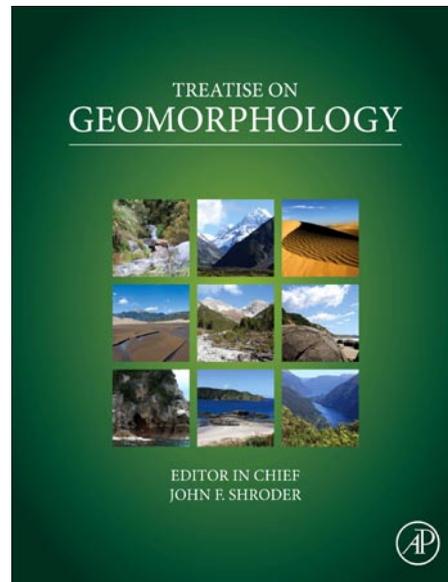


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3.7 Geomorphometry

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Abstract

The study of surface processes and landforms requires quantitative characterization of the topography. New theoretical/conceptual and practical advances in understanding and mapping various aspects of geomorphological systems have emerged from new geospatial data and analysis of the topography. This chapter describes geomorphometry, or the science of quantitative land-surface characterization, and how it can be used to represent and sample the land surface, generate digital elevation models (DEMs), correct errors and artifacts from surface models, compute land-surface parameters and objects, and use various forms of quantitative information in different application domains to address or solve problems.

Glossary

Digital elevation model A digital elevation model (DEM) is generally a land-surface model that attempts to accurately portray the altitude field of the topography. In geomorphology, it commonly takes the form of a raster data layer representing a field of square tessellations. The resolution of the grid cells is usually determined based on the source data utilized and the desired scale for representing the topography.

Digital terrain modeling Digital terrain modeling (DTM) refers to a workflow process of acquiring data that samples the altitude field, preprocessing the data to generate a digital elevation model, and error and uncertainty analysis to identify and remove systematic and random errors.

Error propagation Digital elevation models exhibit an inherent error due to digital terrain modeling that includes choice of sensor in data capture, algorithm and methods selection in DEM generation, and effective implementation of DEM error correction, given DEM error and uncertainty

analysis. Such errors are propagated in terrain analysis in the computation of land-surface parameters and objects and in modeling efforts that utilize parameters and objects.

Geomorphometry The discipline that is concerned with the science of quantitative land-surface characterization.

Land-surface objects Land-surface objects are spatial entities that represent a meaningful segmentation of the Earth's surface. They are generated from land-surface parameters using a variety of algorithms and methods, and generally relate to the morphology of the topography in terms of landform elements, features, or functional units. Terrain segmentation can also relate to topographic position and structure, surface material, or process domains, if properly defined and delineated.

Land-surface parameters Land-surface parameters are also called geomorphometric parameters, and they attempt to quantitatively characterize various aspects of the topography. They can be defined and classified based on geometry, scale, and by surface-process characterization.

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They are used to generate land-surface objects and characterize process mechanics in surface-process modeling. A variety of parameters such as slope, slope azimuth, curvature, surface roughness, and relief are used for studying geomorphological systems and for geomorphological mapping.

Segmentation Segmentation refers to the partitioning of the land surface into meaningful spatial entities.

Segmentation is required for object-oriented analysis of land-surface objects.

Surface-process modeling Surface-process modeling refers to physics-based deterministic modeling that attempts to characterize process mechanics and how topography governs various process rates, and the influence of various processes on topographic landscape evolution.

3.7.1 Introduction

The topography plays a fundamental role in modulating several components of Earth's dynamic systems including atmospheric, geomorphic, hydrologic, ecologic, and geological processes. The topography constrains the operational scale of surface processes, and partially governs both climate and tectonic forcing (Molnar and England, 1990; Bishop et al., 2010; Koons et al., 2012). The strength of the linkage between form and process can range from weak to strong, and may or may not be inherently visible on the landscape depending on the complexity of the topography. Nevertheless, moderate to strong linkages have been observed, such that an understanding of the nature of the land surface can provide insights and understanding of the nature and magnitude of several processes (Hutchinson and Gallant, 2000). Consequently, it is necessary to quantitatively characterize the land surface and segment the topography into fundamental spatial units, as the topography inherently represents the results of the interplay between various systems, and records an imprint of landscape dynamics (over a limited time). Therefore, the utility of digital elevation models (DEMs) and the analysis of topography (geomorphometry) have and will continue to revolutionize the field of geomorphology, as critical information regarding process mechanics, process domains, feedback mechanisms, polygenetic evolution, and landforms continues to be investigated and generated. Furthermore, with the rapid proliferation of geographic information technologies, new data, algorithms, and analysis/modeling techniques allow new capabilities. These capabilities represent the evolution of the field of geomorphometry, which, in its broadest sense, refers to the science of quantitative land-surface characterization (Pike, 1995, 2000) or digital terrain analysis. For more details regarding the definition and terminologies used in geomorphometry, see Wilson and Gallant (2000a), Li et al. (2005), Zhou et al. (2008), Pike et al. (2009), Hengl and Reuter (2009), and Wilson (2012).

Modern geomorphometry focuses on the extraction of land-surface parameters and the segmentation of the landscape into spatial entities/features (land-surface objects) from digital topography. This characterization relies on the so-called specific and general modes of geomorphometric analysis that were first defined by Evans (1972). The specific mode of analysis attempts to describe discrete surface features (i.e., landforms), whereas the general mode attempts to describe the continuous land surface. Pike et al. (2009) have since updated these definitions, such that a land-surface parameter is a descriptive measure of surface form (e.g., slope, slope azimuth, curvature) and a land-surface object is a discrete

surface feature (e.g., watershed, cirque, alluvial fan, drainage network). Although this definition represents an improvement, it is worth noting that this is a somewhat arbitrary distinction, and there are already research examples that demonstrate that these two perspectives are closely linked to one another (e.g., Gallant and Dowling, 2003; Deng and Wilson, 2008). Furthermore, it is clear that formalizing such linkages is necessary in geomorphological research to address concepts such as surface-process overprinting and polygenetic evolution and to address multiple perspectives in geomorphological mapping (Bishop et al., 2012).

Collectively, geomorphometry is a rapidly evolving and complicated field. This is in part due to its multidisciplinary nature and the inclusion of information technology. Similar to the field of geographic information science, it is based on developments in a variety of fields including source and end-user disciplines. It not only attempts to deal with theoretical/conceptual issues involving representation and spatio-temporal variation, but also includes issues of data collection and analysis, numerical modeling, and the utilization of other domain knowledge for conceptual and practical problem solving. Consequently, the field of geomorphometry is based on a scientific treatment of 'land surface' and its characterization that accounts for surface processes and morphology. Rapid evolution has been facilitated by geographic information technology and the widespread availability of DEMs. Geomorphologists now have many new capabilities to manipulate and extract information from a variety of data sources. Nevertheless, it is important to recognize the empirical nature of many forms of spatial analysis and modeling, and many issues raise important questions about the assumptions and validity of various approaches (Bishop et al., 2001).

Many questions still remain, and geomorphologists must be aware of the advantages and limitations associated with various representations and data structures, metrics/indices, spatial modeling approaches, and their utility for geomorphological investigations. Furthermore, investigators must be familiar with the mathematical underpinnings of geomorphometric analysis in order to adequately use information and to interpret the results (Bishop and Shroder, 2004a). Collectively, many issues point to a series of key questions that in general include: (1) How should the land surface be represented? (2) What preprocessing is required to produce a useable DEM? (3) What approach to error and uncertainty analysis is required? (4) What algorithms are best for producing land-surface parameters? (5) What methods are best for producing land-surface objects? (6) Is there a need to develop new parameters and objects to address a particular

problem? (7) What algorithms and approaches are best suited for a particular mapping application or do methods even exist? (8) Does an adequate model exist or is there a need to develop or modify one?

Many of these questions relate to data sources, issues, and capabilities, although it is important to note that considerable research is still required to address a whole host of issues in geomorphology. In many cases, the answers to these questions may not be clear, as software-tool development has focused on the tool-box approach, foregoing formal scientific treatments to mapping and geographic information system (GIS)-based analysis/modeling. These challenges, however, can also be attributed to the steady growth in the development and sheer number of parameters and algorithms for processing DEMs. Consequently, the values of parameters depend on a variety of factors, including the parameterization scheme, measurement scale of data, computational scale of analysis, and many empirical parameters that are used to address several conceptual issues. This represents a serious issue in geomorphology, as the spatial patterns associated with many metrics/indices may not represent real-world phenomena, and the use of empirical parameters reduces the ability to formalize important aspects of the geomorphological system (Bishop et al., 2012).

Notwithstanding these challenges, land-surface parameters and objects have been adopted in a variety of applications and environmental settings. Geomorphometry has been used to predict the distribution of soil properties (e.g., Zhu et al., 1997; Bishop and Minasny, 2005), model soil redistribution (i.e., erosion and deposition) processes (e.g., Mitášová et al., 1995), assess the likelihood of slope hazards (e.g., Guzzetti et al., 2005; Kheir et al., 2007), model solar-radiation potential (e.g., Reuter et al., 2005), improve vegetation mapping (e.g., Bolstad and Lillesand, 1992; Antonić et al., 2003), analyze wildfire propagation (e.g., Hernández Encinas et al., 2007), assess the role of surface processes in mountain topographic evolution (Burbank et al., 1996; Bishop and Shroder, 2000; Bishop et al., 2003), and to predict water flow, drainage, and flooding in many hydrological applications. More applications are rapidly emerging, and geomorphologists play an important role in the development and evaluation of approaches that are based on geomorphological concepts.

Collectively, this chapter examines the data sources and methods used to generate DEMs, and how land-surface parameters and objects can be used in geomorphology. A typical digital terrain analysis workflow is presented that includes basic data capture, data preprocessing, DEM generation, computation of land-surface parameters and objects, landform classification, and surface-process modeling. Throughout, examples are provided of how parameters and geomorphometric analyses can provide new opportunities for geomorphological research. The focus is on presenting current capabilities and issues associated with the quantitative characterization of the topography.

3.7.2 Digital Terrain Modeling

The generation of DEMs involves data modeling or representation choices, sampling the land surface, representing and creating a surface model from the sampled heights, and

correcting the errors and artifacts in the surface model (Hengl and Reuter, 2009). Each phase in the production of a DEM is critical for determining its utility, and in assessing the amount of error that will propagate through the analysis phase. The general workflow is depicted in Figure 1.

3.7.2.1 Representation

Many topics in geomorphology and geomorphometry are inherently related to the space–time representation of topography (Bishop and Shroder, 2004b). This topic is complex, and a variety of philosophical, cognitive, and natural-science perspectives exist. The current use of representation is dominated by static cartographic representations. Although this approach provides many advantages in terms of spatial overlay, management of data, basic spatial analysis, and information distribution, it does not address many issues related to surface processes and landforms.

Topographic variation can be represented in a variety of ways using data models. The common data models are the field (layer), entity (object), and network data models, which can be linked to a relational data model (Goodchild, 1992). These data models are represented in a computer using data structures (i.e., raster and vector). Consequently, topography can be represented by many field models (sampled points, contours, polygons, tessellations, triangular nets) to characterize the continuous spatial variation in altitude. Object models are used to define well-defined features, assuming that discrete boundaries actually exist, whereas indeterminate boundaries have been recognized to pose a unique challenge, as environmental gradients or zones of homogeneous and

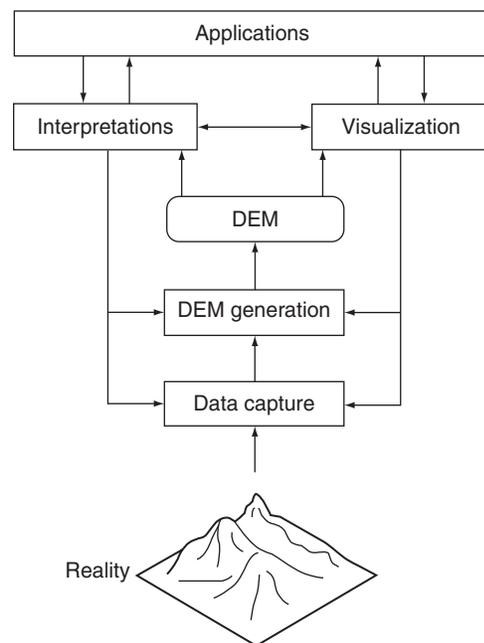


Figure 1 The main tasks associated with digital terrain modeling. Reproduced from Hutchinson, M.F., Gallant, J.C., 2000. Digital elevation models and representation of terrain shape. In: Wilson, J.P., Gallant, J.C. (Eds.), *Terrain Analysis: Principles and Applications*. John Wiley and Sons, New York, pp. 29–50.

heterogeneous surface properties can effectively represent boundaries or limits to the spatial distribution of phenomena (Burrough, 1996; Usery, 1996; Lagacherie et al., 1996). Earth scientists have noted the advantages and disadvantages of such data models and have recognized that these representations do not effectively address process mechanics or dynamics (Raper and Livingstone, 1995). It is also important to note that field and object models do not formally represent the complex nature of landforms, as issues of scale, organization, composition, and age must be taken into consideration. Furthermore, the degree to which qualitative and quantitative analysis should be used to characterize the land surface needs to be determined, as qualitative analysis is supported by the entity view, whereas the science of studying process mechanics, feedback mechanisms, geodynamics and landscape evolution tends to focus on continuous space (Raper and Livingstone, 1995).

