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RESEARCH ARTICLE

The influence of landscape variation on landform categorization

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Abstract: This paper compares the landform vocabularies of residents from two regions in Portugal. Participants described both their own and the other, less familiar landscapes in response to video footage of the regions. The results indicate that participants used more detailed vocabularies to describe the known landscape compared to the less familiar study site, with detail triggered by individual place recognition. A relationship between landform lexica content and landscape type was observed in the relative placement of detail within each vocabulary. The observed drivers of categorization were the salient features of the landscape (elevation and land cover) and utilitarian motivations (land use, context, and familiarity). The results offer support to the notion of non-universality in geographic object categorization.

Keywords: cognitive geography, ethnophysiography, geographic information systems, GIS, landform categorization, landform terms, landscapes

1 Introduction

The conceptualization of objects or phenomena in a geographic information system (GIS) is often poorly considered or understood. This paper presents exploratory research results that contribute to the understanding of geographic object conceptualization through an investigation of landscape categorization variability.

Conceptualization is the process of abstracting the real world into the concepts we use to refer to what is there [16]. Defining the extent of concept non-universality and limitations using empirical studies is important for the development of geographic domain ontologies [20, 32]. Examining variations in concept formation and use is one approach towards better defining the conceptual space each concept occupies, and the locations and contexts within which the concept is relevant.

The categories (or objects) in question in this study are landforms, which are used to describe the features of the earth's surface—mountain, valley, and hill, for example. Landform conceptualization is more subject to influence by language, culture, the environment, and individual perspectives than other domains, due to the continuity of the (Earth's) surface from which categories must be extracted [23]. Landform concept definition is therefore a challenging component of geographic domain formalization.

Research on landform conceptualization and terminology has been conducted with a range of approaches. Within geographic information science, Pires [28] compared Portuguese and American participants' responses to "list a natural earth formation." The question originally formed part of a Battig and Montague geographic category norms survey, given to university students. Pires finds that four of the top five responses are common to both country groups, but concludes that the differences in the top ten responses are of most interest as they reflect the presence and prominence of different types of geographic entities in each country: canyon, cliff, and cave in America and water, sea, and plain in Portugal.

The study presented here follows a similarly comparative approach although in contrast to Pires' work, which was designed to observe the influences of cultural context, the focus lies on the sensitivity of landform vocabularies to localized intra-country landscape variation.

A related body of research is that of ethnophysiography which is concerned with the "categories that people use when conceptualizing and communicating about the landscape" [22]. It is distinct from the related sciences of ethnobiology, ethnozoology, and ethnoecology due to the complex influences driving landform conceptualization compared to those involved in natural kind categorization. Mark and Turk describe the differences between the European-Australian conceptualization of topographic features and that of an Indigenous-Australian group, the Yindjibarndi. This is a cross-cultural comparison of landform vocabularies and concepts within a single region.

The current study applies many of the field methods described by Mark and Turk [22], such as the use of images and participant interviews. The research does not, however, aim for detailed and complete geographic vocabulary elicitation of two groups at one location; rather the work compares colloquial landform terminology between two culturally similar groups residing in different locations. The elicitation methods are designed to capture the landform terms participants use in day-to-day life, as this is where landscape-driven variability will arise.

Geographic vocabularies have been explored in cross-cultural comparisons by linguists Burenhult and Levinson [6, 21]. The linguistic approach focuses on determining the mechanisms driving the formation of geographic concepts and their relative contributions. Burenhult and Levinson [6] identify three main drivers in the formation of landscape categories: 1) "perceptual or cognitive salience"; 2) the "affordances ... or ... constraints [the categories] impose on human activities"; and 3) the presence of "conceptual templates and cultural beliefs."

The current study contributes to the exploration of relative driver contributions using observations of the categorization drivers referenced in participant responses. The adopted approach includes an assessment of landform terminology with respect to place familiarity, giving a new perspective to categorization driver research.

In this paper the effects of landscape type variation and landscape familiarity on rural residents' landform conceptualizations within a single country and language are explored and some comment is made about the observed drivers of categorization. The study was designed to consider the effects of landscape on the categorization process, separate from cultural and linguistic influences, which have been the focus of previous research in the area. Although language and cultural practices are not separate from landscapes and are not constant across a country, for the purposes of this study the influence of these variations and inter-relationships have been assumed to be minimal. An additional component of the study is a comparison of the participant landform categorizations to a simple automated elevation-based landform classification.

The questions posed to drive the research are:

1. Do people identify categorizations with greater degrees of detail in landscapes they are very familiar with, compared to lesser-known landscapes?
2. Is there any evidence suggesting that landscape categories are developed according to utilitarian factors more than salient features?
3. How do the categories people identify compare with a simple elevation-based automated landform classification?

The work complements previous research by aforementioned authors and makes a contribution towards the interoperability of geographic information processing across cultural, linguistic, and domain boundaries [19]. The paper is organized into sections describing the study sites, the methods used, and results obtained, discussed with respect to each research question.

2 Study sites

Two locations with contrasting landscape types were chosen as study sites. Figure 1 shows typical views of each study site. These regions were observed, photographed, and filmed during five field trips. The first site is situated in the Lousã and Góis *concelhos* of the Pinhal Interior Norte region of Portugal and encompasses the town of Lousã as well as several villages (Candal, Talasnal, Aigra Nova, and Aigra Velha) in the Serra da Lousã mountain range (see Figure 2). The range rises steeply to the south-east of Lousã town and has an elevation range of 200 to 1204m. The schist and granite mountains are covered in natural (various oak species and chestnuts) and plantation (pine and eucalyptus) forests, and heath lands at the higher altitudes; great vegetation variability is due to the abrupt changes in elevation and climatic conditions throughout the region [7].

The second study site covers a portion of the Odemira *concelho* which lies in the Alentejo Litoral region in the south of Portugal (see Figure 2). Participants from this study area live in a number of different towns: Odemira, São Luís, Boavista dos Pinheiros, Relíquias, Cabo Sadão, Zambujeira do Mar, São Teotónio, Azenha do Mar, and Moitinhas Sabóia. The area consists largely of lowlands and small undulating hills with a number of higher elevation ranges (up to 341m). The region is characterized by cork oak and holm oak trees (*montado* regions) interspersed with cultivated and grazing land (polyculture). There are also areas of eucalyptus and pine plantations [2, 8].

