



Comparison of Digital Elevation Model (DEM) - and Triangulated Irregular Network (TIN) - Based Slope Calculations' Impact of Data Models on Surface Terrain Indexes

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Abstract:

This paper addressed building an evaluation model to compare slope computed from digital elevation models (DEMs) and triangulated irregular networks (TINs) based on sample slope random points. The study used Moran's statistics to calculate slope differences between DEM and TIN results, where the slope average difference was about 9.46 degrees in the model starting with DEM and about 1.94 degrees in the model starting with TIN. In addition, the midpoint displacement method (MPDM) was employed to calculate differences between slopes computed from the northeast to the southwest corner of the dataset based on sample random points by Monte Carlo simulation; the study found no spatial trend in slope differences running from northeast to southwest through the datasets. The study recommends considering the use of DEM and TIN to create other surface-like slopes, hillshade, aspect, and hydrological analysis or when converting among them.

Introduction and Background

In general, surface terrain models can be classified into two types: the digital elevation model (DEM) and the triangulated irregular network (TIN) model (De Floriani and Magillo, 2001; Magillo et al., 2000; De Floriani, 1996; Sinnakaudan, 2003). In geographic information systems (GISs), DEMs and TINs are now widely used to represent

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a surface, with DEMs classified as raster models (grids) and TINs classified as vector models.

In a DEM, earth's surface is represented as spatially referenced regular grid points, with each grid point representing a ground elevation value, so DEMs have the potential to solve theoretical and applied problems in earth science. Given the availability of DEMs, especially from the United States Geological Survey (USGS), they have a major role to play in GIS and hydrological modeling (O'Callaghan and Mark, 1984), analysis of visibility (Lee and Stucky, 1998), and hazard mapping (Gruber and Haefner, 1995). On the other hand, TINs are a form of vector-based digital geographic data and are constructed by triangulating a set of points. In other words, the TIN is a finite set of points which are stored with their elevation. The model is a piecewise linear model that in three-dimensional (3D) space can be visualized as a simply connected set of triangles (De Berg, 2000; Van Kreveld, 2000; Sinnakaudan, 2009).

Other surfaces can be created from an elevation surface: hillshade, slope, aspect, curvature, hydrological analysis, and viewshed analysis. This paper evaluates methods of calculating slope using DEM and TIN data. In general, slope is simply the change in vertical distance over the change in horizontal distance. Typical slope angle computation methods calculate an average slope based on, roughly, a 3x3 neighborhood (Fairfield and Leymarie, 1991). Slope is calculated for each triangle in TINs and for each cell in rasters. For a TIN, this is the maximum rate of change in elevation across each triangle. For a raster, it is the maximum rate of change in elevation over each cell and its eight neighbors.

In a GIS environment, the most popular method to determine slope is through the use of digital elevation models (DEM_s). Calculating slope from a DEM is a direct and simple, but care must be taken when selecting an algorithm, because there are problems with most of the methods currently available. Slope can be measured in degrees from horizontal (0-90) or percentage slope (which is the rise divided by the run, multiplied by 100).

DEFINITIONS

Digital Elevation Model (DEM): Regular matrix of interpolated elevation data (Kalbermatten, 2011).

A triangulated irregular network (TIN): Finite set of points stored together with their elevation (Van Kreveld, 1997).

Slope: The incline, or steepness, of a surface. Slope can be measured in degrees from horizontal (090), or percent slope (which is the rise divided by the run, multiplied by 100).

The Midpoint Displacement Method (MPDM): The random midpoint displacement method is a widely applied algorithm used for terrain simulation.

Monte Carlo Simulation: utilizes a sequence of algorithms that generate a number of random values. Monte Carlo simulations can be useful in GIS when additional data points are needed to test a model or hypothesis. This process is often used to extrapolate data or generate more data points in a given range.

Research Purpose

The purpose of this paper is to evaluate methods of computing slope from the DEM and TIN models in Arc GIS. Calculating slope in ArcGIS is relatively simple, but care must be taken when selecting a model (DEM, TIN, others) and an algorithm. Because of the different structure of DEMs and TINs, the study tried to answer the following question: Do slopes from DEMs differ from slopes from TINs? Many geographic applications depend on the accuracy of slope calculation, so it is important to test statistical differences between them. The model builder tool in ArcGIS employs different statistical methods to measure variations in the slope values between DEM and TIN.

