

Different methods, different wilds: evaluating alternative mappings of wildness using  
Fuzzy MCE and Dempster Shafer MCE

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4 **Abstract**

5 Different multi-criteria evaluation (MCE) approaches are applied to a fuzzy wildness  
6 mapping problem in Scotland. The result of fuzzy weighted linear combination and  
7 fuzzy order weighted averaging approaches are compared with the application of a  
8 Dempster-Shafer MCE. We discuss the implications of different approaches in light  
9 of decision making associated with suitability in a context where i) suitability  
10 (wildness) may not be very well defined ii) the decision makers may not fully  
11 understand the informatics aspects associated with applying weights, but iii) require  
12 decisions to be accountable and transparent. In such situations we suggest that the  
13 outputs of Dempster-Shafer MCE may be more appropriate than a fully fuzzy model  
14 of suitability.  
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23 **Keywords:** Uncertainty, wildness, Fuzzy, Dempster-Shafer, Multi-criteria Evaluation  
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## 1. Introduction

“Wilderness is what men think it is.”

Roderick Nash, in *Wilderness and the American Mind* (1981, p.3)

Wilderness is an essentially human construct based largely on individual perceptions and often romantic notions about nature and landscape. As such, it is notoriously difficult to define in rigorous, scientific and legal terms. In the USA for example, it took Howard Zahniser eight years to write an acceptable definition of wilderness and get this through congress and onto the statute books as the 1964 Wilderness Act. His poetic and succinct definition identifies wilderness thus: “A wilderness, in contrast with those areas where man and his own works dominate the landscape, is hereby recognized as an area where the earth and its community of life are untrammelled by man, where man himself is a visitor who does not remain.” (US Wilderness Act, 1964, p.1). Various studies have taken this and subsequent refinements and attempted to use GIS to map the world’s remaining wilderness areas at various spatial scales and resolutions. Global scale maps have been developed by McCloskey and Spalding (1989), and Sanderson et al. (2002). Regional level maps have been developed for Australia (Lesslie, Taylor and Maslen, 1993), for the USA (Aplet, 2000), and for Europe (Fritz et al., 2000a). Many of these mapping projects have been based around multi-criteria type approaches as a means of accounting for different priorities between spatial factors relating to wildness (Carver, 1996; Fritz et al., 2000b; Carver et al., 2002) with the resulting maps showing a continuum of environmental modification from the “paved to the primeval” (Nash, 1982, p.3).

Some wildness mapping research has used a multi-criteria evaluation (MCE), using different criteria and combination techniques. The Australian Heritage Commission’s National Wilderness Inventory defined wilderness on the basis of four factors: remoteness from settlement, remoteness from access, apparent naturalness, and biophysical naturalness (Lesslie 1994; Miller, 1995). Minimum levels of remoteness and naturalness were defined and the factors were combined to define a wilderness quality index. Fritz et al (2000b) noted that remoteness and primitiveness cannot be assessed by a single wilderness quality indicator. Instead they proposed that remoteness be described as a proximity function to settled land and settled people and

1 primitiveness could possibly be described as biophysical and apparent disturbance.  
2 They weighted the factors according to the results of an internet questionnaire in a  
3 fuzzy MCE. Carver et al (2002) developed variation of the Australian approach using  
4 similar factors within a fuzzy MCE framework to identify the wilderness continuum  
5 in Britain. This identified wilderness using six factors: remoteness from local  
6 population, remoteness from national population centres, remoteness from  
7 mechanized access, apparent naturalness, biophysical naturalness, and altitude. It used  
8 a web application to allow users to explore the impacts of different factor weights on  
9 the resulting wildness maps. The web mapping allowed users to *explore* their  
10 perceptions of wilderness using simple slider bars and a Java application to  
11 recalculate and then redraw the continuum map.  
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22 A multi-criteria evaluation (MCE) methodology has again been applied in a recent  
23 study to map wildness attributes at high spatial resolutions in the Cairngorm National  
24 Park (CNP) in Scotland. The approach focused on GIS-based MCE using weighted  
25 linear combination (WLC) and fuzzy methods that were developed during previous  
26 work mapping on wild land quality (Carver 1991; Carver, 1996; Carver et al., 2002  
27 and Fritz et al., 2000a) and is reported in Carver et al. (2008). Data were generated for  
28 the four principal factors that contribute to wildness in Scotland as identified Scottish  
29 Natural Heritage - the agency responsible for the natural environmental in Scotland.  
30 These include perceived naturalness of land cover, absence of modern artefacts,  
31 rugged and physically challenging terrain, and remoteness (SNH, 2002). For the  
32 purposes of the original project these data were combined using WLC with equal  
33 weightings for each factor. The resulting map of wildness is fuzzy and based on  
34 perceptions of wildness rather than strict ecological definitions. Planning and decision  
35 making bodies would like to be able to identify boundaries between 'wild' and 'not  
36 wild' for use in supporting decisions related to planning and developments. For  
37 example, those developments that reduce the area of the wild category significantly  
38 might be refused planning permission, whereas those that have no or only minimal  
39 impact might be allowed to go ahead.  
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56 Agencies concerned with planning policy have to determine whether proposed  
57 developments fall inside or outside of planning constraints. In many cases they are  
58 given only guidance about how to interpret and apply planning law rather than a set of  
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1 hard and fast rules. The latter implies a Boolean mapping of different types planning  
2 zones and the former indicates approaches that incorporate some of the uncertainty  
3 relating to the interpretation of planning guidance. The problem faced by planning  
4 agencies is how to convert vague guidelines into crisp decisions, typically through the  
5 identification of thresholds to determine different categories in the continuum of  
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7 'wildness'.  
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12 The problem addressed in this research is complimentary to a broad body of work that  
13 has considered fuzzy definitions and fuzzy extent, exemplified by Hwang and Thill  
14 (2005; 2009) and latterly Ban and Ahlqvist (2009) who illustrated the uncertainties  
15 associated with different definitions and conceptualizations of urban land use. The  
16 work described in this paper differs from Ban and Ahlqvist (2009) in two ways. First  
17 Ban and Ahlqvist (2009) describe the generation alternative fuzzy set membership  
18 values to the set of 'exurban' as derived from exurban definitions from the literature.  
19 In this work we are not concerned with definitions of 'wildness'. Second, Ban and  
20 Ahlqvist explore the effects of fuzzy set combinatory-operations: fuzzy MIN, fuzzy  
21 MAX, fuzzy PRODUCT, a weighted average and an average. In this work we are  
22 concerned with the extensions to fuzzy combinatory-operations such as are included  
23 in Ordered Weighted Averaging (OWA). These were introduced in an informatics  
24 context by Yager (1998) and in a GIS by Jiang and Eastman (2000), Eastman (2006),  
25 Malczewski (2006) and Boroushaki and Malczewski (2008). This paper explores  
26 different MCE approaches based around OWA for determining 'wild' and 'not wild'  
27 areas. These include Boolean MCE, OWA with different order weights, WLC as a  
28 special case of OWA where the order weights are equal and the Dempster-Shafer  
29 combination method. Each of these approaches requires some kind of weighting  
30 (order or factor) and produces different spatial distributions of wildness. The scientific  
31 motivation for this work was to explore the suitability of the different approaches to  
32 support decision making when weightings or expert opinion may not be available.  
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51 This paper introduces wildness mapping and reviews multi-criteria evaluation  
52 approaches in Section 2 before describing the methodology in Section 3. The results  
53 of applying Boolean and Fuzzy MCE approaches are presented in Section 4, showing  
54 different mappings of wildness and the (non-spatial) distribution of wildness values  
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1 generated from the same data by each approach. The results and the different  
2 approaches are discussed in Section 5 before some conclusions are drawn.  
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## 7 **2. Background**

