Distinguishing Actual and Artefact Depressions in Digital Elevation Data: Approaches and Issues

John B. Lindsay[1, 2] and Irena F. Creed[3]

[1]Department of Geography, University of Western Ontario, London, Canada, N6A 5C2

[2]Now at: School of Geography, Mansfield Cooper Building, University of Manchester, Oxford Road, Manchester, UK, M13 9PL

[3]Department of Biology, University of Western Ontario, London, Canada, N6A 5B7

Correspondence to: J. B. Lindsay, Department of Geography, University of Western Ontario, London, Ontario, Canada, N6A 5C2. Phone: (519) 661-2111 ext. 86496, Fax: (519) 661-3935, E-mail: jblindsa@uwo.ca

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Abstract

Topographic depressions in digital elevation models (DEMs) are frequently a combination of artefacts and actual features. It is common practice to remove all digital depressions, from DEMs that are used in hydro-geomorphic applications. This practice is inappropriate because actual depressions affect many of the environmental phenomena at study. Nonetheless, indiscriminate depression removal persists because of an inability to distinguish artefacts from actual depressions.

Five potential approaches for distinguishing artefacts from actual depressions in DEMs are described in this paper: ground inspection, examining the source data, classification approaches, knowledge-based approaches, and modelling approaches. Of the five methods, ground inspection was the only approach that actually confirms the existence of digital depressions. The other four methods that were identified operate by establishing justification for why a digital depression is likely to be an artefact or actual depression. A comparison of the depression validation approaches for a small sub-catchment on the Canadian Shield showed that the modelling approach performed the best. While being highly automated and applicable to all landscape types, this approach also explicitly handles DEM uncertainty. By applying the Monte Carlo method, this approach estimates the likelihood of a digital depression actually occurring in the landscape given the degree of uncertainty in local topography. After artefact and actual depressions are identified, it is then possible to remove the artefacts and to preserve the real features for incorporation into modelling.

Keywords: *topographic depressions; digital elevation models; digital terrain analysis; topography.*

Introduction

DEMs have become standard data for hydro-geomorphic analyses (Moore *et al*., 1991) and many of the techniques for processing these data are now ubiquitous in geographic information systems (GISs). Topographic depressions, also called pits or sinks, are commonly removed from DEMs prior to use in many hydro-geomorphic applications (Burrough and McDonnell 1998, Wilson and Gallant 2000). This practice reflects the fact that digital depressions are often artefacts that have the undesirable effect of altering and truncating simulated overland flow networks (Tarboton *et al*., 1991; Tribe, 1992; McCormack *et al*., 1993). Artefact depressions occur because of data errors, interpolation, and the limited horizontal and vertical resolution of DEMs (Qian *et al*., 1990; Tribe, 1992; Martz and Garbrecht, 1998; 1999; Rieger, 1998; Florinsky, 2002). Grid-based DEMs (i.e. elevation matrices), the most common terrain model format (Wise, 2000), frequently contain artefact depressions because of their inability to explicitly represent ridges and streamlines (Mark, 1988).

The practice of removing every depression from DEMs has been justified in the past in three main ways: 1) the scale and accuracy of a DEM is inadequate to represent actual depressions, which are generally small landforms, 2) depressions rarely occur in natural landscapes and artefact digital depressions are abundant, and 3) actual depressions have minimal impact on hydro-geomorphic processes since they either fill with water and overflow or find sub-surface pathways that are closely approximated by surface topography. These three justifications for removing all digital depressions are, however, largely no longer valid.

Early work in digital terrain modelling focused on environments where real depressions of a comparable scale to the resolution of available DEMs were rare, and therefore, it was justified to consider all digital depressions to be artefacts (e.g., O'Callaghan and Mark, 1984; Band, 1986; Jenson and Dominque, 1988; Hutchinson, 1989; Fairfield and Leymarie, 1991). However, modern DEMs that are created from digital photogrammetry, laser altimetry, and satellite imagery are often capable of representing actual depressions in the landscape because of their fine scale and high level of accuracy (MacMillan *et al.*, 2003). It is no longer justifiable to assume that all digital depressions are artefacts on the basis of DEM quality alone. Actual depressions also occur more extensively than has generally been acknowledged in the digital terrain analysis literature. Muehrcke and Muehrcke (1998) and Mark (1988) both provide descriptions of a variety of landscapes that contain depressions across a range of spatial scales. Furthermore, depressions are also important for environmental processes. Depressions store water, sediment, and nutrients, enhance water loss to the atmosphere and to deep groundwater, and provide critical habitat for plants and animals (Hubbard and Linder, 1986; Rosenberry and Winter, 1997; Hayashi and van der Kamp, 2000; Antonić *et al.*, 2001). These issues have led some terrain-modelling practitioners to question the appropriateness of removing all depressions from DEMs (Martz and deJong, 1988; Tribe, 1992; MacMillan *et al.*, 1993; McCormack *et al.*, 1993; Burrough and McDonnell, 1998; Metcalfe and Buttle, 1999).

Artefact and actual depressions must be distinguished in DEMs. This problem has received little attention in the literature even though fine-resolution DEMs are increasingly widespread in use (Lane and Chandler, 2003; Lindsay and Creed, in press a) and DEM analyses include low-relief landscapes where depressions are abundant (e.g., Martz and deJong, 1988; Liang and Mackay, 2000; Creed *et al.*, 2003). This paper evaluates several potential approaches to distinguishing actual and artefact depressions including ground inspection, examining the source data, classification approaches, knowledge-based approaches, and modelling approaches.

