Research Article

# Exploring geomorphometry through user generated content – comparing an unsupervised geomorphometric classification with terms attached to georeferenced images in Great Britain

Short Running head: Exploring geomorphometry through UGC

Christian Gschwend and Ross S. Purves

Department of Geography

University of Zurich

Winterthurerstrasse 190

CH 8057 Zurich

Switzerland

christian.gschwend@geo.uzh.ch, ross.purves@geo.uzh.ch[1]

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[1] Corresponding author

## Abstract

User generated content such as the georeferenced images and their associated tags found in Flickr provides us with opportunities to explore how the world is described in the non-scientific, everyday language used by contributors. Geomorphometry, the quantitative study of landforms, provides methods to classify Digital Elevation Models (DEMs) according to attributes such as slope and convexity. In this paper we compare the terms used in Flickr and Geograph in Great Britian to describe georeferenced images to a quantitative, unsupervised classification of a DEM using a well established method, and explore the variation of terms across geomorphometric classes and space. Anthropogenic terms are primarily associated with more gentle slopes, whilst terms which refer to objects such as mountains and waterfalls are typical of steeper slopes. Terms vary both across and within classes, and the source of the user generated content has an influence on the type of term used, with Geograph, a collection which aims to document the geography of Great Britain, dominated by features which might be observed on a map.

## 1 Introduction

The advent of large volumes of user generated content (UGC), and more specifically volunteered geographic information (VGI) (Goodchild, 2007), provides new perspectives on how those with access to digital media describe the world around them. Thus, for example, Haklay et al. (2010) have explored the completeness and accuracy of OpenStreetMap road networks by comparison with data sourced from a National Mapping Agency. Girardin et al. (2009) explored urban attractiveness treating the density of images and phone calls with respect to points of interest in New York as a proxy for the popularity of locations over time. Other research has explored the nature of contributions and the motivation of users to contribute, in an attempt to better understand the phenomena of UGC and VGI in general (Coleman et al., 2009).

One area where UGC has considerable potential, is exploring the everyday terms used to describe the world. For instance, many researchers (e.g. Grothe and Schaab, 2009; Hollenstein and Purves, 2010) have identified the potential of georeferenced media as a route to discovering, exploring and delineating the use of vague or vernacular toponyms at scales ranging from regions like the Alps to individual districts within cities. The use of UGC provides an alternative route to empirical experiments (e.g. Montello et al., 2003) in exploring such questions which, potentially, can be applied across very large geographical areas assuming that the data coverage of UGC is in some way representative.

There are a multitude of reasons why identifying terms used in everyday language is important. For example, Davies et al. (2009) argue that vernacular names are important in the dispatch of emergency services, since callers may use toponyms not contained in administrative gazetteers. Equally, indexing information requires the use of terms that are likely to be used in search – for example, in the Tripod project we sought to link spatial data to images through their coordinates. Thus, we used Corine Land Cover data to identify likely land cover at a location, and a concept ontology derived from a range of sources including UGC to map the formal descriptions of Corine onto the everyday terms likely to be used in querying a search engine by lay users for images (Purves et al., 2010). A similar approach could be imagined for generating indexing terms for locations with respect to landforms (e.g. hill, mountain valley). The advent of seamless terrain models covering much of the Earth’s surface has enabled the development of relatively straightforward methods, based on supervised and unsupervised classification, for identification of landform classes through the use of parameters such as gradient or texture (e.g. Wood, 1996; Iwahashi and Pike, 2007).

In this paper we wish to bridge the gap between such quantitative methods suitable for analysing landforms and "folk" descriptions of these landforms. The work extends methods originally developed by Gschwend (2010) and Gschwend and Purves (2011) for analysis of landforms in continental USA. Our approach is to use two databases containing user generated content in the form of georeferenced images and their descriptions and compare these descriptions to a quantitative classification of a DEM using a robust unsupervised method. In particular we wish to explore the following questions:

- Which methods are required to explore the relationship between everyday language descriptions of landforms and quantitative geomorphometric classifications?
- Can individual geomorphometric classes be related to terms used in user generated content?
  How does the use of everyday language describing landforms vary across space and geomorphometric classes?

## 2 State of the art

Our work is concerned primarily with two areas and the intersection between them, firstly research on landform classification and geomorphometry and, secondly, work on user generated content from both Geographic Information Science and Information Science.

### 2.1 Geomorphometry and landform classification

Geomorphometry was defined by Pike et al. (2009: 4) as "the science of topographic quantification; its operational focus is the extraction of land-surface parameters and objects from digital elevation models (DEMs)." In turn, Pike et al. (2009) define land surface parameters as *descriptive measures of surface form*, taking the form of continuous fields. Such land surface parameters are typically described as primary or compound topographic indices with gradient, aspect and flow direction being examples of the former and topographic wetness index or stream power of the latter. Such indices are, given a DEM at a particular resolution, straightforward to derive and widely used. Pike et al. (2009) give as examples of objects extracted from DEMs drainage networks and watershed lines, which are themselves defined through the use of land surface parameters. The values of the parameters, and thus the extents of related objects, are related to scale (e.g. the extent of the moving window used to calculate gradient), data (e.g. horizonzal resolution and vertical accuracy) and the algorithm used (e.g. steepest drop or finite differences for gradient) (Deng, 2007).

An important question relates to how parameters and objects defined by domain experts can be related to everyday conceptualisations of landscapes. These sorts of questions form the basis for much of David Mark's recent work in the field of ethnophysiography, where he and colleagues have demonstrated that people from different cultures and backgrounds also have differing perceptions of the space around them (e.g. Mark and Turk, 2003). Furthermore, they seem to us to be fundamental if one is to advance in the set of challenges set out as *naïve geography* by Egenhofer and Mark (1995), which, simply put, can be considered to be concerned with making GIS capable of more closely matching the expectations of a user unfamiliar with the spatial data models used in GIS or the specialised categories used, in our case, by a geomorphologist in describing landforms.

A wide range of methods which allocate every cell in a DEM to an individual landform class have also been developed. *Unsupervised* methods make initial decisions on the parameters relevant to landform delineation, but then classify landform elements without *a priori* knowledge of the expected classes (e.g. Burrough et al., 2000; Deng et al., 2007). Iwahashi and Pike (2007) developed an unsupervised classification method based on iterative subdivision of DEM cells using gradient, local convexity and surface texture. Their method has the advantage that the parameters used are straightforward to interpret, and its application is illustrated from the global to local scale. However the interpretation of the individual landform classes is still based on an expert geomorphological characterisation of the classes which would unlikely to relate directly to the everyday terms used to describe such landforms. Indeed, as Iwahashi and Pike (2007: 437) state: "The work described here raises fundamental issues in terrain classification that continue to challenge the discipline of geomorphometry … Some of these are semantic and ontological: what's a hill? And when is it not a hill but a mountain?"

Until recently, the primary way to gather information about the everyday terms used to describe landforms was through empirical studies, which required participants to list, for example, "a kind of geographic feature" or "something that could be portrayed on a map" (Smith and Mark, 2003). However, the advent of *user generated content* (UGC), or as it is more specifically known in Geographic Information Science, *volunteered geographic information* (VGI) provides us with new opportunities to explore how individuals describe landforms across space. UGC and VGI, and their application, form the core of the next section.

### 2.2 User generated content and volunteered geographic information

User generated content (UGC) is a relatively recent phenomena, which can take the form of contributions uploaded to the web, for example as blog entries, comments on restaurants, or georeferenced tagged images. Volunteered geographic information (VGI) was defined by Goodchild (2007) as a special case of UGC concerned with the production of specifically geographic information by individuals, in domains which had traditionally been the preserve of professionals.

