

Digital terrain modeling

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ARTICLE INFO

Article history:

Received 8 September 2010
 Received in revised form 2 March 2011
 Accepted 8 March 2011
 Available online 28 March 2011

Keywords:

Digital elevation models
 Data preprocessing
 Land surface parameters
 Erosion modeling
 Error propagation

ABSTRACT

This article examines how the methods and data sources used to generate DEMs and calculate land surface parameters have changed over the past 25 years. The primary goal is to describe the state-of-the-art for a typical digital terrain modeling workflow that starts with data capture, continues with data preprocessing and DEM generation, and concludes with the calculation of one or more primary and secondary land surface parameters. The article first describes some of ways in which LiDAR and RADAR remote sensing technologies have transformed the sources and methods for capturing elevation data. It next discusses the need for and various methods that are currently used to preprocess DEMs along with some of the challenges that confront those who tackle these tasks. The bulk of the article describes some of the subtleties involved in calculating the primary land surface parameters that are derived directly from DEMs without additional inputs and the two sets of secondary land surface parameters that are commonly used to model solar radiation and the accompanying interactions between the land surface and the atmosphere on the one hand and water flow and related surface processes on the other. It concludes with a discussion of the various kinds of errors that are embedded in DEMs, how these may be propagated and carried forward in calculating various land surface parameters, and the consequences of this state-of-affairs for the modern terrain analyst.

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1. Introduction

The land surface plays a fundamental role in modulating the atmospheric, geomorphic, hydrologic, and ecological processes operating on or near the Earth's surface. This linkage is often so strong that an understanding of the character of the land surface can directly inform our understanding of the nature and magnitude of the aforementioned processes (Hutchinson and Gallant, 2000). Applications that exploit this knowledge usually rely on Digital Elevation Models (DEMs) to represent the surface and a steadily increasing and sophisticated range of techniques for topographic analysis and visualization (see Fig. 1 for a typical workflow). These techniques and data are increasingly referred to as geomorphometry, which in its broadest sense, refers to the science of digital terrain modeling [see Hengl and Reuter (2009), Li et al. (2005), Wilson and Gallant (2000a), and Zhou et al. (2008) for examples of recent books that exemplify this view].

Modern geomorphometry focuses on the extraction of measures (land surface parameters) and spatial features (land surface objects) from digital topography. This description relies on the specific and general modes of geomorphometric analysis first distinguished by Evans (1972). The specific mode describes discrete surface features (i.e. landforms) and the general mode describes 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, aspect, topographic wetness index) and a land surface object is a discrete surface feature (e.g. watershed boundary, cirque, alluvial fan, drainage network). While better, it is worth noting that this is a somewhat arbitrary distinction and there are already examples of work that show these two views are intimately linked to one another (e.g. Gallant and Dowling, 2003; Deng and Wilson, 2008) and that anticipating and representing these linkages will grow in importance in future applications.

Geomorphometry is simultaneously a rapidly evolving and yet complicated field. This is in part due to technology – there are an increasing number of digital remote sensing data sources and many subtleties involved in creating DEMs from these as well as traditional sources (e.g. Maune, 2001). The subtleties point to a series of key questions – should unwanted depressions be removed?, should DEMs be smoothed first, and if so, by what method?, what algorithms should be used to propagate DEM error and how should this uncertainty (error) be handled through subsequent analyses?, among others – for which there may not be clear and unambiguous answers. However, these challenges can also be attributed to the steady growth in the number of parameters and algorithms for processing DEMs and extracting both the descriptive measures (parameters) and surface features (objects). The values of these parameters and/or the characteristics of the objects will vary depending on a variety of factors, including the mathematical model by which they are calculated, the size of the search window, and the grid resolution.

Notwithstanding these challenges, the computed land surface parameters and landform objects have been adopted in a large number

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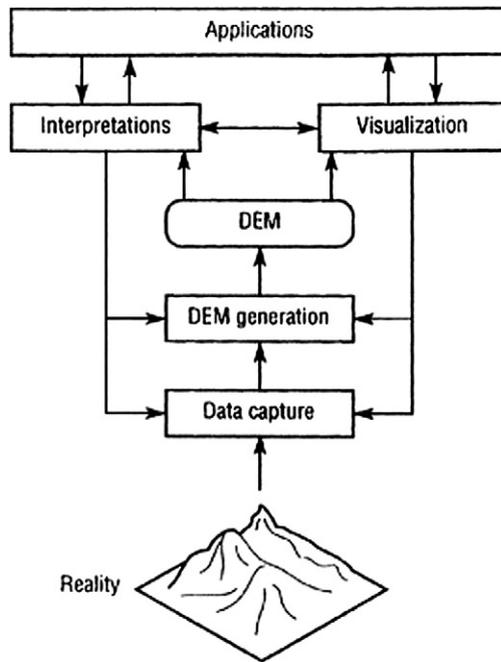


Fig. 1. The main tasks associated with digital terrain modeling. From Hutchinson and Gallant, 2000, p. 30.

and variety of applications and environmental settings – 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. Šúri and Hofierka, 2004; Reuter et al., 2005), improve vegetation mapping (e.g. Antonić et al., 2003; Bolstad and Lillesand, 1992), and analyze wildfire propagation (e.g. Hernández Encinas et al., 2007), among others.

This article examines how the methods and data sources used to generate DEMs and calculate land surface parameters have changed over the past 25 years. The primary goal is to describe the state-of-the-art for a typical digital terrain modeling workflow that starts with data capture, continues with data preprocessing and DEM generation, and concludes with the calculation of one or more primary and secondary land surface parameters. Band (2011–this issue), Bishop (2011–this issue), Evans (2011–this issue), Mitášová et al. (2011–this issue) and Pelletier (2011–this issue) describe the changing role and significance of these land surface parameters in landform classification and a variety of environmental modeling applications.

The remainder of the article is organized as follows. The next section describes how the sources and methods for capturing elevation data have evolved rapidly during the past two decades. Section 3 describes the need for and methods used to preprocess DEMs along with some of the challenges that confront those who tackle these tasks. Section 4 describes the primary land surface parameters that are derived directly from DEMs without additional inputs and the two sets of secondary land surface parameters that are commonly used to model solar radiation and the accompanying interactions between the land surface and the atmosphere on the one hand and water flow and related surface processes on the other. Section 5 discusses the various kinds of errors that are embedded in DEMs and how these may be propagated and carried forward with the calculation of various land surface parameters. The final section offers some concluding remarks and ideas for future work.

2. Data capture

The generation of DEMs incorporates three interrelated tasks: (1) the sampling of the land surface (i.e. the gathering of height measure-

ments); (2) creating a surface model from the sampled heights; and (3) correcting errors and artifacts in the surface model (Hengl and Evans, 2009). We take up the first two tasks below and leave the third to the following section because we are more often than not interested in how these errors and artifacts influence our analysis rather than elevation per se.