Clearly, determining how to best represent the land surface is a complex issue. Dikau (1989) indicated that a digital relief model involving the parameterization of relief units could be used to represent topography that is hierarchically organized. Relief is scale dependent, and the concept of homogeneous relief can be defined based on distance and direction. Nevertheless, relief and many other land-surface parameters are scale dependent. Does this mean that the scale dependence and the anisotropic nature of the topography need to be represented? Should the hierarchical spatial structure of the topography be represented? Furthermore, how should process mechanics, process-form relationships, and temporal dynamics be characterized?

An intriguing proposition for geomorphometry has been presented by Cova and Goodchild (2002) that involves the extension of spatial representation to include fields of spatial objects. This effectively represents the linking of continuous space with object representation. It also allows considerable flexibility in terms of representing the complexity associated with landforms, as the issues of homogeneity, heterogeneity, complexity, and other concepts can be addressed, as a tessellation can have more than one object and the objects can have discrete or fuzzy boundaries. In addition, an object hierarchy can be developed to address issues associated with scale.

Furthermore, it also allows the representation of process via 'process objects,' wherein a multitude of process objects can simultaneously alter the topography at fundamentally different scales. This allows the integration of process modeling and mapping in a seamless way, and raises the important issue of parameterization schemes for characterizing the process mechanics and specific process-form relationships. Such formal representations of the topography in geomorphology are required to validate the results obtained via empirical analysis using geospatial technologies. In addition, such a representation can handle temporally changing spatial patterns by using a dynamic representational scheme that results from the process dynamics. Consequently, spatio-temporal relationships are inherently represented. Several complexities associated with 3-D and temporal representation, however, remain.

3.7.2.2 Data Capture

The data sources and processing methods for generating DEMs have evolved rapidly over the past 20–30 years. Data collection

approaches (Table 1) have been categorized by Nelson et al. (2009) and include: (1) ground-survey techniques (electronic theodolites, total stations, electronic distance measuring (EDM), and global positioning system (GPS) units); (2) existing topographic maps (derivation of contours, streams, lakes, and spot heights from existing hardcopy topographic maps); and (3) remote sensing (both air and space-borne optical, radar, and Light Detection and Ranging (LiDAR) sensors).

Modern-day data collection is based on remote sensing for the production of DEMs, as rapid progress has occurred over the past two decades. Global DEM data products from the Shuttle Radar Topographic Mission (SRTM) and the Advanced Spaceborne Thermal Emission and Reflectance Radiometer Global Digital Elevation Model (ASTER GDEM) were released in 2000 and 2009, respectively. The 3 arc-second SRTM DEM covers a large fraction of the globe (from 60° N to 58° S) and has already emerged as one of the most consistent, complete, and popular environmental datasets in the world (Zandbergen, 2008; Nelson et al., 2009). The 3 arc-second (~90 m) grid spacing is much better than the 1 km spacing of the worldwide GTOPO30 DEM, and an accuracy assessment using kinematic GPS data showed good absolute height accuracy, with 90% of the errors < 5 m (Rodriguez et al., 2006). This product must nevertheless be used carefully because: (1) it represents a digital surface model (DSM) (not a bare-earth model); (2) surface characteristics may affect accuracy; (3) voids generally occur at land-water margins; (4) problems may occur in desert and mountain areas due to foreshadowing and shadowing effects (Rodriguez et al., 2005); and (5) the current 90-m resolution provided by the global SRTM DEM is not fine enough for accurate surface characterization and the mapping of soils, vegetation, and many landforms (Gessler et al., 2009). It represents, however, an excellent dataset for geomorphometric analysis of mountain environments to study the influence of glaciations and tectonics on landscape evolution (Figure 2).

Some, but probably not all of the aforementioned problems, may be addressed by the ASTER GDEM. This relatively new product offers better resolution (1 vs. 3 arc-seconds), improved spatial coverage (83° N to 83° S), as well as comparable vertical and horizontal accuracy (Hiranoa et al., 2003; Nelson et al., 2009; Slater et al., 2009). The release of this product is so recent that there are few published reports documenting the strengths and weaknesses of this new data source for specific locations and applications, although the improvement in the measurement scale should greatly facilitate geomorphological investigations (Figure 3).

Recently, LiDAR surveys have been conducted, resulting in the generation of DEMs with improved resolution (Figure 4). Consequently, the reliance on LiDAR surveys has increased quickly, and this source now dominates local and regional projects everywhere. Belgium and the Netherlands, for example, have produced national LiDAR DSMs at resolutions of 2–5 m, and much finer-resolution DEMs have been produced for many smaller areas as well (Nelson et al., 2009). The advantages of using LiDAR include the high density of sampling, high vertical accuracy, and the opportunity to derive a set of surface models, given that some laser-scanning systems can already provide at least two versions of the surface: the

Table 1 Key characteristics of data sources

Source	Resolution (m)	Accuracy	Footprint (km ²)	Postprocessing requirements	Elevation/surface
Ground survey	Variable but usually <5 m	Very high vertical and horizontal	Variable, but usually small	Low	Elevation
GPS	Variable but usually <5 m	Medium vertical and horizontal	Variable, but usually small	Low	Elevation
Table digitizing	Depends on map scale and contour interval	Medium vertical and horizontal	Depends on map footprint	Medium	Elevation
On-screen digitizing	Depends on map scale and contour interval	Medium vertical and horizontal	Depends on map footprint	Medium	Elevation
Scanned topo-map	Depends on map scale and contour interval	Medium vertical and horizontal	Depends on map footprint	High	Elevation
Ortho photography	<1	Very high vertical and horizontal	–	High	Surface
LiDAR	1–3	0.15–0.11 m vertical, 1 m horizontal	30–50 h ⁻¹	High	Surface
InSAR/IfSAR	2.5–5	1–2 m vertical, 2.5–10 m horizontal	Depends on method of acquisition	High	Surface
SRTM, Band C	90 (30)	16 m vertical, 20 m horizontal	Almost global 60° N–58° S	Potentially high	Surface
SRTM, Band X	30	16 m vertical, 6 m horizontal	Similar to Band C, but only every second path is available	Potentially high	Surface
ASTER	30	7–50 m vertical, 7–50 m horizontal	3600	Medium	Surface
SPOT	30	10 m vertical, 15 m horizontal	72 000 per swath	Medium	Surface

Source: Modified from Nelson, A., Reuter, H.I., Gessler, P., 2009. DEM production methods and sources. In: Hengl, T., Reuter, H.I. (Eds.), *Geomorphometry: Concepts, Software, and Applications*. Elsevier, Amsterdam, pp. 65–85.

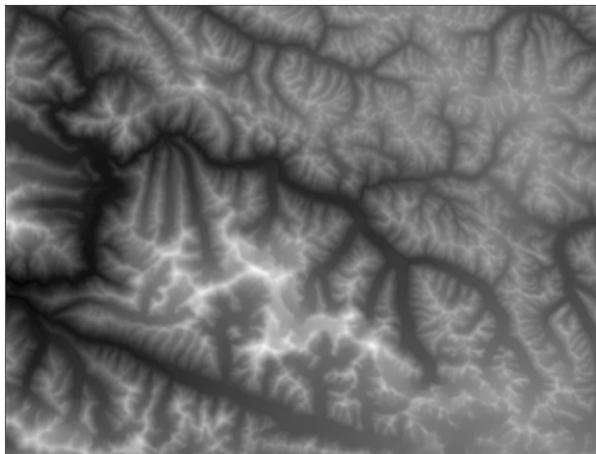


Figure 2 Shuttle Radar Topographic Mission (SRTM) 3 arc-second DEM for the Shimshal Valley in northern Pakistan. The 90 m resolution allows a relatively accurate geomorphometric characterization of the region for studying surface processes and tectonics.

vegetation canopy (first returns) and ground surface (last returns), which should help with the modeling of erosion and water budgets. The smaller footprint and measurement challenges encountered in areas with tall buildings, dense-vegetation canopies, and water surfaces make this a relatively

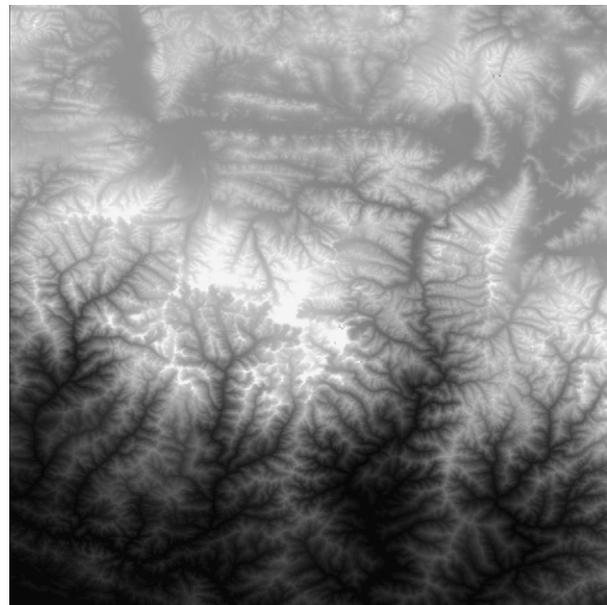


Figure 3 Advanced Spaceborne Thermal Emission and Reflectance Radiometer Global Digital Elevation Model (ASTER GDEM) for the Mt. Everest region in Nepal. The 30 m resolution allows a more detailed assessment of the mountains, although several errors and artifacts are found in such high-mountain environments. ASTER GDEMs in a less complex topography are usually of higher quality. The displayed x and y dimensions are 216 km, respectively.

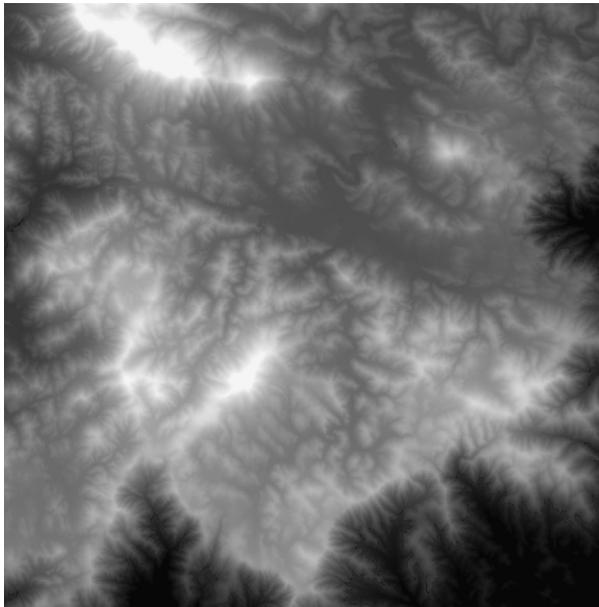


Figure 4 Five-meter resolution digital elevation model (DEM) generated from bare-earth LiDAR data from the North Carolina Floodplain Mapping Program. The area is located in the Blue-Ridge Province of western North Carolina, and is approximately 232 km² in size. The region exhibits an elevation range of 867 m (1454–587 m) and has a mean slope of 17°. The incised terrain in the southeast portion of the DEM represents the beginning of the Blue-Ridge Escarpment. DEM courtesy of Jeffrey Colby, Appalachian State University.

expensive option, and several studies have documented how the elevation accuracy of LiDAR data varies with both the sensor system and the land-cover characteristics (e.g., [Dowman, 2004](#); [Hodgson et al., 2005](#)).

