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A fuzzy *c*-means classification of elevation derivatives to extract the morphometric classification of landforms in Snowdonia, Wales

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Abstract

The increasing global coverage of high resolution/large-scale digital elevation data has allowed the study of geomorphological form to receive renewed attention by providing accessible datasets for the characterisation and quantification of land surfaces. Digital elevation models (DEMs) provide quantitative elevation data, but it is the characterisation and extraction of geomorphologically significant measures (morphometric indices) from these raw data that form more informative and useful datasets. Common to many geographical measures, morphometric measures derived from DEMs are dependent on the scale of observation. This paper reports results of employing a fuzzy *c*-means classification for a sample DEM from Snowdonia, Wales, with a number of morphometric measures at different resolutions as input, and morphometric classification of landforms at each resolution as output. The classifications reveal that different landscape components or morphometric classes are important at different resolutions, and that morphometric classes exhibit resolution dependency in their geographical extents. Examination of the scale dependency and behaviour of morphometric classifications of landforms at different resolutions provides a fuller and more holistic view of the classes present than a single-scale analysis.

Keywords: Landforms; Morphometric classes; Fuzzy; Digital elevation model; Resolution; Snowdonia

1. Introduction

The characterisation and classification of land surfaces to improve our understanding of the processes that have acted, or are acting, upon them, has long been a goal of geomorphological research. Both traditional geomorphometric measures (Evans, 1972) and statistical measures employing spectral (Pike and Rozema, 1975), geostatistical (Mulla, 1988), entropy-based (Culling, 1988) and fractal methods (Chase, 1992) have been employed in this context. Although there is evidence that statistical measures such as fractal dimension describe different components of the land surface more effectively than traditional geomorphometric measures (Klinkenberg, 1992), arguably, the use of geomorphologically significant measures is more clearly linked to process.

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A range of geomorphometric measures can be extracted from a surface, the usefulness of each of these measures being dependent on the type of surface and the specific objectives of the study. However, the first and second derivatives of elevation (slope or gradient, aspect, and plan and profile curvature) are the most commonly used (Evans, 1972; Fisher et al., 2004; Wood, 1996a). Slope determines the effectiveness of gravity for geomorphological work and curvature controls the acceleration and convergence of flow processes. It has been suggested that higher order derivatives do not provide useful information (Evans, 1990; Skidmore, 1989; Wood, 1996a). Slope and curvature are easily extracted from a DEM within a geographical information system (GIS). Typical raster-based GIS facilitate the manipulation of DEMs, and have provided valuable environments for the automated analysis of surface form, in contrast to early manual approaches by Fenneman (1946) and Hammond (1964). Geomorphic or morphometric classes such as ridges, peaks and passes have been widely extracted from DEMs (Wood, 1996a). As with much other environmental information (Burrough, 1989; Moraczewski, 1993; Luo and Dimitrakopoulos, 2003) the clear definition of morphometric classes has been questioned recently, and morphometric classes have been reconceptualised as vague or fuzzy sets (Fisher et al., 2004, 2005; Irvin et al., 1997; Lagacherie et al., 1997). Fuzzy set theory was introduced by Zadeh (1965). Fuzzy set theory allows soft boundaries and vague landform classes to be explicitly represented, providing more information on landscape structure than discrete and often spatially disjointed Boolean landform classes.

The two principal approaches to fuzzy set recognition of landforms are by deductive or inductive classification (using predetermined and self-selecting landform classes, respectively). The first deductive approach examines the DEM with a template of the arrangement of relative elevations within a fixed area (window) and allocates the centre point of that area to one of a limited set of morphometric classes. The number of classes varies depending on the implementation, from the minimal six classes recognised by Evans (1980), Peucker and Douglas (1974) and Wood (1996a) to the 11 classes included in the work of Pellegrini (1995). This deterministic approach leaves no doubt over the allocation of the pixel to a class, but Wood (1996a, b, 2002) has shown that many parameters, including morphometric class, are subject to variation with the resolution of the DEM on which analysis is executed. Classification is therefore consistent with the conception of the land surface as a multiscale composite of scale-dependent and scale-independent elements (Tate and Wood, 2001) where specific morphometric classes that are identifiable as discrete objects are comparatively rare (Fisher and Wood, 1998). Fisher et al. (2004, 2005) exploited this observation by using this uncertainty as a method for populating fuzzy memberships of morphometric classes. The simplest inductive method is that reported by Roberts et al. (1997), who took a number of different elevation derivatives and formulated a fuzzy set membership from steepest to least steep and most to least concave etc., and then combined them to give a fuzzy classification which they related to risk of soil salinisation. Other researchers using inductive methods have employed unsupervised classification with a variety of morphometric derivatives as input to an automated morphometric classification of landforms (Burrough et al., 2000; de Bruin and Stein, 1998; Irvin et al., 1997; Lagacherie et al., 1997; Macmillan et al., 2000; Ventura and Irvin, 2000). Burrough et al. (2001) have gone on to use the same approach in mapping the topo-climatic structure of forest. All these studies of automated classification have employed the fuzzy c-means classification (Bezdek et al., 1984), and they have also worked only at the resolution of the original DEM, ignoring the uncertainty associated with the change of resolution.

The aim of the research reported here is to fuse the fuzzy identification of morphometric landform classes from DEMs by inductive methods with the recognition that the classes identified at one DEM resolution may be different from those identified at another resolution. This paper describes a fuzzy c-means analysis of a DEM representing an area in Snowdonia, Wales, and builds on the studies mentioned above by examining the change in morphometric classes identified at different resolutions. After a description of the study area and data, we outline the methods of derivative extraction and fuzzy classification, and provide three methods of interpreting the resultant clusters of morphometric classes.

2. Study area and data collection

An Ordnance Survey 50 m resolution gridded DEM tile of Snowdonia, Wales, provided the initial data for this investigation and was used to extract

Table 1
Study area characteristics

Feature	Description
National grid coordinates of minimum enclosing rectangle	Bottom left (249 925, 342 825) Top right (270 575, 359 725)
Elevation: min and max	Min: 2 m, max: 1079 m
Slope gradient (tangent)	Min: 0, max: 2.07
Horizontal dimensions	16,900 × 20,650 m (338 rows, 413 cols)
Area	6,979,700 m^2
DEM resolution	50 m

the morphometric classes present in the study area by examination of the first and second derivatives of elevation. The geographical location of the study was chosen as it contained a varied collection of morphometric classes and a variable topography with a significant elevation range. The study area characteristics are summarised in Table 1.