Ground Inspection

Digital depressions can be errors of commission (i.e., they exist in the DEM but should not). The only way that digital depressions can be confirmed to be actual features in the landscape is through ground inspection. This process involves visiting each depression that occurs in the DEM and recording a Boolean 'exists' or 'does not exist' value and possibly mapping the boundaries of the existing features. The global positioning system (GPS) is an invaluable tool for locating and mapping depressions. For larger depressions (i.e., > 100 m in diameter), aerial photographs and published topographic and hydrographic maps are useful for depression validation. Published land-use/land-cover maps are also useful for depression validation because several types of larger depressions related to anthropogenic activities (e.g. open-pit mines, quarries, and wetlands) are often mapped. Depressions can also be errors of omission (i.e., they do not exist in the DEM but should). One advantage to ground inspection of depressions is that depending on how the field campaign is designed it may be possible to identify both errors of commission and omission. While artefact depressions can be repaired by depression removal techniques (e.g. Lindsay and Creed, in press b), omitted depressions can only be resolved by further data collection and re-generation of the DEM.

Ground inspection is the most reliable method for identifying actual depressions. However, selection of the ground inspection method to distinguish actual and artefact depressions must consider the following constraints:

1. Landscapes may be inaccessible.
2. The number of depressions to be included in the ground survey may be unreasonable. The number of depressions in DEMs increases exponentially at smaller scales (MacMillan *et al*., 2003; Lindsay and Creed, in press a) requiring evermore depressions to be inspected on the ground.
3. The critical threshold in area for defining a depression must be considered. Often, this critical threshold is determined by the resolution of the DEM grid; depressions that are smaller than the DEM resolution cannot be represented in the elevation matrix. In fact, depressions that are a single grid cell in size are unlikely to be represented accurately in the DEM and several grid cells may be needed to represent a depression. Ground inspection must screen depressions and include only those that could possibly be represented in the DEM. A digital terrain analyst must be aware of these limitations in representing depressions in a DEM.
4. The challenges in identifying a depression must be considered. For example, it can be difficult to find depressions, particularly in forested regions or areas with extensive wetlands (Ludden *et al*., 1983). Conducting ‘depression hunting’ shortly after a heavy rainfall can lessen these problems because topographic depressions may be at least partly full.

5. The challenges in quantifying the size and shape of a depression must be considered. It may be difficult to determine the size and shape of depressions, particularly shallow depressions (which may be mistaken for a flat) and large depressions.
6. Ground inspection demands significant resources.

Ultimately, the success of a ground inspection campaign will be influenced by the availability of time, equipment for geo-locating and measuring the dimensions of depressions, and the familiarity of the personnel with the landscape.

Examination of the Source Data

When ground inspection is impossible or infeasible, an alternative to distinguishing actual depressions from artefacts in a DEM is examination of the source data from which the DEM was generated. There is potential for identification of both errors of commission and omission when the source data are available. If a depression does not exist in the source data but does exist in the DEM, it is likely to be an artefact resulting from error associated with the process of interpolating the data onto a regular grid. Similarly, if a depression exists in the source data but not in the DEM this reflects an inadequacy of the elevation matrix.

Types of source data for grid-based DEMs include: 1) contours, 2) elevation points (i.e., spot heights), and 3) a combination of contour data and spot heights. Digital contour data are common data sources for DEMs (Wise, 1998; 2000) because of the availability of published topographic maps. Public or government issued DEMs are generally derived from contour data. In contour maps, depressions are represented as closed contours that are at least partly surrounded by contours at a higher elevation and may contain contours of lower elevation. If the contour data contains a depression then there is justification for the feature in the DEM; there is no “proof” of a depression existing in the landscape because contour data invariably contain errors. If a depression occurs in a DEM and not in the contour data then there is no justification for the feature in the DEM and it is safe to assume that it is spurious. Therefore, examination of source data identifies ‘justified’ and ‘unjustified’ digital depressions.

Identifying depressions in a contour map is an easy task for a person with basic topographic map reading skills. Finding depression contours on paper maps is usually made easier by the cartographic convention of labeling depressions with hachure marks. Nevertheless, for large contour coverages containing many depressions, automated methods are preferable. Considerable effort is needed to automate the process of identifying depression contours because depressions occur in a variety of topographic settings and because digital contours do not usually possess hachures. However, once depression contours are identified they can be overlaid on a DEM and justified and unjustified depressions may be distinguished.

Unfortunately, contour maps often do not contain depressions even when these features actually exist, i.e., errors of omission are common. In a comparison of data sources, Applegate (2003) found that even high-resolution contours (1:100 scale, 10 ft contour interval) did not adequately represent the number, density, and size of depressions in a site in Mt. Airy Forest, Ohio. None of the depressions in the study (25 - 65 m in diameter and 3 - 4 m in depth) were represented in the contour maps as closed contours, although some were associated with contour crenulations on steeper slopes

(Applegate, 2003). Depressions are often absent from contour coverages because the depth of depressions is often less than the contour interval of even detailed topographic maps. Also, there is a cartographic rule that depressions are rare. Thus, when two equally valid contour coverages can be fitted to data, one with and one without depressions, the coverage without depressions is considered to be more plausible (Figure 1).

Spot heights can be derived from photogrammetric and remotely sensed data sources, which are becoming increasingly common in digital terrain analysis. Depressions are impossible to identify in spot height maps because spot heights alone cannot define a surface. It is possible however to identify spot heights that are lower than all points in their local neighborhood by fitting a triangular irregular network (TIN) to the data using Delaunay triangulation (Watson and Philip, 1984). Tucker *et al*. (2001) describe an algorithm for identifying depressions in TINs that may be of use for the depression validation problem. Of course, there is always potential that drainage is along flow paths that are obscured by the TIN configuration. Therefore, although examining the source data can build evidence to justify why a depression should or should not be present in a DEM, it is not as conclusive as ground inspection and is limited by data availability, structure, and quality.

Classification Approaches

Source data are not always available to the digital terrain analyst. Consequently, it is necessary to have alternatives for depression validation that only rely on the interpolated DEM. One such approach to the problem of depression validation is to use a classifier such as discriminant analysis or logistic regression. A small test area containing depressions could be used as a training set to develop a classification model to discriminate actual from artefact depressions. Thus, ground inspection is needed to classify all digital depressions in the test area of the DEM as either actual or artefact. The classification model can then be extrapolated to the entire DEM area. The multivariate space for the classification is defined by measurable attributes of digital depressions. For instance, classification could be based on the area, depth, volume, and location within the landscape of digital depressions.

