Automated and Subjective Terrain Feature Extraction: A Comparative Analysis

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1. Introduction

Ethnophysiography, proposed by Mark and Turk (2003), examines people's conceptualizations of landscapes through interviews and description. This paper investigates one aspect of this concept, comparing subjective perception of terrain features with automated extraction techniques, for an area in the English Lake District. The primary research objective is to determine if there is a scale of analysis for automated terrain feature classification which coincides with human perception of the same features in the landscape.

This analysis required subjective tests to occur in rugged terrain where large numbers of candidate features exist and frequented by people. The area chosen, the Old Man of Coniston and its environs, is a region of dramatic relief, of which the summit is a popular destination for hikers.

The remainder of this paper is in two sections: method and discussion. The method, describes a subjective study that identified objects in the landscape that human subjects considered representative of different classes of terrain features; and an automated process which extracts terrain features from a digital elevation model across a range of scales. In the discussion, these datasets are compared to detect the scale of analysis for automated feature extraction processes that coincides with the scale at which people perceive different classes of terrain features.

2. Method and results

2.1 Subjective terrain feature identification

The first dataset created represents a subjective assessment of prominent features in the study area. It was generated by interviewing one hundred hill-walkers from the summit of the Old Man of Coniston between July 25–27 2008. Participants were asked to identify what they considered the first and second most *prominent* of four classes of morphometric features - peaks, channels, ridges and passes - from the observation point. The word prominent used in the interviews as suggested by Greatbatch *et al* (2007) was intended to convey to participants that their choice need not be constrained to the largest or closest feature. Respondents were guided by the schematic feature representations in Figure 1.

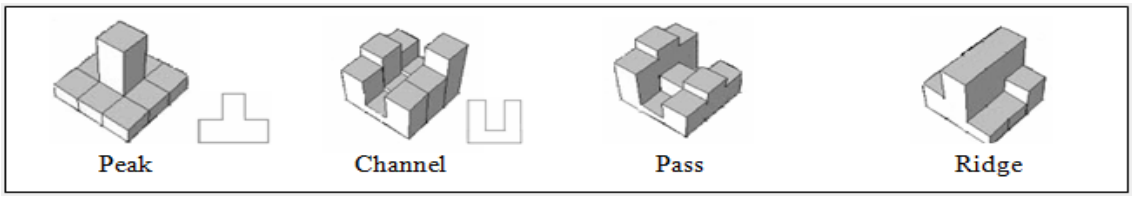

Figure 1. Schematic Morphometric Features (Adopted & modified after Wood, 1996)

One potential source of error was a lack of synchrony between the feature identified by the participant and that recorded by the interviewer. To minimize this error, the 1:25000 Ordnance Survey (OS) map of the subject area was draped over a three dimensional image of the terrain, and a paper copy of this scene annotated in the field to confirm the features identified. Respondents highlighted summits on the OS explorer map to record peaks, while an approximation of the centre of channels and ridges and their lengths were recorded with lines. Shapefiles were created for each feature type by manual digitizing inESRI ArcGIS, then imported to the LandSerfGI System (Wood, 2008).

In all, nine peaks, three ridges, four channels and six passes were identified over the course of 100 interviews (Figure 2). While all respondents were able to identify peaks, ridges and channels, only 43% were able to identify passes.

Initial analysis allowed the following observations to be made:

1. Changes in visibility over the period had no obvious impact on the results.

2. Features identified as being prominent tended to be within a radius of approximately 4 kilometers from the observation point.