In previous work we showed how terms used in Geograph (Edwardes and Purves, 2007) were similarly ranked to those identified in previous experiments seeking to identify category norms (e.g. Smith and Mark, 2003) suggesting that UGC, could provide a valid proxy for empirical experiments aimed at exploring how space was described. Rorissa (2008) demonstrated that participants in an image labeling task preferred to use basic level terms (Tversky and Hemenway, 1983) to label individual images. In further work Rorissa (2010) showed that tags used by Flickr were not only "richer in their semantic content" than terms assigned by professional indexers, but also likely to include perceptual elements of the image in question. The potential of Flickr, and other UGC, as ways of exploring semantics, and the potential strengths and weaknesses of an essentially freeform approach to describing content have also been the subject of considerable study and debate (e.g. Winget, 2006; Guy and Tonkin, 2006; Ames and Naaman, 2007). For instance, Winget (2006) demonstrated that Flickr users not only assigned the correct toponym to images of volcanoes, but that they also embraced the full hierarchical structure of toponyms found in the Thesaurus of Geographic Names (TGN).

Identifying toponyms and delineating their associated regions, especially those which are not found in traditional gazetteers, is one of the main uses to which Flickr data and other UGC have been put in GIScience (e.g. Grothe and Schaab, 2009; Keßler et al., 2009; Popescu et al., 2009; Hollenstein and Purves, 2010). Within information and computing science, UGC has been used to explore the overall distribution of Flickr images and to identify semantically interesting locations (e.g. Crandall et al., 2009; Rattenbury and Naaman, 2009).

In recent work (Purves et al., 2011), we explored the nature of terms used in both Flickr and Geograph. Geograph is a moderated collection of images of the UK, complete with free text descriptions, which focuses on geographic features identifiable on a map. An important difference between Flickr and Geograph is in the nature and way in which terms are used. We classified the 1000 top ranked terms (after removing toponyms, stop words and camera related terms) as either elements (objects likely to be visible in an image), activities (again, likely to be visible in an image) and qualities (modifiers of elements or activities or suggestions of feelings or moods). We found terms describing activities to be more common in Flickr and those describing qualities to be more common in Geograph.

### 2.3 Research gaps

A number of gaps exist in the literature, both in the well established area of geomorphometry, and more recent work with user generated content. As Iwahashi and Pike (2007) observed, important semantic and ontological questions arise in assigning names to the classes generated by quantitative methods from geomorphometry and, to our knowledge, little work has addressed what might termed everyday terms appropriate for labeling such classifications. User generated content appears to provide one potential means of addressing this gap, and in this paper we seek to explore the relationship between, on the one hand the terms assigned to images by a wide range of individuals, and on the other a widely used quantitative classification of landforms. Furthermore, despite initial studies exploring the spatial use of user generated content, relatively little work has explored spatial variation except as a function of either co-occurrence with other terms or, with respect to simple proxies for contributions such as population.

## 3 Data

Our analysis was carried out for data from Great Britain (that is to say the United Kingdom without Northern Ireland). To prepare a land surface form classification we used a post-processed SRTM (Shuttle Radar Topography Mission) DEM (Version 4, made available by the CGIAR Consortium for Spatial Information) with a nominal resolution of 90m projected to the Ordnance Survey National Grid. Gorokhovich and Voustianiouk (2006) evaluated the data quality of this post-processed SRTM data and showed that this DEM was of higher quality than SRTM data which had not been subject to post-processing. Figure 1 shows the relief of the study area, as well as a number of major cities and the borders of England, Wales and Scotland (important in considering some geomorphometrically relevant terms rooted in English, Welsh and Gaelic).

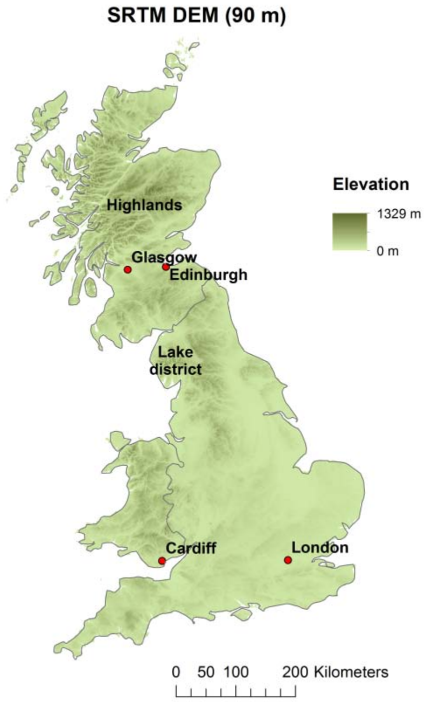



**Figure 1** Relief of Great Britain and some locations discussed in the text

User generated content were derived from two sources, Flickr[2] and Geograph[3]. Flickr is an archetypal Web 2.0 service, where individuals may upload images with a variety of metadata including titles, tags and geographic coordinates. For this work we used the FlickrJ API to mine all georeferenced images within the following bounding box (10W, 50N – 2E, 60N) with a reported precision equivalent to georeferencing at the level of individual streets. In our analysis we used, as well as the locations of images, the (anonymous) individual user identifiers and the tags associated with the images.

Geograph is a project with the aim of collecting "geographically representative photographs for every square kilometer of the UK and Republic of Ireland". Unlike Flickr, all contributions are moderated, and

[2] www.flickr.com
[3] www.geograph.org.uk

only those considered relevant to the stated aim, and thus with geographic relevance, are accepted. A wide range of attributes, as well as locations with varying precisions[4], are stored, including free text titles and descriptions. We used only images with a precision of 100m or more (approximately equivalent to our DEM resolution) and used unique user identifiers and image descriptions in our further analysis.

Figure 2 illustrates the respective densities of the two collections. Note the very different properties of Flickr, with its primary concentration in urban centers such as London or the central belt of Scotland, in comparison to the much more regular distribution of Geograph images.

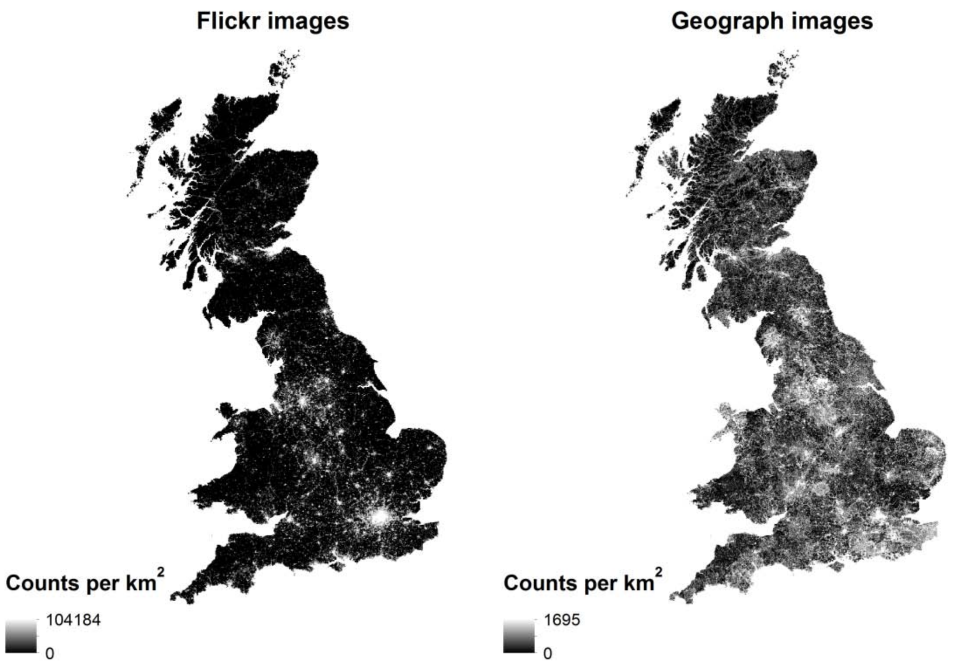



**Figure 2** Image counts per 1km$^2$ visualized on a log scale for Flickr and Geograph

## 4 Relating geomorphometry to user generated content

The aim of this work was to relate quantitatively derived geomorphometric classes to terms extracted from user generated content. There were thus four key stages to the methodology employed:

[4] Images must be located with respect to a 1km grid square, with contributors using various levels of precision – older images were typically located using a 1:50000 map with a precision equivalent to 1km or 100m, whilst more recent images are often located using GPS with precision of the order of 10m.