Instead of conventional linear classifiers, an artificial neural network (ANN) (Lippmann, 1987; Hush and Horne, 1993) could conceivably be used to classify depressions as actual or artefact. However, the weights in an ANN are not easily interpreted in terms of their physical meaning. Furthermore, optimizing ANNs can be subjective and over-optimization (i.e. “over-training”) can lead to problems with generalization (Hush and Horne, 1993). Nevertheless, these models have been successfully applied to many classification problems in engineering and the sciences because of their ability to handle non-linear, multivariate problems (Hush and Horne, 1993). ANN classifiers are also relatively insensitive to noisy data and robust against multicollinearity, i.e., strong correlation among independent variables that hinders statistical modelling. These characteristics of ANNs could be advantageous for depression validation.

The linear and ANN classification approaches to depression validation only work, 1) if there is a significant difference between some attribute, or combination of attributes, of actual and artefact digital depressions, and 2) if this difference is robust across a range of spatial scales. These approaches are highly dependent on data structure and quality, both of which affect the representation of actual depressions in the DEM. Thus, it would not be prudent to use a model developed using one DEM on a second DEM of the same site but different source data or scale. Similarly, linear and ANN classification approaches to depression validation are also site-specific and may not be generalizable to other regions of interest. This is because of the highly variable morphology of natural depressions. For example, there is no reason to expect that sinkhole depressions in karst terrain will have similar morphology to prairie potholes because they result from different geomorphic processes. It is also necessary to ensure that the test area for which the classification model is developed is representative of the DEM as a whole. Therefore, the area must be relatively homogenous in terms of factors affecting depression formation and representation. Clearly, these limitations place severe constraints on the utility of linear and ANN classification models for discriminating actual and artefact digital depressions.

Knowledge-Based Approaches

Knowledge-based approaches to depression validation involve heuristic rules and expert opinion. For example, MacMillan *et al.* (1993) selectively removed depressions with minor extent or volume from their DEM. This takes advantage of the fact that several grid cells are needed to represent topographic variation accurately, and therefore, smaller digital depressions are likely to arise from error and other inadequacies of the DEM. Clearly a size threshold is needed to decide which features are too small or of minor volume, and this threshold is likely to be based on expert knowledge. Also, caution is needed if an area and/or volume threshold is used for depression validation since size is not always a good indicator of how justified a digital depression may be. For example, Lindsay and Creed (in press a) showed that at flow path bottlenecks in DEMs (i.e., areas of high topographic convergence) small elevation errors could result in large, multi-celled depressions upslope of the constriction.

The MacMillan *et al*. (1993) example is a heuristic rule based on a characteristic of data. It is also possible to develop heuristic rules for depression validation based on landscape characteristics. Depressions are generally ephemeral landforms; sediment is continually deposited in depression bottoms from higher elevations while erosion cuts outlets into their sides. The net effect is to lessen a depression's volume and over time eliminate it entirely. As such, the occurrence of depressions in a landscape usually indicates a disturbance by a recent geologic event (Muehrcke and Muehrcke, 1998). Knowledge-based approaches may take advantage of these geomorphic factors by considering how likely depressions are to occur given the local physiography (e.g. is the site one of the landscape types in which depressions occur frequently?), geologic history (e.g. has the site been recently disturbed by a geologic event?), or position within the landscape (e.g. where are individual depression located relative to the ridge and valley and how likely are they to occur in these locations?). If multiple heuristic rules were used, a multi-criteria evaluation could be developed based on a weighted combination of the spatial and aspatial data (Malczewski, 1999).

The difficulty with all knowledge-based approaches is that weighting systems need to be developed and expert opinions are often unavailable. For instance, how more or less likely is an actual depression to occur in a karst environment than in a recently glaciated prairie region? How more or less likely are actual depressions to occur along flat valley bottoms compared with steep mid-slope positions? Some such questions may be answered through extensive field observations of depressions, although their answers may apply only to specific landscapes. Therefore, knowledge-based approaches to depression validation that use landscape characteristics suffer from the same problems as the classification approaches—they are dependent on the source and scale of data and on the specificity of landscapes.

Modelling Approaches

While the depression validation methods described in the preceding sections are affected by error in the DEM, a modelling approach based on the Monte Carlo method explicitly recognizes that elevation matrices contain a degree of uncertainty. Depressions are unlikely to exist in the landscape if the topographic variation (i.e., the signal) is less than the uncertainty in elevations (i.e., the noise). Lane *et al*. (2004) and Lindsay and Creed (in press a) both used a similar stochastic simulation to quantify the sensitivity of digital landscapes to artefact depressions resulting from random elevation error. A related approach is suggested for the purpose of validation of depressions (Figure 2).

Based on the Monte Carlo procedure (Burrough and McDonnell, 1998), each grid cell is assumed to possess a Gaussian error probability distribution function (PDF) with a mean of zero and a specified standard deviation and degree of spatial autocorrelation. A sample is then randomly drawn from the Gaussian error PDF of each grid cell and added to the DEM. Depressions in the error-added DEM are then filled and grid cells that are modified by the depression filling process are flagged. This procedure is repeated numerous times, adding different error terms at each realization. Dividing the number of times that each grid cell is flagged during the simulation by the number of realizations yields the probability that a cell belongs to a depression (p_{dep}) given the distribution of elevation errors. Digital depressions that have topographic signals that are swamped by uncertainty in the DEM will be flagged infrequently during the simulation and therefore will have low p_{dep} values.

In most cases, depression validation is only concerned with whether or not depressions exist (i.e., a Boolean value) and not with their shape. Therefore, the grid cell with the maximum p_{dep} within each depression could be assigned to the feature (Figure 2). This is the grid cell with the strongest topographic signal contained within the depression. A p_{dep} threshold can then be used to determine which depressions are unjustified and later these depressions can be removed from the DEM.