The most common data form is the square-grid DEM, a gridded set of points in Cartesian space attributed with elevation values that describe the Earth's ground surface (see Fig. 5 for an example of this grid structure). However, as Hengl and Evans (2009) have observed, the way we conceptualize the surface is becoming more and more important. There are not only the problems that arise because of the loss of many locally significant terrain features (i.e. ridgelines, stream bottoms) and the scale dependency of many of the descriptors we use to describe the topographic surface when we are limited to coarse DEMs [see Kienzle (2004), Raaflaub and Collins (2006) and Zhang and Montgomery (1994) for descriptions of these kinds of problems], but there is also a need for better algorithms to filter out vegetation, buildings, and other man-made structures in the new and more accurate DEMs that can be generated from remote sensing systems (i.e. LiDAR), and what exactly constitutes the surface then becomes more problematic. Indeed, this same ambiguity is true of stream channels given that the initiation of and paths followed by these features may vary from storm to storm in upland areas (Montgomery and Dietrich, 1989, 1992; Sheng et al., 2007). Finally, the generation of “bare earth” DEMs that is often held up as the preferred result would seem less than optimal for a number of applications, such as non-point source pollutant applications that seek to trace pollutants from their sources to the ocean across large metropolitan regions (Fig. 2).

The data sources and processing methods for generating DEMs have also evolved rapidly over the past 20–30 years – from ground surveying and topographic map conversion to passive methods of remote sensing and more recently to active sensing with LiDAR and RADAR. Nelson et al. (2009) distinguished three general classes of DEM data – those collected from: (1) ground survey techniques (including 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 airborne and satellite photogrammetric/stereo methods, airborne laser systems, and both airborne and satellite radar using interferometry) – and offered a succinct summary of the major features of each of these options (Table 1).

The rapid growth in sources of mass-produced DEMs during the past two decades, such as the Shuttle Radar Topographic Mission (SRTM) and laser ranging (LiDAR) surveys, has seen DEM resolution improve considerably although the current state-of-the-art and range of applications that can be supported are more often than not a function of the geographic extent of the area of coverage or interest.

Hence, reliance on LiDAR surveys has grown quickly and this source now dominates local and regional projects everywhere. Belgium and the Netherlands, for example, have already produced national LiDAR digital surface models (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 vegetation canopy (first returns) and ground surface (last returns), which should help with the modeling of water budgets in heavily vegetated areas (forests) and in built environments (i.e. urban areas). However, the small footprint and measurement challenges encountered in areas with tall buildings, dense vegetation canopies and water surfaces make this a relatively expensive option and numerous studies have documented how the accuracy of LiDAR elevation data varies with both the sensor system that was used



Fig. 2. Schematic showing the complexity of the “land” surface in urban landscapes. From Division of Information Technology, Engineering and the Environment, Barbara Hardy Centre for Sustainable Urban Environments, University of South Australia website; <http://www.unisa.edu.au/barbarahardy/research/3D.asp>.

(Dowman, 2004) and the land cover and other characteristics of the land surface (Hodgson et al., 2005).

Very impressive gains have been made at the continental and global scales (extents). Hence, the 3 arc-second SRTM DEM that was developed from satellite data collected over a nine-day window in 2000 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 (Nelson et al., 2009; Zandbergen, 2008). The three 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 global positioning systems (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 shows a DSM (not a bare-earth model); (2) surface characteristics may affect accuracy; (3) voids often occur at the 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 the mapping of soils, vegetation and similar phenomena (Gessler et al., 2009). Last but not least, a series of recent studies has shown a positive

Table 1
Key characteristics of data sources.
Modified from Nelson et al., 2009, p. 83–84.

Source	Resolution (m)	Accuracy	Footprint (km ²)	Post-processing 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	0.15–1 m vertical, 1 m horizontal	30–50/h	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 to 58° S	Potentially high	Surface
SRTM, Band X	30	16 m vertical, 6 m horizontal	Similar to B and 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

relationship between elevation error and height of the canopy (e.g. Carabjal and Harding, 2006; Hofton et al., 2006; Shortridge, 2006; Berry et al., 2007; Bhang et al., 2007) and one in particular, indicating how low-lying, riparian areas may be represented as substantially higher than the surrounding agricultural areas (leading to an inverted terrain model; LaLonde et al., 2010), highlights the need to assess fitness for use before deploying one or more of these datasets for a specific application or study area. The presence of and propagation of error is taken up again in more detail in Section 5.

Some, but not all of the aforementioned problems, may be addressed by the Advanced Spaceborne Thermal Emission and Reflectance Radiometer Global Digital Elevation Model (ASTER G-DEM) that was released in 2009. This new product offers better resolution (one vs. three arc-seconds) and better spatial coverage (83° N to 83° S vs. 60° N to 58° S) as well as comparable vertical and horizontal accuracy (7–20 m vertically and 30 m horizontally compared to 16 m and 20 m, respectively for SRTM) (Hirano et al., 2003; Nelson et al., 2009; Slater et al., 2009). In addition, the missing data problems caused by clouds will be easier to fill because of the open-ended acquisition schedule but the 30 m resolution will of course still not be sufficient to support the mapping of soils, vegetation and similar phenomena in most landscapes. 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/or applications.

Whatever the data source that is chosen, this is usually just the first step because some preprocessing will usually be required no matter what the source or intended application. These tasks and some of the challenges and issues that accompany them are taken up in the next section.

3. Data preprocessing and DEM construction

The preparation of elevation data for geomorphometric analysis is tricky because elevation, per se, is typically not the attribute of interest and this means that the true geomorphological accuracy can only be assessed by measuring surface parameters and objects such as drainage lines, landforms or viewsheds in the field and then comparing their shapes, distributions, and location with the values obtained by geomorphometric analysis (e.g. Fisher, 1998; Wilson et al., 2008). Reuter et al. (2009, p. 90) suggested that the true applicability of DEMs for geomorphometric analysis can only be assessed by providing answers to the following questions: (1) how accurately is the surface roughness represented?, (2) how accurately is the shape of the land surface represented (i.e. concave and convex shapes, erosion and deposition, water convergence or divergence but see Hutchinson and Gallant (2000) for additional ways to evaluate this component of data quality)?, (3) how accurately are the “real” world ridgelines and streamlines detected?, and (4) how consistently are elevations measured over the whole area of interest? The answers to these and similar questions are interrelated, and there will almost certainly still be errors present in the available and/or preferred DEM(s) notwithstanding the answers to these important questions. 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 characteristics 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 portrayal of surface features and on the values of the land-surface parameters that are computed from a DEM (MacMillan and Shary, 2009). Numerous 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; Hengl, 2006; Raaflaub and Collins, 2006). However, the increasing interest in

various forms of multi-scale analysis [see Gallant and Dowling (2003) and Sulebak and Hjelle (2003) for two recent examples] and the enduring need to be able to move seamlessly across scales mean that more work is needed on these scale relationships and effects.