Objective:

The main objective of this study is to build a model-based GIS to evaluate the slope values from different sources (DEM vs. TIN). The study achieved this purpose via the following goals:

- 1 - Generate artificial dataset - DEM and TIN (Monte Carol simulation).

- 2 - Compare the results of slope values by random sample points from DEM and TIN.
- 3 - Analyze slope pairs (statistical analysis).

Research Questions:

- 1 - Do slopes from DEM differ from slopes from TIN?
- 2 - Are there differences between slopes computed from the northeast to the southwest corner of the datasets?

A Priori Hypothesis:

Assume randomness, that is, no significant difference between slopes computed from the northeast to the southwest corner of the datasets.

Methodology:

To compare DEMs and TINs to computed slope values, this study employed a quantitative approach based on the midpoint displacement method (MPDM) and Moran's coefficient. The methodology involves four phases:

Phase 1: Generate artificial elevation dataset - DEM and TIN.

One way to generate an artificial terrain is by using MPDM (Figure 1). This method works by dividing a grid into regions and changing the altitude of the corners of each region by a random amount, then dividing each of those regions into smaller regions and changing their altitude by a random, but smaller, amount. This process is repeated until the terrain is as detailed as desired (Marak, 1997). In this phase used the MPDM to generate a number of random elevation values computed from DEM and save them in attribute tables.

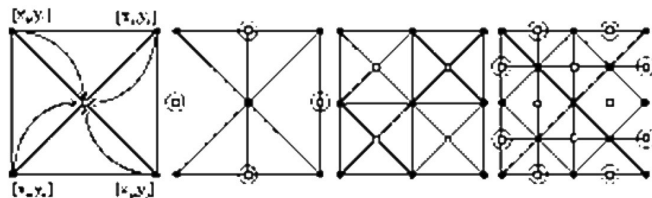


Figure 1- First four steps in the random midpoint displacement method.

The algorithm starts with a 2D grid, then randomly generates terrain height from four seed values arranged in a grid of points so that the entire plane is covered in squares (Figure 2).

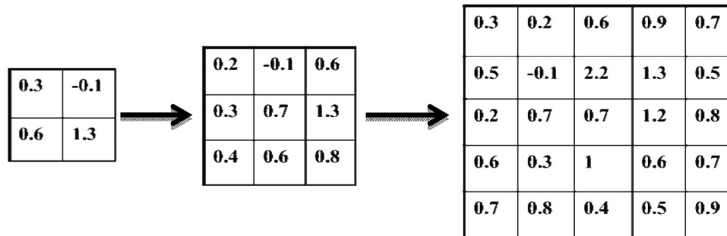


Figure 2 - Example of how the midpoint displacement method works.

Phase 2: Generate Corresponding Elevation Data.

DEM - Create TIN version.

TIN - Create Dem version.

The data test of this study is DEM data (100 columns * 100 rows) for easy and fast process and with 1-meter resolution as the grid format (easy and fast process only) (Figure 3).

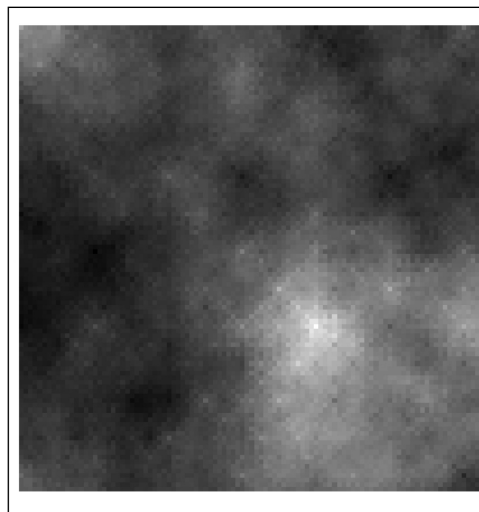


Figure 3 - The DEM data test.

Phase 3: Sample slopes from dataset points.