This modelling approach is an attractive technique for depression validation when extensive ground inspection is impossible; it is automated, applicable in all landscapes, and explicitly handles uncertainty in topography. Also, the stochastic simulation method does not require much additional data (e.g. the source data) or knowledge of physiographic setting and glacial history, etc. Nonetheless, subjectivity may be involved in estimating error PDFs, the degree spatial autocorrelation, and the p_{dep} threshold. Kelly (2004) found that p_{dep} correlates strongly with actual depressions in the field and can therefore be used to identify actual depressions in a topographically diverse set of landscapes. However, Lindsay and Creed (in press a) found that there are ‘topographic hotspots’ (e.g., extremely convergent topography) that contain high p_{dep} values but are artefacts. Therefore, errors of commission can occur since areas of very high p_{dep} that are not associated with a depression can be included in simulations. Subsequent analysis, possibly ground inspection, may therefore be necessary to eliminate depressions with high p_{dep} values in topographic settings where the presence of an actual depression is suspect.

Example

Several algorithms needed to perform depression validation have been implemented in the *Terrain Analysis System* (TAS), a freely available geographic information system (Lindsay, in review). Routines have been programmed into TAS 1) to identify depression contours in a coverage of digital contour lines, 2) to measure depression metrics and to selectively remove depressions that do not meet a specified size threshold, and 3) to perform a Monte Carlo based modelling approach for depression validation.

The methods for depression validation that rely solely on the DEM have been applied to a 2.5 m grid resolution light detection and ranging (LiDAR) DEM (Figure 3). This DEM is of a 3.2 ha sub-catchment in the Turkey Lakes Watershed (TLW). TLW is an experimental watershed located within the Abitibi Uplands of the Canadian Shield, approximately 60 km north of Sault Ste. Marie, Canada. The LiDAR DEM was based on the last return of the laser altimeter, and therefore, the surface corresponds to ground terrain rather than canopy elevations. The source data from which the DEM was generated were unavailable.

The DEM contained 24 depressions. Ground inspection revealed that 15 of these digital depressions were actual features while the remaining nine were artefacts (Figure 3). Actual depressions occurred in all slope positions, with the most extensive depressions occurring within a wetland complex in the catchment bottomland. Artefact depressions also occurred in a variety of slope positions. Compared to the wide range in the size of actual features, most artefact depressions were a couple of grid cells in extent or less.

Four depression validation models were compared in terms of their ability to discriminate actual and artefact depressions. These models included:

1. Classification based on discriminant analysis (DA),
2. A simple heuristic rule based on removing depressions of minor extent (HR1),
3. A complex heuristic rule based on removing depressions of minor extent and depth (HR2), and,
4. Stochastic simulation modelling (SSM).

DA, the classification model, was created by importing the automatically derived depression metrics into a commercial statistical analysis package. The independent variables for this model included the following depression metrics: number of grid cells, maximum depth, average depth, volume, and elevation above sub-catchment outlet. The variables were entered into the model using a stepwise procedure with an F-to-enter = 1; once a variable was entered into the model it could not be removed. The final classification model was found to be statistically significant [$F(2, 21) = 3.88$ $p < 0.037$] and included only two the depression metrics: maximum depth and elevation above sub-catchment outlet.

The two heuristic models (HR1 and HR2) were both based on characteristics of data, and were similar in approach to the depression validation method described by

MacMillan *et al*. (1993). That is, these models removed depressions that were deemed to be of minor dimensions compared to the limitations of the elevation data to accurately represent landforms. HR1 filled all depressions that consisted of less than two grid cells. The more complex HR2 filled all depressions that consisted of less than two grid cells and had a maximum depth of less than 0.30 m. This threshold in depth reflects an estimate of the vertical accuracy of the DEM. Thus, the assumption is that it is reasonable to remove depressions that have maximum depths less than the root-mean-square error of the DEM. Both of the heuristic models were implemented using TAS's selective depression removal capabilities (Figure 4). Multiple filters can be applied to fill depressions based on thresholds in any combination of depression extent (i.e., number of cells or area), maximum depth, average depth, volume, and/or elevation. Depression metrics are measured automatically from a specified DEM, and the user is able to review the fill status for individual depressions before applying the filter.

SSM followed the procedure for depression validation outlined in Figure 2. The error distribution used in the simulation had a mean of zero and a standard deviation of 0.3 m, reflecting the DEM accuracy. Error fields were created to exhibit a small degree of autocorrelation. The simulation ended after 304 realizations, after which point the differences between consecutive realizations were deemed to be minor. A p_{dep} threshold of 0.7 was used to discriminate artefact ($p_{\mathrm{dep}} < 0.7$) and actual ($p_{\mathrm{dep}} \geq 0.7$) depressions for this demonstration. As such, depressions were accepted if they demonstrated a 0.7 probability of existing, given the uncertainty in the DEM. This threshold was found to be suited to these data, and may not be appropriate to other data sets. Many of the artefact depression with lower p_{dep} values likely occur on flat sites.

All of the facilities needed to perform the operations described in Figure 2 have been implemented in TAS. The Monte Carlo method component, i.e. the steps for determining the spatial pattern of p_{dep}, can be performed using the 'Depression Shape Analysis' sub-program. The maximum p_{dep} can then be assigned to individual depressions by using the 'Descriptive Statistics' sub-program and selective filling based on p_{dep} can be achieved using TAS's raster calculator.

Table 1 summarizes the results of the four depression validation methods, compared against the ground inspection findings. Although the overall success in distinguishing actual and artefact depressions did not vary substantially among the four models, SSM did perform slightly better with a 75% classification success. SSM performed relatively well for identifying both artefact and actual depressions and incorrectly classified relatively few features (Table 1). DA performed well at identifying actual depressions, but was far less successful in recognizing artefact depressions. Similarly, HR1 successfully identified each of the artefact depressions in the DEM; however, it was liberal in its classification of artefact depressions, resulting in far fewer 'actual' depressions than were observed by ground inspection. While HR2 was found to be the worst overall model, much of this error was the result of removing actual depressions. The poor performance of both HR1 and HR2 largely resulted because several actual depressions consisting of one or two grid cells (i.e., $\leq$ 5 m) did occur in the sub-catchment. This is not a problem that is likely to be resolved with finer DEM resolutions since the number of actual depressions increases exponentially with finer grid spacings.