Beyond these kinds of relationships and the ensuing impacts, the decisions made about unwanted depressions (i.e. spurious pits or sinks) will have a large impact on the subsequent analysis and interpretation of the results of geomorphometric analysis. Two approaches have found frequent use – one relies on progressively filling the sinks by increasing their elevation values until the elevation of their lowest outflow point is reached (e.g. Jensen and Domingue, 1988; Martz and de Jong, 1988; Soille and Gratin, 1994; Planchon and Darboux, 2001; Wang and Liu, 2006), whereas the second method creates 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. Morris and Heerdegen, 1988; Rieger, 1992; Martz and Garbrecht, 1999; Soille et al., 2003; Soille, 2004). However, 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 DEMs and the output DEMs that did not have sinks were minimized. This combined approach produced superior results for the Baranja Hill study catchment in Croatia [see Grimaldi et al. (2007) for an alternative physically-based approach]. 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 to propose a minimum impact approach for removing the artifact depressions in relatively flat landscapes like those occurring on the Canadian Shield.

There are at least two other related challenges that may need to be addressed as well. 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 as well. 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 (Jensen 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 (Garbrecht and Martz, 1997). The solutions obtained with these approaches will vary slightly from one another and an intimate knowledge of the field conditions will usually 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 source (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). We have used the latter almost exclusively in our own work, in part because the latter approach is embedded in a modeling environment (ANUDEM or the Topo to Raster tool in ArcGIS 10.x) that tackles the last three problems (i.e. unwanted depressions, unresolved flow directions in flat terrain, and reconciliation of elevation and hydrography datasets) simultaneously.

ANUDEM (Hutchinson, 1988, 1989, 1996) can work with contours and spot heights and uses an iterative finite difference interpolation technique to build one or more square-grid DEMs. The four diagrams reproduced in Fig. 3 and accompanying text in Hutchinson (2008) provide a concise summary of the results that can be expected when using this approach. The method basically starts with a coarse grid, enforces the drainage conditions (using one or more depictions of

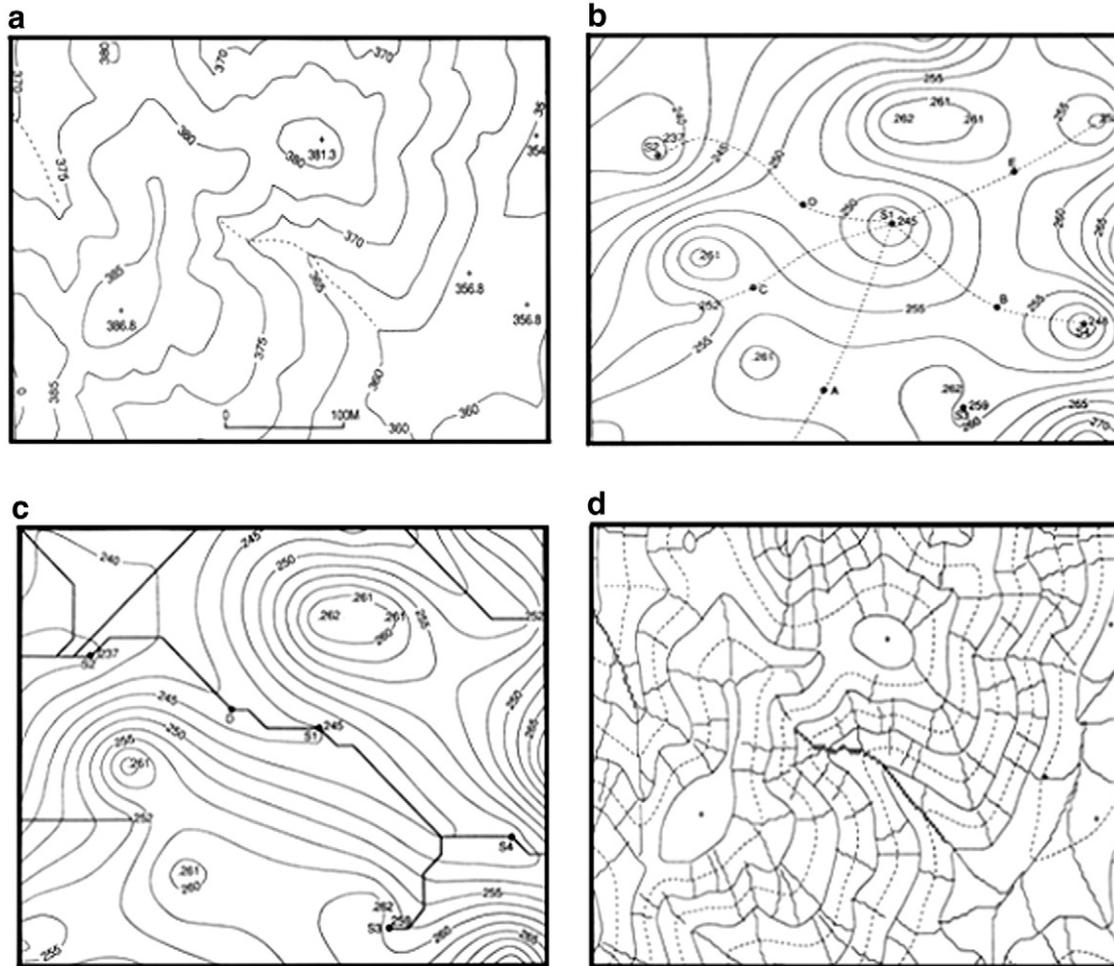


Fig. 3. Key steps and outputs of using the ANUDEM direct gridding methods of Hutchinson (1988, 1989, 1996). The four maps show: (a) contour, point elevation and streamline data; (b) minimum curvature gridding of point elevation data with spurious sinks or depressions; (c) spurious sinks removed from the surface in (b) by the drainage enforcement algorithm; and (d) contour, stream and ridge lines derived by the ANUDEM procedure from the topographic data shown in (a). From Hutchinson, 2008, p. 148, 153–155.

stream lines), increases the spatial resolution, enforces the drainage conditions again, and so on, until the desired resolution is reached. It is a very popular technique because it produces a hydrologically-correct land surface model (i.e. one in which the ridges are retained, streams enforced, and spurious sinks removed) although like all interpolators, this approach may not produce optimal results if poor input parameters are selected (Wise, 2000). That said, the choice of the preferred interpolation technique may depend in part on the source of the data (precise height measurements might lead one to choose an exact interpolator whereas noisy data would direct our attention to an approximate interpolation technique) and the characteristics of the application [see Pain (2005) for an extended discussion of these issues].

