

# Geomorphometric landscape analysis using a semi-automated GIS-approach

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## Abstract

This paper presents LANDFORM, a customized GIS application for semi-automated classification of landform elements, based on topographic attributes like curvature or elevation percentile. These parameters are derived from a Digital Elevation Model (DEM) and used as thresholds for the classification of landform elements like crests, flats, depressions and slopes. With a new method, slopes were further subdivided into upper, mid and lower slopes at significant breakpoints along slope profiles. The paper discusses the results of a fuzzy set algorithm used to compare the similarity between the map generated by LANDFORM and the visual photo-interpretation conducted by a soil expert over the same area. The classification results can be used in applications related to precision agriculture, land degradation studies, and spatial modelling applications where landscape morphometry is identified as an influential factor in the processes under study.

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**Keywords:** Landscape analysis; Terrain analysis; Landform; Geomorphometry; GIS; Terrain attributes; Spatial modelling

## Software availability

Name of software: LANDFORM 2

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Program language: Visual Basic 6.0

Availability and cost: Version 2 for GeoMedia Grid 5.2 (2006), can be ordered for free on the CPSTOF project website: <http://www.cage.curtin.edu.au/~graciela/projects/cpstof/software.html>. Updates following the

development of GeoMedia Grid can be requested from the developer at [bernhard.klingseisen@arcs.ac.at](mailto:bernhard.klingseisen@arcs.ac.at)

System requirements: Version 5.2 of GeoMedia and version 5.2 of GeoMedia Grid, available from Intergraph Corporation (<http://www.intergraph.com>)

## 1. Introduction

A paper on the use of Digital Elevation Models (DEMs) and GIS for geomorphometric landscape analysis (Schmidt and Dikau, 1999) states that whereas methods for the extraction of primary geomorphometric parameters (e.g. slope, aspect, height) are offered by standard GIS, integrated mapping of geomorphometric objects (e.g. landform units) such as valley bottoms, crests, or hillslopes are yet to be developed. Schmidt and Dikau (1999) also identified other limitations of current GIS software concerning effective applications in landform morphometry, such as the simplicity of analytical methods (e.g. filter techniques, cartographic overlay), the close structure of

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methods and tools, and precluding complex geomorphometric analysis. In consideration of these views and the fact that standardised and rapid interpretations of landscape forms over large areas is an essential modelling component in several natural resources' applications (e.g. soil survey, geomorphologic mapping, prediction of avalanches or landslides within catchments), this paper discusses the development of a customized GIS application for semi-automated classification of landform units. The design and implementation of this semi-automated approach, called LANDFORM, was done through customization of GeoMedia GIS technology, enabling a user to test default thresholds and then adjust them to suit a specific landscape type and DEM resolution.

LANDFORM also addresses a problem of subjectivity in delineation of landform units using traditional methods of photo-interpretation for applications such as soil survey or geomorphologic landscape analysis. In traditional methods of soil survey, experienced soil surveyors define soil boundaries utilizing stereo photographic interpretation methods based on soil formation models and functional models of prediction (which incorporate geomorphometric objects), which exist in the minds of the surveyors (McKenzie et al., 2000). Because to a large extent the accuracy of boundary definitions relies on the experience of the photo-interpreter, the output maps are considered subjective. For instance, a test conducted by Van Westen (1993) to assess the variability in outlining geomorphologic units via photo-interpretation showed that only 10% of the test area was assigned the same legend unit by four interpreters. About 17% was mapped identically by three and 53% by two interpreters. It is clear that the cartography of geomorphometric objects has a high degree of subjectivity, depending strongly on the experience of the person making the map. On the other hand, automated landform classifications intend to overcome this degree of subjectivity by extracting information in a repeatable robust fashion, thus becoming a quantitative instead of cognitive expression of the relationship between soil properties and terrain attributes (Ventura and Irvin, 2000).

This paper discusses the conceptual framework, design and implementation of LANDFORM, including a comparison of modelling outputs against the traditional method of photo-interpretation of landform units. Section 1 presents the conceptual modelling adopted for mapping landform units, whereas Sections 2 and 3 describe the data sets, method and techniques used for customising a GIS software, including the development of new algorithms. Using an approach based on fuzzy sets theory, Section 4 discusses and compares the similarities and disagreements between the spatial distribution of landform units derived using the traditional (e.g. photo-interpretation based) versus the semi-automated GIS based approach. Section 5 summarises the main findings of this research.

### 1.1. Conceptual framework

There are several techniques for the development of landform units and these differ in terms of categorical structure (Moore et al., 1993; Gessler et al., 1995; McKenzie and Ryan, 1999). A key Australian classification of landforms

was developed by Speight (1974, 1990). Speight (1974) proposed a two-level descriptive procedure for a systematic and parametric description of landforms into *landform patterns* and *landform elements*. The landform is viewed as a hierarchical mosaic of tiles whereby the larger tiles form landform patterns with an average radius of 300 m. These landform patterns consist of smaller tiles or landform elements that are commonly of the order of 20 m radius (Speight, 1990). Speight (1990) defined about 40 types of landform patterns including, for example, flood plain, dunefield and hills and more than 70 types of landform elements such as cliff, footslope and valley flat. Relief and stream occurrence describe landform patterns while landform elements may be described by five attributes namely slope, morphological type (topographic position), dimensions, mode of geomorphological activity and geomorphological agent. Speight (1990) distinguished 10 types of topographic positions in which landform elements fall into as listed in Table 1. A full description of each morphological type can be found in Speight (1990). Fig. 1 provides examples of profiles across the terrain divided into morphological types of landform elements as classified by Speight (1990).

Speight's (1990) description of landforms is a key component that contributes towards the systematic recording of field observations in Australian soil and land surveys, and as such many existing survey records consist of Speight's (1990) landform descriptions. Coops et al. (1998) produced a set of techniques that allow topographic position to be predicted from 25 m DEMs, in which the classes are equivalent to Speight's (1990) morphological types that are used by field botanists, ecologists and other natural resource scientists and managers. Our research is focusing on the design and implementation of a semi-automated approach for the extraction of landform elements. The methodology developed by Coops et al. (1998) provided key background information in relation to algorithm development and threshold values, and as such was utilised in conjunction with Speight's (1990) descriptions of morphological types.

The resulting landform maps are intended for a scale of 1:10,000 to be used for approaches in precision agriculture. MacMillan et al. (2000) proposed input data with a maximum horizontal resolution of 10 m for this nominal mapping scale. Given the different premises and target scale of the methodology proposed by Coops et al. (1998), threshold values had to be adapted, considering the scale dependency of the underlying topographic attributes. Wood (1996) provides an extensive discussion of the scale relevance for the characterisation of landscape. In the case of the DEM derivatives curvature and slope, coarser resolution and hence a coarser scale means significant generalisation of the landscape and many landscape features relevant for precision farming are lost. On the other hand, high resolution DEMs are often not suitable for general landscape characterisations, where small features are of no special interest.