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### 10 *2.1 Wildness mapping*

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12 There has been a great deal of debate in recent years over the definition and  
13 applicability of wild land in the UK (e.g. Fenton, 1996; Taylor, 2005). Perhaps the  
14 most progress has been in Scotland, where some of the nation's wildest landscapes  
15 can be found in places like the Cairngorm, Rannoch Moor, the Monadhliath and Glen  
16 Affric. Here several organisations, taking their lead from the Scottish Office National  
17 Planning Policy Guideline 14 (NPPG14) on Natural Heritage (Scottish Office, 1999),  
18 have developed their own wild land definitions. These include Scottish Natural  
19 Heritage (SNH, 2002), the National Trust for Scotland (National Trust for Scotland,  
20 2002) and the John Muir Trust. NPPG14 defines wild land as:

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22 *“Uninhabited and often relatively inaccessible countryside where the influence*  
23 *of human activity on the character and quality of the environment has been*  
24 *minimal”* (The Scottish Office, 1999).  
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27 The SNH definition, published in 2002 refers to:

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29 *“parts of Scotland where the wild character of the landscape, its related*  
30 *recreational value and potential for nature are such that these areas should be*  
31 *safeguarded against inappropriate development or land-use change”* (SNH,  
32 p.8),  
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35 while the NTS further define wild land as:

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37 *“relatively remote and inaccessible, not noticeably affected by contemporary*  
38 *human activity, and offers high-quality opportunities to escape from the*  
39 *pressures of everyday living and find physical and spiritual refreshment.”*  
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41 (The National Trust for Scotland, 2002, p.4).  
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45 An important aspect of the wild land concept is its subjective and often shifting  
46 nature. This is characteristic of the nature of peoples' differing perceptions of the  
47 concept of wildness and is captured nicely in a further quote by Roderick Nash where  
48 he suggests *“One man's wilderness is another's roadside picnic ground”* (Nash, 1982,  
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p.1). This presents an interesting problem that in order to manage a landscape value such as wild land quality, we first need to be able to define it sufficiently rigorously from multiple and often conflicting view points, before we can actually identify and map it.

Both Scottish Natural Heritage and the National Trust for Scotland study consider the main features relating to perceptions of wildness to be:

- i) *Perceived naturalness of land cover* – the extent to which land management, or lack of, creates a pattern of vegetation and land cover which *appears* natural to the casual observer.
- ii) *Absence of modern human artefacts* – the lack of obvious artificial forms or structures within the visible landscape, including roads, railways, pylons, hard-edged plantation forestry, buildings and other built structures.
- iii) *Rugged and challenging nature of the terrain* – the physical characteristics of the landscape including effects of steep and rough terrain and harsh weather conditions often found at higher altitudes.
- iv) *Remoteness* – the remoteness of inaccessibility of the landscape based on time taken to walk from the nearest point of mechanised access.

A full description of each factor is given in Table 1.

(Insert Table 1 about here)

Currently, there is little quantitative evidence of consumer opinion regarding the ‘wildness’ of Scotland. Therefore Scottish Natural Heritage and the Cairngorms National Park Authority commissioned a market research study to evaluate public perceptions of wild places amongst a representative cross-section of Scottish residents and a subset amongst those living within the boundaries of the Cairngorms National Park (CNP). The study, conducted by Market Research Partners (2008), identifies the level of support for wild places and whether the views of those who live within CNP match the population of Scotland as a whole. A total of 1,304 face to face interviews were conducted, 1,004 across Scotland and 300 with residents of the CNP area. Whilst the survey sought to identify the features which make an area wild, it did not ask the respondents directly about the four factors identified by Scottish Natural Heritage as contributing to wildness. Instead the survey report inferred support for

1 these factors by categorising the response to other questions. Carver et al (2008)  
2 revisited the results of the survey and extracted slightly different factor weights based  
3 on the responses to unbiased survey questioning. The landscape characteristics and  
4 features identified by the Scottish and CNP residents in response to the question “In  
5 your opinion, what features or characteristics make an area wild?” (Market Research  
6 partners, 2008, p9) such as “wildlife”, “Forests / woods / trees”, “Open space”,  
7 “Lochs”, “Hills / mountains / glens” etc were subjectively allocated to the different  
8 factors by Carver et al (2008). The weights were based on the number of responses  
9 identifying each feature. The purpose of this study is not to explore the weights  
10 themselves but their behaviour under different combination approaches. The question  
11 over which set of factors weights to use in the analysis of fuzzy MCE and the impacts  
12 of different order weights was resolved by taking the average of three sets of weights.  
13 The weights are shown in Table 2.

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22 (Insert Table 2 about here)

## 23 24 25 26 27 28 29 *2.2 Multi-criteria evaluation*

30 Multi-criteria evaluation combines different layers of spatial information or factors in  
31 order to generate an aggregated measure of suitability. In a Boolean MCE, the criteria  
32 are applied as thresholds to partition layers into unsuitable and suitable areas. The  
33 derived layers are then combined in an overlay operation to identify Boolean  
34 suitability in one of two ways

- 35 - Intersect (AND) operation, which identifies areas where all conditions are  
36 satisfied.
- 37 - Union (OR) operation which identifies areas as being suitable if any one of the  
38 criteria are met.

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47 By way of illustration the factors contributing to perceptions of wildness in Table 1  
48 are continuous in nature with values from 0 to 255, as a result of a normalisation  
49 process as part of the original project brief and described in Carver et al (2008). These  
50 were reclassified using a threshold of 127 to create Boolean masks (i.e. of 0 and 1)  
51 and then combined using union and intersect operations to identify wild and non-wild  
52 areas (Figure 1).

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60 (Insert Figure 1 about here)



1 In many analyses, suitability may not be Boolean in character, but has varying degrees  
 2 of membership, and each criterion contributes evidence from which fuzzy  
 3 membership of the set of ‘suitable’ can be determined. The maps in Figure 1 illustrate  
 4 the issues associated with applying a Boolean MCE in the context of decision making:  
 5 thresholds have to be determined for each factor and what Jiang and Eastman (2000)  
 6 called the “trade-off” between factors has to be managed. The maps in Figure 1 show  
 7 different extremes of trade-off. For these reasons and to accommodate some of the  
 8 uncertainty associated with suitability mapping, fuzzy MCE approaches have been  
 9 used in many analyses (e.g. Jiang and Eastman, 2000; Malczewski, 2006a;  
 10 Boroushaki and Malczewski, 2008).

11 In order to overcome the lack of sensitivity in Boolean MCE approaches, various  
 12 fuzzy MCE have been developed by different workers. Weighted Linear Combination  
 13 multi-criteria evaluation (Voogd, 1983), also known the weighted mean, provides a  
 14 refinement to Boolean combination. It determines suitability based on the sum of the  
 15 weighted normalised data layers representing the factors or criteria contributing to  
 16 overall suitability:

$$S_i = \sum_{j=1}^n w_j \cdot x_{i,j} \text{ where } \sum_{j=1}^n w_j = 1 \quad (\text{Eqn 1})$$

17 and where  $S_i$  is the suitability score for site  $i$ ,  $w_j$  is the weight of criterion  $j$ ,  $x_{ij}$  is the  
 18 grading value of site  $i$  under criterion  $j$ , and  $n$  is the total number of criteria. In  
 19 contrast to the Boolean approaches WLC allows trade-off between factors by  
 20 weighting them according to the importance given to a particular criterion in assessing  
 21 suitability. One of the difficulties in applying a WLC is how to determine appropriate  
 22 weights for each of the factors being combined. Analytical Hierarchy Process (AHP)  
 23 offers a method to over come this as weights are generated interactively with the  
 24 respondent (whether they are an expert or not) for input into fuzzy MCE (Banai, 1993;  
 25 Wu, 1998; Boroushaki, and Malczewski, 2008). Numerous AHP interfaces have been  
 26 written for different GIS software (e.g. Eastman, 2006; Marinoni, 2004; Hill et al.,  
 27 2005 and Boroushaki and Malczewski, 2008).