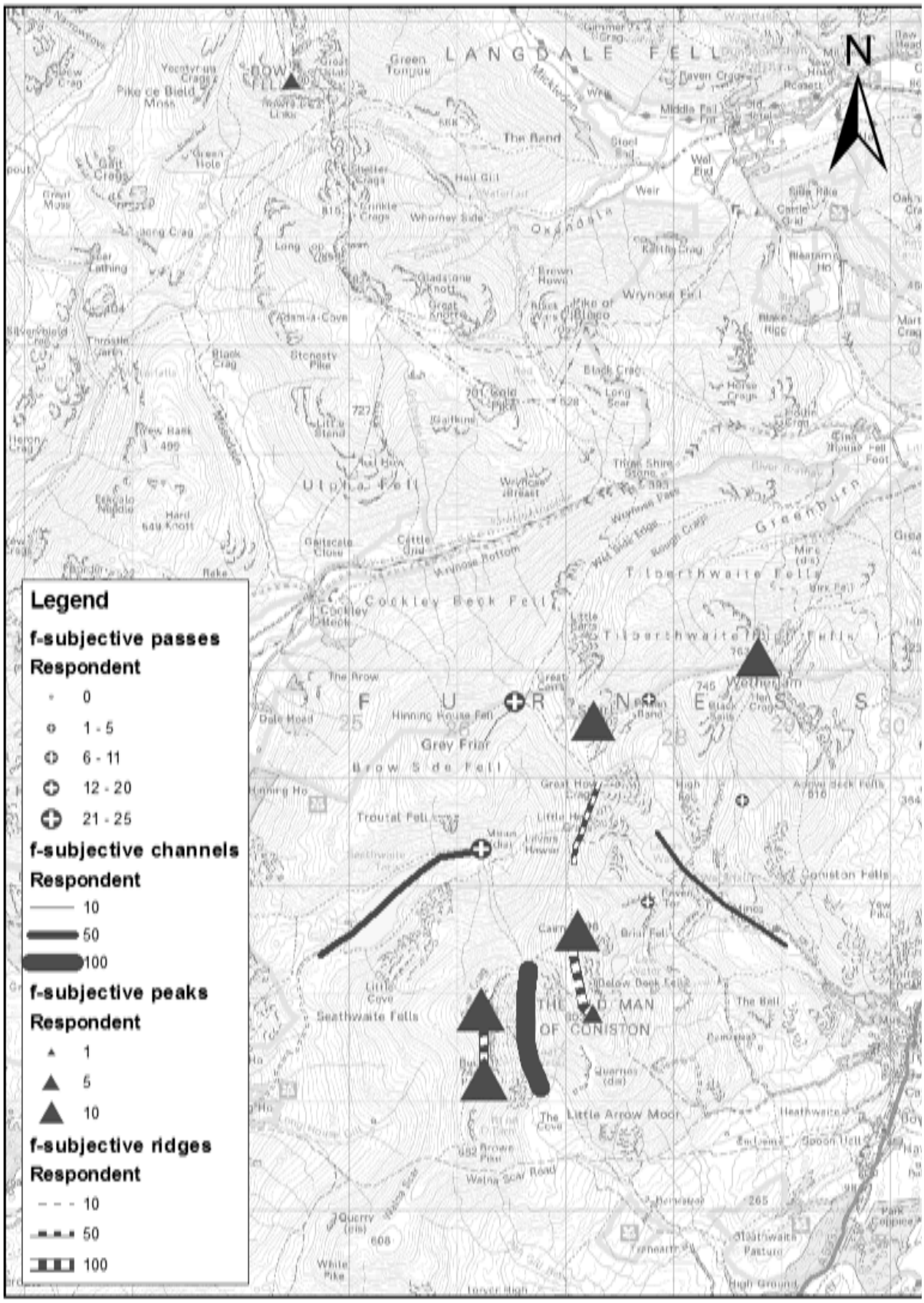

Figure 2: Terrain features identified by hill walkers from the Old Man of Coniston
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2.2 Automated terrain feature extraction

One of the most widely used set of automated morphometric classifications partitions a landscape into distinct terrain features (Wood 1996). Automated feature extraction algorithms, such as Fowler and Little, assigns the individual cells of a Digital Elevation Model (DEM) a single feature class by examination under a 3x3 kernel. Each of the eight neighbors surrounding the mid cell are assigned a positive or negative value depending on their elevation relative to the mid cell. The pattern of these neighbours is then used to define which feature class the cell belongs to: for example, the mid cell would be defined as a peak if all neighbours are lower (Figure 3).

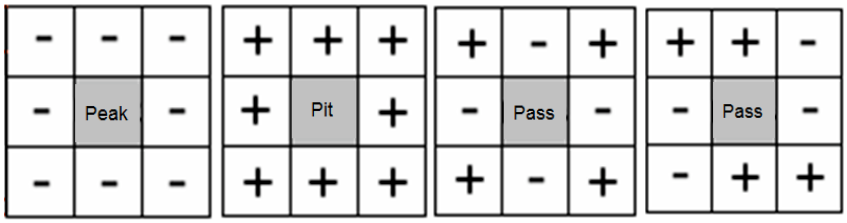

Figure 3: Cell Classification (Fowler and Little Algorithm (Adopted from Wood 2007)

Terrain features were extracted using LandSerf at various scales of analysis using the OS 50m DEM of the study area. This was achieved using the Feature Network tool, which maintains topological integrity of features. A distance decay of 0 was used, assigning equal importance to cells. The output of this process is a continuous surface with cells assigned to one of six candidate feature classes: peak, channel, ridge, pass, pit or plane (Wood, 1996). Figure 4 shows some results of the process.

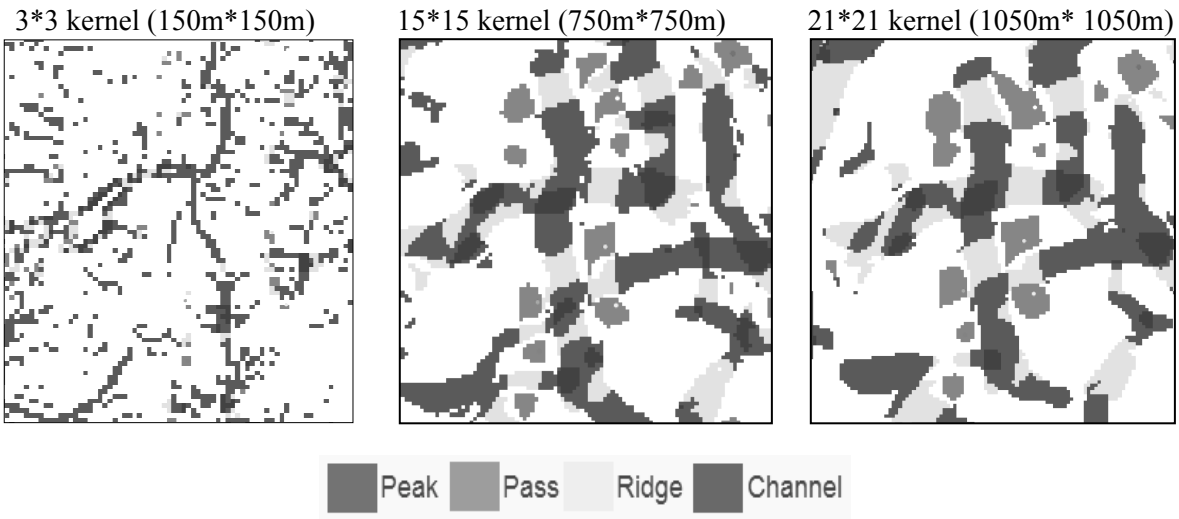

Figure 4: Effect of scale on automated feature classification

3. Discussion: Comparative Analysis

The vector dataset representing subjective terrain features was overlaid and compared against the automatically generated raster datasets. This procedure was repeated for four feature types, peaks, ridges, channels and passes. This section assesses the results of the subjective classification prior to attempting to establish the scale of analysis at which human participants identified terrain features.