Considering the proved correlation between scale and cell size of elevation data and the derived topographic attributes, LANDFORM is designed especially flexible to allow for the alteration of threshold values. The approach is not

Table 1  
Morphological type (topographic position) classes by Speight (1990)

Name	Definitions of Speight (1990)
Crest	Area high in the landscape, having positive plan and/or profile curvature
Depression (open, closed)	Area low in the landscape, having negative plan and/or profile curvature, closed: local elevation minimum; open: extends at same or lower elevation
Flat	Areas having a slope <3%
Slope	Planar element with an average slope >1%, subclassified by relative position
Simple slope	Adjacent below a crest or flat and adjacent above a flat or depression
Upper slope	Adjacent below a crest or flat but not adjacent above a flat or depression
Mid slope	Not adjacent below a crest or flat and not adjacent above a flat or depression
Lower slope	Not adjacent below a crest or flat but adjacent above a flat or depression
Hillock	Compound element where short slope elements meet at a narrow crest <40 m
Ridge	Compound element where short slope elements meet at a narrow crest >40 m

automatically suitable for scale-independent analysis, so thresholds have to be tested for the specific purpose and data characteristics. Hence, the thresholds mentioned in the following sections are only a guideline for a specific type of input data and mapping scale. The steps followed for the design and implementation of LANDFORM as well as the validation of the output classification and discussion of results are described hereafter.

## 2. Study area

The research project was carried out in Australia at the Muresk Institute of Agriculture Farm. Muresk is situated 100 km northeast of Perth in the Shire of Northam in the Western Australian wheat belt (Fig. 2). Muresk Farm covers

an area of 1720 ha used for cropping, sheep farming and cattle production (CPSTOF Team). The elevation of the flat to slightly rolling terrain with a mean slope of 5% ranges from about 154 m to 274 m above sea level. The elevation data for this research were provided by the Department of Agriculture of Western Australia. Heights have been derived with a vertical resolution of 0.01 m on a 10 m grid from stereo aerial photography flown at 1:40,000 scale, using soft copy automatic terrain extraction (image correlation) techniques. The data were smoothed to remove small discontinuities using an iterative adaptive filter (Caccetta, 2000).

## 3. Methodology

The methodology adopted in the design and implementation of LANDFORM, as described in this paper, is based on the ideas of Skidmore (1990)

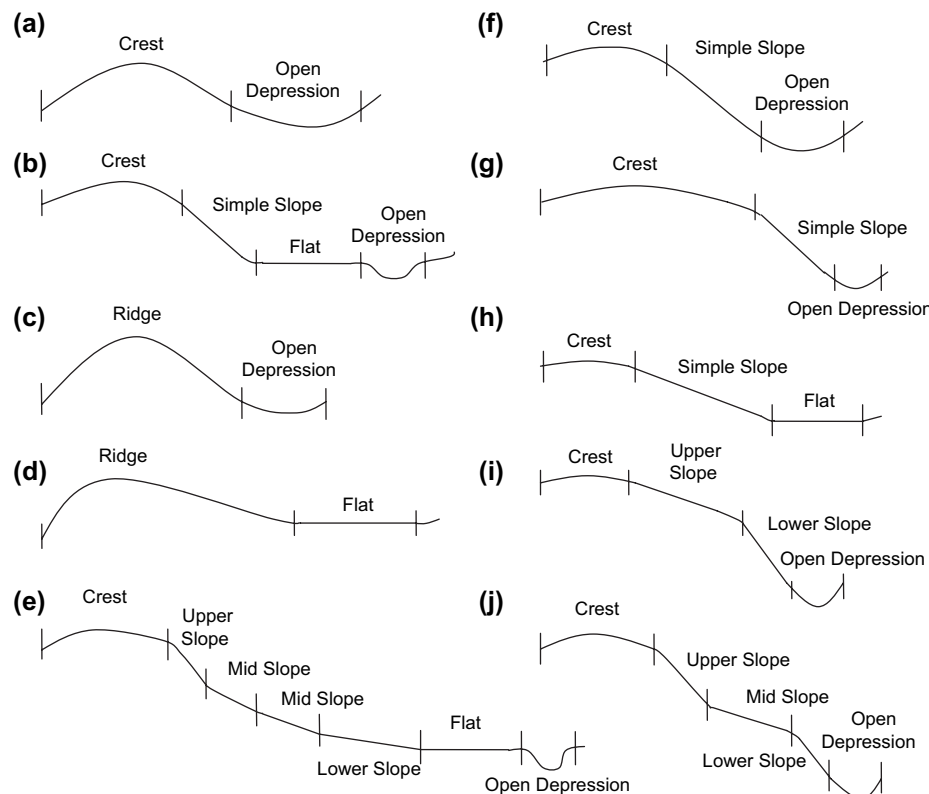


Fig. 1. Examples of profiles across terrain divided into morphological types of landform elements (adapted from Speight, 1990).

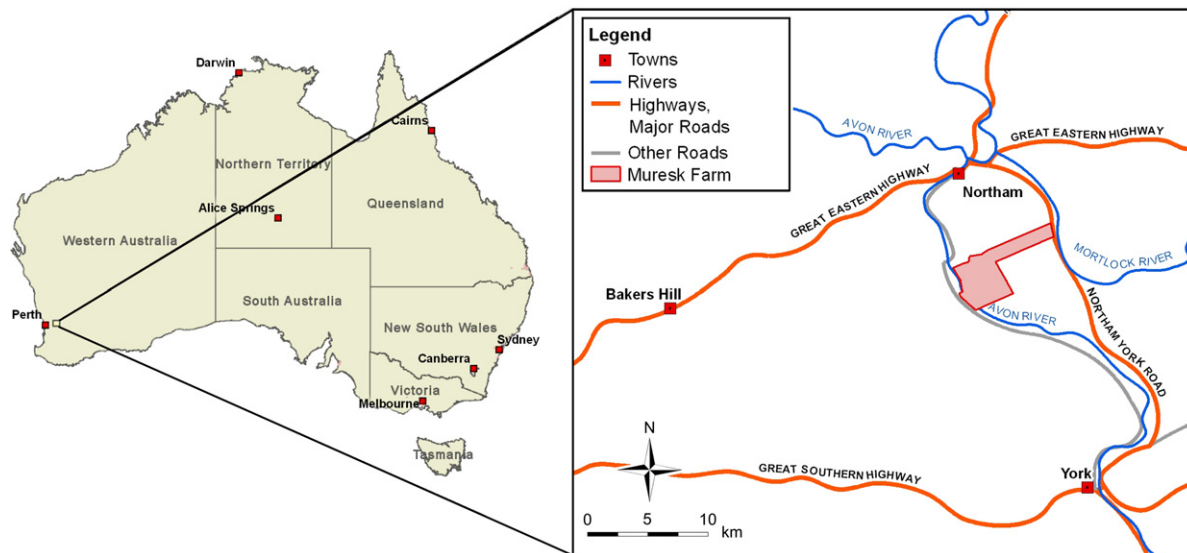


Fig. 2. The study area at Muresk Farm, 100 km northeast of Perth (WA).

and Coops et al. (1998), who developed workflows for the prediction of topographic position from a DEM. LANDFORM is implemented in Visual Basic as a series of custom commands that are accessible individually over a new menu within GeoMedia to generate landform elements according to the definitions of Speight (1990). This approach makes each command additionally useful for analyses outside the scope of landform classification, e.g. to predict avalanche catchments as done by Rauter (2006), and guides the users through the procedure instead of offering a fully automated blackbox with little user interaction. The classification process using the LANDFORM commands consists of four basic steps as shown in Fig. 3.