Study site 1 Study site 2

Figure 1: Photographs of study site 1 (Serra da Lousã) and study site 2 (Odemira).

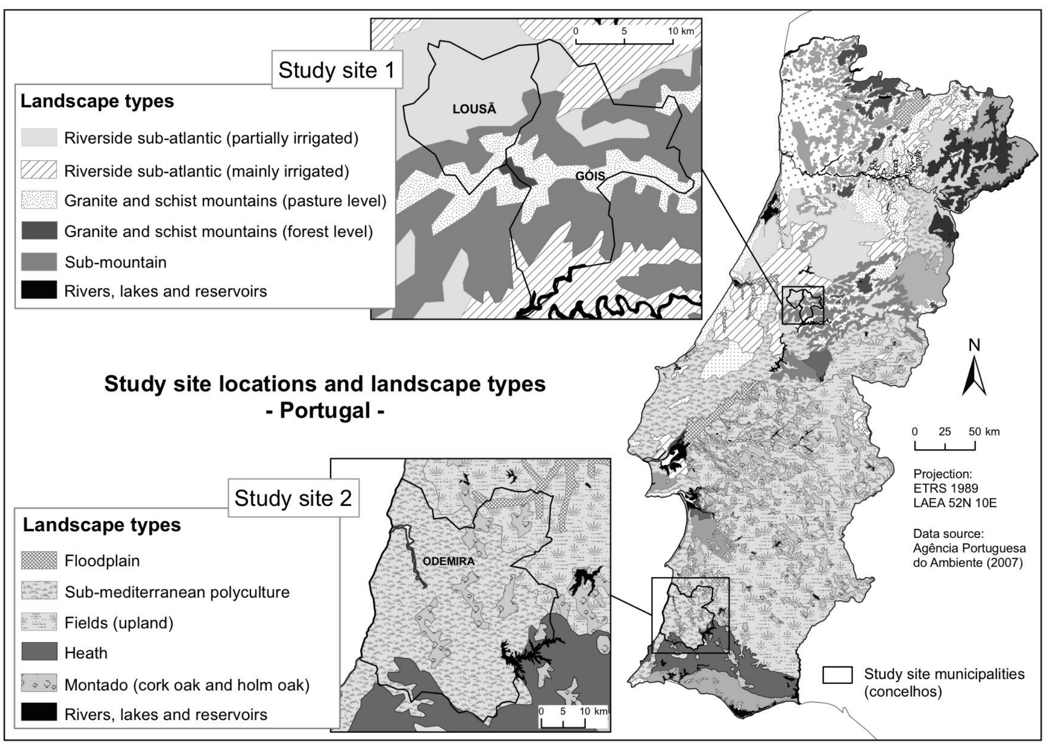

Figure 2: Study site location map.

3 Research methods

The research methods applied in this study are taken from both social and computational sciences. This cross-disciplinary approach gives rise to two different datasets, both expressing landform category information: participant landform categorizations and digital elevation model (DEM)-derived landform classifications. The conceptual framework, and data collection and analysis methodologies are presented in Sections 3.1, 3.2, and 3.3.

3.1 Conceptual framework

A simple conceptual model was designed to approach the research aims of this study. The primary component of the model comprises the landform categorizations given by participants from the two study sites. The secondary component consists of the automated landform classification of each site, as derived from a DEM. The data extracted from participant responses is compared between the two study sites, as well as against the DEM classification. The first of the research questions is addressed with a quantitative exploratory analysis, while the remaining two are presented descriptively. Additional analysis of the participant responses and extracted data is discussed where relevant. Figure 3 shows the steps of the methodology in detail.

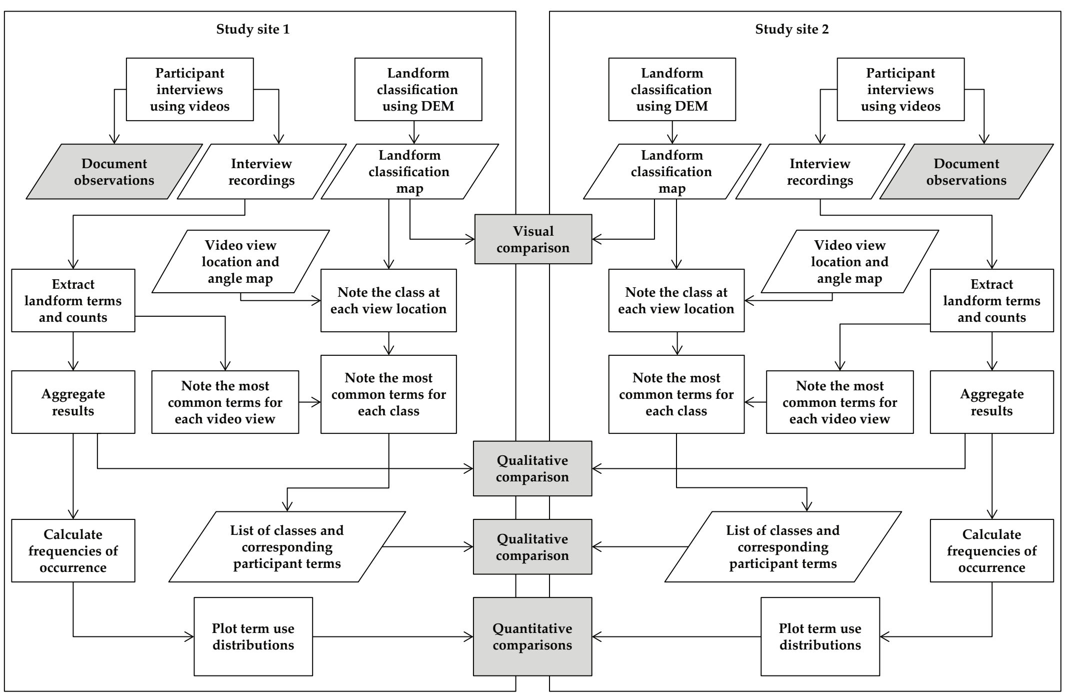

Figure 3: Research methodology.

3.2 Participant landform categorization

3.2.1 Video elicitation

The first component of the research involved interviewing participants from both study sites, using video-elicitation techniques. The purpose of these interviews was to gather data about the landform terms and place names residents use to describe both their local landscape, and the less familiar landscape of the other study site.

