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The Handbook of Geographic Information Science

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Chapter 8

Adding the Z Dimension

Michael F. Hutchinson

The land surface is the natural context for life on Earth. Above sea-level the land surface plays a fundamental role in modulating land surface and atmospheric processes. Below sea-level it forms an important role in modulating ocean tides and currents. Life depends on these Earth surface processes over a wide range of space and time scales. Conversely, the land surface itself is molded by these processes, also over a wide range of time and space scales. It is thus not surprising that models of the land surface of the Earth have played an integral role in GI Science since its inception. Analyses and representations of the land surface have directly stimulated new methods for obtaining digital environmental data, new spatial interpolation methods and new methods for analysing landscape dependent hydrological and ecological processes (Hutchinson and Gallant 1999). The Z dimension, the elevation above or below sea-level of the land surface, is the primary descriptor of this fundamental layer.

Digital elevation models (DEMs) are used to represent the land surface in different ways, depending on the nature of the application. Visualization of landscapes, and of spatially distributed quantities and entities within landscapes, plays an important role in conceptualization and in providing subjective understanding of surface processes. It can also play an important role in assessing data quality. These applications are discussed extensively in "Optimization of DEM Resolution" below. Of central importance for environmental modeling is the accuracy and spatial coverage that can be achieved by incorporating appropriate dependencies on the land surface. Mesoscale representations of surface climate, particularly temperature and precipitation, have a strong direct dependence on elevation, the Z dimension itself, making such representations truly three-dimensional. Modeling applications at finer scales often depend on representations of the shape of the land surface rather than elevation *per se*. These shape-based applications are largely the subject of terrain analysis as discussed by Wilson and Gallant (2000; see also Chapter 23 by Deng, Wilson, and Gallant in this volume).

This chapter is primarily concerned with the generation of regular grid digital elevation models, from a variety of data sources, to support the elevation and

landscape shape requirements of environmental modeling over a range of spatial scales. Issues of data quality and spatial scale naturally arise in this context. An essential shape-based attribute of DEMs for hydrological applications is drainage connectivity. Coupling the process of automatic drainage enforcement to the interpolation and filtering of DEMs, as introduced by Hutchinson (1989), has improved elevation accuracy and directly facilitated hydrological applications. DEM accuracy can also be improved by applying statistical filtering methods that accurately reflect the errors in elevation source data. The issues of drainage connectivity and elevation accuracy are particularly relevant with the advent of fine scale digital elevation data sources.

The chapter also discusses the incorporation of dependencies of environmental variables on elevation and landscape shape. This is largely the domain of multivariate statistical analysis, usually performed by various forms of thin plate smoothing splines and geostatistics. These models normally apply data smoothing, in the same way as can be applied to elevation data, to allow for fine scale variability in the data and produce spatial models with minimal error. The incorporation of dependencies on elevation and landscape shape has played a major role in developing accurate spatial representations of environmental variables such as surface climate and in assessing spatially detailed impacts of projected climate change (Houser, Hutchinson, Viterbo, et al. 2004).

Regular Grid Digital Elevation Models and Spatial Scale

Digital elevation models are commonly based on one of three data structures: triangulated irregular networks, contours, and regular grids. Triangulated irregular networks (TINs) have found most application in visualization where economy of representation is important. This can be achieved if the triangulations are based on well-chosen surface specific points including peaks and points on ridges, streamlines and breaks in slope (Weibel and Heller 1991, Lee 1991). Contour methods tend to be computationally intensive and difficult to apply to larger areas. They are less often used directly as elevation models, but have been used in hydrological applications (Moore, O'Loughlin, and Burch 1988) and in recent derivations of slope (Mizukoshi and Aniya 2002).

On the other hand, regular grid DEMs offer simplicity of representation and of topological relations between points, at the expense of somewhat larger storage requirements than TINs. Regular grid DEMs are readily integrated with remotely sensed environmental data that are normally obtained in regular grid form. The grid spacing can also provide a useful index of scale. If stored with sufficient vertical precision, regular grid DEMs can represent terrain shape in areas of both high and low relief. Thus regular grid DEMs have become the dominant vehicle for environmental applications that depend on elevation and shape of the land surface.

The grid spacing, or spatial resolution, of a regular grid DEM, as well as providing a practical index of scale also provides a measure of information content (Hutchinson 1996). The issue of spatial scale arises at various points in elevation-based environmental analysis and modeling. The scale of source topographic data should guide the choice of grid spacing when generating DEMs from such data. The

Table 8.1 Spatial scales of applications of digital elevation models (DEMs) and common sources of topographic data for generation of DEMs

Scale	DEM Resolution	Common Topographic Data Sources	Hydrological and Ecological Applications
Fine Toposcale	1–50 m	Contour and streamline data from aerial photography and existing topographic maps at scales from 1:5,000 to 1:50,000. Surface specific point and streamline data obtained by ground survey using GPS. Remotely sensed elevation data using airborne and spaceborne radar and laser.	Spatially distributed hydrological modeling. Spatial analysis of soil properties. Topographic aspect corrections to remotely sensed data. Topographic aspect effects on solar radiation, evaporation, and vegetation patterns.
Coarse Toposcale	50–200 m	Contour and streamline data from aerial photography and existing topographic maps at scales from 1:50,000 to 1:200,000. Surface specific point and streamline data digitized from existing topographic maps at 1:100,000 scale.	Broader scale distributed parameter hydrological modeling. Sub-catchment analysis for lumped parameter hydrological modeling and assessment of biodiversity.
Mesoscale	200 m–5 km	Surface specific point and streamline data digitized from existing topographic maps at scales from 1:100,000 to 1:250,000.	Elevation dependent representations of surface temperature and precipitation. Topographic aspect effects on precipitation. Surface roughness effects on wind. Determination of continental drainage divisions.
Macroscale	5–500 km	Surface specific point data digitized from existing topographic maps at scales from 1:250,000 to 1:1,000,000. National archives of ground surveyed topographic data including trigonometric points and bench marks.	Major orographic barriers for general circulation models.

scales of DEMs should also match the natural scales of terrain dependent applications. The determination of appropriate DEM scales for hydrological modeling is an active research issue (for example, Zhang and Montgomery 1994, Blöschl and Sivaplan 1995, Feddes 1995, Sivaplan, Grayson, and Woods 2004). This is particularly relevant in recent years with the advent of high resolution data sources. Incorporation of terrain structure into considerations of spatial scale is also an emerging issue in terrain analysis (Gallant and Dowling 2003).