3.7.2.3 Data Preprocessing and DEM Construction

Regardless of the representational scheme, preprocessing of the elevation data for analysis can be difficult, as altitude is but one of the land-surface characteristics that are required for various applications. The morphological accuracy can only be assessed by measuring surface parameters and objects such as the slope angle, slope azimuth, curvature, drainage lines, and landforms in the field, and then comparing their magnitudes, shapes, distributions, and locations with the values obtained by geomorphometric analysis (e.g., [Fisher, 1998](#); [Wilson et al., 2008](#)). [Reuter et al. \(2009\)](#) suggested that the true utility of DEMs for geomorphometric analysis can only be assessed by determining the following: (1) accuracy of surface-roughness representation; (2) accuracy of land-surface morphology; (3) accurate detection of actual ridge- and stream-lines; and (4) spatial consistency of altitude measurements. Such issues are interrelated, and the frequency and magnitude of errors will depend on the technologies and methods used to collect the source data, the preprocessing algorithms that are applied, and the complexity of the land surface itself.

Not surprisingly, the horizontal and vertical resolution of the elevation data used to portray a terrain surface will have a significant influence on the level of detail and the accuracy of the

DEM, and on the analysis results ([MacMillan and Shary, 2009](#)). Several authors have documented the effects of grid spacing on the value and accuracy of land-surface parameters and landform objects (e.g., [Zhang and Montgomery, 1994](#); [Florinsky, 1998](#); [Jones, 1998](#); [Wilson et al., 2000](#); [Thompson et al., 2001](#); [Shary et al., 2002](#); [Tang et al., 2002](#); [Kienzle, 2004](#); [Warren et al., 2004](#); [Zhou and Liu, 2004](#); [Raaflaub and Collins, 2006](#)). The increasing interest in various forms of multiscale analysis (e.g., [Bishop et al., 2003](#); [Gallant and Dowling, 2003](#); [Sulebak and Hjelle, 2003](#); [Deng and Wilson, 2008](#); [Bishop et al., 2012](#)) and the need to be able to move seamlessly across scales indicate that more research on scale and its effects is required.

Other decisions made about unwanted depressions (i.e., spurious pits or sinks) will also have an impact on subsequent geomorphometric analysis and interpretation of the results. Two approaches have been utilized and include: (1) progressively filling the sinks by increasing their elevation values until the elevation of their lowest outflow point is reached (e.g., [Jenson and Domingue, 1988](#); [Martz and de Jong, 1988](#); [Soille and Gratin, 1994](#); [Planchon and Darboux, 2001](#); [Wang and Liu, 2006](#)) and (2) creating a descending path from the bottom of the sink by carving the terrain along this path until the nearest point is reached, which has an elevation lower than the bottom of the sink (e.g., [Reiger, 1992](#); [Morris and Heerdegen, 1988](#); [Martz and Garbrecht, 1999](#); [Soille et al., 2003](#); [Soille, 2004](#)). [Reuter et al. \(2009\)](#) recently used both of these approaches along with one that combined sink filling and carving, such that the sum of the differences in elevation between the input and the output DEMs that did not have sinks was minimized. [Lindsay and Creed \(2005a, b, 2006\)](#) have also combined elements of the aforementioned approaches and used them to distinguish artifact and real depressions in digital elevation data, and propose a minimum-impact approach for removing artifact depressions in relatively flat landscapes. [Grimaldi et al. \(2007\)](#) have proposed an alternative physically-based approach to remove spurious pits as well.

At least two other related challenges may need to be addressed. The first concerns the problem of unresolved flow directions on flat terrain, because the assignment of flow directions relies on the presence of elevation differences between adjacent cells to drive the flow. The presence of lakes and reservoirs, and reliance on the first of the aforementioned approaches for filling sinks, may exacerbate this challenge by creating artificial flat regions. Whatever the cause, one of two approaches is typically used to remove or minimize these kinds of problems. The first relies on an iterative procedure to assign a single flow direction to a neighboring cell without alteration of the elevation values (e.g., [Jenson and Domingue, 1988](#)), whereas the second method makes small alterations to the elevation of the flat cell(s) in order to create a small artificial gradient (e.g., [Garbrecht and Martz, 1997](#)). The solutions obtained with these approaches will vary slightly from one to the other, and an in-depth knowledge of field conditions will generally be required to know whether one approach produces superior results in most landscape settings.

The second challenge is the need to reconcile the DEM and drainage lines acquired from some other dataset ([Lindsay et al., 2008](#)). One approach relies on 'stream burning,' where the local topography is altered to provide consistency with some existing vector hydrography dataset ([Saunders and](#)

Maidment, 1996) and the second method utilizes the stream network as a part of the surface-fitting approach used to generate square-grid DEMs (Hutchinson, 1989). The latter has been used here almost exclusively in the authors' hydrological work, in part because of existing software tools that tackle the past three problems (i.e., unwanted depressions, unresolved flow directions on flat terrain, and reconciliation of elevation and hydrography datasets) simultaneously.

The rapid growth in sources of mass-produced, remote-sensing-derived DEMs during the past two decades has demanded new forms of DEM preprocessing. For example, Reuter et al. (2009) and Webster and Dias (2006) described various approaches and opportunities for ortho-rectifying DEMs, reducing local outliers and noise, filtering water surfaces, filtering pure noise, filtering forests in SRTM DEMs, reducing padi terraces (i.e., areas with closed contours where all the surrounding pixels show the same value), filling voids and sinks, mosaicking adjacent DEMs, and filtering LiDAR DEMs. Some problems are more difficult to fix than others, and several authors have noted the presence of systematic and random errors that are not so easy to detect and correct in LiDAR datasets (e.g., Filin, 2003; Katzenbeisser, 2003; LaLonde et al., 2010). The detection of varying deflection errors and of time delays between measurements is especially difficult and specific to the composition of the LiDAR sensor system, and the large number of parameters that were assigned when the individual sensor systems were manufactured (Dowman, 2004). Reuter et al. (2009) also noted that two additional trends have emerged in recent years. The first is the integration of topographic and auxiliary information (such that the location of lakes, streams, ridges, and breaks will be identified from satellites and incorporated into the DEM processing chain) and the second is the increased use of fully data-driven simulation methods that reduce some or all of the aforementioned errors by calculating the average value of the land-surface parameter from multiple equi-probable realizations of the DEM (e.g., Burrough et al., 2000b; Hengl et al., 2004; Raafaub and Collins, 2006).

3.7.2.4 Error and Artifacts

With new data sources and information technologies, DEMs can now be produced in a variety of ways. Many subtleties are embedded in the various data sources and methods, and errors can be introduced at many stages of the production process. Some can be attributed to the fact that these errors may vary with the choice of the sensor and a specific application (i.e., method of deployment). Consequently, DEM differencing cannot be accurately used to detect altitude variations for assessing change, erosion, deposition, etc. (Burns et al., 2010). A second set of challenges concerns the propagation of the elevation errors in primary and secondary land-surface parameters, and the considerable effort that is generally required to identify them. The general approach for propagating errors incorporates statistical modeling of the error in the DEM (which is generally only partially known) and running a Monte Carlo analysis (Temme et al., 2009). Digital terrain modeling will utilize various techniques to detect and remove some or all of these errors. Data source errors, however, cannot always be eliminated, and those

interested in using land-surface parameters calculated from DEMs must be cognizant of these errors and how they may affect the analysis and interpretation of results.

It is worth reviewing what is known about the accuracy of DEM elevation values and the land-surface parameters calculated from these elevations. Several approaches have been proposed to assess the accuracy of DEM elevation values (e.g., Hutchinson, 2008; Temme et al., 2009). Many researchers have compared DEM-derived altitudes with elevation values taken from a more accurate source of topographic data, computing the root-mean-square error (Wise, 2000). One problem with this approach is that it ignores both the presence of systematic bias and the spatial pattern of errors, which is critical for those land-surface parameters that are heavily influenced by the shape of the land surface (Hutchinson and Gallant, 2000; Deng et al., 2008). Carara et al. (1997) suggested simple criteria to evaluate DEM quality when the DEM is constructed from contours: (1) the DEM should have the same values as contours close to the contour lines; (2) the DEM values must be in the range given by the bounding contour lines; (3) the DEM values should vary almost linearly between the values of the bounding contour lines; (4) the DEM patterns must reflect realistic shapes in flat areas; and (5) the artifacts must be limited to a small proportion of the data set. Hutchinson and Gallant (2000) have suggested a larger and more diverse list of simple metrics for measuring quality for DEMs constructed from surface-specific point elevation and contour- and stream-line data that incorporate some of the same ideas, and a rapidly growing literature is documenting the quality of DEMs constructed from remotely sensed sources (e.g., Carabajal and Harding, 2006; Hoften et al., 2006; Rodriguez et al., 2006; Shortridge, 2006; Berry et al., 2007; Bhang et al., 2007).

Whatever the source of the elevation data, a high-resolution DEM may still have greater uncertainty than a low-resolution DEM. Furthermore, the errors in DEMs may propagate to the land-surface parameters and modeling results in ways that are not easily predicted. See Bolstad and Stowe (1994), Band et al. (1995), Desmet (1997), Hunter and Goodchild (1997), Wood et al. (1997), Wise (1998), Holmes et al. (2000), Endreny and Wood (2001), Aerts et al. (2003), Van Niel et al. (2004), Lindsay and Creed (2005b), Fisher and Tate (2006), Lindsay (2006), Lindsay and Evans (2006), and Chow and Hodgson (2009), for examples spanning multiple DEM data sources and land-surface parameters.

In one particularly impressive study, Temme et al. (2009) examined the propagation of errors from DEMs in the computation of the slope (a local parameter), the topographic-wetness index (a regional parameter), and the soil redistribution resulting from water erosion (a complex model output) in the Baranja Hill watershed in Croatia. The DEM errors propagated strongly to slope (the mean coefficient of variation across 100 Monte Carlo simulations was 42% for unfilled DEMs and 49% for filled DEMs), but only moderately for the wetness index (the mean coefficient of variation was 10% for unfilled and 16% for filled DEMs), although the coefficient of variation for the index varied more spatially than that of slope. These results show that the wetness index values were less sensitive than slope to the input DEM, but this may have been influenced by the flow-routing algorithm

(Holmgren, 1994) that was used to calculate upslope contributing areas.

Temme et al. (2009) next used the water-erosion module of the LAPSUS landscape-evolution model (Schoorl et al., 2000) to simulate erosion and deposition in the Baranja Hill study area for 10 years. The model utilizes water flow and slope to calculate a sediment-transport capacity, and calculates erosion and deposition by comparing this transport capacity with the predicted amount of sediment in transport. The latter was simulated with the same multiple flow-direction algorithm used to calculate the wetness index, and the approach of Temme et al. (2006) was used to handle the flows of water and sediment into sinks. The latter capability was very important because it meant that the model could simulate erosion and deposition using both unfilled and filled DEMs. The results, at first glance, might be viewed as reassuring because the general erosion and deposition patterns were similar for unfilled and filled DEMs, with erosion occurring in the upper valleys and deposition occurring in flat areas. The mean soil-redistribution maps of the 100 simulations on unfilled DEMs, however, showed considerably more deposition and less erosion than the filled DEMs (in part because the depressions were filled before the model runs in the latter case), and the results in both sets of model runs were very sensitive to errors in the DEM (the mean coefficient of variation of soil redistribution was 4600% for unfilled and 1000% for filled DEMs). Hence, the coefficients of variation were larger and more spatially variable for soil redistribution than they were for the wetness index and slope, because the LAPSUS model results were sensitive to three forms of error in the input DEM – those associated with the error in the DEM and those that were introduced into the slope and topographic wetness index terms by the same source error. These kinds of dependencies are likely to be embedded in many of the analysis and modeling applications that incorporate one or more of the aforementioned primary and secondary terrain parameters. Consequently, error analysis is critical in geomorphometry, and preprocessing error-removal techniques are usually required.

3.7.3 Land-Surface Parameters

Computations of land-surface parameters attempt to characterize various multiscale properties of the terrain, and are used to extract land-surface objects. Consequently, many parameters can be classified based on geometry considerations, scale, or use in process mechanics and numerical modeling. Wilson and Gallant (2000a) classified them as primary and secondary, given that they constitute the basic building blocks for landform classification and other forms of more sophisticated analysis and modeling.

