Modeling the Effect of Data Errors on Feature Extraction from Digital Elevation Models

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ABSTRACT: Controlled simulations were used to document the impact that errors in a digital elevation model (DEM) have on the accuracy of the procedures for the extraction of terrain features. A set of procedures was devised for extracting floodplain cells from a DEM, the most common data source for terrain analysis, with a raster geographical information system (GIS). It is observed that the magnitudes and the spatial patterns of errors in a DEM significantly affect the results of the tested terrain analysis. Maps showing the probabilities of DEM cells being classified as the floodplain cells are included.

INTRODUCTION

IN RECENT DECADES, DIGITAL ELEVATION MODELS (DEM) have been developed and provided to users for performing a wide variety of terrain analyses. The digital elevation models usually take the form of a regular matrix in which elevations are spaced evenly apart in two orthogonal directions. Reviews of the methods for creating DEMs and various applications for DEMs can be found in Burrough (1986).

Published DEMs are usually supplied with reports of accuracy levels as a reference for users. As an example, the accuracy of the DEMs by U. S. Geologic Survey (USGS) is measured by the root-mean-square-error (RMSE or RMS error) (USGS, 1987). Difficulties exist, however, when users wish to assess the reliability of the results from performing terrain analyses given the occurrence of error in the DEM. Specifically, how much more reliability can be placed on the results from a DEM with a 7-metre RMS error as compared with the results from a DEM with a 15-metre RMS error?

In addition, the geometric accuracy of photogrammetrically sampled digital elevation models is mainly dependent on the terrain type and the sampling procedures (Torlegard et al., 1984; Fredericksen et al., 1984; Ostman 1987). For a DEM, the point density is usually homogeneous while the terrain type can be very heterogeneous. This means that one cannot assume the errors in the interpolated elevation to be a stationary random function over the entire DEM. Specifically, how much more reliability can be placed on the results from a DEM with a 7-metre RMS error as compared with the results from a DEM with a 15-metre RMS error?

To assist in the understanding of the roles that elevation errors in DEMs play in terrain analyses, this paper outlines a procedure for imposing simulated elevation errors with controlled magnitudes and spatial patterns onto a DEM. These simulated surfaces are used in the extraction of floodplain cells from the DEM. This operation is chosen because it has a wide variety of application for many purposes. Cells identified as floodplain are then analyzed with respect to the magnitude and the spatial pattern of the simulated elevation errors to examine the impact of these errors on the classification accuracy.

ALGORITHMS FOR EXTRACTING DRAINAGE FEATURES

A large body of literature relevant to the extraction of a floodplain exists in the earlier research on automated extraction of drainage networks. This work was pioneered by Peucker and Douglas (1975) who analyzed topographic features of grid cells according to the patterns of elevation changes between neighbor cells. Later on, Mark (1983), O'Callaghan and Mark (1984), Band (1986), Morris and Heerden (1988), and Jensen and Domine (1988), Hutchinson (1989), Smith et al. (1990), and Skidmore (1990) developed various algorithms for extracting the drainage network based on raster DEMs. These algorithms performed to different degrees of success but all encountered problems with single cell pits in flat areas due to high signal-to-noise ratio, as described in O'Callaghan and Mark (1984). Furthermore, these algorithms extract drainage networks but with one cell in width. The inconsistency shown among these algorithms is partly due to the fact that the single-cell drainage networks are more likely to be affected by error in DEMs.

It was not until Tribe's (1990) work that an algorithm was specifically constrained to extract drainage networks with a width of one cell. Tribe's approach employs two stages and uses both elevation changes and slopes between grid cells to derive more realistic drainage networks. First, a drainage network, one cell in width, is found, and then Tribe's algorithm attempts to expand feature width in all directions by examining the slopes of the cells adjacent to the identified drainage channels, and including them if the slope is within a specified threshold. Tribe's approach that drainage networks may have more than one cell in width is adapted here. In fact, the areas that drainage networks have more than one cell concur to a more practical terrain feature—a floodplain.

In this study, we devised a set of procedures using IDRISI (Eastman, 1990), a raster GIS, to determine which grid cells are part of the floodplain. In this fashion, a more meaningful representation of drainage pattern can be achieved instead of having a drainage network that is highly susceptible to error as is the case of the one-cell networks.