First, general topographic attributes like slope, plan and profile curvature as well as more regionalized attributes such as local relief and elevation percentile are derived from a DEM. These topographic attributes provide the input for the definition of the primary landform elements – crests, depressions, flats and slopes. The landform classification is then performed by testing different threshold values based on the results of Coops et al. (1998). Furthermore, a new method was developed to generate a connected depressions' network. Section 3.3 covers the classification of each landform element and the proposed threshold values. After the generation of the primary landforms the single layers are combined by an overlay operation and any remaining

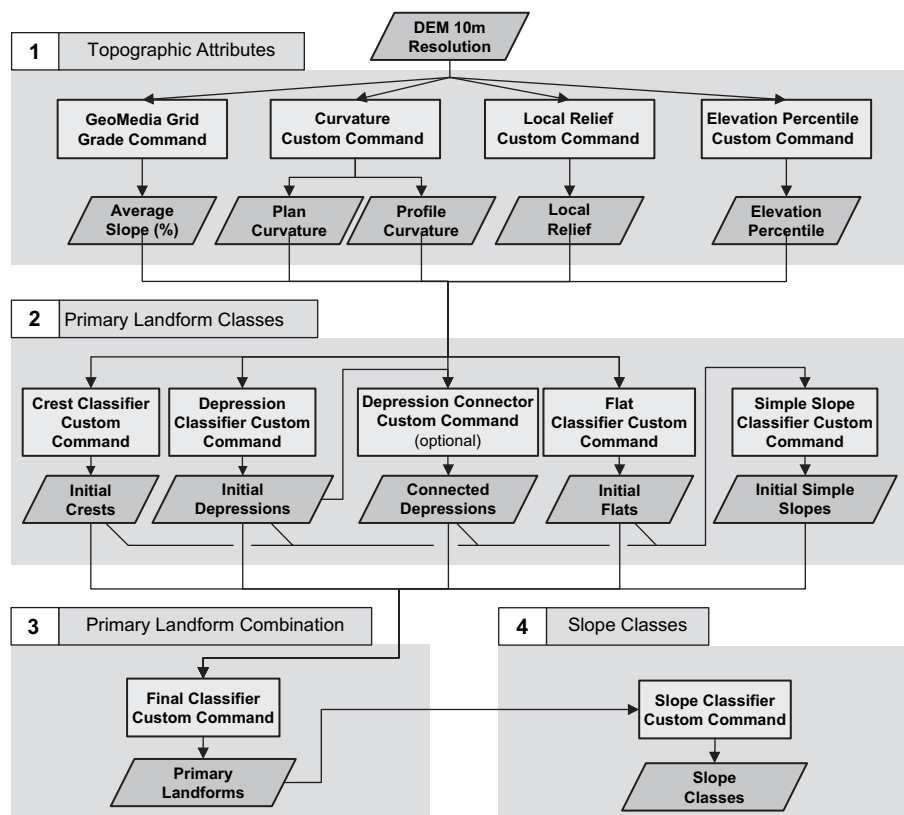


Fig. 3. Flow Chart of the methodology followed for design and implementation of LANDFORM.

singular cells or narrow strips in the classification are removed with a low pass filter as described in Section 3.4. Slope elements are then subdivided into upper, mid and lower slope, following the procedure explained in Section 3.5. Areas initially classified as slopes are broken up at significant changes of slope and classified according to their relative position in a toposequence between crests and depressions. In this toposequence, upper slopes are the highest elements and occur underneath crests, followed by mid and lower slopes near the valley bottom. Areas lacking significant break in slope are classified as Simple slopes.

### 3.1. Developing custom commands for GeoMedia Grid

The GIS software GeoMedia Professional 5.2 and its raster extension GeoMedia Grid 5.2 are chosen to provide the framework technology for this study, offering capabilities to manage all spatial and non-spatial data. GeoMedia Grid can be customized with the COM compliant GeoMedia Grid objects that are accessible through the exposed API for Visual Basic and C++ (Intergraph Corporation, 2006). Customization of a GIS application involves the modification of the standard graphical user interface and the extension of the delivered functionality (Maguire, 1999). For the development of LANDFORM, the objects of GeoMedia Grid were utilised to build practical and functional spatial models, tailored to a specific application and the user needs.

### 3.2. Computing topographic attributes

Topographic attributes can be derived from a DEM to model hydrologic and geomorphologic processes, predict the spatial distribution of soil properties as well as the topographic position of species within a region (Błaszczynski, 1997; Coops et al., 1998; Gallant and Wilson, 2000; Zevenbergen and Thorne, 1987). The topographic attributes used for landform classification are calculated with GeoMedia Grid custom commands, which have been developed especially for this purpose, as described hereafter.

#### 3.2.1. Slope (gradient) [percent, degrees]

Slope is a controlling factor in earth surface processes as it influences surface flow, soil properties and water content as well as the erosion potential of an area. It is calculated as the rate of change in elevation either as steepest downhill slope to one of the eight neighbours or using a second-order finite difference method fitted to four or eight closest neighbours. In the present classification method average slope is calculated with the GeoMedia Grid *Grade* command from all eight neighbour cells using finite differences (Gallant and Wilson, 2000, p. 53; Keigan Systems, 2005) applying Eq. (1).

$$\text{average slope} = 100 \sqrt{\bar{x}^2 + \bar{y}^2} \quad (1)$$

where  $\bar{x}$  is the average slope from west to east and diagonally through the centre cell and  $\bar{y}$  is the average slope from east to west and diagonally through the centre cell. Both average slopes are then squared and added together. The square root of the result, multiplied by 100, gives the average slope in percent as final result of the *Grade* command. The result is further used in the classification process to extract flat areas from the DEM.

#### 3.2.2. Local relief or elevation range [m]

This measure defines the range of elevation values within a circular scan window of predefined radius (Gallant and Wilson, 2000). The algorithm is implemented as the *Local Relief* command with a default window radius of 150 m as proposed by Coops et al. (1998). Local relief is used as an additional threshold in the classification of crests as described in Section 3.3.1

$$\text{local relief} = \max_{i \in C} z_i - \min_{i \in C} z_i \quad (2)$$

where  $\max z_i$  is the highest elevation value within a circular window  $C$  of defined radius around location  $i$ , and  $\min z_i$  is the lowest elevation within this window.

#### 3.2.3. Elevation percentile

Elevation percentile is a ranking of a point's elevation relative to all other points in a circular window (Gallant and Wilson, 2000, p. 75). The number of cells that is lower than the centre cell is divided by the full number of all cells in the window. A radius of 150 m is chosen as default size for the scan window according to the findings of Coops et al. (1998). Percentile ranges from 0 to 1, with a value of 0 indicating that the point is the lowest and 1 indicating that it is the highest. The calculation of elevation percentile is implemented as a custom command. With its well-defined range of resulting values, elevation percentile provides a robust measure to delineate crests and depressions.

$$\text{elevation percentile} = \frac{\text{count}_{i \in C} (z_i < z_0)}{n_c} \quad (3)$$

where  $z_i$  is the elevation at location  $i$ , and  $n_c$  the number of cells in a circular window  $C$ .

