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Automated analysis and classification of landforms using high-resolution digital elevation data: applications and issues

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Abstract. This paper describes recent efforts to use fine spatial resolution digital elevation model (DEM) data, including, but not limited to, lidar DEM data, for automated analysis and classification of geomorphic and hydrologic terrain features. The example applications presented are based on a 3-m horizontal resolution lidar DEM for a 6 km by 8 km agricultural watershed in Alberta and on a similar 5-m horizontal resolution conventional DEM for two forested areas of 14 km by 12 km in the Cariboo Forest Region of British Columbia. The applications illustrate efforts to produce meaningful classifications of ecological and landform spatial entities and to automatically extract hydrological spatial entities required for input into the WEPP water erosion model. Fine spatial resolution DEMs present some unique problems for which solutions are still lacking or are insufficient. Errors of apparently minor extent or degree can seriously affect some forms of analysis, especially analyses that involve hydrological calculations of paths of surface water flow. A need is recognized for improved methods and tools for interpolating and editing fine spatial resolution DEMs to remove or reduce localized errors.

Résumé. Cet article décrit les efforts récents réalisés dans l'utilisation des données de MNE à fine résolution, incluant les données de MNE lidar sans exclure les autres, pour l'analyse et la classification automatisées des formes géomorphique et hydrologique de terrain. Les exemples d'application présentés sont basés sur un MNE lidar d'une résolution horizontale de 3 m pour un bassin versant agricole de 6 km par 8 km en Alberta et sur un MNE conventionnel d'un résolution similaire de 5 m pour deux zones forestières de 14 km par 12 km dans la région de la forêt de Cariboo, en Colombie-Britannique. Ces applications illustrent les efforts réalisés pour produire des classifications valides d'entités spatiales écologiques et de formes et pour l'extraction automatique d'entités spatiales hydrologiques nécessaires comme données d'entrée dans le modèle d'érosion hydrique WEPP. Les MNE à fine résolution spatiale présentent des problèmes uniques pour lesquels des solutions manquent toujours ou sont insuffisantes. Des erreurs, apparemment de faible envergure ou amplitude, peuvent affecter sérieusement certaines formes d'analyse, spécialement les analyses impliquant des calculs hydrologiques de chemins d'eau de surface. On reconnaît le bien-fondé d'apporter des améliorations aux méthodes et aux outils actuels d'interpolation et d'édition des MNE à fine résolution spatiale pour éliminer ou réduire les erreurs localisées.
[Traduit par la Rédaction]

Introduction

Both lidar and conventional technologies are providing rapidly increasing capabilities to acquire very accurate, very fine spatial resolution, digital elevation data in a timely and cost effective manner. These fine spatial resolution digital elevation datasets provide the support required for implementing new applications that were not feasible using previously existing digital elevation model (DEM) data sources. In concert with new opportunities, however, new problems are also arising that challenge us to discover new solutions.

Analysis of digital elevation data to classify landforms and to extract geomorphic and hydrologic features has a long and productive history dating back to early efforts by Strahler (1956), Speight (1968; 1977), Evans (1972), Mark (1975a; 1975b), and Peucker and Douglas (1975). Many recent efforts have outlined techniques for processing DEM data to automatically classify landforms (Burrough et al., 2001; Irwin et al., 1997; Fels and Matson, 1996; Franklin, 1987; Herrington and Pellegrini, 2000; MacMillan et al., 2000; Pennock et al., 1987; 1994; Pike, 1988), to extract hydrologic structure (Band, 1989a; 1989b; 1989c; Flanagan et al., 2000; Maidment, 2000; Moore et al., 1991; O'Loughlin, 1990; Skidmore, 1990) or both (Band et al., 2000; Moore et al., 1991; Weibel and DeLotto, 1988; Skidmore et al., 1991; Wood, 1996).

Automated techniques have been widely used to extract features defined as pits, peaks, passes, channels, divides, and the hillslopes that occupy the space between channels and divides (Wood, 1996; Skidmore, 1990). These conceptual entities have been augmented by subdividing hillslopes

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between divides and channels into convex (shedding) or concave (receiving) components (Herrington and Pellegrini, 2000; Band et al., 2000; Skidmore et al., 1991). Measures of surface shape (convex/concave) and slope gradient (Pennock et al., 1987, 1994; Irwin et al., 1997) or relative landform position and slope gradient (Fels and Matson, 1996) have been used to achieve largely similar results. Another computational approach has used explicit calculations of hydrological flow paths to compute drainage divides and channels and to subdivide hillslopes into convergent and divergent elements in upper, mid, and lower landform positions (Band et al., 2000; O'Loughlin, 1990).

Realization of the importance of computing and analyzing hydrological flow and of establishing explicit hydrological connectivity between defined terrain entities is an increasingly important aspect of many recent efforts in automated terrain analysis. Recent developments have demonstrated significant movement towards defining integrated land and water spatial entities. These include the ArcGIS Hydro data model (Maidment, 2000), the concept of hydrologically linked hillslope patches (Band et al., 2000), and computer programs for automatically delineating hillslopes and hillslope profiles for the WEPP erosion model (Flanagan et al., 2000).

The relatively coarse horizontal and vertical spatial resolution of most existing DEM datasets has limited the applicability of many of these previous efforts. Automated landform classification was restricted to recognition of relatively large landform features observable at fairly small scales. The horizontal and vertical resolution of most widely available existing DEM datasets (25–100 m horizontal and 10 m vertical) precluded recognition of many small or subdued landform features. Similarly, extraction of hydrological structure from existing coarser resolution elevation datasets suffered from an inability to fully capture complete, integrated drainage networks.

Objective

The objective of this paper is to discuss opportunities and problems associated with the use of very fine spatial resolution digital elevation data for large areas. The opportunities are illustrated with reference to two different example applications in two different study areas. In one application, the primary motivation was to automatically extract, for extensive agricultural watersheds in Alberta, Canada, the hydrological spatial entities required as input to the water erosion prediction project (WEPP) model (Flanagan and Nearing, 1995). In the second example application, the primary interest was to evaluate the use of derivatives of elevation data as the main inputs for producing accurate and cost-effective maps of ecological spatial entities in forested areas of the province of British Columbia.

The emphasis in this paper is not on describing the methods or results of these applications in detail, but rather in using them to highlight and discuss issues and problems that have been encountered in using fine spatial resolution DEMs. The discussion aims to identify both efforts that have been successful in addressing issues and problems for which solutions remain to be found.

Example datasets and study areas

This paper presents examples drawn from two different study areas represented by two different kinds of DEMs. The first study area covers a portion of the Haynes Creek agricultural watershed in Alberta measuring approximately 6 km EW and 8 km NS (**Figure 1**). This area is characterized by relatively subdued relief and non-treed agricultural fields. The second study area consists of two 1 : 20 000 scale map sheets measuring approximately 14 km EW and 12 km NS in the Cariboo Forest Region of British Columbia (**Figure 2**). These maps sheets are forested and the terrain varies from very subdued (<10 m relief) to relatively high-relief ridges (>400 m).

A lidar DEM was acquired for the Haynes Creek study area. The footprint for the original lidar DEM was approximately 3 m by 3 m with a vertical elevation accuracy assessed at ±0.30 m RMS (based on in-field differential global positioning system (DGPS) measurements). A DEM for the Cariboo map sheets was created using conventional stereo photogrammetric methods. The *x*, *y*, *z* data for the conventional DEM were collected on roughly a 10-m grid with an approximately equal number of additional elevation points selected to capture significant landform features (ridges, channels, lines of inflection, lakes). These data were interpolated to a raster grid with a horizontal resolution of 5 m and an estimated vertical accuracy of ±0.5 m (based on field evaluations of DEMs produced elsewhere using the same methods).

