A SEMI-AUTOMATED APPROACH FOR GIS BASED GENERATION OF TOPOGRAPHIC ATTRIBUTES FOR LANDFORM CLASSIFICATION

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This paper presents LANDFORM, a customized GIS application for semi-automated classification of landform elements, based on landscape parameters. Using custom commands, topographic attributes like curvature or elevation percentile were derived from a Digital Elevation Model (DEM) and used as thresholds for the classification of Crests, Flats, Depressions and Simple Slopes. With a new method, Simple Slopes were further subdivided in Upper, Mid and Lower Slopes at significant breakpoints along slope profiles. The paper discusses the results of a fuzzy set algorithm that was 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 landform is identified as an influential factor in the processes under study.

1 INTRODUCTION

In traditional methods of soil survey, experienced soil surveyors define soil boundaries utilizing stereo aerial photographic interpretation methods based on soil formation models and functional models of prediction, 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 thus clear that the cartography of landform elements 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 & Irvin 2000).

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 & 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, parametric description of landforms into *landform patterns* and *landform elements*. The landform is viewed as a mosaic of tiles whereby the larger tiles *landform patterns* are generally on the order of 300 m radius. The smaller tiles, which are mosaics within landform patterns, are *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 ten types of topographic positions in which landform elements fall into, as listed in Table 1.

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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%, sub classified 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 < 40m
Ridge	Compound element where short slope elements meet at a narrow crest > 40m

A full description of each morphological type can be found in SPEIGHT (1990). Figure 1 provides an example of a profile across the terrain divided into morphological types of landform elements as classified by SPEIGHT (1990).
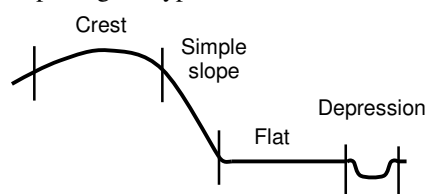

Figure1:   Example of a profile across terrain divided into morphological types of landform elements (adapted from Speight 1990).

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. Given this research focuses on the design an implementation of a semi-automated approach for the mapping 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 design and implementation of this semi-automated approach, called LANDFORM, was done through customisation of GeoMedia GIS technology, enabling a user test default thresholds and then adjust them to suit a specific landscape type and DEM resolution. The output landform classification was used as an input parameter for modelling of Land Management Units intended for the implementation of site specific crop management in precision agriculture (CPSTOF Team, 2005). 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   METHODOLOGY AND DATASETS

The methodology adopted in the design and implementation of LANDFORM, as described in this paper, is based on the ideas of Skidmore (1990) and Coops et al. (1998) who developed workflows for the prediction of topographic position from a DEM. A series of custom commands for GeoMedia Grid was developed and implemented in Visual Basic to generate landform elements according to the definitions of Speight (1990). With these commands the classification was carried out in four basic steps as shown in Figure 2.

First, general topographic attributes like slope, plan and profile curvature as well as more regionalized attributes such as local relief and elevation percentile were derived from a DEM. These topographic attributes provided the input for the definition of the primary landform elements Crests, Depressions, Flats and Simple Slopes. The landform classification was 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 2.3 covers the classification of each landform element and the proposed threshold values. After the generation of the primary landforms the single layers were combined by an overlay operation and any remaining singular cells or narrow strips in the classification were removed with a low pass filter as described in section 2.4. Slope elements were then subdivided into Upper, Mid and