28 Jiang and Eastman (2000) summarised a number of problems with MCE analyses  
 29 based on Boolean and WLC approaches. First, Boolean analyses produce very

different results depending on whether a hard AND or a soft OR operator is used. In contrast, WLC approaches compensate a low score in one criteria with a high score on another, providing trade-off. Second, decision risk (the likelihood that the decision made will be wrong) is not properly dealt with by either approach. In Boolean analyses, decision risk can be estimated by propagating error throughout the decision rule to determine the risk that that decision made at a given location is wrong.

OWA are multi-criteria operators suggested by Yager (1988). Jiang and Eastman (2000) proposed their use in a GIS context as a method to overcome the systematic problems related to risk and trade-off in MCE. OWA provides continuous fuzzy aggregation operations between fuzzy intersection (MIN or AND) and union (MAX or OR), bridging WLC, Boolean and Fuzzy aggregations. It allows a variety of operators between MIN (AND) and MAX (OR), control over the degree of trade-off between factors in MCE and thereby allows the overall level of risk to be controlled. OWA uses two sets of weights: *criterion weights*, which describe the relative significance of a particular criterion (or factor) for the decision as in WLC, and *order weights* which are applied to the ranked criteria after the application of the criterion weights. Consider  $j$  attribute maps, a set of criterion weights ( $w$ ) and a set of order weights ( $v$ ). The criterion weight  $w_j$  is applied uniformly to the  $j^{th}$  map layer reflecting that layer's importance. The order weights are assigned to the  $i^{th}$  location's attribute in decreasing order on a location by location basis (e.g. cell by cell in raster data). Formally, the OWA operator associates a set of order weights  $V = (v_1, v_2, \dots, v_n)$  with the  $i^{th}$  location such that  $v_j \in [0, 1]$  for  $j = 1, 2, \dots, n$ , and  $\sum_{j=1}^n v_j = 1$ . It is defined as follows:

$$OWA_i = \sum_{j=1}^n \left( \frac{u_j v_j}{\sum_{j=1}^n u_j v_j} \right) z_{ij} \quad (\text{Eqn 2})$$

where  $z_{i1} \geq z_{i2} \geq \dots z_{in}$  derives from reordering the criterion values and  $u_j$  is the reordered  $j$ th criterion weight,  $w_j$ . Order weights control the degree of tradeoff between ANDness and ORness and are defined as follows (equations from Jiang and Eastman, 2000):

$$ANDness = (1/(j-1)) \sum (j-i) W_{order \ i} \quad (Eqn \ 3)$$

$$ORness = 1 - ANDness \quad (Eqn \ 4)$$

$$TradeOff = 1 - \sqrt{\frac{j \sum (W_{order \ i} - 1/j)^2}{j-1}} \quad (Eqn \ 5)$$

where  $j$  is the total number of factors (or attribute maps),  $i$  is the order of factors and  $W_{order \ i}$  is the weight for the factor of the  $i$ th order. OWA provides an alternative to WLC, where the level of trade-off is full and not adjustable. A full description of OWA in a GIS context and the relationship between Risk and Trade-off are provided in Jiang and Eastman (2000).

The OWA approach has been used for many different GIS applications: Rinner and Malczewski (2002) describe the application of OWA to ski resort planning, Malczewski (2006a) its use in watershed management, and Bell et al., (2007) use it to quantify socio-economic gradients in health status. Malczewski (2006b) review the use of GIS and MCE. However, whilst OWA provides considerable refinement compared to Boolean overlays and simple WLC, order weights have to be determined. They require a degree of domain expertise in relation to the decision that is to be made using the results of the MCE and an understanding of the informatics aspects of factor weightings.

Thus far the alternatives to Boolean analyses described above have been based around different implementations of fuzzy set theory. Other formalisms for combining data such as Dempster-Shafer Method have also been used to combine spatial data (Kontoes et al, 1993; Tangestani and Moore, 2002; Comber et al, 2004; Wadsworth and Hall, 2007). Malpica et al (2007) review the use of Dempster-Shafer approaches in GIS. Dempster-Shafer assesses the belief that a hypothesis is 'provable' given the evidence (Comber et al., 2004). Dempster-Shafer can be considered as an extension to Bayesian statistics. It assigns a numerical measure of the weight of evidence (mass assignment,  $m$ ) to *sets of hypotheses* as well as individual hypotheses. A second piece of evidence is introduced by combining the mass assignments ( $m$  and  $m'$ ) using

1 Dempster's rule of combination, to create a new mass assignment  $m''$ . Dempster's  
2 rule of combination is defined by:

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$$m''(C) = \sum_{\substack{i,j \\ A_i \cap B_j = C}} m(A_i) \times m'(B_j) \quad (\text{Eqn 6, from Parsons (1994)})$$
  
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10 where the combined mass assignment,  $m''(C)$ , is equal to the sum of the product  
11  $m(A_i)$  and  $m'(B_j)$  for all  $i$  and  $j$  such that set  $A_i B_j$  equals  $C$ . It does not consider the  
12 evidence hypothesis by hypothesis as does Bayes' theorem, rather the evidence is  
13 considered in light of the hypotheses. Much recent work describes modifications to  
14 Dempster-Shafer theory, but Parsons (1994) provides a clear introduction to the  
15 application and mechanics of Dempster-Shafer. Dempster-Shafer explicitly  
16 incorporates uncertainty into belief combinations and generates two measures:  
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- 22 - Belief: a measure of the extent to which the evidence supports the hypothesis;
- 23 - Plausibility: a measure of the extent to which the evidence does not refute the  
24 hypothesis (i.e. Belief with Uncertainty);  
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28 The interval between the Plausibility and Belief provides a measure of uncertainty  
29 about a specific hypothesis and the Disbelief can be derived as the Belief, Uncertainty  
30 and Disbelief sum to unity.  
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### 36 **3. Methods**

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39 This paper compares the application of different fuzzy approaches for combining  
40 spatial data: ordered weighted averaging, weighted linear combination which can be  
41 seen as a special case of OWA, and Dempster-Shafer. The study was conducted using  
42 data covering the Cairngorm National Park area in north eastern Scotland and the  
43 wildness continuum was mapped by combining the four factors contributing to  
44 wildness identified by SNH using the different approaches.  
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#### 52 *3.1 Factor Data*

53 The construction of the factor data is described in Carver et al (2008) and summarised  
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1 Perceived naturalness was derived from a combination of reclassified datasets  
2 including the Land Cover Map 2000 (LCM2000), Land Cover of Scotland  
3 1988 (LCS88) and Highland Birchwoods Woodland Inventory (1999).