3.1 Peaks

Figure 5 shows the peaks identified by the subjective classification, against the number of responses, and figure 6, the relationship between elevation, distance from observation point and number of responses. This demonstrates a relationship between distance and features identified as being prominent. Beyond 3.6 kilometers, very few features were identified.

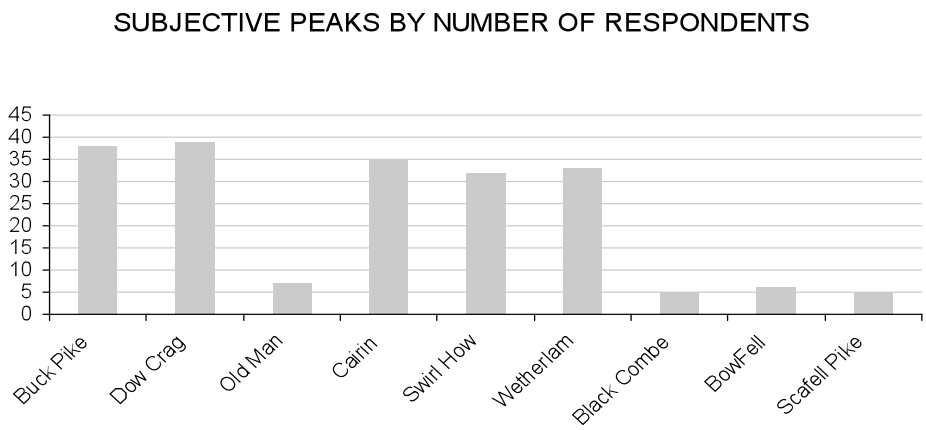

Figure 5: Frequency of specific peaks, from subjective analysis

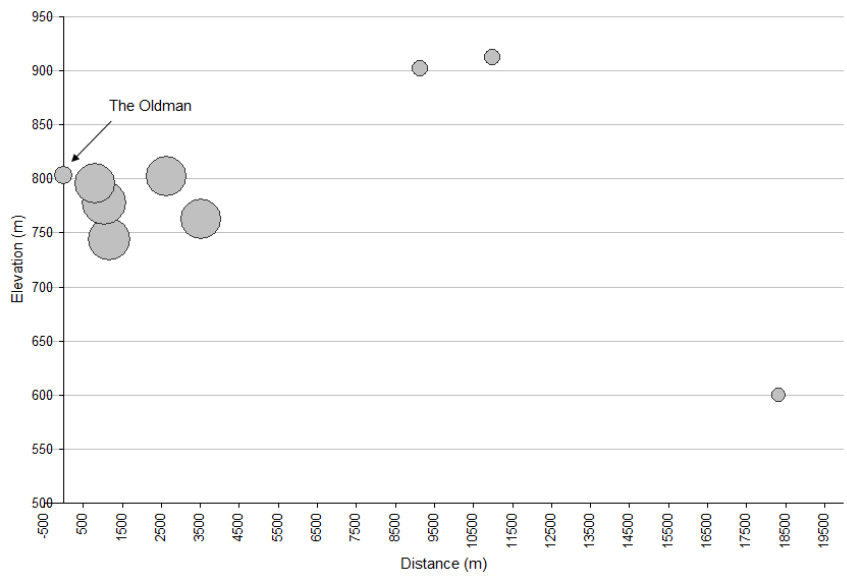

Figure 6: Identified Peaks: elevation (y-axis) vs distance from observer (x axis).
Dot sizes represents number of feature responses

The peaks identified subjectively display the closest alignment with the automated results using kernel sizes between 750m and 1650m (15x15 to 33x33 cell kernels), as in Figure 7. At finer scales, there are many peaks which were not identified by participants, suggesting that features must exceed this threshold before being considered a peak. At wider scales of analysis, what participants considered to be peaks tended to be identified as other features by the automated extraction process. This confirms a known issue in the identification of mountain features: whether a particular feature is a peak on its own or part of a ridge.

