposes of
comparing datasets, only exponential models were fit to the experimental semivariograms discussed in this paper. Models were checked for “goodness” using the modified Cressie goodness of fit method suggested by Clark and Harper (2002), and a cross-validation process. The nugget effect was modeled using the variance of the measured value from the nearest neighbor statistics as the upper bound of the nugget value. The best fit model was selected based on a combination of best possible Cressie goodness factor and cross-validation results.

**Case Study I**

The test area was selected to include three different layered subsurface conditions: (1) compacted sandy lean clay subgrade (CL), (2) compacted gravelly sand subbase material (SW-SM) underlain by the sandy lean clay subgrade, and (3) scarified/uncompacted gravelly sand subbase material underlain by the sandy lean clay subgrade (see Fig. 2). Index properties of these two soil types are summarized in Table 2. The section with subbase material was originally compacted using several roller passes to create a stable platform. A portion of this section adjacent to the subgrade was scarified to approximately 200 to 250 mm to create a loose condition and differences in the compaction measurements. The test area was intentionally prepared with non-stationary conditions to demonstrate the influence of such conditions on semivariogram modeling.

The CS 533E smooth drum roller was used to map the test area in eight parallel roller lanes. CMV and MDP output from the roller are presented in Fig. 3. The roller was operated using amplitude = 2.0 mm and frequency = 27 Hz nominal settings. After mapping the test area, in-situ compaction tests were performed using a dynamic cone penetrometer (DCP) and 200-mm plate Zorn light weight deflectometer (LWD). The 144 test locations are shown on Fig. 2(b). DCP tests were performed in accordance with ASTM D6951 to determine DCP index (DCPI). LWD tests were performed following manufacturer recommendations (Zorn 2003) to determine elastic modulus (E_{LWD}). The spot tests were positioned such that the boundaries of non-stationary conditions (i.e., different subsurface conditions) were captured in the semivariogram modeling and interpolation process.
A frequency distribution plot and the semivariogram results for the CMV measurements are presented in Fig. 4. The frequency distribution is skewed to the right, and the semivariogram plot shows increasing variance above the theoretical sill, which based on the actual sample variance is approximately 95. The findings from Fig. 4(a) are generally indicators of non-stationarity and trend (Gringarten and Deutsch 2001) in the CMV values. However, the semivariogram does not indicate the form of the trend. A polynomial trend surface analysis, common to geological applications (e.g., Whitten 1963), was selected to remove the trend before modeling a semivariogram. This analysis assumes that the measured value is made up of a “trend” component, which is represented by a polynomial function of X and Y (spatial coordinates), and a residual or error component, \( \varepsilon \) (Clark and Harper 2002). The trend is modeled using linear (Eq. (6)), quadratic (Eq. (7)), or cubic models (Eq. (8)). The best fit model was determined using the method of least squares.

\[
g_i = b_0 + b_1X_i + b_2Y_i + \varepsilon_i \quad (6)
\]

\[
g_i = b_0 + b_1X_i + b_2Y_i + b_3X_i^2 + b_4X_iY_i + b_5Y_i^2 + \varepsilon_i \quad (7)
\]

\[
g_i = b_0 + b_1X_i + b_2Y_i + b_3X_i^2 + b_4X_iY_i + b_5Y_i^2 + b_6X_i^3 + b_7X_i^2Y_i + b_8XY_i^2 + b_9XY_i + b_10Y_i^3 + \varepsilon_i \quad (8)
\]

If the trend is removed successfully, the residual values, \( \varepsilon \), of the analysis parameter after detrending should be spatially stationary (Clark and Harper 2002). Analysis of variance (ANOVA) results were used to help judge the suitability of a representative least squares fit from the polynomial trend surface analysis. The higher F ratio statistic of the quadratic trend surface indicated greater significance than linear and cubic trend surfaces. The CMV residuals after quadratic detrending approximate a normal distribution, and the semivariogram plot (Fig. 4(b)) shows a clear spatial structure with well-defined sill and range. Similar polynomial trend surface analysis was used for the roller measurement value MDP and in-situ compaction test measurements DCP (blows/200mm) and \( E_{LWD} \) in developing distribution plots and semivariogram models (Fig. 5). The MDP, DCP, and \( E_{LWD} \) values exhibited a quadratic trend similar to the CMV. Using the semivariogram models, kriged contour surface
maps of roller-integrated measurement values and in-situ spot test measurements were created, as shown in Fig. 6.