SAMPLE DEM

We used a USGS DEM which covers the area of Herbert Domain, Tennessee and is located in the Appalachian Plateau Province. The spatial resolution of this DEM is 30 metres and the DEM covers an area of 9 km², giving a 100 by 100 cell subset. The minimum elevation in the DEM is 474.6 metres and the maximum elevation is 569.0 metres. Figure 1 shows the contour map and a 3D diagram for the studied area. An oblique T-shape

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The process of generating the errors with specified spatial autocorrelation (Goodchild, 1986) onto the DEM surface was outlined by Goodchild (1980) and implemented by Fisher (1991a). First, for each cell in the DEM, a set of random numbers is drawn from a normal distribution with a mean of zero and a specified standard deviation. Then, the spatial autocorrelation of the error matrix is calculated and stored for later comparison. Next, two cells are randomly identified and swapped. Then the new spatial autocorrelation of the errors is calculated. If the new spatial autocorrelation is closer to the specified spatial autocorrelation, then the swap is retained; otherwise, the two cells are swapped back and two other cells are tried. This process is continued until the spatial autocorrelation is within a certain threshold. After an error matrix is generated, it is added to the DEM and the simulation is complete. In the analysis presented here, 30 simulations were run per test: 480 simulations in total. Discussion of an appropriate number of tests and the uniformity of random numbers generated can be seen in Fisher (1991b).

To assess how the magnitudes and the spatial patterns of elevation errors impact the accuracy of the results of terrain analysis, we conducted two sets of simulations. The first set of simulations was run to generate errors of varying magnitudes from ±1 metres to ±7 metres (standard deviations of 1 and 7 metres) with no spatial autocorrelation (Moran's I = 0.0). The second set of the simulations were run to generate errors of varying spatial autocorrelation from Moran's I = 0.0 to 0.9 with a fixed magnitude of ±7 metres. In this manner, we can observe the effects that errors in magnitude or spatial autocorrelation have on the accuracy of terrain analysis.

THE EXTRACTION OF FLOODPLAIN CELLS

The third stage extracted floodplain cells from the DEM through the use of several IDRISI programs. First, an examination of the original DEM and the elevation ranges was made to determine at what elevations the drainage channels were located. Because the DEM of this area is located in a physiographic region characterized by flat plateaus and deeply incised river channels (Figure 1), we assumed that the floodplain can be defined by a certain elevation range. Therefore, the elevation range of the floodplain cells was defined to occur between 474.6 metres (minimum elevation in the DEM) and 505 metres. The elevation image was then reclassified in IDRISI, assigning a value of 1 to those cells with elevations from 474.6 metres to 505 metres and a value of 0 to cells with elevation 506 metres or above.

Next, a slope image was created from the DEM image using the SURFACE program in IDRISI and again reclassified to assign a value of 1 to those cells with slopes between 0 and 10 degrees and a value of 0 to those cells with slopes of 11 degrees or above. The range for the slope map was chosen subjectively because it is assumed that the floodplain cells are relatively flat areas (i.e., slope under 11 degrees). Again, this should not affect the validity of the study here as long as they are kept consistent over all test runs.

The third step was to overlay the reclassified elevation and slope maps using the MULTIPY option in IDRISI's OVERLAY. Cells with both a slope less than 11 degrees and an elevation between 474.6 metres and 505 metres were classified as a floodplain cell. Finally, the AREA program in IDRISI was used to find the number of cells classified as floodplain for analysis in the results.

PROBABILITY MAPS OF FLOODPLAIN CLASSIFICATION

To observe the spatial patterns of the impact that elevation errors may have on the accuracy of the extracted floodplain cells, a series of probability maps will be compiled to compute the probability that any DEM cell would be classified as a floodplain cell with simulated elevation errors. To do this, we use...
the ADD option in the OVERLAY program of IDRISI to accumulate the number of times each cell has been classified as a floodplain cell for all simulations in each test. Next, the overlaid images are divided by the number of simulations in each test (which is 30 in this study) to produce probabilities, using the SCALAR program of IDRISI.

RESULTS

In order for comparisons to be made between the simulations performed and the original DEM, the original DEM needed to be processed using the same IDRISI procedures for extracting the floodplain with the same criteria for RECLASS (as described in the previous section) to be applied to every test. This process was first carried out for the original DEM, and the number of floodplain cells classified was found to be 1,137 out of 10,000 cells. Figure 2 shows the classified floodplain cells without any error applied.

