QUANTIFICATION OF SOIL RANDOM ROUGHNESS AND SURFACE DEPRESSION STORAGE: METHODS, APPLICABILITY, AND LIMITATIONS

X. Chu, J. Yang, Y. Chi

ABSTRACT. *Soil surface microtopography controls surface runoff, infiltration, and other hydrologic processes by storing water in depressions, changing flow directions and accumulations, and even altering the entire drainage system. Studies have been conducted to characterize surface microrelief and quantify surface depression storage. Various indices have been proposed to quantify soil surface roughness, and some indices have been further used to estimate maximum depression storage (MDS). Random roughness (RR) has been one of the widely used indices for estimating MDS over the past four decades. However, there have been some confusions and controversies on the data processing procedures and computation methods associated with the RR index-based approach. The focus of this study is on evaluating the performance and applicability of the RR index-based approach that incorporates four different data processing procedures for a series of microtopographic surfaces. It is demonstrated that selecting proper data processing procedures is critical and helpful to improve the estimation of RR and MDS. Particularly, removal of oriented roughness (slope and tillage marks) is a necessary data processing procedure. For a real soil surface, the relationship of MDS and slope is nonlinear and the changing pattern of MDS with RR varies, depending on the surface microtopographic conditions. In addition, the mean upslope depression (MUD) method is applied to estimate MDS for tillage surfaces. It has been found that the RR index-based approach is better suited for gentle sloping surfaces, while the MUD index method is able to provide improved estimation of MDS for steeper slopes.*

Keywords. *DEM, Depression storage, Microtopography, Random roughness, Surface delineation.*

Surface topography plays an important role in a series of hydrologic and transport processes. Topography can dominate the mechanism of overland flow generation, change the spatial and temporal variability of rainfall-infiltration-runoff processes, alter soil erosion and the associated sediment transport, and affect the fate and transport of nonpoint-source pollutants (Chu, 2011). Land surfaces are generally characterized with various topographic features, such as depressions, mounds, ridges, and channels. Surface depression storage is one of the major variables considered in hydrologic analysis. However, depression storage is often estimated indirectly and treated as a constant in many hydrologic models. An improved estimation of depression storage can be critical to watershed hydrologic and environmental modeling.

Digital elevation models (DEMs) are often used to quantify surface topography. A variety of numerical methods have been developed to calculate surface depression storage from raster DEM data (e.g., Mitchell and Jones, 1976; Moore and Larson, 1979; Ullah and Dickinson, 1979; Onstad, 1984). Such methods take full advantage of the grid data in the computation of maximum depression storage (MDS) (Huang and Bradford, 1990; Hairsine et al., 1991; Planchon et al., 2001; Chu et al., 2010). However, the available DEM data often have relatively low resolution (i.e., large grid sizes, such as 90, 30, or 10 m) and are suitable for larger-scale areas (watersheds). For small field plots, high-resolution DEM data may not be available. Alternative methods have been developed for estimating MDS based on soil surface roughness indices, such as random roughness (RR).

Quantification of soil surface roughness is essential to water and soil management, especially for agricultural fields. Soil surface roughness can be categorized into four types (Römkens and Wang, 1986): (1) microrelief variations determined by individual soil grains and aggregates, (2) random roughness related to cloddiness, (3) oriented roughness characterized by systematic elevation variations from tillage, and (4) higher-order, larger-scale (field or basin scale) roughness. Over the last several decades, a variety of microrelief meters have been developed to quantify soil surface roughness and obtain high-resolution DEMs. Depending on the design, a microrelief meter can be a contact or non-contact one. Most early microrelief meters were designed for contact measurements (e.g., Kuipers, 1957; Burwell et al., 1963; Allmaras et al., 1966; Currence and Lovely, 1970; Curtis and Cole, 1972; Mitchell and Jones,

Submitted for review in April 2011 as manuscript number SW 9153; approved for publication by the Soil & Water Division of ASABE in July 2012.

The authors are **Xuefeng Chu,** Assistant Professor, **Jun Yang,** Graduate Student, and **Yaping Chi,** Graduate Student, Department of Civil Engineering, North Dakota State University, Fargo, North Dakota. **Corresponding author:** Xuefeng Chu, Department of Civil Engineering (Dept. 2470), North Dakota State University, P.O. Box 6050, Fargo, ND 58108-6050; phone: 701-231-9758; e-mail: xuefeng.chu@ndsu.edu.

1973; Moore and Larson, 1979; Radke et al., 1981; Podmore and Huggins, 1981). Since the 1980s, automated non-contact microrelief meters have been developed (e.g., Römkens et al., 1986; Huang et al., 1988). An instantaneous-profile laser scanner (Huang et al., 1988; Huang and Bradford, 1990, 1992; Darboux and Huang, 2003) was used in this study to measure soil surface microtopography and acquire high-resolution DEMs.

Different indices have been proposed to characterize surface variations and quantify soil surface roughness using DEMs (Kamphorst et al., 2000). The indices include RR (Allmaras et al., 1966), which has been most widely used, and several others, such as tortuosity (Boiffin, 1984), microrelief index and peak frequency (Römkens and Wang, 1986), limiting elevation difference and slope (Linden and Van Doren, 1986), mean upslope depression (MUD) (Hansen et al., 1999), and fractal indices (fractal dimension and crossover length) (Huang and Bradford, 1992). Many studies also have been conducted to relate the roughness indices to MDS of soil surfaces (Kamphorst et al., 2000). Various regression equations have been developed to estimate MDS based on surface roughness indices such as RR (Onstad, 1984), limiting elevation difference and slope (Linden et al., 1988), and MUD (Hansen et al., 1999). The capability, performance, and usefulness of these indices for quantifying soil surface roughness, estimating MDS, and describing surface changes from rainfall-induced soil erosion have been examined and evaluated (Bertuzzi et al., 1990; Huang and Bradford, 1992; Hansen et al., 1999; Kamphorst et al., 2000; Govers et al., 2000).

Surface slope (SL) is another factor that needs to be taken into account in the RR index-based approach for estimating MDS. Thus, slope steepness has also been included in most regression equations. Onstad (1984) developed a regression equation that related MDS to RR and SL based on microrelief data from over 1000 plots for slopes up to 12%. Since then, the equation has been widely used for estimation of MDS. Mwendera and Feyen (1992) derived a similar regression equation of MDS as a function of RR and SL for surfaces with slopes from 1% to 15%. Hansen et al. (1999) calculated MDS for 640 data sets with slopes from 1% to 20%. It has been found that surfaces with higher RR generally have greater MDS values for the same slope (Onstad, 1984; Mwendera and Feyen, 1992; Kamphorst et al., 2000). For a rough soil surface, a milder slope retains more water in depressions than a steeper slope does (Moore and Larson, 1979; Ullah and Dickinson, 1979; Onstad, 1984; Huang and Bradford, 1990; Hairsine et al., 1991; Mwendera and Feyen, 1992; Kamphorst et al., 2000).

The aforementioned approaches provide a simple and useful way to estimate surface depression storage based on soil surface roughness indices. For example, the RR index-based approach requires only two parameters (RR and SL), which are very easy to obtain either directly from field measurements or indirectly from empirical data. However, there have been some confusions and controversies in practical applications of the RR index-based approach over the last several decades (Zobeck and Onstad, 1987; Hansen et al., 1999; Kamphorst et al., 2000; Planchon et al., 2001). The confusions are primarily associated with the RR computation methods and the four major data processing procedures (Allmaras et al., 1966), including (A) logarithm transformation of original DEM data, (B) removal of the slope effect, (C) removal of the tillage effect, and (D) removal of the upper and lower 10% extreme data points. Although RR has been widely used for estimating MDS, there is no agreement on the RR computation procedure (Bertuzzi et al., 1990). Statistically, the definition of RR implies that the surface elevation data should possess a normal distribution. Allmaras et al. (1966) indicated that logarithm transformation was necessary to improve the data distribution and achieve nearly normally distributed data. However, Linden and Van Doren (1986) found that, for some data sets, the improvement from logarithm transformation was limited, and they emphasized the non-normal characteristics of microrelief data. In applications of the original approach (Allmaras et al., 1966) to calculate RR, some researchers did not implement logarithm transformation, remove the slope and tillage effects (oriented roughness), and/or eliminate the upper and lower 10% extreme data points (Zobeck and Onstad, 1987; Hansen et al., 1999). A fundamental question is how these four data processing procedures (A to D) affect the computation of RR. Few studies have been performed to systematically examine the impacts of these data processing procedures on the computed RR and further evaluate the influence on estimating MDS based on the RR value.