- calculation of quantitative values assigning DEM cells to a landform class;
- identification and preprocessing of commonly used terms in user generated content from Flickr and Geograph collections in Great Britain;
- ranking of terms according to variation within geomorphometric classes; and
- exploration and analysis of the spatial variation in terms used to describe different geomorphometric classes.

The following describes each of these four stages in more detail. Processing was carried out using ArcGIS, R and Java programmes as appropriate.

### 4.1 Deriving landform classes from a DEM

Iwahashi and Pike's (2007) land surface classification gives each DEM cell a unique value, classifying a location successively in terms of gradient, local convexity and surface texture. We closely followed the method proposed, and chose eight landform classes, rather than the other possibilities of 12 or 16, for our final landform classification, which we felt was an appropriate compromise for the relatively low relief of Great Britain. In order to explore initial variation of landform classes as a function of resolution, we generated landform classes at a resolution of 90m, before calculating modal relief at a resolution of 9km.

Gradient was calculated using a 3x3 moving window, using the finite differences method implemented in ArcGIS. Convexity is argued by Iwahashi and Pike to allow discrimination between low relief features, such as flood plains and alluvial terraces and a Laplacian filter is used to identify areas of positive and negative local convexity. Finally, surface texture is used to classify cells according to relative relief (that is to say pits and peaks) by subtracting the source DEM from median elevation values (again derived using a 3x3 filter). Cells were allocated to one of eight landform classes according to, firstly their mean gradient, followed by mean convexity and finally mean texture.

### 4.2 Extracting terms from user generated content

We worked with two fundamentally different collections of user generated content, Flickr and Geograph, as described in §3. Previous work has shown that georeferenced Flickr images very commonly include toponyms as tags (Sigurbjörnsson and Van Zwol, 2008; Hollenstein and Purves, 2010). Equally, since

Geograph descriptions consist of free text they also include many prepositions and other terms which must first be filtered. In recent work, we generated lists of elements, qualities and activities by exploring the 1200 most commonly used terms in Flickr and Geograph for some 1.6 million images taken before April 2008 (Purves et al., 2011). Although specific events may result in some changes to the terms found in these collections (for example, we would expect the tag riot to have been commonly used during and after the events of the summer of 2011 in London and other UK cities), we suggest that terms used within these lists to describe landform related characteristics are unlikely to have changed and used these word lists[5] to identify candidate terms. Furthermore, we used Porter stemming (Porter, 1980) to normalise terms in our matching procedure. This has the advantage of grouping terms together to a single root, though it is important to note that on occasion this may also increase ambiguity. Having matched stemmed terms with entries in our word lists, we were left with term frequencies for both Flickr and Geograph for each word listed by Purves et al. (2011).

### 4.3 Relating user generated content to Geomorphometry

Having identified commonly used terms by a process of word matching, we wished to explore how these vary with different geomorphometric classes. Rattenbury and Naaman (2009) identified Flickr tags that were significantly localized in space in order to derive *place semantics*, sets of tags that are descriptive of a particular location. In our work, we wished to carry out an analogous procedure and identify terms related to individual geomorphometric classes. We therefore adapted slightly the TagMaps TF-IDF method (Rattenbury and Naaman, 2009) to our purposes. The measure is based on the well known baseline information retrieval ranking algorithm, TF-IDF, which ranks documents for some given search query according to, firstly, *term frequency*, and secondly, *inverse document frequency*. Term frequency is simply the number of times a term occurs in an individual document. The inverse document frequency is the total number of documents in a collection divided by the number of documents containing a term. TF-IDF thus gives higher weight to terms in collections which are common in a small number of documents, but not over the collection as a whole.

In our analysis, term frequency was treated as the total number of occurrences of a particular term in an individual landform class. Inverse document frequency was the total number of images divided by the

[5] The full term lists can be found in the supporting materials for Purves et al. (2011) at: http://gicentre.org/firstMonday

number of images with labeled with the term across all geomorphometric classes. Thus, terms which occur more in a single geomorphometric class are proportionately higher ranked than equally prolific terms across all classes. Finally, in user generated content participation inequality (Nielsen, 2006) is a well known effect which typically manifests itself through small numbers of contributors generating very large volumes of data. Here, we again followed Rattenbury and Naaman's (2009) approach, and sought to minimize this bias by adding a term representing user frequency, where terms used ubiquitously are ranked higher than those suggested by a small number of prolific posters. The final ranking of each term identified in the word list was thus given by the following equation:

$$score(R,x) = tf(R,x) \cdot idf(x) \cdot uf(R,x)$$

where R is classification according to Iwahashi and Pike

x is term to be ranked

tf is the number of photos for a given class and term

idf is the total number of photos divided by the total number of photos with term x

uf is the number of users for a given class and term divided by number of users for a given class

## 4.4 Exploring variation of term use in space

In order to explore the variation of term use in geographic space we generated χ-maps (Wood et al., 2007) which show the variation in term used as a function of some overall expected distribution. Here, the expected distribution was based not on a constant or random distribution in space, but the actual distribution of all images from the collection under analysis (either Flickr or Geograph). χ-values were calculated at a resolution of 9km, and distributions were generated by calculation of kernel density surfaces with a kernel bandwidth of 50km. A 9km resolution was used so that a broad picture of variation could be observed at a regional level. The observed distribution was the kernel density surface for the term under analysis. The volumes of the observed and expected surfaces were normalized, before χ was calculated as:

$$\chi = \frac{\mathrm{O} - \mathrm{E}}{\sqrt{\mathrm{E}}}$$

where O is the observed density of images in a pixel and

E is the expected density of images in a pixel.

To explore the relationship between $\chi$-maps and individual geomorphometric classes, zonal statistics were calculated to derive a range of mean and standard deviation in $\chi$-values for each individual geomorphometric class.

# 5 Results and interpretation

## 5.1 Geomorphometric classification

Figure 3 shows the classes derived according to the scheme proposed by Iwahashi and Pike (2007). In Figure 4 the proportion of grid cells allocated to each class, together with the total number of images from both Flickr and Geograph are illustrated.