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5 Absence of modern human artefacts was constructed from LCM2000 data combined  
6 with detailed terrain data and a digital surface model (DSM) and viewshed  
7 assessment.  
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10 Ruggedness was constructed from a digital terrain model (to derive indices of terrain  
11 complexity that take slope, aspect and relative relief) and climate data from  
12 local weather stations.  
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16 Remoteness was mapped in the CNP based on a GIS implementation of Naismith's  
17 Rule (Naismith, 1892) using detailed terrain and land cover information to  
18 estimate the time required to walk from the nearest road or track (Carver and  
19 Fritz, 1999)  
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### 25 *3.2 Fuzzy MCE using OWA with different order weights*

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27 The ordered weighted averaging was implemented inside IDRISI GIS with its  
28 embedded OWA module (Eastman, 2006). Each of the four factors contributing to  
29 wildness was weighted before combination according to the user defined criterion  
30 weights (the average weights from Table 2). First, the OWA process creates an  
31 intermediary layer for each factor from the product of the factor layer and the criterion  
32 weight for that factor. Next, the weighted values at each location (pixel) are evaluated  
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42 The order weights are then applied in the following way: the first order weight is  
43 applied to the lowest value, the second order weight to the next lowest, etc. In this  
44 case there are four factors requiring four order weights, summing to unity in each set.  
45 The different sets of order weights were decided chosen to represent a spectrum from  
46 full ANDness and no tradeoff, to some ANDness with tradeoff and full ORness. The  
47 selection of order weights is returned to in the discussion.  
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54 Six sets of order weights were applied. Table 3 shows the numerical relationship  
55 between the selected order weights and the ANDness, ORness and TradeOff indices.  
56 The order weights have the following characteristics:  
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2 [1, 0, 0, 0] is risk averse with only the lowest value is given any weight. It yielded the  
3 minimum operator of fuzzy sets with full ANDness and no trade-off.

4 [0, 0, 0, 1] is risk taking with only the highest values given any weight. It yielded the  
5 maximum operator of fuzzy sets with full ORness and no trade-off.

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7 [0, 0.5, 0.5, 0] is an intermediate operator with intermediate ANDness and ORness,  
8 with some trade-off

9  
10 [0.5, 0.3, 0.15, 0.05] is an operator with trade-off and a moderate degree of ANDness.

11 [0.05, 0.15, 0.3, 0.5] is an operator with trade-off and a moderate degree of ORness  
12 (risk).

13  
14 [0.25, 0.25, 0.25, 0.25] is a special case to represent the traditional MCE operator  
15 using WLC. Here the order weights have no impact on the factor weights. This is  
16 equivalent to simple weighted Linear Combination which has intermediate  
17 ANDness and ORness, and full trade-off.

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25 (Insert Table 3 about here)

### 26 27 28 29 *3.3 Dempster-Shafer MCE*

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31 Dempster-Shafer was used to combine the wildness evidence from the four factor  
32 layers. No order weights or factor weights were used but each of the four factors were  
33 linearly normalised to a maximum-minimum range of 0-1 and then split into two  
34 layers (Belief and Disbelief) around their median values (medians were selected as  
35 they were thought to be more representative of a central value than mean which is  
36 more likely to be influenced by outliers). This was done by calculating the slope from  
37 the median to 1 for Belief and from the median to 0 for Disbelief. The slopes for the  
38 Visibility layer are shown by way of example in Figure 2 and the terms for each factor  
39 are shown in Table 4.

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49 (Insert Figure 2 about here)

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53 (Insert Table 4 about here)

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56 The factor belief layers were combined using the IDRISI Belief module (Eastman,  
57 2006) to evaluate a hypothesis of 'wild' producing three aggregated layers: Belief,  
58 Plausibility and Interval. The Belief layer provides a measure of the degree to which  
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1 the evidence provides concrete support for the hypothesis is the lower bound of the  
2 belief in the hypothesis. The Plausibility provides the upper boundary and the Interval  
3 records the range between belief and plausibility, providing a measure of the  
4 uncertainty in the hypothesis.  
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#### 8 **4. Analyses and Results**

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10 Data were combined using the different MCE approaches, with order weights applied  
11 after the average factor weights from Table 2. Dempster-Shafer used neither factor  
12 nor order weights. The results of the Shafer-Method were linearly normalised to a 0-  
13 255 range for comparison with the OWA results.  
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19 The objective of the analysis was to explore the impact of different weightings and  
20 different methods of combining data on the magnitude and spatial distribution of wild  
21 land. Histograms were generated for each result layer, normalised to common axes for  
22 comparison but also with a variable Y axis to show any detail patterns (Figure 3).  
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29 (insert Figure 3 about here)  
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33 The histograms in Figure 3 have very different characteristics as expected.

34 The full ANDness in the first set of order weight [1, 0, 0, 0] results in a very  
35 conservative distribution of values, grouped towards the lower end of the range.  
36 From this distribution, it would be very difficult to label any given pixel as  
37 being wild and the membership functions to the set of wildness are low. The  
38 distribution has peaks and troughs but is not bimodal. It allocates <0.01% of the  
39 pixels a value greater than 127 (from a maximum of 255).  
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45 By contrast the full ORness of the second set of order weights [0,0,0,1] is risk taking  
46 resulting in a distribution of wildness values which allocates 58% of the pixels  
47 to the highest level of wildness (255) and <0.02% to wildness values less than  
48 128.  
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52 The next set of order weights [0,0.5,0.5,0] with intermediate ANDness and ORness,  
53 results in bi-modal distribution of wildness values. The data is cleaved around  
54 the wildness membership function of 138/255, potentially providing a point  
55 which policy makers may wish to use to allocate land into 'wild', 'not wild' and  
56 perhaps to start investigating 'intermediate' or uncertain areas.  
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1 The fourth and fifth sets of order weights ([0.5,0.3,0.15,0.05] and [0.05,0.15,0.3,0.5]  
2 respectively) both have a bimodal pattern. These weights have a moderate  
3 degree of ANDness and some trade-off with ORness. The differences between  
4 their distributions reflected in the degrees of ANDness (more in the latter) and  
5 ORness (more in the former) and the associated skew towards one end of the  
6 continuum of wildness. Each of these potentially indicates a point of bifurcation  
7 between wild and not wild values but with much more uncertainty than with the  
8 third set of order weights.  
9

10 The sixth set of order weights, [0.25,0.25,0.25,0.25] are equal and equivalent to a  
11 simple WLC. The resulting distribution of wildness values is determined only  
12 by the average factor weights in Table 2. The wildness values can be seen as the  
13 baseline from which the other sets of order weights operate. It has a bimodal  
14 distribution with a tail towards the lower end of the continuum. A potential  
15 divide between wild and not wild values may be identified.  
16

17 The final histograms of wildness values are the result of applying the Dempster-  
18 Shafer method of combination. The data are pushed out into the tails of the  
19 distribution which shows a U-shape, providing a separation of wild and non-  
20 wild values.  
21