3. Methods

3.1. Derivative extraction

A modification of the Zevenbergen and Thorne (1987) partial quartic surface equation was chosen to calculate the first and second derivatives of elevation (slope and curvature respectively) from the DEM. The nine coefficients A–I in this locally fitted nine-term partial quartic equation (Eq. (1)) can be determined by Lagrange polynomials. The equation has a degree of flexibility as it alters to fit the surface with the relevant coefficients equalling zero:

$$Z = Ax^2y^2 + Bx^2y + Cxy^2 + Dx^2 + Ey^2 + Fxy + Gx + Hy + I. \quad (1)$$

This equation has a high recorded accuracy (Skidmore, 1989; Hodgson, 1995), is very flexible and can be altered proportional to the complexity of the surface. Using the extracted values of gradient, aspect, plan and profile curvature, it is possible to define different components of the terrain as represented in the DEM, and these components allow the identification of morphometric classes. Thresholds apparent in the derivative values can be used to identify boundaries between different morphometric classes (Dikau, 1989).

3.2. Fuzzy morphometric classification

Morphometric classes derived from combinations of these derivatives are more informative and useful if fuzzy sets are used. In the context of analysing DEMs, any given cell may in fact contain elements of a number of different morphometric classes. This is represented by the degree of *membership* or belonging (values range from zero to one) that any cell has to each of the landforms identified. A membership grade of one would be associated with a cell that exactly meets the ‘ideal’ attribute values (the ‘central concept’) of a particular morphometric class, and a value of zero would indicate that the cell has no similarity or membership to that morphometric class. Fuzzy *c*-means is the fuzzy equivalent of a *c*-means classification, an unsupervised technique that identifies the natural clusters and groupings of the input data in geographical space (Bezdek et al., 1984). The attribute characteristics of these natural clusters are signatures of morphometric class, and are equivalent to spectral signatures in remote sensing. A fuzzy *c*-means classification uses the same methods for identifying clusters, but assigns each data point a membership to each cluster, representing its degree of membership or similarity to that cluster. Morphometric classes might be expected to lie on a continuum, where particular locations exhibit characteristics of different classes. This necessitates a degree of overlap between morphometric clusters; the amount of overlap is controlled by a fuzziness parameter, m. Typically the value of m ranges from 1 (Boolean) to 2.5 (very fuzzy). Values of m above 2.5 are possible but rarely applied in practice.

A fuzzy *c*-means classifier based on code supplied by Bezdek et al. (1984) was used to identify the morphometric classes present in the study area using the extracted elevation derivatives. Selection of the fuzziness parameter, m, and the number of clusters cannot be made in advance, due to the complexity of parameter interactions (Burrough and McDonnell, 1998). Choice of these parameters is only possible by comparing the results of different classifications. A number of values for m were explored, and, as in some other studies (e.g. Macmillan et al., 2000), a value of $m = 1.5$ was used. Classifications with two to seven clusters were conducted, and this range of cluster values allowed the identification of a collection of non-repetitive and complete morphometric clusters. This range of cluster numbers was also used by Lagacherie et al. (1997).

The input raster attribute layers (elevation, gradient, aspect, plan and profile curvature) derived from the DEM provide the criteria against which the clusters are compared. Although Irvin et al. (1997) used all of the elevation derivatives and other secondary derivatives, elevation and aspect have only a limited contribution to identifying morphometric classes and were therefore omitted from the cluster analyses employed here. In the present classification, only gradient and plan and profile curvature were used.

3.3. Multi-resolution analysis

This study differs from previous fuzzy *c*-means morphometric classifications (Burrough et al., 2000; Irvin et al., 1997; Macmillan et al., 2000; Ventura and Irvin, 2000) in that the influence of changing *resolution* on morphometric classification was a key element of the research. It is similar to the analysis by Fisher et al. (2004, 2005), where the varying scale dependency of different morphometric classes is used in their identification and classification. However, here the focus is specifically upon exploring the scale dependence of morphometric class and their associated fuzzy memberships at different resolutions of analysis. Classification was performed at resolutions of 50, 100, 200 and 400 m. The coarser DEM resolutions were obtained by resampling the original 50 m DEM using a mean resampling method.

4. Results

There are four stages to interpreting the geomorphological significance of the clusters generated from the analysis. Initially their average (centre) attributes are examined to gain a geomorphometric understanding of each cluster and how it fills the attribute space in which it lies. The clusters can then be visualised in the context of the landscape draping them over the DEM surface. The third stage is the examination of the spread of membership values through the surface, which provides information about the distribution of the morphometric class within the landscape. The resolution dependence and persistence of the morphometric cluster was also used to further our geomorphological understanding of the clusters and their behaviour at different surface resolutions.

4.1. Clusters in attribute and geographic space

The mean attribute values/centres of each cluster are interpreted in relation to the frequency distributions for each derivative within the study area, allowing evaluation within a local context. Nomenclature of existing landform classifications were used as a reference to allow a more intelligent interpretation (Dikau, 1989; MacMillan et al., 2000). The cluster attribute means and their geomorphological interpretation for four through to seven clusters are shown in Tables 2–5 (concavity is indicated by negative values).

The spatial arrangement of morphometric clusters and the sequences they created in the landscape were examined. The spatial organisation of the resultant morphometric classes were found to provide realistic results and showed a strong zoning and geographical consistency. The morphometric classes corresponded well with the landform types and spatial arrangement commonly associated with the study area, as follows, where landform classes are shown in brackets: ridges (ridge), planar valley floors (planar with low gradient), strongly convex mountain sides/shoulders (strongly diverging slope), gulley and channels (steep and shallow converging slopes) and gentle concave and convex mountain footslopes (converging and diverging slopes). This stage of analysis was enhanced by the defuzzification of the clusters, which examined the fuzzy memberships and identified those classes with the largest memberships to which the

Table 2
Four-cluster solution

Cluster	Landform	Gradient (tangent)	Plan curvature (1/100 z units)	Profile curvature (1/100 z units)
1	Ridge	0.451	0.587	0.661
2	Gently diverging slope	0.354	0.138	0.145
3	Planar with low gradient	0.156	−0.027	−0.041
4	Converging slope	0.431	−0.321	−0.406

