Cognition Based Extraction and Modeling of Topographic Eminences

Gaurav Sinha[1] and David Mark[2]

Contact Information:

1. Gaurav Sinha, PhD
Assistant Professor, Department of Geography, Ohio University, OH, USA
Ph: 001-740-593-0304
Email: sinhag@ohio.edu

2. David M. Mark, PhD
Professor, Department of Geography & Director, National Center for Geographic Information
Analysis (NCGIA), University at Buffalo, SUNY, NY, USA
Email: dmark@buffalo.edu

Keywords

Abstract

Terrain is generally stored in GIS as an elevation field, whereas human cognition of the landscape is usually object based. To address this mismatch of terrain data models, we propose object-based terrain representation, using topographic eminences, which are landforms that rise up conspicuously from the ground to visibly dominate the landscape, to illustrate our case. We propose a cognition based methodology for automated detection and delineation of eminences from DEMs. Alternative conceptualizations of the landscape can be realized by simple manipulation of intuitive parameters such as a peak's relative height and distance. Our approach delimits the extent of eminences based purely on topographic gradient and aspect, much like the delineation of ridges as watershed boundaries. Smaller eminences can be incrementally aggregated into larger cognitive wholes, providing for scale-sensitive landscape reconstruction. The ability to integrate field and object views of the landscape is essential for raster-vector data layer integration. Hence, we also discuss some database modeling and ontology development strategies to manage the extracted landforms within a geographic information system.

Integrated Field-Object Models for Terrain Representation

The earth's physical surface is modeled in most geographic information systems (GIS) as a discrete approximation to a quantitative field capturing the variation in elevation over geographic space. Field based models are useful for geophysical analysis, but are inappropriate for capturing the naïve geographic knowledge of people. The common sense perception of terrain is, predominantly, object based (Mark and Smith 2004; Smith and Mark 2003). People typically cognize and communicate about discrete landforms and conspicuous regions, such as hills or valleys, rather than elevation or its derivative fields. Most natural languages are replete with words, phrases, idioms and expressions for describing the natural landscape in terms of landform entities. Similarly, landforms serve as important cultural landmarks on every topographic map, and hence landform toponymy is an important aspect of topographic mapping. Because digital gazetteers are based on topographic maps, landforms are also important feature types in topographic gazetteers such as the Geographic Names Information System (GNIS) maintained by the U.S. Geological Survey (USGS). However, neither the process of selecting, naming, labeling map features, nor the logic underlying the typology of map features is documented properly. There are also several discrepancies between gazetteers or feature typologies in common use in USA and other countries.

Despite the need to represent macroscopic landforms in databases, object based terrain representation has been practiced mostly for lakes, rivers, streams, forests, and wetlands, etc. rather than for landforms. This is because their boundary can be mapped at the physically observable wetland-dryland interface. Most other landform types such as mountains, hills, mesas, valleys, canyons and gorges are not easily delineated due to the lack of unambiguous criteria for defining their boundaries. Continuous field data models such as the Digital Elevation Model (DEM), the Triangular Irregular Network (TIN), surface patches, and elevation contours have been used traditionally for terrain representation in GIS. This poses a significant problem for metadata models and automated terrain reasoning applications. Without appropriate object-based models of topographic features, it is impossible to build information systems that can directly represent people's naïve landform concepts. For example, the current version of the National Map (maintained by USGS) supports elevation as a data layer, but has no support for querying footprints and spatial attributes of individual landforms. Some other possible applications of object-based topographic models include landform semantic similarity assessment, landform aware wayfinding directions, and geographic information retrieval through online search engines.

Although object-based cognition of terrain appears to be a human universal (Frank 2001; Lakoff 1988), it is also true that spatial cognition including the cognition of landform entities and entity types is subject to cultural and linguistic variation (Mark and Turk 2003; Smith and Mark 1998; Montello 1995; Mark and Frank 1991; Frank and Mark 1991). Hence, the same physical surface may be reconstructed in different ways by different groups of people for different idiographic observation and reasoning contexts. In contrast, the elevation field data model is simple, and relatively independent of conceptual bias. It is better suited as the initial *data storage* model from which multiple context specific object data models can be derived. To account for multiple landform ontologies, we propose that a close link be maintained between the field and object models such that different object based reconstructions of the same landscape can be compared in geographic and conceptual space. In the last few years, researchers have begun to move beyond the traditional field-object divide, and proposed more fundamental approaches to geographic representation that blend fields and objects (Goodchild, Yuan and Cova 2007; Cova and Goodchild 2002). Similarly, we too advocate an integrated hierarchical data modeling framework that combines field, object, and network models of space. The hierarchical nature of

this framework stems from the need for an intuitive and easily customizable framework for context sensitive transitioning from lower-level, computer-oriented field models to higher-level, cognition-oriented object terrain data models.