In this phase, the study used Monte Carlo simulation to generate a number of random slope values computed from DEM and TIN. “The Monte Carlo simulation can be especially useful for analyzing error within a GIS. This is necessary because a GIS cannot fully represent the real world. Thus, approximations are used (for example, in DEM modeling) causing errors to propagate through a model. Therefore, one can use the Monte Carlo method to simulate possible combinations of inputs and parameters in order to create a plausible scenario of the model with one’s data” (Esri, 2009).

Phase 4: Analyze slope pairs (statistical analysis).

Autocorrelation between slope differences was estimated via Moran’s statistics to compare the slope results from DEM and TIN.

Results and Discussion:

The DEM data of the study are available but to generate the slope from TIN the data must be created from DEM with the steps shown in Figure 4.

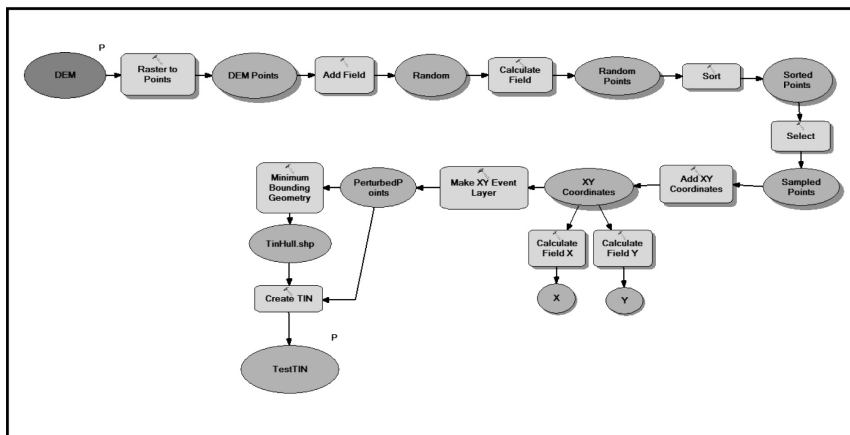


Figure 4 - Steps to generate TIN data from DEM data.

The study built two models to compare the slope value; the first model started with DEM data and created sample slope points (Figure

5), and the second model used the same steps but started from TIN data (Figure 6).

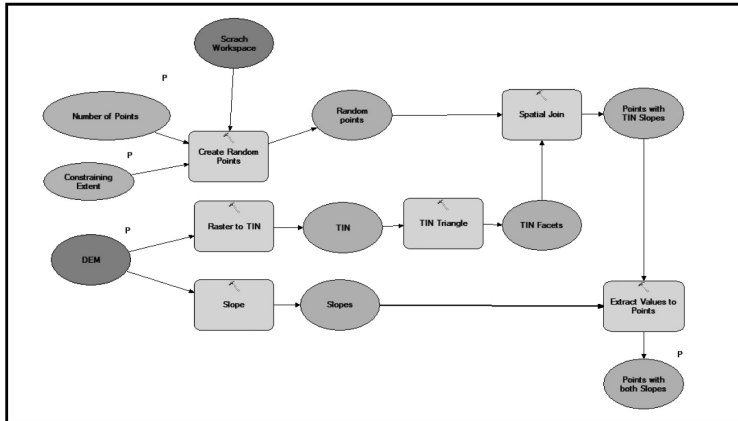


Figure 5 - TIN vs. raster slope comparison (from DEM).

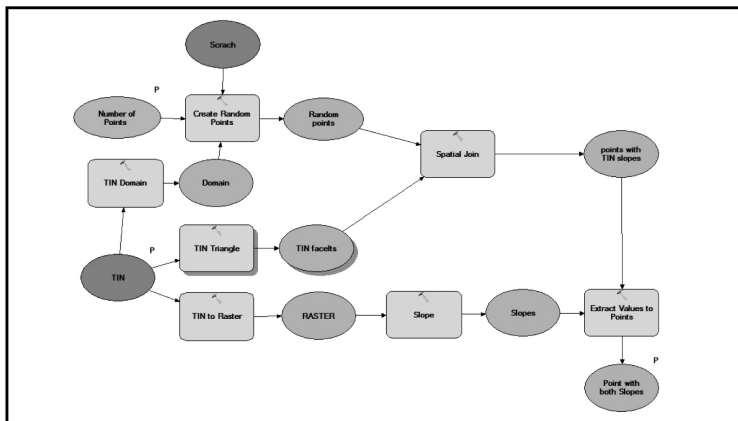


Figure 6 - TIN vs. raster slope comparison (from TIN).