The range of spatial scales of hydro-ecological applications of DEMs, and the corresponding common primary topographic data sources are indicated in Table 8.1, as adapted from Hutchinson and Gallant (2000). The general trend since the 1980s has been to move from broader continental and regional scales, closely allied to the representation of major drainage divisions (Jenson 1991, Hutchinson and Dowling 1991), to mesoscale representations of surface climate (Hutchinson 1995b, Running and Thornton 1996, Daly, Neilson, and Phillips 1994) and associated flora and fauna (Nix 1986), to finer toposcales suited to the modeling of surface hydrology, vegetation, and soil properties (Moore, Grayson, and Ladson 1991, Quinn, Beven, Chevallier, and Planchon 1991, Zhang and Montgomery 1994, Gessler, Moore, McKenzie, and Ryan 1995, Mackey 1996). This has been accompanied by improvements in methods for representing the fine scale shape and structure of DEMs, supported by the steady increase in resolution of DEM data sources and the capacity of computing platforms. Fine scale processes are often the focus of hydrological applications. However, it should be noted that coarser scale processes, particularly mesoscale climate, can have a significant impact on the spatial distribution of elevation dependent environmental processes.

Of the applications listed in Table 8.1, only representations of surface temperature and rainfall have a direct dependence on elevation. All others depend on measures of surface shape and roughness, as exemplified by the primary and secondary terrain attributes listed in Moore, Grayson, and Ladson (1991). This underlines the importance of DEMs providing accurate representations of surface shape and drainage structure. This is particularly so in low relief areas where elevations must be recorded with sub-meter precision to accurately reflect small elevation gradients.

Though actual terrain can vary across a wide range of spatial scales, in practice, source topographic data are commonly acquired at a particular scale. This places practical limits on the range of DEM resolutions that can be truly supported by a particular source data set. The following section describes the data sources commonly supporting generation of DEMs at each of the scales listed in Table 8.1.

Sources of Topographic Data

Three main classes of source topographic data may be recognized, for which different DEM generation techniques are applicable, as discussed below.

Surface specific point elevation data

Surface specific point elevations, including high and low points, saddle points, and points on streams and ridges make up the skeleton of terrain (Clarke 1990). They are an ideal data source for most interpolation techniques, including triangulation methods and specially adapted gridding methods. These data may be obtained by ground survey and by manually assisted photogrammetric stereo models (Makarovic 1984). They can also be obtained from grid DEMs to construct TIN models (Heller 1990, Lee 1991). The advent of the global positioning system (GPS) has enhanced the availability of accurate ground surveyed data (Dixon 1991, Lange and Gilbert 1998). Such data are mainly obtained for detailed survey of relatively small experimental catchments. They are less often used for larger areas.

Contour and streamline data

Contour and streamline data are still a common terrain data source for larger areas. They have found common application at the toposcale (see Table 8.1). Many of these data have been digitized from existing topographic maps that, until the advent of spaceborne survey methods, were the only source of elevation data for some parts of the world. The conversion of contour maps to digital form has been a major activity of mapping organizations world wide (Hobbs 1995). Contours can also be generated automatically from photogrammetric stereo models (Lemmens 1988), although these methods are subject to error due to variations in surface cover. A sample contour and streamline data set, together with some additional point data, is shown in Figure 8.1. Contours implicitly encode a number of terrain features, including points on streamlines and ridges. The main disadvantage of contour data is that they significantly under sample the areas between contour lines, especially in areas of low relief, such as the lower right hand portion of Figure 8.1. This has

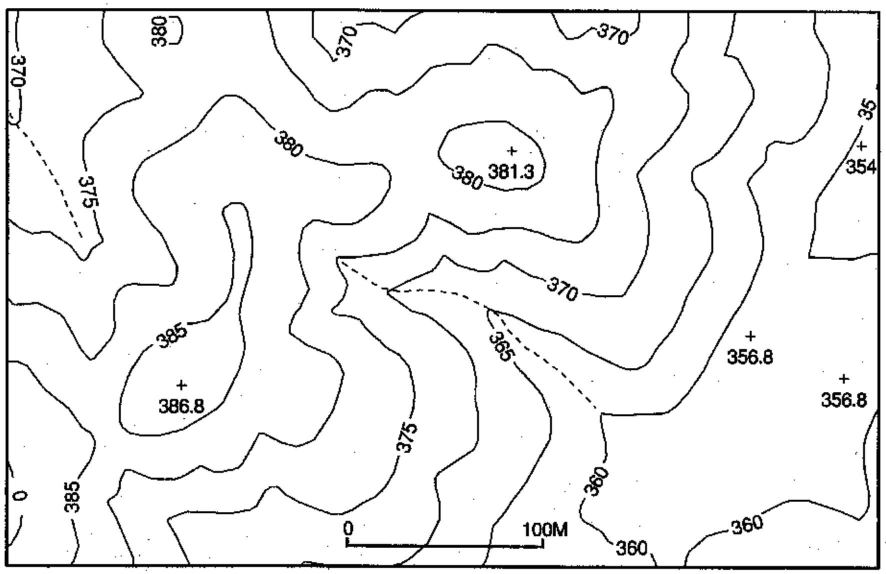

Fig. 8.1 Contour, point elevation, and streamline data

led most investigators to prefer contour specific algorithms over general purpose algorithms when interpolating contour data (Clarke, Grün, and Loon 1982, Mark 1986, Hutchinson 1988, Weibel and Brändl 1995).

Contour data differ from other elevation data sources in that they imply a degree of smoothness of the underlying terrain. When contours are obtained by manually assisted photogrammetric techniques, the operator can remove the effects of obstructions such as vegetation cover and buildings. When coupled with a suitable interpolation technique, contour data can be a superior data source in low relief areas, where moderate elevation errors in remotely sensed data can effectively preclude accurate determination of surface shape and drainage structure (Garbrecht and Starks 1995).

Streamlines are also widely available from topographic maps and provide important structural information about the landscape. However, few interpolation techniques are able to make use of streamline data without associated elevation values. The method developed by Hutchinson (1989) can use such streamline data, provided that the streamlines are digitized in the downslope direction. This imposes a significant editing task, which can be achieved by using a GI System (GIS) with network capabilities.

Remotely sensed elevation data

Gridded DEMs may be calculated directly by stereoscopic interpretation of data collected by airborne and satellite sensors. The traditional source of these data is aerial photography (Kelly, McConnell, and Mildenberger 1977). In the absence of vegetation cover these data can deliver elevations to sub-meter accuracy (Ackermann 1978, Lemmens 1988). Stereoscopic methods have been applied to SPOT imagery (Konecny, Lohmann, Engel, and Kruck 1987, Day and Muller 1988), and more recently to airborne and spaceborne synthetic aperture radar (SAR). Airborne and spaceborne lasers can also provide elevation data in narrow swathes. A major impetus for these developments has been the goal of generating high resolution DEMs with global coverage, recently achieved with the completion of the three-second (90 m) DEM for the globe obtained from the Shuttle Radar Topography Mission (USGS 2005).