Many of the errors made by the DA model were associated with smaller depressions in upland positions (Figure 5). The errors in classification made by HR1 and HR2 were dispersed throughout the sub-catchment in association with the distribution of small depressions (i.e., ≤ 2 grid cells). The classification errors made by SSM were appeared to be more strongly associated with smaller depressions in higher slope positions (Figure 5). Thus, each of the depression validation approaches had difficulties correctly classifying small depressions, while most of the approaches were successful in classifying more extensive depressions.

Summary and Conclusions

The importance of depressions as controls on environmental processes within certain landscapes is widely recognized. Despite this awareness, it is common practice in terrain analysis to remove all depressions in DEMs prior to conducting hydro-geomorphic analyses involving flow phenomena at or near the Earth's surface. This practice stems from historical assumptions that are largely invalid given the quality of modern elevation data and current understanding. Regardless of their resolution and accuracy, however, grid-based DEMs will always contain numerous artefact depressions that should be removed from the data. Consequently, it is important that researchers have the ability to distinguish between actual and artefact depressions in their DEMs and to selectively remove the artefacts. This is a problem that has, until now, received little attention in the literature. Five approaches to digital depression validation were proposed in this paper: ground inspection, examination of the source data, classification approaches, knowledge-based approaches, and a Monte Carlo based modelling approach. None of these approaches to depression validation are perfect; each has various advantages and disadvantages (Table 2).

The aim of this paper was to increase awareness of the problems associated with digital depressions in DEMs, to present a critical analysis of the methods for discriminating between actual (to be preserved) and artefact (to be removed) digital depressions, and to stimulate research which could eventually lead to a more ideal method for discriminating between actual and artefact digital depressions. The following major conclusions are drawn:

1. Ground inspection is the preferred method of depression validation whenever possible because it is the only method that truly confirms the occurrence of depressions in the landscape. However, when ground inspection is impossible or infeasible, alternative means of discriminating actual and artefact depressions are needed, i.e. it is often unacceptable simply to remove all depressions indiscriminately from DEMs.

2. The automated methods provide evidence that the occurrence of digital depressions in DEMs are justified or unjustified. Of the four methods described in this paper, the Monte Carlo modelling approach is the most promising. This method is relatively insensitive to the source or scale of the data used to generate a DEM and is applicable in all landscapes. The modelling approach also performed slightly better than the other depression validation approaches in an example application. Combining the Monte Carlo based modelling approach with restricted ground inspection could provide a method to objectify the selection of error PDF characteristics and the p_{dep}

threshold and to verify depressions with high p_{dep} in topographic settings where actual depressions are unlikely.

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Table 1. Classification results for four depression validation approaches applied to a small sub-catchment on the Canadian Shield. Model names are explained in text.

Model Name	Correctly Removed	Incorrectly Removed	Correctly Preserved	Incorrectly Preserved	Total Correctly Classified	Total Incorrectly Classified
DA	5	3	12	4	17	7
HR1	9	7	8	0	17	7
HR2	7	6	9	2	16	8
SSM	7	4	11	2	18	6

Table 2. Advantages and disadvantages of approaches to depression validation.

Depression validation Method	**Advantages**	**Disadvantages**
Ground inspection	Most accurate; Identifies errors of commission and omission.	Manual; Labour and resource intensive.
Examination of source data	Automated; Identifies errors of commission and omission.	Dependent on the availability of source data; Very sensitive to the quality, structure, and scale of the source data; Contour data subject to biases introduced by map drawing.
Classification approaches	Automated; Requires DEM only.	Model limited to specified data source and scale, leading to problems generalizing; Requires a significant difference in the attributes of actual and artefact depression attributes; Can be scale dependent; Requires some ground inspection; Cannot identify errors of omission.
Knowledge-based approaches	Automated; Applies physically meaningful heuristic rules; Does not involve ground inspection.	Expert opinion needed to develop weighting scheme is often unavailable; Weighting scheme may be sensitive to landscape type; Cannot identify errors of omission.
Monte Carlo based approach	Automated; Requires little additional data and information; Applicable in all landscapes; Accounts for uncertainty in topography.	Need to estimate error distribution and spatial correlation (subjective if ground data are unavailable); Need to estimate threshold p_{dep} value; May require some ground inspection to identify errors of commission.

Figure Captions

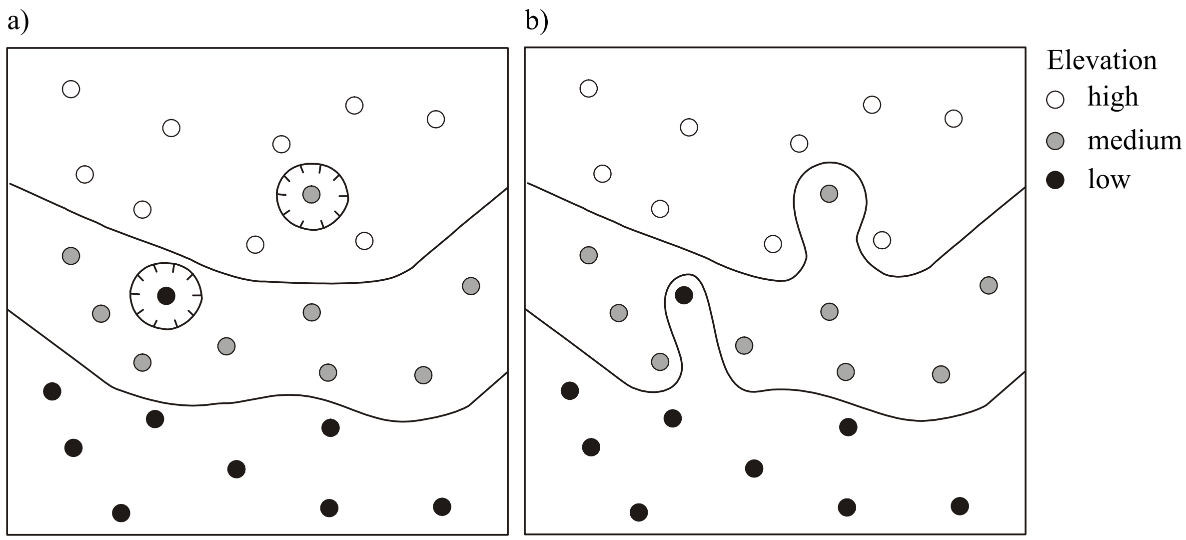
Figure 1. Two equally valid contour coverages, one contains depression contours (a) and one does not (b). The contour coverage without depressions represents the typical cartographic convention for contouring.