The sample slope point results from DEM and TIN are different. Table 1 shows the slopes generated randomly from DEM (raster) and Table 2 shows the slopes generated randomly thesecond time from TIN; one can see big variancetin the slope values of the same sample points.

Table (1)

Shape *	Slopes_ras	Slopes_TIN
Point ZM	0.644073	13.590974
Point ZM	0.931937	13.236505
Point ZM	2.795222	12.916381
Point ZM	2.868918	11.815937
Point ZM	1.80158	9.52661
Point ZM	1.489186	9.346549
Point ZM	3.355998	8.468489
Point ZM	2.459883	8.110208
Point ZM	0.702902	7.980933
Point ZM	3.612478	7.930693
Point ZM	1.949911	6.995772
Point ZM	1.967526	6.761007
Point ZM	0.767847	6.043846
Point ZM	2.160077	5.877266
Point ZM	1.140075	5.825999
Point ZM	1.548305	5.71894
Point ZM	2.536618	5.67527
Point ZM	2.002622	5.585448
Point ZM	3.364467	5.516401
Point ZM	3.808118	5.374503
Point ZM	1.907446	5.359947
Point ZM	1.397397	5.142163
Point ZM	2.668253	4.90349
Point ZM	2.278349	4.836417

Table1

Table (2)

Shape *	Slopes_ras	Slopes_TIN
Point ZM	3.612478	7.930693
Point ZM	3.484304	2.694395
Point ZM	3.364467	5.516401
Point ZM	3.355998	8.468489
Point ZM	3.276109	4.209186
Point ZM	3.195029	2.665153
Point ZM	2.795222	12.916381
Point ZM	2.727355	3.14895
Point ZM	2.668253	4.90349
Point ZM	2.536618	5.67527
Point ZM	2.278349	4.836417
Point ZM	2.172917	2.898013
Point ZM	1.995971	1.85931
Point ZM	1.973931	2.620749
Point ZM	1.957502	3.610115
Point ZM	1.907446	5.359947
Point ZM	1.83415	1.523412
Point ZM	1.689032	1.953619
Point ZM	1.627866	3.454137
Point ZM	1.618301	3.159178
Point ZM	1.598835	2.399416
Point ZM	1.5854	2.933358
Point ZM	1.565029	3.990854
Point ZM	1.544615	0.671531

Table 2

Sample slope point results from both DEM and TIN.

To clearly understand the differences in the results of the two models, one must use statistical analysis to reveal the differences. Table 3 shows the results of the model starting with DEM-based elevation data, where one can see a slope average difference of about 9.46 degrees.

Table 3

Slopes starting with DEM-based elevation data are different.

Average DEM-Based Slope	Average TIN-Based Slope	Average Difference
7.91 Degrees	17.38 Degrees	9.46 Degrees

From Table 4, which shows the results of the model starting with

TIN-based elevation data, one can see a slope average difference of about 1.94 degrees; this means the model starting with TIN-based elevation data achieved the best result because of the small average difference in degree of slope.

Table 4
Slopes starting with DEM-based elevation data are different.

Average DEM-Based Slope	Average TIN-Based Slope	Average Difference
5.74 Degrees	7.68 Degrees	1.94 Degrees

The study used the MPDM method to calculate differences between slopes computed from the northeast to the southwest corner of the datasets. Two simulator models (Monte Carlo simulation) generated a number of random slope values to create a DEM version of that raster in the first model (Figure 7) and a TIN version of that raster in the second model (Figure 8) and slopes were compared at a number of random sample points; results are appended to a point shapefile.