Remote sensing methods can provide broad spatial coverage, but have a number of generic limitations. None of the sensors can reliably measure the ground elevations underneath dense vegetation cover. Even in the absence of ground cover, all methods measure elevations with significant random errors that depend on the inherent limitations of the observing instruments, as well as surface slope and roughness (Harding, Bufton, and Frawley 1994, Dixon 1995). The methods also require accurately located ground control points to minimize systematic error. These points are not always easy to locate, especially in remote regions. Best possible standard elevation errors with spaceborne systems currently range between 1 and 10 m, but elevation errors can be much larger, up to 100 m, under unfavorable conditions (Sasowsky, Peterson, and Evans 1992, Harding, Bufton, and Frawley 1994, Zebker, Werner, Rosen, and Hensley 1994, Lanari, Fornaro, Riccio 1997). Averaging of data obtained from multiple passes of the sensor can reduce these errors, but at greater cost.

Airborne laser scanning (ALS) data are an emerging source of fine-scale, irregularly spaced, elevation data with position and elevation errors around 10–20 cm and typical data spacing around 1–2 m (Flood 2001, Maas 2002). Airborne laser can reliably detect the height of the ground surface below significant tree cover. These data offer the potential for a new generation of accurate fine scale DEMs for a wide range of applications (Lane and Chandler 2003). But, as for coarser scale remotely sensed data, careful filtering and interpolation of such data is required to maximize the quality of the resulting DEMs and dependent representations of surface shape and drainage structure.

DEM interpolation methods

Interpolation is required to generate regular grid DEMs from irregularly spaced elevation data. These include surface specific points, contour data and high resolution data obtained by detailed ground survey and by airborne and spaceborne laser. Streamline data can be incorporated into the interpolation process to improve the drainage properties of the interpolated DEM. Since source topographic data sets are usually very large, high quality global interpolation methods, such as thin plate splines, in which every interpolated point depends explicitly on every data point, are computationally impractical. Such methods cannot be easily adapted to the strong anisotropy evidenced by real terrain surfaces. On the other hand, local interpolation methods – such as inverse distance weighting, local kriging, and unconstrained triangulation methods – achieve computational efficiency at the expense of somewhat arbitrary restrictions on the form of the fitted surface. Three classes of interpolation methods are in use. All achieve a degree of *local adaptivity* to anisotropic terrain structure.

Triangulation

Interpolation based on triangulation is achieved by constructing a triangulation of the data points, which form the vertices of the triangles, and then fitting local polynomial functions across each triangle. Linear interpolation is the simplest case, but a variety of higher order polynomial interpolants have been devised to ensure that the interpolated surface has continuous first derivatives (Akima 1978, Sibson 1981, Watson and Philip 1984, Auerbach and Schaeben 1990, Sambridge, Braun, and McQueen 1995). Considerable attention has been directed towards methods for constructing the triangulation. The Delauney triangulation is the most popular method and several efficient algorithms have been devised (for example, Aurenhammer 1991, Tsai 1993).

Triangulation methods have been seen as attractive because they can be adapted to various terrain structures, such as ridge lines and streams, using a minimal number of data points (McCullagh 1988). However, these points are difficult to obtain as primary data. Triangulation methods are sensitive to the positions of the data points and the triangulation needs to be constrained to produce optimal results (Heller 1990, Weibel and Heller 1991). Triangulation methods are known to have difficulties in interpolating contour data. These data tend to generate many flat triangles unless additional structural data points along streams and ridges can be provided (Clarke 1990, Zhu, Eastman, and Toledano 2001).

Local surface patches

Interpolation by local surface patches is achieved by applying a global interpolation method to overlapping regions, usually rectangular in shape, and then smoothly blending the overlapping surfaces. Franke (1982) and Mitasova and Mitas (1993) have used bivariate spline functions in this way. These methods overcome the computational problems posed by large data sets and permit a degree of local anisotropy. They can also perform data smoothing when the data have elevation errors. There are some difficulties in defining patches when data are very irregularly spaced and anisotropy is limited to one direction across each surface patch. Nevertheless, Mitasova and Mitas (1993) have obtained good performance on contour data. An advantage for applications of this method is that topographic parameters such as slope and curvature, as well as flow lines and catchment areas, can be calculated directly from the fitted surface patches, which have continuous first and second derivatives (Mitasova, Hofierka, Zlocha, and Iverson 1996). Local surface patches can also be readily converted into regular grids.

Locally adaptive gridding

Direct gridding methods can provide a computationally efficient means of applying high quality interpolation methods to large elevation data sets. Iterative methods which fit discretized splines in tension, as represented by a finite difference grid, have been described by Hutchinson (1989) and Smith and Wessel (1990). Both methods have their origin in the minimum curvature method developed by Briggs (1974). Computational efficiency can be achieved by using a simple multi-grid strategy which can make computational time optimal, in the sense that it is proportional to the number of interpolated DEM points (Hutchinson 1989). The use of splines in tension is indicated by the statistical nature of actual terrain surfaces (Frederiksen, Jacobi, and Kubik 1985, Goodchild and Mark 1987). It overcomes the tendency of minimum curvature splines to generate spurious surface oscillations in complex areas.

The ANUDEM direct gridding method of Hutchinson (1988, 1989, 2006) is used widely. It has been shown to be superior in terms of elevation accuracy to a variety of local kriging methods (Bishop and McBratney 2002). It has several *locally adaptive* features. It is best described by first defining an appropriate statistical model for the observed elevation data. Each elevation data value z_i at location x_i,y_i is assumed to be given by:

$$z_i = f(x_i,y_i) + \varepsilon_i \qquad (i = 1, \ldots, n) \tag{8.1}$$

where f is an unknown suitably smooth bivariate function of horizontal location represented as a finite difference grid, n is the number of data points and ε_i is a zero mean error term with standard deviation w_i. For accurately surveyed elevation data the standard deviation is dominated by the natural discretization error of the finite difference representation of f. Assuming that each data point is located randomly within its corresponding grid cell, the standard deviation of the discretization error is given by:

$$w_i = hs_i/\sqrt{12} \tag{8.2}$$

where h is the grid spacing and s_i is the slope of the grid cell associated with the i th data point (Hutchinson 1996). The function f is then estimated by solving for the regular grid finite difference approximation to the bivariate function f that minimizes:

$$\sum_{i=1,n} [(z_i - f(x_i,y_i))/w_i]^2 + \lambda J(f) \tag{8.3}$$

where $J(f)$ is a measure of the roughness of the function f in terms of first and second derivatives (Hutchinson 1989) and λ is a positive number called the smoothing parameter. The smoothing parameter λ is normally chosen so that the weighted residual sum of squares in equation (8.3) is equal to n. This can be achieved with an approximate Newton-Rhapson method coupled with the iterative solution of f (Hutchinson 2000). The spatially varying weights in the residual sum of squares in equation (8.3) is a *locally adaptive* feature that can only be achieved with an iterative interpolation method for which the slopes of the grid cells are available as the iterative solution proceeds.