The objectives of this study are to: (1) examine four data processing procedures (A. logarithm transformation, B. removal of the slope effect, C. removal of the tillage effect, and D. removal of the upper and lower 10% extreme data points) and their impacts on the computation of RR and MDS; (2) further evaluate the performance of the RR index-based approach for estimation of MDS by comparing it with a puddle delineation (PD) program that characterizes surface microtopography (Chu et al., 2010); and (3) examine the relationships of MDS with RR and SL, and identify application conditions of the RR index-based approach. In addition, the MUD method is applied to estimate MDS for tillage surfaces, and the results are compared with those from the PD program and the RR methods.

Materials and Methods

Data Processing Procedures

As stated in the preceding review, four procedures (A to D) are often implemented to process original DEM data in the computation of RR (Allmaras et al., 1966). The four data processing procedures and the related computation details are summarized as follows:

Procedure A: Logarithm Transformation

$$Z'_{i,j} = Ln(Z_{i,j}) \tag{1}$$

where $Z_{i,j}$ is the original elevation at row i and column j, and $Z'_{i,j}$ is the processed elevation at row i and column j.

Procedure B: Slope Correction

Assuming that the overall slope of a surface is along the

y direction (column), the slope effect can be removed by:

$$Z'_{i,j} = Z_{i,j} - (\overline{Z}_i - \overline{Z}_{i,j}) \quad (2)$$

in which

$$\overline{Z}_i = \frac{1}{N_j} \sum_{j=1}^{N_j} Z_{i,j} \quad (3)$$

$$\overline{Z}_{i,j} = \frac{1}{N} \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} Z_{i,j} \quad (4)$$

$$N = N_i \times N_j \quad (5)$$

where N_i is the number of rows, N_j is the number of columns, and N is the total number of grids (all data points). Note that this procedure will also remove the effect of x-directional, oriented roughness from tillage. This procedure implies that the method proposed by Allmaras et al. (1966) does not directly address slope.

Procedure C: Tillage Correction

Assuming that the oriented roughness from tillage is along the y direction, the tillage effect can be removed by:

$$Z'_{i,j} = Z_{i,j} - (\overline{Z}_j - \overline{Z}_{i,j}) \quad (6)$$

in which

$$\overline{Z}_j = \frac{1}{N_i} \sum_{i=1}^{N_i} Z_{i,j} \quad (7)$$

Note that this procedure also will remove the x-directional slope effect.

Procedure D: Removal of Upper and Lower 10% Data

This procedure involves sorting the elevation data processed by procedures A to C (from highest to lowest) and deleting the upper and lower 10% extreme data points. Clearly, this procedure will reduce the total number of data points N.

COMPUTATION OF RANDOM ROUGHNESS

DEM data can be processed by using procedures A to D described above. The processed data are then used for computing RR. In this study, a computer program was developed to facilitate the computations. The program allows users to select any combination of the four procedures (A to D) to process their DEM data for computing RR. Without logarithm transformation (procedure A), the RR of a surface can be expressed as the standard deviation (SD) of the processed elevation data:

$$\mathrm{RR} = \mathrm{SD} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \left(Z'_{i,j} - \overline{Z}'_{i,j}\right)^2} \quad (8)$$

in which

$$\overline{Z}'_{i,j} = \frac{1}{N} \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} Z'_{i,j} \quad (9)$$

In addition, random roughness or the standard deviation along any row (x direction) or column (y direction) can also be calculated:

$$\mathrm{RR}X_i = \mathrm{SD}_i = \sqrt{\frac{1}{N_j - 1} \sum_{j=1}^{N_j} \left(z_{i,j} - \overline{z}_i\right)^2} \quad (10)$$

$$\mathrm{RR}Y_j = \mathrm{SD}_j = \sqrt{\frac{1}{N_i - 1} \sum_{i=1}^{N_i} \left(z_{i,j} - \overline{z}_j\right)^2} \quad (11)$$

The mean of random roughness along the x and y directions can be respectively expressed as:

$$\mathrm{RR}X = \frac{1}{N_i} \sum_{i=1}^{N_i} \mathrm{RR}X_i \quad (12)$$

$$\mathrm{RR}Y = \frac{1}{N_j} \sum_{j=1}^{N_j} \mathrm{RR}Y_j \quad (13)$$

In the method developed by Allmaras et al. (1966), all four data processing procedures are implemented by following the order from A to D. Then, RR is given by the product of the standard deviation of the processed data (eq. 8) and the mean of the original elevation data (eq. 4) as follows:

$$\mathrm{RR} = \mathrm{SD} \times \overline{Z}_{i,j} \quad (14)$$

Note that for any RR computation methods with logarithm transformation data processing (procedure A), equation 14 should be used for calculating RR instead of equation 8.

If only procedures B and C (i.e., removal of slope and tillage effects by using equations 2 and 6) are carried out and RR is calculated by equation 8, the processed elevation $Z'_{i,j}$ in equation 8 is given by:

$$\begin{aligned} Z'_{i,j} &= Z_{i,j} - (\overline{Z}_j - \overline{Z}_{i,j}) - (\overline{Z}_i - \overline{Z}_{i,j}) \\ &= Z_{i,j} - \overline{Z}_j - \overline{Z}_i + 2\overline{Z}_{i,j} \end{aligned} \quad (15)$$

The mean of the processed elevation data $\overline{Z}'_{i,j}$ in equation 8 is given by:

$$\begin{aligned} \overline{Z}'_{i,j} &= \frac{1}{N} \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} Z'_{i,j} \\ &= \frac{1}{N_i N_j} \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \left(Z_{i,j} - \overline{Z}_j - \overline{Z}_i + 2\overline{Z}_{i,j}\right) \\ &= \overline{Z}_{i,j} \end{aligned} \quad (16)$$

That is, data processing procedures for removing the slope and tillage effects (procedures B and C) will not change the overall mean value. Using equations 15 and 16, equation 8 can be rewritten as:

$$\mathrm{RR} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N_i}\sum_{j=1}^{N_j}\left(Z_{i,j} - \bar{Z}_j - \bar{Z}_i + \bar{Z}_{i,j}\right)^2} \qquad (17)$$

Equation 17 is actually the same as the one proposed by Planchon et al. (2001).

If there are no slope and tillage effects and the surface variations can be assumed as a random process, RR can be calculated by using equation 8 without any data processing procedures (procedures A to D). If there is no obvious oriented roughness from tillage, only procedure B can be implemented to remove the slope effect.

Computation of Maximum Depression Storage

Based on the calculated RR, the MDS of a rough surface can be estimated. Following Onstad (1984), this RR index-based approach can be expressed as:

$$\mathrm{MDS} = 0.112\mathrm{RR} + 0.031\mathrm{RR}^2 - 0.012\mathrm{RR}\times\mathrm{SL} \qquad (18)$$

where MDS is the maximum depression storage (cm), RR is the random roughness (cm), and SL is the average slope (%). Given a value of RR, equation 18 implies a linear, decreasing relationship between MDS and SL. Note that equation 18 was derived based on slopes up to 12% (Onstad, 1984).