Figure 2. Monte Carlo procedure for artefact depression identification and removal. p_{dep} is the probability of depression occurrence.

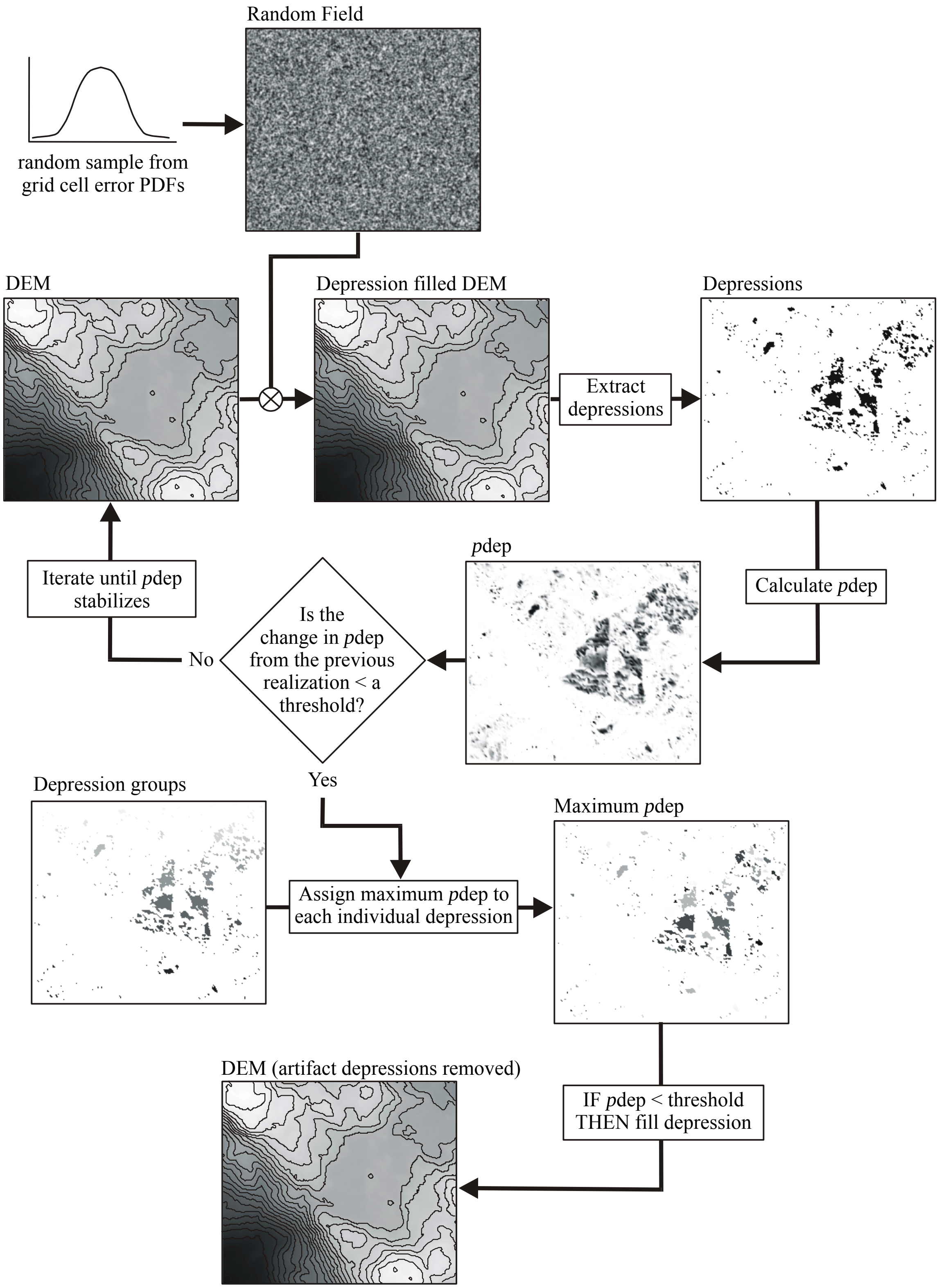
Figure 3. Results of a ground inspection campaign for depressions in a small sub-catchment on the Canadian Shield.