We have implemented this framework as a prototype system for object oriented modeling of the class of landforms that are elevated above their immediate surroundings, which we refer to as *topographic eminences*. Topographic eminences form a fundamental superordinate category of landforms, including all elevated topographic landforms that rise sufficiently above their immediate surroundings to merit human attention (Sinha 2008; Mark and Sinha 2006). In this paper, we will use topographic eminences to demonstrate how our hierarchical terrain modeling framework can help in developing topographic domain ontologies. It is important to note that different approaches might be needed to model topographic entities in other superordinate domains, such as valleys.

In the following sections, we will discuss the conceptual foundations of our framework, give a brief summary of our research on flexible methods of topographic eminence delineation from DEMs, and discuss how we plan to utilize integrated raster and vector database management techniques to ensure "live" connections between object and field representations of terrain. We hope that our research will help in the development of an ontology, and implement a database query model for seamless and dynamic transitions between field and object representations of topographic features.

Computational Extraction of Topographic Eminences from Digital Elevation Data

The identification and delimitation of individual landforms from digital elevation models presents several computational and conceptual challenges. Questions such as "where is the horizontal limit or boundary of a hill?" or "where does the hillside end and where does the valley wall start?" illustrate why delineation of "attached objects" (i.e., *parts* of the earth's surface) such as landforms cannot be addressed without an element of subjective decision making. Moreover, the boundary of a landform may be different depending on what it is supposed to be (e.g., lake vs. marsh).

There has been considerable research on segmenting or classifying landscapes from rasterized terrain data (Brown, Lusch, and Duda 1998; Burrough, van Gaans, and MacMillan 2000; Fels and Matson 1996; Irvin, Ventura, and Slater 1997; MacMillan, Jones, and McNabb 2000; MacMillan and others 2004; Schmidt and Hewitt 2004; Ventura, and Irvin 2000). The basic strategy for all image classification methods has been to directly operate on pixels and assign them to one or more classes depending on whether crisp or fuzzy classification systems are used (Tso, and Mather 2001). Pixel classes have been used to delineate large sized physiographic provinces and ecological regions, and also much smaller regions such as hillslope or soil units. These landscape units are homogenous patches resulting from multivariate statistical classification, and generally not visually salient and structurally whole parts of the landscape. The segmented regions frequently nest within each other since most algorithms classify each pixel independently of another. A cognitively salient landform needs to be represented as one topologically closed unit, whereas segmentation algorithms often yield numerous similarly classified, but spatially disconnected patches. A more relevant pixel classification approach can be found in the geomorphometric literature. As discussed below, we find these more useful for eminence delineation.

A necessary condition for landform object representation and analysis is the existence of a topologically closed shape. The first step is therefore to explicitly establish the approximate extents (boundaries) of landforms. Although automated extraction for boundaries of drainage

basins and river channels has been researched for a long time (cf. O'Callaghan and Mark 1984, Jenson and Domingue 1988), there have been only occasional attempts to extract elevated landforms. In one such study, Graff and Usery (1993) extracted mounts from digital elevation models based on slope thresholds specified by photogrammetric experts. Later, Miliaresis and Argialas (1999) proposed a more complicated rule based approach that combined slope and elevation information to extract mountain objects from the planar surroundings. The limitation of these algorithms is that they cannot guarantee topologically connected "wholes without holes" since small areas may remain unclassified. Also, the heuristic nature of these algorithms makes it difficult to adapt them across terrain types and scales. Another limitation of these DEM segmentation algorithms is inability to resolve between simple and complex landforms, or support partonomic analysis.

A recently proposed research method (Chaudhry and Mackaness 2008) that utilizes nested contours to find summit regions, and then measures the vertical prominence of the summit to identify prominent eminences, partly alleviates these issues. The advantage of using contour trees to find eminences is that the technique applies equally well to all terrain types. Moreover, a single measure of peak prominence is much easier to specify to account for contextual variation than derivation of region specific multi-parameter rules. Following identification of prominent summits, the authors use Wood's (1996) scale dependent, polynomial surface method to classify each location into a morphometric class (pit, channel, pass, peak, ridge, and plane) for several geographic scales (defined as 3*3 to 51*51 pixel wide kernels centered on each location). The dominant class across all scales is selected as the final class for each location. The aggregation of similarly classified pixels yields morphologic polygons which are overlaid with summits to find footprints of summits. Chaudhry and Mackaness also determine summit hierarchies to support partonomic relationships between larger and smaller eminences. Although this method is likely to be relatively robust in varied terrain types, we are reluctant to adopt it because instead of explicitly determining eminence boundaries, the authors rely on the "emergent" method of multi-scale morphometric classification. It is also not clear how localized pixel classification can prevent topologically disconnected polygons dominating the final results. And lastly, as very fine resolution DEM data become available through LIDAR and other such technologies, kernels large enough to cover landform features will become computationally expensive to apply.