22 Figure 4 shows the application of different sets of order weights and different MCE  
23 approaches. The conservative, AND operator [1,0,0,0] produces a hard fuzzy  
24 intersection. It identifies areas as being 'wild', or more correctly 'with high  
25 memberships to the set of wild', only if they have high values in the fuzzy criteria.  
26 Therefore the wild areas are a long way from human settlement, in areas of natural  
27 vegetation, rugged terrain and where evidence of human activity cannot be seen.  
28 Conversely the liberal OR operator [0,0,0,1] identifies a much larger area as being  
29 wild taking any single piece of evidence with a high value as an indicator of overall  
30 wildness. The operators in between the extremes identify similar core areas with  
31 relatively high memberships to wild, but the absolute values and troughs are different.  
32 However they show greater variation in the location of fuzzy wild areas with  
33 intermediate memberships to the fuzzy set of wild. In these areas wildness is more  
34 uncertain as they represent areas where the different factors aggregated in the MCE  
35 into wildness trade-off against each other: some areas may be natural land cover but  
36 with human artefacts visible in the landscape.  
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5 The wild areas identified using the Dempster-Shafer method of combination has  
6 different characteristics to the other in two ways. First, the areas with high belief are  
7 clearly separable from those with low belief clearly not wild areas. Generally pixels  
8 are allocated high or low beliefs but not in between implying that there is little  
9 uncertainty associated with the belief. It is instructive to examine the other two  
10 outputs of the Dempster-Shafer MCE approach: the interval and the plausibility layers  
11 in Figure 5. Recall that the Plausibility layer provides a measure of the upper  
12 boundary of possible belief (with the Belief layer providing the lower). This means it  
13 includes the belief and the ‘plausible belief’ – beliefs that could exist. Many areas  
14 could have a high belief in wild and the distribution is and extent similar to the full  
15 ORness ([0,0,0,1]) layer. The belief Interval records the range between belief and  
16 plausibility and provides a measure of the uncertainty. If the layer is examined, the  
17 lighter areas indicate where there is greater uncertainty in the belief and the gap  
18 between the Belief and the Plausibility is high.  
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32 (Insert Figure 5 about here)  
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## 36 **5. Discussion and Conclusions**

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40 The different mappings produced by the various fuzzy MCE approaches vary from  
41 OR approaches that identify large areas with high wildness memberships to AND  
42 operators that identify small areas. We note that further sets of order weights could  
43 have been selected, for instance possible alternative third sets include [0.5, 0, 0, 0.5],  
44 or [0, 0, 0.5, 0.5] or [0.5, 0.5, 0, 0] instead of [0, 0.5, 0.5, 0]. Undoubtedly this would  
45 produce yet further distributions of wildness values. However the purpose of this  
46 work was to illustrate the variability as a result of applying different order weights in  
47 the light of decision making. We have shown that varying the order weights provides  
48 a range of operators between full MIN (AND) and full MAX (OR) and, if fully  
49 understood, can provide control over the degree of trade-off between factors in MCE  
50 against the overall level of risk, or of being incorrect (Jiang and Eastman, 2000). This  
51 is because different sets of order weights modify the original factor weighted data and  
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can produce very conservative, very liberal and in between (traded off) mappings of wildness.

In comparing Dempster-Shafer MCE with fuzzy MCE this paper highlights the two approaches: The fuzzy approaches can maintain a full fuzzy model of landscape wildness in their output, whilst Dempster-Shafer partitions evidence from the input data in a way that approaches a Boolean aggregation of fuzzy inputs, as well as providing a separate layer of the uncertainty. The fuzzy approach may be difficult to apply where there are vague definitions of suitability (e.g. of 'wildness') held by the decision maker. Dempster-Shafer provides a product which obscures the real doubt by partitioning belief and can give a clear cut definition of wildness and suitability but also provides a model of the uncertainties in the plausibility layer.

The implications of this are that the selection of method and weights has major implications for the mapped outcome of suitability (in this case of wildness). For a well defined problem, with clear and well understood parameters, there are obvious advantages to an OWA approach: the factor and order weights can be used to constrain the aggregation process in a way that represents the current or best understanding of the problem being examined. But this requires a very robust understand of all the parameters involved in the decision and how they interact to influence the final outcome. In many planning situations, such as at a local government level, this is often not the case making the transparent use of order weights difficult in a fuzzy MCE. The safer option is to use only factor weights, which is often the case in the experience of the authors. The use of and setting of factor weights can be justified in terms of consultants, expert or public opinion. Many decision makers are happy with fuzzy representations of features as the fuzzy method produces a more faithful picture, reflecting the continuum.

Fuzzy methods, whether Min (AND) or Max (OR) or in between, provide a full fuzzy models of landscape wildness which are able to better reflect the doubt in the minds of the decision makers about wildland definitions, but only if they are able to understand the GIS technology (common) and understand the informatics aspects involved in order weighting (rare). In many situations where GIS is being applied to map suitability, decision makers may not have a full understanding of how the application

1 of order weights (and therefore trade-off and risk) relate to their problem and how  
2 weights interact with the resulting solutions. This informatics aspect is important  
3 when assessing trade-off and risk in light of decision making. Analytical Hierarchy  
4 Process (AHP) has been suggested as a solution to the problem by providing a tool that  
5 integrates fuzzy linguistic operators (Borouhaki, and Malczewski, 2008). But AHP  
6 still requires the domain knowledge and a well defined understating of suitability to  
7 understand how to parameterise the input appropriately and then to interpret the rich  
8 and fuzzy output in light of those input decisions.  
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16 Malczewski (2006b) noted that many real-world decisions are uncertain because they  
17 involve some aspects that are unknowable with uncertainty in decision-making  
18 relating to “uncertainty associated with limited information about the decision  
19 situation, and ...uncertainty associated with fuzziness (imprecision) concerning the  
20 description of the semantic meaning of the events, phenomena or statements  
21 themselves” (p713). For these reasons the justification by policy makers for the  
22 selection of any given set of order weights is more problematic given the variation in  
23 the results due to trade-off between (already weighted) factors. Although the  
24 application or order weights may be scientifically more attractive, allowing for trade-  
25 off between full AND and full OR, in terms of decision making, their application may  
26 be difficult to justify by non-expert policy makers who need to make transparent  
27 decisions such as demarking wild and non-wild areas. The increasing sophistication of  
28 analysis moving from MCE to factor weights to order weights has not increased the  
29 ease of decision making. It may be that Dempster-Shafer MCE offers some potential  
30 in this area: measures of overall support are clearly separated into high and low  
31 measures of fuzzy belief, with additional evidence pushing the belief in a hypothesis  
32 towards the tails of the distribution. The result is that small and on their own  
33 potentially less significant pieces of information gain in significance when combined  
34 with other evidence. This approach could provide decision makers with a readily  
35 identifiable separation of belief in wildness.  
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54 In conclusion the work has explored different methods for combining spatial data in a  
55 multi-criteria evaluation of wildness. Fuzzy MCE approaches require the selection of  
56 weights the application of which for order weights requires a full understanding of  
57 how the factors trade-off against each other in order to control the resulting  
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1 uncertainty. Combination based on Dempster-Shafer theory of evidence has been  
2 shown to partition the aggregated datasets into wild and not wild in a way that the  
3 fuzzy MCE approaches did not, whilst providing measures of uncertainty in the  
4 plausibility layer. This work has shown that in situations where expert opinion for  
5 whatever reason is not available to parameterise the MCE operation (in terms of  
6 factor weights, order weights, degrees of acceptable trade-off and thresholds to  
7 interpret the resulting aggregation) then Dempster-Shafer can provide an alternative  
8 and / or complement to traditional fuzzy MCE approaches for suitability analyses.  
9 In such situations the outputs of Dempster-Shafer MCE may be more appropriate than  
10 a fully fuzzy model of suitability. Future work will compare the results of this  
11 investigation with an analysis of the distribution of different types of wild land as  
12 described in McMorran et al (2006) and will evaluate the impact of different data  
13 aggregation methods on resulting spatial distributions of different types of wildness.  
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Intersect / AND / MIN operation

Union / OR / MAX operation

Figure 1. The results of Boolean multi-criteria evaluation in the CNP area using union and intersect operators, wild areas are in black and non-wild areas are unshaded.