Through trial and error, we first arrived at the empirical conclusion that DEMs with a horizontal grid resolution of 5–10 m were best suited for extracting the landform classes and hydrological entities of greatest interest to us for operational planning and management purposes. Consequently, prior to analysis, both DEMs for both study areas were resampled to a 10-m grid and smoothed using three passes of a mean filter with dimensions of 5 × 5, 5 × 5, and 7 × 7. Smoothing filters were applied because we have consistently found that results for both landform classification and extraction of hydrological features were more meaningful and interpretable when a succession of mean filters was applied to bring out the longer-range signal and mask the local shorter-range noise.

Example applications

Automated extraction of hydrological networks and spatial entities

The WEPP model (Flanagan and Nearing, 1995) simulates runoff and erosion at the scale of individual hillslopes or small agricultural watersheds. Operation of the WEPP watershed model requires the prior decomposition of space into fundamental hydrological spatial entities. In WEPP, these

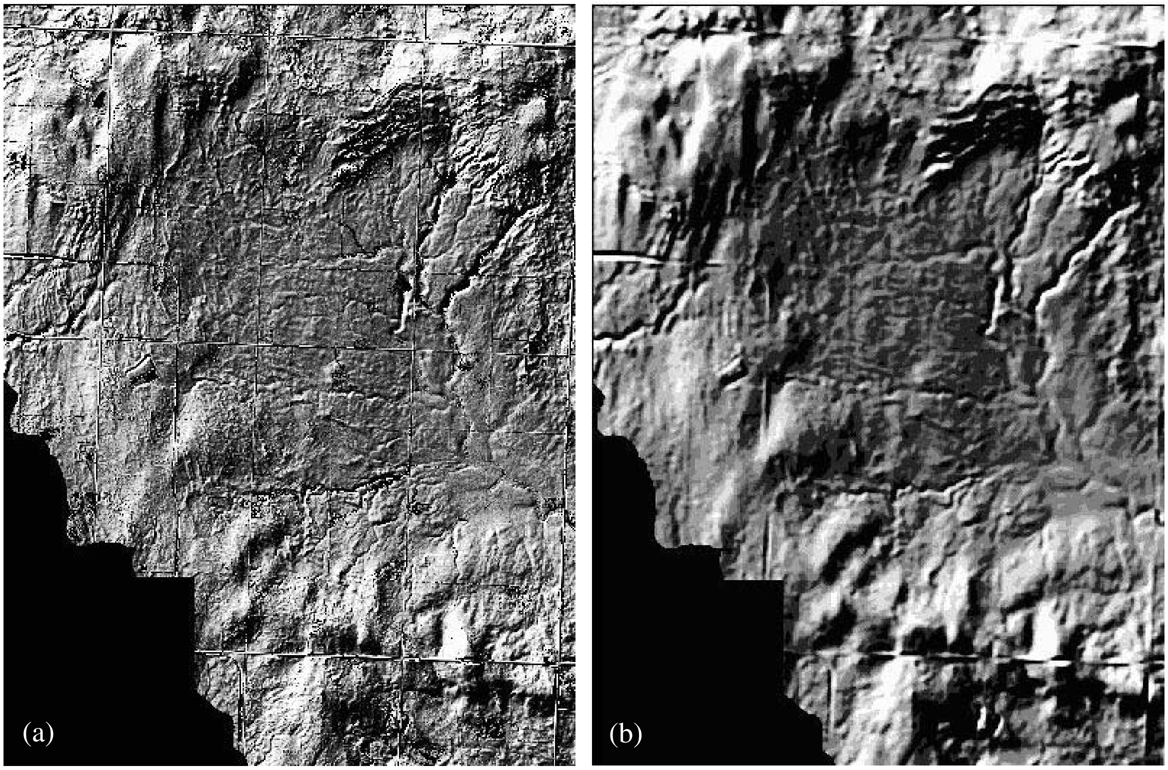

Figure 1. Hillshade images of the lidar DEM for the Haynes Creek M1 watershed near Lacombe, Alberta: (a) original 3-m lidar DEM, (b) final smoothed 10-m lidar DEM.

spatial entities consist of linear segments of ephemeral channels and the hillslopes (or channel segment catchments) that drain to each channel segment. WEPP also recognizes closed depressions as additional spatial features, termed impoundments, which can be fed by up to three channel segments or one hillslope.

Until recently, construction of the data files used to describe WEPP hillslope and channel segments and their topological connectivity required laborious, time-consuming and error-prone manual interpretation of aerial photographs or topographic maps. This application sought to extract the required WEPP spatial entities and define their complete topological connectivity automatically for large areas of complex terrain represented by fine spatial resolution DEMs. A custom program entitled WeppMapR was created that successfully partitioned the entire area represented by the fine resolution DEM for the M1 watershed of the Haynes Creek Basin study area into topologically and hyrologically consistent channel, impoundment, and hillslope spatial entities (**Figure 3**). The basic logic and procedures implemented by the WeppMapR program, summarized in **Table 1**, are documented in detail in internal client reports (MacMillan and Martin, 2001) and non-refereed conference proceedings (MacMillan and Martin, 2002).

The WeppMapR procedures extracted and numbered 4761 WEPP hillslope spatial entities. A tabular database generated by the procedures recorded the significant attributes of each hillslope, including its unique ID number, the ID number of the channel segment (or impoundment) into which it drained, and a representative slope profile used to simulated runoff and erosion for the hillslope entity. The total number of WEPP channel segments extracted was 2495. The channel segments were numbered sequentially from 4762 to 7256. A tabular database was generated containing data for each channel segment, including its unique ID number, the ID numbers of the upslope channel segments (or impoundments) that drained into it, the ID number of the downslope channel segment (or impoundment) into which it drained, and a representative channel profile describing the gradient and shape of the channel segment. A third database documented the attributes and hydrological connectivity of 260 WEPP impoundments. The databases were easily processed to generate all ASCII files required to define the spatial framework for operational application of the WEPP watershed program.

Automated classification of landform facets and ecological units

The initial objective in processing the fine spatial resolution DEM for the 1:20 000 map sheets in the Cariboo Forest Region was to define landform facets as one input layer to assist with predictive mapping of ecological units (Site Series). This original objective was later expanded to include predicting Site Series directly from analysis of the digital elevation data, rather than using the classified landform facets as simply one input in a subsequent predictive ecosystem mapping exercise. A revised