Table 3
Five-cluster solution

Cluster	Landform	Gradient (tangent)	Plan curvature (1/100 z units)	Profile curvature (1/100 z units)
1	Gently diverging slope	0.373	0.181	0.196
2	Ridge	0.456	0.634	0.715
3	Planar with low gradient	0.131	0.009	0.002
4	Gently converging slope	0.326	−0.130	−0.174
5	Strongly converging slope	0.490	−0.452	−0.560

Table 4
Six-cluster solution

Cluster	Landform	Gradient (tangent)	Plan curvature (1/100 z units)	Profile curvature (1/100 z units)
1	Gently diverging slope	0.363	0.213	0.231
2	Ridge	0.467	0.669	0.757
3	Planar with low gradient	0.113	0.017	0.011
4	Shallow converging slope	0.292	−0.054	−0.075
5	Gently converging slope	0.389	−0.211	−0.282
6	Strongly converging slope	0.524	−0.554	−0.666

Table 5
Seven-cluster solution

Cluster	Landform	Gradient (tangent)	Plan curvature (1/100 z units)	Profile curvature (1/100 z units)
1	Gently diverging slope	0.325	0.250	0.271
2	Ridge	0.475	0.700	0.791
3	Planar with low gradient	0.119	0.031	0.026
4	Shallow converging slope	0.213	−0.081	−0.104
5	Steep planar slope	0.514	0.008	−0.007
6	Gently converging slope	0.330	−0.267	−0.343
7	Strongly converging slope	0.582	−0.597	−0.717

pixel was a member. Following Burrough et al. (2000), the ratio of the second to the first highest memberships for each pixel was compared with a value of 0.6, to ensure that the membership values were significantly different. If this condition was not met, then the pixel was identified as part of an intergrade, i.e. lying between two morphometric clusters in attribute space.

4.2. Cluster membership distributions

The cluster membership rasters display the spatial distributions of the memberships to the cluster, allowing the central concept of the cluster (attributes of the centre of a cluster) and its boundary conditions (attributes of the edge of a cluster) to be viewed within a landscape context (Figs. 1–11). Some of the rasters display complex distributions that are difficult to interpret and do not suggest geomorphologically-significant results (if the memberships are not meaningfully arranged in geographical space). However, some of the cluster memberships display spatial patterns that add to the interpretation of the behaviour of the morphometric cluster and provide information that is not visible simply by looking at the cluster means and defuzzified arrangements. Examination of cluster memberships also highlights land surface elements (pixels) that exhibit characteristics of more than one landform class. Inferring process from form, these distributions and landform similarities could imply patterns of erosional and depositional processes.

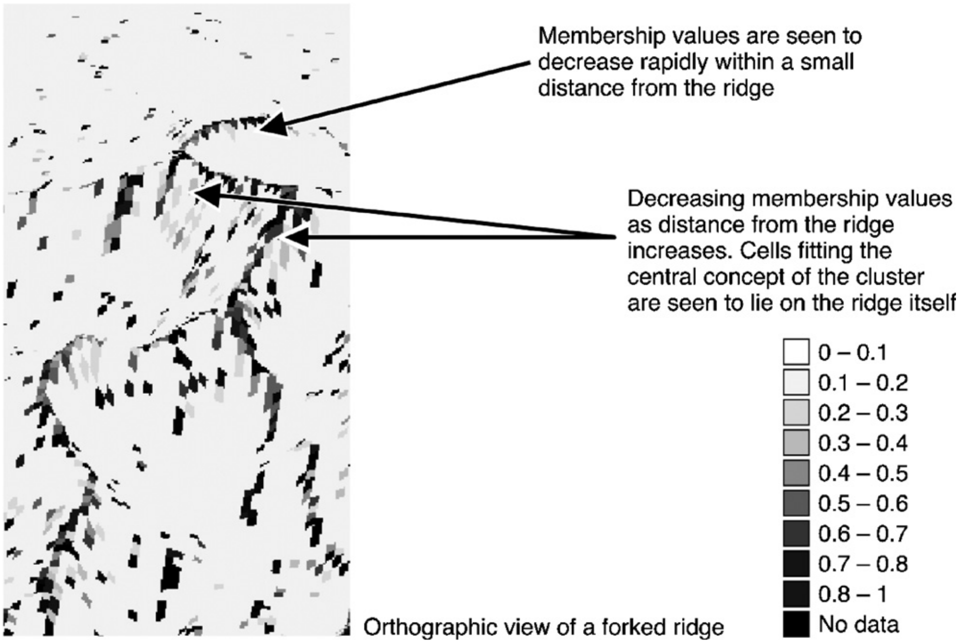

Fig. 1. Spatial distributions of the fuzzy memberships for a ridge. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

Fig. 2. Two-dimensional extract from the converging slope membership raster. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

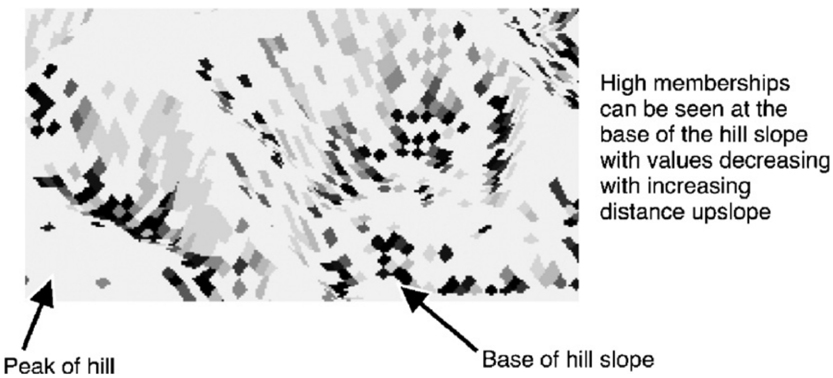

Fig. 3. Orthographic extract from the converging slope membership raster. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