Our independently developed method for eminence detection and selection is similar to this recently published work, since we also rely on peak prominence to distinguish important summit regions. However, for delineation purposes we propose two alternatives: one inspired by the region-growing algorithms discussed above, and another based on the popular watershed segmentation algorithm used in hydrological modeling. We also split the landform delineation process into two phases: *detection* and *delimitation* so that conceptualizations of landscape constituents may be realized easily. Note that readers interested in the detailed technical discussion of our algorithms will have to wait for a future publication or should contact the authors for more information, since a detailed discussion of our algorithms is beyond the scope of this paper. However, we do our best in the following sections to provide enough information for readers to critically assess the merit and limitations of our work.

Detection of Eminences

The detection phase requires analysis of the DEM and extraction of locations that people are likely to recognize as summits or lower edges of eminences. As a first step, we use established terrain analysis techniques to derive morphometric parameters (e.g., slope and curvature thresholds) and features (e.g., peak, pass, and ridge line) that signify the localized presence of eminences. These

eminence 'markers' represent the first hierarchical transition from the elevation field to a feature based representation of the terrain shape. These markers then become the starting points for the detection and subsequent delimitation of individual eminences. For example, eminences with conical summits are detected through peak prominence, whereas eminences with non-conical, flatter tops are best detected through their lower boundaries marked by sudden change from high to much lower gradients. Not all markers will be relevant for analysis. Therefore, we need noise removal techniques to select only those markers which represent cognitively salient eminences.

We use two related parameters: *prominence* (vertical height of a peak in the largest encircling area not containing a higher elevation) and *isolation* (horizontal distance to the next highest elevation/peak) to help users intuitively select the minimum level of dominance for an eminence to be recognized as an independent entity in the landscape. In general, prominence will be more useful in mountainous terrain with several peaks, and isolation will prove to be a more intuitive parameter in flatter landscapes with isolated eminences. Figure 1 illustrates how to calculate the prominence and isolation for an eminence based on the *apex* and the *key col* (which represents the saddle point connecting the eminence to the nearest higher eminence). Prominence and isolation also control the granularity at which the landscape should be cognized. For example, for a test area covering the Presidential Range in the White Mountains of New Hampshire (USA), we found that the number of 'valid' peaks reduces drastically from 893 to 558 if the prominence threshold is set to just 0.3m; the number of valid peaks reduced to 325 at 3m, 92 at 30m, and 49 at 60m prominence threshold values. Interestingly, at about 30m, the selected peaks corresponded quite well with peaks listed in the GNIS database (which is based on named features on USGS topographic maps).

INSERT FIGURE 1 HERE

Delineation of Eminences

The process of eminence delineation follows that of eminence marker detection. We identify two methods of eminence delineation. The first method is an adaptation of the watershed segmentation method commonly used for delineating drainage basins from DEMs (O'Callaghan and Mark 1984; Jenson and Domingue 1988; Riazanoff and Chorowicz 1988; Chorowicz and others 1992). All versions of the watershed segmentation algorithm need to first identify the local drainage direction for each cell. Subsequently, the drainage basin of any point can be identified by recursively tracing all uphill cells that ultimately drain through that point. We modify this algorithm to generate *uphill* steepest direction paths, and then recursively trace cells 'flowing up' toward a prominent peak. Thus, instead of drainage basins, we obtain catchments that represent the dominance regions of peaks; the catchment boundaries coincide with stream channels and valley lines. Note that if an implementation of the traditional drainage basin delineation algorithm is already available, peak catchments can be conveniently derived by 'inverting' the input DEM using a simple mathematical transformation ($z_{new} = z_{max} - z_{old}$). The inverted DEM 'tricks' the delineation algorithm into effectively tracing 'uphill flow' paths and delineating catchments instead of drainage basins.

Just like drainage basins, peak catchments too can be arranged into hierarchies based on their adjacency and the elevations of the peaks. The hierarchy determines how secondary catchments may be aggregated to yield larger dominance regions of a few prominent peaks. These maximal catchments represent the approximate spatial extent of the salient topographic eminences in the area. Note that the aggregation process can result in different catchments depending on

which peaks are deemed important. This flexibility allows the realization of alternative eminence conceptualizations, each reflecting a different cognitive interpretation of the same landscape. We tested our method for the Presidential Range area in the White Mountains, and found meaningful alternative eminence boundaries that corresponded with noticeable valleys (Sinha 2008). Figure 2 shows three eminence conceptualizations for the Presidential Range area. The defining criteria for the conceptualizations are the elevation, prominence or isolation thresholds that result in different subsets of salient peaks, and therefore maximal extents of the corresponding eminences.