Introduction to the PD Program

The Windows-based PD program used in this study was developed for characterizing surface microtopography and delineating puddles and their relationships (Chu et al., 2010; Chu, 2011). It is also capable of determining flow directions and accumulations, and precisely computing MDS, maximum ponding area (MPA), and contributing area based on DEM data. The algorithm involves identifying the center(s) and threshold(s) of each puddle, searching for all other cells included in the puddle, computing the depression storage of the puddle, computing the MDS and MPA of the entire area, and determining the hierarchical relationships of puddles at different levels. The center(s) and threshold(s) of a puddle are respectively defined as the lowest point(s) or cell(s) surrounded by eight neighboring cells and the pour point(s) at which water overflows the puddle. Puddles that share the same threshold will potentially combine and form a larger puddle. The original and combined puddles are respectively referred to as the first and second level puddles. If a second-level puddle combines with other puddles, a third-level puddle will be formed. In this way, puddles at different levels can be identified. Following the identification of all puddles, the MDS of a surface at the highest level can be expressed as:

$$\mathrm{MDS} = \sum_{i=1}^{n}\sum_{j=1}^{m_i}(Z_{t,i} - Z_{i,j})\Delta x\Delta y \qquad (19)$$

where MDS is the maximum depression storage of the entire surface, n is the number of puddles, m_i is the number of cells in puddle i, $Z_{t,i}$ is the elevation of the threshold(s) of puddle i, $Z_{i,j}$ is the elevation of cell j in puddle i, Δx is the size of a cell along the x direction, and Δy is the size of a cell along the y direction. The accuracy of the PD program in the computation of MDS has been verified by a set of experimental tests. For example, in one test for an impervious mold surface that included ten major depressions, the overall relative error of the measured and simulated MDS values was only 2% (Chu et al., 2010).

Mean Upslope Depression (MUD) Index and the MUD-Based Method

Hansen et al. (1999) proposed the MUD index to quantify both surface roughness and slope. The regression relationship between MUD and MDS was derived based on surfaces with slopes varying from 1% to 20% (Hansen et al., 1999). Kamphorst et al. (2000) evaluated the performances of the MUD index and three other roughness indices (RR, limiting elevation difference and slope, and tortuosity) in predicting MDS and concluded that the MUD index method was able to provide very good estimation of MDS.

To calculate MUD, a set of line segments is selected along the surface slope. Each line segment is further divided into a number of subsegments positioned upslope from a reference point (Hansen et al., 1999). MUD quantifies the mean elevation differences between the reference point and upslope points with a lower elevation for all subsegments along the line segment (i.e., mean upslope depressions). MUD can be mathematically expressed as (Hansen et al., 1999):

$$\mathrm{MUD} = \frac{1}{N_s}\sum_{i=1}^{N_s}\left[\frac{1}{N_p}\sum_{j=1}^{N_p}\left(Z_{r,i} - Z_{i,j}\right)\right] \qquad (20)$$

where N_s is the number of subsegments, N_p is the number of upslope points in a subsegment, $Z_{r,i}$ is the elevation of the reference point for subsegment i, and $Z_{i,j}$ is the elevation of upslope point j in subsegment i. In equation 20, $Z_{r,i} - Z_{i,j} = 0$ if this elevation difference is negative (i.e., $Z_{i,j} > Z_{r,i}$). Since the surface slope has been integrated in the computation, MUD decreases nonlinearly with increasing slope (Hansen et al., 1999).

Creation of Soil Surfaces and Acquisition of High-Resolution DEMs

Six laboratory-scale soil surfaces with areas of 0.6 m × 2.0 m (surfaces S1 to S6) were created (figs. 1a to 1f). They were separate surfaces, and the variability in surface roughness of the surfaces was achieved by changing the size of soil aggregates that were obtained in the field and randomly distributed across the area (i.e., no oriented roughness). An instantaneous-profile laser scanner (Huang et al., 1988; Darboux and Huang, 2003; Chu et al., 2010) was used to acquire high-resolution DEMs of the six surfaces. The horizontal and vertical resolutions of the scanned DEMs were 0.98 mm and 0.50 mm, respectively.

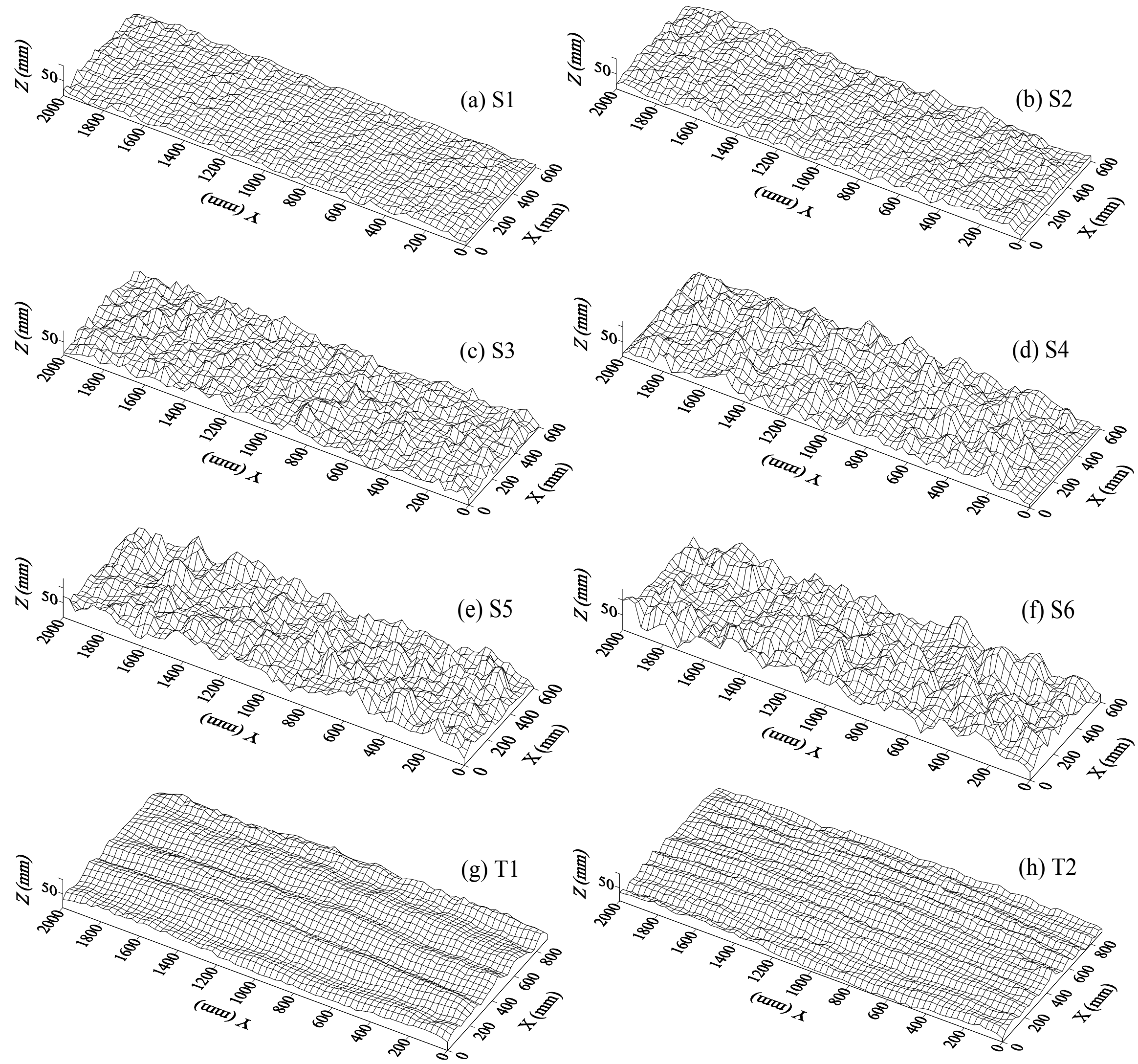

Figure 1. Six basic surfaces (S1 to S6) and two tillage surfaces (T1 and T2) with varying roughness conditions.

All the scanned data were processed, and 2 cm DEMs were generated and used for computations of RR and MDS. To examine the slope effects on the computations of RR and MDS, thirteen sloping surfaces with *y*-directional slopes ranging from 0% to 12% (slope increment = 1%) were also created based on the six basic soil surfaces. A coordinate transformation program (Yang et al., 2010) was used to generate the corresponding DEMs for the sloping surfaces. Thus, a total of 78 soil surfaces were used in the computations of RR and MDS and the relevant analyses.