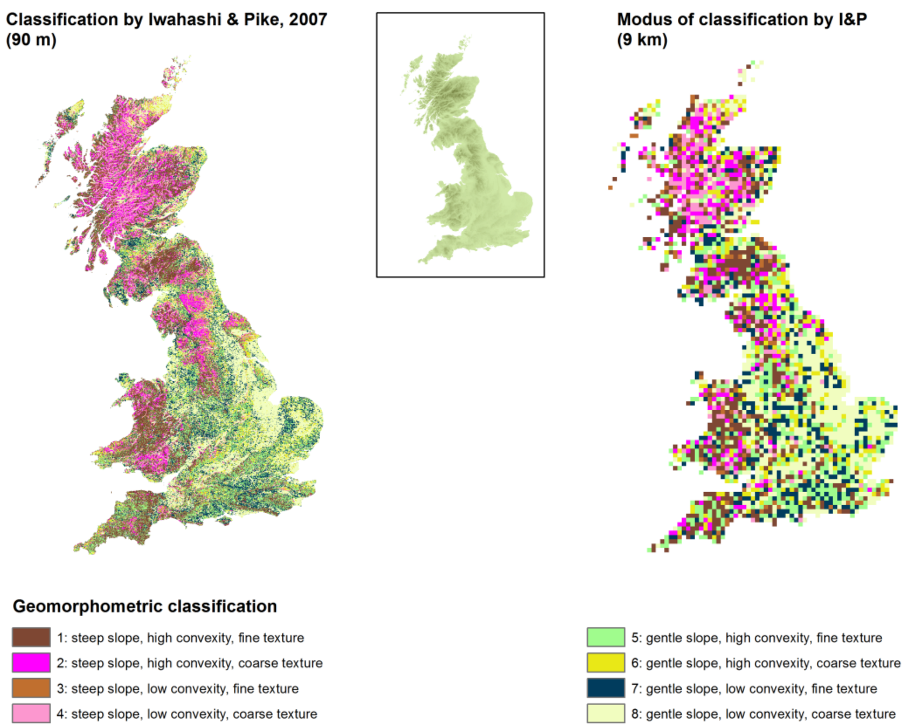
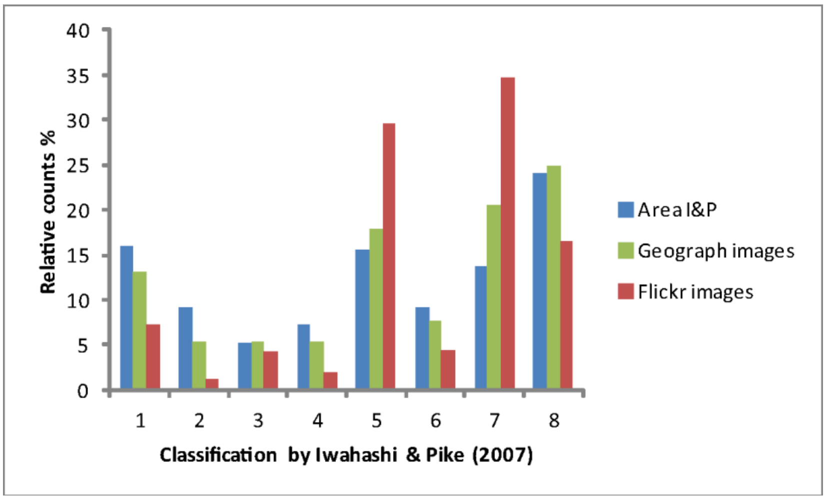
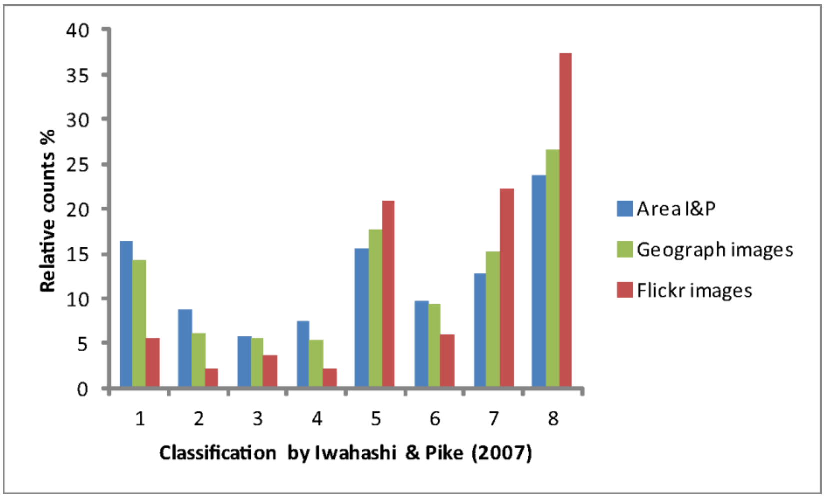



**Figure 3** Geomorphometric classification according to Iwahashi and Pike (2007) at a resolution of 90m and modal values at a resolution of 9km

As Figure 3 shows, at both the 90m and 9km resolutions, broad patterns are visible in Iwahashi and Pike's classification which appear to correlate well with relief. Thus, for example, differences in the classification reflect obvious differences in relief, most obviously visible in terms of the variation between steep (1-4) and gentle (5-8) slopes. Some classes, especially 8 (gentle slope, low convexity, coarse texture) which one would expect to relate to large areas of alluvial deposits or flood plains cover large areas with little variation in class, whilst others, for example 2 and 4 (steep slopes, high and low convexity, coarse texture) form complex patterns probably relating to mountainous regions incised by glacial valleys. Resampling from 90m to 9km using modal values for the 9km grid cells retains the broad overall pattern of variation, at a cost of an obvious loss in detail.




(a)




(b)

**Figure 4** Relative distribution of pixels in Iwahashi and Pike classes (Area I & P) and counts of Geograph and Flickr images at 90m (a) and 9km (b) resolutions

Figure 4 illustrates both the overall distributions of classes as a function of percentage of the total area at both 90m and 9km. All classes represent at least 5% of the total area of Great Britain, with class 8 (gentle slope, low convexity, coarse texture) being the most prominent and representing some 25% of the total area. Class membership appears to be relatively stable, with no changes in area equivalent to more than 1% of the total area of Great Britain when resolution is changed from 90m to 9km. Figure 4 also shows the distribution of images from both Geograph and Flickr across geomorphometric classes. A number of aspects are notable here. Firstly, Flickr is biased, as one would expect, to more gentle slopes (classes 5-8) with around 85% of Flickr images found in these regions. These more gentle slopes also correspond to the most densely populated areas of Great Britain, with large areas with steep slopes such as the Highlands of Scotland having very small populations. By contrast Geograph images are more or less distributed according to geomorphometric classes. Secondly, the distribution of Geograph images is relatively stable across all classes at both resolutions, with a maximum variation of the order of 5% in the allocation of images to geomorphometric classes. However, the number of Flickr images allocated to class 8 (gentle slope, low convexity, coarse texture) varies by up to 20% (more than 500000 images) despite the relatively small change in area allocated to this class. This sensitivity probably reflects the extreme clustering of Flickr images in urban centers in contrast to the much more evenly distributed Geograph images, where a single pixel at 9km resolution covering a large area of London could result in the reallocation of a very large number of images if geomorphometric classes changed.

### 5.2 Term frequencies and their relationship to geomorphometric classes

Table 1 illustrates each of the eight geomorphometric classes, according to their ranking from the whole set of elements, qualities and activities[6]. Table 2 shows the top 20 terms from all facets and the geomorphometric classes in which they occur. Since the word lists are derived from those used in the work of Purves et al. (2011) the potential candidate terms are identical, and thus we refer the reader to that work for a discussion of the overall differences in terms used between Flickr and Geograph.

[6] The top 20 terms are available in the supporting materials for this paper.

**Table 1** Top 5 ranked terms from Flickr (a) and Geograph (b) (from all categories) for the eight geomophometric classes (note terms are always given as the stem used in matching)

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|
| sea | hill | wharf | loch | street | snow | night | tree |
| landscap | landscap | castl | mountain | squar | tree | street | snow |
| hill | mountain | landscap | landscap | citi | flower | water | church |
| castl | waterfal | tree | lake | night | sky | light | bird |
| boat | tree | sky | castl | build | sunset | river | flower |

(a)

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|
| hill | hill | hill | glen | road | road | bridg | river |
| vallei | summit | down | loch | hous | farm | road | bridg |
| down | vallei | castl | hill | park | hous | build | road |
| cliff | down | rock | slope | build | old | hous | church |
| summit | slope | top | down | wood | field | river | hous |

(b)

| | |
|---|---|
| 1 | steep slope, high convexity, fine texture |
| 2 | steep slope, high convexity, coarse texture |
| 3 | steep slope, low convexity, fine texture |
| 4 | steep slope, low convexity, coarse texture |
| 5 | gentle slope, high convexity, fine texture |
| 6 | gentle slope, high convexity, coarse texture |
| 7 | gentle slope, low convexity, fine texture |
| 8 | gentle slope, low convexity, coarse texture |

In exploring Table 1 it is important to note that only the top five terms are shown here, and that many highly ranked terms are relatively ubiquitous across geomorphometric classes (c.f. Table 2). However, it allows us quickly to gain an overview of the types of terms used and key differences between them. Perhaps the most obvious features are the very strong distinction, for both Flickr and Geograph between more natural features for steep classes, which clearly relate to landforms (1-4) (e.g. *sea*, *hill*, *mountain*, *vallei* (the stem of valley etc.)) and more anthropogenic features for more gentle slopes (5-8) (e.g. *hous* (the stem of house etc.), *road*, *street*). It is also clear that the highest ranked terms in Geograph very much take the form of "something that could be portrayed on a map" (Smith and Mark, 2003). Highly ranked Flickr terms on the other hand also include more terms related to the moment at which an image was captured, for example *night*, *sunset*, *light*, *bird* or *snow*. Given the relative rarity of snow in low lying areas of Great Britain, the high ranking of the last term associated with classes 6 and 8 (gentle slope, high/ low convexity, coarse texture) also indicates the prominence of tags from photographs taken to illustrate unusual events.