3.7.3.1 Primary Parameters

Many local parameters are calculated by moving a three-by-three window across a grid and computing land-surface parameters for the target cell (i.e., the central cell in the three-by-three window). There are special rules on how to handle the edges, and this approach produces a new grid or GIS layer with the same dimensions as the DEM for each parameter. The

most frequently used parameters represent the first and second derivatives of the altitude field. The two main geometric properties are the average slope gradient, S , and the slope azimuth, ϕ . The average slope gradient accounts for orthogonal directions such that

$$S = \left(\frac{\partial z}{\partial x} \right)^2 + \left(\frac{\partial z}{\partial y} \right)^2 \quad [1]$$

where z represents the altitude, and x and y represent the directions. Several algorithms or modeling approaches may require the use of S , or the slope angle β , which is defined as

$$\beta = \arctan(S) \quad [2]$$

Slope information can also be expressed as slope percentage and surface area, A_s , which can be approximated by

$$A_s = \frac{A_{\text{cell}}}{\cos \beta} \quad [3]$$

where A_{cell} is the area of a grid cell. Slope is routinely used in sediment-transport modeling, landform mapping, surface-energy-budget studies, and for characterizing various aspects of process mechanics related to fluvial, mass movement, and glacier-erosion dynamics (Figure 5).

The direction of the slope, or slope azimuth, is another critical geometric property that governs water and sediment flows, while also reflecting the orientation structure of the topography as governed by lithology and structural influences. Gallant and Wilson (1996) defined it as

$$\phi = 180 - \arctan\left(\frac{q}{p}\right) + 90 \frac{p}{|p|} \quad [4]$$

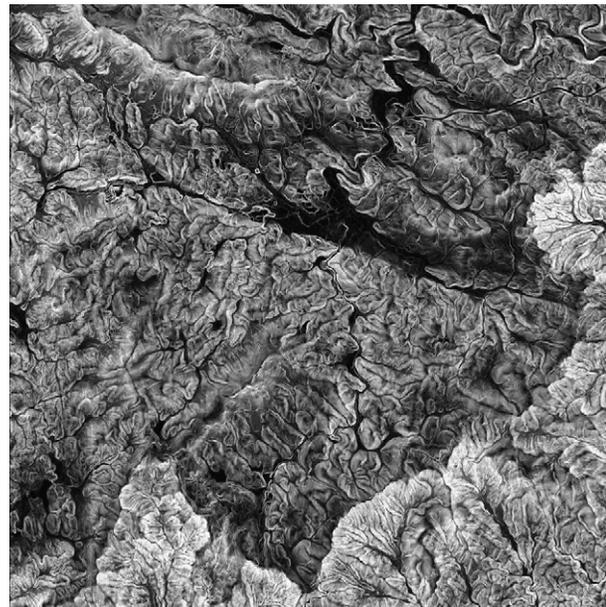


Figure 5 Slope-angle map generated from 5 m LiDAR DEM displayed in Figure 4. Slope variations are significant in mountain environments and can reflect variations in erosion, lithology, and tectonics. Slope information is also critical for evaluating natural-hazard potential and for planning purposes.

where

$$p = \frac{\partial z}{\partial x}, \quad q = \frac{\partial z}{\partial y} \quad [5]$$

Slope azimuth is a circular parameter and is frequently transformed using $\cos \phi$ and $\sin \phi$ to examine linear trends in *northernness* and *easterness*, respectively. Slope azimuth is also important in solar-radiation modeling. As with slope, various algorithms can be used for computation, and each will produce slightly different estimates across a range of land-surface conditions. Details about the performance of various equations can be found in Skidmore (1989) and Hengl and Evans (2009).

Terrain curvature is also frequently used to estimate the magnitude of concavity and convexity of the land surface. The convention followed in the Earth sciences is for a positive curvature value to represent a convex surface shape, whereas a negative value represents a concave surface shape (Olaya, 2009). The profile (or vertical) curvature, C_{profile} , and tangential (horizontal) curvature, $C_{\text{tangential}}$, are generally used to distinguish locally convex and concave shapes. They are defined as

$$C_{\text{profile}} = \frac{p^2(r+2)pqs + q^2t}{(p^2 + q^2)\sqrt{(1 + p^2 + q^2)^3}} \quad [6]$$

$$C_{\text{tangential}} = \frac{q^2(r-2)pqs + p^2t}{(p^2 + q^2)\sqrt{1 + p^2 + q^2}} \quad [7]$$

where r , s , and t represent

$$r = \frac{\partial^2 z}{\partial x^2}, \quad s = \frac{\partial^2 z}{\partial x \partial y}, \quad t = \frac{\partial^2 z}{\partial y^2} \quad [8]$$

Convex profile curvature indicates acceleration of flows and a local increase in potential energy, whereas concave profile curvature indicates a flattening of the slope and therefore a decline in potential energy (Figure 6). Concave tangential curvature indicates convergence and convex tangential curvature indicates divergence of flow lines, which may in turn influence overland flow paths, soil moisture distribution, and soil redistribution (Figure 7). Planform curvature is sometimes used to describe the curvature of contour lines and should yield results similar to tangential curvature, as long as the contour lines describe the shape of the land surface (Gallant and Wilson, 2000). Other forms of curvature can also be utilized, and these include mean curvature, unsphericity curvature (Figure 8), Gaussian curvature, and curvature of flow lines. See Olaya (2009) for the details on their computation and their potential significance in the Earth sciences.

Other local-statistical parameters can also be used to characterize key aspects of the surface. Relief and surface roughness represent two important parameters valuable in geomorphology. Local relief is highly correlated to slope, although a nonlinear relationship has been found in extreme mountain environments that can be useful for differentiating process–form relationships, and the nature of the relationship may be related to the magnitude of erosion and the rate of relief production. It simply represents the range in the altitude

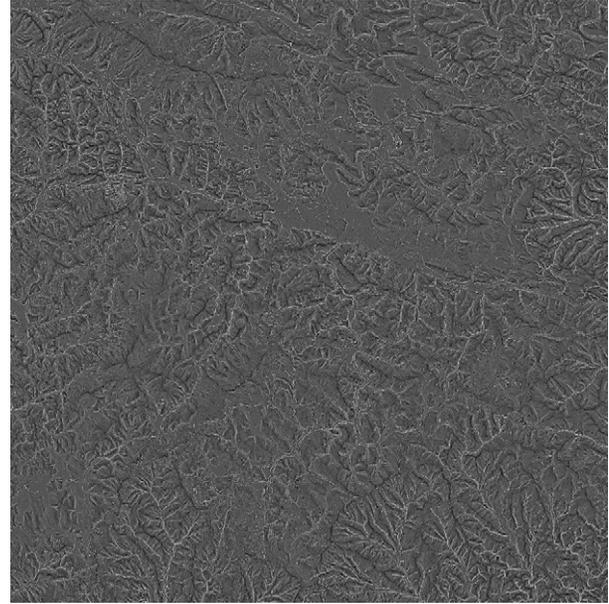


Figure 6 Profile-curvature map generated from the 5 m LiDAR DEM displayed in Figure 4.

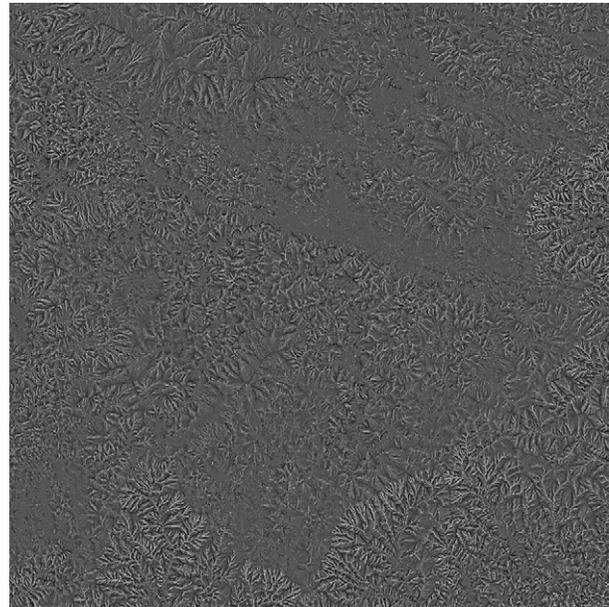


Figure 7 Tangential-curvature map generated from the 5 m LiDAR DEM displayed in Figure 4.

values over the spatial extent of the computational window. It is important to note that relief is scale dependent, and examining relief variation at different scales highlights different aspects of the geomorphological system (i.e., tectonics at larger scales). Similarly, surface roughness can be estimated in a variety of ways. An interesting characterization makes use of the vector approach such that

$$X_i = \sin(\beta) \cos(\phi), \quad Y_i = \sin(\beta) \sin(\phi), \quad Z_i = \cos(\beta) \quad [9]$$



Figure 8 Unsphericity-curvature map generated from the 5 m LiDAR DEM displayed in [Figure 4](#). The unsphericity parameter highlights land-surface conditions that are planar in nature.

where X_i , Y_i , and Z_i are the components of the unit vector normal to the land surface. The surface-roughness factor (SRF) can then be computed as

$$\text{SRF} = \frac{\sqrt{(\sum_i^n X_i)^2 + (\sum_i^n Y_i)^2 + (\sum_i^n Z_i)^2}}{n} \quad [10]$$

where n is the number of cells in a window. Other approaches to characterizing surface roughness include semivariogram analysis and the use of the fractal dimension to characterize terrain complexity. Terrain roughness has utility related to weathering studies, estimating aerodynamic drag, and other surface applications.

The regional (i.e., nonlocal) land-surface parameters are mainly concerned with the climatic, geomorphic, hydrologic, or visual properties of landscapes. The first category relies on the accurate delineation of the shadowing, sky-view, and terrain-view nature of the surrounding topography as it influences irradiance, temperature, and precipitation. The geomorphic and hydrological parameters focus on the movement of water and sediment and, as such, rely on the accurate delineation of flow paths, watersheds, and scale-dependent slope and relief. The most common parameters are sediment flux, upslope contributing area, flow-path length, and a variety of statistical measures. For example, positive and negative openness ([Yokoyama et al., 2002](#)) can be extremely valuable to geomorphologists, as positive openness highlights areas of extreme relief and has been used to discover active erosion zones in the Himalaya ([Bishop et al., 2010](#)). Negative openness ([Figure 9](#)) highlights the scale-dependent hydrological network, and has potential for use in mapping valley bottoms and hydrological modeling. For the final category, the visibility (i.e., from what other points can a single point be seen

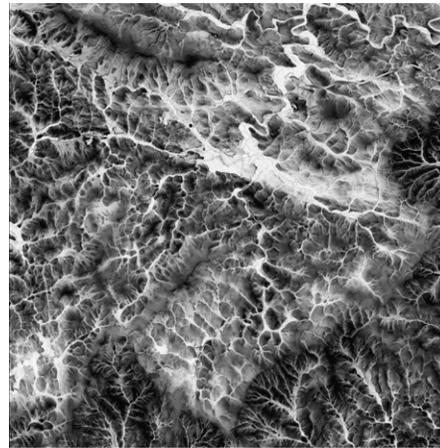


Figure 9 Negative-openness map generated from the 5 m LiDAR DEM displayed in [Figure 4](#). A window search radius of 1 km was used to highlight the scale-dependent hydrological network. This parameter, when combined with other geomorphometric parameters, can greatly facilitate the assessment of local and regional hydrological conditions.

or the reverse, what other points can be seen from a single point) can be calculated by drawing the line of sight from the point of interest to all other points, and checking whether or not the relief forms that occur between them block visibility. From here, various measures of visual exposure, such as the number of cells that can be seen from each cell, can be calculated. See [Fisher \(1991, 1992, 1993, 1995, 1996\)](#) and [Ruiz \(1997\)](#) for examples of these types of applications and some of the pitfalls that should be avoided.

Last but not the least, the complex issue of scale as it relates to representing and characterizing the topography must be discussed. Unfortunately, key issues associated with conceptual and practical treatments of scale have not been appropriately addressed ([Bishop et al., 2012](#)). These issues are related to measurement, cartographic, geographical, computational, and operational scales, coupled with hierarchical organization, and the anisotropic nature of the topography. First, the local terrain shape, which is generally thought of as the continuous variation of the altitude field from point to point, has an enormous impact on local and regional terrain parameters, but this role is primarily influenced by cartographic and computational scale. [Florinsky \(1998\)](#) suggested that local parameters, such as slope gradient, slope azimuth, and curvatures, are mathematical variables rather than real-world characteristics. This statement may be extended to all local terrain parameters for two reasons. First, local terrain shape may rely on different mathematical descriptions, so that the local parameters calculated depend on algorithm selection. Furthermore, the terrain shape portrayed by DEMs is a function of cartographic scale, combining the complexity of the terrain (geographic scale of features), computational scale, and measurement scale at which the terrain surface was sampled (e.g., [Deng et al., 2008](#)). Thus, it is possible to use the same local parameter to describe terrain shape at different scales (resolutions, distances, and directions). The special feature of nonlocal primary attributes is that they rely on the terrain shape of a larger, non-neighbor area (computational scale) and need to be defined with

reference to other nonlocal points. Therefore, calculation of nonlocal attributes is more difficult because it incurs additional efforts in constructing point to-point connections over the landscape and involves more complex algorithms and scale considerations (e.g., Desmet and Govers, 1996; Gallant and Wilson, 2000).