In this study, various data processing methods (i.e., combinations of procedures A to D) were utilized to process the DEMs of the six soil surfaces, which were further used to compute RR and MDS. The results demonstrated that implementation of different procedures (A to D) and selection of different data processing methods were critical to estimation of RR and MDS. For the surfaces selected in this study, procedure B (removal of the slope effect) and procedure D (removal of the upper and lower 10% extreme data points) played an important role in the computation of RR. Additionally, the results with and without procedure A (logarithm transformation) were very close. Considering the fact that the logarithm transformation data processing (procedure A) showed a minimal effect and that the six surfaces did not have any tillage effects, four data processing methods (table 1) involving procedures B and D were used in the computation of RR and MDS and the relevant analysis.

Table 2 shows the basic statistics for the six original soil surfaces without implementing any data processing procedures. With an increase in soil surface roughness from S1

Table 1. Four computation methods for random roughness (RR) and the related data processing procedures B and D.

RR Computation Method	Procedure[a] B	Procedure[a] D	Notes
M1	1	1	B + D
M2	1	0	B
M3	0	1	D
M4	0	0	None

[a] Procedure B = removal of the slope effect, and procedure D = removal of the upper and lower 10% extreme data points; 1 = the procedure is included, and 0 = the procedure is not included.

Table 2. Basic statistics for the six original soil surfaces (S1 to S6).

Surface	Variance (cm^2)	Standard Error of the Mean (cm)	Standard Deviation (cm)
S1	0.63	0.01	0.80
S2	1.17	0.02	1.08
S3	2.15	0.03	1.47
S4	3.73	0.03	1.93
S5	5.32	0.04	2.31
S6	5.98	0.04	2.45

to S6, an increasing pattern can be observed for all statistical quantities, including variance (0.63 to 5.98 cm^2), standard error of the mean (0.01 to 0.04 cm), and standard deviation (0.80 to 2.45 cm).

Tillage surfaces are common in agricultural fields. In addition to the six basic surfaces, two laboratory-scale tillage surfaces of an area of 0.8 m × 2.0 m (T1 and T2, figs. 1g and 1h) were created in this study. The two surfaces were characterized with different sizes and spacing of mimic tillage marks along the surface slope direction. Note that in order to include more tillage marks, T1 and T2 were slightly wider than the six basic surfaces S1 to S6. Like surfaces S1 to S6, the same procedures were implemented to obtain DEM data and create the sloping surfaces (0% to 12%) for T1 and T2. The MUD index method (Hansen et al., 1999) was applied to estimate MDS values for surfaces T1 and T2 with slopes ranging from 0% to 12%. In addition, RR values were calculated for all sloping surfaces by using the RR index method that implemented procedures B and D (like method M1, table 1), as well as procedure C to remove the oriented tillage effect. The estimated RR values were further used for computation of the corresponding MDS. The PD program also was utilized for computing MDS for all surfaces, and the PD results were then compared with those from the MUD and RR index methods.

Results and Discussion

Random Roughness

The four methods that implemented data processing procedures B and D (table 1) were used to calculate RR for the six basic soil surfaces (zero SL) and the 72 derived sloping surfaces. Table 3 details the RR values calculated using the four methods for the six basic surfaces. From S1 to S6, an increasing trend can be observed for RR from all four methods. The average RR values range from 0.63 cm for surface S1 to 1.96 cm for surface S6. The results are consistent with the changes in the surface roughness conditions (fig. 1). For the six surfaces, method M1 provided the lowest RR values, while method M4, with no data processing procedures, yielded the highest RR values (table 3). To examine the directional variability of RR, RR values along the *x* direction (all rows) and the *y* direction (all columns) were calculated using method M2 for the six basic surfaces (fig. 2). Generally, rougher surfaces (e.g., surfaces S5 and S6) have higher RR values and greater spatial variations along both directions. Significant variations in RR distributions along the *x* direction can be observed for the rougher surfaces (e.g., surfaces S5 and S6) (fig. 2a), indicating the directional properties of surface roughness. In contrast, for the surfaces with lower RR values (e.g., surfaces S1 and S2), the changing patterns of RR along both the *x* and *y* directions are similar (fig. 2).

Table 3. Random roughness (cm) of the six basic surfaces (S1 to S6) computed by the four methods (M1 to M4).[a]

Surface	M1	M2	M3	M4	Average
S1	0.47	0.74	0.52	0.80	0.63
S2	0.66	1.01	0.72	1.08	0.87
S3	0.89	1.36	0.97	1.47	1.17
S4	1.11	1.74	1.24	1.93	1.51
S5	1.39	2.11	1.54	2.31	1.84
S6	1.49	2.23	1.65	2.45	1.96

[a] Refer to table 1 for details on RR computation methods M1 to M4.

The relationships between SL and RR calculated using the four methods for the six basic surfaces are shown in figure 3. For the RR values from methods M1 and M2 that implemented procedure B (removal of the effect of the main slope along the *y* direction) (table 1), RR remains approximately constant for all slopes of the six surfaces (fig. 3). Method M1 results in lower RR values because of the removal of the 10% extreme data points (fig. 3). The RR values from methods M3 and M4 exhibit an increasing pattern (fig. 3) because the slope effect is not removed in either method. Due to the removal of the upper and lower 10% extreme data points (procedure D) in method M3, the RR values from this method are smaller than those from method M4.

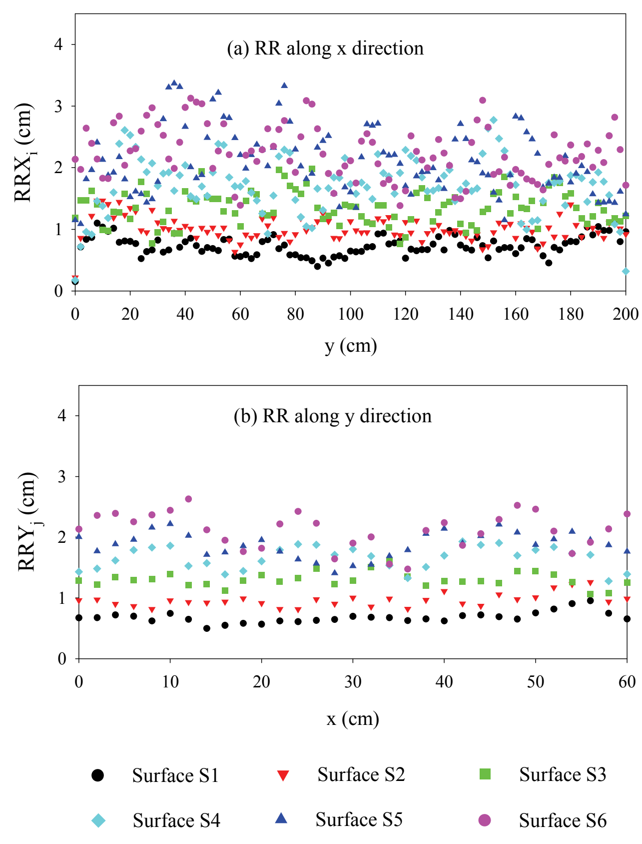

Figure 2. Distributions of random roughness (RR) along the *x* and *y* directions for surfaces S1 to S6 (data from method M2).