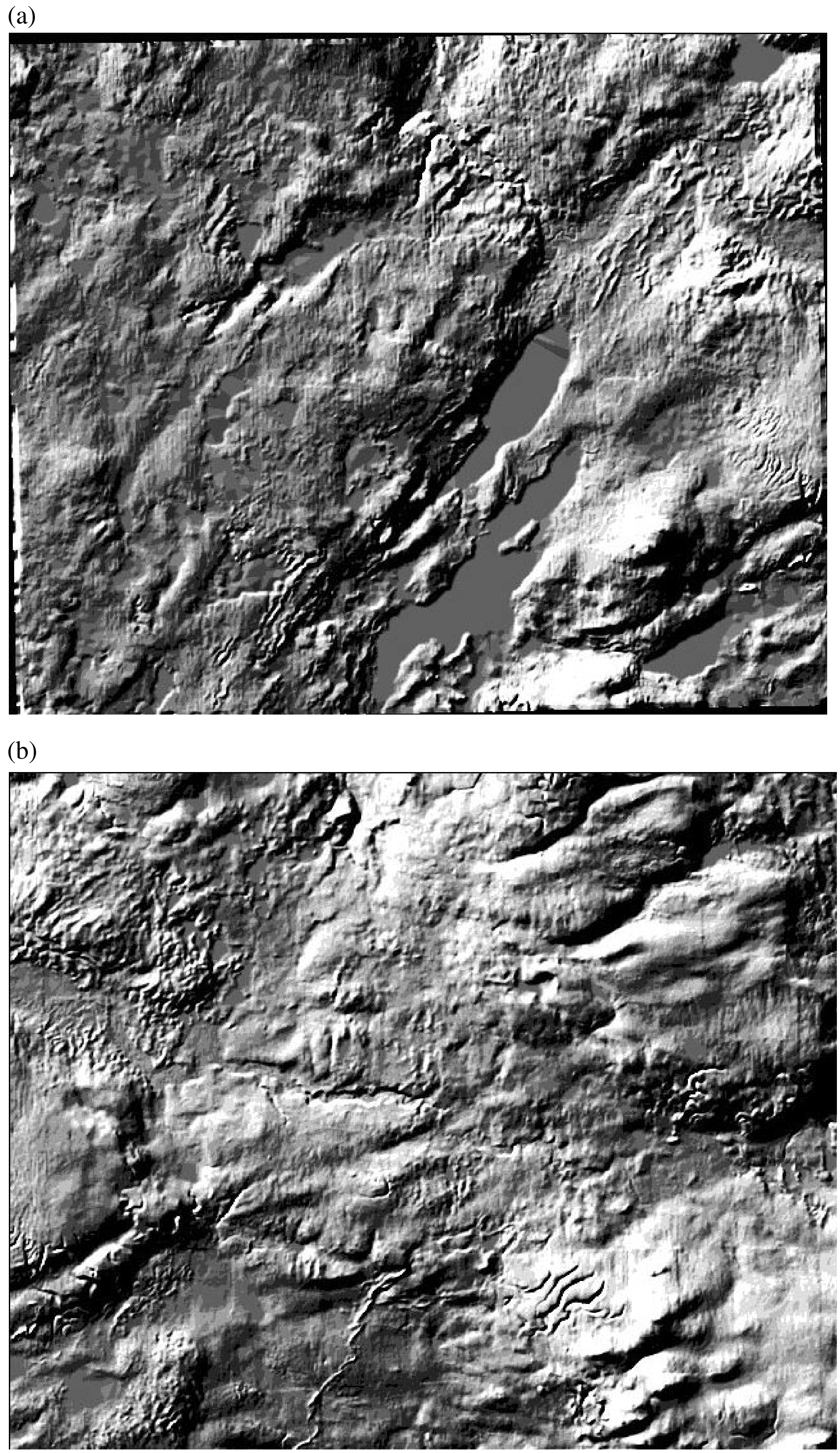

Figure 2. Hillshade images of conventional 5-m DEMs for two 1:20 000 map sheets in the Cariboo Forest Region: (a) map sheet 93a-013, (b) map sheet 93a-014.

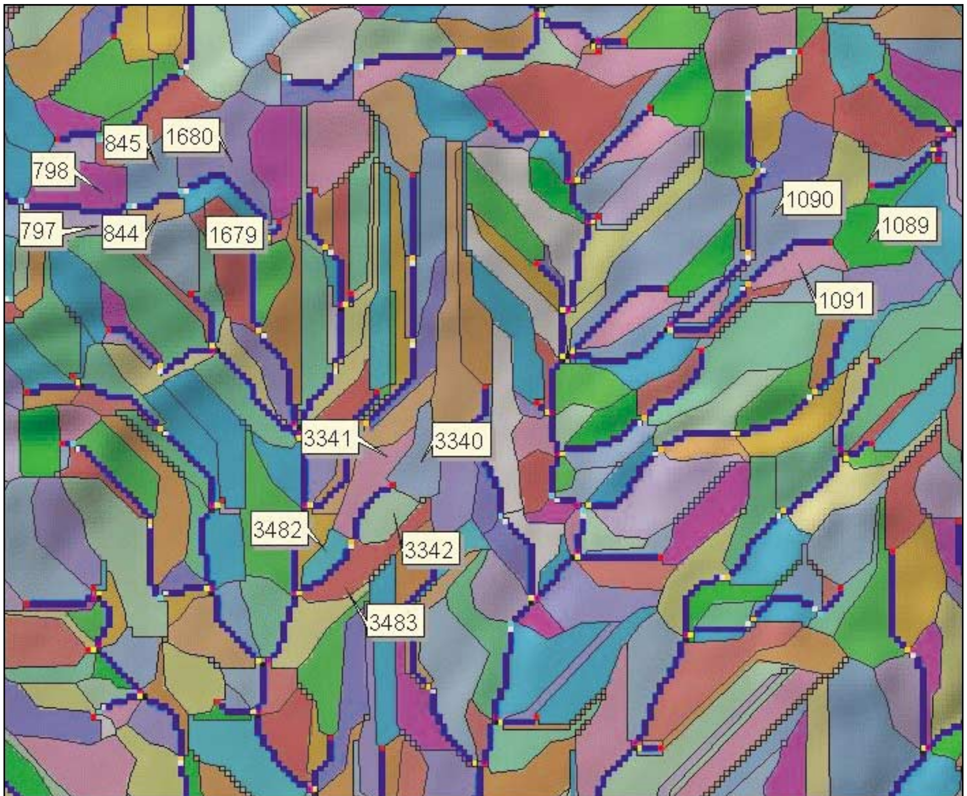

Figure 3. The WEPP hillslope and channel segment spatial entities extracted automatically for a 1.8 km EW by 1.5 km NS portion of the Haynes Creek M1 watershed.

and updated version of the LandMapR program (MacMillan et al., 2000) was used to analyze the DEM data to produce both the landform classifications and the direct classification of Site Series.

Site Series are conceptual ecological units. They are conceived of as portions of the landscape that have similar micro-climates that can support similar potential climax vegetation assemblages as influenced by the availability of moisture, heat, energy, and nutrients. In many locales, the availability of moisture, heat, energy and nutrients is strongly related to terrain attributes including relative landform position, landform shape, slope steepness, and slope orientation. Other salient controls including material depth, texture, and mineralogy exhibit a less direct relationship to terrain facets, but are still at least partially related to landform shape and position. Mapping the spatial distribution of Site Series ecological units can therefore be greatly assisted by including a consideration of landform classes or by direct interpretation of terrain attributes computed from a DEM.

The pilot project in the Cariboo Forest Region produced maps of predicted ecological classes (Site Series) for an area consisting of three 1:20 000 map sheets (45 000 ha) (data presented for two of three map sheets only). The pilot implemented seven different methods of predicting Site Series using each of two DEM datasets (**Table 2**). It compared the classification results obtained using the existing British Columbia provincial terrain resource inventory mapping (TRIM) DEM interpolated to a 10-m grid relative to those obtained using a new custom 5-m DEM for two 1:20 000 map sheets produced specifically for the project using conventional photogrammetric methods.

The relative accuracy of the Site Series maps produced by each method and each DEM data source was assessed by an independent team of consultants using field transect data not available to the original map makers (Moon, 2002). Accuracy was assessed with reference to field evaluations of Site Series along randomly selected “radial arm” transects. Each radial arm transect was centered at a randomly selected point location and had three linear transects (arms) that radiated out from this point in a randomly selected direction for a minimum but randomly determined distance. A line intercept method was used to identify the field-assessed Site Series class along linear segments of each transect arm. Locations along each transect arm at which the Site Series was judged to change were located and recorded using DGPS coordinates. A polygon was created by joining the end points of the three arms of each radial arm transect. The linear extent of each field-recognized Site Series class along all three transect arms was used to estimate the proportion of the polygon occupied by each of the Site Series classes. The polygon area for each radial arm transect was intersected with each of the ecological maps identified in **Table 2** and the proportions of Site Series predicted by each ecological map were compared to the proportions estimated using the field assessments. Accuracy was assessed in terms of

Table 1. Description of the main processing steps implemented by the WeppMapR program.