Of the two roller-integrated compaction measurement values, CMV presented longer spatial continuity \((a = 2\, \text{m})\) compared to MDP \((a = 0.5\, \text{m})\). Also, MDP values showed greater short-scale variability than CMV, as evidenced by the nugget effect present in the MDP semivariogram model (Fig. 5(a)). The reason for this difference can be attributed to the influence depths of the two measurement values and the influence of the rear tires for MDP. MDP, which is a measure of rolling resistance and sinkage of the drum and rear tires combined, may be heavily affected by surficial characteristics of the compacting soil (White et al. 2007a), while CMV is a measure of dynamic roller drum-ground interaction that can be influenced by soil characteristics below the compaction layer. Reportedly, the measurement influence depths for smooth drum vibratory rollers range from 0.4 to 0.6 m for a 2-ton roller to 0.8 to 1.5 m for a 12-ton roller (ISSMGE 2005).

The de-trended semivariograms of DCP (Fig. 5(b)) and \(E_{\text{LWD}}\) (Fig. 5(c)) showed reasonable spatial structure but with more scatter than CMV or MDP. The kriged contour plots of DCPI and \(E_{\text{LWD}}\) showed comparable spatial distributions with CMV (Fig. 6). Some differences should be expected as the DCP values are averaged for the upper 200 mm, and the LWD measurements are taken at the surface. The LWD measurements have a measurement influence depth approximately equal to one plate diameter (Sulewska 1998), which in this case was 200 mm.

**Case Study II**

This case study was conducted at the TH 64 reconstruction project located south of Akeley, Minnesota, USA. The CS-563E smooth drum IC roller was used at the project site. The roller was operated using amplitude = 2.0 mm and frequency = 31 Hz nominal settings. Roller-integrated CMV was used as the primary quality control measurement during the earthwork compaction process (White et al. 2008a). Calibration strips were constructed prior to production compaction for several soil types and fill sections encountered at the project. Target values (referred to as IC-TVs) were established from these calibration strips and used as reference for quality control in the production areas. The criterion for
acceptance in the production area was that at least 90% of the proof area must be between 90% and 130% of the IC-TV. If a significant portion of the area exceeded 130% of the IC-TV, the project engineer re-evaluated the use of an appropriate calibration strip. Index properties of the fill material are summarized in Table 2. Two calibration strips and a proof area were analyzed using geostatistics and are described in the following subsections.

**Analysis of Calibration Strips**

Subsurface conditions for calibration strip 1 consisted of approximately 0.25-m thick fill layer placed over previously compacted fill material. The fill layer was compacted using seven roller passes in three adjacent lanes. Calibration strip 2 consisted of 0.25-m thick fill material placed over natural subgrade and was compacted using eleven roller passes in six adjacent lanes. Both strips were oriented in the north-south direction. A summary of spatial and univariate statistics and comparison to the quality assurance criteria are presented in Table 3. Sill and range values for omnidirectional semivariograms and directional semivariograms with orientation in the roller direction (north-south, N-S) and perpendicular to the rolling lanes (east-west, E-W) are also presented in Table 3.