Figure2

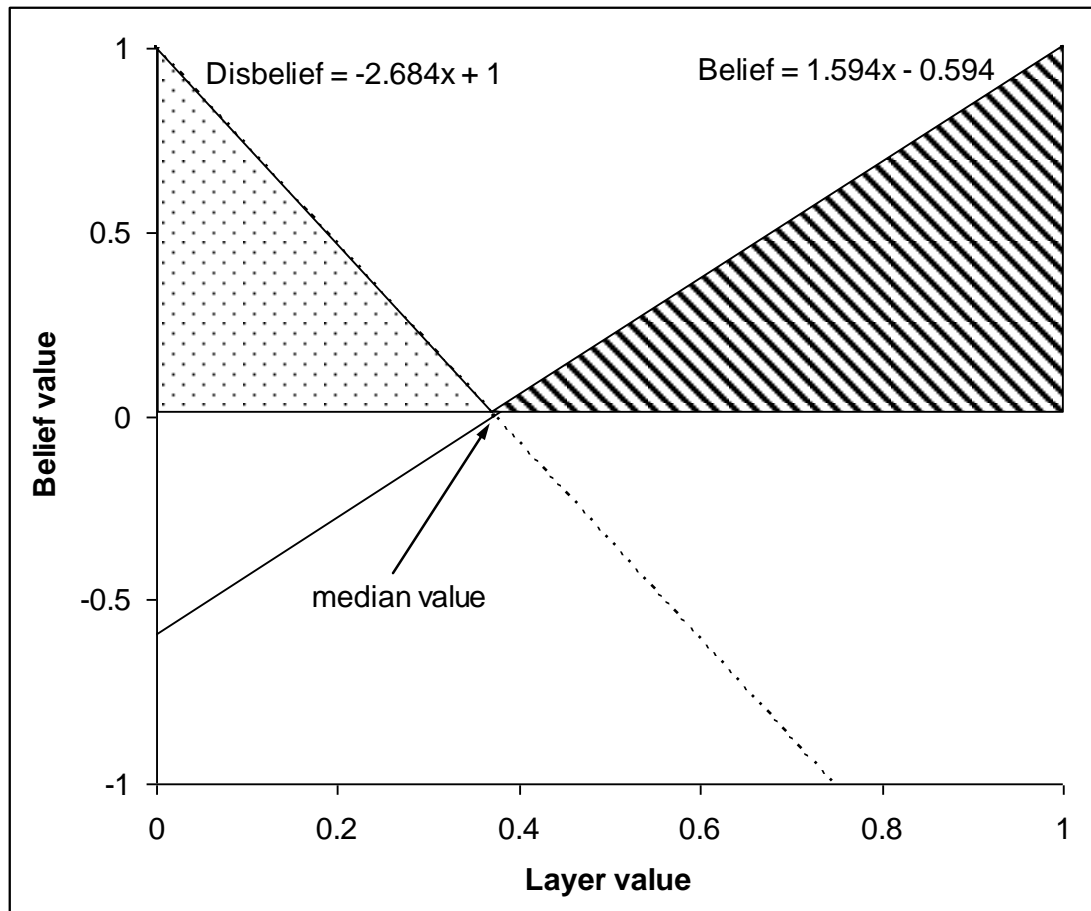
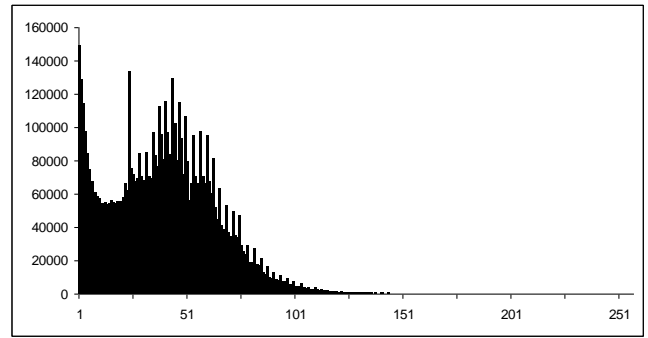
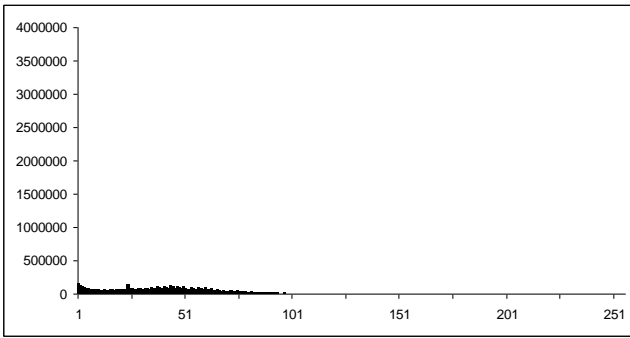


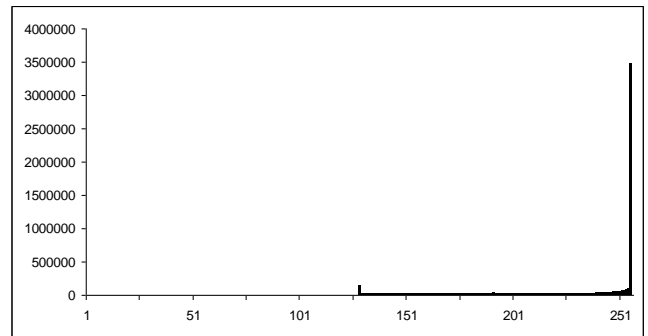
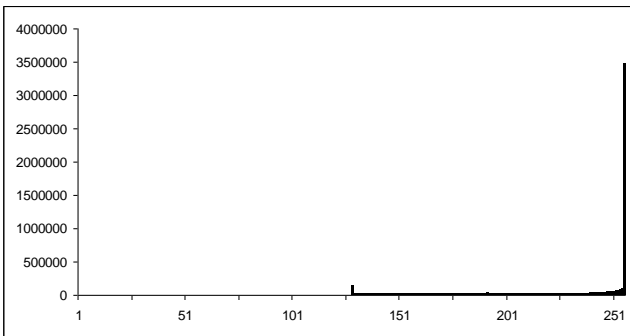
Figure 2. An example of the calculating Belief and Disbelief from the median factor layer value (Visibility).

Standardised Y axis

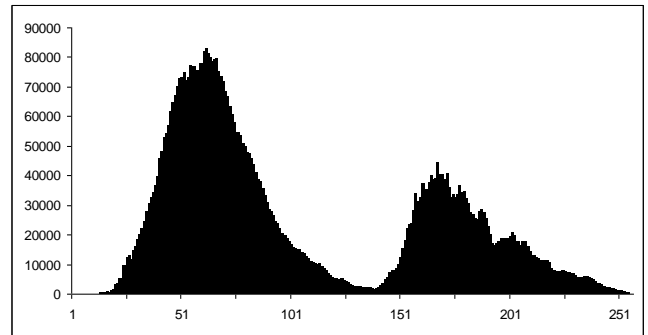
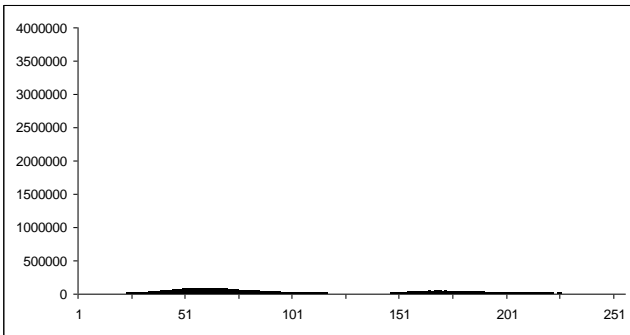
Variable Y axis