Lower Slope; following the procedure explained in section 2.5. The areas initially classified as Simple Slopes were 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 Slopes and Lower Slopes near the valley bottom. If there was no significant break in slope the areas remained classified as Simple Slope.
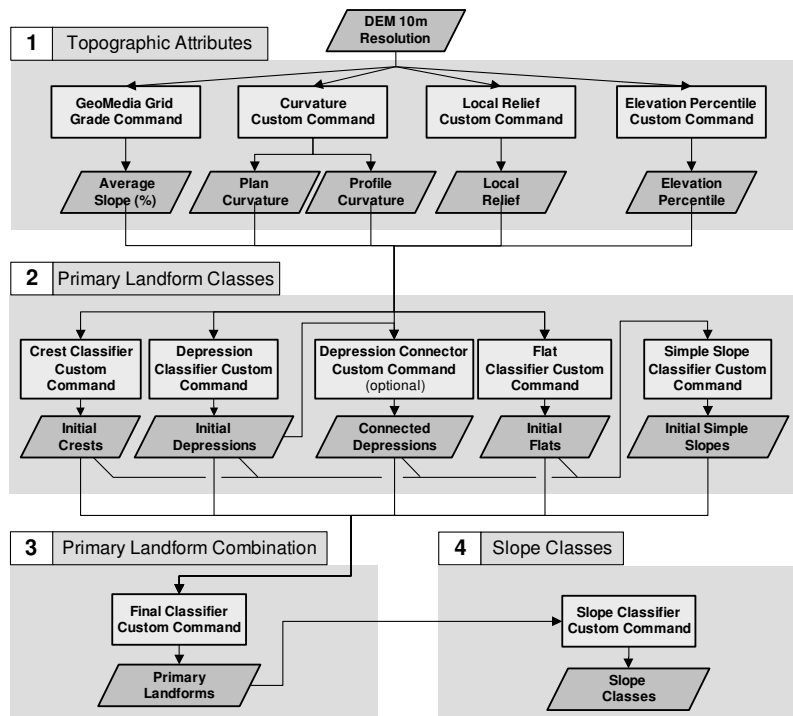

Figure 2: Flow Chart of the methodology followed for design and implementation of LANDFORM

2.1 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 (Figure 3). Muresk Farm covers an area of 1720 ha used for cropping, sheep farming and cattle production (CPSTOF Team 2005). 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.
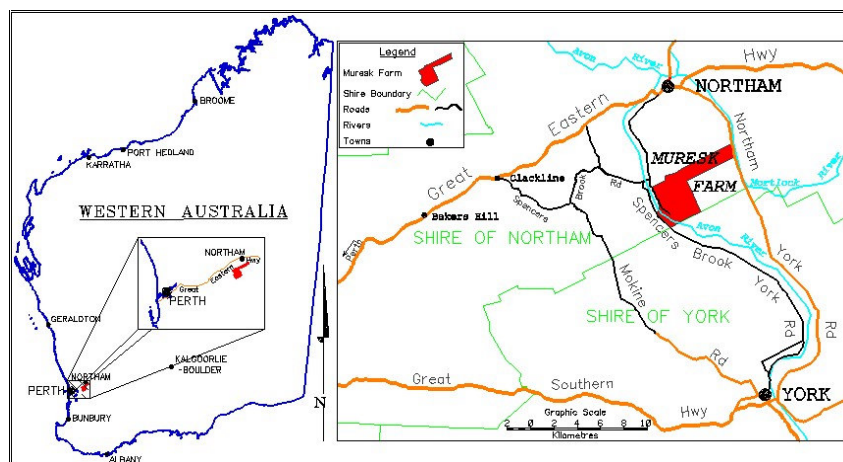

Figure 3: The study area at Muresk farm, 100 km northeast of Perth (WA)

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).

2.2   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 (Blaszczynski 1997, Coops et al. 1998, Gallant & Wilson 2000, Zevenbergen & Thorne 1987). The topographic attributes used for landform classification were calculated with GeoMedia Grid custom commands, which have been developed especially for this purpose.

- **Slope** (in percent) has been calculated as average slope from 9 cells in a 3x3 matrix at the intersection of the north-south plane with the east-west plane through the centre cell. In the classification process slope was used as a threshold to detect flat areas.

- **Local Relief** or elevation range (Gallant & Wilson 2000) defines the range of elevation values within a circular scan window of predefined radius. The algorithm is implemented with a default window radius of 150 m as proposed by Coops et al. (1998). Local relief was used as an additional threshold in the classification of crests as described in section 2.3.1

- **Elevation Percentile** is a ranking of a point's elevation relative to all other points in a circular window (Gallant & Wilson 2000). The number of cells that are lower than the centre cell is divided by the full number of all cells in the window. Based on the findings of Coops et al. (1998) a radius of 150 m was chosen for the scan window. 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. Elevation percentile with its well-defined range of result values provided a robust measure to delineate crests and depressions as described in section 2.3.1

- **Curvature** of a topographic surface is mostly expressed in terms of profile and plan curvature. Blaszczynski (1997) describes profile curvature as the curvature of a surface in the direction of the slope and plan curvature as a surface's curvature perpendicular to the direction of slope. Both curvatures were calculated according to the equations of Zevenbergen & Thorne (1987), using the most common signing convention with negative values for concave areas and positive values for convex areas.