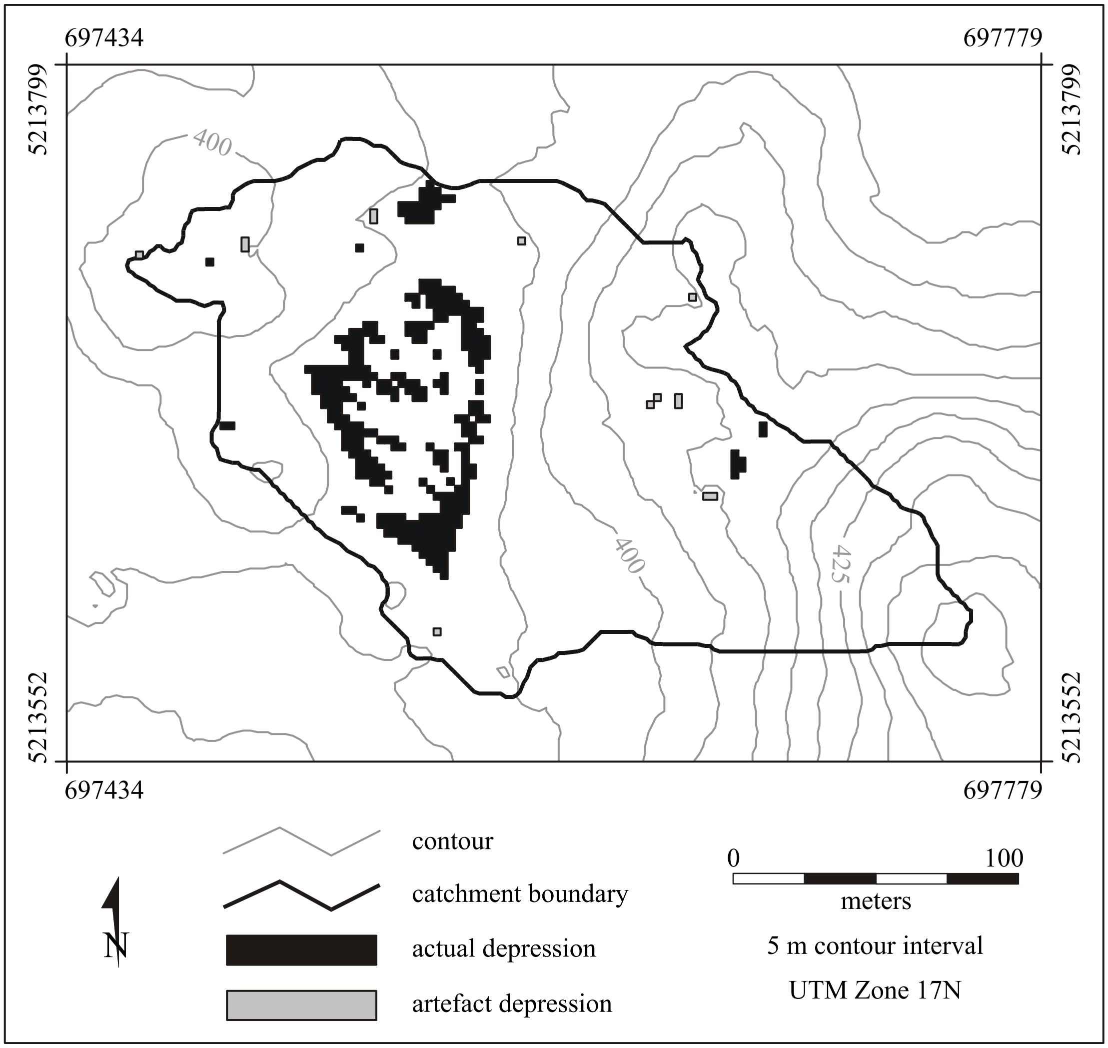
Figure 4. The graphical user interface for a program for measuring depression metrics and selectively filling depressions.

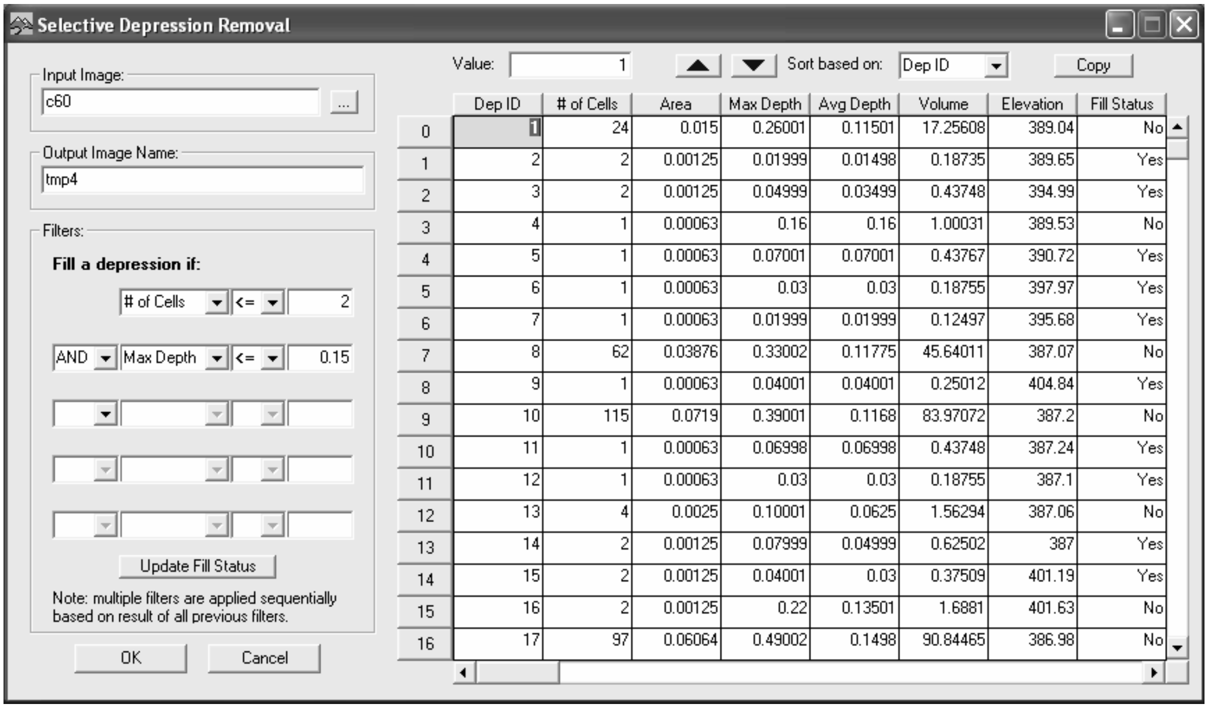
Figure 5. Comparison of four depression validation models applied to catchment in Figure 3.