Step	Description of main action	Description of actions undertaken by key substeps
1	Compute flow topology from the DEM data	Compute a local flow direction for each cell using a custom implementation of the standard D8 flow algorithm. Use custom procedures to identify and remove pits in the DEM but preserve all relevant information about the pits.
2	Compute a simulated channel network	Identify cells with an upslope area count greater than a user selected threshold value as being potential channel cells. Thin the channel network to reduce multiple parallel channels that are common artifacts of the D8 algorithm. Burn the thinned channel network into the DEM (this cuts through artificial dams and saddles at “pour points”).
3	Identify and label channel segments along the simulated channel network	Trace down the thinned channel network to identify and mark specific cells considered to be “seed cells” that identify important points along the channel network. Eight kinds of “seed cells” are recognized: (1) channel start cells, (2) cells at channel junctions, (3) cells immediately upstream of a junction on the main branch of a channel, (4) cells immediately upstream of a junction along a tributary branch of a channel, (5) cells located at the center of a previously removed pit, (6) cells located at the end of a channel, (7) special “split” cells used to break a channel segment into shorter, straighter and more uniform lengths, (8) cells located immediately down slope from a split cell or an impoundment (pit) cell. Trace along each simulated channel and sub-divide channel into marked channel segments. Each channel segment begins at a “start type” seed cell (1, 2, or 8) and ends at an “end type” seed cell (3, 4, 5, 6, or 7). Each channel segment is labeled with a unique integer ID number. Labeled channel segments are sorted by the elevation of their end cell and re-labeled sequentially from highest to lowest to establish the topological order of flow from upper segments (lower ID numbers) into lower segments (higher ID numbers). Trace along all labeled channel segments and label all cells adjacent to each channel as draining into the channel from the left, right, or top (this is a requirement of WEPP).
4	Compute and label WEPP hillslope spatial entities	First trace flow from all cells until flow enters a labeled channel segment. All cells that flow to a given labeled channel segment are part of the catchment for that segment. Next subdivide the channel segment catchments into WEPP hillslopes by grouping all cells according to whether they flow into the channel through cells previously labeled as flowing into the channel from the left, right, or top.
5	Compute and store topological flow linkages	Sort and number WEPP hillslopes sequentially from highest to lowest using the sequential ID of the WEPP channel segment into which they flow to guide ordering. Renumber all channel segments such that the lowest number assigned to a channel segment is one greater than the largest number assigned to a WEPP hillslope. WEPP requires channel segments to have ID numbers larger than any numbered WEPP hillslope. Compute and store in DBF tables the hydrological and topological connectivity for each WEPP hillslope (the channel segment that it drains into) and the connectivity from each channel segment into the down slope segment into which it drains (also the segments that drain into it).
6	Compute measures of terrain morphology for each WEPP spatial entity.	Compute slope, aspect, and distance to channel cell for each grid cell in the DEM. These data are used in the next step to compute notional profiles for hillslopes and channels.
7	Compute notional profiles for each WEPP hillslope and channel segment.	For each WEPP hillslope compute total slope length and statistics on mean slope gradient for up to 20 equal interval increments of slope length from hillslope top to bottom. Use these statistics to prepare and record a notional profile for each hillslope expressed as slope gradient at 20 equal increments of distance along the hillslope profile length. Compute and store notional channel profiles by recording slope gradient at up to 20 equally spaced locations along each defined and labeled channel segment. Store profile data in topologically encoded DBF tables.

Table 2. Listing of the input layers, costs, and relative accuracies of various approaches used to predict ecological classes.

	Number used to identify option											
Input layers and methods used	1a	2	3a	3b	4a	4b	5a	5b	6a	6b	7a	7b
BGC subzone map	×	×	×	×	×	×	×	×	×	×	×	×
Direct to Site Series using manual SoftCopy interpretation of 1:40 000 TRIM diapositives		×										
Bioterrain maps produced using manual heads-up interpretation of 1:40 000 TRIM diapositives in a SoftCopy environment			×	×					×	×		
Bioterrain maps produced using manual interpretation of 1:15 000 stereo air photos					×	×	×	×				
Custom landform facets produced using TRIM II DEM interpolated to a 10-m grid	×		×		×		×		×			
Custom landform facets produced using new custom DEM data interpolated to a 5-m grid				×		×		×		×		
Vegetation information extracted from BC Forest Cover maps							×	×	×	×		
Map of material depth and texture interpreted manually from available secondary source maps and digitized											×	×
Direct to Site Series using LandMapR program and TRIM II DEM interpolated to a 10-m grid											×	
Direct to Site Series using LandMapR program and custom DEM data interpolated to a 5-m grid												×
Relative accuracy (% correct)	ND	62	42	40	55	59	52	56	46	41	66	65
Relative cost (Can$/ha)	ND	0.64	2.16	2.16	2.34	2.34	2.34	2.34	2.16	2.16	0.47	1.30

"percent overlap", which was a measure of the extent to which the measured proportions of each Site Series within each radial arm transect polygon matched the proportions predicted by any given predictive map within the same transect polygon area. This measure evaluated the ability of a predictive map to provide estimates of relative proportions of the desired mapping entities (Site Series) within polygonal areas equivalent in size to "minimum size mapping units" or areas for which management decisions would need to be made. The accuracy determinations did not try to evaluate exact categorical matches at specific points on the land surface. It was felt that positional error present in both the input data used to create the predictive maps and in the DGPS coordinates used to identify locations of field classifications limited our confidence that point data used to compare predicted maps to field classifications came from exactly the same spot. Also, exact classification match at specific locations was not as relevant to the intended use of the data as was close correspondence in estimates of proportions of mapping entities (Site Series) within areas of some minimum size pertinent for management decisions. Finally, in addition to assessing relative accuracy, the relative cost of production of each type of map was also determined and a cost-benefit analysis was performed.

One of the alternate mapping methods involved direct manual interpretation of stereo aerial photos and ancillary map data in a digital (SoftCopy) environment. Several others involved using manually produced maps of soils and landform attributes, termed bioterrain maps, created expressly for the pilot testing as the key landform-based input for automated predictive ecosystem mapping (PEM) procedures. Landform facets extracted automatically from digital elevation data (**Figure 4b**) were used in several other methods, in combination with various other input datasets, including bioterrain maps, as a key layer of terrain information in automated predictive ecosystem mapping procedures.

Finally, the original procedures and the LandMapR program used initially to classify landform facets were modified to permit direct classification of ecological units (Site Series). The revised procedures used three layers of spatial data in addition to derivatives derived solely from analysis of the DEM data. The additional input layers consisted of maps of the estimated depth and texture of the parent material and a map identifying the highest and most prominent of ridge tops. These three additional maps were prepared and digitized manually based on rapid visual interpretation of available secondary source maps of soils and landforms.