Photo- or video-elicitation is the method of conducting interviews based on participants' descriptions of photographs (or video) or the use of images as prompts. Such interview methods have been used by ethnophysiographers and linguists in their work on understanding the language used to describe landscapes, and are well documented in [5] and [36]. The method was also used by Surová and Pinto-Correia [35] in their study of landscape perceptions and preferences in Portugal. For the purposes of this study video was considered a more useful medium; it allows for a sense of movement through the landscape and a continuous view of a wider scene. This has the benefit of giving the viewer a greater sense of perspective, scale, and context.

A range of common landscape features in each study site were filmed. Locations with uninterrupted wide views across the landscape were chosen, and short (approximately 30 second) pan shots were captured. Care was taken to maintain a similar distance from the major landforms in order to retain a consistent scale of view. Five views from each site were used to form a four-minute video and photograph montage of that region.

3.2.2 Interviews

Interview participants were selected according to purposeful criterion sampling; a qualitative research method outlined in [27]. The requirement was that the person had lived in the study area for more than five years, with greater preference given to people who had lived their whole lives in the region. No limitations were placed on age, occupation, or sex.

A total of 10 and 11 participants were interviewed in the Lousã and Odemira study sites, respectively. The small sample size was considered sufficient, given the exploratory and descriptive nature of the study. The usefulness of low count numerical data combined with qualitative observations, for exploratory work, is recognized in usability testing research [26].

The interviews consisted of two parts. Firstly, the purpose and format of the interview was outlined and interviewees watched an introduction video, which helped explain what was required of them. Secondly, two requests were made of the interviewees: they were asked 1) to watch the two videos of the study sites and name the landforms they could identify; and 2) to give the place names of any locations they recognized. They were then free to describe the landforms of their choosing with little prompting or questioning. The intention was to capture participants' unbiased, natural ways of talking about landscapes. Participants were not informed of the study site locations prior to watching the videos. They were also asked to watch the video of the unfamiliar site before that of the study area they live in.

The interviews were conducted in people's homes, workplaces, and study places, and, where possible, alone. The interviews were conducted in Portuguese and recorded using CamStudio software.

3.2.3 Data extraction and aggregation

With the aid of translators the interview recordings were studied, and landform terms and place names extracted. A systematic approach was used to record this information: each of the major landforms shown in the videos (named by at least one participant) was numbered and the term used by each participant was recorded against that number. This allowed for counts of the number of terms used by each participant as well as the number of people who used a certain term. The resultant dataset is nominal discrete primary data with a sample size too low to permit the use of statistical significance tests.

A list of 58 distinct landform terms was compiled and later aggregated into 18 meaningful categories (or groups of terms). Univariate descriptive analysis methods were used to explore the data, including the computation of category distribution graphs using category frequencies of occurrence [4] (see Section 4.1).

During the aggregation process some of the terms formed their own categories (because they were particularly distinct and common), while others were aggregated with similar terms under a category name (e.g., "slopes" or "hills"). The category names are in English, except the single term categories which have been left in Portuguese in accordance with the aim of minimal translation. Rough translations of the remaining Portuguese terms are listed in Table 3, if required.

Due to frequent references to water features and water bodies, despite there being no visible water in the videos shown to participants, these have been included as landforms. Descriptions of land use were included only when given as a part of the landform term, for the purpose of differentiating between similar landforms.

3.2.4 Analysis

In response to the first research question ("Do people identify categorizations with greater degrees of detail in landscapes they are very familiar with, compared to lesser-known landscapes?") an assessment of the effects of landscape familiarity was made at two different scales. The first level was at the scale of the study site, whereby the number of terms used by participants in descriptions of their own study site (the landscape in which they live) is compared to the number of terms used in their description of the other study site. At a smaller scale, the number of places recognized (indicated by providing an accurate place name for a view in the video) was compared to the number of terms used in the landform description of that study site. These comparisons were made using term counts aggregated according to participant groups: Odemira participants and Lousã participants. The results of this analysis are presented in Section 4.1.2

The second research question, regarding the relative contributions of categorization drivers, was analyzed using observations of participants and collated interview content. This qualitative analysis is largely based on the authors' interview records and descriptive details noted during interview translation. The results of this analysis are presented in Section 4.2

Aside from responses to the research questions, the quantitative data analysis yielded additional avenues of exploration. The analysis of an apparent connection between landscape type and landform vocabulary involved ordering the term category frequencies of occurrence from most to least frequently used by each participant group. The results of this analysis are presented in Section 4.1.1.

Examination of the relative frequencies of term use by all participants, ordered from most to least used, yielded a dataset which could be compared to the results of the category norms research of Pires [28]. The results of the comparison are presented in Section 4.1.3.

3.3 Digital elevation model (DEM) landform classification

The second approach to the research involved a deterministic landform classification of the study areas using a digital elevation model (DEM). The classification provides landform classes against which to compare participants' landform categorizations, as posed in the third research question: how do the categories people identify compare with a simple elevation-based automated landform classification? Smith and Mark [33] suggest that elevation-based automated landscape classifications may be useful in determining categorization drivers. However, the DEM classification versus participant categorization presented in this paper does not make a contribution to that discussion. Rather it provides some assessment of the applicability of the selected method as a tool in categorization driver investigation.

The implemented classification method is based on a macro landform classification system developed by geographer Edward Hammond in the 1950s and 60s [11]. It has since been modified into a deterministic analysis, which can be computed using elevation data and performed in a GIS [10, 11]. More recently a step-by-step approach to the pixel-based analysis using ArcGIS tools was published [25]. This approach, with corrections published by Drescher and Frey [12], was followed here.

Given the purpose of the automated classification, the chosen method was considered sufficient and exploration of optimal techniques was considered beyond the scope of the study. The authors acknowledge that a pixel-based method is by no means ideal for deriving an accurate landform classification. The application of object-based methods [30, 34] or multi-scaled morphometry approaches [9, 14] may be considered in future developments of this work.

3.3.1 Implementation

The landform classification was performed using 30 meter pixel ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) DEM datasets. The classification involved the application of thresholds to slope, relief, and profile parameters to form generalized macro scale landform types, achieved using the ArcGIS model builder function and ArcInfo toolbox. The result is a map with a subset of the 24 meaningful landform classes described in [25].