Former limitations in the ability of general gridding methods to adapt to strong anisotropic structure in actual terrain surfaces, as noted by Ebner, Reinhardt, and Hössler (1988), have been largely overcome by applying a series of *locally adaptive* constraints to the basic gridding procedure. Constraints which have direct relevance for hydrological applications are those imposed by the drainage enforcement algorithm devised by Hutchinson (1989). This algorithm removes spurious depressions in the fitted DEM, in recognition of the fact that sinks are usually quite rare in nature (Band 1986, Goodchild and Mark 1987). This can significantly improve the drainage quality and overall structure of the fitted DEM. It can largely remove the need to modify the interpolated DEM to obtain drainage connectivity. Alternatively, this can be achieved by artificially filling remaining depressions (Jenson and Domingue 1988). A grid carving procedure for removing depressions from DEMs has been recently developed by Soille, Vogt, and Colombo. (2003). Its action is similar to the drainage enforcement algorithm of Hutchinson (1989).

The action of the drainage algorithm can be quite strong in data sparse areas, as illustrated in Figures 8.2 and 8.3 reproduced from Hutchinson (1989). The remaining sinks labeled S1, S2, S3, S4 in Figure 8.2, are removed by systematically identifying the lowest saddle point in the drainage divide surrounding each remaining depression. Thus the point D is the lowest saddle associated with the sink S1. Flow lines on each side of this saddle point are used to enforce approximate linear constraints from S1 down to S2. Other sinks are cleared similarly. Sinks are cleared in order of increasing elevation. This yields a derived drainage network aligned with the actual streamline formation process. Thus, the sink S3 in Figure 8.2 was not initially cleared to the next lowest sink S4, but cleared to join the streamline first inferred between S4 and S1. The drainage enforcement procedure can be made

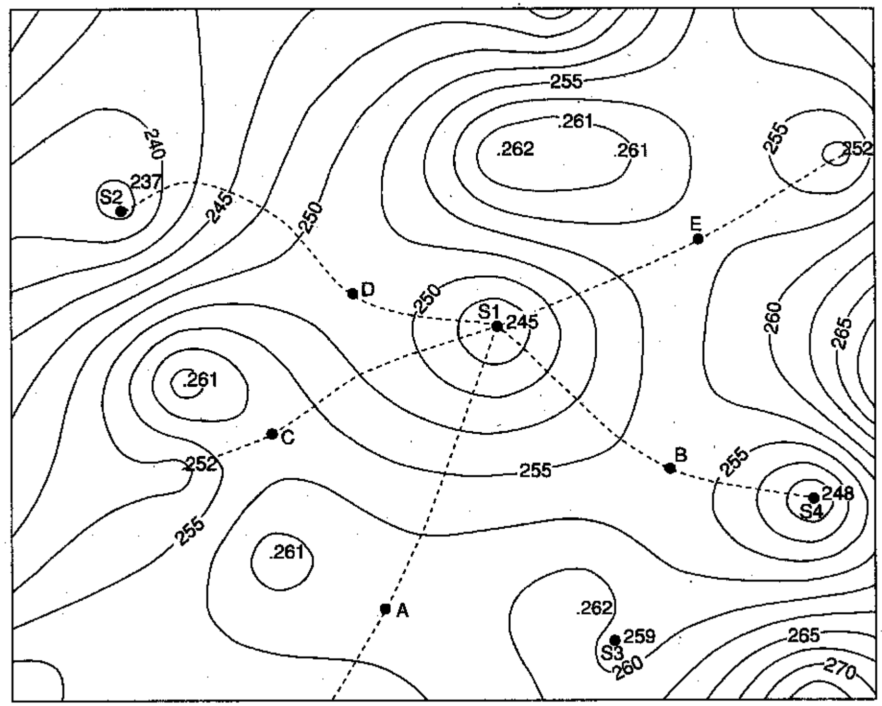

Fig. 8.2 Minimum curvature gridding of point elevation data with spurious sinks or depressions

computationally efficient because both sink points and saddle points can be detected *locally* on the grid DEM as the DEM is being interpolated.

A related *locally adaptive* feature is an algorithm which automatically calculates curvilinear ridge and streamlines from points of locally maximum curvature on contour lines (Hutchinson 1988). This permits interpolation of the fine structure in contours across the area between the contour lines in a more reliable fashion than methods which use linear or cubic interpolation along straight lines in a limited number of directions (Clarke, Grün, and Loon 1982, Oswald and Raetzsch 1984, Legates and Willmott 1986, Cole, MacInnes, and Miller 1990). A partly similar approach, combining triangulation and grid structures, has been described by Aumann, Ebner, and Tang (1992).

The result of applying the ANUDEM program to the contour, streamline and point data in Figure 8.1 is shown Figure 8.4. The inferred stream and ridge lines are particularly curvilinear in the data sparse, low relief portion of the figure, and there are no spurious depressions. The derived contours also closely match the data contours. This locally adaptive method has largely overcome problems formerly encountered by gridding methods in accurately representing drainage structure in low relief areas (Douglas 1986, Carter 1988).