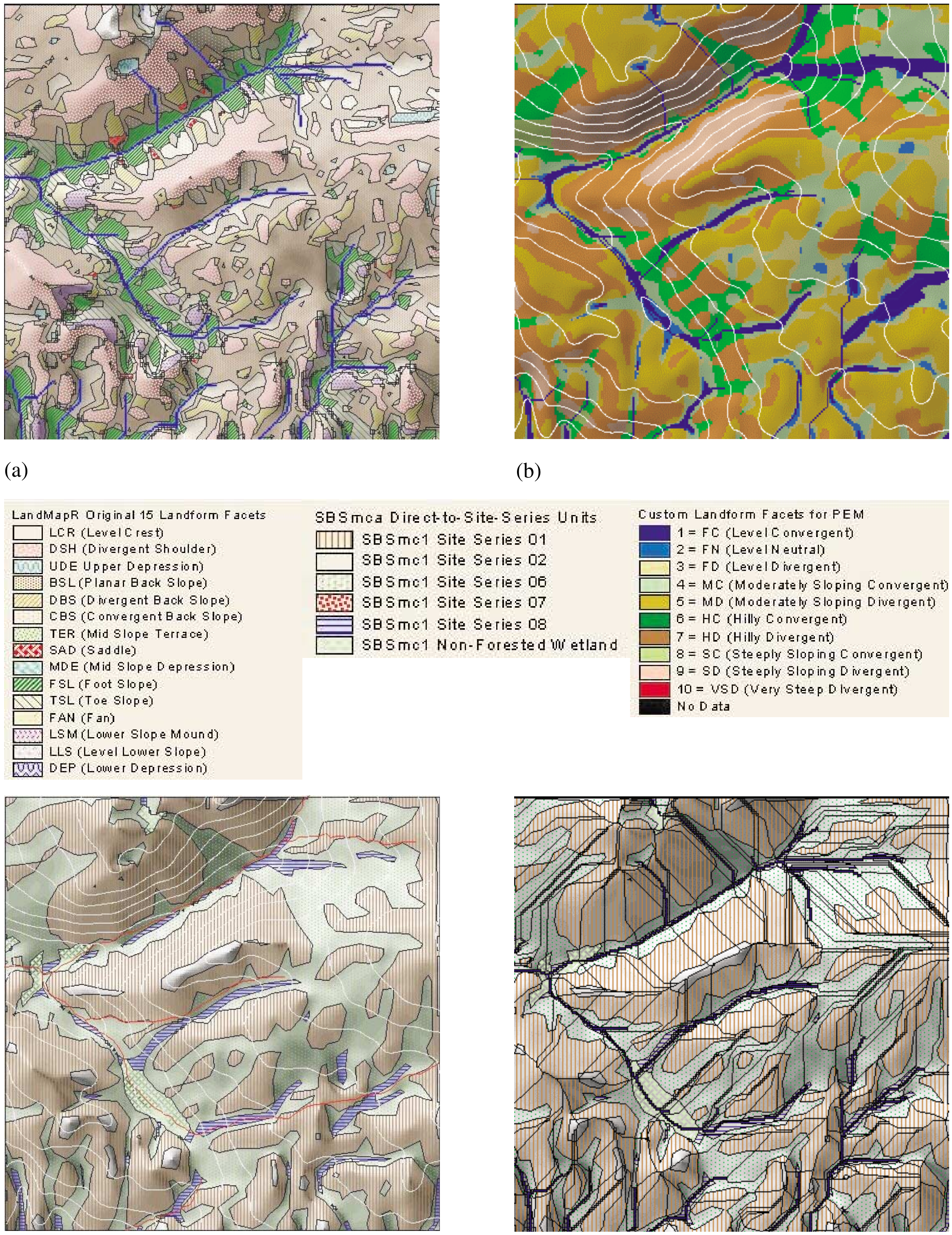

Figure 4. The results obtained by the application of the various landform classification procedures for a small 2 km by 2 km portion of the Cariboo PEM pilot area: (a) original 15 LandMapR landform facets, (b) custom 10 unit landform facets, (c) new Direct-to-Site-Series classification, (d) combined geomorphic-hydrologic units.

The LandMapR program computes a series of terrain derivatives from a raster DEM and then applies fuzzy classification rules to automatically classify landform-based spatial entities (MacMillan et al., 2000). The Cariboo pilot computed both an original set of previously defined landform classes and rule bases (MacMillan et al., 2000) (**Figure 4a**) and a revised set of classes and rules (**Figure 4b**) devised specifically for the Cariboo PEM pilot project. Problems were encountered in applying the original set of LandMapR rules to an overly smooth DEM dataset first obtained for the PEM pilot area. These led to the decision to develop a new custom set of landform classes (**Figure 4b**) and their associated rule bases. A decision was then taken to use these custom landform facets as the key landform classification input layer in the various mapping options that involved application of conventional PEM overlay procedures.

The automated analysis that predicted Site Series directly (**Figure 4c**) proved to be more successful than any of the various options that used the custom landform facets (**Figure 4b**) as one of several input layers in a more traditional PEM classification exercise. The Direct-to-Site-Series method achieved an average accuracy of 65% using the fine spatial resolution DEM data acquired specifically for the PEM pilot project and an average accuracy of 66% using a 10-m DEM compiled from TRIM II DEM data available for the entire province of British Columbia. These Direct-to-Site-Series results were better than the average accuracy of 40% to 59% achieved using the custom landform facets, in combination with various other layers of input data, in a conventional PEM classification exercise.

Since the PEM pilot project did not include any formal procedures for comparing the quality of the custom, fine spatial resolution, DEM to that of the coarser provincial TRIM II DEM data, we could only evaluate their comparative utilities in terms of how well they predicted ecological Site Series. After some early confusion due to errors in how the accuracy procedures were applied, it was determined that there were no observable differences in the relative accuracy of Site Series maps created using the fine spatial resolution, custom DEM data relative to the coarser resolution TRIM II provincial DEM data. We were forced to conclude that both DEM data sources portrayed meso- to macro-scale landscape features with about equal fidelity and that neither portrayed micro-topographic features well enough to be superior to the other. All of the various rule sets and procedures for classifying landform entities and ecological classes were clearly oriented towards recognition of relatively large meso- to macro-topographic features with length dimensions greater than 75–100 m. Features with smaller dimensions were not well recognized by the classification rule sets and were not well captured by either DEM.

The pilot project had begun with the assumption that finer resolution DEM data would invariably produce more accurate maps of predicted ecological entities. We had hoped to quantify the degree of improvement that would be attributable to the finer resolution DEM data and to conduct a cost-benefit analysis to decide if acquisition of the finer resolution DEM data was justified. To our surprise we found that the currently available TRIM II DEM data were as effective as the new fine resolution custom DEM data in addressing our needs. The TRIM II DEM data are essentially free to forest companies operating in British Columbia (having been already paid for), while the cost of acquisition of new fine resolution DEM data was just over Can$1.00/ha for the pilot area. For this application, at least, there appears to be no strong argument for using finer resolution DEM data to predict ecological classifications at a nominal scale of 1:20 000.

Automated extraction of combined hydrologic-geomorphic spatial entities

The WeppMapR procedures for extracting hydrological spatial entities were combined with the LandMapR procedures for automatically classifying landform and ecological spatial entities to compute what are here termed combined geomorphic-hydrologic spatial entities (**Figure 4d**). These spatial entities combine the topological hydrological connectivity required of WEPP hillslopes and channels with the characteristics of defined landform position and landform shape used to classify landform facets.

These combined hydrologic-geomorphic spatial entities provide powerful capabilities to describe and predict the external and internal attributes of portions of the landscape and to model the movement of water and materials carried by water between portions of the landscape. In modeling language, they not only assist in estimating input parameters for models but also define the structural framework for the model and establish the hydrological connectivity between model elements. Each defined entity has a restricted range of landform position, landform shape and other morphological attributes. This leads to the expectation that each entity will also exhibit a more restricted range of internal attributes (e.g., texture, depth, moisture status, organic carbon, hydraulic conductivity) than the landscape as a whole. This is the key to using the entities as a spatial framework for predicting key terrain and material attributes required to support hydrological modeling and ecological management.