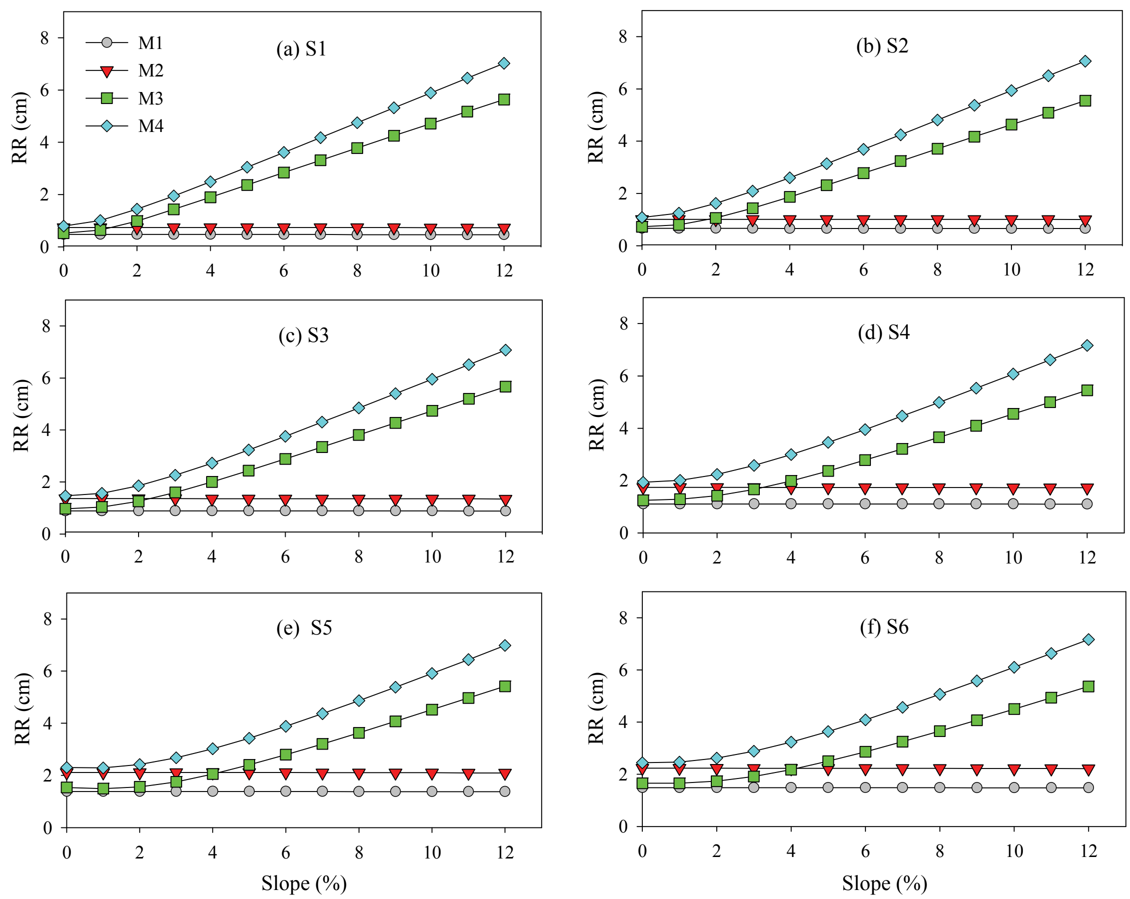

Figure 3. Random roughness (RR) vs. slope from methods M1 to M4 for surfaces S1 to S6.

Maximum Depression Storage

In this study, the RR index-based approach (eq. 18) was used to estimate MDS. To evaluate the performance of the approach, the MDS results were compared with those from the PD program (Chu et al., 2010). Particularly, the four RR computation methods that implemented procedures B and D (table 1) were used for estimating MDS, and their influences were evaluated. Furthermore, two MDS control factors (RR and SL) and their fundamental relationships with MDS were examined.

MDS from the PD Program and its Relationships with SL and RR

To better understand the relationship between SL and MDS, the PD program was used to calculate MDS for the six basic surfaces and their derived sloping surfaces based on their DEMs (fig. 4a). The following can be observed from figure 4a: (1) MDS generally decreases with an increase in SL; (2) for some surfaces (e.g., surface S6), an increasing pattern can also be observed for a certain range of slopes; and (3) surfaces with lower RR values may have higher MDS values. For example, surface S3 has greater MDS values than the rougher surface S4 for higher slopes (fig. 4a).

MDS depends on both RR and SL. Figure 4b shows the relationships between RR and MDS for the six surfaces at seven selected slopes ranging from 0% to 12%. The RR values in figure 4b were calculated by method 2, in which the slope effect was removed. The “true” MDS values were provided by the PD program for all the six basic surfaces and the seven selected slopes (0% to 12%). Figure 4b shows an increasing relationship between MDS and RR for the six surfaces and different slopes as predicted by the PD program.

MDS from the RR Index-Based Approach

The RR index-based approach was used to estimate MDS for the six basic surfaces and their corresponding sloping surfaces (a total of 78 surfaces), and the four methods (M1 to M4) were used to calculate their RR values (table 1). Figure 5 shows the relationships between MDS estimated by equation 18 and RR calculated by using the four methods for the seven selected slopes from 0% to 12%, and figure 6 displays the MDS-SL relationships for surfaces S1 to S6. Equation 18 implies that: (1) for a given slope, MDS increases quadratically with increasing RR (see all curves in figures 5a to 5d); and (2) for a specific surface (given RR), MDS decreases linearly with increasing slope (fig. 6, M1 and M2 lines). Figures 5a and 5b (methods M1 and M2) also verify this point. Note that the slope effect has been removed through procedure B (table 1) in these two RR computation methods. However, for methods M3 and M4 (figs. 5c and 5d), RR is strongly influenced by surface slopes. RR can be remarkably different for various slopes of the same basic surface when methods M3 and M4 are applied (fig. 3). If the slope effect is not removed by im-

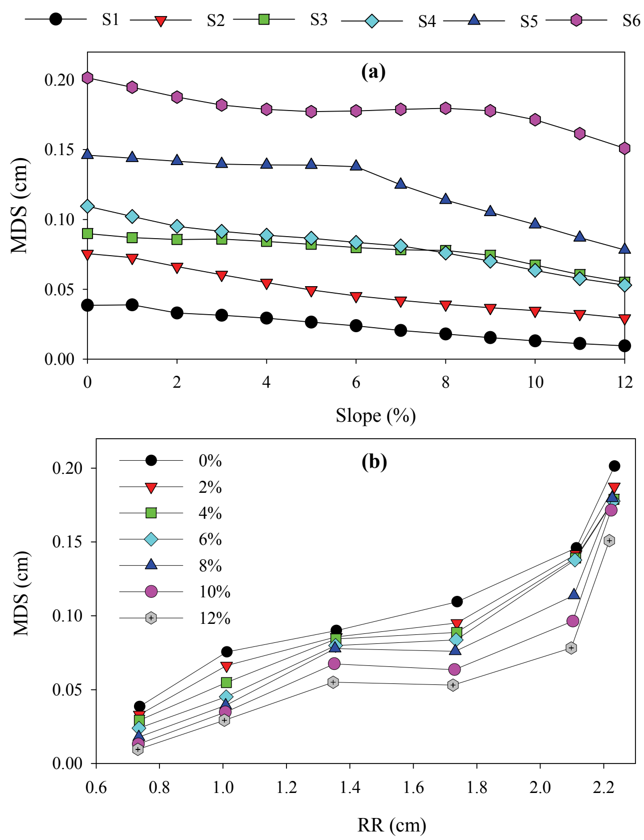

Figure 4. Maximum depression storage (MDS) from the PD program vs. (a) slope and (b) random roughness (RR) calculated by method M2 for surfaces S1 to S6 and the seven selected slopes (0% to 12%).

plementing procedure B (table 1), for the same basic surface, a steeper sloping surface will have a greater MDS due to the higher RR. In reality, MDS tends to decease with increasing slope. These results highlight the importance of selection of the RR computation methods and the relevant data processing procedures (procedures A to D), and emphasize the necessity of removal of the slope effect. Similar to the results for RR, method M1 with both data processing procedures B and D provides the lowest MDS values for all slopes (fig. 5a), while method M4 with no data processing yields the highest MDS (fig. 5d). Different changing patterns of MDS and RR can be observed in figure 4b from the PD program and in figure 5 from the RR index-based approach.

Comparison of RR Index-Based Approach with the PD Program

As mentioned earlier, the DEM-based PD program has been demonstrated to be accurate at predicting MDS for various microtopographic surfaces of different slopes (Chu et al., 2010). To further evaluate the performance of the RR index-based approach (eq. 18) in estimation of MDS by using the four different methods (M1 to M4) and identify their application conditions for various soil surfaces, methods M1 to M4 were compared with the PD program. To quantify the differences between the MDS values predicted by the Onstad equation and the "true" MDS values from the PD program, root mean square error (RMSE) evaluations were carried out. The relationships between MDS and SL were analyzed for the four RR computation methods (M1 to M4) and the six basic surfaces (S1 to S6). Figure 6 shows the comparisons of the MDS-SL curves determined by the PD program and methods M1 to M4 with equation 18.