This procedure also yields a generic classification of the landscape into simple, connected, approximately planar, terrain elements, bounded by contour segments and

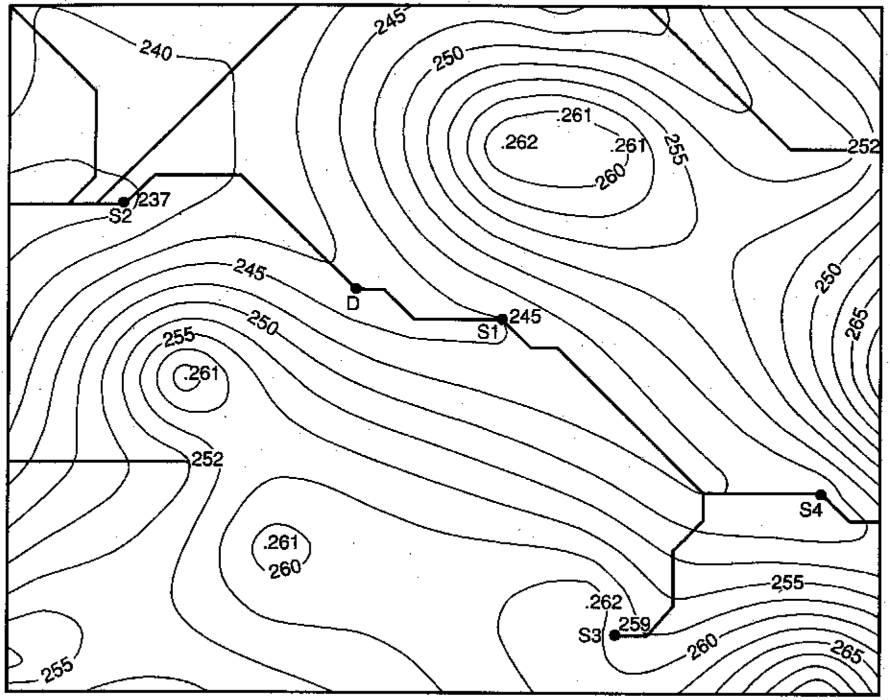

Fig. 8.3 Spurious sinks removed from the surface in Figure 8.2 by the drainage enforcement algorithm

flow line segments. These are similar to the elements calculated by Moore, O'Loughlin, and Burch (1988), but their bounding ridge lines and streamlines are determined in a more stable manner that incorporates uphill searches on ridges and downhill searches in valleys (Hutchinson 1988). A recent development in this elevation gridding method is to include a *locally adaptive* surface roughness penalty defined by profile curvature. This penalty attempts to match fluvial landform processes in a more generic manner and initial results are encouraging (Hutchinson 2000).

Filtering of remotely sensed elevation data

Remotely sensed data can be obtained as regular grid DEMs and as irregularly spaced laser scanned data. Filtering of both forms of data is required to remove errors that can have both random and systematic components. Filtering of DEM data is usually associated with a coarsening of the DEM resolution. Methods include simple nearest neighbor sub-sampling and standard filtering techniques, including median and moving average filtering in the spatial domain, and lowpass filtering in the frequency domain. Several authors have recognized the desirability of filtering remotely sensed DEMs to improve the representation of surface shape.

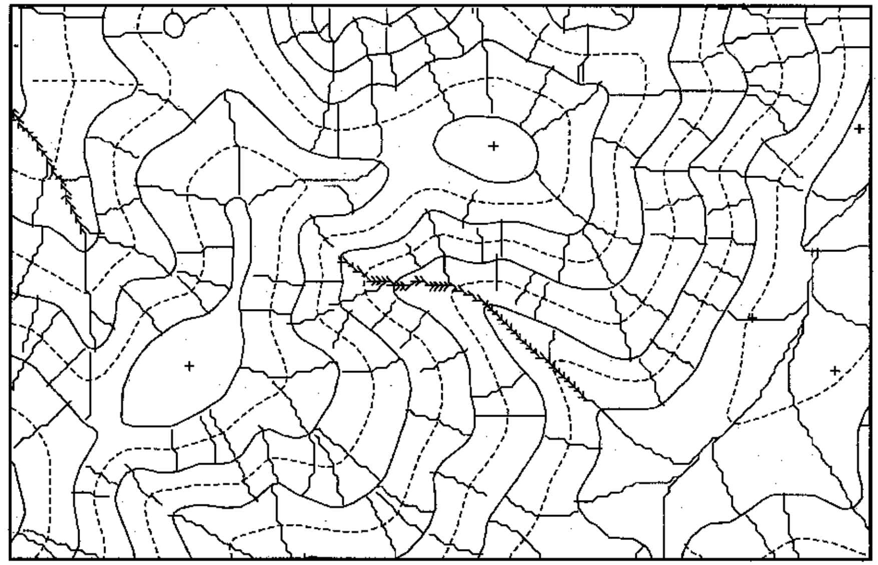

Fig. 8.4 Contours and inferred stream lines and ridge lines derived by the ANUDEM procedure from the topographic data shown in Figure 8.1.

Sasowsky, Peterson, and Evans (1992) and Bolstad and Stowe (1994) used the nearest neighbor method to sub-sample SPOT DEMs, with a spatial resolution of 10 m, to DEMs with spatial resolutions ranging from 20 to 70 m. This generally enhanced the representation of surface shape, although significant errors remained. Giles and Franklin (1996) applied median and moving average filtering methods to a 20 m resolution SPOT DEM. This similarly improved representation of slope and solar incidence angles, although elevation errors were as large as 80 m and no effective representation of profile curvature could be obtained.

Lanari, Fornaro, Riccio (1997) have applied a Kalman filter to spaceborne SAR data obtained on three different wavelengths. Standard elevation errors ranged between about 5 and 80 m, depending on land surface conditions. There is clear potential for the application of smoothing methods that simultaneously maintain sensible morphological constraints, such as connected drainage structure, on the filtered DEM. The locally adaptive finite difference gridding procedure described above is one such method. It can be adapted to DEM data, and to irregularly spaced airborne laser data, by augmenting the error standard deviation described in equation (8.2) to include the standard vertical measurement error in the remotely sensed data.

Optimization of DEM Resolution

Determination of the appropriate resolution of an interpolated or filtered DEM is usually a compromise between achieving fidelity to the true surface and respecting

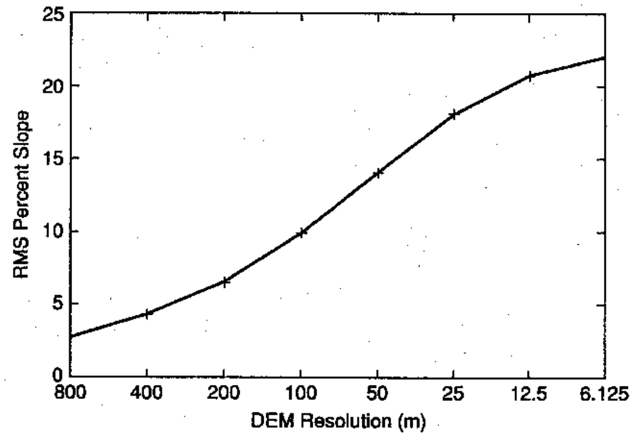

Fig. 8.5 Plot of root mean square slope of a DEM versus DEM resolution

practical limits on the density and accuracy of the source data. Determination of the DEM resolution that matches the information content of the source data is desirable for several reasons. It directly facilitates efficient data inventory, since DEM storage requirements are quite sensitive to resolution. It also permits interpretation of the horizontal resolution of the DEM as an index of information content. This is an important consideration when linking DEMs to other grid data sets and when filtering remotely sensed DEMs. Moreover, it can facilitate assessment of the scale dependence of terrain dependent applications, such as the determination of the spatial distributions of soil properties (Gessler, Moore, McKenzie, and Ryan 1995).