#### 3.2.4. Curvature

The curvature of a topographic surface is mostly expressed in terms of profile and plan curvature. Błaszczynski (1997) describes profile curvature as the curvature of a surface in the direction of the slope and plan curvature as a surface curvature perpendicular to the direction of slope. Both curvatures are calculated with the *Curvature* custom command, which is implemented using the equations provided by Zevenbergen and Thorne (1987). Cells are indexed after the schema in Fig. 4.

$$D = \frac{[(Z_4 + Z_6)/2 - Z_5]}{L^2} \quad (4)$$

$$E = \frac{[(Z_2 + Z_8)/2 - Z_5]}{L^2} \quad (5)$$

$$F = \frac{(-Z_1 + Z_3 + Z_7 - Z_9)}{4L^2} \quad (6)$$

$$G = \frac{(-Z_4 + Z_6)}{2L} \quad (7)$$

$$H = \frac{(Z_2 - Z_8)}{2L} \quad (8)$$

The parameters  $D-H$  are calculated using Eqs. (4)–(8) for each cell of the DEM excluding border cells.  $Z_1-Z_9$  are the elevations of the nine cells in a  $3 \times 3$  matrix, where  $Z_5$  is the elevation of the actual cell.  $L$  is the distance between two cell centres and has to be in the same units as the  $Z$  values.

$$\text{plan curvature} = \frac{-2(DH^2 + EG^2 + FGH)}{(G^2 + H^2)} \quad (9)$$

$$\text{profile curvature} = \frac{-2(DG^2 + EH^2 + FGH)}{(G^2 + H^2)} \quad (10)$$

Unlike the original equations proposed by Zevenbergen and Thorne (1987), Eq. (9) is signed negative in order to ensure consistent signing of convex areas (positive) for both plan and profile curvature. Using Eqs. (9) and (10) the values for plan and profile curvature are calculated for all DEM cells except along the border of the DEM. Border cell values would be calculated on the basis of non-existing cell values outside the raster, which cannot be estimated with sufficient accuracy. For the classification of landforms both curvature values are encoded according to the most common signing convention

$Z_1$	$Z_2$	$Z_3$
$Z_4$	$Z_5$	$Z_6$
$Z_7$	$Z_8$	$Z_9$

Fig. 4.  $3 \times 3$  Submatrix of the DEM with the numbering convention used in Zevenbergen's method.



with negative values for concave areas (depressions) and positive values for convex areas (crests).

### 3.3. Primary landform classification

Landform elements are generated using the topographic attributes as defining parameters according to the definitions of Speight (1990). A combination of thresholds on plan and profile curvature, elevation percentile and local relief defined the input for each landform element. These topographic attributes are calculated with the recommended window sizes as described in the previous section. The proposed thresholds are provided as default values in the LANDFORM commands for the mapping scale of 1:10,000 and a DEM cell size of 10 m and can be changed by the user. As mentioned before, these thresholds are based on the definitions of Coops et al. (1998), and have to be modified to account for the higher resolution of the input data. These changes are mostly related to the category depressions and curvature measures, which are generally more affected by scale changes.

#### 3.3.1. Crests

Crests, according to Speight (1990), are typically areas that stand above most other points in the adjacent terrain and have smoothly convex plan or profile curvature or both. The *Crest Classifier* command is developed to provide an interface for defining the thresholds. Cells are classified as crest if the elevation percentile is  $>0.65$  and plan or profile curvature is positive. Furthermore, local relief has to be greater than 7.5 m to ensure that a crest is a significant elevation above the local terrain. Clearly visible noise caused by discontinuities in the curvature layers is removed with an appropriate noise filter later on in the final classification.

#### 3.3.2. Depressions

Speight (1990) defines depressions as lying below most other points in the adjacent terrain and being concave upwards. Further it is distinguished between open and closed depression, however, this separation has not yet been attempted at this stage of the research. Coops et al. (1998) used thresholds on elevation percentile and plan curvature to extract depressions. These two measures best quantify Speight's definition, as percentile measures the relative elevation of a point and plan curvature is a measure for concavity. In the actual classification, depressions were identified as those morphological types having a percentile less than 0.4 or a plan curvature smaller than  $-0.50$ . Due to the lack of distinct depressions in the rather flat terrain of the study area, depressions identified solely by percentile and curvature did not form a connected network. Therefore, a new methodology was developed to connect the depressions. The idea behind the optional *Depression Connector* function is to begin from cells already classified as depressions, investigating the neighbour cells that lie downwards in flow direction from the starting cell. If these neighbour cells are below a percentile threshold of 0.5 they are classified as depressions. With this approach most of the initially disconnected depressions could be connected to represent a hydrological correct depression network. However, some applications do not rely on such a hydrological correct representation of depressions, e.g. when anthropogenic features like dams, open mines or bridges separate them. Hence, two alternative results are generated and compared to the expert classification as explained in Section 4.

#### 3.3.3. Flats

Flats are defined as areas having a slope gradient smaller than 3%. This alone, however, would include thin strips and small patches of flat areas. Thus, an additional condition is introduced requiring flats to have a minimum width as suggested by Coops et al. (1998). This condition is fulfilled if all cells within a 50 m wide circular window have a slope value below the threshold of 3%. Although this was not explicitly defined by Speight (1990), it ensures the minimum dimension of 40 m determined for landform elements. The classification is implemented as the *Flat Classifier* command, which provides options to change the grade and minimum width thresholds.

#### 3.3.4. Slopes

All remaining areas not classified as crests, flats or depressions are considered to be slopes. Using Boolean algebra unclassified cells are extracted from the crests, flats and depressions' input layers and classified as slopes.

### 3.4. Primary landform combination

After the landform elements had been classified independently there was a small amount of overlap between flats, crests and depressions. This could be resolved by an overlay of the single landform layers with the newly developed *Final Classifier* command, which in the same step combined the four layers into one. The layers were overlaid in the following order to ensure that crests and depressions have priority to flats and slopes: crests  $>$  depressions  $>$  flats  $>$  slopes. Remaining noise in the form of single cells or narrow strips of one landform within another could be removed by applying a low pass filter. For categorical data such as landform or land use classes, the median and majority filters are the most suitable and simplest to implement. In this study a median filter with a window size of  $5 \times 5$  cells was applied to remove most of the noise while preserving narrow crests or depressions.

### 3.5. Slope classification

The methodology for the subdivision of the slope areas into zones of upper, mid, lower or Simple slope consists of three steps as shown in Fig. 4. First, slope profiles are constructed on the DEM following the direction of steepest slope from slope cells. Second, each slope profile is broken up into slope classes at significant changes in slope and, as last step, the cells along the profile are assigned a slope class. The three steps are implemented in the custom command *Slope Classifier* and described in more detail in the subsequent sections.

#### 3.5.1. Constructing slope profiles

The primary landform layer and the DEM define the input for the slope profile construction. For each cell of the DEM the direction of steepest slope (aspect) is calculated from the DEM in degrees ( $1-360^\circ$ ) from north, with a value of  $361^\circ$  indicating flat surfaces. The selection of start cells for the slope profiles begins at the top left corner of the primary landform layer and proceeds cell-by-cell down to the bottom. All cells classified as slope and not marked as part of another slope profile become a starting point. In this way all single slope cells are part of at least one slope profile.