The rapid growth in sources of mass-produced, remotely sensed DEMs during the past two decades has demanded new forms of DEM preprocessing. Reuter et al. (2009) and Webster and Dias (2006), for example, describe various approaches and opportunities for orthorectifying 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 numerous authors have noted the presence of systematic and random errors that are not so easy to detect and correct in LiDAR datasets for example (Filin, 2003; Katzenbeisser, 2003). The detection of distance errors, 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 two additional trends that have emerged in recent years. The first is the integration of topographic and auxiliary information (such that the location of lakes, streams, ridges, and/or breaks will be identified from satellites and incorporated in the DEM processing chain similar to what happens with ANUDEM) 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., 2000; Hengl et al., 2004; Raafaub and Collins, 2006).

4. Calculation of land surface parameters

The typical digital modeling workflow, once there is a suitable DEM at hand, will focus on either the extraction of measures (land surface parameters) and/or spatial features (land surface objects). Two classes of land surface parameters – primary and secondary – are usually distinguished and the same distinction is used in the discussion that follows here. The use of land surface parameters to identify landform classes and features (i.e. objects) can be traced to the pioneering work of Speight (1968) and Dikau (1989) and recent developments include the use of automated fuzzy classification algorithms to detect landform facets (e.g. Burrough et al., 2000; Schmidt and Hewitt, 2004). These

applications will not be discussed further given that they rely on increasingly sophisticated methods and the land surface parameters described in more detail below constitute basic building blocks for these and other forms of more sophisticated analysis.

4.1. Primary land surface parameters

The primary land surface parameters are derived directly from the DEMs without additional inputs. A variety of terms have been used to describe these parameters. Olaya (2009), for example, referred to them as 'basic' land surface parameters and noted that they can be calculated from the DEM without further knowledge of the area represented. He then distinguished local and regional parameters because the latter consider additional parts of the DEM apart from the exact area for which parameters are to be calculated. Florinsky (1998) also distinguished local primary attributes that are calculated as a function of their surroundings and non-local primary attributes that require the analysis of a larger, non-local land surface area from a computational perspective. Wilson and Burrough (1999) later explained the distinction between local vs. non-local terrain attributes in terms of the existence of local interactions between neighboring points and "action-at-a-distance" forces (see Fig. 4 for details). Typical examples of local primary land surface parameters (i.e. attributes) include slope, aspect, and plan and profile curvatures; non-local primary land surface parameters include flow path length, proximity to nearest ridgeline, dispersal area, and upslope contributing area. Table 2 lists the most frequently used primary and secondary land surface parameters and their significance.

Most local parameters are calculated by moving a three-by-three window across a grid and calculating land surface parameters for the target cell (i.e. the central cell in the three-by-three window) (Fig. 5). There are special rules for how to handle the edges and this approach produces a new grid with the same dimensions as the DEM for each parameter. A variety of equations have been proposed to calculate slope and aspect (i.e. the first derivatives) and curvatures (second derivatives) – see Evans (1972), Florinsky (1998), Moore et al. (1993a), Pennock et al. (1987), Shary et al. (2002) and Zevenbergen and Thorne (1987) for well-known examples – and each is likely to produce slightly different estimates across a range of land surface conditions (flat, undulating, steep terrain, etc.). The interested reader will find more details about the performance of these equations in Hengl and Evans (2009) and Skidmore (1989).

The calculation and interpretation of the slope and aspect grids is reasonably straightforward (see Fig. 6 for an example of a slope grid).

Table 2
List of primary and secondary land surface parameters and their significance. Modified from Wilson and Gallant, 2000b, p. 7 and Olaya, 2009, p. 142.

Parameters	Type	Significance
Elevation	Local	Climate, vegetation, potential energy
Slope	Local	Precipitation, overland and subsurface flow velocity and runoff rate, soil water content
Aspect	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 distributions 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)

The profile (or vertical) curvature and tangential (horizontal) curvature are often used to distinguish locally convex and concave shapes (see Fig. 7 for an example of a profile curvature grid). The convention followed in the earth sciences is to write the sign of curvature as positive for a convex surface shape and negative for a concave surface shape (Olaya, 2009, p. 150). That said, 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, soil redistribution, etc.). Convex profile curvature indicates acceleration of flows and a local increase in potential energy

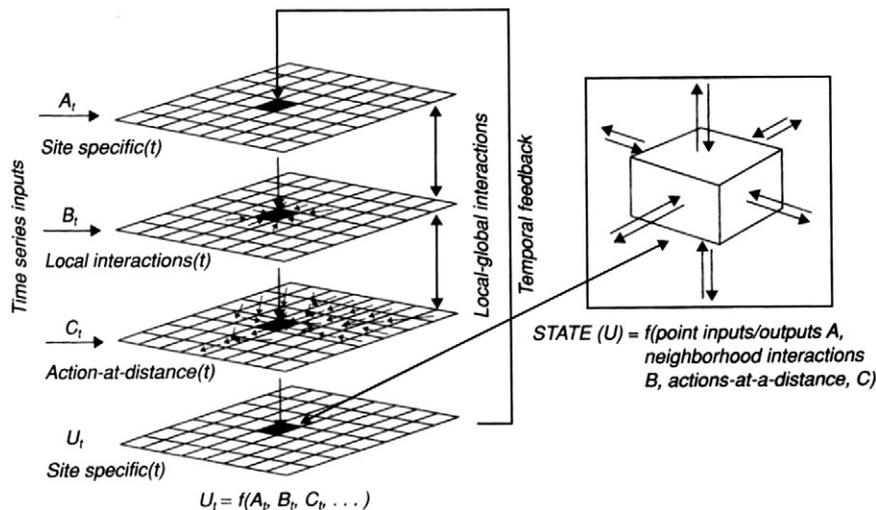


Fig. 4. Schematic showing site-specific, local and regional interactions as a function of time. From Wilson and Burrough, 1999, p. 739.

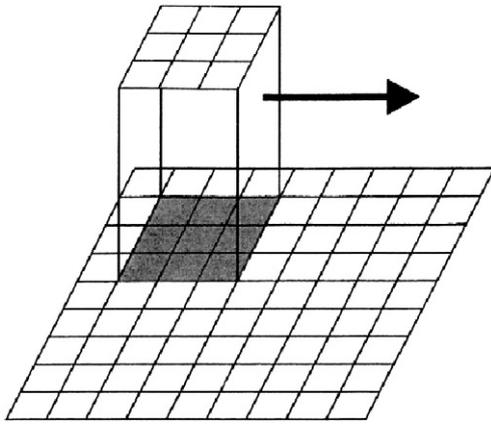


Fig. 5. Local parameters are usually calculated by moving a 3 × 3 grid across the DEM. From Olaya, 2009, p. 143.

whereas concave profile curvature indicates a flattening of the slope and therefore a decline in potential energy (e.g. Fig. 7). Plan curvature is sometimes used to describe the curvature of contour lines and should yield similar results to tangential curvature so long as the contour lines describe the shape of the land surface (Gallant and Wilson, 2000). Olaya (2009) describes several other curvatures and their potential significance in the earth sciences.