2.3   PRIMARY LANDFORM CLASSIFICATION

Landform elements were 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 profile curvature defined the input for each landform element. These topographic attributes had been calculated with the recommended window sizes as described in the previous section. The proposed thresholds are provided as default values in the LANDFORM commands and can be changed by the user.

- **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. Areas were classified as crest, where percentile was > 0.65 and the plan or profile curvature was positive. Furthermore, local relief had to be greater than 7.5 m to ensure that a crest was a significant elevation above the local landscape.

- **Depressions,** as defined by Speight (1990), are characterized as lying below most other points in the adjacent terrain and being concave. 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, the depressions identified solely by percentile and curvature didn't 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 hydrologically correct depression network.

- **Flats** are defined as areas having a slope gradient smaller than 3 %. This alone however would include thin strips of flat areas. Thus an additional condition was introduced requiring flats to have a minimum width as suggested by Coops et al. (1998). This condition was fulfilled if all cells within a 50 m wide circular window had a grade 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.

- **Simple Slopes** are all remaining areas not classified as crests, flats or depressions. Boolean algebra was used to extract the unclassified cells from the Crests, Flats and Depressions input layers and classify them as Simple Slopes.

2.4 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 new developed Final Classifier command, which in the same step combined the 4 layers into one. The layers were overlaid in following order to ensure that Crests and Depressions have priority to Flats and Simple Slopes: Crests > Depressions > Flats > Simple 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 5x5 cells was applied to remove most of the noise while preserving narrow crests or depressions.

2.5 SLOPE CLASSIFICATION

The methodology for the subdivision of the simple slope areas into zones of Upper, Mid and Lower Slope consists of three steps as shown in Figure 4. First, slope profiles are constructed on the DEM following the direction of steepest slope from Simple 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.
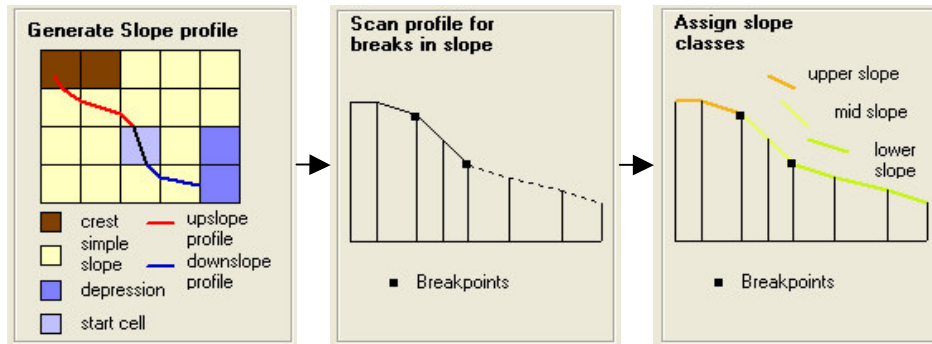

Figure 4: Proposed workflow for slope classification.

- **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°) from north, with a value of 361° 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 simple 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 Figure 4). 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 to prevent them from becoming a start cell in a subsequent iteration.

- **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 the findings of Giles and Franklin (1998), who have calculated slope differences between the mean slope of the two cells above the actual cell and the mean slope of the 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 principles are shown in Figure 6.

The array with the slope profile data from the previous step defines the input for the detection of breakpoints (see Figure 6). The slope values of each cell (denoted as β_k) are used to calculate the change in slope (δ) along the slope profile. Mean slopes are calculated for the actual cell (k) and the cell above the actual cell (k+1) and for of the two cells below the actual cells (k+1 and k+2). The δ value is then calculated for each cell as the difference of the mean slope values.