The analysis is split into three sub-sections, the results from which are then combined to form: landform type = slope + relief + profile.

Slope The slope layer gives the percentage of near-level land for each pixel (which is the value calculated for a 20 pixel radius circular neighborhood and a near-level threshold of 8% slope) split into four classes (Table 1).

Relief The relief layer gives the change in elevation for each pixel, based on the maximum and minimum elevation within a 20 pixel radius circular neighborhood. Morgan and Lesh

[25] defined the relief classes with intervals rounded to the nearest 10 meters. However, Hammond's original relief classes [15] were used in this analysis (Table 1).

Profile The profile layer gives the percentage of near-level ground in upland and lowland areas of the landscape, again with a 20 pixel radius circular neighborhood. The boundary between upland and lowland is defined as the midpoint between the maximum and minimum elevation for the target pixel's neighborhood. The four profile classes are shown in Table 1.

Sub-section	Morgan and Lesh sub-class [25]
Slope (%)	
> 0.8	400
0.5–0.8	300
0.2–0.5	200
< 0.2	100
Relief (m)	
< 30	10
30–91	20
91–152	30
152–305	40
305–914	50
> 914	60
Profile (%)	
> 75	1
50–75	2
25–50	3
< 25	4

Table 1: Class thresholds for landform classification sub-classes. There is an error in the numbering of these classes in Morgan and Lesh's [25] publication (p. 3), noted by Drescher and de Frey [12]. The corrected class numbering is shown here.

The final landform map is produced by adding together the three sub-section layers. The result is a map with 96 possible sub-classes. These classes were aggregated into the 24 meaningful super-classes developed by Dikau et al. [11] (Table 2). The 24 classes were used to produce the landform classification maps presented in Section 4.3 and are referred to as the "Morgan and Lesh landform classes."

It should be noted that the detail of the classification depends on the resolution of the DEM used [12, 15]. The 30m ASTER DEM used in this study was selected according to the Morgan and Lesh methodology (which was developed for that resolution) [25] and other successful implementations [12]. The effect of DEM resolution on the correspondence of human-identified and computed landforms presents an interesting research question for future work. Similarly, further "tuning" of the algorithm thresholds to better represent specific landscapes could change the classification output [15] and comparison with participant categorizations.

Morgan and Lesh sub-classes	Morgan and Lesh class	Description
Plains		
411–414	11	Flat or nearly flat plains
421–424	12	Smooth plains with some local relief
311–314	13	Irregular plains with some local relief
321–324	14	Irregular plains with moderate relief
Plains with hills or mountains		
431, 432, 331, 332	31	Plains with hills
441, 442, 341, 342	32	Plains with high hills
451, 452, 351, 352	33	Plains with low mountains
461, 462, 361, 362	34	Plains with high mountains
Tablelands		
433, 434, 333, 334	21	Tablelands with moderate relief
443, 444, 343, 344	22	Tablelands with considerable relief
453, 454, 353, 354	23	Tablelands with high relief
463, 464, 363, 364	24	Tablelands with very high relief
Open hills and mountains		
211–214	41	Open very low hills
221–224	42	Open low hills
231–234	43	Open moderate hills
241–244	44	Open high hills
251–254	45	Open low mountains
261–264	46	Open high mountains
Hills and mountains		
111–114	51	Very low hills
121–124	52	Low hills
131–134	53	Moderate hills
141–144	54	High hills
151–154	55	Low mountains
161–164	56	High mountains

Table 2: Aggregation of sub-classes into Morgan and Lesh landform classes, and class descriptions.

3.3.2 Data extraction and analysis

The results of the automated landform classification were compared with participant landform terms to assess how effectively the DEM-derived dataset represents the landscape. The comparison was made over a relatively large extent (given that the classes cover areas described as "plains with hills," for example), with no aim to compare at the individual landform scale. The data was extracted by plotting the video scene locations and direction of view onto a map together with the landform classification. For each of the video views the landform classes and the most commonly used participant terms were noted. The result is a list of the participant terms used to describe the corresponding DEM-derived landform classes, aggregated across multiple views and participant responses. The results are presented in Section 4.3.

4 Results and discussion

4.1 Participant categorization

Results of the quantitative data analyses are presented in this section. First, the content of each participant group's vocabulary is explored, then the effects of landscape familiarity are presented in response to the first research question, and, finally, a comparison of the results with category norms research is shown.

4.1.1 Vocabulary reflecting landscape

The quantitative results extracted from participant interviews suggest differences in landform vocabulary size and content between the two study site participant groups. The total number of distinct landform terms used by the Serra da Lousã participants was 44, while the Odemira participants used only 34 terms (see Table 4). The content of these vocabularies is noticeably different, as the two groups place their more detailed landform identification in different parts of the landscape.

The landform vocabulary content appeared to become more detailed surrounding the prominent features of the landscape in which the participants live. This is as expected, because it is useful for inhabitants of a region to become familiar with landform categories with which they can best describe and communicate aspects of their environment. Mark and Turk [22] state that "basic level categories in a language *must* be tuned to the variations in the particular environment in which a speech community lives"; a statement well supported, with respect to landform categories, by this study. This effect is best discussed with an examination of Figure 4, which shows the distribution of aggregated landform-term category use by the two participant groups in their descriptions of the two locations. The graph shows percentage frequencies of occurrence of aggregated landform term counts. Translations of Portuguese terms are given in Table 3.

Portuguese term	English term
Arriba	Cliff
Cordilheira	Mountain range
Lombo	Back
Montanha	Mountain
Monte	Hill
Perfil da montanha	Mountain profile
Planície	Plain
Rio	River
Ribeiro	Stream
Serra	Mountain or mountain range
Vale	Valley

Table 3: Portuguese term translations.