Methods M1 and M2 implemented procedure B (remov-

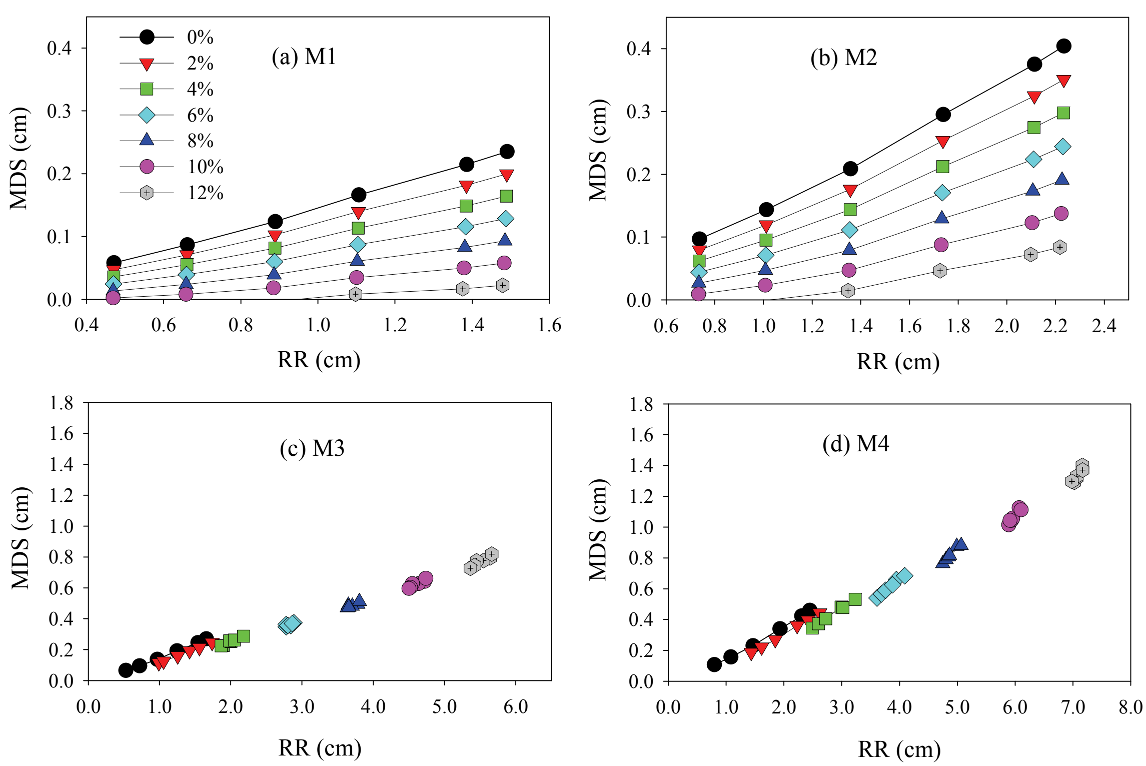

Figure 5. Maximum depression storage (MDS) vs. random roughness (RR) calculated by methods M1 to M4 for the seven slopes (0% to 12%).

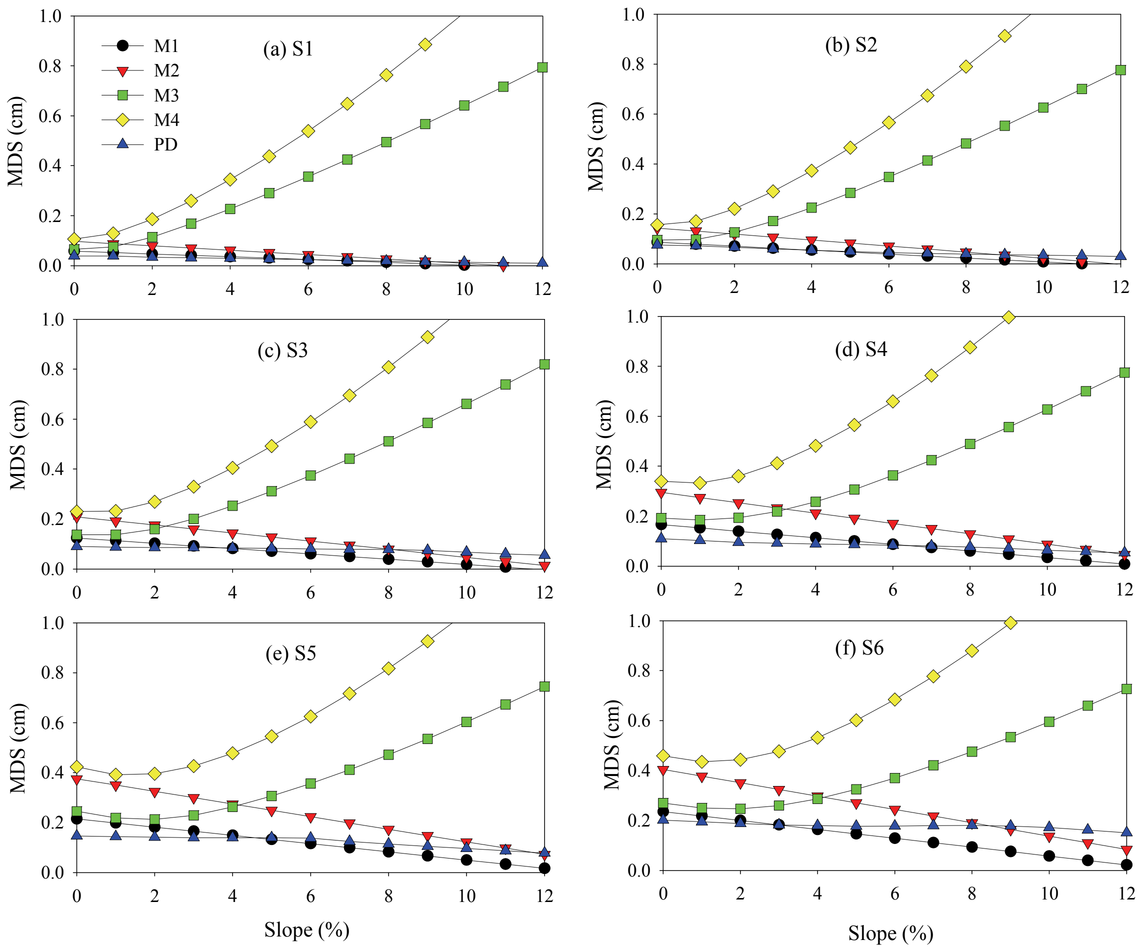

Figure 6. Maximum depression storage (MDS) vs. slope from methods M1 to M4 and the PD program for surfaces S1 to S6.

al of the slope effect), which resulted in approximately identical RR values for all slopes (fig. 3). MDS hence decreases linearly with increasing slope (eq. 18). However, the MDS-SL curves from the PD program deviate from the linear lines predicted by methods M1 and M2 for surfaces S1 to S6 (fig. 6). Due to the removal of the upper and lower 10% extreme data points (procedure D, table 1), method M1 yielded smaller MDS values than those from method M2 (fig. 6). For the MDS estimated by method M1, RMSE values range from 0.011 cm for surface S1 to 0.075 cm for surface S6, with an average RMSE of 0.036 cm for the six surfaces (S1 to S6). For method M2, the RMSE values are 2 to 3 times higher than those from method M1, and the average RMSE is 0.079 cm for surfaces S1 to S6.

Methods M3 and M4 have no slope correction (table 1). Due to the significant slope effect, a remarkable increasing pattern can be observed for the MDS values estimated by M3 and M4 (fig. 6), which is similar to the changing pattern of RR (fig. 3). Method M4 without removal of the upper and lower 10% extreme data points (procedure D) yields much higher MDS values than method M3 for all soil surfaces (fig. 6). These two methods without the slope adjustment provide unrealistic estimates of MDS that deviate far from the "true" MDS values from the PD program, especially for steeper slopes. Thus, removal of the slope effect through procedure B is necessary and important.