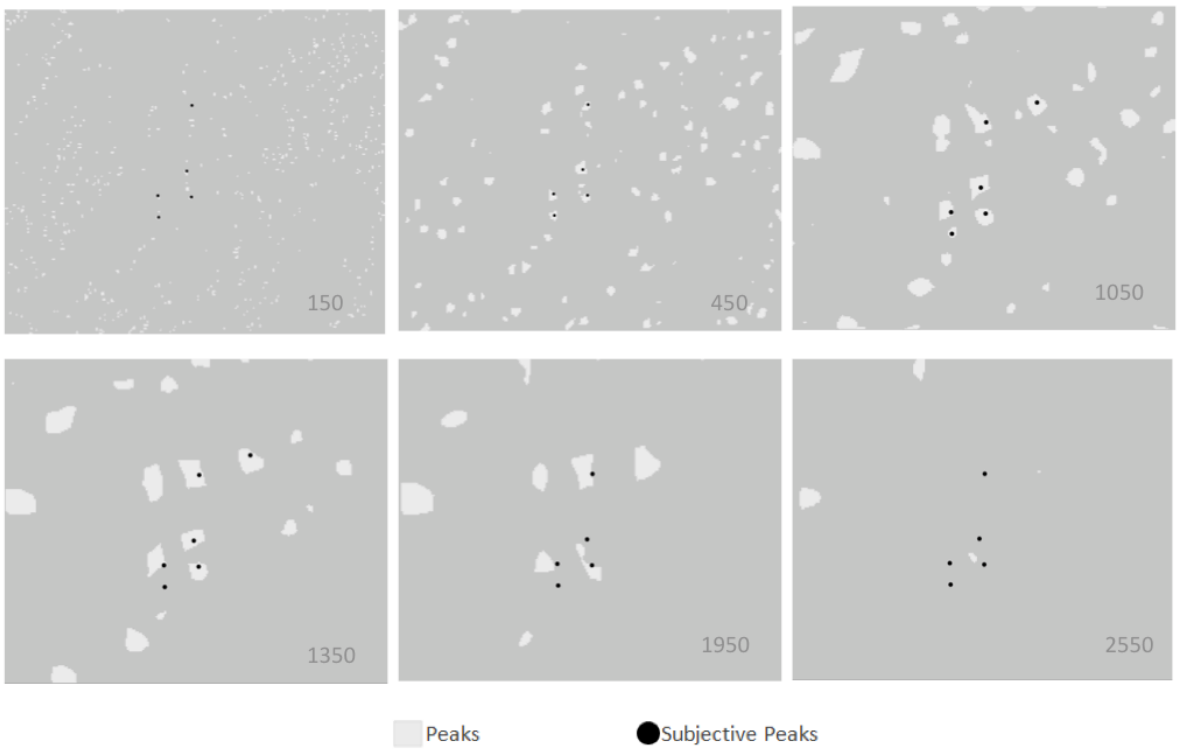

Figure 7: Subjective and Automated Feature Overlay (Peaks)

3.2 Ridges

Participants identified fewer ridges than peaks (just 3), all of which were within 4km of the observation point. Ridges A and B had an almost equal number of responses totaling 78.8 percent, and were both connected to features that were identified as peaks in the subjective feature classification (see Figure 8). At smaller window sizes subjective ridges were a composite of multiple peaks and ridges in a linear manner, and were within 0.9m close proximity to the observation point. At window sizes 9x9 and 21x21, subjective ridges were classified as passes, and a higher degree of synchrony with automated results with sizes 27x27, 33x33, and 39x39.