Finally, the computation of geomorphometric parameters does not usually account for a meaningful computational scale corresponding to the geographic scale of landforms, to the operational scale of surface processes, or to coupled systems dynamics. This disconnect significantly affects the magnitude and interpretation of a land-surface parameter, such that it does not accurately characterize the topography, as governed by theory and practical utility. Such spatial constraint problems of computational scale are related to surface materials and the hierarchical organization of the topography, where hierarchically organized landforms and features effectively represent complex topographic patterns. Such scale dependencies and organizational structure have yet to be formally addressed, and are rarely accounted for by many land-surface parameters. The partial exception to this is basic semivariogram analysis, as it effectively accounts for spatial complexity, although a spatial limit based on hierarchical structure has yet to be rigorously evaluated. Furthermore, the anisotropic nature of the topography at a multitude of distances must also be accounted for. This is demonstrated at the local level using slope computed from the eight directions within a 3×3 window. Principal component analysis of the entire slope data set reveals fundamentally important anisotropic information that can be used to highlight topographic structure related to surface processes, lithology, and tectonics (Figure 10). The second principal component image highlights the local basin structure, such that many spatial

characteristics can be used for geomorphological mapping and system characterization. This aspect of scale is very important in geomorphology, as it may improve the ability to assess new aspects of geomorphological systems. Another example at a larger computation scale is presented by Koons et al. (2012), as they reveal that rock strength may be related to the anisotropic nature of scale-dependent relief. Land-surface parameters and objects that characterize operational scales and structural constraints are urgently needed, and may aid in establishing new theories about landscape evolution. Table 2 lists the most commonly used primary land-surface parameters and their significance.



Figure 10 Second principal-component image representing anisotropic slope information extracted from local slope data over the Shimshal Valley in northern Pakistan. The slope data set was generated from a Shuttle Radar Topographic Mission (SRTM) 3 arc-second DEM. Spatial variation patterns are related to lithological units and tectonics. Less resistant metasedimentary rocks in the northeastern region and less precipitation generate a higher spatial-frequency pattern, compared with a lower spatial-frequency pattern in the southwestern region associated with more resistant lithologic units, active uplift, and greater relief.

Table 2 Select list of primary and secondary land-surface parameters and their significance

<i>Parameters</i>	<i>Type</i>	<i>Significance</i>
Elevation	Local	Climate, vegetation, potential energy
Slope	Local	Precipitation, overland and subsurface flow velocity and runoff rate, soil-water content
Slope azimuth	Local	Flow direction, solar insolation, evapotranspiration, flora and fauna distribution and abundance
Profile curvature	Local	Flow acceleration and deceleration, soil erosion and deposition rates
Tangential curvature	Local	Local flow convergence and divergence
Roughness	Local	Terrain complexity
Elevation percentile	Local	Relative landscape position, flora and fauna distribution and abundance
Flow width	Local	Flow velocity, runoff rate, and sediment load
Upslope contributing area	Regional	Runoff volume, soil water content, soil redistribution
Flow-path length	Regional	Runoff volume, soil water content, soil redistribution
Upslope height, elevation-relief ratio, hypsometric curve, etc.	Regional	Distribution of height values, potential energy, flow characteristics
Mean slope of upslope area	Regional	Runoff velocity and possibly other flow characteristics
Mean slope of dispersal area	Regional	Rate of soil drainage
Visual exposure	Regional	Exposure, solar insolation, wind patterns
Topographic wetness index	Regional	Spatial distribution and extent of zones of saturation (i.e., variable source areas) for runoff generation as a function of upslope contributing area, soil transmissivity, and slope
Stream-power index	Regional	Erosive power of flowing water (based on the assumption that discharge is proportional to the specific catchment area)

Source: Modified from Wilson, J.P., Gallant, J.C., 2000a. Digital terrain analysis. In: Wilson, J.P., Gallant, J.C. (Eds.), *Terrain Analysis: Principles and Applications*. John Wiley and Sons, New York, pp. 1–27, and Olaya, V., 2009. Basic land-surface parameters. In: Hengl, T., Reuter, H.I. (Eds.), *Geomorphometry: Concepts, Software, Applications*. Elsevier, Amsterdam, pp. 141–169.

3.7.3.2 Secondary Land-Surface Parameters

In general, there are two basic sets of secondary land-surface parameters. The first is for hydrologic characterization related to quantifying water flow and related surface processes, and the second is a series of climatology parameters that are related to multiscale topographic influences on radiation, temperature, and precipitation. Collectively, these parameters attempt to quantify the interactions between the atmosphere and surface processes. The underlying theory for both is well established, and the parameterization schemes and computational methods have evolved continuously over the past 20 years.

3.7.3.2.1 Hydrology

The movement of water is primarily driven by gravity and, to some degree, modified by the properties of the material it flows through or over (Gruber and Peckham, 2009). The effect of gravity can be approximated easily with a DEM, but the surface and subsurface properties and conditions are cumbersome to describe and treat. There are steadily improving regional and national databases describing the spatial variability of selected land-surface and soil characteristics (e.g., Miller and White, 1998; Feng et al., 2009), but these have a much coarser resolution than the authors' DEMs, and seldom include the various properties needed for specific applications. The typical approach relies on a series of parameter estimation equations (e.g., Rawls, 1983; Saxton et al., 1986; Abdulla and Lettenmier, 1997; Homann et al., 1998; Waltman et al., 2003; Saxton and Rawls, 2006), although these will undoubtedly introduce some additional uncertainty and error into the analytical workflow or modeling application at hand (e.g., Band, 1993; Wilson et al., 1996; Zhu and Mackay, 2001; Quinn et al., 2005). Given this state of affairs, it can be assumed that the DEM-based parameters will do better where the relative importance of gravity is greatest (i.e., in headwater areas and on steep slopes).

The initial development and use of flow-based land-surface parameters can be traced to the introduction of the D8 algorithm (O'Callaghan and Mark, 1984). This is now but one of more than a dozen flow-routing algorithms, however, and a distinction is usually drawn between single- and multiple-flow direction algorithms. The single flow-routing algorithms, which direct flow to just one downslope or neighboring cell, include the Rho8 (Fairfield and Leymarie, 1991) and aspect-driven kinematic routing (Lea, 1992) algorithms in addition to the D8 algorithm. The multiple flow-routing algorithms, which are capable of directing flow to two or more downslope or neighboring cells, include the FD8 (Freeman, 1991), TOPMODEL (Quinn et al., 1991, 1995), DEMON (Costa-Cabral and Burges, 1994), $D\infty$ (Tarboton, 1997), and Mass-Flux algorithms (Gruber and Peckham, 2009). These flow-routing algorithms will generally generate very different results (Figures 11 and 12).

The performance of many of these flow-routing algorithms has been compared across a variety of landscapes (e.g., Wolock and McCabe, 1995; Desmet and Govers, 1996; Zhou and Liu, 2002; Endreny and Wood, 2003; Chirico et al., 2005; Wilson et al., 2000, 2007). Wilson et al. (2008) recently evaluated the performance of several algorithms including ANSWERS (Beasley and Huggins, 1978), D8 (O'Callaghan and

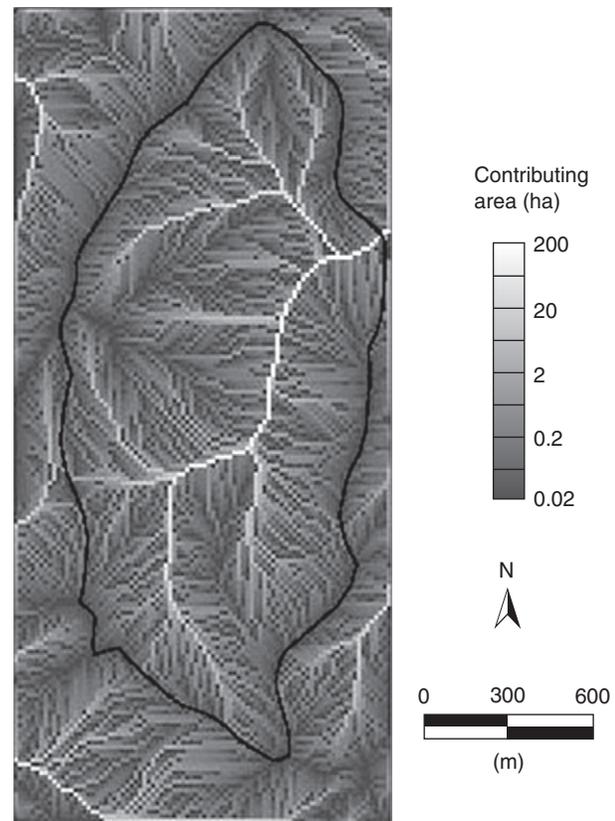


Figure 11 Gridded contributing area (ha) map derived from the Cottonwood Creek, Montana DEM, using the D8 single flow direction algorithm, with the catchment boundary overlaid. Reproduced from Wilson, J.P., Gallant, J.C., 2000b. Secondary topographic attributes. In: Wilson, J.P., Gallant, J.C. (Eds.), *Terrain Analysis: Principles and Applications*. John Wiley and Sons, New York, pp. 51–85.

Mark, 1984), Rho8 (Fairfield and Leymarie, 1991), FD8/TOPMODEL (Freeman, 1991; Quinn et al., 1991, 1995), an aspect-driven kinematic routing algorithm (Lea, 1992), DEMON (Costa-Cabral and Burges, 1994), a flow decomposition algorithm (Desmet and Govers, 1996), $D\infty$ (Tarboton, 1997), and MFD-md (Qin et al., 2007). They showed that various algorithms can be expected to generate different patterns of flow (based on upslope contributing areas) on different parts of a hill slope or a watershed. The gridded contributing area map reproduced in Figure 11 shows how the D8 algorithm often generates many parallel flow lines, which of course do not match the dendritic patterns that characterize most surface and channel flow systems, whereas the DEMON algorithm (Figure 12) produces more realistic patterns, but is computationally slow when used with large DEMs and prone to failure in flat areas. The final choice of the flow-routing algorithm should aim to minimize the most important of these tradeoffs for the particular study area and application at hand.

Notwithstanding the presence of these kinds of tradeoffs, the multiple flow-routing algorithms have grown in popularity over time. The fundamental goal with this class of algorithms is to find a method or a sequence of methods that move water into one or more downslope cells, and Gruber and Peckham (2009)

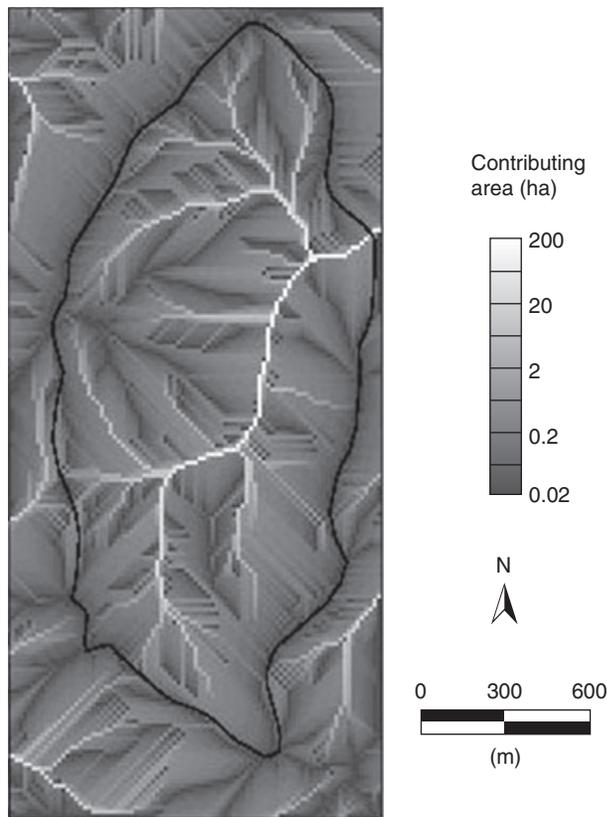


Figure 12 Gridded contributing area (ha) map derived from the Cottonwood Creek, Montana DEM, using the DEMON stream-tube algorithm, with the catchment boundary overlaid. Reproduced from Wilson, J.P., Gallant, J.C., 2000b. Secondary topographic attributes. In: Wilson, J.P., Gallant, J.C. (Eds.), *Terrain Analysis: Principles and Applications*. John Wiley and Sons, New York, pp. 51–85.

have noted how this approach might be justified by actual divergence (i.e., the need to treat flows across convergent and divergent land surfaces) and/or the attempt to overcome the limits of having only eight adjacent cells (i.e., methods to overcome the limitations generated when a continuous flow field is represented with a regular grid that has only eight possible directions in multiples of 45°).