Comparison of the MDS results from the RR index-based approach and the PD program (fig. 6) demonstrates that the RR index-based approach may provide reasonable estimation of MDS. However, the RR computation methods or implementation of the data processing procedures may affect the performance and applicability of the RR index-based approach for estimating MDS. The performance also depends on surface roughness and slope (fig. 6). Figure 6 indicates that the RR index-based approach generally overestimates MDS for lower slopes (e.g., <3%) and underestimates MDS for higher slopes. Method M1 that implements both procedures B and D (table 1) is able to provide much better MDS estimates than the three other methods.

For a specific surface and a given RR, the index-based MDS approach (eq. 18) implies that MDS decreases linearly with increasing slope. In addition, a threshold slope exists at which MDS is equal to zero. For example, the MDS of surface S1 that has a RR value of 0.47 cm from method M1 (table 3) reaches zero when the slope is 10.55% (fig. 6a). In reality, the results from the PD program show a nonlinear relationship between MDS and SL (fig. 6). For surface S1, the MDS from the PD program is about 0.012 cm at a slope of 10.55% (fig. 6a). Thus, the RR index-based approach should be limited to gentle slopes that are smaller than the threshold slope.

The difference between methods M1 and M2 is removal of the upper and lower 10% extreme data points (procedure D, table 1). Comparisons of their estimated MDS values with those from the PD program indicate that method M1 with procedure D provides a better overall estimation of MDS than method M2 for all six soil surfaces (the average RMSE values for S1 to S6 are 0.036 and 0.079 cm for M1 and M2, respectively). Thus, removal of some extreme data points using procedure D can be helpful to improve the data distribution and the accuracy of the estimated MDS. Specifically, method M1 yields better estimation of MDS for gentle slopes (fig. 6), while method M2 without implementing procedure D significantly overestimates MDS (fig. 6). Opposite results can be observed for a relatively higher slope (i.e., method M2 without procedure D may provide better estimates of MDS).

The best way to improve the estimation of MDS for a wide range of slopes by using the RR index-based approach is to modify the Onstad equation (eq. 18). For example, the slope term in equation 18 can be changed from linear to a trigonometric function, as the trigonometry of the system determines storage behind surface roughness elements. That is, the depression storage of a rough surface reaches the maximum if $\tan^{-1}(\mathrm{SL}) = 0$ (i.e., a flat surface with SL = 0), while the storage equals zero for $\tan^{-1}(\mathrm{SL}) = \pi/2$ (i.e., an upright surface with an angle of 90°). Hence, equation 18 can be modified as:

$$\mathrm{MDS} = a\left(0.112\mathrm{RR} + 0.031\mathrm{RR}^2\right) \times \left\{1 - \sin\left[\tan^{-1}(\mathrm{SL})\right]\right\}^b \tag{21}$$

in which the coefficient a will reduce the overprediction of MDS for a flat surface, and the exponent b will determine how quickly the MDS drops with increasing slope. SAS software (SAS Institute, Inc., Cary, N.C.) was then utilized to fit the nonlinear equation 21 for the data shown in figure 4, including RR (0.73 to 2.23), SL (0.0% to 12.0%), and MDS computed by the PD program for the six surfaces (S1 to S6). The two coefficients a and b were consequently determined (a = 0.441 and b = 3.322), and equation 21 can be rewritten as:

$$\mathrm{MDS} = 0.441\left(0.112\mathrm{RR} + 0.031\mathrm{RR}^2\right) \times \left\{1 - \sin\left[\tan^{-1}(\mathrm{SL})\right]\right\}^{3.322} \tag{22}$$

It should be pointed out that there are some potential deficiencies or limitations in using the non-spatially based RR index to quantify the spatially based variable MDS. RR does not take into consideration the spatial location of any individual elevation point in the DEM dataset, while the PD program accounts for the spatial relationships of individual locations with their neighbors. RR may not be able to uniquely represent complex spatial microtopographic characteristics of a surface. That is, different surfaces may have the same RR. The MDS of a surface depends on the surface microtopographic characteristics (e.g., size and number of depressions, thresholds or pour points of depressions), in addition to RR and SL.

Comparison of MDS from Different Methods for Tillage Surfaces

Surfaces T1 and T2 with tillage marks (figs. 1g and 1h) were used to examine the tillage effects on MDS computed by using the MUD index method, the RR index method (that implemented procedures B, C, and D), and the PD program for the selected slopes from 0% to 12%. Figures 7a and 7b, respectively, show the comparisons of the SL-MDS curves determined by the three different methods for surfaces T1 and T2. Compared with the MDS values from the PD program, the average RMSE values for surfaces T1 and T2 are 0.020 and 0.013 cm for the MUD and RR index-based methods, respectively. A nonlinear decreasing relationship can be observed for SL and MDS calculated by the PD program (fig. 7). The MDS from the MUD index method also exhibits a nonlinear decreasing pattern. The MUD index method provides very good estimation of MDS for slopes from 4% to 12%. That is, the estimated MDS values are very close to the “actual” values from the PD program. However, for slopes lower than 4%, the MUD method tends to overestimate MDS (fig. 7). The RR index method provides acceptable MDS values, especially for surface T2 (fig. 7b). However, the estimated MDS decreases linearly with SL, as indicated in equation 18. This study suggests that, for tillage surfaces (tillage along the slope), the RR index method provides better estimates of MDS for surfaces with milder slopes (e.g. <3%), while the MUD index method yields improved MDS values for relatively steeper slopes (fig. 7). Particularly, the nonlinear decreasing pattern of MDS with the MUD method is a significant improvement over the RR index method.

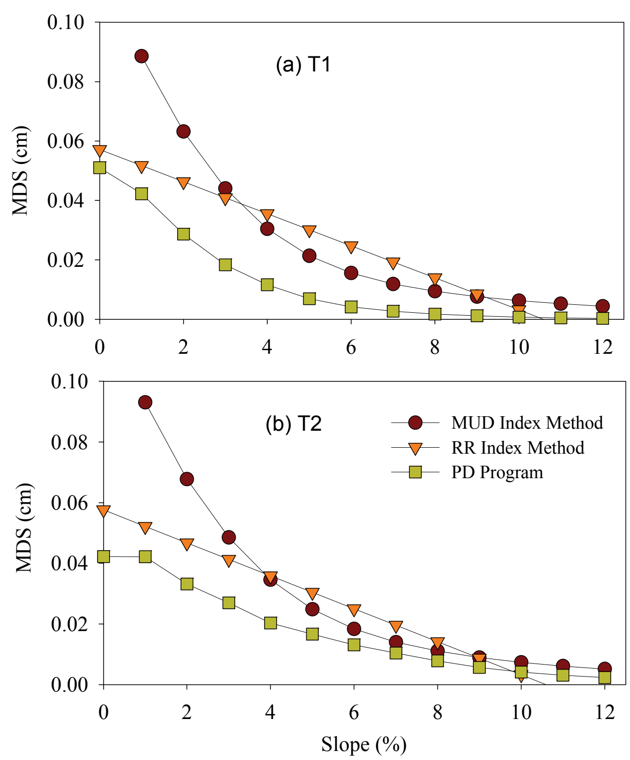

Figure 7. Maximum depression storage (MDS) vs. slope from the PD program, the MUD index method, and the RR index method for the two tillage surfaces (T1 and T2).

It should be noted that the two selected tillage surfaces (T1 and T2, figs. 1g and 1h) have different sizes and spacing of tillage marks, but they have similar RR values (0.45 cm and 0.46 cm for T1 and T2, respectively), resulting in similar MDS values for all slopes from the RR index-based approach (fig. 7). However, the difference in MDS for the two surfaces with dissimilar tillage marks is well depicted by the PD program (fig. 7). This finding indicates that the RR index method may not be able to reflect certain microtopographic variability of surfaces. Consequently, two different tillage surfaces may possess similar RR values, and hence similar MDS values, for a given slope based on the RR index approach.