**Table 2** Occurrence of stemmed terms from top 20 ranked elements(E), qualities(Q) activities(A) for Flickr and Geograph according to geomorphometric class. Terms are sorted according to the (1) number of geomophometric classes in which they appear and (2) overall rank

| Flickr | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | Geograph | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| tree (E) | x | x | x | x | x | x | x | x | road (E) | x | | x | x | x | x | x | x |
| sky (E) | x | x | x | x | x | x | x | x | hill (E) | x | x | x | x | x | x | | |
| cloud (E,Q) | x | x | x | x | | x | | x | old (Q) | | | x | x | x | x | x | x |
| snow (E,Q) | x | x | x | x | | x | | x | down (E) | x | x | x | x | x | | | |
| sunset (Q) | x | x | | x | | x | | x | track (E) | x | x | x | x | | x | | |
| water (E) | x | | x | x | | | x | x | hous (E) | | | x | | x | x | x | x |
| blue (Q) | | | x | | x | x | x | x | build (E) | | | x | | x | x | x | x |
| church (E) | | | x | x | | x | x | x | vallei (E) | x | x | x | x | | | | |
| landscap (Q) | x | x | x | x | | | | | steep (Q) | x | x | x | x | | | | |
| hill (E) | x | x | x | x | | | | | slope (E) | x | x | x | x | | | | |
| mountain (E) | x | x | x | x | | | | | tree (E) | x | | x | x | x | | | |
| flower (E) | | | | x | | x | x | x | new (Q) | | | | | x | x | x | x |
| light (E,Q) | | | | | x | x | x | x | built (Q) | | | | | x | x | x | x |
| red (Q) | | | | | x | x | x | x | top (Q) | x | x | x | | | | | |
| castl (E) | x | | x | x | | | | | rock (E,Q) | x | x | x | | | | | |
| bridg (E) | x | | | | x | | x | | path (E) | x | | x | x | | | | |
| river (E) | x | | | | | | x | x | wood (E,Q) | x | | x | | x | | | |
| natur (Q) | | x | | x | | | | x | hillsid (E) | x | x | | x | | | | |
| winter (Q) | | x | | | | x | | x | river (E) | | | x | | | | x | x |
| build (E) | | | x | | x | | x | | park (E) | | | | | x | x | x | |
| night (Q) | | | | | x | x | x | | farm (E,A) | | | | | x | x | | x |
| park (E) | | | | | x | x | x | | lane (E) | | | | | x | x | | x |
| reflect (E,Q) | | | | | x | | x | x | bridg (E) | | | | | x | | x | x |
| sea (E) | x | | x | | | | | | centr (Q) | | | | | x | | x | x |
| beach (E) | x | | x | | | | | | field (E) | | | | | x | x | | x |
| panorama (Q) | x | x | | | | | | | church (E) | | | | | | x | x | x |
| waterfal (E) | | x | | x | | | | | villag (E) | | | | | | x | x | x |
| walk (A) | | x | | x | | | | | line (E) | | | | | | x | x | x |
| countrysid (Q) | | x | | x | | | | | cliff (E) | x | | x | | | | | |
| field (E) | | x | | | | x | | | summit (E) | x | x | | | | | | |
| lake (E) | | x | | x | | | | | ridg (E) | x | x | | | | | | |
| green (Q) | | | x | | | x | | | quarri (E) | x | | x | | | | | |
| garden (E) | | | x | | | x | | | moor (E) | | x | | | | x | | |
| tower (E) | | | x | | x | | | | mountain (E) | | x | | x | | | | |
| street (E) | | | | | x | | x | | stone (E,Q) | | x | | | | x | | |
| citi (EQ) | | | | | x | | x | | beinn (E) | | x | | x | | | | |
| architectur (Q) | | | | | x | | x | | reservoir (E) | | x | | x | | | | |
| art (A,Q) | | | | | x | | x | | loch (E) | | | x | x | | | | |
| white (Q) | | | | | | x | | x | water (E,Q) | | | | x | | | | x |
| boat (E) | x | | | | | | | | street (E) | | | | | x | | x | |
| coast (E) | x | | | | | | | | junction (E) | | | | | x | x | | |
| monument (E) | x | | | | | | | | entranc (E) | | | | | x | | x | |
| harbour (E) | x | | | | | | | | cross (E) | | | | | x | | | x |
| cow (E) | x | | | | | | | | station (E) | | | | | | | x | x |
| hike (A) | | x | | | | | | | railwai (E) | | | | | | | x | x |
| sheep (E) | | x | | | | | | | forest (E) | x | | | | | | | |
| wood (E,Q) | | x | | | | | | | coast (E) | x | | | | | | | |
| grass (E) | | x | | | | | | | walk (A) | x | | | | | | | |
| wharf (E) | | | x | | | | | | cairn (E) | | x | | | | | | |
| skyscrap (E) | | | x | | | | | | moorland (E) | | x | | | | | | |
| lighthous (E) | | | x | | | | | | fell (E) | | x | | | | | | |
| loch (E) | | | | x | | | | | heather (E) | | x | | | | | | |
| cathedr (E) | | | | x | | | | | castl (E) | | | x | | | | | |
| stone (E,Q) | | | | x | | | | | glen (E) | | | | x | | | | |
| squar (E,Q) | | | | | x | | | | allt (E) | | | | x | | | | |
| statu (E) | | | | | x | | | | ben (E) | | | | x | | | | |
| sign (E) | | | | | x | | | | waterfal (E) | | | | x | | | | |
| museum (E) | | | | | x | | | | run (A) | | | | | | x | | |
| peopl (E) | | | | | x | | | | footpath (E) | | | | | | x | | |
| hous (E) | | | | | | x | | | hall (E) | | | | | | | x | |
| dog (E) | | | | | | x | | | main (Q) | | | | | | | x | |
| black (Q) | | | | | | x | | | canal (E) | | | | | | | x | |
| graffiti (E) | | | | | | | x | | flood (E,Q) | | | | | | | | x |
| window (E) | | | | | | | x | | | | | | | | | | |
| bird (E) | | | | | | | | x | | | | | | | | | |
| railwai (E) | | | | | | | | x | | | | | | | | | |
| train (E,A) | | | | | | | | x | | | | | | | | | |
| car (E) | | | | | | | | x | | | | | | | | | |

| | | | |
|---|---|---|---|
| 1 | steep slope, high convexity, fine texture | 5 | gentle slope, high convexity, fine texture |
| 2 | steep slope, high convexity, coarse texture | 6 | gentle slope, high convexity, coarse texture |
| 3 | steep slope, low convexity, fine texture | 7 | gentle slope, low convexity, fine texture |
| 4 | steep slope, low convexity, coarse texture | 8 | gentle slope, low convexity, coarse texture |

Highly ranked activities, available in the supporting materials, tend to be more similar across classes in Geograph, with for example *farm* being a highly ranked term across all geomorphometric classes. However, Flickr shows interesting differences, with *holida* (the stem of holiday etc.) being in the top five terms for steep slopes (classes 1-4), and, presumably, more urban activities such as *shop* being represented in gentle slopes (classes 5-8). Somewhat the reverse is the case for qualities, where Flickr is much more homogenous across geomorphometric classes, with *cloud* belonging to the top five terms for six out of eight classes. Geograph, shows more variation, with modifiers that might be more commonly used with natural features prominent as terms for steep slopes (classes 1-4), e.g. *steep*, *rock*, *top* and those perhaps more obviously related to settlements prominent for gentle slopes (classes 5-8) e.g. *built*, *centr* (the stem for centre etc.).

When exploring Table 2 it is important to bear in mind that only the top 20 terms for each geomorphometric class were analyzed, and that terms not appearing in conjunction with a particular class (for example in the case of Geograph, *road* in class 2) may simply appear slightly further down the ranking for this class. One obvious feature of Table 2 is the small number of activities and qualities which remain in the top 20 terms ranked, illustrating the relatively higher ranking of elements, that is to say objects which are presumably visible in the images.