$$\delta = \left[\left(\frac{\beta_{k-1} + \beta_k}{2} \right) - \left(\frac{\beta_{k+1} + \beta_{k+2}}{2} \right) \right]$$
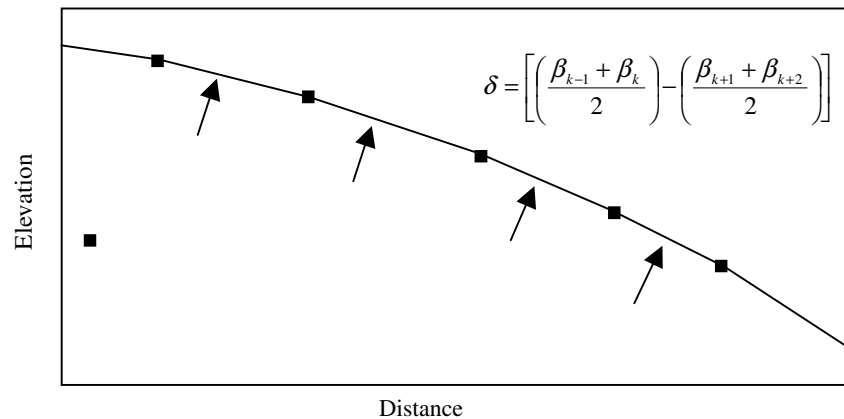
Figure 6: Procedure for the calculation of changes in slope along the slope profile, (after: Giles and Franklin (1987)).

Breakpoints are located at the boundaries between two adjacent cells and are defined by their elevation. A breakpoint is set at the lower border of a cell with a δ value bigger then the user defined threshold and bigger then the δ values of the two nearest neighbours up and down slope on the profile. This restrictions lead 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 δ value of ± 0.1 is chosen based on the findings of Giles and Franklin (1987) and examinations of breakpoint placements with other δ values. 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.

- **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 (see Figure 7).
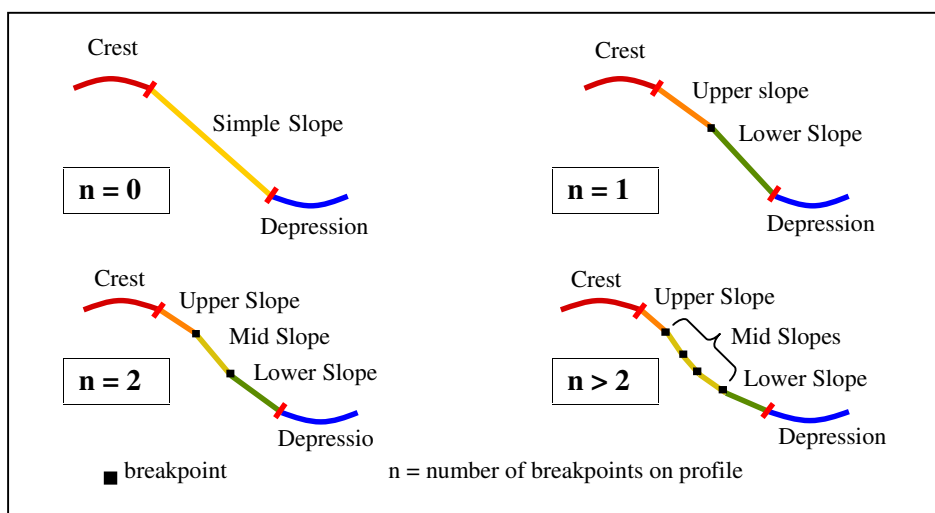
Figure **7:** Four scenarios for the classification of slope elements.

If the number of break points 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 below 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 Mid Slopes.

2.6 MAP COMPARISON

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 semi-automated way. The outcomes of both techniques were compared for their similarity using a fuzzy set approach proposed by Hagen (2003) as the Map Comparison KIT (MCK) software. 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).

Likewise, a category similarity matrix can be applied to highlight or disregard different types of similarity, and thus better characterise the fuzziness of categories. As an example, Mid and Lower Slopes are considered more similar than Crests and Depressions. The result of comparing two maps is a third map, indicating for each cell 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).