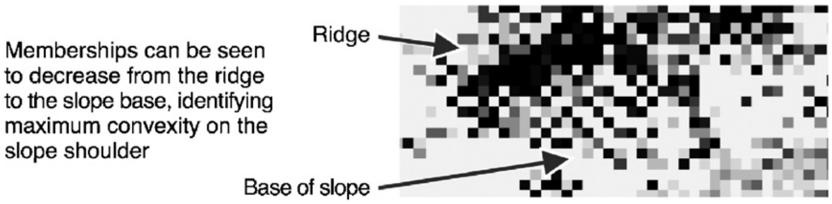

Fig. 4. Two-dimensional extract from the diverging slope membership raster. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

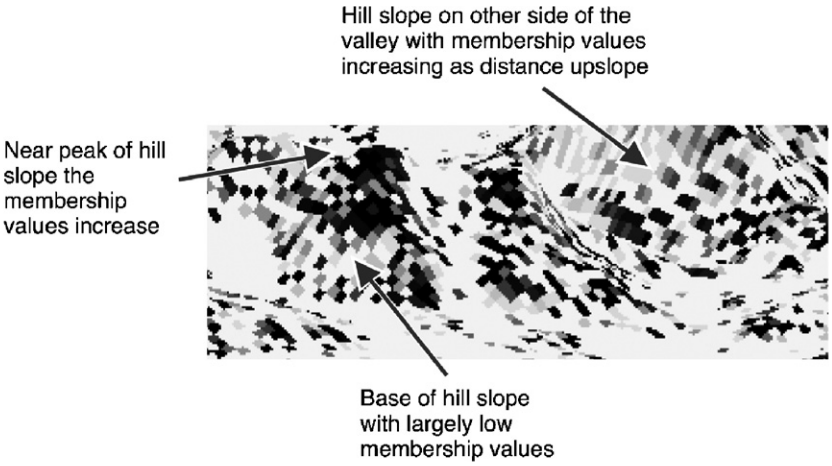

Fig. 5. Orthographic extract from the diverging slope membership raster. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

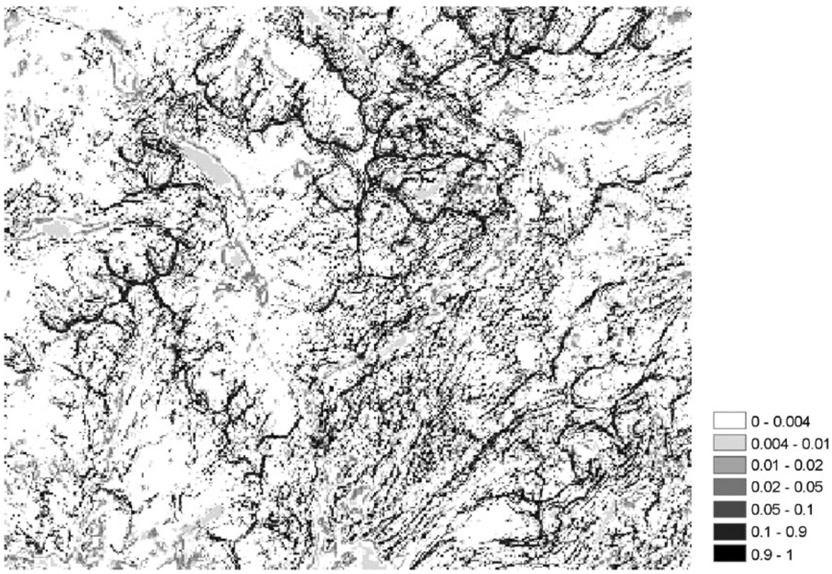

Fig. 6. Fuzzy membership raster of ridge cluster for 50 m five-cluster solution. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

The ridge clusters can be seen as very local, spatially correlated features that form connected networks, in contrast to Boolean classifications where the ridge may frequently be broken by other morphometric classes. High ridge memberships can be seen to form clearly connected, narrow

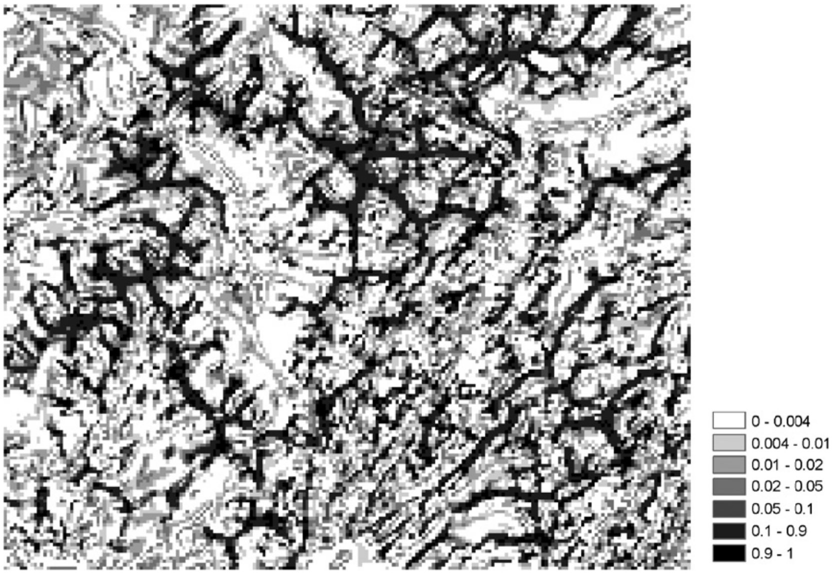

Fig. 7. Fuzzy membership raster of ridge cluster for 100 m five-cluster solution. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

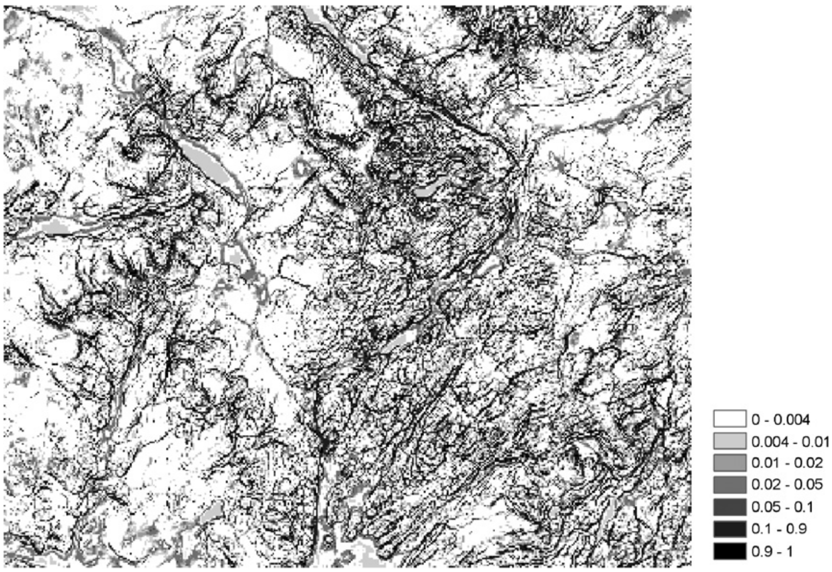

Fig. 8. Fuzzy membership raster of strongly converging slopes for 50 m five-cluster solution. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