Nonetheless, a number of interesting, and we believe meaningful, patterns can be identified in the data and are worthy of note. Some terms appear to be more or less ubiquitous appearing in many or even all geomorphometric classes. For example, *tree*, *sky*, *cloud*, *snow* and *sunset* are all common in Flickr and *road*, *hill* and *old* in Geograph. Indeed, *hill* occurs in all classes except 7 and 8 (gentle slope, low convexity) suggesting that as soon as any convexities are present, they may be referred to as hills. Interestingly, despite Flickr's much greater concentration in urban areas, the term *hill* is only highly ranked in Flickr in steep (1-4) classes. This may be the result of one of two effects. Either there is a real difference in how prominences are perceived in Flickr and Geograph, or more likely, the nature of Flickr's content means that in rural areas users are more likely to use tags related to the physical environment. Both *mountain* and *landscap* (the stem of landscape etc.) are also highly ranked only in steep classes (1-4) in Flickr. Perhaps reflecting the more descriptive nature of the free text in Geograph, the three terms associated with the same steep classes (1-4) in Geograph are *vallei* (the stem of valley etc.), *steep* and *slope*. In general, a very clear difference is visible between terms which are primarily found on steep slopes and those on gentle slopes (5-8) – e.g. in Geograph *park*, *farm*, *lane*, *bridg*, *centr*, *field*, *church*, *villag* etc. and in Flickr *street*, *citi*, *architectur* etc. Thus, there is clearly a preference for more anthropogenic objects on gentle slopes as opposed for more "natural" objects on steep slopes. Zooming into individual classes also reveals some interesting results. The class most likely to be associated with very flat areas (class 8) is strongly related to transport in Flickr (*railwai*, *train* and *car*) and to the term *flood* in Geograph. However, exploration of some other classes, for example class 1 (steep, convex, fine textured areas) demonstrates that the results are not always so amendable to interpretation. Here the terms associated with only such locations in Flickr are *boat*, *coast*, *monument* and *harbour* which appear paradoxical. However, since the equivalent terms in Geograph (*forest*, *coast* and *walk*) also include coast, it seems likely that this class is genuinely associated with images taken in coastal areas. An obvious question, addressed in the following section, is whether the use of coast varies in space, and if so, how this relates to geomorphological classes.

### 5.3 Variation of terms in space and across geomorphometric classes

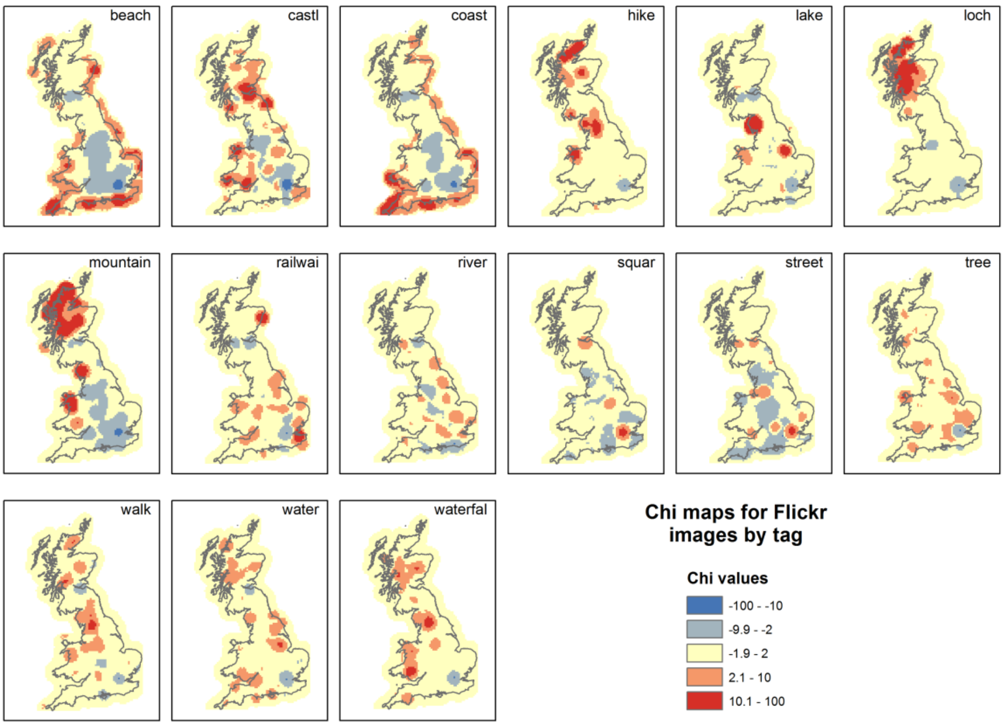



**Figure 5** χ-maps for selected terms from Flickr images, blue areas (negative values) underrepresenting selected term and red areas (positive values) overrepresenting selected term

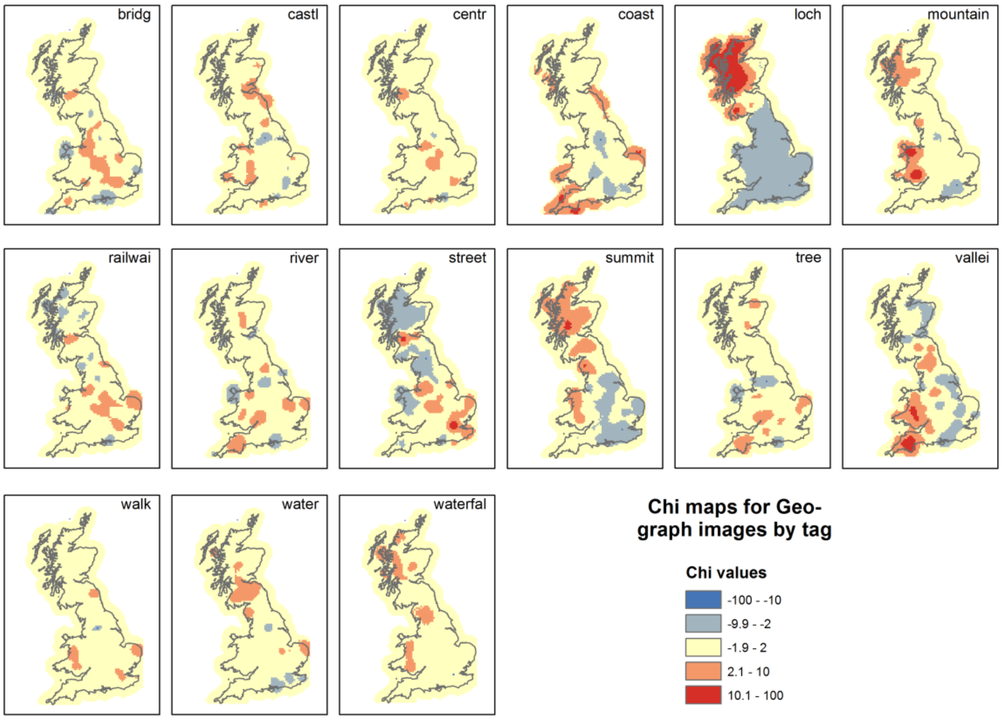



**Figure 6** χ-maps for selected terms from Geograph images, blue areas (negative values) underrepresenting selected term and red areas (positive values) overrepresenting selected term

Figures 5 and 6 show χ-maps for a selection of highly ranked terms from Flickr (Figure 5) and Geograph (Figure 6). Since the number of images in a grid cell is often small at a 90m resolution, we generated χ-maps at a 9km resolution. Effectively the red areas on the map indicate overrepresentation of a term, and the blue areas underrepresentation. It is important to note that the expected distributions were based on the actual distributions in the respective collections, and that thus, for example, the strong urban bias of Flickr is already accounted for in these maps.