INSERT FIGURE 2 HERE

The catchment delineation method does not, however, produce satisfactory results for eminences with flat tops, because the absolute peak is not a cognitively salient feature of the landscape (although flat top eminences are easily identified as whole eminences by people). Problems also arise for isolated eminences rising above relatively flat ground because even a minor gradient induces the peak catchment to extend far out onto the flatter surrounding areas, much beyond what most people would consider the perceptual edge of the eminence. The problem therefore lies in the assumption that every eminence can be defined by a salient peak and that eminences can be bound by ridgelines (watershed boundaries).

We verified this problem by testing the method in an area in northwest New Mexico, USA well known for its isolated, uniquely shaped arid eminences typical in arid landscapes (e.g., Shiprock and Table Mesa). In such an environment, the afore-mentioned region growing segmentation techniques or the multi-scale morphometric classification may be adopted. There is the problem, however, of not being able to easily find a representative, topologically closed region, for *every* cognitively salient eminence. This makes it difficult to characterize the landscape in terms of landform object properties and object relationships. Moreover, the heuristic parameters required for the region growing algorithms do not transfer well across study areas. Consequently, we are currently working on an advanced catchment delineation method to make it applicable across all eminence types. One algorithm we are testing analyzes the initial catchment boundary for overshooting, and then erodes it inwards, till the average boundary gradient increases to a threshold considered high enough to mark a perceptually sharp transition from eminence flanks to surrounding flats (Sinha 2008).

The greatest strength of our method of landform delineation is that we maintain a strong commitment to cognition based parameterization. This ensures that there is an obvious, intuitive connection between concepts people use for real world landform cognition and reasoning, and concepts needed for identification and delineation of landforms computationally. Our method can also easily be customized for multiple granularities and landscape conceptualizations by manipulation of intuitive landscape parameters such as prominence, isolation, elevation, slope, visibility, etc.

Ontology Development and Object-Based Database Modeling

Delineation algorithms themselves are, however, only part of the solution. We also need to ensure that multiple landform conceptualizations can be realized and stored alongside with each other in the same system. Thus, versioning and multiple representation database technologies are essential for storage, management, retrieval, and comparison of alternative landscape conceptualizations. The success of this endeavor is contingent on two factors: a good database model, and an ontology for clearly specifying database semantics.

For our experiments, we conceived an object-oriented database model for storing multiple spatial representations of an eminence: *peak* (point/point collection), *summit area* (point collection/polygon), *peak catchment* (polygon), *lower boundary* (ring), *minimum bounding rectangle* (polygon); additionally, we maintained a link to the DEM from which the eminence was derived so that spatial properties could be measured real time. Morphometric parameters are objective markers, common to all conceptualizations; hence, not only did we maintain links between eminences and morphometric peaks and passes, we also utilized surface network theory (Cayley 1859; Maxwell 1870; Pfaltz 1976; Wood 2000; Rana 2004) by tracing steepest ascent ridgelines from all passes to peaks. We used a graph data structure to store and query the surface network to extract topological information about eminences (e.g., peak hierarchies, peak neighbors, and ridgeline distances between peaks). Such an integrated raster-vector-network topographic data model can support a wide variety of spatial queries: (geometric, topological, mereotopological, continuous field, and attribute based). It also improves information retrieval efficiency if query typologies are constructed to automatically match queries to the most efficient data structure used for eminence representation. We used TerraLib, a freely available and easily extensible open-source GIS library for implementing our object-oriented topographic database model.

For conceptual specification of all database elements, we suggest having separate ontologies of topographic fields, features, and discrete landform objects. The field ontology would require the specification of the elevation layer and its derivative fields (e.g., relative elevation, slope, aspect, and curvature). The morphometric feature ontology would formalize definition parameters and detection techniques for geomorphometric feature primitives (e.g., peak, pass, pit, flat, ridge, and channel) that can be extracted from the elevation and derivative fields. Also included in this middle tier are surface networks. Field and morphometric feature ontologies can be assumed to be relatively free of cultural, linguistic, and idiosyncratic influence. Finally, the uppermost tier is dedicated to the formal specification of eminences as a fundamental category of landscape objects with consistent geometric, topological and partonomic properties. When examined in conjunction, the three ontology tiers can provide even greater insight because they will reveal the incremental process of extraction of landform objects from elevation fields.