Hydrological connectivity is defined between each of the spatial entities and the entities that lie above it, and contribute flow into it and those that lie below it, into which it contributes flow. This defined hydrological connectivity permits the combined entities to be used as a spatial framework for modeling the flow of water, and materials carried in suspension or solution by water, over and through the landscape. The combined geomorphic-hydrologic spatial entities are roughly similar in concept to patches as defined by Band et al. (2000) or to some realizations of hydrologic response units (HRUs) as proposed for the ArcGIS Hydro spatial data model (Maidment, 2000).

Issues encountered in the example applications

The following discussion highlights some of the more common, or more difficult to resolve, issues encountered during the course of implementing the two applications described in this paper. The discussion does not address all issues encountered nor does it provide exhaustive descriptions of the problems or identify all required solutions. It is simply an attempt to identify some of the more significant issues we encountered in the course of using fine spatial resolution DEM data and to identify what we did, or would have liked to have done, to address these issues.

Identifying and correcting gaps or holes in the lidar DEM data

The lidar DEM obtained for the Haynes Creek M1 watershed (**Figure 5a**) was outstanding in its ability to correctly capture and portray the “bare ground” terrain over almost all of its extent. Problems arose with identifying and fixing the very small proportion of the total area for which gaps existed in the “bare ground” data coverage.

A particular concern was how to properly fill holes in the “bare ground” DEM that occurred along strongly linear features that were asymmetric in shape. Examples include roads, ditches, fence lines, and ephemeral stream channels. Reflections from roads and ditches often lead to these features being identified as not being representative of “bare ground” and consequent deletion of the lidar elevation value for points along these features. Similarly, open water and shrubs and trees growing along ditches and stream channels often lead to rejection of lidar data points near these features.

The asymmetry of these linear features created difficulties for efforts to interpolate valid replacement values for elevation in the areas for which data were missing. We lacked a DEM editor with an interpolation procedure that could operate within a narrow elongated window that fully encompassed the gaps and that was intelligent enough to give preference to using known elevation values along the line of the linear feature (e.g., road or ditch) to estimate the elevation values required to fill in the gaps. Consider, for example, how specialized directional interpolation (e.g., directional kriging) might better interpolate elevation values for missing sections of a road by using only elevation values from locations on the road that bracketed the gaps and not using the much lower elevation values from ditches alongside the road. Similarly, filling in gaps along ditches or channels properly requires an ability to minimize use of elevation values from the higher banks along the draws and to emphasize use of elevation values taken looking forward and backward along the direction of the drainage feature.

We adopted a sub-optimal approach to filling gaps to permit us to proceed with the analysis for which the lidar DEM data were obtained. We passed a series of mean filters of dimensions 7 × 7, 5 × 5, and 5 × 5 over the entire original 3-m lidar DEM and computed a mean value for each 3-m pixel, discounting missing values in the calculation of the mean. Since almost all holes were less than 7 pixels across in their narrowest dimension, this approach produced a reasonably complete and useable DEM. However, it did produce unreliable estimates of elevation for missing portions of most linear features.

A more powerful DEM editor would have allowed us to fill in the gaps more intelligently in either an automated or semi-manual fashion. Improved DEM editors are becoming increasingly available in higher-end commercial photogrammetric and remote sensing software packages, but we did not have access to such software. We would have particularly appreciated being able to interactively edit regions of the lidar DEM of any size and shape. Within identified regions, it would have been useful to be able to select from among a number of different approaches for editing the existing elevation values or for interpolating or adding appropriate elevation values to those portions of the region occupied by missing, or suspect, data values. Desirable DEM editing tools would have included capabilities to outline areas of interest with rectangles, circles, lassoes, or irregular polygons. Within these areas, we would have appreciated an ability to replace existing values with new, manually entered elevation values using familiar image editing concepts such as paint brushes, flood fills, and wands. Additionally, we would have liked to have an ability to selectively filter elevations for only those cells within and adjacent to selected areas to smooth the transitions between edited and unedited areas. Patterson (2001) provides a useful elaboration of the reasons why better tools for editing DEMs are needed and explains how such tools have been used to manipulate DEMs used to construct three-dimensional renderings.

Challenges in computing simulated hydrological networks

Both of our applications had, as key components, the use of calculations of cell to cell hydrological connectivity. One notable consequence of using very fine spatial resolution DEM data to compute cell to cell flow paths is the degree to which the increased amount of detail present in these DEMs confounds and complicates calculations of fully integrated paths of simulated surface water flow. Fine spatial resolution DEMs capture and portray numerous linear features (roads, fence lines, crop swaths, ditches) that act as either barriers or conduits to simulated surface water flow. These features deflect simulated flow from what might be considered its natural course. Culverts and bridges are not recognized, so simulated flow may be erroneously diverted when, in fact, it should continue to flow through or under the linear feature.

Fine spatial resolution data inevitably identify many more depressions, or pits, in the DEM surface than are generally recognized using DEM data of coarser horizontal resolution. Many depressions are artifacts of the grid sampling process, but many others are real. Data on the number of depressions of different sizes for one prairie landscape suggested that depression volumes may be fractal over at least three orders of magnitude (MacMillan, 1994). If this proves to be true for most landscapes, then it would be reasonable to expect the number of pits recognized to increase dramatically (perhaps exponentially) with increasing horizontal and vertical resolution of DEM grid data. Increases in the numbers of pits, and in particular in the number of layers of nested pits, can lead to significant increases in the time required to process DEMs to remove pits and compute flow networks for fully integrated surface flow. Most existing commercial programs for computing flow directions and for removing pits to compute fully integrated flow are already at, or near, their limits in terms of the maximum size of DEM that they can reasonably process and the number of layers of nested pits that they can efficiently remove (Arge et al., 2001). As more workers obtain more fine spatial resolution DEMs from lidar and other sources, the ability of existing programs to process very large DEMs containing many