A simple method for matching DEM resolution to source data information content has been developed by Hutchinson (1996). The method is based on the locally adaptive weighting of the residual sum of squares described in equations (8.1) and (8.2) above. The method monitors the root mean square slope of all DEM points associated with elevation data as a function of DEM resolution (Figure 8.5). The optimum resolution is determined by refining the DEM resolution until further refinements produce no significant increase in the root mean square DEM slope. The method is particularly appropriate when source data have been obtained in a spatially uniform manner, such as elevation contours from topographic maps at a fixed scale, or from remotely sensed gridded elevation data.

The root mean square slope criterion appears to be a reliable shape-based way of matching DEM resolution, to within a factor two, to the information content of the source contour and streamline data. This criterion can be refined, especially when source data have positional errors, by examining plots of derived contours and profile curvature, as discussed by Hutchinson and Gallant (2000).

Quality Assessment of DEMs

The quality of a derived DEM can vary greatly depending on the source data and the interpolation technique. The desired quality depends on the application for

which the DEM is to be used, but a DEM created for one application is often used for other purposes. Any DEM should therefore be created with care, using the best available data sources and processing techniques. Efficient detection of spurious features in DEMs can lead to improvements in DEM generation techniques as well as detection of errors in source data. Early detection and correction of data errors can avoid expensive reprocessing of DEM dependent applications.

A first measure of DEM accuracy is summary elevation difference, typically the root mean square difference, of reference elevation data from the DEM. This can provide a useful indication of DEM accuracy. However, since many applications of DEMs depend on representations of surface shape and drainage structure, measures of elevation error do not provide a complete assessment of DEM quality (Hutchinson 1989, Wise 2000). A number of graphical techniques for assessing data quality have been developed. These are non-classical measures that offer means of confirmatory data analysis without the use of accurate reference data. Assessments of DEMs in terms of their representation of surface aspect have also been examined by Wise (1998).

Spurious sinks and drainage analysis

Spurious sinks or local depressions in DEMs are frequently encountered and are a significant source of problems in hydrological applications (Mackay and Band 1998). Sinks may be caused by incorrect or insufficient data, or by an interpolation technique that does not enforce surface drainage. They are easily detected by comparing elevations with surrounding neighbors. Hutchinson and Dowling (1991) noted the sensitivity of this method in detecting elevation errors as small as 20 m in source data used to interpolate a continent-wide DEM with a horizontal resolution of 2.5 km. More subtle drainage artifacts in a DEM can be detected by performing a full drainage analysis to derive catchment boundaries and streamline networks, using the technique of Jenson and Domingue (1988).

Views of shaded relief and other terrain attributes

Computing shaded relief allows a rapid visual inspection of the DEM for local anomalies that show up as bright or dark spots. It can indicate both random and systematic errors. It can identify problems with insufficient vertical resolution, since low relief areas will show as highly visible steps between flat areas. It can also detect edge-matching problems (Hunter and Goodchild 1995). Shaded relief is a graphical way of checking the representation of slope and aspect in the DEM. Views of other primary terrain attributes, particularly profile curvature, can provide a sensitive assessment of the accuracy of the DEM in representing terrain shape. Examination of profile curvature can prevent selection of a DEM resolution which is too fine. Overfine resolution can lead to systematic errors in derived primary terrain attributes, as illustrated by Hutchinson and Gallant (2000).

Derived elevation contours

Contours derived from a DEM provide a sensitive check on terrain structure since their position, aspect, and curvature depend directly on the elevation, aspect, and plan curvature respectively of the DEM. Derived contours are a particularly useful diagnostic tool because of their sensitivity to elevation errors in source data. Subtle errors in labeling source data contours digitized from topographic maps are common, particularly for small contour isolations that may have no label on the printed map. Examination of derived contours can prevent selection of a DEM resolution which is too coarse to adequately represent terrain structure, as illustrated by Hutchinson and Gallant (2000).

Frequency histograms of primary terrain attributes

Other deficiencies in the quality of a DEM can be detected by examining frequency histograms of elevation and aspect. DEMs derived from contour data usually show an increased frequency at the data contour elevations in an elevation histogram. The severity of this bias depends on the interpolation algorithm. Its impact is minimal for applications that depend primarily on drainage analyses that are defined primarily by topographic aspect. Frequency histograms of aspect can be biased towards multiples of 45 and 90 degrees by simpler interpolation algorithms that restrict searching to a few specific directions between pairs of data points.

Topographic Dependent Modeling of Environmental Variables

Environmental quantities are naturally distributed over space so accounting for the spatial distribution of environmental variables plays a key role in environmental modeling. Biophysical variables such as climate, soil and terrain are the primary spatially distributed determinants of plant growth. Dependent quantities such as natural vegetation, agricultural productivity, soil erosion and human and animal populations all have spatial dimensions that can be addressed by making explicit links to these contributing spatial biophysical processes. The type of spatial analysis that is discussed here is usually termed geostatistical. It is applied to data that have been sampled at points across the landscape. The broad aim of geostatistical analysis is to identify the nature of the spatial coherence of these data and use it to estimate (or interpolate) the complete spatial distribution from the sampled points.

Geostatistics arose out of efforts by Krige in the 1950s to estimate the spatial distributions of ore bodies. The theory was largely established by Matheron in the 1960s (Chilès and Delfiner 1999). A significant body of related work on multivariate smoothing spline methods also arose in the late 1970s, largely championed by Wahba (1990). The methods are formally equivalent, and have similar accuracy, but tend to differ in practice (Hutchinson and Gessler 1994). Schimek (2000) provides an extensive survey of spline-based approaches to multivariate modeling. A basic two dimensional spatial model underlying both geostatistics and smoothing splines is that there are n measured data values z_i at spatial locations x_i,y_i, given by

$$z_i = f(x_i,y_i) + \varepsilon_i \quad (i = 1, \ldots, n) \tag{8.4}$$

where f is a function to be estimated from the observations and ε_i is a zero mean error term. In the case of smoothing splines f is assumed to be a smooth unknown function and in the case of geostatistics f is assumed to be a spatially autocorrelated random field.