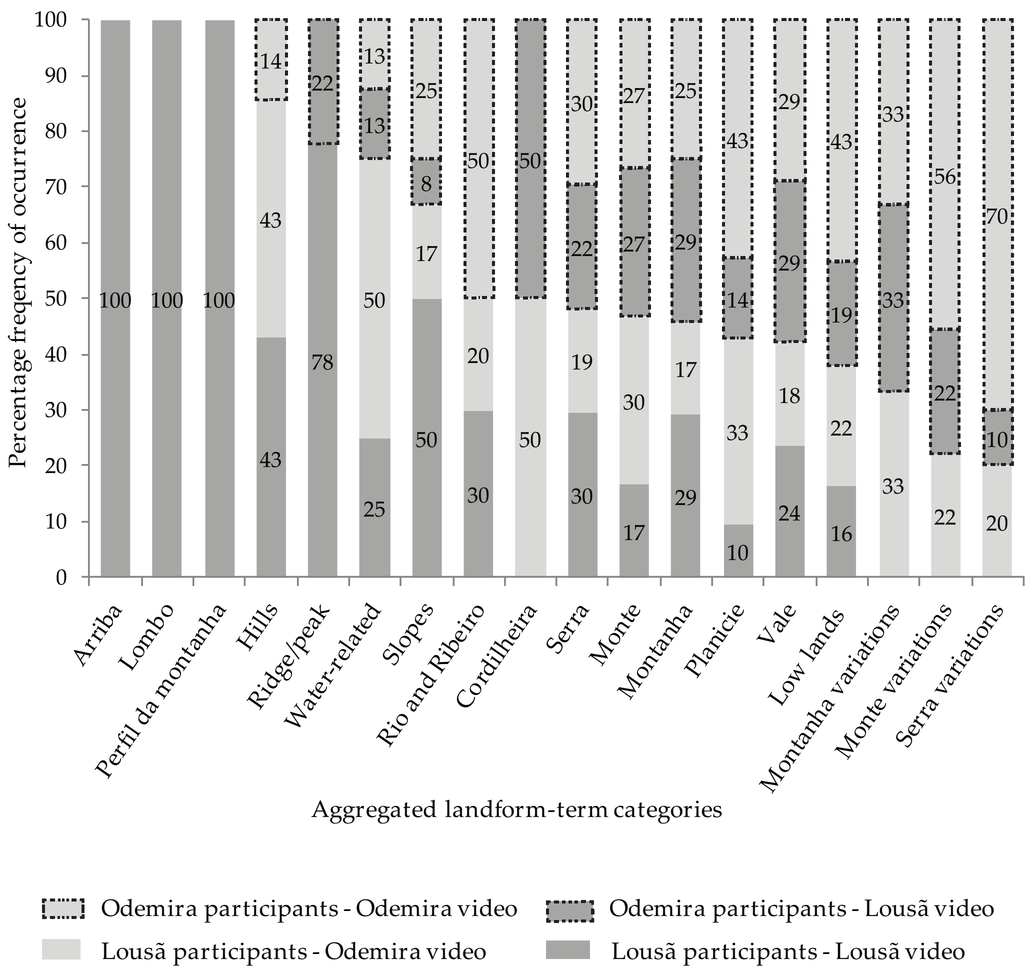

Figure 4: Landform-term category distribution between participant-video groups as percentage frequency of occurrence. The lower (non-bordered) bars represent the percentage frequency occurrence of the Lousã participants' responses to videos of each study site. The upper (bordered) bars represent the percentage frequency occurrence of the Odemira participants' responses to videos of each study site.

At the center of Figure 4 are the terms common to both groups: *serra*, *monte*, *montanha*, *planicie*, and *vale*. These terms have an approximately 50% occurrence in each participant group. The categories to the left and right of the center are used predominantly by the Lousã and Odemira participants, respectively. The most important points of this distribution are as follows:

- the Odemira participants more frequently use variations on the three base terms *serra*, *monte*, and *montanha*;
- in comparison, the Lousã participants are more likely to use various terms for hills, ridges/peaks, and slopes rather than variations on the three common terms (*serra*, *monte*, and *montanha*) to describe topographic eminences;
- the Odemira participants have a greater range of terms for lowlands (other than the common terms *planicie* and *vale*) than the Lousã participants;
- there are three terms used solely by the Lousã participants (*arriba*, *lombo*, and *perfil da montanha*); and
- the Lousã participants make more references to water-related features.

These findings directly reflect the landscapes the vocabularies are applied to. The Serra da Lousã landscape consists of many different shapes, elevations, contours, and profiles and hence inhabitants require many more terms to describe the features; *serra*, *monte*, and *montanha* are not sufficient. There is also the need for an enriched mountain landform vocabulary, hence the use of terms such as peak, ridge, and *lombo* (back). In this landscape lines of water flow are noticeable and provide clear boundaries of, or identifiers for, landforms. The Odemira landscape is less variable, consisting predominantly of plains with occasional convex eminences, which are usually of similar shape (even if not elevation). Thus the inhabitants of Odemira have a smaller landform vocabulary that makes use of descriptors such as “big,” “small,” or “smooth” to modify the common *serra*, *monte*, and *montanha* terms when needed.

The results also suggest that the wide range of landform terms in the Lousã participants’ vocabulary makes it more versatile for use in describing other landscapes. Table 4 shows that both participant groups used more landform terms to describe the video of their region (68% versus 61% and 76 % versus 53%, for Lousã and Odemira participants, respectively). However, the margin of this difference is markedly greater for the Odemira participants. This suggests that they were not able to apply their vocabulary, or that it was not sufficient for the description of the Serra da Lousã region. Conversely, the varied Lousã vocabulary appeared to be almost equally applicable to both landscape types.

	Lousã participants		Odemira participants	
	Term count	Term proportion (%)	Term count	Term proportion (%)
Lousã video	30	68	18	53
Odemira video	27	61	26	76
Total number of terms	44		34	

Table 4: Total term counts and frequencies of occurrence per participant group.

4.1.2 Effects of familiarity and place recognition

The effects of familiarity and place recognition were assessed at two levels. The first impact of familiarity was at a large landscape-type scale and takes the form of vocabulary applicability as discussed in the previous section. Participants showed that they were able to use more landform terms to describe the landscape most familiar to them. Lousã participants used 30 terms in descriptions of Lousã and 27 for descriptions of the unfamiliar

Odemira landscape. Odemira participants used 26 terms to describe Odemira and only 18 for describing the Lousã landscape (Table 4).

The next level of familiarity was that of specific place recognition. Participants were asked if they recognized the locations of the five scenes in the video of their region. A comparison of the number of scenes people recognized and the number of landform terms they used to describe the video yielded positive correlation coefficients of 0.74 and 0.55 for Odemira and Lousã participants, respectively. This suggests that place recognition—indicated by knowing a place name for the video scene location—promoted a more detailed landform categorization.