Implications for the National Map Ontology

As noted in the introductory section, we envisage a range of applications for our research. We use the National Map as an example in this section since this paper was solicited by the as part of the National Map Ontology initiative. The USGS can indeed utilize our ideas by implementing multi-representation database models and tiered ontologies to avoid the present disconnect between the eight data layers comprising the National Map. In our research, we remain committed to three philosophies: *experiential realism* (Lakoff 1990), theory of *landscape affordances* (Gibson 1979), and the *naïve geography* paradigm that promotes information system design based on "formal models of the common sense world" (Egenhofer and Mark 1995). We believe that the National Map Ontology too should adopt a similar commitment to common-sense based ontology development. The National Map Ontology has string cognitive foundations, it will have the potential for becoming a great Upper Level Ontology, which will promote and facilitate a whole suite of niche, application domain specific ontologies.

The USGS has an obvious mandate to make the National Map information system easily accessible to the lay person. Several researchers have discussed the merits of cognition-based database modeling for geographic information systems (Mennis 2003. Mennis, Peuquet, and Qian

2000; Mark and others 1999). Hence, it is critical that the National Map Ontology has a strong cognitive basis. The general user cannot be expected to have advanced understanding of topographic ontologies, but a strong cognitive basis will ensure that most concepts and categories and the semantics of the categories will be intuitively understood by the average information consumer. Only cognition aware ontologies can ensure such resonance between people's naïve geographic concepts and topographic information systems.

Conclusions

Although our approach has a clear cognitive basis and is supported by several studies reported in the literature, we acknowledge the need to further explore several aspects of eminence cognition through extensive human subject testing. Our research is ongoing and we hope to report results from experiments with groups of subjects. An immediate goal is to discover appropriate parameters for delimiting landform boundaries and parts in different landscapes, and for different scales. Also, note that our approach assumes a map-like planimetric view of landforms, but people generally have access to only partial views of landforms. It would be interesting to explore how eminence perception varies with changing vantage points in the landscape. However, visibility based characterization will require substantial computational resources, which we do not have access to at this point.

In this paper, we discuss only the detection and delimitation of eminences. We have also developed methods for characterizing and classification of delimited eminences using a variety of shape, size, proximity, and visibility based descriptors (Sinha 2008). We also believe that methods of eminence delineation will not be applicable to the delineation of concave (hollow) landforms such as valleys, ravines, or basins. Similar to the case of eminences, there are several geomorphometry or landscape segmentation inspired methods that can be adapted and refined to help delineate *cognitively salient* depressions in the landscape. We hope that similar to our efforts for topographic eminences, other researchers will participate in the development of an integrated ontology and in the subsequent use of that ontology to develop cognition-based methods for computational extraction and modeling of topographic depressions.

References

Brown, D. G., D. P. Lusch, and K.A. Duda. 1998. "Supervised Classification of Types of Glaciated Landscapes using Digital Elevation Data." *Geomorphology* 21/4: 233-250.

Burrough, P. A., P. F. M. van Gaans, and R.A. MacMillan. 2000. "High-Resolution Landform Classification Using Fuzzy k-means." *Fuzzy Sets and Systems* 113/1: 37-52.

Cayley, A. 1859. "On Contour Lines and Slope Lines." *Philosophical Magazine: A Journal of Theoretical, Experimental and Applied Physics* 18: 264-268.

Chaudhry, O.Z., and W.A. Mackaness. 2008. "Creating Mountains out of Mole Hills: Automatic Identification of Hills and Ranges Using Morphometric Analysis." *Transactions in GIS* 12/5: 567-589.

Chorowicz, J., C. Ichoku, S. Riazanoff, Y.-J. Kim, and B. Cervelle. 1992. "A Combined Algorithm for Automated Drainage Network Extraction." *Water Resources Research* 28: 1293-1302.

Cova, T., and M.F. Goodchild. 2002. "Extending Geographical Representation to Include Fields of

Spatial Objects." *International Journal of Geographical Information Science* 16/6: 509-532.

Goodchild, M.F., M. Yuan, and T. Cova. 2007. "Towards a General Theory of Geographic Representation in GIS." *International Journal of Geographical Information Science* 21/3: 239-260.

Egenhofer, M., and D.M. Mark. 1995. "Naïve Geography." In *Spatial Information Theory: A Theoretical Basis for GIS, Lecture Notes in Computer Sciences 988*, ed. A. Frank and W. Kuhn. Berlin: Springer-Verlag. 1-15.

Fels, J. E., and K. C. Matson. 1996. "A Cognitively-Based Approach for Hydrogeomorphic Land Classification Using Digital Terrain Models." *Third International Conference/Workshop on Integrating GIS and Environmental Modeling CDROM*, Santa Fe, New Mexico, USA. January 21-25. NCGIA, UCSB, Santa Barbara.