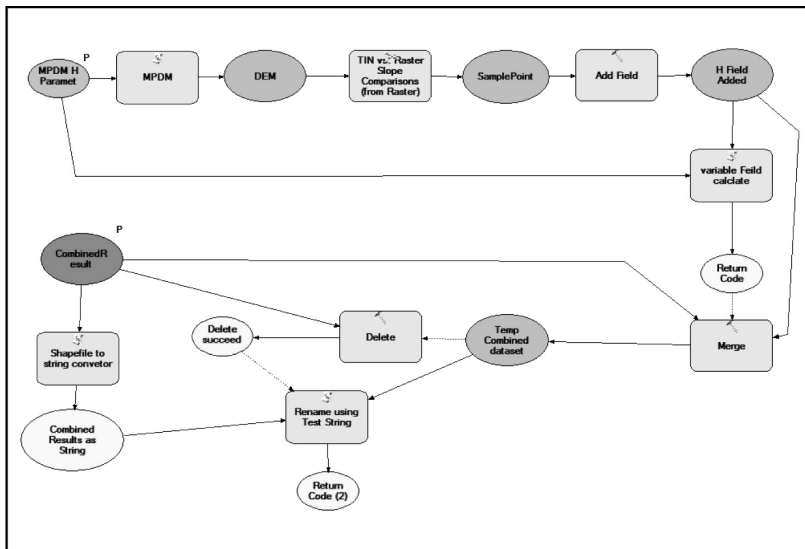


Figure 7 - Rastersimulator from DEM.

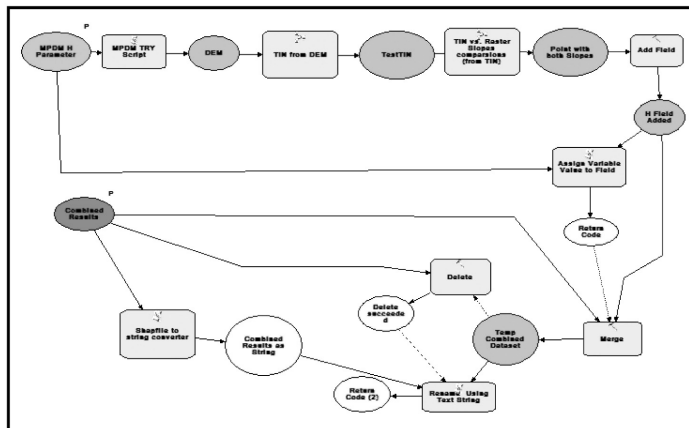


Figure 8 - Raster simulator from TIN.

Figure 9 shows the results of MPDM of the raster simulator from DEM and TIN, so to understand the differences clearly, the results must be analyzed statistically. Autocorrelation between slope differences was estimated via Moran's statistics. A highly clustered spatial pattern can be observed; see Figure 10.

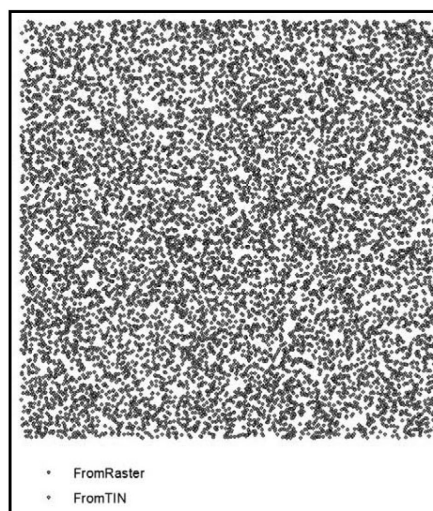


Figure 9 - Raster simulator from DEM and TIN.

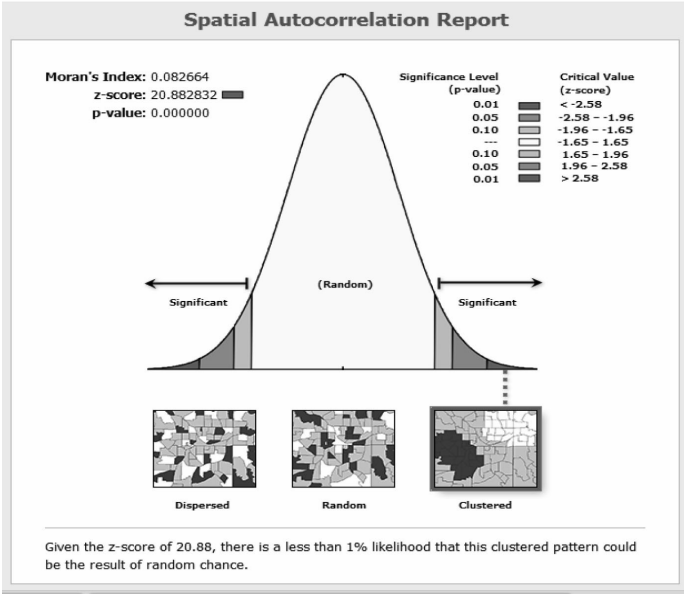


Figure 10 - Spatial autocorrelation between slope from DEM and TIN.