paths where cells are highly convex in plan and profile. The cells that fit the central concept of the cluster seem to be surrounded by a narrow boundary of partial membership cells, where cells are less strongly convex. Clear boundaries demarcate those cells that have a high degree of membership to the ridge class and those that do not. It can therefore be suggested that ridges are linear and delineated features in geographical and attribute space (Fig. 1). Few cells within the landscape have a degree of membership to the ridge class, but those that do have high memberships, with attributes similar to the central concept of the cluster. Consequently, ridges are easily distinguishable and can be seen to be an extreme morphometric class, to which only a few other classes are similar, as they mark the point where two opposing slopes meet.

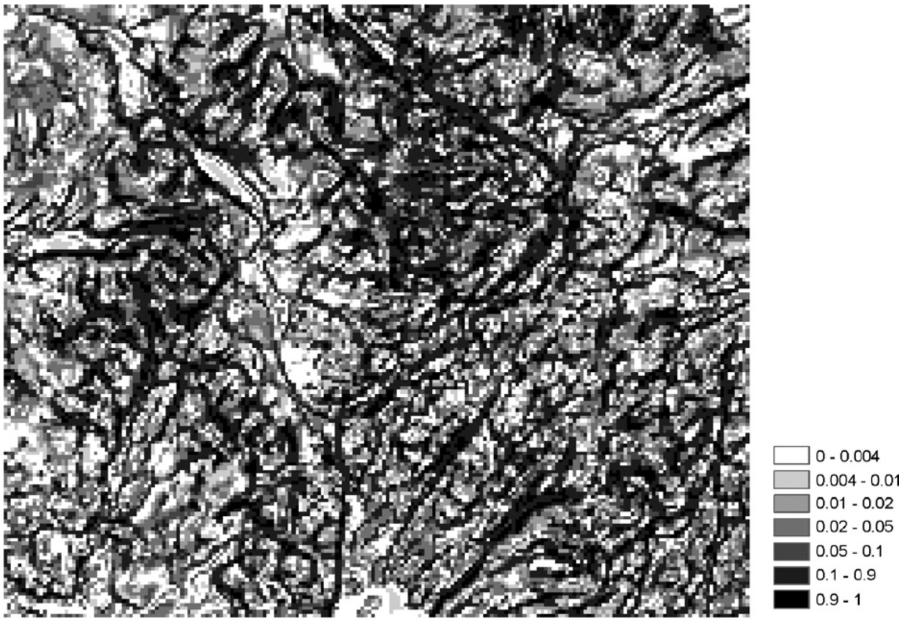

Fig. 9. Fuzzy membership raster of strongly converging slopes for 100 m five-cluster solution. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

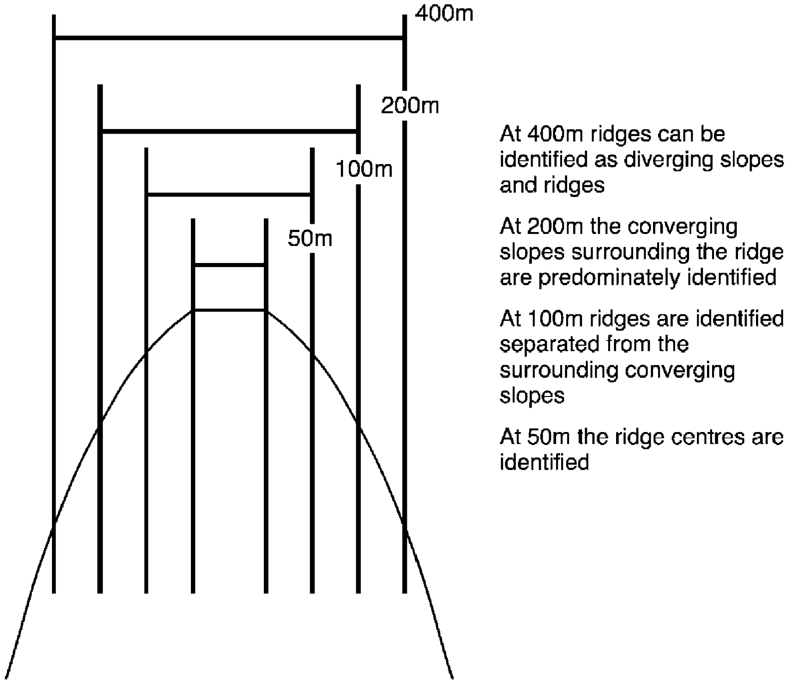

Fig. 10. Resolution-based changes to ridge recognition.

The converging slope class of the four-cluster classification and the gently converging clusters of the other classifications have maximal membership at mid-slope positions; they decrease rapidly as distance up-slope increases, and slowly as distance down-slope increases (Figs. 2 and 3). This is comparable to the characteristics of concave slopes, which have the steepest gradient and the strongest concavity at a mid- to low-slope position. The diverging slope clusters in all of the classifications