Frank, A. U., and D. M. Mark. 1991. "Language Issues for GIS." In *Geographical Information Systems: Principles and Applications*, ed. D.J. Maguire, M.F. Goodchild, and D. Rhind, London: Longmans Publishers. 147-163.

Frank, A. U. 2001. "Tiers of Ontology and Consistency Constraints in Geographical Information Systems." *International Journal of Geographical Information Science*, 15/7: 667- 678.

Gibson, J.J. 1979. *The Ecological Approach to Visual Perception*. Boston, USA: Houghton Mifflin.

Giles, P. T., and S. E. Franklin. 1998. "An Automated Approach to the Classification of the Slope Units using Digital Data." *Geomorphology* 21/4: 251-264.

Graff, L., and E.L. Usery. 1993. "Automated Classification of Terrain Features in Digital Elevation Models." *Photogrammetric Engineering & Remote Sensing* 59: 1409-1417.

Irvin, B. J., S. J. Ventura, and B.K. Slater. 1997. "Fuzzy and Isodata Classification of Landform Elements from Digital Terrain Data in Pleasant Valley, Wisconsin." *Geoderma* 77: 137-154.

Jenson, S.K., and J.O. Domingue. 1988. "Extracting Topographic Structure from Digital Elevation Data for Geographical Information System Analysis." *Photogrammetric Engineering and Remote Sensing* 54: 1593-1600.

Lakoff, G. 1990. *Women, Fire, and Dangerous Things*. Chicago, USA: University Of Chicago Press.

Lakoff, G. 1988. "Cognitive Semantics." In *Meaning and Mental Representations*, ed. U. Eco, M. Santambrogio et al., Bloomington: Indiana University Press. 119-154.

MacMillan, R. A., R. K. Jones, and D.H. McNabb. 2004. "Defining a Hierarchy of Spatial Entities for Environmental Analysis and Modeling Using Digital Elevation Models (DEMs)." *Computers, Environment and Urban Systems* 28/3: 175-200.

MacMillan, R. A., W. W. Pettapiece, S.C. Nolan, and T.W. Goddard. 2000. "A Generic Procedure for Automatically Segmenting Landforms into Landform Elements Using DEMs, Heuristic Rules and Fuzzy Logic." *Fuzzy Sets and Systems* 113/1: 81-109.

Mark, D., and Sinha, G. 2006. "Ontology of Landforms: Delimitation and Classification of Topographic Eminences." In GIScience 2006. LNCS, vol. 4197, ed. M. Raubal, H.J. Miller, A.U. Frank, and M.F. Goodchild. Springer, Heidelberg. 129–132.

Mark D.M., and B. Smith. 2004. "A Science of Topography: From Qualitative Ontology to Digital Representations". In *Geographic Information Science and Mountain Geomorphology*, ed. M.P. Bishop and J.F. Shroder. Chichester, England: Springer-Praxis. 75-100.

Mark, D.M., and A.G. Turk. 2003. "Landscape Categories in Yindjibarndi: Ontology, Environment, and Language." In *Spatial Information Theory: A Theoretical Basis for GIS,*

Lecture Notes in Computer Sciences 2855, ed. W. Kuhn, M. Worboys and S. Timpf. Berlin: Springer-Verlag. 31-49.

Mark, D. M., and A. U. Frank, (editors). 1991. *Cognitive and Linguistic Aspects of Geographic Space*. Dordrecht: Kluwer Academic Publishers.

Mark, D. M., C. Freksa, S.C. Hirtle, R. Lloyd, and B. Tversky. 1999. "Cognitive Models of Geographic Space". *International Journal of Geographical Information Science*, 13/8: 747-774.

Maxwell, J.C. 1870. "On Hills and Dales." *The London, Edinburgh and Dublin Philosophical Magazine* 40: 421-427.

Mennis, J.L., D.J. Peuquet, and L. Qian. 2000. "A Conceptual Framework for Incorporating Cognitive Principles into Geographical Database Representation". *International Journal of Geographical Information Science*, 14/6: 501-520.

Mennis, J.L. 2003. "Derivation and Implementation of a Semantic GIS Data Model Informed by Principles of Cognition". *Computers, Environment, and Urban Systems*, 27: 455-479.

Miliaresis, G.C., and D.P. Argialas. 1999. "Segmentation of Physiographic Features from the Global Digital Elevation Model/GTOPO30." *Computers & Geosciences* 25: 715-728.

Montello, D.R. 1995. "How Significant are Cultural Differences in Spatial Cognition." In A.U.Frank & W.Kuhn (Eds.), *Spatial Information Theory: A Theoretical Basis for GIS. Lecture Notes in Computer Science 988*. Berlin: Springer-Verlag. 485-500.