The extracted floodplain seems to agree well with those displayed on the topographic map (Figure 1). The procedures were then repeated for every simulated DEM. Two of the floodplain maps after error simulation in the DEM are shown in Figure 3 and Figure 4. It is apparent that the error term causes misclassification of many floodplain cells.

RESULTS FROM SIMULATIONS WITH VARYING SPATIAL AUTOCORRELATION

The results of the first set of simulations with varying spatial autocorrelation values and a fixed standard deviation of 7.0 metres show that the number of floodplain cells classified increases as a function of the spatial autocorrelation of the errors. The results shown in Table 1 include average numbers of classified floodplain cells, omission cells, and commission cells. The number of classified floodplain cells for a test was obtained by simply counting the number of cells that were classified as floodplain cells in each simulation. The number of omission cells was obtained by (1) overlaying the floodplain found from the original DEM and the floodplain found for each simulated surface and (2) counting the number of cells that were not classified as floodplain cells when they should have been. In a similar fashion, the number of commission cells was obtained by overlaying the floodplain found from the original DEM and from simulated DEMs and counting those cells that were classified as floodplain cells when they should not have been.

By observing the results listed in Table 1, the average number of cells classified as floodplain cells decreases when spatial autocorrelation decreases. The average number of omission and commission cells change in different directions when spatial autocorrelation increases. It is clear that the higher the spatial autocorrelation among the errors added, the more commission cells and the less omission cells would result.

In graphic form, Figure 5a shows the rate of increase in the average number of classified floodplain cells when the spatial autocorrelation increases. Figure 5b displays the differences between the average number of classified floodplain cells against the spatial autocorrelation values. It is apparent that the trend fluctuates initially but becomes continuously increasing after the spatial autocorrelation value exceeds 0.5 or 0.6.

This analysis seems to suggest that the results of the extracted floodplain will likely be more reliable if the errors are more spatially autocorrelated (i.e., similar magnitude errors being located closer to each other). The increase in the number of floodplain cells corresponding to an increase in the spatial autocorrelation of the errors is thought to be a result of the clustering of errors. The errors that affect those cells making up the floodplain may be lessened as the errors become more clustered (i.e., high spatial autocorrelation).

It is also evident that spatial autocorrelation (from 0.0 to 0.9) has a stronger impact on the number of cells omitted (287 = 741 - 454) (Figure 5c) than on the number of cells committed (88 = 270 - 182) (Figure 5d) to the floodplain.

Linear regression models were run for each measure to examine the relationship between floodplain cells and spatial autocorrelation. The results are listed in Table 2 and Figures 5a, 5c, and 5d. Although spatial autocorrelation has a stronger impact on the number of omission cells than on the number of commission cells, Table 2 suggests that the relationship between spatial autocorrelation and the number of commission cells is more predictable than the number of omission cells (in-

<table>
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<tr>
<th>Test</th>
<th>SA</th>
<th>SD (m)</th>
<th>Mean of Cells Classified</th>
<th>Mean of Omission Cells</th>
<th>Mean of Commission Cells</th>
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<tr>
<td>1</td>
<td>0.9</td>
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<td>952</td>
<td>454</td>
<td>270</td>
</tr>
<tr>
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<td>557</td>
<td>248</td>
</tr>
<tr>
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<td>735</td>
<td>616</td>
<td>235</td>
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<tr>
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<td>0.6</td>
<td>7</td>
<td>706</td>
<td>655</td>
<td>224</td>
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<td>707</td>
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</tr>
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<td>185</td>
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<tr>
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<td>0.0</td>
<td>7</td>
<td>579</td>
<td>741</td>
<td>182</td>
</tr>
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</table>
Results from the Simulations with Varying Standard Deviations

The second set of simulations varied the standard deviation of elevation errors (equivalent to RMS errors) while holding the spatial autocorrelation constant at 0.0. The results of these simulations are listed in Table 3.

From Table 3, it is observed that the average number of classified floodplain cells increases when the magnitude of error decreases, and again, the number of omission cells seems to be more sensitive to varying error magnitudes than the number of commission cells. However, both numbers decrease when the standard deviation increases. Figure 6 shows three diagrams of the relationships between changing standard deviations and the average numbers of classified floodplain cells, omission cells, and commission cells.