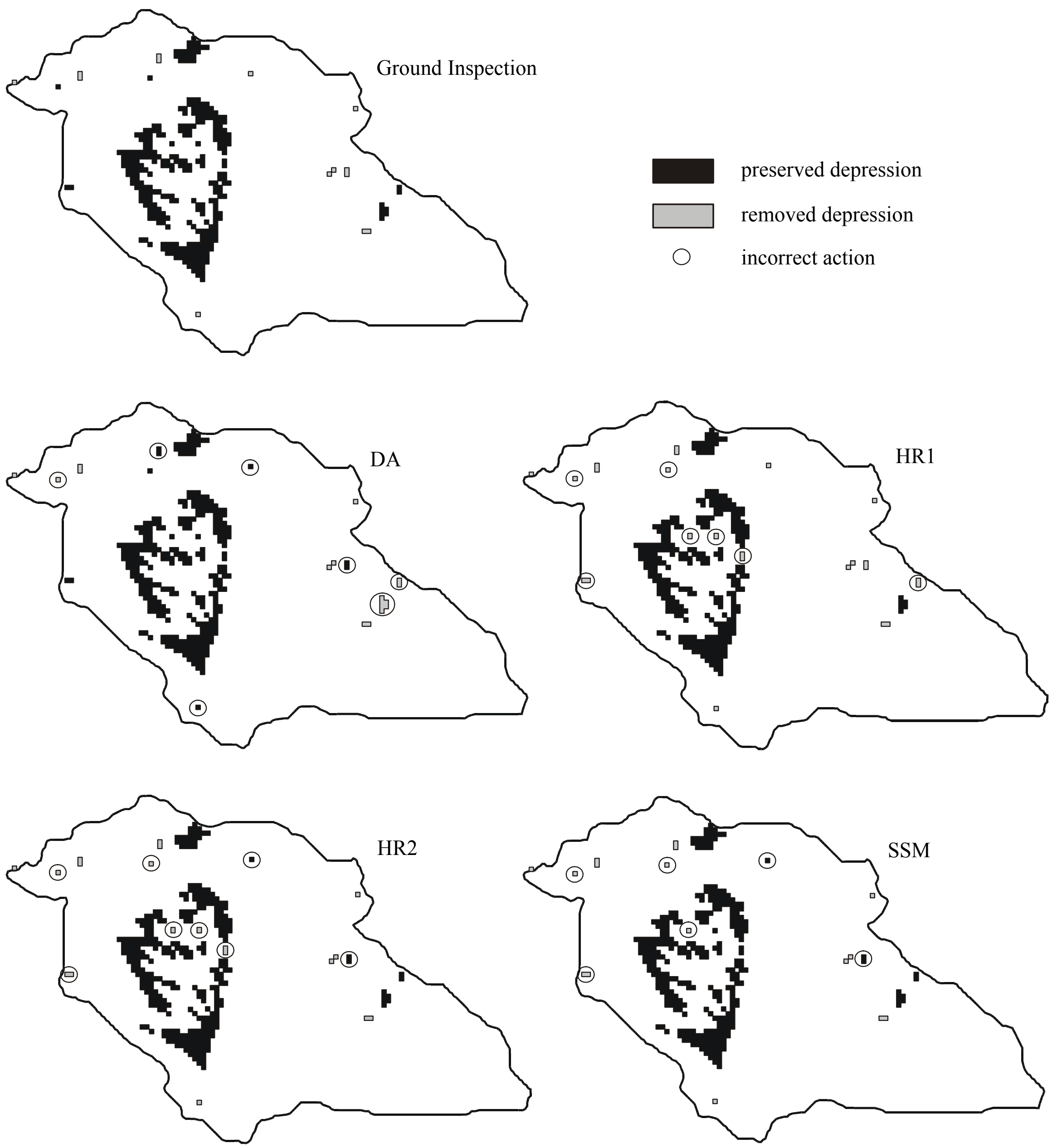
a)
b)
Elevation
high
medium
low


Random Field
random sample from grid cell error PDFs
DEM
Depression filled DEM
Depressions
Extract depressions
Calculate pdep
pdep
Is the change in pdep from the previous realization < a threshold?
No
Iterate until pdep stabilizes
Yes
Depression groups
Assign maximum pdep to each individual depression
Maximum pdep
IF pdep < threshold THEN fill depression
DEM (artifact depressions removed)


697434
697779
5213799
5213799
400
400
425
5213552
5213552
697434
697779
contour
catchment boundary
actual depression
artefact depression
N
0
100
meters
5 m contour interval
UTM Zone 17N



	Dep ID	# of Cells	Area	Max Depth	Avg Depth	Volume	Elevation	Fill Status
0	1	24	0.015	0.26001	0.11501	17.25608	389.04	No
1	2	2	0.00125	0.01999	0.01498	0.18735	389.65	Yes
2	3	2	0.00125	0.04999	0.03499	0.43748	394.99	Yes
3	4	1	0.00063	0.16	0.16	1.00031	389.53	No
4	5	1	0.00063	0.07001	0.07001	0.43767	390.72	Yes
5	6	1	0.00063	0.03	0.03	0.18755	397.97	Yes
6	7	1	0.00063	0.01999	0.01999	0.12497	395.68	Yes
7	8	62	0.03876	0.33002	0.11775	45.64011	387.07	No
8	9	1	0.00063	0.04001	0.04001	0.25012	404.84	Yes
9	10	115	0.0719	0.39001	0.1168	83.97072	387.2	No
10	11	1	0.00063	0.06998	0.06998	0.43748	387.24	Yes
11	12	1	0.00063	0.03	0.03	0.18755	387.1	Yes
12	13	4	0.0025	0.10001	0.0625	1.56294	387.06	No
13	14	2	0.00125	0.07999	0.04999	0.62502	387	Yes
14	15	2	0.00125	0.04001	0.03	0.37509	401.19	Yes
15	16	2	0.00125	0.22	0.13501	1.6881	401.63	No
16	17	97	0.06064	0.49002	0.1498	90.84465	386.98	No


Ground Inspection
preserved depression
removed depression
incorrect action
DA
HR1
HR2
SSM