This spatial model has the same form as equation (8.1) given above for the locally adaptive gridding model for elevation. However, in the case of surface climate data the function can be solved analytically, since climate data sets normally have at most a few thousand points and there is no need to apply locally adaptive constraints to the interpolated function. The degree of data smoothing controls the complexity of the function f and has to be estimated from statistical analysis of the data. This is usually accomplished for smoothing splines by minimizing an estimate of the predictive error of the fitted spline given by the generalized cross validation (GCV) (Wahba 1990). It is often done in geostatistics by variogram analysis (Cressie 1991). Alternatively, maximum likelihood methods can be applied to both splines and geostatistics. Extensions to the basic bivariate model described in equation (8.4) to incorporate dependences on topography are described below in terms of thin plate smoothing splines with their kriging equivalents.

Partial spline model

The simplest way to extend the spline model specified by equation (8.4) to incorporate dependence on topography is to add a parametric linear dependence on elevation. Such a *partial spline* model can be appropriate for representing surface temperature since the environmental lapse rate of temperature is approximately linear. The model can be described as

$$T_i = f(x_i,y_i) + \beta h_i + \varepsilon_i \quad (i = 1, \ldots, n) \tag{8.5}$$

where T_i is the temperature at location x_i,y_i with elevation h_i above sea-level, n is the number of data points, β is a an unknown but fixed elevation lapse rate and f is an unknown function of horizontal location (Hutchinson 2003). The error term ε_i represents not only measurement error, but also deficiencies in the partial spline model due to fine scale variation in surface temperature below the resolution of the data network. The function f represents sea-level temperature and the scalar β represents the environmental lapse rate, usually around 6.5° C per km. The partial spline model permits simultaneous estimation of f and β with the complexity of the function f determined by minimising the GCV. This corresponds to *detrended kriging* in geostatistics, also called regression kriging. In that case the trend β is usually set by initial linear regression on elevation and the residuals are then spatially interpolated using ordinary kriging.

Jarvis and Stuart (2001a, b) have found partial splines and detrended kriging to perform with similar accuracy in interpolating daily temperature data. A range of topographic predictors have also been used in this manner to predict soil moisture (Famiglietti, Rudnicki, and Rodell 1998, Western, Grayson, Blöschl, Willgoose, and McMahon 1999) and other soil properties (Odeh, McBratney, and Chittleborough 1994, Bourennane, King, Cherry, and Bruand 1996). Additional linear predictors, based on topography and other factors, are easily added to partial spline and detrended kriging models, as illustrated in a spatial analysis of precipitation by Kyriakidis, Kim, and Miller (2001). If there is no significant spatial variation in the dependence on topographic predictors the function f in equation (8.5) may be omitted and the analysis reverts to simple linear regression on the topographic predictors. The spatial variation in the fitted model is then due only to the spatial variation in the topographic predictors.

Trivariate spline model

For variables such as precipitation and soil moisture, with more complex topographic dependences, simple linear regression and partial spline models are not always adequate spatial models. Thus Agnew and Palutik (2000) and Kieffer Weisse and Bois (2001) found elevation detrended kriging analyses of precipitation to perform no better than simple linear regression on elevation. This is because topographic dependencies of precipitation are known to vary over larger areas. Similarly, Qiu, Fu, Wang, and Chen (2001) have noted that relationships between soil moisture and environmental variables can be very variable.

There have been several attempts to introduce *spatially varying* topographic dependences into precipitation analyses. A relatively straightforward way is to divide the region into subregions and perform separate linear regression analyses on elevation for each subregion. Subregions may be defined by partitioning the region into latitude and longitude rectangles (Michaud, Auvine, and Penalba 1995), or more commonly by using a succession of local overlapping neighborhoods, each containing a minimum number of data points (Nalder and Wein 1998). The PRISM method makes a further subdivision based on broad classes of topographic aspect (Daly, Neilson, and Phillips 1994). These methods can be effective. Their main limitations are non-robustness of the local regressions, due to the lack of sufficient numbers of stations at high altitude locations in some subregions, and minimal coherence between analyses for adjoining subregions.

These problems can be addressed by applying a multivariate analysis method that uses all the data to simultaneously incorporate a continuous spatially varying dependence on both horizontal position and elevation. This can be implemented with a trivariate smoothing spline model that can be written

$$R_i = f(x_i, y_i, h_i) + \varepsilon_i \qquad (i = 1, \ldots, n) \tag{8.6}$$

where R_i is the measured precipitation at location x_i, y_i with elevation h_i. A similar trivariate extension can be made to kriging analyses. Trivariate thin plate smoothing spline precipitation analyses have been shown by Hutchinson (1995a) to perform significantly better than both bivariate analyses and elevation detrended bivariate analyses.

The accuracy of these analyses depended critically on exaggerating the scale of elevation in relation to horizontal position by a factor of about 100. If horizontal and elevation coordinates were scaled equally then the trivariate smoothing spline analysis performed no better than a bivariate analysis. This underlines the importance of optimizing the vertical scaling in trivariate spline and kriging analyses. Trivariate spline smoothing has been shown to be superior to a local regression method for the interpolation of both precipitation and temperature data, particularly in data sparse areas (Price, McKenney, Nalder, and Hutchinson 2000). Such analyses can also be improved by using elevation data from DEMs at an appropriate horizontal resolution. Several studies have found optimal horizontal resolutions of elevation dependence of precipitation between 4 and 10 km (Schermerhorn 1967, Chuan and Lockwood 1974, Daly, Neilson, and Phillips 1994).

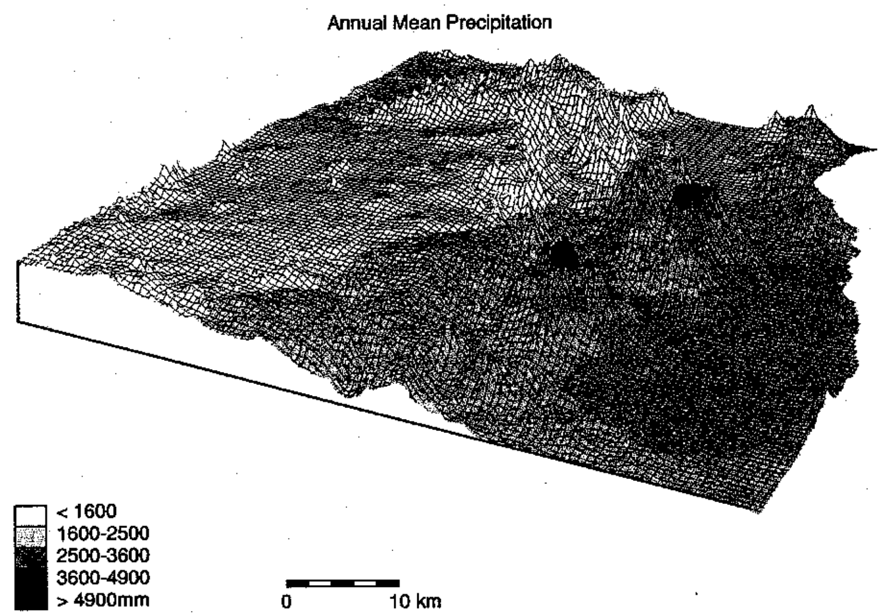

Fig. 8.6 Spline model of annual mean precipitation over topography

Figure 8.6 shows a plot of annual mean precipitation overlaid on a digital elevation model of northeastern Queensland in Australia. This model has been calculated from a three-dimensional spline model fitted to measured point precipitation data as a function of horizontal location and elevation. The resulting spatial precipitation pattern is quite complex, due in large measure to the complexity of the underlying topography. However, close inspection of the figure also reveals an underlying relatively simple, but spatially varying, dependence on elevation. The relative simplicity of this dependence enables its calibration from data sets of modest size.