In §5.2 we observed that the term *coast* was, somewhat surprisingly, associated, in both Flickr and Geograph, with class 1 (steep, convex, fine textured areas). When the corresponding χ-maps are observed, it is clear the term *coast* is not evenly distributed around Great Britain, but appears to be particularly favorably used in both collections in the southwest of England, and in Geograph in general in the south of England. This may suggest either some cultural reason for the more prominent use of *coast* in this region, or perhaps a particularly scenic or commonly photographed coast.

Examining other $\chi$-maps for Flickr a number of observations can be made. Terms such as *squar* (the stem of square etc.) and *street* are overrepresented in urban areas, such as London and Edinburgh, but generally have distributions similar to the underlying image distribution. The terms with the strongest patterns are *mountain* and *loch* (Gaelic for lake). *Mountain* is overrepresented in the Scottish Highlands, the English Lake District and North Wales, while *loch* predominates in areas where Gaelic is used in place names. *Tree* is underrepresented in London, but a zone surrounding the city has some overrepresentation, again suggesting an urban/rural transition in the types of terms used in specific areas. In Geograph, some terms are clearly seen to be geographically rather ubiquitous, for example *bridge*, *walk* and *water* are all found in most areas with relatively little variation in distribution. The strongest patterns are associated with *loch*, *summit* and *vallei* (the stem of valley etc.). *Loch* is once again strongly associated with the Scottish Highlands, while *summit* is overrepresented in areas also associated with *mountain*. *Vallei,* interestingly, is overrepresented in Wales and southwest England.

Overall, $\chi$-maps provide an effective and powerful way to explore the overrepresentation of terms. They allow us both to explore how terms are used in space, and also to identify potential problems which may relate to bias. For example, the term *lake* is overrepresented not only in the Lake District and North Wales, as might be expected, but also in an area of eastern England where a topographic map does not suggest an obvious reason for its use.

Table 3 shows the mean value of the $\chi$-statistics for each geomorphometric class, together with its standard deviation. This provides another way of exploring the relationships illustrated in Table 2, calculated at a different resolution and using the distribution of images and not their ranking (other than in the selection of the images analyzed). Thus, for example, *mountain* which was only ranked within the top 20 terms in classes 2 and 4 (steep slope, high/ low convexity, coarse texture) for Geograph is overrepresented for all four steep slope classes, and underrepresented for all four gentle slope classes. *Coast*, which was strongly associated with class 1 (steep, convex, fine textured areas), has low mean values of $\chi$ overall ($-1.0 \leq \chi \leq 1.0$) for both Geograph and Flickr, suggesting that although many images of coast are taken this class, the relationship is not a general one. By contrast, terms such as *hike* in Flickr and *summit* in Geograph appear to show clear relationships with, in this case, steep slopes (class 1-4) which are relatively general.

**Table 3** Mean and standard deviations of chi values per geomorphometric class for terms illustrated in Figures 5 (Flickr (a)) and 6 (Geograph (b)) calculated at a resolution of 9km

| | beach | castl | coast | hike | lake | loch | mountain | railwai |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.57±4.12 | 1.46±4.28 | 0.72±3.93 | 1.27±4.38 | 1.96±13.17 | 2.05±8.49 | 4.3±12.23 | -0.11±2.08 |
| 2 | 0.13±3.29 | 1.84±3.7 | 0.32±3.45 | 3.87±6.91 | 1.63±11.88 | 6.4±12.19 | 9.3±14.26 | -0.13±2.18 |
| 3 | 0.43±3.88 | 2.37±4.59 | 0.09±2.61 | 2.85±6.21 | 2.61±13.45 | 3.08±8.93 | 8.56±16.54 | 0.16±2.48 |
| 4 | -0.35±2.23 | 1.51±3.34 | -0.41±1.82 | 5.04±7.25 | 1.63±11.06 | 9.54±14.18 | 13.12±15.83 | -0.32±1.84 |
| 5 | -0.13±4.87 | 0.67±5.17 | 0.12±4.46 | 0.24±3.01 | -0.08±6.37 | -0.34±3.59 | -0.06±7.45 | 0.17±3.42 |
| 6 | -0.18±3.58 | 0.88±4.34 | 0.18±3.55 | 1.51±6.05 | -0.22±4.69 | 0.67±6.19 | 1.24±8.97 | 0.9±3.56 |
| 7 | -0.14±5.18 | 0.38±4.52 | -0.29±3.97 | 0.05±3.07 | 0.41±7.88 | 0.06±6.21 | -0.4±7.46 | 0.25±2.8 |
| 8 | -0.28±4.03 | 0.84±4.65 | -0.23±3.4 | 0.29±3.9 | 0.34±5.83 | 0.5±7 | 0.48±8.77 | 1.02±3.6 |
| | **river** | **squar** | **street** | **tree** | **walk** | **water** | **waterfal** | |
| 1 | -0.25±1.41 | -0.91±1.58 | -1.12±1.89 | 0.39±1.44 | 0.93±2.7 | 0.8±1.86 | 1.62±3.5 | |
| 2 | 0.03±1.21 | -1.18±0.61 | -1.18±1.32 | 0.49±1.39 | 2.07±3.41 | 1.22±1.78 | 2.59±4.12 | |
| 3 | -0.35±1.4 | -0.96±1.33 | -1.3±1.5 | 0.59±1.61 | 1.14±2.96 | 0.96±1.81 | 1.92±3.53 | |
| 4 | -0.21±1.12 | -1.17±0.54 | -1.27±1.29 | 0.47±1.38 | 2.15±3.57 | 1.54±2.01 | 2.94±4.17 | |
| 5 | 0.01±1.97 | -0.54±2.48 | -0.6±2.89 | 0.46±1.91 | 0.29±2.37 | 0.21±2.06 | 0.33±2.8 | |
| 6 | 0.23±1.8 | -0.75±1.84 | -0.67±2.07 | 0.5±1.85 | 0.59±2.91 | 0.49±2.06 | 0.36±2.86 | |
| 7 | 0.1±1.92 | -0.43±2.52 | -0.67±2.77 | 0.62±2.24 | -0.08±1.98 | 0.35±2.41 | 0.02±2.21 | |
| 8 | 0.71±2.36 | -0.82±2.08 | -0.55±2.17 | 0.89±2.18 | 0.03±2.07 | 0.7±2.58 | -0.17±1.88 | |

(a)

| | bridg | castl | centr | coast | loch | mountain | railwai | river |
|---|---|---|---|---|---|---|---|---|
| 1 | -0.16±1.43 | 0.17±1.42 | -0.15±1.1 | 0.01±2.35 | 1.79±7.47 | 1.1±3.55 | -0.61±1.31 | 0.33±1.88 |
| 2 | -0.19±1.15 | 0.09±1.24 | -0.43±1.04 | -0.33±2.11 | 5.46±9.06 | 1.83±4.08 | -0.85±1.18 | 0.44±1.57 |
| 3 | -0.27±1.41 | 0.23±1.37 | -0.22±1.07 | -0.4±1.65 | 3.18±8.75 | 1.62±3.85 | -0.6±1.48 | 0.07±1.38 |
| 4 | -0.16±1.1 | -0.12±1.26 | -0.42±1.07 | -0.71±1.05 | 8.28±9.64 | 2.27±3.37 | -1.05±1.22 | 0.36±1.2 |
| 5 | 0.38±1.91 | -0.04±1.54 | 0.36±1.36 | -0.15±2.44 | -1.08±4.87 | -0.35±2.66 | 0.34±1.87 | 0.14±1.79 |
| 6 | 0.27±1.52 | 0.08±1.42 | -0.07±1.35 | -0.22±2.02 | -0.25±5.41 | -0.43±2.64 | 0.2±1.87 | 0.26±1.87 |
| 7 | 0.49±1.9 | 0.08±1.43 | 0.49±1.52 | -0.54±1.83 | -1.06±4.6 | -0.56±2.08 | 0.43±1.81 | 0.21±1.7 |
| 8 | 0.53±1.84 | 0.09±1.53 | 0.02±1.29 | -0.42±1.69 | -0.96±4.85 | -0.61±2.09 | 0.49±1.89 | 0.49±1.88 |
| | **street** | **summit** | **tree** | **Valley** | **walk** | **water** | **waterfal** | |
| 1 | -1.12±2.21 | 1.74±3.35 | 0.41±1.81 | 2.05±4.41 | 0.28±1.2 | 0.68±1.88 | 0.58±1.72 | |
| 2 | -1.7±1.94 | 3.06±3.54 | 0.1±1.51 | 0.94±3.71 | 0.13±0.95 | 0.71±1.41 | 1.39±1.97 | |
| 3 | -1.23±2.13 | 2.32±3.6 | 0.09±1.55 | 0.77±3.44 | 0.24±1.05 | 0.49±1.54 | 0.86±1.9 | |
| 4 | -1.74±1.99 | 4.05±3.94 | -0.14±1.26 | -0.36±2.48 | 0.25±0.93 | 0.71±1.07 | 1.69±2.06 | |
| 5 | 0.64±3.31 | -0.57±2.59 | 0.32±1.76 | 0.5±3.74 | 0.05±1.12 | 0±1.49 | -0.18±1.38 | |
| 6 | 0.13±2.73 | -0.5±2.27 | 0.15±1.73 | 0±3.23 | -0.08±1.12 | 0.07±1.48 | -0.16±1.3 | |
| 7 | 0.81±3.32 | -0.78±2.22 | 0.41±1.45 | -0.45±2.82 | -0.03±1.11 | -0.03±1.47 | -0.32±1.15 | |
| 8 | 0.52±2.6 | -0.84±2.36 | 0.22±1.58 | -0.96±2.07 | -0.04±1.1 | 0.01±1.43 | -0.41±0.96 | |