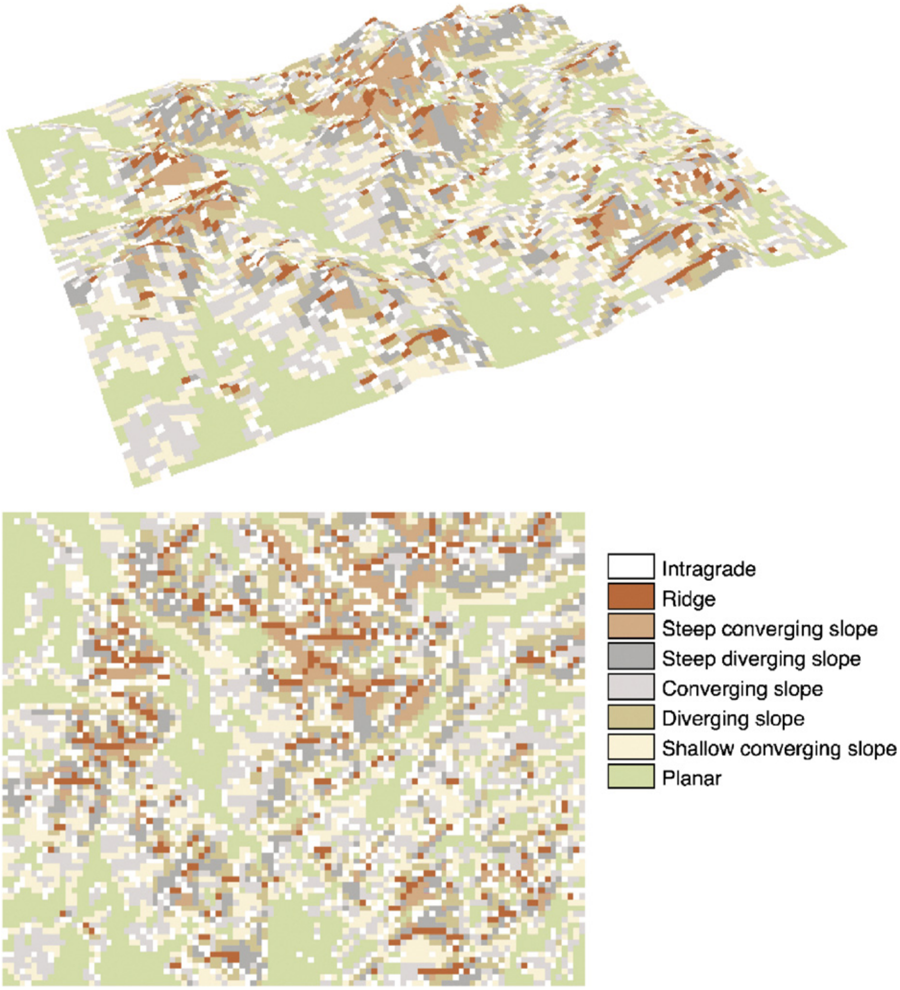

Fig. 11. 100 m seven clusters. © Crown copyright/database Right 2007 An Ordnance Survey/EDINA supplied service.

can be seen to have a different spatial arrangement, with memberships which are the highest at mid- to upper-slope positions, decrease rapidly as ridges are encountered, and decrease slowly towards the base of the slope (Figs. 4 and 5). This pattern can be seen to represent the different shape of convex slopes where greatest convexity is encountered near the top of the slope.

The strongly converging slopes highlight an interesting spatial distribution of memberships, mimicking that of the ridge cluster memberships, suggesting that the two are closely related, perhaps representing upper slope sections or part of gulley and channel networks. This is a valid conclusion as these are the only two morphometric clusters that are seen to display values that form connected linear units and the strongly converging slope cluster can be seen to occupy positions adjacent to ridges in the landscape. Like the ridge clusters, few cells have a large degree of membership (similarity) to the strongly converging slope cluster and equally few have low memberships, again suggesting that this is a morphometric class which is significantly different to other landforms. This argument is reinforced by the fact that the membership values decrease rapidly over short distances, suggesting that the boundary conditions are close to those of the central concept and significantly different from those of the surrounding cells.

4.3. Variation of morphometric class with resolution

The dependence and persistence of morphometric classes at differing resolutions (50, 100, 200 and 400 m) was investigated. It should be noted that the ratio measurements gradient, plan and profile curvature cannot be directly compared between the classifications for different resolution DEMs, as they are dependent on the area over which they are measured. As this denominator increases with a lower resolution and is not matched by an equivalent increase in the numerator, these ratios will decrease. The rate of this decrease is higher for the second derivative curvature measurements than for the first derivative slope measurements, and most pronounced for profile curvature. The mean resampling method also leads to a decrease in derivative measures as a result of their bell-shaped distributions, resulting in minor topographic features disappearing.

4.3.1. *Resolution dependence of morphometric classes*

A morphometric class was considered resolution dependent if it was not equally represented in all resolution classifications. DEM resolution was consequently identified as a dominant control on landform classifications. The percentage of cells at each resolution that were assigned to each morphometric class are shown in Table 6, bold values indicate the resolution at which a morphometric class is most prominent.

The prominence of a morphometric class at one resolution implies that this may be the most appropriate resolution at which to view the morphometric class or series of morphometric classes. For example, gentle slopes and planar areas are most prominent at 50 m resolution (consumed within other landform classes and lost through mean resampling at coarser resolutions). Following the arguments of Schumm and Lichty (1965), it is possible to identify the optimal viewing resolution of these morphometric classes as 50 m for this study area, based on the spatial coherence and landform sequences present within the data. Church and Mark (1980) suggest that the planimetric variation of roughness embodies two primary scales, surface texture (the shortest significant wavelength) and surface grain (the longest significant wavelength). As 50 m is a fine resolution, it can be suggested that it exemplifies the principle of surface texture proposed by Church and Mark (1980) and that planar areas and gentle slopes are the finest scale-surface features present within the DEM. Ridges and the surrounding steeply converging and diverging slopes have a surface width of 100 m; these features are commonly associated with peaks and therefore the peak-to-peak (or ridge-to-ridge) optimal viewing wavelength is 100 m. Although this is an unrealistic distance if the distance between peaks in Snowdonia is considered, these morphometric classes incorporate not only peaks but also most of the upland area surrounding them, and so this figure can be seen as more realistic. The same principle can be applied to the other morphometric classes. This concept can be explained further if the fuzzy memberships of the ridge clusters are examined. The 50 m five cluster solution and 100 m five cluster solution for ridge clusters are displayed in Figs. 6 and 7, respectively. The latter identifies more clearly defined and spatially delineated ridges that are not confused and complicated by noise representing the within ridge information picked up by the former's smaller-than-optimal viewing width or wavelength. These findings follow those of Wood (1996b). The same trend is visible in the membership rasters for strongly converging slopes. The 50 m resolution five cluster solution and 100 m five cluster solution for strongly converging slopes are displayed in Figs. 8 and 9, respectively. The 100 m solution provides a clearer and less 'speckled' classification identifying a more spatially correlated organisation of features that suggests a more accurate classification. The pattern of membership values also suggests a more meaningful classification, with a decay of membership away from the central concept.