This could be due to an effect noted by Agarwal [1] in her research on the sense of place. She noted a correlation between people experiencing a sense of place and their spatial reasoning skills. She further stated that "a 'cognitive sense of place' can be operationalized as a factor of spatial knowledge, degree of familiarity and conceptualization of boundaries." Just as the conceptualization of boundaries is an integral aspect of categorization, a sense of place could similarly be a factor for landform categorization.

Observation of the way participants gave their landscape descriptions yields greater insight into the effects of place recognition. When participants recognized a place in the video, their descriptions began to follow their own understanding of landform connectivity, regardless of the video pan movement. They appeared to be referring to their previously composed mental map of the area rather than the video images in front of them. As Egenhofer and Mark [13] describe, "[w]e explore geographic space by navigating in it, and we conceptualize it from multiple views, which are put together (mentally) like a jigsaw puzzle." It is not surprising then, that a previously made puzzle is more complete and allows for a more detailed landform description than five separate views can elicit.

The effect of place recognition appeared to be equivalent to "zooming in" to the image; participants observed from different perspectives and scales, and consequently identified more boundaries. This observation supports Bian's [3] inclusion of spatial scale and boundary as factors in landscape region delineation.

Another contribution to the effect could be that participants were simply more enthusiastic when they recognized a familiar place. Surová and Pinto-Correia [35] noted in their work that using photographs of landscape scenes, which participants could easily recognize or relate to, stimulated their interest and curiosity. Certainly participants unanimously wanted to recognize the video views (often making incorrect location guesses) before progressing with their descriptions, and enjoyed recognizing scenes close to their homes.

In Montello and Golledge [24] Tim McNamara asks "Are spatial judgments easier ... from familiar views than from unfamiliar views?" and suggests that if they are it indicates that the perception and understanding of a view is orientation-dependent. The results of this study suggest this to be so, that people prefer to orientate themselves in the landscape and describe it with an egocentric relative reference frame.

The aforementioned areas of research originate from many different domains, and highlight the importance of familiarity (and place) in the study of spatial cognition. This paper makes a contribution that wider body of knowledge, from the perspective of landform conceptualization.

4.1.3 Comparison with geographic category norms research

An additional result of this study is evidence in support of geographic category norms research conducted in Portugal [28, 29]. Pires' results included a list of the top ten most commonly given examples of a natural earth formation. Four of those examples were also within the ten most common landform term categories (see Table 5) identified in this current study: *vale*, *montanha*, *planicie*, and *rio*. This suggests that the research methods of this study are successfully capturing the findings of similar studies despite the much smaller sample size.

Three of the mentioned terms (*vale*, *montanha*, *planicie*) form single term categories in the category list of Table 5. *Rio* is a part of the aggregated *rio* and *ribeiro* category. However, the term *rio* dominates the counts in this category 6:1 and hence retains its position in the top ten.

	Lousã video		Odemira video		
Landform-term category	Lousã participant (% freq.)	Odemira participant (% freq.)	Lousã participant (% freq.)	Odemira participant (% freq.)	Total (% freq.)
Vale	13	21	11	13	59
Low lands	9	13	13	19	55
Monte	7	15	15	10	47
Serra	12	12	8	10	41
Montanha	10	13	7	7	38
Planicie	3	6	11	11	31
Hills	9	0	10	2	21
Slopes	9	2	3	4	18
Ridge/peak	10	4	0	0	14
Rio and ribeiro	4	0	3	6	14
Serra variations	0	2	3	8	14
Monte variations	0	4	3	6	13
Water-related	3	2	7	1	13
Montanha variations	0	4	3	2	10
Lombo	6	0	0	0	6
Cordilheira	0	2	2	0	4
Arriba	1	0	0	0	1
Perfil da montanha	1	0	0	0	1
	100	100	100	100	400

Table 5: Aggregated landform-term category distribution within each participant group ordered from most to least common.

Another similarity between the two studies is the finding of the importance of water bodies and water-related features of the landscape. The participants of this study frequently referred to water lines, rivers, streams, and flood lands despite there being no visible water in the videos. Pires [28] also noted the frequent reference to water bodies by Portuguese participants, as compared to their American counterparts. Smith and Mark [31] explain the universal fact that water "is an especially distinctive substance that is critical to life" and Pires suggests that this is particularly well recognized by Portuguese people.

4.2 Categorization drivers

4.2.1 Multiple drivers

Observations of participant landform descriptions suggest there are multiple drivers for categorization. These influences fall broadly into two types: salient perceptual features of the landscape, and landscape affordance or utilitarian motivations. These constitute two of the three drivers described by Burenhult and Levinson [6] and Levinson [20], the third being cultural and linguistic systems of a community which impact landscape categorization. More specifically, the salient features referred to by participants were the shape and profile of the landforms; and the presence of water, vegetation, and other land cover types. The other influences are land use, context (such as the presence of clouds around mountain peaks), and place familiarity with corresponding use of mental maps. This second group of drivers is related to utilitarian motivations as they involve the participant's prior experience of the landscape or knowledge of how it may be used. No participant referred to only a single driver as they described the landforms and certainly no one type of driver (e.g., salient features versus utilitarian motivations) appeared more predominant than the other.

4.2.2 Water, land cover, and land use

Of the drivers mentioned above, participants most consistently referred to water, land cover, and land use. None of the participants could describe the landforms without first describing the vegetation of the area and any understanding they had of the land use. Further, the understanding of the land use and land cover was evident in the landform terms used. For example, low-lying areas were often given terms such as "cultivated plain" (*várzea*) or "floodplain" (*lezíria*) as opposed to just "plain." Water was used in two ways: to identify what could happen at a location or what the land cover is (for example, "flood plain" or "flat land subject to flooding"); and as an understanding of water as a force shaping and dividing the landscape (for example, "water lines," "river," and "basin").

The inability to separate land cover/land use and landforms suggests that the most natural way of observing and categorizing a landscape is not according to landform, but into parts more akin to the "ecotopes" described by Hunn and Meilleur [17]. These are "patches" of land defined by flexible similarity drawn from abiotic and biotic parameters. Participants more readily identified parts of the landscape by using combinations of geomorphological, biological, and affordance factors.

4.2.3 Familiarity and mental maps

The relationship between localized place recognition and the detail of the landform description given by participants was noted in Section 4.1.2. This relationship—both in the quantitative form of the correlation coefficient and the observations of participant responses—suggests that familiarity is a driver for categorization. More specifically it is the mental maps people form for familiar places that drive the identification of landform categories through associated knowledge of what happens at a place or of landform connectivity (topology).