Olaya (2009, pp. 157–163) also described a number of what he called statistical parameters which shares some similarities with the list of elevation residuals proposed by Gallant and Wilson (2000, p. 73–76). We prefer the latter list – it is shorter and the significance of each of the elevation residuals seems straightforward – although just one of these parameters (terrain roughness) has found widespread use (for characterizing wind directions, exposures, etc.). This parameter is usually taken to be the standard deviation or coefficient of variation of elevation in some circular window and is therefore a useful measure of the local relief or roughness of the landscape at the scale specified by the radius of the window (so long as the elevation

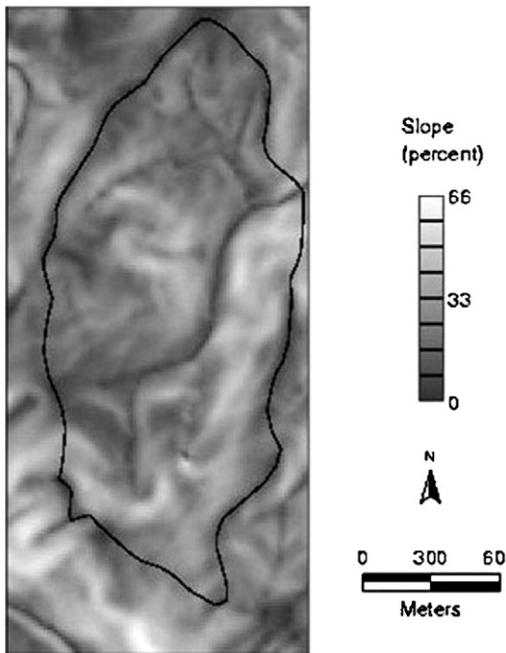


Fig. 6. Percent slope grid derived from the Cottonwood Creek, Montana DEM using the finite difference formula, with the catchment boundary overlaid. From Gallant and Wilson, 2000, p. 54.

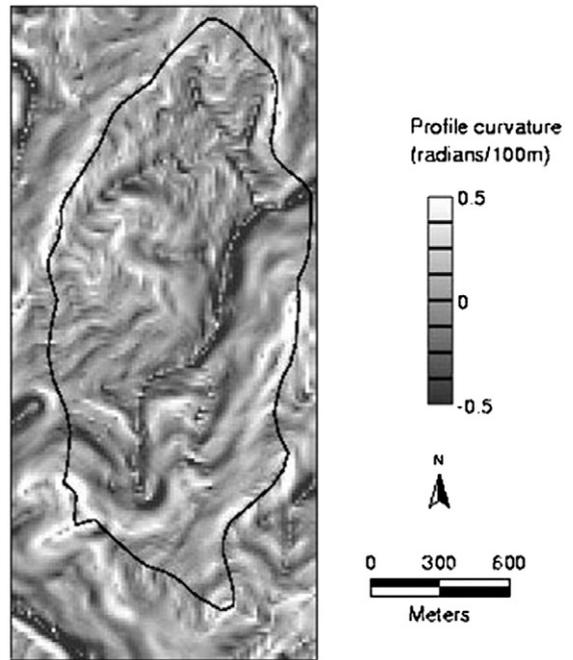


Fig. 7. Profile curvature (radians per 100 m, convex curvatures are positive) grid for the Cottonwood Creek, Montana DEM, with the catchment boundary overlaid. From Gallant and Wilson, 2000, p. 59.

differences with respect to the regression plane are accounted for in mountainous terrain and continental scale applications).

One possible reason for the slow uptake of many of this last group of land surface parameters is that their biophysical meaning is not clear. This problem may be exacerbated by the multi-collinearity of numerous pairs of attributes. There are now 30 or more primary land surface parameters and they are mostly empirical in nature and as such, are based on perhaps two fundamental parameters. This state of affairs means that two or more parameters may yield the same information (the classic example is relief and slope) and they should therefore be used and interpreted carefully. The use of primary and secondary land surface parameters with fuzzy k-means classification to delineate landform classes, for example, should start with correlation analysis to confirm that the candidate inputs are not highly correlated with one another [see Burrough et al. (2000), Deng et al. (2006, 2007), Deng (2007), and Deng and Wilson (2006, 2008) for examples of good practice].

The regional (i.e. non-local) land surface parameters are mainly concerned with the climatic, geomorphic, hydrological or visual properties of landscapes. The first category relies on the accurate delineation of the shadowing, sky view and reflective character of the surrounding terrain (as will be discussed in more detail in the next section). The geomorphic and hydrological parameters focus on the movement of water and sediment and as such, rely on the accurate delineation of watersheds (and by extension, the availability of DEMs that include these features). The most common parameters are upslope contributing area, flow path length and a variety of statistical measures summarizing the elevation and slope values upslope and downslope of each grid cell (see Table 2 for additional details). The subtleties of calculating the flow direction grid from which many of these parameters are derived and the importance of considering climate and soil parameters along with the shape of the land surface itself are taken up in more detail in the next section as well. For the final category, we can calculate the visibility (i.e. from what other points can a single point be seen or the reverse, what other points can we see from a single point) by drawing the line of sight from the point of interest to all other points and check whether or not the relief forms

that occur between them block visibility. From here we can calculate various measures of visual exposure, such as the number of cells that can be seen from each cell [see Fisher (1991, 1992, 1993, 1995, 1996) and Ruiz (1997) for examples of these types of applications and some of the pitfalls that must be avoided].

Last but not least, we need to take up the issue of scale in the context of these primary land surface parameters. The local terrain shape, which is usually thought of as the continuous variation of elevation values over the terrain surface from point to point, has an enormous impact on local and regional terrain attributes, but this role is influenced by data and computational factors as well. Florinsky (1998) suggested that local attributes, such as slope gradient, aspect, and curvatures, are mathematical variables rather than real world values. This statement may be extended to all local terrain attributes for two reasons. First, local terrain shape may rely on different mathematical descriptions, so that calculated local attributes depend on algorithm selection. Second, the terrain shape portrayed by DEMs is a function of scale, combining the complexity of the terrain, scale or resolution of data, and spatial scale at which the terrain surface is observed (e.g. Deng et al., 2008). Thus it is possible to use the same local attribute to describe terrain shape at different scales (resolutions). The special feature of non-local primary attributes is that they rely on the terrain shape of a larger, non-neighbor area and need to be defined with reference to other non-local points. Therefore, calculating non-local 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).