3 RESULTS
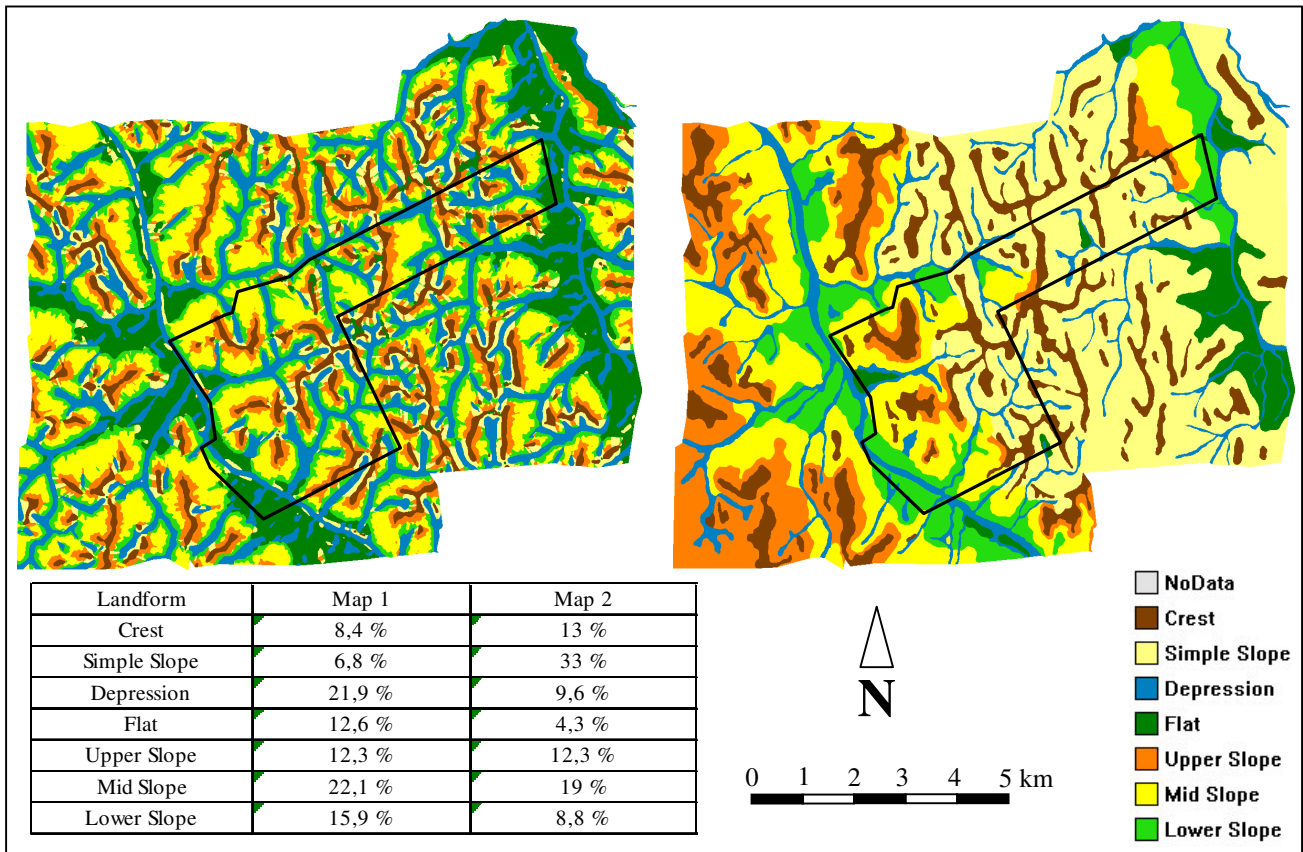
3.1 LANDFORM CLASSIFICATION

With the LANDFORM program the study area was divided up into landform elements as defined by Speight (1974, 1990). The program proved to be accepted as user friendly and defined a significant enhancement of the present capabilities of GeoMedia Grid in terms of digital terrain modelling and interpretation. As a result, a landform map covering the farm area of Muresk and beyond could be generated as presented in Figure 8 (1). Expert Classification of the same area is shown in Figure 8 (2). These maps were input into the Map Comparison Kit (MCK) in order to determine their average similarity.

3.2 COMPARISON OF AUTOMATED AND EXPERT CLASSIFICATION

In a first step the maps were clipped to the same spatial extent and transformed to ESRI Grid file as input for the MCK. The most significant differences can be observed in the structure of the landscape (see Figure 8). While the expert recognises landforms as larger homogenous areas, the semi-automated approach generates smaller landform elements. On of the main reasons is the difficulty for the expert to estimate slope graduation and objectively determine breaks in slope. As a result, larger simple slope areas in the middle of the study area where not further subdivided and areas with a slope smaller than 3 % are often not identified as flats. On the other hand, the expert classification was superior in case of depressions, where the human interpretation resulted in a more naturally 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 buildings.

The two-way fuzzy map comparison requires the creation of a Category Similarity Matrix in order to account for the fuzziness of categories of the two maps being compared. 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. By the use of a categorical similarity matrix, it can be taken into account that some categories are more similar to each other then others. After different trials the Category Similarity Matrix of Table 2 was applied account for fuzziness between the landform types considered. For instance, this matrix considers that landform elements like Upper Slope and Mid Slope are more similar to each other than to the categories Depression and Crest. Further, after trying

different values, a neighbourhood radius equal to 40 cells and halving distance of 10 were applied as they showed the best comparison results.