This pair of explanations helps to explain why the final choice of a flow-routing method for a specific application will be a compromise. The single flow-direction algorithms cannot represent divergent flow, but for the same reason, have no problem with overdispersal (i.e., the dispersal of the available flow over too many cells or too large an area). The multiple flow-direction algorithms, however, can represent divergent flow, but usually also suffer from some overdispersal. In addition, the subtleties and outcomes of the methods are concerned with the need to: (1) treat ambiguous flow directions (as for example occurs along ridgelines or saddles and across flat plains or valley bottoms); and (2) reconcile the DEM-delineated flow lines and the drainage lines acquired from some other source that are also likely to influence the results generated with these different flow-routing algorithms.

Therefore, the flow directions are generally computed to calculate upslope contributing areas (i.e., flow accumulation areas)

and delineate the drainage networks along with the basin boundaries. See Band (1986, 1989), Montgomery and Dietrich (1989, 1992) and Peckham (1998) for examples of methods for delineating drainage networks with single flow-direction algorithms. The topographic wetness and stream-power indices are among the most popular of various stream attributes, and unlike the catchment (basin) boundaries and some other attributes, this pair of attributes can be calculated with both the single and the multiple flow-direction algorithms.

The typical form of the topographic wetness index (TWI) assumes steady-state conditions and describes the spatial distribution and extent of zones of saturation (i.e., variable source areas for runoff generation) as a function of upslope contributing area A_c , slope, and occasionally soil transmissivity (this last term is often excluded because the transmissivity is assumed to be constant throughout the catchment), such that

$$TWI = \ln \left[\frac{A_c}{\tan \beta} \right] \quad [11]$$

The steady-state form of the TWI predicts zones of saturation where the specific catchment area is large (which typically occurs in converging areas of the landscape), the slope is small (which typically occurs at the base of concave slopes), and soil transmissivity is low (which is often characteristic of areas with shallow soils). This index has been used successfully in a variety of hydrological applications because the aforementioned conditions are commonly encountered along drainage paths and in zones of water concentration in many landscapes (e.g., Beven and Kirkby, 1979; Burt and Butcher, 1985; Moore and Burch, 1986; O'Loughlin, 1986; Sivapalan et al., 1987; Moore et al., 1988; Phillips, 1990; Montgomery and Dietrich, 1994; Moore and Wilson, 1992, 1994; Fried et al., 2000; Kheir et al., 2007).

These types of static indices, however, must be used carefully to predict the distribution of dynamic phenomena like soil-water content because surface saturation is a threshold process, the presence of hysteric effects, and the reliance on one or more assumptions. The two most important assumptions in this case are that: (1) the gradient of the piezometric head, which governs the direction of subsurface flow, is parallel to the land surface; and (2) there is sufficient time between rainstorms for the subsurface flow to achieve a steady state (Moore et al., 1993a). Several authors have described the pitfalls of using these kinds of indices in inappropriate ways. For example, Jones (1986, 1987) documented some of the advantages and limitations of using wetness indices to describe the spatial patterns of soil-water content and drainage, and Quinn et al. (1995) summarized the various problems and described how the steady-state TWI can be calculated and used effectively as part of the TOPMODEL hydrologic-modeling framework. Several variants of the original equation have also been proposed. Barling (1992) proposed a quasi-dynamic topographic wetness index (QD-TWI) to overcome the limitations of the steady-state assumption and used it to show how the topographic hollows, and not the drainage channels themselves, determined the response of a semiarid catchment in New South Wales, Australia (see Barling et al. (1994) for additional details). Wood et al. (1997) later proposed an alternative index to predict the saturated-zone thickness that incorporated both

spatial and temporal variation in recharge. Both Fried et al. (2000) and Nguyen and Wilson (2010) calculated QD-TWI using a variety of flow-routing algorithms and showed how the results varied depending on the flow-routing algorithm that was utilized.

3.7.3.2.2 Climatology

The topography also governs microclimate, and surface-energy conditions influence the magnitude of various surface processes. Böhner and Antonić (2009) reviewed topoclimatology parameters, as the land surface controls the spatial variability of near-ground atmospheric processes and meso-scale climatic variations. The regionalization approaches that use kriging, universal kriging, and splines to map the climate variables measured at climate stations are ignored, and the focus is on the land-surface parameters that are used to assess the variability of the short- and long-wave radiation fluxes, as these influence surface temperature, evapotranspiration, air movement, and other surface processes.

Understanding and predicting the magnitude of solar and surface irradiance is of primary concern. Solar irradiance varies as a function of: (1) the changing distance from the Sun to the Earth; (2) intrinsic variation in the output of the Sun; and (3) changes in the radiation field from the Sun toward the Earth. Annual changes in irradiance can be $\sim 6\%$, independent of wavelength. A nonuniform distribution of active regions also occurs on the solar disk that are modulated by a 27-day rotation period, which results in irradiance variations that are wavelength (λ) dependent. Irradiance variations are also caused by solar magnetic activity (22-year cycle). These variations are caused by eruptive phenomena such as flares, and range in temporal scale from minutes, to months, to years, and include the 11-year sunspot cycle.

The exo-atmospheric irradiance, E^0 , is therefore a function of orbital parameters that determine its magnitude. Most GIS-based solar-radiation models do not account for orbital-parameter variation of obliquity and eccentricity; therefore, they cannot be used effectively for paleo-climate and future-scenario studies too far into the past or future. For example, such models cannot be used to study radiative forcing in the Holocene. Rather, such models make use of standard irradiance spectra and account for the annual variation in the Earth-Sun distance to portray seasonal and diurnal variations in E^0 .

Atmospheric conditions then determine the amount of atmospheric attenuation, and atmospheric-transmission functions are wavelength dependent. Atmospheric conditions are generally prescribed based on modeled atmospheric conditions. For solar-radiation modeling and estimation of surface-process rates, there is a need to accurately estimate the surface spectral irradiance (E) which is a composite of three downward irradiance components

$$E(\lambda) = E_b(\lambda) + E_d(\lambda) + E_t(\lambda) \quad [12]$$

The direct/beam irradiance (E_b) is typically dominant, followed by the diffuse-skylight irradiance (E_d) and the adjacent terrain irradiance (E_t). Variations in atmospheric, topographic, and land-cover conditions determine the sequential dominance of irradiance partitioning.

Under cloudless skies, E_b is the dominant term in eqn [12]. Consequently, considerable research has focused on modeling the direct atmospheric-transmittance functions accurately. The atmosphere attenuates the direct irradiance primarily by gaseous absorption and molecular and aerosol scattering (Chavez, 1996). These atmospheric processes are wavelength dependent, and spatially and temporally controlled by changing atmospheric and landscape conditions. The total downward atmospheric transmission (T^\downarrow) is a function of the total optical depth of the atmosphere, which varies with solar-zenith angle and altitude, and can be represented as

$$T^\downarrow(\lambda) = T_r(\lambda)T_a(\lambda)T_{O_3}(\lambda)T_{gas}(\lambda)T_{H_2O}(\lambda) \quad [13]$$

where T_r is the Rayleigh transmittance, T_a is the aerosol transmittance, T_{O_3} is the ozone transmittance, T_{gas} is the transmittance for miscellaneous well-mixed gases, and T_{H_2O} is the water-vapor transmittance. Atmospheric attenuation is highly variable with wavelength, with Rayleigh and aerosol scattering dominating at shorter wavelengths and water vapor dominating at longer wavelengths.

The direct irradiance is also governed by multiscale topographic parameters. Local or microscale topographic variation is represented by the incidence angle of illumination between the Sun and the vector normal to the ground, such that

$$\cos i = \cos \theta_i \cos \beta + \sin \theta_i \sin \beta \cos(\phi - \phi_i) \quad [14]$$

where θ_i is the incident solar-zenith angle and ϕ_i is the incident solar-azimuth angle.

It is possible to estimate $\cos i$ using a DEM, and uncertainty in the estimate is related to the resolution, as subpixel-scale topographic variation is not accounted for. Values of $\cos i$ can be ≤ 0.0 , indicating no direct irradiance due to the orientation of the topography. It is important to note that the incident solar geometry varies across the landscape, although this is usually assumed to be constant when working with image scenes (i.e., small-angle approximation). In addition, the meso-scale topographic relief in the direction of ϕ_i determines whether a pixel is in shadow (S_c). This can be accounted for by ray tracing, shadow detection, and shadow interpolation algorithms that alter $\cos i$ values appropriately (Dozier et al., 1981; Rossi et al., 1994; Giles, 2001). The local and meso-scale topographic influences on the direct irradiance are significant over annual and diurnal time scales (Figure 13). Consequently, direct irradiance exhibits a high degree of spatio-temporal variability. The direct irradiance component can be estimated as

$$E_b(\lambda) = E^0(\lambda)T^\downarrow(\lambda)\cos i S_c \quad [15]$$

Atmospheric scattering also generates a hemispherical source of irradiance that should be calculated as an integration of the total sky irradiance. This source can be simplistically represented as a composite of a Rayleigh-scattered component (E_r), an aerosol-scattered component (E_a), and the ground-backscattered component (E_g) that represent inter-reflections between the land surface and the atmosphere, where

$$E_d(\lambda) = E_r(\lambda) + E_a(\lambda) + E_g(\lambda) \quad [16]$$

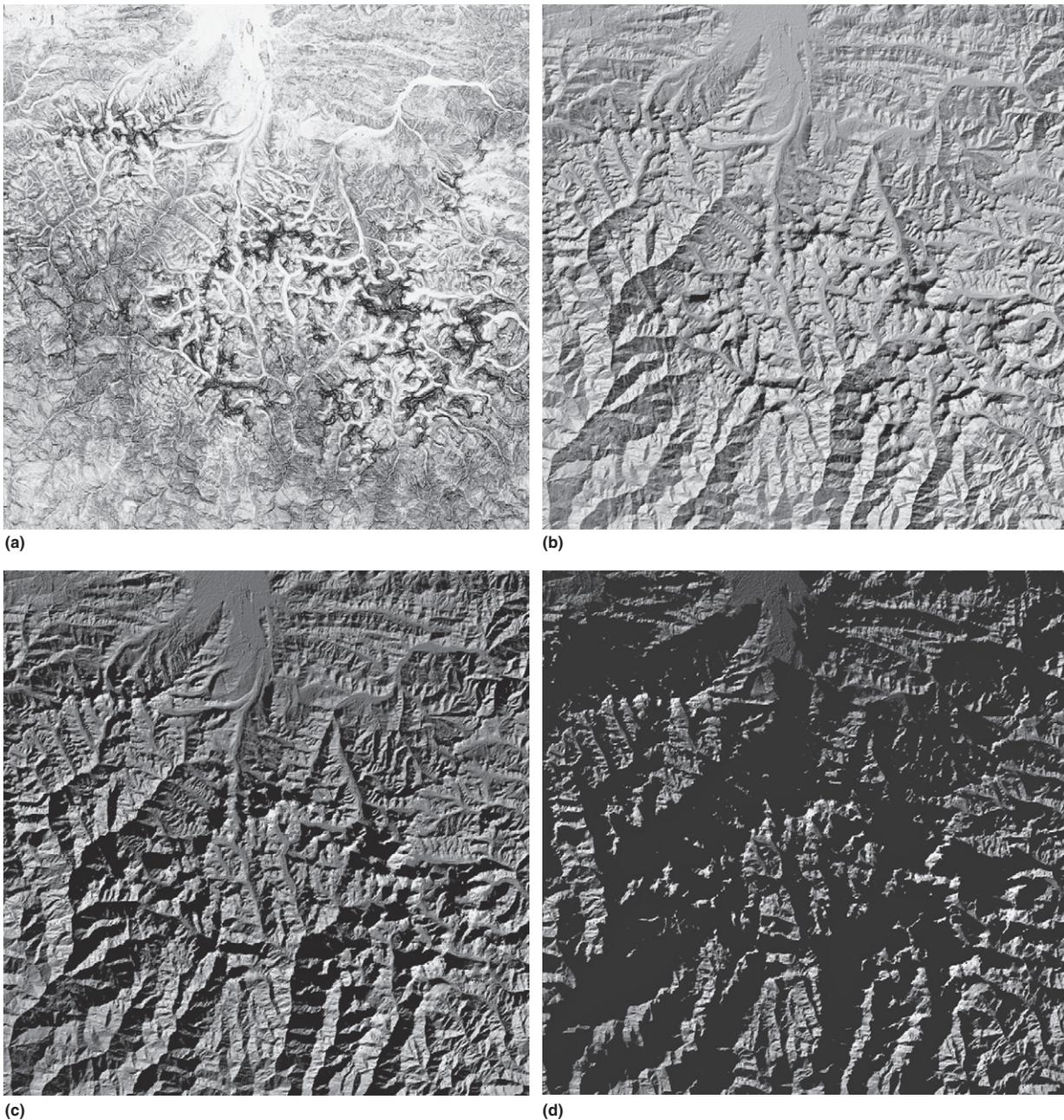


Figure 13 Simulated topographic influences on the direct irradiance ($\cos iS_c$) over the Mt. Everest region in Nepal. Darker tones represent less direct irradiance whereas light tones represent greater direct irradiance. Simulations based on an Advanced Spaceborne Thermal Emission and Reflectance Radiometer Global Digital Elevation Model of the region. Simulations account for local topographic conditions including slope and slope azimuth, as well as meso-scale topographic shielding that casts shadows. The solar azimuth was held constant at 135.0° : (a) Simulation with a solar-zenith angle of 0.0° ; (b) Simulation with a solar-zenith angle of 45.0° ; (c) Simulation with a solar-zenith angle of 70.0° ; and (d) Simulation with a solar-zenith angle of 85.0° . Assuming relatively constant atmospheric conditions, direct irradiance in this region exhibits a high degree of spatiotemporal variability.