When participants referred to their mental maps they zoomed in to the landscape, observed it from their preferred angles and perspectives, and were able to evoke the feeling of being in that place. This drove them to identify landforms that were neither clearly visible (rivers or valleys in the background) nor particularly eminent in the video image. Recognition allowed participants to satisfy their desire to be in the scene, a desire Kaplan [18] describes as the "'involvement' component" of perception. They also appeared to change their conception of the landforms from topologically separated to contiguous [31], driving the identification of more in-between landforms (such as slopes), rather than only mountains and valleys.

The observed effect of familiarity driving landform category conceptualization arises from the study site comparison approach adopted in this study. It suggests that this approach could be useful in further expansion of Levinson's [20] work surrounding categorization drivers.

4.3 Comparison of DEM classification and participants' categorization

The DEM-derived macro landform classification for each study site was produced using the methodology outlined in Section 3.3. The results are shown in Figures 5 and 6. From visual inspection the classifications both appear to characterize well the landscape variations at the classification algorithm operation scale (the macro scale). When compared to participant responses, however, it becomes apparent that in the Serra da Lousã region the topography of the landscape varies at a smaller scale than can be adequately represented by this algorithm applied to a 30m DEM, while the landforms of the Odemira region are better captured.

A direct comparison of the Morgan and Lesh landform classes for areas shown in video views, against the most common participant landform terms given for the same location, is shown in Tables 6 and 7. The classes corresponding to participant descriptions were read from the classification map using the direction of view and distance to recognizable landforms (not shown on the map) from each filming location (labeled as "view" in Figures 5 and 6). Table 7 shows a good correspondence between the participants' terms and the Morgan and Lesh classes for the Odemira region. For example, in areas classified as "31 - Plains with hills," participants gave the terms *planicie* (plain) and *monte* (hill). It is also interesting that the term *monte* was commonly used to describe landforms in classes 42 and 43 (with slope threshold <0.2 %) while it ceased to be used in classes 52, 53, and 54 where the slope threshold of the classification algorithm is higher (at 0.2–0.5%). This suggests that human cognition of slope influences landform categorization in a similar manner to the automated classification algorithm in the Odemira region.

In the Serra da Lousã region there is generally a greater variety of participant terms corresponding to each Morgan and Lesh class. For example, areas classed as "54 - High hills" have received landform terms from *vale* (valley) to *ladeira* (slope) and *cume* (mountain peak) from participants (see Table 6). The automated classification is clearly giving a more generalized representation of this landscape than that which residents perceive.

5 Conclusions

The empirical research results show landform conceptualizations can vary in response to the type of landscape participants live in, as well as the familiarity of the locations they are describing. There was evidence of multiple categorization drivers related to the salient landscape features and utilitarian understandings of the landscapes. Participant descrip-

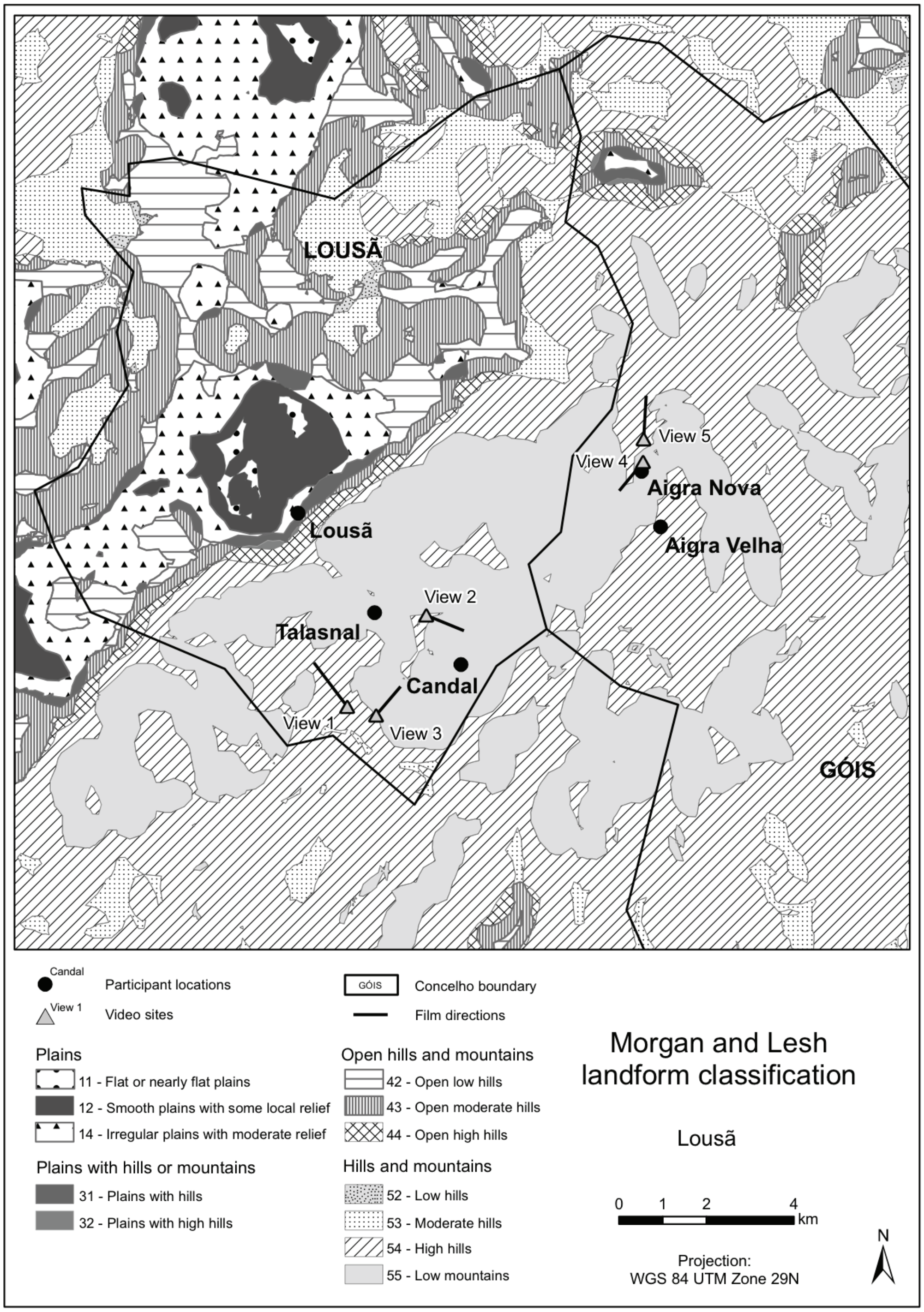

Figure 5: Lousã landform classification.