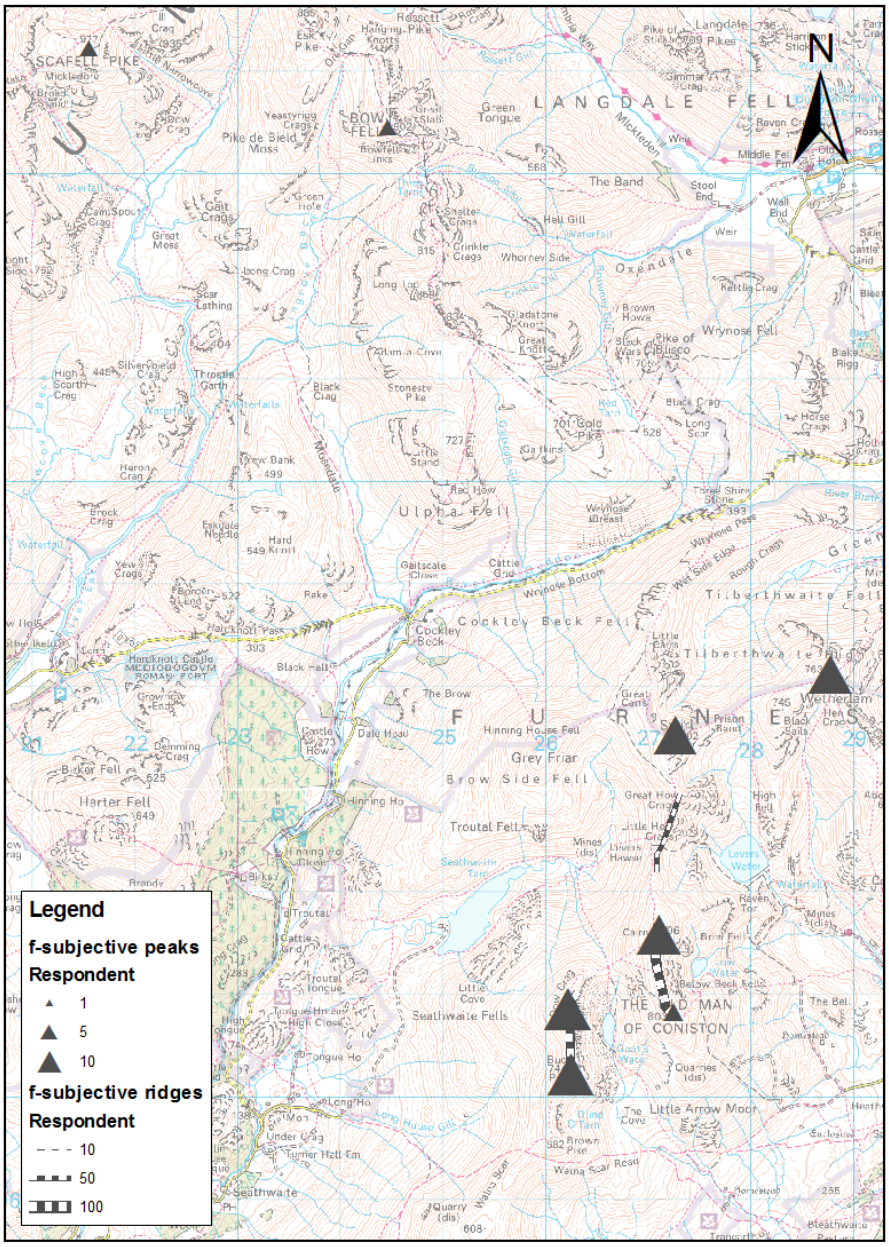

Figure 8: Locations of Subjective Ridges and Peaks
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It was observed that there are similarities in classification with the subjective views using kernel sizes of 1350m – 1950m (27*27 – 39*39 cell kernels), as shown in Figure 9. Features tend to decompose when smaller kernels were used.

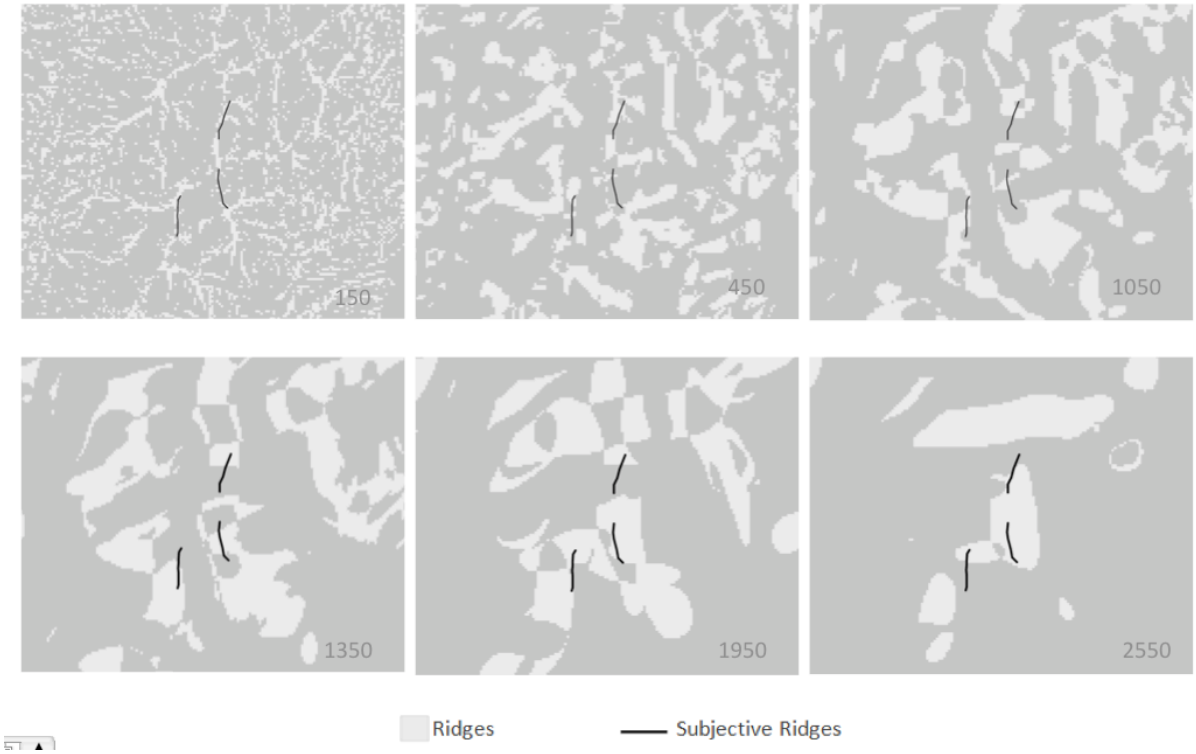

Figure 9: Comparison of subjectively and automatically identified ridges

3.3 Channels

Ninety six percent of the participants identified the same three features (A, B and D) as channels; all of which were within a horizontal distance 3km of the observation point. Figure 10, shows the locations of these subjective channels in relation to peaks. All identified channels were within 3km of the observation point, suggesting that it is harder to identify distant channels than peaks.