4.2. Secondary land surface parameters

There are two basic sets of secondary land surface parameters. The first is the hydrologic land-surface parameters for quantifying water flow and related surface processes and the second is a series of solar radiation models and methods for quantifying the interactions between the land surface and the atmosphere. The underlying theory for both is well established (see Moore et al. (1991) for a review of both the basic principles and some early applications), and the computational methods have evolved continuously over the past 20 years along with the resolution and quality of the underlying digital elevation models.

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 well and 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), but these have a much coarser resolution than our 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 introduce some additional uncertainty and error to 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, we can assume 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). However, this is now but one or more than a dozen flow routing algorithms and a distinction is usually drawn between single- and multiple-flow direction algorithms (Fig. 8). 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^∞ (Tarboton, 1997), and Mass-Flux algorithms (Gruber and Peckham, 2009). These flow routing algorithms will usually generate very different results (see Figs. 9 and 10 for examples of upslope contributing area grids generated with the D8 and DEMON flow routing algorithms). The performance of these flow routing algorithms has been compared across a variety of landscapes (e.g. Wolock and McCabe, 1995; Desmet and Govers, 1996; Wilson et al., 2000; Chirico et al., 2005; Zhou and Liu, 2002; Endreny and Wood, 2003; Wilson et al., 2007) and Wilson et al. (2008) recently evaluated the performance of nine such algorithms – ANSWERS (Beasley and Huggins, 1978), D8 (O'Callaghan and Mark, 1984), Rho8 (Fairfield and Leymarie, 1991), FD8/TOPMODEL (Freeman, 1991; Quinn et al., 1991, 1995), Lea's aspect-driven kinematic routing algorithm (Lea, 1992), DEMON (Costa-Cabral and Burges, 1994), the flow decomposition algorithm of Desmet and Govers (1996), D^∞ (Tarboton, 1997), and MFD-md (Qin et al., 2007) – and showed how the various algorithms can be expected to generate different patterns of flow (based on upslope contributing areas) on different parts of a hillslope or watershed.

It is also clear that 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 sequence of methods that move water into one or more downslope cells, and Gruber and Peckham (2009) 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 limitations generated when we represent a continuous flow field with a regular grid that only has eight possible directions in multiples of 45°).

This pair of explanations helps to explain why the final choice of 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 over-dispersal (i.e. the dispersal of the available flow over too many cells or too large an area); however, the multiple flow direction algorithms can represent divergent flow but usually also suffer from some over-dispersal. The subtleties and outcomes of the methods 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 are also likely to influence the results generated with these different flow routing algorithms.

That said, the flow directions are usually computed so we can calculate upslope contributing areas (i.e. flow accumulation areas) and delineate the drainage networks [see Band (1986, 1989, 1991), Montgomery and Dietrich (1989, 1992) and Peckham (1998) for examples of methods for delineating drainage networks with single flow direction algorithms] along with the basin boundaries and a series of both basin and channel attributes. The topographic wetness and stream power indices are among the most popular of these attributes and unlike the catchment (basin) boundaries and some other attributes, this pair of attributes can be calculated with both the single and multiple flow direction algorithms.

The typical form of the topographic wetness index 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, slope and occasionally soil transmissivity (this last term is often omitted because the transmissivity is assumed to be constant throughout the catchment). The steady state form of the topographic wetness index 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

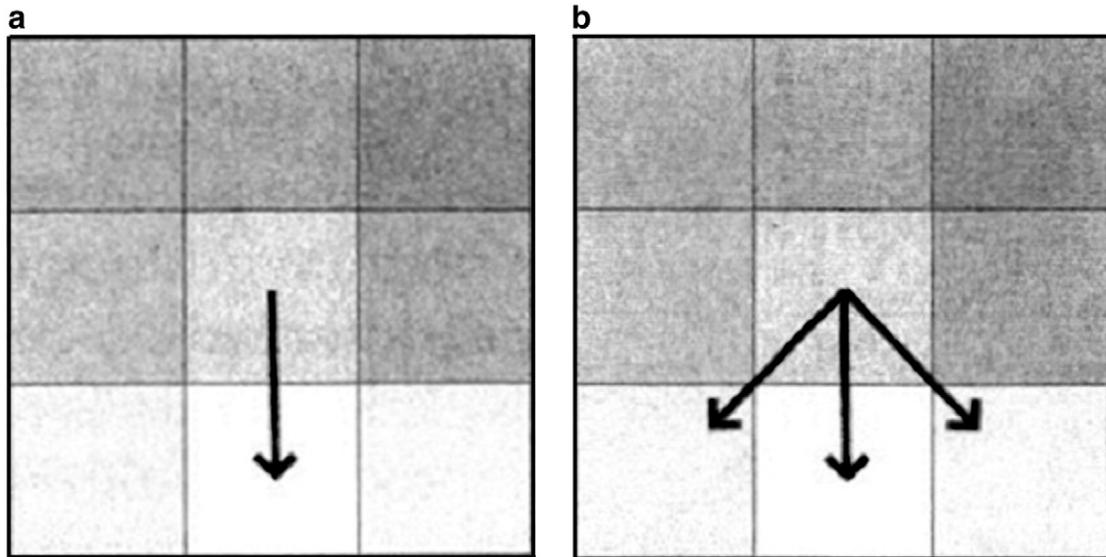


Fig. 8. Single flow direction assigned to the central pixel in a 3×3 neighborhood using D8 (a) and multiple flow directions assigned to the central pixel in a 3×3 neighborhood using MDF (b). Multiple flow directions are assigned and a fraction of the mass of the central cell is distributed to each of the three lower cells that the arrows point to in (b). All mass fractions together must sum to one in order to conserve mass in (b) as well. Gray values represent elevation increasing with darkness of the cell in both instances. From Gruber and Peckham, 2009, pp. 176–177.

been used successfully in a variety of hydrological applications because the aforementioned conditions are frequently 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; Moore and Wilson, 1992; Montgomery and Dietrich, 1994; Moore and Wilson, 1994; Khair et al., 2007).

However, these types of static indices 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 dictates the direction of subsurface flow, is assumed to be 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). Numerous authors have described the pitfalls of using these kinds of indices in inappropriate ways. Jones (1986, 1987), for example, documented some of the advantages and limitations of using wetness indices to describe spatial patterns of soil water content and drainage, and Quinn et al. (1995) summarized the various problems and described how the steady-state topographic wetness index can be calculated and used effectively as part of the TOPMODEL hydrologic modeling framework. Numerous variants of the original equation have also been proposed. Barling (1992), for example, proposed a quasi-

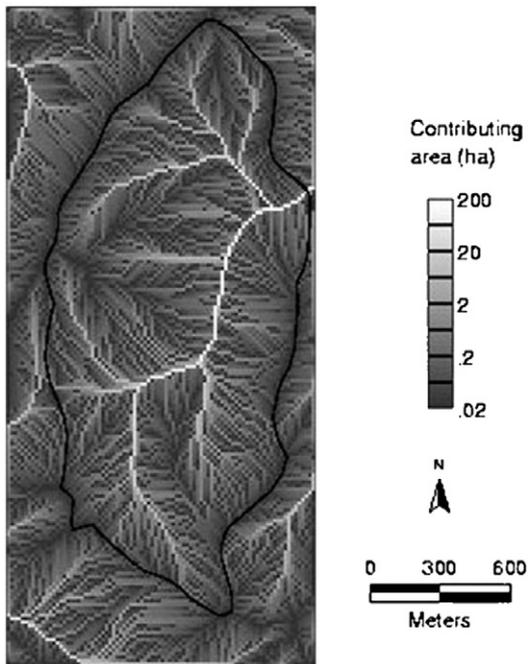


Fig. 9. Contributing area (ha) grid derived from the Cottonwood Creek, Montana DEM using the D8 single flow direction algorithm, with the catchment boundary overlaid. From Wilson and Gallant, 2000c, p. 62.