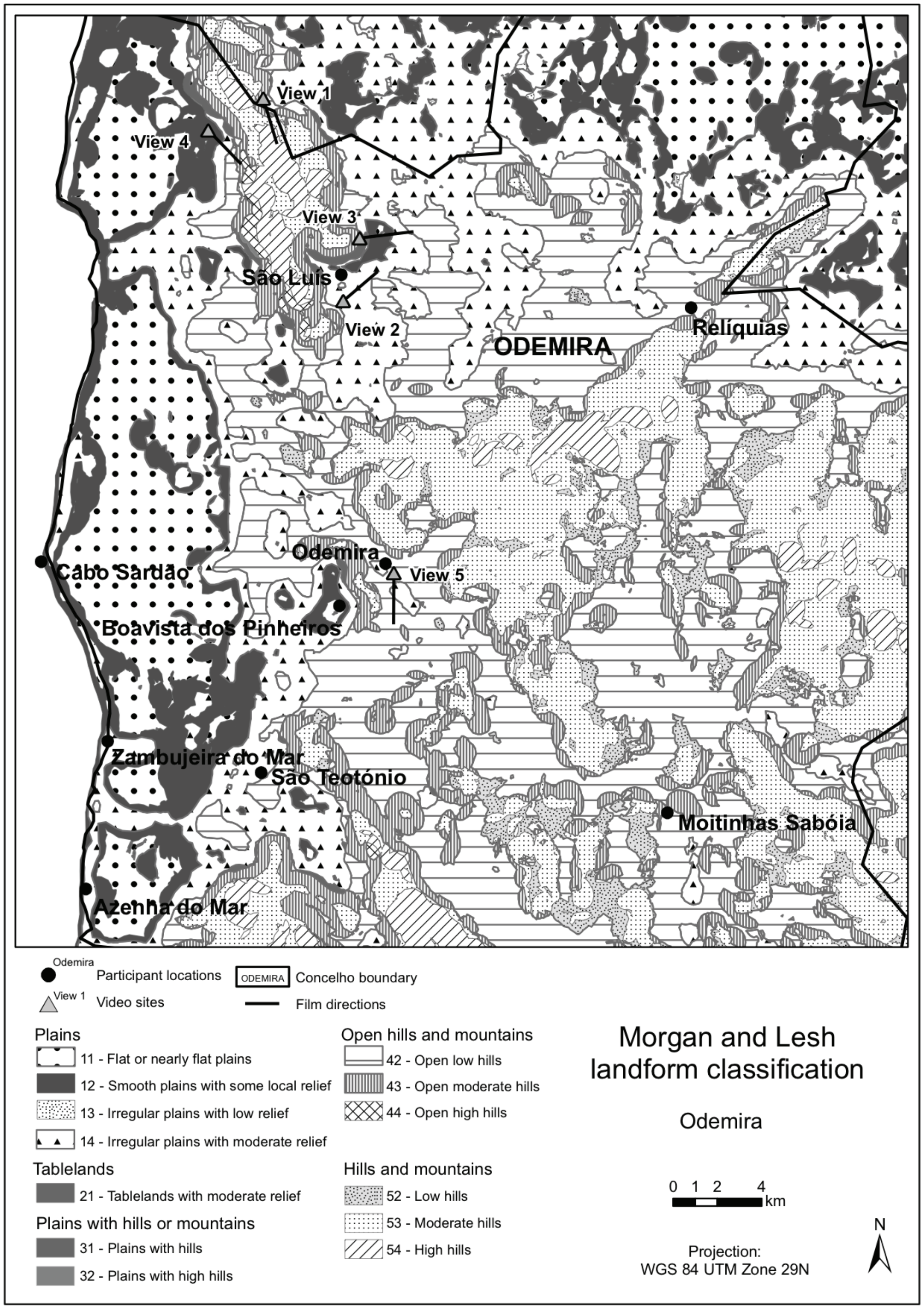

Figure 6: Odemira landform classification.

Morgan and Lesh class	Participant terms (most to least common)
14 - Irregular plains with moderate relief	Vale (valley), Montanha (mountain), Monte (hill)
43 - Open moderate hills	Vale, Montanha, Monte
53 - Moderate hills	Vale, Montanha, Monte
54 - High hills	Montanha, Serra (mountain or mountain range), Vale, Ladeira(slope), Cume (peak), Encostas abruptas (steep slope)
55 - Low mountains	Montanha, Serra, Cume/cumeada (ridge), Montes

Table 6: Morgan and Lesh landform classes with corresponding participant terms, Lousã video.

Morgan and Lesh class	Participant terms (most to least common)
12 - Smooth plains with some local relief	Planicie (plain), Planalto (plateau)
14 - Irregular plains with moderate relief	Várzea (cultivated plain), Planicie, Planalto, Monte (hill), Serra, Rio (river)
31 - Plains with hills	Planicie, Monte
42 - Open low hills	Serra, Montanha, Monte, Vale
43 - Open moderate hills	Monte, Serra, Montanha
52 - Low hills	Serra, Montanha
53 - Moderate hills	Serra, Montanha
54 - High hills	Montanha, Serra

Table 7: Morgan and Lesh landform classes with corresponding participant terms, Odemira video.

tions corresponded well to a DEM-derived macro scale landform classification at the gently undulating study site and were comparatively more detailed at the mountainous site. It is acknowledged that this result will vary with DEM resolution and algorithm parameters used.

The study supports ongoing research towards understanding the variability of geographic category conceptualization. This body of research is required for the successful development of GIS applications suited to cross-location, -discipline, and -cultural geographic knowledge representation and analysis.

If replicated, this study could be refined by considering participant age, occupation, lifestyle, and sex demographics in the data analysis. It could also be useful to use study sites of equal area. Reproductions of the study in different landscapes and languages would be interesting.

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