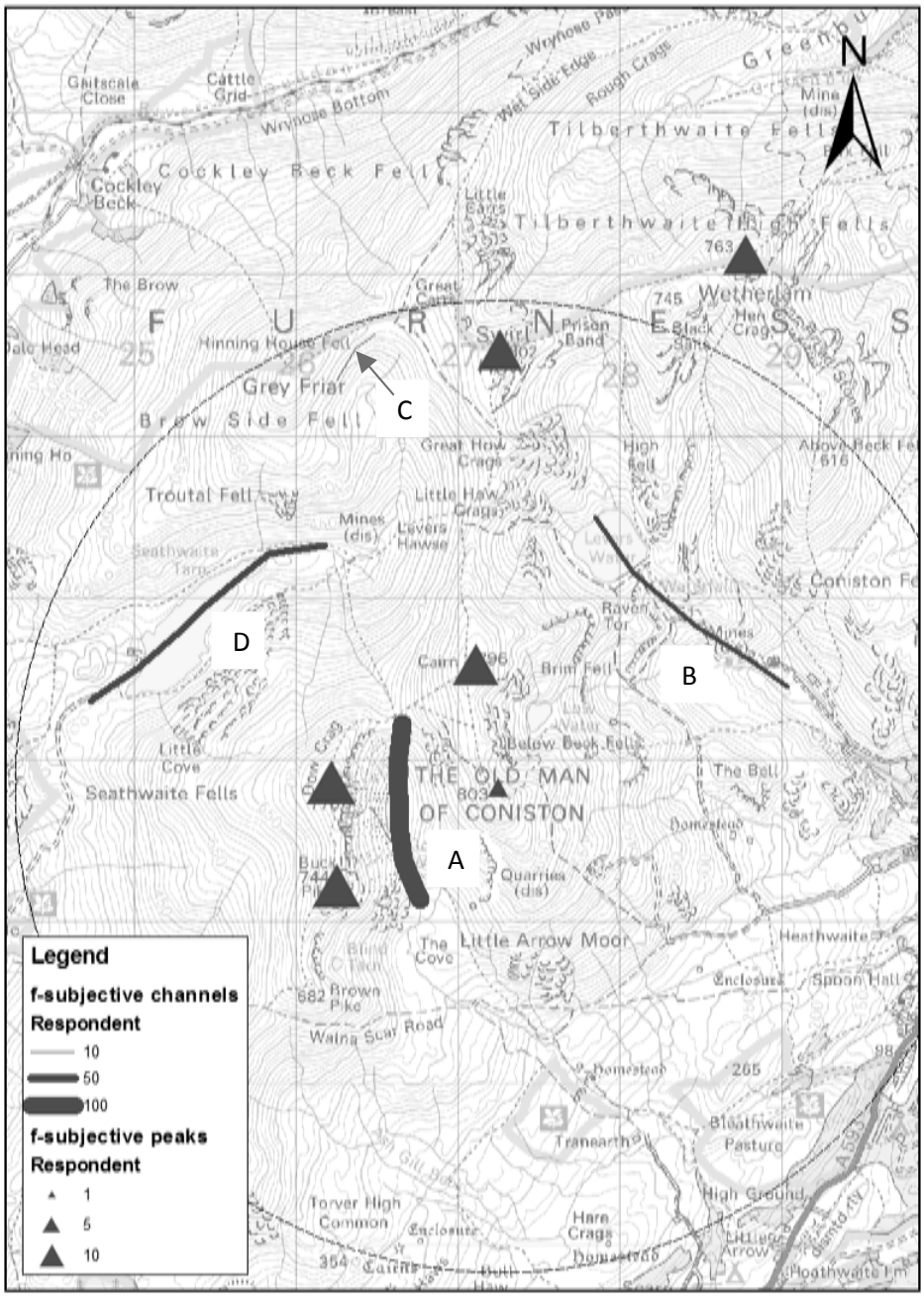

Figure 10: Subjective Channels Shaded-represents Peaks-Threshold-600m

People's perception of channels was consistent with those extracted automatically using kernels between 1050m – 1650m (21*21- 33x33 cell kernels), although there is some discrepancy between human and automated classification across the scales.

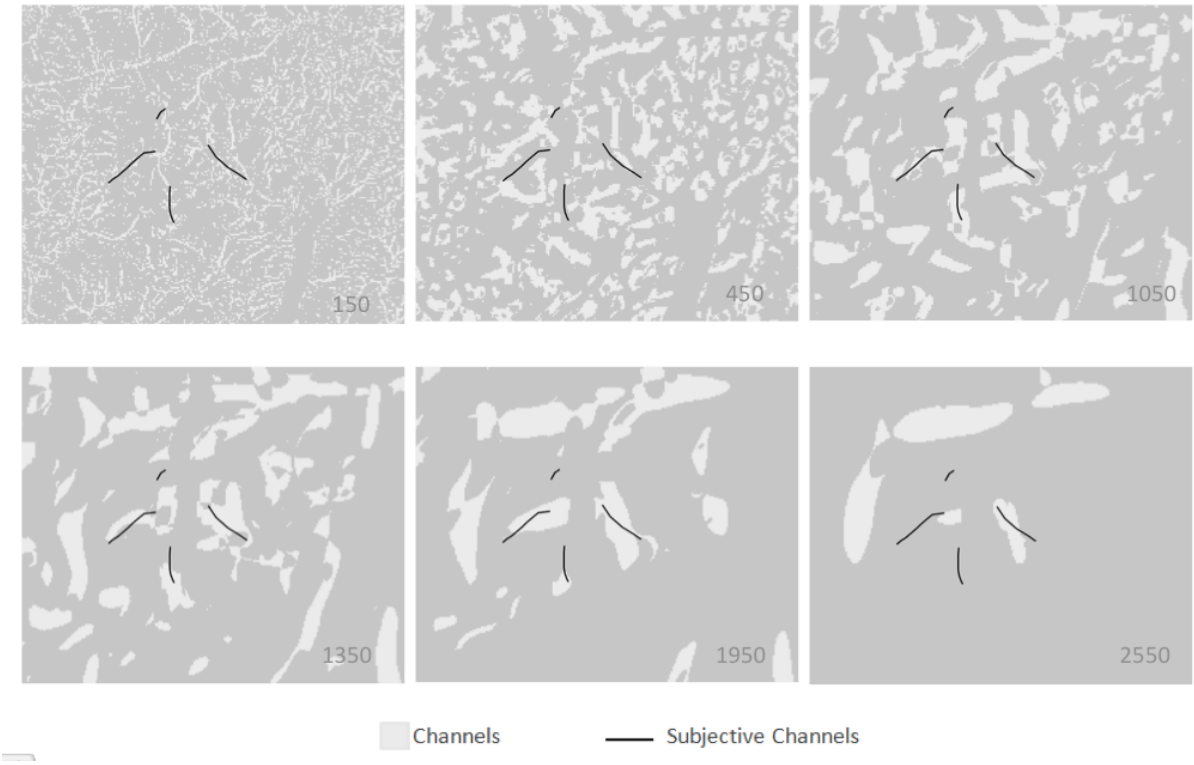

Figure 11: Comparison of subjectively and automatically identified channels

3.4 Passes

Five of six passes were within 3.6 kilometers of the observation point. The data suggests features C, E and F are more prominent examples of, passes with a total of seventy two percent of the responses (Figures 12 and 13). Like the location characteristics of peaks, the passes identified were similar, with a minimum and maximum distance from each subjective peak of 0.6 and 1.9 kilometers.