Analysis of directional semivariograms can help determine principal directions of anisotropy in the data. Results show that the sill values in the E-W direction were consistently lower than in the N-S direction, which indicates less variability in the E-W direction. Longer range values were observed in the N-S direction semivariogram, which suggests greater spatial continuity along the direction of roller travel than in the transverse direction. Comparison between the omnidirectional and N-S directional semivariogram statistics from the two calibration strips did not reveal significant differences in their spatial statistics. This is expected, as the omnidirectional semivariograms are composed of more data that is oriented in the N-S direction than in the E-W direction. Because the compaction was performed in only 3 or 6 adjacent lanes, only a limited number of data points were available to construct the E-W directional semivariograms. This was true for all other areas of production compaction for this project and is typical of road construction projects. The omnidirectional semivariograms account for data in all directions, and
as long as the semivariogram presented a clearly interpretable structure, it did not appear critical to model anisotropy in the semivariogram analysis for this project. Nevertheless, the difference between the N-S and E-W semivariograms is to be expected due to the spatial nonsymmetry of the measurements as the values are located at points in the N-S direction but are integrated over the roller length in the E-W direction.

A summary of the changes in the univariate and spatial statistics for calibration strip 1 as a function of roller passes is presented in Fig. 7(a). The mean CMV increased from approximately 41 to 48, and the coefficient of variation (COV) decreased from approximately 17% to 12% with increasing roller passes. The percentage of CMV values in the 90% to 130% bin for the project acceptance criteria increased from about 71% to 89% (see Table 3), indicating increased compaction and decreased variability of CMV from pass 2 to 7. The sill value for all semivariograms (omnidirectional, N-S, and E-W) generally decreased with increasing roller passes, thus indicating increasing uniformity. No significant changes in range values were observed.

A summary of the changes in the univariate and spatial statistics for calibration strip 2 as a function of roller passes is presented in Fig. 7(b). The mean CMV increased slightly from about 61 to 66, and COV decreased from about 17% to 11% from passes 2 to 11. The percentage of CMV values in the 90% to 130% bin increased from about 75% to 93% (see Table 3), which is an indication of decreasing variability and increasing compaction. No definite trend in sill was observed with increasing roller passes. However, the range value showed a strong second-order polynomial trend with $R^2$ of 0.75. Increasing range with increasing roller passes indicates increasing spatial continuity in the CMV.

**Analysis of Proof Area**

The subgrade conditions in the proof area consisted of fill material varying from about 0.4 m to 1.2 m in thickness, underlain by native sand. Compaction operations were performed longitudinally in the N-S direction, along six adjacent lanes. The CMV target value of 42 established from calibration strip 1 was used as a reference for acceptance in this proof area.
Semivariograms and CMV/RMV kriged contour maps for the proof area, along with comparison to calibration strip 1, are presented in Fig. 8. The influence of RMV on CMV was discussed earlier in the background section of the paper. A review of CMV-RMV data from the proof area indicated that when CMV approached about 60, the RMV increased and consequently the CMV decreased indicating a transition in drum behavior from partial uplift to double jump mode. Although double jump mode is theoretically defined as RMV > 0 (Adam and Kopf 2004), based on the spatial distribution of RMV in the proof area (Fig. 8), a value of RMV > 2 was considered a practical cutoff value for further analysis. In areas with RMV > 2, the CMV measurements were assigned a value of 60 as an indication of stiff ground conditions and no additional need for compaction. The CMV kriged contour maps in Fig. 8 show both actual and filtered/modified measurements.

Comparison of the univariate statistics of the CMV measurements and acceptance criteria is presented in Fig. 8. Results indicate that this proof area “passed” the quality acceptance criterion of achieving 90% of IC-TV in 90% of the evaluated area. However, if spatial statistics between the proof and the calibration strip are compared, the proof area failed to achieve the “sill” and “range” values achieved in the referenced calibration strip. The production area consisted of localized areas of soft ground conditions or “hot spots” that have CMV < 30, especially along the centerline of the alignment. These locations generally match with the locations of grade stakes in the field and were not subjected to construction traffic like the outside lines. Although the proof area meets the acceptance criteria specified for the project based on average values, geostatistical spatial analysis reveals localized areas that perhaps could benefit from additional compaction to improve spatial uniformity.