O'Callaghan, J.F., and D.M. Mark. 1984. "The Extraction of Drainage Networks from Digital Elevation Data." *Computer Vision, Graphics, and Image Processing* 28: 323-344.

Pfaltz, J.L. 1976. "Surface Networks." *Geographical Analysis* 8: 77-93.

Rana, S. 2004. *Topological Data Structures: An Introduction to Geographical Information Science*. Chichester, England: Wiley.

Riazanoff, S., B. Cervelle, J. Chorowicz. 1988. "Ridge and Valley Line Extraction from Digital Terrain Models." *International Journal of Remote Sensing* 9: 1175-1183.

Schmidt, J., and A. Hewitt. 2004. "Fuzzy Land Element Classification from DTMs Based on Geometry and Terrain Position." *Geoderma* 121: 243-256.

Sinha G. 2008. "Delineation, Characterization, and Classification of Topographic Eminences". PhD diss., University at Buffalo, SUNY, New York, USA.

Smith, B., and D.M. Mark. 2003. "Do Mountains Exist: Towards an Ontology of Landforms". Environment and Planning B: Planning and Design 30: 411-427.

Smith, B., and D.M. Mark. 1998. "Ontology and Geographic Kinds". *Proceedings of 8th International Symposium on Spatial Data Handling (SDH98)*, ed. T.K. Poiker and N. Chrisman, Vancouver: International Geographical Union. 308-320.

Tso, B. and P. M. Mather (2001). *Classification Methods for Remotely Sensed Data*. New York, USA: Taylor & Francis.

Ventura, S. J. and B. J. Irvin (2000). "Automated Landform Classification Methods for Soil-Landscape Studies." In *Terrain Analysis: Principles and Applications*, ed. J. P. Wilson and J. C. Gallant, New York, USA: John Wiley & Sons, Inc. 267-294.

Wood, J. 2000. "Constructing Weighted Surface Networks for the Representation and Analysis of Surface Topology." *Proceedings of 5th International Conference on GeoComputation, Chatham, UK.*