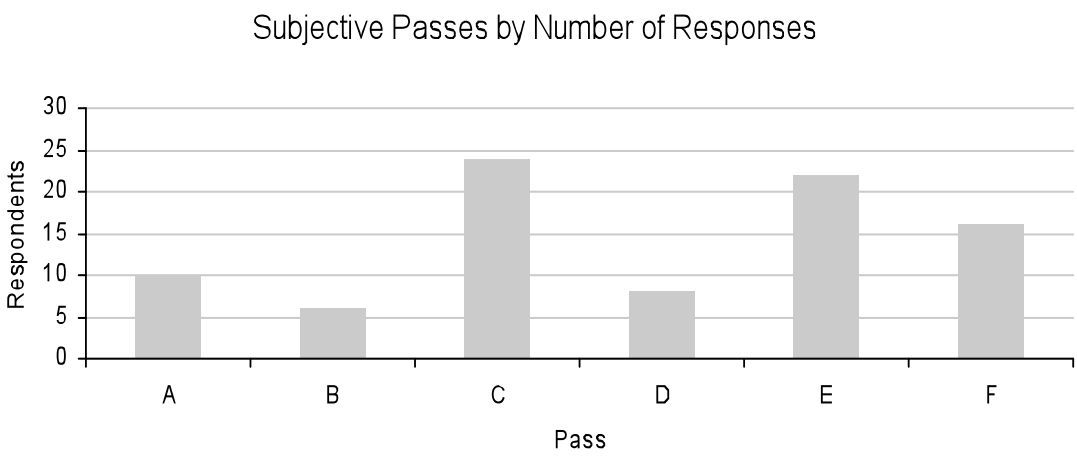

Figure 12: Subjective Passes and Number of Responses

Of the subjective passes, F, E and C remained across the automated scales of analysis from 150m (3*3) – 2150m (43*43), suggesting they are the least scale dependent features. There is consistency at these scales with both results. This suggests that passes are recognized within the range 3x3–33x33.