Landform	Map 1	Map 2
Crest	8,4 %	13 %
Simple Slope	6,8 %	33 %
Depression	21,9 %	9,6 %
Flat	12,6 %	4,3 %
Upper Slope	12,3 %	12,3 %
Mid Slope	22,1 %	19 %
Lower Slope	15,9 %	8,8 %

Figure 8: Landform map derived with the semi-automated approach (1) and from an expert classification (2), including a comparison of the area covered by each category.

Table 2: Fuzzy Similarity Matrix

Auto-mated approach \ Expert classification	Crest	Simple Slope	Depression	Flat	Upper Slope	Mid Slope	Lower Slope
Crest	1	0	0	0	0.2	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	0.2	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

Figure 9 shows the output of the two-way map comparison using the fuzzy approach. Areas of agreement between the semi-automated 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. Areas recording the highest disagreements tend to correspond to Flat and Simple Slope landform elements. It is difficult for a photo-interpreter to gather an exact estimation of slope percentage, and thus there is a tendency to misclassify Simple Slope and Flat areas.

The comparison between the photo-interpreted and semi-automated classifications yielded an average similarity of 0.61. According to Hagen (2003) this measure provides results that are more gradual 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, and those that also involve comparison of fuzziness of category, as it the case in this study.
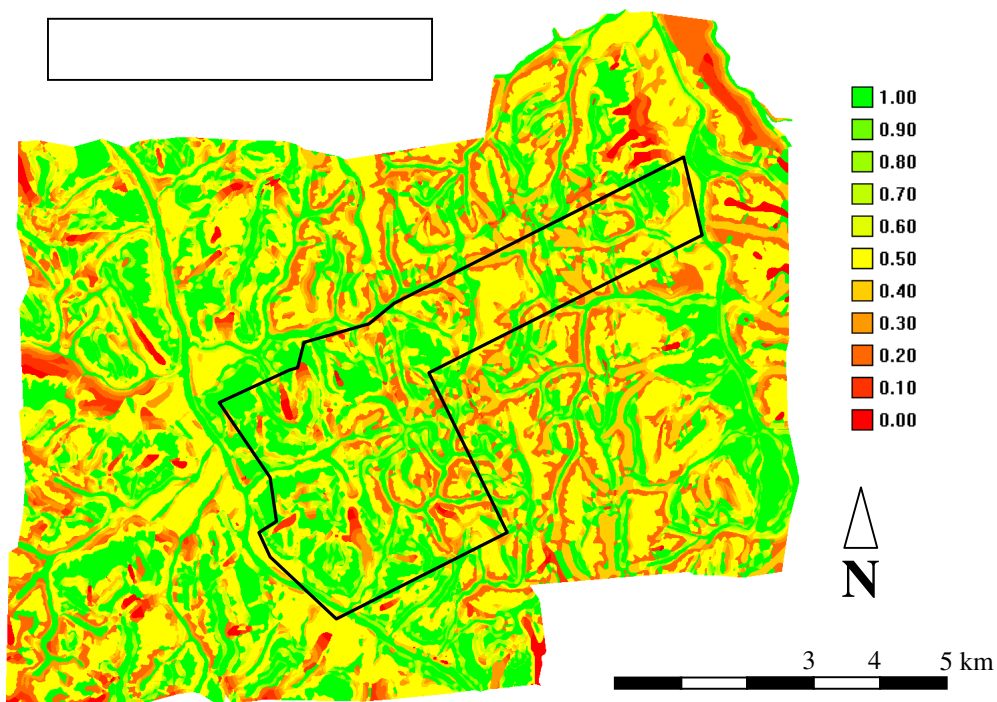

Figure 9: Spatial assessment of similarity using the two-way fuzzy map comparison. Areas mapped identically have values close or equal to 1, while areas of total disagreement show values close or equal to 0.

4   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 of Land Management Units intended for site specific crop management. 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). For instance the software has a limitation for extracting 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 patterns using geomorphometric algorithms within a GIS as done in this study has the advantage of standardisation, 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 landforms, 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. The maps showed an average similarity of 61 %, and disagreement was mostly localised in Flats and Simple Slopes, 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.

5 ACKNOWLEDGEMENTS

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