Fig. 9 illustrates a mathematical exercise to select localized areas within the proof area to target for additional compaction or other treatment that would contribute to improved uniformity. The area shown in Fig. 9 is a section from the proof area about 94 m long, which is of similar length to the calibration strip. Ideally, any given portion of the production area with dimensions equal to that of the calibration area should meet the spatial statistics established from the calibration. This means that the sill values in the production area should be equal to or lower than the sill values achieved in the calibration.
area and likewise the range values in the production area should be equal to or higher than the range values achieved in the calibration area. Kriged surface maps of the original and mathematically adjusted CMV data are presented in Fig. 9. For this exercise, CMV data was adjusted to one of the following: CMV < 45 = 45, CMV < 48 = 48, or CMV M 52 = 52. The semivariograms associated with each adjusted CMV data set are presented in Fig. 9 along with the semivariogram of the calibration strip. Comparatively, the semivariogram for the CMV < 48 = 48 adjusted dataset with sill = 29 closely follows the semivariogram of the target calibration strip with sill = 30. The semivariogram of the CMV < 52 = 52 adjusted dataset shows greater uniformity with a lower sill value, relative to the calibration strip, which would exceed the baseline uniformity criteria established from the calibration strip.

This approach combined with correction of CMV measurements in areas with high RMV provides an optimized solution to target areas that need additional compaction. It also provides quantitative parameters to establish uniformity based on spatial statistics criteria. Geostatistical analysis and spatially referenced roller-integrated compaction monitoring represent a paradigm shift in how compaction analysis and specifications could be implemented in the future.

CONCLUDING REMARKS

Geostatistical analysis using semivariogram modeling provides a unique opportunity to characterize and quantify non-uniformity of compacted earth fill materials, which is often considered a key element for geotechnical structures like pavements. Geostatistical analysis and spatially referenced roller-integrated compaction monitoring represent a paradigm shift in how compaction analysis and specifications could be implemented in the future. However, there are some important steps during semivariogram modeling that need particular attention. These include: (a) performing exploratory data analysis to examine the distribution and assess the need for transformation, (b) determining non-stationarity in the data that may require polynomial trend surface analysis, (c) modeling anisotropy (directional semivariograms herein showed that this is generally not an issue because of limited data points in the transverse direction), and (d) understanding and exercising the semivariogram model fitting process. This paper provided two case study examples that emphasized these issues during
semivariogram modeling. If automated, the described use of geostatistics could aid the contractor in identifying localized, poorly compacted areas or areas with highly non-uniform conditions that need additional compaction or other modification and would contribute to improved uniformity. This information could also be used to target quality assurance testing by the field engineers.

ACKNOWLEDGMENTS

The authors would like to acknowledge to support of the Minnesota Department of Transportation (Mn/DOT), the Federal Highway Administration (FHWA), and Caterpillar Inc. (CAT) for funding these studies. Numerous people from Mn/DOT provided assistance in identifying and providing access to grading projects. John Siekmeier and Ruth Roberson from Mn/DOT and several Mn/DOT field engineers provided assistance in organizing the compaction data. The authors would like to thank Mark Thompson, Heath Gieselman, Michael Kruse, Amy Heurung, and Michael Blahut at Iowa State University and Paul Corcoran, Tom Congdon, Donald Hutchen, Allen Declerk, and Glen Feather at CAT for providing assistance with the field and lab testing.
NOTATIONS

\[ A' = \text{Machine acceleration} \]
\[ a = \text{Range of influence (semi-variogram)} \]
\[ A_\Omega = \text{Acceleration of the fundamental component of the vibration} \]
\[ A_{2\Omega} = \text{Acceleration of the first harmonic component of the vibration} \]
\[ b = \text{machine internal loss coefficient specific to a particular machine} \]
\[ C_0 + C = \text{Sill (semi-variogram)} \]
\[ C_0 = \text{Nugget effect (semi-variogram)} \]
\[ COV = \text{Coefficient of variation} \]
\[ CMV = \text{Compaction meter value} \]
\[ DCPI = \text{Dynamic cone penetration index} \]
\[ E_{LWD} = \text{Elastic modulus determined by the light weight Deflectometer} \]
\[ g = \text{Acceleration due to gravity} \]
\[ h = \text{Lag or separation distance} \]
\[ IC-TV = \text{Roller compaction target value} \]
\[ m = \text{Machine internal loss coefficient specific to a particular machine} \]
\[ MDP = \text{Machine drive power} \]
\[ P_g = \text{Gross power needed to move the machine} \]
\[ V = \text{Roller velocity} \]
\[ W = \text{Weight of the roller} \]
\[ \mu = \text{Statistical mean} \]
\[ \sigma = \text{Standard deviation} \]
\[ \theta = \text{Slope angle (roller pitch)} \]
\[ \hat{\gamma} = \text{Experimental estimate of the underlying variogram function} \]