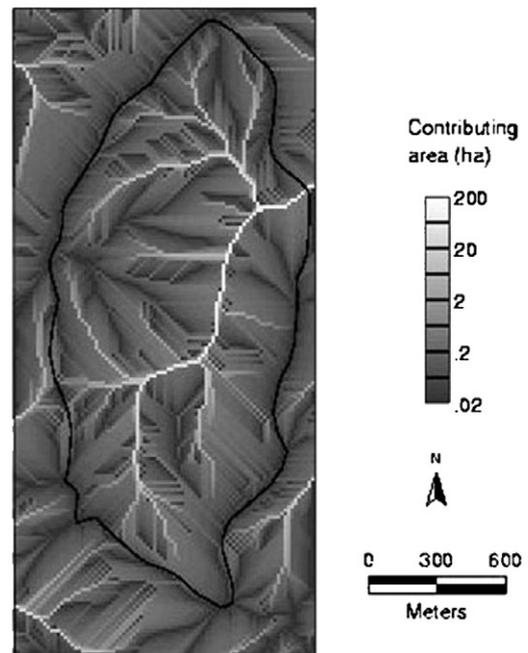


Fig. 10. Contributing area (ha) grid derived from the Cottonwood Creek, Montana DEM using the DEM stream tube algorithm, with the catchment boundary overlaid. From Wilson and Gallant, 2000c, p. 67.

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 semi-arid catchment in New South Wales, Australia [see Barling et al. (1994) for additional details], and Wood et al. (1997) later proposed an alternative index to predict the saturated zone thickness that incorporated both spatial and temporal variation in recharge. Nguyen and Wilson (2010) calculated QD-TWI using a variety of flow routing algorithms (the D8 single flow direction flow routing algorithm was used in the original work) and showed how the results varied depending on the flow routing algorithm that was utilized.

Turning next to the radiation transfer functions, Böhner and Antonić (2009) offer an especially broad and eclectic summary of the land surface parameters that rely on the assertion that the shape and character of the land surface controls the spatial variability of near-ground atmospheric processes and associated climatic variations. We will ignore the regionalization approaches that employ kriging, universal kriging and splines to map the climate variables measured at climate stations [see Daly et al. (2002), Hutchinson (1995, 2008), Jarvis and Stuart (2001), Lloyd (2005), Thornton and Running (1999), Thornton et al. (1997, 2000) for examples of approaches that can generate satisfactory results given a regular distribution of input data and proper representation of topo-climatic settings] and instead focus on the land surface parameters that have been proposed and used to assess the variability of the short- and long-wave radiation fluxes across the land surface.

The best methods for calculating these parameters will account for the three major causes of spatial variability of radiation at the land surface: (1) the orientation of the Earth relative to the sun; (2) the presence of clouds and other atmospheric effects; and (3) the topographic effects. The SRAD model, for example, calculates potential solar radiation as a function of latitude, slope, aspect, topographic shading and time of year, and then modifies these estimates using information about monthly average cloudiness and sunshine hours (Moore et al., 1993b; Wilson and Gallant, 2000a,b,c).

The short-wave irradiance is computed at both flat and sloping sites using a three-part approach in SRAD. The potential or extraterrestrial irradiance on a horizontal surface just outside the earth's atmosphere is calculated first. Next, a series of instantaneous clear-sky, short-wave radiation fluxes are calculated for each of the DEM grid points at 12 minute intervals from sunrise to sunset, and direct beam and diffuse fluxes are calculated for flat sites and direct beam, circumsolar diffuse, isotropic diffuse and reflected fluxes are calculated for sloping sites. These instantaneous values are then summed to obtain daily totals and these values are adjusted to account for the effects of cloudiness. Daily temperature is extrapolated across the surface using a method that corrects for elevation via a lapse rate, slope-aspect effects via a short-wave radiation ratio, and vegetation effects via a leaf area index [see Hungerford et al. (1989), Running (1991), Running and Thornton (1996), and Running et al. (1987) for additional details] and the daily outgoing and incoming long-wave irradiances are calculated from the surface temperatures in the first instance and the air temperatures and fraction of sky visible at each grid point in the second case. The aforementioned short- and long-wave radiation fluxes are then used to estimate the surface energy budget at each grid point for a user-specified period ranging from one day to a year in length.

SRAD is but one of a number of models that have been proposed for calculating the radiation fluxes and the accompanying land surface parameters [see Kumar et al. (1997), r.sun (Hofierka, 1997; Šúri and Hofierka, 2004), Solar Analyst (Fu and Rich, 2000), SolarFlux (Hetrick et al., 1993a,b; Dubyah and Rich, 1995), and Solei (Miklānek, 1993; Mészáros, 1998) for additional examples] and the enduring novelty of SRAD (relative to some of these other approaches) stems from the attempt that was made to incorporate the effects of cloudiness in the calculations. All of the aforementioned models document how spatial

variability in elevation, slope, aspect, and shadowing can create very strong local gradients in solar radiation and thereby exert a large influence on the photosynthesis and evapotranspiration processes and ensuing vegetation diversity and biomass production at specific locations on the land surface [see Austin et al. (1984), Franklin (1995), Moore et al. (1993b) and Tajchman and Lacey (1986) for early examples documenting these kinds of relationships].

One last observation worth noting is the difficulty of verifying these parameter estimates because most radiation stations are located on flat terrain (i.e. horizontal surfaces). One possible way around this problem is to use satellite data for estimating incoming solar radiation. Hence, Böhner and Antonić (2009) described one such study by Dubuyah and Loechel (1997) which combined the coarse spatial resolution data of Geostationary Satellite Server imagery with the fine spatial resolution DEM-based topography using the direct-diffuse partitioning algorithm of Erbs et al. (1982), the elevation correction formulations of Dubuyah and van Katwijk (1992) and the various equations describing the topographic effects on direct, diffuse and reflected radiation (as noted above) and described in detail in Böhner and Antonić (2009, p. 199–207). The main challenges involve developing and validating new parameterization schemes that address process mechanics and space-time issues involving data and analysis (e.g. Sheng et al., 2009).