Wood, J. 1996. "The Geomorphological Characterisation of Digital Elevation Models." PhD diss., Leicester University, Leicester, UK.
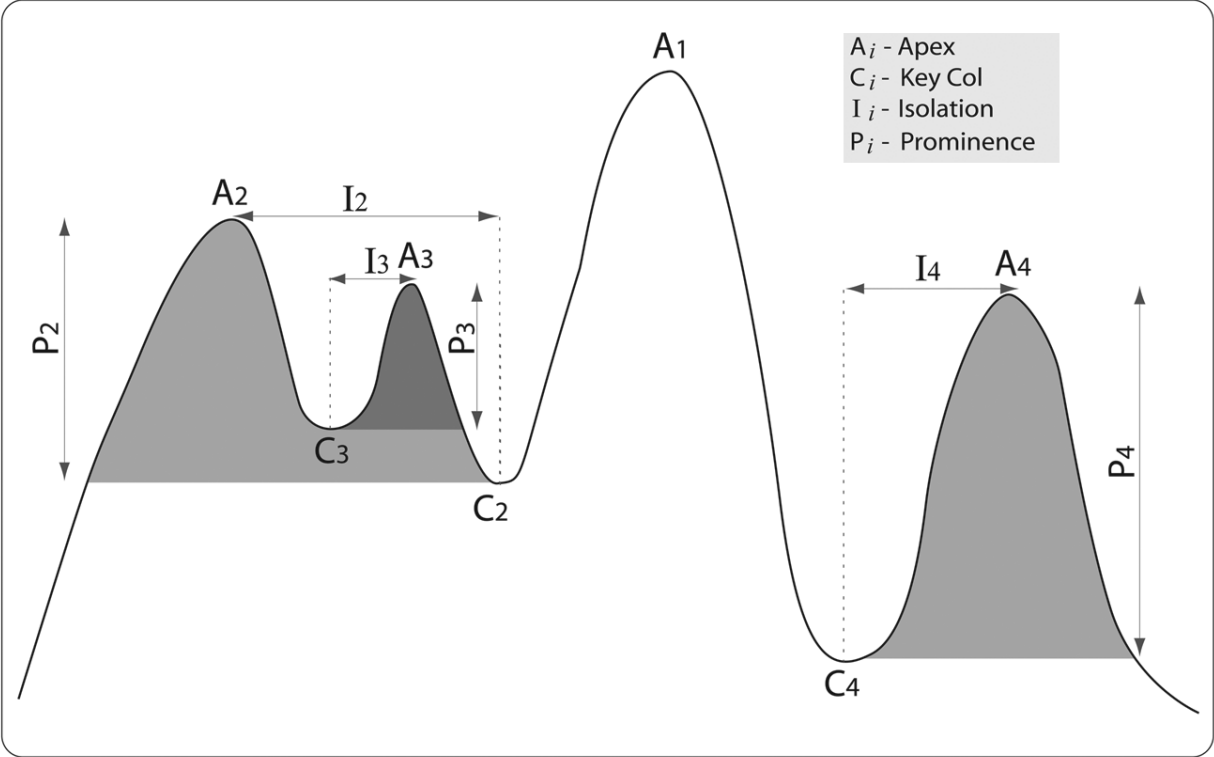
Figure 1. Prominence and Isolation calculation.
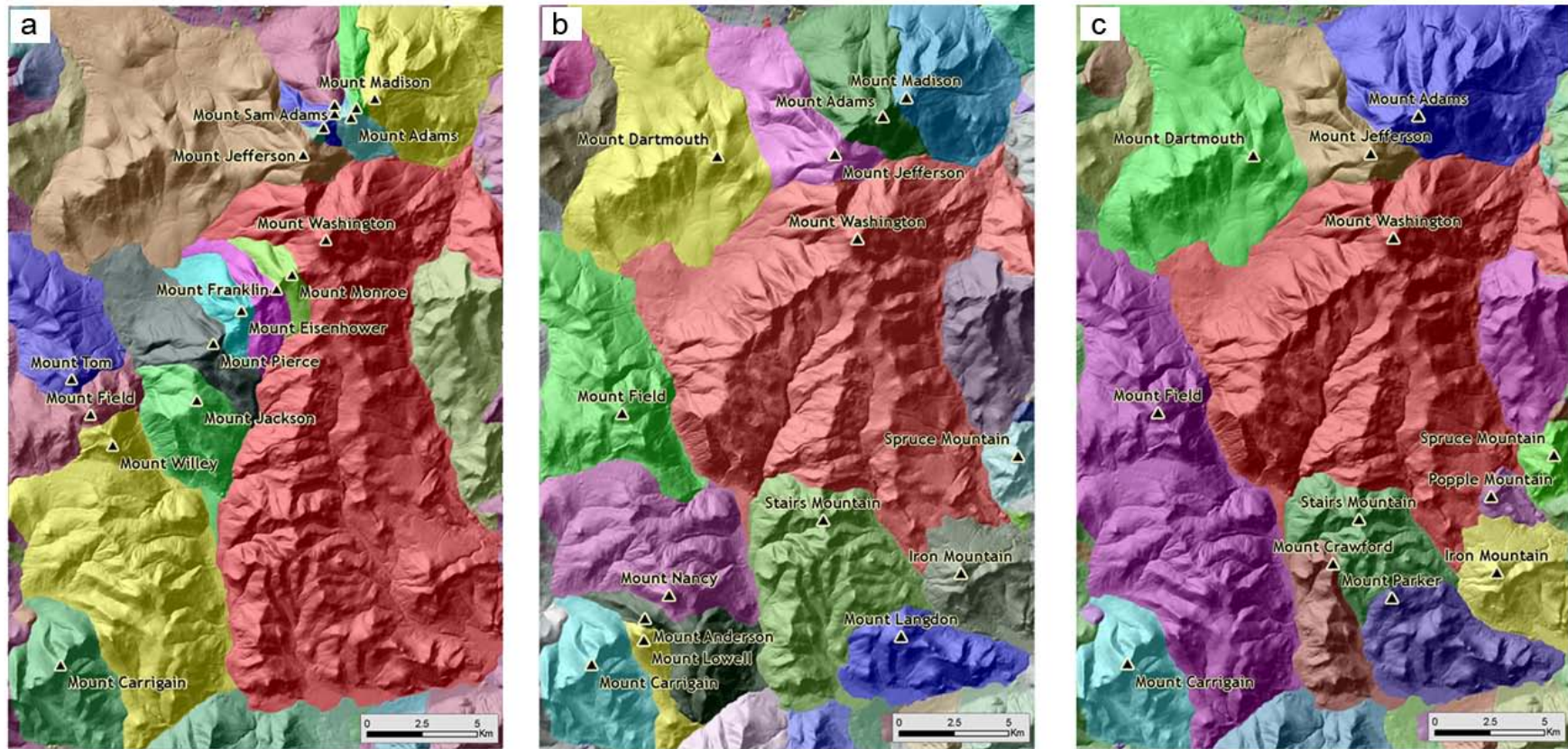
Figure 2. Multiple eminence conceptualizations realized as alternative sets of salient peaks and their corresponding hill catchment regions. The following parameter thresholds were used to select the salient peaks: (a) Elevation > *1200 m*; (b) Elevation > *1200 m* & Prominence > *60 m*; (c) Elevation > *1200 m* & Isolation > *1000m.*