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TABLE 1. Commonly used theoretical semivariogram models (158 words)

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Mathematical Expression</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>$\gamma(0) = 0$</td>
</tr>
<tr>
<td></td>
<td>$\gamma(h) = nC_0 + ph$, when $h &gt; 0$</td>
</tr>
<tr>
<td></td>
<td>$\gamma(0) = 0$</td>
</tr>
<tr>
<td>Spherical</td>
<td>$\gamma(h) = C_0 + C \left[ \frac{3h - h^3}{2a - 2a^3} \right]$ when $0 &lt; h &lt; a$</td>
</tr>
<tr>
<td></td>
<td>$\gamma(h) = C_0 + C$ when $h &gt; a$</td>
</tr>
<tr>
<td></td>
<td>$\gamma(0) = 0$</td>
</tr>
<tr>
<td>Exponential</td>
<td>$\gamma(h) = C_0 + C \left[ 1 - \exp \left( -\frac{h}{a} \right) \right]$ when $h &gt; 0$</td>
</tr>
<tr>
<td>Gaussian</td>
<td>$\gamma(0) = 0$</td>
</tr>
<tr>
<td></td>
<td>$\gamma(h) = C_0 + C \left[ 1 - \exp \left( -\frac{h^2}{a^2} \right) \right]$ when $h &gt; 0$</td>
</tr>
</tbody>
</table>

$p$ = slope of the line
$a$ = range
$C_0$ = nugget effect
$C + C_0$ = sill
<table>
<thead>
<tr>
<th>Soil property</th>
<th>Fill materials</th>
<th>Case study I</th>
<th>Case study II</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unified Soil Classification (USCS)</td>
<td>SW-SM</td>
<td>CL</td>
<td>SP</td>
</tr>
<tr>
<td>AASHTO Classification</td>
<td>A-1-b</td>
<td>A-6</td>
<td>A-3</td>
</tr>
<tr>
<td>Gravel size (%) ( &gt; 4.75mm)</td>
<td>29.5</td>
<td>3.1</td>
<td>4.0</td>
</tr>
<tr>
<td>Sand size (%) (4.75 to 0.075mm)</td>
<td>61.0</td>
<td>28.9</td>
<td>93.0</td>
</tr>
<tr>
<td>Silt + Clay size (%) (&lt; 0.075 mm)</td>
<td>9.5</td>
<td>68.0</td>
<td>3.0</td>
</tr>
<tr>
<td>Liquid Limit, LL (%)</td>
<td>non-plastic</td>
<td>29</td>
<td>non-plastic</td>
</tr>
<tr>
<td>Plasticity Index, PI (%)</td>
<td>non-plastic</td>
<td>12</td>
<td>non-plastic</td>
</tr>
<tr>
<td>Optimum moisture content, (w_{opt}) (%) (ASTM D 698)</td>
<td>8.0</td>
<td>13.0</td>
<td>11.8</td>
</tr>
<tr>
<td>Maximum dry unit weight, (\gamma_{dmax}) (kN/m³) (ASTM D 698)</td>
<td>21.40</td>
<td>18.40</td>
<td>17.83</td>
</tr>
</tbody>
</table>
### TABLE 3. Comparison of spatial and univariate statistics of CMV with quality assurance criteria for calibration strips – case study II (630 words)