From a start cell the slope profile is constructed up and down slope in direction of steepest slope until a crest, depression or flat is reached (see Fig. 5). The line enters a cell at the entry point and follows the direction of steepest slope to the exit point. For each entry and exit point Cartesian coordinates are calculated and the elevations of these points are interpolated from the four neighbouring cells using bilinear interpolation. Slope is then calculated for each cell between entry and exit point.

At the end up and down slope profile are combined to a single slope profile and for each cell the cell coordinates (row, column), slope and the elevation of the lowest point are stored. Cells along the profile are marked in order to prevent them from becoming a start cell in a subsequent iteration.

#### 3.5.2. Breaking slope profiles into segments

A slope profile is divided into slope elements at breakpoints where significant changes in slope occur along the slope profile. The methodology follows Giles and Franklin (1998), who have calculated slope differences between the mean slope of two cells above the actual cell and the mean slope of two cells below the current cell. If this slope difference is higher than a specified threshold, and higher than the slope difference of the neighbouring cells, the actual cell becomes a breakpoint. A modified version of Giles' methodology is implemented in the *Slope Classifier* command.

The array with the slope profile data from the previous step defines the input for the detection of breakpoints. The slope values of each cell (denoted as  $\beta_k$ ) are used to calculate the change in slope ( $\delta$ ) along the slope profile. Mean slopes are calculated for the actual cell ( $k$ ), the cell above the actual cell ( $k+1$ ) and the two cells below the actual cell ( $k+1$  and  $k+2$ ). The

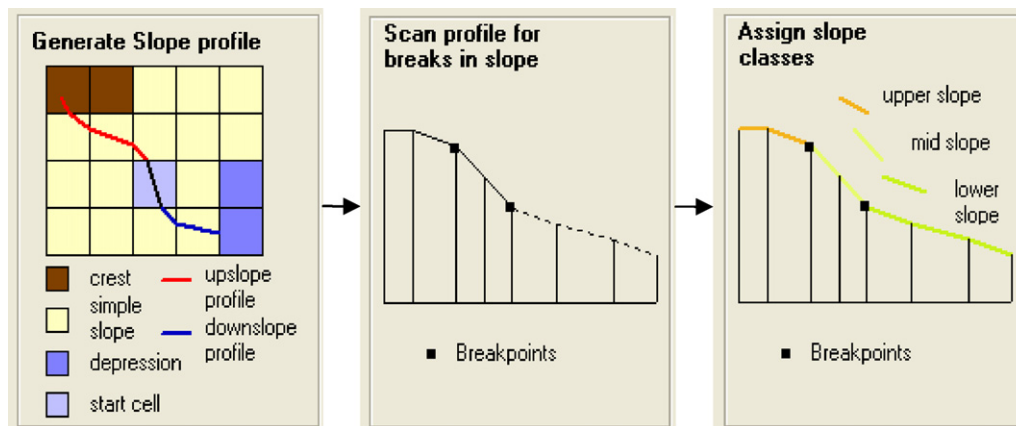


Fig. 5. Proposed workflow for slope classification.

$\delta$  value is then calculated for each cell as the difference of the mean slope values.

$$\delta = \left( \frac{\beta_{k-1} + \beta_k}{2} - \frac{\beta_{k+1} + \beta_{k+2}}{2} \right) \quad (11)$$

where  $k$  is the index of a cell on the profile, and  $\beta_k$  is the slope of the profile at cell  $k$ .

A breakpoint is set at the lower border of a cell with a  $\delta$  value higher than the user defined threshold and higher than the  $\delta$  values of the two nearest neighbours up and down slope on the profile. On a 10 m grid this integration of neighbouring cells leads to a minimum distance of four cells (40 m) between two breakpoints. Thus, Speight's minimum length requirement of 40 m for slope elements is fulfilled. For this study a threshold  $\delta$  value of  $\pm 0.1$  is chosen based on the findings of Giles and Franklin (1998) and examinations of breakpoint placements with other  $\delta$  values. Breakpoints are located at the boundaries between two adjacent cells and are defined by their elevation. For each profile the number of breakpoints and the elevations of the highest and the lowest breakpoints are stored for the following classification of slope elements.

### 3.5.3. Assign slope classes

Slope classes are assigned to the cells on the profile based on the number of breakpoints and the elevation of the cells relative to the breakpoints. Depending on the number of breakpoints four slope classification scenarios are possible. If the number of breakpoints  $n = 0$ , all cells along the profile are classified as Simple slope. In the case of  $n = 1$ , the profile is divided into upper and lower slope. Cells below the breakpoint are classified as upper slope and cells above the breakpoint are classified as lower slope. When two or more breakpoints ( $n = 2$  and  $n > 2$ ) are detected on the slope profile, the profile is split into upper slope, lower slope and one or more mid slopes. Cells above the highest breakpoints are assigned upper slope and cells below the lowest breakpoint are classified as lower slope. Cells remaining between the highest and lowest breakpoints are considered as mid slopes.

### 3.6. Comparing the extent and spatial distribution of landform units derived from different approaches

As a form of validation, and mainly to compare the results against a landform map produced by 'traditional' methods of photo-interpretation, an expert classified the same area by photo-interpretation of colour aerial photographs at scale 1:25,000, determining the same landform elements, following the guidelines for photo-interpretation of geomorphic units established by Zinck (1988). To avoid bias in the mapping of landforms, the photo-interpreter had no access to the landform map derived in the semi-automated way. The outcomes of both techniques were compared for their similarity using a fuzzy set approach proposed by Hagen (2003) as a part of the Map Comparison KIT (MCK) software (Visser and de Nijis, 2006; RIKS, 2006). This software is a tool for exploring

the extent, nature and spatial distribution of differences in pairs of raster maps. The approach is specifically aimed at categorical raster maps, such as landform classifications, and makes use of fuzzy set techniques to account for fuzziness of location and fuzziness of category, as defined in Hagen (2003). Fuzziness of location is taken into account by enabling the fuzzy representation of a cell be partly defined by neighbouring cells. A function (e.g. exponential decay, linear decay or constant value) defines the level to which neighbouring cells exert this influence. The user decides on the type of function to be adopted as well as parameters for its implementation (e.g. slope, value, linear decay). After trying different values, a neighbourhood radius equal to 40 cells and a halving distance of 10 were applied as they showed the best comparison results in previous applications (Hagen, 2004).

Likewise, a category similarity matrix can be applied to highlight or disregard different types of similarity, and thus better characterise the fuzziness of categories. The essence is that the similarity of two identically positioned cells is expressed as a gradual value between identical and completely different, rather than the binary option identical or not identical. Using the categorical similarity matrix, it can be taken into account that some categories are more similar to each other than to others (Hagen, 2003). As an example, mid and lower slopes are considered to be more similar between them than to crests and depressions. Further use of the similarity matrix is exposed by Hagen-Zanker et al. (2005) and includes assessing the similarity of single categories or groups of categories and distinguishes between differences due to omission and commission. These options are used to evaluate the performance of the automatic classification with regard to the determination of single categories, compared to the results from expert classification.

The result of comparing two maps is a third map, indicating for each location the level of agreement in a range from 0 (low similarity) to 1 (identical) between categories. Additionally, statistical values such as average similarity (e.g. the average similarity of all cells in the map), and a similarity index called fuzzy kappa are calculated (Hagen, 2003).