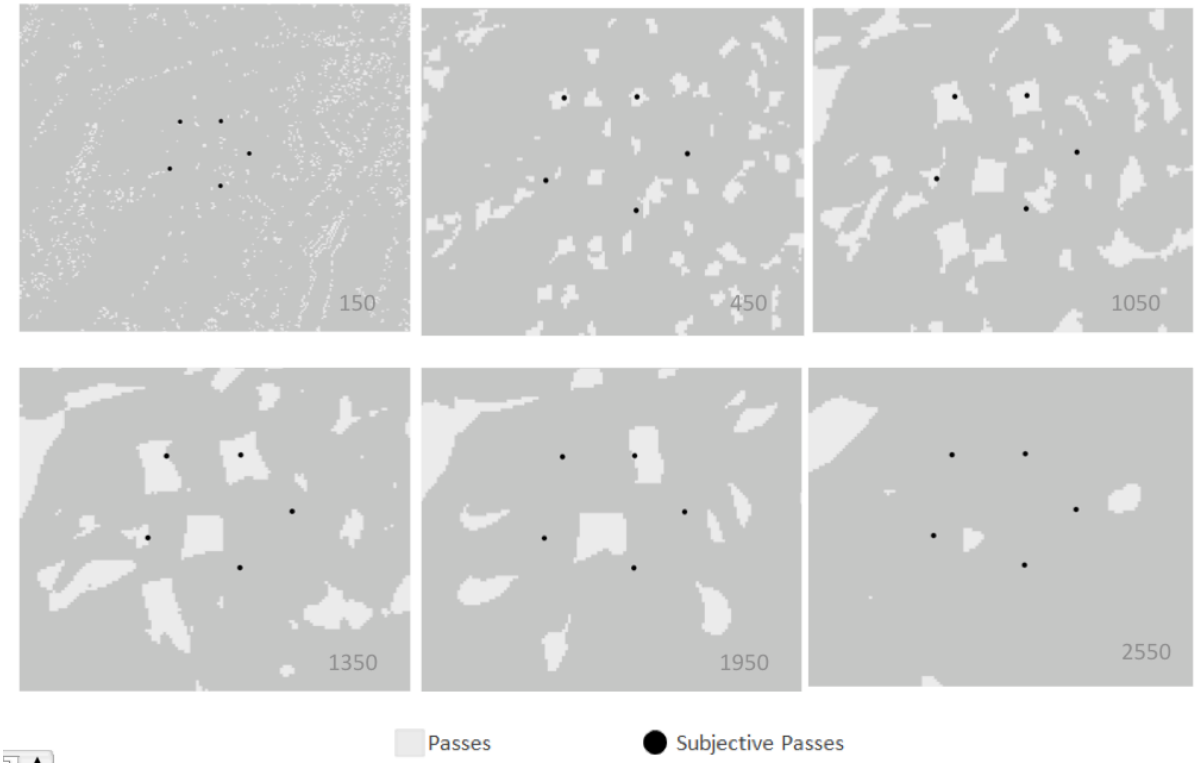

Figure 13: Comparison of subjectively and automatically identified passes

4. Agreement between subjective and algorithmic approaches

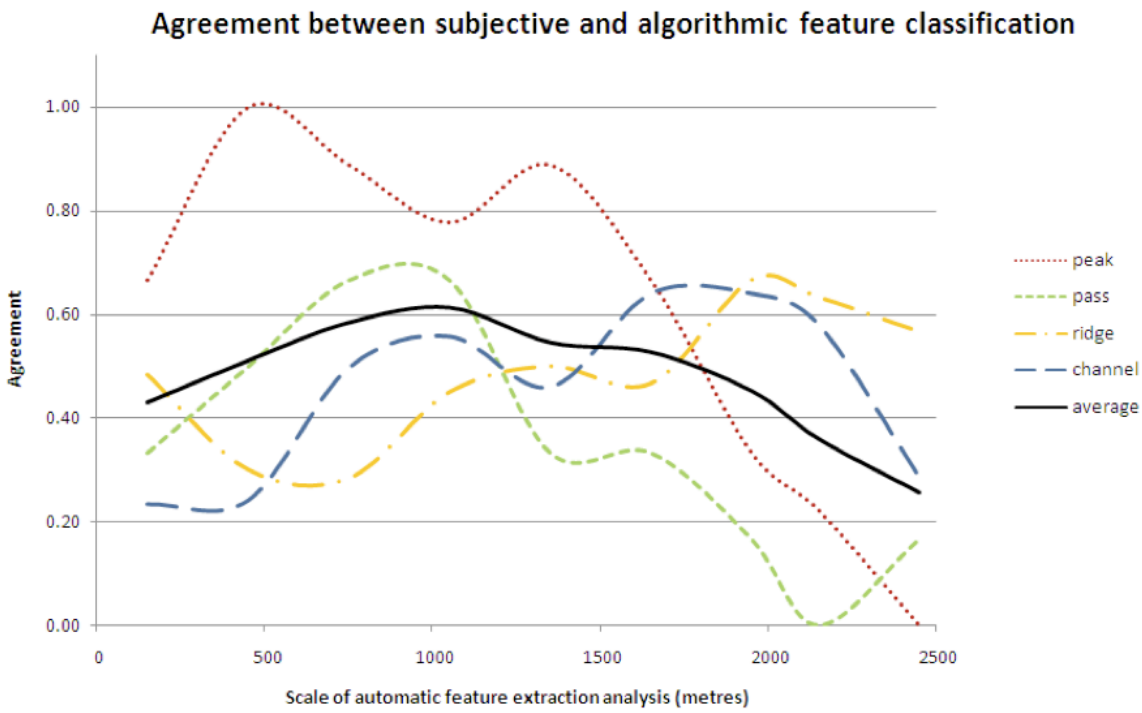

Figure 14: Agreement between subjective and algorithmic feature classification vs scale of analysis

Figure 14 shows the agreement between terrain features identified by participants in the survey (subjective features), and those calculated using LandSerf's surface feature classification algorithm over a range of scales. These values were calculated by sampling the pixels in the feature classification surfaces which intersected the locations at which participants identified terrain features: these locations were points for passes and peaks, and lines for channels and ridges. Higher values suggest greater agreement between the subjective and algorithmic approaches. For example, for peaks at a scale of analysis of 450m, the value of 1 indicates that all those subjectively identified peaks coincided with pixels classified as peaks by the feature classification algorithm.

It can be seen that for peaks there is greatest agreement between the subjective approach with algorithmic analysis conducted at scales of 500-1250 metres. This agreement drops sharply for scales of analysis above 1500m. Closer inspection of figure 7 suggests, that this is due to the algorithm classifying the locations identified as peaks by participants, as being part of a ridge for these coarser scales of analysis.

The profile of passes is similar to that for peaks, with greatest similarity between the subjective identification and algorithmic classification at a scale of roughly 1000m. Significantly, there is far greater overall agreement in the subjective and algorithmic approaches for peaks than for passes, suggesting there may be less ambiguity about what form a peak takes.

The profiles for channels and ridges follow a similar trend: the greatest agreement occurs at scales of around 2000m, but both have secondary peaks at fine scales of analysis. For channels, there is a strong trend for less agreement for fine scale analysis (<750m) and coarse scale analysis (>2250m). The trend for ridges is less clear, however when compared to peaks and passes, the trend for these linear features (ridges and channels) is for greater correspondence at coarser scales of analysis.

These findings provide some evidence for the scale at which to conduct automatic feature classification, in order to correspond with scale at which human's perceive those features in the landscape.

5. Conclusions

This study indicates that for all features people identify specific classes over an identifiable scale range: features with the same morphology at larger or smaller scales may not be perceived as the same class of feature. For this particular study, using a single observation point, the scale of analysis at which there was greatest agreement between the automated feature class extraction and the human perception is indicated below:

1. Peaks ≈ 500m
2. Passes ≈ 1000m
3. Ridges: ≈ 2000m
4. Channels ≈ 1800m

Further research in this area may advance the objectives of ethnophysiography and provide empirical evidence for geographic ontologies. This research may also provide guidance to scales of analysis for researchers use in automatic terrain feature classification, to coincide with human scales of perception.

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Biography

Delroy Brown undertook this work as part of his MSc in GIS at City University London. He has a background in urban planning and interest in spatial analysis and mobile GIS.

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