<table>
<thead>
<tr>
<th>Strip</th>
<th>IC-TV</th>
<th>Pass</th>
<th>Univariate Statistics of CMV</th>
<th>Spatial Statistics of CMV</th>
<th>QA Criteria (Percent of IC-TV)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Omni-Directional</td>
<td>North - South</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$\mu$ (m)</td>
<td>$\sigma$ (m)</td>
<td>C+C$_0$ (CMV)</td>
</tr>
<tr>
<td>2</td>
<td>41.0</td>
<td>6.9</td>
<td>5.0</td>
<td>45.0</td>
<td>5.0</td>
</tr>
<tr>
<td>3</td>
<td>42.6</td>
<td>6.2</td>
<td>5.0</td>
<td>38.0</td>
<td>5.0</td>
</tr>
<tr>
<td>1</td>
<td>42</td>
<td>42</td>
<td>5.0</td>
<td>36.0</td>
<td>5.0</td>
</tr>
<tr>
<td>4</td>
<td>45.9</td>
<td>6.3</td>
<td>5.0</td>
<td>38.0</td>
<td>5.0</td>
</tr>
<tr>
<td>6</td>
<td>47.6</td>
<td>5.6</td>
<td>6.0</td>
<td>30.0</td>
<td>6.0</td>
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<tr>
<td>7</td>
<td>45.4</td>
<td>7.8</td>
<td>4.5</td>
<td>91.0</td>
<td>5.5</td>
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<tr>
<td>8</td>
<td>60.8</td>
<td>9.8</td>
<td>8.0</td>
<td>105.0</td>
<td>7.0</td>
</tr>
<tr>
<td>4</td>
<td>64.1</td>
<td>7.8</td>
<td>4.5</td>
<td>62.0</td>
<td>4.5</td>
</tr>
<tr>
<td>5</td>
<td>64.2</td>
<td>7.6</td>
<td>10.0</td>
<td>74.0</td>
<td>11.0</td>
</tr>
<tr>
<td>6</td>
<td>64.1</td>
<td>7.7</td>
<td>9.0</td>
<td>71.0</td>
<td>10.0</td>
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<tr>
<td>7</td>
<td>67.9</td>
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<td>9.2</td>
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<td>9</td>
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<tr>
<td>10</td>
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<td>8.4</td>
<td>11.0</td>
<td>94.0</td>
<td>11.0</td>
</tr>
<tr>
<td>11</td>
<td>65.9</td>
<td>7.4</td>
<td>12.0</td>
<td>80.0</td>
<td>12.0</td>
</tr>
</tbody>
</table>
Fig. 2

(a) Compacted Subbase  Scarified ~ 200 mm Subbase  Compacted Subgrade

(b) Longitudinal Distance (m)

Compacted Subbase
Scarified Subbase
Compacted Subgrade

Transverse Distance (m)
Fig. 4

(a) Histogram of CMV vs. frequency and semivariogram with separation distance.

(b) CMV residuals with quadratic detrend and exponential variogram with parameters: $a = 2$, $C_0 = 0$, $C + C_0 = 15$. 

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Fig. 5

(a) MDP (KJ/s) Residuals Quadratic Detrend

- $\mu = 0.0$
- $\sigma = 5.0$

- Experimental Variogram
- Exponential Variogram
- $a = 0.5$
- $C_0 = 4$
- $C + C_0 = 33$

(b) DCP (Blows/200mm) Residuals Quadratic Detrend

- $\mu = 0.0$
- $\sigma = 3.1$

- Experimental Variogram
- Exponential Variogram
- $a = 1.5$
- $C_0 = 3$
- $C + C_0 = 10$

(c) $E_{LWD-Z2(83)}$ (MPa) Residuals Quadratic Detrend

- $\mu = 0.0$
- $\sigma = 16.7$

- Experimental Variogram
- Exponential Variogram
- $a = 1.5$
- $C_0 = 3$
- $C + C_0 = 10$
Fig. 6
Fig. 7

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