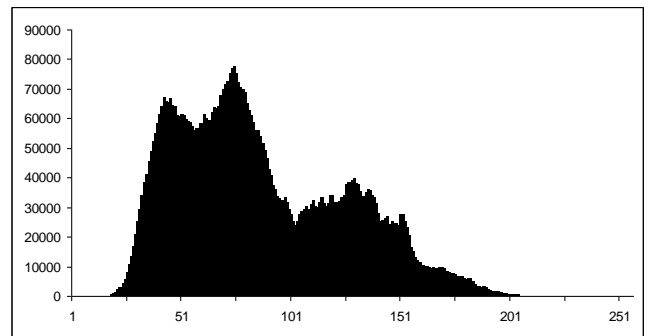
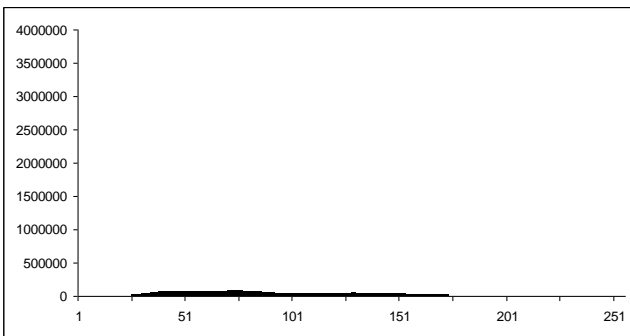
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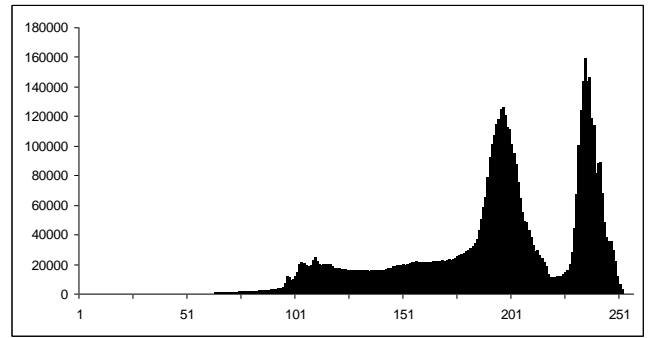
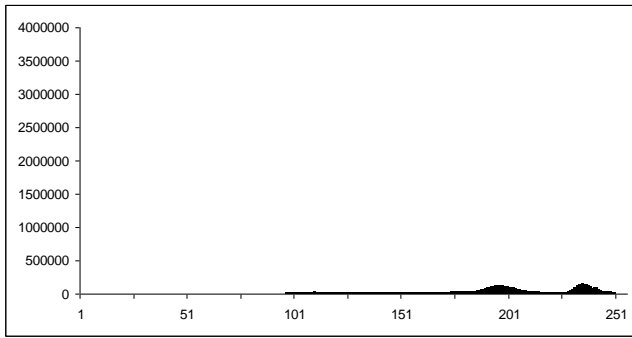
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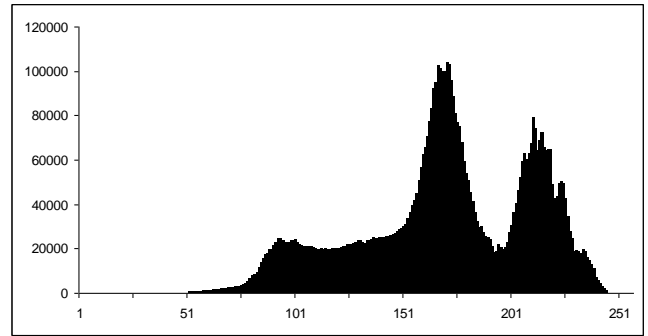
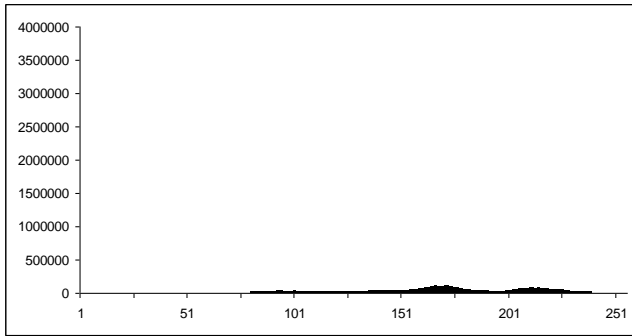
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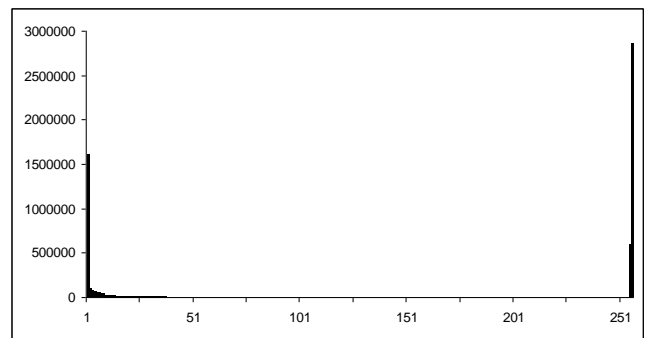
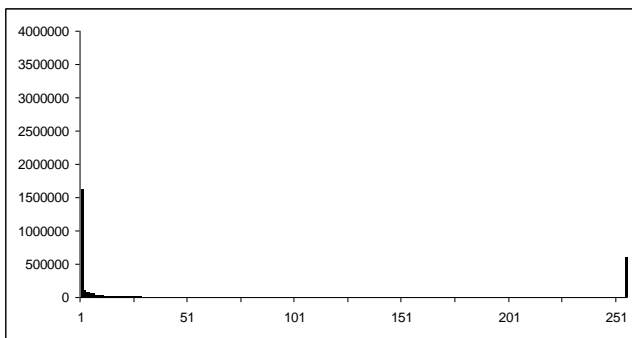
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[0.05,0.15,0.3,0.5]



[0.25,0.25,0.25,0.25]



Dempster-Shafer

Figure 3. Histograms of the distribution of wildness values produced by the different aggregation methods.