Linear regression models were also run for this set of simulations and are listed in Table 4. It should be noted that, in the...
simulation of varying error magnitudes with no spatial autocorrelation, the average number of omission cells tends to be more predictable with a higher r-square value and a lower coefficient of variation than the average number of commission cells.

From the results in the second set of simulations, it is obvious that, as the amount or magnitude of errors decreases, the more similar the DEM will be to the original DEM regardless of the spatial patterns of the errors. For instance, errors of one metre in standard deviation applied to the DEM are so small that, regardless of the spatial pattern, the DEM closely approximates the original DEM. As the magnitude of the errors increases, the simulated DEM will diverge from the original DEM. This result corresponds to our intuitive expectation of deriving more accurate results from less errors.

**Probability Maps**

As described earlier, a series of probability maps was produced to show the likelihood of each cell being classified as a floodplain cell under various simulated situations. Figures 7 and 8 show the results of these mapping procedures.

A close examination of the maps shown in Figure 7 reveals that the spatial patterns of error (simulated by various spatial autocorrelation values) affect the extraction of the floodplain. The more clustered the simulated errors the more likely the floodplain cells are to be correctly extracted. Commission cells are observed at the middle left portion of the maps, and exhibit increased clustering when errors are more spatially autocorrelated.

In Figure 8, a distinct contrast can be observed between the probability maps of SD = 1 metre versus SD = 7 metres. This contrast confirms our intuitive expectation that the lower probabilities would be associated with higher magnitudes of simulated errors. Similarly, as the simulated error magnitude increases, more commission cells appear in the maps.

It would also appear that the areas of highest probability in the floodplain form linear ribbons through the image, and may actually be identifying (or locating) the network of at least primary streams. It is possible that this may enable detection of the drainage network through manipulation of error: the usual cause of problems in extraction by standard algorithms.

**Conclusions**

Because of the time involved in manually mapping the drainage patterns, such as a floodplain, from a topograhic map, the DEM has been seen as an excellent data source and an effective alternative for automating this once tedious and specialized process. In addition to proposing the procedures for extracting a floodplain, this paper demonstrates how the accuracy of a DEM impacts these procedures by simulating DEM errors under controlled circumstances.

By comparing the results of the simulated surfaces with those of the original, a better understanding of how the magnitude and the spatial pattern of the elevation errors can be achieved. The results from the simulations performed in this paper have demonstrated that there is a strong quantifiable impact of the accuracy of a DEM on the floodplain extracted.

**Table 4. The relationship between drainage cells and error standard deviation. Y₁; average number of classified drainage cells, Y₂; average number of omission cells, Y₃; average number of commission cells.**

<table>
<thead>
<tr>
<th>Regression model</th>
<th>r-square</th>
<th>Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y₁ = 1234.7 - 93.9 SD</td>
<td>0.993</td>
<td>2.11</td>
</tr>
<tr>
<td>Y₂ = -39.9 + 113.1 SD</td>
<td>0.998</td>
<td>2.85</td>
</tr>
<tr>
<td>Y₃ = 65.6 + 19.3 SD</td>
<td>0.900</td>
<td>10.62</td>
</tr>
</tbody>
</table>

An understanding of how the accuracy of the procedure for the extraction of floodplain changes as a function of the mag-
Fig. 7. Probability maps—SD = 7 metres, SA = 0.9, 0.6, 0.3, 0.0.

Fig. 8. Probability maps—SA = 0.0, SD = 1, 3, 5, and 7 metres.
Modeling the Effect of Data Errors

The level of accuracy of a particular terrain analysis function for various DEM accuracies may be valuable to organizations wishing to set standards for terrain analysis and GIS operations. By determining the level of accuracy for which results are required, the required accuracy of the data source can be determined. This would alleviate the need for trial and error tests to be performed on DEMs with different levels of accuracy.

A similar approach can be taken to assess the performance of various existing algorithms for extracting drainage patterns and other types of terrain analysis. We hope that, by documenting the impact of error magnitudes and spatial patterns on the accuracy of the results of terrain analyses in this paper, more understanding of the relationship between data accuracy and procedures for analyzing terrain surfaces may be achieved and used for various applications.

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