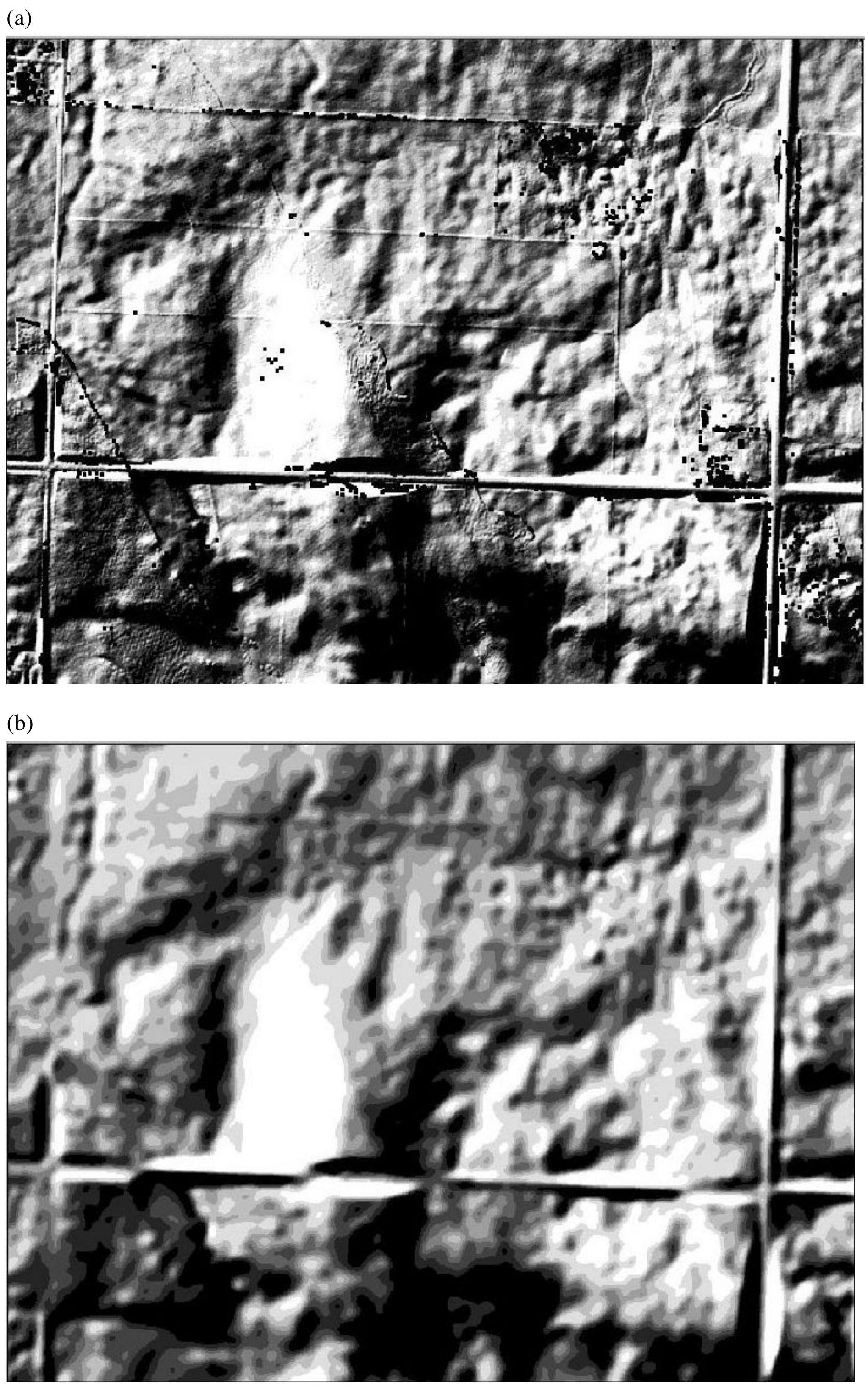

Figure 5. A portion of the 3-m lidar DEM before and after smoothing: (a) hillside image of original, unfiltered 3-m lidar DEM showing gaps and holes; (b) hillshade image of 3-m lidar DEM after filtering to fill gaps and holes.

depressions will be severely tested. It is almost certain that new and more efficient algorithms will be required to process these larger and more detailed datasets. In our applications, we found it convenient, and even necessary, to resample our DEMs from 3- and 5-m grids to a coarser 10-m grid to speed up and simplify processing. We have also found it necessary to develop custom procedures and algorithms for removing pits and computing fully integrated surface flow networks.

Discrepancies between simulated and mapped hydrological networks

One might logically expect to find improvements in the degree of conformance of simulated channel networks to interpreted, blue-line networks with improvement in the horizontal and vertical resolution of the DEM data used to compute simulated networks. However, improved input data lead to increased expectations that are not always met.

Discrepancies between the simulated and mapped channel networks were relatively common in both of the example areas. Perhaps half of the discrepancies arose from errors in calculating flow directions and flow networks using the fine resolution DEM data. The fine spatial resolution DEMs sometimes picked out too much topographic detail, and flow was deflected from its natural course by assumed barriers that effectively did not exist. Discrepancies were more likely to occur for ephemeral (first-order) stream channels than for well-established and well-mapped main channels. In a significant proportion of the cases, discrepancies appeared to be the result of incorrect interpretation of the flow direction and location of the channel as portrayed by the blue-line network. This was particularly true for higher order channels in forested landscapes (the Cariboo area) and in subdued, nearly level topography (both areas).

We lacked suitable tools and techniques for resolving discrepancies between the simulated and the mapped channel networks. Maidment (2000) described an approach in which the original DEM data were modified by “burning-in” the vector blue-line network. The elevations of all cells identified as being along a vector blue-line network were reduced by a constant, large value. This ensured that simulated flow followed the interpreted blue-line network since cells along the blue-line network were forced to have the lowest elevations relative to all adjacent cells not on a mapped blue-line network. This approach, of course, assumes that the blue-line network is completely accurate and that all discrepancies arise from errors in the calculation of simulated flow directions. As noted above, as many as half of the discrepancies we noted appeared to arise from errors in the interpretation and location of the mapped blue-line network.

The approach of Maidment (2000) would resolve discrepancies and produce conformity but at the expense of perpetuating the errors present in the blue-line network. We would have preferred to have had access to a semi-automated method for comparing the blue-line and simulated networks visually and editing the DEM interactively. This kind of capability would let us decide whether to accept and honor the blue-line network and edit the DEM or alternately to accept the simulated network and revise the blue-line network. If the decision was to edit the DEM, it would be desirable to have a capability to trace along the blue-line network in a semi-automated fashion, altering the elevation values of grid cells below the linear feature in a logical and consistent fashion that would enforce continuous down-slope flow and maintain reasonable values for elevation. If the decision was to modify the blue-line network, a vector editing capability would be needed to move vertices along the vector arc so that the resulting blue line conformed to the simulated drainage network. Some existing software packages such as ESRI’s TopoGRID command and ANUDEM (Hutchinson, 2000) offer enhanced capabilities to “produce accurate digital elevation models with sensible drainage properties from point elevations, stream lines, contour lines, and cliff lines” (Hutchinson, 2000). These enhanced interpolation procedures do not, however, provide the DEM editing tools required to identify and resolve discrepancies between mapped blue-line hydrographic networks and drainage networks simulated from DEMs.

Issues concerning increased DEM size and data volumes

Fine spatial resolution DEM datasets can very rapidly achieve a physical size that imposes challenges for processing, display, storage, and transmission. Both of the example applications were, in effect, pilot projects whose aim was to develop and evaluate methods of processing fine resolution DEM data that could be feasibly applied to regions hundreds of kilometers in length and breadth. However, even the relatively modest 5–10 m DEM files developed for the two relatively small pilot areas taxed the capabilities of the available software to process the data in a reasonably efficient manner.

At 5 m, the DEM for the Haynes Creek M1 watershed consisted of 1200 by 1600 cells (total 1.9 million) and the 5-m DEM for the entire PEM pilot area (three map sheets) consisted of 10 000 by 2 600 cells (total 26 million). The algorithms and procedures used in the example applications strained to process even these relatively small datasets. It will not be feasible to apply some of these procedures to datasets much greater than about 10 000 by 10 000 cells. Clearly therefore, it will be necessary to devise a more efficient approach for processing much larger DEM datasets covering much larger areas. Many of these algorithms are of efficiency n^2 or $n \log n$ and so proceed much faster when large datasets are subdivided into a number of smaller tiles.

Efforts underway at present are concentrating on developing techniques for subdividing very large, fine spatial resolution DEMs into smaller, hydrologically independent tiles. The approach being investigated is to resample the fine resolution DEM to a coarser grid (1 in 2 or 1 in 4) and to use this coarser grid to compute the extent of large sub-catchments. A bounding rectangle is then defined that fully encloses each of the defined sub-catchments. The full resolution DEM data are extracted for the area enclosed by each bounding rectangle and the procedures for computing flow topology and applying the classification schemes are applied independently, in sequence, to the full resolution DEM data for each sub-catchment tile. The sub-catchments are assumed to be independent, except that the hydrologic outputs from upslope catchments that cascade into down-slope catchments need to be accounted for by adding them at the input point of the appropriate down-slope catchment.