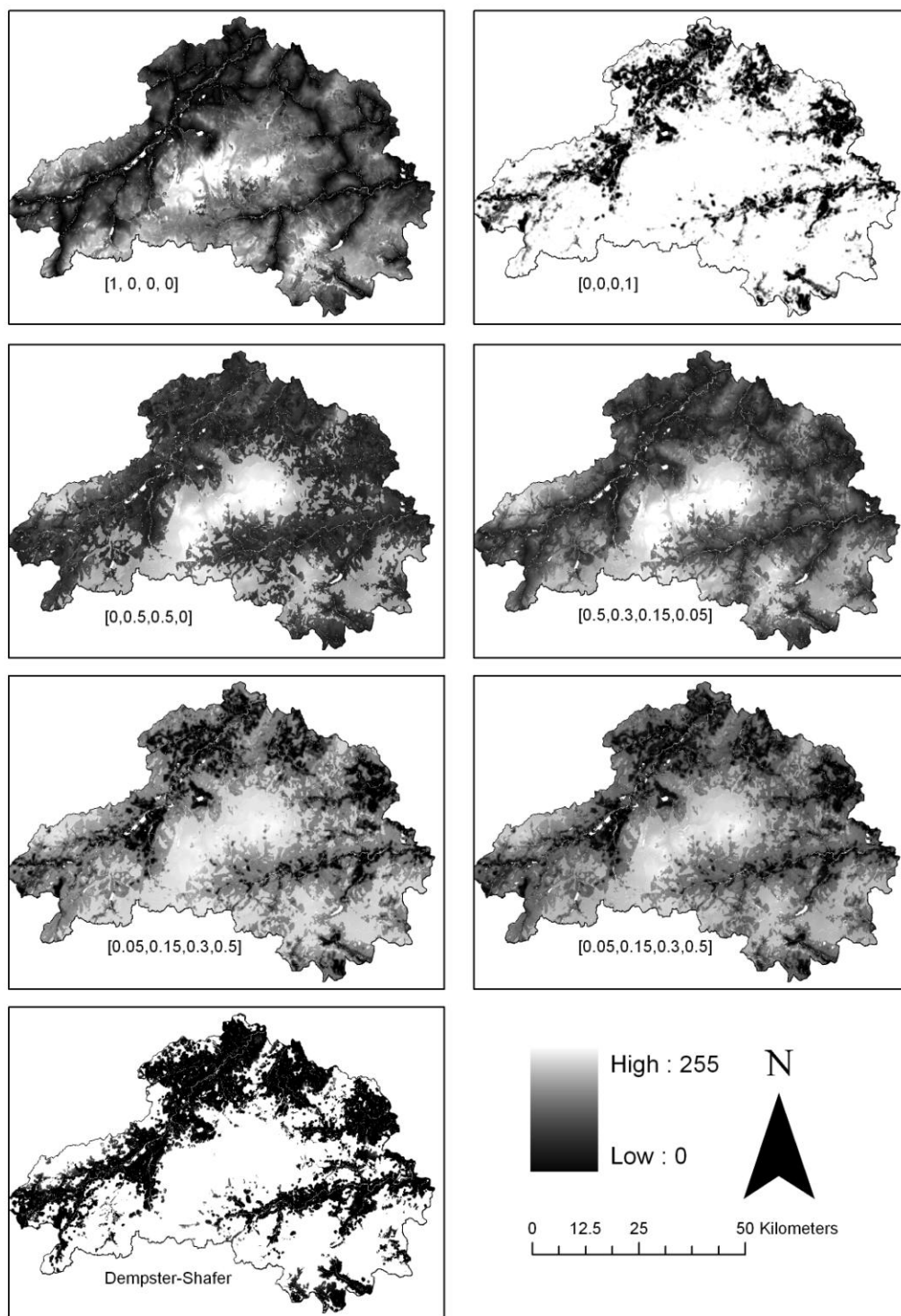


Figure 4. Different mappings of fuzzy wild land in the Cairngorms by multi-criteria evaluation with different order weights and Dempster-Shafer method of combination. The most wild areas are lighter, the least are darker.

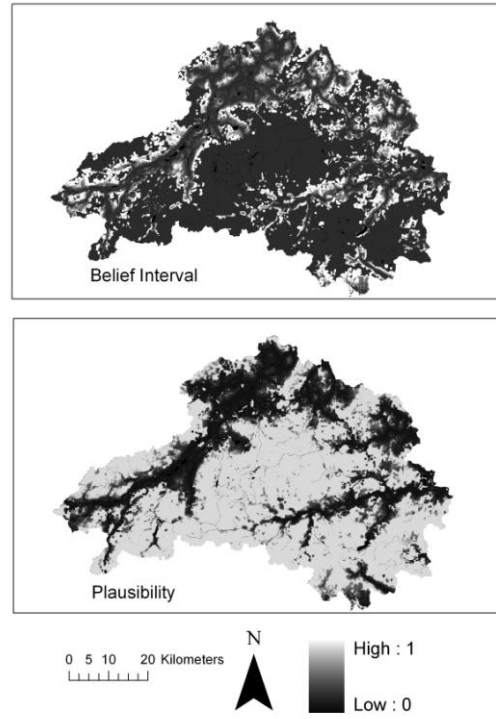


Figure 5. The distribution of Plausibility and the Belief interval



<b>Factor</b>	<b>Main criteria</b>	<b>Further detail</b>
<b>Perceived naturalness</b>	Vegetation cover primarily composed of functioning, natural habitats. Catchment systems largely unmodified, and other geomorphological processes unaffected by land management.	Habitat may often not be in best condition or at optimum ecological status. But there will normally be potential for recovery, and the vegetation cover should be composed of natural components. Some small plantations may be tolerated especially at the edge of an area, if they are the only detracting feature and of limited effect on wildness.
<b>Lack of constructions or other artefacts</b>	No contemporary or recent, built or engineering works within the area. Little impact from out with the area on wild qualities from built development, power lines, or masts or other intensive land uses (say forestry), or from noise or light pollution. Limited effects on the wild qualities of the area from older artefacts.	Older features (fences, bridges, stalking tracks, or small buildings) may be present, if not intrusive overall. Archaeological features (normally a light imprint on the land) will contribute to visitors' appreciation of the continuity of human use of these areas. Some intrusive features (say vehicular tracks which partly penetrate into an area) may be tolerated, where their effects are limited, and where excluding such land would reject an area of high intrinsic quality.
<b>Rugged or otherwise Challenging terrain</b>	Striking topographic features, or land having extensive rough terrain or extensive boglands, difficult to traverse. Natural settings for recreational activities requiring hard physical exercise or providing challenge.	Different kinds of terrain can offer an inspiring or challenging experience for people but, in the main, it is those landscapes which are of arresting character (by virtue of the scale and form of the terrain) which are most valued for their wildness.
<b>Remoteness and inaccessibility</b>	Distance from settlements or modern communications. Limited accessibility, either by scale of the area, difficulty in passage, or the lack of easy access, say by vehicular tracks, bridges, or by boat.	Distance is not an absolute guide on its own, but most of the wild land resource will lie in the remaining remote areas, as defined by distance from private and public roads and other artefacts.

Table 1. Factors contributing to perceptions of wild land (after SNH et al., 2002).

<b>Factor</b>	<b>Scottish</b>	<b>CNP</b>	<b>Carver et al (2008)</b>	<b>Average</b>
Naturalness	0.586	0.568	0.516	0.557
Remoteness	0.250	0.273	0.037	0.187
Ruggedness	0.039	0.038	0.124	0.067
Lack of Modern Artefacts	0.125	0.121	0.323	0.190

Table 2. Sets of factor weights derived from a public perception survey

Table3


OWA operator	OW1	OW2	OW3	OW4	ANDness	ORness	TradeOff
MIN	1	0	0	0	1	0	0
	0.5	0.3	0.15	0.05	0.75	0.25	0.61
	0	0.5	0.5	0	0.5	0.5	0.42
	0.25	0.25	0.25	0.25	0.5	0.5	1
	0.05	0.15	0.3	0.5	0.25	0.75	0.61
MAX	0	0	0	1	0	1	0

Table 3. The relationship between the selected order weights and the ANDness, ORness and TradeOff indices.

	<b>Remoteness</b>	<b>Ruggedness</b>	<b>Visibility</b>	<b>Naturalness</b>
<b>Median, x</b>	0.208	0.180	0.373	1
<b>If greater than median, Belief =</b>	$1.262x - 0.262$	$1.220x - 0.220$	$1.594x - 0.594$	$1x$
<b>If less than median, Disbelief =</b>	$-4.811x + 1$	$-5.545x + 1$	$-2.684x + 1$	$-x + 1$

Table 4. Calculation of factor Belief and Disbelief using median values