Its accurate estimation is complicated by the fact that an anisotropic parameterization scheme is required. In general, the irradiance decreases with angular distance from the Sun. In addition, this irradiance component is also influenced by meso-scale hemispherical shielding of the topography. Consequently, only a solid angle of the sky will contribute to E_d , and this angle will change as a function of pixel location

and direction. In general, the solid angle will increase with altitude. It is frequently referred to as the sky-view factor (V_f) in the remote-sensing and energy-balance literature, and can be estimated using a DEM (Figure 14) such that

$$V_f = \sum_{\phi=0}^{360} \cos^2 \theta_{\max}(\phi, d) \frac{\Delta\phi}{360} \quad [17]$$



Figure 14 Sky-view factor over northern Pakistan. This parameter was computed from a Shuttle Radar Topographic Mission (SRTM) 3 arc-second DEM. Darker tones represent those areas that do not receive as much diffuse-skylight irradiance, whereas lighter tone areas receive more. The spatial patterns reveal that meso-scale relief conditions are highly variable in the Himalaya. Examination of the magnitude and spatial patterns reveals that some glaciers are receiving more diffuse-skylight irradiance than others, whereas different glaciers exhibit different trends in their sky-view-factor altitude profile. Such topographic variation regulates ablation rates and governs the sensitivity of glacier response to climate forcing. This in turn regulates melt-water production and glacial and fluvial erosion.

where θ_{\max} is the maximum local horizon angle at a given azimuth, ϕ , over a radial distance of d .

In mountain environments exhibiting extreme relief and deep valleys, topographic shielding of the skylight-diffuse irradiance can be significant (Proy et al., 1989). Furthermore, difficulties in accurately predicting the bidirectional reflectance distribution function (BRDF) of land-cover characteristics surrounding individual pixels generate uncertainty in the estimation of the ground-backscattered component.

The irradiance components E_b and E_d interact with the terrain and land-cover biophysical characteristics to generate an adjacent-terrain irradiance component. This irradiance component is not generally considered in remote-sensing, GIS-based radiation modeling, and energy-balance studies because it is assumed that its magnitude is relatively minor, and it is a difficult parameter to estimate accurately. A first-order approximation has been formulated by Proy et al. (1989) and assumes that surface radiance is Lambertian. It is then possible to estimate the radiance received at any pixel, by accounting for the geometry between two pixels (p_1 and p_2) such that

$$L_{12} = \cos\theta_1 \left(L_2 \cos\theta_2 \left[\frac{A_p}{d^2} \right] \right) \quad [18]$$

where L_{12} represents the radiance received at p_1 from the luminance of p_2 (L_2), θ_1 and θ_2 are the angles between the normal to the terrain and the direct line of sight from p_1 – p_2 , A_p is the pixel area (p_2), and d represents the distance between p_1 and p_2 .

This equation can be used to estimate E_t for any pixel by integrating over all of the pixels whose slopes are oriented toward a pixel of interest and where the line of sight is not blocked by the topography. High-altitude and extreme local

relief areas can exhibit a strong adjacent-terrain irradiance component due to highly reflective features such as snow and vegetation.

The magnitude of the reflected and emitted radiance at the surface is determined by the conservation of energy, such that

$$\rho(\lambda) + \alpha_a(\lambda) + T(\lambda) = 1.0 \quad [19]$$

where, ρ , α_a , and T represent the reflectance, absorption, and transmission, respectively. For opaque objects, $T=0.0$. It is commonly assumed that reflectance is isotropic (surface reflects radiation equally in all directions) and the surface spectral radiance (L) can be computed as follows

$$L(\lambda) = \rho(\lambda) \left(\frac{E(\lambda)}{\pi} \right) \quad [20]$$

The Lambert assumption, however, is not an accurate characterization of the anisotropic nature of surface reflection. The BRDF describes such reflectance variations and can be used to estimate the surface albedo, a key parameter in surface energy-budget modeling needed to compute the net short-wave radiant flux. Several parameterization schemes exist for the long-wave irradiance and net long-wave radiant flux, and other surface energy-budget components are also dependent on topographic parameters including surface roughness.

Several GIS-based solar-radiation models and surface energy-budget models can be used to produce maps of various surface irradiance and energy parameters. Such models can be used over user-specified periods ranging from 1 day to a year in length. SRAD (Moore et al., 1993b; Wilson and Gallant, 2000b) is but one of a number of models that have been proposed for calculating the radiation fluxes and it incorporates the effects of cloudiness into the calculations. Others include r.sun (Hofierka, 1997), Solar Analyst (Fu and Rich, 2000), Solar Flux (Dubyah and Rich, 1995; Hetrick et al., 1993a, b), and Solei (Mészáros, 1998; Mikláneek, 1993). All the aforementioned models document how spatial variability in elevation, slope, slope azimuth, cast shadows, sky-view factor, and other variables can create very strong local gradients in solar radiation and surface temperature, and thereby exert a large influence on surface processes including photosynthesis, evapotranspiration, ablation, weathering, as well as influencing vegetation diversity and biomass production at specific locations on the land surface.

Analysis of the topography is also required for the characterization of precipitation, air flow, and wind speed, as rainfall is governed by local slopes and meso-scale altitude variations, and air-flow direction and speed is governed by regional relief structure, deformation orientation patterns, and local and meso-scale surface roughness. For more details, see Böhner and Antonić (2009).

Finally, it is important to note that it is difficult to verify some parameter estimates because it is not easy to accurately measure the spatio-temporal variability of key variables (e.g., albedo, BRDF, E_t). Furthermore, climate stations are not generally established in complex terrain, but occur in low-altitude areas in flat terrain, and may not collect data representative of higher-altitude areas or more complex topography. One possible way around this problem is to use satellite data for

estimating incoming solar radiation and precipitation. Consequently, there is a need to develop and validate new parameterization schemes that address process mechanics and the space–time issues connected to data, analysis, and modeling. **Table 2** also lists the most frequently used secondary land-surface parameters and their significance.

3.7.4 Land-Surface Objects and Landforms

The use of land-surface parameters to segment the landscape into terrain features or landform classes (i.e., objects) can be traced to the pioneering work of Speight (1968) and Dikau (1989). Recent developments have included the use of automated fuzzy-classification algorithms to detect landform elements (e.g., Burrough et al., 2000a; Schmidt and Hewitt, 2004). The focus of these kinds of applications may range from the identification of specific landforms (e.g., mountains, valleys, glaciers, alluvial fans) to landform elements (i.e., geometric shapes that constitute part or all of a specific landform) and repeating landforms types (e.g., a series of rolling hills and valleys). Here, the focus is on the extraction and classification of landform elements, since these constitute the basic building blocks for segmenting the landscape into landform classes.

The early landform classification approaches relied on various representations of landscape position and the shape of the land surface itself. For example, Dikau (1989) divided the landscape into combinations of concave, straight, and convex planform curvatures, on the one hand, and concave, straight, and convex profile curvatures on the other. This approach (like many subsequent ones) relies on the inferred relationship between surface shape (i.e., local curvature) and the accumulation of surface flow and consequently that of surface deposition through two accumulation mechanisms. The first mechanism reflects the divergence and convergence of flow across a hill slope, whereas the second reflects the relative deceleration of flow in the downslope direction, as influenced by changes in profile curvature (Moore et al., 1991; MacMillan and Shary, 2009).

Shary and his colleagues have criticized Dikau's (1989) original approach on two levels, and proposed a more robust and predictable classification based on curvatures. Their first suggestion was to use tangential curvature in place of planform curvature in the classification of basic form elements (Figure 15), because both tangential and profile curvatures are curvatures of normal sections and both exhibit similar statistical distributions, unlike planform curvature (MacMillan and Shary, 2009). The second criticism concerned the contradiction in Dikau's (1989) original premise that this approach differentiated form elements with a homogeneous plan and profile curvature, because these facets invariably contain even more homogeneous form facets with similar gradients, aspects, and curvatures. Shary (1995) and Shary et al. (2005), in turn, have proposed an objective, local, scale-specific classification of elemental landform features based only on the consideration of the signs of the tangential, profile, mean, difference, and total Gaussian curvatures, as a way of avoiding both of these sets of problems (Figure 16).

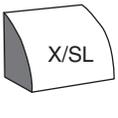
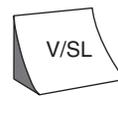
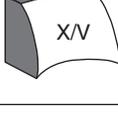
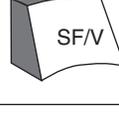
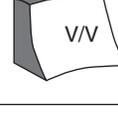
		Profile curvature		
		Convex	Profile-straight	Concave
Tangential curvature	Convex			
	Tangential-straight			
	Concave			

Figure 15 The modified Dikau (1989) classification of form elements based on the profile and tangential (i.e., across slope) curvatures. The elements have been further classified as positive or negative based on the radius of curvatures (>600 or <600 m) and the planform curvature in the original classification was replaced by tangential curvature based on Shary and Stepanov (1991). Reproduced from MacMillan, R.A., Shary, P.A., 2009. Landforms and landform elements in geomorphometry. In: Hengl, T., Reuter, H.I. (Eds.), *Geomorphometry: Concepts, Software, Applications*. Elsevier, Amsterdam, pp. 227–254.

None of the aforementioned approaches, however, incorporates the contextual position of specific facets that make up the landscape. Most of the automated classifications that incorporate context build on the conceptual classifications of hillslopes like those of Ruhe (1960), which divided hill slopes into five units (summits, shoulders, back slopes, foot slopes, and toe slopes). Many other such classifications have been proposed, and Conacher and Dalrymple (1977) and Speight (1990) divided hill slopes into 9 and 10 units, respectively. This was accomplished by delineating finer-resolution hill slope facets or by extending the hill slope to include the channel or various parts of the channel at the bottom of the hill slope. Taken as a whole, these conceptual classes consider slope gradient and relative-slope position along a toposequence from divide to channel. In addition to curvatures and automated classification, various approaches have included absolute and relative horizontal and vertical distance to ridge lines or channels (e.g., Skidmore et al., 1991) and position in the landscape relative to the order of the nearest stream channel below a hillslope (e.g., Schmidt et al., 1998; Schmidt and Dikau, 1999).