Table 6
Resolution dependency of landforms in the study area, showing percentage of cells classified as each landform

	50 m	100 m	200 m	400 m
Converging slope	1.0	1.7	16.3	**20.5**
Strongly converging slope	7.4	**11.9**	8.5	3.3
Ridge	4.5	**18.4**	8.5	13.1
Planar with low gradient	**38.9**	28.8	36.7	27.5
Gently diverging slope	**17.7**	16.9		
Steep planar slope	3.8	4.2		**11**
Shallow converging slope	**12.4**		6.1	
Gently converging slope	**14.3**			
Diverging slope		7	**20.6**	9.3
Steep diverging slope		**11**	3.3	4
Shallow diverging slope				**11.3**
Total	100	100	100	100

4.3.2. *Persistence of morphometric classes*

The resolution dependence of a morphometric class only identifies the resolutions at which that class is present, and does not directly provide information on how the same geographical space is classified at different resolutions. A morphometric class can be recognised as persistent if it is present in the same area of geographical space at different spatial resolutions. Changes to a landform's classification with resolution provides information on the characteristics of that landform, and how its function in the landscape changes when viewed at different resolutions, describing the allometry of a class (Bull, 1975). A morphometric class can be viewed as isometric if its shape and form do not change with scale. This change is displayed quantitatively in Tables 7–9 by showing how the landform classifications change between each successive resolution. Values are the percentage of cells of the parent morphometric class at a coarser resolution that have been assigned to the same morphometric class at a finer resolution. Bold values indicate large changes or persistence.

4.3.2.1. 400–200 m resolution change. Ridges, planar areas and steeply diverging slopes are persistent landforms over this change in resolution, with the highest proportion of cells being assigned to the same landform type. This suggests that the geomorphological processes that create and form them act over both resolutions. Ridges and steeply diverging slopes are similar in form as both are water-shedding surfaces and it is logical therefore that they should both be persistent.

All morphometric classes, except planar areas and shallow diverging slopes at 400 m, can be seen

Table 7
Morphometric classification changes from 400 to 200 m

400 m / 200 m	Steep planar slope	Shallow converging slope	Converging slope	Strongly converging slope	Planar with low gradient	Ridge	Shallow diverging slope	Diverging slope	Steep diverging slope
Steep planar slope	–	–	–	–	–	–	–	–	–
Shallow converging slope	23.5	–	**30.4**	**21.9**	13.9	**30.8**	8.4	**30.3**	**25.1**
Converging slope	**37.3**	–	9.7	11.0	4.8	12.7	2.8	7.8	9.9
Strongly converging slope	4.0	–	**20.3**	17.2	10.6	8.1	**22.3**	**18.5**	16.3
Planar with low gradient	**15.8**	–	**21.9**	11.6	**28.5**	15.6	3.3	11.4	14.4
Ridge	13.1	–	3.5	0.0	**36.1**	**22.4**	**42.5**	16.3	13.6
Shallow diverging slope	–	–	–	–	–	–	–	–	–
Diverging slope	3.1	–	2.6	**23.0**	1.0	2.7	2.5	6.1	0.0
Steep diverging slope	3.1	–	11.5	15.3	5.2	7.7	18.3	9.6	**20.8**

Table 8
Morphometric classifications from 200 to 100 m

200 m / 100 m	Shallow converging slope	Converging slope	Strongly converging slope	Diverging slope	Steep diverging slope	Ridge	Planar with low gradient
Shallow converging slope	–	–	–	–	–	–	–
Converging slope	2.0	2.9	7.6	0.8	14.6	2.9	0.3
Strongly converging slope	22.1	16.7	**23.3**	12.0	**25.9**	**25.1**	7.5
Diverging slope	3.8	12.4	12.0	12.5	16.6	13.3	2.7
Steep diverging slope	**33.3**	**26.4**	**22.3**	12.6	**23.5**	**23.6**	6.3
Ridge	**35.5**	17.9	21.2	**26.1**	8.3	**21.9**	**28.1**
Planar with low gradient	3.4	23.7	13.7	**35.9**	11.1	13.2	**55.1**

Table 9
Morphometric classification changes from 100 to 50 m

100 m / 50 m	Shallow converging slope	Gently converging slope	Converging slope	Strongly converging slope	Ridge	Planar with low gradient	Gently diverging slope	Diverging slope	Steep diverging slope	Steep planar slope
Shallow converging slope	–	–	7.4	12.1	12.0	8.6	11.9	18.3	18.6	**19.6**
Gently converging slope	–	–	11.0	18.2	9.4	8.6	20.5	11.9	**26.2**	13.0
Converging slope	–	–	0.0	1.1	2.2	1.0	0.0	2.1	0.0	0.0
Strongly converging slope	–	–	11.1	9.9	4.2	4.7	9.3	13.3	11.3	3.1
Ridge	–	–	12.6	7.3	3.9	2.9	3.4	6.1	6.2	4.5
Planar with low gradient	–	–	6.3	**24.8**	**51.7**	**62.1**	**33.4**	**21.9**	6.0	14.4
Gently diverging slope	–	–	**18.9**	**22.2**	15.0	11.1	**21.5**	**18.6**	**26.8**	**20.6**
Diverging slope	–	–	–	–	–	–	–	–	–	–
Steep diverging slope	–	–	–	–	–	–	–	–	–	–
Steep planar slope	–	–	**32.7**	4.4	1.5	1.1	0.0	7.7	5.0	**24.8**

to have a large proportion of their cells reclassed as shallow converging slopes at 200 m. This restructuring of the landscape components due to the introduction of this new morphometric class suggests that the resolution change identifies a geomorphological threshold, leading to a change in the balance of processes and the creation of the new morphometric class identified.