(b)

| | | | |
|---|---|---|---|
| 1 | steep slope, high convexity, fine texture | 5 | gentle slope, high convexity, fine texture |
| 2 | steep slope, high convexity, coarse texture | 6 | gentle slope, high convexity, coarse texture |
| 3 | steep slope, low convexity, fine texture | 7 | gentle slope, low convexity, fine texture |
| 4 | steep slope, low convexity, coarse texture | 8 | gentle slope, low convexity, coarse texture |

## 6 Concluding discussion

In setting out the introduction to this work we proposed three broad questions, which we wished to explore in the context of linking quantitative geomorphometric measures to terms used in user generated content. Here, we briefly return to these questions in the context of the results of our work. Perhaps the most important point to make is that there are no silver bullets for analysis of this type. A wide range of methods exist and could doubtless also be developed, but when we wish to explore the meanings of terms applied and their geographic variation, there is no substitute for exploring the results in detail, with a good geographic knowledge of the region in question. Nonetheless, we believe that the methods and results presented here are useful and, with care, generalisable and suggest ways in which new sources of data can be used to explore pressing questions in GIScience.

### 6.1 Which methods are required to explore the relationship between everyday language descriptions of landforms and quantitative geomorphometric classifications?

In this work we have combined a range of methods, developed by other authors and ourselves to explore the linkages between descriptions of landforms and geomorphometric classifications. We knowingly chose an unsupervised classification scheme, since such a method makes no requirements on the naming of classes, is widely applied and in the case of the classification by Iwahashi and Pike (2007) is widely used in geomorphometry and uses terrain attributes which are relatively straightforward to perceive and thus might also be reflected in images. We adapted methods from Rattenbury and Naaman (2009) to rank terms, which consider not only term frequency, but also the distribution of terms in space and user contributions. Such an approach is essential if the effects of bias are to be minimized, since in previous work we have found that very prominent terms can be introduced by small numbers of users (Purves et al. 2011). We adopted the term lists generated in previous work (Purves et al., 2011) from Flickr and Geograph for our term analysis, thus giving us access to a classification of terms. This has undoubted weaknesses, not least since both the actual terms and their types are constrained by this classification, but the advantage that the work is repeatable and comparable to previous studies. Finally, we compared terms using ranked lists, and also generated a number of representations of class membership, for example in the form of highly ranked terms per class or $\chi$-maps indicating over and underrepresentation. Since these methods were also carried out at high (90m) and low (9km) resolutions, we were also able to compare the influence of resolution on the results. Overall, the methods allowed us to explore a number of aspects of the use of UGC and its relationship with geomorphometric classes in detail, and we believe provide an appropriate and useful approach to the data.

### 6.2 Can individual geomorphometric classes be related to terms used in user generated content?

Perhaps the most obvious result is, at least at first glance, disappointing. Relatively few of the terms listed in Table 2 are explicitly related to geomorphometry, and it could be argued that homogenous regions generated through any methods would result in some interesting patterns. Nonetheless, terms such as hill, mountain, valley and glen are all clearly related to geomorphometry demonstrating a clear link between everyday terms found in UGC and an unsupervised classification of a DEM.  Seemingly relatively trivial results (for example the relationship of *steep* to steep slopes (classes 1-4) are of interest, since they demonstrate that a simple unsupervised method using mean values of slope appears to approach everyday perceptions of what steep slopes are. Equally, the most highly ranked terms, especially in Geograph, were typically elements, which accords with Smith and Mark's (2003: 419) argument that "the naïve or folk based disciplines appear to work exclusively – or at least overwhelmingly … with object-based representations of reality". However, it is important to note that the list of terms available may also have biased this result, though it also appears to be supported by Rorissa's (2010) observations on the use of basic levels in labelling images. The nature of the terms used in both collections varied, especially at the level of qualities and activities. Although these differences may be partly due to different term lists, some of the differences appear to represent real differences in the descriptions. Thus, although qualities are somewhat less common in Flickr (Purves et al., 2011) they are nonetheless much more common in our list of highly ranked terms (Table 1), while highly ranked Geograph terms are dominated by elements.

### 6.3 How does the use of everyday language vary across space and geomorphometric classes?

The use of $\chi$-maps based on the underlying distribution of images in a collection allowed us to explore how the use of terms varied with respect to the collection itself. A number of terms show very clear patterns in space, for example, *mountain* or *loch*. These patterns are in some cases clearly related to geomorphometric classes and in turn relief, and in other cases may be the result of some, as yet unidentified bias or cultural differences (Mark and Turk, 2003). Thus, *loch* is a Gaelic term, and associated not only with steep slopes, but also Gaelic speaking regions. The overrepresentation of *coast* in particular areas and for particular geomorphometric classes in both collections, suggest a real difference in the description of coastal areas which is worthy of further examination, for example through studies of co-occurrence or enthnophysiographic methods.

## 6.4 Concluding remarks and outlook

In this paper we set out to explore the relationship between UGC and geomorphometry. We believe that the methods set out have something to offer if we wish to come closer to “folk conceptualizations” of space which relate to the naïve geography proposed by Egenhofer and Mark (1995) as a key need for the development of GIS which more closely matches lay expectations. Our methods show that some terms have clear links to particular geomorphometric classes, and in particular to steep and gentle slopes as identified by an unsupervised classification. Furthermore, differences between two collections of UGC are apparent, with, for example, a clear preference in a more “geographically explicit” collection for elements or objects which might be represented on a map. Such results suggest that our methods have something to offer in the field of ethnophysiography, and that exploring how landforms are described in different locations through UGC may be a useful complement at a broad scale to the finer grained investigations made through ethnographic approaches.

Our long term aim is to be able to link everyday terms to geomorphometric classifications and thus be able to, for example, automatically generate indexing terms for georeferenced information based on widely available geographic data such as DEMs. However, although interesting associations are apparent in the use of terms and geomorphometry investigated in this paper, highly ranked explicitly geomorphometric terms are relatively uncommon. It may be that by investigating lower ranked terms more references to everyday landforms will be found, though the frequency of use of many such terms is likely to be too low to explore spatial patterns. This is a general problem with UGC which might be addressed by:

i) fusion of multiple collections of UGC, especially those likely to explicitly describe landforms (e.g. descriptions of mountaineering routes or hiking holidays);

ii) investigation of terms typically used to query information services, particularly those which deal with landforms; and

iii) text mining methods to link terms used by domain experts to those in everyday use.

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