CONCLUSIONS

Four methods that implemented two different data processing procedures were used to calculate random roughness for six basic soil surfaces and 72 derived sloping surfaces. Furthermore, the RR index-based approach was applied to estimate MDS. The performance of the RR index-based approach was evaluated by comparing it with the PD program. The MUD index method was also applied to estimate MDS for two tillage surfaces and compared with the RR index method (with removal of the tillage effect) and the PD program. Based on the analyses of results, the following conclusions can be reached:

- Selection of the procedures for processing elevation data (i.e., procedures A to D) is critical to estimation of RR and MDS. Different methods may yield completely distinct results.
- Removal of any oriented roughness along both the x and y directions (procedures B and C for slope and tillage effects) is necessary for computation of both RR and the corresponding MDS using the RR index-based approach.
- Removal of the upper and lower extreme data points can be helpful to improve the data distribution and the accuracy of the estimated MDS. A significant improvement in the performance of the RR index-based approach can be achieved by introducing a nonlinear trigonometric function to account for the physical relationship between MDS and surface slope.
- There are certain potential deficiencies or limitations in using the non-spatially based RR index to quantify the spatially based MDS. RR may not be able to uniquely represent the microtopographic characteristics of a surface. That is, surfaces of dissimilar microtopographic conditions may have the same RR. Hence, the real changing pattern of MDS with RR for a given slope varies and is not necessarily a uniform quadratic increasing pattern.
- Generally, MDS decreases with increasing slope steepness. However, the relationship of MDS and slope for a real soil surface is nonlinear. That is, MDS does not linearly decrease with slope. The zero-MDS threshold slope implied in the RR index-based MDS equation is unrealistic and indicates the upper limit of slope for applications of the Onstad equation. Thus, developing a function that relates MDS to RR, slope, and other dominant microtopographic parameters will improve the capability of the RR index-based approach and its practical applicability in MDS estimation.
- The RR index methods with removal of the oriented roughness (e.g., slope and tillage) and the extreme data points yield much better estimation of MDS for gentle slopes.
- The MUD index method is able to provide improved estimation of MDS for tillage surfaces for relatively steeper slopes (>4%) and more realistic nonlinear relationship between MDS and slope, while it may overestimate MDS for gentle slopes.

It should be noted that this study is based on laboratory-scale soil surfaces. Larger-scale field studies will provide useful information for practical applications.

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation under Grant No. EAR-0907588 and the North Dakota NASA EPSCoR program through NASA Grant No. NNXO7AK91A.

REFERENCES

Allmaras, R. R., R. E. Burwell, W. E. Larson, and R. F. Hotl. 1966. Total porosity and random roughness of the interrow zone as influenced by tillage. USDA Conservation Research Report No. 7. Washington, D.C.: USDA Agricultural Research Service.

Bertuzzi, P., G. Rauws, and D. Courault. 1990. Testing roughness indices to estimate soil surface roughness changes due to simulated rainfall. *Soil Tillage Res.* 17(1-2): 87-99.

Boiffin, J. 1984. Structural degradation of the soil surface by the action of rainfall. PhD diss. Paris, France: Institut National d'Agronomie Paris-Grignon.

Burwell, R. E., R. R. Allmaras, and M. Amemiya. 1963. A field measurement of total porosity and surface microrelief of soils. *SSSA Proc.* 27(6): 697-700.

Chu, X. 2011. Characterization of microtopography and its hydrologic significance. In *Modeling Hydrologic Effects of Microtopographic Features*, 1-14. X. Wang, ed. Hauppauge, N.Y.: Nova Science Publishers.

Chu, X., J. Zhang, J. Yang, and Y. Chi. 2010. Quantitative evaluation of the relationship between grid spacing of DEMs and surface depression storage. In *Proc. 2010 World Environ. and Water Resources Congress*, 4447-4457. R. N. Palmer, ed. Reston, Va.: ASCE.

Currence, H. D., and W. G. Lovely. 1970. The analysis of soil surface roughness. *Trans. ASAE* 13(6): 710-714.

Curtis, W. R., and W. D. Cole. 1972. Micro-topographic profile gauge. *Agric. Eng.* 53(1): 17.

Darboux, F., and C. Huang. 2003. An instantaneous-profile laser scanner to measure soil surface microtopography. *SSSA J.* 67(1): 92-99.

Govers, G., I. Takken, and K. Helming. 2000. Soil roughness and overland flow. *Agronomy* 20(2): 131-146.

Hairsine, P. B., C. J. Moran, and C. W. Rose. 1991. Recent developments regarding the influence of soil surface characteristics on overland flow and erosion. *Australian J. Soil Res.* 30(3): 249-264.

Hansen, B., P. Schjønning, and E. Sibbesen. 1999. Roughness indices for estimation of depression storage capacity of tilled soil surfaces. *Soil Tillage Res.* 52(1-2): 103-111.
Huang, C., and J. M. Bradford. 1990. Depressional storage for Markov-Gaussian surfaces. *Water Resources Res.* 26(9): 2235-2242.
Huang, C., and J. M. Bradford. 1992. Applications of laser scanner to quantify soil microtopography. *SSSA J.* 56(1): 14-21.
Huang, C., I. White, E. G. Thwaite, and A. Bendeli. 1988. A noncontact laser system for measuring soil surface topography. *SSSA J.* 52(2): 350-355.
Kamphorst, E. C., V. Jetten, J. Guérif, J. Pitkänen, B. V. Iversen, J. T. Douglas, and A. Paz. 2000. Predicting depression storage from soil surface roughness. *SSSA J.* 64(5): 1749-1758.
Kuipers, H. 1957. A relief meter for soil cultivation studies. *Netherlands J. Agric. Sci.* 5(4): 255-262.
Linden, D. R., and D. M. Van Doren Jr. 1986. Parameters for characterizing tillage-induced soil surface roughness. *SSSA J.* 50(6): 1560-1565.
Linden, D. R., D. M. Van Doren Jr., and R. R. Allmaras. 1988. A model of the effects of tillage-induced soil surface roughness on erosion. In *Proc. 11th ISTRO Conf.: Tillage and Traffic in Crop Production*, 373-378. Haren, The Netherlands: International Soil Tillage Research Organization.
Mitchell, J. K., and B. A. Jones Jr. 1973. Profile measuring device. *Trans. ASAE* 16(3): 546-547.
Mitchell, J. K., and B. A. Jones Jr. 1976. Micro-relief surface depression storage: Analysis of models to describe the depth-storage function. *Water Res. Bull.* 12(6): 1205-1222.
Moore, I. D., and C. L. Larson. 1979. Estimating microrelief surface storage form point data. *Trans. ASAE* 20(5): 1073-1077, 1079.
Mwendera, E. J., and J. Feyen. 1992. Estimation of depression storage and Manning's resistance coefficient from random roughness measurements. *Geoderma* 52(3-4): 235-250.
Onstad, C. A. 1984. Depression storage on tilled soil surfaces. *Trans. ASAE* 27(3): 729-732.
Planchon, O., M. Esteves, N. Silvera, and J. M. Lapetite. 2001. Microrelief induced by tillage: Measurement and modeling of surface storage capacity. *Catena* 46(2-3): 141-157.
Podmore, T. H., and L. F. Huggins. 1981. An automated profile meter for surface roughness measurements. *Trans. ASAE* 24(3): 663-665, 669.
Radke, J. K., M. A. Otterby, R. A. Young, and C. A. Onstad. 1981. A microprocessor automated rillmeter. *Trans. ASAE* 24(2): 401-404.
Römkens, M. J. M., and J. Y. Wang. 1986. Effect of tillage on surface roughness. *Trans. ASAE* 29(2): 429-433.
Römkens, M. J. M., S. Singarayar, and C. J. Gantzer. 1986. An automated non-contact profile meter. *Soil Tillage Res.* 6(3): 193-202.
Ullah, W., and W. T. Dickinson. 1979. Quantitative description of depression storage using a digital surface model: I. Determination of depression storage. *J. Hydrol.* 42(1-2): 63-75.
Yang, J., X. Chu, Y. Chi, and L. Sande. 2010. Effects of rough surface slopes on surface depression storage. In *Proc. 2010 World Environ. and Water Resources Congress*, 4427-4436. R. N. Palmer, ed. Reston, Va.: ASCE.
Zobeck, T. M., and C. A. Onstad. 1987. Tillage and rainfall effects on random roughness: A review. *Soil Tillage Res.* 9(1): 1-20.