One way to compare the slope results between DEM and TIN is to test the hypothesis that assumes randomness makes no significant difference between slopes computed from the northeast to the southwest corner of the datasets by the script code shown in Figure 11.

```
Show Codeblock
Pre-Logic Script Code:
DIM Dist
Dist = (100 - [X_cord])^2 + (100 - [Y_cord])^2
DIST=Sqr ( DIST )

NE_Distans =
DIST
```

Figure 11 - Script code that tests the difference between slopes computed from the northeast to the southwest corner of the datasets.

No spatial trend in slope differences runs from northeast to southwest through the datasets; thus, the a priori hypothesis proved correct (see Figures 12 and 13).

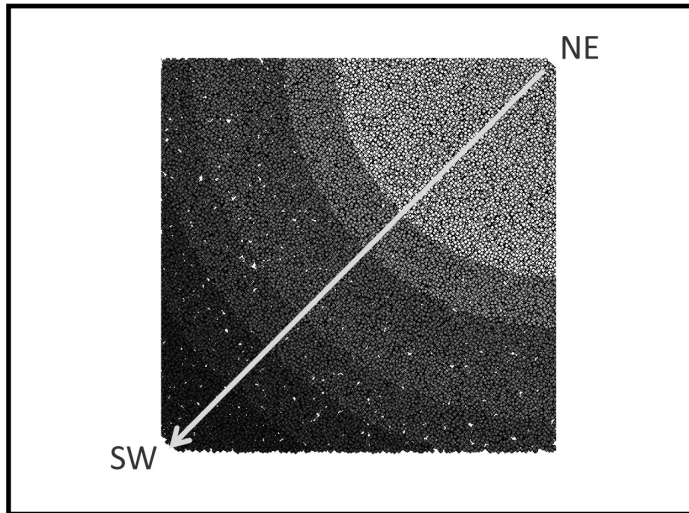


Figure 12 - Difference between slopes computed from the northeast to the southwest corner of the datasets.

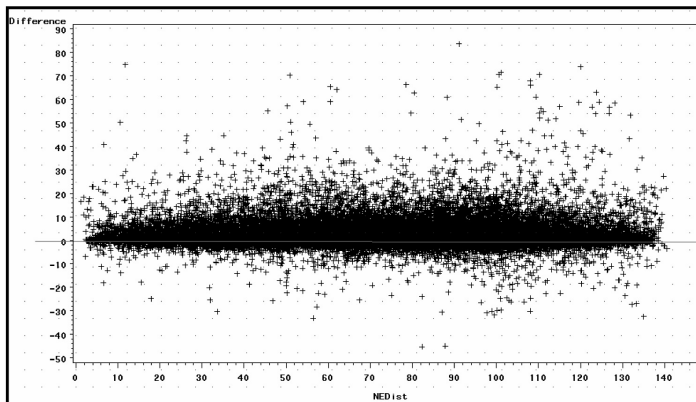


Figure 13 - Spatial trend in slope differences that runs from northeast to southwest through the datasets.

Conclusions:

DEM and TIN data are widely used in many applications in the GIS environment, so it is important to carefully consider their use, especially in conversions among them. DEM and TIN can be used to create other surface data, such as hillshade, slope, aspect, curvature, hydrological analysis, and watershed analysis, but special consideration should be given to errors that may occur due to interpolation and conversion.

This study explores techniques for comparing slope computed from DEM and TIN by sample slope random points based on Monte Carlo simulation. The model starting from TIN data achieved the best result because the average difference was about 1.94 degrees compared to the DEM model at 9.46 degrees. Using the MPDM method, the study tried to test the hypothesis that assumes randomness, that is, no significant difference between slopes computed from the northeast to the southwest corner of the datasets; the study found no spatial trend in slope differences that runs from northeast to southwest through the datasets and, thus, the a priori hypothesis proved correct.

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