The discussion presented above highlights just one example of the processing limitations that can be experienced when using very large DEM datasets. The sheer size of datasets required to cover large areas at a fine horizontal spatial resolution imposes numerous other problems in simply handling, storing, or viewing the data, which are not elaborated on here.

Issues of perception and scale

One consequence of working with very fine spatial resolution DEM data for very large areas is that of potential discord between the level of spatial detail in the data and human abilities to perceive and assimilate the resulting classifications. Our initial work with classifying fine spatial resolution DEM data was applied to rather small areas ranging from 800 m by 800 m up to perhaps 2 km by 2 km. Page- or screen-sized renderings of the results of classifying 5–10 m DEMs for areas of this size tended to have a scale of about 1:5 000 to 1:10 000 and were judged to be meaningful for human visual interpretation. The images or maps were neither too general nor did they display too much fragmentation or spatial detail. Depictions of the classification of 5-m grid DEM data for increasingly larger areas tend to become more fragmented, cluttered, and difficult to interpret visually. Goodchild and Proctor (1997) recognized that map makers and modelers make choices to represent the world at a specified level of cartographic detail, using models and specifications designed for that level. They proposed a measure, termed the large over small ratio (LOS) (computed as the length of the area of interest covered by the dataset divided by the length of a single grid cell) to replace the traditional concept of scale. Constraints of conventional manual cartography have typically imposed an upper limit for LOS of 10^3 to 10^4. Our intuitive reaction to classifications we have produced for large areas using very fine resolution DEM data tends to support Goodchild and Proctor's (1997) arguments that there is an effective upper limit for LOS beyond which it would be better to either move to a coarser grid resolution or reduce the extent of the area of interest displayed. It is apparent that we will need to develop strategies for either generalizing results produced using highly detailed spatial data or for tiling the resulting maps for individual display at an appropriate scale.

The need for smoothing: separating signal from noise

We have consistently found that our results for both landform classification and extraction of hydrological features became more meaningful and interpretable when we applied a succession of mean filters to smooth the original fine resolution DEM datasets. This would seem to be counter-intuitive, especially when one considers the apparent fidelity with which the original, unfiltered, fine resolution DEM data portray the topographic surface (**Figures 1a** and **5a** vs. **1b** and **5b**). Why would we want to reduce the apparent quality of these very accurate and very impressive DEM datasets?

In our experience, filtering provides a useful function in bringing out the longer-range signal and masking much of the local shorter-range noise. As an example, consider that with the landform classification we are more concerned with classifying the components or facets of relatively large (50–300 m) hillslopes (e.g., top, scarp, mid, toe, bottom) than with recognizing individual small furrows or forest scarification ridges. Smoothing filters help to improve the classification of grid cells within the context of the larger landform features of interest. Filtering can also improve the extraction of hydrological features (channels and hillslopes) by reducing extraneous local detail and simplifying calculations of integrated hydrological connectivity. We get to see the "big picture" of where channels flow rather than the more detailed picture of every small meander along the way.

What emerges from our experience to date is a recognition of the absolute need to match the level of detail (or spatial resolution) of the input data to the level of abstraction used to define the target feature(s) of interest. If we wish to extract components of a hillslope, we do not want to capture the terrain surface with a level of detail that portrays smaller rills or furrows superimposed on the hillside. From this experience it follows that more spatial detail (smaller grid cells) does not always lead to an improvement in the desired output results. We have tended to favor working with DEMs with a horizontal grid resolution of 5–10 m and vertical accuracy of ±0.30. We have concluded that these are best suited to extracting the landform classes and hydrological entities of greatest interest to us for operational planning and management purposes. Maps and images of hydrologic and geomorphic spatial entities extracted from 5–10 m DEM datasets have been found to be best suited to display or output using representative fraction scales of from 1:5 000 to 1:20 000. Not surprisingly, most maps produced for operational planning and management also tend to be at similar scales of 1:10 000 to 1:20 000.

Summary and conclusions

We believe that we are at the beginning of an explosion in terms of increased availability and increased use of very fine spatial resolution digital elevation data. Increased demand for both improved datasets and improved tools for operational planning and sustainable ecological management, combined with increased availability and lower costs for very fine spatial resolution DEM data, will result in the emergence of many new, or refined, applications and of the tool kits and algorithms required to implement these applications.

We have provided two examples illustrating how very fine resolution DEM data were successfully analyzed to automatically extract geomorphic and hydrologic spatial entities to assist in hydrological modeling and ecological classification. Such applications add value to the basic DEM data and justify its collection. It is our belief that extraction of both geomorphic and hydrologic spatial entities will become increasingly common terrain analysis applications for fine spatial resolution DEM data. We see the combined entities as potentially providing an ideal spatial framework for a number of important activities. One potential application is defining accounting units for mapping and monitoring levels of organic carbon in soils and vegetation for national and regional greenhouse gas (GHG) reporting programs. Another is to use the combined hydrologic-geomorphic spatial entities as a structural framework for modeling and monitoring the movement and fate of materials such as animal effluent, pesticides, herbicides, nutrients, or sediments carried in solution or suspension by surface water flowing over or through the landscape.

In this paper, we have elected to highlight a number of challenges or issues we have encountered in our use of fine spatial resolution DEM data, rather than just reporting on the selected example applications. The main issues may be summarized as follows:

- We envisage a growing need for much more powerful and feature-rich DEM editors that will provide support for comprehensive, convenient, and intelligent manipulation and correction of fine spatial resolution DEM data.
- We regularly encounter a need to identify and resolve discrepancies between stream channels simulated from the DEM and the mapped blue-line network. We believe that this will continue to be a significant issue impeding the effective use of fine spatial resolution DEM data that will need to be resolved.
- We have encountered issues related to data storage, data transfer, and processing efficiency of critical algorithms related to the very large physical size and increased topographic complexity of our fine spatial resolution DEM datasets. We anticipate having to find, or develop, improved procedures for tiling fine spatial resolution DEM datasets for large areas to permit some of our existing algorithms to be able to process the data within reasonable time frames.
- We were alerted to the likely emerging need to address issues of human perception and cognition when using very fine spatial resolution DEM data for very large areas. We will need to address these issues by developing rules and procedures for either limiting the physical size of any given area of interest portrayed using fine spatial resolution DEM data or for generalizing or agglomerating the output from analysis of very fine spatial resolution data for very large areas.
- Finally, we have developed an appreciation of the importance of properly matching the resolution and precision of our input DEM data with the size and scale of the landscape features that are of interest to us. The horizontal and vertical resolution of the DEM sampling framework effectively determines the size and nature of the geomorphic and hydrologic features extracted using the data. For the present, we have elected to apply a series of mean filters to smooth DEMs to bring out longer-range signal and reduce local noise. We await, with anticipation, improved procedures that will use other approaches (e.g., wavelet filtering, Fourier transforms) to separate the signal from the noise more effectively.

Lidar and other DEM data collection technologies are already finding rapid acceptance and widespread use. They will increasingly provide us with greater quantities of data of increasingly fine spatial resolution. We have demonstrated two existing applications that will benefit from such data and will help to justify its collection. However, the opportunities are not without challenges, and we anticipate a growing need for improved tools to manipulate and process very fine spatial resolution DEM data. We also caution that more is not always better and that it is important that the resolution of the input DEM data be matched to the size and scale of the features of interest for a particular application.

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