After determining the overall similarity of expert and automatic classification, the nature of differences was further investigated for single categories using the categorical similarity matrices proposed by Hagen-Zanker et al. (2005). Based on the single category comparison and the expert's impression, the categorical similarity matrix of Table 5 was applied to determine the average similarity for the landform types under consideration. For instance, this matrix considers that landform elements like upper slope and mid slope are more similar to each other than to categories like depressions and crest.

## 4. Discussion of results

### 4.1. Landform classification

With the LANDFORM program the study area is divided into landform elements as defined by Speight (1974, 1990). The program proved to be accepted as user friendly and

adds up a significant enhancement of the present capabilities of GeoMedia Grid in terms of digital terrain modelling and interpretation. As a result, landform maps covering the farm area of Muresk and beyond were produced as presented in Fig. 6 (1 and 2). An expert classification of the same area is shown in Fig. 6 (3). Pair-wise these maps were input into the Map Comparison Kit (MCK) in order to determine their average similarity and explore spatial differences amongst mapped landform categories.

#### 4.2. Comparison of automated and expert classification

Two semi-automatically derived landform maps, one with the initially generated depressions (referred to as map 1 in Fig. 6) and one using the depression connector explained in Section 3.3.2 (e.g. map 2, Fig. 6) were compared with the expert classification (map 3, Fig. 6), using the software MCK (version 3.0.5). The most significant differences can

be observed in the spatial structure of the landscape mapped (see Fig. 6). Comparing the maps in MCK results in an average similarity of 0.434 between maps 1 and 3 and the same value for maps 2 and 3. Fig. 7 shows the output of the two-way map comparison of map 1 and map 3 using the fuzzy approach. Areas of agreement between the semi-automated classification and the expert photo-interpretation show values close to one, while areas of total disagreement on category assignation take a value close or equal to zero. The rather low agreement of the maps can be explained by difficulties of the expert to exactly quantify the topographic attributes (e.g. slope) used to define boundaries between landform elements such as flats and lower slopes on one hand, and the lack of human logics behind the automated approach (e.g. inability to generate a connected depression network) on the other hand.

To gain more insight in the nature of the differences, categorical similarity matrices (Hagen-Zanker et al., 2005) were

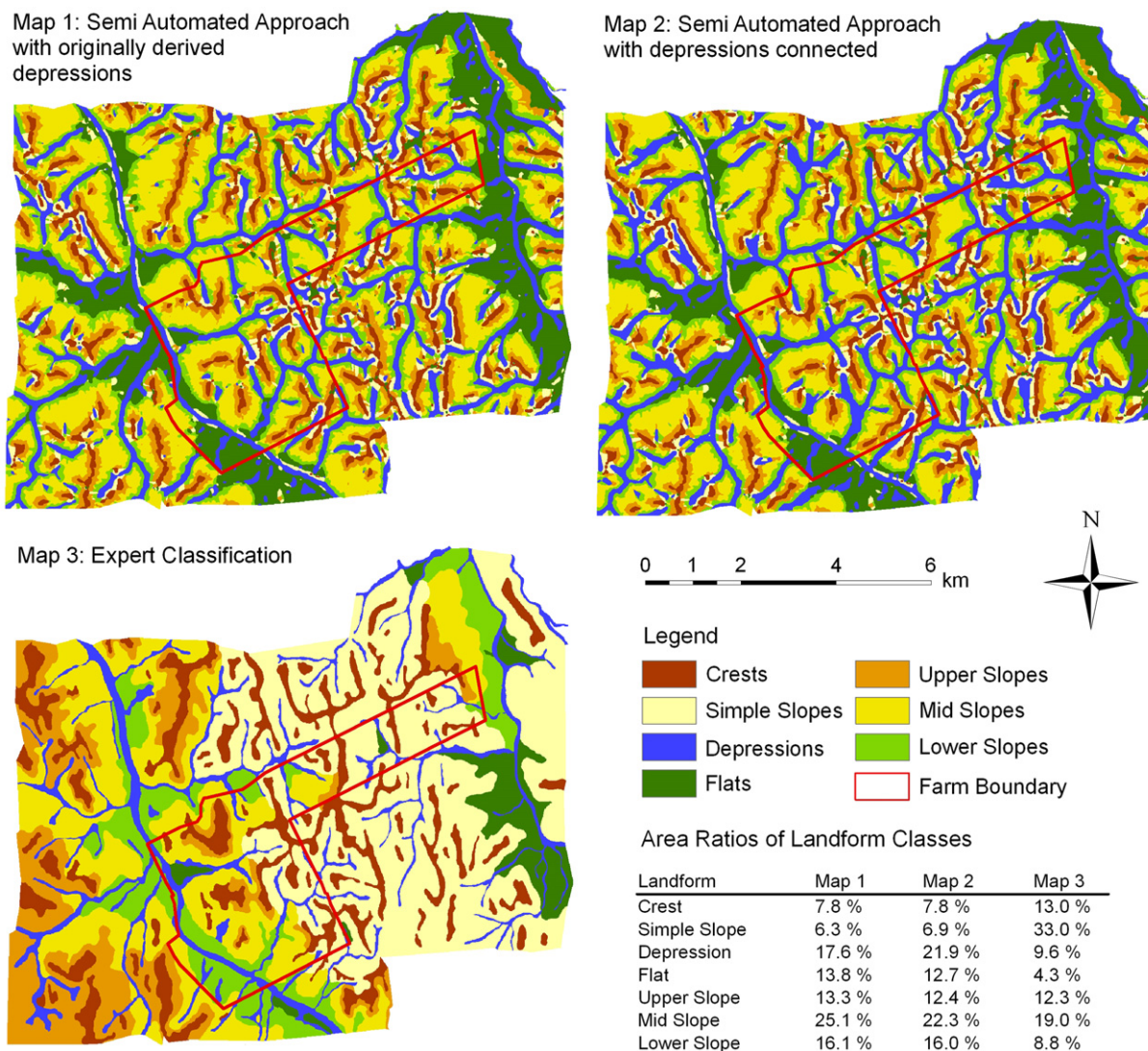


Fig. 6. Landform maps derived with the semi-automated approach with original (1) or connected depressions (2) and from an expert classification (3), including a comparison of the area covered by each category.