4.3.2.2. 200–100 m resolution change. Locations identified as diverging slopes in the analysis of the 200 m resolution DEM resolve into ridges and planar slopes in the 100 m analysis; these two morphometric classes can be identified as similar as they both mark the end of a slope. This shows that as a finer spatial resolution is used, cells that are likely to lie at the end of slope positions can be distinguished as morphometric classes distinct from the slope on which they lie. Ridges can be seen to be persistent between the viewed resolution changes. They are very localised features that do not occupy large areas of geographical space. As a finer resolution is used to view a ridge, it can be seen to be composed of the surrounding strongly converging slopes, with only 21.9% of the cells that were classified as a ridge at 200 m still being classified as a ridge at 100 m, suggesting that a ridge is only one cell wide. This is to be expected, as a ridge is a linear feature in geographical space, which identifies and creates a border between opposing slopes. Ridges can also be seen to be one of the most commonly classified landforms from another morphometric cluster, for five of the seven morphometric classes present at 200 m. This can be meaningfully interpreted when recalling that ridges can be optimally viewed at a 100 m resolution (Section 4.3.1).

Planar areas, steep diverging and strongly converging slopes can also be identified as persistent landforms through this resolution change. As the latter two morphometric classes are closely associated with ridges, they are likely to have similar persistence characteristics. The ridge morphometric class can be viewed as extreme and is likely to exhibit a degree of resolution independence and persistence, since it is a dominant class in the landscape and can be viewed as such at most resolutions.

4.3.2.3. 100–50 m resolution change. As the resolution decreases to 50 m, ridges are commonly classified as planar areas (Table 9). This suggests that this is too fine a resolution to view ridges, as ridge centres are being identified (again confirmed as this is not their optimal viewing width), which means that ridges are only persistent to resolutions of 100 m (Fig. 10).

Diverging slopes and planar slopes are persistent through this resolution change, with the largest proportion of cells (20–26%) that were classified as these morphometric classes being similarly classified at the finer spatial resolution. This suggests that the processes that create these morphometric classes act over both of the spatial resolutions (100 and 50 m). In contrast, converging and strongly converging slopes at 100 m are predominantly classified as planar and diverging slopes at 50 m. The planar cells are likely to represent ridge centres (Fig. 11), and the diverging slopes the surrounding ridge cells. Planar areas are the only landform to be significantly persistent at all resolutions, with the majority of planar cells reclassified as planar cells at each successive scale change. The persistence of this landform type can be explained as they are an example of a relatively distinct morphometric class and their form does not change with scale, since flat areas are isometric rather than scale dependent.

4.4. Optimal solution

Although the purpose of examining a landscape at different resolutions is to gain a fuller understanding of the morphometric classes and the landscape's allometric characteristics, as has been shown in the preceding section, it also poses the question of which is the best resolution at which to view the landscape. The results discussed identify that an optimal solution is not possible as different morphometric classes are optimally viewed at different resolutions. However, with a 50 m resolution source dataset, it is felt that a resolution of 50 m is too sensitive to surface noise and therefore impairs the success of geomorphometric interpretation, which necessitates the separation of surface noise from morphometric signatures.

These results imply that for the 50 m source dataset, a resolution of 100 m provides a suitable compromise between delineating fine scale landform divisions and smoothing the data to reduce surface noise. It can be suggested that as the resolution increases, the number of morphometric classes that can be meaningfully delineated will decrease and therefore the optimal number of clusters will decrease, although it should be noted that as the resolution changes different landforms become evident and significant. This can be seen in the 100 m resolution solution, where a restructuring of the morphometric clusters occurs when seven clusters are identified. The solutions for this resolution with fewer clusters had been dominated by diverging slope landforms, which, although dominant at this resolution, would require cluster merging to create more geomorphologically significant results. The seven-cluster solution identifies converging and planar slopes, suggesting that, although less significant morphometric classes, they are still present in the landscape (Fig. 11).

It is therefore evident that it is not possible to identify an optimal solution which can be generalised across contexts, since the resolution and number of clusters chosen should be dependent on the morphometric classes of interest and the type of classification required, i.e. whether the fine resolution landform delineations found in the 100 m six-cluster solution are desired or whether a more comprehensive classification is required. The optimal resolution suggested is only true for the 50 m data product corresponding to this landscape and study area.

5. Discussion and conclusions

This work has confirmed the observations of Burrough et al. (2000) and Irvin et al. (1997) that performing a fuzzy *c*-means classification on a landscape is both possible and sensible, allowing the extraction of geomorphologically significant classes. The clusters created provide a classification with high information content, allowing fine-scale and subtle landform delineations to become apparent. Examination of the fuzzy memberships provided information on the distribution of morphometric classes in attribute space, differentiating between discrete and broad morphometric classes, ridges and converging slopes.

The examination of the defuzzified classifications identified resolution as a dominating factor in landform identification and classification. The resolution at which a landscape is viewed determines the morphometric classes that will be identified. In part, this reflects the changing importance of geomorphic processes operating on the landscape with scale, ranging from weathering and erosion at high resolution/fine scales through to transport and depositional processes at hillslope scale to fluvial and glacial processes at the landscape scale. Examination of morphometric classes at different resolutions showed the different amounts of geographical space they occupied at each and the resolutions at which they were most prominent, with shallow and gentle slopes representing the surface texture at a resolution of 50 m and converging slopes at a resolution of 400 m.

Extreme morphometric classes such as ridges and planar low gradient areas were found to occupy the same area of geographical space at all resolutions, identifying them as persistent morphometric classes within this environment. It was found that as the resolution of the DEM decreased the noise of the classification decreased, as less of the fine scale within-morphometric-class variation was identified. However, although a coarser DEM resolution reduced the classification noise, it increased surface generalisation and consequently generalisation of morphometric classes. It is proposed that increasing the spatial resolution (using finer scale DEMs) will increase the resolution of the landforms resolved within the classification, but, in doing so, may identify features within the landscape that are micro or components of morphometric landforms that do not form useful classification elements. The scale of the landscape features of interest should be the critical factor in selecting an appropriate terrain surface resolution. To define an optimal resolution at which to view a landscape, it is necessary to achieve a balance between noise reduction and generalisation of morphometric classes; for this context and dataset, a resolution of 100 m achieved such a balance.

By combining fuzzy set theory and geomorphometry to analyse DEMs, a powerful toolbox is created that can extract large amounts of information from a landscape. Future work will apply this methodology to other areas to examine the context dependency of morphometric classifications and look at changing the entropy (the degree of fuzziness) of classifications. Classification results from varying the data resolution of the DEM source will also be explored and wavelet transforms will be used to generate multiscale representations of morphometric classifications.

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