The adoption and use of fuzzy-classification algorithms to detect landform elements marked an important step forward. The importance of this innovation can be traced to the fact that each of the aforementioned approaches will work in some instances and not others, and they will seldom produce satisfactory answers to questions linked to the locations of a specific mountain or valley (Fisher et al., 2004). Indeed, there are many phenomena that are difficult to locate or delineate because their meaning is not well defined or because of the subjectivity, vagueness, and ambiguity that have often characterized the ways in which the world is described

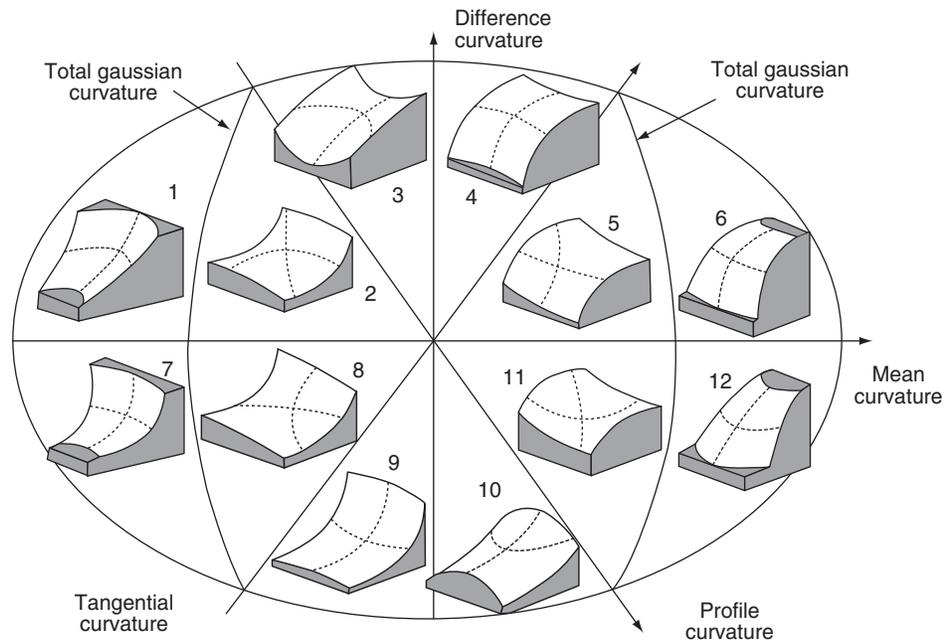


Figure 16 Shary's complete system of classification of landform elements based on signs of tangential, profile, mean, difference, and total Gaussian curvatures. Reproduced from Shary, P.A., Sharaya, L.S., Mitusov, A.V., 2005. The problem of scale-specific and scale-free approaches to geomorphometry. *Geografica Fisica e Dinamica Quaternaria* 28, 81–101.

(Burrough, 1996; Wilson and Burrough, 1999). Fuzzy-set theory represents an alternative approach to classic set theory (Burrough and McDonnell, 1998; Robinson, 2003) and has been used in many environmental domains to solve these kinds of problems. Hence, one or more forms of fuzzy classification have been used to describe soil variability (e.g., McBratney and Odeh, 1997; Zhu, 1997a, b, 1999; Ahn et al., 1999), land cover (e.g., Fisher and Pathirana, 1994; Foody, 1996, Brown, 1998; DeBruin, 2000), site selection and multicriteria evaluation (Charnpratheep et al., 1997; Jiang and Eastman, 2000), and the parameterization of land-surface models (e.g., Mackay et al., 2003).

The above mentioned examples indicate how many authors have used fuzzy sets and fuzzy-logic operators with land-surface parameters to generate partial and multiple memberships of spatial objects of various kinds during the past 15 years. The various membership functions that have been described in considerable detail by Robinson (2003) represent the core of the method because they allow the expression of irreducible observation and measurement uncertainties in their various manifestations, and make these uncertainties intrinsic to the classification (i.e., using grades of membership). In this way, the fuzzy-logic approach will associate a fuzzy likelihood of each output class with each value or class on each input map (Figure 17). This means that when fuzzy data are processed, their intrinsic uncertainties are processed as well, and their results are more meaningful than their counterparts obtained by processing the usual crisp data (Klir and Yuan, 1995; Robinson, 2003). The advantages of using such an approach are evident in the landform elements specified by MacMillan et al. (2000) on the basis of a combination of measures of local-surface shape (convexity/concavity) plus the relative-slope position for a 64 ha site in Alberta, Canada.

Two basic fuzzy-set approaches exist. The first relies on expert knowledge and is often referred to as the Semantic-Import model, whereas the second approach relies on the identification and characterization of feature-space clusters (e.g., Bezdek et al., 1984). The fuzzy sets generated in both of these instances will often provide tremendous expressive power (Robinson, 2003). For example, Zhu (1997a, b, 1999) work clearly demonstrates the utility of the fuzzy paradigm for capturing and representing spatially explicit soils knowledge from human experts. Zhu and his colleagues used knowledge of observable environmental inputs including several land-surface parameters, and targeted outputs (soil-map units), and adopted a limiting-factor approach for computing the overall similarity. The value for the overall similarity between an unclassified entity and a reference entity was obtained by simply selecting the smallest similarity value from among all similarity values computed for all attributes for an unclassified entity in this application.

Both the expert- and data-driven fuzzy-classification approaches will result in multiple maps of membership, where each class will be represented on a separate map. The advantages of using memberships are threefold since it is possible to: (1) determine which classes are connected with which land-surface parameters; (2) assess the confusion between the classes; and thereby (3) detect the areas where the confusion between two or more classes is high (Burrough and McDonnell, 1998; Hengl et al., 2004; Shi et al., 2005; Evans et al., 2009).

There are many subtleties, however, connected to these fuzzy-classification methods. The knowledge in the aforementioned approach could have been acquired via several methods, and each would have varied in the degree to which it is theoretically, empirically, or statistically valid. See Qi and

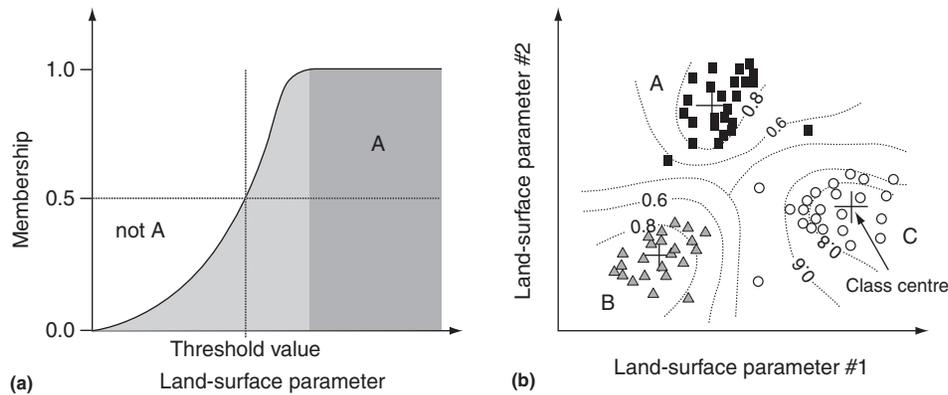


Figure 17 Schematic showing the derivation of fuzzy memberships using (a) the definition of thresholds and (b) the definition of class centers. Reproduced from Hengl, T., Reuter, H.I. (Eds.), 2009. *Geomorphometry: Concepts, Software, and Applications*. Developments in Soil Science. Elsevier, Amsterdam.

Zhu (2003), Qi (2004), and Qi et al. (2006) for an extended discussion of these issues. Similarly, the results can be expected to vary with the method used to compute the overall similarity scores. MacMillan et al. (2000), in their implementation of the Semantic-Import model, relied on a weighted-average method to calculate the overall similarity of an unclassified site to a reference entity, based on the assumption that all input variables should be included in calculating the similarity of a site to a reference entity. However, a case can also be made, that some inputs may deserve to be afforded a greater importance or weight than others (Hengl and MacMillan, 2009). Indeed, the sensitivity of the fuzzy c-means approach to the choice of input variables and weights assigned to them when calculating the overall similarity values has been explored extensively (e.g., Deng et al., 2006; Deng and Wilson, 2006).

There is also the need to choose an appropriate scale for both the Semantic-Import model and the fuzzy c-means fuzzy-classification approaches. The fact that there is no single true or fixed value for local land-surface parameters such as slope or curvature at a point, but rather a whole range of values that are dependent on the horizontal and vertical resolution has already been noted. Not unexpectedly, no best resolution can be singled out at which to compute local land-surface parameters to portray and classify terrain (Hengl, 2006; Smith et al., 2006; Deng et al., 2007), and the final scale that is chosen should be appropriate for capturing and describing the surface features of interest for a particular application (Deng et al., 2008). The size or the extent of the study area needs to be added to this list of sensitive variables since some land-surface parameters will vary in systematic ways across the landscape, and may generate locally specific results when the fuzzy classification is implemented for a limited area (Evans et al., 2009).

The aforementioned discussion gives some sense of the great progress that has been made with automated landform classification during the past quarter century. The successful deployment of these techniques, however, requires considerable knowledge and experience with the techniques themselves, and of the study area to which they are to be applied. Furthermore, the generation of land-surface objects requires better formalization that links process and form. Addressing

various issues associated with the formal characterization of topographic structure and the use of object-oriented technology also has the potential to lead to significant progress. Unfortunately, new representational schemes and the use of Earth-science concepts in analysis and modeling have not kept pace with empirical exploration (Bishop et al., 2012). Both are required for formalizing the generation of land-surface objects that will facilitate diagnostic geomorphological mapping efforts.

3.7.5 Conclusions

There have been tremendous advances in DEM data sources, digital terrain modeling techniques, new algorithms for land-surface parameterization, and new geomorphological applications driven by geomorphometry. Nevertheless, new theoretical/conceptual and information technology advances must also occur that formalize the understanding of geomorphological systems and topographic complexity. There are at least four research paths that can be expected to yield substantial benefits.

1. Knowledge of the presence of, and propagation of, errors in both the current and the new remote-sensing data sources that emerge needs to be improved. This is a challenging task because many of the systematic and random errors in the current data streams are specific to the sensor used and the specific protocols and methods that have been used in individual projects (Dowman, 2004). This suggests that ways to clarify and publish information related to data quality need to be established, since much of this is proprietary information of firms that have built and deployed the aforementioned technologies.
2. Field observations and the development and testing of new analytical methods are required. Taking the modeling of flow directions and upslope contributing areas as examples, there is an urgent need to learn more about the ways in which the land surface and the interactions with the underlying soil and regolith influence rainfall-runoff relationships and the growth and contraction of flow networks in specific environments. Lindsay and colleagues

at the University of Guelph in Ontario, Canada, for example, are exploring the spatial pattern and timing of ephemeral flows in headwater channels that may provide some important new insights. These kinds of projects are time-consuming, but are vital for the development of DEM datasets and analytical methods that support the representation of the key hydrologic and geomorphic processes (i.e., those influencing nonpoint source pollution) operating in specific landscapes (e.g., Mitášová et al., 1995).

3. The critical evaluation and adoption of key algorithms and best approaches for solving specific problems is required. This is similar to the second path, although it is likely to yield faster returns. The goal here would be to combine and integrate 'best' practices, as exemplified by the following example. The QD-TWI model proposed by Barling (1992) would appear to have considerable merit, given what is known about the distribution of soil moisture along with both the surface and subsurface flow patterns in a variety of semiarid and arid landscapes. The original QD-TWI model, however, incorporated the D8 flow-routing algorithm, and several studies have demonstrated that D8 generates many undesirable artifacts. The DEMON flow-routing algorithm, however, offers many advantages but sometimes fails in areas with flat terrain, and shows slow performance when applied to relatively fine-resolution DEMs covering large areas. Nguyen (2011) has exploited this opportunity by building a faster and more robust version of DEMON along with a flexible version of the QD-TWI model that allows the user to choose from a variety of flow-routing algorithms. Consequently, a terrain analyst can work with both approaches simultaneously. There are many opportunities like this that can be exploited in the immediate future.
4. The final research path concerns issues of scale. The rapid advent and adoption of fine-resolution remote-sensing data sources, and the need to characterize coupled geomorphological systems, means that there is an urgent need to address multiple issues of scale that affect the ability to: (1) collect, represent, and integrate data and information across multiple scales; (2) characterize land-surface parameters; (3) generate meaningful land-surface objects that are based on scientific principles and concepts; and (4) develop and refine techniques that allow multiscale characterization and visualization to address a variety of problems. These topics have been recognized by a variety of researchers as key agendas (Gallant et al., 2000; Gallant and Dowling, 2003; Sulebak and Hjelle, 2003; Fisher et al., 2005; Deng, 2007; Deng and Wilson, 2008; Bishop et al., 2012).

Finally, various equations have been included for those interested in calculating one or more of the aforementioned land-surface parameters, as these can be used for segmenting the topography into land-surface objects that are useful for geomorphological mapping. Furthermore, many of the secondary parameters can be used in geomorphological research related to assessment of hydrological, glaciological, and geological conditions. The current state of the art suggests that the present-day terrain analyst will need to choose wisely among the extreme multitude of options (i.e., data, algorithms, analysis approaches, and models), while paying special attention

to their own project goals, the advantages and disadvantages of different data sources and digital terrain modeling techniques, the characteristics of their study area(s), and how errors might have been introduced and propagated, and the likely significance of these errors, given the results that are produced.

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