Limits to complexity of multivariate spatial models

There is a fundamental limit to the complexity of multivariate spatial models fitted to data. The process indicated above of adding additional predictors, such as elevation and other topographic predictors, to a full multivariate spatial model cannot be continued without limit. Additional predictors rapidly enlarge the space in which the model is fitted. This is called the *curse of dimensionality*. In practice it means that general multivariate functions with no constraints on structure other than surface smoothness cannot be fitted to data sets of typical size if the dimension of the function is more than about four or five.

This has led to a variety of multivariate analysis methods that do impose constraints on the nature of their dependences on additional predictors. These include additive tensor product spline models described by Wahba (1990) and additive regression splines (Sharples and Hutchinson 2004). The latter closely resemble local kriging with external drift. A large variety of cokriging methods have also been developed (Chilès and Delfiner 1999). These methods can be effective provided the constraints on model structure are consistent with the processes being modeled. Thus Phillips, Dolph, and Marks (1992) found that cokriging of precipitation data with elevation peformed no better than ordinary kriging applied to elevation detrended precipitation data. Similarly Odeh, McBratney, and Chittleborough (1994) found cokriging methods to perform less well than regression kriging in predicting soil properties in terms of landform attributes derived from a digital elevation model.

CONCLUSIONS

Digital elevation models play a central role in environmental modeling across a range of spatial scales (see Chapter 23 by Deng, Wilson, Gallant in this volume for additional discussion of numerous environmental modeling applications). The regular grid mode of representation has become the dominant form for digital elevation models used in these applications. This form is directly compatible with remotely sensed geographic data sources and can simplify terrain-based analyses, including assessments of spatial scale. A distinguishing feature for many applications, particularly those that operate at finer scale, is a primary requirement for information about terrain shape and drainage structure, rather than elevation. For this reason, elevation contours and streamlines have remained popular sources of primary topographic data. They can be used to construct fine scale digital elevation models by gridding methods that are locally adaptive to surface shape and drainage structure. Remotely sensed digital topographic data, particularly from airborne sensors, are an emerging source of fine scale digital elevation data. The random errors associated with these data require appropriate filtering, without degrading shape and drainage structure, to maximize the utility of these data in environmental applications, particularly in areas with low relief or with significant surface cover.

Locally adaptive gridding procedures can be used to construct digital elevation models from digital elevation contours, point elevations and streamlines so that the elevation models preserve terrain shape and drainage structure. Grid resolution can be optimized to match the true information content of the source data and to maximize the quality of primary terrain parameters derived from the interpolated DEM. The process of producing a DEM from source data requires careful attention to the accuracy of the source data and the quality of the interpolated DEM. Several shape-based measures of DEM quality, that are readily plotted, can greatly assist in assessing DEM quality and in detecting data errors. These measures do not require the existence of separate reference elevation data. In particular, remaining sinks or depressions in a DEM are an excellent indicator of deficiencies in its representation of terrain shape and drainage structure.

Multivariate smoothing spline and kriging analysis methods of varying complexity have been used to incorporate dependences on topographic predictors to enhance the spatial analysis and mapping of environmental variables. Climate variables dependent on elevation and soil moisture dependent on various shape-based terrain parameters are common applications. The methods include simple regression and partial spline and detrended kriging methods. These often perform as well or better than more complex methods such as various forms of cokriging. Full multivariate spline and kriging models offer the most flexibility and have been successfully applied to the spatial interpolation of precipitation for which there is a spatially varying dependence on elevation. Both the relative vertical scale of elevation and its horizontal resolution need to be chosen carefully in such analyses to produce optimal results. Incorporating additional predictors may require imposition of restrictions on model structure to avoid the instabilities that can arise with higher dimensional analyses. Such methods are still the subject of active investigation. They should be successful if the restrictions on model structure are consistent with the spatial processes being modeled.

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Chapter 9

Adding Time into Geographic Information System Databases

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Despite substantial advances, Geographic Information Systems (GIS) technology still lacks the ability to handle geospatial information of all kinds. One of the most significant and long-standing issues is integration of spatial and temporal data and support for spatio-temporal analysis. Nevertheless, time is central to geographic inquiry and understanding, and the significance of adding time to GIS databases cannot be over-stated. John Jakle argues that "it is doubtful . . . that geography can continue its search for spatial understanding by ignoring the integral dictates of time and space as a natural unity; thus have geographers come to focus on the processes of spatial organization through time" (Jakle 1972). While the need to incorporate temporal data is common to many information systems, the challenge is arguably much greater in GIS because space and time in geography are interrelated. Consequently, spatio-temporal information about geography cannot be fully captured by simply adding an attribute field "time" in a GIS database. Much research progress has been made in temporal GIS since the 1980s. However, a temporal GIS that is considered sufficiently robust to support spatio-temporal information management, query, analysis, and modeling has still to be developed.

Challenges to the development of a full-fledged temporal GIS arise deep within the conceptual, computational, and presentational foundations of GIS. Conceptually, we need an ontology to categorize and communicate spatio-temporal concepts; we need GIS representations that can capture and frame these concepts; and, furthermore, we need spatio-temporal data models to organize geographic data so that spatio-temporal concepts can be computed and extracted from temporal GIS databases. Computationally, we need query languages to manipulate spatio-temporal data and retrieve information about space, time, and geographic dynamics; we need spatio-temporal logic to reason about geographic dynamics and their relationships; and we need analytical and modeling frameworks to examine spatio-temporal data and make predictions or retrospections in space and time. At the presentation level, we need means to visually communicate the multi-dimensional and dynamic nature of spatial change through time. The challenges demand a fundamental and comprehensive examination of the underlying design of GIS and innovative ways to integrate spatial and temporal information.