5. DEM error and propagation

A chronologically ordered review of the many books and articles which have been written on digital terrain modeling during the past 25 years would show how DEMs can be produced and analyzed in both an increasing number and variety of ways nowadays. Such a review would also demonstrate the many subtleties that are embedded in the various data sources and methods and how errors can be introduced at many stages of the production process. The tendency for different sensors (i.e. radar vs. optical vs. LiDAR for example) to incorporate systematic and random errors that, in turn, generate bias in elevation and the computed land surface parameters (slope, aspect, etc.) was noted earlier.

There are many challenges here. Some can be attributed to the fact that these errors may vary with the choice of sensor and/or specific application (i.e. method of deployment) which means that it will be difficult to subtract one DEM from another to detect altitude variations for assessing change, erosion, deposition, etc. (e.g. Burns et al., 2010). A second set of challenges concerns the propagation of the elevation errors in the primary and secondary land surface parameters and the considerable effort that usually is required to identify them. The usual approach for propagating errors incorporates statistically modeling the error in the DEM (which is usually only partially known) and running a Monte Carlo analysis (Temme et al., 2009). The best workflows will utilize these techniques to check for and hopefully remove some or all of these errors; however, the errors in the source data cannot always be eliminated and those interested in using the land surface parameters calculated from DEMs must be cognizant of these errors and how they may affect their own workflows and the interpretation of the significance of their results.

That said, it is worth taking stock of what we know about the accuracy of DEM elevation values and the land surface parameters calculated from these elevations. Numerous approaches have been proposed to assess the accuracy of DEM elevation values [see Hutchinson (2008) and Temme et al. (2009) for additional details]. Many researchers have compared a set of heights derived from the DEM with 'real' elevation values taken from a more accurate source of topographic data and then calculated the root mean square error of elevation (RMSE) to represent the difference between the estimated and true values (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 five simple criteria to evaluate DEM quality when the DEM is constructed from contours – the DEM should have the same values as contours close to the contour lines, the DEM values must be in the range given by the bounding contour lines, the DEM values should vary almost linearly between the values of the bounding contour lines, the DEM patterns must reflect realistic shapes in flat areas, and the artifacts must be limited to a small proportion of the data set – that may have broader relevance. 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 there is a rapidly growing literature documenting the quality of the DEMs constructed from remote sensed sources (e.g. Carabajal and Harding, 2006; Hofton 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 if we are less certain of its attribute values and the errors in DEMs may propagate to the land surface parameters and modeling results in ways that are not easily predicted – see Aerts et al. (2003), Band et al. (1995), Bolstad and Stowe (1994), Chow and Hodgson (2009), Desmet (1997), Endreny and Wood (2001), Fisher and Tate (2006), Holmes et al. (2000), Hunter and Goodchild (1997), Lindsay (2006), Lindsay and Creed (2005b), Lindsay and Evans (2006), Van Niel et al. (2004), Wise (1998), and Wood et al. (1997) for examples spanning a large variety of land surface parameters and DEM data sources.

In one particularly impressive study of this kind, Temme et al. (2009) examined the propagation of errors from DEMs for the slope (a local land surface parameter), the topographic wetness index (a regional land surface parameter) and the soil redistribution resulting from water erosion (a complex model output) in the Baranja Hill, Croatia watershed. 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 TWI (the mean coefficient of variation of TWI was 10% for unfilled and 16% for filled DEMs) although the coefficient of variation for TWI varied more spatially than that of slope. These results show that the TWI 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 to the predicted amount of sediment in transport. The latter was simulated with the same multiple flow direction algorithm used to calculate TWI above and the approach of Temme et al. (2006) was used to handle the flows of water and sediment into sinks. The latter capability was vitally 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. However, the mean soil redistribution maps of the 100 simulations on unfilled DEMs showed considerably more deposition and less erosion than the filled DEMs (in part because the depressions were filled prior to 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 TWI 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 TWI terms by the same source error.

6. Conclusions

The foregoing review directs attention not only to the tremendous advances in DEM data sources and digital terrain modeling techniques that have characterized the past 25 years, but also to the kinds of research that will be needed to continue making progress during the next quarter century. There are at least four research paths that can be expected to yield substantial benefits over such a timeframe.

The first path should focus on improving our knowledge of the presence of and propagation of errors in both the current and new remote sensing data sources that emerge. This is a challenging task because many of the systematic and random errors in the current data streams are specific to the sensor that is used and the protocols and methods that have been used in individual projects to guide its deployment (Dowman, 2004). This state of affairs suggests that we will need to find ways to clarify and publish this information (since much of it has been held as proprietary information by the firms that have built and deployed the aforementioned technologies until now) and that in many instances we will need to develop sensor-specific solutions to solve whatever problems are uncovered.

The second path combines field observation and the development and testing of new analytical methods. 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 the 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 [see Lindsay and Evans (2006) and Lindsay et al. (2008) for some additional background]. These kinds of projects are time-consuming but vital if we are to develop DEM datasets and analytical methods that support the representation of the key hydrologic and geomorphic processes (i.e. those influencing non-point source pollution) operating in specific landscapes (e.g. Mitášová et al., 1995).

The third research path is similar to the second line but 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 semi-arid and arid landscapes. However, the original QD-TWI model incorporated the D8 flow routing algorithm and numerous studies have demonstrated that D8 generates many unfortunate artifacts. The DEMON flow routing algorithm, on the other hand, offers numerous advantages but sometimes fails in areas with flat terrain and suffers from 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 – so that terrain analysts can work with both approaches simultaneously. There are many opportunities like this one that can be exploited in the immediate future.

The fourth and final research path concerns scale effects. An enduring need [see Gallant et al. (2000) for example], the rapid advent and adoption of fine resolution remote sensing digital elevation data sources means that there is not only an urgent need to improve our understanding of the ways in which these fine scale (i.e. resolution) data sources influence the computed land surface parameters, but also a continuing need to develop and refine techniques that: (1) combine representations of the land surface across multiple scales (e.g. Gallant

and Dowling, 2003; Deng and Wilson, 2008); and (2) permit the modern terrain analyst to move seamlessly across scales.

Finally, the foregoing review is hopefully also instructive for those interested in calculating one or more of the aforementioned land surface parameters as a part of some digital terrain modeling workflow and using the results as inputs in some environmental modeling application(s). The current state-of-the-art suggests that the present-day terrain analyst will need to choose wisely among the various options 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 in their workflows, and the significance of these errors for the results that are produced.

Acknowledgments

The thoughtful criticisms and suggestions of two anonymous reviewers and the continued encouragement of the Binghamton Symposium organizers are greatly appreciated and helped strengthen an earlier draft of this manuscript.

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