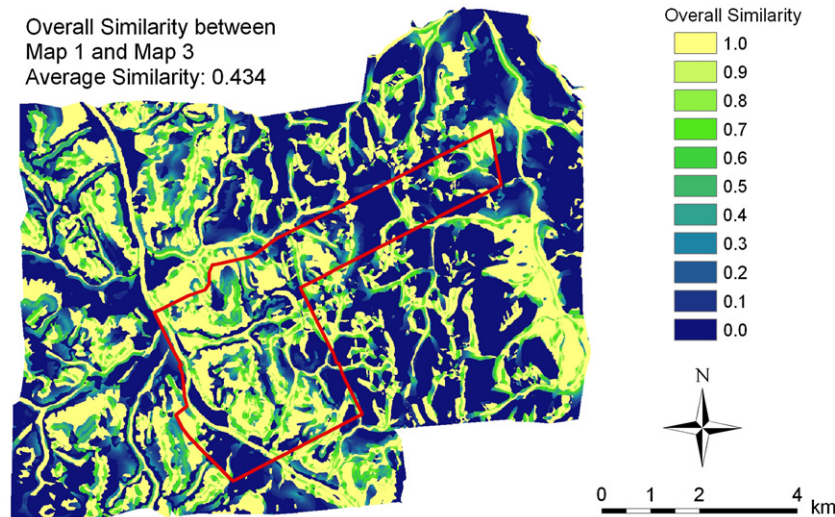


Fig. 7. Spatial assessment of similarity between maps 1 and 3 using the two-way fuzzy map comparison. Areas mapped identically have values close or equal to 1, while areas of total disagreement show values close or equal to 0.

applied to: (a) highlight single categories; and (b) obtain information about overall difference and differences due to omission and commission errors. Commission errors occur when a category is placed in a wrong location, and omission errors refer to categories which should be found at a location but are absent. As an example for the similarity matrices that are applied, the matrices used for the category flats are shown in Tables 2–4. To assess the overall similarity of a single category (e.g. flats), all other categories are set as being identical to each other in the similarity matrix and therefore receive a value of 1 (see Table 2). Table 3 shows that to assess commission errors of the category ‘flats’ (in this case between maps 1 and 3) only cells with this label are set dissimilar in the matrix (i.e. where ‘flats’ are found in map 3 and not in map 1). Likewise, the transposed matrix evaluates the differences due to omission (Table 4). The results of the analysis are shown in Table 5, highlighting two main differences between expert and semi-automated classification discussed hereafter.

Firstly, there are disagreements in the category depressions. The human interpretation resulted in a more natural network, with logical connections (e.g. below bridges) that could not be

detected by the semi-automated approach due to barriers in the DEM from roads or other anthropogenic features. The applied depression connection partly solved this problem, but on the other hand generated overall wider depressions, resulting in a decreased similarity due to omission (Table 5). The comparison of the depressions in maps 1 and 3, and maps 2 and 3, respectively, highlights these differences. Fig. 8a shows the disagreements between maps 1 and 3, where the differences due to the missing connections between depressions become visible. Fig. 8b shows the differences due to a widening of the depressions, when the depression connection method was applied. Considering the overall similarity, the original classification (map 1) better fitted the result of the human interpreter.

Secondly, a high disagreement is present in the categories that are derived from topographic attributes, like slope percentage. For instance, in Fig. 6 (3), the expert recognises landforms as larger homogenous areas, whereas the semi-automated approach generates smaller landform elements. One of the main reasons is the difficulty of a photo-interpreter to gather an exact estimation of slope percentage, and thus

Table 2

Similarity matrix to determine disagreement (overall) of maps 1 and 3 with regard to the category ‘flats’

Map 3: expert classification	Crest	Simple slope	Depression	Flat	Upper slope	Mid slope	Lower slope
Map 1: automated approach							
Crest	1	1	1	0	1	1	1
Simple slope	1	1	1	0	1	1	1
Depression	1	1	1	0	1	1	1
Flat	0	0	0	1	0	0	0
Upper slope	1	1	1	0	1	1	1
Mid slope	1	1	1	0	1	1	1
Lower slope	1	1	1	0	1	1	1

Table 3

Similarity matrix to determine disagreement due to commission of maps 1 and 3 with regard to the category ‘flats’

Map 3: automated approach	Crest	Simple slope	Depression	Flat	Upper slope	Mid slope	Lower slope
Map 1: expert classification							
Crest	1	1	1	1	1	1	1
Simple slope	1	1	1	1	1	1	1
Depression	1	1	1	1	1	1	1
Flat	0	0	0	1	0	0	0
Upper slope	1	1	1	1	1	1	1
Mid slope	1	1	1	1	1	1	1
Lower slope	1	1	1	1	1	1	1

Table 4  
Similarity matrix to determine disagreement due omission of maps 1 and 3 with regard to the category ‘flats’

Map 3: automated approach:	Crest	Simple slope	Depression	Flat	Upper slope	Mid slope	Lower slope
Map 1: expert classification							
Crest	1	1	1	0	1	1	1
Simple slope	1	1	1	0	1	1	1
Depression	1	1	1	0	1	1	1
Flat	1	1	1	1	1	1	1
Upper slope	1	1	1	0	1	1	1
Mid slope	1	1	1	0	1	1	1
Lower slope	1	1	1	0	1	1	1

there is a tendency to misclassify Simple slopes. Table 5 reflects this observation, where Simple slopes have the lowest similarity of all categories. The human interpreter appears unable to break Simple slopes into lower, mid and upper slopes, when subtle changes in slope percentage are present in the landscape. A similar situation appears to occur with the drawing of a clear boundary between lower slopes and depressions. Another effect of the false estimation of slope values is that areas with a slope smaller than 3% are often not identified as flats by the expert. This explains the relatively low agreement of this category in Table 5.

To account for similarities between categories as perceived by the expert, the similarity matrix in Table 6 was defined. Using this matrix the fuzzy comparison between the photo-interpreted and semi-automated classifications yielded an average similarity of 0.629 (Fig. 9) for the original classification and a slightly lower value of 0.621, if depressions were connected. According to Hagen (2003), average similarity provides results that are more gradual (e.g. changes in nature tend to be gradual than abrupt) than those from other methods such as kappa statistics or a crisp cell-by-cell comparison, and hence, it is more likely to furnish a suitable indication of small differences. Results of the fuzzy kappa statistics were disregarded because Hagen (2003) mentions this measure has not yet been developed for small or irregularly shaped maps as this is the case for the analysed data set.

## 5. Conclusions

LANDFORM was conceived as a GIS based software to generate morphological types for a semi-automated derivation

of landform elements, which are envisaged as an input in the spatial modelling and management units intended for site specific crop management (Warren et al., 2005). Besides landform classification in the Western Australian Landscape, the proposed classification method has also been applied to an area in upper Austria, as described by Klingseisen et al. (2004).

With the presented methodology landform elements have been generated according to Speight (1990) and the results reflect his definitions. The conceptual model of landform elements has a very strong focus on hydrological structures and drainage patterns (e.g. the *Depression Connector* developed to connect open depressions). In some cases this connection enforcement breaks up anthropogenic features and also yields a widening of the depressions, which is not desired if analysing the landscape structure is the primary focus. Accordingly, the unconnected depression network is a better representation of the human impression as observed during the map comparison. A limitation of the software could be identified in the extraction of close, isolated depressions as concave structures just following crest and upper slopes (e.g. a situation that may occur in alpine environments with a glacial overprint). Further validation of the semi-automated classification still has to be undertaken by soil scientists for a comparison with a subjective expert interpretation of Speight's (1990) definitions. Furthermore, tests of the approach with data characterising other landscape types (e.g. alpine) have to be carried out.

Although semi-automated techniques require some subjective decisions on the input parameters and a basic understanding of landforms and their morphometry (e.g. geomorphometry), derivation of landform elements using topographic attributes and geomorphometric algorithms within a GIS as done in

Table 5  
Average similarity per category

Map 3: automated approach	Overall similarity	Commission	Omission
Map 1: expert classification			
Crest	0.956	0.968	0.988
Simple slope	0.794	0.816	0.978
Depression	0.937	0.991	0.946
Depression (compared with Map 2 – connected depressions)	0.917	0.993	0.923
Flat	0.896	0.995	0.901
Upper slope	0.862	0.948	0.914
Mid slope	0.818	0.951	0.868
Lower slope	0.818	0.952	0.867

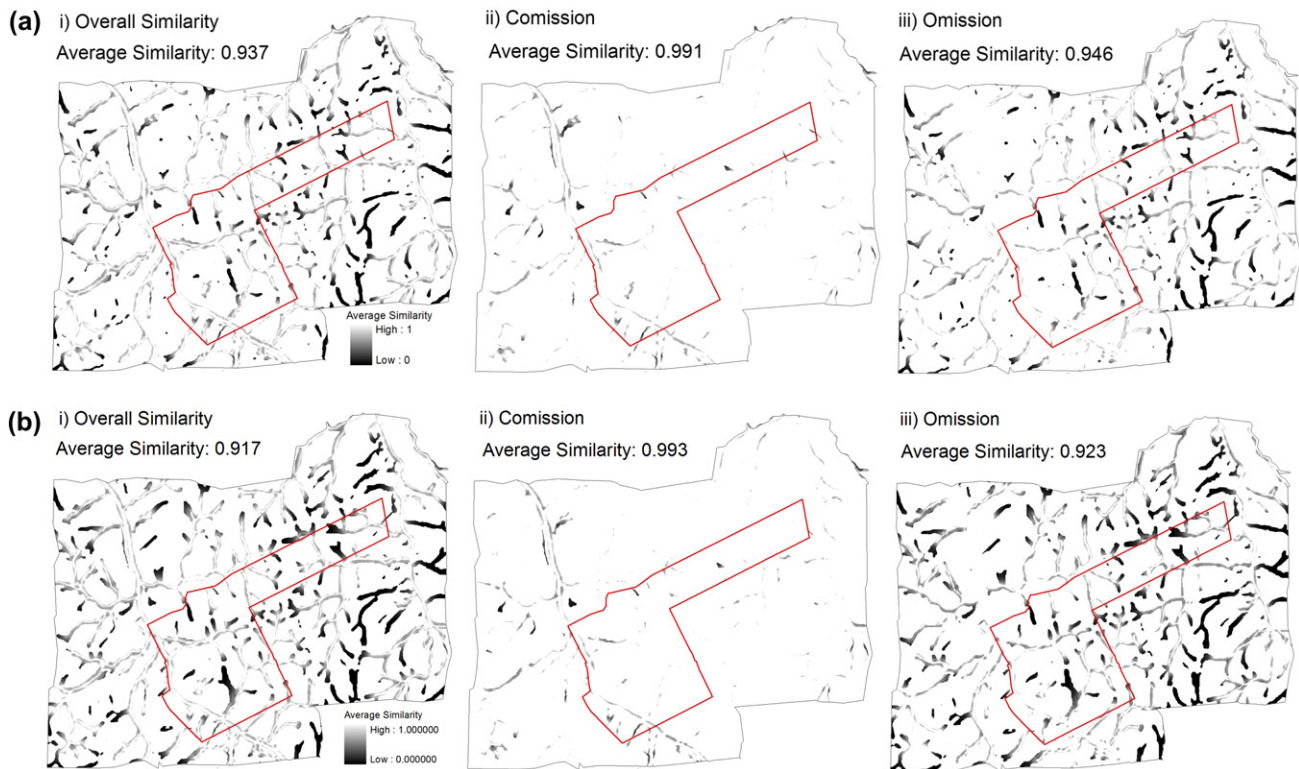


Fig. 8. (a) Difference between maps 1 and 3 with respect to the category 'depressions': (i) overall; (ii) omission; (iii) commission. (b) Difference between map 2 and map 3 with respect to the category 'depressions': (i) overall; (ii) omission; (iii) commission.

this study has the advantage of standardisation, time efficiency, more objectivity and repeatability of the procedure. This represents a tremendous advantage in studies undertaken over large areas (e.g. catchments, regions) because in addition to standardisation of the way in which landforms are determined, there is a considerable reduction on the time involved in their cartography.

Given the vagueness and uncertainty attached to the mapping of , as well as the gradual transition in which landforms occur within the rural landscape of this study, the two-way fuzzy comparison approach provided an excellent means of assessing the degree of agreement between landform categories derived by the semi-automated LANDFORM software and an expert photo-interpretation following methods traditionally applied in soil survey. Considering similarities

between categories, the maps showed an average similarity of 62.9%, and disagreement was mostly localised in flat and Simple slope areas where the human photo-interpreter manifested the largest degree of difficulty to clearly separate them.

The methodology for landform classification described in the paper shows the need for customizable GIS software. Most industrial GIS software does not include all functions to calculate the necessary topographic attributes for landform classification. Therefore a well-documented developer environment is essential for efficient and effective customization. Though implemented in GeoMedia (Intergraph Corporation, 2006), the proposed methodology and algorithms are not bound to specific GIS software and could be implemented in any customizable or open source package.

Table 6

Fuzzy similarity matrix, where some categories are considered equal to each other by the expert

Map 3: expert classification	Crest	Simple slope	Depression	Flat	Upper slope	Mid slope	Lower slope
Map 1/2: automated approach							
Crest	1	0	0	0	0.7	0	0
Simple slope	0	1	0.4	0.2	0.5	0.5	0.2
Depression	0	0.4	1	0.5	0	0	0.3
Flat	0	0.2	0.5	1	0	0	0.5
Upper slope	0.7	0.5	0	0	1	0.5	0.2
Mid slope	0	0.5	0	0	0.5	1	0.5
Lower slope	0	0.2	0.3	0.5	0.2	0.5	1



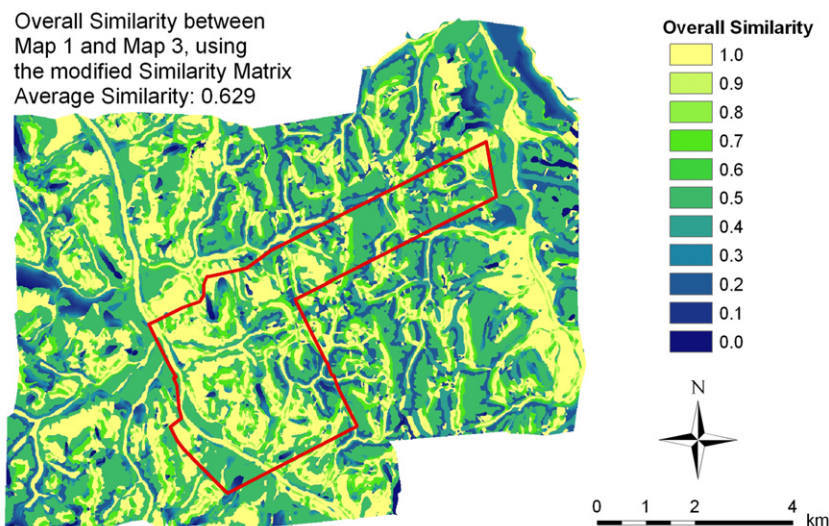


Fig. 9. Spatial assessment of similarity between maps 1 and 3, applying the similarity matrix in Table 6.

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